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Fuzzy Self-tuning Model for Analysis of Project Risks

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Abstract

The article states that risk management decision-making systems often operate on models of subject areas that are characterized by significant uncertainty. Traditional models of decision-making systems do not allow to take into consideration both quantitative and qualitative characteristics of objects in a complex manner. In addition, for the construction of traditional analytical, probable and simulation models, there is often no reliable data.The solution of these problems is proposed to be obtained on the basis of the theory of fuzzy sets. A fuzzy self-tuning model and its training approach is proposed, which assumes that presented sample is formed on the basis of the learning examples presented by sets of α-levels of fuzzy numbers.

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1. Introduction

At present, decision-making systems are supported by various information technologies. Both in technical and in economic projects mathematical models for decision-making are created and introduced, the wide use of which allows to give a quantitative description of the problem and to find the best way for its solution. However, complex systems management faces some problems, namely, the processes of making managerial decisions take place in conditions of significant uncertainty, which manifests itself in the form of limited or unclear information about the conditions for the realization of the project product (PP) and can lead to unfavorable situations characterized by risk [1], [2].

Within the framework of research, the project risk is considered to be as ”an uncertain event or condition that could have a negative impact on one of the project objectives at least” [3].

Existing methods of analysis and management of risks, in general, are based on the usage of probable constructions [4], [5], [6], [7]. However, in most cases, it is not possible to obtain a sufficient data for conducting reliable analysis, due to the uniqueness of most projects. Different methods are used for identifying project risks based on complex work with checklists [8]. They can include more than a hundred items, and require additional involvement of experienced specialists in the subject area. In addition, it is difficult to combine quantitative and qualitative factors in one model.

The use of fuzzy mathematics apparatus is an alternative variant in those cases when classical methods can't give us a sufficiently adequate result [9]. Methods and models of fuzzy logic allow to perform formalization and transformation of fuzzy quantitative (qualitative) concepts, which managers and experts operate in the process of project implementation.

The domestic and foreign scientists in their works (researches) consider, various theoretical and practical aspects of fuzzy sets and models use, but the usage of fuzzy models in decision-making systems, characterized by uncertainty is paid to insufficient attention.

The research of methods and models of fuzzy logic in decision-making systems for risk management will increase the efficiency of systems, by integrating the actions of quantitative and qualitative factors.

The scientific novelty of the study is to develop a methodology for analyzing and managing risks based on fuzzy logic to ensure the adoption of effective solutions in the process of designing and implementing projects.

2. Statement of the problem

In research [10], [11], [12] we proposed fuzzy production models for decision support systems in problems of investment planning risk assessment, information systems projects, information security for enterprises and software systems.

The constructed models are based on expert knowledge of simulated systems. Obtaining information about the systems was conducted with the help of experts of the relevant subject area, after which the transformation of the received information into a fuzzy model was performed. This method is effective if the expert has enough knowledge of the system. In practice, the knowledge of experts is often not complete and accurate, and sometimes even contains contradictions. Therefore, it is necessary that the model to be based on objective information about the system, which can be the data on the results of measuring the values of the inputs and outputs of the system [13].

These circumstances predetermine the urgency of developing a fuzzy self-tuning model for the analysis of project risks. Under the fuzzy model setting, first of all, we mean the process of determining the parameters of the membership functions of input and output linguistic variables, in which the error of the model outputs relative to the observed simulated system is minimized.

Adjusting the model, i.e. optimization of its parameters, is proposed to carry out by methods based on the use of neural-fuzzy networks (NFN). Now they are the most studied and allow: adjust the parameters of the membership functions to linguistic variables on the basis of measurements of the input and output of the real system dependences; to correct fuzzy models, which are not accurately formed by the experts; to expand the fuzzy models formed by experts on the area of the system in research, in which the knowledge of experts is limited [14].

3. Construction and training of a neural-fuzzy network

Transformation of the fuzzy production model into a neural-fuzzy network assumes the alternate transformation of the blocks of fuzzification, the base of rules and defuzzification into fragments of the NFN. As a result, a neural-fuzzy network corresponding to some fuzzy model will have a similar structure to that shown in Figure 1.

Existing methods of learning the neural-fuzzy network suggest that a training sample will be formed, representing a vector from the exact values of the input and output linguistic variable.

However, it is difficult for experts to evaluate the levels of risk factors to identify accurately quantitative value to linguistic variables, which make it difficult to form training sets [15]. Table 1 represents an example of the formed expert evaluation, which is a set of linguistic descriptions of risk factors and level of confidence in their decisions.

Table 1: Identified project risk factors (fragment).

Notation	Name of risk factor	The meaning and description of the level of the risk factor	Degree of confidence
x_1	Objective of the project	*High* – fully consistent with the goals and objectives of the organization	0,8μ
x_2	Project scope	*High* – have redundant or inaccurately defined functionality	0,9μ

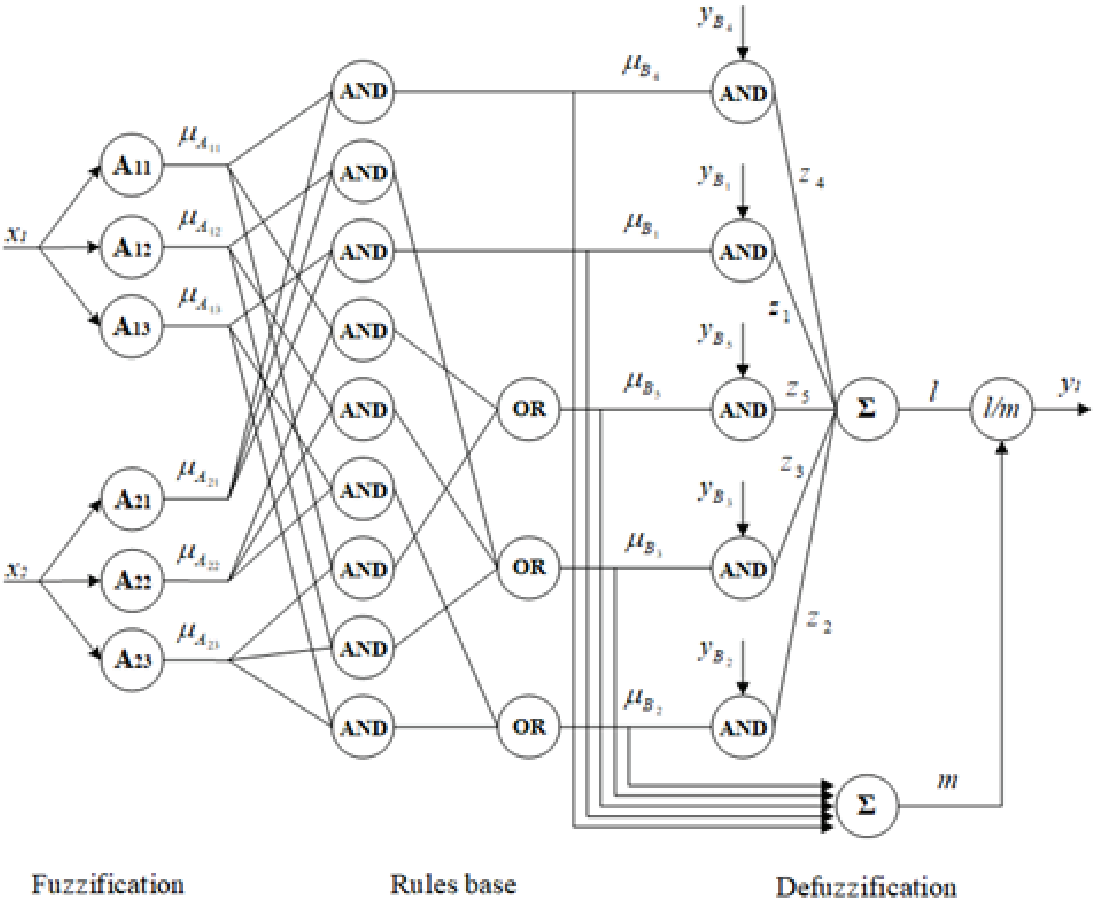

Figure 1: Neuro-fuzzy network.

The solution of this problem can be an approach, based on the presentation of the examples of training sample sets for α-levels of fuzzy numbers, and the training of the NFN can be carried out by the method of the error back propagation.

In the fuzzy production model, the base of fuzzy rules can be defined as follows:

$$R_k\ :\quad IF\ x\ is\ A_k\ \text{THEN}\ y =_k,\ k = 1,\ \ldots,\ n, \tag{1}$$

where A_k and B_k - fuzzy numbers.

Each rule (1) can be interpreted as a training example of a neural-fuzzy network, where the rule antecedent point is the input, and the point of the consequent is the required output.

Let $[A_k]^{\alpha_i}$ denote the set α_i-level of fuzzy numbers A_k, and let $[B_k]^{\alpha_i}$ be the set of the α_i-level of fuzzy numbers $B_k,\ i =\ 1,\ \ldots, p$:

$$\begin{gathered}[A_k]^{\alpha_i} = \{x\ A_k(x) \geq \alpha_i\} = [a^L_{ki}, a^R_{ki}],\\ [B_k]^{\alpha_i} = \{y\ B_k(y) \geq \alpha_i\} = [b^L_{ki}, b^R_{ki}].\end{gathered} \tag{2}$$

Then the digitized version of the learning sample of the neural network consists of the following sets of input-output values:

$$\{(a_{k1}^L,\ a_{k1}^R,\ \ldots,\ a_{kp}^L,\ a_{kp}^R),\ (b_{k1}^L,\ b_{k1}^R,\ \ldots,\ b_{kp}^L,\ b_{kp}^R)\},\ k = 1,\ \ldots,\ n. \quad (3)$$

Figure 2 shows an example of a representation of sets of input-output values (sets of α-levels of fuzzy numbers) relative to a neural-fuzzy network.

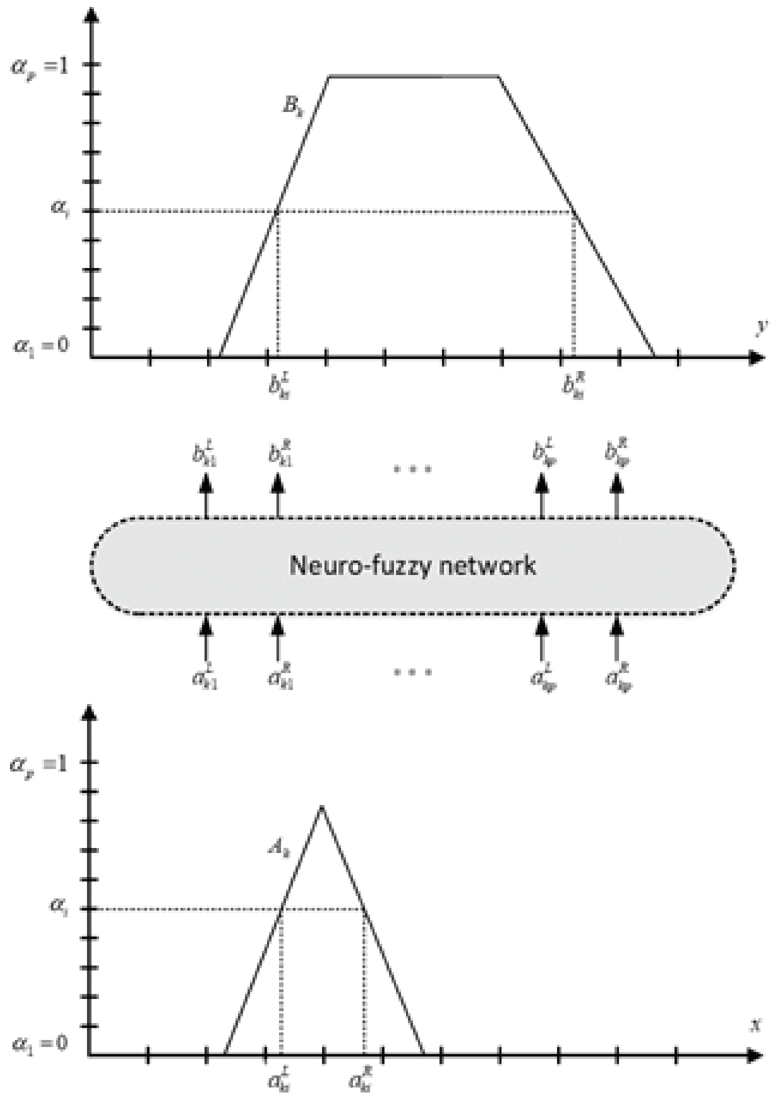

Figure 2: Representation of set values by sets of α-levels of fuzzy numbers.

According to the rules base presented in the NFN (Figure 1), where the membership functions to linguistic variables are determined by the formulas:

$$\mu_L(x) = \begin{cases} 1,\ if\ 0 \le x \le 0.2 \\ 1 - (x - 0.2)/0.3,\ if\ 0.2 \le x \le 0.5 \\ 0,\ if\ x > 0.5 \end{cases} \quad (4)$$

$$\mu_H(x) = \begin{cases} 1, \; if \; 0.8 \le x \le 1 \\ 1 - (0.8 - x)/0.3, \; if \; 0.5 \le x \le 0.8 \\ 0, \; if \; x < 0.5 \end{cases} \tag{5}$$

$$\mu_M(x) = \begin{cases} 1 - 4\,|x - 0.5|\,, \; if \; 0.25 \le x \le 0.75 \\ 0, \; if \; x < 0.25 \; and \; x > 0.75 \end{cases} \tag{6}$$

The functions of the graphs of the membership functions to linguistic variables are presented in Figure 3.

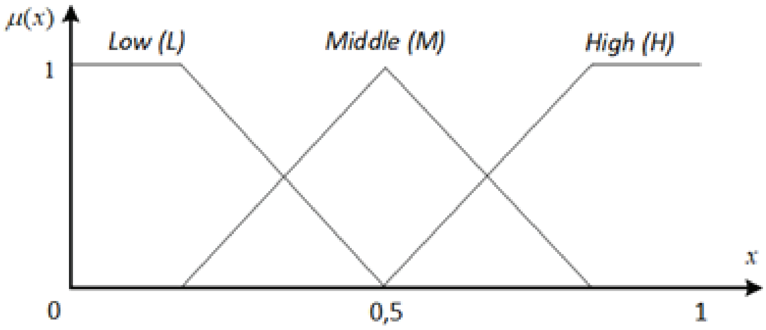

Figure 3: Membership functions to linguistic variables.

Let the number of α-levels be m = 6, then:

$$\alpha_i = \frac{i-1}{m-1}, \; i = 1, \; ..., \; 6 \tag{7}$$

in the interval [0, 1]. Then the discrete version of the training set, consisting of the following three input/output pairs, will look like this:

$$\begin{gathered} \{(a^L_{11}, a^R_{11}, ..., a^L_{16}, a^R_{16}), \; (a^L_{11}, a^R_{11}, ..., a^L_{16}, a^R_{16}), \; (b^L_{11}, b^R_{11}, ..., b^L_{16}, b^R_{16})\} \\ \{(a^L_{21}, a^R_{21}, ..., a^L_{26}, a^R_{26}), \; (a^L_{21}, a^R_{21}, ..., a^L_{26}, a^R_{26}), \; (b^L_{21}, b^R_{21}, ..., b^L_{26}, b^R_{26})\} \\ \{(a^L_{31}, a^R_{31}, ..., a^L_{36}, a^R_{36}), \; (a^L_{31}, a^R_{31}, ..., a^L_{36}, a^R_{36}), \; (b^L_{31}, b^R_{31}, ..., b^L_{36}, b^R_{36})\} \end{gathered} \tag{8}$$

where

$$\begin{gathered} [a^L_{1i}, a^R_{1i}] = [a^L_{1i}, a^R_{1i}] = [b^L_{1i}, b^R_{1i}] = [H]^{\alpha_i} \\ [a^L_{2i}, a^R_{2i}] = [a^L_{2i}, a^R_{2i}] = [b^L_{2i}, b^R_{2i}] = [C]^{\alpha_i} \\ [a^L_{3i}, a^R_{3i}] = [a^L_{3i}, a^R_{3i}] = [b^L_{3i}, b^R_{3i}] = [B]^{\alpha_i} \end{gathered} \tag{9}$$

Representing the training set in numerical terms, we get the following:

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{(0, 0.5, 0, 0.44, 0, 0.38, 0, 0.32, 0, 0.26, 0, 0.2), (0, 0.5, 0, 0.44, 0, 0.38, 0, 0.32, 0, 0.26, 0, 0.2), (0, 0.5, 0, 0.44, 0, 0.38, 0, 0.32, 0, 0.26, 0, 0.2)}

{(0.5, 1, 0.56, 1, 0.62, 1, 0.68, 1, 0.74, 1, 0.8, 1), (0.5, 1, 0.56, 1, 0.62, 1, 0.68, 1, 0.74, 1, 0.8, 1), (0.5, 1, 0.56, 1, 0.62, 1, 0.68, 1, 0.74, 1, 0.8, 1)}

{(0.25, 0.75, 0.3, 0.7, 0.35, 0.65, 0.4, 0.6, 0.45, 0.55, 0.5, 0.5), (0.25, 0.75, 0.3, 0.7, 0.35, 0.65, 0.4, 0.6, 0.45, 0.55, 0.5, 0.5), (0.25, 0.75, 0.3, 0.7, 0.35, 0.65, 0.4, 0.6, 0.45, 0.55, 0.5, 0.5)}.

The presented training set can be used as initial data for adjusting the parameters of the fuzzy model by the method of back propagation of the error [13].

The average error of the learning layer of the NFN for the *j*-th training image is calculated by the formula:

$$E_j^{layer} = \frac{1}{n}\sum_{i=0}^{n} E_j^i, \tag{10}$$

where *n* is the number of layer neurons, and for the entire training sample containing *m* examples, the network output error will be calculated as follows:

$$E^{out} = \frac{1}{m}\sum_{j=0}^{m} E_j^{layer}. \tag{11}$$

The error E^{out} is used to check the learning outcomes of the entire network and is compared to the error ΔE that is set during the selection of learning parameters at the beginning of the work. With $E^{out} \le \Delta E$the membership function, the neurons are adjusted to the specified level, and the process of learning stops (Figure 4).

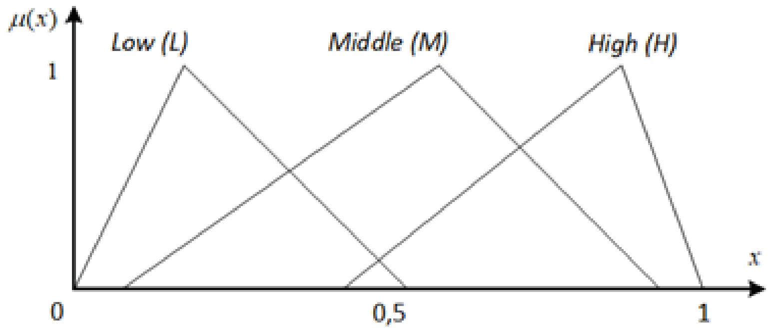

Figure 4: Adjusted membership functions for three fuzzy sets of risk assessment.

Thus, the developed fuzzy self-tuning model for the analysis of design risks allowed to adjust the parameters of NFN (parameters of the functions to belong to linguistic variables) for the systems to be researched and to obtain a more adequate model attitude to the first proposed fuzzy production-rule models that were the first approximation for the subject area consideration.

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4. Conclusion

The implemented self-tuning fuzzy model allows to provide analysis of project risks, which increases the efficiency of decision-making under uncertainty conditions, allows to take into account both qualitative and quantitative indicators and is characterized by the possibility of representing the risk scale in natural language categories, and the resulting information allows project managers to prioritize risks (from ”very high” to ”very low”) and work out effective plans for activities to reduce the most dangerous threats impact.

Theoretical significance of the given research is the expansion of the scope of network-base fuzzy model application for the project risks analysis, created methodological support for risk management in the design and projects implementation.

The practical importance of the research is the development of a methodology for integrated analysis and risk management of projects that has the ability to take into account both qualitative and quantitative indicators and allows to increase significantly the decision-making efficiency in uncertain conditions and to reduce costs in the event of unfavorable situations.

The further direction of the research is focused on the development of an alternative option of adjustment parameters of the fuzzy model with the help of a genetic algorithm, the development of software services for the implementation of the proposed self-tuning models for the analysis of project risks, and the approbation of the results obtained.

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References

[1] Doljenko A I 2009 Risk analysis model of consumer quality of economic information systems projects Vestnik of the North Caucasus state technical university 1 pp 129-34 W397W9116

[2] Dubois D and Prade H 2012 Gradualness, uncertainty and bipolarity: making sense of fuzzy sets Fuzzy Sets and Systems 192 pp 3-24 W397W9116

[3] Walker R 2002 Project Management for Software Development. The unified approach (Moscow: Lori) p 424W397W9116

[4] A Guide to the Project Management Body of Knowledge 2009 Available: http://www.pmi.org/pmbok-guide-standards/foundational/pmbok.htmlW397W9116

[5] National Standard of the Russian Federation 2011 Project Management. Requirements for project management (GOST R 54869-2011) W397W9116

[6] Thipwiwatpotjana P and Lodwick W A 2014 Pessimistic, optimistic, and minimax regret approaches for linear programs under uncertainty Fuzzy Optimization and Decision Making 2 pp 151-171 W397W9116

[7] Huang X 2011 Mean-risk model for uncertain portfolio selection Fuzzy Optimization and Decision Making 1 pp 71-89W397W9116

[8] Khubaev G N 1999 Complex systems: expert methods of comparison Izvestiya Vuzov. The North Caucasus region. Social Sciences 3 pp 7-24W397W9116

[9] Popova A Yu 2006 Risk assessment of the investment project Scientific journal KubSAU 19 pp 73-98 W397W9116

[10] Doljenko A I 2007 Fuzzy productivity models for Risk assessment of Information systems projects Problems of the Federal and Regional Economy: Uchenye zapiski 10 pp 83-89 W397W9116

[11] Glushenko S.A. 2014 Application of the Fuzzy logic mechanism for the estimation of the Risk of investment construction projects Vestnik of Rostov state university of economics (RINH) 3 pp 71-80 W397W9116

[12] Glushenko S A and Doljenko A I 2015 Decision support system for Fuzzy modeling of Information security risks of the organization Information Technologies 1 pp 68-74 W397W9116

[13] Borisov V V, Kruglov A S and Fedulov A S 2012 Fuzzy models and networks (Moscow: Hot line-Telecom) p 284W397W9116

[14] Rutkovskaya D, Pilinsky M and Rutkovsky L 2006 Neural networks, genetic algorithms and fuzzy systems (Moscow: Hot line-Telecom) p 452W397W9116

[15] Muñoz-Velasco E, Ojeda-Aciego M and Burrieza A 2014 A logic framework for reasoning with movement based on fuzzy qualitative representation Fuzzy Sets and Systems 242 pp 114-31 W397W9116