Fuzzy Performance Measures for Noise Annoyance Models

(Invited Paper)

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***Abstract*— In this paper, noise annoyance is studied within the framework of fuzzy set theory in order to allow dealing with fuzziness in the concept and imperfect information. It is shown how models can be constructed that take this inherent fuzziness into account in model performance measurement and visualization of results.**

I. Introduction

Noise as an environmental pollution factor has several adverse effects on health, e.g. annoyance due to interference with activities [1], higher blood pressure [2], tiredness because of sleep disturbances [3],... However, the level of experienced noise annoyance is generally accepted as a good indicator to describe the impact of environmental noise on man [1]. Accurate monitoring and prediction of noise annoyance is required to assess the impact of planned changes (e.g. new roads or plants) and to tackle problem areas in an efficient way. Obviously, the experienced degree of annoyance will largely depend on the characteristics of the noise, but also personal, emotional, situational,... factors play an important role.

The modeling of noise annoyance has to deal with several issues inherently linked to the domain. Concepts are subjective and vague (e.g. annoyance describes a feeling, a state of mind). Data is scarce, imprecise and uncertain (e.g. annoyance cannot be measured, it must be obtained by social surveys). Knowledge is vague, uncertain or even lacking (e.g. even experts in the field can only give vague expressions of assumed relationships).

Imperfect information such as imprecise, vague or uncertain information can be mathematically modeled within the framework of fuzzy set theory and possibility theory. In this paper, the concept of noise annoyance will be approached as an inherently fuzzy concept. Fuzzy reasoning techniques will be applied to model and to reason with noise annoyance and related concepts.

Section II will deal with representation issues of noise annoyance. The modeling framework will be discussed in section III. After obtaining output from the model, it will often be necessary to present the results to people, e.g. policy decision makers. Several techniques for the visualization of fuzzy annoyance are briefly described in section IV. In section V, the model is put into action by feeding it with data collected through social surveys. These results are analyzed in detail using fuzzy performance measures. Finally, section VI draws some conclusions.

II. Representing Noise Annoyance

One of the most important questions in social surveys ask for the level of experienced noise annoyance, e.g. "Thinking about the last (..12 months or so..), when you are here at home, how much does noise from (..noise source, such as road or railway traffic..) bother, disturb, or annoy you?". Several schemes for answering this type of question are in existence, e.g. by providing some kind of numerical scale. Yet, one of the most common ways uses a scale with four or five linguistic terms (e.g. "not at all", "slightly", "moderately", "very", "extremely") and let the respondent choose one of them. Historically, such terms have been represented by crisp cut-off points, e.g. 2.8 for "little annoyed" and 7.2 for "highly annoyed" (on a $[0, 10]$ scale). Such sharp boundaries are not in correspondence with the real meaning of a term. As annoyance is an inherently vague concept, they should be mathematically represented as fuzzy sets.

For constructing these fuzzy sets, the results of an International Annoyance Scaling Study [4] have been used. In this study, originally performed for 9 languages, people had to mark the meaning they associate with 21 different terms on a continuous line of 10 centimeters. The left side of the line meant "no annoyance at all" while the right side represented the "worst possible level of annoyance". The fuzzy set representations for five English terms on the universe $\mathbb{H} = [0, 10]$ are shown in figure 1. They are the result of an aggregation of individually constructed curves that were obtained by fuzzifying each individual mark to a bi-Gaussian distribution so that the overlap between two adjacent curves of a respondent is equal to a given constant α [5]. This provides an accurate representation of the intended meaning of a term while assuring practical useability in fuzzy rule based models.

Using fuzzy set representations of linguistic terms based on the results of this International Annoyance Scaling Study, an automated translation tool has been built. The obtained translations are quite intuitive which prove the usefulness of the representations. For more information on this application, we refer to [6].

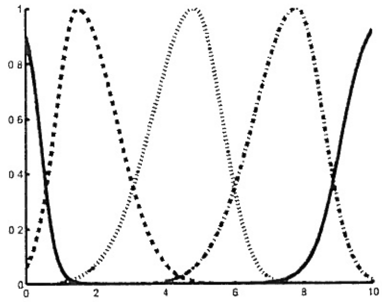

Fig. 1. Representation of five English annoyance terms ("not at all", "slightly", "moderately", "very" and extremely" annoyed) for $\alpha = 0.1$.

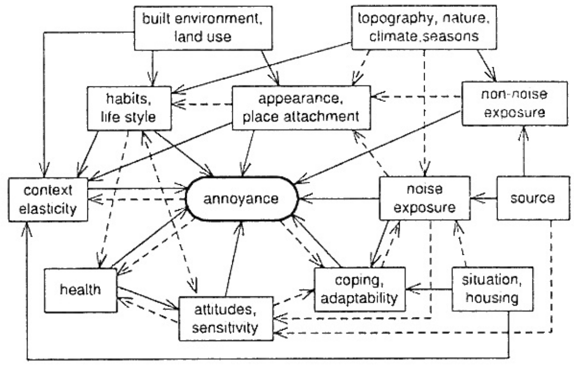

Fig. 3. Conceptual noise annoyance model.

III. Modeling Noise Annoyance

A. Overview

Using the developed representations, a fuzzy system has been constructed that is capable of judging the level of noise annoyance experienced by an individual person (see figure 2). Three layers can be identified: the conceptual annoyance model which describes the relations between various influencing factors, the noise annoyance advisor which instantiates the model and implements the reasoning logic and finally the execution layer that triggers the system with actual data and results in an annoyance judgement. The first two layers are discussed in more detail below, the third layer is exemplified in section V.

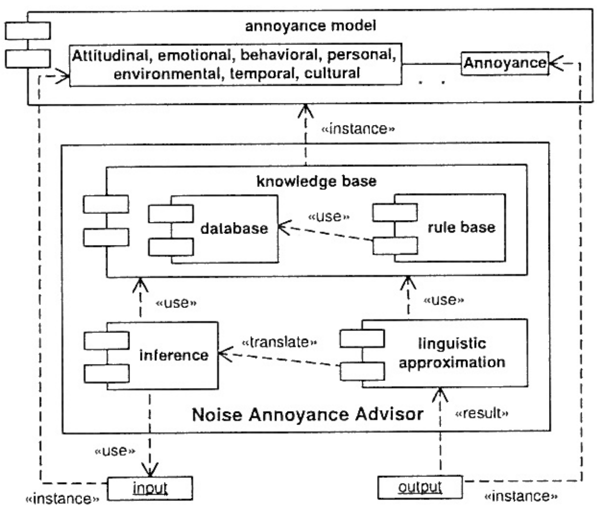

Fig. 2. Component model for a noise annoyance system.

B. Conceptual Model

The conceptual noise annoyance model identifies the relevant factors (for annoyance) and their associations with each other and annoyance in particular. The details of this annoyance model are shown in figure 3. In this figure, clear paths are shown in full lines, while uncertain paths that could turn out completely different are shown in dashed lines. For a description of each factor, the reader is referred to [7].

Note that this model reveals some complicating issues, such as paths that counteract with each other and the occurrence of cycles. Also, many of the identified relationships are still rather hypothetical. Therefore, the system should be capable of including hypothetical knowledge and provide a mechanism to check whether such hypotheses hold or should be rejected.

C. Instantiating the Annoyance Model

The "noise annoyance advisor" layer instantiates each conceptual association (e.g. "noise exposure"—"annoyance") into a number of links or concrete relationships (e.g. "high exposure"—"very annoyed") which are represented by fuzzy IF-THEN rules. This allows experts to formulate their knowledge in a linguistic way, which in turn makes the model easy to comprehend. The main internal components are briefly discussed below.

1) Database: Contains the definitions of the linguistic terms that are used in the fuzzy IF-THEN rules. See section II for the construction of the fuzzy sets that represent noise annoyance terms. Because other concepts cannot rely on such an extensive amount of data specifically collected for representational purposes and their definition is often much more straightforward, these terms have been defined in a more ad hoc way. In most cases, they have been put forward by experts in the field.

2) Rule base: The rule base contains the fuzzy 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 from the same association in the conceptual model form a set of parallel rules, rules expressed between the same variables.

All rules implemented in the noise annoyance advisor have been derived from expert opinions found in the literature. No knowledge extraction algorithms have been applied, because the focus is more on building a stable model that performs equally well on different data sets.

3) Inference: In the inference component the knowledge base and the provided input are used to produce a fuzzy set that represents the possibility distribution on annoyance. The inference engine is based on the compositional rule of inference [8], given by, for all $v \in V$,

$$B'(v) = \max_{i=1}^{n} \left(\sup_{u \in U} \min(A_i'(u), \min(A_i(u), B_i(v))) \right) \quad (1)$$

where U and V are universes, A_i, A_i' are fuzzy sets on U, B_i, B' are fuzzy sets on V and $i \in \{1, 2, \ldots, n\}$ runs through a number of parallel rules of the form "IF $X_i = A_i$ THEN $Y = B_i$" with X_i a variable on U and Y a variable on V.

The partial results of the parallel rule sets can be regarded as estimates for the annoyance result based on the variables used in the antecedent of the particular rule set. They should be combined to produce the ultimate annoyance outcome H. As all variables can be seen as modifiers of the annoyance reaction, an and-like aggregation of the partial possibility restrictions seems appropriate. Hence, the product norm will be used, as this operator uses the maximum amount of available information.

4) Linguistic Approximation: The final component maps the inferred possibility distribution H into the vocabulary used by the model for output, $\mathbb{L} = \{L_1, L_2, \ldots, L_m\}$ where L_j denotes a linguistic term and m is the number of defined terms. Mathematically, approximate descriptors [9] can be applied for this linguistic approximation. Here, the lower approximate descriptor $\pi_{\mathbb{L}}$, the fuzzy set of terms which certainly entail H, is adopted,

$$\pi_{\mathbb{L}}(L_j) = \inf_{h \in \mathbb{H}} \max(1 - L_j(h), H(h)) \quad (2)$$

The lower approximation gathers all terms L_j more or less included in H. The result of an approximate descriptor is a possibility distribution over all terms in the vocabulary, indicating the possibility that a term is a good description of H.

D. Tuning the Annoyance Model

1) Rule Qualification: Of course, not all fuzzy rules will have an equal impact on the final result. 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 [10]. In [10] it has been shown that a certainty qualified proposition "$X = A$ is λ-certain", is equivalent with the unqualified proposition "$X = B$" when B is calculated as $B(u) = \max(1 - \lambda, A(u))$ for all $u \in U$. Remark that the consequent of a rule with $\lambda = 1$ will remain unchanged, having full impact as intended, while a completely uncertain rule ($\lambda = 0$) will not have any effect.

2) 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. In the presented framework, this would mean that the term with the highest possibility in $\pi_{\mathbb{L}}$ should be selected as the single model outcome. However, starting from the viewpoint that noise annoyance is an inherently vague concept, this approach seems untenable. In the possibility distribution $\pi_{\mathbb{L}}$ that results from the linguistic approximation, 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. A more natural quality measure fully taking the vagueness of annoyance into 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 $1 - \pi_{\mathbb{L}}(L_*)$.

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 [11] of the possibility 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 decisiveness. This measure is defined as

$$N(\pi_{\mathbb{L}}) = \sum_{j=2}^{m} \pi_{\mathbb{L}}(L_j) \log_2 \left(\frac{j}{j-1} \right) \quad (3)$$

where $\pi_{\mathbb{L}}$ has been put in decreasing order so that $\pi_{\mathbb{L}}(L_1) \geq \pi_{\mathbb{L}}(L_2) \geq \ldots \geq \pi_{\mathbb{L}}(L_m)$.

3) Tuning the Model: 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 noise annoyance advisor and test whether they hold or not in the sample data set.

The error measure used for this tuning has been defined as a combination of its two constituting parts,

$$e_F = \sum_{k=1}^{N} \frac{\alpha(1 - \pi_{\mathbb{L}}^k(L_*^k))^2 + (1 - \alpha)(N(\pi_{\mathbb{L}}^k))^2}{p(L_*^k)} \quad (4)$$

where the index k runs over all N records in the data set, p is the probability distribution of the linguistic terms in the data. and α is a parameter in $[0, 1]$.

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). The optimization problem of the weights is solved using a genetic algorithm (GA) [12] 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.

IV. Visualizing Annoyance

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 and thus the model is imprecise at this location. An example of such a map where road traffic noise annoyance is predicted, is shown in figure 4. 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 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 for this is to include the non-specificity as an indication of the uncertainty of the result, e.g. by varying the size of the mark.

V. Modeling Results

A. Survey Data

Two databases were used to tune and test the fuzzy noise annoyance model: a survey conducted in the Inn Valley in Tirol, Austria and a survey conducted in Flanders, Belgium.

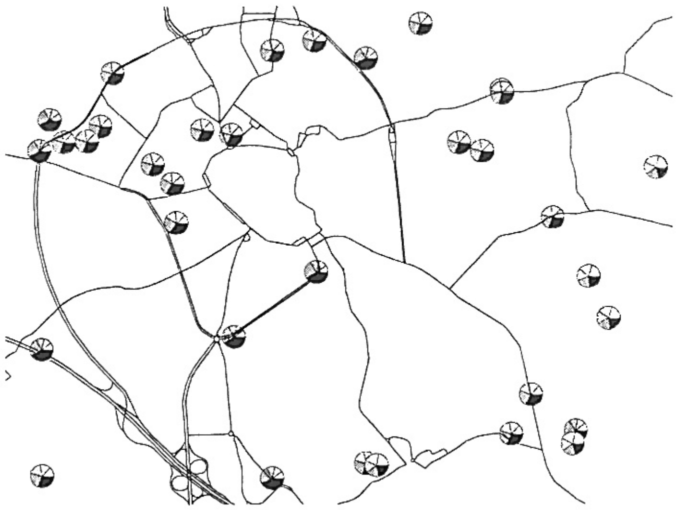

Fig. 4. Map with possibility distribution represented as a pie-chart. White indicates the lowest level of annoyance ("not at all annoyed") while black indicates the highest level of annoyance ("extremely annoyed").

A representative phone survey was conducted within an ongoing environmental health impact assessments 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 rail 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 %. Noise exposure was assessed first by modeling (Soundplan) according to Austrian guidelines Afterwards calibration was conducted and corrections were applied to the modeled data based on the recordings of 31 measuring stations. For the annoyance questions, four German terms were presented to the respondents, "überhaupt nicht", "teilweise", "mittelmäßig" and "erheblich"

The social survey conducted in Flanders involved 3200 subjects. The general topic of the survey was the influence of odor, noise and too much light on the living environment. The questionnaire covered socio-demographic data, housing, satisfaction with public services and the environment, general annoyance and annoyance caused by various sources, coping with noise and odor. The survey was presented as such to the subjects. 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. The overall response was 64 %. Road and rail traffic noise levels were calculated for each respondent's home. 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 and propagation is calculated according to ISO 9613. In this survey, five Dutch linguistic annoyance terms have been used, "helemaal niet", "een beetje", "tamelijk", "ernstig" and "extreem".

For both data sets, the linguistic terms have been represented as fuzzy sets using the method as outlined in section II.

B. Fuzzy Performance

A road traffic annoyance model tuned to the Flemish data set will be used to illustrate the effect of the parameter α that was included in the fuzzy quality measure. The road traffic annoyance model that has been tuned, included rules on noise exposure (5 rules), distance to roads (6 rules), urbanization degree (4 rules), reported traffic density (4 rules), household size (3 rules), age (3 rules) and gender (2 rules). See table I for some example rules. For more details on the implemented rules and additional model results, the reader is referred to [13].

TABLE I
OVERVIEW OF SOME FUZZY RULES.

IF noise exposure	THEN annoyance
very low	not at all
low	slightly
moderate	moderately
high	very
very high	extreme
IF distance to highway	THEN annoyance
close	high
far	not high
IF age	THEN annoyance
young	below average
middle	at least somewhat
old	below average

Recall that the parameter α can be used to obtain a model that is never 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 5.

TABLE II
PERCENTAGE OF SUBJECTS RESPONDING DIFFERENT NOISE ANNOYANCE IN TWO OF THE CLUSTERS FROM THE LEFT FIGURE 5.

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 top figure shows the results of a model that is more precise, but often incorrect. The bottom 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 top figure are further analyzed. In table II the percentage of respondents

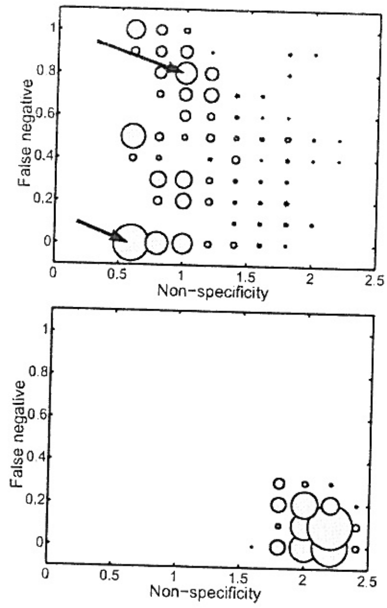

Fig. 5. Distribution of the subjects over a false negative versus non-specificity plane for a model tuned with $\alpha = 0.75$ (top) and $\alpha = 0.99$ (bottom). The area of the bubbles is proportional to the number of subjects.

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.

C. Model Generality

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 fuzzy 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). The following variables have been included in this model, noise exposure (5 rules), distance to railway (2 rules), age (2 rules) and gender (2 rules).

Before it is possible to test a model on two different data sets, some problems related to the comparison of surveys must be resolved. 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. This is because any term in any language can be accurately represented in a uniform way, as a fuzzy set on the same universe $\mathbb{H}$.

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. 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.

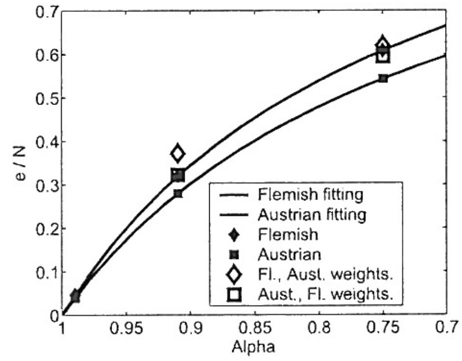

Fig. 6. Scaled prediction error as a function of α for Austrian and Flemish road traffic annoyance prediction.

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, 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.

VI. Conclusion

In this paper, a framework for noise annoyance modeling has been presented. In the framework, the concept noise annoyance is considered as an inherent fuzzy concept from beginning to end. Although the model is capable of predicting a single linguistic term to describe the level of annoyance as output, it is argued that this approach discards a lot of useful information about the uncertainties involved in the model. As an alternative, it is shown how fuzzy performance measures can be constructed to evaluate the model in a completely fuzzy way. These measures are based on the notion of false negative (the degree to which the reported term was not considered possible) and the non-specificity of the resulting possibility distribution over all terms. In view of presenting the modeling results to policy decision makers, some visualization techniques are also briefly discussed. Finally, the framework has been applied to two real data sets collected through social surveys, illustrating the use of the fuzzy performance measures that have been introduced.

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