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REGULATOR OF PARAMETERS OF NON-STATIONARY OBJECTS BASED ON HYBRID MODELS OF NEURAL NETWORK LEARNING OPTIMIZATION

Annotation

The problem of improving existing and developing new methods and algorithms for data mining based on the combination of dynamic models, neural network, neuro-fuzzy network, genetic algorithms for identifying non-stationary objects is formulated and solved. The developed mechanisms are aimed at obtaining tools that can significantly improve the accuracy of data analysis and processing, the stability of neural network training algorithms with the least time costs. Simplified search procedures and mechanisms for setting parameters using genetic algorithms are implemented to optimize network learning.

Key words: non-stationary objects, identification, optimization, neural network, neuro-fuzzy network, genetic algorithm.

Relevance of the topic. The knowledge, useful properties and regularities extracted from the data expand the possibilities of developing tools for solving demanded practical problems such as recognition, classification, forecasting and decision-making based on objective logical conclusions. Therefore, the development of methods, algorithms and systems of data mining (SDM) that make it possible to increase the efficiency of implementation and the possibilities of models for identifying and processing data of non-stationary objects with multivariate actions and serving to improve and develop information technologies is a topical research topic [1,2].

In existing approaches, the processes of processing primary data into information, and information into knowledge, are carried out by constructing methods based on technologies for searching for correlations, characteristic trends, relationships and patterns through various statistical algorithms for recognition and clustering, regression and correlation analyses. However, analysis methods based on statistical models are focused on testing pre-formulated hypotheses and produce a “rough” result of operational-analytical data processing [3, 4].

Even at the initial stage, SDM algorithms involve the use of data processing technology based on methods and models for extracting and using knowledge of a new type and supports solving the following problems [5]:

- recognition and classification, diagnostics of situations, phenomena, non-stationary processes based on the synthesis of methods and algorithms of fuzzy sets, fuzzy inferences, neural networks;
- forecasting of non-stationary objects, processes based on samples of dynamic data based on the apparatus of soft computing - neuro-fuzzy networks and genetic algorithms;
- Optimization of the description of non-stationary objects, determination and tuning of parameters of data mining models based on the combination of capabilities, development of methods and algorithms for fuzzy inferences, neural networks and evolutionary modeling.

Optimization of information processing of non-stationary objects. As effective tools for building data mining systems (DMS) of non-stationary objects serve the components of the mathematical apparatus of soft computing based on neural networks (NN), evolutionary modeling, genetic algorithms (GA), which are used in the identification and approximation of non-stationary objects [6].

It is proposed to train neural networks with forwarding and backpropagation of errors using traditional gradient methods, least-squares methods, and their modifications, which are associated with solving large-scale problems and significant computational costs [7]. The mechanisms for searching and setting the parameters of the structural components of a multilayer NN are aimed at optimizing learning and suggest methods for synthesizing stochastic modeling algorithms, search with annealing, bans, as well as a self-organizing learning mechanism [8].

A feature of the developed hybrid model for optimizing NN learning is the use of genetic algorithms (GA) as a parameter controller and a mechanism for providing simplified settings for neuron weights, synaptic connection coefficients, rational network structure, and the number of neurons in NN layers [9].

Improvement and development of methods for optimizing NN learning is carried out by executing genetic operators to generate a bank of individuals that serve as additional information support in determining and setting the parameters of synaptic connections, neuron weights, and activation functions [10].

The definition and tuning of the parameters of the NN components are based on the use of the length of the chromosome (individuals), the content of the chromosome (locuses and alleles) and private parameters determined using the operators of crossover, mutation, inversion, selection of the best individuals, generation of initial and subsequent populations. For a probabilistic selection of a chromosome from a bank of individuals, a random number generator is used, rational training samples are formed, a database (DB) from the time series of a non-stationary object [11].

The composition of the algorithms of the DMS system includes mechanisms for the synthesis of random search with annealing and with stochastic modeling, which is used to select informative parameters about successful previous searches.

To determine the set of parameters of the NN components and reduce the search time, the tasks of saving the necessary data on previous searches (successful and unsuccessful), setting heuristic algorithms at each new training iteration, forming knowledge bases (KB), logging all runs that represent the results of analysis, extracting statistical parameters, dynamic characteristics, useful properties, and data patterns [12]. On fig. Figure 1 shows the topology of a hybrid learning model for the NN with the help of a GA.

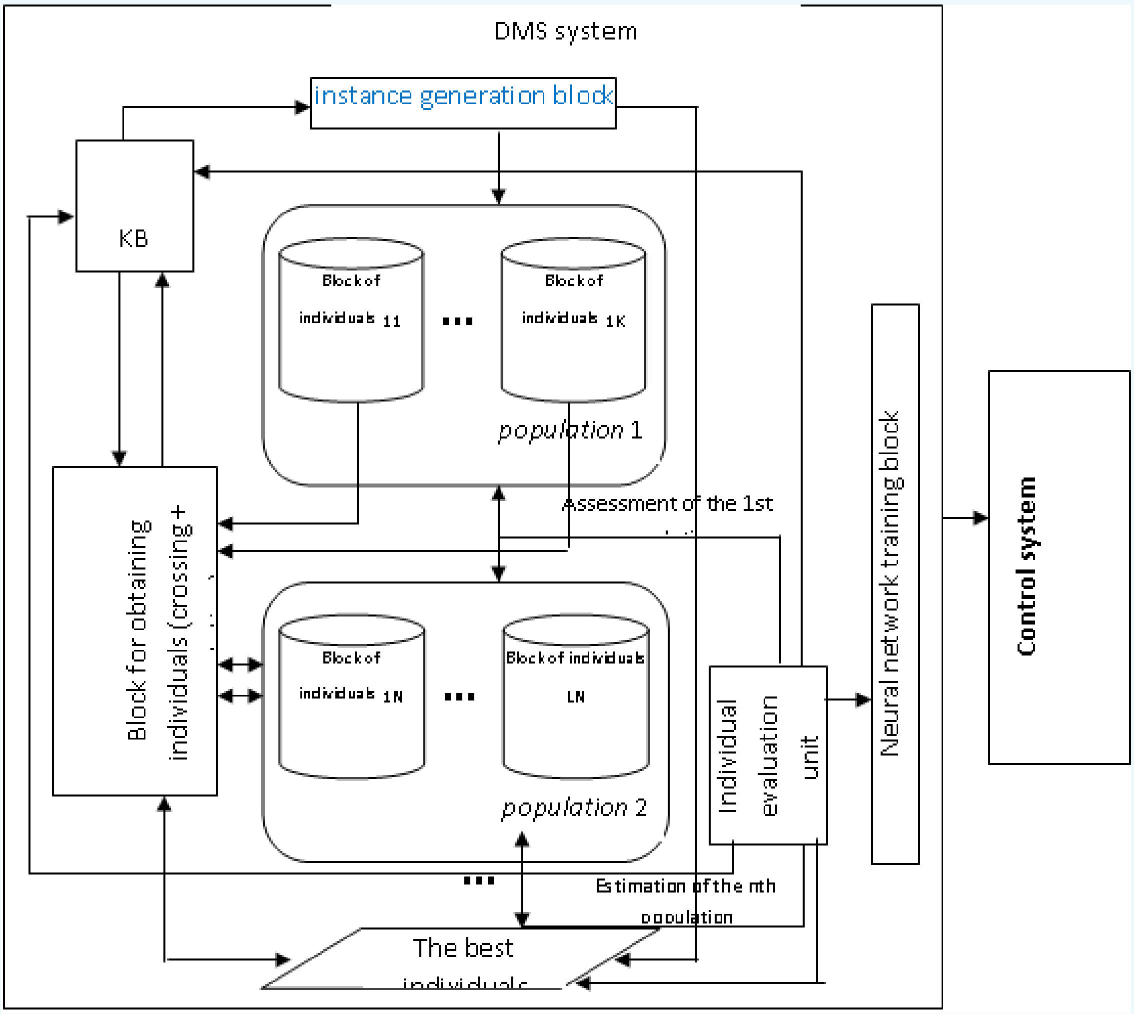

Figure 1. Synthesis of NN with GA.

The key tasks of optimizing the training of the NN are the formation of a knowledge base, the creation of a generation block, and the acquisition of new individuals.

The individual evaluation block selects the next generation according to the principle of "roulette" and tournament selection of individuals for crossing and mutation and is independent of the other topology blocks.

The unit for generating individuals works not only during the formation of initial banks, but also in subsequent stages.

The KB defines the rules for generating individuals starting from the starting position. The learning block of the NN receives data on the common chromosome, the parameters of the designed NN, the learning process, the method, speed, and schedule of learning [13].

At the output of each layer of the network, matrices of weights of synaptic connections are issued.

Further development of methods for constructing DMS systems is based on the implementation of a neuro-fuzzy network (NFN) based on GA, in which fuzzy coding and tuning of membership functions of linguistic variables of inputs and outputs are performed [14].

Optimization of NFN training based on GA. A five-layer NFN with an error backpropagation algorithm is implemented.

The proposed network synthesizes a zero-order Sugeno fuzzy inference model, has two input variables EZ and EF, and the network output is determined by the linguistic variable VK [15].

Algorithms for tuning the membership functions (MF) of linguistic terms are implemented, which are performed in accordance with the information for one training cycle of the NN.

The considered fuzzy network inference algorithm contains 8 fuzzy rules.

The dimension of the term set of the output variable T_{VK} is equal to the number of rules.

The coinciding values of the terms correspond to the condition $v_{k7} = v_{k8} = 0$.

In a five-layer NFN, the layers have the following destination [16].

Layer 1. Defines the fuzzy terms of the input parameters. The outputs of the nodes of this layer are the values of the MF for specific values of the inputs. Each layer node is adaptive with MF $\mu_{A_i}(x)$, where x is the input of the i-th node, $i = 1,\ldots,n$; A_i is a linguistic fuzzy variable associated with this node.

Triangular, trapezoidal, S-shaped, and Z-shaped MFs are chosen for the terms of input variables.

Layer 2. This layer is non-adaptive and generates messages of fuzzy rules. Each node is connected to those nodes of the first layer that form the prerequisites of the corresponding rule. In the layer, a fuzzy logical operation "AND" is performed on the parameters of the rule's premises. The outputs of the neurons of this layer are the degrees of truth (weight) of the messages of each -th fuzzy rule, calculated by the condition

$$w_j = \min\lfloor \mu_{EZj}(EZ), \mu_{EFj}(EF) \rfloor, \; j = 1,\ldots,7.$$

The weight of eight fuzzy rules is determined by the formula

$$w_8 = 1 - \mu_{EF8}(EF).$$

Layer 3. Carries out the normalization of the degree of execution of the rules. The non-adaptive nodes of this layer calculate the relative degree (weight) of the execution of the fuzzy rule

$$\overline{w_j} = w_j \sum_{j=1}^{8} w_j$$

Layer 4. A crisp number v_{kj} defining the conclusion of each j-th rule is considered as a fuzzy set with a singleton MF. The adaptive nodes of this layer calculate the contribution of each fuzzy rule to the network output

$$y_j = \overline{w_j v_{kj}}, \ j = 1,\ldots,8.$$

Layer 5. The non-adaptive node of this layer summarizes the contributions of all rules:

$$y = \sum_{j=1}^{8} y_j .$$

The discrepancy error between the experimentally measured parameter v_L and the calculated network output VK is determined by the condition

$$\delta = \sqrt{\frac{1}{N} \sum_{t=1}^{N} [v_L(t) - VK(t)]^2} \to \min ,$$

where N is the number of measurements in the training data sample v_L.

Hybrid learning is optimized by a combination of least squares and backpropagation.

Experimental results. Modeling of control processes was carried out in the MATLAB environment with the Fuzzy Logic Toolbox extension package [17].

The training sample contains $N = 947$ observations. The initial value of step 10^{-4} in the direction of criterion δ is set when changing the parameters of the MF. The allowable change in the step size per iteration is 20%. Before training the network, the value of the learning criterion is $\delta = 0{,}0972$, and after 200 iterations, $\delta = 0{,}0859$.

The decrease in the parameter δ is achieved due to the mechanisms of synthesis of heuristic search algorithms with annealing and with stochastic modeling based on the Markov chain.

A feature of learning the NN is the prohibition of changing the terms of the output variable $v_{k7} = v_{k8} = 0$, i.e. the introduction of threshold regulation of the value of workflow indicators and the transparency of NN learning through inference algorithms.

The results of testing algorithms for learning NN with backpropagation of errors, modified on the basis of synthesis of NN with GA and synthesized with NFN and GA, are obtained.

Conclusion. The analysis of the results of identifying a conditional process parameter shows that the combination of NN with GA and NFN with GA makes it possible to reduce the variation of the statistical parameters of the initial non-stationary process at the output of the DMS system. At the same time, the relative sample variance of the calculated data does not exceed 5%, which confirms the achievement of the required accuracy of analysis and data processing at much lower computational costs. There is a significant decrease in low-frequency fluctuations of the identified parameter.

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