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Improving the Accuracy of Identification of Non-Stationary Objects Based on the Regulation of Model Variables

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Abstract. Researched and developed mechanisms for optimizing the identification of random time series based on mechanisms for searching for unknown knowledge, hidden properties, patterns, relationships, features of non-stationary objects under the condition of limited a priori information, uncertainty, non-stationary processes. A generalized model for optimizing the identification of RTS based on the use of neural networks, neuro-fuzzy networks of dynamic models, as well as fuzzy logic algorithms is implemented. Instruments for data reliability control are obtained based on statistical, dynamic, intelligent approaches suitable for the conditions of transmission of incomplete, heterogeneous, partially given information with large parametric uncertainty. The principles and methods of data reliability control in a fuzzy environment are developed based on the generalization and use of the properties of neural networks, fuzzy logic and statistical modeling methods. Algorithms for searching for correlations, trends, interrelations and regularities in data, forming training, control and test sets for solving problems of recognition, classifying images of micro-objects and predicting power supply indicators are synthesized. The results of the research are implemented in the form of a software package for identifying non-stationary objects, which ensures the adaptability of model variables, high data processing performance and accuracy of results.

1. Introduction

In systems for monitoring technical, economic, social, technological indicators, as well as for managing industrial complexes, methods are used to identify non-stationary objects with mechanisms for converting primary data into knowledge, searching for correlations, characteristic trends, relationships and patterns, recognition, classification, forecasting, etc [1-3].

Existing approaches are mainly aimed at using identification mechanisms based on statistical, dynamic models that present results with a large error, require extended data history, lack of parametric uncertainty and non-stationarity [4-6].

Relevant and in demand is the research and development of new mechanisms for optimizing identification based on the use of mechanisms for searching for unknown knowledge, hidden properties, patterns, relationships, features of random time series (RTS) of non-stationary objects under the condition of a continuous increase in information volumes, limited a priori information, uncertainty, non-stationarity of processes [7-10].

It is supposed to implement RTS identification mechanisms based on the use of dynamic models generalized with neural networks (NN), neuro-fuzzy networks (NFN), as well as the features of fuzzy logic algorithms.

2. Main Part

2.1. *Mechanisms for identification of non-stationary objects based on soft computing*

The mathematical apparatus of soft computing, in particular NN, acquires unique properties and becomes capable of creating tools for adequate identification of RTS, optimization, increasing the reliability of data processing under conditions of incomplete, heterogeneous information, parametric uncertainty and non-stationarity [11, 12].

In it is proved that the efficiency of mechanisms for identifying and processing data of non-stationary objects increases when using statistical parameters, dynamic and specific characteristics of objects, extracting hidden patterns, relationships between elements of the RTS.

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The following key issues of identification optimization have been investigated:
- optimization through the use of statistical, dynamic, specific properties of information of non-stationary objects, the creation of combined mechanisms for identifying RTS in an integrated environment;
– application of soft calculations in the identification of non-stationary objects;
– implementation of a software package for identifying non-stationary objects in the form of a unified framework that provides adaptability to changes in model variables with high data processing performance.

The effectiveness of common mechanisms for checking the reliability of processing the results of experimental studies according to the rules $\pm 3\sigma$, statistical criteria χ^2 - Pearson, t - distributions of Student, Kolmogorov, Romanovsky, etc. has been studied.

It is determined that they are applicable only in the presence of extensive data statistics, constant values of the mean, variance and the use of tabulated distribution functions [13, 14-16].

The statistical approach aimed at increasing the reliability of information has been improved on the basis of the construction and implementation of mechanisms for monitoring the results of data processing by optimal thresholds that divide the set of elements (measurements) of the RTS into subsets of allowed and prohibited values [17, 18, 19].

Information is considered reliable if the RTS element belongs to the subset of allowed values and unreliable if it belongs to the subset of prohibited values. The studies were carried out according to the criteria of the probability of undetected errors, and the minimum root-mean-square error of data processing.

Estimates are obtained for the probabilities of undetected errors of two kinds allowed by the information control mechanism. The reliability index of data processing is optimized by adjusting the values of the average probability of information errors, with a wide range of probability distribution functions, using the mathematical expectation, variance, and RTS correlation function. As a result of theoretical studies, expressions for estimating the minimum standard deviation, optimal boundaries for controlling the error of identification and data processing were obtained [20-22].

The resulting equation of extreme thresholds for information reliability control is given as:

$$w(a_x - \overset{o}{x}) = w(a_y - \overset{o}{y}) = \frac{P\sigma_x}{(1-P)B}, \tag{1}$$

where $\overset{o}{x}$ and $\overset{o}{y}$ are, respectively, the lower and upper extreme threshold limits for information reliability control; P is the average probability of errors; a_x, a_y - mathematical expectations; σ_x - dispersion of RTS elements; B is the range of the practical range of values of the RTS element; $x_{\max} - x_{\min}$ is the interval of change of the values of the RTS element, given by the decimal code, which are equal to 10, 10^2, 10^3; $w(a_x - \overset{o}{x})$ is the probability density function of the RTS element.

The issues of minimizing the error of identification of the RTS are studied on the basis of polynomial functions, algebraic polynomials of Newton, Lagrange, Bessel, linear and nonlinear filters, parabolic and cubic splines, as well as regression dependencies [23-25].

Adaptation mechanisms are based on the principles of determining, adjusting the lower and upper thresholds, coefficients and degrees of polynomials, polynomials, smoothing filters, parabolic and cubic spline functions, which manifest themselves with different properties of mean variation, variance, distribution function and autocorrelation.

Equations are obtained for constructing adaptive mechanisms for controlling the reliability of information using the correlation characteristics of the RTS in the form

$$w_{con}(a_x - \overset{o}{x}) = w_{con}(a_y - \overset{o}{y}) \frac{P\sigma_x[1 - B_x(\omega\tau)]}{(1-P)B}, \tag{2}$$

where $w_{con}(a_x - \overset{o}{x})$ are the conditional probability distribution densities of the RTS elements; $B_x(\omega\tau)$ - autocorrelation functions given in the form of triangular, exponential, cosine forms; $\omega\tau$ is the correlation frequency of RTS elements.

Implemented mechanisms for translating RTS properties to dynamic models and NN. It is determined that NN with these mechanisms become effective identifiers of the RTS, capable of improving the results of calculations under conditions of insufficient a priori information, non-stationary properties of information. The implementations of the mechanisms for optimizing the identification of the RTS based on the regulation of the parameters of the structural components, the training set, and the learning algorithms of the NN have been studied [26-29].

Mechanisms are proposed that use the generalized properties of fuzzy sets, fuzzy logic algorithms, five-layer NN, which are effective tools in conditions of uncertainty and non-stationarity of identification processes [30, 31, 32].

2.2. Mechanisms for optimizing the identification of RTS in a fuzzy environment.

The RTS of a non-stationary object is given in the form of the following state vectors: input $x = (x_1, x_2, ..., x_j)$, output $y = (y_1, y_2, ..., y_n)$, as well as the impact of interference from the external environment $u = (u_1, u_2, ..., u_i)$, which lead to an identification error $\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_m)$. Models with nonlinear and interrelated variables are studied.

The mechanisms for regulating the variables u and y are implemented, as well as setting the parameters of the computational circuits of the neuro-fuzzy network (NFN), the formation of a rational set of learning real processes. A reference non-linear function $y = f(x, \varepsilon, u)$ is presented, on the basis of which the state of a non-stationary object is regulated [33-35].

The classical approach is aimed at solving the problem based on linearized differential (difference) equations with specific initial conditions. However, when an adequate RTS identifier is needed with an estimate of the vectors u, x, ε, y, then it is required to design a simplified identification model $y = \varphi(u)$ with incomplete a priori information that meets the requirements of accuracy and minimization of time and material costs.

A mechanism has been developed and implemented to regulate the boundaries of the control of the error in the identification of the RTS, in which the vectors of variables u and y are used to set the membership functions (MF) with the determination of the center and initial states u_0 and y_0. The qualitative output of the model in a fuzzy environment is determined by the logical condition

$$\mu_{notN}(u, y) = 1\,. \tag{3}$$

This condition corresponds to the output of the term N (normal) of the fuzzy model, when the value of the variable y is outside the established limits. The result of the identification of the RTS at point n is represented by the output $Y(n)$. Its quality is evaluated by the values of the characteristics of the modal example $Y_{\text{mod}}(n)$ according to the criterion

$$\mathrm{E} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}(Y_{\text{mod}}(n) - Y(n))^2} \to \min\,,$$

where N is the number of training set points.

Information is considered reliable if the following condition is met

$$\mu_N(u, y) = K_{\mathrm{R}}\,. \tag{4}$$

Problem solving is related to determining the type of membership functions, the optimal boundaries of the membership functions for each term of input linguistic variables, as well as $K_{\mathrm{R}} = \mathrm{E}_{\min}/\mathrm{E}_{\text{cur}}$ - a generalized indicator of the reliability of data processing.

Implemented are typical computational schemes based on the use of the properties of fuzzy sets, fuzzy logic, NN, which use tools for calculating estimates of information content, the importance of heterogeneous and heterogeneous features of the objects under study [36-39].

A technique has been developed that contributes to the assessment of the degree of relatedness, mutual equivalence, equivalence, decorrelation, destructurization of RTS elements and optimization of RTS identification. The reliability of data processing is estimated by the proximity function of the elements of the RTS. It is set by checking the membership of the RTS element for subsets of allowed and forbidden values. The peculiarity of the question under study is the following.

The elements of the input vector X_i at the moment of time make up a certain alphabet, which includes the following sets: quantitative features in the scale of the binary relation $X_i \in \{0,1\}$ and intervals $X_i \in [a, b]$; qualitative features in the nominal scale in the form of a finite set and the ordinal scale in the form of a finite ordered set.

Sets of allowed RTS values are formed according to k features $\Omega_1, ..., \Omega_k$ from the full set $(X_1, ..., X_n)$, $i = 1, 2, ..., n$.

Data processing is carried out according to a matrix, in which $\widetilde{\omega}$ denotes a part of the columns $\Omega_i = (X_{i_1}, ..., X_{il})$, where l is the length of the sets selected from n measurements of the RTS. Reliability optimization consists in assigning the value of the RTS element to the subset of allowed values, comparing it with the characteristics of the set of allowed values, with the elements of the RTS of the reference object S. Estimates of the proximity function are determined over various sets of $r(\tilde{\omega}S_j, \tilde{\omega}S_q)$. In this case, the $\tilde{\omega}$-parts of strings $\tilde{\omega}S_j$ and $\tilde{\omega}S_q$ are considered similar if they match.

2.3. Identification optimization mechanisms based on neuro-fuzzy networks

A reliability control mechanism is implemented based on the use of estimates of the proximity function for sets $r(\tilde{\omega}S_j, \tilde{\omega}S_q)$ with the metric $\rho(x_{i_v j}, x_{i_v q})$, which is represented by the distribution function of the RTS elements. The metric validation rule is as follows:

$$r(\tilde{\omega}S, \tilde{\omega}S_q) = \begin{cases} 1, & \text{if} \quad \tilde{\omega}S = \tilde{\omega}S_q; \\ 0, & \text{otherwise.} \end{cases}$$

In the case of using the binary proximity function, as

$$\rho(x_{ij}, x_{iq}) = \begin{cases} 1, & if \quad x_{ij} = x_{iq}; \\ 0, & if \quad x_{ij} \neq x_{iq}. \end{cases}$$

In the case of using the threshold control mechanism, as

$$r(\tilde{\omega}S, \tilde{\omega}S_q) = \begin{cases} 1, & \text{if} \quad \sum_{v=1}^{л} \tilde{\rho}(x_{i_v j}, x_{i_v q}) \le \varepsilon; \\ 0, & \text{otherwise,} \end{cases}$$

where $\tilde{\rho}(x_{i_v j}, x_{i_v q})$ is the function of the difference between the values of the elements $x_{i_v j}$ and $x_{i_v q}$ of the input and reference objects; ε - threshold.

A mechanism has been implemented in which the universe $U(A_1, A_2, ..., A_i)$ is considered, on which the set of pairs $\langle \mu_{A_v}(x)/x \rangle$, $\mu_{A_v}(x)$ is determined - the membership function of the carrier x to a fuzzy set with a specific type and parameters.

The mechanism control rule is as follows.

$$\rho(x_{ij}, x_{iq}) = \begin{cases} 1, & \mu^*_{A_v}(x_{ij}) = \mu^*_{A_v}(x_{iq}); \\ 0, & \text{otherwise,} \end{cases}$$

$$\mu^*_{A_v}(x_{ij}) = \max_{v=\overline{1,t}}(\mu_{A_v}(x_{ij})), \ \mu^*_{A_v}(x_{iq}) = \max_{v=\overline{1,t}}(\mu_{A_v}(x_{iq}));$$

where x_{ij} are the values of the RTS element, reduced to one universal interval $[0, c]$ according to the relation

$$x_{ij} = c\frac{x_{ij} - \underline{x_{ij}}}{\overline{x_{ij}} - \underline{x_{ij}}};$$

$\overline{x_{ij}}$, $\underline{x_{ij}}$ - interval of change of variable x_{ij}, $i = \overline{1,n}$;

x_{ij} is the normalized value of the element.

The value of the RTS element is considered reliable "1" if two membership function in one term - set are equal; and invalid "0" otherwise.

Linguistic terms are defined as preconditions for fuzzy "IF-THEN" rules, knowledge bases (KB) with fuzzy rules are formed that most fully reflect the influence of external factors u on changes in the output vector y.

The operator of the influence of extraneous interference and disturbances is set by the vector $u = (u_1, u_2, ..., u_i)$ with the following terms:

L (low), when the value of the RTS element is outside the boundaries of the membership function and below the lower boundary;

N (normal) when the value of the RTS element does not go beyond the boundaries of the membership function;

H (high) when the value of the RTS element is outside the boundaries of the membership function and above the upper limit;

The KB of fuzzy rules is used when adjusting values to increase, decrease, or maintain the same in the range $u_{i0} \pm \Delta$ of input linguistic variables.

The fuzzy approximation model is tuned by the number of terms and fuzzy rules to possible changes in the statistical parameters of the RTS. The boundaries of the membership function of linguistic terms are set by rigid numerical values, and then adjusted to changes in the non-stationarity of the RTS.

Permissible deviation $\pm dx$ is set for the term of normalized values x_i in binary symbolic form. The deviation dx is set by the boundaries of the membership function for the terms L and H. The study was carried out for a symmetric membership function of the Gaussian type and a Z - shaped curve.

To expand the capabilities of methods, models, identification algorithms, the following mechanisms are included in the generalized model:

- search for correlations, characteristic trends, relationships and patterns in the data to be placed in databases (DB);
- extraction of useful properties, specific characteristics, patterns of data distribution;
- selection of informative elements of the RTS, cluster analysis, multicomponent structure;
- data pre-processing, in which the space of RTS elements is divided into segments;
- recognition, classification, identification, forecasting;
- formation of sets of training, control and test data.

The identification model of the RTS based on fuzzy rules is given as

$$\bigcup_{j=1}^{M}\left(\bigcap_{i=1}^{n} X_i = x_{ji}\cdot B\right) \to y_j = b_{mo} + b_{m1}x_{1j} + \ldots + b_{mn}x_{nj},$$

where $B = (b_{ij})$ is the input matrix of regression coefficients, $i = \overline{1,m}$, $j = \overline{0,n}$.

The input matrix X_r is determined

$y_r^f = \dfrac{\sum_{i=1}^{m}\mu_{d_i}(X_r)\cdot d_i}{\sum_{i=1}^{m}\mu_{d_i}(X_r)}$, where $d_i = b_{i0} + b_{i1}x_{r1} + b_{i2}x_{r2} + \ldots + b_{in}x_{rn}$; $\mu_{d_i}(X_r)$ - member function (MF),

each input variable, which is defined as:

$$\begin{aligned}&\mu_{d_i}(X_r) = \mu_{i1}(x_{r1})\cdot\mu_{i1}(x_{r2})\cdot\mu_{i1}(x_{r3})\cdot\ldots\cdot\mu_{i1}(x_{rn})\vee\\ &\vee\,\mu_{i2}(x_{r1})\cdot\mu_{i2}(x_{r2})\cdot\mu_{i2}(x_{r3})\cdot\ldots\cdot\mu_{i2}(x_{rn})\vee\ \ldots\\ &\ldots\ \vee\,\mu_{im}(x_{r1})\cdot\mu_{im}(x_{r2})\cdot\mu_{im}(x_{r3})\cdot\ldots\cdot\mu_{im}(x_{rn}),\end{aligned}$$

Denoting $\beta_{ir} = \dfrac{\mu_{d_i}(X_r)\cdot d_i}{\sum_{i=1}^{m}\mu_{d_i}(X_r)}$, and write in the form

$$y_r^f = \sum_{i=1}^{m}\beta_{ir}d_i = \sum_{i=1}^{m}\left(\beta_{ir}\cdot b_{i0} + \beta_{ir}\cdot b_{i1}\cdot x_{r1} + \beta_{ir}\cdot b_{i2}\cdot x_{r2} + \ldots\beta_{ir}\cdot b_{in}\cdot x_{rn}\right). \tag{7}$$

We introduce new notation:

$$Y^f = \left(y_1^f, y_2^f, \ldots, y_M^f\right)^T;\ \ Y = (y_1, y_2, \ldots, y_M)^T. \tag{8}$$

The KB of fuzzy rules based on the functional (6) is given in the form

$$E = \left(Y - Y^f\right)^T\cdot\left(Y - Y^f\right) \to \min. \tag{9}$$

The Mamdani model is given with fuzzy rules of types:

IF $(x_1 = a_{1,j1})$ AND $(x_2 = a_{2,j1})$ AND...AND $(x_n = a_{n,j1})$,

OR $(x_1 = a_{1,j2})$ AND $(x_2 = a_{2,j2})$ AND...AND $(x_n = a_{n,j2})$,

...

OR $(x_1 = a_{1,jk_j})$ AND $(x_2 = a_{2,jk_j})$ AND...AND $(x_n = a_{n,jk_j})$,

THEN $\mathrm{y_i} = d_j, i = \overline{1,m}$,

where $a_{i,jp}$ are the estimates of the linguistic term and the variable x_i, which are written in the row of the matrix with the number jp ($p = \overline{1,k_j}$);

k_j is the number of conjunction strings by which the linguistic term d_j of the output y is evaluated;
m - the number of terms of the linguistic variable y.
The membership of an input variable to a fuzzy term is given as

$$a_{i,jp} = \int_{\underline{x_i}}^{\overline{x_i}} \mu_{jp}(x_i)/x_i\,, \qquad x_i \in [\underline{x_i}, \overline{x_i}],$$

where $\mu_{jp}(x_i)$ is the membership function of the input linguistic terms of the variable x_i.
The membership coefficients of the output variable to the fuzzy term d_j, $j = \overline{1,m}$ are given as

$$d_j = \int_{\underline{y}}^{\overline{y}} \mu_{d_j}(y)/y\,, \qquad y \in [\underline{y}, \overline{y}].$$

where $\mu_{d_j}(y)$ is the membership function corresponding to the output variable y.
2.4. Implementation of mechanisms for optimizing the identification of non-stationary objects.

A software package (SP) for identification has been developed and implemented for recognition and classification, prediction of the RTS of non-stationary objects based on the use of combined properties of dynamic, models, NN, fuzzy sets, fuzzy logic and NFN.
The SP is based on the implementation of NFN computational schemes:
- a fuzzifier that converts a fixed vector of input factors X into a vector of values of fuzzy sets $\tilde{X}$;
- KB of fuzzy rules that determine the linguistic dependencies "inputs-outputs" $Y = f(X)$;
- a fuzzy inference generator that implements fuzzy KB rules to determine the value of the output variable corresponding to the fuzzy values of the input $\tilde{X}$ and output variables $\tilde{Y}$, as well as the membership function of linguistic variables;
- a defuzzifier that converts the output value from the fuzzy set $\tilde{Y}$ to crisp numbers Y.
As part of the PC, a six-layer NFN is implemented.

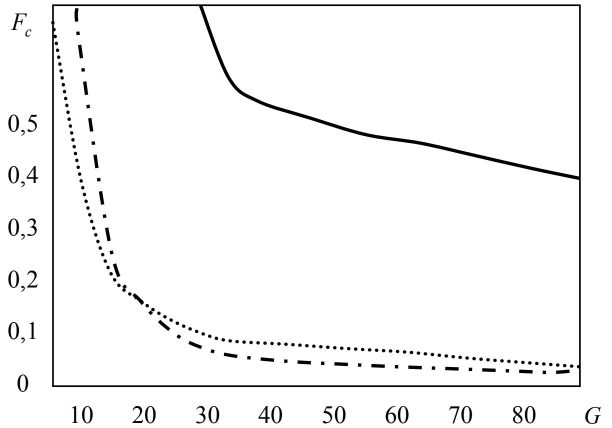

Fig. 1. SP efficiency function

The SP includes modules that implement Mamdani and Sugeno fuzzy inference algorithms, NN learning with forward and back propagation of errors. Programs for parametric identification of nonlinear dependencies based on a fuzzy hybrid model in the MATLAB environment are implemented. The parametric identification module based on the fuzzy Mamdani model performs the following functions of formations: m - scenarios that configure the correspondence of the output to the vectors of the initial data and extraneous disturbances, given in the form of a nonlinear dependence r; m - goal_fun functions that calculate mismatch errors between the values of the output variable and the reference characteristic of the modal example with a rational size of the training data set.

In experimental studies, the number of linguistic variables is assumed to be sixteen. Of these, eleven are the concentration coefficients of the membership function of the input and output variable terms; two are the coordinates of the maxima of the centers of the membership function of the terms "average" of the input variables; three are the coordinates of the maxima of the membership function centers of non-extreme terms of the output variables: "below average", "average" and "above average". The coordinates of the maximums of the membership function of the extreme terms "low" and "high" are not adjustable.

The root-mean-square error of the RTS identification algorithms on a control sample of 1000 points, according to the conditional parameter with the Mamdani model, is 4.61.

Each input linguistic variable is estimated as a membership function given as a symmetric Gaussian-type membership function and a Z-shape. 24 parameters are divided according to the following principle: 3 parameters are determined for each of the 4 knowledge base rules; 3 parameters are determined for each of the 4 terms of the input variables.

The number of adjustable parameters for the Sugeno model with two inputs and one output is minimal. At the same time, the root-mean-square error of data processing algorithms on a control sample of 1000 points is 1.81.

Figure 1 highlights SP efficiency are illustrated by the function of relative error $F_c = \frac{\sigma_E}{B}$ depending on the generalized characteristic of information $G = \frac{P\sigma_x}{(1-P)B}$.

The graphs of the function are obtained at $P = 10^{-4}$; $B = 10$; $\sigma_x = 0{,}5$. The effectiveness of the following identification algorithms is compared: the dashed line plot of the Mamdani model; dash-dotted line of the Sugeno model; solid line of the 4th degree polynomial. It is determined that the efficiency of the Mamdani model is an order of magnitude higher than that of Sugeno. However, with small training set sizes, the Mamdani model is effective with fewer iterations. When the training sample size is twice the number of tunable linguistic variables, the Sugeno model becomes more stable. When the size of the training set exceeds the number of linguistic variables by more than three times, then the efficiency of the SP does not improve much. The value of the information reliability indicator obtained by fuzzy models is two orders of magnitude higher than that of polynomial models.

3. Conclusions

Scientific and methodological foundations for improving and developing methods for identifying non-stationary objects based on the mechanisms for using generalized properties, statistical, dynamic models, soft computing - NN, fuzzy sets, fuzzy logic and NFN, knowledge extraction, hidden properties, regularities, RTS relationships have been developed.

Investigated and implemented are the mechanisms for controlling the error in identifying the RTS by optimal control thresholds and adaptive error limits, the mathematical expressions of which are obtained for various polynomial approximation functions, Newton, Lagrange, Bessel algebraic polynomials, linear and nonlinear filters, parabolic and cubic splines, regression dependencies.

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