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Adaptive Processing of Technological Time Series for Forecasting Based on Neuro-Fuzzy Networks

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Annotation: Methodological bases for identification, data processing for forecasting technological time series based on the synthesis of soft computing apparatus (dynamic models, neural networks, neuro-fuzzy networks, genetic algorithms) in various combinations have been developed. A generalized prediction optimization algorithm based on a hybrid model with mechanisms for determining and adjusting the weights of neurons, coefficients of synaptic connections, activation functions, determining the number of layers and neurons in the layers of neural networks with a rational architecture is proposed.

Keywords: technological time series, neural network, neuro-fuzzy network, genetic algorithms, hybrid model.

Relevance of the topic. Currently, in the scientific publications of leading scientists and specialists on the creation of methods and algorithms for solving problems of forecasting non-stationary time series of technological processes, improvement of existing, development and development of new methods of identification, data processing and forecasting based on soft computing is noted as a priority area of research [1-3]. Methods and algorithms for forecasting technological time series (TTS) are based on the approaches, principles of stochastic, neural network, fuzzy modeling, which make it possible to obtain effective tools for optimizing identification, approximation, analysis, data processing based on the use of genetic algorithms (GA) [4].

This study proposes an approach that is aimed at applying various principles of stochastic, evolutionary modeling, probabilistic methods, feature extraction mechanisms, hidden patterns, as well as using the properties of self-adaptation, self-organization, self-learning of neural networks (NN) in predicting technological time series (TTS) [5.6].

A generalized algorithm for optimizing TTS prediction based on a hybrid model has been developed that combines the computational schemes of NN and GA, mechanisms for determining and adjusting neuron weights, synaptic connection coefficients, activation functions, the number of layers and neurons in layers, as well as variables of rational network architecture [7].

Generalized TTS prediction algorithm. As a basic model, a three-layer NN and a simple GA with a mechanism for determining and setting the parameters of computational network schemes are considered [8].

At the initial stage, the number of layers and neurons in the layers of the NS, the weights of neurons, and the coefficients of synaptic connections are determined. And at the next stage, the tasks of finding and setting the

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parameters of a suitable activation function, rational architecture NN, establishing linear and nonlinear dependencies between the inputs and outputs of the hybrid model are solved.

When determining and adjusting parameters based on GA, the coefficients of synaptic connections and weights of neurons are calculated using genetic operators that perform procedures for generating an individual bank.

The optimization methods used in the developed algorithms are based on statistical models of TTS prediction with mechanisms for adapting to the growth of the dimension taken into account in the feature set of the object. Algorithms should provide a reduction in computational costs caused by heuristic search methods [9].

NN and GA provide an opportunity to develop and improve the efficiency of an adequate description of an object, search for local and global minima, optimization of NN training, and adaptive control of forecast reliability.

Another feature of the approach is that the mechanisms of adaptive prediction are based on the principles of selecting the length of the chromosome in an individual and filling the chromosome in loci and alleles. Genetic operators are executed to generate the initial population, select the best individual, run the crossover, mutation, inversion, generation of subsequent populations of the individual. The GA implements a probabilistic selection of a chromosome, which uses a random number generator [10].

A GA computational scheme has been developed based on the use of generation mechanisms and banks of individuals, population estimation, fitness functions, selection of individuals, crossing, and mutation. The key issues of determining the parameters of computational schemes of structural components, learning algorithms for neural networks and setting their parameters are solved [11].

To save the necessary data on previous searches, reduce the search time for new iterations, a knowledge base (KB) is used, the presence of which makes it possible to perform the GA [12].

The KB logs all launches related to the search for the optimal NN model. Along with such solutions, the results of extracting statistical parameters, dynamic characteristics, useful properties and patterns from the database (DB) are obtained. The generation and formation of new individuals used in setting the parameters of computational schemes provide a high convergence of the network [11].

One of the requirements for the GA is that the individual generation block must eliminate the shortcomings of stochastic search, use the unique features of evolutionary modeling, work on the basis of the initial data banks generated, and generate individuals for the subsequent stages of the algorithm. The KB determines the starting position of the generation of an individual, which helps to quickly reach the solution of the problem of learning the NN. The NN learning block receives a common chromosome with the parameters of the corresponding designed NN structures, the optimization method used, and the NN learning algorithm. At the output of the NN layers, matrices of weights of synaptic connections are issued. The features of the operators of mutation, crossover, and inversion of GA are as follows:

- crossover works only with the main chromosome;
- inversion works with the main chromosome and child ones, which are responsible for the inputs and outputs of the network;
- the mutation works with the main chromosome and the daughter one, which is responsible for the number of neurons in the NS;
- Generation of a new individual in the KB.

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The integrated operator at each iteration of the GA with a modified chromosome is represented as:

{Mutation $_{OX}$ (γ_1); mutation$_{X3}$ (γ_2); crossover $_{OX}$(γ_{31}); inversion $_{OX}$(γ_4); inversion$_{X1}$(γ_5); inversion$_{X2}$(γ_6)},

Where γ_i is the probability of executing a certain statement?

Segmentation of the generated chromosomes is proposed, which serve as a tool for optimizing the display of TTS [13].

Let the TTS be described by a sequence of discrete $z(t_1), z(t_2), \ldots, z(t_N)$ measurements ordered at equally spaced points in time. The representation of the TTS in the system involves segmentation, which is associated with the division of the time series into sections corresponding to certain structural units taken as constants. The segmentation procedure makes it possible to determine the behavior and properties of the TTS, each homogeneous segment in which is evaluated by the function

$$F = M(A, \sigma),$$

Where A the weight coefficients of the TTS are points; σ is the variance of the error when comparing the obtained point with the desired one based on the NN.

The segmentation error variance is based on the generalized ratio of determining the likelihood function at each time point n:

$$D_n = -(n-r)\ln\sigma_2^2 - r\ln\sigma_1^2 + n\ln\sigma_0^2.$$

The decision about the presence of a jump in the TTS at the time of r is made if the predetermined threshold value of the D_0 is exceeded.

The TTS segmentation algorithm uses a multi-step regression model, which is synthesized with a NN with a time delay.

The NN learning algorithm is modified based on the Kalman filtering algorithm. The combination of algorithms made it possible to speed up the learning process and improve the accuracy of TTS identification [14, 15]. The following tuning parameters were used to optimize the coupled models:

n_0 - Segment start;

m_0 Is the length of the reference window?

k_0 Is the length of the test window?

W_g, W_t, W_c - reference, test and expanding windows;

ε_g, ε_t, ε_c - prediction errors for the corresponding window;

$s(n:m)$ -section TVR;

U_{inp}, U_{hid}, U_{out} is the number of neurons by network layers;

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H_g, H_t, H_c – is the maximum log-likelihood estimate for the reference, test, and expanding windows;

d – Estimation of the distance of the reference window;

$d(n)$ - Threshold comparison of the distance of the reference window.

The TTS segmentation algorithm is performed in the following steps:

Step 1. Setting parameters for TTS segmentation is carried out when the value of $d(n) < Th_1$. Subsequently, the test window is attached to the expandable and reference windows.

Step 2. The test window is shifted. If the value is $d(n) > Th_1$, then the segment boundary is set.

Step 3. The cyclic procedure of creating a set of windows and setting parameters continues until the processing of all time series is completed. Next, the TTS segmentation algorithm tunes the NN parameters by implementing the learning algorithm and determining the U_{inp}, U_{hid}, U_{out} -number of layers and neurons in the network layers. The minimum segment size is calculated;

$O_j(S_i)$, $j = 1,...,K$ - activity of neurons in the output layer of the NN;

$S(i = 1,...,N)$ - Examples incoming in the test sample;

P_m is the interpretation vector of each example from the S sequence.

The segmentation algorithm determines the number of features; checks if the split segment matches the required one; merges it with the left segment "neighbor". Due to this, the number of TTS states transients to be detected is expanded.

A software-algorithmic complex for predicting the TTS of non-stationary objects has been developed, which includes the following software modules:

- ✓ preliminary data processing (segmentation);
- ✓ formation of training sets;
- ✓ calculation according to computational schemes of the components of the NN, the issuance of results according to the fuzzy rules of the NFN;
- ✓ NN training; setting parameters of TTS models;
- ✓ Forecast of TTS and control of reliability (accuracy) of the forecast.

The accuracy of the forecast is estimated by the averaged value of the criterion of relative standard deviation from modal examples.

Table 1 shows the results of testing the implemented algorithms, in which dynamic models, NN, NFN and GA are synthesized in different versions of performing the functions of segmentation, classification of conditional indicators. It can be seen from the results of the table that the design of the complex allows obtaining the best results with a smaller number of segments and a large number of classes.

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Table 1 TTS forecasting efficiency

Complex structures	Number of allocated segments / classes of TTS	Forecast accuracy (in %)
Synthesis of NN with GA	548/19	78,7
Synthesis of dynamic models, NN with GA	471/20	82
Synthesis of dynamic models, NFN with GA	230/29	87

Conclusion. Thus, scientific and methodological foundations have been developed for creating a software-algorithmic complex for identification, data processing for predicting TTS based on dynamic models, NN, NFN, GA, which allow you to optimize the definitions and settings of the object model parameters and improve the accuracy of forecasting compared to traditionally used statistical models.

The proposed methods and algorithms are implemented in the tasks of analyzing and predicting the parameters of power supply in large regions of the Republic of Uzbekistan.

The practical significance of the obtained research results is the proposed algorithm of simple and adaptive segmentation for extracting the hidden properties of the TTS. It has been established that the segmentation algorithm more accurately classifies the areas of change of quasi-stationary processes and provides prediction with an accuracy of 10–12%.

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