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MECHANISMS FOR FORECASTING TIME SERIES OF INDICATORS OF POWER SUPPLY SYSTEMS BASED ON SOFT CALCULATIONS IN NON-STATIONARY CONDITIONS

***Abstract**: Scientific and methodological foundations for the application of methods and algorithms for data mining based on neural networks, fuzzy sets and fuzzy inferences, neuro-fuzzy networks, and genetic algorithms have been developed and implemented. As tools for the analysis and forecasting of time series of random processes, optimization mechanisms for determining and setting the parameters of genetic operators, dynamic identification models are proposed. The results of the study were obtained by solving forecasting problems in real conditions.*

***Key words**: fuzzy inference, fuzzy logic, neural network, neuro-fuzzy network, genetic algorithms, forecast, time series.*
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Introduction

Relevance of the topic. Important tasks of creating, improving, developing methods and algorithms for data mining (ADM) and optimizing the forecasting of time series of non-stationary processes are the selection of informative features, finding empirical patterns of various types, building analytical descriptions of sets (classes) of objects, finding critical cases and generating descriptions of reference examples [1,2].

The tools of technologies for intellectualization of information processing of non-stationary objects make it possible to find such regularities independently and build hypotheses about relationships to ensure time series forecasting with high accuracy at minimal material and time costs [3,4].

However, most ADM algorithms, when identifying and evaluating relationships in data, use the concept of averaging over a sample, which often leads to operations on non-existent values, and operate with long historical data. The key objectives of this study are the following [5]:

– development of efficient algorithms for data analysis and processing, forecasting systems in interactive and integrated environments;

- the use of methods of the mathematical apparatus of soft computing, formed to solve complex applied problems and obtain various applications;

– designing the latest areas of application of problem-oriented ADM systems embedded in various services, as well as including tools for specific application tasks;

– implementation of ADM systems in the form of an easily interpretable and unified framework that provides reliability, adaptability and high performance of data processing.

In this paper, we have developed time series forecasting mechanisms based on NN, neuro-fuzzy networks (NFN) and genetic algorithms (GA), which, compared with traditional methods, have advantages that differ in mechanisms: finding acceptable solutions, avoiding local extrema, data transformation, application probabilistic rules and the search for randomness in optimizing the solution of high-dimensional problems.

Time series forecasting based on NN, NFN with GA. Algorithms and computational schemes for determining the appropriate activation function, coefficients of synaptic connections, rational architecture of the neural network, calculation of weight coefficients, and the number of neurons in layers during training of the neural network have been developed to build ADM systems for non-stationary objects based on NN [6,7].

For the development of the use of ADM systems, an important issue is the optimization of identification and approximation of complex non-stationary objects with discrete time based on the determination and tuning of the parameters of the NN model using GA [8,9].

The mechanisms of genetic parameter tuning are built on the basis of the following rules:

- "adaptive mutation", which makes it possible to sharply increase the level of mutation in the case when there is a deterioration in the quality of the GA;

- an increase in the level of mutation after a decrease in the average value of the quality function is recorded;

- using a small mutation and changing only the last bits of the binary encoding of the real number.

If this does not lead to an increase in the average value of the quality function within a given time of the population of an individual, then the range of the local search is increased by mutating more bits; adaptation of the level of mutation and the probability of crossing, which are regulated when performing GA. Let a sample of fuzzy data be given

$$(X_r, y_r),\ r=\overline{1,M}, \qquad (1)$$

where is $X_r=(x_{r1},x_{r2},...,x_{rn})$ the input n-dimensional vector;

$y_r=(y_1,y_2,...,y_M)$ – is the corresponding output vector.

The NFN model based on fuzzy inference rules is given as

$$\bigcup_{p=1}^{k_j}\left(\bigcap_{i=1}^{n} x_i = a_{i,jp} - с\ весом\ w_{jp}\right) \to y_j = b_{mo} + b_{m1}x_1^j + ... + b_{mn}x_n^j. \qquad (2)$$

The coefficients $B=(b_{ij})$, $i=\overline{1,m}$, $j=\overline{0,n}$, are found such that the minimum of the expression is reached

$$\sum_{r=1}^{M}\left(y_r - y_r^f\right) \to \min, \qquad (3)$$

where is y_r^f – the result of fuzzy rules with the parameter B in the r th line (X_r).

The input matrix X_r corresponds to the result of the following fuzzy inference

$$y_r^f = \frac{\sum_{i=1}^{m}\mu_{d_i}(X_r)\cdot d_i}{\sum_{i=1}^{m}\mu_{d_i}(X_r)}, \qquad (4)$$

where is $d_i = b_{i0} + b_{i1}x_{r1} + b_{i2}x_{r2} + ... + b_{in}x_{rn}$ the NFN output according to the i-rule;

$\mu_{d_i}(X_r)$ – is the membership function (MF) corresponding to each input variable:

$$\mu_{d_i}(X_r) = \mu_{i1}(x_{r1})\cdot\mu_{i1}(x_{r2})\cdot\mu_{i1}(x_{r3})\cdot...\cdot\mu_{i1}(x_{rn})\vee$$
$$\vee\ \mu_{i2}(x_{r1})\cdot\mu_{i2}(x_{r2})\cdot\mu_{i2}(x_{r3})\cdot...\cdot\mu_{i2}(x_{rn})\vee\ ...$$
$$...\ \vee\ \mu_{im}(x_{r1})\cdot\mu_{im}(x_{r2})\cdot\mu_{im}(x_{r3})\cdot...\cdot\mu_{im}(x_{rn}),$$
$$\beta_{ir} = \frac{\mu_{d_i}(X_r)\cdot d_i}{\sum_{i=1}^{m}\mu_{d_i}(X_r)}. \qquad (5)$$

Let's rewrite (8) in the form:

$$y_r^f = \sum_{i=1}^{m}\beta_{ir}d_i = \sum_{i=1}^{m}(\beta_{ir}\cdot b_{i0} + \beta_{ir}\cdot b_{i1}\cdot x_{r1} + \beta_{ir}\cdot b_{i2}\cdot x_{r2} + ...\beta_{ir}\cdot b_{in}\cdot x_{rn}). \qquad (6)$$

Let us introduce the following notation:

$$Y^f = \left(y_1^f, y_2^f, \ldots, y_M^f\right)^T,$$

$$Y = (y_1, y_2, \ldots, y_M)^T.$$

Let us rewrite problem (3) in matrix form so that the condition

$$E = \left(Y - Y^f\right)^T \cdot \left(Y - Y^f\right) \to \min. \quad (7)$$

At each moment of time, the current population of chromosomes is identified with a population - a complex of points in the search space, and in addition, in contrast to the traditional genetic operators of mutation, crossing and selection in this case, a complex of search operators is additionally introduced, such as selection, reflection, stretching and compression [10,11].

Optimization of time series forecasting based on GA. For optimization, it is required to find the minimum of some function

$$E(x) = \sum_{r=1}^{M}\left(y_r - y_r^f\right)^2 \to \min. \quad (8)$$

Fuzzy GA is performed from the formation of a complex of initial values

$$x_i(0) \to \begin{pmatrix} x_1(0) \\ x_2(0) \\ \vdots \\ x_N(0) \end{pmatrix} \to \begin{pmatrix} x_{11}(0) & x_{12}(0) & \ldots & x_{1n}(0) \\ x_{21}(0) & x_{22}(0) & \ldots & x_{2n}(0) \\ \vdots & & & \\ x_{N1}(0) & x_{N2}(0) & \ldots & x_{Nn}(0) \end{pmatrix}, \; i = \overline{1,N} \geq n+1$$

which is a population of chromosomes, rather arbitrarily located in the -dimensional search space.

Next, the selection operation is performed, then crossover and mutation, and a new population of chromosomes $x_i(1)$ is obtained, after which the selection operation is performed [12,13].

At this stage, the value of the suitability function (fitness) in all chromosomes is calculated and the average fitness of the population is found

$$E_{\text{average}} = \frac{1}{N}\sum_{i=1}^{N} E(x_i(k)). \quad (9)$$

Chromosomes with a fitness function less than the average for the entire population are replaced by the best ones [14,15].

Moreover, if $E_{\text{average}} < E(x_i(k))$, and $x_i(k+1) = x_i(k)$, then

$$\min_{i=\overline{1,N}}(E(x_i(k))). \quad (10)$$

From the set of these chromosomes, the worst is found - $x_i(1)$, in which the value of the function $E(x_H(1))$ is maximum.

Then this point is reflected through the center of gravity of all other vertices - points, forming a new complex , $x_i(1)$, $i = \overline{1,N}$.

Such a reflection, together with stretching and compression, ensures the movement of the fuzzy GA to the extremum of the function $E(x)$.

Due to the random distribution of chromosomes in the population, the search is global in nature [16].

Consider the optimization process at the k th iteration of the search, when the complex $x_i(k)$, $i = \overline{1,N}$.

We assume that among the set $x_i(k)$ there is the worst chromosome such that

$$E(x_H(k)) = \min_i \{E(x_1(k)), \ldots, E(x_H(k))\}. \quad (11)$$

The center of gravity of a population without the worst point is defined as

$$x_{cj}(k) = (x_{1j}(k) + x_{2j}(k) + \ldots + x_{Nj}(k) - x_{Hj}(k))/(N-1), \; j = \overline{1,n}. \quad (12)$$

Next, $x_H(k)$ is reflected through the center of gravity $x_c(k)$.

The new vertex of the $x_R(k)$ complex is located closer to the extremum than $x_H(k)$ and $x_c(k)$, etc

$$E(x_R(k)) < E(x_c(k)) < E(x_H(k)).$$

The GA reflection operator can be written in the form

$$\begin{aligned} x_R(k) &= x_c(k) + \eta_R(x_c(k) - x_H(k)) = \frac{1}{N-1}x_1(k) + \ldots + \frac{1}{N-1}x_{N-1}(k) + \\ &+ \frac{\eta_R}{N-1}x_1(k) + \ldots + \frac{\eta_R}{N-1}x_{N-1}(k) - \eta_R x_H(k) = X(k)R, \end{aligned} \quad (13)$$

where is η_R – the parameter of the reflection operator, assumed to be equal to one;

If the reflection of the vertex $x_R(k)$ is the best among all other populations of chromosomes

$$E(x_R(k)) < E(x_i(k)) < E(x_H(k)),$$
$$i = 1,2,\dots,N-1,$$

then the stretching operation is performed in the direction from the center of gravity $x_R(k)$ to $x_H(k)$.

When $x_E(k) = x_c(k) + \eta_E(x_R(k) - x_c(k)) = X(k)E$, where η_E is a parameter of the stretch operator, is often set equal to two, then the fitness function is defined as

$$E = \left(-\eta_E, \eta_R, \frac{1-\eta_E(1-\eta_R)}{N-1}, \dots, \frac{1-\eta_E(1-\eta_R)}{N-1}\right)^T. \quad (14)$$

If $x_R(k)$ turns out to be the worst among all $x_i(k)$, then the contraction operator according to $x_S(k) = x_c(k) + \eta_S(x_R(k) - x_c(k)) = X(k)S$ will be written as

$$S = \left(-\eta_S, \eta_R, \frac{1-\eta_S(1-\eta_R)}{N-1}, \dots, \frac{1-\eta_S(1-\eta_R)}{N-1}\right)^T, \quad (15)$$

where η_S –is the compression step parameter, which is usually set equal to 0.5.

In the process of its movement to the extremum, a GA with an optimized fitness function at each iteration loses one worst vertex in the graph search model. Acquires one new point so that at the $(k+1)$ th iteration, the new adjusted graph search model also has N vertex points.

Thus, the theoretical results obtained form the scientific and methodological basis of time series forecasting algorithms in automated power supply systems of a large region of the Republic of Uzbekistan, which operate on the basis of NFN and GA tools. The results are also recommended for solving problems of recognition, classification of non-stationary objects, ensuring the reliability of information in electronic document management systems.

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