Applying fuzzy inference
in the supervision system of mobile telecommunication networks

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In mobile telecommunication networks the transmission level is affected by objects located between transmitter and receiver stations in the so-called Fresnel-zone. These obstacles may get temporally or permanently into the zone, they can be artificial or natural objects, or they can be of meteorological origin, too, like rain or fog. It is reasonable to use intelligent decision making subsystems which can decide from the degree of attenuation and from its time dependent behaviour what the reason of the attenuation could be. The paper demonstrates the intelligent module of a network supervision system created in the framework of a successfully completed National R&D Programme project. Intelligent decision support systems and the basics of fuzzy logics are introduced. In the next an application for automatically identifying the weather situation is discussed in some detail.

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1. Introduction

It is a widely known fact in connection with microwave networks that the transmission level is strongly affected (namely, decreased) by objects or substances located between any pairs of transmitter and receiver stations, in the so-called Fresnel-zone. These objects and substances, simply obstacles, may get into the zone temporally or permanently. Also, they may be artificial or natural objects, and they might be of meteorological origin, too, like rain or fog. If unexpected decrease of the transmission quality is perceived, an alarm or indication of some action to be immediately done is usually indicated at the operator screen. While the investigation of the reason of such service degradation by human staff is a generally successful method for taking care of the problem, it is far from being the most economical solution. In such cases it is reasonable to use intelligent decision making in the network supervision system which can autonomously decide from the degree of attenuation and from its time dependent behaviour what the original reason of the decrease in the signal level could be. The system might automatically recommend the necessary action in order to eliminate or compensate the unwanted behaviour at the user interface of the supervision system.

This paper presents the intelligent module of a network supervision system created in the framework of a successfully completed National R&D Programme project [5]. This module performs intelligent inference taken from the change of the transmission level (decrease values calculated from the signal levels at the transmitter and receiver end). Such changes are deduced from the values read by the sensors of the supervision system. The result of this inference is presented via the Graphical User Interface (GUI) of the system. Here, we focus only on one issue in this study, namely on the intelligent recognition of different precipitation categories that may occur in the temperate continental climatic zone.

Different alarm levels, which will be illustrated later by some examples, can be divided into two categories. The first one contains hardware failures and functional decay of the equipment at the microwave stations which may occur suddenly or gradually during a longer period of operation time. The system initiates some (human staff related) maintenance action in such cases. The second category covers the phenomena when the received signal level decreases because of various obstacles gotten into the Fresnel-zone. A typical example is the setting up of a poster in an urban environment, which can significantly damage the quality of transmission between two stations. (This often happens on the roof of a building, while stations are also located at various roofs, thus a bigger poster might completely block the visibility of the two stations from each other.) In such a case a measure totally different from the previously mentioned maintenance action is needed, e.g. the relocation of the transmitter and/or the receiver station will be necessary.

Another example for this category of phenomenon is when in a rural neighbourhood a forest located between transmitter and receiver stations gets leaves in the spring. By this the total area of covered cross section within the Fresnel zone increases tremendously, thus decreasing the transmission quality. This phenomenon may be compensated by the automatic resetting of the transmitter performance cyclically and annually. The previous two examples were typical illustrations for an artificial and a natural obstacle.

The scope of problems investigated in our demonstration system belongs to the category of meteorological phenomena. The separation of the phenomenon of fading caused by rain/fog and the transmission problems caused by different obstacles can be done by recognising the more or less isotropic behaviour of the decrease of the received signal level occuring in a geographically closed area. The lack of directionality and simultaneousity of the decrease are usually good indicators of rainfall in the neighbourhood of a given station. Often a group of stations with a number of station pairs are observed at the same time in order to recognise isotropy.

It is worth mentioning that these two phenomenon groups may exceptionally result in a combined effect, such as when a leafy forest located between the transmitter and receiver stations receives rain that is accumulated on the surface of the leaves, and so, even for longer period after the rainfall, may cause strong anisotropic fading because of the water drops on the leaves that act together as thousands of tiny refractors for the microwave signals.

Next, the background of the computational intelligence method applied to intelligent decision making is discussed. In Section 2, the foundations of fuzzy systems are introduced. Hierarchical fuzzy systems are briefly presented in Section 3. The fuzzy system applied for the supervision of mobile telecommunication network is demonstrated in Section 4.

2. Foundations of fuzzy systems

Human reasoning and some other phenomena cannot be accurately described by two-valued logic. The desire for extending two-valued logic to multiple valued ones came up long time ago. The basic concept was that instead of using only the "true" and "false" logical values, the use of other values between true and false should also be allowed. There are many statements that cannot be evaluated as true or false, only their respective "degree of truth" can be determined.

This idea led L. A. Zadeh to the creation of fuzzy logic in 1965 [2]. Nowadays, in computers and in many areas of life, the classical binary (Aristotlean or Boolean) logic is used. However, if we want to create more intelligent tools, better results can be achieved if the behaviour of the systems is described in a way that is closer to human thinking. Fuzzy logic is an extension of the classical logic. A fuzzy logic variable may assume any value between 0 and 1. Here, 0 means that the statement is "totally false", while 1 means that it is "totally true". According to this definition, the value 0.5 corresponds to "half true", and value 0.9 to "almost true". The operations of classical logic can also be extended to fuzzy logic. Based on this concept, fuzzy sets can be defined, fuzzy rules and fuzzy inference systems can be created. The next sections give a brief overview of the basic ideas (for more detailed description refer to [1]).

2.1. Fuzzy sets

A fuzzy set A defined over a universe of discourse X is characterised by the so-called membership function (which is the extension of the characteristic function of ordinary sets). The membership function μ_A assigns a real value from the closed unit interval to every element of X describing the degrees for elements x to which they are belonging to the fuzzy set A:

$$\mu_A : X \rightarrow [0,1]$$

μ_A unambiguously characterises the fuzzy set A if the universe of discourse X is also known. In the practical applications the most commonly used shapes for membership functions are triangular, trapezoidal, or sometimes more general piecewise linear (like in the very first real application by Mamdani [3]) and symmetrical or asymmetrical Gaussian.

In *Figure 1* examples for simple attenuation "values" described by fuzzy sets can be seen. Three categories are distinguished here, "moderate", "medium" and "high". Obviously these fuzzy values are rather extended intervals which comprise whole sets of concrete values which are considered to be more or less equivalent from the point of view of a certain application. Very likely, in another application the number of sets and corresponding labels and the extension of each set will be different.

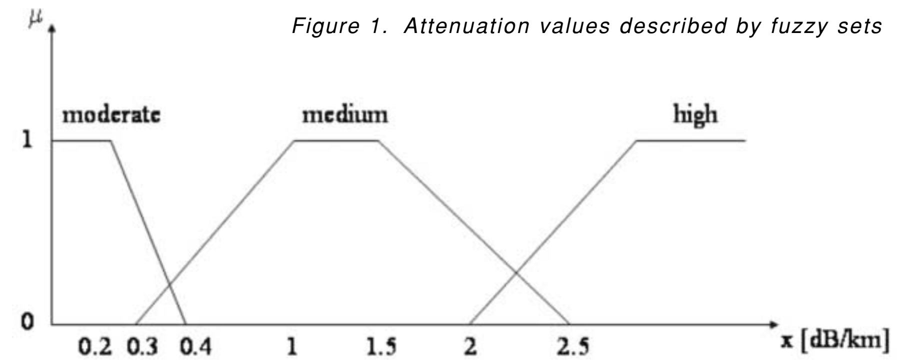
In this example the shape of the membership functions is trapezoidal. Two important basic definitions need to be mentioned in connection with fuzzy sets, namely the *support* and the *core* of a fuzzy set. The support of fuzzy set A is the (ordinary) set of those elements of the universe which have positive membership value in A:

$$\text{supp}(A) = \{x \in X \mid \mu_A(x) > 0\}.$$

The core of A means those elements of the universe whose membership value is equal to 1, i.e. which belong to the fuzzy set in the ordinary sense or completely:

$$\text{core}(A) = \{x \in X \mid \mu_A(x) = 1\}.$$

Figure 1. Attenuation values described by fuzzy sets



The three main set operators union, intersection and complementation of classical set theory can be extended to fuzzy sets in several (in fact infinite many) ways. The most commonly used ones are the standard definitions introduced originally by Zadeh [2], but the so-called algebraic operators have also some advantageous properties. The *standard complement* of fuzzy set A on a universe X is $\bar{A}$, where for each

$$\{x \in X : \mu_{\bar{A}}(x) = 1 - \mu_A(x).$$

The *standard intersection* of fuzzy sets A and B is given by

$$\mu^Z_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)),$$

while the *standard union* is

$$\mu^Z_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)).$$

The *algebraic intersection* can be calculated from

$$\mu^I_{A \cap B}(x) = \mu_A(x) \cdot \mu_B(x),$$

and the *algebraic union* is defined by

$$\mu^I_{A \cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x) \cdot \mu_B(x)$$

There is no separate definition for the algebraic complementation, moreover, the standard complementation satisfies De Morgan's Laws together with the two algebraic operations, just like it does the same with the standard operations. Such triplets of fuzzy operations are referred to as De Morgan triplets.

2.2. Fuzzy rules

Fuzzy knowledge bases form the essence of fuzzy control and decision support. They are constructed from a set of fuzzy rules. Fuzzy rules can be formulated by fuzzy sets and linguistic labels using o*-ften natural human language. In a supervision system for telecommunication networks, e.g. the following rule can be formulated:

"**If** the decrease of the received signal level is *moderate* **and** the elapsed time is *short* **then** the precipitation is *moderate rainfall.*"

If the membership functions for "moderate", "short", and "moderate rainfall" are exactly defined over the universal sets "received signal levels", "time between two observations" and "amount of precipitation", then fuzzy rules are obtained. The general form of a fuzzy rule with one input and one output dimension is as follows:

R : **If** x is A **then** y is B,

where $x \in X$ is the input and $y \in Y$ is the output variable, X is the universe of discourse for the input and Y is the universe of discourse for the output variable. A and B are linguistic labels that are expressed by fuzzy sets. Set A is the antecedent while B is the consequent of rule R. The general form of a fuzzy rule with multiple inputs and one output dimension can be written in the following, so called Mamdani type orthogonally decomposed form [3]:

R : **If** x_1 is A_1 **and** ... **and** x_n is A_n **then** y is B,

where $x = (x_1, ..., x_n)$ is the input vector, $x_j \in X_j$, $X = X_1 \times ... \times X_n$ is the n-dimensional universe, $A = (A_1,..., A_n)$ is the antecedent vector, $A \tilde{\subset} X$, $y \in Y$ is the output variable, Y is the universe for the output and B is the consequent set, $B \tilde{\subset} Y$. (Here $\tilde{\subset}$ denotes fuzzy subsethood.) A rule can be applied if every input variable has a positive membership value in its corresponding antecedent set. In case of multiple output rules, the outputs are independent from each other, thus this kind of rules can be decomposed to fuzzy rules with one single output, reducing the computational demand in this way.

2.3. Fuzzy inference systems

The fuzzy sets based approach is suitable for describing (very) complex systems which cannot be modelled analytically. By fuzzy sets, operations and rules, inference systems may be created which imitate in some sense the ways of everyday human thinking. Such systems are referred to in the literature as *fuzzy* systems. The structure of a typical fuzzy system is illustrated in *Figure 2*.

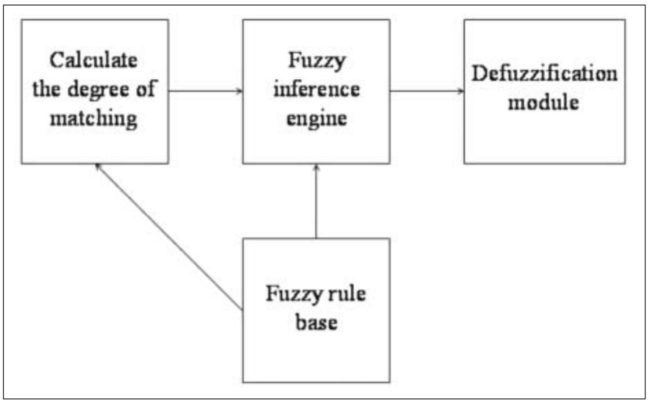


Figure 2. Structure of a fuzzy inference system

The first (top left) module compares the actual observation with the antecedent parts of the fuzzy rules in the rule base (located in the bottom block of the system). Based on this comparison, the inference engine (top middle unit) determines the resulting output fuzzy set by some inference algorithm. There are some well-known inference techniques, however, the Mamdani method is the most commonly used one in practical applications [3]. The inference engine may be viewed as a special kind of genralised function generator as it maps the set of all possible input fuzzy sets into the set of all possible fuzzy outputs. The output is converted to a so-called "crisp" value by the defuzzification module (top right). The Mamdani inference algorithm is illustrated with fuzzy membership functions in *Figure 3.*

At the beginning of the inference the degree of matching between the observation and the rules is determined. Each component of the observation vector is compared to the same component of the antecedent of each rule. Let A^* be the n-dimensional observation vector. The degree of matching (firing) in the j^{th} dimension in the i^{th} rule can be computed as:

$$w_{j,i} = \max_{x_j} \left\{ \min \left\{ A^*_j(x_j), A_{j,i}(x_j) \right\} \right\}$$

where $A_{j,i}$ is the membership function of the i^{th} rule in the j^{th} dimension. If the observation is a crisp vector then the above calculation is simpler: in case of state-vector x^*, the degree of matching in the j^{th} dimension is:

$$w_{j,i} = A_{j,i}(x_j^*).$$

After the degree of matching was calculated in each dimension, the resultant for the whole antecedent is determined. The degree of applicability of a rule is affected by the degree of matching of its each dimension. Thus, the firing degree of the i^{th} rule can be computed by taking the minimum value of the degrees of matching of the rule's antecedents:

$$w_i = \min_{j=1}^{n} w_{j,i}.$$

w_i shows that how important the role of rule R_i will be in the calculation of the conclusion for observation A^*.

After the degree of firing was determined for each rule, each conclusion is separately calculated. This can be made by cutting the consequent fuzzy set of the rule at height w_i: $B_i^* = \min(w_i, B_i(y)).$

The conclusion for the whole rule base can be computed by taking the union of the previously calculated sub-conclusions: $B^*(y) = \max_{i=1}^{r} B_i^*(y).$

After the inference a $B^*(y)$ conclusion fuzzy set was obtained. However, in most of the cases, the expected conclusion is not a fuzzy set, but a crisp value. Hence, the crisp value needs to be determined, which describes the conclusion fuzzy set in the best way. This procedure is called defuzzification. There are many different defuzzification methods described in the literature, in this particular application the Centre of Gravity (COG) method is applied, which is one of the most commonly used defuzzification techniques in practical applications. The COG method provides a crisp result that can be calculated as follows:

$$y_{COG} = \frac{\sum_{i=1}^{r} \int_{y \in B_i^*} B_i^*(y) y dy}{\sum_{i=1}^{r} \int_{y \in B_i^*} B_i^*(y) dy}$$

In the next section a more advanced approach is briefly sketched that is suitable for handling systems with a very large number of components.

3. Hierarchical fuzzy systems

The idea of structuring very large system in a hierarchical way came up at the beginning of 1990s. Hierarchical fuzzy systems have been successfully applied for some special problems, where the hierarchical structure is more or less obvious, eminently the unmanned helicopter control experiment by Sugeno [4].

The basic idea of using hierarchical fuzzy rule bases is the following: If the multi-dimensional input space $X = X_1 \times X_2 \times \ldots \times X_m$ can be decomposed, so that some of its components, e.g. $Z_0 = X_1 \times X_2 \times \ldots \times X_p$ determine a subspace of X ($p < m$), where in Z_0 a partition $\Pi = \{D_1, D_2, \ldots, D_n\}$ can be determined: $\bigcup_{i=1}^{n} D_i = Z_0$

E.g. in the unmanned helicopter control application, different variables are dominating the behaviour when hovering, landing, or flying forward and each of these manoeuvres means a different local subsystem.

In each element of Π, i.e. D_i, a sub-rule base R_i can be constructed with local validity. In the worst case, each sub-rule base refers to exactly $X/Z_0 = X_{p+1} \times \ldots \times X_m$.

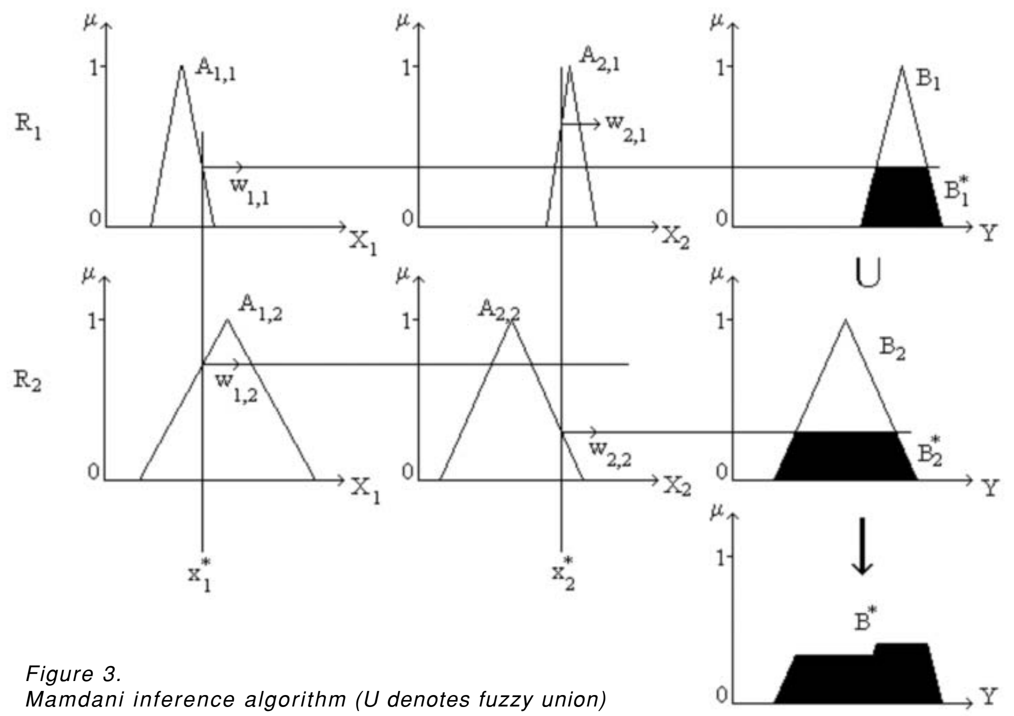


Figure 3.
Mamdani inference algorithm (U denotes fuzzy union)

The complexity of the whole rule base $O(T^m)$ is not decreased, as the size of R_0 is $O(T^p)$, and each R_i, $i > 0$, is of order $O(T^{m-p})$, $O(T^p) \times O(T^{m-p}) = O(T^m)$.

A way to decrease the complexity would be finding in each D_i a proper subset of $\{X_{p+1} \times \ldots \times X_m\}$, so that each R_i contains only less than m-p input variables. In some concrete applications in each D_i a proper subset of $\{X_{p+1}, \ldots, X_m\}$ can be found so that each R_i contains less than m-p input variables.

The rule base has the following structure:

R_0: **If** z_0 is D_1 **then** use R_1
If z_0 is D_2 **then** use R_2
...
If z_0 is D_n **then** use R_n

R_1: **If** z_1 is A_{11} **then** y is B_{11}
If z_1 is A_{12} **then** y is B_{12}
...
If z_1 is A_{1r1} **then** y is B_{1r1}

R_2: **If** z_2 is A_{21} **then** y is B_{21}
If z_2 is A_{22} **then** y is B_{22}
...
If z_2 is A_{2r2} **then** y is B_{2r2}

...

R_n: **If** z_n is A_{n1} **then** y is B_{n1}
If z_n is A_{n2} **then** y is B_{n2}
...
If z_n is A_{nrn} **then** y is B_{nrn}

where $z_i \in Z_i$, $Z_0 \times Z_i$ being a proper subspace of X for $i = 1,..,n$. The fuzzy rules in rule base R_0 are termed meta-rules since the consequences of the rules are pointers to other sub-rule bases instead of fuzzy sets.

If the number of variables in each Z_i is $k_i < m-p$ and $\max_{i=1}^{n} k_i = K < m-p$, then the resulting complexity will be $O(T^{p+k}) < O(T^m)$, so the structured rule base leads to a reduction of the complexity.

The task of finding such a partition is often difficult, if not impossible. (Sometimes such a partition does not even exist). There are cases when, locally, some variables unambiguously dominate the behaviour of the system, and consequently the omission of the other variables allows an acceptably accurate approximation. The bordering regions of the local domains might not be however crisp or even worse, these domains overlap. For example, there might be a region D_1, where the proper subspace Z_1 dominates, and another region D_2, where another proper subspace Z_2 is sufficient for the description of the system, however, in the region between D_1 and D_2 all variables in $[Z_1 \times Z_2]$ play a significant role ([.×.] denoting the space that contains all variable that occur in either argument within the brackets).

In this case, sparse fuzzy partitions can be used, so that in each element of the partition a proper subset of the remaining input state variables is identified as exclusively dominant. Such a sparse fuzzy partition can be described as follows:

$$\hat{\Pi} = \{D_1, D_2, \ldots, D_n\} \text{ and } \bigcup_{i=1}^{n} Core(D_i) \subset Z_0$$

in the proper sense (fuzzy partition).

Even $\bigcup_{i=1}^{n} Supp(D_i) \subset Z_0$ is possible (sparse partition).

If the fuzzy partition chosen is informative enough concerning the behaviour of the system, it is possible to interpolate its model among the elements of $\hat{\Pi}$.

Each element D_i will determine a sub-rule base R_i referring to another subset of variables.

A part of the hierarchically fuzzy rule base in the above mentioned helicopter control problem is:

R_0: **If** *distance* (from obstacle) is *small* **then** *hover*
Hover: **If** (helicopter) *body* rolls *right* then move *lateral* stick *leftward*
If (helicopter) *body* pitches *forward* then move *longitudinal* stick *backward*

4. Application of the fuzzy system approach

As it has been already mentioned, in the frame of this project [5] a fuzzy system was applied as the supervision module of a telecommunication network. In this paper just one function is described. The system determines the type of precipitation in the geographical area under supervision, based on the available transmitted and received signal levels coming from the telecommunication network. Based on these data, a human operator can get a clear idea of the network's actual status, and therefore the operator can make an optimal decision about the necessary action. The system makes the decision based on two input parameters, the first one being the decrease of the received signal level, the second one the elapsed time.

The application is able to receive data from base stations, and these data are stored in a database together with the corresponding time stamps. It gets the data from the stations cyclically, and it determines the change of signal level and the corresponding time by the comparison of the new and old data, and it makes an inference based on these informations. The possible results of the inference may be divided into two groups. The first group contains coclusions which refer to events of meteorological origin, while the other one is related to some breakdown that might cause an alarm signal.

The alarms will usually cause some activity triggered by a human operator while the conclusion that unambiguously refers to transmission trouble caused by weather conditions clearly excludes the necessity of any maintanance type action rather than the mere compensation of the decreased transmission level by pushing up the power on th etransmitter side. Any technical problem will have a very different behavioural pattern.

The mathematical relationship between the change of signal level and the amount of precipitation can be calculated as follows: $\gamma = kR^{\alpha}$ where γ is the decrease of signal level, R is the amount of precipitation, k and α are parameters, which depend primarily on the used frequency.

We would like to replace the inverse of this equation by a fuzzy model, i.e. to determine the amount of precipitation from the decrease of signal level taking into account the elapsed time, as well. The relationship between individual variables can be described better by using fuzzy rule bases, because the fuzzy sets used in the rules separate the possible values of the variables not by a crisp border but in a smooth gradual way similarly to everyday human thinking.

4.1. Determination of the fuzzy sets

The fuzzy rule based system uses two input variables for each pair of stations, the decrease of the signal level, and the elapsed time. The decrease of the signal level is divided into six categories:

- very moderate attenuation: 0 – 0.05 dB/km
- moderate attenuation: 0.03 – 0.18 dB/km
- medium attenuation: 0.15 – 0.7 dB/km
- significant attenuation: 0.5 – 2.5 dB/km
- high attenuation: 1.8 – 5.5 dB/km
- very high attenuation: 3.3 – 18 dB/km

The fuzzy sets are determined by these intervals. The intervals give the support of the fuzzy sets. The fuzzy sets for the decrease of the signal level can be seen in *Figure 4*. It can be observed in Figure 4 that the supports of the fuzzy sets overlap each other, which means that the borders between the different attenuation groups are not crisp.

The elapsed time is divided into four categories: short, medium, long, very long. The corresponding approximate intervals are:

- short: 0 – 1 hour
- medium: 0,5 – 4 hours
- long: 3 hours – 4 days
- very long: 3 days – 1 year

The fuzzy sets are constructed from the intervals in a similar way as previously. The fuzzy sets for the elapsed time are illustrated in *Figure 5*. The supports overlap in this case, too.

The output of the fuzzy system contains the reference to different precipitation types/intensities. The precipitation can be categorised as follows:

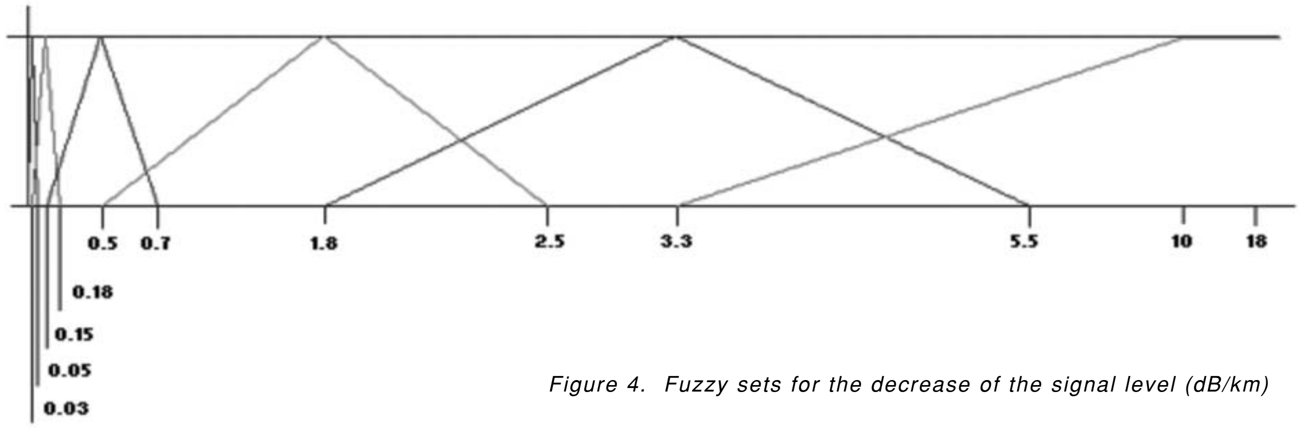


Figure 4. Fuzzy sets for the decrease of the signal level (dB/km)

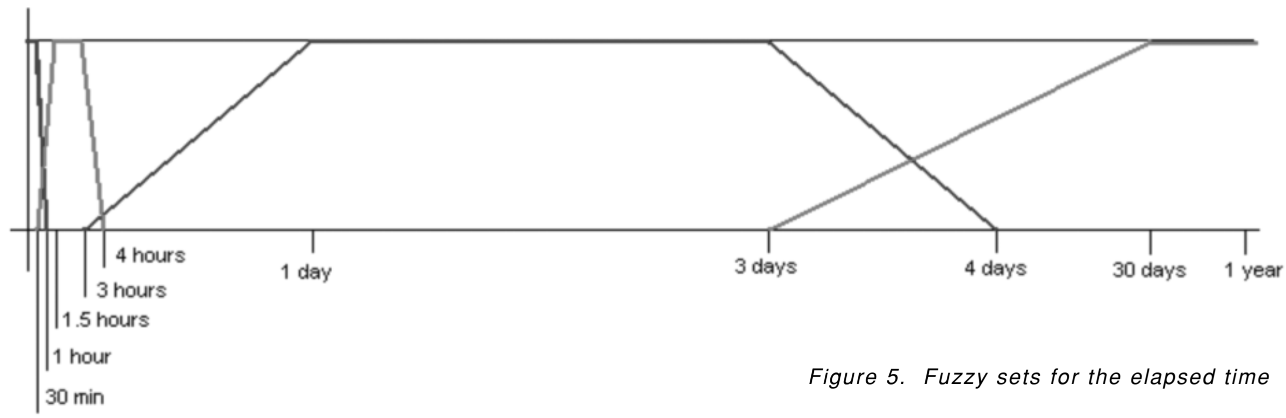


Figure 5. Fuzzy sets for the elapsed time

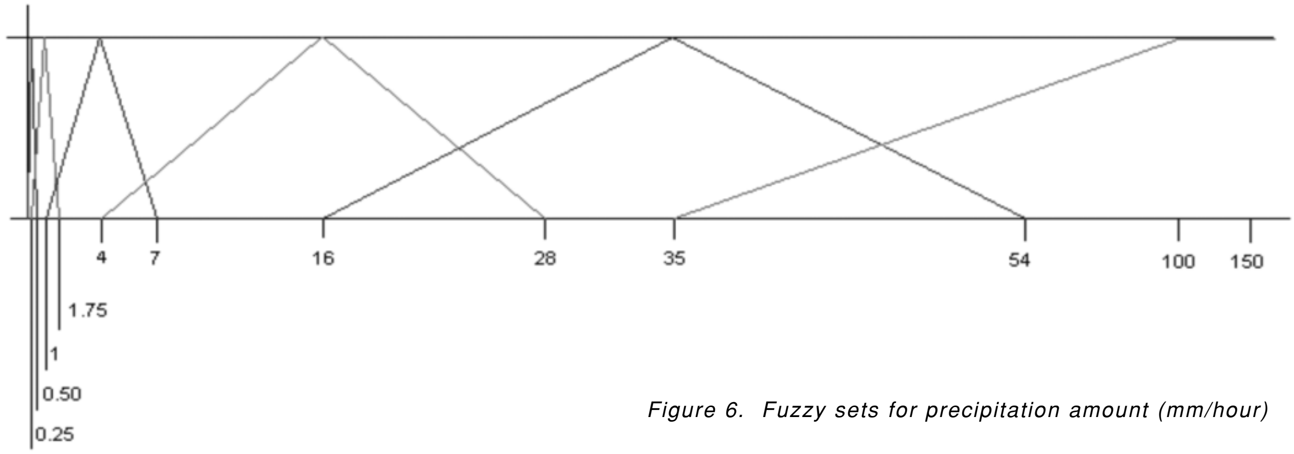


Figure 6. Fuzzy sets for precipitation amount (mm/hour)

- drizzle: 0 – 0,5 mm/hour
- moderate rainfall: 0,25 – 1,75 mm/hour
- medium rainfall: 1 – 7 mm/hour
- heavy rainfall: 4 – 28 mm/hour
- thunderstorm: 16 – 54 mm/hour
- intensive thunderstorm: 35 – 150 mm/hour

The fuzzy sets belonging to the precipitation categories can be seen in *Figure 6*.

4.2. The fuzzy rules of the system

The first input of the system was described by six fuzzy sets, the second one by four, therefore the total number of possible combinations is 24, which means that 24 rules are needed to cover all possibilities. In the conclusion part of the fuzzy rules may occur not only precipitation categories, but also various types of alarms. These alarms denote reasons for service deterioration which are of non-meteorological origin.

The first input is characterised by six labels. The decrease of signal level is A_i, where *i* might be:

- very moderate attenuation: 1
- moderate attenuation: 2
- medium attenuation: 3
- significant attenuation: 4
- high attenuation: 5
- very high attenuation: 6

The elapsed time is characterised by labels T_i, where *i* might assume:

- short: 1
- medium: 2
- long: 3
- very long: 4

Using the above labels the following rules were constructed:

R_1: **If** the attenuation is A_1 and the elapsed time is T_1 **then** the precipitation is *drizzle*
R_2: **If** the attenuation is A_1 and the elapsed time is T_2 **then** the precipitation is *drizzle*
R_3: **If** the attenuation is A_1 and the elapsed time is T_3 **then** the precipitation is *drizzle*
R_4: **If** the attenuation is A_1 and the elapsed time is T_4 **then** *Warning*
R_5: **If** the attenuation is A_2 and the elapsed time is T_1 **then** the precipitation is *moderate rainfall*
R_6: **If** the attenuation is A_2 and the elapsed time is T_2 **then** the precipitation is *moderate rainfall*
R_7: **If** the attenuation is A_2 and the elapsed time is T_3 **then** the precipitation is *moderate rainfall*
R_8: **If** the attenuation is A_2 and the elapsed time is T_4 **then** *Warning*
R_9: **If** the attenuation is A_3 and the elapsed time is T_1 **then** the precipitation is *medium rainfall*
R_{10}: **If** the attenuation is A_3 and the elapsed time is T_2 **then** the precipitation is *medium rainfall*
R_{11}: **If** the attenuation is A_3 and the elapsed time is T_3 **then** the precipitation is *medium rainfall*
R_{12}: **If** the attenuation is A_3 and the elapsed time is T_4 **then** *Minor alarm*
R_{13}: **If** the attenuation is A_4 and the elapsed time is T_1 **then** the precipitation is *heavy rainfall*
R_{14}: **If** the attenuation is A_4 and the elapsed time is T_2 **then** the precipitation is *heavy rainfall*
R_{15}: **If** the attenuation is A_4 and the elapsed time is T_3 **then** *Minor alarm*
R_{16}: **If** the attenuation is A_4 and the elapsed time is T_4 **then** *Minor alarm*
R_{17}: **If** the attenuation is A_5 and the elapsed time is T_1 **then** the precipitation is *thunderstorm*
R_{18}: **If** the attenuation is A_5 and the elapsed time is T_2 **then** the precipitation is *thunderstorm*
R_{19}: **If** the attenuation is A_5 and the elapsed time is T_3 **then** *Major alarm*
R_{20}: **If** the attenuation is A_5 and the elapsed time is T_4 **then** *Major alarm*
R_{21}: **If** the attenuation is A_6 and the elapsed time is T_1 **then** the precipitation is *intensive thunderstorm*
R_{22}: **If** the attenuation is A_6 and the elapsed time is T_2 **then** *Major alarm*
R_{23}: **If** the attenuation is A_6 and the elapsed time is T_3 **then** *Major alarm*
R_{24}: **If** the attenuation is A_6 and the elapsed time is T_4 **then** *Major alarm*

This rule base is used as a single unit of a more complex hierarchically structured knowledge base where the (approximate) isotropy of the attenuation observed playes the decisive role concerning the original cause for alarm.

It must also be mentioned that the values of attenuation are not identical with the directly observed ones but are deduced values from interpolating and avaraging the values calculated from the direct measurement values according to th ephysical and geographical locations of the base stations in a particular neighbourhood.

4.3. The inference method

At first, the firing values of the rules are determined based on the comparison of the given observation and the antecedent parts of the rules. The rules can be divided into two groups according to their outputs. If the firing values for those rules are greater than for those which contain an alarm indication in their respective consequent, the conclusion of the fuzzy system will be the same as the conclusion of the alarm type fuzzy rule with the highest firing degree. In the opposite case, when the firing values for those rules are greater than for those, which have weather related information in their respective consequent, a normal Mamdani inference is performed on all the involved precipitation type rules. As the result, the most possible type of precipitation will come out as dominating in the overall consequent.

The conclusion given by the fuzzy system can be displayed in a map. The colours of the cells refer to precipitations.

Colour	Precipitation type	Colour code
	Drizzle	1
	Moderate rainfall	2
	Medium rainfall	3
	Heavy rainfall	4
	Rainstorm	5
	Intense thunderstorm	6

Table 1. Precipitation types and the assigned colours

The assignment of colours and precipitation types can be seen in *Table 1.* The different alarm categories can also be represented by colour codes. The assignment is shown in *Table 2.*

The operation of the system is illustrated in *Figure 7* with a map, which was created by simulated precipitation. The map of Hungary is covered by a grid, giving a natural, hierarchical structure for the whole system in this way. On such locations where more stations can be found within one cell, an average behaviour is calculated and displayed, on the other hand, on such places where there is no station within one cell, interpolation is used to estimate the amount of precipitation. The blue and purple colours show the estimated amount of precipitations based on simulation data.

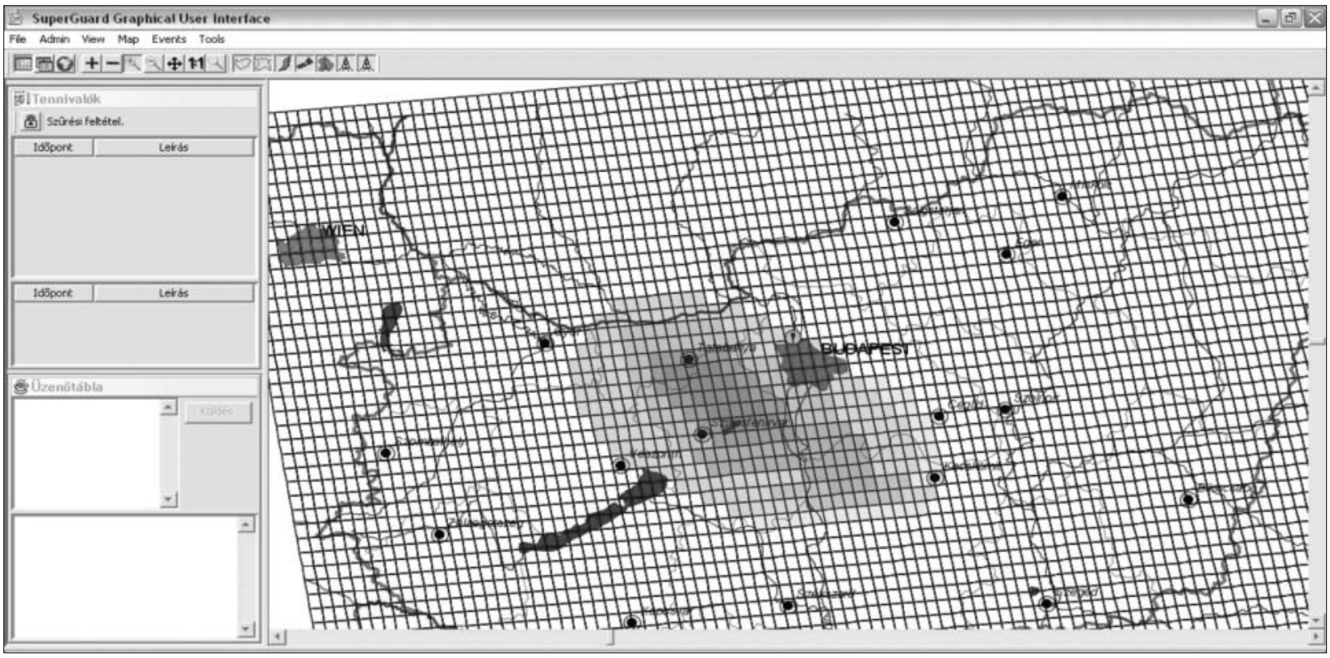
Colour	Alarm	Colour code
	Warning	7
	Minor alarm	8
	Major alarms	9

Table 2. Alarms and their colours

5. Summary

In this study the foundations of fuzzy systems were introduced, hierarchical fuzzy systems were also discussed, and an application example was demonstrated. Fuzzy systems can be used well as a decision support tool in such applications, where the expert knowledge can be easily represented in form of fuzzy rules. In laboratory environment an application was demonstrated, which can separate alarms of meteorological origin from different kinds of hardware failures based on a cyclically refreshed database in a central supervision system of a nationwide microwave telecommunication network, as well as it can identify the intensity

Figure 7. Rain cloud and simultaneous Warning in Budapest on the map of Hungary



map of precipitation on the whole geographical area of the telecommunication network.

Our plan for the future is to extend the intelligent decision support system to proper hierarchical fuzzy rule based system, making the model more general and more sensitive in this way. Currently a network provider in Hungary indicated their possible interest in experimentally integrating the intelligent decision support subsystem into their real operating supervision system.

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"Dennis Gabor" Award *for Prof. Gyula Sallai*

The prestigous "Dennis Gabor" Award was founded by Novofer Co. 18 years ago. It's title bears the name of the world-famous Hungarian scientist, Dennis Gabor, the inventor of the holography who received a Nobel prize for this invention an for his achievements in information theory. The Dennis Gabor Award is granted yearly to selected Hungarian professionals for their excellence in innovation. It also has an international edition, which is granted once in every three years.

In the past, several prominent professionals, who played a leading role in our Scientific Society and in the Journal of Telecommunications, received this prize, including Professors Géza Gordos, György Lajtha and László Pap.

The award ceremony this year was held in the prestigeous building of the Hungarian Parliament. Congratulations to Prof. Dr. Gyula Sallai, the President of the Scientific Society of Infocommunications who was among this year's winners of the Dennis Gabor award. As it was emphasized at the award ceremony, Professor Sallai played a leading role in the radical re-organization of the Hungarian telecommunication industry and contributed to the process of convergence of telecommunications and information technology. At present, Professor Sallai is the Head of the Department of Telecommunications and Media Informatics of Budapest University of Technology and Economics, where he is also Vice Rector for Strategy. He is also President of the Telecommunication Systems Committee of the Hungarian Academy of Sciences.