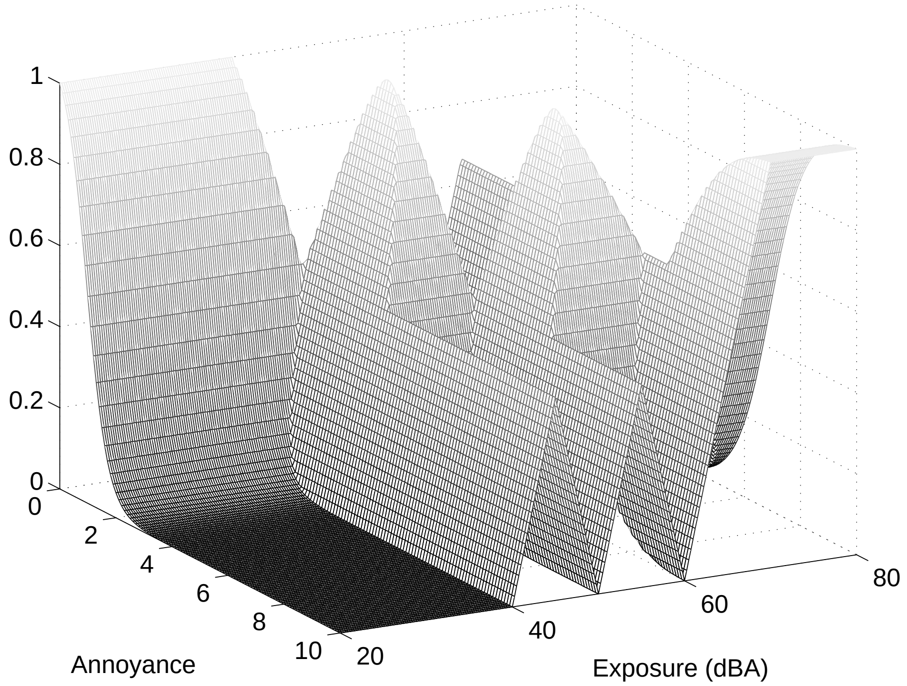
Universiteit Gent
Faculteit Toegepaste Wetenschappen
Vakgroep Informatietechnologie

Introductie van vaagheid in geluidshindermodellen

Fuzzy modeling of noise annoyance

Andy Verkeyn



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In memory of Gino Landerwyn.
A good friend, student, colleague, and above all, my tutor.

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As long as we have memories, yesterday remains,
As long as we have hope, tomorrow awaits.
As long as we have friendship, each day is never a waste.

Anonymous

When I decided to start the study of computer science at the Ghent University in 1993, I was hoping that my time at university would not take any longer than the four obligatory years. However, it turned out quite differently. During those years, I got attracted to the education and research atmosphere of the university. After obtaining my degree, I therefore grabbed the offered opportunity to start working at the university with both hands. I started as a project researcher, later I became a teaching assistant and doctoral student. The latter activities took six years, thus actually extending my university time to more than ten years. The research part resulted in the Ph.D. thesis that is currently in front of you. During all those years, I have been inspired both professionally and personally by many people. I would like to take the opportunity here to express them my sincerest gratitude.

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Samenvatting

Brevity is the soul of wit.

William Shakespeare (1564-1616)
Engels schrijver

1 Probleemstelling

1.1 Ervaren van geluidshinder

Tijdens het uitvoeren van activiteiten worden mensen vaak geconfronteerd met lawaai. Die perceptie van geluid uit onze omgeving kan de activiteiten belemmeren, zoals bv. tijdens praten, luisteren naar de radio, televisie kijken, rusten, slapen, lezen, werken, studeren,... Het geluid stoort of hindert ons. De mate waarin we hinder ervaren zal natuurlijk sterk afhangen van de karakteristieken van het geluid waaraan we blootgesteld worden (de bron van het geluid, luidheid,...). Maar toch zijn dit niet de enige bepalende factoren. Ook persoonlijke, emotionele, situationele,... factoren spelen hierbij een heel belangrijke rol. Een huisvader die 's avonds na een zware dagtaak rustig in zijn zetel zijn krant wil lezen, zal zich sneller ergeren aan lawaai dan een tiener die zich na een saaie schooldag wil ontspannen en buiten gaan spelen.

Naast het ervaren van hinder door omgevingslawaai, kan geluid ook fysiologische gevolgen hebben. Fysiologie is de studie van de functie van het menselijk lichaam. Fysiologische gevolgen hebben dan ook betrekking op veranderingen in het lichaam, zoals bv. een hogere bloeddruk, sneller hartritme en stress hormonen [147]. Het is trouwens goed mogelijk dat deze effecten eerder een gevolg zijn van het ervaren van hinder dan rechtstreeks van de blootstelling aan geluid zelf. Nachtlawaai kan ervoor zorgen dat we ontwaken [66]. Maar verstoring van rust of slaap, zelfs zonder dat we er van wakker worden of het ons herinneren, kan leiden tot loomheid, slaperigheid en nervositeit overdag omdat we minder diep slapen [146].

Een studie onder internationale experten in het vakgebied akoestiek en effecten van geluid, toonde echter aan dat geluidshinder algemeen beschouwd wordt als het belangrijkste gevolg van geluid [79]. Het concept "geluidshinder" is sterk gekoppeld met termen zoals "verstoring" en "overlast". Het wordt algemeen aanvaard als een goede indicator voor het beschrijven van de effecten van omgevingsgeluid op de mens. Formeel is geluidshinder een psychologisch concept dat gedefiniëerd is als "een negatieve evaluatie van de toestand van de omgeving, een reactie voortgebracht door belemmering van activiteiten zoals verstoring van communicatie" [79].

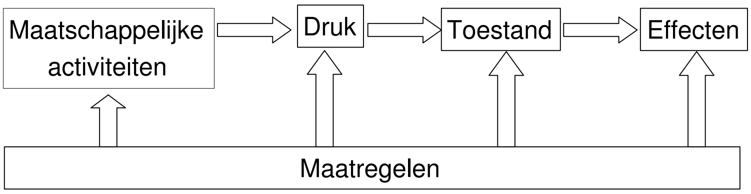
1.2 Duurzame ontwikkeling

De laatste decennia streeft men meer en meer naar een maatschappij gebaseerd op duurzame ontwikkeling, "een maatschappij die voorziet in de behoeften van de huidige generatie zonder daarmee voor toekomstige generaties de mogelijkheden in gevaar te brengen om ook in hun behoeften te voorzien" [1]. Hiervoor is het echter noodzakelijk dat men de effecten van milieuhinder voortdurend opvolgt en kan controleren. Hinder door lawaai is hierbij een belangrijke component die ook moet in rekening gebracht worden.

Om de effecten van geluid op een kordate manier te kunnen opvolgen, moet men in de eerste plaats weten waarvan het geluid komt. Om op dergelijke vragen te kunnen antwoorden, maakt de Europese Commissie gebruik van het DPSI-R model (*Eng.:* Driving forces, Pressure, State, Impact, Responses) [3], zie figuur 1. Dit model vertrekt van de maatschappelijke activiteiten (D) die druk (P) uitoefenen op het milieu door de uitstoot van deeltjes of energie. Deze emissie wijzigt de toestand (S) van het milieu, de immissie, die op haar beurt een effect heeft op de ecosystemen en de mens (I). Het onder controle houden van deze effecten, vereist maatregelen (R) op alle niveaus. Sommige maatregelen ontstaan spontaan in de natuur (zelfregulatie), anderen worden door de beleidsmakers genomen.

Specifiek voor omgevingslawaai neemt dit model volgende vorm aan.

Maatschappelijke activiteiten Een belangrijke activiteit die heel veel geluid produceert is ongetwijfeld verkeer en vervoer. Dit omvat alle mogelijke soorten voertuigen, op de weg, op sporen (treinen, trams en metro), op het water en in de lucht. Natuurlijk kunnen ook andere economische activiteiten geluid veroorzaken, zoals KMO's, fabrieken, bouwindustrie en landbouwwerktuigen. Verder zijn onze vrijetijdsbestedingen eveneens bronnen van geluid, zoals bv. op restaurant en



Figuur 1: DPSI-R model

café gaan, een pretpark of kermis bezoeken,... Gewoon thuisblijven kan dan weer geluid veroorzaken voor onze buren, bv. door het spelen van muziek of geluiden van dieren en kinderen.

Druk De druk die een activiteit op het milieu uitoefent is rechtstreeks verbonden met de bron van het geluid op de specifieke plaats van de bron. Elk type bron heeft haar eigen karakteristieken, zoals frekwentie, tonaliteit, duur,... Een van de belangrijkste karakteristieken is echter het geluidsniveau, uitgedrukt in decibel (dB). Dit is een logaritmische schaal gebaseerd op de fysische geluidsdruk. Ter referentie, een gewone conversatie produceert 60 dB op normale luisterafstand. De gehoordrempel is 0 dB, terwijl de pijngrens ergens op 120 dB ligt.

Toestand De toestand van het milieu beschouwt vooral het geluid dat aanwezig is op een bepaalde plaats, ongeacht de bron waarvan het geluid komt. Het is de immissie van geluid die op een bepaalde locatie door een persoon wordt waargenomen. Hierbij worden de fysiologische aspecten van het menselijk gehoor ook in rekening gebracht. Men heeft immers vastgesteld dat het menselijk gehoor voor bepaalde frekwenties gevoeliger is dan voor andere, sommige frekwenties horen we dus luider dan andere. Dit betekent dat de geluidsniveaus in dB niet geschikt zijn om de luidheid waaraan men blootgesteld is uit te drukken. Ze worden daarom gecorrigeerd volgens de frekwentie-afhankelijke gevoeligheden van het menselijk gehoor. Dit noemt men de A-weging. Het resultaat is het A-gewogen geluidsniveau, uitgedrukt in de A-gewogen decibel dB_A.

Gedurende een bepaalde periode in de tijd is men vaak blootgesteld aan diverse gebeurtenissen die geluid produceren, bv. een vrachtwagen die passeert of een vliegtuig dat overvliegt. Voor het modelleren van hinder zijn die afzonderlijke gebeurtenissen niet belangrijk, men is eerder geïnteresseerd in de globale geluidsniveaus op die plaats. Zo'n algemene maat wordt bekomen door het gemiddelde A-gewogen geluidsniveau over een dag van 24 uur te berekenen waarbij 10 dB_A

extra gerekend wordt voor de nachtelijke uren tussen 22u en 7u. Dit noemt men het dag-nacht geluidsniveau (DNL, L_{dn}). Op dezelfde wijze definiëert men ook het dag-avond-nacht geluidsniveau (DENL, L_{den}) waarbij men 5 $\mathrm{dB_A}$ extra rekent voor de avonduren (19u tot 23u) en 10 $\mathrm{dB_A}$ voor de nachtelijke uren (23u tot 7u).

Effect De gevolgen van geluid op de mens werden al uitvoerig besproken in de vorige sectie.

Maatregelen Men kan verschillende beslissingen nemen om zowel de emissie, immissie als de gevolgen van geluid te beperken. Zo kan men kiezen voor stillere voertuigen en wegenoppervlakken om de geluidsemissie van wegverkeer te verminderen. De immissie kan men verminderen door lawaaierige omgevingen zo veel mogelijk gescheiden te houden van leefomgevingen die meer stilte vragen, bv. door het plaatsen van geluidsschermen en betere isolatie van huizen. Het is de taak van de politieke overheid om dergelijke maatregelen te nemen. Het nauwgezet opvolgen van de hinder die door geluid veroorzaakt wordt en –indien mogelijk– het voorspellen van de hinder na geplande wijzigingen aan de omgeving, bv. de aanleg van een nieuwe weg, is hierbij van essentieel belang.

1.3 Geluidshindermodellen

Geïnspireerd door de DPSI-R ketting, zou men zich dus een model kunnen voorstellen dat vertrekt van de maatschappelijke activiteiten en de ketting vervolgens doorloopt om uiteindelijk te resulteren in een uitdrukking van de hinder die men op een bepaalde plaats zal ondervinden. Helaas is deze simpele gedachtengang in de praktijk niet zo eenvoudig. De problemen die hierbij komen kijken hebben allemaal betrekking op het verwerven, voorstellen en verwerken van informatie. Laat ons daarom eerst even de verschillende soorten informatie van naderbij onderzoeken [131].

De meest eenvoudige soort informatie is precieze informatie, gegeven door een (scherp) getal, bv. “het geluidsniveau van de muziek is 100 $\mathrm{dB_A}$”. Maar in de realiteit is informatie vaak niet zo precies. De uitdrukking “het geluidsniveau van de muziek is tussen 90 en 110 $\mathrm{dB_A}$” bevat onnauwkeurige informatie. Vage informatie is onnauwkeurige informatie die zelfs niet tussen scherpe grenzen kan opgegeven worden, bv. “het geluidsniveau van de muziek is luid”. Soms kan er twijfel zijn omtrent de waarheid van informatie, men spreekt dan over onzekere informatie, bv. “het geluidsniveau van de muziek is mogelijks 100 $\mathrm{dB_A}$”. Deze onzekerheid kan bv. te wijten zijn aan fouten aan de meetapparatuur, slechte afstelling,... Onnauwkeurigheid en onzekerheid zijn orthogonale concepten die ook gecombineerd kunnen voorkomen, bv. "het geluidsniveau van de muziek is mogelijks tussen 90 en 110 dB_A". Informatie die onnauwkeurig en/of onzeker is, noemt men ook wel eens imperfecte informatie.

Als men nu het DPSI-R model wil volgen vanaf de maatschappelijke activiteiten tot de effecten van geluid, krijgt men te maken met volgende problemen. De concepten worden subjectiever en vager. Waar men de emissie van geluidsniveaus kan meten en uitdrukken op een fysische, numerieke schaal, is dit niet meer mogelijk voor concepten zoals geluidshinder en gevoeligheid voor geluid. Ten eerste bestaat er voor dergelijke concepten geen fysische schaal meer en ten tweede, beschrijven deze concepten veeleer een gevoel, die men niet als een scherp getal kan communiceren. Gegevens worden zeldzamer, onnauwkeuriger en onzekerder. Het verzamelen van grote hoeveelheden gegevens om modellen te valideren is een tijdrovende en dure aangelegenheid. Vaak is men dan ook aangewezen op veralgemeningen of extra- en interpolaties waardoor de onzekerheid toeneemt. Gegevens die gemeten worden, zijn vaak onderhevig aan onzekerheden door meetfouten. Aan de andere kant zijn er ook concepten die niet eens kunnen gemeten worden, bv. geluidshinder. Gegevens over dergelijke concepten worden typisch verzameld via enquêtes, uitgevoerd per post, per telefoon of persoonlijk aan de deur. Hierbij worden mensen gevraagd om een aantal vragen te beantwoorden. Gegevens op zo'n manier verzameld zijn vaak onvolledig (mensen kunnen vragen vergeten te beantwoorden), onnauwkeurig (door slecht gekozen antwoordmogelijkheden) en onzeker (door menselijke fouten tijdens het aankruisen van het gekozen antwoord). Kennis wordt schaarser, vager en onzekerder. Hoewel er fysische wetten bestaan die de voortplanting van geluid beschrijven, is nog maar weinig gekend over de voortplanting van geluid over grotere afstanden (zelfs al vanaf enkele honderden meters). Over variabelen die de ervaring van geluidshinder beinvloeden en de precieze relaties is echter nog veel minder gekend. Vaak kunnen experten in het domein enkel vage uitdrukkingen geven over de relaties die momenteel verondersteld worden. Dergelijke kwalitatieve kennis gebruiken in rekenmodellen is niet triviaal.

In dit werk wordt hinder als het belangrijkste effect van omgevingslawaai gemodelleerd. Vertrekkende van het einde van de DPSI-R ketting, wordt het concept geluidshinder ontleed tot aan de toestand van de omgeving en alle factoren die de perceptie van geluid beinvloeden. Hierbij moet het ontwikkelde model in staat zijn om op een natuurlijke, zinvolle manier om te gaan met vage en onzekere concepten, gegevens en kennis. Meerbepaald stellen we volgende doelstellingen voorop.

Tolerant De aanpak moet tolerant zijn voor informatie –zowel gegevens als kennis– die onnauwkeurig, vaag of onzeker is of die ontbreekt. Het model moet zo nauwkeurig mogelijk functioneren met de beschikbare informatie.

Betrouwbaar De resulterende uitdrukking van geluidshinder moet zinvol zijn. Het resultaat mag niet nauwkeuriger zijn dan haalbaar op basis van de beschikbare informatie. Als het resultaat niet op een natuurlijke manier kan uitgedrukt worden als een getal, dan mag het systeem dat ook niet doen. De uitvoer moet betrouwbaar zijn binnen de grenzen van de invoer, en een hint geven omtrent de bereikte betrouwbaarheid.

Robuust Het model moet robuust zijn. Kleine schommelingen in de invoergegevens (bv. door onzekerheid op meetapparatuur) mag geen grote invloed hebben op het resultaat.

Interpreteerbaar De werking van het model moet transparant en eenvoudig te begrijpen zijn voor een expert. De betekenis en het interne redeneerproces moet duidelijk zijn.

Persoonlijk De hindervoorspelling moet op een persoonlijke basis zijn en niet statistisch uitgemiddeld. De invloed van persoonlijke, emotionele, situationele,... variabelen moet men in rekening kunnen brengen.

Adaptief Het systeem moet de mogelijkheid bieden om de waarheid van hypothetische kennis te testen. Het moet een werkinstrument zijn waarmee men kan onderzoeken welke variabelen een invloed hebben op de ervaring van hinder, en hoe de relaties tussen die variabelen en hinder zijn.

Op basis van het voorgaande, spreekt het voor zich dat de behandeling van vaagheid en onzekerheid van informatie speciale aandacht zal vragen. Dit is echter niet eenvoudig in een wiskundige wereld die volledig gedragen wordt door de wetten van de binaire logica. Het is op die manier immers onmogelijk om op een wiskundige manier gradaties uit te drukken, alles is ofwel volledig waar ofwel volledig vals.

Om toch op een wiskundig verantwoorde manier te kunnen omgaan met de graduele overgangen van concepten uit de reële wereld, introduceerde Zadeh in 1965 de vaagverzamelingenleer [183]. In een vaagverzameling heeft een object een lidmaatschapsgraad die uitdrukt in welke mate het object behoort tot een klasse van objecten die geen scherpe grenzen heeft, bv. de klasse van mooie vrouwen. Sindsdien zijn de vaagverzamelingenleer en de daarmee samenhangende vaaglogica [188] en possibiliteitstheorie [191] [54] uitgegroeid tot de instrumenten bij uitstek om vage en onzekere informatie te modelleren. In dit werk zal aangetoond worden dat de theorie van vaagverzamelingen uitermate geschikt is om de problemen rond het modelleren van hinder aan te pakken en de naar voor geschoven doelstellingen te bereiken.

Voor een uitvoerige bespreking van de relevante wiskundige concepten uit de vaagverzamelingenleer wordt verwezen naar de literatuur [53] [58] [97] [132], of naar hoofdstuk 2 in dit werk.

2 Voorstellen van geluidshinder

2.1 Hinderschalen

Vooraleer men kan spreken over het modelleren van geluidshinder moet men eerst weten hoe men geluidshinder wil gaan voorstellen, wat een geschikte representatievorm is voor het concept geluidshinder. Voor geluidshinder ontbreekt een algemeen aanvaarde schaal. Dit komt wellicht door het feit dat geluidshinder geen fysische, onderliggende schaal heeft, het is een puur psychologisch concept. Dit heeft twee belangrijke gevolgen. Ten eerste moet men zijn toevlucht nemen tot een denkbeeldige schaal en ten tweede kan men geluidshinder niet meten. Informatie over geluidshinder moet men verzamelen via enquêtes. Om de vraag naar de ervaring van geluidshinder te beantwoorden, worden diverse hinderschalen gebruikt, zoals numerieke categorieën (bv. 1 tot 5 of 0 tot 10), een continue lijnschaal of een verbale schaal met vier of vijf linguïstische termen. Deze laatste schaal levert de bijkomende moeilijkheid van taalgebruik, maar anderzijds is het ook een veel natuurlijker manier om een niveau van hinder uit te drukken. Deze methode heeft wel als nadeel dat men nu niet meer zeker kan zijn dat het universum opgedeeld is in categorieën die op gelijke afstand van elkaar liggen. Uit een laboratoriumexperiment van Rohrmann is echter wel gebleken dat mensen niet uitsluitend de betekenis van woorden in rekening te brengen maar de neiging hebben om alle termen op de schaal op een gelijke afstand van elkaar te verdelen.

Een groot nadeel van het gebruik van deze uiteenlopende schalen, is dat men de resultaten van twee enquêtes heel moeilijk met elkaar kan vergelijken. Vaak is men voor het opstellen van een model gebonden door de gegevens die in één welbepaalde enquête verzameld zijn. Zelfs wanneer enquêtes een verbale schaal gebruiken, kunnen er veel verschillen zijn die onderling vergelijken moeilijk maken: verschillen in taal, verschillen in terminologie en verschillen in het aantal termen op de schaal. Daarnaast kunnen de formulering van de hindervraag, verschillen in cultuur en de contekst van de enquête uiteraard ook nog de resultaten beïnvloeden

Historisch heeft de term “erg gehinderd” een bijzondere plaats ingenomen, als een belangrijke term om te modelleren. Om een numerieke (of continue schaal) “om te rekenen” naar ernstige hinder, wordt traditioneel 7.2 op een schaal tussen 0 en 10 als scheidingspunt genomen [140]. Andere gekende scheidingspunten zijn 5.0 voor “gehinderd” en 2.8 voor “minstens een beetje gehinderd” [123]. Beneden 2.8 wordt dan geïnterpreteerd als “helemaal niet gehinderd”. Het spreekt voor zich dat dergelijke scherpe scheidingspunten op zijn zachtst gezegd arbitrair zijn en totaal niet in overeenstemming zijn met de eigenlijke betekenis van de termen.

In dit werk wordt hinder benaderd als een inherent vaag en subjectief concept. Het is een gevoel, een gemoedstoestand die voortvloeit uit de perceptie van geluid die men niet kan uitdrukken met een (scherp) getal. Men kan er echter wel over communiceren in natuurlijke taal. Als iemand beweert dat hij “een beetje” gehinderd is, dan weten we min of meer hoe die persoon zich voelt. Er is hier echter geen sprake van scherpe grenzen, de grenzen zijn gebieden waarin de term langzaam overgaat van passend tot niet-passend. Dergelijke concepten zijn ideaal om te modelleren als linguïstische variabelen in de vaagverzamelingentheorie [188] [82]. Een linguïstische variabele is een variabele die als waarden geen getallen aanneemt maar woorden of zinnen uit een natuurlijke taal. In de uitdrukking “Cindy is jong” kan “jong” beschouwd worden als een linguïstische waarde van de linguïstische variabele “Leeftijd”. Een vaagverzameling kan dan gebruikt worden om de betekenis van een linguïstische waarde voor te stellen, bv. een vaagverzameling met als domein het interval $[0, 120]$.

Vooraleer hinder te modelleren als een linguïstische variabele, zullen de resultaten van een internationale hinderschaalstudie besproken worden.

2.2 Internationale hinderschaalstudie

In 1993 heeft team 6 van de Internationale Commissie voor de Biologische Effecten van Geluid (ICBEN) een studie opgezet om tot een internationale consensus te komen voor de keuze van linguïstische termen voor een hinderschaal in enquêtes [65]. De bedoeling was de constructie van een linguïstische schaal met termen op een gelijke afstand van elkaar gelegen. De procedure begon met de selectie van 21 hindertermen (bijwoorden). Vervolgens werden deze gepresenteerd aan zowel universitaire studenten als aan personeel van bedrijven. Zij werden gevraagd om voor elke term een tekentje te plaatsen op een lijn van 10 cm die de intensiteit van de betekenis van de term aangeeft. Hierbij stond de meest linkse kant van de lijn voor "helemaal geen hinder" terwijl de uiterst rechtse kant het "grootste mogelijke niveau van hinder" voorstelde. Daarna moesten ze de termen aangeven die ze verkiezen voor een vijfpuntsschaal en een vierpuntsschaal. De term voor de laagste categorie lag telkens vast op "helemaal niet gehinderd". Deze enquête werd afgenomen bij 1754 personen verspreid over negen verschillende talen in twaalf landen. De resultaten werden voor elke taal afzonderlijk geanalyseerd, waarbij de termen voor een vierpunts– en vijfpuntsschaal werden vastgelegd. De gemiddelde intensiteit op de 10 cm lijn van elke Engelse en Nederlandse term, alsook de bijhorende standaardafwijking en de gekozen termen zijn samengevat in tabel 1.

Tabel 1: Engelse en Nederlandse hindertermen met hun gemiddelde intensiteit μ en de standaardafwijking σ. De geselecteerde termen voor een vijfpuntsschaal staan in **vet**, de vierpuntsschaal termen in *schuinschrift*.

Code	Engels	μ	σ	Nederlands	μ	σ
L01	***not at all***	0.08	0.50	***helemaal niet***	0.04	0.07
L02	insignificantly	0.76	0.86	niet	0.14	0.26
L03	barely	0.81	0.81	nauwelijks	0.94	0.77
L04	hardly	1.03	1.24	weinig	1.24	0.65
L05	a little	1.32	0.81	iets	1.57	1.03
L06	**slightly**	1.54	0.94	lichtelijk	1.64	1.00
L07	partially	2.96	1.30	**een beetje**	1.65	0.94
L08	*somewhat*	3.57	1.53	enigzins	2.59	1.35
L09	fairly	4.05	1.49	*matig*	3.44	1.39
L10	**moderately**	4.37	1.09	**tamelijk**	3.92	1.47
L11	rather	4.79	1.72	behoorlijk	6.21	1.70
L12	importantly	6.51	1.43	*aanzienlijk*	6.81	1.57
L13	considerably	6.22	1.70	veel	6.90	1.20
L14	substantially	6.45	1.53	**erg**	7.42	1.08
L15	*significantly*	6.72	1.42	sterk	7.79	1.06
L16	**very**	7.56	1.21	zeer	8.03	0.87
L17	highly	7.87	1.08	ernstig	8.05	1.02
L18	strongly	7.97	0.94	enorm	8.59	0.99
L19	severely	9.07	1.14	ontzettend	8.74	0.93
L20	tremendously	9.23	0.94	uitermate	8.91	1.03
L21	***extremely***	9.49	0.87	***extreem***	9.78	0.27

Tijdens deze studie werd voor elke taal ook de formulering van de vragen omtrent hinder vastgelegd.

2.3 Vaagverzamelingen voor hindertermen

2.3.1 Inleiding

Om hinder te kunnen voorstellen als een linguïstische variabele, moet men voor elke hinderterm een vaagverzameling definiëren. In overeenstemming met de internationale hinderschaalstudie wordt het interval $[0, 10]$ gekozen als domein voor deze vaagverzamelingen. Doorheen dit werk zal het symbool $\mathcal{H}$ gebruikt worden om de linguïstische variabele "hinder" aan te duiden. Het domein zal genoteerd worden als $\mathbb{H} = [0, 10]$. De verzameling van de linguïstische waarden die $\mathcal{H}$ kan aannemen zal genoteerd worden als $\mathbb{L} = \{L_1, L_2, \ldots, L_m\}$ met $m \in \mathbb{N}$, L is dan een generiek element van deze verzameling.

In een van de eerste vage analyses van linguïstische termen, kwamen Hersch en Caramazza [82] tot de conclusie dat vaagverzamelingen uitermate geschikt zijn voor de voorstelling van termen uit de natuurlijke taal. Ze stelden eveneens vast dat er twee interpretaties mogelijk zijn: de logische en de linguïstische interpretatie. De logische interpretatie, hier "inclusieve interpretatie" [46] genoemd, gaat ervan uit dat iedereen die "extreem gehinderd" is ook kan beschouwd worden als zijnde (tenminste) "ernstig gehinderd". Elke term wordt in principe vooraf gegaan door "tenminste". De lidmaatschapsfunctie van elke term is stijgend en omvat de lidmaatschapsfuncties van alle volgende termen. De linguïstische interpretatie, hier de "niet-inclusieve interpretatie" [46] genoemd, is niet uitsluitend geïnspireerd op de (logische) waarheid, maar houdt vooral rekening met de betekenis van de woorden in het dagelijks taalgebruik. Iemand die gevraagd wordt naar de mate waarin hij gehinderd is, zal niet "ernstig gehinderd" antwoorden als hij in feite "extreem gehinderd" is. De lidmaatschapsfuncties zijn klokvormig, behalve de lidmaatschapsfunctie van de eerste en de laatste term die respectievelijk dalend en stijgend zijn.

Twee methodes om vaagverzamelingen te construeren zullen besproken worden, methodes gebaseerd op probabiliteitsdistributies en op basis van vervagingen van scherpe punten die de betekenis van termen weergeven. Deze zullen geïllustreerd worden met de vijf Engelse hindertermen die in de hinderschaalstudie gekozen werden, L_1 = "not at all annoyed" ("helemaal niet gehinderd"), L_2 = "slightly annoyed" ("een beetje gehinderd"), L_3 = "moderately annoyed" ("tamelijk gehinderd"), L_4 = "very annoyed" ("erg gehinderd") en L_5 = "extremely annoyed" ("extreem gehinderd"), met

$\mathbb{L} = \{L_1, L_2, \ldots, L_5\}$.

2.3.2 Probabilistische methodes

De probabilistische methodes vertrekken van het frekwentiehistogram van punten die geëvalueerd werden als passend bij de betekenis van een bepaalde term L, bv. op basis van de resultaten van de internationale hinderschaalstudie. Deze frekwentiedistributie wordt dan genormaliseerd naar een probabiliteitsdistributie die vervolgens omgezet wordt in een possibiliteitsdistributie. Dit resulteert in een vaagverzameling die de niet–inclusieve interpretatie van de term L voorstelt. Wanneer men gebruik maakt van de cumulatieve probabiliteitsdistributie, dan verkrijgt men de inclusieve interpretatie.

Om de ruis in de staarten van de distributies te onderdrukken, kan men ofwel de schaal discretiseren in een beperkter aantal intervallen, ofwel de best passende, vloeiende curve zoeken bij de possibiliteitsdistributie. In de laatste techniek kan de aanwezige ruis in de probabiliteitsdistributie echter een invloed hebben op de transformatie naar de possibiliteitsdistributie.

Er zijn drie soorten transformaties om probabiliteit om te zetten naar possibiliteit. Veronderstel de probabiliteitsdistributie p en de possibiliteitsdistributie π over het discrete domein $\{h_1, h_2, \ldots, h_n\}$, met $h_i \in \mathbb{H}$ voor $i \in \{1, 2, \ldots, n\}$ en $p_i = p(h_i)$ en $\pi_i = \pi(h_i)$.

Maximum-normalisatie Hierbij wordt de distributie enkel (possibilistisch) genormaliseerd door te delen door de grootste probabiliteit [93].

Onzekerheidsbehoudende transformatie Deze transformatie voorgesteld door Klir, gaat ervan uit dat bij een overgang van een theorie naar een andere, de hoeveelheid onzekerheid ongewijzigd moet blijven. De onzekerheid van een probabiliteitsdistributie wordt gegeven door de entropie, gedefineerd als,

$$H(p) = -\sum_{i=1}^{n} p_i \log_2 p_i \ . \tag{1}$$

Bij possibiliteitsdistributies maakt men onderscheid tussen de niet-specificiteit $N(\pi)$ en de ambiguïteit $D(\pi)$. In de definities van N en D veronderstelt men de ordening $\pi_1 \geq \pi_2 \geq \ldots \geq \pi_n$.

$$N(\pi) = \sum_{i=2}^{n} \pi_i \log_2 \frac{i}{i-1} \tag{2}$$

$$D(\pi) = -\sum_{i=1}^{n-1} (\pi_i - \pi_{i+1}) \log_2 \left(1 - i \sum_{j=i+1}^{n} \frac{\pi_j}{j(j-1)} \right) \tag{3}$$

Om de hoeveelheid onzekerheid te behouden moet aan volgende vergelijking voldaan zijn: $H(p) = N(\pi) + D(\pi)$. Klir poneerde dat enkel volgende transformatie voor alle distributies bestaat en uniek is.

$$\pi_i = \left(\frac{p_i}{p_{\max}}\right)^{\alpha} \tag{4}$$

met $p_{\max}$ de grootste probabiliteit. De constante α wordt bepaald door minimalisatie van het verschil tussen H en $N + D$ en ligt in het interval $[0, 1]$.

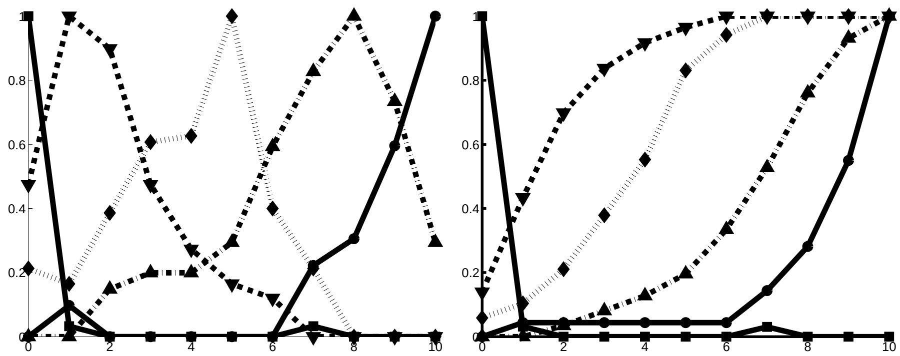
Probabilistisch-verschiltransformatie Deze methode werd gedefiniëerd door Dubois en Prade. Ze gaat uit van drie basisprincipes: de consistentie tussen probabiliteit en possibiliteit, behoud van voorkeur uitgedrukt door de distributies en het optimaal gebruik van de aanwezige informatie. De transformatie wordt gegeven door

$$\pi_i = \sum_{j=1}^{n} \min(p_i, p_j) \ . \tag{5}$$

De vaagverzamelingen voor de vijf Engelse hindertermen geconstrueerd met deze methode (onzekerheidsbehoudende transformatie) worden getoond in figuur 2. Hierbij werden de gegevens van de hinderschaalstudie eerst gediscretiseerd in 11 intervallen. Aangezien deze methode enkel steunt op de gegevens van de term zelf, is ze bijzonder geschikt om de werkelijke betekenis van de termen te modelleren, los van relaties tussen de termen onderling.

2.3.3 Vervagingsmethodes

Het uitgangspunt van deze methodes is het feit dat het teken h_j^k geplaatst door persoon k, $k \in \{1, 2, \ldots, N\}$ met N het totaal aantal personen, voor een term L_j, $j \in \{1, 2, \ldots, 5\}$, omgeven is door onnauwkeurigheden. Mensen hebben immers het teken geplaatst “in de buurt” van de betekenis van de term, zonder exact de afstand te meten. Het is dus gerechtvaardigd om een vaagverzameling te definiëren rond het teken h_j^k van elke persoon om deze onnauwkeurigheden uit te drukken. Met het oog op een inclusieve interpretatie zullen deze onnauwkeurigheden zich enkel langs de linkerkant van het teken bevinden (rechts van het teken zal de lidmaatschapsgraad overal 1 zijn). Voor de niet-inclusieve interpretatie, zijn de onnauwkeurigheden aan beide zijden aanwezig (behalve voor de eerste en laatste term). Wanneer al deze individuele vaagverzamelingen voor een bepaalde term



Figuur 2: Vage representatie van de betekenis van vijf hindertermen ("not at all", "slightly", "moderately", "very", "extremely") op basis van de onzekerheidsbehoudende transformatie (links: niet-inclusieve interpretatie, rechts: inclusieve interpretatie)

L_j uitgemiddeld worden over alle personen, bekomt men een vaagverzameling die de consensus van de betekenis van de term voorstelt. Om ruis te onderdrukken, kan men hier ook een best passende, vloeiende curve bepalen.

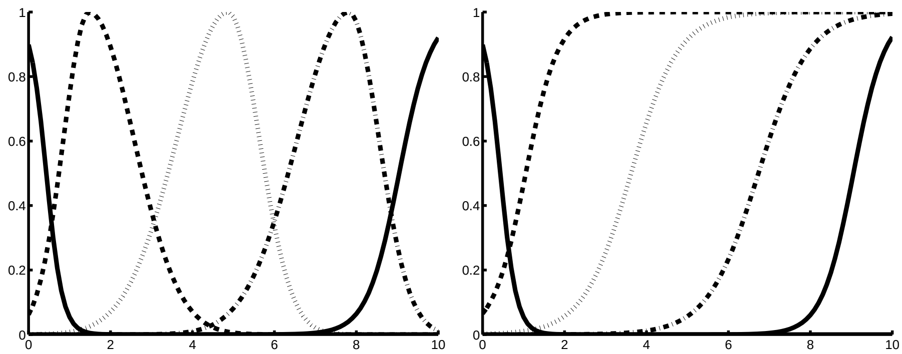
In [36] stelde Cleeren voor om het teken h_j^k van elke persoon te vervagen met flanken gebaseerd op de globale standaardafwijking van alle merktekens van de term L_j. Hierin komt immers de consistentie van de betekenis van de term over de ganse groep van personen tot uitdrukking. Toch heeft deze aanpak enkele nadelen. Ten eerste, wordt geen rekening gehouden met de relaties tussen de termen die een bepaalde persoon in zijn gedachten heeft. Dit is echter wel belangrijk om een correcte vervaging van een term te kunnen bepalen. Ten tweede, veronderstelt men dat de standaardafwijking van één persoon 100 keer de betekenis van een term vragen, gelijk is aan de standaardafwijking van die vraag 1 keer aan 100 verschillende personen te stellen. Dit impliceert dat elke term dezelfde betekenis zou hebben voor alle personen. En ten derde, levert deze aanpak vaagverzamelingen op die elkaar een flink stuk overlappen, waardoor hun praktische bruikbaarheid daalt.

Om deze problemen op te lossen, wordt hier een methode voorgesteld waarbij men elk teken vervaagt zodat het snijpunt van de flanken van twee opeenvolgende termen altijd gelijk is aan een vooraf gekozen constante α. Bijvoorbeeld voor de constructie van een asymmetrische Gaussiaanse curve rond het teken h_j^k met linkerflank σ_j^k en rechterflank δ_j^k voor twee opeenvolgende termen j en $j+1$,

$$\delta_j^k = \sigma_{j+1}^k = \left(\frac{1}{\sqrt{-2\ln(\alpha)}}\right)\frac{h_{j+1}^k - h_j^k}{2} \tag{6}$$

De limiet waarbij α naar 0 gaat, resulteert in $\lim_{\alpha\to 0}\frac{1}{\sqrt{-2\ln(\alpha)}} = 0$, wat impliceert dat de standaardafwijking van de flanken 0 wordt en de methode zich reduceert tot de probabilistische methoden.

Het resultaat van deze methode voor de vijf Engelse termen die in de internationale hinderschaalstudie gekozen werden, wordt getoond in figuur 3. Hier worden de onderlinge relaties tussen de termen wel gebruikt. Het resultaat is dus afhankelijk van de verzameling termen die gemodelleerd worden, en heeft de neiging om het volledige domein te bedekken. De mate van overlapping kan gecontroleerd worden met de parameter α. De vaagverzamelingen zijn hierdoor uitermate geschikt om te gebruiken in regelgebaseerde toepassingen, waarin een zekere overlappingsgraad wenselijk is.



Figuur 3: Vage representatie van de betekenis van vijf hindertermen ("not at all", "slightly", "moderately", "very", "extremely") op basis van de vervagingsmethode met $\alpha = 0.1$ (links: niet-inclusieve interpretatie, rechts: inclusieve interpretatie)

2.4 Vertalen van hindertermen

Nu we beschikken over vaagverzamelingen die de betekenis van linguïstische termen in diverse talen op een uniforme manier voorstellen, kunnen alle wiskundige operatoren erop los gelaten worden. Zo kan men gebruik maken van een similariteitsmaat om de gelijkaardigheid van twee vaagverzamelingen te bepalen. Hoe beter twee vaagverzamelingen op elkaar gelijken, hoe meer ze eenzelfde betekenis van termen voorstellen en dus, hoe beter ze in aanmerking komen als vertalingen van elkaar.

Dit principe kan men aanwenden om met behulp van de gegevens van de internationale hinderschaalstudie een automatische vertalingsapplicatie te ontwerpen. Voor alle termen wordt een vaagverzameling opgebouwd. Aangezien deze vaagverzamelingen zo goed mogelijk de echte betekenis moeten weergeven, wordt de probabilistische constructiemethode met de onzekerheidsbehoudende transformatie gebruikt. Uit experimenten is gebleken dat de parameter α altijd min of meer rond 0.5 ligt. Om een automatische verwerking te vereenvoudigen zal deze parameter dan ook vast gekozen worden op 0.5.

In [151] werd een geparameteriseerde similariteitsmaat voorgesteld die bruikbaar is in een brede waaier van toepassingen, voor twee vaagverzamelingen A en B over het universum U,

$$\mathrm{Sim}_{\mathcal{T}}(A,B) = \mathcal{T}(C_{1,\mathcal{T}}(A,B), S(E_{\mathcal{T}}(A,B), C_{2,\mathcal{T}}(A,B)))$$

met $\mathcal{T}$ een driehoeksnorm en S zijn duale driehoeksconorm. De operator $E_{\mathcal{T}}$ is een $\mathcal{T}$-gelijkheid gedefiniëerd als [44],

$$E_{\mathcal{T}}(A,B) = \mathcal{T}\left(\inf_{u\in U} \mathcal{I}_{\mathcal{T}}(A(u),B(u)), \inf_{u\in U} \mathcal{I}_{\mathcal{T}}(B(u),A(u))\right)$$

met $\mathcal{T}$ een driehoeksnorm en $\mathcal{I}_{\mathcal{T}}$ de residuele implicator voortgebracht door deze driehoeksnorm. $C_{1,\mathcal{T}}$ en $C_{2,\mathcal{T}}$ zijn twee compatibiliteismaten, gegeven door

$$C_{1,\mathcal{T}}(A,B) = \frac{\sup\limits_{u\in U} \mathcal{T}(A(u),B(u))}{\sup\limits_{u\in U} S(A(u),B(u))} \quad C_{2,\mathcal{T}}(A,B) = \frac{\sum\limits_{u\in U} \mathcal{T}(A(u),B(u))}{\sum\limits_{u\in U} S(A(u),B(u))}$$

met $\mathcal{T}$ een driehoeksnorm en S zijn duale driehoeksconorm.

Voor een automatische vertalingsapplicatie kiezen we $\mathrm{Sim}_{\mathcal{T}} = \mathrm{Sim}_{\mathcal{T}_M}$, $C_{1,\mathcal{T}} = C_{1,\mathcal{T}_M}$, $C_{2,\mathcal{T}} = C_{2,\mathcal{T}_M}$ en $E_{\mathcal{T}} = E_{\mathcal{T}_W}$ [39].

Om nu op basis van de similariteit tussen een term en een aantal andere termen een "goede" vertaling te kiezen, kan men ofwel alle termen boven een drempelwaarde s_0 behouden, ofwel enkel de term met de hoogste similariteitsgraad $s_{\max}$ kiezen, ofwel alle termen binnen een klein bereik δ van $s_{\max}$ aanvaarden. De laatste optie lijkt het meest aangewezen om te vermijden dat er binnen een beperkte woordenschat geen vertaling gevonden wordt (bij te hoge s_0) en om de resultaten niet te laten beïnvloeden door kleine storingen in het bepalen van de lidmaatschapsfuncties.

In tabel 2 worden de engelse termen van de vijfpuntsschaal vertaald naar het Nederlands en worden al de gevonden vertalingen terug naar het Engels vertaald. Er mogen hierbij alternatieven bijkomen, maar het belangrijkste is dat de oorspronkelijke term teruggevonden wordt. Dit is meestal het geval maar niet altijd, bv. voor "moderately" waarvoor geen echt goede vertaling bestaat binnen de beschikbare woordenschat. Over het algemeen corresponderen de resultaten met de nederlandse vijfpuntsschaal (behalve voor "een beetje"). De automatische vertalingen lijken vrij goed vanuit intuïtief oogpunt. Het vertalen van een ideale vage taal waarbij het volledig universum perfect verdeeld wordt over vijf termen met driehoekige lidmaatschapsfuncties, levert zowel voor het Engels als het Nederlands de voorgestelde termen op, behalve voor het eerste label (zie tabel 3). Bemerk dat net deze termen vooraf vastgelegd werden in de internationale hinderschaalstudie.

Een grondige gevoeligheidsanalyse van de gebruikte discretisatie en operatoren toont aan dat deze vertalingsprocedure vrij stabiel is voor een groot aantal keuzes.

Tabel 2: Vertaling van het Engels naar het Nederlands en terug. De voorkeurstermen staan in schuinschrift, niet automatisch gevonden voorkeurstermen zijn apart gegeven tussen haakjes. Voor elke Nederlandse term is de similariteitsgraad met het Engels tussen haakjes geplaatst.

Engels	Nederlands	Engels
not at all	*helemaal niet* (0.93)	**not at all**
slightly	lichtelijk (0.91)	**slightly**
	(*een beetje* (0.85)	slightly)
moderately	matig (0.57) *tamelijk* (0.53)	partially somewhat fairly
very	*erg* (0.82)	**very**
extremely	*extreem* (0.70)	**extremely**

Tabel 3: Vertaling van een ideale vage taal met $\delta = 0.05$.

Ideale taal	Engels	Nederlands
Label 1	insignificantly	niet
Label 2	**slightly** partially	iets lichtelijk **een beetje** enigzins matig
Label 3	**moderately**	matig **tamelijk** behoorlijk
Label 4	**very** strongly	**erg** sterk
Label 5	**extremely**	**extreem**

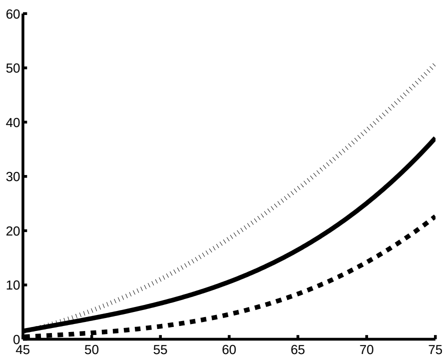
3 Modelleren van geluidshinder

3.1 Hinder door specifieke brontypes

3.1.1 Inleiding

De huidige methode voor het inschatten van geluidshinder afkomstig van één brontype (bv. wegverkeer) is gebaseerd op een statistische aanpak die een indicatie geeft voor het percentage “erg gehinderden”. Hierbij wordt een lineair verband met een normaal verdeelde variabele component verondersteld tussen de blootstelling aan geluid (DNL) en de ervaring van hinder. Het percentage “erg gehinderden” wordt dan berekend op basis van een (scherpe) grens van 7.2 op een schaal van 0 tot 10 (5.0 voor het percentage “gehinderden” en 2.8 voor het percentage “minstens enigzins gehinderden”). Miedema en Oudshoorn hebben voor dergelijke meta-analyses momenteel de grootste verzameling geluidshinderstudies verzameld. Hierbij maken zij onderscheid tussen hinder door wegverkeer, treinverkeer en luchtverkeer [122]. Hun resulterende dosis-effect relaties worden getoond in figuur 4.

Hoewel dergelijke dosis-effect relaties al lang gebruikt worden, was er al van bij hun ontstaan veel kritiek te horen. Zo veronderstelt deze aanpak dat persoonlijke factoren uitmiddelen over grote groepen, DNL een goede



Figuur 4: Dosis-effect relaties van Miedema & Oudshoorn [122] waarbij het percentage erg gehinderden uitgezet wordt in functie van DNL voor lawaai van vliegtuigen (puntlijn), wegverkeer (volle lijn) en treinverkeer (stippel lijn).

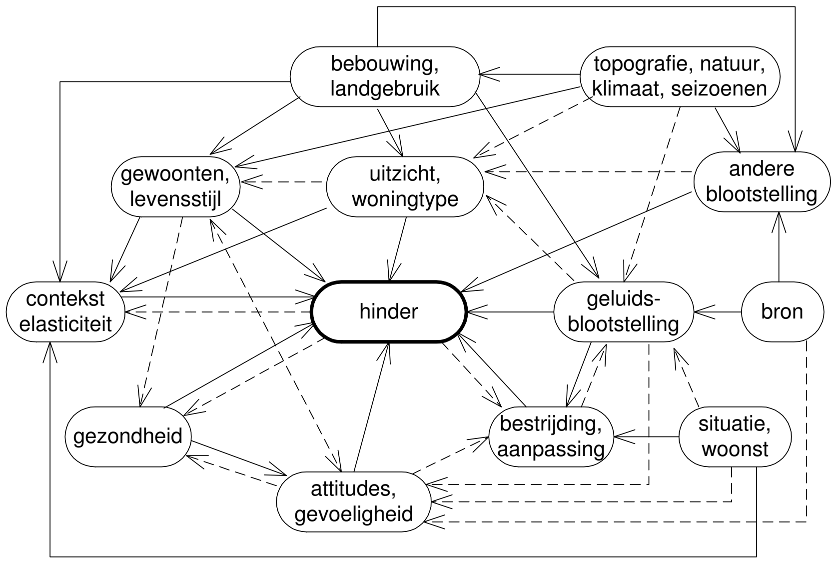
maat is voor de blootstelling aan geluid en er geen recente nieuwkomers in of wijzigingen aan de omgeving zijn (de mensen zijn het omgevingslawaai "gewoon") [100]. Met behulp van dergelijke meta-analyses heeft men ook een aantal persoonlijke, emotionele, situationele,... factoren proberen te identificeren die invloed hebben op de ervaring van hinder [89] [63] [124].

Deze statistische methodes kunnen echter enkel gebruikt worden als indicator voor de geluidshinder over grote groepen, bv. voor administratieve doeleinden en voor het vergelijken van de hinder tussen landen. Een dosis-effect relatie kan niet beschouwd worden als een natuurgetrouw model voor de ervaring van diverse gradaties van hinder (bv. door de scherpe –onrealistische– grenzen). Meta-analyses kunnen enkel factoren identificeren die een invloed hebben, de onderliggende relaties zijn moeilijk te vinden en op een eenvoudig te interpreteren manier weer te geven. Algemeen wordt aanvaard dat de blootstelling aan geluid alleen slechts 30 % van de variatie in geluidshinder kan verklaren [144]. De rest is afhankelijk van persoonlijke variabelen.

In dit werk wordt een instrument geïmplementeerd, de geluidshinderadviseur, dat toelaat om de mate van geluidshinder in te schatten op individuele basis. Hierin worden een aantal concrete relaties (links) geïmplementeerd, bv. "hoge blootstelling"–"ernstige hinder", gebaseerd op een conceptueel hindermodel dat vastlegt welke factoren met elkaar geassocieerd zijn (bv. "blootstelling"–"hinder"). Dit conceptueel model zal eerst besproken worden, gevolgd door een uiteenzetting over de manier waarop een concrete instantiëring kan gebruikt worden om de mate van hinder te voorspellen.

3.1.2 Conceptueel model

Het conceptueel geluidshindermodel, zie figuur 5, is gebaseerd op de beschikbare literatuur, zie [25] voor een overzicht. Duidelijk aangetoonde associaties zijn weergegeven in een volle lijn, associaties die eerder hypothetisch of onzeker zijn, staan in stippellijn. Voor een bespreking van dit model en enkele resultaten die met de geluidshinderadviseur bekomen werden op basis van concrete instanties van deze associaties, wordt verwezen naar sectie 4.



Figuur 5: Conceptueel geluidshindermodel. Duidelijke verbanden zijn weergegeven met een volle lijn, onzekere verbanden staan in stippellijn.

Merk op dat de geluidshinderadviseur vanwege de complexiteit van dit model en de grote hoeveelheid factoren zeker zal te maken krijgen met conflicterende relaties en lussen. Zo zal een open bebouwing de verspreiding van geluid in de hand werken en de ervaring van hinder versterken. Anderzijds wijst het op een landelijke omgeving waar mensen graag wonen en toleranter zijn voor geluid. Enkel bij erge hinder zal men de overlast actief bestrijden, bv. door het sluiten van een venster, waardoor de hinder terug daalt.

Globaal gesproken kan men drie soorten variabelen identificeren.

Initiators De variabelen van het akoestisch veld die de rechtstreekse aanleiding zijn van hinder. De term “akoestisch veld” wordt gebruikt als groepering van de volledige akoestische karakterisering, niet uitsluitend beperkt tot uitgemiddelde grootheden zoals L_{dn}.

Wijzigers Niet-akoestische variabelen die de ervaring van geluidshinder wijzigen.

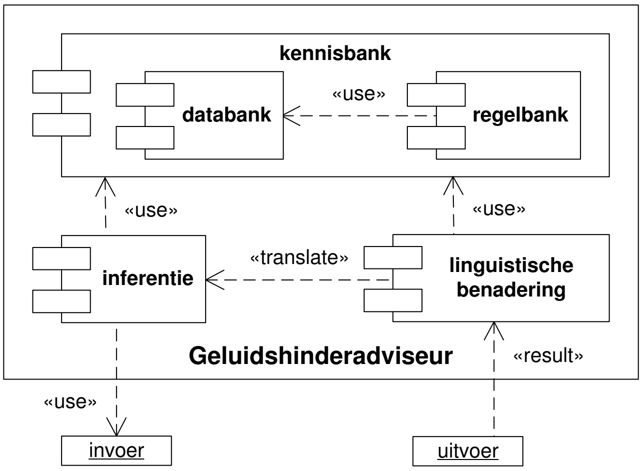
Groeperingsindicatoren Een mens is een heel complex systeem van karaktereigenschappen en innerlijke toestanden die mede-bepaald worden door vroegere ervaringen. Om alle menselijke gedragingen te modelleren moet men dus in principe tot op het genetische niveau afdalen. Dit zal hier echter niet zo ver doorgedreven worden. Mensen met een sterk gelijkaardig gedrag voor een bepaalde karaktereigenschap zullen gegroepeerd worden op basis van een aantal indicatoren. Zo is gevoeligheid aan geluid niet afhankelijk van externe factoren, maar kunnen er wel indicatoren gevonden worden (bv. leeftijd, aantal kinderen) die wijzen op een verhoogde gevoeligheid.

Vanuit wiskundig standpunt gezien, zullen deze drie soorten variabelen echter op eenzelfde manier behandeld worden in de geluidshinderadviseur.

3.1.3 Geluidshinderadviseur

De geluidshinderadviseur zal een concrete instantie van het conceptueel model moeten kunnen realiseren. De links (instanties van de associaties) drukken de precieze relatie tussen de variabelen uit. In de geluidshinderadviseur zullen de links voorgesteld worden met vage ALS–DAN regels, bv. “Als de blootstelling hoog is, dan is de geluidshinder erg”. Deze voorstelling laat experten toe om hun kennis op een linguïstische manier uit te drukken. Tevens zorgt dit ervoor dat het systeem op een eenvoudige manier te begrijpen is, ook voor niet-wiskundigen en niet-akoestiekers. Een verzameling van vaagregels wordt een vaagregelbank genoemd. De algemene structuur van een vaagregelgebaseerd systeem is getoond in figuur 6.

De specifieke kennis over het domein is opgeslagen in de kennisbank. Deze bestaat uit twee componenten, de databank en de (vaag)regelbank. De aanwezige kennis wordt samen met de invoergegevens door het inferentiesysteem gebruikt om tot een conclusie te komen omtrent de mate van geluidshinder. Het resultaat wordt vervolgens benaderd door een linguïstische term. Deze componenten worden nu kort toegelicht.



Figuur 6: Structuur van de geluidshinderadviseur als een vaagregelgebaseerd systeem.

Databank

De databank bevat de definities van de termen en concepten die in de formulering van de vaagregels gebruikt worden. Om het concept geluidshinder voor te stellen, werden de vaagverzamelingen geconstrueerd met de vervagingsmethode (zie sectie 2.3.3). Deze geven een goed beeld van de werkelijke betekenis van de termen en zijn tevens erg geschikt voor gebruik in regelgebaseerde toepassingen. De definitie van de representatie van andere concepten zal meer ad hoc gebeuren door experten (bv. voor "jonge leeftijd"). Bemerk dat er geen gegevens uit geluidshinderstudies gebruikt worden om de vaagverzamelingen automatisch te bepalen of aan te passen. Het model moet zo algemeen mogelijk zijn, los van een specifieke verzameling gegevens.

Regelbank

In de regelbank zijn de ALS-DAN regels opgeslagen die de links tussen de variabelen in natuurlijke taal beschrijven. Alle regels die de links representeren op basis van eenzelfde associatie in het conceptueel model, vormen een parallele verzameling van regels tussen dezelfde variabelen. Door de linguïstische aanpak kunnen experten hun kennis op een heel intuïtieve manier formuleren. Alle vaagregels werden dan ook volgens dit principe bekomen, op basis van de bestaande literatuur. Er werden geen automatische regelextractie algoritmen gebruikt, om het model niet te sterk te koppelen aan een welbepaalde verzameling gegevens. De klemtoon ligt hier op een algemeen bruikbaar model dat de werkelijke onderliggende relaties zo goed mogelijk tot uiting laat komen. Later zal het systeem ook uitgebreid worden met een methode om regelhypothesen te testen.

Inferentie

Voor het afleiden van kennis op basis van een vaagregel "ALS $X = A$ DAN $Y = B$" (X en Y variabelen over de respectievelijke universa U en V, A en B vaagverzamelingen in respectievelijk U en V) en een gegeven vaagfeit "$X = A'$" (A' een vaagverzameling in U) wordt de veralgemeende modus ponens gebruikt, gebaseerd op de compositieregel voor inferentie [189]. Bemerk dat A' niet noodzakelijk identiek is aan A! Deze regel stelt dat men als conclusie "$Y = B'$" mag besluiten, met B' een vaagverzameling in V gegeven door

$$(\forall v \in V)(B'(v) = \sup_{u \in U} \min(A'(u), R(u, v))) \tag{7}$$

met R de representatie van de vaagregel. De semantiek van de vaagregel bepaalt hoe de vaagrelatie R moet berekend worden [55] [56]. In dit werk zijn twee soorten regels van belang.

Zekerheidsregels "Hoe beter X gelijkt op A, hoe zekerder Y gelijk is aan B", bv. "hoe jonger een persoon, hoe zekerder hij vrijgezel is". In dit geval moet R berekend worden met een S-implicator.

Mogelijkheidsregels "Hoe beter X gelijkt op A, hoe meer mogelijk het is dat Y gelijk is aan B", bv. "hoe meer bewolkt dat de lucht is, hoe meer mogelijk het is dat het snel regent". Voor deze semantiek moet men R berekenen met een driehoeksnorm.

Bij mogelijkheidsregels drukt het consequent de mate uit waarin een punt $h \in \mathbb{H}$ gegarandeerd mogelijk is. Bijkomende kennis kan een hogere mogelijkheid voor h garanderen. Gezien de beperkte kennis en de grote hoeveelheid factoren die een invloed kunnen hebben op hinder, is het moeilijk om alle kennis die hinderniveaus kan garanderen toe te voegen aan het systeem. Daarom is het beter om te vertrekken van het feit dat alle gradaties van hinder mogelijk zijn. Kennis kan de mogelijkheid van bepaalde gradaties beperken als deze zeker niet kunnen optreden. Dit leidt tot het gebruik van zekerheidsregels. Als implicator wordt de Kleene-Dienes implicator gebruikt, een vooraanstaand lid van de S-implicatoren. De resultaten van regels die parallel zijn, worden samengevoegd met de minimum driehoeksnorm zoals vereist door de theorie.

Elke verzameling parallelle regels resulteert in een benadering van de hinder H_i voor $i \in \{1, 2, \ldots, n\}$ met n het aantal verzamelingen met parallelle regels. Deze resultaten leggen beperkingen op aan de uiteindelijke possibiliteitsdistributie van hinder H, volgens een bepaalde variabele. Uiteraard moeten alle beperkingen samen in acht genomen worden. Hiertoe zal de produkt driehoeksnorm gebruikt worden, omdat deze meer informatie in rekening brengt dan de minimum driehoeksnorm.

Linguïstische benadering

Om het resultaat van de inferentie op een linguïstische manier uit te drukken, kan men een beroep doen op de volgende benaderingsoperatoren, voor elke term L_j uit de verzameling van termen $\mathbb{L}$ die in aanmerking komen om H mee te benaderen [51],

$$D_H^+(L_j) = \sup_{h \in \mathbb{H}} \mathcal{T}(H(h), L_j(h)) \quad D_H^*(L_j) = \inf_{h \in \mathbb{H}} \mathcal{I}(L_j(h), H(h)) \tag{8}$$

De bovenbenadering D_H^+ berekent de consistentie tussen H en elke term, terwijl de benedenbenadering D_H^* de termen verzamelt die in een bepaalde mate bevat zijn in H.

Men kan ofwel de possibiliteitsdistributie van de linguïstische benadering $\pi_{\mathbb{L}}$ volledig behouden ofwel één enkele term selecteren, de term met de hoogste possibiliteitsgraad. Beide methodes zullen hier gebruikt worden. Als operator voor de benadering zal de bovenbenadering (met de minimum driehoeksnorm) en de benedenbenadering (met de Kleene-Dienes implicator) aangewend worden. De resulterende possibiliteitsdistributies zullen respectievelijk genoteerd worden als $\pi_{\mathbb{L}}^+$ en $\pi_{\mathbb{L}}^*$.

3.1.4 Regelkwalificaties

Uiteraard zullen niet alle regels evenveel invloed hebben op het resultaat en zullen sommige regels al meer onzeker zijn dan andere. Zo zullen de regels omtrent de blootstelling aan geluid wellicht belangrijker en ook beter gekend zijn dan de leeftijdsregels. Om dit in rekening te brengen, kan men de regels of de proposities wijzigen met kwalificaties [192], bv. “...is mogelijk” en “...is vrij zeker”. Een kwalificatie impliceert een relatie tussen een gekwalificeerde uitdrukking en een niet-gekwalificeerde uitdrukking [191]. Beschouw een variabele X over een universum U en de twee proposities “$X = A_1$ is (tenminste) λ_1-zeker” en “$X = A_2$ is (tenminste) λ_2-mogelijk” met $\lambda_1, \lambda_2 \in [0, 1]$. De relaties met de ongekwalificeerde proposities “$X = B_1$” en “$X = B_2$”worden gegeven door [55],

$$(\forall u \in U)(B_1(u) = \mathcal{I}_{S,\mathcal{N}}^S(\lambda_1, A_1(u)) \wedge B_2(u) = \mathcal{T}(\lambda_2, A_2(u))) \tag{9}$$

met $\mathcal{T}$ een driehoeksnorm en $\mathcal{I}_{S,\mathcal{N}}^S$ een S-implicator. Aangezien we in de geluidshinderadviseur vooral geïnteresseerd zijn in de zekerheid van regels en hypothesen, zal elke regel een zekerheidskwalificatie krijgen. De zekerheidsgraad geeft aan in welke mate aan het antecedent van de regel moet voldaan worden, om het consequent waar te maken. Zoals gebruikelijk in toepassingen, zal de zekerheidskwalificiatie berekend worden op het consequent in plaats van op de regel zelf [55]. Als implicator zal de Kleene-Dienes implicator gebruikt worden.

3.1.5 Prestatiematen

Indien men niet alleen beschikt over invoergegevens voor de geluidshinderadviseur, maar via enquêtes ook het gerapporteerde geluidshinderniveau L_* kent, is het zinvol om de prestaties van het ontwikkeld model te controleren.

Een klassiek, scherp model is correct als het de gerapporteerde term exact kan voorspellen. Dit principe kan hier ook toegepast worden. Als de linguïstische benadering enkel de best passende term als resultaat geeft, kan deze term vergeleken worden met de gerapporteerde term. Op die manier bekomt men het percentage correcte voorspellingen als prestatiemaat.

In dit werk zijn we echter vertrokken van het standpunt dat hinder een inherent vaag begrip is. Het heeft dus weinig zin om te eisen dat de best passende term overeenkomt met de gerapporteerde. Zo kan het bijvoorbeeld zijn dat twee of meer termen als bijna even goed mogelijk naar voor komen. Men moet in feite de ganse possibiliteitsdistributie $\pi_{\mathbb{L}}$ in rekening brengen om de mate waarin het resultaat niet verkeerd is en de nauwkeurigheid ervan te beoordelen. Hiertoe kan men een vage extensie van “vals negatief” beschouwen. Vals negatief drukt de mate uit waarin het gerapporteerde label L_* niet aanzien wordt als een mogelijke benadering van het resultaat H, zijnde $1-\pi_{\mathbb{L}}(L_*)$. Maar enkel deze prestatiemaat beschouwen, neigt naar een systeem dat besluiteloos is. Geen enkele term uitsluiten zou altijd goed zijn. Hiervoor kan de niet-specificiteit van $\pi_{\mathbb{L}}$ [116] een oplossing bieden (zie formule 2). Als meerdere termen even goede benaderingen zijn met even hoge possibiliteit, dan zal de niet-specificiteit hoog zijn en op een mindere prestatie duiden.

3.1.6 Regels aanpassen

Men kan gebruik maken van de resultaten van geluidshinderstudies om de zekerheidskwalificaties van de regels op een automatische manier te laten bepalen zodat een foutmaat geminimaliseerd wordt. Dit maakt het ook mogelijk om regelhypothesen te testen. Als een regel slecht presteert, zal zijn zekerheidskwalificatie heel klein worden zodat de regel geen enkele invloed meer zal hebben op het resultaat. Voor de optimalisatie van deze gewichten, in een multi-modale, niet lineaire zoekruimte, kan een genetisch algoritme (GA) gebruikt worden.

Voor de optimalisatie van de "scherpe" prestatie, kan men volgende foutmaat gebruiken.

$$e_C = \frac{\sum\limits_{k=1}^{N} \frac{\max\limits_{\substack{j=1 \\ L_j^k \neq L_*^k}}^{m} (\pi_{\mathbb{L}}(L_j^k)) - \pi_{\mathbb{L}}(L_*^k)}{p(L_*^k)}}{\sum\limits_{\substack{k=1 \\ L_p^k \neq L_*^k}}^{N} \frac{\left| \max\limits_{\substack{j=1 \\ L_j^k \neq L_*^k}}^{m} (\pi_{\mathbb{L}}(L_j^k)) - \pi_{\mathbb{L}}(L_*^k) \right|}{p(L_*^k)}} + \sum_{\substack{k=1 \\ L_p^k \neq L_*^k}}^{N} \frac{\alpha}{p(L_*^k)} \tag{10}$$

waarbij de index k over alle N records in de gegevens loopt. De probabiliteitsdistributie p geeft de probabiliteit van het voorkomen van een term in de gegevens. L_p en L_* staan respectievelijk voor de voorspelde en gerapporteerde term. De noemer is nodig om de linguïstische benadering te normaliseren, anders kan men een benadering met overal kleine possibiliteitsgraden bekomen. De parameter α is een bijkomende foutbonus voor elke verkeerde voorspelling, bv. $\alpha = 0.1$.

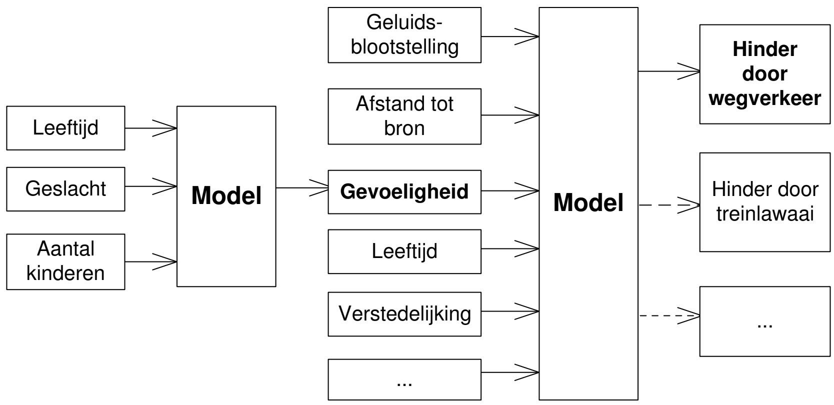
De optimalisatie van de vage prestatiemaat kan gebruik maken van de volgende foutmaat die beide componenten van de prestatiemaat in rekening brengt, met $\alpha \in [0, 1]$.

$$e_F = \sum_{k=1}^{N} \frac{\alpha(1 - \pi_{\mathbb{L}}^k(L_*^k))^2 + (1 - \alpha)(N(\pi_{\mathbb{L}}^k))^2}{p(L_*^k)} \tag{11}$$

Het in rekening brengen van de probabiliteit van de labels is nodig om de ongelijke verdeling van geluidshinderniveaus te compenseren. Gelukkig komen de hoge niveaus minder vaak voor dan de lage, hoewel ze minstens even belangrijk zijn om met het model correct te voorspellen.

3.1.7 Bouwstenen

In het conceptueel geluidshindermodel werden groeperingsindicatoren gebruikt om mensen met eenzelfde gedrag voor bepaalde karaktereigenschappen te groeperen. Het is voordelig om de vaagregelbank op dezelfde manier te structureren (zie figuur 7). Voor dergelijke tussenliggende variabelen, zoals bv. gevoeligheid aan geluid, kan op die manier een apart submodel gebouwd worden, gebaseerd op zijn groeperingsindicatoren. Het laat toe om subjectieve, tussenliggende variabelen te ontrafelen in meer objectieve variabelen. Hierdoor kunnen bepaalde variabelen (bv. leeftijd) meerdere keren voorkomen als zij hinder langs meerdere associaties beïnvloeden, soms zelfs in tegenstrijdige richting. Wanneer gegevens over zo'n tussenliggende variabelen beschikbaar zijn uit enquêtes, kunnen de gewichten van deze submodellen ook afzonderlijk geoptimaliseerd worden. In deze hiërarchische structuur kan men de uitvoer van de submodellen gebruiken als invoer voor de rest van het model ofwel rechtstreeks de gerapporteerde gegevens gebruiken. Eventueel kan men ook de uitvoer van submodellen linguïstisch benaderen naar een term uit de enquête en deze term als invoer gebruiken. Bemerk dat in deze laatste aanpak, de onnauwkeurigheid en onzekerheid van het deelresultaat verloren gaan.



Figuur 7: Hiërarchische structuur van de vaagregelbank.

3.1.8 Invloed van inferentiesystemen

De optimalisatie van de gewichten vereisen een groot aantal evaluaties van het model. De snelheid van het model is dus belangrijk. Helaas zijn de zekerheidsregels heel rekenintensief aangezien ze de expliciete opbouw van de vaagrelatie R die de regel voorstelt vereisen. Doordat de zekerheidskwalificatie van elke regel voortdurend kan veranderen, kunnen de vaagrelaties ook niet herbruikt worden. Een eerste methode om de uitvoering van het model te versnellen, is de zekerheidskwalificatie toepassen op het resultaat van de regel in plaats van op de regel zelf. Het resultaat is immers zo zeker als de regel zelf is. Het voordeel is dat men nu inderdaad de vaagrelaties eenmalig vooraf kan berekenen. Wanneer men de Kleene-Dienes implicator $\mathcal{I}_{KD}$ gebruikt voor zowel de regel als de zekerheidskwalificatie, staaft de volgende (bewezen) stelling dat de resultaten dan zelfs identiek zijn.

Stelling. *Beschouw de regel "*ALS $X = A$ DAN $Y = B$ IS λ ZEKER*" met X en Y variabelen respectievelijk over de universa U en V, A en B vaagverzamelingen over respectievelijk U en V en $\lambda \in [0,1]$. De invoer van de regel is een genormaliseerde vaagverzameling A' over U.*

$$\begin{aligned}\sup_{u\in U}\min\left(A'(u), \mathcal{I}_{KD}(A(u), \mathcal{I}_{KD}(\lambda, B(v)))\right)\\ = \mathcal{I}_{KD}\left(\lambda, \sup_{u\in U}\min(A'(u), \mathcal{I}_{KD}(A(u), B(v)))\right)\end{aligned} \tag{12}$$

Een experimentele snelheidsvergelijking in [165] toonde een snelheidswinst van factor twee aan.

Een tweede manier om het model te versnellen is overschakelen op possibiliteitsregels. Deze regels gebruiken een driehoeksnorm (meestal het minimum) als implicator. Er bestaat een heel snel en eenvoudig algoritme om resultaten van dergelijke regels te berekenen, eveneens zonder een expliciete uitdrukking van de vaagrelatie R. Het verschil in semantiek mag echter niet verwaarloosd worden. Zo verliest men bij het gebruik van een commutatieve driehoeksnorm als inferentie operator de causaliteit die door de implicatie uitgedrukt wordt. Als de richting van de causaliteit belangrijk is, kunnen deze possibiliteitsregels dus niet gebruikt worden. Dit inferentiealgoritme levert nogmaals een factor twee snelheidswinst op [165]. Onderzoek naar de voorspellingsprestatie van beide inferentiesystemen op eenzelfde model met eenzelfde verzameling gegevens, toonde aan dat de verschillen kleiner zijn dan 1 % in functie van het gewogen gemiddelde van correct voorspelde termen [165]. De gewichten van de regels kunnen blijkbaar het verschil in semantiek van de regels compenseren.

3.2 Hinderaccumulatie

3.2.1 Inleiding

Mensen zijn zelden blootgesteld aan slechts één brontype (bv. wegverkeer), meestal is het omgevingslawaai samengesteld uit diverse types van geluidsbronnen, zoals bv. wegverkeer, treinverkeer, industrie,... die samen of opeenvolgend optreden. Uit laboratoriumexperimenten is gebleken dat het "ergste bron" model momenteel de beste indicatie kan geven van deze accumulatie van hinder. Toch zijn er belangrijke verschillen tussen laboratoriumsimulaties en de ervaring van hinder in veldstudies. Een van de belangrijkste verschilpunten is het zogenaamde "compromis-principe" of "gecombineerde-geluidsbronnenparadox". Dit principe stelt dat in veldstudies de gerapporteerde geaccumuleerde hinder over het algemeen lager is dan verwacht, zelfs lager dan de hinder veroorzaakt door een van de bronnen alleen [134] [13]. Dit is bijna nooit zo in laboratoriumstudies [11], waar de geluiden altijd terzelfder tijd afgespeeld worden.

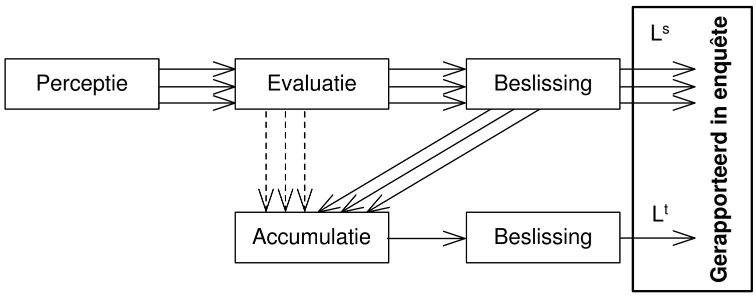
Het “ergste-bron” model wordt gegeven door

$$\mathcal{H}_t = \max_{s=1}^{S}(\mathcal{H}_s) \tag{13}$$

waarbij $\mathcal{H}_s$ de hinder van een bepaald brontype s voorstelt, en $\mathcal{H}_t$ de geaccumuleerde hinder is. Helaas is de theoretische achtergrond van dit model redelijk zwak omdat het onderliggend cognitief proces niet duidelijk is.

3.2.2 Vaagregelgebaseerd model

Hier zal een vaagmodel voor accumulatie van geluidshinder opgesteld worden, met bijzondere aandacht voor het onderliggend cognitief proces. Algemeen, kan men in een accumulatiemodel de processen uit figuur 8 onderscheiden. Tijdens de perceptie registreren onze zintuigen de geluiden.



Figuur 8: Verschillende processen van een accumulatiemodel.

In het evaluatieproces worden ze geëvalueerd in ons referentiekader. Via de stippellijnen van figuur 8 worden de evaluaties geaccumuleerd tot een globale evaluatie. Uiteindelijk wordt tijdens de beslissingsfase uitgemaakt welk niveau van geluidshinder gerapporteerd wordt, als men daarnaar gevraagd wordt. Om een accumulatiemodel gemakkelijk te kunnen testen met behulp van gegevens afkomstig van een enquête, zal hier de volgende veronderstelling gemaakt worden. We nemen aan dat de evaluatiefase gevolgd wordt door een beslissingsfase voor elk type bron afzonderlijk, en dat uiteindelijk de resultaten van deze beslissingen geaccumuleerd worden. Dit gaat ervan uit dat de effecten van de beslissingsprocessen voor de bronnen verwaarloosbaar zijn, in combinatie met de globale beslissingsfase.

Vertrekkende van het ergste bron model, kan men het cognitief accumulatieproces schrijven zonder de maximumoperator te gebruiken. Dit leidt tot volgende regels.

ALS hinder door een van de bronnen is extreem
DAN globale hinder is extreem.

ALS hinder door een van de bronnen is erg
DAN globale hinder is erg
TENZIJ globale hinder is al extreem.

ALS hinder door een van de bronnen is matig
DAN globale hinder is matig
TENZIJ globale hinder is al erg of extreem.

...

De ALS-DAN-TENZIJ regels kunnen in binaire logica als volgt geformuleerd worden, voor $\mathcal{H}_s$ de hinder van de bronnen $s \in \{1, 2, \ldots, S\}$, $\mathbb{L} = \{L_1, L_2, \ldots, L_m\}$ de hindertermen (bv. "helemaal niet", "een beetje", "tamelijk", "erg", "extreem") en $j = m, m-1, \ldots, 1$,

$$\text{ALS} \left(\bigvee_{s=1}^{S} (\mathcal{H}_s = L_j) \right) \wedge \left(\neg \bigvee_{j' > j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'}) \right) \text{ DAN } \mathcal{A}^{(m-j+1)} = L_j \quad (14)$$

$$\mathcal{H}_t^{(m-j+1)} = \bigvee_{i=1}^{m-j+1} \mathcal{A}^{(i)} \quad (15)$$

met $\mathcal{A}^{(i)}$ de hinderbijdrage van regel i, de initiële $\mathcal{H}_t^{(0)}$ geen enkele van de hindertermen en de totale geaccumuleerde hinder $\mathcal{H}_t = \mathcal{H}_t^{(m)}$.

De gevonden formulering van het onderliggend cognitief accumulatieproces van het ergste bron model, kan nu op een eenvoudige manier vervaagd worden tot een vaagregelgebaseerd systeem. Dit heeft als belangrijk voordeel dat er beter kan rekening gehouden worden met de onnauwkeurigheden en onzekerheden die inherent aanwezig zijn in het concept geluidshinder. De componenten van zo'n systeem worden hieronder kort toegelicht (zie figuur 6).

Databank Een eerste stap in de vervaging van het binair model, bestaat uit het vervagen van de linguïstische termen in de antecedenten en consequenten van de regels. Hiervoor wordt opnieuw beroep gedaan op de lidmaatschapsfuncties die met de vervagingsmethode uit sectie 2.3.3 geconstrueerd zijn. Deze zijn immers erg geschikt voor gebruik in vaagregelgebaseerde systemen.

Regelbank In plaats van direct de regels (14) te gebruiken, wordt het eerste antecedent ontvouwd tot aparte regels. Hierdoor wordt de disjunctie van hindertermen van een bron vervangen door een disjunctie van regels die betrekking hebben op één bepaalde bron. Dit geeft meer controle over de bijdrage van elke bron wat later handig zal blijken. Na deze ontvouwing zien de regels er als volgt uit, voor elke $s \in \{1, 2, \dots, S\}$,

$$\text{ALS } (\mathcal{H}_s = L_j) \wedge \left(\neg \bigvee_{j'>j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'}) \right) \text{ DAN } \mathcal{A}_s^{(m-j+1)} = L_j \quad (16)$$

Inferentie In sectie 3.1.3 werden de verschillende interpretaties van vaagregels besproken. Het accumulatieproces is duidelijk een proces dat informatie verzamelend: elke regel maakt een niveau van hinder mogelijk. We hebben hier dus te maken met mogelijkheidsregels. De voorstelling van de regel zal berekend worden met de minimum driehoeksnorm. Dit betekent dat men ook het snelle inferentiealgoritme kan implementeren.

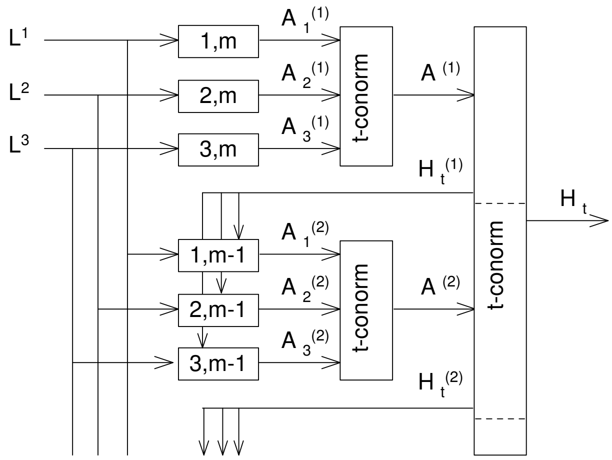
Voor de conjunctie van de antecedenten, komt elke driehoeksnorm in aanmerking. Een kleine driehoeksnorm zal de mate waarin de regels afgevuurd worden verkleinen (behalve de eerste regel). Gelet op het "compromis principe" is dit niet aangewezen, daarom zal het minimum, de grootste driehoeksnorm, hier gebruikt worden.

Tot slot, de disjunctie van de resultaten per bron en uiteindelijk ook per geluidshinderniveau zal gemodelleerd worden met de maximum driehoeksconorm.

Figuur 9 toont het ganse inferentieproces.

Linguïstische benadering Net zoals in sectie 3.1.3 zal voor de linguïstische benadering van de berekende possibiliteitsdistributie H_t naar een term, beroep gedaan worden op de boven- en benedenbenaderingsoperatoren. De resulterende possibiliteitsdistributies over de termen, respectievelijke genoteerd als $\pi_{\mathbb{L}}^{+}$ en $\pi_{\mathbb{L}}^{*}$, kan men volledig in rekening nemen, ofwel enkel de best passende term (met de hoogste possibiliteitsgraad) beschouwen. De eerste methode zal vooral nuttig zijn om de resultaten te vergelijken met andere, scherpe modellen. De tweede methode respecteert de vaagheid van het hinderconcept beter en maakt een interpretatie in functie van vals negatief en de niet-specificiteit mogelijk (zie sectie 3.1.3).

In het huidig model hebben alle bronnen evenveel impact op het resultaat. Dit is uiteraard niet erg realistisch. In sectie 3.1.4 werden enkele soor-



Figuur 9: Structuur van een vervaagd, regelgebaseerd accumulatie model.

ten van regelkwalificaties besproken. Elke regel in het model garandeert de mogelijkheid van een bepaald hinderniveau op basis van een bron. De mogelijkheidskwalificatie $\lambda \in [0,1]$ (op basis van de minimum driehoeksnorm) is daarom het meest aangewezen. Deze kwalificatie drukt uit in welke mate het consequent gegarandeerd mogelijk is als aan het antecedent voldaan is. Voor elke combinatie van een type bron en een geluidshinderniveau is er een regel in het model. Er zijn dus $\lambda_{s,j}$ voor $s \in \{1, 2, \ldots, S\}$ en $j \in \{1, 2, \ldots, m\}$ parameters nodig. Om dit aantal enigzins binnen de perken te houden, veronderstellen we $\lambda_{s,j} = \lambda_s \cdot \lambda_j$, waarbij $\lambda_s \in [0,1]$ afhangt van de bron en $\lambda_j \in [0,1]$ afhangt van het geluidshinderniveau. Deze veronderstelling is zinvol aangezien de invloed van een bron gelijk zal zijn voor alle hinderniveaus en de invloed van een hinderniveau gelijk zal zijn voor alle bronnen.

De gewichten van de regels kunnen automatisch bepaald worden op basis van enquêtegegevens die de gerapporteerde totale geluidshinder alsook de gerapporteerde geluidshinder per afzonderlijke bron bevatten. Hiervoor kan een genetisch algoritme gebruikt worden, dat een foutmaat minimaliseert. Dezelfde foutmaten als beschreven in sectie 3.1.6 kunnen hier ook dienst doen.

Voor de inschatting van de geluidshinder veroorzaakt door een aantal afzonderlijke brontypes, kan uiteraard ook beroep gedaan worden op het model beschreven in sectie 3.1.

3.2.3 Aggregatie met vaagintegralen

Het probleem van de hinderaccumulatie zal hier benaderd worden als een multi-criteria beslissingsprobleem. In deze theorie evalueert men verschillende beslissingsalternatieven op basis van diverse criteria [119]. Wanneer met elk alternatief een vooraf gedefiniëerde categorie overeenstemt, dan spreekt men over een classificatieprobleem. Om tot een beslissing te komen, worden diverse criteria $U = \{u_1, u_2, \ldots, u_n\}$ met $n \in \mathbb{N} \setminus \{0\}$ geëvalueerd op basis van een evaluatiefunctie f. Deze evaluaties worden vervolgens geaggregeerd om tot een globale evaluatie van het doelcriterium v te komen, $D(v) = G(f(u_1), f(u_2), \ldots, f(u_n))$ met G een aggregatie operator.

In het hindermodel zal de hinder van elke bron een criterium zijn dat geëvalueerd wordt om tot de globale hinderevaluatie te komen. Noteer de verzameling van alle bronnen als $\mathbb{S} = \{r_1, r_2, \ldots, r_S\}$. Als evaluatiefunctie gebruiken we $f : \mathbb{S} \to L^s = \{0 = l_1^s \prec l_2^s \prec \ldots \prec l_m^s = 1\} \subseteq [0,1]$ met $m \in \mathbb{N}$ het aantal linguïstische termen en l_j^s de evaluatie van de hinderterm voor bron s. De relatie $\prec$ definiëert een orderelatie op de hinderniveaus. De verzamelingen L^s leggen een ordinale schaal vast voor de hindertermen afkomstig van bron s. In navolging van hinderstudies waarbij deze ordinale schaal meestal onafhankelijk is van de bron, stellen we $L = L^1 = \ldots = L^S$. Deze schaal zal ook gebruikt worden voor de evaluatie van de globale hinder. Bemerk dat men voor de ordinale schaal L het bestaan van een onderliggende kardinale schaal kan vooropstellen, zoals bv. het geval was in de internationale hinderschaalstudie [65].

Een flexibele aggregatie operator kan gevonden worden in de vorm van vaagintegralen, de Choquet-integraal en de Sugeno-integraal. Dit zijn veralgemeningen van de klassieke integraal waarbij de onderliggende maat niet noodzakelijk additief is. Men spreekt in dit geval over een vaagmaat. Een vaagmaat μ is een functie over $\mathcal{P}(U)$, met $\mathcal{P}(U)$ de machtsverzameling van een universum U, die aan elke deelverzameling van U een bepaald gewicht in het interval $[0,1]$ toekent, en voldoet aan een grensvoorwaarde, een normeringsvoorwaarde, monotoniteit en continuïteit. Door het wegvallen van de additiviteit heeft men een grote flexibiliteit, bv. om de combinatie van twee elementen een veel groter of kleiner gewicht toe te kennen dan het gewicht van de elementen afzonderlijk. Wanneer een vaagintegraal $\mathcal{G}_\mu$ gebruikt wordt als aggregatie operator levert dit voor de hinderaccumulatie $d = D(\mathcal{H}_t) = \mathcal{G}_\mu(f)$, waarbij $d \in [0,1]$ een evaluatie is van de globale hinder. Om de resulterende classificatie in functie van de hindertermen te bepalen, kan men de elementen in L beschouwen als punten in het midden van intervallen die corresponderen met een bepaalde term. De klasse $l \in L$ wordt gekozen als de waarde d in dit interval valt, noteer $d' = l$. Hoewel de Sugeno-integraal enkel gebruik maakt van de eigenschappen van de ordinale schaal, zal deze aanpak ook voor de Sugeno-integraal gehanteerd worden, zoals in de praktijk vaak gebeurt [30].

De vaagmaat zal met een genetisch algoritme automatisch geëxtraheerd worden op basis van enquête resultaten [171]. Veronderstel N records van de vorm $(f(r_1), f(r_2), \ldots, f(r_S), d^*)$ met d^* de gerapporteerde globale hinder. Een te minimaliseren foutmaat die de ongelijke verdeling van optreden van globale hinderniveaus compenseert, is gegeven door,

$$e = \sum_{k=1}^{N} \frac{(d_k - d_k^*)^2}{p(d_k^*)} + \sum_{\substack{k=1 \\ d_k' \neq d_k^*}}^{N} \frac{\alpha}{p(d_k^*)} \tag{17}$$

met p de probabiliteitsdistributie van de globale hindertermen in de enquêtegegevens en α een experimenteel bepaalde foutbonus voor elke verkeerde classificatie.

Het bepalen van een vaagmaat impliceert het bepalen van $2^n - 2$ parameters met n het aantal criteria. Voor een groot aantal criteria, in hinderstudies typisch rond de 20, is dit niet haalbaar. Er zijn dus andere methodes nodig om een vaagmaat te definiëren met behulp van minder parameters. Twee mogelijkheden worden telkens in combinatie met een vaagintegraal geïllustreerd, via een relatie (met de Choquet-integraal) en via een alternatieve representatie (met de Sugeno-integraal).

Als de vaagmaat van combinaties van elementen kan berekend worden uit de vaagmaat van de singletons met volgende relatie, $\mu(A \cup B) = S(\mu(A), \mu(B))$ met S een driehoeksconorm, en $A, B \subseteq U$ dan spreekt men over een veralgemeende possibiliteitsmaat. In [180] wordt een algoritme beschreven waarmee de Choquet-integraal $C_\mu(f)$ heel gemakkelijk kan berekend worden op basis van zo'n maat, namelijk,

$$C_\mu(f) = w^T b = \sum_{j=1}^{n} w_j \, b_j \tag{18}$$

met b de n-dimensionale geordende vector zodat de j-de component het j-de grootste argument $f(u_i)$ is en w een n-dimensionale vector gewichten. Deze worden gegeven door $w_j = \mu(H_{(j)}) - \mu(H_{(j-1)})$ voor alle $j \in \{1, 2, \ldots, n\}$ met $H_{(j)}$ de deelverzameling van de criteria met de j-de hoogste evaluatiewaarden en $H_{(0)} = \emptyset$. Merk op dat zowel b als w veranderen voor verschillende evaluaties van criteria. Gezien het sterke verband tussen de hinderaccumulatie en de maximumoperator, lijkt de gewone possibiliteitsmaat met S de maximum driehoeksconorm een goede keuze. In dit geval worden de gewichten gegeven door,

$$w_j = \max(\mu(u_j) - \sum_{i=1}^{j-1} w_i, 0) \tag{19}$$

In dit model moeten slechts n parameters in $[0,1]$ bepaald worden om de ganse vaagmaat te definiëren. In het genetisch algoritme kan een individu (een potentiële oplossing) voorgesteld worden met een chromosoom dat bestaat uit een rij van n reële getallen.

Een tweede mogelijkheid om de parameters van een vaagmaat te reduceren, steunt op een alternatieve representatie, zoals bv. met de possibilistische Möbius-transformatie [118]. Dit is een transformatie van een functie μ over $\mathcal{P}(U)$ naar een functie $m^\vee$ gedefiniëerd als $m^\vee(A) = \mu(A)$ als $\mu(A) > \max_{B\subset A} \mu(B)$, anders $m^\vee(A) = 0$, voor elke $A \subseteq U$. Er bestaat ook een inverse transformatie, de Zeta-transformatie, $Z_m^\vee(A) = \max_{B\subseteq A} m^\vee(B)$ voor elke $A \subseteq U$.

Niet elke functie over $\mathcal{P}(U)$ is de possibilistische Möbius-representatie van een vaagmaat. In [45] werd bewezen dat volgende voorwaarden moeten voldaan zijn: de grensvoorwaarde, $m^\vee(\emptyset) = 0$, de normaliseringsvoorwaarde, $\max_{A\subseteq X} m^\vee(A) = 1$ en de monotoniteit, $(\forall A \in \mathcal{P}(U))(m^\vee(A) \leq \max_{B\subset A} m^\vee(B) \Rightarrow m^\vee(A) = 0)$. Een vaagmaat waarvan zijn possibilistische Möbius getransformeerde voldoet aan $m^\vee(A) = 0$ voor elke $A \subseteq U$ met $|A| > k$ voor een $k \in \{1, 2, \ldots, n\}$ en er op zijn minst één deelverzameling B van U bestaat met $|B| = k$ zodat $m^\vee(B) \neq 0$, noemt men een k-maxitieve vaagmaat [118].

De Sugeno-integraal $S_\mu(f)$ kan eenvoudig berekend worden op basis van de possibilistische Möbius-representatie $m^\vee$ van een k-maxitieve maat [113],

$$S_\mu(f) = \max_{A\subseteq U} \min\left(m^\vee(A), \bigwedge_{i\in A} f(u_i)\right) \tag{20}$$

Een k-maxitieve vaagmaat is volledig bepaald door $\sum_{i=1}^{k} \binom{n}{i}$ parameters [30]. Hoewel dit aantal veel kleiner is dan $2^n - 2$ is het toch nog aanzienlijk veel voor grote n. Daarom zal de optimalisatie van k-maxitieve vaagmaten zich beperken tot $k = 2$.

Voor elke $A \subseteq U$ bevat het chromosoom dat de possibilistische Möbius getransformeerde vaagmaat in het genetisch algoritme voorstelt, een gen met een reëel getal in $[0,1]$. Voor 2-maxitieve maten zijn er dus genen g_r die bij een singleton $\{u_r\}$ horen en genen g_{pq} die bij een niet-geordend paar $\{u_p, u_q\}$ horen, met $p \neq q$ en $p, q, r \in \{1, 2, \ldots, n\}$. Om ervoor te zorgen dat er enkel geldige vaagmaten in beschouwing genomen worden, wordt de possibilistische Möbius vaagmaat op basis van deze interne voorstelling berekend als

$$
\begin{aligned}
m^{\vee}(\{u_r\}) &= g_r && (21)\\
m^{\vee}(\{u_p, u_q\}) &= \begin{cases} \bar{m} + (1-\bar{m})g_{pq} & \text{als } g_{pq} \neq 0 \\ 0 & \text{als } g_{pq} = 0 \end{cases} && (22)
\end{aligned}
$$

met $\bar{m} = \max\left(m^{\vee}(\{u_p\}), m^{\vee}(\{u_q\})\right)$. Enkel de normalisatievoorwaarde moet dan nog voldaan worden door te delen door het maximum van de $m^{\vee}$ waarden. Na de normalisatie wordt de vaagmaat terug gecodeerd naar de interne representatie om zinvolle kruisingen in het genetisch algoritme mogelijk te maken.

4 Resultaten

Om de ontwikkelde hindermodellen te valideren en de gewichten automatisch te laten bepalen, zijn enquêtegegevens nodig, die zowel de noodzakelijke invoergegevens als de gerapporteerde hinderniveaus bevatten. Twee dergelijke enquêtes waren beschikbaar. Enkele resultaten die met de modellen bekomen werden, zullen hier kort besproken worden. Tenzij anders vermeld werd telkens de snellere implementatie van het inferentiesysteem met possibiliteitsregels gebruikt. Deze resultaten werden al gerapporteerd in internationale tijdschriften [18] [25] [26] en op conferenties [17] [22] [23] [24] [15] [158] [159] [160] [163] en [164].

4.1 Enquêtes

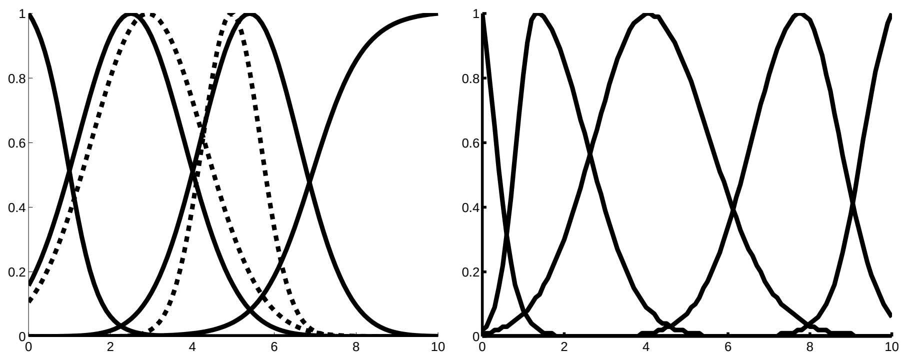
Een eerste enquête is afkomstig van een studie naar de gezondheidseffecten door de aanleg van een nieuwe spoorweg in het Oostenrijks deel van de Alpen, in de buurt van Innsbruck. In dit landelijk gebied met kleine dorpen, zijn wegverkeer en treinverkeer de belangrijkste geluidsbronnen. De telefonische enquête heeft 2007 inwoners bevraagd. 1500 personen werden willekeurig gekozen, de rest werd binnen een straal van 150 m rond de bestaande spoorweg en hoofdweg of 50 m rond de lokale wegen geselecteerd om te garanderen dat een voldoende aantal mensen aan hogere geluidsniveaus blootgesteld zijn. Nadien werden de L_{dn} waarden gesimuleerd en bijgesteld op basis van enkele meetgegevens. De vragen omtrent de ervaring van hinder maakten gebruik van vier hindertermen, "überhaupt nicht" ("helemaal niet", 1), "gering oder teilweise" ("matig", 0.75), "mittelmäßig" ("matig", 0.34) en "stark oder erheblich" ("ernstig", 0.67). De nederlandse vertalingen op basis van de automatische vertalingsapplicatie uit sectie 2.4 en de gevonden similariteitsgraad staan tussen haakjes. De Duitse termen komen niet overeen met de termen zoals voorgesteld in de internationale hinderschaalstudie [65]. Vooral “teilweise” en “mittelmäßig” liggen vrij dicht bij elkaar wat ook blijkt uit de Nederlandse vertalingen, met het bijkomende probleem dat er geen goede Nederlandse termen bestaan voor de middelste gradaties van hinder. Vandaar dat de geconstrueerde – symmetrische Gaussiaanse– lidmaatschapsfuncties lichtjes aangepast werden, zie figuur 10.

Een tweede gegevensverzameling werd bekomen uit een Vlaamse enquête die per post uitgevoerd werd bij 3200 mensen. Het onderwerp van de studie was de invloed van geluid, geur en te veel licht op de leefomgeving. De personen die op vrijwillige basis hun adres opgeschreven hadden (1709 in totaal), werden gelokaliseerd met behulp van een Geografisch Informatie Systeem (GIS). Voor deze personen werden de wegverkeer en treinverkeer L_{dn} geluidsniveaus berekend en bijgesteld op basis van meetresultaten. Bovendien werden ook andere geografische variabelen bepaald, zoals bv. het landgebruik. Naast een vraag naar de algemene geluidshinder, bevatte deze enquête ook een vraag naar de geluidshinder veroorzaakt door een aantal individuele geluidsbronnen. Deze gegevens zijn nuttig voor de validatie van de accumulatiemodellen. De hinderschaal bestond uit vijf termen, “helemaal niet”, “een beetje”, “tamelijk”, “ernstig” en “extreem”. Hoewel deze schaal niet identiek is aan de termen voorgesteld in [65], zijn de verschillen vrij klein. De asymmetrische Gaussiaanse lidmaatschapsfuncties zijn getoond in figuur 10.

4.2 Voorspellen van hinder door verkeer

Alle kennis die in het systeem opgeslagen is, de vaagregels die de relaties tussen variabelen uitdrukken, werden geformuleerd door experten in het domein van de akoestiek. De regels zijn een instantie van de associaties die in het conceptueel hindermodel geïdentificeerd werden (zie sectie 3.1.2). De regels zelf worden niet aangepast aan de gegevens. Dit garandeert een stabiel model, onafhankelijk van welbepaalde gegevens. Enkel de zekerheidsgraden van de regels worden automatisch aangepast, wat nodig is om het testen van hypotheses mogelijk te maken.

De resultaten van een model voor wegverkeer en treinverkeer op basis van de Oostenrijkse gegevens, zijn samengevat in tabel 4. Het model werd hierbij ingesteld om het (scherpe) gewogen percentage correcte voorspellingen te optimaliseren (met de bovenbenadering om de best passende term te vinden). De tabel geeft telkens ook de vergelijking met multivariate regressie. Er wordt onderscheid gemaakt tussen het gebruik van regels



Figuur 10: Links: Representatie van de vier Duitse hindertermen ("überhaupt nicht", "teilweise", "mittelmäßig", "erheblich"). De oorspronkelijke curven voor "teilweise" en "mittelmäßig" staan in stippellijn. Rechts: Representatie van de vijf Nederlandse hindertermen ("helemaal niet", "een beetje", "tamelijk", "ernstig", "extreem").

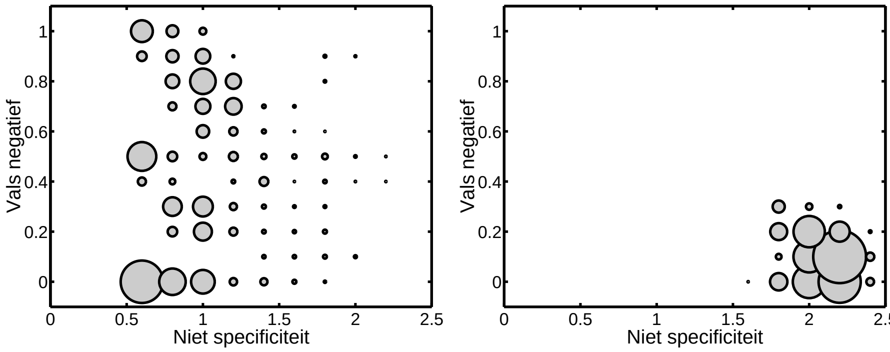
op basis van subjectieve invoer en zonder dergelijke regels. Dit is nodig omdat men moet oppassen dat men geen variabelen gebruikt die mogelijks ook bijdragen tot het antwoord op de hindervraag. Een voorbeeld van zo'n subjectieve variabele is de gerapporteerde geluidsgevoeligheid.

Tabel 4: Resultaten na optimalisatie met scherpe prestatiematen op de Oostenrijkse gegevens.

Model	Wegverkeer	Treinverkeer
Lineaire regressie met DNL	29.5 %	30.2 %
Vaagmodel / geen subjectieve invoer	41.1 %	43.8 %
Regressie / geen subjectieve invoer	36.8 %	37.0 %
Vaagmodel / subjectieve invoer	43.0 %	45.3 %
Regressie / subjectieve invoer	40.0 %	38.6 %

De invloed van de parameter α bij de optimalisatie van een model voor de vage prestatiematen, vals negatief en niet-specificiteit, zal geïllustreerd worden met een model voor hinder door wegverkeer op basis van de Vlaamse gegevens. Voor de linguïstische benadering werd de benedenbenadering gebruikt. Met een hoge α kan men een model bekomen dat niet fout is (in een vage interpretatie) maar redelijk niet-specifiek. Een lage α resulteert in een specifiek model maar ten koste van meer foutieve voorspellingen.

De linkse figuur 11 toont een specifiek model dat vaak fout is. De rechtse figuur geeft de resultaten van een meer onzeker model dat echter minder vaak de gerapporteerde term uitsluit.



Figuur 11: Verdeling van de testpersonen over een vals negatief versus niet specifiek vlak voor een model met $\alpha = 0.75$ (links) en $\alpha = 0.99$ (rechts). De grootte van de cirkels is proportioneel met het aantal personen.

Verdere analyse van de resultaten toonde aan dat een combinatie van lage niet-specificiteit en geen vals negatief, enkel kan bekomen worden wanneer de hinderniveaus “helemaal niet” of “extreem” voorspeld worden. Dit is eenvoudig te verklaren. Ook voor de menselijke expert is het gemakkelijker om een zeker oordeel te vellen over de uiterste hinderniveaus. Een zekere uitspraak doen over de middenste hinderniveaus is veel moeilijker.

Het vergelijken van de resultaten van enquêtes is typisch een moeilijk probleem voor de klassieke methodes. Dit is te wijten aan de vele verschillen tussen de manier waarop de enquêtes opgesteld zijn, zoals bv. verschillen in taal, verschillende keuzes van termen (als het enquêtes in dezelfde taal betreft) en verschillende hinderschalen (bv. vier termen versus vijf termen of numerieke schalen). Dankzij een uniforme voorstelling van hindertermen als vaagverzamelingen, vormen deze verschillen geen struikelblok voor het vaagmodel. Om de algemeenheid van hindermodellen te testen, werd een model voor de hinder door treinverkeer, op basis van L_{dn} en de afstand tot de spoorweg, vergeleken voor de Oostenrijkse en de Vlaamse gegevens. Hierbij werd de similariteitsmaat uit de automatische vertalingsapplicatie gebruikt voor de linguïstische benadering naar de best passende term (zie sectie 2.4). De resultaten zijn samengevat in tabel 5. Het model werd telkens geoptimaliseerd op basis van de Vlaamse gegevens en vervolgens ongewijzigd uitgevoerd voor de Oostenrijkse gegevens (zelfde zekerheidsgraden van de regels). Intern in het model werden voor de antecedenten en consequenten van de regels enkel –taalonafhankelijke– stuksgewijs-lineaire vaagverzamelingen gebruikt. Linguïstische benadering van de modeluitvoer naar de taalafhankelijke vaagverzamelingen op basis van de vervagingsmethode levert de beste resultaten op. Wanneer de uitvoer benaderd wordt met stuksgewijs–lineaire vaagverzamelingen op een gelijke afstand van elkaar (vier voor de Oostenrijkse en vijf voor de Vlaamse) of met de vaagverzamelingen op basis van de probabilistische methode, dan daalt de prestatie evenredig. Dit betekent dat de voorstelling van de termen wel degelijk belangrijk is en dat de vervagingsmethode realistische vaagverzamelingen produceert. Aangezien de resultaten dicht bij elkaar liggen, bewijst dit de algemeenheid van het model. Eenzelfde conclusie werd bekomen bij het vergelijken van de foutmaat na optimalisatie voor de vage prestatiemaat.

Tabel 5: Gewogen percentage correcte voorspellingen in een model dat voor de Vlaamse gegevens geoptimaliseerd werd.

Linguïstische termen	Vlaams	Oostenrijks
Nauwkeurige voorstelling	37.14 %	37.13 %
Stuksgewijs-lineaire voorstelling	34.07 %	34.03 %
Voorstelling met probabilistische methode	36.19 %	36.69 %

Als voorbeeld van de manier waarop de geluidshinderadviseur kan gebruikt worden om hypotheses te testen, zal een model voor hinder door treinlawaai beschouwd worden (op basis van de Oostenrijkse gegevens). Wanneer een basismodel met regels die de invloed van fysische aspecten van geluid beschrijven (L_{dn}, afstand tot bron,...) uitgebreid wordt met regels die het maskeereffect in rekening brengen, dan wordt de fout kleiner. Het fysiologisch maskeereffect treedt op als het geluid van een bron (bv. wegverkeer) het geluid van een andere bron (bv. treinen) zodanig domineert dat de tweede bron niet meer waargenomen wordt. Uit de analyses met klassieke methodes weet men dat maskering enkel wordt waargenomen bij hoge geluidsniveaus van beide bronnen, wat eigenlijk vreemd is [23]. Een uitbreiding met regels die de gerapporteerde gevoeligheid aan geluid beschouwen, levert ook een kleinere fout. Bemerk dat men ook gebruik kan maken van een submodel om de gevoeligheid te voorspellen op basis van meer objectieve variabelen. Als men nu echter zowel de maskeerregels als de gevoeligheidsregels toevoegt, wordt de fout niet meer kleiner (zie tabel 6, tussen haakjes staat het verschil met de kleinste fout in de tabel). Hieruit kan men afleiden dat beide verzamelingen regels eigenlijk hetzelfde beschrijven, of met andere woorden dat het geregistreerde maskeereffect te wijten is aan het feit dat gevoelige mensen daar niet wonen. Als deze hypothese klopt, dan moet het submodel voor gevoeligheid ook minder gevoeligheid voorspellen in situaties die met maskering overeenkomen. Een toevoeging van een dergelijke regel bij het submodel voor gevoeligheid, resulteert in een kleine toename (weinig mensen voldoen immers aan de regel) van het gewogen percentage correct voorspelde gevoeligheid. Dit bevestigt de hypothese.

Tabel 6: Vergelijking van de foutmaat met maskering- en gevoeligheidsregels.

	Zonder maskering	Met maskering
Zonder gevoeligheid	15 (909)	7 (901)
Met gevoeligheid	2 (896)	0 (894)

4.3 Voorspellen van hinderaccumulatie

Voor de voorspelling van de geaccumuleerde hinder kunnen enkel de Vlaamse gegevens gebruikt worden, aangezien dit niet bevraagd werd in de Oostenrijkse enquête. In totaal waren 2661 records volledig bruikbaar. De Vlaamse enquête vermelde 21 verschillende bronnen van geluid, eventueel kon de persoon zelf nog een bijkomende bron noteren maar deze extra gegevens werden hier niet in beschouwing genomen. De relatieve frekwentie van de globale hinderniveaus is 35.59 % ("helemaal niet"), 35.67 % ("een beetje"), 18.19 % ("tamelijk"), 8.57 % ("ernstig") en 1.99 % ("extreem"). De resultaten van alle modellen zijn samengevat in tabel 7. Het beste scherpe model, het "ergste-bron" model is ter referentie ook opgenomen. In figuur 12 (links) wordt het geclassificeerde hinderniveau van dit model vergeleken met het gerapporteerde hinderniveau (voor globale hinder). De percentages zijn gewogen om de aantallen in elke categorie in rekening te brengen. De termen zijn weggelaten maar lopen van links naar rechts ("helemaal niet", "een beetje", "tamelijk" "ernstig" en "extreem") en van onder naar boven. De resultaten van alle modellen zullen telkens op deze manier gepresenteerd worden. Bemerk het effect van het "compromis-principe", waardoor elke categorie overschat wordt.

Het vaagregelgebaseerd model is een weinig beter dan het ergste-bron-model. Dit is niet verwonderlijk aangezien dit model eigenlijk een rechtstreekse vervaging is van dit scherpe model. Het model overschat vooral

Tabel 7: Gewogen percentages correct geclassificeerde hinderaccumulatie voor verschillende modellen.

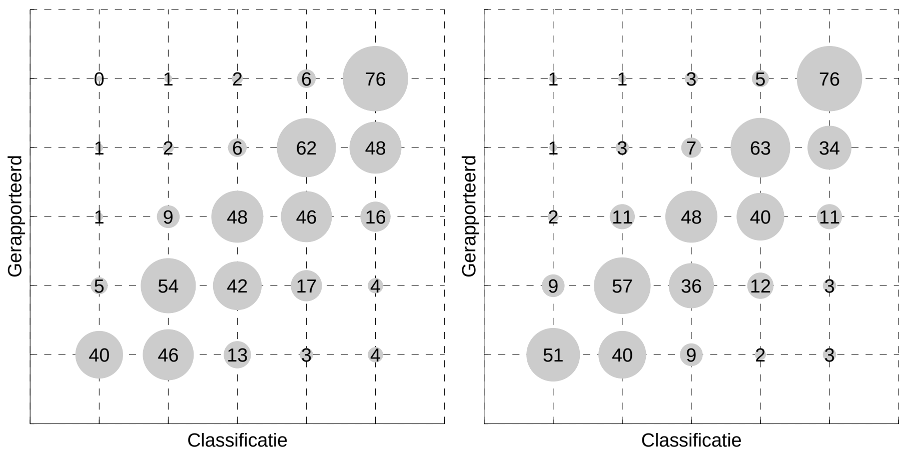
Model	Resultaat (in %)
Scherpe ergst-bronmodel	55.5
Vaagregelgebaseerd model	59.0
1-maxitieve Choquet-integraal	61.3
1-maxitieve Sugeno-integraal	60.9
2-maxitieve Sugeno-integraal	61.4

de laagste hinderniveaus een stuk minder (zie figuur 12, rechts). Zowel het model gebaseerd op de Choquet-integraal als de Sugeno-integraal presteren gelijkaardig, en lichtjes beter dan het vaagregelgebaseerd model. Een uitvoerige analyse van de gewichten berekent in het Choquet model, leert dat bijna uitsluitend de bron die de hoogste hinder veroorzaakt een hoog gewicht krijg. Alle andere gewichten zijn verwaarloosbaar klein. Dit toont aan dat de hinderaccumulatie inderdaad “maxitief” van aard is (in overstemming met het scherpe ergste bron model). De Sugeno-integraal op basis van een 2-maxitieve maat is iets beter in vergelijking met een 1-maxitieve maat. Dit geeft aan dat de hinder door twee bronnen samen een sterker effect op het cognitief accumulatieproces kan hebben dan het maximum van de bronnen. Zie figuur 13 voor een grafische voorstelling van de resultaten van de vaagintegraal modellen.

5 Besluit

In dit werk werd een grondige analyse van het concept geluidshinder uitgevoerd. Als uitgangspunt werd hinder beschouwd als een inherent vaag concept, dat gemodelleerd wordt met de vaagverzamelingenleer. Deze aanpak dringt zich op omdat de mate waarin geluidshinder ervaren wordt niet kan gemeten worden, hoewel mensen er wel met elkaar kunnen over communiceren met behulp van natuurlijke taal.

Eerst werden een aantal voorstellingsmethodes onderzocht. De huidige werkwijze met behulp van scherpe scheidingspunten voor het voorstellen van linguïstische hindertermen (bv. 7.2 voor “erge hinder”) faalt om een bepaalde mate van hinder op een correcte manier uit te drukken. De methodes besproken en uitgebreid in sectie 2 zijn veel beter geschikt om de betekenis van deze hindertermen weer te geven. Met het gebruik van de

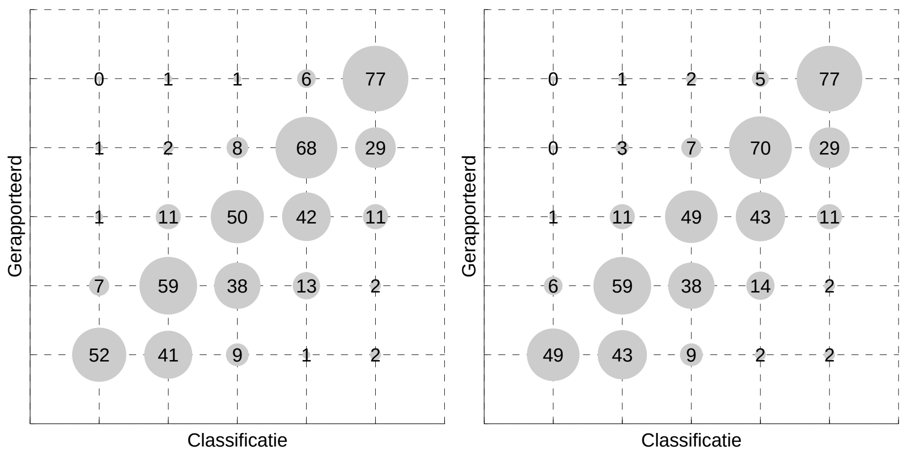


Figuur 12: Relatieve frequentie van de verschillende combinaties van geclassificeerde en gerapporteerde hinder met het ergste bron model (links) en de vaagregelgebaseerd model (rechts).

vaagverzamelingenleer kunnen ze de graduele overgangen op een realistische manier uitdrukken. Om dit te illustreren werd een automatische vertalingsapplicatie ontworpen om de termen te vertalen, louter en alleen gebaseerd op hun voorstelling als vaagverzameling.

Vervolgens werd een conceptueel hindermodel bestudeerd. De complexe relaties en interacties die geïdentificeerd werden staan in schril contrast met de huidige indicatormodellen die enkel de geluidsniveaus in rekening nemen. In tegenstelling tot deze statistisch gebaseerde methodes (enkel geschikt voor grote regio's), werd in sectie 3 een model ontworpen dat de hinder op een individuale basis kan voorspellen. Hierbij kunnen alle persoonlijke, emotionele, situationele,... variabelen meegenomen worden. Intern gebruikt het model vaaglogica om conclusies te trekken op basis van de beschikbare informatie. Het gebruik van vaaglogica impliceert dat het model tolerant is voor gegevens en kennis die vaag en/of onzeker is. De kennis is voorgesteld als vaagregels die de verbanden tussen de variabelen op een linguïstische manier vastleggen. Hierdoor is het model gemakkelijk interpreteerbaar, ook voor niet-akoestici en niet-wiskundigen. De uitvoer is robuust, en geeft een indicatie van hoe betrouwbaar de gevonden conclusie is, in functie van de aanwezige informatie. Door het optimaliseren van gewichten die de zekerheid van de regels aanduiden, kan men regelhypotheses testen.

De werking van een model voor de hinder door wegverkeer en trein-



Figuur 13: Relatieve frequentie van de verschillende combinaties van geclassificeerde en gerapporteerde hinder met het vage integraal modellen (links: 1-maxitief Choquet, rechts: 1-maxitief Sugeno).

verkeer werd in sectie 4 geïllustreerd met gegevens afkomstig van twee verschillende enquêtes, één uit Oostenrijk en één uit Vlaanderen. Het vaagmodel kan scherpe uitvoer geven als het nodig is om de resultaten te vergelijken met andere, scherpe modellen. Zo'n vergelijkingen werden door het vaagmodel glansrijk doorstaan. Een meer aangewezen behandeling van hinder als een vaagconcept wordt bekomen door het model in te stellen om vage uitvoer te produceren. Hierbij kan men dan met een parameter de mate aangeven waarin men een model wenst dat vaak correct is (in scherpe termen) tegen de prijs van niet specifieke resultaten. Er werd aangetoond dat de vage voorstellingen van hinder en de kennis toelaten om het model te veralgemenen tot meerdere verzamelingen van gegevens afkomstig van meerdere enquêtes in verschillende talen. De bekomen resultaten waren in overeenstemming met de klassieke analysetechnieken. Bovendien liet het model toe nog verdere analyses uit te voeren.

Vaak is men niet enkel geïnteresseerd in de hinder afkomstig van een bepaalde bron, maar in de evaluatie van de globale hinder. In sectie 3 werd het cognitief model achter het beste scherpe model, het ergste bron model, blootgelegd en vervolgens vervaagd met behulp van vaagregels. Deze linguïstische regels zijn eenvoudig te interpreteren. Dit vaagmodel presteert lichtjes beter dan het scherpe model. Er werden ook nog twee andere accumulatiemodellen onderzocht, op basis van de Choquet en de Sugeno-integraal. Deze bleken ook nog een beetje beter te presteren dan het vaagregelgebaseerd systeem.

Om de toepasbaarheid van het vaagmodel te verhogen zou men er in eerste instantie voor moeten kunnen zorgen dat de invoergegevens een indicatie bevatten van hun betrouwbaarheid. Dit kan bv. door de modellen vanaf de maatschappelijke activiteiten tot en met de toestand van het milieu eveneens te vervagen. De modellen die in dit werk uitgewerkt werden kunnen dan de effecten van die toestand voorspellen op basis van die vage invoer. Dit zou resulteren in een veel correctere voorspelling (in vage termen) dan nu het geval is, waar enkel scherpe getallen als invoer gebruikt worden (zonder een inschatting van hun zekerheid). Uiteraard kan het model ook nog verbeterd worden door meer (en zekerder) kennis over de relaties tussen variabelen toe te voegen (bv. relatie tussen bloeddruk en hinder). Tot slot kan men de accumulatiemodellen nog verder doortrekken om algemene variabelen zoals de levenskwaliteit te kunnen voorspellen met behulp van dezelfde vage technieken.

Recent worden deze vage technieken meer en meer gebruikt, zowel voor het modelleren van de effecten van geluid [150] [94] als in andere milieudomeinen [76] [83] [136] [95]. Ze vormen de noodzakelijke methode om de nauwkeurigheid van milieupollutiemodellen te verhogen en de onderliggende complexe processen beter te leren begrijpen.

Abbreviations

A	Annoyed
AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANSI	American National Standards Institute
CI	Computational Intelligence
CRI	Compositional Rule of Inference
dB	deciBel
DENL	Day Evening Night Level
DNL	Day Night Level
DPSI-R	Driving forces - Pressure - State - Impact - Response
EC	Evolutionary Computing
FATI	First Aggregate Then Infer
FITA	First Infer Then Aggregate
FCM	Fuzzy C-Means
FOU	Footprint Of Uncertainty
FRB	Fuzzy Rule Base
GA	Genetic Algorithm
GIS	Geographic Information System
GMP	Generalized Modus Ponens
HA	Highly Annoyed
ICBEN	International Commission on the Biological Effects of Noise
ISO	International Standards Institute

LA	Little Annoyed
MCDM	Multi-Criteria Decision Making
MIT	Massachusetts Institute of Technology
NAFIPS	North American Fuzzy Information Processing Society
OECD	Organization for Economic Co-operation and Development
OO	Object Oriented
OSDL	Ordinal Stochastic Dominance Learner
OWA	Ordered Weighted Averaging
STL	Standard Template Library
TOMASO	Tool for Ordinal Multi-Attribute Sorting and Ordering
UML	Unified Modeling Language
WAM	Weighted Arithmetic Mean
XML	eXtensible Modeling Language

List of symbols

dB	decibel
$\mathrm{dB_A}$	A-weighted decibel
L_{dn}	day-night level
L_{den}	day-evening-night level
U, V, W	universes
X, Y, Z	variables
A, B, C	fuzzy sets
$\tilde{A}, \tilde{B}, \tilde{C}$	type-2 fuzzy sets
u_i, $i \in \{1, \ldots, n\}$	elements from the set U
$\alpha, \beta, \gamma, \delta$	constants, parameters
$\mathcal{H}$	linguistic variable "annoyance"
$\mathbb{H}$	universe of discourse for "annoyance", equals $[0, 10]$
$\mathbb{L}$	set of all linguistic terms for "annoyance"
$\mathbb{S}$	set of all noise sources
L_j, $j \in \{1, \ldots, m\}$	elements from the set $\mathbb{L}$, linguistic "annoyance" terms
r_s, $s \in \{1, \ldots, S\}$	elements from the set $\mathbb{S}$
h_i, $i \in \{1, \ldots, n\}$	discrete elements in the set $\mathbb{H}$
H	fuzzy set in $\mathcal{F}(\mathbb{H})$
$k \in \{1, \ldots, N\}$	respondents of a survey
L_*^k	reported annoyance term by respondent k
$\mathcal{H}_s$, $s \in \{1, \ldots, S\}$	linguistic variable "annoyance" from a specific source
$\mathcal{H}_t$	linguistic variable global (accumulated) "annoyance"
$\mathcal{P}(U)$	(crisp) powerset of the set U

$\mathcal{F}(U)$	fuzzy powerset, set of all fuzzy sets on U
$\mathcal{I}$	implicator
$\mathcal{S}$	triangular conorm
$\mathcal{T}$	triangular norm
$\mathbb{N}$	set of all natural numbers
$\mathbb{R}$	set of all real numbers
μ	membership function or fuzzy measure
P	probability measure
Π	possibility measure
p	probability distribution
π	possibility distribution
m	Möbius representation of a fuzzy measure
$m^{\vee}$	possibilistic Möbius representation of a fuzzy measure
$C_\mu(f)$	Choquet integral of f with respect to μ
$S_\mu(f)$	Sugeno integral of f with respect to μ

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CHAPTER 1

Introduction

The beginning of wisdom is found in doubting;
by doubting we come to the question,
and by seeking we may come upon the truth.

Pierre Abelard (1079-1142)
French philosopher

1 PERCEPTION OF NOISE ANNOYANCE

1.1 Noise exposure

"John interrupts his sentences to Mike a few seconds because of the noise of an airplane that flies over". "Catherine wakes up in the middle of the night because of her neighbors arriving home". "Jodie closes her window. She can't concentrate of her study due to the noises of playing children on the street".

Probably everyone will recognize himself in one of the above situations. Situations in which the perception of environmental noise interferes with the activities we are currently doing, such as communicating, listening to the radio, watching television, resting, sleeping, reading, working, studying,... The noise bothers, disturbs or annoys us. Obviously, the degree of annoyance we experience will largely depend on the characteristics of the noise we are exposed to, e.g. the source of the noise, the loudness,... But this alone is not sufficient to completely explain the way we perceive noise annoyance. A young boy who is used to go to rock concerts will probably not feel annoyed when he hears his favorite music loud and clear coming from the neighbors, contrary to his dad who equals rock music with awful noise. Walking in a forest people will generally feel more annoyed by noises than walking through an amusement park, because they only expect noises from animals. So, personal, emotional, situational, environmental,... factors also play an important role. Often, these contextual factors in which noises occur together with the acoustical characteristics of the noises are referred to as the *soundscape*.

Besides the effects of environmental noise already mentioned, there are also some physiological health effects. *Physiology* is the study of the functions of the human body. Hence, physiological effects relate to changes in the functioning of the body, such as higher blood pressure, faster heartbeat and stress hormones [147]. In fact, these symptoms are more a consequence of the experience of annoyance instead of the exposure to noise itself. Noise during nighttime can induce awakenings from sleep [66]. However, rest or sleep disturbances, even if we don't wake up or remember it, may also lead to tiredness, decreased performance and depressed mood because of transitions from deep sleep to a lighter phase of sleep [146]. Ultimately, really high noise levels can cause loss of hearing. It remains to be firmly proven that long term exposure to loud noise can lead to severe health effects such as heart diseases, although there is growing evidence that it might increase the risk for ischaemic heart diseases [6].

An experiment conducted among international experts in the field of acoustics and noise effects revealed that noise annoyance is primarily seen as the most important effect of noise [79]. It was also shown that the concept "*noise annoyance*" is closely related to terms such as "nuisance", "unpleasantness" and "disturbance". So internationally, noise annoyance is generally considered as the main effect of noise and a good indicator to describe the impact of environmental noise on man. More formally, noise annoyance is a psychological concept that can be defined as a "negative evaluation of environmental conditions, a secondary reaction produced by disturbances of activities, such as disturbance of communication" [79].

1.2 Environmental noise pollution

During the last decades, people have aimed at a society based on the principles of *sustainable development*, "a society that can meet its needs of the present without compromising the ability of future generations to meet their own needs" [1]. A major condition to reach this goal is the ability to monitor and control the impact of environmental pollution. This includes the impact of noise pollution as an environmental stressor, for which noise annoyance has been shown to be an excellent indicator. An important question that must be solved for this monitoring and controlling purpose is, "where" exactly does the environmental noise come from?

To provide an answer to this question, we will use the DPSI-R model (Driving forces - Pressure - State - Impact - Response) as adopted by the European Commission [3], inspired by the earlier PSR model developed by the OECD [2]. This theoretical framework is widely used for the purpose of integrated environmental assessment studies, see figure 1.1. It begins with the socio-economic *driving forces* (D) that exert *pressure* on the environment (P) by emitting particles or energy. These emissions modify the *state* of the environment (S), the immission, which in turn has an *impact* on ecosystems and health (I). Finally, controlling this impact requires *responses* (R) on all levels. These responses can come from natural systems (e.g. self regulation) and environmental policy makers.

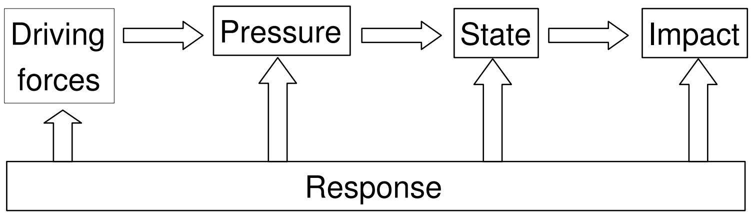

Figure 1.1: DPSI-R model

Specifically for environmental noise, the DPSI-R model takes the following form.

Driving forces An activity that produces a great deal of noise is undoubtedly traffic and transportation. This includes all possible kinds of vehicles on roads, railways (trains, streetcars and subway), water and air. Of course, also economic activities such as small businesses, factories, building industry and agricultural equipment produce a lot of noise. Other sources include the things we do in our spare time, such as visiting restaurants and bars, going to entertainment parks and fairs,... But simply staying home can also produce noise for our neighbors, e.g. playing loud music and noises caused by the presence of pets and children.

Pressure The pressure that an activity puts on the environment is directly related to the source of the noise, it is the *emission* of that source on that location. Each type of source has its own typical noise, which is characterized by frequency, tonality, duration,... One of the most important characteristics is the produced *sound pressure level* or *sound exposure*. This is typically expressed in *decibels* (dB) which is a logarithmical scale based on the physical sound pressure. As a reference, a normal conversation produces about 60 dB at normal listening distance. The hearing threshold is 0 dB, while the pain level is situated around 120 dB.

State The state of the environment focuses on the exposure of noise at a certain location, independent of a specific source. It is the *immission* of noise, linked to a human observer at that location. Additionally, the way we hear noise, the physiological aspects of the human ear are also taken into account, e.g. loudness and possibly other noise characteristics that can negatively influence annoyance such as tonality. It was found that human ears are more sensitive for certain frequency ranges than for others, we observe some frequencies louder than others. This means that sound pressure levels in dB are not well suited to express the loudness we are exposed to. Therefore, they are corrected to correlate overall sound pressure with the frequency sensitivities of the human ear. This process is called *A-weighting*, the resulting quantity is the *A-weighted sound exposure* expressed in the *A-weighted decibel* (dB_A).

During a time period, we are exposed to many single noise events, e.g. the passing of a heavy truck or an airplane that flies over. However, for the purpose of annoyance monitoring, we are not really interested in the sound exposure of each individual noise event. We are only concerned with the overall sound exposure at a location. To calculate such an overall measure, the A-weighted decibels are averaged over a 24-hour day, with a 10 dB_A penalty applied to noise occurring during the nighttime period (from 10 pm until 7 am). The obtained quantity is called the *Day-Night-Level* (DNL, L_{dn}). Similarly, also the *Day-Evening-Night-Level* (DENL, L_{den}), has been defined with an extra 5 dB_A penalty for the evening hours (from 7 pm till 11 pm) and again a 10 dB_A penalty for the night hours (from 11 pm till 7 am).

Impact The effects of noise on man have already been discussed in the previous section. The impact of noise on ecosystems and economy is not yet well-studied. For a review of studies on the noise effects on animals, see [101].

Response Various decisions can be made to lower the emission, immission and impact of noise. To reduce the noise emission of traffic, one can opt for more quiet vehicles and road surfaces. Immission can be decreased by separating noisy areas from areas that require more silence such as living areas (e.g. by prohibiting heavy traffic), by placing noise shields and with better isolation of houses. Finally, quiet areas,

areas with a comforting soundscape, can be marked and protected from noisy activities. It is up to the politicians to make such decisions and to write appropriate regulations. The accurate monitoring of noise annoyance, and –if possible– also the prediction of noise annoyance after planned changes to the neighborhood (e.g. new roads, railways or plants) is an important instrument for these purposes. Modeling noise annoyance may even allow to suggest response at the level of noise impact. For instance, it could be found that merely paying attention to complaints, listening instead of brushing them aside, might help to soften the feeling of annoyance.

1.3 Noise annoyance

Although the physical "where" question is a significant one, it is not sufficient to fully grasp the concept of noise annoyance. It is also primordial to shed light on the "how" question: "How is noise annoyance psychologically constructed?". In [107] the evolution of psychological noise-health models is described. Here, only the *transactional model* as introduced by Lazarus and Folkman [104] will be explained, just to give an idea of the complex psychological processes that are involved (see figure 1.2).

In the *primary appraisal* phase the personal significance of the perceived noise exposure is evaluated. If the exposure is assessed as stressful, it is followed by a *secondary appraisal*. In this phase the personal opportunities to deal with the burden are evaluated. Finally, the result of this evaluation is implemented in the process of *coping*. Coping refers to efforts to manage the noise exposure, the actions that have emerged as necessary from the secondary appraisal. There are many varieties of coping styles. Behavioral actions include the closing of windows and even changing the bedroom to the other side of the house. Emotional or palliative coping are actions such as seeking social support or simply feeling helpless. Finally, cognitive approaches are efforts that change the meaning of the situation without changing the actual environment, e.g. social comparisons, minimization and information gathering. After the coping phase, this noise-health loop is endlessly repeated through re-appraisals directed at changes in the personal experience of the noise environment.

The transactional model also acknowledges the importance of personal and situational factors on the appraisal processes and the coping efforts that are considered appropriate. Noise sensitivity, fear of the source, satisfaction of the neighborhood and cultural differences can significantly influence the way we perceive and evaluate noise.

To conclude, from a psychological viewpoint *noise annoyance* describes a relation between an acoustic situation and a person who is forced by noise to do things he does not want to do, who cognitively and emotionally evaluates this situation [79].

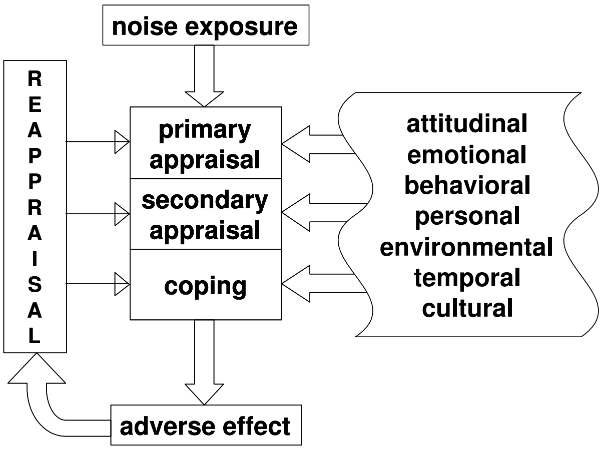

Figure 1.2: Transactional model

2 Modeling issues

We already know that the modeling and prediction of noise annoyance is important to achieve sustainable development. It depends on a multitude of factors, acoustical as well as non-acoustical, that are involved in complex psychological processes that lead to its construct. Furthermore, noise annoyance can be traced back to the human activities that pollute the environment with noise. With this in mind, we can imagine a model that walks down the DPSI-R model and results in an expression of the noise annoyance an observer would experience at a given location. However, there are a few issues that complicate this apparently simple idea. As they are all related to the acquisition, representation and processing of information, let us first elaborate a bit on the different types of information that exist [131].

The simplest type of information is *precise information*. Information that is given as a (crisp) number, e.g. “the sound level of the music is 100 dB_A”. But in real life, we do not always know things that precise. For example, the statement “the sound level of the music is between 90 and 110 dB_A” conveys *imprecise information* of the sound level. We only know that the sound level is a particular value in the given range, but we do not have knowledge of the exact value. *Vague information* is imprecise information that cannot be described within precise boundaries, e.g. “the sound level of the music is loud”. In this case, sharp boundaries are completely lacking. Some sound levels are definitely “loud”, while others can only be called “loud” to a certain degree. There is a gradual transition. Sometimes there can be doubt about the truth of a statement, e.g. “the sound level of the music is possibly 100 dB_A”. In this case, we have *uncertain information*, we are not really sure that the sound level is 100 dB_A. There can be several different causes for the uncertainty. The measurement of the noise level could have been affected because the location was not well chosen or because the meter was not calibrated. Imprecision and uncertainty are orthogonal concepts, they can also occur together. As an example of this consider the expression “the sound level of the music is possibly between 90 and 110 dB_A”.

Let us now return to the difficulties associated with the application of the DPSI-R model. When moving from the driving forces to the impact, we have to deal with the following issues.

- The involved concepts become more subjective and vague. Where the emitted noise levels can be measured and expressed on a physical, numerical scale, this is not possible with concepts such as noise annoyance and sensitivity to noise, which are fundamental in the modeling of the impact of noise. First of all, for such concepts there is no underlying physical scale. Secondly, those concepts describe a feeling, a state of mind, which cannot be communicated by a precise number.

- Data is scarce, imprecise and uncertain. Every modeling approach requires a lot of data to build or verify the resulting model. But collecting data is a time-consuming and expensive process. Yet, generalizations, interpolations and extrapolations to reduce costs are important sources of uncertainty, e.g. counting the amount of traffic on a single day for fifteen minutes during evening rush-hour and using this as representative for the average amount of traffic in a year. Furthermore, measured data always suffers from some imprecision typical for the measuring equipment. Even worse, due to temporary equipment failures, some data values may be missing. On the other hand, there are also a number of subjective concepts that cannot be directly measured at all. These must be obtained by other means. A common approach to gather information on e.g. experienced noise annoyance is through *social surveys*, conducted by post, phone, or face-to-face. In such studies collaborative respondents are asked to answer a few questions, usually by selecting one of the proposed answers. It is clear that this kind of data is often incomplete (people can skip questions), imprecise (e.g. if the proposed answers are not well chosen) and error-prone because of the involved human interaction.

- Knowledge is lacking, vague or uncertain. For gravity, the crisp laws of Newton and more generally the laws of Einstein have been found. However, this kind of precise knowledge is not –yet?– available in all scientific fields. Although there are physical laws describing the propagation of noise, noise propagation over large distances (already starting at a few hundred meters) is still not fully known. Even less is known about the variables that influence the experience of noise annoyance, and their precise relations with annoyance. Experts in the field can only give vague expressions of some assumed relations. Using such qualitative statements in calculation models is not a trivial task. Furthermore, it can be doubted that it is even possible to make such knowledge as precise as the gravity laws since this would require a complete biological characterization of human beings, including their thoughts, experiences,...

3 Towards a solution

Considering its importance for policy makers, this work will tackle the modeling of the impact of environmental noise. Starting at the end of the DPSI-R chain, the concept of noise annoyance will be disentangled to the state of the noise environment and other factors that influence our perception of noise. Our objective is to propose a framework that is capable of handling the mentioned vagueness and uncertainty of the concepts, data and knowledge in a natural and useful way. More concrete, a framework with the following properties is put forward as a goal.

Tolerant The framework should be tolerant for vague, imprecise, uncertain or missing information. This includes the information that is stored inside the model (knowledge) as well as the information that is fed to the system (input data). The framework should try to make a well-founded, best guess based on the available information.

Reliable The resulting expression of noise annoyance should be meaningful and not more precise than feasible. If the result cannot be naturally expressed as a single –precise– number, then the model should not try to do so. The outcome of the system must be reliable within the limits of the provided inputs. If it cannot draw a firm conclusion, it must give a hint about the reliability of its output.

Robust Small changes to the input values, e.g. due to measurement noise, should not lead to big changes of the output.

Interpretable The model should expose the way it works. Instead of being a “black box” model, it must be easily comprehensible by experts in the field. Its underlying semantics and reasoning processes must be clear.

Individual The modeling of noise annoyance should be done on a personal level, not averaged over a whole neighborhood or community. It must be possible to take into account a number of personal variables, and produce an estimate of the experienced noise annoyance on an individual basis.

Adaptable The framework must be able to adapt rules when they represent hypothetical knowledge that does not hold. It should allow to use available input and compare the output with the results obtained through a social survey. This feature will provide an instrument to determine “what” variables are important for the construct of noise annoyance, and how they influence annoyance.

To accomplish these ambitious goals, it is clear that the handling of vague and uncertain information will require special care. Although these kinds of information occur quite often in real life, they are difficult to work with in a mathematical world based on binary logic. The main cause of the difficulties is the lack of a mathematical notion of gradation. In a binary setting something is either completely true or completely false. Smooth transitions are not possible. It is obvious that other tools will be needed in order to succeed in our goals.

In 1965, Zadeh introduced the concept of a fuzzy set [183]. His aim was to represent in a sound mathematical way gradual membership to classes of objects that do not have crisp boundaries. He already noted that such imprecisely defined classes are often encountered in the real physical world, e.g. the class of beautiful women. Since then the theory of fuzzy sets and the related fuzzy logic [191] and possibility theories [191] [54] have been further expanded and have proven to be appropriate tools to model vague and uncertain information and knowledge. In this work, we will show that fuzzy set theory is perfectly suited to address the problems of noise annoyance modeling and to achieve the goals put forward.

Fuzzy logic fits into the ideas of what is called “*soft computing*”. The aim of soft computing is “to exploit the tolerance for imprecision, uncertainty, approximate reasoning, and partial truth in order to achieve tractability, robustness, low cost solutions, and close resemblance to human like decision making". Contrary to traditional "hard computing" which is focused on binary logic and crisp numerical analysis. Other methodologies that enable "soft computing" are *neural networks*, *evolutionary computing* and *probabilistic reasoning*. They are all imitating the way that humans reason in a vague and uncertain world.

An important aspect of fuzzy sets in the context of soft computing is that they enable what Zadeh calls "*computing with words*" [193] [194] [195]. Computing with words is a methodology in which the objects of computation are words and propositions drawn from a natural language. It allows to reason with linguistical expressions represented by fuzzy sets. Computing with words is inspired by the human capabilities to operate based on perceptions instead of crisp numbers and measurements. For example, when driving a car, we do not measure the distance to the car in front of us. We do not slam on the brakes at exact three meters distance, instead, we slowly start braking when we are gradually approaching the other car. Such models where perceptions are linguistically expressed are much more interpretable by humans.

Computing with words as a foundation for a computational theory of perceptions, and the other soft computing methodologies that imitate human like intelligence has given rise to the new paradigm of *computational intelligence* (CI). It is based on the manipulation of perceptions instead of the manipulation of numbers and symbols as in the field of artificial intelligence (AI). Computational intelligence is very promising in scientific areas in which perceptions play a key role in an imprecise and uncertain environment, e.g. medical diagnosis [86] [127] and financial analysis [128] [182]. In this work, the perception-based approach will be investigated in the context of the modeling of noise annoyance.

In chapter 2 the necessary mathematical concepts are introduced. Chapter 3 uses those tools to represent the concept of (noise) annoyance. These representations are utilized in chapter 4 to build a framework for the modeling of noise annoyance caused by a specific type of source. How the framework can be applied for the modeling of the accumulation of annoyance caused by several types of sources is shown in chapter 5. Obtained results based on real data sets are discussed in chapter 6. Finally, chapter 7 draws some conclusions and suggests directions for further research.

CHAPTER 2

Basic concepts of fuzzy sets and fuzzy logic

> If people do not believe that mathematics is simple,
> it is only because they do not realize how complicated life is.
>
> *John von Neumann (1903-57)*
> *Hungarian-American mathematician*

1 A Greek tale

A single grain of sand is certainly not a heap. Nor is the addition of a single grain of sand enough to transform a non-heap into a heap. When we have a collection of grains of sand that is not a heap, then adding but one single grain will not create a heap. And so by adding successive grains, moving from 1 to 2 to 3 and so on, we will never arrive at a heap. And yet we know full well that a collection of 1,000,000 grains of sand is a heap, even if not an enormous one.

This "*sorites paradox*" [155] is attributed to Eubulides of Miletus, a Greek philosopher who lived in the 4th century BC. He was a contemporary and rival of the great Aristotle (384 BC–322 BC). The name "sorites" derives from the Greek word "soros" (meaning "heap") and originally referred, not to a paradox, but rather to a puzzle known as "The Heap".

> Would you describe a single grain of wheat as a heap? No. Would you describe two grains of wheat as a heap? No. And three grains? Four? And so on... – You must admit the presence of a heap sooner or later, so where do you draw the line?

The sorites line of reasoning was also known as little-by-little argument which alludes to the gradual process of change that takes place. The smooth transition from a proposition to its opposite proposition. But Aristotle had just created the foundations of binary logic as the universal laws of thought. In this Aristotelian logic, such transitions were impossible because of the law of the excluded middle which states that every proposition must either be true or false.

Although this paradox in binary logic was noted very early in history, it took a long time before an attempted solution was formalized. In 1920 the Polish logician and philosopher Jan Łukasiewicz (1878–1956) introduced the notion of a multi-valued logic by proposing a third additional truth value. This third value was "possibly true or false" and belonged somewhere between true and false. Later on, he also explored a four-valued and five-valued logic. But it was Lotfi Zadeh (1921–) who developed the mathematical framework to reason with vagueness and gradedness of concepts in 1965. In his fuzzy set theory and associated fuzzy logic, which is in fact an infinite valued logic, a proposition can take any truth value in the interval $[0, 1]$. Truth and belonging to a set become a matter of degree. This allows to resolve the sorites paradox in a mathematically sound way with a gradual transition of the degree of belonging to a heap (from 0 to 1), without crossing any sharp boundaries.

In this chapter, the basic notions of fuzzy set theory and fuzzy logic are briefly introduced. They will be needed in the remainder of this work to handle the vagueness and uncertainty in the annoyance concept. For a more thorough discussion of fuzzy sets and fuzzy logic, please refer to [97] and [58].

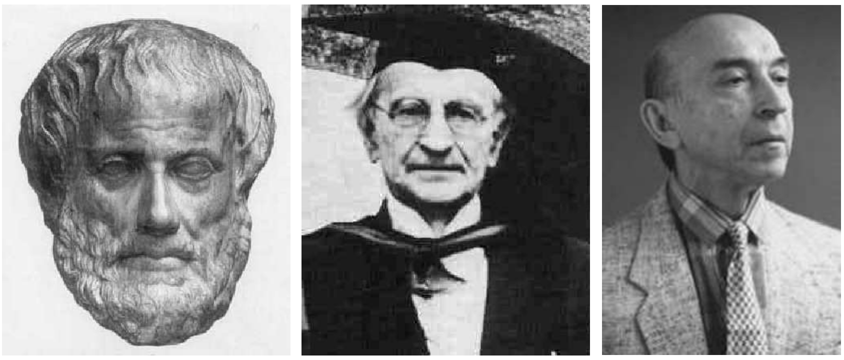

Figure 2.1: The founding fathers of logic: Aristotle, Łukasiewicz and Zadeh.

2 Basic definitions

2.1 Fuzzy sets and fuzzy logic

In classical set theory, or within the field of fuzzy set theory also called "crisp" set theory, a characteristic function is associated with each crisp set. This function is defined on the universe of discourse and yields the value 0 or 1 whether the argument belongs to the set or not.

Definition 1 (*Set*). *A (crisp) set A on a universe U is characterized by its characteristic function $\chi_A : U \to \{0, 1\}$*

$$\chi_A(u) = \begin{cases} 0 & \text{if } u \notin A \\ 1 & \text{if } u \in A \end{cases} \tag{2.1}$$

The powerset of U, the set of all subsets of U, will be denoted as $\mathcal{P}(U)$.

Fuzzy set theory generalizes the concept of set membership by extending the range of the characteristic function from $\{0, 1\}$ to the unit interval $[0, 1]$. This extension allows a gradual transition from "not belonging to a set" to "belonging to a set".

Definition 2 (*Fuzzy set* [183]). *A fuzzy set A on a universe U is characterized by its membership function $\mu_A : U \to [0, 1]$, where $\mu_A(u)$ denotes the degree to which $u \in U$ belongs to A. $\mu_A(u)$ is called the membership degree or grade of membership of u in A.*

The set of all fuzzy sets on a universe U is denoted as $\mathcal{F}(U)$. Every crisp set is in fact a fuzzy set restricted to $\{0, 1\}$. Therefore the following relation holds: $\mathcal{P}(U) \subseteq \mathcal{F}(U)$.

In [183] Zadeh also introduced extensions of the classical operations on sets.

Definition 3 (*Fuzzy set union, intersection* and *complement* [183]). *For A and B fuzzy sets over a universe U and for all $u \in U$,*

$$\mu_{A\cup B}(u) = \max(\mu_A(u), \mu_B(u)) \tag{2.2}$$

$$\mu_{A\cap B}(u) = \min(\mu_A(u), \mu_B(u)) \tag{2.3}$$

$$\mu_{\overline{A}}(u) = 1 - \mu_A(u) \tag{2.4}$$

A natural requirement of fuzzy operators is that they coincide with their crisp counterparts when they operate on crisp sets. It can be verified that the above definitions satisfy this property.

As *fuzzy set theory* is an extension of classical set theory, it is also possible to extend binary logic along the same lines to *fuzzy logic*. Instead of evaluating a logical proposition as either true (1) or false (0), the truth function is extended to range in the unit interval $[0, 1]$. Hence, truth also becomes a matter of degree. Based on the strong analogy between set theory and logic, the operations defined for sets, like union, intersection and complement, have a corresponding logical meaning, like disjunction (OR, $A \vee B$), conjunction (AND, $A \wedge B$) and negation (NOT, $\neg A$) respectively.

2.2 Properties of fuzzy sets

Definition 4 (*Alpha-cut*, *strong alpha-cut* [97]). *For A a fuzzy set on the universe U and $\alpha \in [0, 1]$, the alpha-cut A_α and strong alpha-cut $A_{\overline{\alpha}}$ are defined by*

$$A_\alpha = \{u | \mu_A(u) \geq \alpha\} \tag{2.5}$$

$$A_{\overline{\alpha}} = \{u | \mu_A(u) > \alpha\} \tag{2.6}$$

Definition 5 (*Support*, *core* [97]). *For A a fuzzy set on the universe U, the support* $\mathrm{supp}(A)$ *and core* $\ker(A)$ *are defined by*

$$\mathrm{supp}(A) = \{u | \mu_A(u) > 0\} = A_{\overline{0}} \tag{2.7}$$

$$\ker(A) = \{u | \mu_A(u) = 1\} = A_1 \tag{2.8}$$

Definition 6 (*Height*, *plinth* [97]). *Given a set U and a fuzzy set A on U, the height and plinth of A are defined by*

$$\mathrm{hgt}(A) = \sup_{u \in U} \mu_A(u) \tag{2.9}$$

$$\mathrm{plt}(A) = \inf_{u \in U} \mu_A(u) \tag{2.10}$$

Definition 7 (*Normal fuzzy set* [132]). *A fuzzy set A on U is normal if it satisfies* $\mathrm{hgt}(A) = 1$.

When a fuzzy set A on U is not normal, it can be normalized with the following transformation.

Definition 8 (*Fuzzy set normalization* [132]).

$$\mathrm{norm}(A) = \begin{cases} \frac{\mu_A(x)}{\mathrm{hgt}(A)} & \textit{if } \mathrm{hgt}(A) \neq 0 \\ 1 & \textit{if } \mathrm{hgt}(A) = 0 \end{cases} \tag{2.11}$$

Definition 9 (*Scalar cardinality* [132]). *The cardinality of a fuzzy set A on a finite universe U is defined by*

$$|A| = \sum_{u \in U} \mu_A(u) \tag{2.12}$$

For a fuzzy set A on the real line $\mathbb{R}$, *it is defined by*

$$|A| = \int_U \mu_A(u)du \tag{2.13}$$

Definition 10 (*Fuzzy subset* [183]). *A fuzzy set* $A \in \mathcal{F}(U)$ *is a subset of a fuzzy set* $B \in \mathcal{F}(U)$ *if the following condition is satisfied.*

$$A \subseteq B \Leftrightarrow (\forall u \in U)(\mu_A(u) \leq \mu_B(u)) \tag{2.14}$$

Definition 11 (*Fuzzy equality* [183]). *A fuzzy set* $A \in \mathcal{F}(U)$ *is equal to a fuzzy set* $B \in \mathcal{F}(U)$ *if the following condition is satisfied.*

$$A = B \Leftrightarrow (\forall u \in U)(\mu_A(u) = \mu_B(u)) \tag{2.15}$$

2.3 Fuzzy set representations

A fuzzy set A on a universe U is completely defined by its membership function. When U is a countable set, the fuzzy set A can be specified by a list of ordered (membership degree, set element) pairs. If U is a non-countable domain, the membership function of A is usually given by a functional representation. In the literature, a number of parametric shapes can be found [132]. They can be used to define fuzzy sets in the special case that the universe U is the real line $\mathbb{R}$. In the following it is always assumed that α, β, γ and δ are parameters in $\mathbb{R}$ and $\alpha < \beta < \gamma < \delta$.

Definition 12 (*Linear membership function*).

$$\begin{aligned} \textsc{Lin}(.;\alpha,\beta): \quad & \mathbb{R} \to [0,1] \\ & u \mapsto \begin{cases} 0 & \textit{if } u \leq \alpha \\ \frac{u-\alpha}{\beta-\alpha} & \textit{if } u \in [\alpha,\beta] \\ 1 & \textit{if } u \geq \beta \end{cases} \end{aligned} \tag{2.16}$$

Definition 13 (*Triangular membership function*).

$$\begin{aligned} \textsc{Tri}(.;\alpha,\beta,\gamma): \quad & \mathbb{R} \to [0,1] \\ & u \mapsto \begin{cases} 0 & \textit{if } u \leq \alpha \\ \frac{u-\alpha}{\beta-\alpha} & \textit{if } u \in [\alpha,\beta] \\ \frac{\gamma-u}{\gamma-\beta} & \textit{if } u \in [\beta,\gamma] \\ 0 & \textit{if } u \geq \gamma \end{cases} \end{aligned} \tag{2.17}$$

Definition 14 (*Trapezoidal membership function*).

$$\begin{aligned}\textsc{Trap}(.;\alpha,\beta,\gamma,\delta): \quad & \mathbb{R} \to [0,1] \\ u \mapsto & \begin{cases} 0 & \textit{if } u \le \alpha \\ \frac{u-\alpha}{\beta-\alpha} & \textit{if } u \in [\alpha,\beta] \\ 1 & \textit{if } u \in [\beta,\gamma] \\ \frac{\delta-u}{\delta-\gamma} & \textit{if } u \in [\gamma,\delta] \\ 0 & \textit{if } u \ge \delta \end{cases}\end{aligned} \tag{2.18}$$

A trapezoidal membership function with $\beta = \gamma$ reduces to a triangular membership function.

Definition 15 (*Sigmoidal membership function*).

$$\begin{aligned}\mathrm{S}(.;\alpha,\beta): \quad & \mathbb{R} \to [0,1] \\ u \mapsto & \begin{cases} 0 & \textit{if } u \le \alpha \\ 2\left(\frac{u-\alpha}{\beta-\alpha}\right)^2 & \textit{if } u \in \left[\alpha, \frac{\alpha+\beta}{2}\right] \\ 1-2\left(\frac{u-\beta}{\beta-\alpha}\right)^2 & \textit{if } u \in \left[\frac{\alpha+\beta}{2}, \beta\right] \\ 1 & \textit{if } u \ge \beta \end{cases}\end{aligned} \tag{2.19}$$

This shape is almost everywhere identical to the exponential curve with $\mu, \sigma \in \mathbb{R}$ that is defined by

$$\begin{aligned}\mathrm{S}_E(.;\mu,\sigma): \quad & \mathbb{R} \to [0,1] \\ u \mapsto & \tfrac{1}{1+\exp(\mu-\sigma x)}\end{aligned} \tag{2.20}$$

Definition 16 (*Asymmetric Gaussian membership function*).

$$\begin{aligned}\textsc{AGauss}(.;\alpha,\beta,\gamma): \quad & \mathbb{R} \to [0,1] \\ u \mapsto & \begin{cases} 0 & \textit{if } u \le \alpha \\ 2\left(\frac{u-\alpha}{\beta-\alpha}\right)^2 & \textit{if } u \in \left[\alpha, \frac{\alpha+\beta}{2}\right] \\ 1-2\left(\frac{u-\beta}{\beta-\alpha}\right)^2 & \textit{if } u \in \left[\frac{\alpha+\beta}{2}, \beta\right] \\ 1 & \textit{if } u = \beta \\ 1-2\left(\frac{u-\beta}{\gamma-\beta}\right)^2 & \textit{if } u \in \left[\beta, \frac{\beta+\gamma}{2}\right] \\ 2\left(\frac{u-\gamma}{\gamma-\beta}\right)^2 & \textit{if } u \in \left[\frac{\beta+\gamma}{2}, \gamma\right] \\ 0 & \textit{if } u \ge \gamma \end{cases}\end{aligned} \tag{2.21}$$

This membership function is almost everywhere identical to a continuous asymmetric Gaussian curve with $\mu, \sigma, \delta \in \mathbb{R}$ defined by

$$\begin{aligned} \text{AGAUSS}_E(.;\mu,\sigma,\delta): \quad & \mathbb{R} \to [0,1] \\ & u \mapsto \begin{cases} \exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right) & \text{if } u \leq \mu \\ \exp\left(\frac{-(x-\mu)^2}{2\delta^2}\right) & \text{if } u > \mu \end{cases} \end{aligned} \tag{2.22}$$

The linear membership function $\text{LIN}(.;\alpha,\beta)$ and the membership function $\text{S}(.;\alpha,\beta)$ are increasing functions. The corresponding decreasing functions can be obtained by using the complement operation. They will be denoted $\overline{\text{LIN}}(.;\alpha,\beta)$ and $\overline{\text{S}}(.;\alpha,\beta)$ and are defined as $1 - \text{LIN}(.;\alpha,\beta)$ and $1 - \text{S}(.;\alpha,\beta)$ respectively.

3 Triangular norms and conorms

3.1 Definitions

It has already been stressed that fuzzy set and fuzzy logic operators should coincide with their binary counterparts when applied to crisp sets. The fuzzy operators defined by Zadeh [183] are obviously not the only possible extensions of classical set union and intersection that satisfy this requirement. The concept of triangular norms was originally proposed by Schweizer and Sklar [142] to model triangular inequalities in the context of probabilistic metric spaces. In the development of fuzzy logic, it turned out that triangular norms and conorms can be used as general models for the intersection (conjunction) and union (disjunction) operations.

Definition 17 (*Triangular norm* [142]). *A triangular norm $\mathcal{T}$ (or t-norm for short) is a $[0,1]^2 \to [0,1]$ mapping satisfying*

(i) Boundary condition: $(\forall x \in [0,1])(\mathcal{T}(1,x) = x)$

(ii) Monotonicity:

$$(\forall (x_1,x_2,y_1,y_2) \in [0,1]^4)$$
$$(x_1 \leq x_2 \wedge y_1 \leq y_2 \Rightarrow \mathcal{T}(x_1,y_1) \leq \mathcal{T}(x_2,y_2))$$

(iii) Associativity: $(\forall (x,y,z) \in [0,1]^3)(\mathcal{T}(\mathcal{T}(x,y),z) = \mathcal{T}(x,\mathcal{T}(y,z)))$

(iv) Commutativity: $(\forall (x,y) \in [0,1]^2)(\mathcal{T}(x,y) = \mathcal{T}(y,x))$

Definition 18 (*Triangular conorm* [142]). *A triangular conorm $\mathcal{S}$ (or t-conorm for short) is a $[0,1]^2 \to [0,1]$ mapping satisfying*

(i) *Boundary condition:* $(\forall x \in [0,1])(\mathcal{S}(0,x) = x)$

(ii) *Monotonicity:*

$$(\forall (x_1, x_2, y_1, y_2) \in [0,1]^4) \\ (x_1 \le x_2 \wedge y_1 \le y_2 \Rightarrow \mathcal{S}(x_1, y_1) \le \mathcal{S}(x_2, y_2))$$

(iii) *Associativity:* $(\forall (x,y,z) \in [0,1]^3)(\mathcal{S}(\mathcal{S}(x,y),z) = \mathcal{S}(x,\mathcal{S}(y,z)))$

(iv) *Commutativity:* $(\forall (x,y) \in [0,1]^2)(\mathcal{S}(x,y) = \mathcal{S}(y,x))$

Any triangular norm can be applied to model (fuzzy) set intersection and logical conjunction, while any triangular conorm models (fuzzy) set union and logical disjunction. Triangular norms and triangular conorms are in fact dual operators. To express their duality, we must first introduce negators.

Definition 19 (*Negator* [172]). *A negator $\mathcal{N}$ is a $[0,1] \to [0,1]$ mapping satisfying*

(i) *Boundary condition:* $\mathcal{N}(0) = 1 \wedge \mathcal{N}(1) = 0$

(ii) *Monotonicity:* $(\forall (x,y) \in [0,1]^2)(x \le y \Rightarrow \mathcal{N}(y) \le \mathcal{N}(x))$

Definition 20 (*Strong negator* [58]). *A negator $\mathcal{N}$ additionally satisfying involution, $(\forall x \in [0,1])(\mathcal{N}(\mathcal{N}(x)) = x)$, is called a strong negator.*

All negators are ideally suited to model the fuzzy complement (logical negation) operation. They are monotonically decreasing functions that coincide with their crisp counterpart when applied to $\{0,1\}$. Examples of negator functions are summarized in table 2.1. The negator $\mathcal{N}_\perp$ is the smallest possible negator, while $\mathcal{N}_\top$ is the largest possible negator. Despite the many possibilities to define a negator, in practice, the Zadeh –*standard–negator* $\mathcal{N}_Z$ is the one that is almost exclusively used.

Definition 21 (*Triangular norm and conorm duality* [58]). *A triangular norm $\mathcal{T}$ and a triangular conorm $\mathcal{S}$ are dual with respect to a strong negator $\mathcal{N}$ when they satisfy,*

$$(\forall (x,y) \in [0,1]^2)(\mathcal{S}(x,y) = \mathcal{N}(\mathcal{T}(\mathcal{N}(x),\mathcal{N}(y)))) \tag{2.23}$$

which is equivalent with

$$(\forall (x,y) \in [0,1]^2)(\mathcal{T}(x,y) = \mathcal{N}(\mathcal{S}(\mathcal{N}(x),\mathcal{N}(y)))) \tag{2.24}$$

Examples of triangular norms and their dual conorms (with respect to the standard negator $\mathcal{N}_Z$) frequently encountered in the fuzzy literature are shown in table 2.2. For more examples and a thorough discussion of t-norms and t-conorms, the interested reader is referred to [58] [97] and [132].

Table 2.1: Negators.

Name	Negator	Parameter
Zadeh [183]	$\mathcal{N}_Z(x) = 1 - x$	-
Intuitionistic [58]	$\mathcal{N}_{\perp}(x) = \begin{cases} 1 & (x = 0) \\ 0 & (x \neq 0) \end{cases}$	-
Dual intuitionistic [58]	$\mathcal{N}_{\top}(x) = \begin{cases} 0 & (x = 1) \\ 1 & (x \neq 1) \end{cases}$	-
Threshold [40]	$\mathcal{N}_{T,\alpha}(x) = \begin{cases} 1 & (x < \alpha) \\ 0 & (x \geq \alpha) \end{cases}$	$\alpha \in [0, 1]$
Sugeno [149]	$\mathcal{N}_{S,\alpha}(x) = \frac{1-x}{1+\alpha x}$	$\alpha \in]-1, +\infty[$
Yager [175]	$\mathcal{N}_{Y,\alpha}(x) = \sqrt[\alpha]{1 - x^{\alpha}}$	$\alpha \in]0, +\infty[$

3.2 Properties

Definition 22 (*Idempotent* [97]). *A triangular norm $\mathcal{T}$ is idempotent if it satisfies $(\forall x \in [0,1])(\mathcal{T}(x,x) = x)$. A triangular conorm $\mathcal{S}$ is idempotent if it satisfies $(\forall x \in [0,1])(\mathcal{S}(x,x) = x)$.*

$\mathcal{T}_M$ and $\mathcal{S}_M$ are the only idempotent triangular norm and conorm.

In [143] the following theorem has been proven.

Theorem 1. *For every triangular norm $\mathcal{T}$ and triangular conorm $\mathcal{S}$ it holds:*

$$\mathcal{T}_Z \leq \mathcal{T} \leq \mathcal{T}_M \tag{2.25}$$

$$\mathcal{S}_M \leq \mathcal{S} \leq \mathcal{S}_Z \tag{2.26}$$

where the order relation $\leq$ for two binary $[0,1]^2 \to [0,1]$ mappings is pointwise defined as

$$f_1 \leq f_2 \Leftrightarrow (\forall (x,y) \in [0,1]^2)(f_1(x,y) \leq f_2(x,y)) \tag{2.27}$$

In fact, for the given triangular norms and conorms the following ordering can be proven [143]: $\mathcal{T}_Z \leq \mathcal{T}_W \leq \mathcal{T}_P \leq \mathcal{T}_M \leq \mathcal{S}_M \leq \mathcal{S}_P \leq \mathcal{S}_W \leq \mathcal{S}_Z$.

Because of the associativity property of triangular norms and conorms, they can be extended to n-ary operators.

Definition 23 (*n-ary t-norm* and *n-ary t-conorm* [43]). *Let $(x_i)_{i=1}^n$ be a finite family in $[0,1]$ with $n \in \mathbb{N} \setminus \{0\}$, $\mathcal{T}$ is a triangular norm and $\mathcal{S}$ is a*

Table 2.2: Triangular norms and their dual conorms.

Triangular norm	Triangular conorm
Weber = Drastic [172]	
$\mathcal{T}_Z(x,y) = \begin{cases} y & (x=1) \\ x & (y=1) \\ 0 & \text{(else)} \end{cases}$	$\mathcal{S}_Z(x,y) = \begin{cases} y & (x=0) \\ x & (y=0) \\ 1 & \text{(else)} \end{cases}$
Łukasiewicz [58]	
Bold intersection $\mathcal{T}_W(x,y) = \max(0, x+y-1)$	Bounded sum $\mathcal{S}_W(x,y) = \min(x+y, 1)$
Bandler and Kohout [58]	
Product $\mathcal{T}_P(x,y) = xy$	Probabilistic sum $\mathcal{S}_P(x,y) = x+y-xy$
Zadeh [183]	
Minimum $\mathcal{T}_M(x,y) = \min(x,y)$	Maximum $\mathcal{S}_M(x,y) = \max(x,y)$

triangular conorm, then

$$\mathcal{T}_n(x_1, x_2, \ldots, x_n) = \mathcal{T}\left(\mathcal{T}_{n-1}(x_1, x_2, \ldots, x_{n-1}), x_n\right) \tag{2.28}$$

$$\mathcal{S}_n(x_1, x_2, \ldots, x_n) = \mathcal{S}\left(\mathcal{S}_{n-1}(x_1, x_2, \ldots, x_{n-1}), x_n\right) \tag{2.29}$$

where $\mathcal{T}_2 = \mathcal{T}$, $\mathcal{S}_2 = \mathcal{S}$ *and* $\mathcal{T}_1$, $\mathcal{S}_1$ *are the identity operation on* $[0,1]$. *The index* n *can be dropped as there can be no misinterpretation.*

4 Fuzzy relations

So far, only fuzzy sets on a single universe have been defined. Just as classical set theory can define relations between two or more universes, fuzzy sets can be extended to multidimensional fuzzy sets that relate the elements of several universes. Multidimensional fuzzy sets are usually called fuzzy relations.

Definition 24 (*Fuzzy relation* [183]). *An n-ary fuzzy relation* R $(n \in \mathbb{N}\backslash\{0\})$ *between the universes* $U_1, U_2, \ldots, U_n$ *is a fuzzy set on the universe* $U_1 \times U_2 \times \ldots \times U_n$. *For such fuzzy sets, the membership function* μ_R *is a mapping* $U_1 \times U_2 \times \ldots \times U_n \to [0,1]$ *which assigns a membership degree to all* n*-tuples* $(u_1, u_2, \ldots, u_n)$ *where* $u_i \in U_i$ *for all* $i \in \{1, 2, \ldots, n\}$.

The basic notions regarding fuzzy relations are defined below. Although their definition is always given for the case of fuzzy relations on two universes U and V, it is straightforward that they can be generalized to fuzzy relations on the universes $U_1, U_2, \ldots, U_n$ with $n \in \mathbb{N} \setminus \{0\}$.

Definition 25 (*Cartesian product* [183]). *The Cartesian product $A \times B$ where $A \in \mathcal{F}(U)$ and $B \in \mathcal{F}(V)$ is the fuzzy set $\mu_{A\times B}$ in $U \times V$ defined by*

$$(\forall(u,v) \in U \times V)(\mu_{A\times B}(u,v) = \mathcal{T}(\mu_A(u), \mu_B(v)) \tag{2.30}$$

where $\mathcal{T}$ is a triangular norm.

Definition 26 (*Projection* [187]). *For A a fuzzy relation on U and V, $A \in \mathcal{F}(U \times V)$, the projection of A onto U is the mapping $\textsc{Proj}_U : \mathcal{F}(U \times V) \to \mathcal{F}(U)$ defined as*

$$(\forall u \in U)(\mu_{\textsc{Proj}_U(A)}(u) = \sup_{v \in V} \mu_A(u,v)) \tag{2.31}$$

Definition 27 (*Cylindrical extension* [187]). *For two universes U and V, let A be a fuzzy set on U, $A \in \mathcal{F}(U)$. The cylindrical extension of A onto $U \times V$ is the mapping $\textsc{Cext}_U : \mathcal{F}(U) \to \mathcal{F}(U \times V)$ defined as*

$$(\forall(u,v) \in U \times V)(\mu_{\textsc{Cext}_U(A)}(u,v) = \mu_A(u)) \tag{2.32}$$

The projection operation reduces the number of dimensions on which a fuzzy set is defined, while the cylindrical extension extends the Cartesian product space. These concepts can be used to define the important notion of composition of fuzzy relations.

Definition 28 (*Composition* [186]). *Consider the fuzzy relations $R \in \mathcal{F}(U \times V)$ and $S \in \mathcal{F}(V \times W)$. The composition $R \circ_{\mathcal{T}} S$ is given by*

$$R \circ_{\mathcal{T}} S = \textsc{Proj}_{U\times W}\left(\textsc{Cext}_{U\times V\times W}(R) \cap_{\mathcal{T}} \textsc{Cext}_{U\times V\times W}(S)\right) \tag{2.33}$$

where $\mathcal{T}$ is the triangular norm to model the intersection operation.

Based on this definition, the fuzzy composition $R \circ_{\mathcal{T}} S$ should be calculated as the mapping $\mathcal{F}(U \times W) \to [0,1]$,

$$(\forall(u,w) \in U \times W)(\mu_{R\circ_{\mathcal{T}} S}(u,w) = \sup_{v \in V} \mathcal{T}(R(u,v), S(v,w))) \tag{2.34}$$

Zadeh proposed to use the sup-min composition, $R \circ_{\min} S$ which is usually simply denoted as $R \circ S$.

In literature, a large number of types of fuzzy relations can be found. Formally, an extension of a crisp equivalence relation is called a similarity relation and defined as follows.

Definition 29 (*Similarity relation* [184]). *A binary relation R on $U \times U$ is called a similarity relation when it satisfies,*

(i) Reflexivity: $(\forall u \in U)(R(u,u) = 1)$

(ii) Symmetry: $(\forall (u_1, u_2) \in U^2)(R(u_1,u_2) = R(u_2,u_1))$

(iii) Transitivity:

$$(\forall (u_1,u_2,u_3) \in U^3)(\min(R(u_1,u_2), R(u_2,u_3)) \leq R(u_1,u_3))$$

A *similarity measure* on a universe U is defined as a $[0,1]$-valued, binary fuzzy relation on $\mathcal{F}(U)$, that is useful for the comparison of fuzzy sets. In this work, a similarity measure will not necessarily satisfy the definition of a similarity relation, although this is often assumed in literature. However, all the similarity measures used in this work will at least satisfy the reflexivity and symmetry properties (when the fuzzy sets are normalized).

5 Semantics

Although the membership degree $\mu_A(u)$ of an element $u \in U$ is mathematically defined as the degree to which the element u belongs to the fuzzy set A, in practical applications the membership degrees can be interpreted in several different ways. In [57], Dubois and Prade have distinguished three semantics for the membership degree.

Similarity This is historically the oldest interpretation of membership degrees as introduced by Zadeh in 1965 [183]. In this view the membership degree $\mu_A(u)$ expresses the degree of similarity (or proximity) of the element u to prototypical elements of A, elements that fully belong to A. This interpretation is primarily at use in classification and data analysis applications (e.g. clustering), in the process of abstracting a representation from data by exploiting proximity between pieces of information. It is used in applications that are oriented towards clarifying information.

Example: When it is known that a car is four meters, you can ask the question whether it is a "big" car.

Note that this interpretation is used to model vagueness inherent in concepts, gradual transitions from a concept to its opposite (e.g. sorites). This vagueness should not be confused with probability.

Example: When a bottle contains an unknown liquid, consider the difference between saying that the liquid is poisonous to the (fuzzy) degree 0.5 and saying that the probability that the liquid is poison is 0.5. In the former, the liquid will not be lethal but it is not healthy either while the latter expresses that it is completely healthy or fully deadly both with a 0.5 chance. This example stresses the fact that probability models in fact binary propositions, contrary to the fuzzy approach. If someone tells us that he filled the bottle with potable water, the uncertainty of the probability vanishes. This cannot be said from the fuzzy expression, additional information will not resolve the vagueness, it is intrinsic to the concept.

Uncertainty In 1978 Zadeh proposed fuzzy set theory as a basis for a theory of possibility [191]. If it is known that "X is A" where X is a variable on U, $\mu_A(u)$ is the degree of possibility that X has the value u. This view is at work in expert systems, automated reasoning and flexible querying of databases, applications that are oriented towards retrieving information.

Example: When it is known that someone has seen a "big" car, you can ask the question whether it was four meters.

In this context, the term "possibility" can have an *epistemological meaning* ("plausibility") or a *physical meaning* ("feasibility").

Example: At breakfast Hans has the habit of eating eggs. The uncertainty regarding the number of eggs that Hans will eat is possibilistic in the physical sense of eating at most x eggs in the morning.

More information about possibility theory and its relationship with probability theory is given in section 6.

Preference In this view, put forward by Bellman and Zadeh in 1970 [9], A represents a set of preferred objects of a variable X and $\mu_A(u)$ expresses the preference in favor of element u as a value for X. Typical applications are optimization and decision making problems, applications oriented towards exploiting information.

Example: When someone wants to buy a "big" car, the question is whether a car of four meters satisfies this preference.

Note that the definition of a membership function is always context dependent and subjective. E.g. to define a membership function for the concept "big", it is important to know if the context is the modeling of mice, dogs, humans, buildings,... Obviously, the definition will also be subject dependent. A "big" person will have a different meaning for a little child and for a basketball player. However, this subjectivity should not be seen as a problem. On the contrary, it is an advantage that provides a lot of flexibility. It should also not be confused with subjective probabilities. The theory of subjective probability still operates on binary propositions, while a subjective membership function allows to model gradual transitions.

6 Possibility theory

It has already been stated that fuzzy sets can be interpreted as representing degrees of uncertainty, the possibility that a variable takes a specific value. This idea was introduced by Zadeh [191] and has been actively studied by Dubois and Prade [54]. In this section, the basic notions of *possibility theory* needed for the rest of this work will be explained.

6.1 Possibility measures

Just as Kolmogorov has placed *probability theory* on a firm axiomatic basis by means of a probability measure, possibility theory can be put on an analogous basis. Let us start with a definition of the required mathematical tools.

Definition 30 (*Fuzzy measure* [148]). *A fuzzy measure on a universe U is a set function $\mu : \mathcal{P}(U) \to [0,1]$ satisfying*

(i) Boundary condition: $\mu(\emptyset) = 0$

(ii) Normalization: $\mu(U) = 1$

(iii) Monotonicity: $(\forall A, B \in \mathcal{P}(U))(A \subseteq B \Rightarrow \mu(A) \leq \mu(B))$

(iv) Continuity from below:

$$(\forall A_1 \subseteq A_2 \subseteq \ldots \subseteq A_n \subset \ldots \in \mathcal{F}(U)) \left(\lim_{n\to\infty} \mu(A_n) = \mu(\bigcup_{n=1}^{\infty} A_n) \right)$$

(v) Continuity from above:

$$(\forall A_1 \supseteq A_2 \supseteq \ldots \supseteq A_n \supseteq \ldots \in \mathcal{F}(U)) \left(\lim_{n\to\infty} \mu(A_n) = \mu(\bigcap_{n=1}^{\infty} A_n) \right)$$

The continuity requirements are only important for infinite sequences of sets and can be ignored for any finite family.

Definition 31 (*Possibility measure* [191]). *A possibility measure on a universe U is a fuzzy measure $\Pi : \mathcal{P}(U) \to [0,1]$ satisfying for any family $(A_i)_{i\in I}$ of elements of $\mathcal{P}(U)$ with I an index set,*

$$\Pi\left(\bigcup_{i\in I} A_i\right) = \sup_{i\in I} \Pi(A_i) \tag{2.35}$$

Definition 32 (*Necessity measure* or *certainty measure* [53]). *A necessity measure on a universe U is a fuzzy measure $N : \mathcal{P}(U) \to [0,1]$ satisfying for any family $(A_i)_{i\in I}$ of elements of $\mathcal{P}(U)$ with I an index set,*

$$N\left(\bigcap_{i\in I} A_i\right) = \inf_{i\in I} N(A_i) \tag{2.36}$$

In possibility theory, a possibility measure always refers to some variable X on a universe U, e.g. the age of a man, the size of a building,... The possibility measure $\Pi_X(A)$ then expresses the possibility that the exact value of X belongs to the set $A \in \mathcal{P}(U)$. Analogous, $N_X(A)$ expresses the certainty or necessity that the exact value of X belongs to the set $A \in \mathcal{P}(U)$.

It is important to observe that a possibility measure is defined by means of the maximum whereas a probability measure is additively defined. For two finite subsets A and B of U, $\Pi(A \bigcup B) = \max(\Pi(A), \Pi(B))$ while the *probability measure* P on U is defined as $P(A \bigcup B) \leq P(A) + P(B)$ with the equality when A and B are disjoint.

There is an interesting relationship between possibility and necessity. The less it is possible that the value of X lies in $\overline{A}$, the more certain it is that it lies in A. This duality can be stated as the following equation [132].

$$N(A) = 1 - \Pi(\overline{A}) \tag{2.37}$$

6.2 Possibility distributions

Every possibility measure can be characterized by a *possibility distribution*. A possibility distribution [191] is a mapping $\pi : U \to [0,1]$ where

$$\pi(u) = \Pi(\{u\}) \tag{2.38}$$

From (2.38) it follows that for U an infinite universe and $A \in \mathcal{P}(U)$,

$$\Pi(A) = \sup_{u\in A} \pi(u) \tag{2.39}$$

When U is a finite universe, this can be written as,

$$\Pi(A) = \max_{u\in A} \pi(u) \tag{2.40}$$

A possibility distribution π_X attached to a variable X on U represents a flexible restriction on the values of X. The number $\pi_X(u) \in [0, 1]$ with $u \in U$ expresses the degree of possibility of the assignment $X = u$ where some values of u are more possible than others. If U is the complete range for X, at least one of the elements of U should be fully possible as a value of X. Hence, $(\exists u \in U)(\pi_X(u) = 1)$ which is the normalization requirement.

In [191] Zadeh introduced the *possibility assignment equation*

$$(\forall u \in U)(\pi_X(u) = \mu_A(u)) \tag{2.41}$$

where X is a variable over U, π_X is the possibility distribution of X and A is a fuzzy set defined on U. The following example illustrates the practical implications of this equation. Consider the variable "age of a person" (X) on the universe $[0, 120]$ (U). On this universe, a fuzzy set "young" (A) can be defined that expresses the similarity between the age of a person and a young person (interpretation of a fuzzy set as degrees of *similarity*). The possibility assignment equation states that if we know that a person "Sarah is young" ("Age(Sarah) is young" or "$X = A$"), the degree of possibility that her age is u can be evaluated as the membership degree of u in the fuzzy set "young".

Note that there is a fundamental difference between degrees of possibility and degrees of probability. This important point will be exemplified with a classical example taken from [191]. Consider the statement "Hans ate X eggs for breakfast", with X taking values in $U = \{1, 2, 3, \ldots\}$. We may associate a possibility distribution with X by interpreting $\pi_X(u)$ as the degree of ease with which Hans can eat u eggs (*physical* "feasibility" interpretation of possibility). We may also associate a probability distribution with X by interpreting $p_X(u)$ as the probability of Hans eating u eggs for breakfast (see figure 2.2). Although the possibility that Hans eats three eggs is 1, the probability that he may do so can be quite low, e.g. 0.1. Thus, a high degree of possibility does not imply a high probability, nor does a low degree of probability imply a low degree of possibility. However, if an event is impossible, it is bound to be improbable, or stated more general,

$$(\forall A \in \mathcal{P}(U))(P(A) \leq \Pi(A)) \tag{2.42}$$

where P is a probability measure and Π is a possibility measure on the same variable. This equation is known as the *possibility/probability consistency principle* [191].

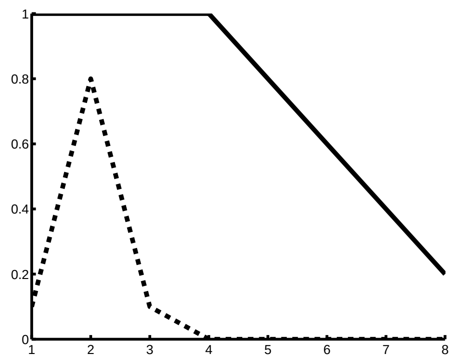

Figure 2.2: Hans eats eggs for breakfast (full line: possibility distribution, dashed line: probability distribution)

6.3 Interpretations of possibility distributions

In [55] Dubois and Prade have distinguished two interpretations of a possibility distribution, which result in two derived versions of the possibility assignment equation of Zadeh (2.41). They state that a proposition "$X = A$" (e.g. "Sarah is young") can be interpreted as *degrees of possibility* and *degrees of certainty*.

"$X = A$ is possible" This interpretation is modeled with the inequality,

$$(\forall u \in U)(\mu_A(u) \leq \pi_X(u)) \tag{2.43}$$

The fuzzy set A is a *lower bound* for the possibility distribution. This means that the proposition gives less information for values that belong to a lesser degree to the fuzzy set. In the extreme cases where $\mu_A(u) = 0$ the possibility of $X = u$ is unspecified. This interpretation is useful when the possibility of values for X can be guaranteed. When more information becomes available, the guaranteed possibility of values will increase, the lower bound will be made more tight.

The combination of information on two variables X and Y that are both interpreted as "possible" is dictated by the "*principle of maximum specificity*".

Definition 33 (Principle of maximum specificity [55]). *For X and Y two variables over the universes U and V respectively, let π_X and π_Y denote their possibility distributions. Consider the propositions "$X = A$ is possible" and "$Y = B$ is possible" where $A \in \mathcal{F}(U)$ and $B \in \mathcal{F}(V)$.*

The principle of maximum specificity states that their joint distribution $\pi_{X,Y}$ must be chosen as

$$(\forall(u,v) \in U \times V)(\pi_{X,Y}(u,v) = \max(\pi_X(u), \pi_Y(v))) \qquad (2.44)$$

In fact, this principle should be seen as a lower bound. The equality only applies if the variables X and Y are non-interactive, when there are no relational links between them. In the other case, the possibility distribution will be less informative than the actual joint distribution. However, using all the available information, it is the best that can be done.

"$X = A$ is certain" In this view, the fuzzy set provides an *upper bound* for the possibility distribution,

$$(\forall u \in U)(\pi_X(u) \leq \mu_A(u)) \qquad (2.45)$$

Hence, the values in the universe become less possible as they belong to a lesser degree to the fuzzy set. The proposition provides less information for values that have a high membership degree in the fuzzy set. When $\mu_A(u) = 1$ the possibility of $X = u$ is unspecified. If more information becomes available, the certainty of values will decrease (making them more impossible), the upper bound will be made more tight.

The combination of information on two variables X and Y that are both interpreted as "certain" is dictated by the "*principle of minimum specificity*".

Definition 34 (Principle of minimum specificity [177]). *For X and Y two variables over the universes U and V respectively, let π_X and π_Y denote their possibility distributions. Consider the propositions "$X = A$ is certain" and "$Y = B$ is certain" where $A \in \mathcal{F}(U)$ and $B \in \mathcal{F}(V)$. The principle of minimum specificity states that their joint distribution $\pi_{X,Y}$ must be chosen as*

$$(\forall(u,v) \in U \times V)(\pi_{X,Y}(u,v) = \min(\pi_X(u), \pi_Y(v))) \qquad (2.46)$$

The reasoning behind this principle is analogous to that of the principle of maximum specificity.

The *possibility assignment equation* (2.41) can thus be interpreted as a special case, representing the statement "$X = A$ is possible and certain". It restricts the lower as well as the upper bound of the possibility distribution $\pi_X(u)$.

7 Aggregation operators

7.1 Definitions

A collection of fuzzy sets on the universe U can be combined into a single fuzzy set on U through an aggregation operation.

Definition 35 (*Aggregator* [132]). *An aggregation operator or aggregator is an n-ary operator $h : [0,1]^n \to [0,1]$ with $n \in \mathbb{N} \setminus \{0\}$ satisfying,*

(i) Boundaries: $h(0,0,\ldots,0) = 0 \wedge h(1,1,\ldots,1) = 1$

(ii) Monotonicity:

$$(\forall (x_1,x_2,\ldots,x_n),(y_1,y_2,\ldots,y_n) \in [0,1]^n)$$
$$((\forall i \in \{1,2,\ldots,n\})(x_i \leq y_i) \Rightarrow h(x_1,x_2,\ldots,x_n) \leq h(y_1,y_2,\ldots,y_n))$$

From this definition, it is clear that n-ary triangular norms and conorms are also aggregation operators.

As examples consider the *generalized mean* (averaging), *Weighted Arithmetic Mean* (WAM), *Ordered Weighted Averaging* (OWA) and *Ordered Weighted Maximum* (OWMax) operators.

Definition 36 (Generalized mean [132]). *A generalized mean operator is an aggregation operator defined by*

$$\text{MEAN}_\alpha(x_1,x_2,\ldots,x_n) = \sqrt[\alpha]{\frac{1}{n}\sum_{i=1}^{n} x_i^\alpha} \tag{2.47}$$

with $\alpha \in \mathbb{R} \setminus \{0\}$ and $x_i \neq 0$ for all $i \in \{1,2,\ldots,n\}$ when $\alpha < 0$.

Definition 37 (Weighted Arithmetic Mean). *A WAM operator is an aggregation operator defined by*

$$\text{WAM}_w(x_1,x_2,\ldots,x_n) = \sum_{i=1}^{n} w_i x_i \tag{2.48}$$

where $w = (w_1,w_2,\ldots,w_n) \in [0,1]^n$ is a weight vector such that $\sum_{i=1}^n w_i = 1$.

Definition 38 (Ordered Weighted Averaging [178]). *An OWA operator is an aggregation operator defined by*

$$\text{OWA}_w(x_1,x_2,\ldots,x_n) = \sum_{i=1}^{n} w_i x_{(i)} \tag{2.49}$$

where $w = (w_1,w_2,\ldots,w_n) \in [0,1]^n$ is a weight vector such that $\sum_{i=1}^n w_i = 1$ and the arguments are ordered such that $x_{(1)} \leq x_{(2)} \leq \ldots \leq x_{(n)}$.

Definition 39 (Ordered Weighted Maximum [179]). *An OWMax operator (or ordinal OWA) is an aggregation operator defined by*

$$\text{OWM}\textsc{ax}_w(x_1, x_2, \ldots, x_n) = \max_{i=1}^{n} \min(w_i, x_{(i)}) \tag{2.50}$$

where $w = (w_1, w_2, \ldots, w_n) \in [0,1]^n$ *is a weight vector such that* $\max_{i=1}^{n} w_i = 1$ *and the arguments are ordered such that* $x_{(1)} \leq x_{(2)} \leq \ldots \leq x_{(n)}$.

7.2 Fuzzy integrals

7.2.1 Evaluation scales

Before discussing some more advanced aggregation operators, it is important to touch upon the different kinds of scales that can be used to measure a quantity.

Nominal A *nominal scale* has no notion of order, e.g. color (red, blue, yellow) or gender (male, female). The only operation that is allowed is a frequency count.

Ordinal On an *ordinal scale*, the categories have a logical or natural ordering, e.g. small, medium and large, but the difference between each category is not necessarily the same. Hence, we can rank them, but we cannot quantify the difference between two ordinal values. Arithmetic operations are not legal. For example, a 2-star hotel is definitely "less than" a 3-star hotel, but we cannot say "how much less". Also, the difference between a 2-star hotel and a 3-star hotel is not necessarily the same as the difference between a 4-star hotel and a 5-star hotel.

Cardinal (interval) If the distance between the ordered categories is always the same but there is no natural zero point, then we have a *cardinal scale* or an *interval scale*. E.g. the temperature scale in degrees Celsius cannot express an absence of temperature, 0 °C is arbitrary chosen as the temperature when water freezes. A cardinal scale allows the addition and subtraction operation. The expression of ratios is invalid although the mean of two cardinal values can be calculated. The difference between 20 °C and 25 °C has the same physical meaning as the difference between 50 °C and 55 °C. But we cannot really say that 20 °C is twice as hot as 10 °C, because 0 °C is arbitrary chosen.

Ratio In a *ratio scale*, the categories are equidistant and there is a natural zero point, e.g. age, length and weight. Ratio's have a clear meaning.

A length of 10 m is twice as long as 5 m, even if we would use yards instead of meters this ratio would hold. This is because there is a natural zero point.

7.2.2 Fuzzy measures

In section 6.1 a *fuzzy measure* $\mu : \mathcal{P}(U) \to [0, 1]$ has been defined as a basis for probability, possibility and necessity measures. However, a fuzzy measure can also be used as an extension of a weight vector. It then becomes not only possible to assign weights to single elements but also to combinations of elements. This offers a lot of flexibility to assign weights, but at the same time adds complexity in defining the fuzzy measure. There are in fact three different approaches to specify a fuzzy measure. Consider a fuzzy measure μ on the universe $U = \{u_1, u_2, \ldots, u_n\}$ with $n \in \mathbb{N} \setminus \{0\}$.

Enumeration The most straightforward specification of a fuzzy measure is by enumerating the fuzzy measure value for all elements and all subsets of elements of U. This means that $2^n - 2$ values in $[0, 1]$ must be given!

Relationship Another option is to rely on a relationship that specifies how to calculate the fuzzy measure value of a combination of elements based on the fuzzy measure values of the individual elements. It is then sufficient to specify only the fuzzy measure values of the n singletons $\{u_i\}$ with $i \in \{1, 2, \ldots, n\}$.

The prototypical example of such a defining relationship leads to the *probability or additive measures* P given by $P(A \cup B) = P(A) + P(B)$ if $A \cap B = \emptyset$ with $A, B \in \mathcal{P}(U)$. Due to the normalization requirement of fuzzy measures, one must make sure that $P(U) = \sum_{i=1}^{n} P(\{u_i\}) = 1$.

Another example is the *possibility measure* Π defined by $\Pi(A \cup B) = \max(\Pi(A), \Pi(B))$ for all $A, B \in \mathcal{P}(U)$. It is easy to see that this fuzzy measure satisfies the normalization requirement if at least one of the values $\Pi(\{u_i\})$ equals 1 for $i \in \{1, 2, \ldots, n\}$.

One can also consider a generalization of possibility measures. If S is a t-conorm, then it can be shown that the following μ is a fuzzy measure.

Definition 40 (*S-decomposable fuzzy measure* [173]). *A fuzzy measure μ is S-decomposable if there is a t-conorm S such that $\mu(A \cup B) = S(\mu(A), \mu(B))$ for all $A, B \in \mathcal{P}(U)$.*

Alternative representation Finally, a completely different representation scheme can be used based on some kind of transformation of the fuzzy measure (e.g. [73]). For examples of such alternative representations, see chapter 5, section 3.2.

7.2.3 Fuzzy integrals

Classical integrals are defined with respect to classical (additive) measures. As fuzzy measures are extensions of such measures, the notion of *fuzzy integrals* arises naturally. Just as their crisp counterparts, fuzzy integrals are defined on a function. In the context of aggregation operators, we will restrict the discussion of fuzzy integrals to discrete domains $U = \{u_1, u_2, \ldots, u_n\}$. Hence the function will be a mapping $f : U \to E$ that associates with each element in U an evaluation value on the evaluation scale E.

Definition 41 (*Choquet integral* [35]). *Consider a fuzzy measure μ on U and a mapping $f : U \to \mathbb{R}$. The discrete Choquet integral of f with respect to μ is defined as*

$$C_\mu(f) = \sum_{i=1}^{n} \left(\mu(H_{(i)}) - \mu(H_{(i+1)})\right) f(u_{(i)}) \tag{2.51}$$

where the arguments are ordered such that $f(u_{(1)}) \leq f(u_{(2)}) \leq \ldots \leq f(u_{(n)})$, $H_{(i)} = \{u_{(i)}, u_{(i+1)}, \ldots, u_{(n)}\}$ and $H_{(n+1)} = \emptyset$.

Note that the Choquet integral equals the classical Lebesgue integral when the underlying fuzzy measure is additive. The Choquet integral requires a *cardinal scale* in its calculation. Therefore, the evaluation scale E must be a cardinal scale with $E \subseteq \mathbb{R}$.

Definition 42 (*Sugeno integral* [148]). *Consider a fuzzy measure μ on U and a mapping $f : U \to [0,1]$. The discrete Sugeno integral of f with respect to μ is defined as*

$$S_\mu(f) = \max_{i=1}^{n} \min\left(\mu(H_{(i)}), f(u_{(i)})\right) \tag{2.52}$$

where the arguments are ordered such that $f(u_{(1)}) \leq f(u_{(2)}) \leq \ldots \leq f(u_{(n)})$ and $H_{(i)} = \{u_{(i)}, u_{(i+1)}, \ldots, u_{(n)}\}$.

The Sugeno integral is derived by substituting the multiplication by the minimum and the summation by the maximum operation. Contrary to the Choquet integral, the Sugeno integral only requires an *ordinal scale*. Hence, E must represent an ordinal scale with $E \subseteq [0,1]$.

Some properties of a fuzzy integral $\mathcal{F}_\mu$ (either Choquet or Sugeno) with respect to a fuzzy measure μ that are useful in the remaining of this work are shown below [75].

1. Compensating behavior:

$$\min_{i=1}^{n} f(x_i) \leq \mathcal{F}_\mu(f) \leq \max_{i=1}^{n} f(x_i) \tag{2.53}$$

2. Monotonicity with respect to integrand:

$$f \leq f' \Rightarrow \mathcal{F}_\mu(f) \leq \mathcal{F}_\mu(f') \tag{2.54}$$

3. The WAM_w operators are a subclass of the Choquet integrals.

4. The OWA_w operators are a subclass of the Choquet integrals.

5. The OWMAX_w operators are a subclass of the Sugeno integrals.

8 Approximate reasoning

8.1 Implicators

8.1.1 Definition

To be able to reason with fuzzy propositions, the concept of logical implication must also be extended to the fuzzy case. We have already shown that there are an infinite number of possibilities to model the logical conjunction, disjunction and negation in fuzzy logic. As the crisp implication operator can be formulated in terms of these operations in several different ways, it is clear that there are even a larger number of possible extensions to fuzzy implications.

Definition 43 (*Implicator* [58]). *An implicator $\mathcal{I}$ is a $[0,1]^2 \to [0,1]$ mapping satisfying*

(i) Border: $\mathcal{I}(0,0) = 1 \wedge \mathcal{I}(0,1) = 1 \wedge \mathcal{I}(1,1) = 1 \wedge \mathcal{I}(1,0) = 0$

(ii) Hybrid monotonicity:

$$(\forall y \in [0,1])(\forall (x_1,x_2) \in [0,1]^2)(x_1 \leq x_2 \Rightarrow \mathcal{I}(x_1,y) \geq \mathcal{I}(x_2,y))$$
$$(\forall x \in [0,1])(\forall (y_1,y_2) \in [0,1]^2)(y_1 \leq y_2 \Rightarrow \mathcal{I}(x,y_1) \leq \mathcal{I}(x,y_2))$$

The given definition is very general and allows many implicators that do not make sense from an intuitive point of view. Therefore, additional axioms for implicators have been put forward [145]. Here, some of them are simply considered as properties and useful for the rest of this work.

(I.1) $(\forall(x,y)\in[0,1]^2)(x\leq y\Rightarrow \mathcal{I}(x,y)=1)$

(I.2) Neutrality: $(\forall x\in[0,1])(\mathcal{I}(1,x)=x)$

(I.3) Contrapositivity with respect to a negator $\mathcal{N}$:

$$(\forall(x,y)\in[0,1]^2)(\mathcal{I}(x,y)=\mathcal{I}(\mathcal{N}(y),\mathcal{N}(x)))$$

(I.4) Exchange principle:

$$(\forall(x,y,z)\in[0,1]^3)(\mathcal{I}(x,\mathcal{I}(y,z))=\mathcal{I}(y,\mathcal{I}(x,z)))$$

Definition 44 (*Border implicator* [41]). *An implicator that additionally satisfies the neutrality condition is called a border implicator.*

Definition 45 (*Dual implicator* [58]). *An implicator $\mathcal{I}^*_{\mathcal{N}}$ is dual to an implicator $\mathcal{I}$ with respect to a negator $\mathcal{N}$ when it is defined as*

$$(\forall(x,y)\in[0,1]^2)(\mathcal{I}^*_{\mathcal{N}}(x,y)=\mathcal{I}(\mathcal{N}(y),\mathcal{N}(x))) \tag{2.55}$$

If an implicator $\mathcal{I}$ is contrapositive with respect to $\mathcal{N}$ then $\mathcal{I}^*_{\mathcal{N}}=\mathcal{I}$.

A dual implicator $\mathcal{I}^*_{\mathcal{N}}$ with respect to the standard negator $\mathcal{N}_Z$, $\mathcal{N}=\mathcal{N}_Z$, will be denoted as $\mathcal{I}^*$.

8.1.2 Classification of implicators

In classical logic, the implication operator can be defined using a number of tautologies, e.g. for the binary propositions P and Q, $P\rightarrow Q\equiv\neg P\vee Q$. Based on such tautologies and fuzzification of the underlying operators, the following classes of implicators can be defined [58].

Definition 46 (*S-implicator* [58]). *For S a t-conorm and $\mathcal{N}$ a strong negator, the $[0,1]^2\rightarrow[0,1]$ mapping defined by*

$$\mathcal{I}^S_{S,\mathcal{N}}(x,y)=S(\mathcal{N}(x),y) \tag{2.56}$$

is called a material implicator or S-implicator.

Table 2.3: Implicators.

Name	Implicator	Class
Kleene-Dienes	$\mathcal{I}_{KD}(x,y) = \max(1-x,y)$	$\mathcal{I}^S_{\mathcal{S}_M,\mathcal{N}_Z}$
Łukasiewicz	$\mathcal{I}_W(x,y) = \min(1,1-x+y)$	$\mathcal{I}^S_{\mathcal{S}_W,\mathcal{N}_Z}, \mathcal{I}^R_{\mathcal{T}_W}$
K-D-Łukasiewicz = Reichenbach	$\mathcal{I}_{KDL}(x,y) = 1-x+xy$	$\mathcal{I}^S_{\mathcal{S}_P,\mathcal{N}_Z}$
Gödel (-Brouwer) = Standard Star	$\mathcal{I}_{GB}(x,y) = \begin{cases} 1 & (x \le y) \\ y & (x > y) \end{cases}$	$\mathcal{I}^R_{\mathcal{T}_M}$
Gaines = Goguen	$\mathcal{I}_G(x,y) = \begin{cases} 1 & (x \le y) \\ \frac{y}{x} & (x > y) \end{cases}$	$\mathcal{I}^R_{\mathcal{T}_P}$

Definition 47 (*R-implicator* [58]). *For $\mathcal{T}$ a t-norm, the $[0,1]^2 \to [0,1]$ mapping defined as*

$$\mathcal{I}^R_{\mathcal{T}}(x,y) = \sup\{z \in [0,1] \mid \mathcal{T}(x,z) \le y\} \tag{2.57}$$

is called a residual implicator or R-implicator.

A collection of the most prominent members of the defined classes of implicators is listed in table 2.3.

8.1.3 Properties

Both families of S-implicators and R-implicators satisfy the neutrality (I.2) and exchange principle (I.4). Only the residual implicators satisfy property (I.1). The dual of S-implicators with respect to the standard negator $\mathcal{N}_Z$ are again S-implicators (which is not true for R-implicators). For more details on the properties of implicators, see [43] and [58].

8.2 Linguistic variable

It has already been stated that fuzzy sets are perfectly suited to model gradual transitions of concepts in a context dependent and subjective way. Such concepts are typically used in natural language statements, e.g. “Sarah is young”. In [188] Zadeh has introduced the notion of a *linguistic variable*, a variable whose values are not numbers but words or sentences in a natural language. In the expression “Sarah is young”, “young” can be interpreted as a *linguistic value* of the linguistic variable “Age”. However, “age” is also interpretable as a numerical variable, whose values are the numbers $0, 1, \ldots, 120$. The numerical variable “age” is said to be the *base variable* of the linguistic variable “Age”. Fuzzy sets on the universe $[0, 120]$ can be used to represent the meaning of a linguistic value (“young”). Formally, this leads to the following definition.

Definition 48 (*Linguistic variable* [190]). *A linguistic variable is characterized by a quintuple* $(X, T(X), U, G, M)$

(i) X *is the name of the variable*

(ii) $T(X)$ *is the term set of* X*, the set of its linguistic values or linguistic terms*

(iii) U *is the universe of discourse*

(iv) G *is a syntactic rule which usually has the form of a grammar for generating the terms in* $T(X)$

(v) M *is a semantic rule which associates with each linguistic value* A *its meaning* $M(A)$*, where* $M(A)$ *denotes a fuzzy set in* U*. It is a mapping* $T(X) \to \mathcal{F}(U)$*.*

As an example [190], consider the term set for X = Age on $U = [0, 120]$,

T(Age) = { young, very young, not young, not very young,...
middle-aged, not middle-aged,...
old, not old, very old, more or less old, not very old,...
not very young and not very old,... }

With each element of T(Age) is a fuzzy set on $\mathcal{F}(U)$ associated which represents the meaning of the term.

In general, the term set consists of several primary terms (young, middle-aged, old) modified by negation (not) and/or adverbs (*linguistic modifiers* or *hedges* such as “very” and “more or less”) combined with connectives (and, or). The negation, connectives and hedges are usually interpreted as operators that modify the meaning of their operands. For the modeling of the negation and the connectives, the fuzzy set operators have already been extensively discussed. To model a hedge on a universe U, which is defined as a mapping $m : \mathcal{F}(U) \to \mathcal{F}(U)$ that modifies the meaning of a linguistic term, there are several possibilities. Some of them are briefly given below.

Table 2.4: Powering hedges.

Name	α	Linguistic modifier
Dilatation	0.5	more or less
Deaccentuation	0.75	minus
Accentuation	1.25	plus
Concentration	2	very

Definition 49 (*Powering hedge* [185]). *For $\alpha \in [0, +\infty[$, a powering hedge m on U is a hedge defined by*

$$(\forall u \in U)(\mu_{m(A)}(u) = (\mu_A(u))^{\alpha}) \tag{2.58}$$

Typical values that are used for α and their associated linguistic modifier are shown in table 2.4.

Definition 50 (*Shifting hedge* [102]). *A shifting hedge m on $\mathbb{R}$ with $\alpha \in \mathbb{R}$ is a hedge defined by*

$$(\forall u \in \mathbb{R})(\mu_{m(A)}(u) = \mu_A(u - \alpha)) \tag{2.59}$$

A linguistic variable that plays an important role in reasoning applications is the *fuzzy* or *linguistic truth variable* [190]. The *fuzzy truth values* that this variable can take are terms that characterize the degree of truth of a statement, e.g. “absolutely false”, “very false”, “false”, “fairly false”, “not absolutely true”, “not absolutely false”, “fairly true”, “true”, “very true”, “absolutely true” [196]. The underlying universe of discourse of this variable is $[0, 1]$, where “true” and “false” can be defined as

$$(\forall x \in [0, 1])(\mu_{\text{true}}(x) = x) \tag{2.60}$$

$$(\forall x \in [0, 1])(\mu_{\text{false}}(x) = 1 - x) \tag{2.61}$$

8.3 Fuzzy rules

All elements that have been introduced so far can now be combined to delve into the realm of *approximate reasoning*. In 1975, Zadeh has introduced approximate reasoning [190] as

> A mode of reasoning in which the truth values and the rules of inference are fuzzy rather than precise. In many ways, approximate reasoning is akin to the reasoning used by humans

> in ill-defined or unquantifiable situations. Indeed, it may well be the case that much –perhaps most– of human reasoning is approximate rather than precise in nature.

More recently, Zadeh defined the notions of "*computing with words*" [193] and "*computing with perceptions*" [195]. In these computing methodologies, the fuzziness in the reasoning process is only present behind the scenes. The fuzzy sets are hidden behind the natural language statements that represent the knowledge. In these statements, *linguistic variables* and their *values* are used to represent human perceptions, e.g. "Sarah is young", "A car is big". Approximate reasoning is used as a tool to raise the level of abstraction from reasoning with numbers to reasoning with perceptions. This is more closely linked to the way humans reason in everyday life situations.

The mechanisms that enable approximate reasoning are in fact fuzzifications from the reasoning principles found in binary logic. Special attention is paid to the fuzzification of the classical modus ponens. The *modus ponens*, derived from Latin "mode that affirms", reads

$$\begin{array}{rllll} \text{Rule:} & \text{IF} & X = A & \text{THEN} & Y = B \\ \text{Fact:} & & X = A & & \\ \hline \text{Conclusion:} & & & & Y = B \end{array}$$

The rule expresses a relation between "$X = A$" (the rule antecedent) and "$Y = B$" (the rule consequent).

The fuzzification of the modus ponens is called the *Generalized Modus Ponens* (GMP) and is defined as

$$\begin{array}{rllll} \text{Rule:} & \text{IF} & X = A & \text{THEN} & Y = B \\ \text{Fact:} & & X = A' & & \\ \hline \text{Conclusion:} & & & & Y = B' \end{array}$$

where X and Y are (linguistic) variables on U and V respectively, $A, A' \in \mathcal{F}(U)$ and $B, B' \in \mathcal{F}(V)$. Just as in the crisp case, the *fuzzy rule* represents a relation R between the variables X and Y, with $R \in \mathcal{F}(U \times V)$. It is very important to observe that the fact "$X = A'$" does not need to match the antecedent of the rule "$X = A$" in an exact way anymore. This explains what "approximate" is all about. To illustrate the fact that this resembles human reasoning more closely, consider the rule "If a tomato is red then it is ripe". Given the fact that "A tomato is more or less red", people will immediately deduce the conclusion that "The tomato is more or less ripe". This simple conclusion cannot be achieved with binary logic as the fact and the antecedent of the rule do not match. Of course, one could argue that the problem can be solved by adding another rule, "If a tomato is more or less red then it is more or less ripe". However, this increases the complexity of the system. Furthermore, in practical applications the domain can be so complex with rather limited knowledge available, that it is impossible to elaborate on all possible combinations of antecedents and consequents. Zadeh refers to this observation as the "*principle of incompatibility*" which states that high precision is incompatible with high complexity [190]. In order to make significant assertions about the behavior of complex systems, it may be necessary to abandon mathematical precision and become more tolerant of approaches which are approximate in nature.

In the literature, different types of reasoning are found to actually calculate the inferred knowledge "$Y = B'$". These are generally called inference schemes. The most widely adopted class of inference schemes are those that were originally introduced by Zadeh [189]. They are based on the *Compositional Rule of Inference* (CRI), which is described next. Thereafter, some other inference schemes are briefly mentioned.

8.4 Compositional rule of inference

8.4.1 Definition

The original inference scheme introduced by Zadeh is based on the expression of the rule as a *fuzzy relation* R and the composition of fuzzy relations.

Definition 51 (*Compositional Rule of Inference* (CRI) [189]). *For X and Y, two variables on the universes U and V respectively. Let "$X = A'$" and R the fuzzy relation expressing the rule "If $X = A$ then $Y = B$", with $A' \in \mathcal{F}(U)$ and $R \in \mathcal{F}(U \times V)$. The following conclusion can be deduced: "$Y = A' \circ_{\mathcal{T}} R$", with $A' \circ_{\mathcal{T}} R$ defined by*

$$(\forall v \in V)(\mu_{A' \circ_{\mathcal{T}} R}(v) = \sup_{u \in U} \mathcal{T}(\mu_{A'}(u), \mu_R(u, v))) \tag{2.62}$$

In most applications, the sup-min composition is adopted.

In binary logic, an implication operator is used to enable the *modus ponens*. As the CRI enables the use of the *generalized modus ponens*, it is natural to adopt an implicator $\mathcal{I}$ to calculate the fuzzy relation R that expresses a fuzzy rule,

$$(\forall u \in U)(\forall v \in V)(\mu_R(u, v) = \mathcal{I}(\mu_A(u), \mu_B(v))) \tag{2.63}$$

8.4.2 Parallel rules

In practical applications, the relation between variables is seldom fully described by a single rule. Usually, multiple rules are needed to completely specify their interactions. A set of rules that describe a relation between the same variables are called *parallel fuzzy rules*. The reasoning process of the GMP then becomes as follow, with $n \in \mathbb{N} \setminus \{0\}$.

$$\begin{array}{rllll}
\text{Rule 1:} & \textsc{If} & X = A_1 & \textsc{Then} & Y = B_1 \\
\text{Rule 2:} & \textsc{If} & X = A_2 & \textsc{Then} & Y = B_2 \\
 & & \quad\ldots & & \\
\text{Rule n:} & \textsc{If} & X = A_n & \textsc{Then} & Y = B_n \\
\text{Fact:} & & X = A' & & \\
\hline
\text{Conclusion:} & & & & Y = B'
\end{array}$$

Basically, there are two methods to handle parallel rules [97].

Local inference In this approach, also called First Infer Then Aggregate (FITA), inference is performed with each individual rule. Afterwards the results are aggregated.

Global inference In the First Aggregate Then Infer (FATI) strategy, the fuzzy relations expressing the rules are first aggregated. After that, there is a single inference step with the input fact and the aggregated fuzzy relation.

Hence, in both cases an appropriate *aggregator* is required. Logical considerations lead to the use of the intersection, so a n-ary triangular norm must be adopted as aggregator.

Consider multiple crisp rules that describe a relationship between two variables. When the antecedents and the consequents of the rules form a complete partition of U and V respectively, it can be shown that the final result of the intersection of all rules, will be equivalent with the union of the relations $R_i = A_i \times B_i$, $i \in \{1, 2, \ldots, n\}$ with $n \in \mathbb{N} \setminus \{0\}$ the number of rules and A_i, B_i respectively the antecedent and consequent of rule i [42]. This observation has inspired engineers to represent a fuzzy rule "IF $X = A_i$ THEN $Y = B_i$", X and Y variables over the universes U and V respectively, $A_i \in \mathcal{F}(U)$, $B_i \in \mathcal{F}(V)$ for $i \in \{1, 2, \ldots, n\}$, with the fuzzy relation R_i defined by,

$$(\forall u \in U)(\forall v \in V)(\mu_{R_i}(u, v) = \mathcal{T}(\mu_{A_i}(u), \mu_{B_i}(v))) \qquad (2.64)$$

with $\mathcal{T}$ a triangular norm (most commonly the minimum t-norm). Of course, a triangular conorm must then be used to combine the fuzzy relations R_i

(FATI) or the results from the fuzzy rules B'_i (FITA). These schemes are called a Mamdani controller [112]. They will be referred to as the "*conjunction model*", whereas the natural extension of the logical implication will be called the "*implication model*".

The resulting inference schemes are summarized in table 2.5.

Table 2.5: Fuzzy inference schemes where R_i denotes the fuzzy relation between X and Y expressed by the i-th fuzzy rule, $i \in \{1, 2, \ldots, n\}$ with $n \in \mathbb{N} \setminus \{0\}$.

	FATI	FITA
Conjunction model	$B'_1 = A' \circ (\bigcup_{i=1}^{n} R_i)$	$B'_3 = \bigcup_{i=1}^{n} (A' \circ R_i)$
Implication model	$B'_2 = A' \circ (\bigcap_{i=1}^{n} R_i)$	$B'_4 = \bigcap_{i=1}^{n} (A' \circ R_i)$

An often stated theorem proofs that $B'_2 \subseteq B'_4 \subseteq B'_1 = B'_3$ [97]. However, this is only true when the same fuzzy relations R_i, $i \in \{1, 2, \ldots, n\}$, are used in all four formulas. As already shown, the relations R_i in the conjunction model are modeled by a triangular norm and with a logical implicator in the implication model. Therefore, the theorem is not very useful in practice, except for the relations $B'_2 \subseteq B'_4$ and $B'_1 = B'_3$ separately. From this it follows that FITA or FATI does not make a difference in the conjunction model. In the implication model, FATI produces a more specific result, more informative as the reasoning is restrictive. However, this does not mean that FITA is wrong, it is just less informative.

8.4.3 Semantics

When multiple rules are used to describe the relationship between two variables, it has been shown that an individual rule representation R_i satisfies

$$\mu_{A_i}(u) \wedge \mu_{B_i}(v) \leq \mu_{R_i}(u, v) \leq \mu_{A_i}(u) \to \mu_{B_i}(v) \qquad (2.65)$$

The conjunction offers a lower bound which is not completely representing the available information but just provides a representation that is not inconsistent with the information.

In [55] and [56], Dubois and Prade have investigated the semantics of *fuzzy IF-THEN rules*. They distinguish three different rule interpretations, depending on the operator used to construct the rule representation R. In their analysis, they treat the two inequalities of (2.65) separately and view the rule as a partial specification of a possibility distribution $\pi_{Y|X}$ pertaining to the value of Y given the value of X. Here, we content ourselves with a brief discussion of their obtained results. For more details, the reader is referred to [55] [56] and [60].

Possibility qualifying In this interpretation, the rule relation is modeled with a t-norm (*conjunction model*). The consequent is viewed as a lower bound, the values that are guaranteed possible, when the antecedent is satisfied. The underlying semantics of the rule is "the more X is A, the more possible B is a range for Y", e.g. "the more cloudy the sky is, the more possible it will rain soon".

Certainty qualifying When an *S-implicator* is used to represent the rule (*implication model*), the possibility degree of the consequent (interpreted as "certain") is decreased when the satisfaction of the antecedent (the matching between A and A') decreases. The associated rule semantic is "the more X is A, the more certain Y is B", e.g. "the younger the man, the more certainly he is single".

Truth qualifying In the case the relation is modeled with an *R-implicator* (*implication model*), the core of the consequent is extended when the satisfaction of the antecedent decreases. The result is a gradual or truth qualifying rule, "the more X is A, the more Y is B", e.g. "the more a tomato is red, the more ripe the tomato is".

In the *conjunction model*, the rules represent the lower bound of the inequality (2.65). They express a knowledge gathering process [56], additional information may raise the lower bound (with a triangular conorm). If the rules are modeled with an extension of the logical implication operator, e.g. S-implicator or R-implicator (*implication model*), they are viewed as constraints that restrict the possible set of solutions (the upper bound of the inequality (2.65)). Improving precision with more information leads to eliminating some of the remaining solutions (with a triangular norm).

8.4.4 Implementation

In a Mamdani controller (*conjunction model*) in which the same triangular norm $\mathcal{T}$ is used both to construct the fuzzy relations and to compose the relations and the input, e.g. minimum t-norm based on sup-min composition, the calculation of the rule result "If $X = A$ then $Y = B$" can be significantly simplified. Based on the associativity and the left-continuity of a triangular norm, the inference scheme can in these cases be reformulated as, $\forall v \in V$,

$$\mu_{B'}(v) = \sup_{u \in U} \mathcal{T}(\mu_{A'}(u), \mathcal{T}(\mu_A(u), \mu_B(v))) \tag{2.66}$$

$$= \sup_{u \in U} \mathcal{T}(\mathcal{T}(\mu_{A'}(u), \mu_A(u)), \mu_B(v)) \tag{2.67}$$

$$= \mathcal{T}(\sup_{u \in U} \mathcal{T}(\mu_{A'}(u), \mu_A(u)), \mu_B(v)) \tag{2.68}$$

$$= \mathcal{T}(\mathrm{hgt}(\mathcal{T}(A', A)), \mu_B(v)) \tag{2.69}$$

$$= \mathcal{T}(\alpha, \mu_B(v)) \tag{2.70}$$

where $\alpha = \mathrm{hgt}(\mathcal{T}(A', A))$ is called the *degree of fulfillment* or the *adaptability* or the *firing strength* of the fuzzy rule.

This simplification eliminates the need to explicitly calculate the fuzzy relations and the fuzzy composition. As an additional advantage, the simplification can be extended to multiple rule antecedents. In the general CRI, this would require the explicit calculation of three-or more dimensional fuzzy relations which becomes quite complex.

8.5 Other inference schemes

Although the CRI is widely used in practice, it is not the only inference engine to implement fuzzy rules. However, it provides clear semantics and therefore will be exclusively used in this work. For the sake of completeness, some other proposed methods are briefly mentioned.

The method proposed by Baldwin [8] is based on *fuzzy truth values*. First of all, the fuzzy truth value of the rule antecedent is calculated based on the knowledge of the given input fact. Next, the fuzzy truth value of the rule itself, calculated as $\mathcal{I}(\mathrm{true}, \mathrm{true})$, is modified to reflect the partial truth of the antecedent. Finally, the rule consequent is modified to take into account this obtained truth value of the rule, given the input fact. These methods have the advantage that the inference step is exclusively calculated in the interval $[0, 1]$. However, this mapping into the unit interval may also affect the precision of the rule outcome, especially in computer implementations.

Yager has introduced what is now called "approximate analogical reasoning" [176]. It is a two step inference procedure. In the first step, the similarity degree between the rule antecedent and the input fact are measured with a *similarity measure*. Secondly, the rule result is obtained by applying a modification function to the rule consequent which takes the calculated similarity degree as parameter. This inference scheme for the rule "If $X = A$ then $Y = B$" given the input fact "$X = A'$" can be formulated as

$$B' = f(\mathrm{Sim}(A, A'), B) \tag{2.71}$$

where Sim and f are appropriate functions. For some possibilities we refer to [176] and [153]. Note that the *conjunction model* based on a t-norm $\mathcal{T}$ can be obtained when $\mathrm{Sim}(A, A') = \mathrm{hgt}(\mathcal{T}(A, A'))$ and $f = \mathcal{T}$.

9 Generalizations

Quite shortly after the introduction of fuzzy sets, generalizations of the concept have been published. Some of them are briefly mentioned here.

***L*-fuzzy sets** Fuzzy sets over a general lattice L instead of the unit interval $[0, 1]$ have been introduced in 1967 by Goguen [72]. The lattice L must be a complete lattice $(L, \wedge, \vee, 0, 1)$. An L-fuzzy set is then characterized by the membership mapping $\mu_A : U \to L$ where U is the universe of discourse. This generalization is especially useful to model incomparable information, because such incomparable elements do not exist in the unit interval $[0, 1]$. The set of all L-fuzzy sets on the universe U is denoted as $\mathcal{F}_L(U)$. Hence, the following equalities can be stated: $\mathcal{F}(U) = \mathcal{F}_{[0,1]}(U)$ and $\mathcal{P}(U) = \mathcal{F}_{\{0,1\}}(U)$.

Level-2 fuzzy sets These fuzzy sets allow to express the uncertainty over fuzzy sets. They were proposed by Zadeh in [185].

Definition 52 (Level-2 fuzzy set [58]). *Let U denote the universe of discourse. Define the (level-1) fuzzy sets $A_i = \{(u, \mu_{A_i}(u)) \mid \forall u \in U : \mu_{A_i}(u) > 0\}$. The level-2 fuzzy set B is then defined as $B = \{(A_i, \mu_B(A_i)) \mid \forall A_i \in \mathcal{F}(U) : \mu_B(A_i) > 0\}$.*

Type-2 fuzzy sets A fuzzy set is of type-2 (or more generally type-n) if its membership function ranges over fuzzy sets of type-1 (type-$(n-1)$). The membership function of a type-1 fuzzy set ranges over the unit interval $[0, 1]$ [188]. A point-wise definition is given in [117].

Definition 53 (Type-2 fuzzy set). *A type-2 fuzzy set $\tilde{\mathrm{A}}$ is characterized by a type-2 membership function $\mu_{\tilde{\mathrm{A}}}(x, u)$, where $x \in X$ and $u \in J_x \subseteq [0, 1]$, i.e.*

$$\tilde{\mathrm{A}} = \{((x, u), \mu_{\tilde{\mathrm{A}}}(x, u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0, 1]\} \tag{2.72}$$

in which $0 \leq \mu_{\tilde{\mathrm{A}}}(x, u) \leq 1$.

It should be mentioned that a type-2 fuzzy set is in fact a L-fuzzy set with $L = (\mathcal{F}(X), \cap, \cup)$.

10 Notational conventions

In the rest of this work, we will adopt the convention to use the same symbol to denote a linguistic term, the fuzzy set representing the meaning of this term as well as the membership function that characterizes the fuzzy set. So instead of $\mu_A(u)$ we will simply write $A(u)$ where A is the fuzzy set that models the linguistic term A.

Chapter 3

Representing noise annoyance

> 'When I use a word,' Humpty Dumpty said in rather a scornful tone, 'it means just what I choose it to mean — neither more nor less.' 'The question is,' said Alice, 'whether you can make words mean so many different things.'
>
> *Lewis Carroll (1832-98)*
> *English mathematician and writer*

1 Annoyance scales

The first thing one must do before even starting to consider modeling a concept is to devise a suitable representation for it. As this work is concerned with the modeling of noise annoyance, we need a way to represent the concept of noise annoyance. How should the model express its result to us, what do we expect as output from the model?

An important aspect of representation is the underlying scale. Contrary to many quantities encountered in every day life, such as length and weight, there is no universally accepted scale for noise annoyance (although even for length and weight several scales are in existence, e.g. the British system and the metric system). This could be explained by the absence of some kind of physical scale. In case of the meter, it can be defined as the distance light travels in vacuum within a specified amount of time, which is in turn defined by some radiation properties of chemical elements. Instead, noise annoyance is a psychological construct. This fact has two consequences. First of all, an imaginary scale with an appropriate granularity has to be created for its representation. As a heuristical guiding principle for the granularity, the analysis performed by Miller is useful here [125]. He has shown that the "span of absolute judgement" of a unidimensional stimulus variable (e.g. sound tones, sound loudness, taste of salt solutions,...) is seven plus or minus two. This means that people can roughly distinguish seven levels, five for the man in the street and nine for an expert in the field. It is assumed that these results also apply to the noise annoyance concept. Secondly, annoyance cannot be measured with equipment. Data about the level of experienced noise annoyance must be gathered by means of *social surveys*. Such studies can be performed face-to-face or by telephone, in which an interviewer asks questions directly to the participants and writes down their answers on a form. More commonly they are conducted by mail. In this setting, respondents are kindly requested to fill in a questionnaire and send it back. Several ways to answer the questions regarding the experienced noise annoyance have been used in surveys. A first approach gives the respondents some categories numerically labeled from 1 till 4, 5, 7 or 9, or from 0 till 10. They must choose one of these, where 1 (or 0) indicates no annoyance at all and the highest number means the highest possible degree of annoyance one can imagine. Sometimes, a continuous line is used. In this type of question, the respondents must put a mark to indicate their level of annoyance. The left point of the line is labeled as not at all annoyed, while the right point is labeled as the highest degree of annoyance. A third approach uses a verbal scale with four or five linguistic labels. This kind of scale introduces the additional complexity of language, although a linguistic expression is a far more natural way for people to describe their perception of annoyance than using any kind of numbers. However, it can no longer be guaranteed that all presented categories are equidistant. Yet, it is important to mention the results of a small laboratory experiment by Rohrmann. He gave two different surveys to two different groups. In the first survey, the annoyance question had to be answered on a 5-point linguistic scale on which "very" was the label for the fourth term, and "extremely" was the label for the fifth term. The other group had to answer the annoyance question on a 4-point linguistic scale on which "very" was the last label. After judging the same 13 noises, 31 % was at least very annoyed in the first group, while in the second group only 14 % was at least very annoyed. This could indicate that people not only judge the meaning of the word but also tend to equally distribute the meaning over the number of presented categories.

An obvious disadvantage of this plethora of scales is the difficulty to compare the results of *surveys*. This greatly reduces the available amount of data one can use to model annoyance and to extract as much knowledge as possible from all collected data. This is even a bigger problem for surveys using verbal scales. For such studies, six comparison issues can be identified which are mainly depending on the vocabulary used in the survey [160].

Language As the translation of words to another language is probably never really exact, the language of the survey is an important comparison barrier.

Terminology Although the results of the experiment by Rohrmann indicate the tendency to equidistantly distribute the number of categories, even in case of verbal labels, the meaning of the given terms will undoubtedly play an important role. Perhaps this will be especially true in studies conducted face-to-face or by phone. Then, people not really see the number of labels, they only remember the words and will answer according to the meaning they associate to them. Anyway, the annoyance terms should be carefully selected to cover the whole universe. E.g. one should avoid that no term is available to describe the middle category of annoyance or that almost synonyms are used for the two upper-categories.

Scale Surveys using a 4-point scale are difficult to compare with a 5-point scale from another study.

Questioning The exact phrasing of the annoyance question can also influence the way people answer. Even the position of the annoyance question in the survey, the preceding and following questions, are important.

Culture Differences in the language culture, e.g. the tendency to choose extreme categories, can also affect the results of a survey.

Survey context What is the survey about, how is the annoyance question related to the topic of the survey, and how is the topic of the survey presented to the people. These context questions set the trend for all answers given by the participants.

Historically, in the acoustical literature the term "*highly annoyed*" (HA) has achieved special status as an important degree of annoyance to model. Therefore researchers needed a way to convert the results of surveys with numerical scales into the linguistic term "highly". A common cutoff point for "highly annoyed" is 7.2 on a scale from 0 to 10 [140]. Other common cutoff points used are 5.0 for "*annoyed*" (A) and 2.8 for "*little annoyed*" (LA) [123]. Below 2.8 is interpreted as "not at all annoyed". Everyone will undoubtedly agree that such cutoff points are arbitrary and such sharp transitions are not in true correspondence with the actual meaning of the terms.

In this thesis, noise annoyance is addressed as an inherent vague concept. It is a feeling, a state of mind that results from the perception of noise, which cannot be expressed using either (crisp) numbers or crisp intervals. However, this feeling can be communicated with natural language. If someone says that he's "somewhat annoyed", we will all know more or less how that person feels, although the term has no exact numerical meaning. It is merely a vague expression with blurred boundaries. Its boundaries are not sharp points but regions where the term gradually moves from being applicable to nonapplicable. Furthermore, noise annoyance is subjective and context-dependent. An annoyance term can have a slightly different meaning to different people, and in different contexts, such as the modeling of noise versus annoyance caused by odor or light.

Vague concepts that are subjective and context-dependent are perfect candidates to be modeled as *linguistic variables* (see chapter 2, section 8.2) in the framework of fuzzy set theory [188] [82]. This allows an accurate mathematical representation of the blurred boundaries of annoyance expressions.

In order to represent the noise annoyance concept as a linguistic variable, the following tasks must be performed.

- Determine an appropriate universe of discourse.
- Construct for each linguistic value for noise annoyance a fuzzy set that represents its meaning.

Before addressing these points, we will first describe the International Annoyance Scaling Study. This research project has been set up by the acoustical community in order to facilitate comparisons between future surveys. Please note that this study was performed with statistical (non-fuzzy) processing in mind. Still, the results will also turn out quite useful for our purposes.

2 International Annoyance Scaling Study

In 1993 the Community Response to Noise Team (Team 6) of the International Commission on the Biological Effects of Noise (ICBEN) developed a program to reach an international agreement on the choice of linguistic labels for answering annoyance questions in surveys [65]. The goal was to devise an equally distributed, linguistic interval scale. In all participating languages the terminology for a four-point as well as a five-point linguistic noise annoyance scale has been carefully selected. In the same process standardized noise reaction questions have been agreed upon, to remove issues with the questioning dependency.

The procedure started with selecting a pool of 21 modifiers (adverbs) of annoyance. These terms were then presented to a mixture of university students and employees of technical firms. The average age was about 35 years, but varied from 19 to 44 for different study sites. After providing some background information the subjects completed the questionnaire by performing the following four tasks to evaluate the 21 words.

Task 1 Subjects placed each word in one of nine groups ranked from "no annoyance at all" to "the most annoyance you can imagine." The purpose of this task was mainly to get the respondents acquainted with the words. Its results have not been used in the final analysis.

Task 2 Subjects indicated the intensity associated with each word by placing a mark on a 10 cm line that extended from "No/lowest degree of annoyance" to "Highest degree of annoyance."

Task 3 Subjects selected one preferred word to describe each category on a 5-point scale. First by choosing a word "that you would be most likely to use" for the "greatest amount of bother or annoyance you might feel" and then expressing a preference for the three words that should complete the remaining three points on a 5-point scale. The lowest point was predetermined as "not at all annoyed".

Task 4 The same preference question as task 3 but for a 4-point scale.

For both the 4- and 5-point preference questions subjects were instructed to choose words that "people would normally use when talking". Subjects were instructed to select words that were "equally spaced" between "not at all annoyed" and the previously chosen high annoyance word. The questionnaires were completed by 1 754 subjects at over 25 sites in 12 countries in nine languages. The number of respondents for each language: Dutch/Flemish=93, English=231, French=45, German=61, Hungarian=47, Japanese=1102, Norwegian=56, Spanish=59, Turkish=60.

A separate but identical analysis has been conducted for each language. The results of this analysis have been used to select the labels of a four-point and five-point annoyance scale. The selection procedure was based on eight different ratings including the average and standard deviation of the positions of the intensity marks placed on the 10 cm line. These two ratings for the English and Dutch terms as well as the final selected words are shown in table 3.1. Furthermore, the results of the analysis indicated that the top two categories of the 5-point scale can be combined to define the popular "*highly annoyed*" expression.

Table 3.1: English and Dutch annoyance terms with their intensity average μ and standard deviation σ. Selected labels for the 5-point scale are in **bold**, 4-point scale in *italic*.

Code	English	μ	σ	Dutch	μ	σ
L01	***not at all***	0.08	0.50	***helemaal niet***	0.04	0.07
L02	insignificantly	0.76	0.86	niet	0.14	0.26
L03	barely	0.81	0.81	nauwelijks	0.94	0.77
L04	hardly	1.03	1.24	weinig	1.24	0.65
L05	a little	1.32	0.81	iets	1.57	1.03
L06	**slightly**	1.54	0.94	lichtelijk	1.64	1.00
L07	partially	2.96	1.30	**een beetje**	1.65	0.94
L08	*somewhat*	3.57	1.53	enigzins	2.59	1.35
L09	fairly	4.05	1.49	*matig*	3.44	1.39
L10	**moderately**	4.37	1.09	**tamelijk**	3.92	1.47
L11	rather	4.79	1.72	behoorlijk	6.21	1.70
L12	importantly	6.51	1.43	*aanzienlijk*	6.81	1.57
L13	considerably	6.22	1.70	veel	6.90	1.20
L14	substantially	6.45	1.53	**erg**	7.42	1.08
L15	*significantly*	6.72	1.42	sterk	7.79	1.06
L16	**very**	7.56	1.21	zeer	8.03	0.87
L17	highly	7.87	1.08	ernstig	8.05	1.02
L18	strongly	7.97	0.94	enorm	8.59	0.99
L19	severely	9.07	1.14	ontzettend	8.74	0.93
L20	tremendously	9.23	0.94	uitermate	8.91	1.03
L21	***extremely***	9.49	0.87	***extreem***	9.78	0.27

It has already been pointed out that the same research project also proposed standardized noise annoyance reaction questions. The preferred wording that has been agreed upon is "Thinking about the last (..12 months or so..), when you are here at home, how much does noise from (..noise source..) bother, disturb, or annoy you: Extremely, Very, Moderately, Slightly or Not at all?" The words appearing in parentheses are to be replaced by phrases that are most appropriate for the noise source and time period being studied. An extensive report on this research and its results can be found in [65] and [61].

In [114] the results of this study for English and Japanese have been compared to the results of a similar experiment conducted with bilingual subjects. In total, 39 respondents had English as their first language and 37 respondents had Japanese as first language. All subjects had to fill in basically the same questionnaire as in the ICBEN study, both in English and in Japanese. According to their conclusions, the English and Japanese scales proposed by the ICBEN team are indeed equivalent.

Recently, an analogous noise annoyance scaling study and analysis has been conducted for other languages such as Korean [88] and Chinese and Vietnamese [181]. These results are not considered in this work.

3 Constructing annoyance terms

3.1 Overview

The foregoing discussion brings us back to the first problem of determining a universe for the linguistic noise annoyance variable. Based on the International Annoyance Scaling Study and other existing literature, the continuous interval $[0, 10]$ has been chosen. This choice is justified by the observation that all numerical scales that have been used in the past social surveys can be easily mapped onto this domain, the equidistant numeric categories as well as the continuous line marks. This is important in order to obtain an annoyance representation that solves all previous comparison issues. Throughout this work the *linguistic variable* "annoyance" will be denoted with the symbol $\mathcal{H}$. For the universe of annoyance the notation $\mathbb{H} = [0, 10]$ is used. The set of *linguistic values* $\mathcal{H}$ can take will be written as $\mathbb{L} = \{L_1, L_2, \ldots, L_m\}$ with $m \in \mathbb{N}$. L is then a generic element from this set.

Remark that the reduction of a linguistic term to a single interval $\mathbb{H}$ is in fact an oversimplification. Words in a language are a complex construct and involve many different dimensions such as the frequency of usage, the atmosphere,... and the intensity. Here, we are only interested in the latter, so we limit ourselves to this single dimension.

The fuzzy literature has historically interpreted adverbs such as "slightly", "very",... as *linguistic modifiers* or *hedges* that alter the meaning of a linguistic term. Although this approach is also applicable for the concept of noise annoyance, it is our belief that the base term "*annoyed*" not really expresses a certain degree of annoyance. It is merely a statement that there is annoyance. Hence, we will treat linguistic expressions such as "slightly annoyed", "very annoyed" as single terms rather than as a term modified by a hedge. This view is in accordance with the viewpoint that has been taken in the International Annoyance Scaling Study. It should be noted that the fuzzy literature usually does not modify middle terms, such as "middle aged" either [46].

One of the first experiments conducted on the fuzzy analysis of linguistic terms has been done by Hersch and Caramazza [82] in 1976. Besides the conclusion that natural language concepts can be described more completely and manipulated more precisely in the framework of fuzzy set theory, their research has also revealed that there are two fundamentally different interpretations of linguistic terms, what they have called the *logical* and the *linguistical interpretation*. The logical approach, which we will refer to as the *inclusive interpretation* [46], assumes that everyone who is "extremely annoyed" is also considered to be "very annoyed". Each membership function takes the form of an S-shape. The terms obey the semantical entailment principle which means as much as the following relationship: extremely annoyed $\subseteq$ very annoyed. In this view, the terms are implicitly interpreted with the prefix "at least", e.g. everyone who is "extremely annoyed" will also be "at least very annoyed". To illustrate this interpretation, consider a boy who is asked to name the "very beautiful" girls from a row of ten girls. After this difficult task, if the same boy is then asked to name the "extremely beautiful" girls, he will surely choose only within his previous selection. Hence his first selection contained in fact the girls that are "at least very beautiful", including the "extremely beautiful" ones. The linguistical interpretation, which we will call the *non-inclusive interpretation* [46], does not satisfy the semantical entailment principle and results in bell-shaped membership functions (except for the left-most and right-most terms that are usually decreasing and increasing respectively) that do overlap each other. This view is a much more pragmatical one which is not only guided by (logical) truth. Also the "added value" of the word, as it is used in daily life, is taken into account. When a boy is asked to write down the names of the "very beautiful" girls and those of the "extremely beautiful" girls, he will not write down the same name twice in both categories.

In the remaining part of the section, for each noise annoyance term, each linguistic value L of the noise annoyance linguistic variable $\mathcal{H}$, a fuzzy set that represent its meaning will be constructed. Several such construction methods have been described in the literature. They can be roughly categorized as followed.

Inquiry-driven This group of methods poses questions to experts of which the answers can be rather directly used to construct the fuzzy set representation of a linguistic term.

Fuzzy clustering With this approach, data is first clustered and the relevant fuzzy sets are then automatically extracted from these clusters.

Probability based Using the links between probability theory and possibility theory, it is possible to transform a probability distribution into a possibility distribution (see section 3.2.2). This also results in a fuzzy set.

Fuzzification based Fuzzification methods are based on the assumption that an answer to an inquiry should not be interpreted as a crisp point but rather as a possibility distribution. Therefore, inquiry answers are first fuzzified and then aggregated.

The first two methods will only be discussed briefly for the sake of completeness. The latter two categories will be investigated more thoroughly in separate sections and extended for our specific purposes. They will be demonstrated for the case of the five English noise annoyance terms that have been selected by the International Annoyance Scaling Study: L_1 = "not at all annoyed", L_2 = "slightly annoyed", L_3 = "moderately annoyed", L_4 = "very annoyed" and L_5 = "extremely annoyed", with $\mathbb{L} = \{L_1, L_2, \ldots, L_5\}$.

As a fifth category of techniques, modifier methods could be mentioned, which try to model a term (e.g. "very annoyed") by applying a *hedge* ("very") to some representation for the base term "*annoyed*". However, as already explained, in this work the annoyance terms will be considered as one, so these methods will not be pursued any further.

3.1.1 Inquiry-driven methods

In order to obtain the degree of compatibility $A(u)$ for a certain linguistic term A for each element u of the universe U, these methods pose questions to experts that more or less directly allow to map the results into a fuzzy set representation of A. However, for the wording of the questions, several possibilities are in use. Each time a number of discrete elements $u_i \in U$, with $i \in \{1, 2, \ldots, n\}$, are presented.

Direct rating One possibility is to directly ask one or more experts, or the group in which the experiment is conducted, for the membership degree of some elements u_i, for example: "How A is u_i?" [152].

Reverse rating In this approach, the questions are formulated in reverse form: "Which element u_i has a given degree $A(u_i)$ of membership in A?" [152].

Polling In the two methods described above, people are asked very directly to assign a certain degree of membership to some elements. This is for most domains very difficult and at the same time somewhat arbitrary. Hersh and Caramazza [82] overcome this, by asking only yes/no questions of the form: "Does u_i belong to A?". Afterwards, $A(u_i)$ is calculated as the total number of "yes" responses for u_i divided by the total number of responses for u_i (yes and no together).

Indirect rating These methods also try to replace the direct assignments of degrees with simpler tasks, for instance with pairwise comparisons which are generally easier to estimate. One such method is the *analytic hierarchy process* (AHP) [115], where questions are asked as "To what degree does u_i imply A in comparison with u_j?" with $j \in \{1, 2, \ldots, n\}$ and $i \neq j$. If the cardinality of the universe is an integer n, then all those answers, for instance on a discrete scale from 1 till 10, result in a square matrix P of order n with $P_{ij} = 1/P_{ji}$. After column-wise normalization, $A(u_i)$ is then calculated as the (if desirable, again normalized) row average of the i-th row of P.

These questions always result in couples $(u_i, A(u_i))$. To finally determine the fuzzy set representation, any curve fitting method can be used, such as Lagrange interpolation and the least-square-error method. Other techniques such as learning through neural networks can also be applied for this purpose [97] [167].

Because the universe of the annoyance concept is quite abstract, the scale $[0, 10]$ does not correspond to any quantity people can experience, inquiry-driven methods are not suited for our purposes.

3.1.2 Fuzzy clustering methods

The primary goal of fuzzy clustering algorithms, such as the fuzzy c-means (FCM) algorithm [85], is to partition a given set of data or objects into fuzzy subsets called clusters such that objects strongly belonging to the same cluster (the membership degree of both objects to that cluster are close to 1) are as "similar" as possible and objects that belong to different clusters (the membership degree of one of those objects to that cluster is close to 0) are as "different" as possible. The notions "similar" and "different" are defined by a user given dissimilarity measure d (for instance, the Euclidean distance in a metric space). The aim of the clustering procedure is then to globally minimize this dissimilarity between elements belonging to the same cluster. In a two-dimensional universe $U \times V$, clustering is often used to extract the relationship between a variable X on U and a variable

Y on V. Each cluster C (which is a fuzzy set on $U \times V$) gives rise to a fuzzy rule of the form: "IF $X = A$ THEN $Y = B$", in which A and B are fuzzy sets on U and V respectively, obtained by "projecting" C on U and V respectively. A common practice in the field of fuzzy clustering is to assign ad hoc linguistic terms to the obtained fuzzy sets A and B. This way, the resulting rules are fully linguistical and easy to understand by domain experts, not necessarily having much knowledge of fuzzy logic.

By way of construction it is obvious that there will be a strong coupling between the representation of the terms and the training data. This has two significant consequences. First of all, the training data as well as the resulting fuzzy sets may be biased and not necessarily represent a generalizable relationship. Secondly, the number of terms is dependent on the number of clusters in the data. Furthermore, the assignment of linguistic terms to the retrieved fuzzy sets is ad hoc, so in general the membership functions associated with the terms do not represent the meaning that people give to the terms. At least there is no well-defined link between the linguistic meaning of a term and the generated fuzzy set. For these reasons, fuzzy clustering is not well suited to construct a representation for the meaning of linguistic terms.

3.2 Probabilistic methods

3.2.1 Basic procedure

The construction of membership functions presented in this section is based on a pure probabilistic approach, which resembles more or less to the polling method. The underpinnings of these methods can be found in the *possibility/probability consistency principle* [191]. Although it is not a precise law, it provides a heuristic relationship that forms a basis for the computation of a possibility distribution out of a probability distribution. The general strategy is to calculate the frequency histogram of points that have been evaluated as being suitable for a given linguistic term L by a number of people. This frequency distribution is then interpreted as – normalized to– a probability distribution and transformed into a possibility distribution for that linguistic term. Hence, this results in a fuzzy set that represents the meaning of the term L. Several such *probability-possibility transformation* schemes have been proposed which will be described in detail further on.

This procedure does not depend on any other data than the evaluation of the terms itself, so there can be no bias towards accidental relations in data. Also, the questions asked to collect the data can be formulated in many different ways, contrary to the inquiry-driven methods such as polling. This means that one can use the most natural formulation for the problem at hand. It allows to use data sets that were not specifically gathered for fuzzy processing. These qualities make the probabilistic methods ideally suited to generate the meaning of the noise annoyance terms. In fact, the data collected in the framework of the International Annoyance Scaling Study turn out to be useful for this purpose. Another property of these approaches is that the construction of the representation of the meaning of a given term, is completely independent of the other linguistic terms involved.

Corresponding to the notations L_1 to L_5 for the five English annoyance terms from the International Annoyance Scaling Study and their associated membership functions, the marks placed by a respondent k will be represented as h_1^k to h_5^k (in $\mathbb{H} = [0, 10]$), with $k \in \{1, 2, \ldots, N\}$ and N the total number of English respondents. The index j will run through $\{1, 2, \ldots, 5\}$. The link with the polling method is obvious when the mark h_j^k of a respondent for one of the terms L_j is interpreted as a pair (h_j^k, yes) for L_j in the polling method. The answers for the other points $h \in \mathbb{H}\setminus\{h_j^k\}$ can be added based on some intuitively justified assumptions. If we assume "no" as the answer for all unknown points, the average number of "yes" answers for all h taken over all respondents leads to the construction of the probability distribution function. After the transformation to a possibility distribution, the result will be a representation of the *non-inclusive* meaning of the linguistic term. Another realistic assumption is that the respondent would have answered "yes" for all points $h \geq h_j^k$, that his mark h_j^k really meant "at least L_j". In this case, the average number of "yes" responses for all h over all respondents corresponds to the cumulative probability distribution function. Hence, this assumption will lead to a representation for the *inclusive* meaning of the term L_j^k. This approach works well for all annoyance terms, except for L_1 = "not at all annoyed". For this term, the respondent would have meant "yes" for all $h \leq h_1^k$ and "no" for all $h > h_1^k$. As a consequence, the reverse cumulative probability distribution function should be used. Note that the probability density function can also be constructed as the derivative of the cumulative distribution function, which avoids discretization.

The resulting fuzzy sets may be cluttered with noise that originates from noise in the probability distribution. This noise appears especially in the tails of the distribution and can be removed in a number of ways. The scale can be reduced by discretizing the data into a smaller number of intervals. Alternatively, a smooth curve, e.g. a sigmoidal or a bell-shaped membership function, can be fitted to the possibility distribution that results from the transformation. This has the additional advantage that the representation of the meaning of a term can then be described by a small number of parameters. However, one should be aware that the noise in the probability distribution will affect the transformation procedure which may disturb the outcome. Therefore, this approach is perhaps only feasible when a transformation method is applied which is not influenced by such noise. Another reasonable approach is to fit a curve on the probability distribution, although the transformation must then be applied to these fitted curve values.

3.2.2 Probability-Possibility transformations

The simplest transformation is the *maximum normalization frequency transformation* [93]. It is based on the fact that probability theory is additive normalized while possibility theory is maximum normalized. So, instead of normalizing the absolute frequency distribution to a probability distribution such that the sum of all frequencies is 1, it is normalized to give the maximum frequency the value 1. Starting from the probability distribution p on a discrete domain $\{h_1, h_2, \ldots, h_n\}$ with $i \in \{1, 2, \ldots, n\}$ and using $p_i = p(h_i)$, this leads to the following possibility distribution π using $\pi_i = \pi(h_i)$,

$$\pi_i = \frac{p_i}{p_{\max}} \tag{3.1}$$

where $p_{\max}$ is the highest probability. There is also an inverse transformation defined by

$$p_i = \frac{\pi_i}{\sum_{j=1}^{n} \pi_j} \tag{3.2}$$

Note that the cumulative probability distribution function is already maximum normalized by construction, so no further transformations are necessary. As the formulas are purely point-wise, they only depend on the value in one point, there is no danger to disturb the result in the presence of noise e.g. in the tails. Hence, a smooth curve can be safely fitted afterwards. The results for our five annoyance terms are shown in figure 3.1.

Another transformation method is called the *uncertainty invariance frequency transformation* and has been introduced by Klir [116]. The underlying *principle of uncertainty conservation* states that a switch from one theory to another must conserve the uncertainty. In probability theory the well-known Shannon *entropy* $H(p)$ is used to measure the uncertainty of the probability distribution p which is defined as

$$H(p) = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{3.3}$$

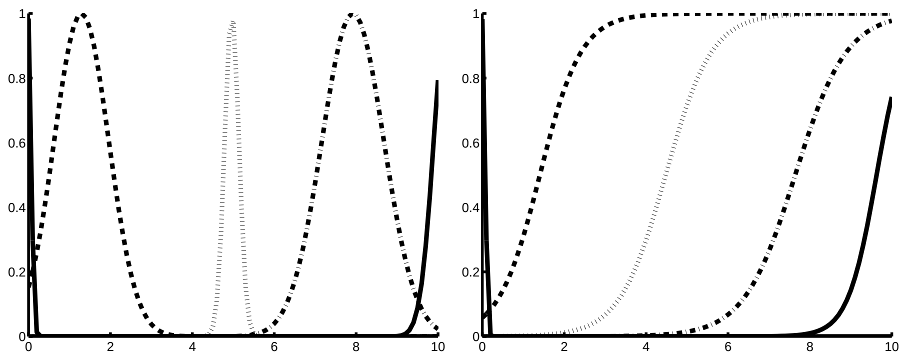

Figure 3.1: Representation of the meaning of five annoyance terms (not at all, slightly, moderately, very, extremely) when the maximum frequency normalization transformation is applied (left: non-inclusive, right: inclusive)

In possibility theory there are two different types of uncertainty that must be taken into account, the *non-specificity* (spread, diversity) $N(\pi)$ and the *discord* (ambiguity, strife) $D(\pi)$ of the possibility distribution π. The former provides an indication for the size of the distribution (in terms of cardinality) while the latter measures the degree of inconsistency (conflict) in the information. To calculate N and D, it is assumed that the possibilities are ordered so that $\pi_1 \geq \pi_2 \geq \ldots \geq \pi_n$, which results in the definitions [116]

$$N(\pi) = \sum_{i=2}^{n} \pi_i \log_2 \frac{i}{i-1} \tag{3.4}$$

$$D(\pi) = -\sum_{i=1}^{n-1} (\pi_i - \pi_{i+1}) \log_2 \left(1 - i \sum_{j=i+1}^{n} \frac{\pi_j}{j(j-1)}\right) \tag{3.5}$$

The total amount of uncertainty of a possibility distribution is given by their sum. This means that the principle of uncertainty conservation states that $H(p) = N(\pi) + D(\pi)$.

It is conjectured that there is only one such *uncertainty conservation transformation* from probability theory to possibility theory that exists for all distributions and is unique. In [116] it is defined by

$$\pi_i = \left(\frac{p_i}{p_{\max}}\right)^{\alpha} \tag{3.6}$$

with $p_{\max}$ the highest probability. The positive constant α is determined by minimizing the difference between H and $N + D$ and lies in the interval $[0, 1]$.

To obtain the inclusive interpretation for the linguistic terms, the non-inclusive possibility degrees can be summed –as if the cumulative distribution is calculated– and normalized in the possibilistic sense.

After discretization into the 11 intervals

$$[0, 0.5[, [0.5, 1.5[, [1.5, 2.5[, \ldots, [9.5, 10] \tag{3.7}$$

the optimal α values for all English and Dutch annoyance terms are summarized in table 3.2. The membership functions for the five English terms that are produced with this method are shown in figure 3.2. To test the impact of discretization on the resulting curves, for the English terms another discretization scheme into 20 intervals

$$[0, 0.5[, [0.5, 1[, [1, 1.5[, \ldots, [9.5, 10] \tag{3.8}$$

has also been investigated. The optimal α values are shown in table 3.2 and do not differ much. The same can be said about the non-inclusive representations that are depicted in figure 3.4, however, there are slightly more fluctuations in the tails. This is natural as the noise in the data is reduced to a lesser extent.

Table 3.2: Optimal α values for annoyance terms, in English (E) with discretization into 11 and 20 points and in Dutch (D) with discretization into 11 points.

Term	E-11	E-20	D-11	Term	E-11	E-20	D-11
L01	0.63	0.63	0.50	L12	0.39	0.33	0.52
L02	0.48	0.39	0.59	L13	0.41	0.33	0.42
L03	0.51	0.50	0.43	L14	0.44	0.40	0.48
L04	0.45	0.48	0.44	L15	0.41	0.43	0.50
L05	0.42	0.39	0.39	L16	0.42	0.39	0.48
L06	0.46	0.46	0.43	L17	0.51	0.52	0.53
L07	0.47	0.42	0.46	L18	0.47	0.45	0.44
L08	0.43	0.45	0.36	L19	0.49	0.35	0.38
L09	0.43	0.43	0.37	L20	0.46	0.36	0.45
L10	0.37	0.35	0.39	L21	0.46	0.40	0.56
L11	0.47	0.43	0.41				

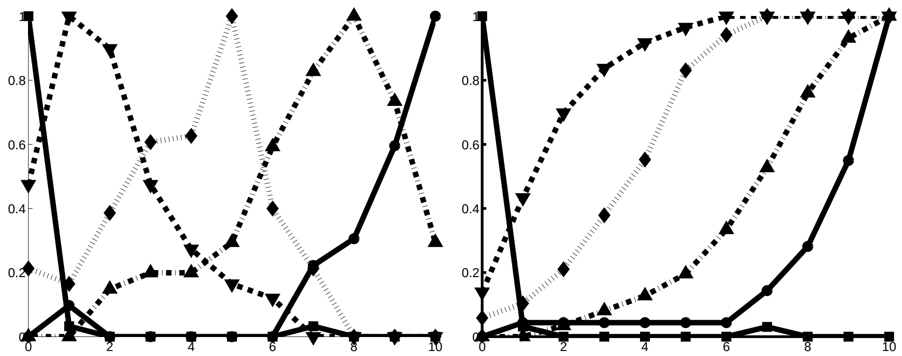

Figure 3.2: Representation of the meaning of five annoyance terms (not at all, slightly, moderately, very, extremely) when the uncertainty conservation transformation is applied (left: non-inclusive, right: inclusive)

Finally, there is also the *probabilistic difference frequency transformation* (or bijective transformation), which has been defined by Dubois and Prade [59]. This mapping is based on the following three principles.

- *Possibility/probability consistency*, $(\forall A \in \mathcal{P}(U))(P(A) \leq \Pi(A))$.
- The basic feature of a possibility distribution is the preference ordering that it induces on U. It seems natural to require it to be in accordance with the probability distribution. This is the preference preservation principle,
$$(\forall u, u' \in U)(\pi(u) > \pi(u') \Leftrightarrow p(u) > p(u')) \ . \tag{3.9}$$
- The possibility distribution, which is by definition weaker than a probability distribution, should be maximally specific so that the least amount of information gets lost.

Let us first order the probabilities such that $p_1 \geq p_2 \geq \ldots \geq p_n$. A possible *probabilistic difference transformation* satisfying the above principles is defined as

$$\pi_i = ip_i + \sum_{j=i+1}^{n} p_j = \sum_{j=1}^{n} \min(p_i, p_j) \ . \tag{3.10}$$

Remark that the righthand side of formula (3.10) does not require the reordering of the probabilities. An inverse transformation can be defined as

$$p_i = \sum_{j=1}^{n} \frac{\pi_j - \pi_{j+1}}{j} \tag{3.11}$$

with the convention that $\pi_{n+1} = 0$. Note that formula (3.10) is in fact not the most specific transformation [59]. However, the maximally specific conversion has the property that equal probabilities do not transform into equal possibilities. Therefore, the given transformation was preferred here.

The results of this method on the five annoyance terms are shown in figure 3.3, again after applying the discretization into 11 intervals. For the inclusive interpretation the same procedure as for the uncertainty conservation transformation has been used. Also in this case, the influence of a different discretization scheme has been tested using the same 20 points discretization as defined before. The results shown in figure 3.4 indicate that this transformation is even more "insensitive" to noise than the method proposed by Klir.

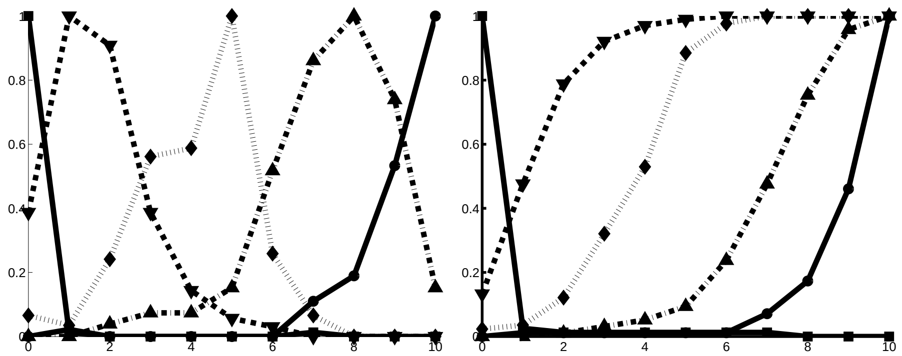

Figure 3.3: Representation of the meaning of five annoyance terms (not at all, slightly, moderately, very, extremely) when the probabilistic difference transformation is applied (left: non-inclusive, right: inclusive)

3.3 Fuzzification methods

3.3.1 Basic procedure

Contrary to the probabilistic methods which are based on theoretical principles, the fuzzification methods have a much more pragmatic starting point. The general underlying idea is that the mark h_j^k placed by a respondent k for a term L_j, $j \in \{1, 2, \ldots, 5\}$, can be considered as a value with some uncertainty. This uncertainty comes from two facts. First of all, when filling in the survey, people will not have had the intention of marking the position 7.1. They may have had the intention of marking "about" 7, so it might have been 6.8 or 7.2 as well. Secondly, the respondents will not have used

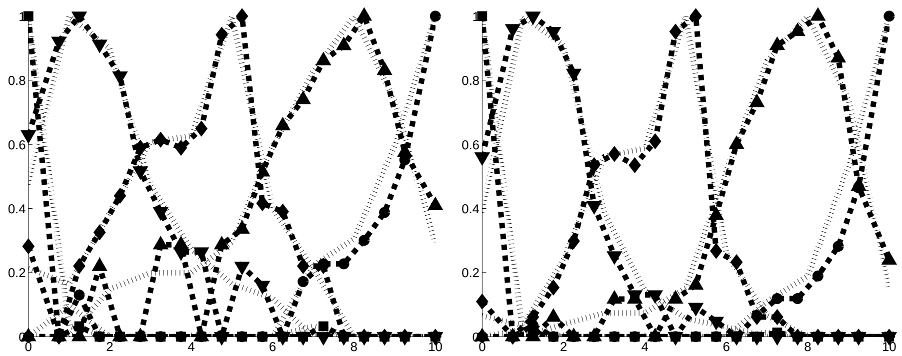

Figure 3.4: Comparison of discretization into 11 or 20 intervals for the five annoyance terms (not at all, slightly, moderately, very, extremely) (left: uncertainty conservation method, right: probabilistic difference method)

any measuring rule. Instead they have judged the line visually and have marked the position “somewhere” around their intended spot. Hence, it is justified to draw a membership function around the mark h_j^k of each individual respondent to indicate the region where the mark could have been placed. The membership degree will decrease if that point seems “less compatible” with the given point h_j^k. If one wishes to obtain a representation for the *non-inclusive interpretation* of L_j, any bell-shaped membership function will suit the purpose. For the *inclusive interpretation*, it is reasonable to assume that, by placing a mark h_j^k, $j \in \{2, \ldots, 5\}$, the respondent indicated that all levels greater than that mark are surely “at least” L_j (L_j to degree 1). Hence, the only uncertainty is situated left from the mark h_j^k, so a sigmoidal membership function should be used. In case of the term L_1, the uncertainty is situated only on the right side of h_1^k, therefore an inverted sigmoidal shape is appropriate.

After having constructed these individual fuzzy sets for a linguistic term L_j for all respondents, they are numerically added and normalized. Finally, a smooth membership function can be fitted to the resulting curve to remove noise issues and to produce the final representation for the meaning of term L_j.

The only remaining question is how to choose the membership function to fuzzify the marks for each individual respondent. In the following subsections, two methods will be outlined. One method that has been proposed in [36], followed by a new proposal which is better suited for practical applications.

3.3.2 Fixed width

To determine an appropriate way to fuzzify a mark h_j^k, Cleeren [36] suggested to use the standard deviation of all marks for L_j as the standard deviation of the bell-shaped fuzzy set drawn around h_j^k (or the sigmoidal shape in case of the inclusive interpretation). This captures more or less the consistency in meaning of a linguistic term of one respondent compared to the whole group of respondents. However this approach has a few serious drawbacks.

- Although this technique uses more information than the probabilistic methods and the use of the standard deviation is justified by Cleeren, it cannot be argued that the individual curves really reflect the intentions of the respondents. After all, the relationships between different linguistic terms in the vision of each individual respondent are not used.

- This approach assumes that the standard deviation of 100 times asking one person for the meaning of a linguistic term is the same as the standard deviation of asking this question a single time to 100 different persons. Essentially, this would mean that this term has the same meaning in the mind of all people.

- The fuzzy sets that result from this method tend to overlap each other a lot, which makes them less suitable for practical purposes.

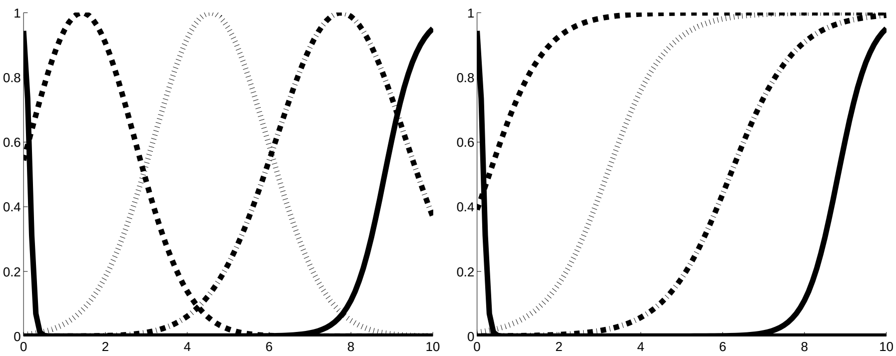

Figure 3.5: Representation of the meaning of five annoyance terms when the fuzzification method with fixed width is applied (left: non-inclusive, right: inclusive)

3.3.3 Fixed degree of overlap

To alleviate some of the problems mentioned with the previous approach, a new fuzzification scheme is introduced here. It allows to control the degree of overlap between two adjacent linguistic terms with a parameter which will be denoted as α. The amount of uncertainty inherently associated with a mark h_j^k, $j \in \{2,3,4\}$, will be related to the distance to the previous mark h_{j-1}^k and the next mark h_{j+1}^k placed by the same respondent k. Since there is no previous mark for h_1^k, we can only take the distance to the next mark h_2^k into account to construct a curve for L_1. Likewise there is no next mark for h_5^k, hence we will only use the distance to the previous mark h_4^k.

The individual curves will be constructed so that the height of the intersection of two succeeding curves L_j and L_{j+1} is α. For each respondent k and for each term L_j, $j \in \{2,3,4\}$, an individual bell-shaped function $L_j = \text{AGAUSS}_E(h_j^k, \sigma_j^k, \delta_j^k; .)$ is constructed so that for $\Delta h_j^k = (h_{j+1}^k - h_j^k)/2$

$$L_j\left(h_j^k + \Delta h_j^k\right) = \alpha = L_{j+1}\left(h_{j+1}^k - \Delta h_j^k\right) \quad . \tag{3.12}$$

The top of the bell for L_j corresponds to the mark h_j^k placed by the informant, and the width of the flanks is determined by the distance of the mark h_j^k to the previous mark h_{j-1}^k and the next mark h_{j+1}^k, as well as by the parameter $\alpha \in [0,1]$. Solving this equation results in the value for δ_j^k and σ_{j+1}^k

$$\delta_j^k = \sigma_{j+1}^k = \left(\frac{1}{\sqrt{-2\ln(\alpha)}}\right)\Delta_j^k \quad . \tag{3.13}$$

For the leftmost and the rightmost terms L_1 and L_5, the functions $\overline{\text{S}}_E(h_1^k, \delta_1^k; .)$ and $\text{S}_E(h_5^k, \sigma_5^k; .)$ are used respectively.

It can be observed that this method leads down to the probabilistic histogram method for the limit value 0 of parameter α, where $\lim_{\alpha\to 0} \frac{1}{\sqrt{-2\ln(\alpha)}} = 0$, which means that the width of all flanks is 0. Stated otherwise, no flanks are added at all. Hence only the given crisp points are summed, which is exactly the same as the histogram approach.

The results of this technique for the five annoyance terms and the parameter value $\alpha = 0.1$ are depicted in figure 3.6.

3.4 Comparison

In the previous sections 3.2 and 3.3 two families of construction methods for fuzzy sets representing the meaning of linguistic terms have been studied in detail. They have been applied to the five English linguistic terms

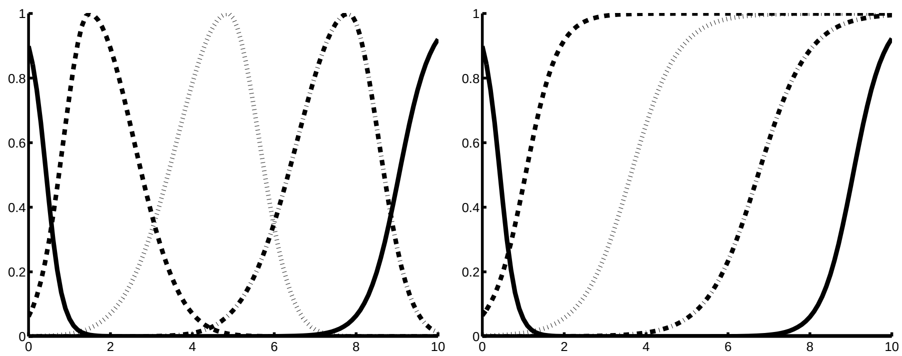

Figure 3.6: Representation of the meaning of five annoyance terms when the fuzzification method is applied with $\alpha = 0.1$ (left: non-inclusive, right: inclusive)

that have been selected by an international study as preferred for the description of levels of (noise) annoyance. This has resulted in a number of continuous shapes as well as discrete curves. In general the following can be concluded. Neither the probabilistic methods nor the fuzzification method with fixed width do care about the relationship with other terms. They focus on the meaning of one term independently. Hence, they reflect the exact meaning of an isolated term as close as possible. They are the ideal choice from a linguistic point of view. Nothing in particular can be said about the expected degree of overlap between different fuzzy sets. However the latter method tends to generate wide, non-specific fuzzy sets, which make them a bit less usable. Also, the degree of overlap between fuzzy sets is larger. The fuzzification method with fixed degree of overlap, allows to control the degree of overlap between adjacent curves. Hence, it requires a selection of terms before the method can be applied in the first place. A large number of terms will result in smaller, more specific fuzzy sets while a small number of terms will result in wider fuzzy sets. It is guaranteed that the universe will be more or less completely covered depending on the parameter. This makes this procedure less trustworthy to represent the exact meaning of a term in isolation, but generates fuzzy sets that are ideally suited for applications that require a reasonable coverage of the whole universe while still reflecting the meaning and especially the relationships between the number of chosen terms. As an example of such applications, fuzzy control and fuzzy rule bases in general can be mentioned, which represent a large portion of the applications of fuzzy theory in use today. A rule of thumb is to allow at least an overlap of membership degree 0.25 between adjacent membership functions [28], although this also depends on the models and choice of operators. This overlap is necessary to ensure adequate actions. For example, what should happen when there is not a single term that corresponds to a received input signal with membership degree larger than 0 (e.g. consider $h = 4$ in figure 3.1). What rules should be fired? If the whole universe is covered, such a situation cannot occur.

In the introduction of this chapter, some of the difficulties to use all data collected in noise annoyance surveys, conducted in several languages, have been described. The presented methods are able to generate a mathematical representation of linguistic terms in several languages, especially for the nine languages that participated in the International Annoyance Scaling Study. This means that the data obtained from annoyance surveys can be uniformly represented as fuzzy sets which eases comparison.

For fuzzy analyzes of the same data set performed by other researchers, see [150] and [94].

4 Translating annoyance terms

4.1 Overview

It has been shown that the meaning of any linguistic term in any language can be adequately and uniformly represented as a fuzzy set. This means that all mathematical tools become available to operate on them. In this context, an interesting class of operators are the *similarity measures*. More specifically, similarity measures can be used to measure the degree of compatibility between two fuzzy sets, and as a consequence, the degree of compatibility between the two associated linguistic terms. If two terms from different languages are compared and they turn out to be similar to a high degree, then they should more or less capture the same meaning. In fact, they should be potential translations of each other.

An important down to earth remark is in order here. It is recognized that language is a very complex, multidimensional construct. Therefore, one can never claim to make a good translation by solely taking the meaning of words into account as in the case of this application. For instance, cultural and social differences will impose different frequencies of word usage, an important aspect that is completely disregarded here. Still, for simplicity, the words “translation”, “synonyms”,... will be used further.

Using the fuzzy set representations of all linguistic terms in all languages that participated in the International Annoyance Scaling Study and using the above observation, a mathematical translation tool can be envisaged. First, the similarity degree between a given term in one language and all other terms in the database of a target language are calculated. Then, the terms with a high similarity can be proposed as potential translations of the first term. In this section, such a tool will be developed and tested.

Of course, the choice of the construction method for the fuzzy set representations plays a key role in this application. As the fuzzy sets should express the linguistic meaning of the terms as closely as possible, the probabilistic methods look most appealing. Also, as there are a large number of terms in our database, a numerically "easy" method is favored in order to make automatic fuzzy set construction possible. Therefore, the uncertainty conservation transformation has been used after discretization into 11 intervals. As a further simplification, the parameter α has been fixed to 0.5 for all terms. This simplifies automation a lot and can be empirically justified by observing that most α-values for the English and Dutch terms are close to 0.5 (see table 3.2).

Next, the properties of similarity measures are under investigation in order to find an appropriate measure for our purposes. Afterwards this similarity measure will be applied to the annoyance terms to mathematically find the best translations. Of course, the obtained translations will be verified from a human perspective. If the proposed translations make sense, it will prove the adequacy of the fuzzy sets that represent the meaning of the linguistic terms and their construction method. Although the tool can be applied to all languages in the database, here we will limit ourselves to translations between English and Dutch. For a more detailed exposition of the mathematical translation tool and the results for the other languages, the reader is referred to [20].

4.2 Similarity between fuzzy sets

In chapter 2, section 4, a *similarity measure* on a universe U has been defined as a $[0,1]$-valued indicator suitable for the comparison of fuzzy sets on U, i.e. a binary fuzzy relation on $\mathcal{F}(U)$. Depending on the requirements imposed on the measures, different indicators with varying behavior can be selected. Intuitively speaking, a good similarity measure should

- Consider coincidence of the maximum of the membership functions.
- Consider the similarity in general shape of the membership functions.

Following Tsiporkova and Zimmermann [151], we make a basic distinction between measures inspired by set equality, and degrees of compatibility or overlap.

Definition 54 ($\mathcal{T}$-equality). *A binary fuzzy relation E on $\mathcal{F}(U)$ is called a $\mathcal{T}$-equality if*

(i) $E(A,B) = 1 \Leftrightarrow A = B$

(ii) $E(A,B) = E(B,A)$

(iii) $\mathcal{T}(E(A,B), E(B,C)) \leq E(A,C)$

where $\mathcal{T}$ is any t-norm.

In [44] an interesting class of $\mathcal{T}$-equalities is studied in detail. They are defined by translating the logic relation that states that A and B are equal when A is a subset of B and at the same time B is a subset of A, into the equation

$$E_{\mathcal{T}}(A,B) = \mathcal{T}\left(\inf_{u\in U} \mathcal{I}_{\mathcal{T}}^{R}(A(u),B(u)), \inf_{u\in U} \mathcal{I}_{\mathcal{T}}^{R}(B(u),A(u))\right) \tag{3.14}$$

for any A, B in $\mathcal{F}(U)$. $\mathcal{T}$ can be any t-norm and $\mathcal{I}_{\mathcal{T}}^{R}$ is the associated residual implicator. The choice of t-norm in this expression is guided by performance of the equality measure in the particular application context.

Definition 55 (Degree of compatibility). *A reflexive, symmetric binary fuzzy relation C on $\mathcal{F}(U)$ is called a degree of compatibility if it satisfies the condition* $C(A,B) = 0 \Leftrightarrow \sup_{u\in U} \min(A(u), B(u)) = 0$ *for any A, B in $\mathcal{F}(U)$.*

As degree of compatibility two measures S_1 and S_2 are considered. They are defined as

$$S_1(A,B) = \frac{\sup_{u\in U} \mathcal{T}(A(u),B(u))}{\sup_{u\in U} S(A(u),B(u))} \tag{3.15}$$

$$S_2(A,B) = \frac{\sum_{u\in U} \mathcal{T}(A(u),B(u))}{\sum_{u\in U} S(A(u),B(u))} \tag{3.16}$$

where $\mathcal{T}$ is a t-norm and S a t-conorm. S_1 compares peak regions of both fuzzy sets by assessing the height of their intersection. S_2 focuses on an overall overlap of the membership functions. Common choices for the t-norm and t-conorm in these compatibility measures are the min/max operators as introduced by Zadeh.

It is clear from the above examples that no single best similarity measure can be found. Based on the findings of [151], where ways of combining the best of different worlds into a robust similarity indicator are outlined, we opted for the following generic hybrid measure (it is noted that several variations exist on this theme):

$$\mathrm{Sim}_{\mathcal{T}}(A,B) = \mathcal{T}(C_1(A,B), S(E_{\mathcal{T}}(A,B), C_2(A,B))) \tag{3.17}$$

where C_1 and C_2 are degrees of compatibility, $E_{\mathcal{T}}$ is a $\mathcal{T}$-equality, $\mathcal{T}$ is a t-norm and S is its dual t-conorm. For our translation tool we will choose $C_1 = S_1$, $C_2 = S_2$, and $E_{\mathcal{T}} = E_{\mathcal{T}_W}$ and use the Zadeh operators (min/max) for $\mathcal{T}$ and S [39]. As these choices obviously have an impact on the results, a detailed comparison of various combinations of operators is obligatory. This will be deferred until section 4.5.

4.3 Translations based on similarity

Using the theory described above, a mathematical translation table can be constructed for all combinations of the English and Dutch terms in the database by simply calculating the similarity between all the membership functions involved. The result is shown in table 3.3.

A remaining issue is the problem of translating a linguistic term using this table, e.g. to publish or communicate the results of a noise annoyance survey to another language. The result of a translation of a particular English word to Dutch can itself be regarded as a fuzzy set on the universe of all relevant terms contained in the database (21 in this case), the calculated similarity being the membership degree. For all practical purposes one term or at least a small set of terms has to be selected. Several techniques can be used for this selection.

- All terms with similarity above a predefined threshold s_0 are good translations.
- The term with the highest similarity is the translation.
- All terms within a range δ from the highest similarity $s_{\max}$ are good translations.

The first approach looks quite appealing at first sight but it does not always result in a translation using a limited vocabulary, as is the case for the noise annoyance modifiers. Lowering s_0 does not solve this problem since this would result in too many translations for other words. The second approach must be rejected on the basis that it is too sensitive for measurement error in the determination of the membership functions. The third approach is used to translate the 21 English modifiers into Dutch ($\delta = 0.05$), results are shown in table 3.4.

The attention of the reader is drawn to some particular features in this table. It is for example easy to see that terms like “barely annoyed” (L03) and “hardly annoyed” (L04) are so close in meaning that they translate into the same terms in Dutch (and also in many of the other languages). For “moderately annoyed” (L10) the similarities with all Dutch terms are low,

Table 3.3: Similarity degrees between English (in rows) and Dutch (in columns) terms.

L	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21
01	.93	.82	.26	.16	.15	.13	.09	.05	.01	.02	.02	.01	.01	.01	.01	.02	.01	.01	.02	.02	.00
02	.36	.46	.75	.56	.57	.58	.51	.38	.27	.20	.13	.10	.08	.05	.02	.02	.02	.00	.03	.02	.00
03	.30	.39	.85	.66	.62	.57	.55	.32	.22	.17	.11	.08	.06	.03	.02	.02	.01	.02	.03	.02	.02
04	.23	.32	.80	.61	.63	.58	.56	.36	.26	.21	.16	.13	.12	.09	.07	.08	.07	.06	.07	.07	.03
05	.15	.23	.80	.85	.85	.82	.77	.48	.36	.27	.13	.11	.07	.04	.01	.02	.01	.00	.03	.02	.00
06	.12	.19	.67	.78	.85	.91	.85	.59	.43	.32	.15	.13	.10	.06	.04	.04	.03	.02	.02	.04	.00
07	.02	.07	.31	.36	.45	.51	.49	.79	.77	.69	.30	.24	.18	.13	.10	.08	.08	.06	.04	.08	.00
08	.02	.07	.24	.28	.36	.39	.39	.64	.73	.83	.44	.35	.29	.21	.18	.14	.15	.12	.10	.14	.04
09	.00	.04	.20	.22	.31	.32	.31	.56	.77	.85	.48	.37	.31	.23	.20	.15	.16	.13	.10	.15	.02
10	.03	.08	.19	.17	.29	.31	.29	.46	.57	.53	.40	.32	.23	.16	.12	.10	.09	.07	.05	.10	.00
11	.00	.04	.17	.16	.24	.25	.24	.45	.59	.67	.61	.53	.42	.34	.28	.25	.26	.20	.17	.22	.06
12	.00	.03	.12	.10	.18	.17	.16	.30	.34	.46	.84	.77	.69	.60	.48	.41	.46	.35	.28	.32	.10
13	.00	.01	.08	.07	.14	.14	.13	.27	.30	.42	.83	.83	.76	.64	.56	.44	.48	.35	.27	.31	.06
14	.00	.05	.12	.10	.17	.16	.15	.26	.26	.38	.81	.81	.79	.62	.53	.41	.46	.33	.27	.31	.07
15	.00	.02	.08	.06	.13	.13	.12	.23	.23	.35	.75	.80	.80	.72	.57	.49	.55	.41	.33	.37	.10
16	.00	.02	.06	.04	.09	.08	.09	.14	.14	.25	.57	.63	.67	.82	.76	.71	.73	.56	.45	.49	.13
17	.00	.02	.04	.02	.06	.04	.07	.09	.09	.17	.48	.54	.54	.74	.76	.75	.80	.67	.56	.55	.15
18	.00	.00	.00	.00	.02	.02	.02	.07	.06	.14	.43	.52	.52	.72	.80	.84	.87	.73	.55	.63	.18
19	.00	.02	.04	.04	.06	.04	.06	.05	.05	.11	.27	.31	.26	.34	.36	.46	.48	.63	.66	.76	.46
20	.00	.00	.02	.00	.04	.02	.04	.03	.03	.09	.24	.26	.25	.36	.32	.41	.43	.58	.67	.71	.55
21	.00	.02	.02	.02	.02	.01	.02	.01	.01	.07	.17	.16	.17	.26	.23	.30	.34	.47	.52	.61	.70

meaning that a good Dutch fit cannot be found. For all other English terms exists at least one term with rather high similarity.

A technique often used to check the quality of translation is to translate back into the original language and compare the results. It is indeed known that linguistic translation is not a symmetric process. The procedure based on fuzzy sets proposed here is also not symmetric although it takes into account less subtleties than human translation does. Table 3.4 shows fuzzy translation from English into Dutch and back. The final result being the accumulation of all English terms that can be found as translations of the Dutch terms in the second column. Typically this process results in an increase of alternatives, although this is not necessarily the case (e.g. “strongly”). The number of alternatives finally obtained depends strongly on the size of the vocabulary that is used. Therefore it is not a good indicator of the quality of the translation process. It is however important that the original term is amongst the final list. This is not the case for “insignificantly”, “moderately”, and “rather”. The exact meaning of these modifiers (in a fuzzy sense) gets lost when translated into Dutch because no translation is accurately enough for them in this language. However, based on this table it can be verified that the proposed translations make sense from a human perspective. Hence, it can be concluded that the translation tool performs reasonably good, which illustrates the soundness of the fuzzy set representation and their construction method.

Table 3.4: Translation from English to Dutch and back (in order of high similarity) with $\delta = 0.05$.

L	English	Dutch	English
L01	not at all	helemaal niet	**not at all**
L02	insignificantly	nauwelijks	barely hardly
L03	barely	nauwelijks	**barely** hardly
L04	hardly	nauwelijks	barely **hardly**
L05	a little	weinig iets	**a little** slightly

Table 3.4 (continued)

L	English	Dutch	English
		lichtelijk	
L06	slightly	lichtelijk	**slightly**
L07	partially	enigzins matig	**partially** somewhat fairly
L08	somewhat	tamelijk	**somewhat** fairly
L09	fairly	tamelijk	somewhat **fairly**
L10	moderately	matig tamelijk	partially somewhat fairly
L11	rather	tamelijk	somewhat fairly
L12	considerably	behoorlijk	**considerably** substantially importantly
L13	substantially	behoorlijk aanzienlijk	considerably **substantially** importantly significantly
L14	importantly	behoorlijk aanzienlijk veel	considerably substantially **importantly** significantly
L15	significantly	aanzienlijk veel	substantially importantly **significantly**
L16	very	erg	**very**
L17	highly	sterk zeer	very **highly**

Table 3.4 (continued)

L	English	Dutch	English
		ernstig	strongly
L18	strongly	zeer ernstig	strongly
L19	severely	uitermate	**severely** tremendously
L20	tremendously	ontzettend uitermate	severely **tremendously**
L21	extremely	extreem	**extremely**

Equipped with the translation table, it is tempting to verify the translations of the five English and Dutch terms that were selected in the International Annoyance Scaling Study. These terms and their similarity degree are recapitulated in table 3.5. The terms seem to be quite similar and hence well chosen, except perhaps for "moderately" for which no better Dutch translation exists in the database.

Table 3.5: Similarity between the selected terms in the scaling study.

English	Dutch	Similarity
Not at all	Helemaal niet	0.93
Slightly	Een beetje	0.85
Moderately	Tamelijk	0.53
Very	Erg	0.82
Extremely	Extreem	0.70

4.4 Translation of an ideal fuzzy language

In fuzzy set applications, it is common to prefer a set of membership functions that cover the universe completely and subdivide it in equal portions forming a fuzzy partition. Such a typical set of five triangular membership functions is shown in figure 3.7. It can be argued that a language containing words that can be represented by these membership functions would be ideal to label a five-point scale, if results of a survey are to be used in (fuzzy) modeling. The modifiers are not only equidistant on the annoyance scale, but also have the same degree of vagueness. Most analyzes and modeling efforts have assumed that the verbal adjectives are equally spaced, thus guaranteeing this property as much as possible is essential anyhow. Instead of triangles, one could also opt for trapeziums. However, this raises the question as how wide the top should be chosen. Therefore, we will stick to triangles here. The five labels constructed in the ideal language can now be translated into the natural languages in the database using the fuzzy similarity approach. In this process all 21 terms from the modifier study are considered.

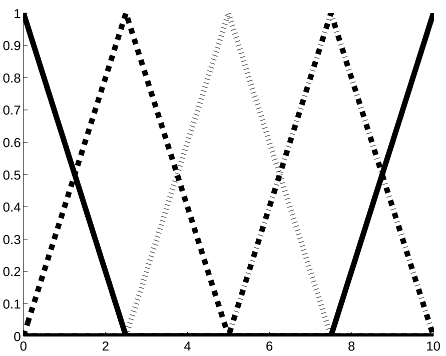

Figure 3.7: Membership functions for an ideal partition of the annoyance universe.

Table 3.6 lists the best matches for the English and Dutch languages, again taking into account a margin of $\delta = 0.05$. Terms corresponding to the five-point scale labels considered in the International Annoyance Scaling Study are shown in bold. Although the results for the other languages are not given in this work, they will be discussed very briefly. For more details, the reader is referred to [20].

In most languages, similarity is better for the first and the last label. The middle label seems hard to translate into Japanese and Dutch within the available vocabulary. The second label translates somewhat less easy into Turkish, Japanese, and English. For most languages three to four of the terms proposed by the ICBEN team [65] are recovered. It is striking that the first label does not seem to correspond to the proposed label for any of the languages except Hungarian. Precisely this label was predetermined in tasks 3 and 4 of the International Annoyance Scaling Study, see section 2!

Table 3.6: Translations between an ideal fuzzy language with $\delta = 0.05$.

Ideal language	English	Dutch
Label 1	insignificantly	niet
Label 2	**slightly** partially	iets lichtelijk **een beetje** enigzins matig
Label 3	**moderately**	matig **tamelijk** behoorlijk
Label 4	**very** strongly	**erg** sterk
Label 5	**extremely**	**extreem**

4.5 Sensitivity analysis

We have seen that the translation tool involves many choices of operators. The choices that have been made have proven to be very appropriate. However, a more thoroughly study of the impact of the operators urges itself. Here, two questions will be investigated. First, we will look at the behavior of the combined similarity measure Sim in function of its constituents. Secondly, various combinations of operators will be examined with respect to the produced translations. To keep the discussion focused, we will stick to S_1 and S_2 for the compatibility measures C_1 and C_2 respectively. From now on, an index indicating the applied t-norm (and its dual t-conorm) is added, with the convention that $S_1 = S_{1,\mathcal{T}_M}$ and $S_2 = S_{2,\mathcal{T}_M}$. The combination of chosen operators in the similarity measures will be denoted as "$ABCD$" with $A, B, C, D \in \{M, P, W\}$, for $\mathrm{Sim}_{\mathcal{T}_A}$, $S_{1,\mathcal{T}_B}$, $S_{2,\mathcal{T}_C}$ and $E_{\mathcal{T}_D}$.

As the *similarity measure* $\mathrm{Sim}_{\mathcal{T}}$ is based on three other measures, it is interesting to see which measure dominates the result. Table 3.7 lists the three individual measures and their combined $\mathrm{Sim}_{\mathcal{T}_M}$ outcome for the Dutch term "tamelijk" and five English annoyance modifiers. From this table, two points can be observed. For $S_{1,\mathcal{T}}$ the t-norm that is used does not matter as all values are equal. Therefore, the $\mathrm{Sim}_{\mathcal{T}_M}$ combinations in the table only include $S_{1,\mathcal{T}_M}$. Furthermore, in most cases the result of $\mathrm{Sim}_{\mathcal{T}_M}$ is dominated by $S_{2,\mathcal{T}}$ comparing the overall shape of the fuzzy sets. Where

$S_{2,\mathcal{T}}$ is not dominant, the value in the table is shown in bold. Intuitively speaking, in general the dominance of $S_{2,\mathcal{T}}$ is a good thing for our application. The overlap is one of the most important factors when comparing the meaning of linguistic terms. Note that in other applications with fundamentally different membership functions, the combined similarity measure may behave differently as it has been constructed to apply for a wide range of applications.

Table 3.7: Dominance of operator in the combined similarity measure Sim_{T_M} tested with “tamelijk”.

	partially	somewhat	fairly	moderately	rather
S_{1,T_M}	1	1	0.86	0.82	0.82
S_{1,T_P}	1	1	0.86	0.82	0.82
S_{1,T_W}	1	1	0.86	0.82	0.82
S_{2,T_M}	0.69	0.83	0.85	0.53	0.67
S_{2,T_P}	0.53	0.54	0.56	0.40	0.52
S_{2,T_W}	0.41	0.43	0.43	0.27	0.43
E_{T_M}	0	0	0.18	0	0
E_{T_P}	0	0	0.86	0	0.74
E_{T_W}	0.34	0.69	0.68	0.33	0.38
MMMM	0.69	0.83	0.85	0.53	0.67
MMMP	0.69	0.83	**0.86**	0.53	**0.74**
MMMW	0.69	0.83	0.85	0.53	0.67
MMPM	0.53	0.54	0.56	0.40	0.52
MMPP	0.53	0.54	**0.86**	0.40	**0.74**
MMPW	0.53	**0.69**	**0.68**	0.40	0.52
MMWM	0.41	0.43	0.43	0.27	0.43
MMWP	0.41	0.43	**0.86**	0.27	**0.74**
MMWW	0.41	**0.69**	**0.68**	**0.33**	0.43

A second issue is the impact of the combination of t-norm operators in $\text{Sim}_{\mathcal{T}}$ on the produced translations. To elaborate on this point, the English term “very annoyed” was translated into Dutch and back into English for different combinations of operators using a subset of the vocabulary, for English { considerably, substantially, importantly, significantly, very, highly, strongly } and for Dutch { veel, erg, sterk, zeer, ernstig }. The results are shown in table 3.8. As already mentioned, it is important that the original term "very" is in the list of English back-translations. Additionally, a system is preferred that does not result in too many alternatives. A system that gives all terms in the data base as a potential translation is obviously not desired. But the parameter δ also has an influence on this number of proposed alternatives. Therefore, δ has been minimized to include at least "very" in the final list. It turns out that a number of combinations perform equally well. Yet, a number of combinations must be rejected because they result in three or more alternatives, or the parameter δ must be set rather high to include the original term "very", e.g. "MMWM", "WMMP", "WMPW",... It is important to observe that the combination 'MMMW" that has been applied in our translation tool proves to be a good choice.

5 Uncertainty on linguistic terms

Proponents of *type-2 fuzzy set* theory argue that it is not possible to assign a precise membership degree to every point in the universe. Instead, this membership assignment is uncertain itself and hence should be modeled by a *secondary membership function*. This leads to the notion of a type-2 fuzzy set. A type-2 fuzzy set allows to express the uncertainty over the vagueness of a linguistic term that we have modeled in previous sections. An important characteristic of a type-2 fuzzy set is that it reduces to a (type-1) fuzzy set if its secondary membership functions reduce to a crisp number (fuzzy sets with membership degree 1 in one point of its universe). This is very natural as there is no longer uncertainty over the *primary membership value* in this case. It merely states the sample principle that a (type-1) fuzzy set reduces to a crisp number when there is no longer vagueness.

In his book [117] Mendel gives a complete overview of type-2 fuzzy set theory and some applications. He also considers the problem of constructing a (type-2) representation of a set of linguistic terms. Therefore, he has conducted a small scale survey in which 87 engineering students participated. In total 16 terms have been under investigation: "none", "some", "a good amount", "an extreme amount", "a substantial amount", "a maximum amount", "a fair amount", "a moderate amount", "a large amount", "a small amount", "very little", "a lot", "a sizeable amount", "a bit", "a considerable amount" and "a little bit". The question that has been asked to the students was:

> "Below are a number of labels that describe an interval or a "range" that falls somewhere between 0 to 10. For each label, please tell us where this range would start and where it would

> stop. (In other words, please tell us how much of the distance from 0 to 10 this range would cover.) For example, the range "quite a bit" might start at 6 and end at 8. It is important to note that not all the ranges are the same size."

Each participant received a form on which the terms were listed in random order, followed by two columns that had to be filled in. The first column was meant for the start of the range and the second column was meant for the end of the range. Both columns had to be filled in with numbers in the interval $[0, 10]$. In total, 70 valid surveys were completed.

Although this experiment shows many similarities with the survey from the International Annoyance Scaling Study, there are also important differences.

- Mendel explicitly asks for a range instead of a single number.
- Participants have to write an exact number instead of placing a mark on a visual line. Even though a bit more precise, this may be assumed to be a more difficult exercise.
- The context of the terms differs, "an amount" instead of a "degree of annoyance".
- Finally, the set of terms is not equal, not in number (16 versus 21) and not in selection.

Nevertheless, it is interesting to compare the results for the modifiers that have appeared in both surveys, see table 3.9. In this table, the average start point and end point of the range of Mendel, has been averaged into a single number μ for easy comparison with the results from the international study. The same averaging process has also been done for the standard deviations. It is striking that the order of the terms is the same, except for "fair" and "moderate" which are very close anyway. Also note that the standard deviations are pretty much the same. This seems to indicate that the terms have an inherent equal amount of doubt across people, even in different contexts. Furthermore, the value for "extreme" is lower, probably because Mendel included an even stronger term "a maximum amount". Contrary to the International Annoyance Scaling Study where "extremely annoyed" was the highest amount of annoyance. Based on his survey, Mendel also selected five terms to cover the whole universe, just as has been done in the international survey. His selection was "none to very little", "some", "a moderate amount", "a large amount" and "a maximum amount". As his first label, Mendel combined the terms "none" and "very little" because there was a gap between them. He also observed that:

> "People seem to agree that "none" starts at zero–and there is very little uncertainty about this. To people, the word "none" seems to have a very strong connotation with the number "zero"."

More or less the same has been observed for "not at all annoyed" internationally.

The theory of type-2 fuzzy sets is quite general, in the sense that it allows any shape for the secondary membership functions. However, calculations can soon become very complex and unfeasible for all practical purposes. Therefore, so called *interval type-2 fuzzy sets* are often used. These are type-2 fuzzy sets in which the secondary membership functions are all intervals over the domain of primary membership values. This choice simplifies all involved calculations a lot. A common graphical representation of interval type-2 fuzzy sets with triangular primary membership functions is depicted in figure 3.8(a). The shaded area shows the *footprint of uncertainty* (FOU), it is the union of all primary values where the secondary membership value is greater than 0. The uniformly shading indicates that it concerns an interval type-2 fuzzy set where all secondary membership values are equal to 1. The upper bound of the FOU is called the *upper membership function*, the lower bound of the FOU is analogically called the *lower membership function*.

Using the results of his survey, Mendel outlines a method to construct interval type-2 fuzzy sets with triangular primary membership functions. Here, we will apply the same method for our database and our five English annoyance terms. However, whereas Mendel uses his range start and end points $[a, b]$, we will use μ for both points and its associated standard deviation σ (see table 3.9) instead of σ_a and σ_b. The type-2 fuzzy sets will be denoted as $\tilde{L_j}$ for $j \in \{1, 2, \ldots, 5\}$, with upper membership function $\overline{\mathrm{FOU}\left(\tilde{L_j}\right)}$ and lower membership function $\underline{\mathrm{FOU}\left(\tilde{L_j}\right)}$. The construction process can then be described as followed, with parameter $\rho \in [0, 1]$.

- For the terms $j \in \{2, 3, 4\}$,

$$\overline{\mathrm{FOU}\left(\tilde{L_j}\right)} = \mathrm{TRI}\left(\mu - (1+\rho)\sigma, \mu, \mu + (1+\rho)\sigma\right) \tag{3.18}$$

$$\underline{\mathrm{FOU}\left(\tilde{L_j}\right)} = \mathrm{TRI}\left(\mu - (1-\rho)\sigma, \mu, \mu + (1-\rho)\sigma\right) \tag{3.19}$$

- For the left most term $\tilde{L_1}$,

$$\overline{\mathrm{FOU}\left(\tilde{L_1}\right)} = \overline{\mathrm{LIN}}\left(\mu + \rho\sigma, \mu + (1+\rho)\sigma\right) \tag{3.20}$$

$$\underline{\mathrm{FOU}\left(\tilde{L_1}\right)} = \overline{\mathrm{LIN}}\left(\mu - \rho\sigma, \mu + (1-\rho)\sigma\right) \tag{3.21}$$

- For the right most term $\tilde{L_5}$,

$$\overline{\mathrm{FOU}\left(\tilde{L_5}\right)} = \mathrm{LIN}\,(\mu - (1+\rho)\sigma, \mu - \rho\sigma) \tag{3.22}$$

$$\underline{\mathrm{FOU}\left(\tilde{L_5}\right)} = \mathrm{LIN}\,(\mu - (1-\rho)\sigma, \mu + \rho\sigma) \tag{3.23}$$

The parameter ρ expresses the fraction of uncertainty. Resulting interval type-2 fuzzy sets for $\rho = 0.5$ are shown in figure 3.8. When this fraction of uncertainty reduces to zero, type-1 fuzzy sets are obtained, also shown in the same figure. Observe that this method suffers from the same disadvantage as the probabilistic methods, there is no intrinsic way to control the degree of overlap between fuzzy sets.

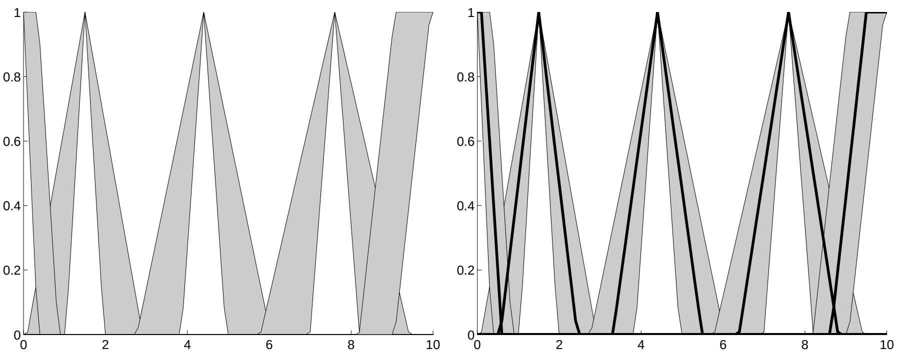

Figure 3.8: (a) Type-2 fuzzy sets for the representation of the five English annoyance terms ($\rho = 0.5$), (b) same construction for $\rho = 0$ reduces to type-1 fuzzy sets (black lines).

Finally, a closer look is taken at the membership construction process as outlined by Mendel and the one adapted for our purposes. In figure 3.9, the results of both procedures for two linguistic terms are compared. Clearly, the Mendel curves can be asymmetrical because they have different standard deviations for the left and right point of the range. They determine both the position and the width of the side of the triangles. This seems advantageous as in general the standard deviation is smaller on the side that is closest to an end point of the interval $[0, 10]$. Unfortunately, this kind of data was not available in the annoyance study. Yet, it is surprising that Mendel chooses triangular primary membership functions to model this kind of data, whereas a trapezoidal shape would be expected to reflect his separate range end points a and b.

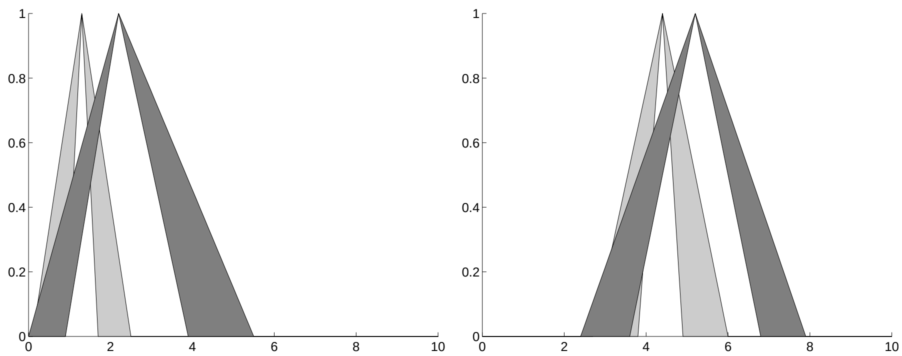

Figure 3.9: Comparison between the curves for two linguistic terms from Mendel (dark) and the annoyance study (light) for $\rho = 0.5$ (left: “a little bit”/“a little”, right: “moderate”/“moderately”)

Although type-2 fuzzy set theory provides a fresh and interesting look at the different kinds of uncertainties involved in linguistic modeling, this topic will not be pursued any further in this work for the following reasons.

- Far better methods exist for constructing fuzzy set representations of linguistic terms than the inquiry-driven approaches, in which experts directly assign a membership degree to each point in the universe (which is obviously rather uncertain). Other methods already take into account an average amount of uncertainty on the provided membership degrees. Just as in the case of type-2 fuzzy sets this is done based on the standard deviation.

- Computations with general type-2 fuzzy sets is numerically very intensive. Hence, practical applications rely almost completely on interval type-2 fuzzy sets. This makes calculations much more feasible, but seriously reduces the expressive power of the uncertainties involved in the type-2 fuzzy sets. Even then, the required calculations are an order of magnitude higher.

The representation of noise annoyance as a linguistic variable will help to overcome the comparison problems that have been described in the beginning of this section. This will allow to construct language neutral models that make use of all available data. Not only data to be collected in future surveys with the recently proposed and internationally accepted annoyance scale, based on the annoyance scaling study, but also the data collected in all past surveys. How such language neutral noise annoyance models can be developed will be explained in subsequent chapters.

Table 3.8: Sensitivity analysis of $\mathrm{Sim}_{\mathcal{T}}$ for various combinations of operators with back-translation from "very annoyed".

t-Norms	δ	Dutch	English
MMMM	0	erg	very
MMMP	0	erg	very
MMMW	0	erg	very
MMPM	0.03	erg, sterk, ernstig	very, highly, strongly
MMPP	0	sterk	very
MMPW	0	erg	very
MMWM	0.07	erg, sterk, zeer, ernstig	very, highly, strongly
MMWP	0	sterk	very
MMWW	0	erg	very
PMMM	0	erg	very
PMMP	0.02	erg	significantly, very
PMMW	0	erg	very
PMPM	0.05	erg, sterk, ernstig	substantially, significantly, very, highly, strongly
PMPP	0	sterk	very
PMPW	0	erg	very
PMWM	0.07	erg, sterk, zeer, ernstig	very, highly, strongly
PMWP	0	sterk	very
PMWW	0	erg	very
WMMM	0	erg	very
WMMP	0.03	erg	considerably, significantly, very
WMMW	0	sterk, zeer	very, highly, strongly
WMPM	0.06	sterk, zeer, ernstig	very, highly, strongly
WMPP	0	sterk	very
WMPW	0	sterk, zeer	very, highly, strongly
WMWM	0.08	erg, sterk, zeer, ernstig	substantially, importantly, significantly, very, highly, strongly
WMWP	0	sterk	very
WMWW	0	sterk	very

Table 3.9: Comparison between the results from the Mendel survey and the international annoyance survey.

Label	Mendel		Annoyance	
	μ	σ	μ	σ
none (not at all)	0.19	0.51	0.08	0.50
a little bit (a little)	2.19	1.23	1.32	0.81
some (somewhat)	3.06	1.45	3.57	1.53
fair (fairly)	5.24	1.32	4.05	1.49
moderate (moderately)	5.16	1.16	4.37	1.09
considerable (considerably)	6.67	1.58	6.22	1.70
substantial (substantially)	7.45	1.56	6.45	1.53
extreme (extremely)	8.74	1.44	9.49	0.87

CHAPTER 4

Modeling noise annoyance

It is through science that we prove,
but through intuition that we discover.

Henri Poincaré (1854-1912)
French mathematician

1 CURRENT STATE OF THE ART

The history of modern community *noise annoyance* modeling started in 1978, when Schultz re-analyzed the English language data from several *social surveys* on the noise of airway, railway and road traffic [140]. He plotted the reported annoyance levels in function of the *sound exposure* (L_{dn}) and calculated the percentage of people that were "*highly annoyed*" (%HA) for each dose. For 11 surveys which became known as the clustering surveys, these curves showed a remarkable consistency. Hence, the average of these curves was proposed as the best estimate to predict community noise annoyance from transportation noise sources. In his meta-analysis, Schultz used a third order polynomial to fit the 161 data points in his clustering surveys. This publication of the so called *dose-response relationships*, was criticized by several authors and led to a public debate [98] [141] [99] [64]. Some of the comments that were made concerned the selection process of studies, the definition of the percentage highly annoyed (as the percentage above a crisp cutoff point of 7.2 on 10), the assignment of equal weights to data points that represent different numbers of cases,... Notwithstanding this debate, authors continued to include more surveys in the synthesis process and refined the meta-analysis methodology in order to resolve most of the criticism, resulting in updated curves. More recently, Miedema & Vos have compiled the largest database so far (from 45 surveys). In their meta-analysis, they acknowledge three different dose-response relationships, one for airway, railway and road traffic, and assume a linear relationship with normal distributed random component between the measured noise exposure and the experienced degree of annoyance [123]. Based on the same data set, these curves have been updated by Miedema & Oudshoorn in [122], see figure 4.1.

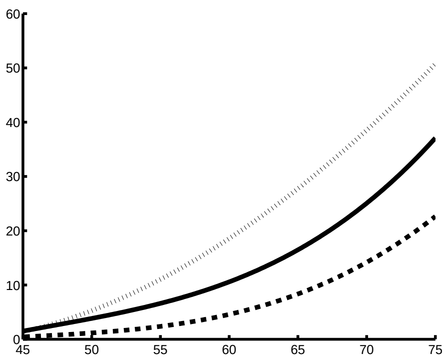

Figure 4.1: Dose-response relationships of Miedema & Oudshoorn [122] where the percentage of "highly annoyed" people is plotted against DNL for airway (dotted), road (solid) and railway (dashed) traffic.

Although widely accepted, these kinds of *dose-response relationships* assume the following important restrictions [100].

Non-acoustic factors are averaged out People with different basic psychological and physiological sensitivities to stimulation, and with different emotion-arousing associations to specific noise sources, are randomly distributed among neighborhoods.

L_{dn} **is a good exposure descriptor** The amount of annoyance will depend on the activity of an individual when a noise event occurs and on the intensity and duration of the event. Furthermore, averaged over large groups, the degree of annoyance experienced in a given L_{dn} noise area will be about the same.

No recent changes and newcomers A majority of people in a given neighborhood has been exposed for months and years to the noises, so that knowledge of the sources, the psychological effects of unexpectedness, and within limits startle are considered to be non-dominant variables.

Moreover, this meta-analysis approach is only suitable for modeling the annoyance impact on large groups or neighborhoods: the community response to noise. Because of these restrictions, simple *dose-response relationships* can not actually claim to model the real life experience of degrees of annoyance. They are merely suited as an annoyance indicator that can be used for basic administrative information and comparison across European countries [111]. For such purposes, their simplicity is an advantage.

Even in the early days, researchers recognized that not only noise exposure variables affect the way people experience annoyance. Using the same kind of meta-analysis, several contextual variables such as attitude to the noise source, sensitivity to noise, social status, dwelling type,... have been examined in order to explain the variance of the *dose-response relationships* [89] [63] [78] [96]. Later, Miedema & Vos tried to quantify the impact of demographic and attitudinal factors by calculating the extra noise annoyance in L_{dn} equivalents [124]. However, these meta-analysis based approaches can only give a clue on the significance of variables. It is very difficult to really discover the underlying relationships in a way which is easy to comprehend.

Nevertheless, this direction of research has led to the introduction of the term *soundscape* in noise annoyance modeling. The soundscape concept as originally coined by Schafer back in 1978 [137], refers to the interaction between people and sound, the way people are consciously perceiving music when listening. In the field of annoyance modeling, authors have defined the soundscape concept as the acoustical as well as other sensory, aesthetic, geographic, social, psychological and cultural stimuli in the context of human activity across space, time and society. Soundscape assessment is essential for a more complete, holistic modeling of annoyance. It is required for more complex tasks such as environmental health impact assessment and the design and planning of sustainable environments which are supportive to health [111]. Remark that there is in fact no universally accepted definition of the meaning of the term soundscape. Some authors use it in a much more narrow interpretation to denote exclusively the acoustical part of this holistic picture. They introduced analogous terms to refer to the other contextual variables, e.g. the "*enviroscape*" for non-acoustical features of the physical environment and "*psychscape*" for person related factors [92].

It is currently believed that noise exposure alone can only explain about 30 % of noise annoyance in the sense of statistical explained variance [144]. In this context, an interesting experiment was setup by Schomer [138] to investigate the relationship between noise noticeability and noise annoyance. Clusters of subjects were chosen at three different locations. An outdoor sound monitor was used to measure the noise exposure (in *A-weighted decibels*) of single "events" and record the times at which they occurred. A noise event was defined as a 20-seconds sound exceeding a certain threshold noise level. The subjects carried a palm-top computer on their body or kept it nearby. They were instructed to fill in a short questionnaire on the palm-top every time they noticed an outdoor sound with a noise character and level sufficient to motivate them to respond. They also had to indicate on the computer when they left the house or returned. Using all daytime (7h till 22h) collected data, subject responses were correlated with the largest qualifying noise event that occurred within two minutes prior to the subject's response. Only occasionally, subjects responded to noise events that were not recorded by the sound monitor. Two variables have been analyzed in function of noise exposure, the rate of response (the number of responses divided by the total number of measured noise events during the time when the subject was home) and the reported annoyance per event. The results revealed that the largest group (15 subjects) responded by varying their rate of response as a function of noise exposure and maintaining a constant annoyance judgement which was independent of the sound level. A smaller set of subjects (8) varied their annoyance per event response as a function of noise exposure but kept their rate of response constant. A similar sized group of subjects (8) had responses which were entirely independent of the noise exposure. The smallest group (5) varied both variables as functions of the sound level. These results support the hypothesis that to a large extent noise is only the trigger for annoyance. The actual degree of annoyance is mainly determined by personal traits, which act as *pre-conditioners* or modifiers on the perceived noise.

2 Noise annoyance advisor

In this work, the goal is to build a system that is capable of judging the impact of noise on an individual person. The complete picture of the system that will be constructed is shown as an *Unified Modeling Language* (UML) component diagram in figure 4.2. UML is a graphical language for visualizing, specifying, constructing, and documenting the artifacts of a (software-intensive) system [5] and was accepted as a standard by the OMG (Object Management Group) in 1997. Artifacts include models, source files,... UML is widely used in the *object oriented* (OO) software engineering community, but also system engineers are adopting this modeling language. On the diagram, three separate layers of the system can be identified (the dashed arrows indicate a "dependency relationship", where the source of the ar-

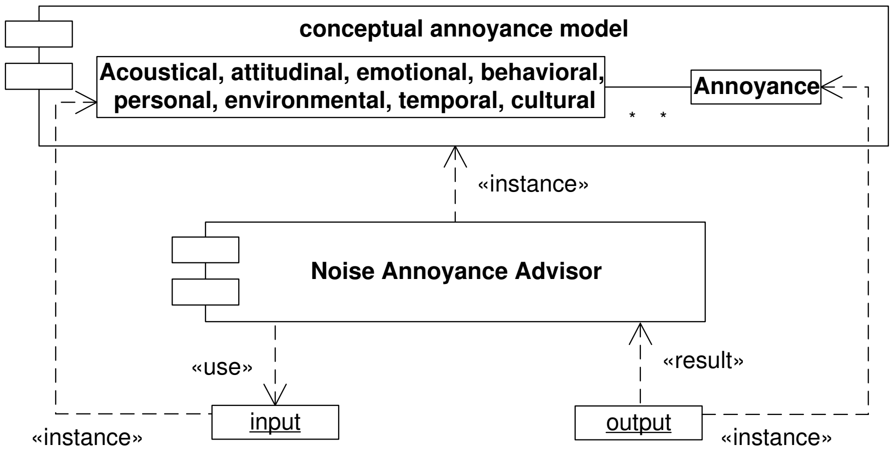

Figure 4.2: UML component model for a noise annoyance system.

row depends on the target of the arrow).

The upper layer consists of a *conceptual annoyance model*. It describes the various factors that are important in the context of *noise annoyance* (acoustical, contextual, attitudinal, personal, temporal,...), and how they relate to each other and noise annoyance of an individual in particular (see section 2.1 for more details). Utilizing the UML terminology further, the conceptual model contains the relevant classes (factors) and their associations, which define semantic relationships between the classes, in the modeling domain.

In the middle layer, the *noise annoyance advisor* is found. The annoyance advisor instantiates the conceptual model and provides the necessary machinery to use this instantiation when input data is available. When an association between two classes from the conceptual model, e.g. "noise exposure"—"annoyance", is instantiated, it results in a number of links. Each link describes a concrete relationship between two objects or instances of the classes, e.g. "high noise exposure"—"very annoyed". Because of the vague and uncertain domain, and to continue working in the fuzzy framework in which the annoyance concept has succesfully been represented in chapter 3, the noise annoyance advisor will use *fuzzy IF-THEN rules* to represent these links. This allows experts to express their knowledge in a linguistical way, which in turn makes the system easy to comprehend. A collection of fuzzy rules, which describe the interactions between variables in a linguistic way, is known as a *fuzzy rule base* (FRB). The other parts of this layer are responsible for inferring an annoyance expression by using these fuzzy rules. For this layer, the name "*noise annoyance advisor*" has been chosen because it helps policy makers and managers to predict the level of annoyance that people will experience. It can also be seen as a software agent that mimics human perception of the *soundscape* stimuli and makes the decision for reporting noise annoyance. A software agent is a piece of software that assists an individual to accomplish a task (e.g. reading news facts) according to his own personal profile, customs and preferences (e.g. specifically interested in financially related events).

In fact the description given above can be interpreted as using a fuzzy extension to the UML, where the classes and objects represent fuzzy entities with fuzzy associations. Among the different kinds of associations there should be one with IF-THEN semantics. Although the integration of a formal fuzzy and object oriented data model has been and is still actively studied from a database [14], as well as from a software perspective [106] (see [105] for a survey), a standardized fuzzy extension to UML has not yet been published. However, this topic is beyond the scope of this work.

A third and final layer depicts the operationalization of the system by a user. He feeds the noise annoyance advisor with objects that instantiate the input classes from the conceptual model and retrieves an object that expresses a degree of annoyance in some way. Missing information should pose no problems, except for a possible less precise and certain result.

Please note that we are modeling here what Zadeh calls a "*humanistic system*", a system whose behavior is strongly influenced by human judgement, perception or emotions, e.g. economic systems, political systems, legal systems and educational systems. A single human and his thought processes may also be viewed as a humanistic system. Contrary to mechanistic systems, the humanistic systems are not governed by the laws of mechanics, physics, chemistry and electromagnetism [188]. Hence, the underlying knowledge is much harder to find and to formulate.

In subsequent sections, the components of the system will be described and analyzed in more detail. We will start by taking a look at the conceptual annoyance model in order to expose the requirements of the noise annoyance advisor to be implemented.

2.1 Conceptual annoyance model

In [25] we have studied the available literature for factors that have been found or have been assumed to influence the noise annoyance construction process. These factors and their association paths to annoyance have been summarized in the *conceptual annoyance model* that is shown in figure 4.3.

Clear forward paths as well as adaptation (internal and external) are shown in full lines, while paths that are considered more hypothetical and could ultimately turn out to follow a completely different route are marked in dashed lines.

Note that this figure is not yet drawn as an UML static class diagram because it still has to be refined to allow the actual formulation of rules. A thorough discussion and refinement of this conceptual annoyance model and results obtained with a concrete noise annoyance advisor instance tested on a sample data set is deferred to chapter 6. Here, the model is only important to identify what sort of relations we will have to deal with in the *noise annoyance advisor*. Therefore, we will confine to a brief description of these fundamental concepts and the complexities of this real world model.

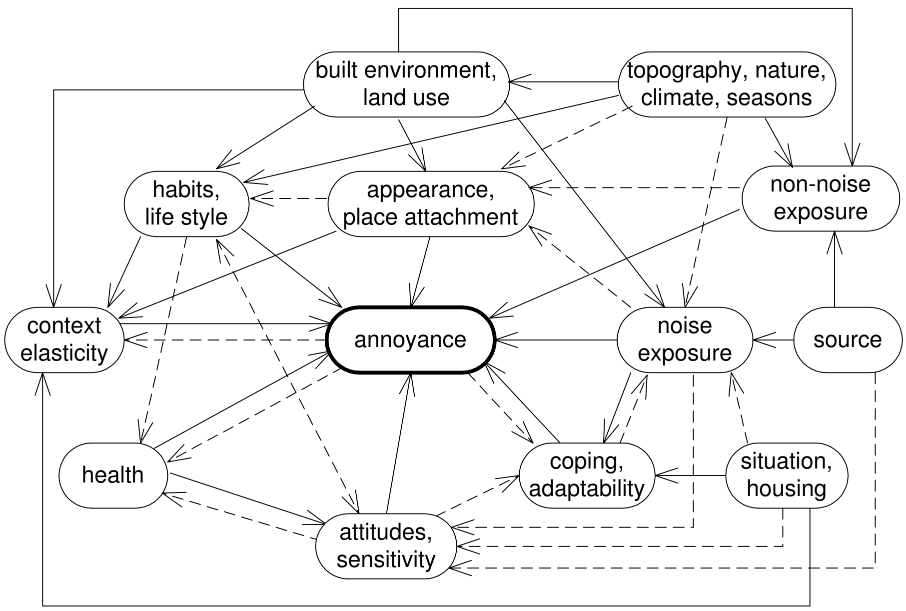

Figure 4.3: Conceptual annoyance model. Clear forward paths are in full lines, more hypothetical paths are in dashed lines.

Source The source that emits the noise, and possibly other pollution factors such as odor and fumes, triggers the whole process.

Situation and housing The size of the household, the number of children running and playing in the house, the facing of the bedroom and living room windows towards a quiet side (e.g. backyard) or directed to the noise source,... are important determinants for our housing situation in relation with noise annoyance [29] [103]. This factor is concerned with everything inside the house.

Topography, nature, climate and seasons The general setting of the environment in a broader context, e.g. a mountainous landscape, the presence of lakes,...

Built environment and land use This describes the way in which the area is built up in a much more local sense, the percentage of buildings and green area, open-space or closed-space development, on the country side or in a city center,...

The built environment is influenced by the topography as certain types of topography will not allow certain built types (e.g. closed-space development on a mountain side).

Noise exposure Groups all the physical characteristics of the noise and the background noise at home. Data from social surveys usually includes only a very limited description of the noise exposure. Commonly, only the calculated A-weighted *DNL* or *DENL* is available, although other measures such as peak levels and time distributions would also be very useful.

Obviously, the noise exposure has a direct impact on the experienced noise annoyance [144].

It has been found that the source of the noise exposure significantly influences the annoyance response [62] [123]. For transportation noises, airway traffic noise triggers the strongest response, while railway traffic has a more modest impact. Road traffic falls somewhere in between [120]. Streetcar noise appears to be equally annoying as road noise [100]. In this work, focus is mainly on road and railway noise, which have a long modeling history and a large amount of collected data, contrary to other sources such as noise from industry. Two possible approaches to deal with this source dependency should be mentioned. The first one varies the links from noise exposure to annoyance (represented by fuzzy rules) depending on the source. Another approach tries to derive the source and hence the impact on annoyance based on a detailed noise exposure description. E.g. railway traffic will have a different time distribution and peak level than road and airway traffic. However, because such detailed noise exposure characteristics are usually not available, the first approach is implemented in this work. Another important aspect that modifies the noise exposure is the distance to the source.

In an open topography and especially in an open built environment, noise exposure will propagate more easily, increasing noise exposure, than shielded by natural barriers (e.g. mountains and trees) and other barriers (buildings).

The orientation of the house, living room and bedroom windows faced towards the noise source, is also an important factor in the determination of noise exposure [63].

Finally, the noise exposure is influenced by the way people cope with the noise (e.g. closing windows).

Non-noise exposure Of course, noise is not the only pollution factor in our environment, others include odor and light pollution.

Fields [63] has found that the presence of other (non-noise) pollutants can enforce the degree of experienced noise annoyance.

Of course, non-noise exposure also originates from a source. Often, this will be the same source that is responsible for the noise exposure, e.g. traffic also emits exhaust fumes (odor).

As in the case of the noise exposure, an open topography and an open built environment will increase the propagation of other pollution factors.

Appearance and place attachment Factors that determine the visual esthetics of the environment and the type of house (detached house, semidetached house, terrace house or apartment). This factor groups everything that is related with the outside of the house.

It has been shown in laboratory that non-human sounds (bird songs as well as traffic noise) are all rated more annoying when heard in a less visual appealing setting (varied from woods, detached house to apartment blocks) [168]. This is not true for human sounds (footsteps, whispering). A possible explanation is that human sounds draw more attention to the auditory stimuli because people can imagine themselves participating to the noise. The fact that the negative effect on traffic noise is equally strong, raises the hypothesis that the expectation of traffic noise in apartment blocks is less important.

There also seems a weak link from annoyance to the visual appearance as the setting is rated less appealing when the sound heard is not expected in that visual environment [168].

The possibilities for the appearance of a house are of course related to the topography and the built environment.

Habits and lifestyle The social context, having a demanding and stressful job,...

Miedema & Vos [124] have found a small influence of the level of education on noise annoyance. People with a higher education report a higher degree of annoyance. Higher education might indicate a more stressful job. However, they have also found a less important effect of occupational status but this could be attributed to the poor quality of their occupational status data.

It is clear that the outside environment (topography, land use and house appearance) will determine our life style (living on the countryside compared to the habits in a city center).

Furthermore, our life style is also influenced by our attitudes and sensitivity. Sensitive people are more likely to be stressed.

Attitudes and sensitivity Our general attitude towards a source depends on several factors, such as our view on the importance of a source (e.g. for the economy), if we make use of it ourselves (e.g. frequent air flyer), fear (e.g. for a plane crash),... Also our general sensitivity to noise has been found to be significantly linked to noise annoyance [107] [130] [129].

Our attitudes can influence annoyance [89] [63] [124], and also there is a possibility that our attitudes and especially our sensitivity are influenced by annoyance [89].

Our attitudes towards the exposure are of course directly depending on its source, e.g. aircrafts. Also, besides general noise sensitivity there seems to exist noise-specific sensitivity [91].

A stressful life, bad health,... can make us more sensitive.

Attitudes and sensitivity may also depend on the noise exposure.

Coping and adaptability *Coping* refers to the way in which we deal with the annoyance we experience, such as the closing of windows (*active coping*), feeling helpless (*emotional coping*), filing a complaint (*political coping*),... Migration from noisy areas or avoidance of moving into noisy areas are examples of (external) adaptation.

Coping behavior is triggered by noise exposure and modifies our degree of annoyance. However, it can also legitimately be seen from the other viewpoint, coping is triggered from annoyance and modifies the noise to which we are exposed [154] [110] [108].

Different forms of coping require a certain attitude, e.g. assertivity is required to file a complaint.

Health Describes the medical state, e.g. chronic diseases.

As explained in the introduction chapter, annoyance is seen as an intermediate variable between noise and other health effects. However, there will also be an influence in the opposite direction as ill people will perceive noises differently.

Furthermore, our health can be influenced by our habits (e.g. smoking), general life style and also our sensitivity and attitudes (e.g. attitudes that provoke emotional coping can also lead to depressions).

Context elasticity Expresses to what degree people are happy with the attractiveness and safety of the neighborhood, the available leisure facilities, the quality of their environment and their general quality of life,...

In general, a good living environment and quality of life makes people more tolerant for noise.

A closer look at the relationships reveals three complicating issues.

- The multitude of factors arouses suspicion that there will be paths that counteract with each other. As an example consider an open built environment (open-spaced development). This will increase the noise exposure and non-noise exposure (such as odor pollution) and thus the level of annoyance. However, it also indicates a more rural (land use) area with a pleasant appearance, where people are in general happy with their living environment (context elasticity). Hence, they are more tolerant for noise which has a positive effect on the annoyance. So the noise annoyance advisor will likely have to deal with conflicting rules. Additionally, in investigating the relationships between variables one should be very cautious and try to address each factor separately before drawing conclusions.

- Another problem that appears in the model is the occurrences of cycles, e.g. coping. One will only close a window due to a certain degree of annoyance, however, because of that the annoyance will decrease. A possible approach consists of multiple loops through the annoyance model, using the outcome of the previous loop as input for such variables, until a stable outcome is obtained.

- Many of the identified relationships are still not firmly known and rather hypothetical. Therefore, the noise annoyance advisor should be capable of including hypothetical rules and provide a mechanism to test whether such hypotheses hold or should be rejected.

Constructing a completely determined noise annoyance model would require to model each described factor into full detail. As a human is a complex system of traits and inner states which is influenced by many inputs from the past and even cross-individual inheritance, this would even require the modeling at the level of chromosomal behavior. For such complex systems, a deterministic model seems unfeasible. Therefore, the focus here is shifted from the modeling of all aspects of a human to the modeling of a cluster of individuals with similar behavior described by a set of indicators or factors. The indicators can be quite fundamental and closely linked to the traits or states they describe, but they can also be intermediates of other influences. As an example consider general noise sensitivity. This important trait variable cannot be described as triggered by a few external factors. However, indicators (e.g. number of children in household, age, number of rooms compared to number of people living in a house) could be found that determine clusters of people for which the noise sensitivity variable is higher than average in a fuzzy way. Note that this shift does not mean that the developed annoyance advisor is not capable of handling every individual with its own values for each indicator used in the model.

To conclude the description of the conceptual annoyance model, three different groups of input variables that have been identified are summarized.

Triggers According to the results of the Schomer experiment, the primary input variables triggering the whole process come from the acoustic field. The term acoustic field is used to stress that the acoustical characterization is not limited to averaging acoustical indices such as L_{dn} or L_{den}. Nor is it limited to a single point in time or space.

***Pre-conditioners* or modifiers** Non-acoustic factors can be regarded as preconditioners or modifiers that alter the experience of annoyance.

Clustering indicators Variables that together indicate a strong similar behavior for a human trait.

In the rule based implementation that will be proposed in this work, all these variables will be treated very similarly from a mathematical point of view. In particular all of them can be crisp numbers or vague notions of perceptions that are described by words. However, other implementation methods may decide to treat them differently, e.g. by modeling the *noise pre-conditioners* as *linguistic hedges*.

2.2 Instantiating the annoyance model

As we now have a good understanding of the concepts and their associations in the domain of discourse, we can start thinking about implementing this model as a *noise annoyance advisor*. First of all, it will be necessary to instantiate the identified associations to concrete links. Then, components capable of handling this knowledge to predict the degree of noise annoyance experienced by a person, will have to be developed. Furthermore, we have already decided that a *fuzzy rule based system* would be an ideal framework for this task. In [38] the components that are commonly found in FRB systems have been described. This set up will also perfectly suit our needs, see figure 4.4.

At an abstract level, the system can be regarded as a black box that produces as output a description of the degree of annoyance, that is associated with the given input data. Internally, the domain specific intelligence is incorporated in a *knowledge base* that is formally defined as a combination of a *database* and a *(fuzzy) rule base*. Using this pool of knowledge, conclusions about the level of annoyance are drawn from the input data by the *inference* mechanism. Finally, the result is interpreted in the *linguistic approximation* part. In what follows, these components are described in more detail.

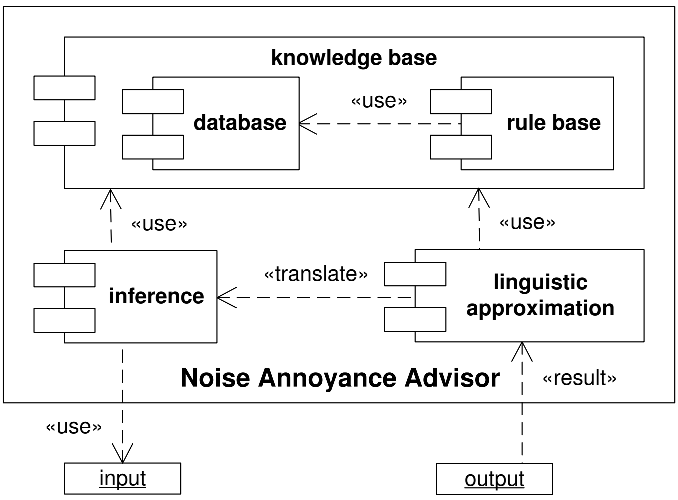

Figure 4.4: Structure of the noise annoyance advisor implemented as a fuzzy rule based system.

2.2.1 Database

An important part of the knowledge base is the *database* that contains the definitions of the words and concepts that will be used in the formulation of rules.

In fact, the whole range of techniques that have been described in chapter 3 can be used to define the meaning of linguistic terms in the model. Specifically, to represent the concept of noise annoyance, we will use the membership functions that were constructed with the fuzzification method with fixed overlap, based on the data collected in the International Annoyance Scaling Study. As argued, this method reflects the intended meaning of the terms quite well and is optimally suited for this kind of FRB applications. Additionally, the availability of this large data set allows the construction of appropriate annoyance representations for a wide diversity of linguistic terms in different languages. This is useful when we have to work with data from social surveys in multiple languages.

Because other concepts cannot rely on such an extensive amount of collected data solely for representation purposes, and their definition is often much more straightforward, other terms will generally be defined in a more ad hoc fashion, e.g. to represent linguistic labels that describe age, such as "young" and "old". In most cases, they have been put forward by experts in the field. Remark that membership functions are not tuned in order not to bias their definition towards a specific data set. However, for some of the variables, fuzzy data clustering techniques [85] have been used to obtain the membership functions. This was exclusively done when a data set external to a noise annoyance survey was available, e.g. population sizes in cities to label a city as "small" or "large".

2.2.2 Rule base

The *fuzzy rule base* contains a collection of IF-THEN rules that describe the instantiated links between the variables in natural language, using the vocabulary defined in the database. All rules that implement links derived from the same association in the conceptual model form a set of *parallel rules*, rules expressed between the same variables. Because the knowledge is expressed as linguistic rules, the model is easy to comprehend, even by non-mathematicians and non-acousticians. At the same time, experts in the field of acoustics can express their knowledge in a very straightforward and intuitive way.

All rules implemented in the *noise annoyance advisor* have been acquired based on this principle. They are derived from expert opinions that have been found in the literature. Another option to acquire rules is to apply rule deduction or knowledge extraction algorithms, e.g. fuzzy clustering, on available survey data. However, as the obtained rules are tightly fitted to the data, this approach can easily lead to rules that are only valid in the given data set. The goal of this work is more oriented towards a stable model that performs equally well on any data set and really represents the common underlying relations. Therefore, these rule generation techniques have not been adopted. Yet, as it is even for experts in the vague and uncertain world of noise annoyance modeling very difficult to formulate firmly proven rules, all rules should be interpreted as hypotheses. Later, the system will be extended with facilities to detect whether a rule hypothesis holds or not.

Concerning the FRB, there is still one important issue that must be mentioned. People do not live in isolation, instead they interact with each other and belong to some sort of local community. It has been shown that the response to noise can differ from community to community [69]. This can be explained as a sort of culture or local subculture formed by interactions between individuals that lead to common interpretation and reaction to stimuli from the soundscape. In the FRB a primitive form of such a culture could possibly emerge by allowing the exchange of rules between FRB's as illustrated in figure 4.5. However, at this stage the *noise annoyance advisor* does not yet address such possible differences in culture, so a uniform culture is assumed over all subjects in the region that is modeled.

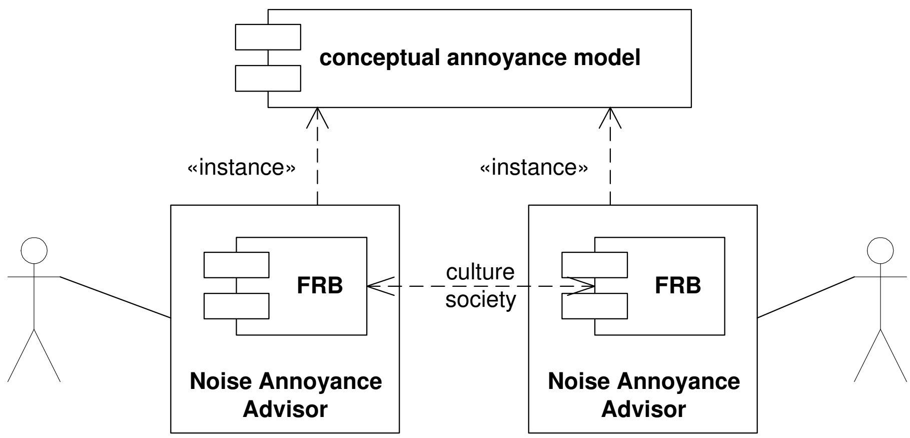

Figure 4.5: Instances of the annoyance model with interacting fuzzy rule bases.

2.2.3 Inference

In chapter 2 various *inference* mechanisms which allow to draw a conclusion based on a fuzzy rule and an input have been described. It has been shown that the most widely adopted scheme, the *compositional rule of inference*, allows three distinct rule interpretations: certainty, possibility and truth qualifying rules. The choice is determined by the *implicator* that is used to model the relation R that expresses the linguistic rule in a mathematical way, and the operator that aggregates the results of *parallel rules*.

Truth qualifying rules, "IF $X = A$ THEN $Y = B$" with the associated connotation "the more X is A, the more Y is B" do not seem to provide the right semantics. For example, consider the antecedent of a rule "distance to the noise source is far" (the higher degrees of annoyance are less possible). It may be of no effect if the distance to the source is then even further as the impact of the source may already be negligible because of the "far" distance. *Possibility qualifying rules*, "the more X is A, the more possible Y is B", already look much better suited for our purposes. With this kind of rules, the consequent represents the degree to which a point $h \in \mathbb{H}$ is considered at least possible. The information gathering process can then search for additional information (through other rules) that guarantees a higher possibility degree for h. However, as our knowledge of the field is still incomplete, it may be difficult to make sure that all rules for guaranteeing possibility are included. It is more natural to start with the initial premise that all levels of annoyance are possible. The knowledge that is already available can then restrict the possibility of some annoyance regions. This leads us to an information restriction process expressed with *certainty qualifying rules*, "the more X is A, the more certain Y is B".

In accordance with the literature, certainty qualifying rules should be modeled with an *S-implicator*, in particular the Kleene-Dienes implicator $\mathcal{I}_{KD}$ is chosen which is a prominent member of the S-implicator family. The results of inference from parallel rules are aggregated with the minimum norm as is required.

Each set of *parallel rules* thus results in a fuzzy set H_i, $i \in \{1, 2, \ldots, n\}$ where n denotes the number of sets of parallel rules. Every fuzzy set H_i provides a possibility restriction on the annoyance universe $\mathbb{H}$ based on the variable used in the rule antecedents. Of course, all restrictions should be taken into account together. This aggregation should clearly express an AND operation, hence a triangular norm operator is required. Instead of adopting the minimum norm again, the product norm $\mathcal{T}_P$ is preferred here because it exploits the maximum amount of available information. The fuzzy set for noise annoyance H is thus obtained as

$$H = \prod_{i=1}^{n} H_i \tag{4.1}$$

2.2.4 Linguistic approximation

The result of the inference process is handled by the linguistic approximation unit. Here, the fuzzy set H is converted into a form that is easier to interpret by humans, and expresses the result in function of a set of linguistic annoyance terms that are a priori defined in the database. Let $\mathcal{H}$ denote the linguistic annoyance variable that can take the linguistic values $\mathbb{L} = \{L_1, L_2, \ldots, L_m\}$, $m \in \mathbb{N}$, on the annoyance universe $\mathbb{H} = [0, 10]$ and $j \in \{1, 2, \ldots, m\}$.

Mathematically, the *linguistic approximation* process is based on the concept of an *approximate descriptor*, which is defined as a mapping from $\mathcal{F}(\mathbb{H})$ to $\mathcal{F}(\mathbb{L})$ [51]. Depending on the intended semantics, several approximate descriptions of H can be obtained by using different approximate descriptors.

Upper approximation The upper approximation descriptor D_H^+ calculates the degree of consistency of H with each L_j and is defined as,

$$D_H^+(L_j) = \textsc{Overl}(H, L_j) = \sup_{h \in \mathbb{H}} \mathcal{T}(H(h), L_j(h)) \tag{4.2}$$

D_H^+ is the set of terms each of which is possibly an appropriate term for H.

Degree of necessity* or *certainty This descriptor D_H^- is the degree of inclusion of H into each L_j and estimates the certainty that an ill-known value restricted by H is fully compatible with the label L_j. It is defined as,

$$D_H^-(L_j) = \textsc{Incl}(H, L_j) = \inf_{h \in \mathbb{H}} \mathcal{I}(H(h), L_j(h)) \tag{4.3}$$

D_H^- is the set of terms each of which is certainly an appropriate term for H.

Lower approximation The descriptor D_H^* is the fuzzy set of terms which certainly entail H,

$$D_H^*(L_j) = \textsc{Incl}(L_j, H) = \inf_{h \in \mathbb{H}} \mathcal{I}(L_j(h), H(h)) \tag{4.4}$$

The lower approximation gathers all terms L_j more or less included in H.

A duality property holds between the lower approximation and the upper approximation.

$$\overline{D_H^*} = D_{\overline{H}}^+ \tag{4.5}$$

In fact, besides the descriptors that were mentioned, all *similarity measures* (see chapter 2, section 29 and chapter 3, section 4.2) can be adopted to measure a degree of approximate similarity between H and each label L_j.

An interesting alternative is to calculate for each L_j the *inverse truth functional modification* [55] or compatibility $\textsc{Comp}(H, L_j)$ [132]. This is a mapping $\mathcal{F}(\mathbb{H}) \to \mathcal{F}([0,1])$ defined by

$$(\forall t \in [0,1]) \quad \left(\tau(t) = \begin{cases} \sup_{h \in \mathbb{H}} (H(h) | L_j(h) = t) & \left(L_j^{-1}(t) \neq \emptyset\right) \\ 0 & \left(L_j^{-1}(t) = \emptyset\right) \end{cases} \right) \tag{4.6}$$

The calculated *fuzzy truth value* τ represents the degree of compatibility between the two statements, "$\mathcal{H} = H$" and "$\mathcal{H} = L_j$ is τ-true". Taken over all linguistic labels, the final result of this approach is a fuzzy set over $\mathbb{L} \times [0,1]$, which obviously takes more time to compute than the previous methods. Furthermore, it is also less easy to correctly interpret, by humans as well as by computers. Therefore, this procedure will not be used in the noise annoyance advisor.

When using approximate descriptors (or similarity measures) for the *linguistic approximation* process, there are still three rather distinct approaches to report the final outcome of the noise annoyance advisor.

Matching distribution The result of the annoyance advisor is a possibility distribution over the terms $\mathbb{L}$, indicating the possibility that a term is a good description of the result. This possibility distribution will be denoted as $\pi_{\mathbb{L}}$.

Matching term In this setting, the result is not a possibility distribution but just the best matching –single– annoyance term. Here, the term with the highest $\pi_{\mathbb{L}}$ value is chosen as the final output.

Descriptive expression A totally different strategy tries to formulate a description of the result H using the basic annoyance terms in $\mathbb{L}$, connectives (and, or, except,...) and linguistic hedges (possibly, more or less,...) [174]. Again, because of the more expensive calculations, this approach is not used in the annoyance advisor.

Depending on the intended purpose, the first two methods are used in this work and implemented in the system. As underlying *approximate descriptors*, the upper approximation based on the minimum t-norm $\mathcal{T}_M$ and the lower approximation based on the Kleene-Dienes implicator $\mathcal{I}_{KD}$ have been used. These specific "matching possibility distributions" will be noted as $\pi_{\mathbb{L}}^{+}$ and $\pi_{\mathbb{L}}^{*}$, resulting in

$$(\forall j \in \{1,2,\ldots,m\})(\pi_{\mathbb{L}}^{+}(L_j) = D_H^{+}(L_j) = \sup_{h\in\mathbb{H}} \min(L_j(h), H(h))) \quad (4.7)$$

$$(\forall j \in \{1,2,\ldots,m\})(\pi_{\mathbb{L}}^{*}(L_j) = D_H^{*}(L_j) = \inf_{h\in\mathbb{H}} \max(1 - L_j(h), H(h))) \quad (4.8)$$

2.3 Rule qualification

Of course, not all rules have an equal impact on the result and not all rules will be equally certain. It is obvious that the noise exposure rules will have a larger impact on noise annoyance and will be better known than age for example. In natural language, an important mechanism to take such differences into account is the adjunction of a qualifier to a proposition [192], e.g. "for certain", "quite possible", "more or less true",... *Fuzzy qualifiers* are local notions in the sense that they always relate the qualified statement to another statement that is not qualified. What is needed then, is a translation rule that maps the meaning of a qualified proposition into an unqualified equivalent [191]. Let us first briefly discuss several translation rules for a number of common qualifiers [55]. Thereafter, their application in the noise annoyance advisor will be described.

2.3.1 Translation rules

Let us denote A and B for fuzzy sets on the variable X defined on a universe U, so $A, B \in \mathcal{F}(U)$. First, propositions that are qualified with a degree of certainty, also called degree of necessity or sufficiency, are considered. Given that "$X = B$" the certainty of a fuzzy statement "$X = A$" reflects the logical entailment of A from B. In [55], a *certainty qualified* proposition "$X = A$ is (at least) λ-certain" with $\lambda \in [0,1]$ is linked to a certainty or necessity measure, given "$X = B$"

$$N(A) = \inf_{u\in U} \mathcal{I}(B(u), A(u)) \geq \lambda \quad (4.9)$$

where $\mathcal{I}$ is an implicator. In order to find the underlying sure statement "$X = B$", the inequality must be solved. Dubois and Prade [55] argue that the identity principle, $(\forall x \in [0,1])(\mathcal{I}(x,x) = 1)$, is required to guarantee that the statements "$X = A$" and "$X = A$ is (1-)certain" are equivalent as expected. Only a residual implicator and the dual of a residual implicator fulfill this axiom. Furthermore, assuming that the solution of (4.9) is a true extension of the case when A is crisp implies that a dual of a residual implicator, $(\mathcal{I}_{\mathcal{T}}^{R})^*$, must be chosen [55]. Then, the solution is given by

$$(\forall u \in U)(B(u) \leq \mathcal{I}_{S,\mathcal{N}}^{S}(\lambda, A(u))) \tag{4.10}$$

with S the triangular conorm that is dual to the norm $\mathcal{T}$ with respect to the negator $\mathcal{N}$ that is used in the dual R-implicator. Specifically, choosing the dual of the Gödel-Brouwer implicator $\mathcal{I}_{GB}$, the Goguen implicator $\mathcal{I}_G$ or the Łukasiewicz implicator $\mathcal{I}_W$ results in respectively the Kleene-Dienes implicator $\mathcal{I}_{KD}$, the Kleene-Dienes-Łukasiewicz implicator $\mathcal{I}_{KDL}$ or the Łukasiewicz implicator $\mathcal{I}_W$. As shown by formula (4.10), a certainty qualified statement provides an upper bound for a possibility distribution, which depends on the choice of the S-implicator.

A second kind of qualification is *possibility qualification*, "$X = A$ is (at least) λ-possible" with $\lambda \in [0, 1]$, which means "all elements of A are possible values for X at least with degree λ". The possibility should really be interpreted as a kind of guaranteed possibility, expressing a degree of evidential support. Hence, a possibility qualification is linked to a guaranteed possibility measure Δ,

$$\Delta(A) = \inf_{u \in U} \mathcal{I}_{\mathcal{T}}^{R}(A(u), B(u)) \geq \lambda \tag{4.11}$$

where $\mathcal{I}_{\mathcal{T}}^{R}$ denotes a residual implicator. Solving this inequality to find the underlying unqualified statement "$X = B$" results in

$$(\forall u \in U)(B(u) \geq \mathcal{T}(\lambda, A(u))) \tag{4.12}$$

where the triangular norm $\mathcal{T}$ is the same as the one used in the residual implicator $\mathcal{I}_{\mathcal{T}}^{R}$. In this case, the possibility qualified statement provides a lower bound for the possibility distribution, which depends on the choice of t-norm.

In fact, certainty and possibility qualification are just special cases of *truth qualification* [56]. A truth qualified statement takes the form "$X = A$ is τ-true" where τ is a *linguistic truth value* of the *linguistic truth variable* T on the universe $[0, 1]$ (see chapter 2, section 8.2). Such a truth qualified proposition can be converted to the underlying sure statement "$X = B$" by applying the *truth functional modification*,

$$(\forall u \in U)(B(u) = \tau(A(u))) \tag{4.13}$$

Based on the above translation rule, it is easy to verify that the application of a certainty or possibility qualification Q to a fuzzy statement "$X = A$"

will result in the same unqualified proposition as "$X = A$ is τ'-true" when τ' is obtained as the unqualified result of "$T = \tau_1$ is Q". This property provides a way to compute a certainty and/or possibility qualification by virtue of a truth qualification.

Remark that the degree of truth τ of "$X = A$" given that "$X = B$" is taken for granted, can be calculated with the *inverse truth functional modification* that was used in section 2.2.4.

2.3.2 Qualification of noise annoyance rules

In the noise annoyance advisor, we are primarily interested in the certainty that a rule is valid. Therefore, each rule is assigned a certainty or sufficiency degree $\lambda \in [0, 1]$. This degree expresses to what extent it is sufficient that the antecedent is true for also having the consequent true. Actually, this certainty degree will be applied to the rule consequent instead of the rule itself. Although both interpretations only coincide when the antecedent is not fuzzy, this is common practice [55].

As a model to implement the upper bound of the *certainty qualification* in (4.10), the Kleene-Dienes implicator $\mathcal{I}_{KD}$ has been chosen, resulting in

$$B(u) = \max(1 - \lambda, A(u)) \tag{4.14}$$

As can be seen from the above formula, the consequent of a rule with $\lambda = 1$ (high rule certainty) will remain unchanged, having full impact as intended. On the other hand, a completely uncertain rule ($\lambda = 0$) will not have any effect because the consequent will have possibility 1 over the whole universe (concluding from the antecedent that everything is possible and thus providing no additional information).

Note that the certainty degrees will not be explicitly interpreted to judge the usefulness of a rule. How they are used and how rules are compared in general will be explained in chapter 6, section 3.6.

2.4 Measuring performance

The *noise annoyance advisor* that has been described so far, allows to predict the degree of annoyance experienced by an individual if input data is given. But in case the reported label L_* corresponding to the input data is also available, e.g. from a social survey, we should be able to verify the result of the system. Therefore, appropriate performance measures must be constructed.

A classical crisp annoyance model is correct only if it predicts the reported annoyance label of an individual exactly. Extending this principle to our fuzzy noise annoyance advisor calls for the "*matching term*" linguistic approximation scheme. The result can then be deemed correct if this term corresponds to the reported label. This performance measure will be called the "*crisp quality measure*".

However, starting from the viewpoint that noise annoyance is an inherently vague concept, this approach seems untenable. The "*matching distribution*" scheme returns the possibility that the terms in the vocabulary are considered good descriptions of the annoyance level. It might well be the case that two or even more terms are almost equally possible descriptions for the annoyance. In this situation it is not justified to call the output simply "wrong" if the possibility degree of the reported label is not the highest, although the difference is very small. A more natural quality measure taking the vagueness of annoyance into full account, is a fuzzy extension of *false negative.* It expresses the degree to which the reported label L_* is not considered a possible description for the system result H. This can be easily calculated as $1 - \pi_{\mathbb{L}}(L_*)$. When the lower approximation is used as underlying descriptor, $\pi_{\mathbb{L}}^*$, the false negative measure can be interpreted as an upper approximation descriptor of the complement of the fuzzy annoyance output H.

$$\begin{aligned}
1 - \pi_{\mathbb{L}}^*(L_*) &= 1 - D_H^*(L_*) && \text{(def. } \pi_{\mathbb{L}}^*\text{)} && (4.15)\\
&= \overline{D_H^*(L_*)} && \text{(def. complement)} && (4.16)\\
&= D_{\overline{H}}^+(L_*) && \text{(duality property)} && (4.17)
\end{aligned}$$

The *false negative* measure favors a system that is indecisive. Never excluding any label always results in a very low false negative. Obviously, such a system would be useless. The *non-specificity* [116] of the matching distribution $\pi_{\mathbb{L}}$ is perfectly suited to measure this indecisiveness. If multiple terms are equally good descriptions all having a high possibility degree, the non-specificity will be high indicating poor quality. This measure is defined as

$$N(\pi_{\mathbb{L}}) = \sum_{j=2}^{m} \pi_{\mathbb{L}}(L_j) \log_2 \left(\frac{j}{j-1} \right) \tag{4.18}$$

where $\pi_{\mathbb{L}}$ has been put in decreasing order so that $\pi_{\mathbb{L}}(L_1) \geq \pi_{\mathbb{L}}(L_2) \geq \ldots \geq \pi_{\mathbb{L}}(L_m)$. The combination of *false negative* and the *non-specificity* measure will be referred to as the "*fuzzy quality measure*".

2.5 Tuning rules

Before finishing the description of the *noise annoyance advisor*, two questions still must be solved.

- How to find optimal rule certainty degrees?
- How to use the system to test rule hypotheses?

The answer to both questions is the same. By modifying the certainty degree of each rule, the model is tuned to minimize a suitable error measure on a sample data set obtained from a social survey. This optimization process will extract reasonable weights from the data set which can then be used to predict the annoyance level for other input data. Additionally, if a rule performs badly (increasing the error measure) the optimization will lower the certainty degree of that rule to practically zero. The rule will then no longer have any (negative) effect on the performance of the system. This principle enables the user to include rule hypotheses in the FRB and test whether they hold or not in the sample data set.

The *error measure* used for this tuning can be defined in several ways. When the *crisp quality measure* is adopted, an appropriate error measure e_C is defined as

$$e_C = \frac{\displaystyle\sum_{k=1}^{N} \frac{\displaystyle\max_{\substack{j=1 \\ L_j^k \neq L_*^k}}^{m} \pi_{\mathbb{L}}(L_j^k) - \pi_{\mathbb{L}}(L_*^k)}{p(L_*^k)}}{\displaystyle\sum_{\substack{k=1 \\ L_p^k \neq L_*^k}}^{N} \frac{\left| \displaystyle\max_{\substack{j=1 \\ L_j^k \neq L_*^k}}^{m} \pi_{\mathbb{L}}(L_j^k) - \pi_{\mathbb{L}}(L_*^k) \right|}{p(L_*^k)}} + \sum_{\substack{k=1 \\ L_p^k \neq L_*^k}}^{N} \frac{\alpha}{p(L_*^k)} \tag{4.19}$$

where the index k runs over all N records in the data set and p is the probability distribution of the linguistic terms in the data. L_p and L_* denote the predicted and reported term respectively. The left term of the addition in e_C expresses an appreciation for a strong belief in a correct prediction. It is included to avoid an indecisive, non-specific model. The denominator is required to normalize the approximate descriptor, otherwise a linguistic approximation with only very small possibility degrees would be a good strategy. The constant α is an additional penalty for each wrong prediction, e.g. $\alpha = 0.1$. For the *fuzzy quality measure*, the error function e_F has been defined as a combination of its two constituting parts,

$$e_F = \sum_{k=1}^{N} \frac{\alpha(1 - \pi_{\mathbb{L}}^k(L_*^k))^2 + (1-\alpha)(N(\pi_{\mathbb{L}}^k))^2}{p(L_*^k)} \tag{4.20}$$

with $\alpha \in [0, 1]$, e.g. $\alpha = 0.5$. Here, the non-specificity measure will already penalize an approximate descriptor that has relative small possibility degrees everywhere. A denominator to normalize is therefore not required.

The frequency scaling using p is necessary to compensate the unequally distributed frequency of annoyance labels. Fortunately, the higher annoyance levels occur less often than the lower ones. But of course, they are equally important (or even more important) to model accurately. The weight α is introduced to express the *non-specificity* that is allowed in the obtained model after tuning. The higher α the more indecisive the model, where the price to pay for decisiveness or specificity is more frequent misses (or higher false negatives).

Using the "*crisp quality measure*", the performance of the model can easily be communicated by giving the weighted percentage of correctly predicted annoyance terms. This percentage can then be compared with the performance of other (crisp) models by calculating the same percentage. An example representation for the quality of a model after tuning with the *fuzzy quality measure* and its associated error measure e_F is shown in figure 4.6.

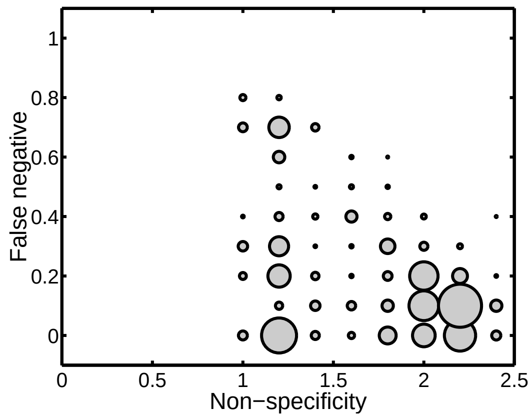

Figure 4.6: Distribution of the subjects over a false negative versus non-specificity plane that is tuned with $\alpha = 0.5$. The area of the bubbles is proportional to the number of subjects.

The optimization problem is solved using a *genetic algorithm* (GA) (see appendix A) because of the highly multimodal and non-continuous search space. Each individual in the population evolved by the GA, is in this case an instance of the model, and is completely represented by a string of real values in $[0, 1]$ that is formed by the certainty degree of each rule. The *fitness* of the individuals is maximized by the GA (in its imitation of natural selection) by minimizing the error measure of the associated models on the data set. As operators the *uniform crossover* and a *self-adaptive mutation* step operator are applied. The GA also performs linear fitness scaling.

Remark that a model tuned with the *fuzzy quality measures* turns out to almost never peak on the middle annoyance terms, although the possibility degrees of these terms are sometimes reasonably high. This indicates that a middle annoyance term would –also– be a good candidate description for the experienced annoyance. The reason for this observation must be sought in the *knowledge base*. When acoustical experts formulate rules, they will often have a clear understanding of circumstances that have a very low/high possibility for low or high annoyance. However, expressing situations when the possibility for middle degrees of annoyance is low/high, is far more difficult. This lack of specific knowledge about the occurrence of middle annoyance levels, results in more indecisiveness of the middle terms in the model.

3 Building blocks

The conceptual annoyance model has been built based on cluster indicators that group people with similar behavior for a characteristic. These characteristics can be fundamental or intermediate ones. It has been found useful to internally structure the implementing FRB in a hierarchical way, reflecting this conceptual layout. Additional –intermediate– variables can be introduced for which a separate submodel FRB is constructed. In figure 4.7 an example is shown where the noise sensitivity trait is implemented with a submodel FRB based on its *clustering indicators*, in a larger annoyance model designed to predict noise annoyance from road traffic. Using this set up, intermediate variables can be further decomposed into more easily measurable variables. Note that variables (e.g. age) may appear multiple times when they influence annoyance through different paths, possibly even in opposite directions.

If survey questionnaires explicitly assess such intermediate variables, the resulting data set can be used to test and tune submodel(s) separately. In these cases, the user has several options for running the whole annoyance model: using the reported value for an intermediate variable directly in the annoyance model, or calculating a value with the submodel anyway. There is even a third option that consists of using the submodel but performing *linguistic approximation* on the result to obtain one of the terms in the vocabulary of the survey. However, this is not recommended as part of the uncertainty, the *non-specificity*, gets lost with this approach.

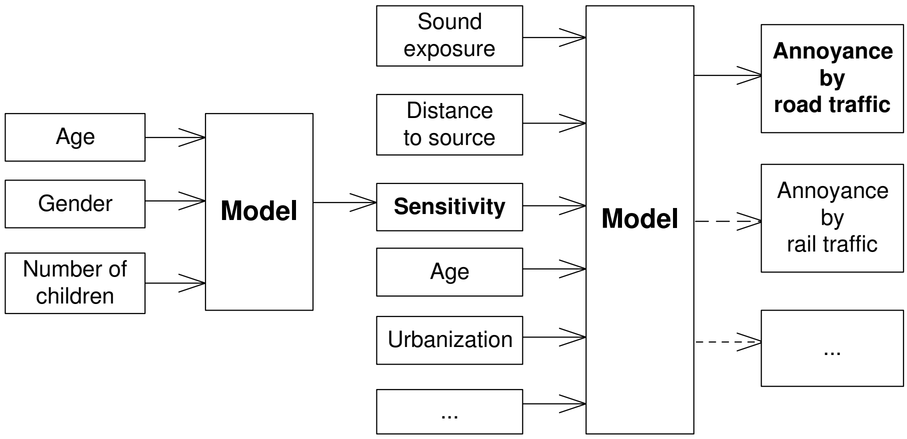

Figure 4.7: Hierarchical decomposition of the FRB.

4 Visualization

When the *noise annoyance advisor* is applied with noise policy decision support in mind, it is advantageous to visualize the results on a map. This includes the possibility distribution $\pi_{\mathbb{L}}$ over the available annoyance terms and the non-specificity variable which is an indication of the uncertainty of the outcome.

Depending on the purpose of the map, these model results can be shown in several ways. One approach could be to create one map for each annoyance term and visualize its possibility degree by varying the color intensity of a point. Although such maps would show all available data, it would be hard to interpret the maps in a general way. This representation is only suggested if colored surface maps are required.

Alternatively a map which depicts the possibility distributions in a more condensed form can be created. Of course, it is more difficult to represent a possibility distribution over five labels in a single point. A feasible solution is the use of a pie-chart as a mark. The greater the possibility of a label, the larger the piece of the pie that is assigned to it. In this case, the uncertainty is implicitly shown. If one label receives a dominant part of the pie, then the uncertainty will be small. However, if the pie is equally distributed among the labels, then there is high uncertainty about the result. An example of such a map where road traffic noise annoyance is predicted, is shown in figure 4.8. It is easy to see that the more closely located to a large road, the larger the fraction of the pie-chart that is filled in black, indicating extreme

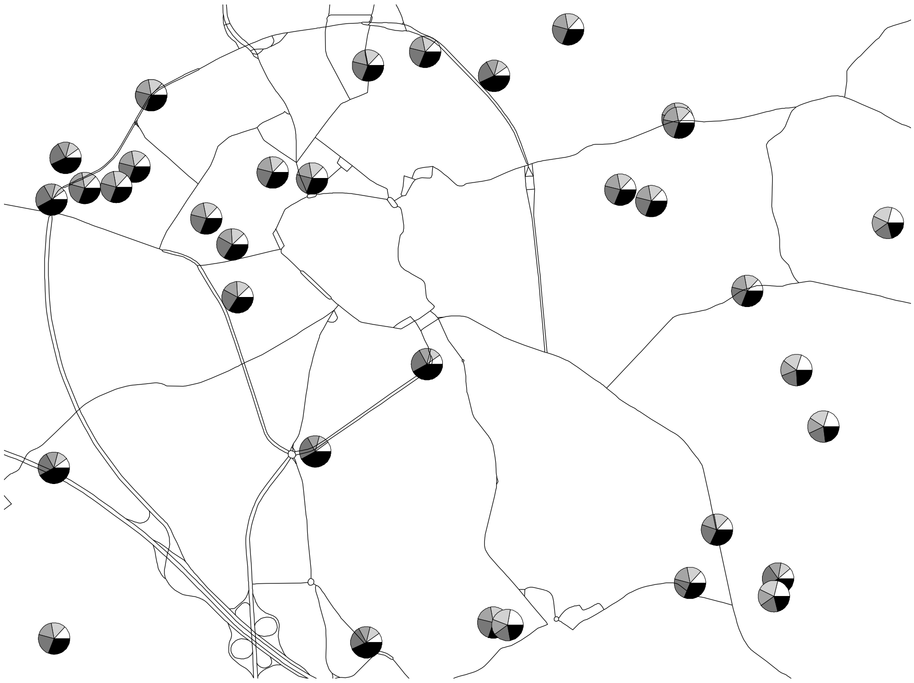

Figure 4.8: Map with possibility distribution represented as a pie-chart. White indicates the lowest level of annoyance ("not at all annoyed") while black indicates the highest level of annoyance ("extremely annoyed").

annoyance.

Another option is to visualize only the most plausible label, i.e. the annoyance term with the highest possibility. Hence, a significant amount of information on the almost equal plausibility of other annoyance terms gets lost in this type of map. One way to compensate the situation is to include the non-specificity as an indication of the uncertainty of the result, e.g. by varying the size of the mark. The resulting map of the same region and the same model is shown in figure 4.9. Again, note the large black (certainly extremely annoyed) and occasionally small white points located near large roads. Remark that the annoyance model is better optimized with the "crisp performance measures" if this kind of map is set as a goal. As already explained, the "fuzzy performance measures" tend to peak only at the more extreme annoyance terms.

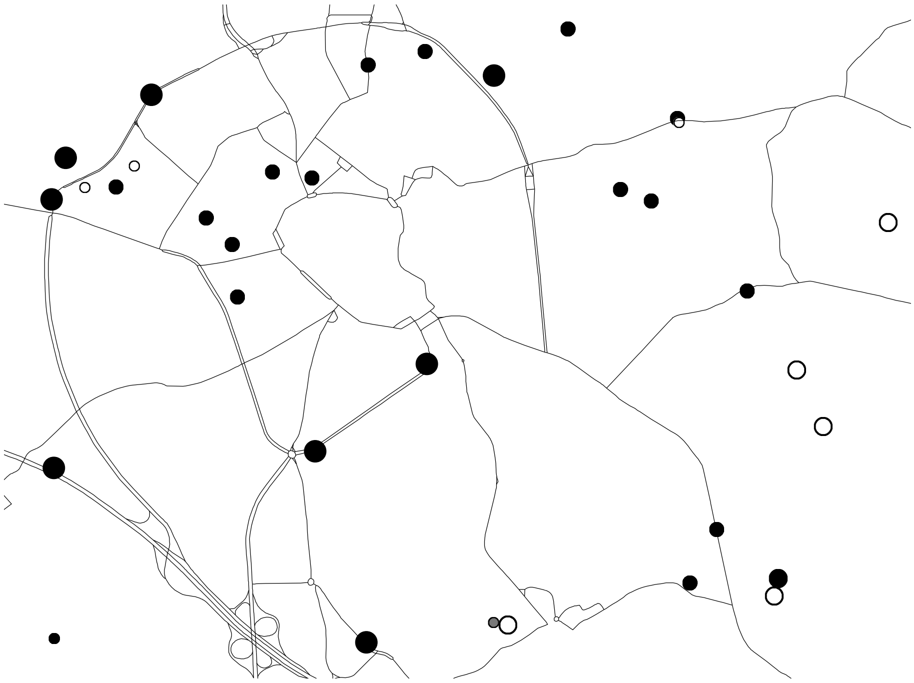

Figure 4.9: Map with most plausible label and the associated non-specificity. White indicates the lowest level of annoyance ("not at all annoyed") while black indicates the highest level of annoyance ("extremely annoyed"). The smaller the mark, the more uncertain.

5 Impact of inference schemes

5.1 Computational complexity

The optimization of the rule weights requires many evaluations of the model with different weights. This means that the calculation speed of the model is an important issue. Unfortunately, *certainty qualifying rules* have a high computational complexity. This is because the mathematical rule representation R has to be explicitly calculated for each rule. Even worse, each individual in the *genetic algorithm* optimization procedure can change the weight associated to a rule and thus modify the consequent of the rule. Hence, it is not possible to compute the rule matrices once and re-use them, they must be re-calculated for each GA individual. So, although the annoyance prediction of a single data record for a model with a single set of (a priory known and fixed) weights only requires a few seconds, the optimization of the weights on a large data set becomes very time consuming and impractical. Especially because an optimization is required, each time a noise annoyance expert adds, removes or changes a rule (or a set of related rules) to test the relationships between the various factors influencing annoyance and each other.

Yet, the certainty qualifying rule scheme can be simplified by applying the rule weight modification to the result of the rule, instead of to the rule consequent. Computationally, this has the very important consequence that the calculation of the rule representation R can be done once and for all for the model. A re-calculation of R for each set of different rule weights is not required anymore, as the rule itself is no longer affected during the optimization process. Semantically, this simplification expresses that the result of the rule is as certain as the rule itself is, which is a logical assumption. In fact, the following theorem proves that both calculation schemes with the Kleene-Dienes implicator $\mathcal{I}_{KD}$ used both as rule implicator and as certainty modification operator, always have the same result when the rule input is normalized.

Theorem 2. *Consider a rule "*IF $X = A$ THEN $Y = B$ IS λ CERTAIN*" where X and Y are variables over the universes U and V respectively, $A \in \mathcal{F}(U), B \in \mathcal{F}(V)$ and $\lambda \in [0,1]$. Let the input of the rule $A' \in \mathcal{F}(U)$ be a normalized fuzzy set.*

$$\begin{aligned} &\sup_{u \in U} \min\left(A'(u), \mathcal{I}_{KD}(A(u), \mathcal{I}_{KD}(\lambda, B(v)))\right) \\ &\qquad = \mathcal{I}_{KD}\left(\lambda, \sup_{u \in U} \min(A'(u), \mathcal{I}_{KD}(A(u), B(v)))\right) \end{aligned} \tag{4.21}$$

Proof.

$$
\begin{aligned}
& \sup_{u\in U} \min\left(A'(u), \mathcal{I}_{KD}(A(u), \mathcal{I}_{KD}(\lambda, B(v)))\right) \\
= \;& \sup_{u\in U} \min\left(A'(u), \mathcal{I}_{KD}(\lambda, \mathcal{I}_{KD}(A(u), B(v)))\right) \\
& \text{(exchange principle satisfied by S-implicators)} \\
= \;& \sup_{u\in U} \min\left(A'(u), \max(1-\lambda, \mathcal{I}_{KD}(A(u), B(v)))\right) \\
& \text{(definition of } \mathcal{I}_{KD}\text{)} \\
= \;& \sup_{u\in U} \max\left(\min(A'(u), 1-\lambda), \min(A'(u), \mathcal{I}_{KD}(A(u), B(v)))\right) \\
& \text{(distributivity of min with respect to max)} \\
= \;& \max(\sup_{u\in U}(\min(A'(u), 1-\lambda)), \\
& \qquad \sup_{u\in U}(\min(A'(u), \mathcal{I}_{KD}(A(u), B(v))))) \\
& \text{(distributivity of sup with respect to max)} \\
= \;& \max\left(1-\lambda, \sup_{u\in U}(\min(A'(u), \mathcal{I}_{KD}(A(u), B(v))))\right) \\
& (A' \text{ is normalized}) \\
= \;& \mathcal{I}_{KD}\left(\lambda, \sup_{u\in U}(\min(A'(u), \mathcal{I}_{KD}(A(u), B(v))))\right) \\
& \text{(definition of } \mathcal{I}_{KD}\text{)}
\end{aligned}
$$

□

An experimental speed comparison in [165] revealed that this modified calculation scheme performs twice as fast as the original scheme with certainty qualification applied to the rule consequents on the same model with the same data set.

In order to speed up calculation even further, another type of rule must be considered. In the comparison of rule semantics for the noise annoyance advisor (see section 2.2.3), *possibility qualifying rules* also seemed applicable. This type of rule has several advantages that could be useful in the noise annoyance advisor.

Lower computational complexity For possibility qualifying rules there exists a very efficient practical algorithm, that does not require the explicit calculation of the rule representation matrix R.

Easy support for multiple antecedents Adding two antecedents in a certainty qualifying rule requires the calculation of a three dimensional

> matrix that represents the relation between the two antecedents and the rule consequent. Of course, this is a very time consuming computation. Because a possibility qualifying rule does not need an explicit relation matrix, this type of rule supports multiple antecedents in a very efficient and straightforward way. The conceptual noise annoyance model (see section 2.1) has been shown to be quite complex. Therefore, this multiple rule antecedent feature could turn out to be useful in the formulation of fuzzy rules for modeling annoyance.

Obviously, possibility qualifying rules also have their drawback. The *material implicators* (S-implicators) used in the certainty qualifying rules, an extension of the classical, binary implication, are not commutative. The implication expresses a causality, the antecedent implies the consequent. The "implication" operators used in possibility qualifying rules are commutative triangular norms. Causality is lost, it is impossible to determine whether the antecedent implies the consequent or if it is the other way around. Therefore, these rules are unsuitable if the direction of the causality is important or under investigation. Furthermore, there are of course also semantical differences between the two types of rules. The impact of these differences on the noise annoyance advisor are further analyzed in the next section.

As implicator in the possibility qualifying rules, the minimum t-norm is adopted. This is the operator most typically found for this type of rules. The inference results from *parallel rules* are aggregated with the maximum t-conorm as prescribed by the theory. This leads to a single fuzzy set H_i, $i \in \{1, 2, \dots, n\}$, for every set of *parallel rules*, which can be seen as an estimate for the outcome of the FRB, the noise annoyance fuzzy set H. Of course, all H_i sets must be somehow combined to produce this ultimate outcome. Commonly the maximum t-conorm is also used for this aggregation. However, in the noise annoyance advisor the maximum t-conorm often leads to possibility distributions that are almost one everywhere. This is caused by the way rule hypotheses are eliminated with the certainty weights. An uncertain rule generates a rule consequent with high possibility for all levels of annoyance. Also the consequents of rules on variables that have a relative low impact on the global result, will have high possibility degrees everywhere. In order to solve this, the interpretation of noise exposure as a basic trigger and the other variables as modifiers is useful. The modifiers should be implemented so that they allow the possibility distribution of the trigger, except when some regions are considered less plausible by the expert who formulated the rule. This clearly requires an and-like operation. In the *noise annoyance advisor*, the product norm $\mathcal{T}_P$ is applied for this purpose, because the product uses the maximum amount of available information. To avoid situations where a modifier influences the trigger (in combination with the other modifiers) too drastically because its H_i is unnormalized (which is typically the case when using possibility qualifying rules), the H_i fuzzy sets are first normalized. By doing so, the opinion of the expert that formulated the rule is fully respected. His most plausible region of annoyance does not contribute, while the regions that are less plausible do modify the result. The fuzzy set for noise annoyance is thus obtained as

$$H = \prod_{i=1}^{n} \mathrm{norm}(H_i) \tag{4.22}$$

The experimental speed comparison in [165] showed that this scheme performs again twice as fast as the certainty qualifying rules with the certainty modification applied to the rule result on the same model with the same data set.

5.2 Prediction performance

In the previous section two calculation schemes, certainty qualifying rules and possibility qualifying rules, have been compared for speed. However, there is also an important semantical difference between both inference engines. It is therefore important to investigate their influence on the prediction performance of the noise annoyance advisor.

Using two inference operators, the $\mathcal{T}_M$ t-norm and the $\mathcal{I}_{KD}$ implicator, and the normalized versus unnormalized aggregation of results of parallel rules, four combinations exist which have been compared in [165]. Note that the combination of the $\mathcal{I}_{KD}$ implicator with normalized aggregation of results of parallel rules has been included only for the sake of completeness. Resulting annoyance possibility distributions of the four calculation schemes, with the same rules and rule weights, for two records in a sample data set are shown in figure 4.10.

The prediction performance in function of the weighted percentage correctly predicted annoyance terms of all four schemes has been tested on a large data set. As expected, the unnormalized $\mathcal{T}_M$ combination performed very badly because of the tendency to have a very small membership degrees for all values in $\mathbb{H}$. Although the normalized $\mathcal{I}_{KD}$ scheme performed slightly better, the difference between the schemes after optimization of the rule weights turned out to be less than about 1 %. Apparently, the rule weights are more or less capable of compensating for the different semantics of the schemes. For the comparison, the “crisp performance measures” with “matching term” *linguistic approximation* have been used in the noise annoyance advisor.

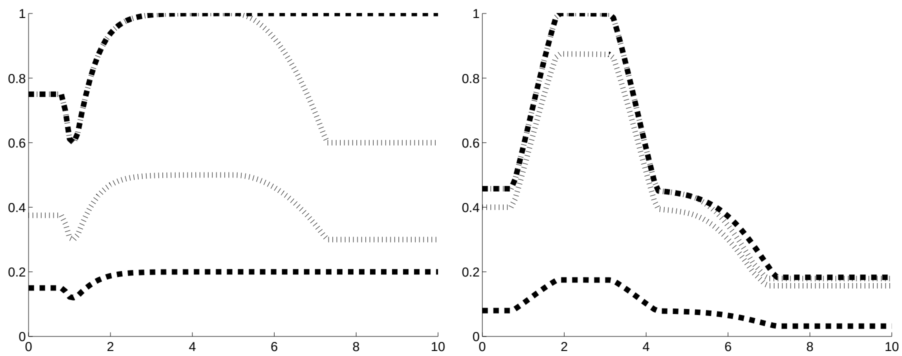

Figure 4.10: Comparison of different inference interpretations (dashed: Possibility interpretation unnormalized and normalized, dotted: Certainty interpretation unnormalized and normalized).

Based on the theoretical principles of approximate reasoning, the unnormalized $\mathcal{T}_M$ scheme provides a lower bound and the unnormalized $\mathcal{I}_{KD}$ scheme provides an upper bound for the actual inference result. When more and more (accurate) knowledge about the noise annoyance construct becomes available, both interpretations may come closer to each other. At that time, it could be useful to use both interpretation results in the linguistic approximation process.

In conclusion, it can be stated that the possibility qualifying rules in combination with optimized rule weights provide a fast alternative to the certainty qualifying rules, with almost equal prediction capabilities for the noise annoyance advisor. However, when the causality of the rules is important, the certainty qualifying scheme must be used, as the direction of the causality gets lost in the other scheme.

CHAPTER 5

Modeling noise annoyance accumulation

Knowledge is a process of piling up facts,
wisdom lies in their simplification.

Harold Fabing and Ray Marr

1 CURRENT STATE OF THE ART

1.1 Problem statement

People are usually not exposed to one type of noise source in isolation, where a type of source means a clearly distinguishable kind of noise with its own characteristics, e.g. road traffic, railway traffic, industry... Instead, community noise is composed of different types of noises that occur simultaneously and/or successively. Therefore, to be able to reduce the number of annoyed people in an area, insight is needed into the accumulation of annoyance from different sources. The problem of how to model *noise annoyance* from combined sources is addressed in this chapter.

From psycho–acoustical laboratory studies in which a group of test subjects is exposed to a variety of controlled stimuli, several annoyance accumulation models have resulted. But when these models are applied to predict the total annoyance reported in a *social survey*, they turn out to be less accurate. This should not be too surprising as several conditions are significantly different between laboratory research and field situations. In the field the retrospective time window is long-term [11] and not particularly related to the short time periods in which for example a plane flies over. In a laboratory setting, the combined stimuli are always produced by playing separate noises at the same time, while the noises are heard more alternately spread over time in the field. Also, the meaning of annoyance can differ. In a laboratory, people are told to listen and write down whether they think the sound is annoying or not. This is in fact a completely different situation compared to people that are watching television in their home, getting disturbed by noise. The former is much more related to physical loudness of noise than the spontaneous experience of annoyance. One of the most striking differences is the so called "*principle of compromise*" or the "*combined noise sources paradox*". This paradox states that in field studies the reported total annoyance level is generally lower than expected or even lower than the annoyance caused by one of the sources alone. Although this paradox is almost always present in field studies [134] [13], it is not found in laboratory studies [11]. Hence, several models that have been constructed based on laboratory experiments tend to overestimate the total annoyance level reported in field studies. It has been shown that the wording of the questions in a survey can at least partly explain this paradox [90]. If the phrasing explicitly includes the statement "when the noises occur at the same time", the paradox is significantly reduced although not completely eliminated.

In chapter 4, section 2.1 it has been shown that the perception of noise is not only related to the exposure of the noise. It is influenced by a large number of attitudinal, personal, situational,... factors. Besides their influence on the experience of annoyance from a source, authors have pointed out that several factors can also influence the global annoyance judgement, such as attitudes, social environment and general lifestyle [139] and general and specific noise sensitivity [91].

In the literature two types of accumulation models are distinguished [11]. The first group of models, the *psychophysical models*, express total annoyance $\mathcal{H}_t$ in function of the acoustical variables D_s which describe the *sound exposure* level of the source $s \in \{1, 2, \ldots, S\}$ (usually DNL or DENL). Hence, they all depend on some exposure-annoyance model h that maps the total exposure into annoyance. The second group of models, *perceptual models*, directly express the total annoyance $\mathcal{H}_t$ in function of the perceptual variables $\mathcal{H}_s$ which describe the experienced annoyance from source s. Based on the complexities involved in an individual exposure-annoyance mapping (see chapter 4) and the influence of the type of the sources especially through non-acoustical variables (e.g. attitude towards the source), the perceptual models are preferred in this work. They are the only accumulation models that are capable of incorporating source specific issues such as *masking*, when they are adequately considered in the source specific annoyance models. A sound masks another sound in a physiological sense, if the latter can not be heard because of the former one. Including such effects is more difficult in psychophysical models. A perceptual model usually distinguishes three variables: annoyance caused by a source X alone, annoyance caused by source X in presence of another source Y, and the total annoyance (caused by X, Y and possibly also by other sources). Before addressing the annoyance accumulation problem from a fuzzy annoyance perspective, some classical models are briefly discussed. For a more detailed elaboration and complete overview, the reader is referred to [11] and [134].

1.2 Energy summation models

These *psychophysical models* start by calculating the total exposure D_t logarithmically from the exposures of the individual sources D_s,

$$D_t = 10 \log_{10} \sum_{s=1}^{S} 10^{\frac{D_s}{10}} \tag{5.1}$$

Total annoyance then follows from an exposure-annoyance relation h.

$$\mathcal{H}_t = h(D_t) \tag{5.2}$$

It has been noted that equal exposure levels to different noise sources do not necessarily evoke equal annoyance levels. Therefore, several variations on this theme have been proposed. The *summation and inhibition model* of Powell [133] adds a correction factor E to the total exposure D_t before estimating total annoyance.

$$\mathcal{H}_t = h(D_t + E) \tag{5.3}$$

The correction factor E depends on the differences between the *sound exposure* level of the sources that trigger equal annoyance responses. In the *quantitative model* of Vos [169], subjective correction factors C_s are taking into account the differences in perceived annoyance between various sources. These correction factors are relative to a reference source for which the correction factor is 0 and are derived from source specific exposure-annoyance relations. Hence, they do not only depend on the source type but also on the exposure level of the source. Furthermore, the model also allows a more general weighted summation by introducing a free parameter k.

$$D_t = k \log_{10} \sum_{s=1}^{S} 10^{\frac{D_s + C_s}{k}} \tag{5.4}$$

Energetic addition is achieved when $k = 10$. Experimentally good results have been obtained for $k = 15$. This parameter allows to model the situation in which two equally annoying sources are perceived to be twice as annoying as one single source. This situation occurs frequently in laboratory studies but is usually not present in field studies. Of course, in order to calculate the total annoyance, the exposure-annoyance relationship of the source type that was chosen as reference should be used. In [70] [121] [71] Miedema and Gjestland have developed a similar approach, which they call the *annoyance equivalents model*. They start from the assumption that an invertible, source specific exposure-annoyance relationship is available for a reference source, e.g. the *dose-response relationship* for road traffic noise constructed by Miedema [123]. For all other sources, the exposure level of the reference source that has equal annoyance as the source specific exposure level is calculated,

$$D'_s = h_*^{-1}(h_s(D_s)) \tag{5.5}$$

where h_* is the exposure-annoyance relationship of the reference source. All those equal annoyance transformed exposure levels are energetically summed and used in h_*, the exposure-annoyance relationship of the reference source, to calculate total annoyance.

$$D_t = 10\log_{10}\sum_{s=1}^{S} 10^{\frac{D'_s}{10}} = 10\log_{10}\sum_{s=1}^{S} 10^{\frac{h_*^{-1}(h_s(D_s))}{10}} \tag{5.6}$$

$$\mathcal{H}_t = h_*(D_t) \tag{5.7}$$

It is important to remark that not all exposure-annoyance relationships are invertible, especially when they take into account the contextual variables that modify the experience of annoyance, e.g. the *noise annoyance advisor* as described in chapter 4. Therefore, in general, these models are only suitable in combination with indicators that are easy to calculate.

1.3 Vector summation model

In this *perceptual model* proposed by Berglund [10], general noise annoyance for two sources with their independently caused annoyance level represented by the variables $\mathcal{H}_i$ and $\mathcal{H}_j$ is calculated as

$$\mathcal{H}_t = \sqrt{\mathcal{H}_i^2 + \mathcal{H}_j^2 + 2\mathcal{H}_i\mathcal{H}_j\cos(\alpha_{ij})} \tag{5.8}$$

where α_{ij} is a constant that depends on the combination of the sources.

The constant α_{ij} has to be determined from experimental data. Values for α_{ij} of about 90° have been found for summation of loudness and annoyance as occurring in field conditions, thus in the presence of other sources that may partly mask the loudness [12]. Increasing the constant above 90° can lead to a general annoyance that is lower than the annoyance caused by one source alone, thus indirectly solving the *combined noise sources paradox*. Generalization of this model to more than two sources is a rather cumbersome task, except if $\alpha_{ij} = 90°$ is assumed for all i and j, leading to the extended model

$$\mathcal{H}_t = \sqrt{\sum_{s=1}^{S} \mathcal{H}_s^2} \tag{5.9}$$

However, this model excludes the possibility for reducing the overestimation. Changing the α_{ij} for all combinations of sources involved would improve performance, but it is not clear how this should be done in a multi-source (more than two source) environment.

1.4 Strongest component model

The *perceptual strongest component model* simply states that the level of general noise annoyance reported by a test subject, is the strongest of the annoyance levels caused by any of the particular noise sources that the subject may be exposed to

$$\mathcal{H}_t = \max_{s=1}^{S}(\mathcal{H}_s) \tag{5.10}$$

Several authors have reported very successful prediction of annoyance accumulation using the strongest component model both in field study [134] and in lab research [10], especially when one of the sources dominates. The theoretical background of this model is nevertheless very weak as its underlying *cognitive process* is not clear. One can even argue that it is counter-intuitive. Indeed one expects several sources of comparable (but unequal) loudness to result in higher annoyance than the annoyance caused by the loudest source. Nevertheless, even the strongest component model has the tendency to overestimate global predictions!

Note that there is also a *psychophysical* formulation of this model which is then commonly referred to as the *dominant source model*,

$$\mathcal{H}_t = h\left(\max_{s=1}^{S}(D_s)\right) \tag{5.11}$$

As this formulation requires a source unspecific exposure-annoyance mapping h, this version is not considered any further in this work.

2 Fuzzy accumulation rules

2.1 Introduction

In this section, a fuzzy *perceptual model* is developed with a special emphasis on the underlying *cognitive process*. The goal is not to create a black box model (e.g. *strongest component model*), the internal reasoning should be conceptually sound and consistent with the current knowledge in the field. Furthermore, as already extensively argued in chapter 1, annoyance is regarded as an inherent fuzzy concept which should also be modeled in a fuzzy way.

The various processes involved in a *perceptual accumulation model* are shown in figure 5.1. The *perception process* is where our senses register

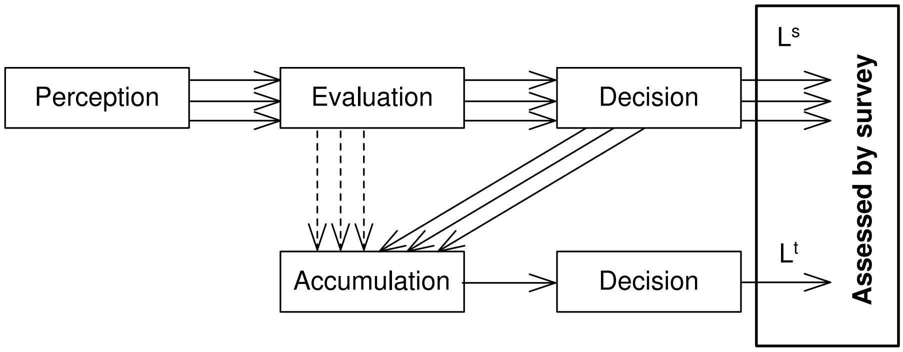

Figure 5.1: Overall cognitive process of a perceptual accumulation model.

the surrounding environment. This process also deals with the physiological effects of *masking* (one source that "hides" what we hear from another source when exposed to two or more sources at a time). In the *evaluation process* that follows, the perceptions are projected into our *frame of reference*, the framework in which we judge our senses. Several different senses (e.g. noise and odor) may influence each other and personal and attitudinal factors are taken into account in this evaluation. Following the dashed lines in figure 5.1, the *accumulation process* combines the evaluations of all sources and activities into a global evaluation. This process will be discussed further on in detail. Finally, when a global noise annoyance judgement is asked, one will have to make a *decision* about what level of annoyance to report. This may also be influenced by the phrasing of the questions and the order in which the questions are asked in the survey. However, in order to construct a model and to be able to test this model with data collected in a *social survey*, a critical assumption has to be made. In the model, it will be assumed that the evaluation process leads to a decision on every source or activity (reported in surveys when asked about the level of annoyance of one source in particular) and that these decisions are accumulated. This means that the decision to report annoyance from a specific type of source should be straightforward, and that these decision effects are negligible when a decision on the accumulated annoyance follows. This hypothesis will allow the model for accumulation to use the reported annoyance levels of individual sources to predict the reported global annoyance level.

The remaining issue is the modeling of the "cognitive accumulation process". The simplicity and relative success of the strongest component model suggests using it as a starting point for deriving a fuzzy annoyance accumulation model in a formal way. But before doing so, the strongest component model is further analyzed to identify the underlying cognitive process. This will provide the key for the fuzzification.

2.2 Cognitive process modeling in binary logic

The maximum-operator in formula (5.10) is a mathematical construct that has become very common in everyday tasks performed by many people. However an explicit formulation using classical logic, may be more closely related to the cognitive task that is performed when a subject tries to answer a general noise annoyance question. In language the *strongest component model* is equivalent to using the following set of logical rules. In the rules, the expression "one of the sources" refers to the types of sources that come spontaneously into mind when asked to judge accumulated annoyance.

IF annoyance by one of the sources is extremely (annoying)
THEN general annoyance is extremely (annoying).

IF annoyance by one of the sources is very (annoying)
THEN general annoyance is very (annoying)
UNLESS general annoyance is already extremely (annoying).

IF annoyance by one of the sources is moderately (annoying)
THEN general annoyance is moderately (annoying)
UNLESS general annoyance is already very or extremely (annoying).

...

These rules use the general annoyance variable two times with a slightly different meaning, once to represent the contribution of a single rule (THEN-part) and once to represent the aggregated result of all previously processed rules (UNLESS-part). For easy mathematical formulation, the annoyance contribution of a single rule will be denoted as the variable $\mathcal{A}^{(i)}$ for rule i and the subsequent disjunctive aggregation of these contributions from rule 1 to rule i will be referred to as $\mathcal{H}_t^{(i)}$. Strictly speaking, a variable in binary logic can only take one value and not an aggregation of values. However, in this binary logic formulation only one of the rules will fire and result in a contribution, so this aggregation does not really pose a problem. Furthermore using $\mathcal{H}_s$ for the annoyance from source $s = \{1, 2, \ldots, S\}$, $\mathbb{L} = \{L_1, L_2, \ldots, L_m\}$ for the set of the possible linguistic terms that describe annoyance levels (e.g. "not at all", "slightly", "moderately", "very", "extremely") and $j = m, m-1, \ldots, 1$, these rules read in mathematical form,

$$\text{IF} \bigvee_{s=1}^{S} (\mathcal{H}_s = L_j) \text{ THEN } \mathcal{A}^{(m-j+1)} = L_j \text{ UNLESS} \bigvee_{j'>j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'}) \quad (5.12)$$

$$\mathcal{H}_t^{(m-j+1)} = \bigvee_{i=1}^{m-j+1} \mathcal{A}^{(i)} \quad (5.13)$$

where the initial $\mathcal{H}_t^{(0)}$ is none of the available linguistic annoyance terms. The final result of the cognitive process is then found as $\mathcal{H}_t = \mathcal{H}_t^{(m)}$. These logical rules can only be executed in the indicated order, that is from the highest annoyance level L_m (e.g. "extremely annoyed") to the lowest one L_1 (e.g. "not at all annoyed"). The antecedent of each rule is true if and only if any of the noise sources s is rated as L_j annoying.

It is very important to point out that, according to the cognitive process derived from the successful strongest component model, total annoyance is always related to the annoyance caused by the sources or activities.

In preparation of the fuzzification that will be introduced, the IF-THEN-UNLESS rules (5.12) can be transformed into an equivalent IF-THEN expression.

$$\text{IF} \left(\bigvee_{s=1}^{S} (\mathcal{H}_s = L_j) \right) \wedge \left(\neg \bigvee_{j'>j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'}) \right) \text{ THEN } \mathcal{A}^{(m-j+1)} = L_j \quad (5.14)$$

This reformulation emphasizes that the rules (5.12) do not say anything about the result when the IF-part is false or the UNLESS-part is true.

2.3 Fuzzifying the cognitive process

The formulation of the cognitive process behind the *strongest component model* in binary logic that has been found, is perfectly suited to implement using fuzzy logic. This fuzzification has a clear advantage over the binary logic model, which is best exemplified by considering the following situation. Assume that a person has primary knowledge of the meaning of words describing the degree of annoyance that a person can experience. Additionally, assume that our test subject only knows about a single relation: "IF annoyance by road traffic noise is extreme THEN general annoyance is extreme". Given the fact that road traffic noise annoyance is "strong", can this person give any information on the expected general annoyance? In classical logic the answer is clearly "NO". Since the condition that is stated in the antecedent of the single known rule is not met, the rule does not fire and no information becomes available. A human reasoner may argue that "strong" is not that much weaker than "extreme" so it is possible to some extent that the consequent is true. The test subject may also argue that since "strong" is weaker than "extreme", the consequent of the rule should also be weakened to read "general annoyance is strong". Finally the human reasoner may conclude that since "not at all" or "slightly" are so different from "extreme" it is unlikely that general noise annoyance will take these values. The above example illustrates why fuzzy logic is such an interesting approach. *Fuzzy logic* provides the mathematical background to imitate human-like reasoning. Because of this, a fuzzy rule based model is also very well suited to construct a model that aims to imitate human cognition.

As already pointed out in chapter 4, section 2.2, a fuzzy rule based model always has more or less the same components: a *knowledge base* that comprises a *database* and a *fuzzy rule base*, an *inference* engine and a *linguistic approximation* unit (see figure 4.4). This fuzzy rule based accumulation model is no exception. These components and their implementation in this model will now be briefly discussed.

Database A first step in the fuzzification process consists in fuzzifying the facts. Hence, the linguistic terms L_j, $j \in \{1, 2, \ldots, m\}$, used in the antecedents and the consequents of the rules will be represented as fuzzy sets on a base variable $\mathbb{H} = [0, 10]$. See chapter 3 for a number of techniques to generate these fuzzy sets. Here we will adopt the curves constructed with the fuzzification method with fixed overlap, based on the data collected in the International Annoyance Scaling Study. The resulting membership functions from this method represent the semantics of the linguistic terms quite well while also being perfectly suited to be used in fuzzy rule based applications because of their overlap.

Rule base Instead of directly incorporating the rules (5.14) in the *fuzzy rule base*, the first antecedent is unfolded. This change moves the disjunction of the annoyance labels of the sources into a disjunction of several fuzzy rules, each relating to a single annoyance source. The unfolded scheme (5.15)–(5.17) is preferred because it allows more control over the contribution of each annoyance source which will become handy in the remaining part of this section. The notation $\mathcal{A}_s^{(m-j+1)}$ will be used to denote the annoyance contribution by the rule for annoyance level $j \in \{1, 2, \dots, m\}$ and source $s \in \{1, 2, \dots, S\}$.

The rules now have the following structure for $j = m, m-1, \dots, 1$.

$$\textsc{If}\ (\mathcal{H}_1 = L_j) \wedge \left(\neg \bigvee_{j'>j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'}) \right)\ \textsc{Then}\ \mathcal{A}_1^{(m-j+1)} = L_j \tag{5.15}$$

$$\textsc{If}\ (\mathcal{H}_2 = L_j) \wedge \left(\neg \bigvee_{j'>j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'}) \right)\ \textsc{Then}\ \mathcal{A}_2^{(m-j+1)} = L_j \tag{5.16}$$

$$\dots$$

$$\textsc{If}\ (\mathcal{H}_S = L_j) \wedge \left(\neg \bigvee_{j'>j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'}) \right)\ \textsc{Then}\ \mathcal{A}_S^{(m-j+1)} = L_j \tag{5.17}$$

Inference In order to infer results from the fuzzy rules combined with actual input data, all binary operations (conjunction, disjunction, negation, modus ponens) also have to be replaced by their fuzzy extensions (t-norm, t-conorm, negator, generalized modus ponens). The various choices that have been made are now discussed in detail.

The rules described above are clearly a knowledge gathering procedure: each rule creates the possibility of an annoyance level. They are *possibility qualifying rules*, therefore the rule relation R should be represented by a t-norm (see chapter 2). Most commonly the Zadeh norm $\mathcal{T}_M$ is used for this purpose. The fact that possibility qualifying rules provide the right semantics implies that the very efficient rule implementation algorithm can be applied.

For the conjunction of both antecedents, any t-norm can be used. However, a small t-norm (such as the product norm $\mathcal{T}_P$ and the Łukasiewicz norm $\mathcal{T}_W$) will decrease the degree of fulfillment of the rules except for the first rule in which the second part of the antecedent will always be 1 (the neutral element for t-norms). Hence, the highest level of annoyance in the first rule would be favored. Considering the *principle of compromise* and the tendency of the strongest component to overestimate the level of annoyance, this is obviously not desired. Therefore, the largest t-norm $\mathcal{T}_M$ is preferred for the conjunction. For the negation, the typical Zadeh negator $\mathcal{N}_Z$ is adopted.

The set of rules (5.15)–(5.17) have been obtained by unfolding the disjunctive antecedent from (5.14) into a number of disjunctive rules. So the inferred rule results $A_s^{(i)}$ should also be aggregated with a disjunction,

$$A^{(i)} = \bigvee_{s=1}^{S} A_s^{(i)} \ . \tag{5.18}$$

This fits nicely into the knowledge gathering semantics of our possibility qualifying rules. As a model for the disjunction, any t-conorm can be used. Note that the rule results are in fact possibility distributions that should be interpreted here as degrees of (guaranteed) possibility (not degrees of certainty, see chapter 2, section 6.3). According to the related principle of maximum specificity, such possibility distributions should be combined with the maximum operator as this assures that no additional information is included. Therefore, the S_Z –maximum– t-conorm is adopted.

Finally, the information gathered so far, denoted as $H_t^{(m-j+1)}$, is necessary in the following set of rules for a lower annoyance level. It can be calculated with formula (5.13). To model the disjunction operator, the *principle of maximum specificity* should be taken into consideration again. Hence, the Zadeh t-conorm S_M is used. The complete fuzzy rule inference process is shown in figure 5.2.

Linguistic approximation Finally, the *linguistic approximation* component is responsible for mapping the fuzzy rule base result $H_t = H_t^{(m)}$ into an expression that is meaningful to the user.

For this purpose we will once again use the *approximate descriptor* concept that has been described in chapter 4, section 2.2.4. An approximate descriptor is a mapping from $\mathcal{F}(\mathbb{H})$ to $\mathcal{F}(\mathbb{L})$. The obtained possibility distribution over the available linguistic terms expresses the possibility that a linguistic term is a good description of the original fuzzy set. Two approximate descriptors seemed interesting, the upper approximation $\pi_{\mathbb{L}}^{+}$ and the lower approximation $\pi_{\mathbb{L}}^{*}$.

Depending on the context, one can prefer to look only at the term with the highest possibility ("*matching term*") or take the whole possibility distribution into account ("*matching distribution*"). The first

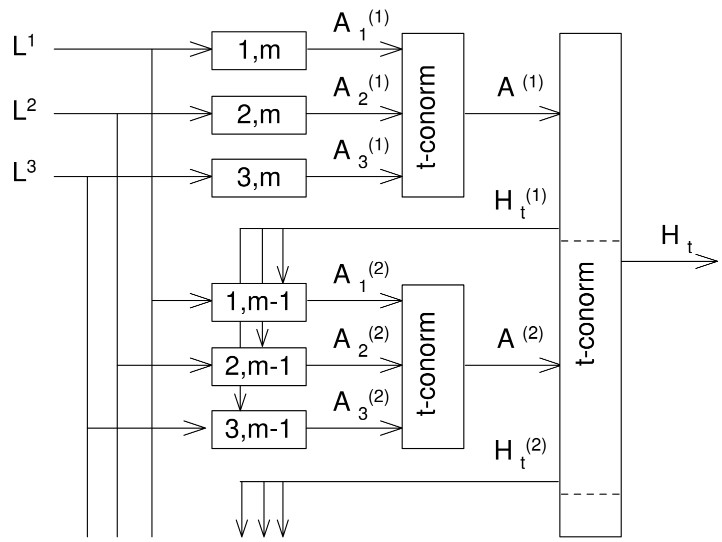

Figure 5.2: Structure of the fuzzified accumulation rule base model.

approach can be useful when a comparison with a survey answer or a crisp model is necessary, while the latter is a more natural fuzzy approach. In that case, the performance of the model should be measured with the *false negative* and *non-specificity* measures as explained in chapter 4, section 2.4.

The cognitive accumulation process underlying the crisp *strongest component model* has been identified and has been formulated using binary logic rules. By replacing the binary operators by their extensions from fuzzy logic, a fuzzy rule based model for the cognitive process has been constructed. Although various choices for the involved operators offer additional modeling freedom, the nature of the cognitive process (information gathering) and the *principle of compromise* have pushed choices into a specific direction. As this fuzzy rule based model is in fact a direct extension of the reasoning behind the strongest component model, results are expected to be almost the same (although small differences may occur). There seems to be no benefit in making the logic model fuzzy unless additional features are added. This will be the topic of subsequent sections.

2.4 Rule qualification

In the model described so far, all noise sources and activities have an equal impact on the final accumulation result. This is of course not very realistic. Therefore, an improved annoyance accumulation model should differentiate between sources. In fuzzy rule based systems, rules can be qualified to express their relevance. In chapter 4, section 2.3, three distinct *fuzzy qualifiers* have been discussed, certainty qualification, possibility qualification and the more general truth qualification.

In the cognitive model, the execution order of the rules is important. Each rule guarantees the possibility of an accumulated annoyance level based on a particular source, so a *possibility qualification* $\lambda \in [0, 1]$ seems most appropriate. This degree expresses to what extent the consequent can be guaranteed possible when the antecedent is true. In the noise annoyance accumulation model, a possibility qualified linguistic rule could read for example:

IF annoyance by road traffic is very (annoying)
THEN general annoyance is very (annoying)
IS 0.8 possible
UNLESS general annoyance is already extremely (annoying).

In our fuzzy rule base, we have one rule for each combination of a source and a linguistic annoyance term, so a possibility degree $\lambda_{s,j}$ with $s \in \{1, 2, \ldots, S\}$ and $j \in \{1, 2, \ldots, m\}$ has to be determined. This leads to the following fuzzy rules, for $j = m, m-1, \ldots, 1$ and $s = 1, 2, \ldots, S$,

$$\begin{aligned} &\textsc{If } (\mathcal{H}_s = L_j) \wedge \left(\neg \bigvee_{j'>j}^{m} (\mathcal{H}_t^{(m-j)} = L_{j'})\right) \\ &\textsc{Then } \mathcal{A}_s^{(m-j+1)} = L_j \textsc{ Is } \lambda_{s,j} \textsc{ Possible} \end{aligned} \tag{5.19}$$

As the possibility degrees are implemented on the rule consequents and the triangular norm $\mathcal{T}_M$ is used for the calculation of the lower bound of the possibility distributions chapter 4, section 2.3, the rule consequents become,

$$(\forall h \in \mathbb{H})(L_j^*(h) = \min(\lambda_{s,j}, L_j(h))) \tag{5.20}$$

To reduce complexity, we assume $\lambda_{s,j} = \lambda_s \cdot \lambda_j$, where $\lambda_s \in [0, 1]$ depends on the source and $\lambda_j \in [0, 1]$ on the level of annoyance. Indeed, it is legitimate to assume that the importance of a noise source will be the same for all levels of annoyance, and that in the accumulation the annoyance levels will have an equal weight over all sources. In fact, in [13] and [81] the relative importance of sources in the accumulated judgement has been related to the "on time" of the source, the period of time of annoyance by that source.

Both sets of possibility degrees are extracted from survey data by minimization of an *error measure* e. The same error measures as defined in chapter 4, section 2.5 can be used,

$$e_C = \frac{\displaystyle\sum_{k=1}^{N} \frac{\max_{\substack{j=1 \\ L_j^k \neq L_*^k}}^{m} \pi_{\mathbb{L}}(L_j^k) - \pi_{\mathbb{L}}(L_*^k)}{p(L_*^k)}}{\displaystyle\sum_{\substack{k=1 \\ L_p^k \neq L_*^k}}^{N} \frac{\left| \max_{\substack{j=1 \\ L_j^k \neq L_*^k}}^{m} \pi_{\mathbb{L}}(L_j^k) - \pi_{\mathbb{L}}(L_*^k) \right|}{p(L_*^k)}} + \sum_{\substack{k=1 \\ L_p^k \neq L_*^k}}^{N} \frac{\alpha}{p(L_*^k)} \tag{5.21}$$

and

$$e_F = \sum_{k=1}^{N} \frac{\alpha(1 - \pi_{\mathbb{L}}^k(L_*^k))^2 + (1 - \alpha)(N(\pi_{\mathbb{L}}^k))^2}{p(L_*^k)} \tag{5.22}$$

where the index k runs over all N records in the data set, $\pi_{\mathbb{L}}$ is the possibility distribution over the set $\mathbb{L}$ that results from the linguistic approximation and $N(\pi_{\mathbb{L}})$ is the non-specificity of this distribution. p is the probability distribution of the linguistic terms in the data. L_p and L_* denote the predicted ("matching term") and reported term respectively. The weight $\alpha \in [0, 1]$ is introduced to express the non-specificity that is allowed in the model after tuning. The higher α the more indecisive the model. The error measure e_C is preferred when the aim is to compare the performance of the model with the performance of a crisp model.

Data from surveys in which people are asked to judge their experience of total annoyance and annoyance caused by several types of sources separately, can be used to minimize the error measure. This optimization is performed by a *genetic algorithm* (GA) (see appendix A). Each individual in the population evolved by the GA is in this case an instance of the model and is completely represented by a string of real values in $[0, 1]$ that is formed by the possibility degrees of the sources λ_s ($s \in \{1, 2, \ldots, S\}$) and the linguistic labels λ_j ($j \in \{1, 2, \ldots, m\}$). The *fitness* of the individuals is maximized by the GA by minimizing the error measure of the associated models on the data set. As operators the *uniform crossover* and a *self-adaptive mutation* step operator are applied.

2.5 Changing the frame of reference

Adding relative importance by means of qualifiers is not the only way the fuzzy model can be made source dependent. Rating a particular characteristic of an object or a situation always involves a *frame of reference*. In [132] the frame of reference is also called the frame of cognition. It is known that fuzzy sets and the linguistic terms associated with them are context-dependent, e.g. when rating the height of people or buildings the frame of reference will be different because of the different context. The fuzzy sets used for the representation of the annoyance terms in the fuzzy rule base are based on data specifically collected in the context of the perception of annoyance. However, there is no particular reason to assume that the frame of reference for rating road traffic noise annoyance will be exactly the same as for rating general noise annoyance. Although the differences will probably be rather small, they are nevertheless not necessarily negligible.

In the proposed fuzzy rule based model, the frame of reference can be different for the antecedent and the consequent of a rule. This leads to different universes $\mathbb{L}_s$ and $\mathbb{L}_t$, containing possibly different definitions for the same linguistic terms and/or additional linguistic terms, that can be used in the antecedents and/or the consequents. To avoid confusion here, we will not redefine the basic annoyance terms. Instead, additional terms and slightly modified terms will be considered. When the universe $\mathbb{L}_t$ contains additional linguistic terms, more possibilities for the verbal descriptions of the rules are allowed. For example a rule may read,

IF rail traffic noise annoyance is extremely (annoying),
THEN general annoyance is strongly (annoying).

Another option is to use *linguistic modifiers* (or *hedges*) to modify the meaning of terms. This approach can incorporate more subtler changes caused by frame of reference differences that cannot be accurately described otherwise. The example could then read,

IF rail traffic noise annoyance is extremely (annoying),
THEN general annoyance is a bit less than extremely (annoying).

Several mathematical models for hedges have been developed [53], see also chapter 2, section 8.2.

In the accumulation model, a *shifting hedge* is preferred. Shifting modifiers have the desirable properties that they change the support (contrary to powering hedges) of the fuzzy set and that they are very simple to implement. Using shifting hedges, the modified membership function $L_j^*(h)$

for the representation of the linguistic expression "a bit less than L_j" is defined as,

$$(\forall h \in \mathbb{H})(L_j^*(h) = L_j(h - \varphi)) \tag{5.23}$$

where φ is a suitable constant. It is straightforward to make φ dependent on the source since the change in the *frame of reference* can depend on the source. This results in S additional parameters φ_s with $s \in \{1, 2, \ldots, S\}$ where S denotes the number of sources.

Just as the parameters λ_s and λ_j, the parameters φ_s can be included in the optimization by the genetic algorithm (GA).

2.6 Integration in the noise annoyance advisor

The fuzzy annoyance accumulation model that has been built can be used separately, or it can be seen as a building block in the noise annoyance modeling framework that has been developed in chapter 4. How this building block fits in the overall fuzzy framework is shown in figure 5.3.

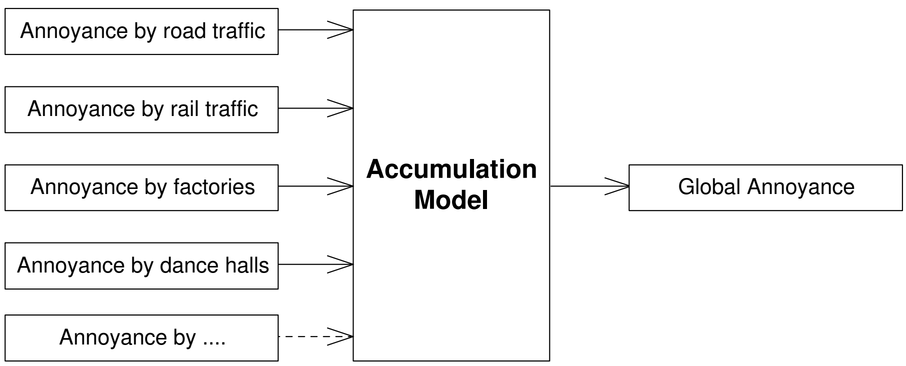

Figure 5.3: Fitting the accumulation model in the overall framework.

Just as in the case of the other building blocks, input data from surveys can be used to tune the accumulation (sub)model separately. But if desired, the (sub)model can also be executed (or even tuned) with the output of the models for the annoyance caused by individual sources. This decision will largely depend on the availability of data and the purpose of the modeling or prediction effort.

3 Models based on fuzzy integrals

3.1 Multi-criteria decision making

3.1.1 Introduction

In the previous section, we have examined the cognitive process underlying the successful (crisp) strongest component model by means of fuzzy –linguistical– rules. In this section, the noise annoyance accumulation problem will be regarded from a different perspective. It will be approached as a *multi-criteria decision making* (MCDM) problem.

Multi-criteria decision making consists of comparing decision alternatives according to several points of view or criteria [119]. Three different flavors of MCDM problems can be identified.

Choice* or *selection selects a subset of alternatives judged as the most appropriate. The number of elements in the subset should be kept as low as possible.

Sorting* or *classification assigns each alternative to one of a number of predefined categories. Classification into the real line $\mathbb{R}$ is usually called regression.

Ranking* or *ordering ranks the alternatives in decreasing order of preference.

To be able to make its decision, the MCDM process requires the evaluation of each alternative on each criterion. These evaluations are then aggregated to obtain a global ranking of the alternatives, a sorting into different classes or a selection of acceptable alternatives. The criteria can be evaluated on an *ordinal* or *cardinal scale* or by means of a fuzzy value.

Let us now restate the MCDM approach in a more rigid mathematical terminology. Let U be the finite set of n predictive criteria $\{u_1, u_2, \dots, u_n\}$, and denote the evaluation of a criterion u_i by $f(u_i)$. The problem is then to aggregate the evaluation of each of the individual criteria to obtain the overall evaluation of the objective criterion v.

$$D(v) = G(f(u_1), f(u_2), \dots, f(u_n)), \tag{5.24}$$

where G is an aggregation function. Typical examples of MCDM problems are the assignment of grades to students based on their results for multiple courses and the selection of the best candidate for a job vacancy.

To model the aggregation, several approaches are available. The most classical being linear multiregression where the evaluation of the objective criterion is modeled as a weighted arithmetic means of the evaluations of the predictive criteria.

$$D(v) = \sum_{i=1}^{n} w_i f(u_i) \tag{5.25}$$

with $\sum_{i=1}^{n} w_i = 1$ and $w_i \geq 0$ for all $i \in \{1, 2, \ldots, n\}$. A presumption of such models is the fact that there is no interaction among the predictive criteria towards the objective criterion. However, in many real-life problems, such as annoyance modeling, this interaction between criteria must be taken into consideration. In order to represent interactions between the criteria, the purely additive weight vector w can be substituted by a *fuzzy measure*. A fuzzy measure allows not only to assign a weight to each criterion but also to each subset of criteria.

The extension of an additive weight vector to more general fuzzy measures naturally leads to the use of *fuzzy integrals* such as the *Choquet integral* and the *Sugeno integral* (see chapter 2) as aggregation functions. In fact, the Choquet integral coincides with the weighted arithmetic means when the fuzzy measure is additive. Both fuzzy integrals have been applied successfully in the framework of MCDM [171] [170] [52].

3.1.2 Noise annoyance accumulation as MCDM

Adopting the MCDM view on the noise annoyance accumulation problem, the evaluation of the level of total annoyance will be the decision that has to be made. As the possible levels of annoyance will be usually predetermined and depending on the labels that were available in a survey, the modeling and prediction of the accumulated noise annoyance is a *classification* problem on an ordered scale in MCDM. Each source of annoyance is a predictive criterion, while total annoyance is the objective criterion. The alternatives are the elements of the ordered set of annoyance levels. Let $\mathbb{S} = \{r_1, r_2, \ldots, r_S\}$ denote the set of all annoyance sources. The domain of the evaluation of the alternatives for an annoyance source $s \in \{1, 2, \ldots, S\}$ can be represented as the set L^s in the interval $[0, 1]$. Define $L^s = \{0 = l_1^s \prec l_2^s \prec \ldots \prec l_m^s = 1\}$ with $m \in \mathbb{N}$ and l_j^s, $j \in \{1, 2, \ldots, m\}$, as the evaluation of a linguistic annoyance term for source s. The relation $\prec$ defines the order of the annoyance levels where the lowest number in L^s denotes the lowest level of annoyance for source s. The sets L^s define an *ordinal scale* that is based on the linguistic labels used in a *social survey*. However, as the annoyance scale in a survey is usually independent of the source and for the sake of simplicity of model parameters, we will assume $L = L^1 = \ldots = L^S$ here. Yet, the subtle differences in the *frame of reference* of the annoyance of each source should be taken into account using different sets L^s. Note that although the set L defines an ordinal scale, an underlying *cardinal annoyance scale* can be assumed. In fact, the idea of a cardinal annoyance scale is used in several annoyance surveys as well as in the International Annoyance Scaling Study [65] where the annoyance had to be rated on a continuous line. Based on the previous notations, the evaluation function f is a mapping $\mathbb{S} \to L \subseteq [0,1]$. Also for the domain of the evaluation of total annoyance, the same scale L will be adopted.

Using the *Choquet integral* as aggregation operator,

$$D(\mathcal{H}_t) = C_\mu(f) \tag{5.26}$$

results in an evaluation of the total annoyance $\mathcal{H}_t$, expressed as a number in the interval $[0,1]$. The Choquet integral explicitly requires the existence of a *cardinal scale* in its calculations. Considering the elements in L as midpoints of intervals on the underlying cardinal scale, the result $D(\mathcal{H}_t)$ can be expressed in function of the input categories L. The category $l \in L$ is chosen as the classification result if $D(\mathcal{H}_t)$ falls in the interval around l. In the following we will assume the shorthand notations $d = D(\mathcal{H}_t)$ and the value of l will be denoted as d'.

When the *Sugeno integral* is adopted as aggregation operator,

$$D(\mathcal{H}_t) = S_\mu(f) \tag{5.27}$$

only the properties of an *ordinal scale* are used. However, the result of this aggregation will only be an element of the ordinal scale L^s, if all the fuzzy measure values are also drawn from this ordinal scale. In the case of a more general fuzzy measure, the result will simply be a number in the interval $[0,1]$, not necessarily in L^s. In these cases, an engineering approach is followed. The same post-processing, based on the assumption of a *cardinal scale* with intervals, will be applied to classify the result to one of the predetermined levels of annoyance. Although this violates the principles of the ordinal scale, this approach is commonly used in practice [30].

The approach sketched above leaves only the question of finding the optimal fuzzy measure that can be used by one of the integrals. The fuzzy measure associated with the fuzzy integral provides a means to represent the relationships between the predictive criteria. It expresses the confidence in the adequacy of a subset of annoyance sources to predict the total annoyance. The adopted strategy is to extract the fuzzy measure from survey data by optimizing the prediction –or in MCDM terminology classification– capabilities of the integral based model. But let us first recall from chapter 2 how a fuzzy measure can be specified.

Enumeration The most straightforward representation of a fuzzy measure is by enumerating the fuzzy measure value for all criteria and all subsets of criteria.

Relationship Another possibility is to rely on a relationship that specifies how to calculate the fuzzy measure of an union of criteria based on the fuzzy measure values of the individual criteria, e.g. probability and possibility measures.

Alternative representation Finally, a completely different representation scheme can be used based on some kind of transformation of the fuzzy measure.

As the number of parameters in the enumeration approach grows exponentially with the number of sources S, $2^S - 2$, and S is typically rather high in annoyance modeling (around 20), this approach seems not feasible. The other ways of specifying a fuzzy measure require far less parameters and will be examined in detail in section 3.2.

No matter how the fuzzy measure is represented and how many parameters are needed, the solution landscape of the annoyance accumulation classification is complex and highly non-linear. Therefore, the optimization of the parameters of the fuzzy measure is performed with a *genetic algorithm* [171] (see appendix A). Of course, this requires an appropriate *error measure* that can be minimized by the GA. Let the data set from a survey consist of N records of the form $(f(r_1), f(r_2), \ldots, f(r_S), d^*)$ where d^* denotes the reported evaluation of the total annoyance. A suitable error measure e which equalizes the different frequencies of occurrence of d^* values in the data set can be defined as

$$e = \sum_{k=1}^{N} \frac{(d_k - d_k^*)^2}{p(d_k^*)} + \sum_{\substack{k=1 \\ d'_k \neq d_k^*}}^{N} \frac{\alpha}{p(d_k^*)} \tag{5.28}$$

where p is the probability distribution of the linguistic terms in the data set and α is an experimentally determined, additional penalty for each wrong prediction.

3.1.3 Inconsistent decision maker

Usually, a decision maker is supposed to follow some kind of logical pattern in making its decision. Students expect that they are all judged in the same fair way and that the weights of courses and combinations of courses are equal for all students in calculating their final score. However, in the case of grading students there is typically only a single teacher or decision maker responsible for this job. In the noise annoyance accumulation classification, we are trying to classify the decisions of N different persons, in order to find the common logic behind the accumulation process. So our MCDM tool is likely to be confronted with data from different respondents that look inconsistent

Two kinds of inconsistencies can be identified which are called "*doubt*" and "*reversed preference*" in [32].

Doubt Consider the following two different respondents p and q,

$$(f(r_1), f(r_2), \ldots, f(r_S), d_p^*)$$

and

$$(f(r_1), f(r_2), \ldots, f(r_S), d_q^*)$$

Seeing only the evaluations of the predictive criteria,

$$(f(r_1), f(r_2), \ldots, f(r_S))$$

the MCDM will be in doubt whether the objective criterion should be classified as d_p^* or d_q^*.

Reversed preference There is also a problem if for two different respondents p and q,

$$(f_p(r_1), f_p(r_2), \ldots, f_p(r_S), d_p^*)$$

and

$$(f_q(r_1), f_q(r_2), \ldots, f_q(r_S), d_q^*)$$

the following property holds,

$$(\forall i \in \{1, 2, \ldots, S\})(f_p(r_i) \preceq f_q(r_i) \wedge d_p^* \succeq d_q^*)$$

where $\prec$ denotes the relation that defines the order of the annoyance levels. Here, for all sources, person p is less or equally annoyed than person q, although p has evaluated his total annoyance level higher than q. Because of the monotonicity property of fuzzy integrals (see chapter 2, section 7.2.3), it is impossible to classify both respondents correctly.

Finally, there is also a type of inconsistency that is inherent to the choice of fuzzy integrals and the problem of annoyance accumulation at hand. Notwithstanding the *principle of compromise*, accumulated annoyance can be less than expected and even less than the most annoying source. But total annoyance can sometimes also be rated higher than the most annoying source. Yet, the compensating behavior of fuzzy integrals states that the aggregated result can never be less than the minimum evaluation of all sources and never be higher than the maximum evaluation of all sources. Hence, if the reported global annoyance is lower/higher than the minimum/maximum of the annoyance of all sources, the data record can never be classified correctly.

Luckily, the GA is capable of handling all these inconsistencies in a transparent way, there is no need to filter them out manually. By minimizing the error function, the GA will automatically try to classify the maximum number of data records correctly.

3.2 Learning fuzzy measures

3.2.1 k-additive Choquet integrals

Choquet integrals have a strong affinity with a class of fuzzy measures known as *k-additive measures* [31]. Therefore, it is straightforward to start our modeling attempts with the combination of these measures and the Choquet integral. Before discussing this class of measures, we must first present the alternative representation that is used in their definition, which is based on the *Möbius transform* of a fuzzy measure.

Definition 56 (*Möbius transform* [74]). *The Möbius transform of a set function (not necessarily a fuzzy measure) μ on U is the set function $m : \mathcal{P}(U) \to \mathbb{R}$ defined by*

$$m(A) = \sum_{B \subseteq A} (-1)^{|A \setminus B|} \mu(B) \tag{5.29}$$

for all $A \in \mathcal{P}(U)$.

Definition 57 (*Zeta transform* [31]). *The Zeta transform of a set function m on U is the set function $Z_m : \mathcal{P}(U) \to \mathbb{R}$ defined by*

$$Z_m(A) = \sum_{B \subseteq A} m(B) \tag{5.30}$$

for all $A \in \mathcal{P}(U)$.

The Möbius and the Zeta transform are each others inverse, so when the Zeta transform is applied to the Möbius representation of a set function, the original set function is recovered. However, not every Möbius representation of a set function is a fuzzy measure, but there exist necessary and sufficient conditions as expressed in theorem 3.

Theorem 3. [34] *A set function $m : \mathcal{P}(U) \to \mathbb{R}$ is the Möbius transform of a fuzzy measure μ on U if and only if*

(i) Boundary: $m(\emptyset) = 0$

(ii) Normalization: $\sum_{A \subseteq U} m(A) = 1$

(iii) Monotonicity: $(\forall A \in \mathcal{P}(U))(\forall i \in A)(\sum_{i \in B \subseteq A} m(B) \geq 0)$

Now that it is shown that a fuzzy measure can be represented by its Möbius coefficients, the concept of k-additive (fuzzy) measures can be defined.

Definition 58 (*k-Additive measure* [74]). *Let $k \in \{1, 2, \ldots, n\}$ and $A \in \mathcal{P}(U)$. A fuzzy measure μ on U is called k-additive if its Möbius transform satisfies $m(A) = 0$ whenever $|A| > k$ and there exists at least one subset B of U such that $|B| = k$ and $m(B) \neq 0$.*

Note that *probability measures* (see chapter 2, section 7.2.2) are in fact 1-additive measures. Usually, they are simply called additive measures.

As already stated, the complete specification of a fuzzy measure requires $2^n - 2$ parameters for n criteria. Relying on k-additive measures, this number of parameters reduces to $\sum_{i=1}^{k} \binom{n}{i}$ [30].

As has been shown in [34], there exists a very efficient calculation algorithm for the Choquet integral when based on a k-additive measure. A Choquet integral with respect to a k-additive measure will be shortly referred to as a *k-additive Choquet integral*. A k-additive Choquet integral can be directly written as a function of the Möbius representation m of μ.

$$C_\mu(f) = \sum_{A \subseteq U} m(A) \bigwedge_{i \in A} f(x_i) \ . \tag{5.31}$$

This representation of the Choquet integral has the advantage that is does not require the reordering of the criteria, contrary to the definition given in chapter 2, section 7.2.3.

Let us now return to our annoyance accumulation problem and the optimization of a k-additive Choquet integral model with a GA. An important issue in a GA is the representation of an individual in the population. In the case of a k-additive measure, a representation as a string of real values, one for each Möbius coefficient, seems trivial. But care must be taken that all individuals represent a true fuzzy measure and hence, satisfy all conditions of theorem 3. The boundary condition is automatically fulfilled by definition. The normalization requirement is easy to satisfy by dividing all Möbius coefficients by their sum. Yet, the monotonicity constraint is much harder to realize. In [37] it has been shown that a convex combination of two Möbius representations of fuzzy measures is again a Möbius representation of a fuzzy measure. However, for the noise accumulation modeling with typically a rather high number of sources, it will be difficult to optimize for any k higher than 2. In the case of 2-additive measures, another efficient monotonicity test can be derived as shown in the next theorem.

Theorem 4. *A 2-additive Möbius transform m on a universe* $U = \{u_1, \ldots, u_n\}$ *satisfies the monotonicity constraint,*

$$(\forall A \in \mathcal{P}(U))(\forall i \in A)\left(\sum_{i \in B \subseteq A} m(B) \geq 0\right)$$

if and only if

$$(\forall j \in \{1, 2, \ldots, n\})(m(\{u_j\}) + s_j \geq 0) \tag{5.32}$$

where $S_j = \{T | T \in \mathcal{P}(U) \wedge u_j \in T \wedge |T| = 2 \wedge m(T) < 0\}$ *and* $s_j = \sum_{T \in S_j} m(T)$.

Proof. Let $E_j = \bigcup_{T \in S_j} T$.

1. Necessary. Because m is 2-additive ($m(T) = 0$ for all T with $|T| > 2$), the condition $m(\{u_j\}) + s_j \geq 0$ for all $j \in \{1, 2, \ldots, n\}$ is necessary to fulfill the monotonicity constraint for $A = E_j$ and $i = u_j$.

2. Sufficient.

   (a) For all $K \in S_j$, let $S'_j = S_j \setminus K$, $s'_j = \sum_{A \in S'_j} m(A)$ and $E'_j = \bigcup_{T \in S'_j} T$. From this follows that $E'_j \subset E_j$.

$$\begin{aligned} & K \in S_j && (5.33)\\ \Leftrightarrow\ & m(K) < 0 \quad (\text{definition } S_j) && (5.34)\\ \Leftrightarrow\ & s'_j > s_j && (5.35)\\ \Leftrightarrow\ & m(\{u_j\}) + s'_j > m(\{u_j\}) + s_j && (5.36)\\ \Leftrightarrow\ & m(\{u_j\}) + s'_j > 0 \quad (m(\{u_j\}) + s_j \geq 0) && (5.37) \end{aligned}$$

   This guarantees the monotonicity constraint for $A = E'_j$ and $i = u_j$ because m is 2-additive ($m(T) = 0$ for all T with $|T| > 2$). Applying this reasoning recursively for all elements of S_j shows that the condition $m(\{x_j\}) + s_j \geq 0$ for all $j \in \{1, 2, \ldots, n\}$ is sufficient to fulfill the monotonicity constraint for $\{u_j\} \subseteq A \subset E_j$ and $i = u_j$.

   (b) For all $u_k \notin E_j$, let $K = \{u_j, u_k\}$, $S''_j = S_j \cup K$, $s''_j = \sum_{T \in S''_j} m(T)$ and $E''_j = \bigcup_{T \in S''_j} T$. From this follows that $E_j \subset E''_j$.

$$\begin{aligned} & K \notin S_j \quad (\text{definition } E_j) && (5.38)\\ \Leftrightarrow\ & m(K) \geq 0 \quad (\text{definition } S_j) && (5.39)\\ \Leftrightarrow\ & s''_j > s_j && (5.40)\\ \Leftrightarrow\ & m(\{u_j\}) + s''_j > m(\{u_j\}) + s_j && (5.41)\\ \Leftrightarrow\ & m(\{u_j\}) + s''_j \geq 0 \quad (m(\{u_j\}) + s_j \geq 0) && (5.42) \end{aligned}$$

This guarantees the monotonicity constraint for $A = E_j''$ and $i = u_j$ because m is 2-additive ($m(T) = 0$ for all T with $|T| > 2$). Applying this reasoning recursively for all elements of $U \setminus E_j$ shows that the condition $m(\{u_j\}) + s_j \geq 0$ for all $j \in \{1, 2, \ldots, n\}$ is sufficient to fulfill the monotonicity constraint for $E_j \subset A \subseteq U$ and $i = u_j$.

□

This theorem provides a convenient test to verify that an individual in the population represents a valid 2-additive measure. Besides, when the test for a singleton $\{u_j\}$, $j \in \{1, 2, \ldots, n\}$, fails, the negative contributions to the sum s_j can all be divided by $-s_j/m(\{u_j\})$ to ensure that the test for $\{u_j\}$ passes. It provides a means to adapt "faulty" individuals to correct fuzzy measures that can be used in the k-additive Choquet integral (although this adaptation significantly modifies the information contained in the parents). Also note that the monotonicity is not affected by normalizing the fuzzy measure when the sum of all Möbius coefficients is positive.

By using a string of real values (one for each Möbius coefficient) to represent an individual in combination with the outlined monotonicity check and normalization, the GA only explores meaningful fuzzy measures and is allowed to apply a *uniform crossover* operator and a *self-adaptive mutation* step operator in its search for the optimal 2-additive measure.

It turned out that a 2-additive Choquet integral did not work well for the noise annoyance accumulation modeling. Performance was not much better than can be obtained by a single –constant– source alone. An explanation could be found in the success of the strongest component model which is rather "maxitive" instead of "additive". Therefore, attention is switched to possibility measures and their generalized variations.

3.2.2 Possibilistic measures for the Choquet integral

Although the Choquet integral is easy to express in function of a k-additive measure, in [180] Yager has outlined an algorithm to calculate a Choquet integral based on a (generalized) possibility measure. Recall from chapter 2 that a generalized possibility measure or a *S-decomposable measure* is defined as

$$\mu(A \cup B) = S(\mu(A), \mu(B)) \tag{5.43}$$

with S a t-conorm. When $S = S_M$ the measure reduces to the *possibility measure.* Formula (5.43) makes clear that generalized possibility measures are fully specified by the n fuzzy measure values of the singletons $\mu(\{u_i\})$ for $i \in \{1, 2, \ldots, n\}$. Furthermore, the normalization constraint of a fuzzy measure is always satisfied when at least one of these singleton values is equal to 1, whatever t-conorm S is chosen. For the following, the notational short-hands $e_i = \mu(\{u_i\})$ and $a_i = f(u_i)$ are convenient.

In accordance with [180], the *Choquet integral* will be expressed as

$$C_\mu(f) = w^T b = \sum_{j=1}^{n} w_j \, b_j \tag{5.44}$$

with b the n-dimensional ordered vector whose j^{th} component is the j^{th} largest of the arguments a_i and w the n-dimensional weighting vector such that $w_j = \mu(H_{(j)}) - \mu(H_{(j-1)})$ for all $j \in \{1, 2, \ldots, n\}$ with $H_{(j)}$ the subset of criteria with the j^{th} highest evaluation values and $H_{(0)} = \emptyset$. It is important to note that due to the required ordering both b and w change as the evaluations of the criteria change.

With the above notations and using the generalized possibility measure, the weights can be calculated in function of the fuzzy measure values of the singletons as [180],

$$w_j = S_{i=1}^{j}(e_i) - S_{i=1}^{j-1}(e_i) \tag{5.45}$$

In case of the basic possibility measure where $S = S_M$, this reduces to

$$w_j = \max(e_j - \sum_{i=1}^{j-1} w_i, 0) \tag{5.46}$$

To optimize a Choquet integral model based on a generalized possibility measure with a GA, every fuzzy measure value of a singleton must be represented as part of an individual in the GA population. In the noise annoyance accumulation model, a fuzzy measure value of a singleton $\mu(\{r_s\})$, $s \in \{1, 2, \ldots, S\}$, will be coded as a real-valued gene in the interval $[0, 1]$. An individual then consists of S such genes, one for each annoyance source. In the search process of the GA, a *uniform crossover* and *self-adaptive mutation* step operator have been used [67]. To ensure correct normalization of the generalized possibility measure, it is verified whether at least one of the genes has a value of 1. If this is not the case, a randomly selected gene is set to 1. Alternatively, the genes could be rescaled to make sure that the largest element is 1.

3.2.3 k-maxitive Sugeno integrals

It has been observed that the noise accumulation problem has a strong modeling affection with the maximum operator. In literature, it is known that the *Sugeno integral* fits perfectly with the class of *k-maxitive fuzzy* *measures* [31]. Hence, it is worthwhile to investigate this class of measures and the combination with the Sugeno integral in more detail. We start with an introduction to these measures, based on the *possibilistic Möbius transform* representation.

Definition 59 (*Possibilistic Möbius transform* [118]). *The possibilistic Möbius transform of a set function (not necessarily a fuzzy measure) μ on U is the set function $m^\vee : \mathcal{P}(U) \to [0,1]$ defined by*

$$m^\vee(A) = \begin{cases} \mu(A) & \text{if } \mu(A) > \max_{B \subset A} \mu(B) \\ 0 & \text{otherwise.} \end{cases} \tag{5.47}$$

for all $A \in \mathcal{P}(U)$.

Definition 60 (*Possibilistic Zeta transform* [118]). *The possibilistic Zeta transform of a set function m on U is the set function $Z_m^\vee : \mathcal{P}(U) \to [0,1]$ defined by*

$$Z_m^\vee(A) = \max_{B \subseteq A} m^\vee(B) \tag{5.48}$$

for all $A \in \mathcal{P}(U)$.

The possibilisitic Möbius and Zeta transforms are each others inverse, so when the possibilistic Zeta transform is applied to $m^\vee$ the original set function μ is recovered. However, not every set function $m^\vee$ is the possibilistic Möbius representation of a fuzzy measure, but there exist necessary and sufficient conditions as shown in theorem 5.

Theorem 5. [45] *A set function $m^\vee : \mathcal{P}(U) \to [0,1]$ is the possibilistic Möbius transform of a fuzzy measure μ on U if and only if*

(i) Boundary condition: $m^\vee(\emptyset) = 0$

(ii) Normalization: $\max_{A \subseteq X} m^\vee(A) = 1$

(iii) Monotonicity: $(\forall A \in \mathcal{P}(U))(m^\vee(A) \leq \max_{B \subset A} m^\vee(B) \Rightarrow m^\vee(A) = 0)$

The special class of k-maxitive measures can easily be defined using the possibilistic Möbius representation.

Definition 61 (*k-Maxitive measure* [118]). *Let $k \in \{1, 2, \ldots, n\}$ and $A \in \mathcal{P}(U)$. A fuzzy measure μ on U is called k-maxitive if its possibilistic Möbius transform satisfies $m^\vee(A) = 0$ whenever $|A| > k$ and there exists at least one subset B of U such that $|B| = k$ and $m^\vee(B) \neq 0$.*

Note that *possibility measures* are in fact 1-maxitive measures.

The Sugeno integral w.r.t. a k-maxitive measure will be shortly referred to as a *k-maxitive Sugeno integral*. A k-maxitive Sugeno integral $S_\mu(f)$ can be written as a function of the possibilistic Möbius representation $m^\vee$ of μ [113].

$$S_\mu(f) = \max_{A\subseteq U} \min\left(m^\vee(A), \bigwedge_{i\in A} f(u_i)\right) . \tag{5.49}$$

It is important to note that (5.49) does not require the reordering of the arguments.

Let us now consider the optimization of a k-maxitive measure with a GA. Because of the alternative representation of a fuzzy measure, the number of parameters is $\sum_{i=1}^{k}\binom{n}{i}$ [30], as in the case of k-additive measures. Although this number is considerably lower than the $2^n - 2$ parameters which are required for a full specification of a fuzzy measure, for high n this number remains quite high. Therefore, the optimization of a k-maxitive measure for the noise annoyance accumulation model will be limited to $k = 2$.

A genetic algorithm makes a distinction between *genotype*, the internal representation of an individual in the genetic algorithm, and its *phenotype*, how the individual looks like in its external context (see appendix A). A *genome* represents the genotype of a k-maxitive measure. For each $A \in \mathcal{P}(U)$ the genome contains a single real-valued gene in the interval $[0, 1]$. For 2-maxitive measures, there are genes g_r corresponding to a singleton $\{u_r\}$ and genes g_{pq} corresponding to a doubleton $\{u_p, u_q\}$ with $p \neq q$, and $p, q, r \in \{1, \ldots, n\}$. The phenotype of the maxitive measure is calculated using the following formulas.

$$m^\vee(\{u_r\}) = g_r \tag{5.50}$$

$$m^\vee(\{u_p, u_q\}) = \begin{cases} \bar{m} + (1 - \bar{m})g_{pq} & \text{if } g_{pq} \neq 0 \\ 0 & \text{if } g_{pq} = 0 \end{cases} \tag{5.51}$$

where $\bar{m} = \max\left(m^\vee(\{u_p\}), m^\vee(\{u_q\})\right)$. By using this representation of an individual, the monotonicity constraint for possibilistic Möbius coefficients is always satisfied. To ensure the normalization requirement, the phenotype is divided by the maximum of all $m^\vee$ values. The normalized phenotype is then coded back into the genotype. This guarantees only normalized individuals in the population, which raises the chances for sensible exchanges of genes. Using the above procedure, the GA only explores meaningful fuzzy measures that obey the conditions of theorem 5. Furthermore, the GA uses a *uniform crossover* and *self-adaptive mutation* operator [67].

3.3 Other approaches for learning fuzzy measures

In the MCDM approach to model noise annoyance accumulation, the fuzzy measure has been identified with a GA. However, there are also other methods for this identification process. In [135] Roubens has introduced the TOMASO (Technique for Ordinal Multi-Attribute Sorting and Ordering) method (see also [119] for some extensions). The TOMASO approach calculates a classifying *k-additive Choquet integral* (with k a system parameter). The constraints imposed by the monotonicity and the data sample are linearized and the Möbius coefficients are determined by solving a linear program that minimizes an error function. Yet, if the quality of the data set is bad, the linear program has no solution, in which case the fuzzy measure has to be identified using a quadratic program. In [126] the identification of a fuzzy measure is expressed as a quadratic problem using fractal and cardinality transformations.

However, these methods have some disadvantages for our noise annoyance accumulation modeling.

- As the annoyance aggregation is rather maxitive than additive, a k-additive representation of the optimal fuzzy measure requires a high k, especially when the number of sources is high. Because of this, the number of coefficients can be very high, which poses representation problems in computer implementations.

- The systems of inequalities have difficulties to deal with data inconsistencies such as *doubt* and *reversed preference*. Unfortunately these inconsistencies occur very often in noise annoyance data from *social surveys*.

In [119] the TOMASO method is applied to a small and consistent sample of the noise annoyance accumulation problem.

4 Other fuzzy accumulation models

Besides the fuzzy rule base and the MCDM approaches that have been studied in this chapter, other methodologies may be used to identify classification models.

Artificial *neural networks* (ANN) have a long history as classifier systems. A neural network tries to imitate the human brain in order to simulate the learning behavior of humans, and is mainly used for data prediction, classification and clustering. Because of their biologically inspired underpinnings and their inherent tolerance for imprecision, they are also recognized as an integral part of the technologies that are collectively referred to as *soft computing* techniques. In fact, the combination of *fuzzy set theory* and *neural networks* has recently given rise to the fruitful field of *neuro-fuzzy computing* [87]. In [47] a neuro-fuzzy classifier for annoyance accumulation has been constructed and various network topologies have been compared. A disadvantage of neural networks in general, is the fact that they are black box models. The knowledge of the neural network is hidden in the interconnections between the neurons and the weights attached to these interconnections. However, these weights do not have a clear semantical interpretation, contrary to a fuzzy measure.

In [33], Cao-Van has introduced the OSDL (Ordinal Stochastic Dominance Learner) method. This ordered *classification* algorithm uses the available data set to extract a weak stochastic dominance relation based on the cumulative distribution functions. This process requires a few iterations over the complete data set in order to optimize a system parameter, and one iteration over the whole data set to classify a new data record. Therefore, the algorithm does not scale very well for large data sets.

5 Related applications

In this chapter, the experienced annoyance levels of several sources have been aggregated into a single, global annoyance level. But this aggregation does not need to stop there. The evaluations of the global annoyance caused by noise and odor, and possibly also other factors such as a general feeling of safety in the neighborhood, leisure possibilities, health conditions,... can be aggregated into a global "*quality of life*" variable. Because of the many similarities with the accumulation of noise annoyance, the presented techniques can also be useful for this aggregation.

An important complication that typically arises in this context, is the handling of bipolar scales. A *bipolar scale* is a scale which allows positive and negative evaluations (with a neutral evaluation in between), e.g. the quality of life is "good" or the quality of life is "very bad". Fortunately, it is possible to extend the notion of a fuzzy measure (and the associated fuzzy integrals) to bipolar scales, resulting in *bipolar fuzzy measures*, *bipolar Choquet integrals* and *bipolar Sugeno integrals* [77].

CHAPTER 6

Modeling results

> No one knows what power lies yet undeveloped in that wiry system of mine.
>
> *Ada Lovelace (1815-52)*
> *First computer programmer*

1 INTRODUCTION

So far, we have described the goals (and associated challenges) of this work in the domain of noise annoyance modeling (chapter 1) and the mathematical tools at our disposal (chapter 2). This has enabled us to construct an accurate representation of the central annoyance concept (chapter 3) and to develop a framework that is capable of modeling noise annoyance from the state of the environment to the perception of accumulated noise annoyance (chapters 4 and 5). Finally, the time has come to fill the framework with expert knowledge, including hypotheses that are under investigation, and to feed the system with data. To optimize the weights of the rules and to validate the reasoning processes of the framework, a data set containing the reported noise annoyance can be used.

Two data sets obtained from *social surveys* have been acquired for this purpose. The first data set resulted from an investigation conducted in Austria.[1] The second one was collected in Flanders (Belgium). In this chapter, these surveys will first be described in more detail. The full text of both surveys in the original language (German and Dutch respectively) can be found in appendix C. After an introduction to the available data, some results obtained with the framework (after optimization) are dis-

[1] Thanks to Prof. Peter Lercher for providing this data set.

cussed. Several factors identified in the general conceptual noise annoyance model as presented in chapter 4, section 2.1, have been investigated. Note that most of the results have already been published in international journals [18] [25] [26] and conferences [17] [22] [23] [24] [15] [158] [159] [160] [163] and [164].

Remark that all results have been obtained while the proposed framework was under continuous development and modification. Changes to the modeling framework were driven by the observations made during the research on various factors influencing the experience of noise annoyance. Therefore, some results are based on earlier incarnations of the framework. In the text, it will be clearly stated when such older techniques have been used to produce the described results.

2 Surveys

2.1 Austrian survey

2.1.1 Overview

A representative phone *survey* was conducted within an ongoing environmental health impact assessment of a new rail track in the Austrian part of the Alps near Innsbruck, which covers an area of about 40 km. This mainly rural area consists of small towns and villages with a mix of industrial, small business and agricultural activities. The primary noise sources are road and railway traffic. In total, 2007 inhabitants were interviewed. The standardized interview (typical length 20 minutes) covered socio-demographic data, housing, satisfaction with public services and the environment, general annoyance, interference, coping with noise and health. The overall response was 83 %. Subjects were selected using a Geographical Information System (GIS). Initially, 1500 inhabitants (aged 18 to 75) were sampled at random from the whole Inn-valley area (sample 1). This sample was enriched by another random sampling of 500 residents living within 150 m of the existing railway track and the highway, or within 50 m of local roads (sample 2) to guarantee a sufficient number of people with higher exposure to noise and vibrations. Noise exposure was assessed first by modeling (Soundplan) according to Austrian guidelines (ÖAL Nr 28+30, ÖNORM S 5011). Afterwards the modeled data has been calibrated and corrected based on the recordings of 31 measuring stations. Based on both data sources approximate day-night levels (L_{dn}) were calculated for each respondent to simplify comparison with typical dose-response data.

For a more detailed description of the Austrian data set, the reader is referred to [109] and appendix C for the full German text of the survey.

2.1.2 Annoyance questions

For our purposes, the two most important questions are those of which the answer can be used as a modeling target by our noise annoyance advisor: the questions on noise annoyance caused by road traffic (question 15) and railway traffic (question 17). The wording of the questions is in overall agreement with the international guidelines proposed by the ICBEN team in [65].

Because there was no question on total, accumulated annoyance, this data set can only be used to validate the model for road and railway traffic annoyance specifically.

2.1.3 Representing the annoyance terms

The questionnaire used a four point scale for the annoyance questions: “überhaupt nicht gestört”, “gering oder teilweise gestört”, “mittelmäßig gestört” and “stark oder erheblich gestört”. For the convenience of the reader, table 6.1 shows how these terms can be approximately translated in English using the fuzzy translation tool that has been developed in chapter 3, section 4. When discussing results, the bold English terms will be used instead of the German terms to refer to the four point scale of the Austrian data set.

Table 6.1: Translations of German modifiers into English (including the similarity degree of the terms).

German	English
überhaupt nicht	**not at all** (0.93)
teilweise	**fairly** (0.74), partially (0.72), somewhat (0.70)
mittelmäßig	**moderately** (0.74)
stark	**strongly** (0.76), highly (0.73), very (0.73)
erheblich	**strongly** (0.79), highly (0.72), very (0.72)

The German modifier “gering” was not included in the International Annoyance Scaling Study [65], so no reliable data is available to represent this term. Therefore, we opted to stick to the term “teilweise” for the second label. A closer look at the terms “stark” and “erheblich” revealed that they are quite similar in meaning. Configured to "translate" from German into German, the fuzzy translation tool reports a similarity of 0.72 between them. Their high similarity was in fact already noticeable from the similar English translations of both. Therefore, only the term "erheblich" has been selected as the fourth annoyance label.

Unfortunately, the labels of the four point scale that have been used in the survey do not correspond well with the German terms that were proposed by the ICBEN team ("überhaupt nicht", "teilweise", "beträchtlich" and "total") [65]. Although the first two labels of the categories do match, the similarity between "beträchtlich"–"mittelmäßig" and "total"–"erheblich" was reported as low as 0.21 and 0.27 respectively by the translation tool. A rather poor match.

The representation of the German modifiers to be used in the noise annoyance advisor has been constructed with the fixed overlap method as discussed in chapter 3, section 3.3.3. However, after summation of the individual curves, a symmetric Gaussian shape has been fitted, $\text{AGAUSS}_E(.;\mu,\sigma,\sigma)$, instead of an asymmetric Gaussian shape as preferred. The resulting fuzzy sets are shown in figure 6.1.

Because of the poor choice of terms compared with the International guidelines, the fuzzy sets of the second and third label are very close and do overlap a lot. They have been slightly modified. The representation of "mittelmäßig" was made a bit more wide and both terms, "teilweise" and "mittelmäßig", were moved a little further from each other. Justification of these minor adaptations can be found in the experiment and observations of Rohrmann: people tend to divide a scale equidistantly (see chapter 3, section 1).

2.2 Flemish survey

2.2.1 Overview

A *social survey* was conducted with 3200 people in Flanders, Belgium. The general topic of the survey was the influence of odor, noise and too much light on the living environment. The survey was presented as such to the subjects. Selection of subjects was done in two stages. In a first stage, households were randomly selected. The member of each selected household aged above 16 that had its birthday coming up first, was contacted by telephone, convincing him or her to participate in the study. This process was repeated, making sure that the sample was representative of the demographic factors age, gender, and province. The selected subjects were then sent the questionnaire by mail. They were reminded to participate in the

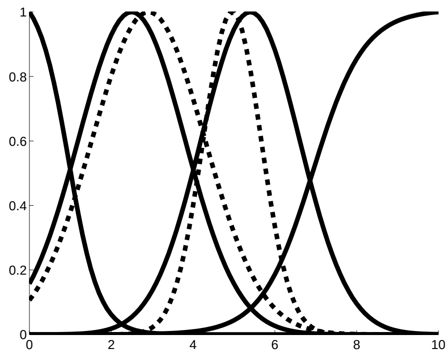

Figure 6.1: Representation of the four German annoyance terms ("überhaupt nicht", "teilweise", "mittelmäßig", "erheblich"). The original curves for "teilweise" and "mittelmäßig" are dashed.

survey after 3 weeks by telephone, if they did not send the questionnaire back promptly. Finally, 64 % of the questionnaires sent out were received.

The survey was part of the Investigation of the Environmental Living Quality performed on behalf of the Flemish Environmental Administration (AMINAL) by Deloitte & Touche and M.A.S. See appendix C for the full Dutch text of the survey.

The respondents who had freely given their address, were located on a GIS (1749 respondents could be localized successfully). Road and railway traffic noise levels were calculated for these respondent's home. Exact railway traffic data and average noise emission of each type of train, were used. For road traffic on major roads, simulated traffic intensity validated by results of several hundreds of counting stations, were used. For the local roads, an estimate of surface traffic for each geographic zone was made. The car and truck emission is taken from the recent revision of the Dutch guideline [4] and propagation is calculated according to ISO 9613. Additionally, distances to the nearest road and railway, and land use data, were added, based on maps and associated data available in the GIS.

2.2.2 Annoyance questions

The most important questions are the general noise annoyance question (I.3) and the questions concerning noise annoyance by particular sources (II.1, III.1 and IV.1). The general noise annoyance question appears on the first page of the questionnaire and is preceded by two questions only [80]. The first one inquires about the general appreciation of the living environment. The second one asks whether the subject would stimulate a friend to live in this neighborhood and why (not). The general noise annoyance question then appears in a group of three questions concerning noise, odor and light in that order. The formulation of the question is in overall agreement with the ICBEN recommendation put forward in [65]. The subjects are asked to answer this question using a five point categorical scale. The question concerning noise annoyance by particular sources follows on the third page, the second page being devoted to coping, change in situation, and description of the living environment. With this arrangement, subjects do not see the detailed list while answering the total annoyance question, unless they turn back to the first page after reading the third one. A small pre-study learned that the majority of subjects tends to fill in the written questionnaire from beginning to end without ever returning to previously answered questions. The detailed annoyance questions show a list of sources: road traffic, air traffic, railway traffic, etc. For reasons beyond our control, the list contains a few very specific sources that are not expected to cause much annoyance. At the end of the list of named sources of noise annoyance, the possibility was given to the subjects to add additional sources also rating them on a five point annoyance scale.

Although this data set contains rather limited useful information for the modeling of a specific type of noise source, the combination with the data extracted from a GIS, allows to investigate aspects not available in the Austrian data set, such as land use variables. However, this data set will be primarily used for the modeling of accumulated noise annoyance and for testing independence of language and region.

2.2.3 Representing the annoyance terms

The five point scale used in the Flemish survey was labeled “helemaal niet gehinderd”, “een beetje gehinderd”, “tamelijk gehinderd”, “ernstig gehinderd” and “extreem gehinderd”. For the convenience of the reader, the best English translations of these Dutch linguistic terms as calculated by the fuzzy translation tool, are shown in table 6.2. When discussing results, the bold English terms will be used to refer to the five point scale of the Flemish survey.

The representation of the five Dutch terms has been constructed with the fixed degree of overlap method as described in chapter 3, section 3.3.3. The results of this process, fitted with an asymmetric Gaussian curve, $\text{AGAUSS}_E(.;\mu,\sigma,\delta)$, are shown in figure 6.2. In fact, the choice of terms does not completely correspond to the scale proposed by the ICBEN team: “helemaal niet”, “een beetje”, “matig”, “erg”, “extreem”. However, the sim-

Table 6.2: Translations of Dutch modifiers into English (including the similarity degree of the terms).

Dutch	English
helemaal niet	**not at all** (0.93)
een beetje	**slightly** (0.85)
tamelijk	**fairly** (0.85), somewhat (0.83)
ernstig	**strongly** (0.87), highly (0.80), very (0.73)
extreem	**extremely** (0.70)

ilarity degree between the proposed terms and those that have been used, “tamelijk”–“matig” and “ernstig”–“erg” turned out to be quite high, 0.71 and 0.73 respectively. Hence, no modifications to the modeled terms were necessary.

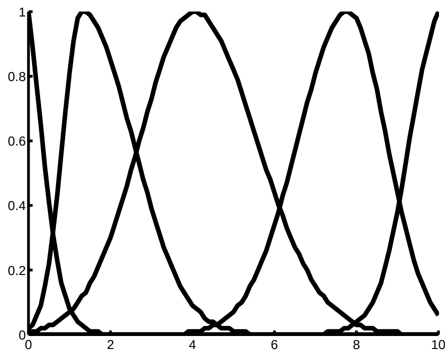

Figure 6.2: Representation of the five Dutch annoyance terms (“helemaal niet”, “een beetje”, “tamelijk”, “ernstig”, “extreem”).

3 Traffic noise annoyance advisor

3.1 Introduction

In this section, the application of the *noise annoyance advisor* framework for the modeling of road and railway traffic noise annoyance, will be investigated in detail.

First, global best performance results are given. Once for the crisp optimization scheme (see chapter 4, section 2.4–2.5) on the Austrian data set, and once for the fuzzy optimization scheme on the Flemish data set. Thereafter, various aspects of the framework that have already been discussed theoretically, will be verified in practice (inference scheme, generality). Finally, the knowledge in the rule base is analyzed more thoroughly. Interactions between variables, and the investigated rule hypotheses are discussed.

All rules included in the noise annoyance advisor were formulated by experts in the field of acoustics, based on the knowledge and hypotheses available in literature. They are an instantiation of the conceptual annoyance model described in chapter 4, section 2.1.

Unless otherwise stated, all results have been calculated with the (faster) possibility qualifying rule inference scheme (see chapter 4, section 5).

3.2 Analyzing crisp optimized results

Focus is first on the results of the noise annoyance advisor after optimization for the modeling of road traffic noise annoyance and railway traffic noise annoyance, based on the Austrian data set. The model was optimized with the "*crisp quality measure*" and the associated crisp error measure (see chapter 4, section 2.4–2.5). This means that the output of the model is a single linguistic term, the term from the term set of the survey which best approximates the annoyance possibility distribution as calculated by the inference engine. For the linguistic approximation, the upper approximate descriptor was used (see chapter 4, section 2.2.4). The single output term is useful to compare the result with other crisp models, such as linear regression techniques. Because the objective is a high weighted percentage of correctly predicted noise annoyance responses, the α parameter was chosen high. This forces the model to few misses at the expense of lower specificity. The results presented here have already been reported in [27].

If no knowledge is available on the subjects taking part in the survey, the (weighted) number of correct predictions is 25 % because the Austrian data set uses an annoyance scale with four linguistic terms. Traditionally a linear relation between reported level of annoyance and DNL is often assumed. If such a linear relation is fitted to the noise annoyance data at hand, 30.2 % of the responses are predicted correctly for railway noise and 29.5 % for road noise, assuming a uniform distribution of the annoyance labels on a numerical scale. This means that DNL explains only a very small part of individual annoyance variations, when used in a traditional way. In fact, this corresponds well to the observation in literature stating that noise exposure can only explain about 30 % of the *noise annoyance* [144]. Note that the definition of (weighted) correct prediction includes all four levels of annoyance: “not at all”, “fairly”, “moderately” and “strongly”.

When variables reported by the subjects of a noise annoyance survey are included in the model one must be very careful when analyzing performance. Indeed, if an answer includes a certain degree of subjectivity, one may as well be sampling an underlying variable also contributing to the answer on the annoyance question. Therefore, a distinction is made between variables that can be measured without the cooperation of the subject and variables that require information that can only be provided by the subject. The model could be extended with more knowledge in order to model these variables “from scratch” (see section 3.6).

Table 6.3: Crisp optimization performance on the Austrian data set.

Model	Road	Railway
Linear regression on DNL	29.5 %	30.2 %
Fuzzy advisor / no subjective input	41.1 %	43.8 %
Multivariate / no subjective input	36.8 %	37.0 %
Fuzzy advisor / subjective input	43.0 %	45.3 %
Multivariate / subjective input	40.0 %	38.6 %

Table 6.3 summarizes results. The label “no subjective input” refers to the situation where all input to the model can be measured objectively. When the label “subjective input” is used, additional rules rely on data obtained by inquiring the subjects (e.g. sensitivity to noise). Also in this case, variables that correlate in a trivial way to the reported noise annoyance (e.g. speech disturbance) are carefully omitted. The table also includes the results of a multivariate linear regression based on the same input variables. The fuzzy *noise annoyance advisor* always performs better than the regression models. Additionally, the interpretability of the linguistic rules is much more straightforward. This is a very important benefit of the fuzzy approach over blind techniques, because it allows to really gain insight in the underlying relations between the variables. It also allows the incorporation of information from literature.

In table 6.4 an overview is given of all rules included in the model. The table also lists the definitions of the antecedents and the consequents used in the rules. See chapter 2, section 2.3 for the definition of the membership functions that appear in the table. These membership functions have not been optimized they were defined by experts based on available knowledge and intuition. Most of the universes and the associated linguistic terms are defined in a rather ad hoc way. The consequences on the annoyance scale have not been limited to the linguistic terms that were used in the survey, or that are available in the International Annoyance Scaling Study. Although this could have been done, it would have restricted the expressiveness of the rules. There is not necessarily a perfect match between the contents of the model and the linguistic expression of the rule, which is only for convenience. However, it is important that the correct fuzzy set representation of the linguistic terms in the survey is used for the linguistic approximation of the fuzzy inference result. Note that the same definitions of terms have also been used on the sensitivity scale.

Table 6.4: Overview of fuzzy rules for the Austrian data set. Used abbreviations: “at least” (at l.).

Nr	Label	Definition	Label	Definition
	IF L_{dn} noise exposure (dB$_\mathrm{A}$)		THEN annoyance	
A1	very low	$\overline{\text{LIN}}(40, 50)$	not at all	$\text{norm}(\overline{S_E}(2.59, 2.70))$
A2	low	$\text{TRI}(40, 50, 60)$	fairly	$\text{AGAUSS}_E(2.5, 1.3, 1.3)$
A3	high	$\text{TRI}(50, 60, 70)$	moderately	$\text{AGAUSS}_E(5.4, 1.2, 1.2)$
A4	very high	$\text{LIN}(60, 80)$	strongly	$\text{norm}(S_E(11.10, 1.60))$
	IF distance to source (m)		THEN annoyance	
A5	close	$\overline{\text{LIN}}(0, 390)$	at l. somewhat	$S(0, 4)$
A6	far	$\text{LIN}(1050, 1950)$	not high	$\overline{S}(5, 10)$
	IF living room window faces		THEN annoyance	
A7	source	Enum(road/rail)	high	$S(2, 8)$
A8	quiet	Enum(quiet)	not very high	$\overline{S}(8, 10)$
	IF bedroom window faces		THEN annoyance	
A9	source	Enum(road/rail)	high	$S(2, 8)$
A10	quiet	Enum(quiet)	not very high	$\overline{S}(8, 10)$
	IF $L_{\mathrm{dn,rail}} - L_{\mathrm{dn,road}}$ (dB)		THEN annoyance	
A11	low	$\overline{\text{LIN}}(3, 6)$	not high	$\overline{S}(4, 7)$
	IF L_{dn} masker (dB)		THEN annoyance	
A12	high	$S(48, 62)$	not very high	$\overline{S}(7, 9)$
	IF distance to masker (m)		THEN annoyance	
A13	close	$\overline{S}(0, 300)$	not very high	$\overline{S}(8, 9)$
	IF living room window faces		THEN annoyance	
A14	masker	Enum(–/road)	not very high	$\overline{S}(8, 10)$
	IF bedroom window faces		THEN annoyance	
A15	masker	Enum(–/road)	not very high	$\overline{S}(8, 10)$

Table 6.4 (continued)

Nr	Label	Definition	Label	Definition
	If sensitivity to noise		Then annoyance	
A16	strongly	$\mathrm{norm}(S_E(11.10, 1.60))$	at l. somewhat	$\mathrm{norm}(S_E(2.59, 2.70))$
A17	not at all	$\mathrm{norm}(\overline{S_E}(2.59, 2.70))$	not strongly	$\mathrm{norm}(\overline{S_E}(11.10, 1.60))$
	If context elasticity		Then annoyance	
A18	high	$S(7, 10)$	below average	$\overline{S}(4, 8)$
A19	low	$\overline{S}(2, 6)$	at l. somewhat	$S(1, 5)$
	If health		Then annoyance	
A20	very good	$S(7, 10)$	not high	$\overline{S}(7, 9)$
A21	poor	$\overline{S}(2, 6)$	at l. somewhat	$S(1, 5)$
	If age (years)		Then annoyance	
A22	young	$\overline{\mathrm{Lin}}(20, 30)$	below average	$\overline{S}(4, 10)$
A23	middle	$\mathrm{Trap}(20, 30, 50, 60)$	at l. somewhat	$S(0, 6)$
A24	old	$\mathrm{Lin}(50, 60)$	below average	$\overline{S}(4, 10)$
	If gender		Then annoyance	
A25	male	Enum(1,0)	above average	$S(0, 4)$
A26	female	Enum(0,1)	at l. somewhat	$\mathrm{norm}(S_E(2.59, 2.70))$
	If nr of children		Then annoyance	
A27	none	$\overline{\mathrm{Lin}}(0, 2)$	not high	$\overline{S}(2, 10)$
A28	few	$\mathrm{Tri}(0, 1, 4)$	high	$S(3, 9)$
A29	many	$\mathrm{Lin}(2, 5)$	not high	$\overline{S}(3, 9)$
	If crowding		Then annoyance	
A30	few	$\overline{\mathrm{Lin}}(1, 4)$	below moderate	$\overline{S}(2, 8)$
A31	many	$\mathrm{Lin}(1, 8)$	high	$S(4, 10)$

3.3 Analyzing fuzzy optimized results

Turning our attention to the Flemish data set for the modeling of road traffic annoyance, the achieved results will be used to illustrate the effect of the parameter α in the fuzzy quality measure approach. These results have already been reported in [26].

With the "*fuzzy quality measure*" and the associated error measure (see chapter 4, section 2.4–2.5), the fuzziness and the uncertainty of the annoyance outcome is fully exploited. The linguistic approximation from the annoyance possibility distribution to each of the linguistic terms from the survey, was performed with the "lower approximate descriptor" (see chapter 4, section 2.2.4). Note that the Flemish data set distinguishes five linguistic annoyance terms, "not at all", "slightly", "fairly", "strongly" and "extremely". Recall from chapter 4, section 2.5 that the parameter α can be used to obtain a model that is not incorrect (in a fuzzy sense) but rather non-specific (high α) or is usually specific but at the price of more misses (low α). The effect of the parameter α can be seen on figure 6.3.

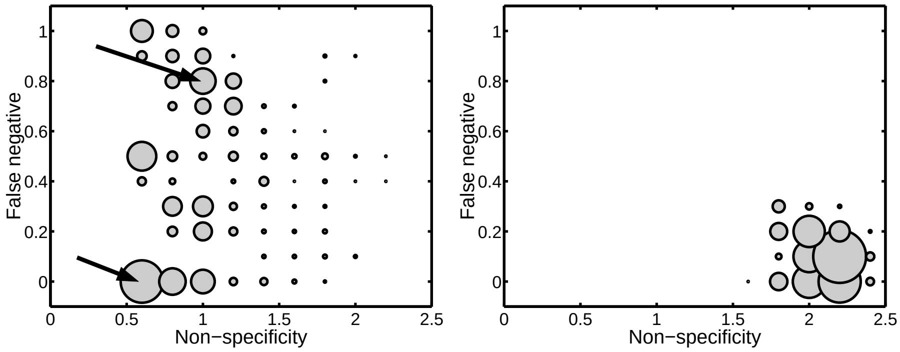

Figure 6.3: Distribution of the subjects over a false negative versus non-specificity plane for a model tuned with $\alpha = 0.75$ (left) and $\alpha = 0.99$ (right). The area of the bubbles is proportional to the number of subjects.

Table 6.5: Percentage of subjects responding different noise annoyance in two of the clusters from the left figure 6.3.

Label	Population	High FN	No FN
not at all	39 %	3 %	94 %
slightly	31 %	11 %	0 %
fairly	17 %	69 %	0 %
strongly	11 %	17 %	0 %
extremely	2 %	0 %	6 %
Nr of subjects	2472	379	890

The figure on the left shows the results of a model that is more precise, but often incorrect. The right figure shows the results of a model that is more fuzzy (has on the average more uncertainty in its output) but less often excludes the label chosen by the subject from its prediction. The area of the bubbles in these figures is proportional to the number of subjects in each category formed by a combination of *non-specificity* and *false negative*. To illustrate more clearly the effect of tuning, the two clusters emerging in the left figure are further analyzed. In table 6.5 the percentage of respondents in each of the five annoyance categories is given for the cluster with approximately zero false negative ("no FN" cluster) and for the cluster with moderate non-specificity and rather high false negative ("high FN" cluster). A combination of low non-specificity and no false negative, is obtained only when predicting no annoyance at all or extreme annoyance. High false negative is more often found in combination with non-specificity when predicting the middle noise annoyance categories. This result is not unexpected. Also for the human expert it is easier to be specific when predicting the extremes of the annoyance scale, while it is rather difficult to differentiate situations that can go either way.

The road traffic annoyance model that has been tuned here, included rules on DNL, distance to roads, urbanization degree, reported traffic density, household size, age and gender (see table 6.6).

Table 6.6: Overview of fuzzy rules for the Flemish data set. Used abbreviations: "at least" (at l.).

Nr	Label	Definition	Label	Definition
	IF L_{dn} noise exposure ($\mathrm{dB_A}$)		THEN annoyance	
F1	very low	$\overline{\textsc{Lin}}(52.5, 60)$	not at all	norm($\overline{S_E}(1.05, 3.78)$)
F2	low	$\textsc{Tri}(52.5, 57.5, 65)$	slightly	$\textsc{AGauss}_E(1.29, 0.46, 1.25)$
F3	moderate	$\textsc{Tri}(57.5, 65, 70)$	moderately	$\textsc{AGauss}_E(4.04, 1.32, 1.53)$
F4	high	$\textsc{Tri}(65, 70, 75)$	very	$\textsc{AGauss}_E(7.80, 1.22, 0.94)$
F5	very high	$\textsc{Lin}(70, 75)$	extreme	norm($S_E(25.98, 2.75)$)
	IF distance to highway (m)		THEN annoyance	
F6	close	$\textsc{Lin}(500, 1500)$	high	$S(5, 7.5)$
F7	far	$\overline{\textsc{Lin}}(500, 1500)$	not high	$\overline{S}(3.5, 7.5)$
	IF dist. to main road (m)		THEN annoyance	
F8	close	$\textsc{Lin}(200, 600)$	high	$S(5, 7.5)$
F9	far	$\overline{\textsc{Lin}}(200, 600)$	not high	$\overline{S}(3.5, 7.5)$
	IF dist. to through road (m)		THEN annoyance	
F10	close	$\textsc{Lin}(60, 250)$	high	$S(5, 7.5)$
F11	far	$\overline{\textsc{Lin}}(60, 250)$	not high	$\overline{S}(3.5, 7.5)$
	IF age (years)		THEN annoyance	
F12	young	$\overline{\textsc{Lin}}(20, 30)$	below average	$\overline{S}(4, 10)$
F13	middle	$\textsc{Trap}(20, 30, 50, 60)$	at l. somewhat	$S(0, 6)$
F14	old	$\textsc{Lin}(50, 60)$	below average	$\overline{S}(4, 10)$
	IF gender		THEN annoyance	
F15	male	Enum(1,0)	above average	$S(0, 4)$
F16	female	Enum(0,1)	at l. somewhat	norm($S_E(2.59, 2.70)$)
	IF size of household		THEN annoyance	
F17	small	$\overline{\textsc{Lin}}(1, 3)$	not high	$\overline{S}(2, 10)$
F18	middle	$\textsc{Tri}(1, 3, 5)$	high	$S(3, 9)$

Table 6.6 (continued)

Nr	Label	Definition	Label	Definition
F19	big	LIN(3, 5)	not high	$\overline{S}(3, 9)$
	IF urbanization		THEN annoyance	
F20	country	Enum(0,0,0,1)	low	$\overline{S}(1, 8, 5.8)$
F21	suburb	Enum(0,0,1,0)	below mod.	$\overline{S}(2.2, 6.6)$
F22	city	Enum(0,1,0,0)	above mod.	$S(2.2, 7)$
F23	center	Enum(1,0,0,0)	above mod.	$S(3, 6.2)$
	IF traffic amount		THEN annoyance	
F24	very much	Enum(1,0,0,0,0)	high	$\overline{S}(5, 6.6)$
F25	much	Enum(0,1,0,0,0)	above mod.	$\overline{S}(3, 5)$
F26	few	Enum(0,0,0,1,0)	below mod.	$\overline{S}(3, 4.5)$
F27	very few	Enum(0,0,0,0,1)	not high	$\overline{S}(2, 3.5)$

3.4 Analyzing inference scheme impact

It has been stated in chapter 4, section 5, that the execution speed of the proposed framework with *certainty qualifying fuzzy rules* is rather low for practical purposes. Especially when the model is under optimization and a large number of model evaluations are required by the GA. Therefore, the inference scheme of the fuzzy rules was switched to the much faster Mamdani controller algorithm for *possibility qualifying fuzzy rules*. The impact of this change is investigated here. The obtained results have already been presented in [165].

The *noise annoyance advisor* was configured with the crisp optimization measures, using the upper approximate descriptor for linguistic approximation to the single crisp term that results as output. It was optimized against the Austrian data set and included the following 20 rules in its rule base (see table 6.4): exposure (A1)–(A4), distance to source (A5)–(A6), living room and bedroom windows facing side (A7)–(A10), masking (A11)–(A15), sensitivity to noise (A16)–(A17) and age (A23)–(A25).

A performance comparison was made between the use of the certainty qualifying rule inference scheme (with the Kleene-Dienes implicator) and the possibility qualifying rule inference scheme (with the minimum t-norm) after optimization of the model. The rules itself were not reformulated or modified, except for the modifications to the rule consequents due to the attached (and optimized) certainty degrees.

The achieved (crisp) performance with the Kleene-Dienes implicator was 40.8 % (weighted) correct predictions and 40.0 % with the minimum t-norm. So although the certainty qualifying rules perform slightly better, the difference is only very small. Yet, the average gain in speed was a factor 5 (6.98 ms versus 1.49 ms). The Kleene-Dienes inference scheme with the certainty degrees of the rules applied to the rule result (instead of the rule consequents) was a factor 3 faster (2.49 ms), giving the same prediction performance. Apparently, the optimization process compensates the certainty degrees attached to possibility qualifying rules versus the certainty degrees attached to certainty qualifying rules. However, it is important to remark that the use of possibility qualifying rules loses the causality relation explicitly expressed by the implicator used in certainty qualifying rules. Hence, the possibility qualifying inference scheme can not be used to investigate the direction of causality between the variables in the rules.

3.5 Analyzing the generality of the model

The knowledge incorporated in the *noise annoyance advisor* is not extracted from data but proposed, as a kind of hypotheses by the experts, based on literature. Tuning involves only modifying the certainty degree of each rule. Nevertheless overfitting on a particular data set cannot be completely excluded. To find out exactly how general the noise annoyance advisor is, the performance of railway noise annoyance prediction on the Flemish and Austrian data sets is compared (after it is tuned to one of the data sets).

Before it is possible to test a model on two different data sets, some problems related to the comparison of surveys must be resolved. In chapter 3, section 1, six difficult issues associated with the comparison of two surveys were identified. Three of them are directly related to the use of linguistic terms in the surveys: the language can be different, the terminology or the meaning of the linguistic terms can be different and finally, the number of categories on the scale can be different (four point scale versus five point scale). Note that all three problems arise in the Austrian and Flemish surveys. Fortunately, they can all be handled very well by the fuzzy noise annoyance advisor (taking into account that only the meaning of terms on a single dimension is considered here). This is because any term in any language can be accurately represented in a uniform way, as a fuzzy set on the same universe $\mathbb{H}$ ($[0, 10]$). The fourth complication is due to the phrasing of the questions. As both the Flemish and Austrian surveys follow the international guidelines proposed by the ICBEN team, this is not an issue here. Furthermore, the survey results can be culture dependent (response behavior of the subjects) and survey dependent (presentation of the survey to the subjects). The noise annoyance advisor should be capable of handling these dependencies, at least if appropriate rules can be formulated to take them into account. However, such rules are not implemented here.

3.5.1 Crisp analysis

To demonstrate the language independence, a noise annoyance advisor containing the seven rules shown in table 6.7 was constructed, configured with the *crisp quality measures*. For the *linguistic approximation* to the single best matching term of the survey, the *similarity measure* as defined in the translation tool (see chapter 3, section 4.2) has been used. It is for two fuzzy sets $A, B \in \mathcal{F}(U)$, given by,

$$\mathrm{Sim}(A,B) = \mathcal{T}_M(C_1(A,B), S_M(E_{\mathcal{T}_W}(A,B), C_2(A,B))) \tag{6.1}$$

with

$$C_1(A,B) = \frac{\sup_{u\in U} \mathcal{T}_M(A(u),B(u))}{\sup_{u\in U} S_M(A(u),B(u))} \tag{6.2}$$

$$C_2(A,B) = \frac{\sum_{u\in U} \mathcal{T}_M(A(u),B(u))}{\sum_{u\in U} S_M(A(u),B(u))} \tag{6.3}$$

$$E_{\mathcal{T}}(A,B) = \mathcal{T}\left(\inf_{u\in U} \mathcal{I}_{\mathcal{T}}(A(u),B(u)), \inf_{u\in U} \mathcal{I}_{\mathcal{T}}(B(u),A(u))\right) \tag{6.4}$$

After optimization of the model on the Flemish data set, the performance of the model was 37.14 %, expressed as (weighted) percentage of correct predictions. When the same model with the same certainty degrees attached to the rules was run on the Austrian data set with linguistic approximation to the four German terms, performance was 37.13 %.

Table 6.7: Overview of fuzzy rules to test the language independence of a model. Used abbreviations: “at least” (at l.).

	IF L_{dn} noise exposure (dB$_{\mathrm{A}}$)		THEN annoyance	
T1	very low	$\overline{\mathrm{LIN}}(50,50)$	very low	$\overline{\mathrm{LIN}}(0,1.2))$
T2	low	$\mathrm{TRI}(42,50,58)$	low	$\mathrm{TRI}(0,1.8,4.2)$
T3	moderate	$\mathrm{TRI}(50,58,66)$	moderately	$\mathrm{TRI}(1.8,4.2,7)$
T4	high	$\mathrm{TRI}(58,66,74)$	high	$\mathrm{TRI}(4.2,7,8.5)$
T5	very high	$\mathrm{LIN}(66,74)$	very high	$\mathrm{LIN}(7,8.8))$
	IF distance to railway (m)		THEN annoyance	
T6	close	$\overline{\mathrm{LIN}}(0,390)$	at l. somewhat	$\mathrm{S}(0,4)$
T7	far	$\mathrm{LIN}(1050,1950)$	not high	$\overline{\mathrm{S}}(5,10)$

To test the influence of the shape of the fuzzy sets representing the German terms, they were changed to four equidistant triangular shaped fuzzy sets. The same model was run with linguistic approximation to the newly defined fuzzy sets. The performance on the Austrian data set dropped to

34.07 %. When the same model was run on the Flemish data set with approximation to five equidistant triangular shaped fuzzy sets, the obtained performance was 34.03 %.

In another experiment, fuzzy set representations for the German and Dutch terms constructed with the Klir *probability-possibility transformation* method (see chapter 3, section 3.2) were used. The model outcome on the universe $[0, 10]$ was aggregated to match the discretized distribution intervals and approximated to these fuzzy sets, using the same similarity measure as before. For the Austrian data set the performance was 36.19 %, 36.69 % for the Flemish data. The slight decrease in performance on both data sets seems correlated to the degrees of freedom in the representation of the membership functions. However, the results are still much better than those obtained with language neutral triangular shaped fuzzy sets. Table 6.8 summarizes all given results.

Table 6.8: Weighted percentage of correctly predicted terms in the language independent model (optimized for Flemish data).

Linguistic terms	Flemish	Austrian
Accurate representation	37.14 %	37.13 %
Equidistant piecewise-linear representation	34.07 %	34.03 %
Probability based representation	36.19 %	36.69 %

The above experiments and results show the following.

- The fuzzy noise annoyance advisor enables a language neutral model that can use all available data, even when the surveys collecting the data were conducted in different languages, using different terminology and annoyance scales. This feature is useful to find a general model and to test rule hypotheses on multiple data sets, only limited by the amount of variables that are common to all data sets.

- An accurate representation of linguistic terms by fuzzy sets is important for the performance.

- The construction method based on the fixed overlap degree is better suited for this kind of applications than the probability based construction methods.

See [160] for more detailed language-related comparisons.

3.5.2 Fuzzy analysis

To further demonstrate the generality of the *noise annoyance advisor*, two more variables were included in the model: age and gender (see table 6.9). The analysis reported here was performed with the *fuzzy quality measures* and associated error measure. For linguistic approximation, the lower approximate descriptor was used. These results have already been published in [26].

Table 6.9: Additional fuzzy rules to test the language independence of a model. Used abbreviations: “at least” (at l.).

	If age (years)		Then annoyance	
T8	young	$\text{Lin}(20,30)$	below moderate	$\overline{\text{S}}(5,7.5)$
T9	old	$\overline{\text{Lin}}(50,60)$	below moderate	$\overline{\text{S}}(5,7.5)$
	If gender		Then annoyance	
T10	male	Enum(1,0)	above average	$\text{S}(0,4)$
T11	female	Enum(0,1)	at l. somewhat	$\text{norm}(\text{S}_E(2.59,2.70))$

Tuning was done on the Flemish data set. The model was subsequently run on the Austrian data too, changing only the linguistic approximation to the correct terms. Because predicting the response on a five point scale is inherently more difficult than predicting the response on a four point scale, the prediction error e is divided by the highest non-specificity for each scale N_5 and N_4. This exercise is repeated for several values of the parameter α. The results are shown in figure 6.4. The prediction error for the Austrian data produced by a model tuned to Flemish data (open squares) is surprisingly similar to the prediction error obtained on the Flemish data set (closed diamond). Optimization on the Austrian data results in a lower prediction error (closed squares), but the rule certainty degrees tuned to the Austrian data make the performance of the model on the Flemish data slightly worse (open diamond). A possible explanation could be that the Austrian data are all taken in the vicinity of the same major railway track following the Inn Valley, while the Flemish data include railway tracks with different type and density of rolling material on them. This makes the Austrian data more specific and thus the tuning slightly overfitted to this particular situation.

The *noise annoyance advisor* seems to generalize quite well, at least on the data used here. The fuzziness in the outcome of the model and evaluation based on purely fuzzy quality measures, allows the model to give a very uncertain result in those situations that are not absolutely clear. This is not possible using crisp noise annoyance prediction. Moreover,

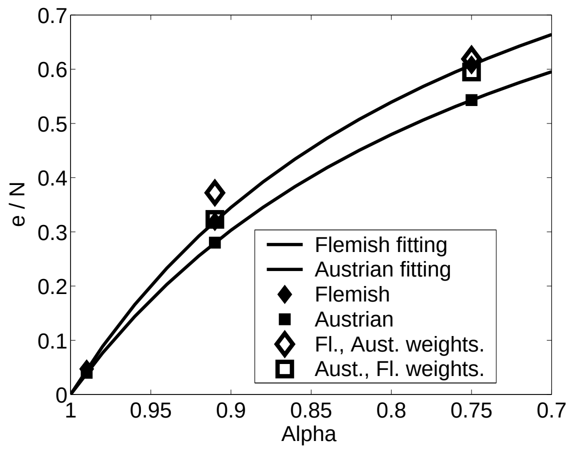

Figure 6.4: Scaled prediction error as a function of α for Austrian and Flemish road traffic annoyance prediction.

fuzzy relations between variables and annoyance are not optimized for a particular data set; they are merely included or excluded by tuning. Both features explain why the fuzzy model generalizes quite well.

3.6 Analyzing the rule base

In this section, the fuzzy rules in the *rule base* will be examined closely. The use of the fuzzy rule based framework to test the importance of hypotheses will be explored in more detail.

An indication of the importance of a particular rule in the optimized fuzzy rule base system can be gained from studying the certainty degrees and the adaptability of each rule. Certainty degrees can be interpreted as the degree to which the particular rule dominates the outcome of the system, if fired. A rule with certainty degree 0 has completely no effect on the inference result. *Adaptability* as defined in chapter 2, section 8.4.4, indicates in a fuzzy way how often and to what extend a rule is fired or triggered when evaluating the data set. In other words, the percentage of the population for which the rule results in some kind of clue for predicting annoyance. Rule adaptability is explicitly used in the fast implementation scheme of the possibility qualifying rule inference, but it can be calculated for certainty qualifying rules as well. However, certainty degrees and adaptability give only a first indication. There are several reasons for this. First, rules with a low certainty degree can still be important if they provide information on a region of the annoyance universe where information is scarce (e.g. they allow distinguishing between "fairly" and "moderately"). Secondly, rules are in general not orthogonal. This means that more than one rule in the system describes the same underlying (possibly more dimensional) mechanism. The choice between such rules that is made by the optimization, is often not very stable and cannot be used as decisive about which rule is best or which underlying variable is more important.

To assess the validity of rule hypotheses, a more thorough analysis is required. Assume a model that contains two rules operating on non-orthogonal data that partly compensate. Minimizing the model error, may give quite high certainty degrees to both rules. When one of the rules is then omitted, this could lead to a very bad model which could be falsely interpreted as proof for the rule being very important. Yet, the reduced system should also be optimized separately. If this tuning automatically removes the other rule (assigning a very low certainty degree), it would show that both rules probably do not represent hypotheses that lead to a better prediction of noise annoyance.

So, in case compensation between two sets of rules R_1 and R_2 is suspected, four models should be tuned and compared for their performance: a model without the rules R_1 and R_2, adding only R_1, adding only R_2 and adding both. This approach allows to really check the validity of (potentially compensating) rule hypotheses. The next subsections will provide examples of this procedure for several aspects of the noise annoyance model.

3.6.1 Exposure and masking

The analysis reported in this section is based on the modeling of railway traffic noise annoyance, optimized with the crisp quality measures (upper approximate descriptor) on the Austrian data set [22] [23] [25], see table 6.4 for an overview of the rules.

Exposure to noise at home, as defined in the *conceptual annoyance model* (see chapter 4, section 2.1), includes all physical characteristics of the intruding noise and the background noise level. The basic exposure variable is a calculated A-weighted *day-night sound level*. However, sound level calculations do not include the dwelling of the respondent. Additional exposure information can be extracted from the orientation of the house. The view from the living room main window and the main bedroom window (towards a noise source or towards a quiet side of the house, e.g. a garden) provides some clues. Also, the average day-night sound level L_{dn} does not take into account specific variations of the sound level. Here, the distance to the source can provide additional information. The rules based on these variables turned out to be very useful.

Railway noise exposure can be masked by background noise. Since *masking* requires a loud continuous background, only sound from highways and main roads is considered as the masker. Masking is generally understood in a pure physiological sense, referring to what is heard. When a noise physiologically masks another noise, it means that the second noise cannot be heard. However, there might also be some kind of psychological masking effect. Both noise sources are perceived, but one of the noises is so much more annoying than the other so that the second is neglected.

Several indicators for masking can be proposed,

- Difference between $L_{\mathrm{dn,road}}$ and $L_{\mathrm{dn,rail}}$ (A11).
- Masker noise level (L_{dn}) (A12).
- Distance to masker (A13).
- Windows (living room and bedroom) facing towards the masker (A14)–(A15).

Multivariate linear regression fails for analyzing how road noise influences the annoyance caused by railway noise [23]. Categorizing exposure in intervals of 3 $\mathrm{dB_A}$ only allows to discover some features visually. This visual evaluation becomes difficult when more variables are introduced. However, in the classical approach masking is only observed at high exposure levels for railway noise. This is a somewhat strange observation that deserves some special attention. A possible explanation is given in section 3.6.2. In accordance with the crisp results, the fuzzy rules are only formulated for these high exposure levels.

Comparing a model only including the DNL based rules (A1)–(A4), with a model that also includes one of the masking rules shows some reduction in error value. If all the masking rules are used together the result is similar. When looking in detail at the outcome of the optimization, it is further observed that the certainty degree of a particular rule related to masking decreases when an additional rule is added. From this it can be concluded that the masking rules indeed sample more or less the same feature. In table 6.10, the decrease of the error measure without masking versus with masking is shown (between brackets). For easy comparison the performance difference to the best value in the table is shown.

Note that the increase in performance is rather low. This is not surprising since only a very limited part of the population is exposed to both sources at high levels. In the fuzzy *noise annoyance advisor*, the masking rules reduce the possibility of being highly annoyed when there is a chance of masking. Nothing is assumed concerning a lower degree of annoyance.

Table 6.10: Comparison of the error measure value of exposure rules and masking rules combinations.

	No masking	Masking
L_{dn}	70 (975)	57 (962)
L_{dn} and other exposure rules	10 (915)	0 (905)

Hence, the performance of the masking rules is in agreement with the classical analysis. See [22] and [23] for a more detailed comparison between classical and fuzzy analyzes.

However, both analyzes neither prove that the observed relation is causal nor that the effect is physiological masking. There may be many indirect ways through which living close to a highway reduces annoyance caused by railway noise. To check whether the presumed masking effect could be due to the (indirect) more accurate description of exposure, additional rules for modeling exposure were added. These rules include variables such as the distance to the source and the direction of the living room and bedroom windows (A5)–(A10). As expected, the performance of the enhanced fuzzy rule based model increases. To analyze the relative contributions of sets of rules to the model performance, the modeling error is compared for four combinations of rules in table 6.10. Although additional exposure rules reduce the model error significantly, masking rules show a similar benefit independently of the presence of more accurate exposure modeling. Thus masking rules are orthogonal to exposure-related rules [23]. Adding more rules for sensitivity (A16)–(A17) and age (A22)–(A24) confirms this orthogonal masking effect [22].

Showing this masking effect in combination with many other variables, is quite simple in the fuzzy noise annoyance framework, but far more difficult with classical techniques.

3.6.2 Sensitivity to noise

Sensitivity to noise is found to be significantly linked with noise annoyance in most noise surveys [63]. Particularly high noise sensitivity seems to be a relatively stable personality trait in time. See chapter 4, section 2.1 and [25] for a review of relevant literature. The Austrian survey is used to test the effect of sensitivity rules in a railway noise annoyance model. The survey contains a question asking explicitly for noise sensitivity, providing a verbal answer scale using the same four linguistic labels as for the annoyance questions. The rules (A16) and (A17) (see table 6.4) based on the reported sensitivity are included in a model that contains only L_{dn} based rules (A1)–(A4). The *noise annoyance advisor* is optimized with the crisp performance measures using the upper approximate descriptor for linguistic approximation. The results obtained with the optimized models are shown in table 6.11. They have already been reported in [26]. The sensitivity rules clearly increase performance, expressed as the (weighted) percentage correctly predicted annoyance labels.

Table 6.11: Comparison of the model performance with sensitivity rules.

Model	Austrian Road	Austrian Railway
L_{dn} rules	32.5 %	37.5 %
L_{dn} and sensitivity rules	35.4 %	38.7 %

Quantifying reported noise sensitivity requires input from the subject. Sensitivity is therefore chosen as an example of a *pre-conditioner*, which is estimated internally on the basis of a number of well chosen indicators. Such a separate building block (submodel) for sensitivity (see chapter 4, section 3) can be more attractive than the reported sensitivity, e.g. when noise sensitivity is not directly assessed in a survey. The rules for the sensitivity submodel are shown in table 6.12 (S1)–(S6) [129]. The linguistic approximation and interpretation of the fuzzy estimate of noise sensitivity is not required. It can be used directly as an input to subsequent rules automatically taking into account the uncertainty and vagueness of the result. In extreme cases, when there is insufficient evidence to draw conclusions on noise sensitivity, the result will be very non-specific and will not trigger any subsequent fuzzy rules based on this variable. This is a great strength of the fuzzy noise annoyance advisor.

The submodel, to model the response to noise sensitivity on the Austrian data set, predicts about 30 % of the subjects correctly (weighted on the four labels used in the reported sensitivity question). This is because only very few indicators are available that allow estimating whether a person has a higher possibility of being sensitive to noise.

In [22] the annoyance caused by railway noise near highways and through roads was studied (based on the Austrian data set). It has been observed that railway noise annoyance is lower than expected based on the exposure close to highways. Two possible explanations for this were proposed: physiological masking (see section 3.6.1) and external adaptation of the population to the noisy situation (sensitive people will not stay there). This typical analysis is based on the comparison of the performance of four partial models. Table 6.13 shows the error *e* (between brackets) and the differ-

Table 6.12: Fuzzy rules modeling sensitivity to noise. Used abbreviations: "at least" (at l.).

	IF age (years)		THEN sensitivity	
S1	young	LIN(20, 30)	below moderate	$\overline{\text{S}}(5, 7.5)$
S2	old	$\overline{\text{LIN}}(50, 60)$	below moderate	$\overline{\text{S}}(5, 7.5)$
	IF size of household (people)		THEN sensitivity	
S3	small	$\overline{\text{LIN}}(0, 2)$	below average	$\overline{\text{S}}(2, 8)$
S4	moderately	TRAP(0, 1, 2, 4)	high	S(5, 7.5)
S5	big	LIN(3, 5)	not high	$\overline{\text{S}}(5, 7.5)$
	IF gender		THEN sensitivity	
S6	female	Enum(0,1)	at l. somewhat	S(0, 2)
	IF distance to highway (m)		THEN sensitivity	
S7	close	$\overline{\text{S}}(0, 300)$	not very high	$\overline{\text{S}}(8, 10)$

ence with the best value in the table. The rules based on reported sensitivity (A16) and (A17) (decrease 13) are more general than the rules based on physiological masking (A11)–(A15) (decrease 8) as expected (see table 6.4). However a clear overlap between both sets of rules is observed. The sensitivity based rules predict most of the variation which is also predicted by the masking rules. This leads to the conclusion that near highways and through roads, annoyance caused by railway noise is lower because sensitive people move out or do not choose to live there. If this conclusion holds, it should also be observed that reported sensitivity is lower than expected under conditions that correspond to masking. When rule (S7) is added to the sensitivity submodel, predictability of noise sensitivity increases to 31 %. This improvement is small because this rule does not apply to many people. However, it confirms the conclusion.

Table 6.13: Comparison of the error measure value of sensitivity rules and masking rules combinations.

	No masking	Masking
No sensitivity	15 (909)	7 (901)
Sensitivity	2 (896)	0 (894)

3.6.3 Context elasticity

There has been some evidence that people living in a generally pleasing environment might tolerate more noise before feeling annoyed or reporting this annoyance. However, also opposite effects on annoyance have been reported. See [25] for a review of relevant literature. This makes it especially difficult to find the appropriate relationships that will express the higher elasticity in more pleasing surroundings.

The context elasticity variable is used as an example of a combined variable in the noise annoyance advisor. It is modeled based on several primary variables, and implemented as a separate building block (submodel). The resulting possibility distributions for this variable, can be translated into a linguistic term that can then be used in classical analyzes. Alternatively, it can be used directly in subsequent rules. The rules included to take into account the elasticity of a more pleasant surrounding are (A18)–(A19) (see table 6.4).

For the modeling of context elasticity, three indicators are identified to extract knowledge about this variable.

- The general attractiveness of the area
- The living quality of the neighborhood
- The availability of leisure facilities

The rules (E1)–(E12) (see table 6.14) are tuned with the road traffic noise annoyance model on the Austrian data set. The optimization uses the crisp quality measures based on the upper approximate descriptor. The outcome of the context elasticity rules is not approximated, the possibility distribution is directly used in the subsequent (A18)–(A19) rules (see table 6.4). This ensures that the uncertainty of the context elasticity is fully taken into account. Results show a decrease of the error measure with 30 units, confirming the usefulness of the submodel. These results have been published in [24] and [25].

3.6.4 Land use

Land use may be a good indicator for more fundamental factors such as the visual setting, non-noise pollution levels, expectation concerning noise levels, etc. The effect of a visual setting on perception of noise has regained attention in the framework of *soundscape* research [68], and a clear influence of a visual setting on judgement (pleasant/relaxing) of auditory stimuli has been demonstrated in laboratory studies [168].

Table 6.14: Fuzzy rules modeling context elasticity.

	IF attractiveness satisfaction		THEN context elasticity	
E1	very happy	Enum(1,0,0,0,0)	above moderate	$S(2,7)$
E2	happy	Enum(0,1,0,0,0)	above average	$S(0,4)$
E3	unhappy	Enum(0,0,0,1,0)	below average	$\overline{S}(7,10)$
E4	very unhappy	Enum(0,0,0,0,1)	below moderate	$\overline{S}(3,8)$
	IF living quality satisfaction		THEN context elasticity	
E5	very happy	Enum(1,0,0,0,0)	above moderate	$S(4,7)$
E6	happy	Enum(0,1,0,0,0)	above average	$S(0,4)$
E7	unhappy	Enum(0,0,0,1,0)	below average	$\overline{S}(6,10)$
E8	very unhappy	Enum(0,0,0,0,1)	below moderate	$\overline{S}(3,6)$
	IF leisure facilities satisfaction		THEN context elasticity	
E9	very happy	Enum(1,0,0,0,0)	above moderate	$S(4,7)$
E10	happy	Enum(0,1,0,0,0)	above average	$S(0,4)$
E11	unhappy	Enum(0,0,0,1,0)	below average	$\overline{S}(6,10)$
E12	very unhappy	Enum(0,0,0,0,1)	below moderate	$\overline{S}(3,6)$

To illustrate the effects of land use related variables the Flemish data set will be used on a road traffic noise annoyance model. The base model includes the rules (F1)–(F19) (see table 6.6). The *noise annoyance advisor* is optimized for the crisp quality measures using the upper approximate descriptor.

Crisp analysis performed in [159] showed a slight influence of the percentage of agricultural land use within a radius of 500 m on the experience of annoyance. Inspired by those results, the rules shown in table 6.15 were formulated and added to the rule base. As the prediction error decreases slightly, the fuzzy model confirms the crisp analysis.

Table 6.15: Overview of fuzzy rules for the effect of agricultural land use.

	IF agriculture land (% of area)		THEN annoyance	
L1	higher than approx. 65	$\mathrm{LIN}(60,70)$	at most fairly	$\overline{S}(5,8)$
L2	lower than approx. 65	$\overline{\mathrm{LIN}}(60,70)$	at least fairly	$S(2,4)$

To test the hypothesis whether the land use rules are basically a way to describe the urbanization as reported by the subjects, the land use rules were substituted with the rules (F20)–(F23) (see table 6.6). This model was optimized (see table 6.16), leading to a slight performance improvement with regard to the model with the land use rules. Finally, both rule sets were added together but optimization could not improve performance further.

These results confirm the hypothesis that both variables indeed sample the same relationship.

Table 6.16: Comparison of the error measure value of land use and urbanization rules in combination with reported traffic rules.

	Base	Base + land use	Base + urbanization
No traffic	3.9 (174.9)	1.7 (172.7)	0 (171.0)
Traffic	7.4 (148.4)	5.3 (146.3)	0 (141)

The degree of urbanization may not be a fundamental variable but just an indicator for traffic density. To evaluate this possibility, the reported amount of traffic is included through the rules (F24)–(F27). The results shown in table 6.16 indicate that the reported amount of traffic is indeed an important predictor. However, the traffic rules do not compensate the land use or urbanization rules, as both can further improve performance. Again, the combination of land use and urbanization rules did not result in a decreased error, which is in accordance with the previous analysis. Apparently the human perception of urbanization and the amount of traffic are more orthogonal variables than expected. The high impact of the reported amount of traffic on the level of annoyance could indicate that the mere presence of traffic induces noise annoyance not only through the noise it generates. However, it could also mean that the model to calculate the traffic flow is incorrect, or L_{dn} is not a good measure or L_{dn} is not accurate enough.

To investigate the factors that influence the human perception of urbanization more thoroughly, a fuzzy submodel was constructed (see table 6.18). The aim is to predict the (subjectively) reported degree of urbanization, based on more objective criteria. The degree of closed-space development within a radius of 500 m and the average population density within an area of radius 500 m surrounding the house of the respondent, proved to be very good indicators, as they can predict about 37.6 % correctly, weighted over all urbanization categories.

Driven by the observation that the urbanization rules compensate for the land use rules, four rules (U9)–(U12) (see table 6.18) on the percentage of agricultural land use within a radius of 500 m (one for each category of urbanization) were incorporated in the submodel. However, these could not improve prediction performance. A closer look at the data revealed a possible explanation. Calculating the average and the standard deviation of the percentage of agricultural fields per urbanization category shows that it is very hard to distinguish between center, city and suburb (see table 6.17). Based on this variable, it only seems possible to separate between countryside and non-countryside, which is exactly what our land use rules successfully did. Trying to include the percentage of closed-spaced development directly, experienced the same problem.

Table 6.17: Percentage of agricultural fields per urbanization category.

Urbanization	Center	City	Suburb	Countryside
Average	0.15	0.25	0.29	0.49
Standard deviation	0.19	0.19	0.21	0.23

It could be argued that the subjective perception of urbanization is a concept that is also strongly influenced by the surrounding neighborhood in a larger area. People living in a suburb of a very large city will perceive the same population density differently than people living in the center of a very small city. However, it seems that crisp GIS land use queries based on counting equal land occupation in circles around the observation point are not accurate enough. More flexible, fuzzy querying functionalities in the GIS could help to identify such spots that are "close to a local concentration in population density" or "close to a sufficiently large green area".

Table 6.18: Overview of fuzzy land use rules for the Flemish data set.

	IF closed-spaced development (% of area)		THEN urbanization [country, ...]	
U1	low	$\overline{\text{LIN}}(15, 25)$	country	Enum(0,0,0,1)
U2	around 25 %	TRI(15, 25, 30)	suburb	Enum(0,0,1,0)
U3	around 35 %	TRI(25, 30, 35)	city	Enum(0,1,0,0)
U4	high	LIN(30, 35)	center	Enum(1,0,0,0)
	IF population density (nr/km^2)		THEN urbanization [country, ...]	
U5	low	$\overline{\text{LIN}}(770, 1300)$	country	Enum(0,0,0,1)
U6	below medium	TRI(1000, 2200, 3200)	suburb	Enum(0,0,1,0)
U7	above medium	TRI(1300, 2800, 3800)	city	Enum(0,1,0,0)
U8	high	LIN(2200, 3400)	center	Enum(1,0,0,0)
	IF agriculture land (% of area)		THEN urbanization [country, ...]	
U9	little	$\overline{\text{LIN}}(15, 25)$	center	Enum(1,0,0,0)
U10	around 23 %	TRI(13, 23, 33)	city	Enum(0,1,0,0)
U11	around 30 %	TRI(20, 30, 50)	suburb	Enum(0,0,1,0)
U12	a lot	LIN(30, 50)	country	Enum(0,0,0,1)

4 Annoyance accumulation advisor

4.1 Overview

Because the Austrian data set does not contain a question on global accumulated noise annoyance, all tests of the accumulation models have been performed with the Flemish data set. All results are optimized for crisp prediction to ease comparison between the crisp and fuzzy models.

Before discussing the results, the data is investigated in more detail. Table 6.19 shows the number of complete records N, containing an evaluation of each noise annoyance source (with n number of sources) and a global evaluation. The distribution of records on the five linguistic terms, L_1 ("not at all") to L_5 ("extremely"), for global annoyance is also given. The same information about the odor data is only included as a reference.

Table 6.19: The number of complete records N, number of sources n and the relative occurrence of each total annoyance level (in %) in the data set.

Stressor	N	n	L_1	L_2	L_3	L_4	L_5
Noise	2661	21	35.59	35.67	18.19	8.57	1.99
Odor	2719	23	54.69	27.73	11.51	4.93	1.14

In view of the models, the data contains three kinds of inconsistencies, in the sense that some data records can never be correctly classified by the model (see section chapter 5, section 3.1.3). A first type of inconsistency comes from the compensating behavior. If the reported global annoyance is lower/higher than the minimum/maximum of the annoyance of any of the sources, the data record will certainly not be correctly classified, which is the case for noise and odor in 5.34 % and 6.66 % respectively. This is true if a fuzzy integral based accumulation model is used because of the integral properties. It has been experimentally observed that this is also true for the optimized fuzzy rule based accumulation model, if no *frame of reference* adaptation is taken into account. A second kind of inconsistency (*doubt*) occurs when two people report the same annoyance levels for all sources, but rate the accumulated annoyance differently. Finally, there is also a problem if a person rates the annoyance level for all sources equally or higher (more annoying) than another person, but still reports less accumulated annoyance (*reversed preference*). After removing the smallest number of data records to get rid of all inconsistencies of the first and second type (keeping 2141 of the 2661 records), the maximum performance that can be achieved has been calculated as being 78.99 %. The third type of inconsistencies was left untouched because it is more difficult to remove (also due to its interaction with the second type) while retaining the maximum number of consistent records. Therefore, the theoretical upper limit performance will be even lower than the cited maximum performance of 78.99 %.

In table 6.20 an overview is given of all classification results with the different models.

Table 6.20: Classification performance of accumulation models.

Model	Performance (in %)
Crisp strongest component	55.5
Fuzzy rule base	59.0
1-maxitive Choquet integral	61.3
1-maxitive Sugeno integral	60.9
2-maxitive Sugeno integral	61.4

As a reference, table 6.20 also includes the results with the (crisp) *strongest component model* which performs best of the crisp models that were tested: vector summation, summation and inhibition and linear regression [18]. In figure 6.7 the classified general annoyance from the strongest component model is compared to the reported general annoyance. The percentages are scaled to take into account the number of observations in each category. Category labels have been omitted and run from left to right ("not at all annoyed", "slightly annoyed", "fairly annoyed", "strongly annoyed" and "extremely annoyed") and from bottom to top. The area of the bubbles is proportional to the percentage. All results from the accumulation models will be presented in the same way.

From this figure, it is obvious that the model overestimates general annoyance and that the overestimation is independent of the annoyance level. This is exactly what has been called the "*principle of compromise*" (see chapter 5, section 1.1).

4.2 Fuzzy rule based model

The results of the fuzzy rule based model have already been presented in [17] [19] and [18].

The (weighted) percentage of correct classifications is only slightly better than the *strongest component model*. This is not surprising, as the

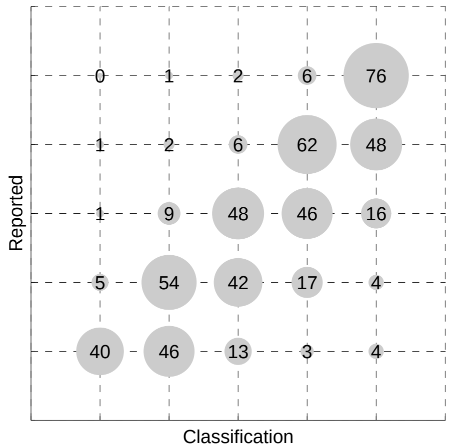

Figure 6.5: Relative occurrence of various combinations of classified and reported accumulated annoyance with the strongest component model.

fuzzy rules are in fact only a fuzzy expression of the cognitive processes involved in the strongest component model. Figure 6.6 shows the relative occurrence of each combination of the classified and reported general annoyance level. The fuzzy model overpredicts the general annoyance level less often than the strongest component model, especially at low annoyance levels.

It turns out that a model including a change of the *frame of reference*, does not significantly performs better. This failure is attributed to a lack of increase in the uncertainty of the contribution of annoyance by unimportant sources to the accumulated annoyance.

For an analysis of the remaining error, see [18] and [19]. Only age seems to have a slight influence in the sense that young people report less accumulated annoyance even if they report the same annoyance levels for particular sources.

4.3 Fuzzy integral based models

The results from the Choquet integral based model have been reported in [163], while the Sugeno model results have been presented in [164].

Figure 6.7 shows the results for an optimized 1-maxitive fuzzy measure with the *Choquet integral* (left) and the *Sugeno integral* (right). Both integrals perform more or less similarly and slightly better than the fuzzy rule

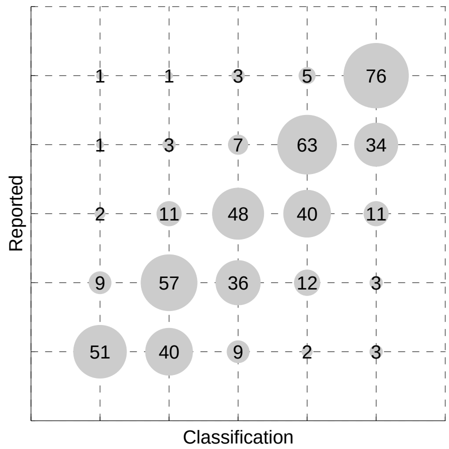

Figure 6.6: Relative occurrence of various combinations of classified and reported accumulated annoyance with the fuzzy rule based model.

based model. However, they also tend to overestimate the global annoyance.

Besides the 1-maxitive measure, also other generalized possibility measures (see chapter 5, section 3.2.2) together with the Choquet integral were used. However, there were no significant differences between the performance of different t-conorms. A closer examination of the weights used in the calculation of the Choquet integral, revealed that the most annoying source receives a very high weight compared to all other sources and hence dominates the outcome. This is in accordance with the *strongest component model* that exclusively uses the most annoying source. It proves that the cognitive accumulation process is indeed very maxitive in nature. This is probably also the reason why the 1-additive and 2-additive Choquet integral models completely fail to model the annoyance accumulation. Representing a maxitive fuzzy measure is not attainable with only second order (2-additive) Möbius coefficients.

As can be seen, the Sugeno integral is also a good model for the accumulation of noise annoyance. A 2-maxitive measure performs slightly better (but not significantly) than a 1-maxitive measure. This indicates that annoyance by two sources can accumulate to a stronger effect on the aggregation than the maximum of both sources. This enforcement effect is illustrated in figure 6.8. The left figure shows the accumulated annoyance level (in the interval $[0, 1]$) in function of the annoyance caused by building activities (X-axis) for an annoyance level of 0.5 due to truck (un)loading.

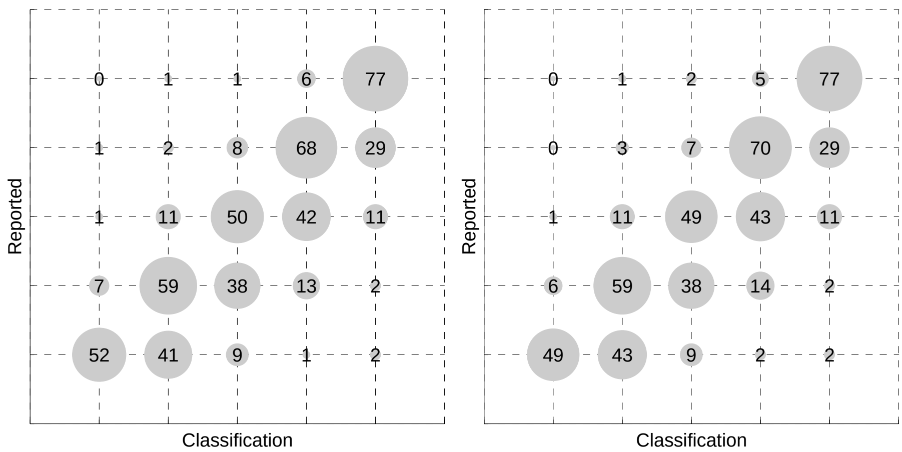

Figure 6.7: Relative occurrence of various combinations of classified and reported accumulated annoyance with the fuzzy integral based model (left: 1-maxitive Choquet, right: 1-maxitive Sugeno).

The annoyance caused by all other sources is not taken into account. Compared to the 1-maxitive measure with $\mu(\{\text{building activities}\}) = 0.02$ and $\mu(\{\text{truck (un)loading}\}) = 0.07$ (dashed line), the 2-maxitive measure with $\mu(\{\text{building activities, truck (un)loading}\}) = 0.79$ (solid line) enforces the accumulation of both sources (dotted line indicates maximum annoyance of both sources). The right figure shows the same for accumulated annoyance in function of annoyance caused by small businesses for an annoyance level of 0.75 caused by commercial activities, with the 1-maxitive measure $\mu(\{\text{small businesses}\}) = 0.13$ and $\mu(\{\text{commercial activities}\}) = 0.45$ and the 2-maxitive measure $\mu(\{\text{small businesses, commercial activities}\}) = 0.69$.

Table 6.21 shows a comparison between the fuzzy measure singleton values of an optimized 1-maxitive Choquet and 1-maxitive Sugeno model. They are quite similar as expected. Sources may receive very low importance (e.g. fancy fairs and festivals, agricultural equipment and pet animals) because they are not thought of when rating global annoyance or because they do not occur frequently enough.

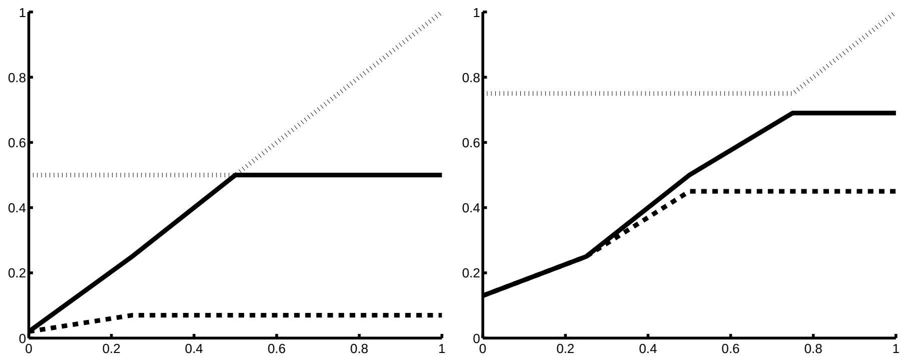

Figure 6.8: Enforcement of annoyance by two sources with a 2-maxitive measure (solid) versus a 1-maxitive measure (dashed) and the maximum annoyance (dotted). Left: building activities w.r.t. truck (un)loading with annoyance level 0.5. Right: small businesses w.r.t. commercial activities with annoyance level 0.75).

Table 6.21: The optimized fuzzy measure singleton values for each source of noise.

Source	Choquet	Sugeno
Road traffic	0.91	0.94
Railway traffic	0.52	0.65
Air traffic	1.00	1.00
Water traffic	0.81	0.99
Truck (un)loading	0.28	0.10
Small businesses	0.47	0.23
Factories	0.92	0.99
Commerce	0.97	0.99
Building activities	0.87	0.97
Dance halls	0.94	0.95
Restaurants and cafes	0.52	0.28
Entertainment parks	0.41	0.15
Fancy-fairs and festivals	0.29	0.22
Sports events	0.30	0.68
Car and motor racing	0.88	0.99
Agricultural equipment	0.28	0.08
Farm animals	0.15	0.37
Stable ventilators	0.11	0.83
Playing children	0.89	0.88
Pet animals	0.24	0.06
DIY noises	0.92	0.88

CHAPTER 7

Conclusions

The future cannot be predicted: it has to be invented.

Dennis Gabor (1900-79)
Hungarian-English physicist

In this work, the *noise annoyance* concept has been thoroughly analyzed. Annoyance has been approached as an inherent vague concept that is modeled with the use of *fuzzy set theory*. This approach was motivated by the way people usually deal with annoyance in reality. How they express and communicate their level of annoyance to other people by means of natural language.

First, representational aspects have been studied. It was argued that commonly applied crisp cut-off points are not well suited to represent linguistic terms (e.g. 7.2 on 10 for "*highly annoyed*") that express a certain level of annoyance. In chapter 3 a number of techniques have been investigated and extended, which are much better suited to accurately represent these linguistic annoyance expressions. They are based on *fuzzy set theory*. This theory has been specifically developed to model gradual, smooth transitions of concepts (instead of the black-white view of classical, crisp set theory). It allows to represent linguistic terms by fuzzy sets, taking into account the inherent vagueness in a mathematically sound way. In particular, two representation methods have been examined in detail: probability based transformations and individual curve construction methods. The latter have been extended to enhance their use in practical applications, such as *fuzzy rule bases*. To demonstrate the accuracy of the fuzzy set representations, an automated translation tool for linguistic terms in several languages has been built. This tool operates solely on the fuzzy sets underlying the linguistic terms and on the similarity between these fuzzy sets.

Next, a *conceptual noise annoyance model* was studied. The complex relations that have been identified, contrast sharply with the currently adopted standard practice of predicting the percentage of highly annoyed people only based on the DNL noise exposure levels. Instead of this statistical based annoyance indicator (for large regions), in chapter 4 a *noise annoyance advisor* framework has been proposed to calculate the degree of annoyance on an individual person basis. This allows to predict the level of annoyance starting from the state of the environment, taking all influencing variables into account, including attitudinal, personal, emotional, demographical,... factors. Internally, the framework is driven by *fuzzy logic*. In this fuzzy extension of binary logic, truth also becomes a matter of degree. Fuzzy logic allows to infer conclusions, such as binary logic, but it can do so even in the presence of vague and uncertain data and knowledge. The available knowledge is represented as *fuzzy rules* stored in the *fuzzy rule base*, expressing relations between variables in a linguistical way. To evaluate the constructed noise annoyance advisor, recall the annoyance modeling goals that were put forward in chapter 1.

Tolerant The framework can make use of any kind of data, being a crisp, precise number or a fuzzy set that is vague and very uncertain. Also the knowledge stored in the fuzzy rule base can include vague notions as antecedents and consequents of the fuzzy rules. Each rule has attached a certainty degree expressing the uncertainty of the rule.

Reliable The noise annoyance advisor can be configured to have a possibility distribution on the known annoyance levels as output (fuzzy quality measures). This reflects the vagueness and uncertainty of the conclusion, drawn from the given input data and available knowledge. The result can be very specific, meaning that the system is rather sure about the provided outcome. In other situations, the result may be very non-specific indicating that more than one linguistic label is equally possible for the level of annoyance.

Robust The knowledge in the noise annoyance advisor is gray-colored, not black-white. Small deviations in the input (or the knowledge) will not lead to radically different results.

Interpretable The fuzzy rules are formulated using linguistic terms in natural language. These linguistically expressed relations between variables are being offered by experts in the field, but they have a natural meaning to everyone who “reads the rules”. Furthermore the inference processes (depending on the operators that are used) and the weights assigned to each rule, have clear semantics in terms of possibility qualification or certainty qualification.

Individual The outcome of the noise annoyance advisor is the annoyance level predicted for an individual person. The knowledge that is available in the framework can include any variable that influences the experience of annoyance. As new relations between variables become available in literature, they can be added as fuzzy rules inside the framework. These variables can be very specific, e.g. the direction of the window of a house.

Adaptable Each fuzzy rule is assigned a weight expressing the certainty of the rule. When data is available from social surveys, the data set can be used to tune these weights. If the optimization procedure lowers the certainty degree of a rule hypothesis to almost zero, the rule has no effect anymore. This means that the rule does not contribute to a better annoyance prediction and the hypothesis should be rejected. However, care must be taken in order not to draw wrong conclusions, because of interactions between compensating rules. It may also happen that a rule seems to have no or little effect because it samples the same underlying relationship as already expressed by another rule. Hence, careful comparisons are necessary to estimate the value of hypotheses. Yet, some methods to evaluate hypotheses in an accurate way have been proposed and demonstrated.

In chapter 6 all these features have been illustrated for the modeling of road and railway traffic noise annoyance, based on two data sets from *social surveys*. It has been shown how the noise annoyance advisor can produce crisp output for easy comparison with other crisp models. These are outperformed by the fuzzy *noise annoyance advisor*. However, a more appropriate treatment of the fuzzy annoyance concept is obtained when the noise annoyance advisor is configured for fuzzy output. The model can be tuned with a parameter to force the outcome into high (crisp) correctness at the cost of *non-specificity*. The effect of this parameter has been demonstrated on the fuzzy output of the framework. A difficult issue is the comparison of data collected in different surveys, especially when conducted in other languages, using different terminology, scales,... The noise annoyance advisor has been proven to be capable of handling these language related problems. Except that linguistic labels are assigned to the rule antecedents and consequents for convenience, the fuzzy rules are in fact language neutral. They can operate on the fuzzy set representation of any linguistic term in any language. Similarly, the fuzzy output of the system can be mapped to any set of linguistic terms. This makes it possible to extract relationships between variables, based on all available data from various surveys in multiple languages. Finally, it has been demonstrated how the noise annoyance advisor can be used to check rule hypotheses. The obtained results were in agreement with classical analysis techniques and allowed more advanced analyzes and conclusions.

Starting from a description of the *state* of the environment, the noise annoyance advisor enables the prediction of the level of annoyance induced by a type of noise source (e.g. road traffic). But what is wanted is often an estimation of the global annoyance level. Currently, this accumulated noise annoyance level is best modeled with the *strongest component model*, which simply takes the highest level of annoyance caused by all considered sources. A disadvantage is the black box behavior of this model. In chapter 5, the underlying *cognitive process* has been identified. The formulation of this cognitive process in binary logic has been fuzzified to a fuzzy rule based model. These fuzzy –linguistic– rules are expressed in natural language, providing a clear semantical interpretation. In chapter 6 it has been shown that this fuzzy model performs slightly better than the strongest component model. However, its main advantage is its interpretability.

Two other approaches for the classification of accumulated noise annoyance have been explored. The *Choquet* and *Sugeno integrals*, frequently applied in the domain of *multi-criteria decision making*, both turned out quite successful, slightly improving the performance of the fuzzy rule based model.

Fuzzy set theory in combination with *fuzzy logic* and the "*computing with words*" paradigm has been proven to be a suitable mathematical framework for the modeling of the inherent vagueness and uncertainty of *noise annoyance*. However, the availability or better, the lack of reliable input data, remains a problem. Typically, the collected and measured data comes as crisp numbers without any indication of its associated error or uncertainty. Ultimately, the data should come as fuzzy sets expressing its quality more accurately. The noise annoyance advisor is perfectly capable of handling such input uncertainties which would even improve the accurateness of the model (in a fuzzy way). However, generating fuzzy input data for the noise annoyance advisor requires models that are capable of propagating data uncertainties from the *driving forces* of environmental pollution to the environmental *pressure*, and from the *pressure* to the *state* of the environment. See [48] for work that has been initiated in this area.

Another option to raise the performance of the noise annoyance advisor, is to add additional knowledge about variables (e.g. blood pressure) and their relationship with annoyance. Although the framework is already capable of handling a variety of complex types of relations, other variables may require extensions to the proposed system.

A third line of further research can pursue the aggregation of noise annoyance beyond the accumulated annoyance rating, and investigate more global variables such as *quality of life*. In this view, also the modeling of other sources of annoyance (e.g. odor) and other health effects of noise may be explored, using the same fuzzy tools.

Recently, also other researchers have started to adopt fuzzy techniques, in the field of annoyance modeling [150] [94], as well as in other environmental sciences [76] [83] [136] [95]. They provide the necessary tools to raise the accuracy of environmental pollution models and to contribute to a better understanding of the relationships that guide these complex processes. Hopefully, this knowledge will allow more accurate actions and responses to create an agreeably environment and to lead to a society respecting all principles of *sustainable development*. Therefore, I wish to conclude with the following statement, quoted from the North American Fuzzy Information Processing Society (NAFIPS),

The future is FUZZY!

Appendix A

Genetic algorithms

One generation plants the trees; another gets the shade.

Chinese proverb

1 Introduction

Genetic algorithms (GA) were pioneered by John Holland in 1975 [84]. They are search algorithms based on the principles of biological evolution theory, which were formulated for the first time by Charles Darwin (1809–1882). Earlier research on optimization methods (mid-sixties) inspired by evolution theory had resulted in methodologies called Evolutionary Programming (L. Fogel) and Evolutionary Strategies (Schwefel and Rechenberg). The similarities between these three methods have always been much more important than their differences. Yet, only recently their similarities have received the attention they truly deserve. Techniques have been mixed and matched, blurring the boundaries of the field names. This has lead to the uniform field of research coined *Evolutionary Computing* (EC) [67].

Evolutionary computing is a stochastic search methodology that is robust, and usually achieves a "good" solution "quite fast". However, it cannot guarantee that the global optimum solution is found. Therefore, EC fits perfectly under the umbrella of *soft computing*, which is tolerant for imprecision and uncertainty in favor of robustness and close resemblance to natural processes (in this case biological evolution).

In this work, EC has been successfully applied as a non-linear optimization method. The basics of this methodology are briefly introduced in this appendix, with special emphasis on the techniques that were actually used. First, the biological principles of evolution theory as simulated by EC are described. Secondly, it is explained how these principles are used in a computer algorithm to find solutions for optimization problems. For a more complete and thorough study of modern evolutionary computing, the interested reader is referred to [7] and [67].

2 Biological principles

In 1859 Charles Darwin published his famous book *"On the origin of species"* containing his views on biological evolution. At that time, his *principle of natural selection* was a source of much controversy. It states that the species best adapted to their environment are favored for survival and further evolution. This is also known as the "survival of the fittest". Together with the occurrence of small, apparently random changes in the external responses between parents and their offsprings, it provides the basis for his macroscopic theory of evolution. Later, microscopic findings in the field of biochemistry and genetics concerning the mechanisms of heredity were pioneered by Gregor Johann Mendel (1822–1884). The synthesis of the theories put forward by Darwin and Mendel is called *neo-darwinism*, which is presently generally accepted as the correct explanation of evolution.

The most important points of this synthesis are briefly discussed below. For more details, see [7] and [67].

Structure and behavior Individuals can be viewed as a duality of their *genotype*, the underlying genetic coding, and their *phenotype*, the manner of response contained in the behavior, physiology and morphology of the organism [67].

Natural selection The individuals best adapted to their environment have more chance to survive and to reproduce. An individual is well adapted when its functional behavior (phenotypic variation) is highly appropriate in light of the physics of its environment. The individual is said to have a high "*fitness*" degree. The goal of natural selection is to maintain or increase the fitness of the population.

Heredity Genes are the transfer unit of heredity. The collection of all genes is called the "*genome*", and represents the *genotype* of an individual. Highly fit individuals that are capable to reproduce, can transfer (part of) their genetic information into the next generation. During sexual reproduction, the genes of the parents are recombined. This will ultimately expose a wide variety of genotypes to the environment. However, errors are inevitable during this reshuffle of information which will lead to mutational variation.

Three advantages of recombination have been identified: greater efficiency for adjusting to a changing environment, bringing together beneficial mutations and removing deleterious mutations [67].

3 Computer simulation

3.1 Basic algorithm

The biological principles of evolution are simulated by the following algorithm to handle optimization problems.

1. Create an initial population of random individuals, represented by their genetic information (*genome* which consists of genes). Each individual must represent a possible solution to the optimization problem.

2. Repeat the following loop until a termination condition has been satisfied.

   (a) Evaluate the fitness of each individual in the population. This fitness score specifies the quality of the individual as a solution to the problem.

   (b) Apply the genetic operators to form a new generation.

   Selection Select two individuals from the population with a probability based on their fitness score. The higher their fitness, the more chance they have to be selected for reproduction.

   Crossover Create two new individuals (offsprings) by random recombination of the genomes of the selected individuals (parents).

   Mutation Alter a randomly chosen gene of the offsprings with a certain probability.

3. Designate the best solution in the final population, the individual with the highest fitness score, as the result. It may represent an optimal solution or an approximate solution to the optimization problem.

The historical differences between Genetic Algorithms, Evolutionary Programming and Evolutionary Strategies, were only concerned with the specific techniques to implement the representation of an individual, select individuals, and perform the genetic operations. One methodology had no crossover, while another had no mutation,... The above algorithm generalizes all three and forms the basis algorithm in Evolutionary Computing.

Usually, the population size is kept constant with non-overlapping generations ("simple genetic algorithms"), although this is not a strict requirement. There are also variants with overlapping populations in subsequent generations ("steady state algorithms"). Even algorithms that evolve multiple populations in parallel with migration of individuals between populations have been constructed ("deme genetic algorithms"). In this appendix, we will only discuss the simple genetic algorithms which have been used in this work. Below, the different steps of the basic algorithm and some possible implementations are presented in more detail.

3.2 Representation

The first important thing to decide is the choice of data structure to represent the *genotype* of an individual (by a *genome*). An appropriate representation of a possible solution to an optimization problem is largely dependent on the problem at hand. A good choice is minimal but completely expressive. All possible solutions should be representable with the chosen data structure. But at the same time, it should be impossible to represent an infeasible solution to the problem. The possibilities are really endless, arrays containing real values, strings of bits, tree structures,... Of course, the choice of representation is not independent of the choice of operators that will act on the genome. The operators must be able to maintain its integrity.

One of the most simple data structures to code a genome is an array of values, which can be of variable or fixed length. Each element in the array is then called a gene. The set of values that each gene can take is called the allele set.

3.3 Selection

Each individual represented by its *genotype* (*genome*) is associated with a *fitness* score that is calculated by a fitness function or objective function. The fitness score expresses the quality of the solution in the optimization problem. Therefore, it can be regarded as the expression of the phenotype of the individual, the way the individual looks like and behaves in its environment. In case of an optimization problem, the environment is in fact the solution space in which the search for an optimal solution takes place. The fitness function evaluates the behavior of the individual in that solution space. The ultimate goal of the search process is the maximization of the fitness value of individuals. The higher the fitness value, the better the solution. However, in practical applications it is sometimes convenient to evaluate the individuals by an error function. Of course, the search must then be oriented towards a minimization of this error value. Formally, the error function can be considered as the inverse of a fitness function. Hence, both approaches are theoretically equivalent. The remaining part of this appendix will stick to the view of maximizing a fitness value.

The selection mechanism has to choose the individuals for mating, the parents that will have to produce offsprings. Where the genetic operators create individuals in a largely undirected way, the purpose of the selection operator is to direct the search towards individuals that perform well in the solution space. Individuals whose genome may contain genes that make them well adapted to the environment and are likely to survive in next generations. The following selection schemes are commonly encountered in the literature [7].

Roulette wheel This selection method picks an individual based on the magnitude of its fitness score relative to the rest of the population. The higher the fitness score, the more likely an individual will be selected. The name derives from the analogy with a biased roulette wheel where each individual is assigned a slot sized in proportion to its fitness. The probability that an individual is chosen is equal to its fitness score divided by the sum of the fitness scores of each individual in the population.

Uniform In an uniform selection process, each individual in the population has the same probability of being chosen.

Tournament When a q-tournament selection operator is adopted, q individuals are chosen using another selection strategy (e.g. roulette wheel, uniform,...). The best individual from this group is then selected as the winner of the tournament.

An important aspect of a selection operator and of an evolutionary algorithm in general, is its *selection pressure*. It is the probability to select the best individual compared to the average selection probability of all individuals. Under high selection pressure, only the best individuals will have the chance to produce offsprings. Their genes are maximally exploited and will soon become dominant in the population. This will eliminate the ability of the algorithm to find better solutions. This phenomenon is called *premature convergence*, the algorithm converges quite fast to a local optimum. However, when the selection pressure is low (e.g. uniform selection), the search is rather undirected. Many areas of the solution space will be explored but none will be used to direct the search towards an optimum. Tournament selection enforces more pressure than the underlying selection operator that is used.

The selection pressure can be adjusted by using *fitness scaling*. Fitness scaling transforms the raw fitness scores calculated by the objective function to the fitness scores that are taken into account by the selection operator. The most common adopted scaling method is linear scaling. Linear scaling transforms the raw fitness scores such that the average fitness score in the population remains unaffected and the maximum fitness score in the population is equal to a fixed constant (usually 2) times this average fitness. In the beginning, convergence is slowed down because a super fit individual cannot entirely dominate the selection process. This would dramatically reduce the genetic diversity of the population too early. (the amount of exploration is increased). With the progression of the search, the differences between the raw fitness scores are reduced. Linear scaling then makes sure that the slightly better individuals get a higher chance for selection than the others. Hence, the search is more effectively focussed towards the optimum (better exploitation).

Because genetic operators cannot guarantee that the offsprings have a higher fitness value than their parents, the population may loose its best individual and never be able to find it (or better individuals) again. To avoid this situation, the elitist strategy can be adopted. Elitism makes sure that the best individual of the population always survives to the next generation without any modification.

3.4 Crossover and mutation

The primary genetic operators used in evolutionary computing are *crossover* and *mutation*. Usually, crossover recombines the genetic information of two parents to produce two offsprings (although variations do exist, e.g. asexual crossover). Its purpose is mainly to preserve the genes of well adapted individuals in the next generations (*exploitation*). The mutation operator is executed on a single genome with a smaller probability than crossover. Its goal is to create new genetic information and to keep a certain amount of genetic diversity in the population (*exploration*).

The choice of crossover and mutation operator largely depends on the adopted representation of the genome, e.g. swapping sub trees in a tree structure representation, shuffling a list representation,...

When the representation is a simple array, the following crossover operators are common (see figure A.1).

One point crossover The genome of both parents is cut in two pieces at the same randomly chosen location and the parts are swapped.

Two point crossover Two points are randomly selected along the genome and the segments in between these points are swapped.

Uniform crossover Uniform crossover creates two offsprings by randomly choosing each gene from either parent.

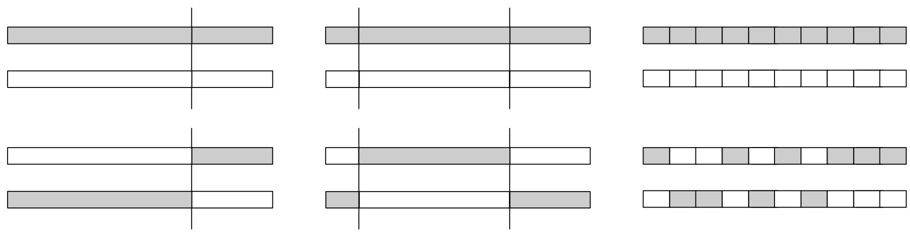

Figure A.1: Genetic crossover operators on arrays of fixed size. Left: one point crossover, middle: two point crossover, right: uniform crossover.

The mutation operators usually perform some small, random perturbations to genes with a rather small probability. However, the effect of the mutation operator also depends on the representation of the genome. When an individual is represented as a bit string, the mutation commonly takes the form of a bit flip operation. The mutation of real values often consists of modifications according to a Gaussian distribution with a specified standard deviation. In [67], a *self-adaptive mutation* operator is used. This operator modifies a gene with Gaussian perturbations, but now the standard deviations are also part of the optimization procedure performed by the GA. For x a genome as an array of genes $(x_1, x_2, \ldots, x_n)$ with $n \in \mathbb{N} \setminus \{0\}$, and σ an equal sized array of standard deviation parameters, the self-adaptive mutator is defined as, for each $i \in \{1, 2, \ldots, n\}$,

$$x'_i = x_i + N(0, \sigma_i) \tag{A.1}$$

$$\sigma'_i = \sigma_i + N(0, \sigma_i) \tag{A.2}$$

where $N(0, \delta)$ denotes a Gaussian distribution with average 0 and standard deviation δ. Care should be taken that the standard deviations remain positive.

4 Summary

In this work EC has been used as an optimization method because they are known for their robustness in non-linear, multi-modal search spaces [67].

All *genomes* have been represented by simple (fixed length) array data structures. The unit interval $[0, 1]$ has been used as allele set with a discretized step size of 0.01. The *uniform crossover* operator has been implemented for recombination. Mutation has been performed with the *self-adaptive mutation* operator. The array with the standard deviations was also recombined with the uniform crossover operator. For the standard deviations, the allele set $[0, 0.5]$ with a step size of 0.005 has been adopted. To prevent a mutation outside the allele sets (for the genes as well as the standard deviations), the mutation step was divided by two as long as necessary to make the value valid. The population size was 50, mutation probability has been set to 0.1. The optimization loop has been repeated for 100–300 generations, depending on the number of parameters that had to be optimized. Most optimizations have been performed multiple times to avoid local optima and to verify the performance of the genetic algorithm.

Appendix B

Software

Keep it simple, as simple as possible, but no simpler.

Albert Einstein (1879-1955)
German-American physicist

1 Introduction

The *noise annoyance advisor* that has been described in this work, has been implemented to test it on a real data set. Because of the numerical nature of the framework and the use of large data sets, the programming language of choice had to be very fast. An *object oriented* (OO) approach was preferred because it provides a robust design philosophy for software that scales very well, promotes code reuse, and increases maintainability. It is easier to use because it allows to express the relations between components on a high level. It raises the level of abstraction from (artificial) procedures to real life objects.[1] Therefore, as programming language to implement the noise annoyance advisor, C++ has been chosen. It is a modern, ANSI/ISO standardized language that is known to be very efficient and fast. It has all OO features, including operator overloading which is very convenient for numerical operations on specialized data structures. C++ comes with the Standard Template Library (STL) containing many data structures and algorithms, and has a large community base of already developed libraries that are freely available to use.

Two software libraries were necessary to develop the noise annoyance advisor.

[1]In this respect, OO is in fact comparable with fuzzy set theory that raises the level of abstraction from (artificial) binary concepts to gradual concepts as encountered in the real world.

- Fuzzy sets and fuzzy logic related software. This library should allow to define fuzzy sets, formulate fuzzy rules, infer rule results based on input data,...

- Genetic algorithm software, which is used to optimize the weights of the fuzzy rules.

For the implementation of the *genetic algorithm*, the GAlib library version 2.4.5 has been used, written by Matthew Wall at the Massachusetts Institute of Technology (MIT). This C++ library can be downloaded for free on http://lancet.mit.edu/ga. Although it already contains a large number of standard algorithms and genetic operators, it is highly customizable. In fact, it was only necessary to implement the genome representation used in the noise annoyance advisor, and the *self-adaptive mutation* operator.

However, libraries for fuzzy set modeling and inference, typically implement only a single technique, e.g. one inference algorithm, one integral,... They are usually not very customizable either. Therefore, it has been decided to implement the fuzzy software library from scratch. This library is briefly described in the next sections.

2 Overview

An UML diagram with the structure of the fuzzy library is shown in figure B.1.

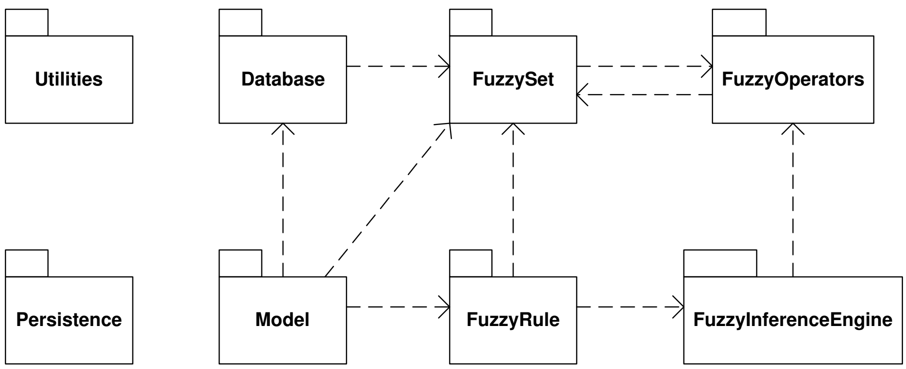

Figure B.1: UML Package diagram of the fuzzy software.

3 Package descriptions

3.1 General utilities

This package contains various general purpose classes, e.g. smart pointers, string utilities,... They are used by many other parts of the library.

3.2 Persistence

Persistence, or the storage and retrieval of objects to extend their lifetime beyond the execution of the program, is an important aspect in software design. The noise annoyance advisor must retrieve the survey data and should be able to store its results for further analysis.

All classes that need persistent objects have to derive from a template Persistent class, which provides methods to read and write those objects. This class can be configured with various input and output formatter objects. These objects specify the format (e.g. text, XML, data table) and the source/destination (e.g. file, console/screen) of the retrieval/storage process. They provide a very flexible way to specify how the objects of each class should be made persistent. An XML-based formatter object is supported for all classes. To parse XML, the expat library version 1.2 has been used, which is freely available on ftp://ftp.jclark.com/pub/xml/.

3.3 Fuzzy sets

For the computer implementation of a fuzzy set, a discretized representation has been chosen. Other commonly encountered representations are based on parameterized shapes (e.g. triangular or trapezoidal shapes) or more general piece-wise linear functions. Although the discretized representation may not be the most efficient one, it is by far the most flexible. It allows operations that would otherwise be less easy to perform or would make the representation inefficient anyway.

Internally, a vector is used to store the discretized membership function. The vector is completely shielded from the outside world with a small utility class. This class translates a point on the axis of a represented concept (e.g. 6.5 on the annoyance scale $[0, 10]$) onto a specific vector location, taking into account the precision of the axis as specified by construction (e.g. a vector with 101 discretized points).

The fuzzy set class implements basic functionality, such as creating various kinds of fuzzy sets, taking the union and intersection with another fuzzy set and various other operations such as calculating alpha-cut sets.

3.4 Fuzzy operators

This package provides many fuzzy operators such as triangular norms and conorms, negators, implicators, linguistic hedges, fuzzy qualifiers, similarity measures,... They are all implemented as separate function objects (functors) in the same spirit as defined by STL. This feature allows them to be passed as arguments to algorithms (e.g. inference algorithms), operators (e.g. an implicator based on a triangular conorm and negator) and other methods. It enables classes, e.g. FuzzySet, to be configured with default operators, e.g. for performing the fuzzy set union and intersection.

The fuzzy operators are hierarchically structured to reflect their mathematical properties, e.g. being a t-norm or t-conorm. On top of the hierarchy are interfaces for binary and unary operators. They are further specialized to various operator types and subtypes. Most of the interfaces are empty, they are simply tag interfaces as used in Java to designate a certain type. At the bottom, the tag interfaces are implemented as concrete function objects. A representative sample of the structure is shown in figure B.2.

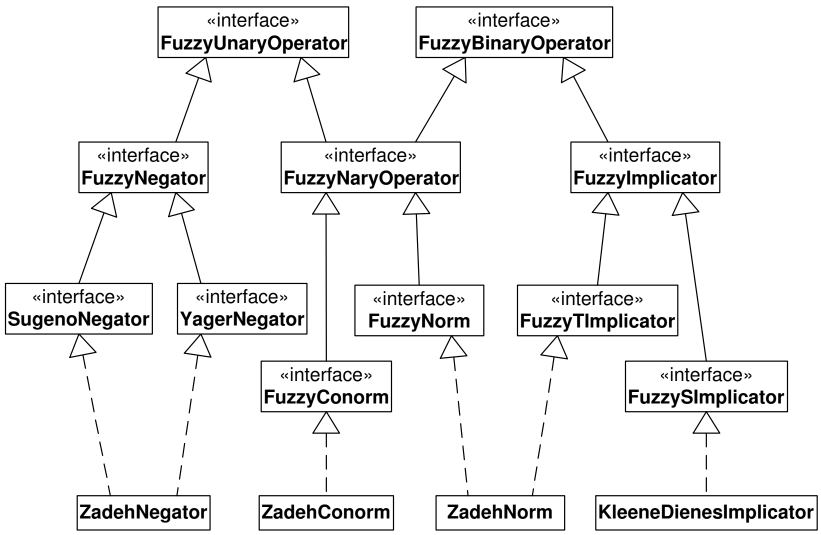

Figure B.2: Static UML diagram of the fuzzy operator hierarchy.

The tag interfaces can be used to denote specific argument types, e.g. an S-implicator in combination with a triangular conorm to aggregate rule results in a certainty qualifying rule inference scheme. This approach ensures that only semantically valid arguments can be passed to algorithmic functions, an R-implicator instead of an S-implicator will not be accepted. The compiler can check for such semantic errors at compile-time. In C++, the interfaces are implemented as pure virtual classes. Multiple inheritance is applied to provide the structure.

3.5 Fuzzy rules

The classes in this package are responsible to represent fuzzy facts that can be used as antecedent and consequents in fuzzy rules. A fuzzy rule also contains the inference scheme configuration that should be used to calculate its result. Fuzzy rules can be adorned with fuzzy qualifiers (possibility or certainty degree qualification). They can be grouped into a fuzzy rule base that aggregates the rule results using a FITA or FATI inference scheme.

3.6 Fuzzy inference engines

These classes supply the actual algorithms to apply a fuzzy rule or rule base to given input data to infer new fuzzy knowledge. Possibility and certainty qualifying FITA and FATI inference schemes are supported.

3.7 Database

The primary purpose of the database class is to store the data from the social survey that is used to test and tune the implemented fuzzy noise annoyance model. However, the class can also be used to store intermediate and final (rule) results for further analysis.

The database can contain crisp numbers as well a fuzzy sets. It is structured as a large dynamically table with rows and columns, e.g. to address survey records (rows) and the various variables (columns). Internally, an STL map data structure is used. It is possible to switch the addressing of data in the database with a few typedefs that modify the argument types of the internal map and related getter/setter methods. To store general data or parameters that are independent of a record, the database class allows the omission of a row number.

3.8 Model

The model package actually contains the implementation of the building blocks from the noise annoyance advisor. A model class contains the fuzzy rule(s) or fuzzy rule base(s) (and possibly other submodels) together with the model parameters (e.g. rule weights). A model has an association with a database from which it retrieves the input for its rules. It also knows how to map the outcome of the inference process to a (set of) linguistic term(s) and is capable of calculating an error measure based on the predicted and reported data.

The model package can be coupled with a genetic algorithm that optimizes the model parameters to obtain a minimal error. This requires subsequent evaluations of the model with different parameter sets.

APPENDIX C

Surveys

Where is the wisdom we have lost in knowledge?
Where is the knowledge we have lost in information?

Thomas Stearns Eliot (1888-1965)
American-British poet and critic

1 AUSTRIAN SURVEY

REPRÄSENTATIVERHEBUNG – UNTERINNTAL 5/98

Grüß Gott, hier spricht... für das Institut für Sozialmedizin, Universität Innsbruck. Wir führen zur Zeit im Unterinntal eine Erhebung der persönlichen Lebens- und Umweltbedingungen zur Ergänzung der Umweltverträglichkeitsprüfung der geplanten Bahntrasse durch. Darf ich Ihnen dazu bitte ein paar Fragen stellen?

1. In welchem Jahr sind Sie geboren? .... (1923–1980)

2. Wenn Sie an das letzte Monat denken, wie zufrieden sind Sie insgesamt mit Ihrer persönlichen Lebensqualität?

   1) sehr zufrieden   2) ziemlich zufrieden
   3) weder zufrieden noch unzufrieden
   4) ziemlich unzufrieden   5) sehr unzufrieden

3. Denken Sie jetzt an Ihre Wohngegend: Wie zufrieden sind Sie mit folgenden Bereichen Ihrer Wohngegend:

   a) Dem Aussehen/ der Attraktivität ihrer Wohngegend
   b) Der allgemeinen Wohnqualität der Wohngegend

c) Den Erholungsmöglichkeiten der Wohngegend
d) Der allgemeinen Sicherheit in der Wohngegend
e) Der nachbarschaftlichen Unterstützung in der Wohngegend

1) sehr zufrieden 2) ziemlich zufrieden
3) weder zufrieden noch unzufrieden
4) ziemlich unzufrieden 5) sehr unzufrieden

4. Denken Sie jetzt an Ihren Wohnort: Wie zufrieden sind Sie mit...

a) Den Einkaufsmöglichkeiten des Wohnortes
b) Dem Veranstaltungsangebot des Wohnortes
c) Den Kindergärten/ Schulen des Wohnortes
d) Den öffentlichen Verkehrsmitteln

1) sehr zufrieden 2) ziemlich zufrieden
3) weder zufrieden noch unzufrieden
4) ziemlich unzufrieden 5) sehr unzufrieden

5. Denken Sie bitte wieder an Ihren Wohnort – Haben Sie Grund, sich über folgende Dinge zu beklagen:

a) Luftverschmutzung
b) Lärm
c) Schlechte Gerüche
d) Art der Müllbeseitigung
e) Landschaftszerstörung
f) Verkehrsaufkommen
g) Industriebetriebe/ Handwerksbetriebe in Ihrer Nähe

1) sehr großen Grund 2) ziemlich großen Grund
3) weniger großen Grund 4) überhaupt keinen Grund

6. Ist das Haus bzw. die Wohnung in der Sie wohnen ein:

1) Alleinstehendes Haus 2) Doppelhaus
3) Reihenhaus 4) Wohnblock oder Apartmenthaus
5) anderer Wohntyp

7. Seit wann leben Sie schon in diesem Haus / dieser Wohnung?
Seit: ....

8. Wieviele Wohnräume, ohne Küche, Bad und Vorraum, hat ihr Haus/ Ihre Wohnung?
Anzahl der Wohnräume: ....

9. Hat ihr Haus/ ihre Wohnung einen: (Mehrfachantwort möglich)

   1) Garten — 3) Gemeinsam nutzbare Grünfläche
   2) Balkon, Veranda, Terasse — 4) Kinderspielplatz
   (5) hat nichts davon)

10. In welchem Stockwerk befindet sich

    a) ihr Wohnzimmer: ....
    b) ihr Schlafzimmer: ....

11. Wohin ist

    a) ihr Schlafzimmerfenster
    b) ihr Wohnzimmerfenster

    gerichtet? (Mehrfachantwort möglich)

    1) auf eine ruhige Wohnstrasse
    2) auf eine Strasse mit Durchzugsverkehr
    3) auf eine Autobahn
    4) auf eine Bahntrasse
    5) auf einen ruhigen Hinterhof/ Garten

12. Wieviele Personen wohnen ständig in diesem Haushalt, Sie selbst miteingeschlossen?
    Anzahl der Personen: ....
    (Wenn Interviewte einzige Person im HH, weiter Fr. 15)

13. Wie viele Kinder unter 18 Jahre leben ständig in diesem Haushalt?
    Anzahl der Kinder: ....

14. Wie alt sind diese Kinder? ....

Allgemeine Bewertung der Wohnumwelt
Auszeichnungsschlüssel Frage 15 bis Frage 20

1) überhaupt nicht — 2) gering oder teilweise
3) mittelmäßig — 4) stark/ erheblich

15. Wenn Sie an die letzten 12 Monate denken, wie sehr fühlen Sie sich insgesamt in Ihrer Wohnung und auf Ihrem Wohngrund durch STRASSENLÄRM belästigt?

16. Wenn Sie an die letzten 12 Monate denken, wie sehr fühlen Sie sich insgesamt in Ihrer Wohnung und auf Ihrem Wohngrund durch ERSCHÜTTERUNGEN vom STRASSENVERKEHR belästigt?

17. Wenn Sie an die letzten 12 Monate denken, wie sehr fühlen Sie sich insgesamt in Ihrer Wohnung und auf Ihrem Wohngrund durch SCHIENENVERKEHRSLÄRM belästigt?

18. Wenn Sie an die letzten 12 Monate denken, wie sehr fühlen Sie sich insgesamt in Ihrer Wohnung und auf Ihrem Wohngrund durch ERSCHÜTTERUNGEN vom SCHIENENVERKEHR belästigt?

19. Wenn Sie an die letzten 12 Monate denken, wie sehr fühlen Sie sich insgesamt in Ihrer Wohnung und auf Ihrem Wohngrund durch den GERUCH von AUTOABGASEN belästigt?

20. Wenn Sie an die letzten 12 Monate denken, wie sehr fühlen Sie sich insgesamt in Ihrer Wohnung und auf Ihrem Wohngrund durch STAUB und RUSS vom STRASSENVERKEHR belästigt?

Spezielle Bewertung

21. Wenn Sie an die letzten 12 Monate denken, bei welchen Tätigkeiten und wie oft fühlen Sie sich durch

    I) Straßenverkehrslärm
    II) Schienenverkehrslärm

    gestört?

    a) beim Fernsehen oder Radiohören
    b) beim Ausruhen/ Ausspannen (nach der Arbeit)
    c) bei Unterhaltungen in der Wohnung
    d) bei Unterhaltungen im Freien

    Auszeichnungsschlüssel:

    1) nie 2) manchmal 3) öfters 4) meistens

22. Wenn Sie an die letzten 12 Monate denken, bei welchen Tätigkeiten und wie oft fühlen Sie sich gestört durch

    I) Erschütterungen vom Straßenverkehr
    II) Erschütterungen vom Schienenverkehr

    gestört?

    a) beim Fernsehen oder Radiohören
    b) beim Ausruhen/ Ausspannen (nach der Arbeit)
    c) bei Unterhaltungen in der Wohnung
    d) bei Unterhaltungen im Freien

    Auszeichnungsschlüssel:

    1) nie 2) manchmal 3) öfters 4) meistens

23. Wenn Sie an die letzten 12 Monate denken, bei welchen Tätigkeiten und wie oft fühlen Sie sich gestört durch Autoabgasgeruch?

    a) beim Fernsehen oder Radiohören
    b) beim Ausruhen/ Ausspannen (nach der Arbeit)
    c) bei Unterhaltungen in der Wohnung
    d) bei Unterhaltungen im Freien

    Auszeichnungsschlüssel:

    1) nie 2) manchmal 3) öfters 4) meistens

24. Wenn Sie an die Verkehrsbelastungen der letzten 12 Monate denken, haben Sie Folgendes getan/gedacht/gefühlt?

    a) Ich habe die Fenster auch im Sommer tagsüber geschlossen gehalten
    b) Ich habe die Fenster auch im Sommer nachts geschlossen gehalten.
    c) Ich habe mich geärgert.
    d) Ich habe mit Ohrstöpsel geschlafen.
    e) Ich habe mich hilflos gefühlt.
    f) Ich denke ich bin weniger empfindlich als andere.
    g) Ich habe mit Nachbarn darüber gesprochen.
    h) Ich habe mit Vertretern der Gemeinde/Behörden darüber gesprochen.

    1) ja 2) nein

25. Sie können nun Schulnoten zwischen 1 (sehr gut) und 5 (nicht genügend) vergeben.
    Wie beurteilen Sie die Aktivitäten der öffentlichen Stellen (Behörden/ Entscheidungsträger) um:

    a) die Luftverschmutzung zu verringern
    b) die Lärmbelastung zu verringern
    c) die Erschütterungsbelastung zu verringern
    d) den Verkehr zu verringern

26. Wenn Sie an den geplanten Ausbau der Bahn im Unterinntal denken, glauben Sie persönlich, daß dieser Ausbau die Transit-Verkehrsbelastung auf der Straße verringern wird?

    1) erheblich verringern 4) wenig verringern
    2) mittelmäßig verringern 5) überhaupt nicht verringern

27. Die Bewältigung des Transitverkehrs ist ein anerkannt großes Problem in Tirol. Würden sie eine der folgenden Aktionen selber tun bzw. unterstützen?

a) Eine Unterstützungserklärung für eine Bürgerinitiative unterschreiben.
b) Einen Leserbrief an die Tages-/ Regionalzeitung schreiben.
c) In einer Bürgerinitiative selbst mitarbeiten.
d) An einer genehmigten Protestaktion teilnehmen.

1) eher Ja 2) eher Nein

28. Fühlen Sie sich an Ihrem Arbeitsplatz durch:

a) Lärm
b) Erschütterungen
c) Gerüche/ Abgase
d) Staub und Schmutz
e) Hitze/ Kälte/ Nässe oder Zugluft

1) überhaupt nicht gestört 2) wenig gestört
3) mittelmäßig gestört 4) stark gestört

29. Arbeiten Sie:

1) in normaler Arbeitszeit untertags
2) im Schichtdienst
3) während der Nacht (20 Uhr bis 6 Uhr Früh)
4) am Samstag
5) am Sonntag

30. Sind Sie selbst Raucher?

1) Ja, Wieviele Zigaretten rauchen Sie im Durchschnitt am Tag? (letzten 12 Monate)
2) Nein

31. Leben andere Raucher in Ihrem Haushalt

1) Nein
2) Ja, Wieviele Zigaretten rauchen diese Personen im Durchschnitt zu Hause?

32. Wie häufig haben Sie für gewöhnlich ein Auto zur Verfügung?

1) nie 2) manchmal 3) öfters 4) meistens bzw. fast immer

33. Wie häufig benützen Sie für gewöhnlich ein öffentliches Verkehrsmittel?

1) nie 2) manchmal 3) öfters 4) meistens bzw. fast immer

34. Wenn Sie alle Vor- und Nachteile Ihrer Wohngegend betrachten, würde es Ihnen schwerfallen, anderswo hinzuziehen?

    1) eher ja 2) eher nein (3) ist mir egal)

Gesundheit

35. Wenn Sie an die letzten 12 Monate denken, wie würden Sie Ihren Gesundheitszustand insgesamt beurteilen?

    1) sehr gut 2) gut 3) zufriedenstellend
    4) weniger gut 5) schlecht

36. Leiden Sie an einer chronischen Erkrankung oder Behinderung?

    1) Ja 2) Nein (Weiter mit Frage 38)

37. Schränkt Sie diese Erkrankung oder Behinderung in Ihren täglichen Arbeiten/ Aktivitäten ein?

    1) sehr stark 2) stark 3) mittelmäßig
    4) ein wenig 5) überhaupt nicht

38. Denken Sie bitte an die letzten 3 Monate - Wie oft hatten Sie folgende Beschwerden:

    a) gerötete/ tränende/ oder juckende Augen
    b) gereizte/ laufende/ oder verstopfte Nase
    c) Rachen-/ Halsschmerzen
    d) Kopfschmerzen/Migräne
    e) Gereiztheit/Nervosität
    f) Müdigkeit/ Erschöpfung

    1) fast täglich 2) mehrmals pro Woche
    3) mehrmals pro Monat 4) noch seltener

39. Hatten Sie während der letzten 3 Monate Schlafprobleme oder fühlten Sie sich trotz normaler Schlafzeit unausgeschlafen?

    1) fast täglich 2) mehrmals pro Woche
    3) mehrmals pro Monat 4) noch seltener oder nie

40. Welche Art von Schlafproblemen war das? (Mehrfachantwort möglich)

    1) Einschlafprobleme
    2) Häufiges Erwachen
    3) Probleme mit Wiedereinschlafen
    4) Zu frühes Erwachen
    5) Müdigkeit/ Zerschlagenheitsgefühl am Morgen

41. Hat Ihnen ein Arzt JEMALS gesagt, daß Sie eines der folgenden Gesundheitsprobleme haben?

    I) Jemals
    II) in letzten 12 Monaten

    a) Heuschnupfen/ allergische Nase
    b) andere allergische Reaktionen
    c) Chronisches Ekzem
    d) Asthma
    e) Chronische Bronchitis
    f) Bluthochdruck
    g) Herzinfarkt oder Angina pectoris
    h) Magen- oder Zwölffingerdarmgeschwür

    1) Ja 2) Nein

42. Haben Sie während der letzten 12 Monate Medikamente wegen folgender Gesundheitsprobleme eingenommen?

    a) wegen Kopfschmerzen/Migräne
    b) wegen Heuschnupfen
    c) wegen Magenbeschwerden
    d) wegen Nervosität
    e) wegen Schlafproblemen
    f) wegen Asthma
    g) wegen Bluthochdruck
    h) wegen Herzkrankheit

    1) fast täglich 2) mehrmals pro Woche
    3) mehrmals pro Monat 4) noch seltener

Reaktionsweise auf die Umwelt
Auszeichnungsschlüssel Frage 43 bis Frage 47

1) überhaupt nicht 2) gering
3) mittelmäßig 4) stark

43. Wie wetterfühlig/ wetterempfindlich schätzen Sie sich im allgemeinen ein?

44. Wie lärmempfindlich schätzen Sie sich im allgemeinen ein?

45. Wie empfindlich gegenüber schlechten Gerüchen schätzen Sie sich im allgemeinen ein?

46. Wie empfindlich gegenüber Luftverschmutzung schätzen Sie sich im allgemeinen ein?

47. Wie empfindlich gegenüber Erschütterungen schätzen Sie sich im allgemeinen ein?

Einige Fragen zu statistischen Zwecken

1. Geschlecht

   1) männlich 2) weiblich

2. Haushaltstyp: Wohnen Sie:

   1) alleine (mit/ohne Kind)
   2) Ehe oder Lebensgemeinschaft (mit/ohne Kind)
   3) Mehrgenerationenfamilie

3. Beruf: Welche berufliche Stellung haben Sie dzt? Sind Sie

1) Selbständig	2) Landwirt
3) Angestellter/VB	4) Beamter
5) Facharbeiter	6) angelernter Arbeiter/Hilfsarbeiter
7) In Lehrlingsausbildung	8) Schüler/ Student
9) Hausfrau/-mann	10) mithelfend im Familienbetrieb
11) Pensionist/ Rentner	12) derzeit nicht berufstätig

4. Schulbildung: Was ist Ihr höchster Schulabschluß?

1) Pflichtschulabschluß	2) abgeschlossene Lehre
3) Fachschule ohne Matura	4) Matura
5) Hochschule/ Uni/ Akademie	

5. Sind Sie:

   1) Eigentümer der Wohnung/ des Hauses 2) Mieter

6. Haben Sie Lärmschutzfenster?

   1) Ja 2) Nein

Danke für das Interview!

2 Flemish survey

What follows is the actual text of the Flemish survey. Because this survey was conducted by postal mail, the page layout is important. All text was placed inside the table headers, where it is here replaced by numbers which are described below the table. The real page breaks are replaced by horizontal lines over the page width.

Uw mening over hinder door geluid, geur en licht

Gelieve alle vragen te beantwoorden door het overeenkomstige bolletje te kleuren of door het antwoord op de stippellijntjes te noteren.

I ALGEMENE VRAGEN LEEFKWALITEIT & LEEFOMGEVING

1. Hoe tevreden bent U in het algemeem over de leefkwaliteit (veiligheid, kindvriendelijkheid, leefmilieu,...) in uw buurt? Bent U hierover...

   o zeer tevreden
   o tevreden
   o min of meer tevreden
   o niet tevreden
   o helemaal niet tevreden

2. Als we enkel kijken naar de leefkwaliteit (veiligheid, kindvriendelijkheid, leefmilieu,...) van uw buurt, zou u vrienden en kennissen dan aanraden om hier te komen wonen?

   o ja
   o nee
   o weet niet

   Waarom wel? ....
   ....

   Waarom niet? ....
   ....

3. Als u denkt aan **de voorbije 12 maanden**, in welke mate bent u gehinderd of niet gehinderd door GELUID of GEUR of LICHT **in en om uw woning?**

   Kleur **voor elke bron** één bolletje.

   Wanneer er **geen GELUID, GEUR of LICHT waar te nemen** is, kleur DAN OOK het bolletje bij **'helemaal niet gehinderd'**.

	Hoe gehinderd bent u?				
Bronnen van hinder	(1)	(2)	(3)	(4)	(5)
Geluid	o	o	o	o	o
Geur	o	o	o	o	o
Licht	o	o	o	o	o

(1) Helemaal niet gehinderd

(2) Een beetje gehinderd
(3) Tamelijk gehinderd
(4) Ernstig gehinderd
(5) Extreem gehinderd

---

4. Hebt u in de loop van **de voorbije 12 maanden** in verband met geluids-, geur- of lichthinder... (meerdere antwoorden zijn mogelijk). Wanneer u dit **niet gedaan** heeft, kleur dan **telkens het bolletje bij "neen".**

	(1)	(2)	(3)	(4)
eraan gedacht om klacht in te dienen?	o	o	o	o
reeds éénmaal een klacht ingediend?	o	o	o	o
reeds meermaals klacht ingediend?	o	o	o	o
eraan gedacht om te verhuizen?	o	o	o	o
een advocaat gecontacteerd?	o	o	o	o
lid geworden van een actiecomité?	o	o	o	o
gepraat met zij die het veroorzaken?	o	o	o	o
meer aandacht besteed aan het sluiten van deuren, ramen, gordijnen of rolluiken?	o	o	o	o
uw woning aangepast en/of verbouwd?	o	o	o	o
andere: welke:	o	o	o	o

(1) **ja**, i.v.m. geluidshinder
(2) **ja**, i.v.m. geurhinder
(3) **ja**, i.v.m. lichthinder
(4) **neen**, heb dit niet gedaan

5. Als u denkt aan uw situatie thuis, dit wil zeggen in en om uw woning, in welke mate is de hinder door volgende bronnen **veranderd in de laatste twee jaar**?

   Als u nu geen hinder ondervindt en twee jaar geleden ook niet, kleur dan het bolletje bij **"situatie is dezelfde gebleven".** Als u nu nog evenveel hinder ondervindt als twee jaar geleden, kleur dan óók het bolletje bij **"situatie is dezelfde gebleven".**

Bronnen van hinder	(1)	(2)	De hinder is...			
			(3)	(4)	(5)	(6)
Geluid	o	o	o	o	o	o
Geur	o	o	o	o	o	o
Licht	o	o	o	o	o	o

(1) Ik woon hier nog geen 2 jaar
(2) Situatie is dezelfde gebleven
(3) Sterk toegenomen
(4) Enigzins toegenomen
(5) Enigzins afgenomen
(6) Sterk afgenomen

6. Hoe zou u best de omgeving waar u woont omschrijven?

   o centrum van een stad
   o stad maar niet het centrum
   o randgemeente van een stad
   o landelijke gemeente of plattelandsgemeente

7. Hoe ver van uw woning is de dichtst gelegen industrieterrein of fabriek?

o minder dan 50 m	o 500 m tot 1 km
o 50 tot 100 m	o 1 km tot 5 km
o 100 m tot 500 m	o meer dan 5 km

8. Woont u in een omgeving met...?

   o zeer veel verkeer
   o veel verkeer
   o normaal verkeer
   o weinig verkeer
   o zeer weinig verkeer

Op de pagina's hierna volgen enkele specifieke vragen met betrekking tot elk van de drie hinderaspecten.

II GELUIDSHINDER

1. In volgende tabel worden enkele mogelijke bronnen van geluidshinder aangegeven. Als u denkt aan de voorbije 12 maanden, hoe gehinderd

of niet gehinderd bent u door het geluid van de volgende bronnen **in en om uw woning**?

Als u **géén hinder** ondervindt van een bepaalde bron, **kleur dan** het bolletje **'Helemaal niet gehinderd'**!

Wanneer **u de geluidsbron niet hoort in en om uw woning**, kleur DAN OOK het bolletje bij **'Helemaal niet gehinderd'.**

	Hoe gehinderd bent u?				
Bronnen van geluidshinder	(1)	(2)	(3)	(4)	(5)
VERKEER EN VERVOER					
Straatverkeer	o	o	o	o	o
Treinverkeer	o	o	o	o	o
Luchtvaart	o	o	o	o	o
Scheepvaart	o	o	o	o	o
Kleine en Middelgrote Ondernemingen & INDUSTRIE					
Laden en lossen van vrachtwagens	o	o	o	o	o
Zelfstandige beroepsactiviteiten (timmerman, bakker,...)	o	o	o	o	o
Bedrijven, fabrieken	o	o	o	o	o
Handel en diensten	o	o	o	o	o
Bouw- en sloopactiviteiten	o	o	o	o	o
RECREATIE EN TOERISME					
Muziek van dancings	o	o	o	o	o
Muziek van cafés en restaurants	o	o	o	o	o
Pretparken	o	o	o	o	o
Kermissen, braderijen en muziekfestivals	o	o	o	o	o
Sportvelden en -stadia	o	o	o	o	o
Race- en crosscircuits	o	o	o	o	o
LANDBOUW					
Landbouwwerktuigen	o	o	o	o	o
Vee (koeien, schapen, pluimvee,...)	o	o	o	o	o
Geluid van ventilatoren van stallen	o	o	o	o	o
BUREN					

Spelende kinderen	o	o	o	o	o
Huisdieren van buren	o	o	o	o	o
Doe-het-zelf-activiteiten van buren	o	o	o	o	o
ANDERE of ONBEKENDE [1] **BRON**: noteer welke:					
–	o	o	o	o	o
–	o	o	o	o	o
–	o	o	o	o	o

[1] Met *onbekende bron* bedoelen we de hinder die u ondervindt of ondervonden heeft, zonder juist te weten wat de oorzaak hiervan was.

(1) Helemaal niet gehinderd
(2) Een beetje gehinderd
(3) Tamelijk gehinderd
(4) Ernstig gehinderd
(5) Extreem gehinderd

2. Welke andere opmerkingen heeft u nog over deze geluidshinder?
....
....
....

III GEURHINDER

1. In volgende tabel worden enkele mogelijke bronnen van geurhinder aangegeven.

   Als u denkt aan de voorbije 12 maanden, hoe gehinderd of niet gehinderd bent u door de geur van de volgende bronnen **in en om uw woning**?

   Als u **géén hinder** ondervindt **of** wanneer er **geen bron van hinder** is, kleur DAN OOK het bolletje bij **'Helemaal niet gehinderd'.**

	Hoe gehinderd bent u?				
Bronnen van geurhinder	(1)	(2)	(3)	(4)	(5)
VERKEER EN VERVOER					

Straatverkeer (uitlaatgassen van auto's , vrachtwagens, bussen)	o	o	o	o	o
Luchtvaart (militaire en burgervluchten, heli's,...)	o	o	o	o	o
Kleine en Middelgrote Ondernemingen & INDUSTRIE					
Slachterijen en verwerken dierlijk afval, vetsmelterijen	o	o	o	o	o
Verfspuitcabines	o	o	o	o	o
Chemische en petrochemische nijverheid	o	o	o	o	o
Textielbedrijven	o	o	o	o	o
Voedings- en drankenindustrie, inclusief brouwerijen	o	o	o	o	o
Composteringsinstallaties voor groenafval en GFT-afval	o	o	o	o	o
Veevoederbedrijven	o	o	o	o	o
Metaal- en metaalverwerkende industrie	o	o	o	o	o
HANDEL, DIENSTEN, RECREATIE EN TOERISME					
Horeca (restaurant, frituur, bakker, beenhouwer)	o	o	o	o	o
Benzinestations	o	o	o	o	o
LAND- EN TUINBOUW					
Varkensstallen	o	o	o	o	o
Uitspreiden van dierlijke mest	o	o	o	o	o
Stookinstallaties tuinbouw	o	o	o	o	o
Pluimveehouderijen	o	o	o	o	o
Rundveekwekerijen	o	o	o	o	o
WATER EN ZUIVERING					
Waterlopen (beek, rivier, kanaal)	o	o	o	o	o
Waterzuivering	o	o	o	o	o
Riolering	o	o	o	o	o
BUREN					
Verbranden van afval	o	o	o	o	o
Opslaan van afval (composthopen,...)	o	o	o	o	o

Huisdieren (honden, kippen)	o	o	o	o	o
ANDERE of ONBEKENDE [1] **BRON**: noteer welke:					
–	o	o	o	o	o
–	o	o	o	o	o
–	o	o	o	o	o

[1] Met *onbekende bron* bedoelen we de hinder die u ondervindt of ondervonden heeft, zonder juist te weten wat de oorzaak hiervan was.

(1) Helemaal niet gehinderd
(2) Een beetje gehinderd
(3) Tamelijk gehinderd
(4) Ernstig gehinderd
(5) Extreem gehinderd

2. Welke andere opmerkingen heeft u nog over deze geurhinder?
   ....
   ....
   ....

IV LICHTHINDER

1. In volgende tabel worden enkele mogelijke bronnen van lichthinder aangegeven.

   Als u denkt aan de voorbije 12 maanden, hoe gehinderd of niet gehinderd bent u door het licht van volgende bronnen **in en om uw woning**?

   Als u **géén hinder** ondervindt **of** wanneer er **geen bron van hinder** is, kleur DAN OOK het bolletje bij **'Helemaal niet gehinderd'.**

	Hoe gehinderd bent u?				
Bronnen van lichthinder	(1)	(2)	(3)	(4)	(5)
VERKEER EN VERVOER					
Verlichting van autosnelwegen	o	o	o	o	o
Verlichting van gemeente- en gewestwegen	o	o	o	o	o

Verlichting parkeerterreinen	o	o	o	o	o
Kleine en Middelgrote Ondernemingen & INDUSTRIE					
Verlichting van industrieterreinen	o	o	o	o	o
HANDEL, DIENSTEN, RECREATIE EN TOERISME					
Lichtreclame	o	o	o	o	o
Verlichte uitstalramen	o	o	o	o	o
Laserverlichting (dancings, bioscopen)	o	o	o	o	o
Verlichting sport- en recreatieterreinen	o	o	o	o	o
Feestverlichting	o	o	o	o	o
Verlichting gebouwen en/of monumenten	o	o	o	o	o
LANDBOUW					
Verlichting serres	o	o	o	o	o
BUREN					
Verlichting tuinen en opritten	o	o	o	o	o
ANDERE of ONBEKENDE [1] **BRON**: noteer welke:					
–	o	o	o	o	o
–	o	o	o	o	o
–	o	o	o	o	o

[1] Met *onbekende bron* bedoelen we de hinder die u ondervindt of ondervonden heeft, zonder juist te weten wat de oorzaak hiervan was.

(1) Helemaal niet gehinderd
(2) Een beetje gehinderd
(3) Tamelijk gehinderd
(4) Ernstig gehinderd
(5) Extreem gehinderd

2. Welke andere opmerkingen heeft u nog over deze lichthinder?
....
....
....

V BELEID

1. **In het algemeen**, hoe belangrijk vindt u het dat de overheid een oplossing zoekt om hinder weg te nemen? Kleur het bolletje **voor elke bron.** Probeer niet enkel aan uw eigen situatie te denken, maar wel in het algemeen.

	Ik vind dit:				
	(1)	(2)	(3)	(4)	(5)
Geluid	o	o	o	o	o
Geur	o	o	o	o	o
Licht	o	o	o	o	o

(1) Totaal onbelangrijk
(2) Niet belangrijk
(3) Belangrijk
(4) Zeer belangrijk
(5) Uitzonderlijk belangrijk

2. Welke andere opmerkingen heeft u nog over dit **beleid in het algemeen**?
....
....
....
....

VI ALGEMENE VRAGEN

1. Wat is uw geslacht?

   o man
   o vrouw

2. Wat is uw leeftijd? ....

3. Hoeveel personen wonen er bij u thuis, uzelf meegeteld?
   .... personen

4. Wat is uw hoogst behaalde diploma? (Het gaat over het onderwijs dat u volledig gevolgd heeft tot en mét het behalen van het overeenkomstig diploma.)

   o geen
   o lager onderwijs
   o lager technisch of lager beroeps
   o lager algemeen middelbaar

- o hoger technisch of hoger beroeps
- o hoger algemeen middelbaar
- o hoger niet universitair onderwijs
- o universitair onderwijs

5. Bent u...? (u mag zo nodig meer dan één antwoord aanduiden)

- o voltijds beroepsmatig actief
- o deeltijds beroepsmatig actief
- o werkzoekende
- o student
- o huisvrouw/-man
- o bruggepensioneerd/gepensioneerd
- o andere (ziekte, invaliditeit, loopbaanonderbreking,...)

---

6. Duid aan wanneer u thuis bent op dit adres tijdens een gewone week in het jaar. Gelieve geen rekening te houden met vakanties.

		meestal of altijd	soms	zelden of nooit
dag tijdens de week	voormiddag	o	o	o
	namiddag	o	o	o
	avond	o	o	o
	nacht	o	o	o
zaterdag	voormiddag	o	o	o
	namiddag	o	o	o
	avond	o	o	o
	nacht	o	o	o
zondag	voormiddag	o	o	o
	namiddag	o	o	o
	avond	o	o	o
	nacht	o	o	o

7. In welk type woning woont u?

o apartement/loft/studio	o halfopen bebouwing
o rijwoning zonder tuin	o open bebouwing
o rijwoning met tuin	o andere

8. Bent u (of iemand anders van uw gezin) eigenaar of huurder van de woning die u op dit adres bewoont?

   o eigenaar
   o huurder

9. Hoelang woont u reeds op dit adres? .... jaar

10. Wat is de postcode van de gemeente waar u woont? ....

11. Wat is de straat en het huisnummer van uw woning? (*)
    straat: ...., nr: ...., bus: ....

Kijkt u tot slot nog eens **na** of u **alle vragen beantwoord** heeft A.U.B..

Wij danken u voor uw medewerking.

(*) Uw antwoord wordt vertrouwelijk behandeld. Het invullen van uw adres is vrijblijvend. Toch vragen we u dit te doen omdat dit nuttig is voor dit onderzoek.

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