Fuzzy Noise Maps

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ABSTRACT Noise mapping of large urban areas is becoming increasingly popular and the European Commission even insists on Member States building these maps. However, accurate data on local noise producing activities (including traffic) and local meteorological conditions are not always available. This research tackles the problem by using fuzzy sets to include uncertainty in propagation and emission models. The fuzzy logic replaces crisp decisions needed in most models. All this results in a decoupled fuzzy propagation and emission model. By using the fuzzy model a more realistic picture of the immissions is given in the form of "fuzzy Leq"maps.

INTRODUCTION

Sustainable urban development is becoming an increasingly important theme. Creating a viable urban environment without compromising natural or human resources of future generations forms a great challenge. Urban viability is probably the most threatened by the growing demand for mobility and the traffic this generates. An important aspect of this traffic is the noise it produces and the impact it has on viability. This importance is reflected in a growing interest in noise mapping and its use in local and national policy. On a higher policy level the European Commission even insists on Member states to produce noise maps for cities containing a larger number of inhabitants and for important infrastructure. Standardised calculation methods are proposed for this purpose. However data for producing these noise maps is not always available or is of low quality and contains a lot of uncertainty [1]. Moreover, commonly used noise mapping approaches fail to include features that may influence the impact on inhabitants considerably such as quiet background [11]~~[1]~~, indoor exposure and orientation of the house.

This research explores the soft computing paradigm put forward by Zadeh [10]: "*Softcomputing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant for imprecision, uncertainty, partial truth and approximation. The guiding principle of soft computing is: exploit the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness, and low solution cost.*" This is applied to outdoor noise prediction and used to exchange numerical accuracy for more accurate model approximations while keeping computational overhead within limits. Soft computing allows to treat balancing between model approximation and data uncertainty more formally robust and mathematically correct. The soft computing technique used in this research is fuzzy set theory, more specific fuzzy number theory and fuzzy number arithmetic. This research introduces "Fuzzy Noise

Maps" as a more descriptive noise map with the purpose of improving general outdoor noise impact prediction.

NOISE ASSESSMENT USING DPSIR

To assess the impact of traffic noise on inhabitants a DPSIR (Driving forces, Pressures, States, Impact, Response) model is used. Each stage in the chain has over the years evolved from "empirical" to more advanced physical models. This is due to the more thorough understanding of each process and to the rapidly growing computational power. But as the models become more accurate more detailed data is needed which is not always available. The lack of data or uncertainty on available data forms a major problem for most current calculation models. There is a need to include also vaguely known data and still come to a valid noise prediction.

Uncertainty manifests itself at all levels in the DPSIR chain. It can be divided into two parts. First there is the uncertainty on the model and secondly there is the uncertainty on the data or the lack of it. Model uncertainty comes from the fact that the models are an abstraction of the real world and even with complete knowledge of all data will produce results deviating from reality to some extend. The more advanced the model, the smaller the fault is and consequently the less the uncertainty about the result will be.

Data forms the second source of uncertainty. Data feeding the models is not always available or only a rough estimate can be made. The more sophisticated the model, the more data is needed and the more detail is required. For each level in the DPSIR chain these two sources of uncertainty can be identified (Figure 1~~Figure 1~~). Although the project involves the whole chain, focus in this paper will be on the first three phases of the DPSIR chain.

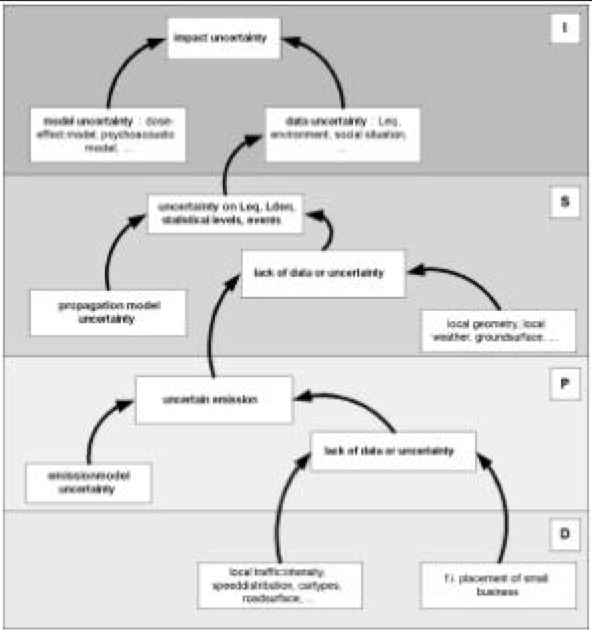

Figure 1~~1~~ DPSI chain and uncertainty

The *Driving Forces* that feed the DPSIR chain introduce the first source of uncertainty that will propagate upwards. In noise assessment the driving forces are road traffic, industrial activities, air and rail traffic, … In an urban environment road traffic streams and the small businesses dominate the soundscape. The data uncertainty comes from the fact that the location and presence of noise sources in small businesses is not known and that information about the traffic is only an estimation.

Traffic intensity is often only measured at highways and main roads. Traffic on local roads is ignored or is estimated by distributing so called surface traffic over local roads in a statistical manner. A more advanced approach is to use an urban traffic model but here lack of knowledge on the local traffic demand adds additional uncertainty.

Pressure on the environment is characterised by the emission caused by the driving forces. To accurately predict the emission of a stream of vehicles, the driving speed, intensity and composition of the car park must be known. This is seldom the case. Accurate data on emission per type of vehicle under various driving conditions is still scarce.

The *State* of the environment is in most cases described by an $L_{A,eq}$ or $L_{A,den}$. Starting from the pressure layer the emission is transformed into immission. Propagation models have been standardised for this purpose. For predicting the actual impact more accurately, additional information may be required in the state layer. Recent research has suggested that the noise levels at the back of the house may be as important as the facade exposure [11]~~[1]~~. The number of noise events and their level or statistical noise levels may also be useful indicators. To determine this additional information, diffraction and reflection have to be included in more detail. They depend on information that is rarely known accurately: e.g. height of houses and rooftop structure, facade reflection coefficients (specular and diffuse). Other well-known problems are the only vaguely known parameters like the local ground and road surface. Local weather conditions such as temperature; air humidity, temperature and wind gradients also play an important role in the propagation of sound but are hard to measure on a local scale. Studies such as [5] illustrate just how important the difference between noise propagation simulations may be.

The *Impact* layer that models the effect on the inhabitants, inherits the uncertainty of previous layers and also depends on personal and situational factors that can only be assessed in a statistical manner. Since this layer is not within the scope of the current paper we will not elaborate on it.

FUZZY SETS AND SYSTEMS

Fuzzy Sets

Fuzzy sets are a generalization of crisp sets. A fuzzy set *F* is defined on a universe *X* and is characterised by a membership function $M_F(x)$ that takes on values in the interval [0,1]. This in contrast to crisp sets where the possible values are 0 (is not an element of the set) or 1 (is element of the set). The interpretation of this membership can be threefold [9]:

- Similarity: $M_F(x)$ is the degree of proximity of *x* to prototype elements of *F*.
- Uncertainty: $M_F(x)$ is the degree of possibility that a parameter *y* has value *x*, given that all that is known about it is that "*y* is *F*". This is not the same as probability where $M_F(x)$ would mean the chance that *y* is *x*.
- Preference: $M_F(x)$ represents the intensity of preference in favour of object *x* in a set of more or less preferred objects.

The interpretation used throughout this article is that of uncertainty. Commonly used shapes for membership functions are triangular, trapezoidal, piecewise linear, Gaussian and bell-shaped.

Set theoretic operations and inference rules can also be defined. The result is a fuzzy inference system capable of reasoning with linguistic or vague variables. Such a system exists of a set of IF-THEN rules organised in an appropriate way.

Extension Principle

The Extension Principle introduced by Zadeh is an important tool in fuzzy set theory [8]. It allows extending mathematical relationships between non-fuzzy variables to relations between fuzzy variables.

$$m_{f(A_1,A_2)}(y) \equiv m_B(y) = \begin{cases} \sup\limits_{(x_1,x_2)\in f^{-1}(y)} \min\left\{m_{A_1}(x_1), m_{A_2}(x_2)\right\} \\ 0 \text{ if } f^{-1}(y)=\varnothing \end{cases}$$

Where A_1, A_2 and *B* are fuzzy sets. x_1, x_2 and *y* are variables defined on their respective universe. *f* is a relationship between variables, such as multiplication. A fuzzy number (also called fuzzy quantity) is a fuzzy set defined on the set of the real numbers. If we limit ourselves to convex fuzzy number, which are the most common ones, then the membership function consists of a monotone increasing part followed by a monotone decreasing part. Aforementioned membership functions could all be used as membership functions for fuzzy numbers. If we define an á-cut as the set of all elements of *X* whose degree of membership in *A* is at least equal to alpha then it can be proven that all arithmetic operations on convex fuzzy numbers can be reduced to the interval arithmetic on their á-cuts. 1-á can be interpreted as the certainty that the true value is in the interval of the á-cut. The zero á-cut is also called the *support* and defines the range of possible values. In short, the arithmetic operators like addition, subtraction, multiplication and division can be defined on fuzzy numbers. With a little more effort this is also possible for the trigonometric, exponential and logarithmic functions yielding a complete calculus on fuzzy numbers. By using parametric fuzzy numbers that are fuzzy numbers with their membership function described by a few parameters the computational cost can be acceptable. The fuzzy numbers implemented for fuzzy noise map calculation have piecewise linear membership functions with 8 control points. The cost for using these instead of the regular floating-point data types is less than a factor 10.

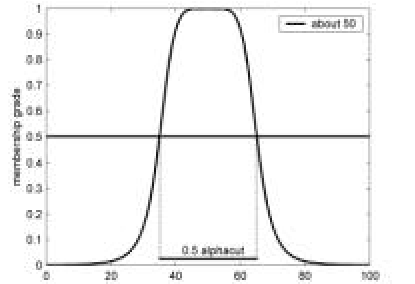

Figure 2~~3~~ Fuzzy number "about 50"

FUZZY EMISSION

The Nord2000 model for road sources [4] is used to model the emission caused by traffic. The traffic is described by its intensity(number of cars passing in one hour) and by it's speed distribution (percentage of cars driving at a certain speed). Uncertainty on traffic intensity follows directly from the traffic model or measurement. The right half of Figure 3~~Figure 4~~ shows the membership function of a fuzzy number for the traffic intensity including this uncertainty. Using a fuzzy intensity has other advantages. It allows to represent vague knowledge such as "traffic intensity is lower than about *N* vehicles per hour" and to calculate with it. This can be useful to include traffic on roads that are not included in the traffic model or measurements. The intensity can then be based on common sense or on questionnaires. In Figure 3~~Figure 4~~ this would mean that the support of the fuzzy intensity would be [0,±*N*]. For noise emission calculations various types of vehicles are treated separately since their emission is different. At the moment, the model includes only a few categories: cars, light trucks, heavy trucks, but in future more detailed categories will be used. Identifying the fraction of each category in the traffic flow adds additional uncertainty.

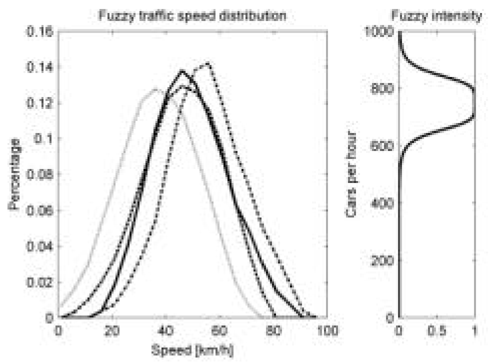

Figure 3~~4~~ Fuzzy traffic intensity distributions

Traffic speed distribution is influenced by a number of factors: speed limit, degree of saturation of the road, traffic restraining features such as speed humps, number of crossings, visual setting (trees and houses influencing the perceived width of the road), fraction of heavy trucks. At the moment, the model includes only the speed limit. This introduces a rather large uncertainty. It is included by associating a possibility to all members of a set of measured speed distributions (Figure 3~~Figure 4~~) at the same speed limit condition. Introducing additional parameters to describe the speed distribution may reduce the uncertainty on it, but will introduce new uncertainty through the determination of the parameters. Fuzzy calculus allows to accurately compare the impact of both sources of uncertainty.

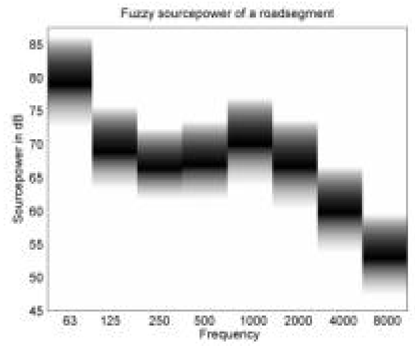

Figure 4~~5~~ Fuzzy sourcepower of a roadsegment

The Nordic standard suggests a standard deviation of 1 dB on the values in the database with source power levels. This uncertainty has been applied by using a fuzzy number with a Gaussian-like uncertainty distribution. The uncertainty can also be related to the characteristic composition of the vehicle fleet that will certainly differ from country to country due to different averaged weather conditions, taxation system and legislation.

Fuzzy traffic information and the fuzzified Nord2000 database are combined into a source power for each road segment of interest following the procedure outlined in Nord2000 with all floating point arithmetic replaced by fuzzy arithmetic. The resulting emission is a fuzzy number describing the emission in dB for each octave band.

Figure 4~~Figure 5~~ shows an example of the source power for a road segment. On the x-axis is the frequency, on the y-axis is the power level and the grey level is an indication of the certainty or confidence that this is the sound power level in the octave band. The current model for the source power level also includes the effect of the road surface. Because the exact type and age of a road is not always known for the local roads the uncertainty on these parameters is included.

FUZZY PROPAGATION

The base for the propagation model is the ISO9613-2 calculation standard for outdoor sound propagation [2]. The treatment of diffraction in this calculation standard was refined as described in the Nord2000 model. Object precise polygonal beam tracing was used for path searching between sources and receivers [6]~~[1]~~. Polygonal beam tracing has its roots in radio and light propagation and has some advantages over ray tracing or conic beam tracing. Problems that are more easily resolved are aliasing, missed receivers and straightforward inclusion of diffraction [6]~~[1]~~. The price to be paid is increased algorithmic complexity.

The first step to fuzzy propagation is converting the propagation model to calculation with fuzzy numbers. Using an object oriented programming language capable of operator overloading like C++ this can be done quite painlessly. Formulas calculating the respective attenuations can be

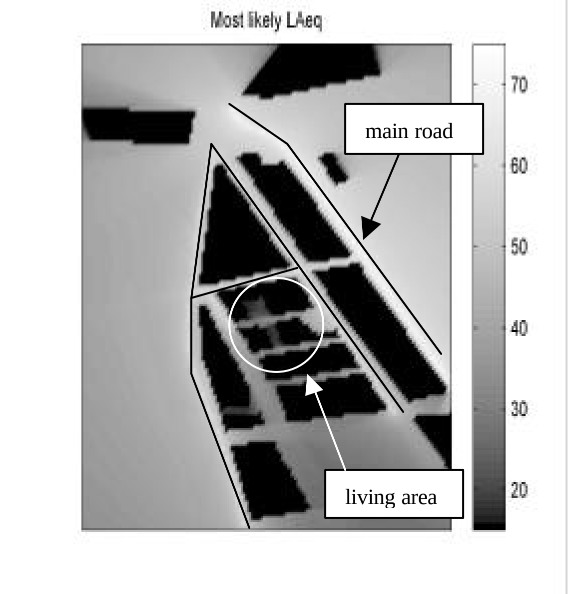

Figure 5~~6~~ Most likely $L_{A,eq}$

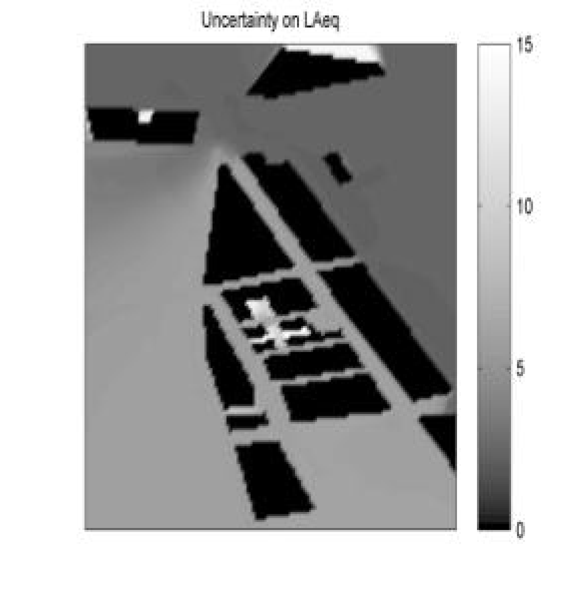

Figure 6~~7~~ Uncertainty on $L_{A,eq}$

used without a lot of modification by replacing the base types with fuzzy number types.

The fuzzified propagation model allows to include fuzzy emission of sources and vaguely known model parameters. Still there remains the uncertainty on the model itself. Certainly not all propagation models come with a complete uncertainty analysis. However most models give an estimation of their correctness and some additional information can be found in literature. The uncertainty on the propagation model is function of several parameters but the most important are the distance from source to receiver and the presence of a barrier between source and receiver. An estimate of propagation model uncertainty is included by multiplying with an uncertain "one"

The final result is an $L_{A,eq}$ which is the product of the fuzzy source power and fuzzy propagation attenuation. Visualisation of a map of such fuzzy L_{eq}'s is difficult but using several maps it is possible to get a more lucid picture of the immission in an urban area. Possible maps are the most likely $L_{A,eq}$, the lower bound and upper bound on the $L_{A,eq}$ and maps showing a confidence interval on the $L_{A,eq}$. Figure 5~~Figure 6~~ shows the most likely $L_{A,eq}$ in an urban neighbourhood. Only the main road on the right and some smaller roads on the left and middle are modeled. The black zones are houses. The example illustrates the effect of these roads on the living area in middle zone of the map. As shown in Figure 5~~Figure 6~~ the most likely $L_{A,eq}$ is pretty low but there is large uncertainty on it as illustrated by Figure 6~~Figure 7~~. This is because the sound only reaches the area by multiple reflection and/or diffraction and by diffraction over houses. The uncertainty on these models and their data adds up to more than 15 dB in the worst place. The right half of Figure 6~~Figure 7~~ has little uncertainty because the traffic on the main road is measured and hence has little uncertainty to start with: the source power level is known quite accurately. The large uncertainty that may come from reflections in the middle into the zone on the right is masked by the large value of the direct sound. When a high noise level with little uncertainty is added to a low noise level with large uncertainty the result will be a high noise level with small uncertainty as is expected.

CONCLUSIONS

This research explores the soft computing paradigm applied to the DPSIR model for outdoor noise prediction. The paradigm allows exchanging numerical accuracy for more accurate model approximations. As a result low quality or vaguely known data, often described in linguistic form, can easily be included in the calculation. This can be used to calculate a more descriptive state layer, in the form of a fuzzy $L_{A,eq}$ map, at little expense. A more lucid picture of the immission in urban neighbourhoods is therefore obtained. This will be advantageous in going beyond the state layer and assess the impact of the noise on the inhabitants and their response to it.

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