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Risk Assessment of Natural Disasters Using Fuzzy Logic System of Type 2

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Risk assessment of natural and other disasters in the Republic of Serbia is defined using special methodology. This paper presents a model of improving the existing methodology by using a new generation of fuzzy logic systems (fuzzy logic systems of type 2). This type of fuzzy logic systems is a significant improvement of the existing fuzzy logic systems of type 1. Fuzzy logic systems type 2 are based on the application of new interval fuzzy numbers that consider undetermined relative to classic fuzzy numbers in a better way. The fuzzy logic system presented in this paper translates vagueness and uncertainty, those that accompany risk assessment of natural disasters and other catastrophes, into an algorithm. This kind of algorithm makes the difference between data that are absolutely correct and those less accurate, those that clearly fit in the defined evaluation scales and those that are on the limit of values and so on. This kind of a model can help decision-makers who conduct risk assessment of natural and other disasters since it is rather easy to use and does not require prior knowledge. Thereby, the existing methodology is used as a cornerstone in the developed model. Also, the model is significant for persons engaged in decision-making in other areas because it is a method that has not been extensively applied in science and practice, and whose development is at the beginning.

Keywords: fuzzy logic, interval fuzzy number, fuzzy logic system type 2, risk assessment, natural disasters

1. Introduction

Risk management is still a field of human interests not explored to an adequate extent. For that purpose, a large number of models are being developed. In scientific and professional community there is no unanimous agreement that there is a unique risk management method that can be used across the board. On the other hand, it is generally agreed that each system is unique and so that is consequently necessary to develop models which differ one from another. For that purpose, a large number of methods for assessing and managing risk are being used. Methods that support decision-making are an important part in risk management, and also have specific role in risk quantification. Fuzzy sets and fuzzy logic represent major areas of risk quantification. They are applied in different ways, individually or combined with other methods. One way of applying is the Fuzzy Logic Systems (FLS).

2. Description of the Problem

Despite significant technological progress, modern society is not free from the burden of crises that "a particular community, nation, or entire world may push into a state of chaotic conditions" (Keković & Kešetović, 2006, p. 15). A devastating impact of the crisis on parts of or on the whole of the community, as well as assumptions that such a crisis may emerge are the most important parameters which indicate a need to research this issue. One of the segments of this problem is predicting the occurrence of adverse events, in order to reduce their impacts as much as possible, and even to prevent any negative consequences. An indispensable element of such prediction is risk assessment.

Risk is a term that has been established in the field of crisis management. Besides, like most concepts in social sciences, risk is defined in different ways. Keković et al. (2011) suggest that risk is "any possibility in the present system, which with a certain probability, can cause an unexpected change of quality, that is, cause the change or loss of the system" (p. 25). For Avakumović et al. (2010) risk is usually considered to be the "uncertainty of loss" (p. 387). Also, "Risk is a condition in which there is a possibility of an adverse deviation from a desired outcome that is expected or hoped for" (Vaughan & Vaughan, 2008, p. 2). Karović and Komazec (2010) define risk as a "deviation from the expected" (p. 149). Huang and Rouen (2008) define risk as "a scene in the future associated with some adverse incident" (p. 682). Usually, risk is defined as "a combination of possibility (probability) of an event and its consequences" (Risk management terminology paper - ISO / RMTP, International Organization for Standardization - ISO TC 223 / SC).

It can be concluded from these definitions that risk is usually associated with uncertainty, that is, something that is not safe. In that sense, Williams et al. (1998) explain uncertainty on several levels:

- State of absence of uncertainty, when the outcome can be predicted very accurately;
- Level of uncertainty 1, when the outcomes are identified and probabilities are known;
- Level of uncertainty 2, when the outcomes are identified and probabilities are unknown and
- Level of uncertainty 3, when the outcomes are not identified and probabilities are unknown.

In order to prevent adverse events from happening or minimize their consequences, constant risk assessment is performed. There are several risk assessment methods[1]. For the purpose of assessing risk of natural and other disasters in the Republic of Serbia a specific methodology has been developed. It can be found in the Guidelines on the methodology for risk assessment development and protection and rescue plans in emergency situations (2012). According to this methodology, risk assessment consists of three phases: identification, risk analysis and assessment. The focus of this paper is on risk analysis. This includes determining the level of risk, i.e., quantification of risk. Very suitable mechanisms for quantifying risk are fuzzy sets theory and fuzzy logic. Their contribution is reflected in the possibility of translating a completely unstructured set of heuristic assertions expressed in words into an algorithm (Pamučar, 2014, p. 73). Creating a fuzzy logic system based on an already existing methodology of risk assessment of natural and other disasters, can lead to developing new, more advanced models.

3. Development of Fuzzy Sets and Fuzzy Logic Systems of Type 2

Fuzzy sets and fuzzy logic systems (FLS) of type 2 generalize fuzzy sets and FLS of type 1, which allows managing a larger number of unreliabilities, insecurities and uncertainties. From the very beginning of fuzzy sets application, many have claimed that in case of fuzzy sets of type 1, affiliation functions do not demonstrate uncertainty, which contradicts the word fuzzy, since the meaning of the word refers to a large number of uncertainties. The question is what to do when there is uncertainty in the degree of affiliation to fuzzy sets (membership functions). The answer to this question was given in 1975 by Lotfi A. Zadeh. Zadeh proposed a more sophisticated type of fuzzy sets, called fuzzy sets of type 2. A fuzzy set of type 2 allows uncertainty of affiliation function to be incorporated into the theory of fuzzy sets, and is a direct way to correct the deficiencies of fuzzy sets of type 1. This means that if there is no uncertainty, fuzzy set of type 2 reduces to a fuzzy set of type 1, which is analogous to reducing the probability to determination when unpredictability disappears. In order to symbolically distinguish the fuzzy set of type 1 from the fuzzy set type 2, the symbol (~) is placed above the symbol for the fuzzy set of type 2. Thus, A denotes a fuzzy set of type 1, while $\tilde{A}$ indicates a comparable fuzzy set of type 2. Zadeh did not stop at fuzzy sets of type 2; in his work of 1976 (Zadeh, 1976), he carried out a generalization of fuzzy sets of type 2 into fuzzy set of type-n. This paper focuses only on fuzzy sets of type 2, since they are the next logical step in the progression of the fuzzy set of type 1 to fuzzy set of type-n (n = 1, 2,.... N). the work on fuzzy sets of type 2 stagnated in the period between 1980s and early 2000s, during which only a small number of papers regarding this topic was published. The researchers in this period were still trying to understand how to implement the fuzzy sets of type 1. That changed in the early 2000s as a result of work of Professor Jerry Mendel on fuzzy sets and FLS of type 2

[1] The best known methods are: Preliminary Hazard Analysis (PHA), rapid method of ranking risk, study of risk of material and technological processes (HAZOP), fault tree and event tree, Hazard Analysis (HAZAN), Analysis of errors/failures and their impacts (FMEA), methods of maintenance management based on risk, the method for the analysis and assessment of the risks and dangers that may cause adverse events in the community, etc.. (Vujović, 2009, p. 191).

(Liang & Mendel, 2000; Mendel, 2001; Karnik & Mendel, 2001). Although researchers started to explore fuzzy sets of type 2 and FLS of type 2 on a larger scale at the beginning of 2009, the implementation of these sets remained at almost an initial stage .

A function that belongs to the set type 2 occurs when we show type 1, Figure 1, right and left confidence interval limit, as it is shown in Figure 1b. Then we get type 2 function which is shown in Figure 2.

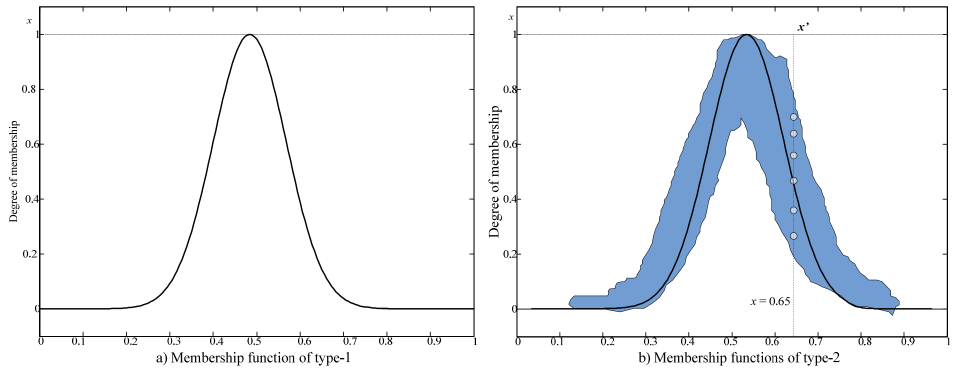


Figure 1: The membership function type 1 (a) and membership function type 2 (b)

In this case, for a particular value of x', membership functions have different values of the degree of affiliation, so that we can determine the degree for each point (x'). By repeating the presented procedure for all the elements *x*X, we get a three-dimensional membership function which describes the type 2 fuzzy sets (Castillo & Melin, 2008; Wu & Mendel, 2008; Mendoza et al, 2009).

In three-dimensional membership functions of general fuzzy sets of type 2 (Ã), Figure 2, the value of the membership function at each point of the third dimension is described by the two-dimensional domain called footprint of uncertainty (FOU). In the interval of fuzzy sets of type 2, the value of the third dimension is the same everywhere, which means that there is no new information contained in the third dimension. For that kind of set the third dimension is ignored and only FOU is used to describe it. For this reason, the interval fuzzy set of type 2 model is sometimes called the fuzzy set of the first order of uncertainty, while the general fuzzy set of type 2 (with useful third dimension) is sometimes referred to as a model of fuzzy set of the second order of uncertainty.

The footprint of uncertainty represents a blurring of membership functions for type 1 (Figure 2). Type 2 membership functions are defined (bordered by) with two membership functions of type 1, $\overline{X}$ and $\underline{X}$, which are also called upper membership functions (UMF) and lower membership functions (LMF), respectively. Both functions, UMF and LMF, are represented by a fuzzy set of type 1. Therefore, it is possible to use only a set of fuzzy arithmetic operations of type 1 and to work to characterize the fuzzy sets of type 2. This means that those who know fuzzy sets of type 1 will not have to invest a lot of time to understand and use fuzzy sets of type 2.

The restricted areas UMF and LMF are called the footprints of uncertainty (FOU), Figure 2.

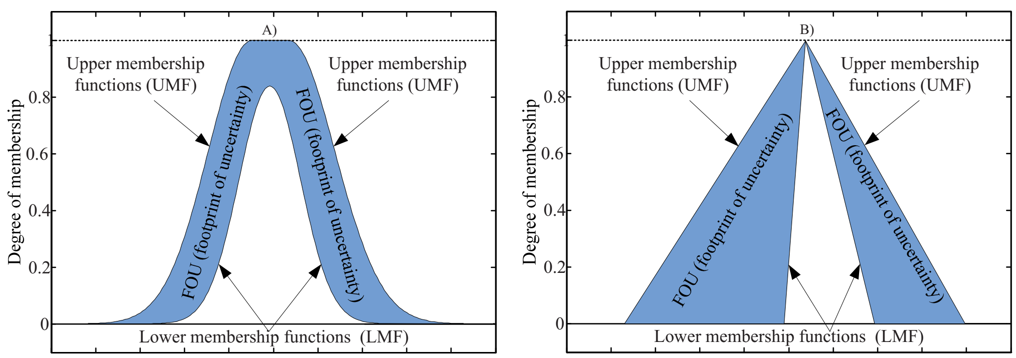


Figure 2: FOU fuzzy sets of type 2 (Gaussian and triangular membership functions)

The fuzzy set of type 2 describes the “membership function” as shown bellow (Melgarejo, 2007; Khosravi & Nahavand, 2014):

$$\tilde{A} = \left\{ \left((x,u), \mu_{\tilde{A}}(x,u) \right) \middle| \forall x \in X, \forall u \in J_x \subseteq [0.1] \right\} \quad (1)$$

where the membership function of the fuzzy set of values taken from the interval $J_x \subseteq [0.1]$ that represents the primary level of affiliation of *x*, and $\mu_{\tilde{A}}(x,u)$ represents the membership function of fuzzy set of type 1. In the case of the normalized fuzzy set of type 2 where $\mu_{\tilde{A}}(x,u) = 1,\ \forall u \in J_x \subseteq [0,1]$ the membership function is shown in Figure 2.

Fuzzy sets of type 2 are widely used in fuzzy logic systems (FLS), as they allow modelling of uncertainty that cannot be modeled by fuzzy sets of type 1. Fuzzy logic systems described by at least one type 2 fuzzy set are also called type 2 FLS. Type 1 FLS do not have the ability to describe and process the uncertainties that exist in FLS rules, because they use fuzzy sets of type 1 in which the degree of affiliation is presented by individual numerical values. On the other hand, FLS of type 2 are useful for operations in environments where it is difficult to determine the type and individual parameters of cryptographic affiliation and allow exploitation of uncertainties that occur in database rules. Fuzzy sets of type 1 emerged as a consequence of inability to rigidly define membership of x in a set. It happens very often that a degree of membership of x in X cannot be determined only by 0 or 1. To describe the above uncertainties type 2 fuzzy sets are in use. Similarly, in cases when it is difficult to determine the degree of membership of x as a real number in the interval [0,1], fuzzy sets of type 2 are in use.

As well as with type 1 FLS, type 2 FLS input-output variables are related to IF-THEN rules, where consequence (conclusion) rules are presented by fuzzy sets of type 2. Type 2 FLS are mostly used when circumstances of their application are too uncertain, or when the data set for training is “hit” by trees (uncertainty). Generally, the type 2 FLS consists of five elements: fuzzifier rule base, approximate reasoning algorithm (input-output processing), type-reducer and defuzzifier. The block diagram of the FLS type 2 is shown in Figure 3.

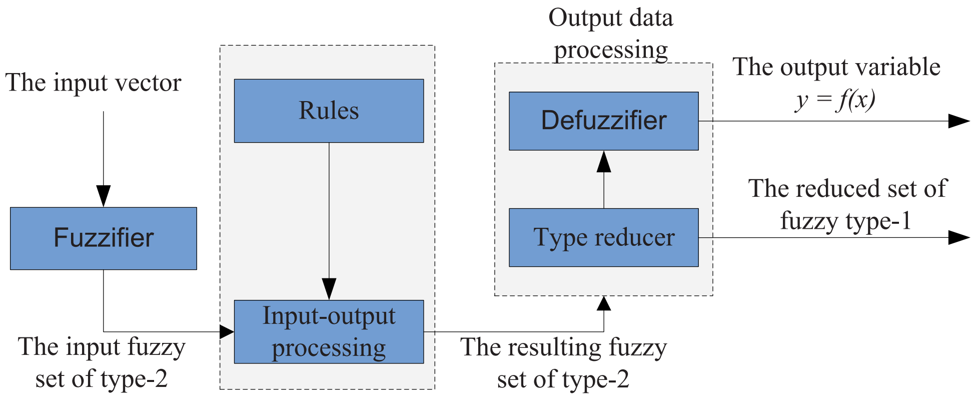


Figure 3: A fuzzy logic system of the type 2

It is known that the use of type 2 FLS enables modelling and minimizing the effects of uncertainty in the base of rules. Unfortunately, FLS type 2 are more complex to model and understand than FLS type 1 and therefore their use is not widespread yet (Mendel, 2001; Liu & Mendel, 2008). As a justification for the use of FLS type 2, Castro (2008) suggests four sources of uncertainty with which the FLS type 1 cannot be successfully handled:

- Meanings of words used in premises and in conclusion of rules can be uncertain (words mean different things to different people),
- Conclusion in rules may have uncertain (histogram) values, especially when the rule is formed on the basis of knowledge separated from the group of experts who do not have the same opinion on all matters,

• Values (measured values) that trigger input variables FLS type 1 may be fuzzy, and thus uncertain,
• Data used for setting parameters FLS type 1 may be uncertain (fuzzy).

To describe these uncertainties we use fuzzy membership function type 2. Fuzzy sets of type 1 are not able to describe such uncertainties because the functions of affiliation of type 1 have clearly defined levels of membership which are described with real numbers. On the other hand, FLS type 2 enables modelling of such uncertainty since affiliation functions of type 2 are themselves degrees of fuzzy membership. The next section describes the basic elements of FLS and type 2 risk assessment.

4. Description of the Model

Using the criteria and the matrix for risk analysis as defined in the Guidelines on the Methodology for risk assessment development and protection and rescue plans in emergency situations (2012), we can conduct a quantification of risk. The data analysis principle can be described in three steps (Figure 4):

- step 1 - the values of four input criteria are defining: frequency, vulnerability, damage and criticality. The values are determined by using a five-point scale (each one of the five values of this scale is a standard methodology,
- step 2 - based on the values of input criteria, using the matrix defined in the standard methodology, the criteria became more closely defined (probability and consequences),
- step 3 - based on the values of the criteria, by applying the matrix defined in the standard methodology, the level of risk is determined.

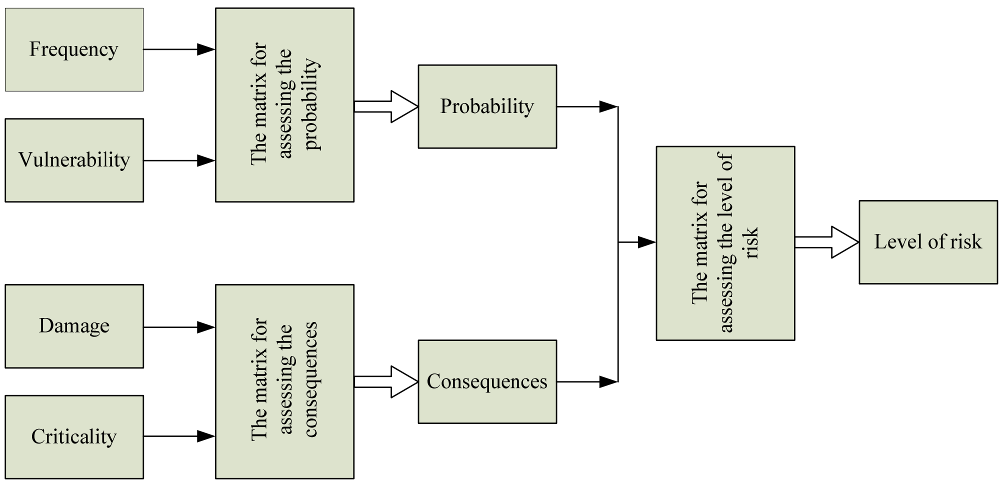


Figure 4: The process of risk quantification

The main problem of this methodology is that it only recognizes the integer values of input criteria, among the criteria and the level of risk. Firstly, the linguistic descriptions of input criteria are used to define size, by assigning integers in the interval 1-5. Next, only those values across all matrices are taken into account. The real situation often requires intermediate values not defined by the explanation given in the methodology. This is particularly important in the case of limit values between the size of the risk (very low, low, moderate, large or very large risk), as well as the acceptability of the risk (acceptable or unacceptable risk). Since the methodology has three steps, due to rounding values into whole numbers in each step, a part of the reality is lost. In order to avoid this problem, a fuzzy logic system based on interval fuzzy numbers was developed (Figure 5).

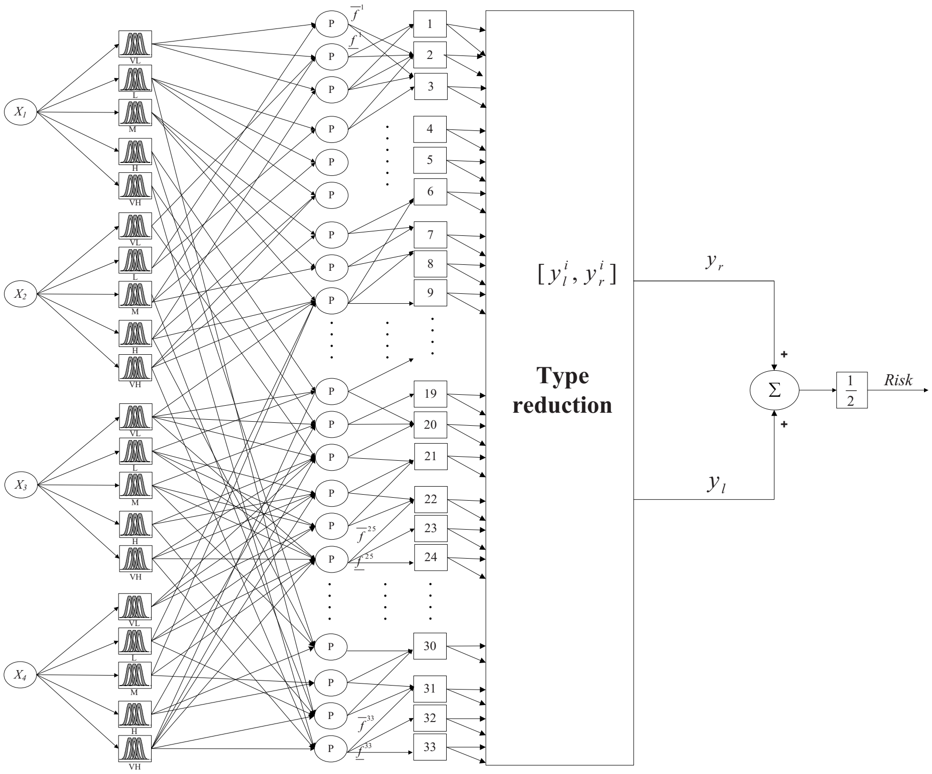


Figure 5: Architecture Fuzzy Logic System Type 2 Risk Assessment

As has been noted earlier, the input criteria in the fuzzy logic system are the same as the standard methodology for assessing the risk of natural and other disasters:

- C_1 - Frequency – repetition of a specific adverse event in a given time unit. The criterion is described by five linguistic descriptors: very rarely, periodically, often, predominantly and very often;
- C_2 - Vulnerability - current state of protection of the subject, or the sensitivity of the subject to potential hazards. The criterion is described by five linguistic descriptors: very large, large, medium, small and very small;
- C_3 - Damage - measures the damage of the protected values. The criterion is described using five linguistic descriptors: very small, small, medium, large and very large;
- C_4 – Criticality (C) is a measure of value and importance of the protected values and sensitivity to the effects of adverse events on the protected values. The criterion is described using five linguistic descriptors: minimal, small, medium, large and very large.

The output variable is the level of risk, which describes the five linguistic variables: very small, small, moderate, large or very large risk (Figure 6). The scope of confidence interval for each input variable is standardized as a numeric interval from 1 to 5.

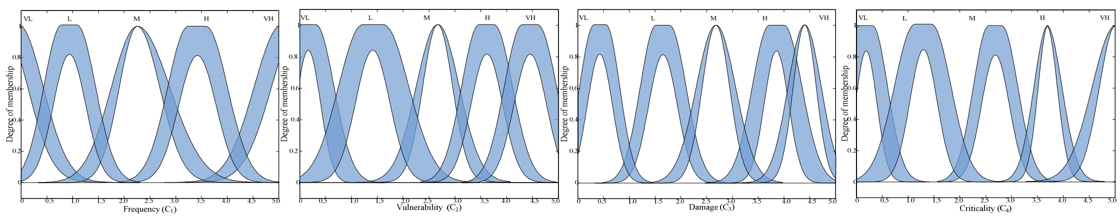
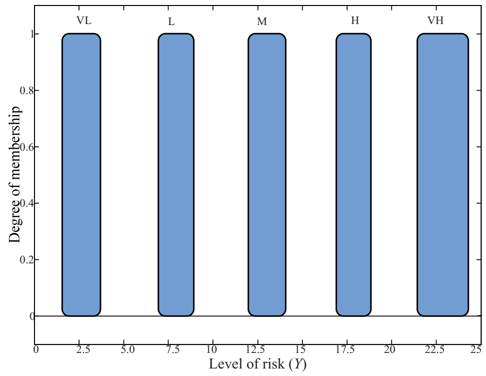


Figure 6: Fuzzy sets of type 2 which describes the input variables FLS

The value of the output variable is in the interval [1, 25]. Functions of affiliation of output variables are shown in Figure 7. As this is Takagi-Sugeno type of FLS and type 2 membership function (MF), output variables are described by singleton functions.

Figure 7: Membership functions of output variables of FLS



Parameters of output function of FLS variables are given in Table 1.

Table 1: Parameters of "singleton" functions of FLS type 2

Tag MF	UMF and LMF
Y_{VL}	$Y^{VL}=[\underline{y}^{VL},\overline{y}^{VL}]=[1.22,3.20]$
Y_{L}	$Y^{L}=[\underline{y}^{L},\overline{y}^{L}]=[6.80,8.90]$
Y_{M}	$Y^{M}=[\underline{y}^{M},\overline{y}^{M}]=[12.0,14.2]$
Y_{H}	$Y^{H}=[\underline{y}^{H},\overline{y}^{H}]=[17.1,18.8]$
Y_{VH}	$Y^{VH}=[\underline{y}^{VH},\overline{y}^{VH}]=[21.3,24.5]$

The matrix from the standard methodology represents the basis for defining the rule base of FLS for risk assessment. The structure of the rule base of FLS type 1 and type 2 is the same. The only difference is in premises and conclusion rules. FLS type 2 premises and conclusion rules describe the fuzzy sets of type 2, while in FLS type 1 fuzzy sets describe the type 1. If we look at FLS type 2 with n input variables $x\in X_1\times X_2\times\ldots\times$ and one output variable $y\in Y$ assuming that FLS has M rules, l-rule can be presented in the following form

$$R^l:\ IF\ x_1\ is\ \tilde{F}_1^l\ and\ \ldots\ and\ x_n\ is\ \tilde{F}_n^l\ THEN\ y\ is\ \tilde{G}^l,\ (l=1,\ldots,M),$$

where F and G all represent fuzzy sets of type 2 input and output variables, respectively. When generating a rule base at the beginning it is important that each pair of membership functions ($\tilde{x}_i^{(i)}, i=1,\ldots,5$) and input variables ($X_i, i=1,\ldots,4$) join the corresponding membership function ($\tilde{Y}^i$) and output variable (Y). This leads to maximization of the number of rules in the database, which is 5^4=625. The base rules can be defined through accumulation of knowledge of experts to one of the known methods for basing the rules of the known range of numerical data such as methods which are shown in the Wang and Mendel (1992), Kao and Chen (2000) and Ravi (2001) or some of the methods for creating a database of rules when there is no numerical data, such as the method shown in Božanić and Pamučar (2014). In the present case, the rule base is made on the basis of the matrix which is an integral part of standard methodologies for risk assessment.

After a fuzzification of input data, the obtained input fuzzy sets are mapped to the output fuzzy sets by means of subsequent blocks. This is achieved by quantifying each rule using the theory of fuzzy sets in the mechanism of approximate reasoning. The approximate reasoning algorithm is implemented through stages of activation and accumulation of fuzzy sets (Wu & Mendel, 2002; Wu & Mendel, 2007; Castillo & Melin, 2008; Yeh et al., 2011). Results in fuzzy set of type 2 are obtained by laying out the significance of the rules (accumulation phase) (Zhou et al., 2009).

In most cases where FLS is applied it is required a real number should be obtained at the output that is measurable value, not a fuzzy set. For example, the result of “risk level is medium” rule is a fuzzy set. If the output from FLS provides a fuzzy set, such information will not be of great benefit to the decision maker, because the “middle level of risk” is a linguistic term and the decision-maker should receive a numeric value, based on which he/she should determine the scale of the real level of the risk. Hence, the resultant fuzzy set which is obtained as a result of the aggregation phase should be converted to a number. The conversion of the resulting fuzzy set into the number is performed in the block processing output (type reducer and defuzzifier).

In FLS type 1, output processing is called defuzzification where a fuzzy set of type 1 is mapped in the „crisp number“. There are several ways of “defuzzification” of FLS type 1 which can be found in (Pamučar et al., 2011). In type 2 FLS output processing is somewhat more complex, because in order to move from a fuzzy interval set of type 2 to the number, you need two steps which are shown in Figure 3. The first step is the application of type reducer, where the interval fuzzy set type 2 is reduced to a fuzzy set of type 1. There are several methods for reducing (Khosravi & Nahavand, 2014). The most commonly used type-reducer is the center-of-sets - COS (Mendel, 2001), which was used in this paper.

In Figure 3 we can see that the FLS type 2 can have two outputs. The first output of FLS of type 2 (out from type reducer) can be represented by a fuzzy set of type 1, which is a measure of uncertainty of the resulting output. Other output FLS and type 2 (output from defuzzifier) represent clear numerical values. The first output is a measure of uncertainty, due to uncertain input measurements that activated rules whose premises and conclusions are uncertain. As the standard deviation is used in probability and statistics for measuring unpredictable uncertainty around the mean values, the reduction of costly type 2 to type 1 provides a measure of uncertainty about a clear output of interval type FLS of type 2.

5. Testing Models

Testing fuzzy logic system was carried out in the examples shown in Table 2. In the same table results are compared to fuzzy logic system and standard methodology applied in the Republic of Serbia.

Table 2: Comparative review of the results

No.	Frequency	Vulnerability	Damage	Criticality	Risk *	Risk **
1.	1	4	4	2	4	4.02
2.	5	4	4	2	12	12.07
3.	5	3	3	2	16	15.98
4.	1	5	2	4	2	2.01
5.	3	1	5	2	25	24.88
6.	5	2	3	4	10	10.00
7.	4	1	3	4	10	10.00
8.	2	1	4	4	12	12.06
9.	3	4	4	3	6	6.04
10.	4	1	5	1	20	19.99
11.	2	5	1	3	1	1.02
12.	5	1	2	5	5	5.04
13.	2	3	5	3	8	7.99
14.	2	1	2	1	16	15.99
15.	1	5	1	1	3	3.02
16.	5	4	3	3	9	9.00
17.	4	3	5	2	15	15.03
18.	3	5	5	3	8	8.04
19.	4	2	4	1	20	19.98
20.	4	4	4	3	9	8.99

* Risk - risk obtained using standard methodology
** Risk - risk obtained using fuzzy logic system of type 2

In Table 2 we can see that the developed fuzzy logic system gives approximately identical results as the standard methodology, with a negligible average error that amounts to 0.027. By mapping the fuzzy logic systems into the adaptive neural network, the error can be further reduced.

Conslusion

Fuzzy approach presented in this paper enables the quantification of uncertainties that arise in the analysis of risk of natural and other disasters. This model can represent a significant support when formulating strategy-making in risk assessment.

By using a fuzzy logic system the risk analysis of natural and other disasters has become more sensitive. The fuzzy logic allows measurement of input criteria for which we cannot reliably assess the value. It is thus possible to enter any parameters from the interval 1-5 into a fuzzy logic system, whereas the standard methodology considers only integer values 1, 2, 3, 4 or 5. This is particularly important at the stage of collecting data from a field, as the value of the input criteria depend on several parameters.

This model enables us to save time required for risk analysis. The performance of the developed fuzzy logic system can effectively improve the mapping of the adaptive neural network of type 2, which has the capability to learn and imitate decision-making performed by experts. The development of the above mentioned adaptive neural network will be the topic of some future research in this field.

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