

**CONSTRUCTION OF FUZZY RISK ASSESSMENT MODELS****T.F.Bekmuratov¹, B.T.Solieva²**

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Abstract: The tasks of making decisions on risk assessment, depending on the conditions of uncertainty, are divided into two types: decision-making tasks under conditions where the initial data are stochastic; decision-making tasks under conditions when the initial data are of a non-stochastic nature, and the necessary confidence limits for the parameters of the processes under investigation are unknown or unclear. In problems of the second type, risks are manifested to a greater extent than the first, since in solving problems it is necessary to take into account not only statistical uncertainty, but also linguistic. At the same time, one should consider risk as information uncertainty and fuzziness of the system and its individual elements. The measure of this uncertainty determines the measure of danger, possible damage, loss from the realization of some decision or event. Proceeding from this, it is necessary to allocate the basic property of risk: the risk takes place only in relation to the future and is inseparably connected with forecasting, and hence with decision-making on risk assessment.

In the article the construction of soft risk assessment models based on fuzzy inference rules and neural networks have been discussed for learning fuzzy knowledge bases. The essence of training is in the selection of such parameters of membership functions that minimize the difference between the results of neuron-fuzzy approximation and the actual behavior of the object.

Keywords: fuzzy sets, fuzzy models, neural networks, estimation, risk, knowledge base, membership function, decision making.

Introduction

In view of the limited possibilities of traditional methods of mathematical modeling, in solving weakly formalizable tasks, including tasks related to risk, data mining technologies are used. They are based on the methods of artificial intelligence

and, especially, methods of soft computing (Soft Calculation, Soft Computing) and emerging on this theoretical and methodological basis of the direction of Computational Intelligence - intelligent computing technology. The main components of these directions are theories of fuzzy sets, fuzzy inference, genetic algorithms, artificial neural networks and neural network calculations. The technology of Computational Intelligence allows to obtain solutions with acceptable accuracy for practice, by learning from available source data available in limited, incomplete volumes, and also presented in a qualitative form [1-3].

1. Statement of a problem

The tasks of making decisions on risk assessment, depending on the conditions of uncertainty, are divided into two types:

1) decision-making tasks under conditions where the initial data are stochastic;

2) decision-making tasks under conditions when the initial data are of a non-stochastic nature, and the necessary confidence limits for the parameters of the processes under investigation are unknown or unclear.

In problems of the second type, risks are manifested to a greater extent than the first, since in solving problems it is necessary to take into account not only statistical uncertainty, but also linguistic. At the same time, one should consider risk as information uncertainty and fuzziness of the

system and its individual elements. The measure of this uncertainty determines the measure of danger, possible damage, loss from the realization of some decision or event. Proceeding from this, it is necessary to allocate the basic property of risk: the risk takes place only in relation to the future and is inseparably connected with forecasting, and hence with decision-making on risk assessment. In this regard, modeling is an integral tool for analyzing risk assessment, where fuzzy modeling is preferred [4-8].

2. The concept of the problem decision

The construction of fuzzy risk models, as a rule, begins with a qualitative analysis, the purpose of which is to identify risks. Achievement of this goal is divided into the following tasks: identification of the full range of risks; description of risks; classification and grouping of risks; analysis of initial assumptions.

The second and most difficult stage in the construction of fuzzy models for risk assessment is a quantitative risk analysis, the purpose of which is to measure risk, which determines the following tasks: formalization of uncertainty; calculation of risks; risk assessment; risk accounting.

The third stage is the construction of fuzzy risk models and the beginning of its implementation.

The fourth stage is control.

The risk assessment model is described using fuzzy inference rules:

$$\bigcup_{p=1}^{k_j} \left(\bigcap_{i=1}^n x_i = a_{i,jp} - \text{with weight } w_{jp} \right) \rightarrow r = f(x_1, x_2, \dots, x_n) \quad (1)$$

Here $a_{i,jp}$ - the linguistic term, which evaluates the variable x_i in the line with the number jp ;

w_{jp} - the weight coefficient of the rule with the serial number jp ;

$r = f(x_1, x_2, \dots, x_n)$ - output of fuzzy rule.

Fuzzy logic equations (of the type if <input>, <output>), together with the fuzzy term membership functions, make it possible to make a decision on risk assessment using the following algorithm:

1. The values of the object's state parameters are fixed:

$$X^* = (x_1^*, x_2^*, \dots, x_n^*)$$

2. The values of the membership functions $\mu^j(x_i^*)$ are determined for fixed parameter values $x_i^*, i = \overline{1, n}$.

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3. Using the logical equations, the values of the membership functions $\mu^{r_j}(x_1^*, x_2^*, \dots, x_n^*)$ are calculated for the state vector $X^* = (x_1^*, x_2^*, \dots, x_n^*)$.

4. A decision r_j^* is defined for which:

$$\mu^{r_j^*}(x_1^*, x_2^*, \dots, x_n^*) = \max_{j=1, n} [\mu^{r_j}(x_1^*, x_2^*, \dots, x_n^*)]$$

The essence of training is in the selection of such parameters of membership functions that minimize the difference between the results of neuron-fuzzy approximation and the actual behavior of the object. For training, the system of recurrence relations is used [2]:

$$\begin{aligned} b_k^j(t+1) &= b_k^j(t) - \eta(r_t - \hat{r}_t) \cdot \\ & \cdot \frac{r_j \sum_{i=1}^m \mu^{r_i}(r_i) - \sum_{i=1}^m r_i \mu^{r_i}(r_i)}{\left(\sum_{i=1}^m \mu^{r_i}(r_i) \right)^2} \frac{1}{\mu^k(x_i^j)} \cdot \\ & \cdot \prod_{i=1}^n \mu^j(x_i^j) \frac{2c_k^j(x_i^j - b_k^j)^2}{((c_k^j)^2 + (x_i^j - b_k^j)^2)^2} \quad (2) \\ c_k^j(t+1) &= c_k^j(t) - \eta(r_t - \hat{r}_t) \cdot \\ & \cdot \frac{r_j \sum_{i=1}^m \mu^{r_i}(r_i) - \sum_{i=1}^m r_i \mu^{r_i}(r_i)}{\left(\sum_{i=1}^m \mu^{r_i}(r_i) \right)^2} \frac{1}{\mu^k(x_i^j)} \cdot \\ & \cdot \prod_{i=1}^n \mu^j(x_i^j) \frac{2(c_k^j)^2(x_i^j - b_k^j)}{((c_k^j)^2 + (x_i^j - b_k^j)^2)^2} \end{aligned}$$

The learning algorithm for a neuron-fuzzy network consists of two phases. In the first phase, the model value of the output of the object (r) corresponding to the specified network architecture is calculated. In the second phase, the value of the

residual (E_t) is calculated and the parameters of the membership functions are recalculated.

3. Realization of the concept

Three types of risk assessment model for crop failure based on fuzzy inference rules have been developed.

1. A risk assessment model, the output of which is expressed by a linear relationship.

If $x_1^1=L$ and $x_2^1=L$ and $x_3^1=L$ and $x_4^1=A$

$$\text{Then } r_1 = 0,33 - 0,05 \frac{\sum_{j=1}^n \mu(x_1^{1j})x_1^{1j}}{\sum_{j=1}^n \mu(x_1^{1j})} - 0,02 \frac{\sum_{j=1}^n \mu(x_2^{1j})x_2^{1j}}{\sum_{j=1}^n \mu(x_2^{1j})} - 0,21 \frac{\sum_{j=1}^n \mu(x_3^{1j})x_3^{1j}}{\sum_{j=1}^n \mu(x_3^{1j})} - 0,1 \frac{\sum_{j=1}^n \mu(x_4^{1j})x_4^{1j}}{\sum_{j=1}^n \mu(x_4^{1j})} .$$

If $x_1^2=L$ and $x_2^2=L$ and $x_3^2=A$ and $x_4^2=A$

$$\text{Then } r_2 = 0,257 - 0,0393 \frac{\sum_{j=1}^n \mu(x_1^{2j})x_1^{2j}}{\sum_{j=1}^n \mu(x_1^{2j})} - 0,112 \frac{\sum_{j=1}^n \mu(x_4^{2j})x_4^{2j}}{\sum_{j=1}^n \mu(x_4^{2j})} .$$

If $x_1^3=L$ and $x_2^3=A$ and $x_3^3=L$ and $x_4^3=A$

$$\text{Then } r_3 = 0,18 - 0,01 \frac{\sum_{j=1}^n \mu(x_1^{3j})x_1^{3j}}{\sum_{j=1}^n \mu(x_1^{3j})} - 0,07 \frac{\sum_{j=1}^n \mu(x_2^{3j})x_2^{3j}}{\sum_{j=1}^n \mu(x_2^{3j})} - 0,05 \frac{\sum_{j=1}^n \mu(x_3^{3j})x_3^{3j}}{\sum_{j=1}^n \mu(x_3^{3j})} - 0,111 \frac{\sum_{j=1}^n \mu(x_4^{3j})x_4^{3j}}{\sum_{j=1}^n \mu(x_4^{3j})} .$$

If $x_1^4=L$ and $x_2^4=A$ and $x_3^4=A$ and $x_4^4=A$

$$\text{Then } r_4 = 0,26 - 0,02 \frac{\sum_{j=1}^n \mu(x_1^{4j})x_1^{4j}}{\sum_{j=1}^n \mu(x_1^{4j})} - 0,05 \frac{\sum_{j=1}^n \mu(x_2^{4j})x_2^{4j}}{\sum_{j=1}^n \mu(x_2^{4j})} - 0,03 \frac{\sum_{j=1}^n \mu(x_3^{4j})x_3^{4j}}{\sum_{j=1}^n \mu(x_3^{4j})} - 0,134 \frac{\sum_{j=1}^n \mu(x_4^{4j})x_4^{4j}}{\sum_{j=1}^n \mu(x_4^{4j})} .$$

If $x_1^5=L$ and $x_2^5=A$ and $x_3^5=H$ and $x_4^5=A$

$$\text{Then } r_5 = 0,202 - 0,10 \frac{\sum_{j=1}^n \mu(x_1^{5j})x_1^{5j}}{\sum_{j=1}^n \mu(x_1^{5j})} - 0,08 \frac{\sum_{j=1}^n \mu(x_2^{5j})x_2^{5j}}{\sum_{j=1}^n \mu(x_2^{5j})} - 0,04 \frac{\sum_{j=1}^n \mu(x_3^{5j})x_3^{5j}}{\sum_{j=1}^n \mu(x_3^{5j})} - 0,12 \frac{\sum_{j=1}^n \mu(x_4^{5j})x_4^{5j}}{\sum_{j=1}^n \mu(x_4^{5j})} .$$

2. The risk assessment model, the output of which is expressed by a fuzzy term.

If $x_1^1=L$ and $x_2^1=L$ and $x_3^1=L$ and $x_4^1=L$ with weight 0.5 or $x_1^1=A$ and $x_2^1=L$ and $x_3^1=L$ and $x_4^1=L$ with weight 0.5 Then $r_1=H$.

If $x_1^2=L$ and $x_2^2=L$ and $x_3^2=L$ and $x_4^2=A$ with weight 0.33 or $x_1^2=L$ and $x_2^2=L$ and $x_3^2=L$ and $x_4^2=H$ with weight 0.33

or $x_1^2=L$ and $x_2^2=L$ and $x_3^2=A$ and $x_4^2=L$ with weight 0.33 Then $r_2=HA$.

If $x_1^3=L$ and $x_2^3=L$ and $x_3^3=L$ and $x_4^3=H$ with weight 0.33 or $x_1^3=L$ and $x_2^3=L$ and $x_3^3=A$ and $x_4^3=A$ with weight 0.33 or $x_1^3=L$ and $x_2^3=L$ and $x_3^3=A$ and $x_4^3=H$ with weight 0.33 Then $r_3=A$.

If $x_1^4=L$ and $x_2^4=H$ and $x_3^4=A$ and $x_4^4=A$ with weight 0.5 or $x_1^4=L$ and $x_2^4=H$ and $x_3^4=A$ and $x_4^4=H$ with weight 0.5 Then $r_4=LA$.

If $x_1^5=A$ and $x_2^5=H$ and $x_3^5=A$ and $x_4^5=H$ with weight 0.33 or $x_1^5=H$ and $x_2^5=H$ and $x_3^5=A$ and $x_4^5=H$ with weight 0.33 or $x_1^5=H$ and $x_2^5=H$ and $x_3^5=H$ and $x_4^5=H$ with weight 0.33 Then $r_5=L$.

3. The risk assessment model, the output of which is expressed by a nonlinear dependence.

If $x_1^1=L$ and $x_2^1=L$ and $x_3^1=H$ and $x_4^1=A$

$$r_1 = 0,33 - 0,05 \frac{\sum_{j=1}^n \mu(x_1^{1j})x_1^{1j}}{\sum_{j=1}^n \mu(x_1^{1j})} - 0,02 \frac{\sum_{j=1}^n \mu(x_2^{1j})x_2^{1j}}{\sum_{j=1}^n \mu(x_2^{1j})} -$$

Then

$$- 0,21 \frac{\sum_{j=1}^n \mu(x_3^{1j})x_3^{1j}}{\sum_{j=1}^n \mu(x_3^{1j})} - 0,1 \frac{\sum_{j=1}^n \mu(x_4^{1j})x_4^{1j}}{\sum_{j=1}^n \mu(x_4^{1j})} +$$

$$+ 0,003 \left[\frac{\sum_{j=1}^n \mu(x_1^{1j})x_1^{1j}}{\sum_{j=1}^n \mu(x_1^{1j})} \right]^2 - 0,004 \left[\frac{\sum_{j=1}^n \mu(x_2^{1j})x_2^{1j}}{\sum_{j=1}^n \mu(x_2^{1j})} \right]^2 +$$

$$+ 0,007 \left[\frac{\sum_{j=1}^n \mu(x_3^{1j})x_3^{1j}}{\sum_{j=1}^n \mu(x_3^{1j})} \right]^2 + 0,0011 \left[\frac{\sum_{j=1}^n \mu(x_4^{1j})x_4^{1j}}{\sum_{j=1}^n \mu(x_4^{1j})} \right]^2$$

If $x_1^{16}=A$ and $x_2^{16}=H$ and $x_3^{16}=L$ and $x_4^{16}=A$

Then

$$r_{16} = 0,184 - 0,007 \frac{\sum_{j=1}^n \mu(x_1^{16j})x_1^{16j}}{\sum_{j=1}^n \mu(x_1^{16j})} - 0,005 \frac{\sum_{j=1}^n \mu(x_2^{16j})x_2^{16j}}{\sum_{j=1}^n \mu(x_2^{16j})} -$$

$$- 0,003 \frac{\sum_{j=1}^n \mu(x_3^{16j})x_3^{16j}}{\sum_{j=1}^n \mu(x_3^{16j})} - 0,09 \frac{\sum_{j=1}^n \mu(x_4^{16j})x_4^{16j}}{\sum_{j=1}^n \mu(x_4^{16j})} +$$

$$+ 0,002 \left[\frac{\sum_{j=1}^n \mu(x_1^{16j})x_1^{16j}}{\sum_{j=1}^n \mu(x_1^{16j})} \right]^2 - 0,0009 \left[\frac{\sum_{j=1}^n \mu(x_2^{16j})x_2^{16j}}{\sum_{j=1}^n \mu(x_2^{16j})} \right]^2 +$$

$$+ 0,0005 \left[\frac{\sum_{j=1}^n \mu(x_3^{16j})x_3^{16j}}{\sum_{j=1}^n \mu(x_3^{16j})} \right]^2 + 0,0015 \left[\frac{\sum_{j=1}^n \mu(x_4^{16j})x_4^{16j}}{\sum_{j=1}^n \mu(x_4^{16j})} \right]^2$$

If $x_1^{27}=H$ and $x_2^{27}=H$ and $x_3^{27}=A$ and $x_4^{27}=A$

Then

$$r_{27} = 0,17 - 0,003 \frac{\sum_{j=1}^n \mu(x_1^{27j})x_1^{27j}}{\sum_{j=1}^n \mu(x_1^{27j})} - 0,001 \frac{\sum_{j=1}^n \mu(x_2^{27j})x_2^{27j}}{\sum_{j=1}^n \mu(x_2^{27j})} -$$

$$- 0,07 \frac{\sum_{j=1}^n \mu(x_3^{27j})x_3^{27j}}{\sum_{j=1}^n \mu(x_3^{27j})} - 0,09 \frac{\sum_{j=1}^n \mu(x_4^{27j})x_4^{27j}}{\sum_{j=1}^n \mu(x_4^{27j})} +$$

$$+ 0,01 \left[\frac{\sum_{j=1}^n \mu(x_1^{27j})x_1^{27j}}{\sum_{j=1}^n \mu(x_1^{27j})} \right]^2 - 0,0005 \left[\frac{\sum_{j=1}^n \mu(x_2^{27j})x_2^{27j}}{\sum_{j=1}^n \mu(x_2^{27j})} \right]^2 +$$

$$+ 0,0002 \left[\frac{\sum_{j=1}^n \mu(x_3^{27j})x_3^{27j}}{\sum_{j=1}^n \mu(x_3^{27j})} \right]^2 + 0,0024 \left[\frac{\sum_{j=1}^n \mu(x_4^{27j})x_4^{27j}}{\sum_{j=1}^n \mu(x_4^{27j})} \right]^2$$

In the proposed models, each input variable has its own membership functions for fuzzy terms (L, LA, A, HA, H) that are used in the equations.

The membership function has the following form:

$$\tilde{\mu}^k(x_i^j) = \frac{1}{1 + \left(\frac{x_i^j - b_k^j}{c_k^j} \right)^2}$$

The result of the fuzzy model (1) is the input parameter of the multicriteria optimal combination problem "risk-utility". Obviously, to find the ideal option "maximum utility - the minimum risk" is possible only in very rare cases.

Conclusion

System analysis of risk characteristics in conditions of uncertainty based on the processing of fuzzy information was carried out. The expediency of using the theory of fuzzy sets and neural networks in problems with incomplete or linguistic information is revealed, as well as in problems for which intuitive solutions are characteristic.

The advantage of fuzzy logic is the possibility of using expert knowledge about the structure of the object in the form of linguistic utterances. However, the apparatus of fuzzy logic does not contain training mechanisms. The combination of

fuzzy logic with neural networks gives a fundamentally new quality. The neural network obtained as a result of such a combination possesses intellectual properties of using knowledge in natural language.

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