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# Soft Computing-Based Risk Management - Fuzzy, Hierarchical Structured Decision-Making System

Márta Takács  
*Óbuda University Budapest  
Hungary*

## 1. Introduction

Since its introduction in the mid-sixties (Zadeh, L. A., (1965)), fuzzy set theory has gained recognition in a number of fields in the cases of uncertain, or qualitative or linguistically described system parameters or processes based on approximate reasoning, and has proven suitable and applicable with system describing rules of similar characteristics. It can be successfully applied with numerous reasoning-based systems while these also apply experiences stemming from the fields of engineering and control theory.

Generally, the basis of the decision making in fuzzy based system models is the approximate reasoning, which is a rule-based system. Knowledge representation in a rule-based system is done by means of IF...THEN rules. Furthermore, approximate reasoning systems allow fuzzy inputs, fuzzy antecedents, fuzzy consequents. "Informally, by approximate or, equivalently, fuzzy reasoning, we mean the process or processes by which a possibly imprecise conclusion is deduced from a collection of imprecise premises. Such reasoning is, for the most part, qualitative rather than quantitative in nature and almost all of it falls outside of the domain of applicability of classical logic", (Zadeh, L. A., (1979)).

Fuzzy computing, as one of the components of soft computing methods differs from conventional (hard) computing in its tolerant approach. The model for soft computing is the human mind, and after the earlier influences of successful fuzzy applications, the inclusion of neural computing and genetic computing in soft computing came at a later point. Soft Computing (SC) methods are Fuzzy Logic (FL), Neural Computing (NC), Evolutionary Computation (EC), Machine Learning (ML) and Probabilistic Reasoning (PR), and are more complementary than competitive (Jin, Y. 2010 ).

The economic crisis situations and the complex environmental and societal processes over the past years indicate the need for new mathematical model constructions to predict their effects (Bárdossy, Gy., Fodor, J., 2004.). The health diagnostic as a multi-parameter and multi-criteria decision making system is, as well, one of the models where, as in the previous examples, a risk model should be managed.

Haimes in (Hames, Y. Y. 2009.) gives an extensive overview of risk modeling, assessment, and management. The presented quantitative methods for risk analysis in (Vose, D. 2008) are based on well-known mathematical models of expert systems, quantitative optimum calculation models, statistical hypothesis and possibility theory. The case studies present applications in

the fields of economics and environmental protection. It is observable that the statistical-based numerical reasoning methods need long-term experiments and that they are time- and computationally demanding. The complexity of the systems increases the runtime factor, and the system parameter representation is usually not user-friendly. The numerical methods and operation research models are ready to give acceptable results for some finite dimensional problems, but without management of the uncertainties. The complexity and uncertainties in those systems raise the necessity of soft computing based models.

Nowadays the expert engineer's experiences are suited for modeling operational risks, not only in the engineering sciences, but also for a broad range of applications (Németh-Erdődi, K., 2008.). Wang introduces the term of risk engineering related to the risk of costs and schedules on a project in which there is the potential for doing better as well as worse than expected. The presented case studies in his book are particularly based on long-term engineering experiences, for example on fuzzy applications, which offer the promised alternative measuring of operational risks and risk management globally (Wang, J. X., Roush, M. L., 2000.).

The use of fuzzy sets to describe the risk factors and fuzzy-based decision techniques to help incorporate inherent imprecision, uncertainties and subjectivity of available data, as well as to propagate these attributes throughout the model, yield more realistic results. Fuzzy logic modeling techniques can also be used in risk management systems to assess risk levels in cases where the experts do not have enough reliable data to apply statistical approaches. There are even more applications to deal with risk management and based on fuzzy environments. Fuzzy-based techniques seem to be particularly suited to modeling data which are scarce and where the cause-effect knowledge is imprecise and observations and criteria can be expressed in linguistic terms (Kleiner, Y., et al 2009.).

The structural modeling of risk and disaster management is case-specific, but the hierarchical model is widely applied (Carr, J.H. , Tah, M. ,2001). The system characteristics are as follows: it is a multi-parametrical, multi-criteria decision process, where the input parameters are the measured risk factors, and the multi-criteria rules of the system behaviors are included in the decision process. In the complex, the multilayer, and multi-criteria systems the question arises how to construct the reasoning system, how to incorporate it into the well structured environment. In terms of architectures next to the hierarchical system the cognitive maps (Kosko, 1986.) or ontology (Neumayr, B, Schre, M. 2008.) are also often used. A further possibility is for the system to incorporate the mutual effects of the system parameters with the help of the AHP (Analytic Hierarchy Process) methods (Mikhailov, L., 2003).

Considering the necessary attributes to build a fuzzy-based representation of the risk management system, the following sections will be included in the chapter:

- Fuzzy set theory (fuzzy sets and fuzzy numbers; operators used in fuzzy approximate reasoning models; approximate reasoning models).
- Fuzzy knowledge-base: rule system construction and the approximate reasoning method (Mamadani-type reasoning method).
- Different system architecture representations (hierarchical and multilevel structure of the rule system; weighted subsystems).

Case studies and examples are represented particularly in the Matlab Fuzzy Toolbox environment, particularly in the self-improved software environment representing risk assessment problems.

## 2. Fuzzy set theory background of risk management

Let  $X$  be a finite, countable or overcountable set, the Universe. For the representation of the properties of the elements of  $X$  different ways can be used. For example if the universe is the set of real numbers, and the property is "the element is negative", it can be represented in an analytical form, describing it as a subset of the universe :  $A=\{x \mid x < 0, x \in \mathbb{R}\}$ . The members  $x$  of subset  $A$  can be defined in a *crisp form* by using characteristic function, where 1 indicates the membership and 0 the non-membership:

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

Let we assume, that the characteristic function is a mapping  $\chi_A : X \rightarrow \{0,1\}$ .

Fuzzy sets serve as a means of representing and manipulating data that is not precise, but rather *fuzzy*, vague, ambiguous. A fuzzy subset  $A$  of set  $X$  can be defined as a set of ordered pairs, each with the first element  $x$  from  $X$ , and the second element from the *interval*. This defines a mapping  $\mu_A : X \rightarrow [0,1]$ . The degree to which the statement " $x$  is in  $A$ " is true is determined by finding the ordered pair  $(x, \mu_A(x))$ .

### Definition 2.1

Let be  $X$  an non-empty set. A fuzzy subset  $A$  on  $X$  is represented by its membership function

$$\mu_A : X \rightarrow [0,1] \quad (2.2)$$

where the value  $\mu_A(x)$  is interpreted as the degree to which the value  $x \in X$  is contained in  $A$ . The set of all fuzzy subsets on  $X$  is called set of fuzzy sets on  $X$ , and denoted by  $F(X)$ <sup>1</sup>.

It is clear, that  $A$  as a *fuzzy set* or *fuzzy subset* is completely determined by  $A = \{(x, \mu_A(x)) \mid x \in X\}$ . The terms *membership function* and *fuzzy subset* (get) are used interchangeably and parallel depending on the situation, and it is convenient (to write) for writing simply  $A(x)$  instead of  $\mu_A(x)$ .

### Definition 2.2

Let be  $A \in F(X)$ . Fuzzy subset  $A$  is called *normal*, if  $(\exists x \in X)(A(x) = 1)$  Otherwise  $A$  is *subnormal*.

### Definition 2.3

Let be  $A \in F(X)$ .

The *height* of the fuzzy set  $A$  is  $\text{height}(A) = \sup(\mu_A(x))$ .

The *support* of the fuzzy set  $A$  is  $\text{supp}(A) = \{x \in X \mid \mu_A(x) > 0\}$ .

The *kernel* of the fuzzy set  $A$  is  $\text{ker}(A) = \{x \in X \mid \mu_A(x) = 1\}$ .

The *ceiling* of the fuzzy set  $A$  is  $\text{ceil}(A) = \{x \in X \mid \mu_A(x) = \text{height}(A)\}$ .

The  $\alpha$ -*cut* (an  $\alpha$  *level*) of fuzzy the set  $A$  is

<sup>1</sup> The notions and results from this section are based on the reference (Klement, E.P. at all 2000.)

$$[A]^{\alpha} = \begin{cases} \{x \in X | \mu_A(x) \geq \alpha\} & \text{if } \alpha > 0 \\ \text{cl}(\text{supp}(A)) & \text{if } \alpha = 0 \end{cases}$$

where  $\text{cl}(\text{supp}(A))$  denotes the closure of the support of  $A$ .

**Definition 2.4**

Let be  $A \in F(X)$ . A fuzzy set  $A$  is *convex*, if  $[A]^{\alpha}$  is a convex (in the sense of classical set-theory) subset of  $X$  for all  $x \in X$ .

It should be noted, that  $\text{supp}(A)$ ,  $\text{ker}(A)$ ,  $\text{ceil}(A)$  and  $[A]^{\alpha}$  are ordinary, *crisp sets* on  $X$ .

**Definition 2.5**

Let be  $A, B \in F(X)$ .  $A$  and  $B$  are equal ( $A=B$ ), if  $\mu_A(x) = \mu_B(x), (\forall x \in X)$ .  $A$  is subset of  $B$ , ( $A \leq B$  or  $A \subset B$ ), (i.e.  $B$  is superset of  $A$ ), if  $\mu_A(x) \leq \mu_B(x), (\forall x \in X)$ .

**Definition 2.6**

For fuzzy subsets  $A_1(x), A_2(x), \dots, A_n(x) \in F(X)$  their *convex hull* is the smallest convex fuzzy set  $C(x)$  satisfying  $A_i(x) \leq C(x)$  for  $\forall i \in \{1, 2, \dots, n\}$  and for  $\forall x \in X$ .

**Example 2.1.**

The Body Mass Index (BMI) is a useful measure of too much weight and obesity. It is calculated from the patients' height and weight. (NHLB, 2011.) The higher their BMI, the higher their risk for certain diseases such as heart disease, high blood pressure, diabetes and others. The BMI score means are presented in the following Table 1.

	BMI
Underweight	BMI<18.5
Normal	18.5≤BMI<24.9 -
Overweight	24.9≤BMI<30
Obesity	BMI≥30

Table 1. The BMI score means

Representing the classification (BMI property) of the patients on the scale (BMI universe) of  $[0,40]$  with fuzzy membership functions Underweight ( $U(x)$ ), Normal ( $N(x)$ ), Overweight ( $OW(x)$ ) and Obesity ( $Ob(x)$ ) more acceptable descriptions are attained, where the crisp bounds between classes are fuzzified. Figure 1. shows the BMI universe covered over with four fuzzy subsets, representing the above-mentioned, linguistically described meanings, and constructed in Matlab Fuzzy Toolbox environment.

**2.1 Fuzzy sets operations**

It is convenient to introduce operations on set of all fuzzy sets like in other ordinary sets. So union and intersection operations are needed for fuzzy sets, to represent respectively in the fuzzy logic environment *or* and *and* operators. To represent fuzzy *and* and *or* t-norm and conorms are commonly used.

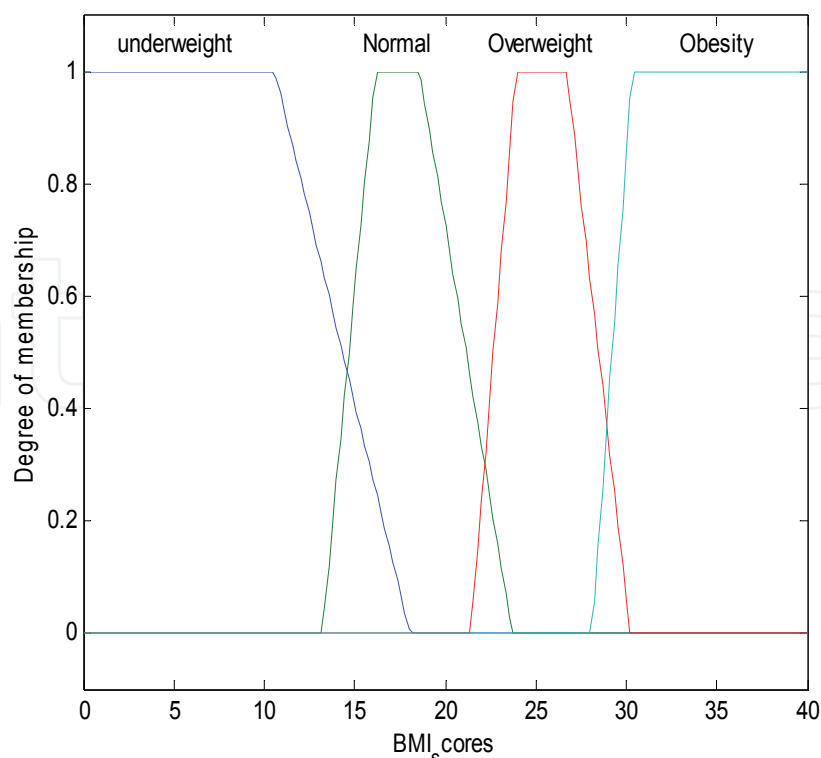


Fig. 1. The BMI universe is covered over with four fuzzy subsets

### Definition 2.1.1

A function  $T : [0,1]^2 \rightarrow [0,1]$  is called *triangular norm (t-norm)* if and only if it fulfils the following properties for all  $x, y, z \in [0,1]$

- (T1)  $T(x, y) = T(y, x)$ , i.e., the t-norm is commutative,
- (T2)  $T(T(x, y), z) = T(x, T(y, z))$ , i.e., the t-norm is associative,
- (T3)  $x \leq y \Rightarrow T(x, z) \leq T(y, z)$ , i.e., the t-norm is monotone,
- (T4)  $T(x, 1) = x$ , i.e., a neutral element exists, which is 1.

The basic t-norms are:

$T_M(x, y) = \min(x, y)$ , the minimum t-norm,

$T_P(x, y) = x \cdot y$ , the product t-norm,

$T_L(x, y) = \max(x + y - 1, 0)$ , the Lukasiewicz t-norm,

$T_D(x, y) = \begin{cases} 0 & \text{if } (x, y) \in [0, 1]^2 \\ 1 & \text{otherwise} \end{cases}$ , the drastic product.

### Definition 2.1.2

The associativity (T2) allows us to extend each t-norm  $T$  in a unique way to an  $n$ -ary operation by induction, defined for each  $n$ -tuple  $(x_1, x_2, \dots, x_n) \in [0, 1]^n$ , ( $n \in \mathbb{N} \cup \{0\}$ ) as

$$\underset{i=1}{\overset{0}{T}} x_i = 1, \quad \underset{i=1}{\overset{n}{T}} x_i = T\left(\underset{i=1}{\overset{n-1}{T}} x_i, x_n\right) = T(x_1, x_2, \dots, x_n) \quad (2.3)$$



**Definition 2. 1.3**

A function  $S : [0,1]^2 \rightarrow [0,1]$  is called *triangular conorm (t-conorm)* if and only if it fulfils the following properties for all  $x, y, z \in [0,1]$  :

- (S1)  $S(x, y) = S(y, x)$ , i.e., the t-conorm is commutative,  
 (S2)  $S(S(x, y), z) = S(x, S(y, z))$ , i.e., the t-conorm is associative,  
 (S3)  $x \leq y \Rightarrow S(x, z) \leq S(y, z)$ , i.e., the t-conorm is monotone,  
 (S4)  $S(x, 0) = x$ , i.e., a neutral element exists, which is 0.

The basic *t*-conorms are:

$S_M(x, y) = \max(x, y)$ , the maximum *t*-conorm,

$S_P(x, y) = x + y - x \cdot y$ , the probabilistic sum,

$S_L(x, y) = \min(x + y, 1)$ , the bounded sum,

$S_D(x, y) = \begin{cases} 1 & \text{if } (x, y) \in ]0, 1]^2 \\ \max(x, y) & \text{otherwise} \end{cases}$ , the drastic sum.

The original definition of *t*-norms and conorms are described in (Schweizer, Sklar (1960)).

At the beginnings of fuzzy theory investigations (and in applications very often today also) *min* and *max* operators are favourites, but new application fields, and mathematical background of them prefers generally *t*-norms and *t*-conorms.

Introduce the *fuzzy intersection*  $\cap_T$  and *union*  $\cup_S$  on  $F(X)$ , based on *t*-norm  $T$ , *t*-conorm  $S$ , and negation  $N$  respectively (Klement, Mesiar, Pap (2000a)) in following way

$\mu_{A \cap_T B}(x) = T(\mu_{A(x)}, \mu_{B(x)})$  or shortly  $\mu_{A \cap_T B}(x) = T(A(x), B(x))$ ,

$\mu_{A \cup_S B}(x) = S(\mu_{A(x)}, \mu_{B(x)})$  or shortly  $\mu_{A \cup_S B}(x) = S(A(x), B(x))$ .

The properties of the operations  $\cap_T$  and  $\cup_S$  on  $F(X)$  are directly derived from properties of the *t*-norm  $T$  and *t*-conorm  $S$ . The details about operators you can find in (Klement, E. P. et al., 2000.).

**2.2 Fuzzy approximate reasoning**

Approximate reasoning introduced by Zadeh (Zadeh, L. A., 1979) plays a very important rule in Fuzzy Logic Control (FLC), and also in other fuzzy decision making applications. The theoretical background of the fuzzy approximate reasoning is the fuzzy logic (Fodor, J., Rubens, M., 1994.), (De Baets, B., Kerre, E.E., 1993.), but the experts try to find simplest user-friendly models and applications. One of them is the Mamdani approach (Mamdani, E. H., Assilian, 1975.).

Considering the input parameter  $x$  from the universe  $X$ , and the output parameter  $y$  from the universe  $Y$ , the statement of a system can be described with a rule base (RB) system in the following form:

Rule1: IF  $x = A_1$  THEN  $y = B_1$

Rule2: IF  $x = A_2$  THEN  $y = B_2$

Rule n: IF  $x = A_n$  THEN  $y = B_{n1}$

This is denoted as a *single input, single output* (SISO) system.

If there is more than one rule proposition, i.e. the  $i^{th}$  rule has the following form

Rule $i$ : IF  $x_1 = A_{1i}$  AND  $x_2 = A_{2i}$  ..... THEN  $y = B_i$  ,

then this is denoted as a *multi input, single output* (MISO) system.

The global structure of an FLC approximate reasoning system is represented in Figure 2.

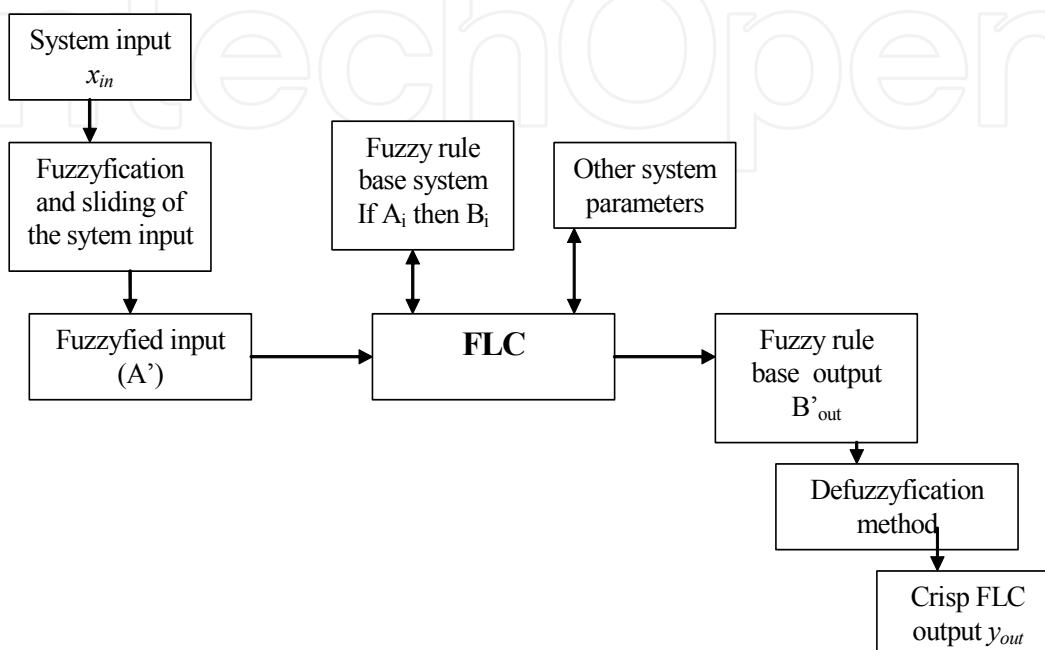


Fig. 2. The global structure of an FLC approximate reasoning system

In the Mamadani-based fuzzy approximate reasoning model (MFAM) the rule output  $B_i'(y)$  of the  $i^{th}$  rule if  $x$  is  $A_i$  then  $y$  is  $B_i$  in the rule system of  $n$  rules is represented usually with the expression

$$B_i'(y) = \sup_{x \in X} \left( T \left( A'(x), T \left( A_i(x), B_i(y) \right) \right) \right) \quad (2.4)$$

where  $A'(x)$  is the system input,  $x$  is from the universe  $X$  of the inputs and of the rule premises, and  $y$  is from the universe of the output.

For a continuous associative t-norm  $T$ , it is possible to represent the rule consequence model by

$$B_i'(y) = T \left( \sup_{x \in X} T \left( A_i(x), A'(x) \right), B_i(y) \right) \quad (2.5)$$

The consequence (rule output) is given with a fuzzy set  $B_i'(y)$ , which is derived from rule consequence  $B_i(y)$ , as an upper bounded, cutting membership function. The cut,

$$DOF_i = \sup_{x \in X} T \left( A_i(x), A'(x) \right) \quad (2.6)$$



is the generalized degree of firing level of the rule, considering actual rule base input  $A'(x)$ , and usually depends on the covering over  $A_i(x)$  and  $A'(x)$ , i.e. on the *sup* of the membership function of  $T(A'(x), A_i(x))$ . If there is more than one input in a rule, the degree of firing for the  $i^{th}$  rule is calculated as the minimum of all firing levels for the mentioned inputs  $x_i$  in the  $i^{th}$  rule. If the input  $A'$  is not fuzzified (i.e. it is a crisp value), the degree of firing is calculated with  $DOF_i = \sup_{x \in X} T(A_i(x), A')$ .

Rule base output,  $B'_{out}$  is an aggregation of all rule consequences  $B_i'(y)$  from the rule base. As aggregation operator usually *S* conorm fuzzy operator is used.

$$B'_{out}(y) = S(B'_n(y), S(B'_{n-1}(y), S(...., S(B'_2(y), B'_1(y)))). \quad (2.7)$$

If the crisp MFAR output  $y_{out}$  is needed, it can be constructed as a value calculated with a defuzzification method., for example with the Central of Gravity (COG) method:

$$y_{out} = \frac{\int_Y B'_{out}(y) \cdot y dy}{\int_Y B'_{out}(y) \cdot dy} \quad (2.8)$$

In FLC applications and other fuzzy approximate reasoning applications based on the experiences from FLC, usually minimum and maximum operators are used as t-norm and conorm in the reasoning process.

If the basic expectations of this fuzzy decision method are satisfied (Moser, B., Navara, M., 2002.), then the  $B'_{out}$  rule subsystem output belongs to the convex hull of disjunction of all rule outputs  $B_i(y)$ , and can be used as the input to the next decision level in the hierarchical decision making or reasoning structure without defuzzification. Two important issues arise: the first is, that the  $B'_{out}$  is usually not a normalized fuzzy set (should not have a kernel). The solution of the problem can be the use of other operators instead of t-norm or minimum in Mamdani approximate reasoning process to calculate expression(2.6). The second question is, how to manage the weighted output, representing the importance of the handled risk factors group in the observed rule base system. The solution can be the multiplication of the membership values in the expression of  $B'_{out}$  with the number from [0,1].

### Example 2.2

Continuing the previous example let us consider one more risk factor (risk factor2), and calculate the risk level for the patient taking into account the input risk factors BMI and riskfactor2. Figure 3. shows the membership functions representing the riskfactor2 categories (scaling on the interval [0,1], representing the highest level of risk with 1 and the lower level with 0, i.e. on an unipolar scale). Figure 4. represents the membership functions of the output risk level categories (scaling on the unipolar scale too). Figure 5. shows the system structure, Figure 6. the graphical representation of the Mamdani type reasoning method, and Figure 7. the so called *control surface*, the 3D representation of the risk level calculation, considering both inputs. (Constructions are made in Matlab Fuzzy Toolbox environment).

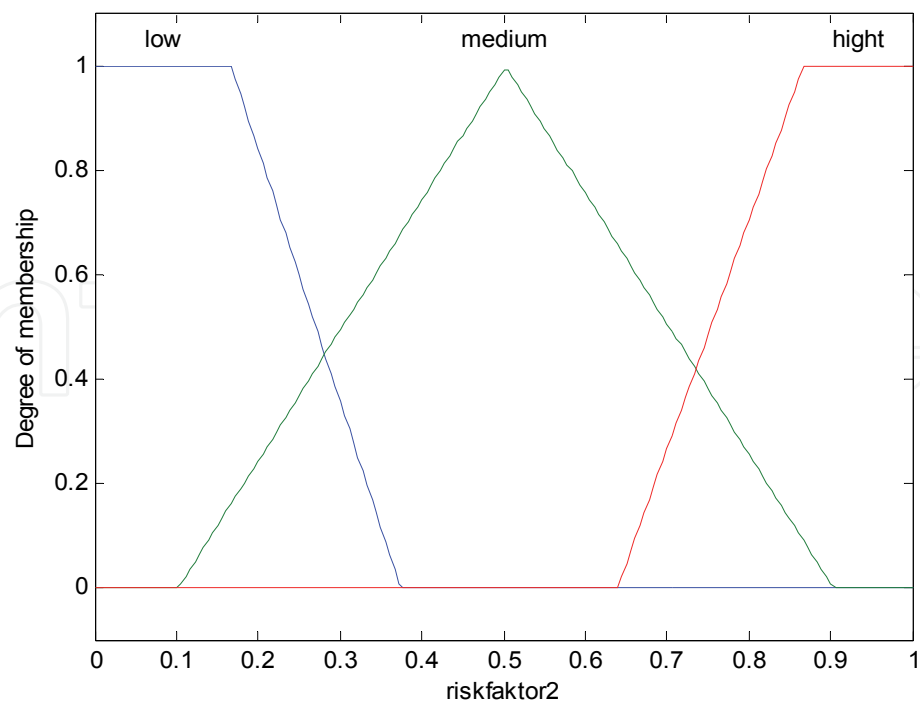


Fig. 3. The membership functions representing the riskfactor2 categories

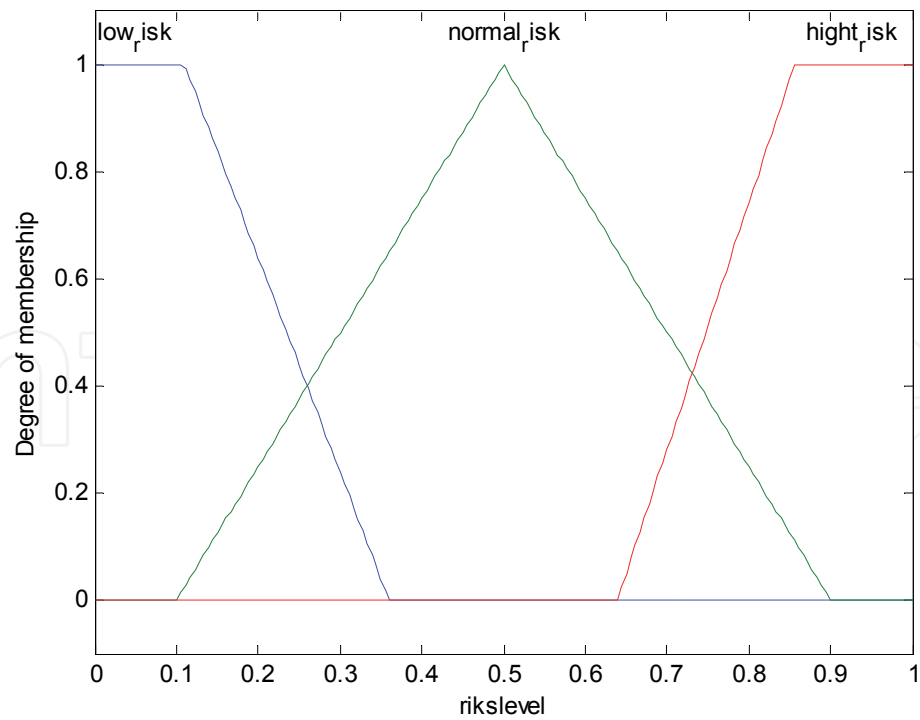
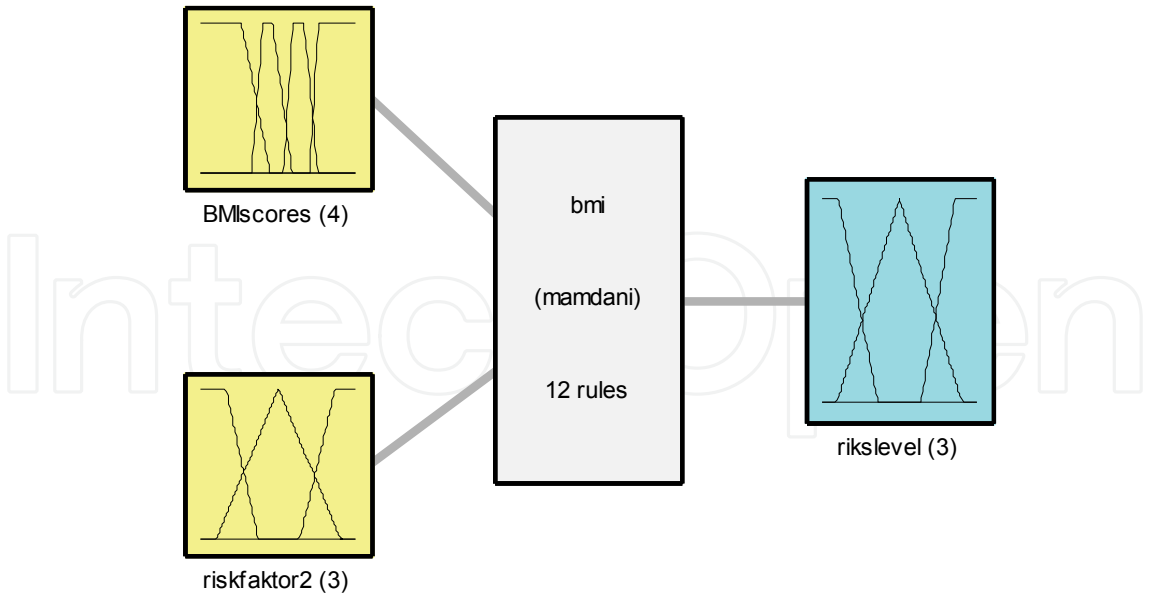


Fig. 4. Represents the membership functions of the output risk level categories



System bmi: 2 inputs, 1 outputs, 12 rules

Fig. 5. The system structure

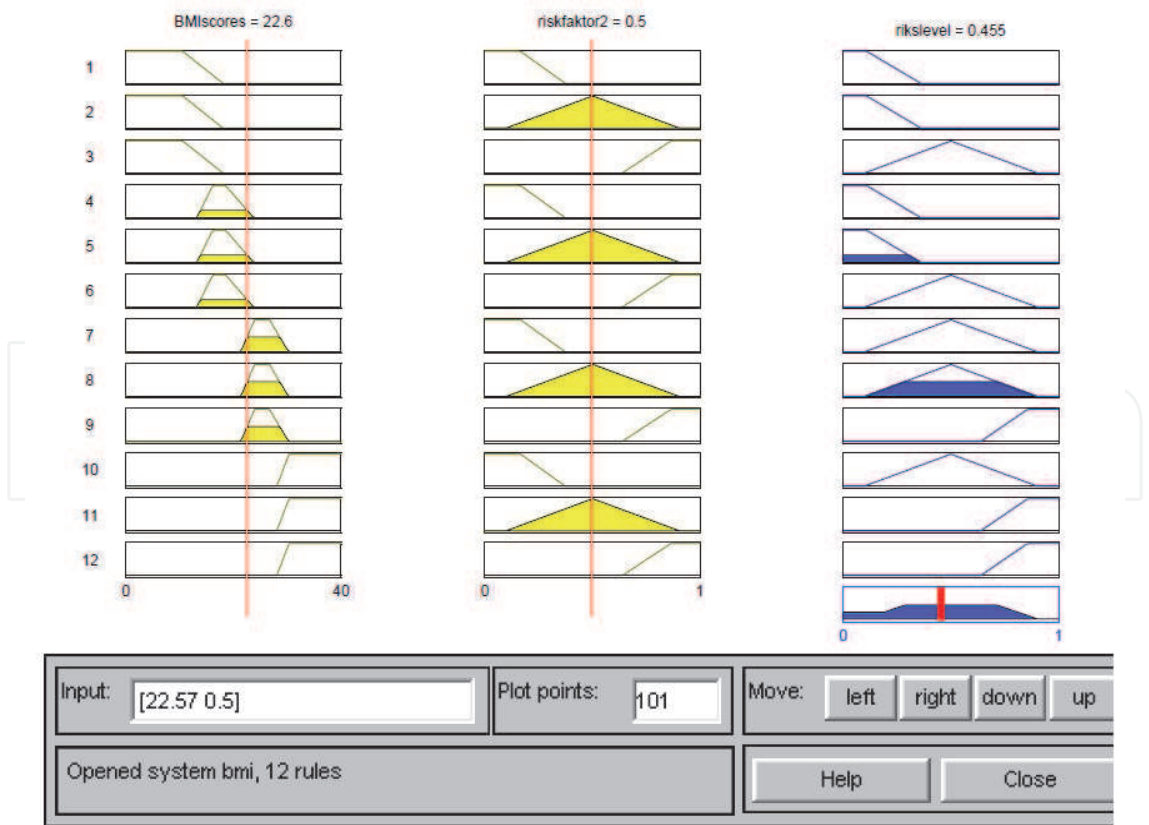


Fig. 6. The graphical representation of the Mamdani type reasoning method

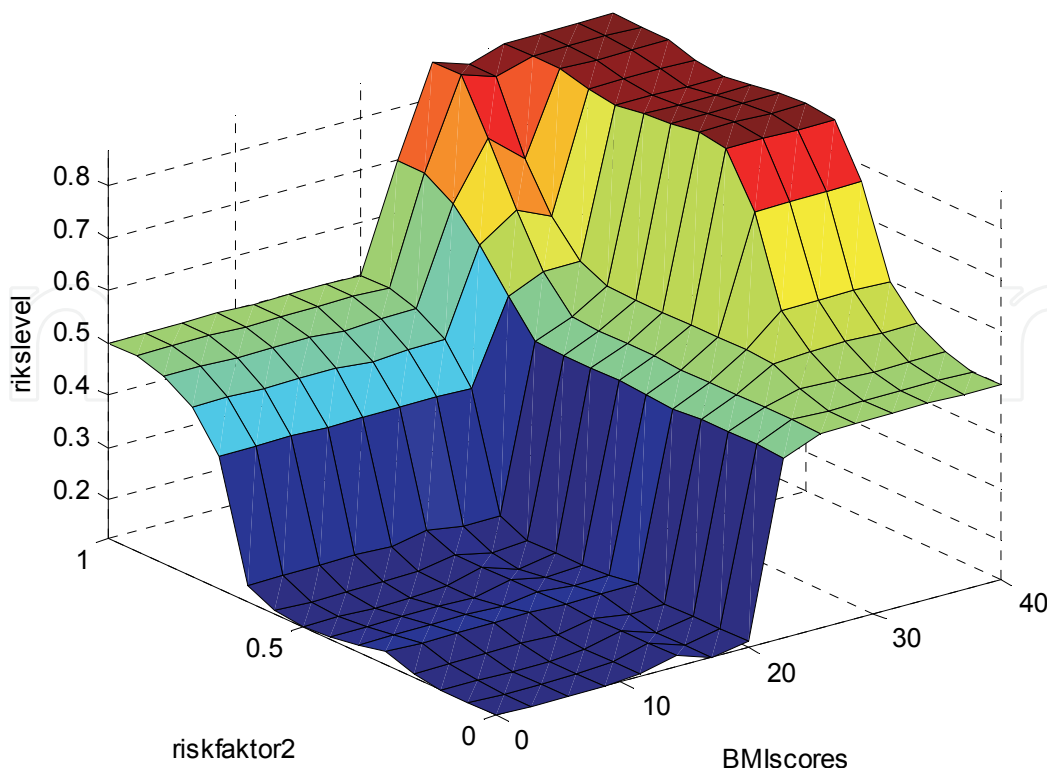


Fig. 7. *Control surface*, the 3D representation of the risk level calculation, considering both inputs

### 3. Fuzzy logic based risk management

Risk management is the identification, assessment, and prioritization of risks, defined as the effects of uncertainty of objectives, whether positive or negative, followed by the coordinated and economical application of resources to minimize, monitor, and control the probability and/or impact of unfortunate events (Douglas, H. 2009.).

The techniques used in risk management have been taken from other areas of system management. Information technology, the availability of resources, and other facts have helped to develop the new risk management with the methods to identify, measure and manage the risks, or risk levels thereby reducing the potential for unexpected loss or harm (NHSS, 2008.). Generally, a risk management process involves the following main stages.

The first step is the identification of risks and potential risks to the system operation at all levels. Evaluation, the measure and structural systematization of the identified risks, is the next step. Measurement is defined by how serious the risks are in terms of consequences and the likelihood of occurrence. It can be a qualitative or quantitative description of their effects on the environment. Plan and control are the next stages to prepare the risk management system. This can include the development of response actions to these risks, and the applied decision or reasoning method. Monitoring and review, as the next stage, is important if the aim is to have a system with feedback, and the risk management system is open to improvement. This will ensure that the risk management process is dynamic and continuous, with correct verification and validity control. The review process includes the possibility of new additional risks and new forms of risk description. In the future the role of complex risk management will be to try to increase the damaging effects of risk factors.

### 3.1 Fuzzy risk management

Risk management is a complex, multi-criteria and multi-parametrical system full of uncertainties and vagueness. Generally the risk management system in its preliminary form contains the identification of the risk factors of the investigated process, the representation of the measured risks, and the decision model. The system can be enlarged by monitoring and review in order to improve the risk measure description and decision system. The models for solving are knowledge-based models, where linguistically communicated modelling is needed, and objective and subjective knowledge (definitional, causal, statistical, and heuristic knowledge) is included in the decision process. Considering all these conditions, fuzzy set theory helps manage complexity and uncertainties and gives a user-friendly visualization of the system construction and working model.

Fuzzy-based risk management models assume that the risk factors are fuzzified (because of their uncertainties or linguistic representation); furthermore the risk management and risk level calculation statements are represented in the form of *if premises then conclusion* rule forms, and the risk factor or risk level calculation or output decision (summarized output) is obtained using fuzzy approximate reasoning methods. Considering the fuzzy logic and fuzzy set theory results, there are further possibilities to extend fuzzy-based risk management models modeling risk factors with type-2 fuzzy sets, representing the level of the uncertainties of the membership values, or using special, problem-oriented types of operators in the fuzzy decision making process (Rudas, I., Kaynak, O., 1998. ).

The hierarchical or multilevel construction of the decision process, the grouped structural systematization of the factors, with the possibility of gaining some subsystems, depending on their importance or other significant environment characteristics or on laying emphasis on risk management actors, is a possible way to manage the complexity of the system. Carr and Tah describe a common hierarchical-risk breakdown structure for developing knowledge-driven risk management, which is suitable for the fuzzy approach (Carr, J.H. , Tah, M. 2001.).

Starting with a simple definition of the risk as the adverse consequences of an event, such events and consequences are full of uncertainty, and inherent precautionary principles, such as sufficient certainty, prevention, and desired level of protection. All of these can be represented as fuzzy sets. The strategy of the risk management may be viewed as a simplified example of a precautionary decision process based on the principles of fuzzy logic decision making (Cameron, E., Peloso, G. F. 2005.).

Based on the main ideas from (Carr, J.H. , Tah, M. 2001.) a risk management system can be built up as a hierarchical system of risk factors (inputs), risk management actions (decision making system) and direction or directions for the next level of risk situation solving algorithm. Actually, those directions are risk factors for the action on the next level of the risk management process. To sum this up: risk factors in a complex system are grouped to the risk event where they figure. The risk event determinates the necessary actions to calculate and/or increase the negative effects. Actions are described by 'if ... then' type rules.

With the output those components frame one unit in the whole risk management system, where the items are attached on the principle of the time-scheduling, significance or other criteria (Fig. 8). Input Risk Factors (RF) grouped and assigned to the current action are described by the Fuzzy Risk Measure Sets (FRMS) such as 'low', 'normal', 'high', and so on. Some of the risk factor groups, risk factors or management actions have a different weighted role in the system operation. The system parameters are represented with fuzzy sets, and the

grouped risk factors values give intermitted results. Considering some system input parameters, which determine the risk factors’ role in the decision making system, intermitted results can be weighted and forwarded to the next level of the reasoning process.

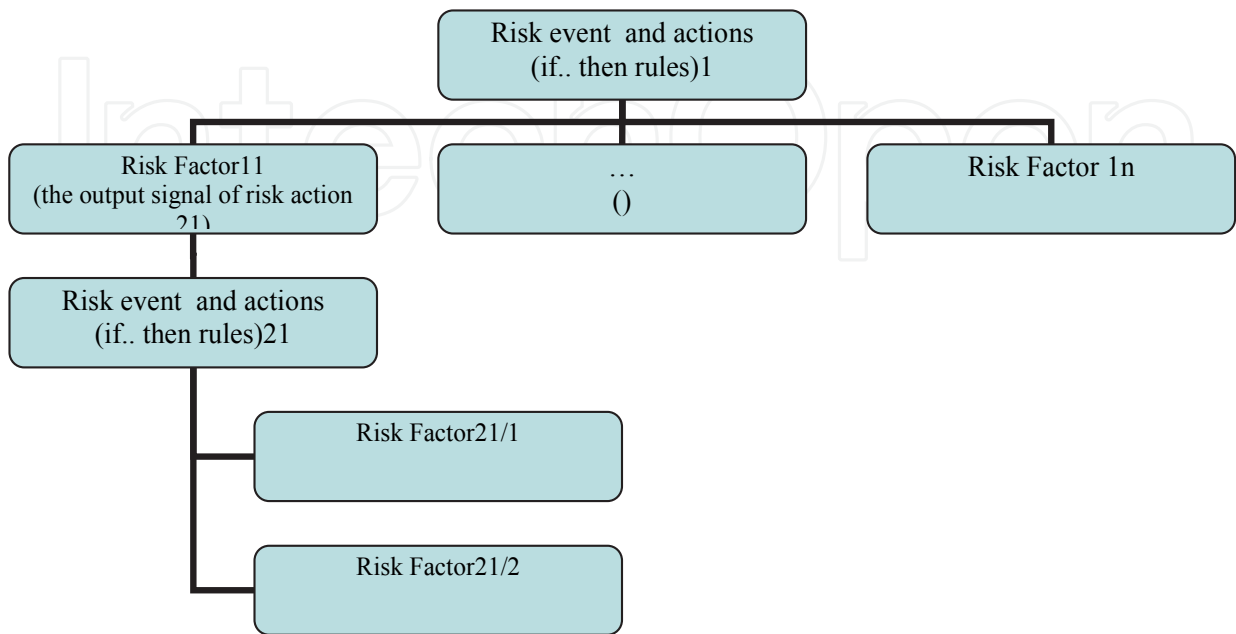


Fig. 8. The hierarchical risk management construction

3.2. Case studies

3.2.1 The brain stroke risk level calculation

Health is commonly recognized as the absence of disease in the body. The fundamental problem with using probability-based statistics for patient diagnosis and treatment is the long time statistical data collection, complex calculation process and the elimination of the real-time human experience (at the actual medical examination) (Helgason, C. M., Jobe, T. H., 2007).The influence of human perception, information collection, experiences involved in diagnosis and therapy realizations support the main fact, namely, that patients are unique. Medical staff has various levels of expertise and the perceptions are often expressed in language. Diagnosis and treatment decisions are determined factors which are either unknown or are not represented within the framework of probability based statistics. As it is stated in the information brochure published for patients by the University of Pittsburgh Medical Center, the risk factor in health diagnostics is anything that increases chance of illness, accidents, or other negative events. Stroke is one of the most important health issues, because it is not only a frequent cause of death, but also because of the high expenses the treatment of the patients demands. Stroke occurs when the brain’s blood flow stops or when blood leaks into brain tissue. The oxygen supply to a part of the brain is interrupted by a stroke, causing brain cells in that area to die. This means that some parts of the body may not be able to function. There are a large number of risk factors that increase the chances of having a stroke. Risk factors may include medical history, genetic make-up, personal habits, life style and aspects of the environment of the patient.



This classification is suitable for grouping the factors, but further different aspects can be applied for grouping. One of them is the classification depending on the possibilities of elimination. Some risk factors cannot be reversed or changed. They are uncontrollable. But some of the risk factors can be eliminated, like smoking, for example. There are other risk factors that the patient cannot get rid of, but can control, like diabetes.

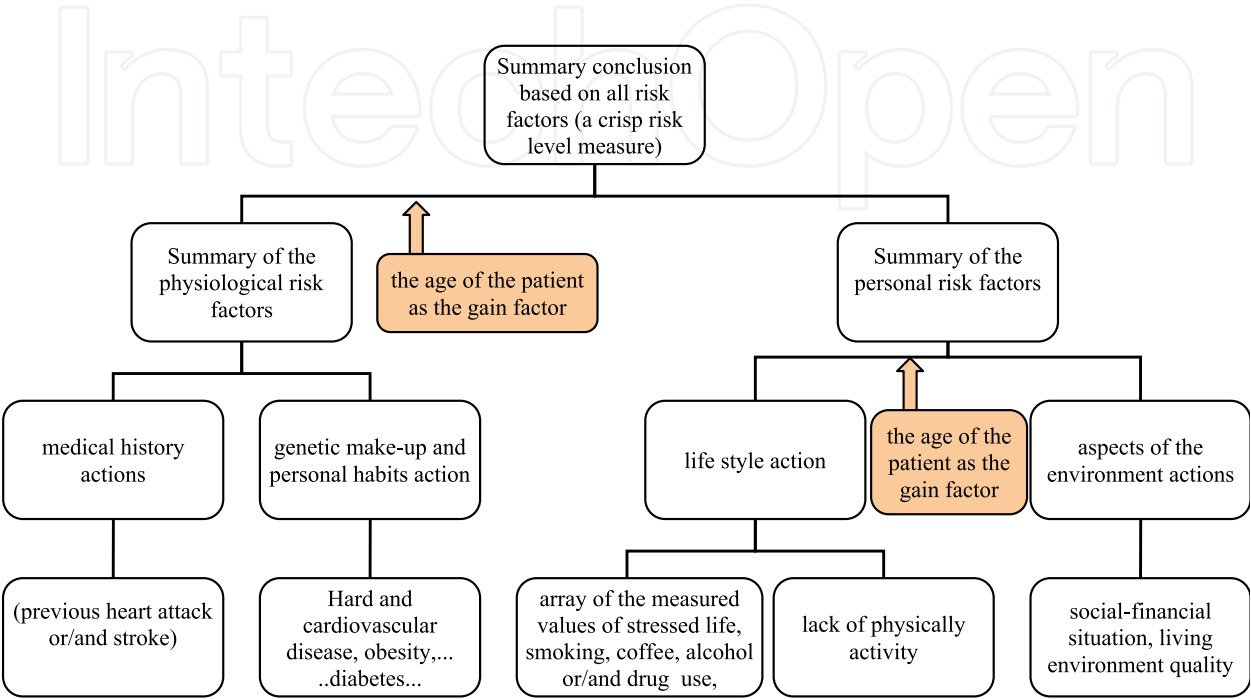


Fig. 9. Brain stroke risk factors - classification, gains and actions

In regard to the theoretical introduction, in the present application a restricted risk factors set is used. The factors are classified in the next *events* – groups (all of risk factors and theirs values are represented with fuzzy membership values)

- medical history (heart attack, previous stroke, ...)
- genetic make-up and personal habits (diabetes, obesity, Heart and cardiovascular disease,...)
- life style (stressed life, smoking, coffee, alcohol and drug use, Lack of Physical Activity, ...)
- aspects of the environment (social-financial situation, living environment,...).

Grouping physiological events (medical history, genetic make-up and personal habits) and personal controllable events (life style and aspects of the environment) in the separated next level actions, there are two inputs on the final level of actions: summarized physiological factors and summarized personal controllable factors. The final output is the global stroke risk factor based on hierarchically investigated elementary risk factors.

The risk calculation actions are the if then rules regarding to the input variables of the current action level. The outputs at the actions are calculated using the Mamdani type reasoning method, the crisp outputs are achieved with the central of gravity defuzzification. The complex risk calculation system is constructed in a Matlab Fuzzy and Simulink environment.



It ought to be considered, that different events or risk factors have different impact on the stroke occur. Very often the sex or age of the patient will significantly affect the illness. In this experimental system these factors will be the input variables of the system, by which some of the risk factors or events will be gained before the transmission to the next level of action (Figure 9).

Figure 10. shows the final risk calculation surface.

**3.3.2 Disaster management**

Disaster event monitoring as one of the steps in risk and crisis management is a very complex system with uncertain input parameters. Fuzzified inputs, the fuzzy rule base, which is constructed using objective and subjective definitional, causal, statistical, and heuristic knowledge, is able to present the problem in a user-friendly form. The complexity of the system can be managed by the hierarchically-structured reasoning model, with a thematically-grouped, and if necessary, gained risk factor structure.

Crisis or disaster event monitoring provides basic information for many decisions in today’s social life. The disaster recovery strategies of countries, the financial investments plans of investors, or the level of the tourism activities all depend on different groups of disaster or crisis factors. A disaster can be defined as an unforeseen event that causes great damage, destruction and human suffering, evolved from a natural or man-made event that negatively affects life, property, livelihood or industry. A disaster is the start of a crisis, and often results in permanent changes to human societies, ecosystems and the environment.

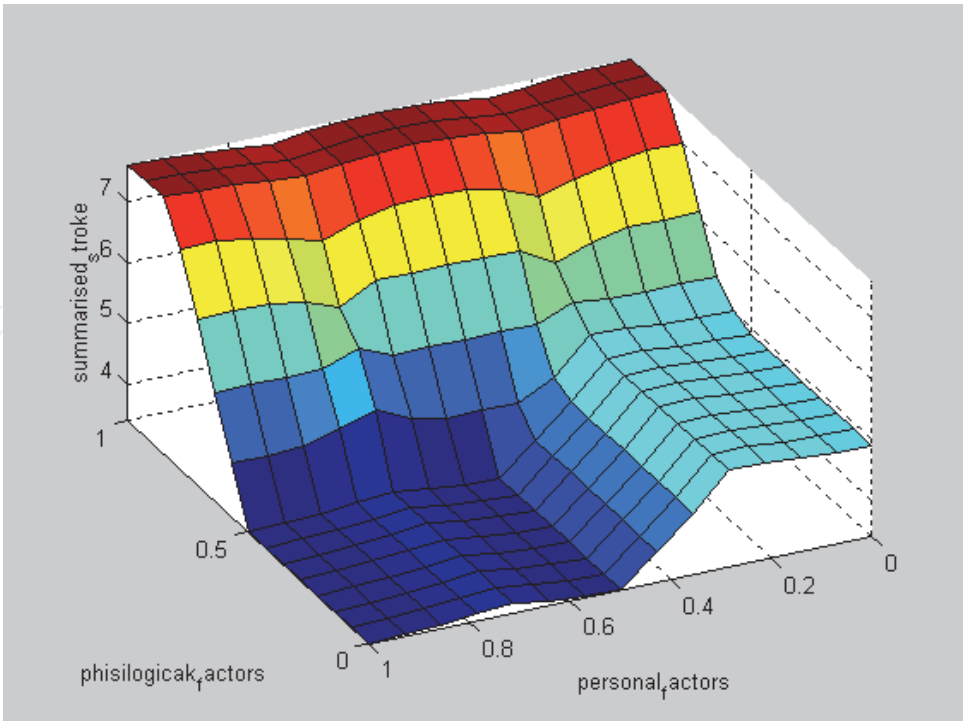


Fig. 10. The summarized risk factor’ decision surface

Based on the experts’ observations (Yasuyuki S., 2008.), the risk factors which predict a disaster situation can be classified as follows:

- natural disasters;
- man-made disasters (unintended events or wilful events).

Natural disasters arise without direct human involvement, but may often occur, because of human actions prior, during or after the disaster itself (for example, a hurricane may cause flooding by rain or by a storm surge).

The natural disasters can also be grouped primarily based on the root cause:

- hydro-meteorological disasters: floods, storms, and droughts;
- geophysical disasters: earthquakes, tsunamis and volcanic eruptions;
- biological disasters: epidemics and insect infestations;

or they can be structured hierarchically, based on sequential supervision.

The example, presented in this paper, is constructed based on the first principle, with fuzzified inputs and a hierarchically-constructed rule base system (Figure 11.). The risk or disaster factors, as the inputs of one subsystem of the global fuzzy decision making system, give outputs for the next level of decision, where the main natural disaster classes result is the total impact of this risk category.

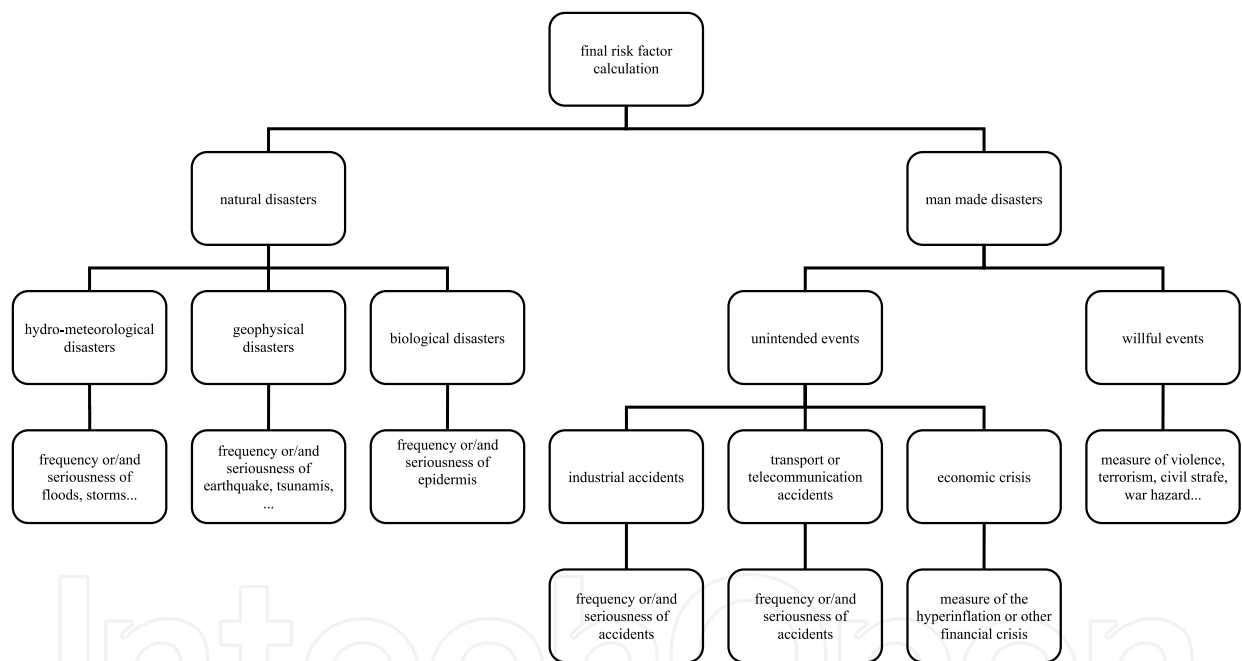


Fig. 11. Hierarchically constructed rule base system representing disaster management

This approach allows additional possibilities to handle the set of risk factors. It is easy to add one factor to a factors-subset; the complexity of the rule base system is changed only in the affected subsystem.

In different seasons, environmental situations etc., some of the risk groups are more important for the global conclusion than others, and this can be achieved with an importance factor (number from the [0,1]). Man-made disasters have an element of human intent or negligence. However, some of those events can also occur as the result of a natural disaster. Man-made factors and disasters can be structured in a manner similar to the natural risks and events.

One of the possible classifications of the basic man-made risk factors or disaster events (applied in our example) is as follows:

- Industrial accidents (chemical spills, collapses of industrial infrastructures);
- Transport or telecommunication accidents (by air, rail, road or water means of transport);
- Economic crises (growth collapse, hyperinflation, and financial crisis);
- wilful events (violence, terrorism, civil strife, riots, and war).

In the investigated example, the effects of man-made disasters as inputs in the decision making process are represented with their relative frequency, and the premises of the related fuzzy rules are very often represented with the membership functions: never, rarely, frequently, etc.<sup>2</sup>

The input parameters are represented on the unit universe [0,1] with triangular or trapezoidal membership functions describing the linguistic variables such as the frequency of the floods, for example: "low", "medium" or "high" (Fig. 12). The system was built in the Matlab Fuzzy Toolbox and Simulink environment.

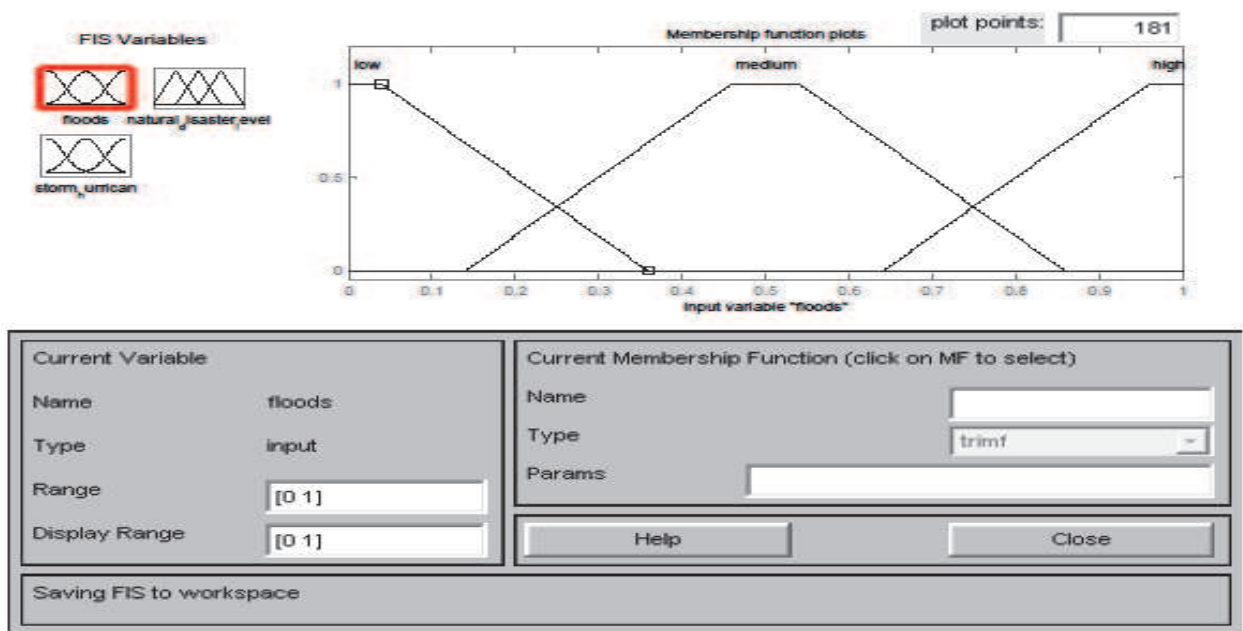


Fig. 12. Membership functions of the flood frequencies

The risk and disaster factors are grouped in two main groups: human- and nature-based group. The inputs are crisp, but the rule base system is hierarchically constructed (Fig. 13), and the decision making is Mamdani type approximate reasoning with basic *min* and *max* operators.

The final conclusion based on both disasters' as risk factors' groups is shown in Figure 14.

<sup>2</sup> The Matlab Fuzzy Toolbox and Simulink elements were in the preliminary, partial form constructed by Attila Karnis, student of the Óbuda University as part of the project in the course "Fuzzy systems for engineers".

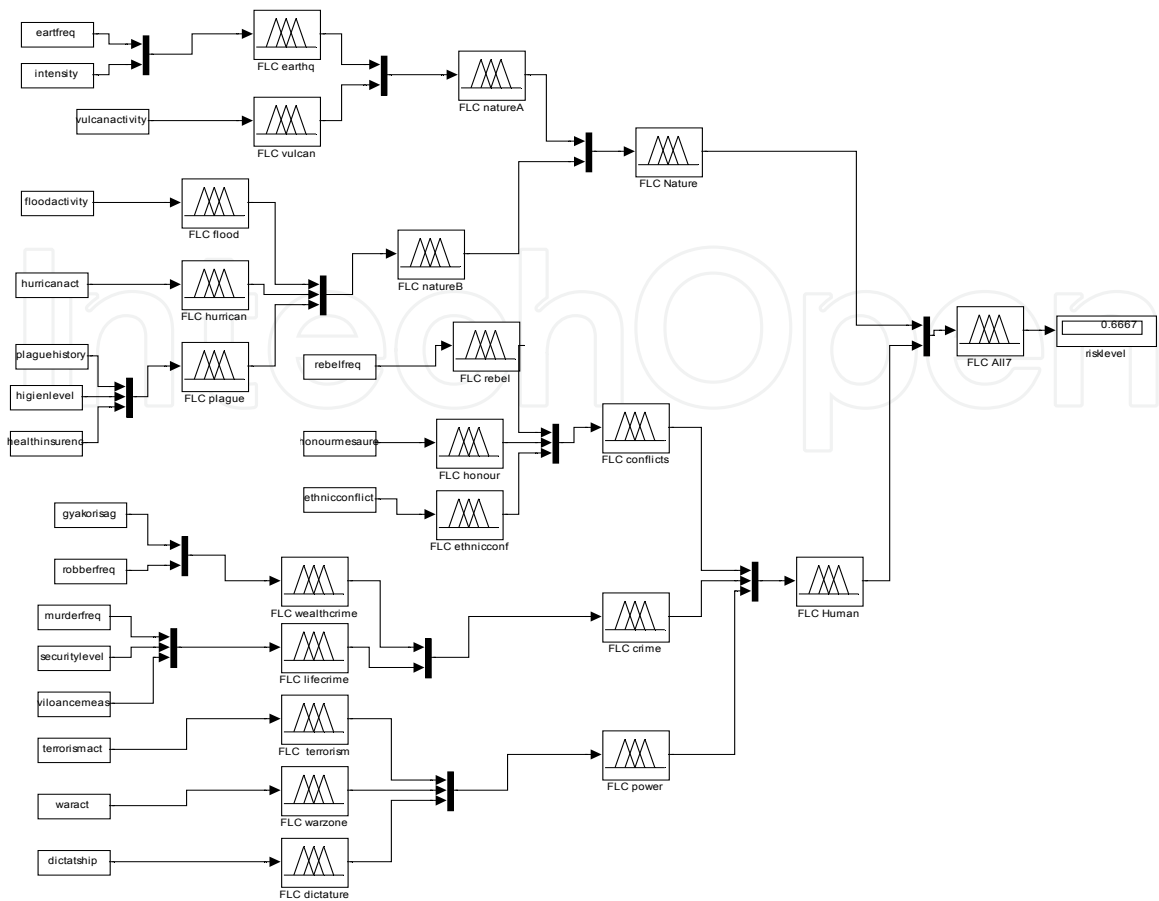


Fig. 13. The Simulink model construction calculating the travel risk level in a country

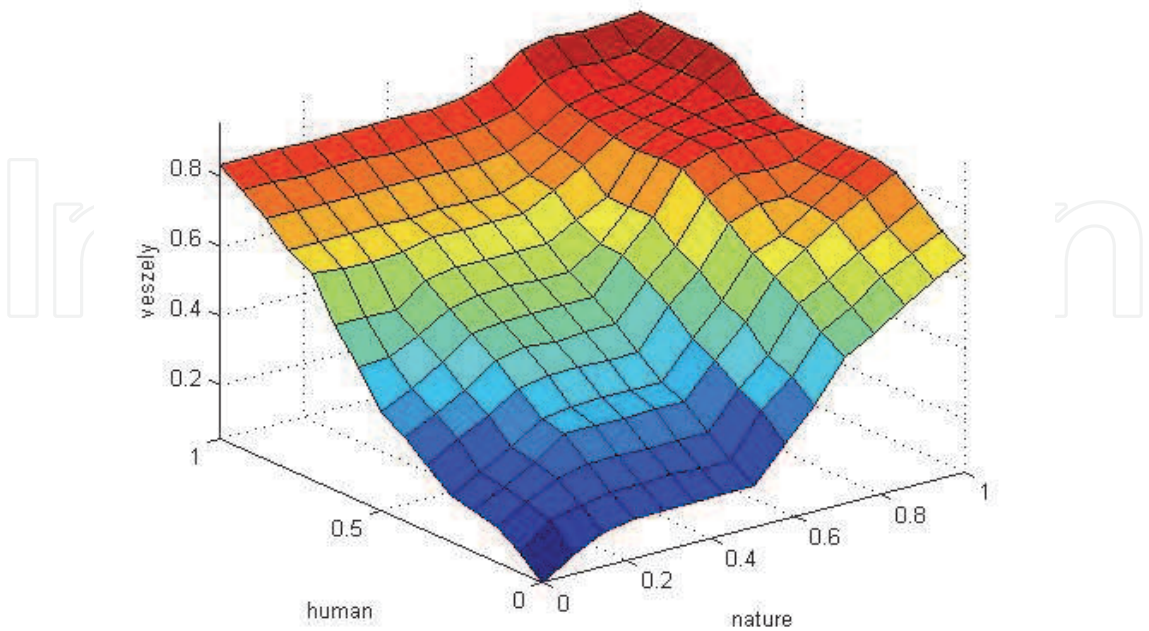


Fig. 14. The final conclusion based on both disasters' as risk factors' groups

## 4. Conclusion

In this chapter a preliminary system construction of the risk management principle is given based on the structured risk factors' classification and further, based on the fact that some risk factor groups, risk factors or management actions have a weighted role in the system operation. The system parameters are represented with fuzzy sets, and the grouped risk factors' values give intermitted result. Considering some system input parameters, which determine risk factors role in the decision making system, intermitted results can be weighted and forwarded to the next level of the reasoning process. The experimental applications are related to the disaster risk level and stroke risk level calculation.

Considering the fuzzy logic and fuzzy set theory results, there are further possibilities to extend the fuzzy-based risk management models:

- modeling of the risk factors with type 2 fuzzy sets, representing the level of the uncertainties of the membership values;
- use of special, problem oriented types of operators in the fuzzy decision making process;
- the hierarchical or multilevel construction of the decision process, with the possibility of gaining some subsystems, depending on their importance or other significant environment characteristics or on laying emphasis on risk management actors'.

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In many human activities risk is unavoidable. It pervades our life and can have a negative impact on individual, business and social levels. Luckily, risk can be assessed and we can cope with it through appropriate management methodologies. The book Risk Management Trends offers to both, researchers and practitioners, new ideas, experiences and research that can be used either to better understand risks in a rapidly changing world or to implement a risk management program in many fields. With contributions from researchers and practitioners, Risk Management Trends will empower the reader with the state of the art knowledge necessary to understand and manage risks in the fields of enterprise management, medicine, insurance and safety.

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