ACTUAL PROBLEMS OF MODERN SCIENCE

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MODELING OF INFORMATION AND ANALYTICAL SYSTEMS BASED ON THE THEORY OF FUZZY LOGIC

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Introduction

Looking for new methodological approaches and methods of mathematical modeling of complex systems, researchers are increasingly paying attention to the world around them, wildlife, discovering new ideas there. Thus appeared the methods of neural networks, fuzzy set theory and fuzzy logic (the mechanism of implementation of formal-logical language structures that reproduce human thought processes, using linguistic categories and logical rules of decision making), genetic algorithms, evolutionary programming, intelligent methods of multiagent optimization, etc. [1; 2].

The main part

When building mathematical models, it is always necessary to follow the rule according to which from two models with approximately equal modeling errors it is recommended to choose the one with a simpler configuration. The new economic paradigm should provide for the use of such mathematical tools, that will allow for financial and economic analysis and forecasting, taking into account all available information about the object of study (including expert knowledge) and effectively adjust economic and mathematical models, based on real statistics [2; 3]. Neuro-fuzzy technology is a mathematical tool that can be successfully used to solve almost any economic problem. They are a methodology and mathematical apparatus that provides an opportunity to set and mathematically solve even such problems for which there is no complete statistics, or when among the informative factors are only qualitative indicators, while providing the ability to adapt economic and mathematical models to changing economic conditions.

Artificial neural networks - mathematical tools, a universal reproducer of complex nonlinear functional dependencies, based on the principles of biological neural structures. This toolkit is used in various sections of modeling, such as data analysis, time series forecasting, signal processing, pattern recognition and many others due to such an important feature as the ability to learn real statistics with or without a teacher [3]. The suitability of neural networks for solving a wide range of problems, related to the search for hidden patterns in the studied data, has contributed to the rapid development of these tools and the creation of a significant variety of types of artificial neural network structures. Moreover, individual methods of parameter optimization have been developed for each separate type of neural networks, taking into account their structure and peculiarities of functioning. Similarly, the human brain has the ability to organize their own structural components - neurons, so that they can perform specific tasks [3]. We can identify the main characteristics of functional transducers of neurons for the application of these functions in the design of neural networks.

The linear activation function does not convert the signal - that is, with its application, the output of the neuron will be equal to the pulse received at its adder:

$$\psi(s) = s = \sum_{i=1}^{n} w_i \cdot x_i + b \,, \quad (1)$$

where s is the calculation of the neuron adder.

This type of activation function is appropriate to use, for example, for neurons of the source layer of the perceptron, if the resulting variable has no limitations and can take on any values.

Sigmoid activation function. Building a neural network, it is important to ensure its ability to efficiently adjust parameters, which can be done using differentiated activation functions. One of the basic functions often used in the construction of artificial neural networks is the sigmoid, which is analytically represented by expressions (2) and (3):

$$\psi(s) = \frac{2}{1+e^{-ks}} - 1 \,, \quad (2)$$

$$\psi(s) = \frac{1}{1+e^{-ks}} \,, \quad (3)$$

where k is the compression-extension coefficient of the function along the abscissa.

The compression-tensile factor can be used as a gain parameter. The advantage of using the sigmoid function as a nonlinear element is that it has limitations similar to the threshold activation function and exhibits behavior similar to a natural neuron. Thus, as the value of the compression-tensile coefficient decreases, the activation function becomes flatter, in the extreme case (at k = 0) taking the form of a straight line at the level of 0 for relation (2) and at the level of 0.5 for (3). As the coefficient k increases, the sigmoid function becomes more and more compressed, resembling the threshold function of activation. This leaves the possibility of its differentiation, which allows you to use gradient methods to optimize the parameters of the model (in particular, the method of error backpropagation). With this activation function, the neural network can receive large signals and remain sensitive to weak signal changes. This activation function can be used for both the neurons of the intermediate layers and the source layer of the perceptron. However, considering that this function has a limited range of values, in the case of its application to the original neuron, it is necessary to ensure that the range of values of the resulting variable does not exceed these limits ([-1; 1] for the activation function (2) and [0; 1] for (3)). The value of the resulting variable can be normalized.

The radial-based activation function is also differentiated, but has different properties from sigmoid functions and is used to solve other problems. It is determined by the formula:

$$\psi(s) = \exp(-ks^2)\,. \tag{4}$$

Graphically, the radial-basis activation function (4) is presented in Fig. 1. A similar activation function can be used to solve problems where the values of variables are distributed according to the normal law, or in radial-based neural networks. This function can also be used in self-organizing maps to reduce the effect of the input vector on neurons, that are further away from the winning neuron.

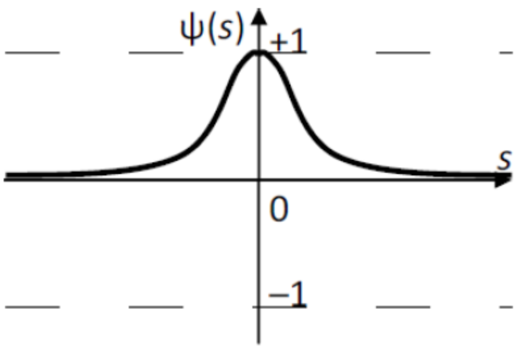

Fig. 1. Radial-basis activation function [3]

It is important to note that such a significant advantage of neural networks as parallelism in performing computational calculations is to some extent offset by the Neumann architecture of modern computers, where information processing is carried out sequentially [1]. If computer systems capable of performing parallel computations similar to information processing in the human brain are created, it is even possible to assume the fundamental possibility of implementing artificial intelligence systems based on artificial neural network technology provided that large groups of neurons are activated simultaneously [2].

The fuzzy set concept was formed in 1965 by Lofty Zadeh in response to "dissatisfaction with the mathematical methods of classical systems theory, which led to the achievement of artificial accuracy, not inherent in many real-world systems, especially the so-called humanistic systems" [4]. The theory is based on the understanding that elements that form a set and belong to it on a certain basis, can be characterized by this feature to varying degrees and, accordingly, belong to this set with varying degrees (unlike classical set theory, when an element belongs to some plural or does not).

With the introduction of fuzzy sets, an attempt was made to formalize linguistic information to build mathematical models. Accordingly, the central concept of fuzzy set theory is the concept of a linguistic variable. According to L. Zade, a variable is called linguistic, the meanings of which are words or expressions of natural or artificial language. An example of a linguistic variable can be a fall in production if it acquires not numerical but linguistic values: insignificant, noticeable, significant, catastrophic. The set of all possible values of a linguistic variable (terms) is called a term set.

For the linguistic variable "Fall in production" the set of values can be formed from the terms {Insignificant, Significant, Significant, Catastrophic}. Linguistic meanings vaguely characterize the current situation and can be obtained as a result of the transformation of quantitative data. For example, a 3% drop in production can be seen to some extent as insignificant and to some extent as noticeable. In this case, the degree that such a fall is catastrophic should be very small, as shown in Fig. 2.

The degree of such confidence can be established with the introduction of a special quantitative feature that determines the affiliation of the rate of decline in production to each of its linguistic terms, and is calculated by the so-called membership function.

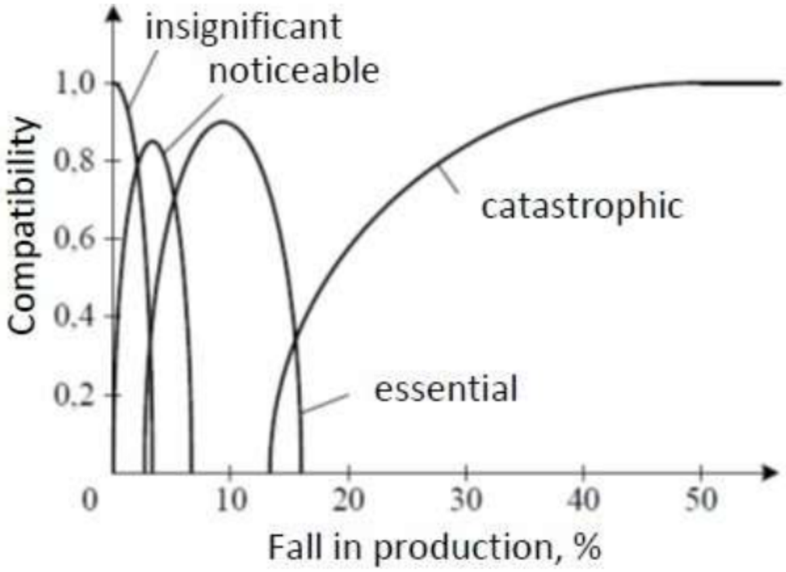

Fig. 2. Compatibility of membership functions [4]

The membership function is a function $\mu^A(u): U \rightarrow [0; 1]$, that allows for an arbitrary element *u* of the universal set *U* to calculate the degree of its belonging to a fuzzy set $\tilde{A}$ (which represents the linguistic term *A*). A universal set *U* is a complete set of values covering the entire problem area. In fig. 2 universal set is the set of all possible values of the rate of decline in production (from 0 to 100%).

With the introduction of the membership function, the theory of fuzzy sets expands the classical Cantorian concept of the set, assuming that the membership of an element to the set can be determined by any value in the interval [0; 1], and not only the value 0 or 1. Such sets Zade called fuzzy (fuzzy). A fuzzy set $\tilde{A}$ on a universal set *U* is a set of pairs $(\mu^A(u), u)$, where $\mu^A(u)$ is the degree to which the element $u \in U$ belongs to a fuzzy set $\tilde{A}$. The degree of belonging is calculated on the basis of the membership function and acquires a value in the range [0; 1]. The higher the degree of belonging is the more the element of the universal set corresponds to the properties of the fuzzy set.

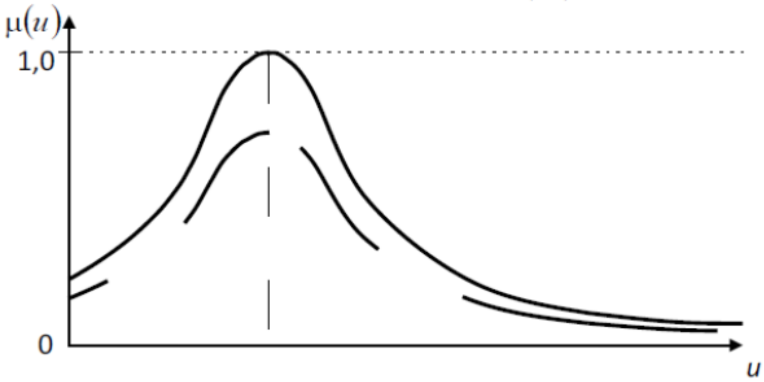

Fig. 3. Functions of belonging to the subnormal (dashed line) and normalized (solid line) fuzzy sets [4]

A fuzzy set is said to be normal if its height is equal to one. A fuzzy set that is not normal is called a subnormal. In fig. 3 shows a subnormal fuzzy set (dashed line) and a normal fuzzy set (solid line) obtained as a result of the procedure of normalization of the subnormal set. The fuzzy set can be convex or concave. Calculations in fuzzy set theory are based on the application of membership functions, that determine the degree of correspondence of an arbitrary element of a universal set to a fuzzy set, which is a subset of a universal set and is described by a certain linguistic term. There are several common approaches of constructing membership functions, that are used depending on whether the universal set is discrete or continuous.

For a discrete universal set U in the construction of membership functions approaches are usually used according to which all or some elements u_i, $i = \overline{1, k}$, of the universal set are matched to the value of the membership function, $\mu^A(u_i)$, $i = \overline{1, k}$, to a fuzzy set $\tilde{A}$, thus forming set of pairs $(\mu^A(u), u)$, $i = \overline{1, k}$. Setting the appropriate values of membership functions is usually done expertly. For a continuous universal set U, it is convenient to set the membership functions in parametric form. In this case, the construction of the membership function is reduced to choosing the type of function and setting its parameters.

After an analytical description of the linguistic variable, the establishment of operations on fuzzy sets and sets of equivalence sets, it is possible to use them as a mathematical object in problems with incomplete information or under the influence of subjective factors.

One of the distinguishing features of artificial intelligence systems in the classical formulation is the usage of symbolic language to present general knowledge about the subject area and specific knowledge about ways to solve the problem [5]. Accordingly, the key point in the design of intelligent systems is the presentation of knowledge, their interpretation and processing. Since the basis of artificial intelligence systems, according to the generally accepted Newell-Simon hypothesis, is the language of thought, the linguistic structure of which is characterized by a symbolic representation of knowledge, this justifies the creation of intellectual symbolic systems to generate intelligent solutions. Fuzzy logic is one of the most adequate approaches to the implementation of artificial intelligence on the principle of "top down" (semiotic approach) by constructing expert systems, knowledge bases and systems of logical inference, which reproduce the decision-making process of the expert in the subject area. Thus, if the rules of decision-making are unknown, then you can first form all possible combinations of all linguistic terms of the input variables, which will correspond to each of the terms of the resulting variable [5].

As a result, we obtain a knowledge base with $K = m \cdot q_1 \cdot \ldots \cdot q_i \cdot \ldots \cdot q_n$ rules, where m is the number of linguistic terms of the performance indicator, q_i is the number of terms i - of the input variable, and n is the number of input variables. Next, the model is optimized on fuzzy logic only by the weights of decision-making rules. At this stage, all other parameters of the model (parameters of all membership functions of the input and result variables) remain unchanged. After adjusting the model to real data, the weights will indicate the rules, that correctly determine the term of the performance indicator, based on a given combination of terms of the input variables. As a result of such optimization, the rules will be eliminated in such a way that each conditional part is matched with only one conclusion, for which the weighting factor was the largest among the same rules.

Conclusions

Fuzzy knowledge bases are a convenient way to formalize the causal relationships of the behavior of the modeling object, as they contain descriptive sequences of its functioning in the form of expressions in natural language. These statements combine input and output indicators, given in the form of linguistic terms. The methods of fuzzy logic provide an opportunity to model any socio-economic systems, even for which there are no full-fledged statistics, or among the informative factors there are only qualitative indicators, and also allow to take into account expertise in the subject area.

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