# Application of neuro-fuzzy models in the information-analytical system of prediction of forest fires

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**Abstract:** This article describes the information support for the functioning of the forest fire monitoring system, provides an overview of the principles for predicting the likelihood of a forest fire based on fuzzy logic, and presents a comparison of a fuzzy inference system such as Sugano and Mamdani in Matlab Fuzzy Logic as a neuro-fuzzy network. For implementation, a decision module on fire risk prediction is proposed. This decision will improve the efficiency and quality of management decisions to prevent and eliminate crisis and emergency situations. The structure of the algorithm of the module designed to determine the probability of occurrence of forest fires in a controlled area.

**Keywords:** fuzzy logic, fuzzy neural networks, forest fire forecasting.



## 1 Relevance of predicting the likelihood of a risk of natural fire

Recently, in most countries, the main efforts are aimed at eliminating the consequences of natural hazards, including wildfires. Despite the scientific and technological progress, the issue of forecasting natural disasters is acute and not fully resolved. Today, the task of predicting and preventing natural disasters is a priority. *The first place in this strategy is occupied by the problem of natural risk assessment and management.* The considered problem includes a number of fundamental scientific problems, such as: ***forecasting dangerous natural processes and phenomena, modeling the mechanism of their development, developing methods for managing risks*** [1]. The main direction in the fight against natural threats is the task of developing new scientific methods and technologies for assessing the risk of occurrence, analyzing the causes and consequences of wildfires, the formation of new criteria for risk assessment.The solution of these problems will allow to solve a complex of important problems of the stable development of society [2]. In accordance with the definition of risk as an emergency situation (ES), the fire risk is the risk measure characterizing the possibility of a forest fire in a certain area covered with forest vegetation and the severity of the consequences of this fire (economic, environmental, social, etc.) [3]. Thus, it is necessary to develop a system for assessing the risk of a natural fire, taking into account as many factors as possible, including the social factor, the industrial nature of the territory, the presence of hazardous industrial enterprises, and the analysis of the causes of past strong wildfires. For implementation, a decision module on fire risk prediction is proposed This solution will improve the efficiency and quality of management decisions to prevent and eliminate crisis and emergency situations.

The risk assessment procedure involves performing a series of sequential operations, namely: hazard identification, hazard prediction, vulnerability assessment, risk assessment [4]. To solve the forecasting problem itself, it is necessary to form evaluation criteria and determine a mathematical model.

## 2 Overview of mathematical models used in modeling disasters

In mathematical modeling of such tasks, the following types of mathematical models of catastrophes are used [2]:
1) deterministic;
2) probabilistic;
3) mixed (deterministic probabilistic);
4) imitation

A deterministic mathematical model of a physicochemical phenomenon is a set of differential, integral, integro-differential, transcendental and algebraic equations and the corresponding boundary and initial conditions that adequately describe motion, deformation and destruction of bodies (velocity, pressure, density, temperature, concentration) for the studied catastrophic phenomena [5].

However, the process of the emergence and development of a fire is complex, which depends on a variety of heterogeneous parameters and under different conditions proceeds in different ways. That is why any mathematical representation of this process is confronted with the problem of uncertainty of the calculated physicochemical characteristics and difficult to predict the conditions for the occurrence and spread of natural fires.

Mixed mathematical models have proven themselves very well in the field of the theory of catastrophes. However, it should be noted that when modeling global, regional catastrophes (including the occurrence of forest fires), a probabilistic analysis of these problems is performed before using deterministic mathematical models. It is very important that the results of mathematical modeling of the development of natural disasters, including prediction of wildfires should be obtained in the mode ahead of the time of occurrence and development of the simulated process.

The model should demonstrate quantitative and qualitative assessments of the importance of factors influencing the development of a fire or natural disaster process, identify strategic factors, etc. on the basis of formalized knowledge of experts presented in the form of decision rules. These requirements are met by the theory of fuzzy sets, which allows modeling both a smooth change in the properties of an object, and unknown functional dependencies expressed in the form of qualitative connections.

The process of natural fire can be considered as a phenomenon that can turn into a natural disaster that is difficult to control. Of course, up to a certain stage the process is not catastrophic, but the boundary of the transition to the stage representing a danger to the environment is difficult to determine, but very important. The development scenario of the natural fire process is multifactorial, the boundaries are blurred.

In such conditions, it is convenient to use soft computing for describing not clear numerical methods. L. Zadeh wrote: “The essence of soft computing (Soft Computing) is that, unlike traditional, hard computing, they are aimed at adapting to the comprehensive inaccuracies of the real world. The guiding principle of soft computing is: “tolerance for inaccuracy, uncertainty, and partial truth in order to achieve ease of manipulation, robustness, low solution costs, and better agreement with reality”.

The original model for soft computing is human thinking [6]. The use of a wide range of hard-to-imagine variables to predict catastrophes and natural phenomena makes it possible to use soft calculations.

## 3 Development of a fuzzy model of decision-making system for predicting the risk of fire.

The main areas of intellectual technology are neural networks, fuzzy logic and genetic computation (learning theory). The listed technologies implement not only new knowledge representation models, but also modern heuristic algorithms for obtaining approximate solutions, when an exact solution is either impossible or difficult to find [7].

A forecast is an approximate assessment of future changes, course of events, and behavior based on a model of dynamics in the past and present.

***Formulation of the problem.*** It is necessary to determine the sequence of fuzzy values of one variable, obtained as a result of observation in a given time interval. It is required to identify the type of change of this variable Tr in the next time interval. The type of change in the Tr variable can be specified in fuzzy terms used in the interpretation task to be considered as the probability of occurrence and development of different degrees of risk due to different circumstances. This task includes a preliminary solution to the problems of interpretation and diagnostics [7].

In terms of risk, it is customary to describe the dangers from reliable events occurring with a probability equal to 1, which makes it possible to consider “risk” equivalent to damage and the amount of risk to equate the magnitude of damage. Therefore, quantitative risk assessment is the process of evaluating the numerical values of the likelihood and consequences of undesirable processes, phenomena, events. When the consequences are unknown, by risk we mean the probability of a certain combination of undesirable events.

Thus, information support of the functioning of the forest fire monitoring system is an important element in diagnosing the current and forecasting the future state of the ecosystem as a whole. In general, the risk of the likelihood of catastrophes, natural disasters, to which natural (forest fires) can be attributed, can be viewed as the probability of causing a certain damage to the environment or the mathematical expectation of damage. The magnitude of the specified probability R can be expressed as the product of risks from Ri to Ri + 1 risk factors

$$R = R_i \times R_{i+1} \times R_{i+n} \tag{1.1}$$

where: Ri – the probability of occurrence of risk from i factor.

In our case, the risk of a natural fire is denoted by P, respectively, we obtain the formula:

$$P=P(A)\times P(T)\times P(C)\times P(Л), \quad (1.2)$$

Where the following factors of probability of occurrence of risk of natural fire: P (A) - anthropogenic load factor; P (T) - peat fire factor; P (C) is a factor of weather conditions; P (L) –factor of vegetation layer ignition (LGM).

When describing the decision-making process and analyzing fire forecasting methods, the following was noted that each Pi values (probable, possible, unlikely and unbelievable) are determined by variables, unchanged and changing over time and causing a specific level of probability of fire risk.

The probability scale determines the value of A - the threshold at which a decision is made to classify the fire risk to a certain probability, the value of B - the threshold at which a decision is made to classify the risk of fire into another category of probability. The fire risk period is considered to be from April 1 to October 31, which is divided into 6 day intervals (the current day + 5 days ahead). Table 1 presents the characteristics of the probability of occurrence of the risk of natural fire.

Table 1

| Pi probabilities | Probability Scale | Affecting variables | linguistic variable |
|---|---|---|---|
| $P_B$ probability | 0.8 – 1.0 | P(A),P(T),P(C),P(Л) | Probable |
| $P_Z$ Probability | 0.79- 0.5 | | Possible |
| $P_M$ Probability | 0.49 – 0.3 | | Unlikely |
| $P_N$ robability | 0.29- 0.0 | | Incredible |

Linguistic variables taken components of the risk of fire for the following reasons:

weather conditions, human factor, ignition factor from burning peatlands, the state of the territory. To formalize the task, the characteristics of the incoming variables are described on a scale from 0 to 1. Based on statistical data and expert estimates, the characteristics of fire risk factors are presented in Table 2.

Let the risk categories of natural fire P (A), P (C), P (T), P (L) are denoted by YPk Based on expert assessments and analysis of a large amount of statistical information, variables (ranking variables) that are constant and time-varying (table 3) affecting the prediction process of the wildfire Ypk are determined.

Table 2

| Fire risk P | Anthropogenic factor P(A) | Meteo factor P(C) | Peat bogs P(T) | Forest Type P(Л) |
|---|---|---|---|---|
| Small 0 -0,600 | Small 0-0,4 | Small 0,-0,3 | Small 0,0-0,25 | Small 0 -0,35 |
| Average 0,600 -0, 800 | Average 0,2-0,4 | Average 0,3-0,5 | Average 0,25-0,4 | Average 0,35 -0,750 |
| High 0,800-1,000 | High 04-0,6 | High 0,5-0,75 | High 0,40-0,75 | High 0,75-0,85 |
| Extremely high 1,000 -1,200 | Extremely high 0,6-1 | Extremely high 0,75-1,0 | Extremely high 0,75-1,0 | Extremely high 0,85-1,00 |

Then, the vector of input variables for $Y_{Pk}$, respectively, for each risk category, the values of the input variables are different:

$$x = (x_1, x_2 x_3 \dots \ x_m \ ) = (z^q, u_r, z_r) \quad (1.3)$$

$$x = (x_1, x_2 \dots x_m \ ) \quad (1.4)$$

$$R^i: \ if \ x_1 is \ X_1^i \ and \ x_2 \ is \ X_2^i, \ x_3 \ is \ X_3^i, x_4 \ is \ X_4^i, \ that \ y=c^i \quad (1.5)$$

and linear equations:

$$R^i: \ if \ x_1 is \ X_1^i \ and \ x_2 \ is \ X_2^i, \ \dots\dots x_m \ is \ X_m^i, \quad (1.6)$$

*that*

$$y^i = c_0^i + \sum_{l=1}^{m} c_l x_l, \tag{1.7}$$

where: i - the rule number; n is the number of rules; l - number of input; m - number of input variables;

$$c^i = \left(c_0^i, c_1^i, \dots, c_m^i\right) \text{ -coefficient vector;}$$

$X_j^i, Y^i$ - fuzzy sets, characteristics that depend on the vectors of the parameters $d_j^i$, $d^i$.

Table 3

| № | Ranged parameters | |
|---|---|---|
| 1 | air temperature T | $x_1$ |
| 2 | dew point t | $x_2$ |
| 3 | wind coefficient Kv | $x_3$ |
| 4 | amount of precipitation m | $x_4$ |
| 5 | type of peat on the site | $x_5$ |
| 6 | peat moisture ωt | $x_6$ |
| 7 | storm activity Kgr | $x_7$ |
| 8 | area of the i-th area of the forest Si | $x_8$ |
| 9 | total monitoring area S | $x_9$ |
| 10 | population of the monitoring area N | $x_{10}$ |
| 11 | population density in the area of monitoring P | $x_{11}$ |
| 12 | debris debris | $x_{12}$ |
| 13 | total area s | $x_{13}$ |
| 14 | presence of water barriers δω | $x_{14}$ |
| 15 | average peat temperature T t | $x_{15}$ |

To predict the probability of risk of occurrence of a natural fire P = $Y_i$, time-dependent $x_1$, $x_2$, $x_3$, $x_4$, $x_6$, $x_7$, $x_{12}$ are required (air temperature, dew point, humidity, etc.). varying over the time interval [t, $t_n$], and variables (area of land, population density, etc.) remaining unchanged over the time interval [t, $t_n$].

The structure of the output of a fuzzy model is shown in Figure 1. The degree of correspondence of the input variables $x_l$ to some predetermined intervals

$X = \{x_l : x_l^{min} \leq x_l \leq x_l^{max}\}$ are determined by the values of the membership functions $X_l^i(x_l), i = \overline{1,n}, l = \overline{1,m}$ (phasing operation. Using the mechanism of fuzzy inference, using the T-norm operations [8], the output value of each rule $z^i, i = \overline{1,n}$ is determined.

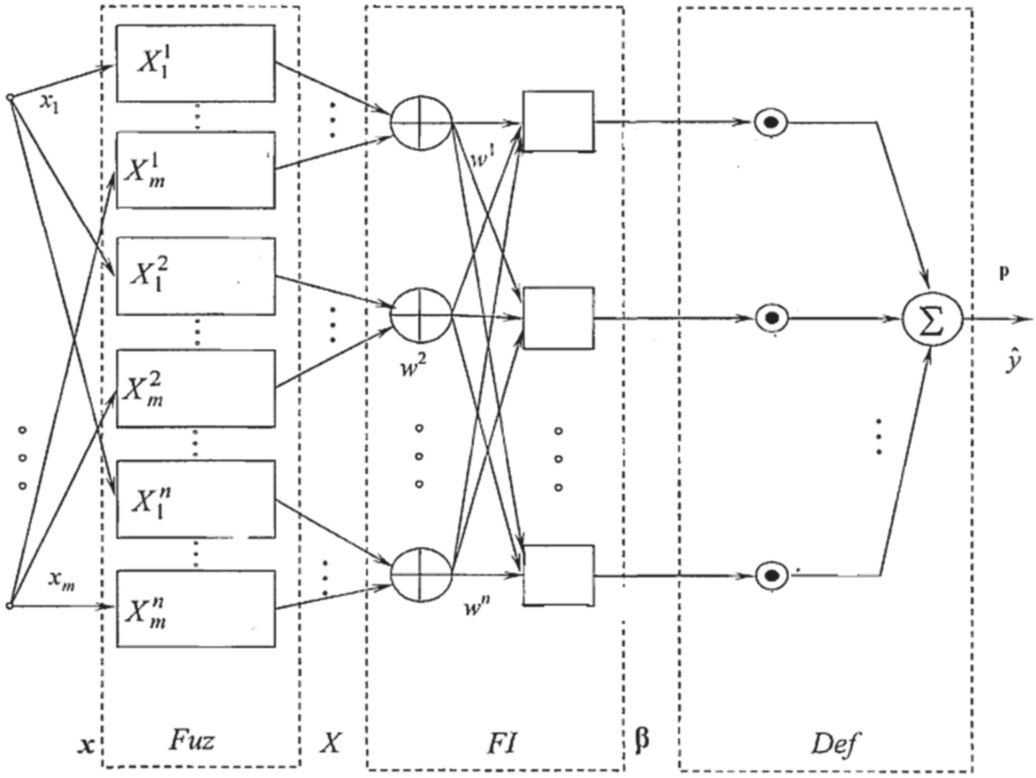


Fig. 1 – The structure of the output of a fuzzy model

The averaging procedure (dephasing operation) allows obtaining the output of a fuzzy model. The fuzzy model has a neural network structure. Input effects

$x_j\ (t_{jk}), j = \overline{1,m}$, acting at times $t_{jk}$ and forming the probability $y_i$ (p) at time $t_s$, can be written as a vector:

$x(p) = (x_1(p), x_2(p), x_3(p), x_4(p)) = (x_1(t_{1k}), x_2(t_{2k}), x_3(t_{3k}), x_4(t_{4k}))$, (1.8)

showing the connection of inputs

$x_j\ (s), j = \overline{1,m}$

and exit $y_j\ (s)$ at time $t_s$.

Thus, to predict the development of flammable situations, you can calculate the values of the probability of risk $Y_i$(p) fires at times $t_s, s = \overline{1,N}$

$$\widehat{y_i}(p) => \mu(x(s), \rho_i),\ \ \forall i = \overline{1,q}$$

where: $\rho_i$ - is the vector of parameters and structural elements of the model.

Thus, to predict the development of flammable situations, you can calculate the values of the probability of risk $Y_i$(p) fires at times $t_s, s = \overline{1,N}$:

$$\widehat{y_i}(p) => \mu(x(s), \rho_i),\ \ \forall i = \overline{1,q}\ , \tag{1.9}$$

where ρi - the vector of parameters and structural elements of the model.

The accuracy of the forecast, this is the proximity of the calculated y^(p)i to the actual (p)i criterion value:

$$J_i = \frac{1}{N}\sum_{s=1}^{N} |y_i(p) - \widehat{y_i}p|\,, \forall i = \overline{1,q} \tag{1.10}$$

$$0\ \le\ J_i\ \le\ 0{,}2$$

For the probability of the risk of a natural fire with the use of a fuzzy TS model (Takagi - Sugeno), production rules are used, in the right-hand sides of which there are linear equations [9].

$$R_j^i: if\ x_1(p)\ is\ X_{j1}^i, x_2(p)\ is\ X_{j2}^i, x_3(p) is\ X_{j3}^i x_4(p)\ is\ X_{j4}^i, \tag{1.11}$$

That:

$$y_j^i p = c_{j0}^i + c_{j1}^i x_1 p +\ \ldots + c_j^i x_j p +\ \ldots + c_m^i x_m p, i = \overline{1, n_\iota}, \tag{1.12}$$

where:

X - fuzzy sets, described by membership functions;

$X(x_j, d_j^i)$, dependent on input variables $x_j$ and parameters

$$d_j^i = \left(d_{j1}^i, d_{j2}^i, \ldots, d_{j\sigma}^i\right), i = \overline{1,n}, \qquad j = \overline{1,m}$$

$i, n_j$ – the number and number of production rules of a fuzzy model, predicting the i-th probability indicator $y_j$;

$c_j^i$ - coefficients of linear equations.

The production rules, together with the operations of phasing, fuzzy inference and phasing, form a fuzzy model.

## 4 The calculation of this model is carried out in the Fuzzy Logic Toolbox MATLAB environment

The implementation of this method of fuzzy modeling in the Fuzzy Logic Toolbox environment allows you to perform most of the steps, including the construction of a universe based on a set of task source data, in automatic mode.

To accomplish the task, it is necessary to identify risks, determine the degree of influence of factors on the overall risk of a fire, introduce variables, and define rules.

$$X(x) = \exp(-d, (x - d_1)^2), \tag{1.13}$$

We introduce input variables input: P (A). For the linguistic evaluation of this variable, 5 terms were used with the Gaussian membership function described by the parameter vector B = {σ, c}: where c - the mean value, σ -the standard deviation of membership functions

$$X(x) = \exp(-d, (x - d_1)^2)$$

For linguistic evaluation of the membership function of the variable Y (P) variable, terms with triangular membership functions, a bell-shaped membership function were used. The following types of rule rules are formulated to represent a fuzzy inference system:

1. If the <Fire hazard class corresponds to Category 1> and the anthropogenic load is low> and <low forest risk> <low peat bog fire risk> then <Unbelievable risk>

2. If <Fire hazard class corresponds to Category 2> and <low man-made load> and <medium-type forest risk> <small peat bog fire risk> then <Unbelievable risk> etc. 10 rules governing the conditions of fire hazard probability of varying degrees. For each task, the output fuzzy set was calculated and the degrees of truth of each of the fuzzy rules were found. Graphs of fuzzy inference by Mamdani and Sugeno are shown in Figure 3.

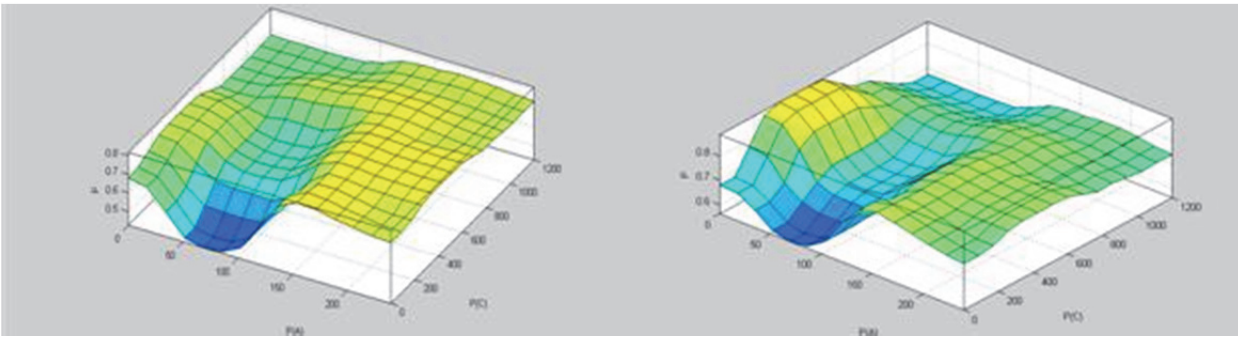

Fig. 2 – Fuzzy inference schemes by Mamdani and Sugeno

Comparing the surfaces of fuzzy inference by Mamdani and Sugano, they came to the conclusion that the fuzzy rules describe a complex non-linear relationship quite accurately. But a model of the Sugeno type has a lower degree of error and is therefore more accurate. The advantage of Mamdani-type models is that the rules of the knowledge base are transparent and intuitive, whereas for models of the Sugeno type, it is not always clear which linear "input-output" dependencies should be used.

## 5 Representation of systems of fuzzy inference type Sugeno in the form of a neuro-fuzzy network

The ANFIS module allows you to automatically synthesize neuro-fuzzy networks from experimental data. Neuro-fuzzy network can be considered as one of the types of systems of fuzzy inference of the Sugano type [9]. Using the FIS data of the Sugano type fuzzy inference, we generate the neuro-fuzzy network of figure 3. This fuzzy inference system contains four input variables with five terms each, 32 fuzzy output rules, one output variable with 32 terms.

In a fuzzy model for determining the probability of risk of a natural fire, the concentration coefficients for the membership functions of the terms "Low", "Permissible" and "Dangerous" of variables $X_1$ -$X_{16}$ and $Y_1$, $Y_2$, $Y_3$, as well as 5 factors in the conclusions of each of the four rules of the upper knowledge base hierarchy level. Thus, the total number of adjustable parameters is 4 * 18 + 5 * 4 = 92.

Before learning the hybrid network, the following learning parameters were set:

1) the training method of the hybrid network — reverse propagation (backpropo) or hybrid (hybrid), which is a combination of the least squares method and the decreasing method of the inverse gradient.

2) Level of learning error (Error Tolerance) –0

3) the number of training cycles (Epochs) - 40

neural network of fuzzy inference FIS type Sugano, presented in Figure 3.

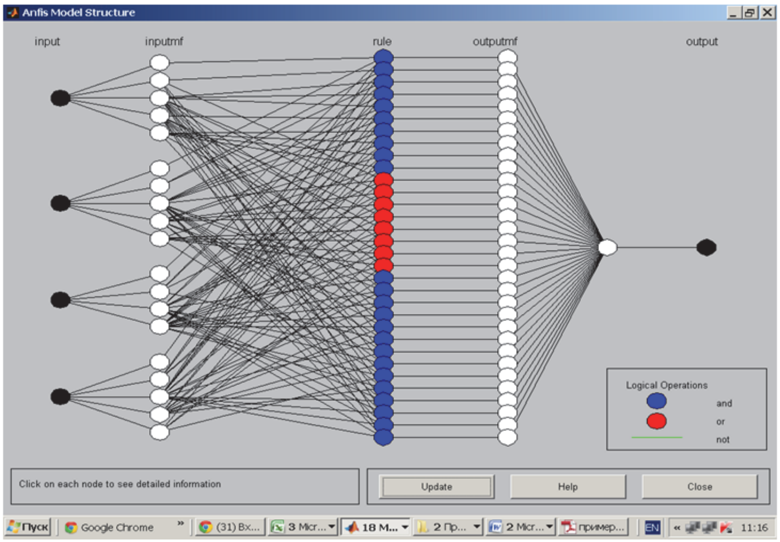


Fig. 3 – Neuron-fuzzy network of the probability of the risk of a risk of natural fire P

When assessing the potential risk of a natural fire, a high convergence of the results was revealed, which made it possible to conclude that all the laws inherent in the traditional approach are followed in the developed fuzzy systems, the correctness of their construction and the reliability of the results obtained. And also allowed to substantiate the possibility and correctness of the application of the mathematical apparatus of fuzzy logic to the studied area. Table 4 presents a fragment of a sample of test results of the resulting model.

Table 4

| Calculated Risk in a Fuzzy Inference System (Mamdani) | Calculated Risk in a Fuzzy Inference System (Sugeno) | Actual P Wild Fire Risk |
|---|---|---|
| 0,875 | 0,784 | 0,782 |
| 0,945 | 0,992 | 1 |
| 0,972 | 0,989 | 0,987 |
| 0,953 | 0,983 | 1 |
| 0,943 | 0,925 | 0,935 |

## 6 Comparison of the results of calculations JFuzzyTool, Matlab Fuzzy Logic

The results of two fuzzy inference schemes for Mamdani and Sugeno, which adequately meet the requirements of the task, were reviewed and compared. Figure 4 shows the graphs of the results of risk calculations using the Mamdani and Sugano algorithms.

From the analysis of the results, it was concluded that with the complication of hierarchies (increase in the number of tasks), the results obtained using the Mamdani Matlab algorithm differ from the calculated ones by about 7-12%. This is caused by the accumulation of mathematical error due to the intermediate operation of fuzzification — defuzzification. the use of a model of fuzzy inference in assessing the risk of forest fires, shows a reduction in the time needed to make a decision on forecasting the development of a forest fire process and assessing the factors affecting it.

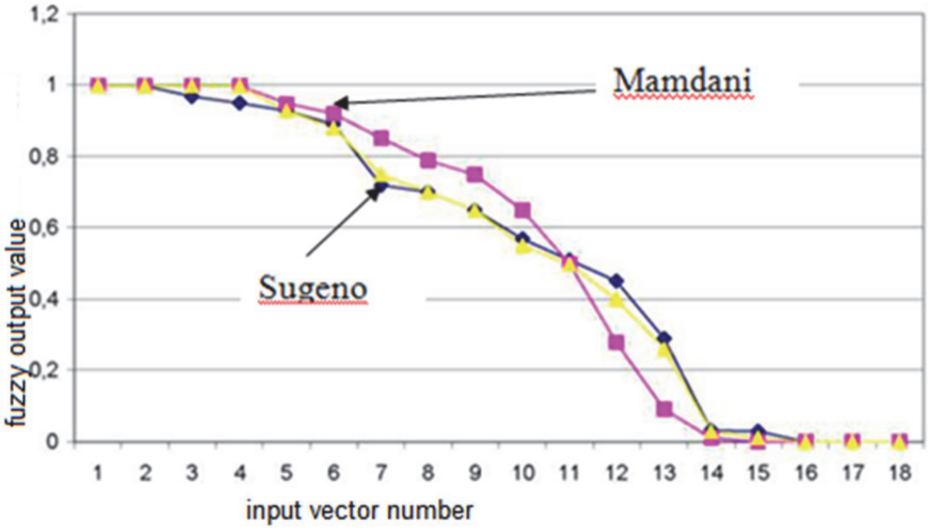


Fig. 4 – Charts the results of calculations of risk systems for fuzzy inference Mamdani and Sugeno

Fuzzy models were taught using the developed algorithms for determining the constants and coefficients of linear equations with the parameters of the membership functions, the number of rules when specifying the initial data. The proposed model is designed to determine the likelihood of natural fires in a controlled area.

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