Problems of constructing models of intellectual analysis of states of weakly formalizable processes

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Abstract. The paper discusses various options for constructing models of intellectual analysis of the state of poorly formalizable processes, described using fuzzy inference rules. A hybrid algorithm is proposed that combines fuzzy logic methods with a genetic algorithm that gives a fundamentally new quality.

1. Introduction
When solving practical problems for constructing a system of classification, estimation and forecasting in conditions of uncertainty, the necessary fuzzy information with no stochastic characteristics can be divided into two parts: numerical (quantitative) and linguistic (qualitative) part obtained from the expert. Most fuzzy systems use knowledge of the second type - most often data described as bases of fuzzy inference rules, which are combined into systems of fuzzy inferences. The algorithms for constructing fuzzy logic models based on fuzzy inference rules play a major role in solving problems of classification, estimation and forecasting under conditions of uncertainty of input data.

Formation of the rules of fuzzy conclusion in the construction of models for the classification, evaluation and prediction of the state of weakly formalized processes determine the importance of an optimal reduction in the number of rules.

Correct use of current information about the object in the process of modeling, that is, determining the adequacy of the model, is important. In this plan, the main problems of the development of models of weakly formalized processes are formulated [1-3].

Traditional fuzzy systems have some drawbacks, so it is imperative to involve experts from one or another field to formulate rules and functions of ownership. This in turn is a factor in the occurrence of a number of inconveniences. Adaptive fuzzy systems (adaptive fuzzy systems) solve this problem. In such systems, during the training, their parameters are adjusted on the basis of experimental data. The process of adapting fuzzy systems consists of two stages: 1) the creation of linguistic rules; 2) adjustment of model parameters. To create fuzzy rules, you need the appropriate functions, and to make a fuzzy conclusion, you need rules [4-7].

In a complex environment with a large number of heterogeneous interacting agents, there is a high degree of uncertainty about their interaction and related information. Agents are also constantly trying to find the best views of observable reality and for this reason they will learn and gain experience. A method is needed for constructing “intellectual models” of economic agents that function in such an economic environment.

The main reasons why economic theories have not been sufficiently successful in modeling economic reality are that these theories are formulated from the standpoint of classical mathematics, binary logic, and the classical theory of additive measures. This fact is the key to the topic of this article. Human reasoning and decision making is based on a high degree of uncertainty (usually non-
statistical), and classical mathematics is not capable of reflecting this type of uncertainty. Human preference in complex elections as a whole cannot be determined by the laws of additive measures. As mentioned above, well-known economists, such as Akerlof, Kahneman and Altman, pro-Mongad reformed economic models in order to include such factors as the motivation and norms of agents that have a significant impact on the economic behavior of the latter. However, adequate mathematical models were not presented for these paradigms.

In our studies, we will consider the economic system as a human-centric, realistic multi-agent system, characterized by incomplete and partial reliability of information, in which the behavior of agents is represented using fuzzy logic.

2. Constructing fuzzy models

The problems of constructing fuzzy models of classification, estimation and forecasting can be expressed as a multicriteria optimization problem with four objective functions

\[ f_1(S) \rightarrow \max, f_2(S) \rightarrow \min, f_3(S) \rightarrow \min, f_4(S) = \frac{1}{2} \sum_{j=1}^{M} (y_j - \hat{y}_j)^2 \rightarrow \min \]

Here \( f_1(S) \) is the number of correctly classified objects using the set of rules \( S \); \( f_2(S) \) – the number of fuzzy rules in the set of rules \( S \); \( f_3(S) \) – the total number of elements of the set \( S \) and \( f_4(S) \) – the standard error between the obtained and expected results of the model. Thus, the problem reduces to solving the multicriteria optimization problem.

The main problem that needs to be solved is overcome by constructing a logical model based on the rules of fuzzy inference, using the method of fuzzy clustering.

The difference between the proposed approach and traditional approaches is the use of modern technologies for intellectual data analysis (knowledge base, components of Soft Computing - neural networks, bee swarm algorithms) for the development of algorithmic and software tools for constructing logical models based on the method of fuzzy clustering of problems of classification, estimation and forecasting.

Models of classification, estimation and forecasting of states of weakly formalized processes are determined through the following rules of fuzzy inference:

\[
\bigcup_{p=1}^{k_j} \bigcap_{i=1}^{n} x_i = a_{i,jp}, \text{ with weight } w_{jp} \rightarrow y_j = f_j(x_1, x_2, ..., x_n). \tag{1}
\]

Where \( a_{i,jp} \) expresses the linguistic term of the variable \( x_i \) string \( jp \); \( w_{jp} \) is the weight coefficient of the rule \( jp \); \( y_j = f_j(x_1, x_2, ..., x_n) \) - fuzzy rule of inference.

Developed three types of fuzzy models of intellectual analysis of the state of weakly formalized processes, described using the rules of fuzzy inference.

1. Fuzzy model of classification, estimation and forecasting of states of weakly formalized processes in the form of derivation of nonlinear connection

\[
\bigcup_{p=1}^{k_j} \bigcap_{i=1}^{n} x_i = a_{i,jp}, \text{ with weight } w_{jp} \rightarrow y_j = b_{j0} + \sum_{h=1}^{H} b_{j+h,i=0} \left(x_i^h\right) + ... + b_{jH} \left(x_i^H\right). \tag{2}
\]

2. Fuzzy model for the classification, estimation and prediction of process states in the form of a linear connection

\[
\bigcup_{p=1}^{k_j} \bigcap_{i=1}^{n} x_i = a_{i,jp}, \text{ with weight } w_{jp} \rightarrow y_j = b_{j0} + b_{j1} x_1 + ... b_{jn} x_n. \tag{3}
\]

3. Fuzzy model for the classification, estimation and prediction of process states in the form of fuzzy term output

\[
\bigcup_{p=1}^{k_j} \bigcap_{i=1}^{n} x_i = a_{i,jp}, \text{ with weight } w_{jp} \rightarrow y_j = r_j, j = 1,M. \tag{4}
\]
When constructing a logical model for the classification, estimation and forecasting of states of weakly formalized processes, a fuzzy clustering algorithm consisting of seven steps.

In constructing the fuzzy model in the case of various types of membership functions is tuned parameters of the model based on neural networks and swarm, that is, to solve the problem of learning fuzzy logic model. The essence of training consists in solving the optimization task of minimizing the differences between the real properties of the object and the results of fuzzy approximation.

Tuning of parameters of the fuzzy logic model consists of two steps. At the first stage, the values of the model \( y \) are determined. At the second stage, the error value \( E \) is determined and the values of the membership function parameters.

In this process, using membership functions that result in the highest values, a model is created that consists of fuzzy inference rules (2) – (4). Here it is required to find the values of the coefficients \( b_{ji} \) \((i=0,1,2,\ldots; j=1,\ldots,m)\).

Here, if the model is of linear type, then \( t = n \), while the model is nonlinear \( t = 2n \).

The values of the obtained coefficients (3) are considered values minimizing the quadratic deviation. The input vector \( X_r = (x_{r,1}, x_{r,2}, \ldots, x_{r,n}) \) has the following fuzzy output:

\[
y_r = \frac{\sum_{j=1}^{m} \mu_{ij}(x_r) \cdot y_j}{\sum_{j=1}^{m} \mu_{ij}(x_r)}.
\]

The level of execution of the fuzzy rule of inference \( j \) is determined using an expression

\[
\mu_{ij}(x_r) = \mu_{ij}(x_{r,1}) \cdot \mu_{ij}(x_{r,2}) \cdots \mu_{ij}(x_{r,n}).
\]

By means of an expression \( \beta_{ij} = \frac{\mu_{ij}(x_r)}{\sum_{k=1}^{m} \mu_{ij}(x_r)} \) for the input vector \( X_r \) the relative level of the fuzzy rule of output \( j \) is determined.

Then:

a) with a linear dependence of the output:

\[
y_r = \sum_{j=1}^{m} \beta_{ij} \cdot y_j = \sum_{j=1}^{m} \left( \beta_{ij} \cdot b_{ji} \cdot x_n + \ldots + \beta_{ij} \cdot b_{ji} \cdot x_n \right).
\]

b) with a nonlinear dependence of the output:

\[
y_r = \sum_{j=1}^{m} \beta_{ij} \cdot y_j = \sum_{j=1}^{m} \left( \beta_{ij} \cdot b_{ji} \cdot x_n + \ldots + \beta_{ij} \cdot b_{ji} \cdot x_n \right) + \ldots + \beta_{ij} \cdot b_{ji} \cdot x_{im} \cdot x_{im} + \ldots + \beta_{ij} \cdot b_{ji} \cdot x_{im} \cdot x_{im} \right).
\]

The parameter values \( \beta_{ij} \) are determined according to the membership function type (Table 1):

| Membership function | Value of parameter \( \beta_{ij} \) |
|----------------------|----------------------------------|
| Gaussian Form: \( \mu(x) = \exp \left(-\left(\frac{x-c}{\sigma}\right)^2\right) \) | \( \beta_{ij} = \exp \left[ -\frac{1}{2} \sum_{k=1}^{i} \left( \frac{x_k - c_{ij}}{\sigma_{ij}} \right)^2 \right] \cdot \prod_{i=1}^{m} \left[ \frac{1}{1 + \left( \frac{x_k - c_{ij}}{\sigma_{ij}} \right)^2} \right] \) |
| Bell-shaped form: \( \mu(x) = \frac{1}{1 + \left( \frac{x-c}{\sigma} \right)^2} \) | \( \beta_{ij} = \prod_{i=1}^{i} \frac{1}{\left( 1 + \left( \frac{x_k - c_{ij}}{\sigma_{ij}} \right)^2 \right)^{\frac{1}{2}}} \cdot \prod_{i=1}^{m} \left[ \frac{1}{1 + \left( \frac{x_k - c_{ij}}{\sigma_{ij}} \right)^2} \right] \) |
In the form of a parabola:
\[ \mu(x) = 1 - \left( \frac{x-c}{\sigma} \right)^2 \]

\[ \beta_i = \prod_{i=1}^t \left[ 1 - \left( \frac{x_i - c_{ij}}{\sigma_{ij}} \right)^2 \right] / \sum_{k=1}^m \prod_{i=1}^t \left[ 1 - \left( \frac{x_i - c_{ik}}{\sigma_{ik}} \right)^2 \right]. \]

In the form of a triangle:
\[ \mu(x) = \begin{cases} \frac{x-a}{b-a}, & a \leq x \leq b, \\ \frac{x-c}{b-c}, & b \leq x \leq c, \\ 0, & \text{in other cases.} \end{cases} \]

\[ \beta_i = \begin{cases} \prod_{i=1}^t \left[ \frac{x_i - a_{ij}}{b_{ij} - a_{ij}} \right] / \sum_{k=1}^m \prod_{i=1}^t \left[ \frac{x_i - a_{ik}}{b_{ik} - a_{ik}} \right], & \text{if } a \leq x \leq b, \\ \prod_{i=1}^t \left[ \frac{x_i - c_{ij}}{b_{ij} - c_{ij}} \right] / \sum_{k=1}^m \prod_{i=1}^t \left[ \frac{x_i - c_{ik}}{b_{ik} - c_{ik}} \right], & \text{if } b \leq x \leq c. \end{cases} \]

Introduce the following notation:
\[ Y = (y_1, y_2, \ldots, y_M)^T, \]
\[ \hat{Y} = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_M)^T, \]
\[ A = \begin{bmatrix} \beta_{1,1}, \ldots, \beta_{1,n}, & x_{1,1} \cdot \beta_{1,1}, \ldots, x_{1,1} \cdot \beta_{1,n}, & \ldots, & x_{1,n} \cdot \beta_{1,1}, \ldots, x_{1,n} \cdot \beta_{1,n} \\ \vdots & \vdots & & \vdots \\ \beta_{M,1}, \ldots, \beta_{M,n}, & x_{M,1} \cdot \beta_{M,1}, \ldots, x_{M,1} \cdot \beta_{M,n}, & \ldots, & x_{M,n} \cdot \beta_{M,1}, \ldots, x_{M,n} \cdot \beta_{M,n} \end{bmatrix}. \]

Then problem (3) reduces to the matrix form: it is necessary to find the vector B corresponding to the following requirements:
\[ E = (Y - \hat{Y})^T \cdot (Y - \hat{Y}) \rightarrow \min. \]

### 3. Using a genetic algorithm with artificial selection

To solve problem (5), we use a genetic algorithm with artificial selection [2-3].

On the basis of the proposed algorithm lies the synthesis of the usual evolutionary genetic approach with the ideas of adaptation optimization [1] and, first of all, the sequential complex-method of finding the extremum of functions of several variables [3]. At the same time, the current population is identified with a population-a complex of points in the search space at each moment of time, and in addition to the traditional genetic operators of mutation, crossing and selection, operators of the search complex such as selection, reflection, stretching and compression are additionally introduced. In this case, unlike the traditional complex-method, it is proposed to reflect not one worst vertex of the complex, but a whole lot of the worst individuals of the population.

In general, the optimization procedure based on the usual sequential complex-method looks like this: it is required to find a minimum of some function
\[ E(x) = \sum_{i=1}^M \left( y_i - y_i^* \right)^2 \rightarrow \min \]

It is rather general in nature, and there are practically no a priori sentences about the nature of this function. The work of the algorithm begins with the formation of the initial complex
\[ x_i(0) = \begin{bmatrix} x_{i1}(0) \\ x_{i2}(0) \\ \vdots \\ x_{in}(0) \end{bmatrix}, \quad i = 1, N \geq n + 1, \]

which is a population of chromosomes that are arbitrarily located in the \( n \)-dimensional search space.

First, selections are performed, then crosses and mutations. This results in a new population of chromosomes \( x_i(1) \).
After this, the selection operation is performed. At this stage, the value of the function in all chromosomes is calculated and found the average fitness of the population
\[ E_{\text{pop}} = \frac{1}{N} \sum_{i=1}^{N} E(x_i(k)). \]

Then, chromosomes with a fitness below the mean for the entire population are replaced by the "best" chromosome.

If \( E_{\text{pop}} < E(x_i(k)) \) that will be \( x_i(k+1) = x_i(k) \), which gives \( \min_{i=1,...,N} E(x_i(k)) \).

Among the set of these chromosomes is the "worst" \( x_i(1) \), in which the value of the function \( E(x_i(1)) \) is maximum, after which this point is reflected through the center of gravity of all other vertices-points, forming a new complex \( x_i(1), i=1,N \). Such reflection, together with stretching and compression, ensures the movement of the complex to the extremum of the function \( E(x) \), while, due to a fairly random distribution of chromosomes in the population, the search is of a global nature.

From a formal point of view, consider the optimization process at the \( k \)-th iteration of the search, when a complex \( x_i(k), i=1,2,...,N \) is formed. Among the set \( x_i(k) \) is the "worst" such that
\[ E(x_{ih}(k)) = \min_{i} \{ E(x_i(k)) \} = E(x_{ih}(k)), \]

after which the center of gravity of the population without the worst point is determined:
\[ x_{ij}(k) = (x_{aj}(k) + x_{aj}(k) + ... + x_{ij}(k) - x_{ij}(k))/ (N-1), \quad j=1,n \]

Further, \( x_{ih}(k) \) is reflected through the center of gravity \( x_c(k) \), forming a new vertex of the complex \( x_r(k) \), which is theoretically located closer to the extremum than \( x_{ip}(k) \) and \( x_i(k) \), i.e.
\[ E(x_{ip}(R)) < E(x_{ih}(k)) < E(x_{ih}(k)). \]

The reflection operation formally has the following form:
\[ x_r(k) = x_v(k) + \eta_R (x_v(k) - x_{ih}(k)) = \frac{1}{N-1} x_i(k) + \cdots + \frac{1}{N-1} x_{N-1}(k) + \]
\[ + \frac{\eta_R}{N-1} x_i(k) + \cdots + \frac{\eta_R}{N-1} x_{N-1}(k) - \eta_R x_{ih}(k) = X(k)R, \]

where \( \eta_R \) – the reflection step parameter, often assumed to be equal to unity,
\( X(k) = (x_{ih}(k),...,x_{N-1}(k)) - (n \times N) \) – matrix of coordinates of the vertices of the complex,
\( R = \left( -\eta_R, \frac{1+\eta_R}{N-1}, \ldots, \frac{1+\eta_R}{N-1}, \ldots, \frac{1+\eta_R}{N-1} \right) \) – vector.

In the event that the reflection of the vertex \( x_r(k) \) is "best" among all the other populations of chromosomes, i.e.
\[ E(x_{ip}(k)) < E(x_i(k)) < E(x_{ip}(k)), \quad i=1,2,...,N-1, \]

then the operation of stretching the complex in the direction from the center of gravity \( x_v(k) \) to \( x_r(k) \) is performed according to expression
\[ x_s(k) = x_v(k) + \eta_E (x_v(k) - x_i(k)) = X(k)E, \]

where \( \eta_E \) – the parameter of the stretching step, often assumed to be equal to two,
\[ R = \left( -\eta_E, \eta_E, \frac{1-\eta_E}{N-1}, \ldots, \frac{1-\eta_E}{N-1}, \ldots, \frac{1-\eta_E}{N-1} \right) \).

If \( x_{ip}(k) \) turns out to be the worst among all \( x_i(k) \), then the complex is compressed according to the relation
\[ x_s(k) = x_v(k) + \eta_S (x_v(k) - x_i(k)) = X(k)S, \]

where \( \eta_S \) – the parameter of the compression step, usually assumed to be 0.5,
Thus, in the course of its movement to the extremum of the optimized function, the complex at each iteration loses one worst vertex and acquires one new point so that at the $k+1$th iteration the new complex also has N vertex points.

Unlike the complex method, in genetic algorithms, as a result of selection from the population, several individuals with the worst (maximum) fitness function values are excluded at the same time. Thus, the complex-method acquires the features of the genetic algorithm, which as a result of selection at each iteration removes several of the worst individuals from the population.

Combining the introduced modification of the method complex with the Holland genetic procedure, we come to the algorithm realizing the idea of artificial selection, consisting in this case of not only removing the worst individuals from the population, but simultaneously creating their "antipodes" that have improved properties.

The operation of such an algorithm is formed by the sequence of the following steps:

- creation of the initial population formed by individuals of chromosomes - the vertices of the complex;
- cross-crossing with increasing population $P_{CR}(0) > P(0)$;
- mutation operation $P_{M}(0) > P_{CR}(0)$;
- first selection (determination of the worst individuals) without population reduction $P_{SEL1}(0) = P_{t}(0)$;
- the operation of choice replaces the values with the best in the whole population;
- reflection operation with removal $P$ of the worst specimens $P_{M}(0) < P_{SEL1}(0)$;
- stretching operation without increasing the population $P_{e}(0) = P_{e}(0)$;
- compression operation without increasing the population $P_{c}(0) = P_{c}(0)$;
- the second selection with removal $P_{w}(0)$ of the worst individuals $P_{SEL2}(0) = P_{t}(0) - P_{w}(0) = P(1)$ and the formation of the population $P(1)$ of the next iteration of the algorithm.

With the help of the proposed approach, the problem of creating a model of fuzzy inference based on the use of a genetic algorithm with artificial selection is solved, and software.

4. Computational experiment

The proposed approach was tested in solving the problem of estimation and prediction using real data. Three types of risk assessment models for crop failure based on fuzzy inference rules were developed.

1. The risk assessment model, the output of which is expressed in a linear relationship.

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

$$R = \left\{-\eta_t, \eta_t, \frac{1-\eta_t(1-\eta_t)}{N-1}, \ldots, \frac{1-\eta_t(1-\eta_t)}{N-1}\right\}^T.$$  

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

$$r_1 = 0.33 - 0.05 \sum_{j=1}^{n} \mu(x_i^{1j})x_1^{1j} - 0.02 \sum_{j=1}^{n} \mu(x_i^{2j})x_2^{2j} - 0.21 \sum_{j=1}^{n} \mu(x_i^{3j})x_3^{3j} - 0.1 \sum_{j=1}^{n} \mu(x_i^{4j})x_4^{4j}.$$  

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

$$r_2 = 0.257 - 0.0393 \sum_{j=1}^{n} \mu(x_i^{1j})x_1^{2j} - 0.112 $$  

If $x_1^3=L$ and $x_2^3=M$ and $x_3^3=L$ and $x_4^3=M$
Then \[ r_3 = 0.18 - 0.01 \frac{\sum_{j=1}^{n} \mu(x_1^j)x_3^j}{\sum_{j=1}^{n} \mu(x_1^j)} - 0.07 \frac{\sum_{j=1}^{n} \mu(x_2^j)x_3^j}{\sum_{j=1}^{n} \mu(x_2^j)} - 0.05 \frac{\sum_{j=1}^{n} \mu(x_3^j)x_3^j}{\sum_{j=1}^{n} \mu(x_3^j)} - 0.111 \frac{\sum_{j=1}^{n} \mu(x_4^j)x_3^j}{\sum_{j=1}^{n} \mu(x_4^j)} \].

If \( x_1^i = L \) and \( x_2^i = M \) and \( x_3^i = M \) and \( x_4^i = M \)

Then \[ r_4 = 0.26 - 0.02 \frac{\sum_{j=1}^{n} \mu(x_1^j)x_4^j}{\sum_{j=1}^{n} \mu(x_1^j)} - 0.05 \frac{\sum_{j=1}^{n} \mu(x_2^j)x_4^j}{\sum_{j=1}^{n} \mu(x_2^j)} - 0.03 \frac{\sum_{j=1}^{n} \mu(x_3^j)x_4^j}{\sum_{j=1}^{n} \mu(x_3^j)} - 0.134 \frac{\sum_{j=1}^{n} \mu(x_4^j)x_4^j}{\sum_{j=1}^{n} \mu(x_4^j)} \].

If \( x_1^i = L \) and \( x_2^i = M \) and \( x_3^i = H \) and \( x_4^i = M \)

Then \[ r_5 = 0.202 - 0.10 \frac{\sum_{j=1}^{n} \mu(x_1^j)x_5^j}{\sum_{j=1}^{n} \mu(x_1^j)} - 0.08 \frac{\sum_{j=1}^{n} \mu(x_2^j)x_5^j}{\sum_{j=1}^{n} \mu(x_2^j)} - 0.12 \frac{\sum_{j=1}^{n} \mu(x_3^j)x_5^j}{\sum_{j=1}^{n} \mu(x_3^j)} - 0.12 \frac{\sum_{j=1}^{n} \mu(x_4^j)x_5^j}{\sum_{j=1}^{n} \mu(x_4^j)} \].

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

If \( x_1^i = L \) and \( x_2^i = L \) and \( x_3^i = H \) and \( x_4^i = M \)

Then \[ r_6 = 0.33 - 0.05 \frac{\sum_{j=1}^{n} \mu(x_1^j)x_6^j}{\sum_{j=1}^{n} \mu(x_1^j)} - 0.02 \frac{\sum_{j=1}^{n} \mu(x_2^j)x_6^j}{\sum_{j=1}^{n} \mu(x_2^j)} - 0.21 \frac{\sum_{j=1}^{n} \mu(x_3^j)x_6^j}{\sum_{j=1}^{n} \mu(x_3^j)} - 0.1 \frac{\sum_{j=1}^{n} \mu(x_4^j)x_6^j}{\sum_{j=1}^{n} \mu(x_4^j)} + 
\quad + 0.003 \left[ \frac{\sum_{j=1}^{n} \mu(x_1^j)x_6^j}{\sum_{j=1}^{n} \mu(x_1^j)} \right]^2 - 0.004 \left[ \frac{\sum_{j=1}^{n} \mu(x_2^j)x_6^j}{\sum_{j=1}^{n} \mu(x_2^j)} \right]^2 + 0.007 \left[ \frac{\sum_{j=1}^{n} \mu(x_3^j)x_6^j}{\sum_{j=1}^{n} \mu(x_3^j)} \right]^2 + 0.0011 \left[ \frac{\sum_{j=1}^{n} \mu(x_4^j)x_6^j}{\sum_{j=1}^{n} \mu(x_4^j)} \right]^2 \].

If \( x_1^i = M \) and \( x_2^i = H \) and \( x_3^i = L \) and \( x_4^i = M \)

Then \[ r_7 = 0.184 - 0.007 \frac{\sum_{j=1}^{n} \mu(x_1^j)x_7^j}{\sum_{j=1}^{n} \mu(x_1^j)} - 0.005 \frac{\sum_{j=1}^{n} \mu(x_2^j)x_7^j}{\sum_{j=1}^{n} \mu(x_2^j)} - 0.003 \frac{\sum_{j=1}^{n} \mu(x_3^j)x_7^j}{\sum_{j=1}^{n} \mu(x_3^j)} - 0.09 \frac{\sum_{j=1}^{n} \mu(x_4^j)x_7^j}{\sum_{j=1}^{n} \mu(x_4^j)} + 
\quad + 0.002 \left[ \frac{\sum_{j=1}^{n} \mu(x_1^j)x_7^j}{\sum_{j=1}^{n} \mu(x_1^j)} \right]^2 - 0.0009 \left[ \frac{\sum_{j=1}^{n} \mu(x_2^j)x_7^j}{\sum_{j=1}^{n} \mu(x_2^j)} \right]^2 + 0.0005 \left[ \frac{\sum_{j=1}^{n} \mu(x_3^j)x_7^j}{\sum_{j=1}^{n} \mu(x_3^j)} \right]^2 + 0.0015 \left[ \frac{\sum_{j=1}^{n} \mu(x_4^j)x_7^j}{\sum_{j=1}^{n} \mu(x_4^j)} \right]^2 \].

If \( x_1^i = H \) and \( x_2^i = H \) and \( x_3^i = M \) and \( x_4^i = M \)

Then \[ r_8 = 0.17 - 0.003 \frac{\sum_{j=1}^{n} \mu(x_1^j)x_8^j}{\sum_{j=1}^{n} \mu(x_1^j)} - 0.001 \frac{\sum_{j=1}^{n} \mu(x_2^j)x_8^j}{\sum_{j=1}^{n} \mu(x_2^j)} - 0.07 \frac{\sum_{j=1}^{n} \mu(x_3^j)x_8^j}{\sum_{j=1}^{n} \mu(x_3^j)} - 0.09 \frac{\sum_{j=1}^{n} \mu(x_4^j)x_8^j}{\sum_{j=1}^{n} \mu(x_4^j)} + 
\quad + 0.002 \left[ \frac{\sum_{j=1}^{n} \mu(x_1^j)x_8^j}{\sum_{j=1}^{n} \mu(x_1^j)} \right]^2 - 0.0009 \left[ \frac{\sum_{j=1}^{n} \mu(x_2^j)x_8^j}{\sum_{j=1}^{n} \mu(x_2^j)} \right]^2 + 0.0005 \left[ \frac{\sum_{j=1}^{n} \mu(x_3^j)x_8^j}{\sum_{j=1}^{n} \mu(x_3^j)} \right]^2 + 0.0015 \left[ \frac{\sum_{j=1}^{n} \mu(x_4^j)x_8^j}{\sum_{j=1}^{n} \mu(x_4^j)} \right]^2 \].
3. The risk assessment model, the output of which is expressed by a fuzzy term.

If $x_1 = L$ and $x_2 = L$ and $x_3 = L$ and $x_4 = L$ with weight 0.5

or $x_1 = M$ and $x_2 = L$ and $x_3 = L$ and $x_4 = L$ with weight 0.5

Then $r_1 = H$.

If $x_1 = L$ and $x_2 = L$ and $x_3 = L$ and $x_4 = M$ with weight 0.33

or $x_1 = L$ and $x_2 = L$ and $x_3 = H$ and $x_4 = L$ with weight 0.33

Then $r_2 = H.M$.

If $x_1 = L$ and $x_2 = L$ and $x_3 = H$ and $x_4 = L$ with weight 0.33

or $x_1 = L$ and $x_2 = L$ and $x_3 = M$ and $x_4 = H$ with weight 0.33

Then $r_3 = M$.

If $x_1 = L$ and $x_2 = H$ and $x_3 = M$ and $x_4 = M$ with weight 0.5

or $x_1 = L$ and $x_2 = H$ and $x_3 = M$ and $x_4 = H$ with weight 0.5

Then $r_4 = L.M$.

If $x_1 = M$ and $x_2 = H$ and $x_3 = M$ and $x_4 = H$ with weight 0.33

or $x_1 = H$ and $x_2 = H$ and $x_3 = M$ and $x_4 = H$ with weight 0.33

or $x_1 = H$ and $x_2 = H$ and $x_3 = H$ and $x_4 = H$ with weight 0.33

Then $r_5 = L$.

The membership function has the following form [1]:

$$
\mu^k(x') = \frac{1}{1 + \left( \frac{x' - c^k}{\sigma^k} \right)^2}
$$

5. Conclusion

Thus, an algorithm and a program for constructing a fuzzy model of intellectual analysis of the state of poorly formalized processes with the possibility of learning, dynamically adjusting and updating fuzzy knowledge bases have been developed. The proposed algorithm allows solving the problems of classification, estimation and forecasting under conditions of uncertainty of information about these processes. Combining fuzzy logic with a genetic algorithm gives a fundamentally new quality. In order to assess the effectiveness of the developed software, computational experiments were carried out to solve a number of applied problems of estimating and forecasting poorly formalized processes.

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