Identification of Non-Stationary Objects Based on Training a Neural Network and Tuning the Parameters of a Generalized Model

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Abstract. Methods and algorithms have been developed for identifying non-stationary objects of various types using statistical, dynamic, neural network models, which are taken into account when solving problems of conditions of a priori insufficiency, uncertainty, low reliability of data. Mechanisms are proposed that provide effective identification based on combining the features of dynamic models with the properties of random time series. The possibilities of algorithms based on mechanisms that use statistical, dynamic, specific data characteristics, as well as the properties of self-adaptation, approximation, organization, self-learning of neural networks have been expanded. A generalized function identification algorithm has been developed and its functions have been expanded by adaptive segmentation of time series, setting the informative interval of element values, the size of the training set, training multilayer neural networks, database, and knowledge base. The training algorithms for a three-layer neural network are modified based on the mechanisms for regulating interneuronal connections in layers, weight coefficients of neurons, variable activation functions, network architecture, and superposition of continuous input-output dependencies. A software package for identifying random time series in the C++ language in the CUDA parallel computing environment has been developed to predict the annual power consumption of the industrial zone of the Samarkand region using software tools for data preprocessing, filtering, smoothing; determining the boundaries of the informative interval of time series elements.

1. Introduction

In automated production and technological complexes for various purposes (industrial, agricultural, water resources management, power consumption), information on technical and economic indicators when solving problems for identification is considered as non-stationary objects. The proposed approach allows, in turn, the widespread use of methods and algorithms for data mining (DM) based on neural networks, optimization tools for dynamic identification of random time series (RTS) in substitutions, differential, recurrent equations, and other complex dependencies [1, 2, 3, 4]. Existing technologies for solving problems of identification, search for extrema, optimization, are determined by labor-intensive calculations and the use of highly iterative algorithms. In addition, they are characterized by insufficient generalization, the use of properties of non-stationary objects, models, statistical parameters, dynamic, specific characteristics [5, 6, 7, 8].

It is necessary to research and develop a wide range of identification algorithms that contribute to the achievement of a higher quality of information processing in conditions of insufficient a priori information, parametric uncertainty, non-stationary and low data reliability [9, 10, 11, 12]. Of great importance are methods and algorithms for data processing based on the generalization of the properties and features of neural networks (NN) with the properties of dynamic models for describing random time series (RTS), as well as aimed at improving the accuracy of calculations, reducing time and cost [13, 14, 15, 16].

This work is devoted to the study, and development of methods and models, as well as the implementation of mechanisms for using the statistical, dynamic, specific characteristics of the information of non-stationary objects, the properties of self-adaptation, approximation, organization, and self-learning of the NN, designed to significantly expand the capabilities of the traditional technology of identification of the RTS [17, 18, 19, 20]..

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2. Main Part

2.1. *Basic approaches, principles and mechanisms for optimizing the identification of non-stationary objects*

An approach is proposed aimed at solving the following problems of identification of non-stationary objects: determining and setting the size of a set of training data; informative interval of parameter values; reduction of redundant features and parameters in the structure of the object description model; search for global and local extrema of the optimization function; extraction and use of statistical, specific characteristics, dynamic properties of data, features of the National Assembly; adaptive learning of NN; non-linear identification; formation of a database (DB) and a knowledge base (KB), setting model parameters [21 - 25].

The issue of optimizing the identification of non-stationary objects with the mechanism of selecting informative elements of the RTS and adaptive learning of the NN has been studied. Experimental training sets are defined and will be presented for data analysis and processing. Selected from the attribute space of the object for each identification parameter, the rules for the selection of informative elements of the RTS are defined. A training set with a RTS element is denoted by x, and S is a separate set. The attributes of the set of elements of the RTS x_j^s are: j - the serial number of the element $j = 1,2,\ldots,N$; s - sequence number of the set, where $s = 1,2,..., S$. Each input set x_j^s at the model output corresponds to the value of the variable y^s. The total interval of possible values of the RTS element is divided into a sequence of sections (segments).

The initial task is to determine the number of separating planes perpendicular to the axis of each feature, the number of segments in the total interval, the serial numbers of the segments, the left and right boundaries of the segments, and the rational size of the training set [26-29].

The task algorithm is presented in the following steps.

Step 1. Initialization of RTS identification parameters.

The vector of the input element x is specified as a matrix, the rows of which are linearized, and the columns form an array $y^* = \{y^s\}$ with binary elements.

Step 1.1. Formation of an array $\{D_j\}$, which has a size equal to the number of RTS elements N. For each parameter, the number of segments in the total range of values of the RTS element is determined.

Step 1.2. Set: $D_j = 0$, $j = 1,2,\ldots,N$, where j is the ordinal number of the current element. The number of training data set is fixed as a variable S.

Step 1.3. Set the sequence number of the current RTS element, starting from $i = 1$.

Step 2. If $i \le N$, then go to step 3. Otherwise, go to step 11.

Step 3. Enter the set $x(j) = x_i^s$ by the i-th parameter of the object into the array buffer x.

Step 3.1. Put a copy of the array $y^*: y(s) = y^s$ into the class buffer y.

Step 4. Sorting the RTS elements in the x and y arrays.

Step 4.1. Form arrays x and y in ascending order of the numbers of elements of the RTS.

Step 4.2. The sequence number of the training data set, $s = 1$, is set.

Step 4.3. If $s \le S$, then go to step 4.4, otherwise go to step 5.

Step 4.4. The serial number of the set $k = s + 1$ is set.

Step 4.5. If $k \le S$, then go to step 4.6, otherwise go to step 4.8.

Step 4.6. If $x(s) > x(k)$, then set the following variables:

$z = x(s)$; $x(s) = x(k)$; $x(k) = z$; $z = y(s)$; $y(s) = y(k)$; $y(k) = z$.

Step 4.7. Set: $k = k + 1$ and go to step 4.5.

Step 4.8. Set: $s = s + 1$ and go to step 4.3.

Step 5 Install: $s = 1$, $k = 1$.

Step 6. If $s \le S$, then to store in the buffer of arrays the k th segment from the total range of values of RTS elements, set $a^t = x(s)$ and go to step 7. Otherwise, go to step 11.

Step 7. If $s < S$, then $y(s) = y(s+1)$ is set.

Step 8. If $s = S$, then $y(s) = y(s-1)$ is set.

Step 8.1. Segment $K(i,k)$ is fixed from the total range of RTS values, k is the serial number of the segment; i -th element in inside the k -th segment.
Step 8.2. Set $A(i,k)$ and $B(i,k)$, respectively, the left and right boundaries of the segment. Go to step 10.
Step 9. If $s < S$ and $y(s) \neq y(s+1)$, then set
$K(i,k) = y(s)$; $A(i,k) = a^t$; $B(i,k) = x(s)$; $k = k+1$; $s = s+1$.
Go to step 6.
Step 10. Install: $i = i+1$, go to step 2.
Step 11. Stop.
A generalized RTS identification algorithm has been developed, which is synthesized with the mechanisms of segment selection, determination of segment boundaries in the general range of RTS element values for each parameter, selection of informative elements, formation of a rational learning set, and adaptive learning of the NN [30-34].

2.2. A generalized algorithm for optimizing the identification of the RTS.

A mechanism is proposed aimed at reducing the number of segments in the total range of values of the RTS element. It is believed that the smaller the number of segments, the more rational the set of training data will be. The segmentation-based identification mechanism uses the following parameters: $\{x, y\}$ – sets of pairs that are presented as arrays of information; $\{D_j\}$ is the number of segments in the total range of values of the RTS element; $\{A(i,k)\}$, $\{B(i,k)\}$ are the boundaries of segments $\{K(i,k)\}$; $\{K(q)\}$ are serial numbers of each segment.
The mechanism includes algorithms designed to compare the calculation results for each set of x_k and x_q, check the equivalence of RTS $[A(i,k); B(i,k)]$ and $[A(j,q); B(j,q)]$ segments, and form an informative set of training data. The informativeness of the RTS element within the boundaries of each segment and in the general range of values is estimated by the coefficient of equivalence of elements x_k and x_q. The equivalence coefficient between the k -th segment of the i -th parameter, the s -th set and the q -th segment of the j -th parameter of the g -th set in the general range of values of the RTS elements is determined from the following conditions:

$$n(x_i^s, x_j^g, k, q) = \begin{cases} 0, \ \ if \ \ K(i,k) \neq K(j,q); \\ 0, \ \ if \ \ B(i,k) < x_i^s \ or \ x_i^s < A(i,k); \\ 0, \ \ if \ \ B(j,q) < x_j^g \ or \ x_j^g < A(j,q); \\ 1, \ \ if \ \ K(i,k) = K(j,q), \\ A(i,k) \leq x_i^s \leq B(i,k), A(j,q) \leq x_j^g \leq B(j,q), \end{cases}$$

where $s = 1,2,..., S$; $g = 1,2,\ldots,S$; $i = 1,2,..., N$; $j = 1,2,\ldots,N$; $k = 1,2,..., k_i$; $q = 1,2,\ldots,k_q$.

The equivalence ratio between sets is defined as $N(i,k,j,q) = \sum_{s=1}^{S} \sum_{\substack{g=1, \\ g \neq s}}^{S} n(x_i^s, x_j^g, k, q)$.

The coefficient of mutual equivalence of sets is given as $E_{i,k,j,q} = \min\left\{\frac{N(i,k,j,q)}{N_{i,k}}, \frac{N(i,k,j,q)}{N_{j,q}}\right\} = \frac{N(i,k,j,q)}{\min\{N_{i,k}, N_{j,q}\}}$.

The coefficient of mutual equivalence between the k -segment of the i -th feature and the q -th segment of the j -th feature in the total range of values of the RTS elements for each parameter of the object is determined.
An algorithm for reducing the number of segments by equivalence coefficients with the following steps has been developed.
Step 1. Initialization. Formation of a set of training pairs $x = \{x_i\}$ and $y = \{y_s\}$, $i = 1,2,..., N$, $s = 1,2,..., S$.
Step 2. Calculate the characteristics of the training datasets.
Step 2.1. Find parameters: $A(i,k)$, $B(i,k)$, $K(i,k)$, $N_{i,k}$, k_i.
Step 2.2. Determine coefficients: $N(i,k,j,q)$, $E_{i,k,j,q}$, $E_{i,j}$.
Step 3 Install: $i = N$.
Step 4. If $i > 1$, then follow steps 4.1 and 4.2.

Step 4.1. When $\forall j$, $j \neq i$, $j = 1,2,..., (i-1)$ and $E_{i,j} = 1$, then remove x_i and install $N = N - 1$.

Step 4.2. Install: $i = i + 1$. Go to step 4.

Step 5. Install: $i = N$.

Step 6. If $i \geq 1$, then follow steps 6.1 and 6.2.

Step 6.1. Install: $k = k_i$.

Step 6.2. If $k \geq 1$, then follow steps 6.2.1 - 6.2.3, otherwise go to step 7.

Step 6.2.1. Calculate: $c = \sum_{j=1}^{N-1} \sum_{q=1}^{k_j} E_{i,k,j,q}, Ei, k, j, q = 1$.

Step 6.2.2. If $c \geq 1$, then delete the k-th segment of the i-th feature in the total range of values of the RTS element.

Step 6.2.3. Install: $k_i = k_i - 1$. Go to step 6.2.

Step 7. Stop.

An algorithm for optimizing the size of the training set based on setting the boundaries of the RTS segments has been developed. To adjust the boundaries of segments, a rule is specified, which is executed in the form if $A(i,k) \leq \mu_{i,k}(x_i) \leq B(i,k)$, then $y_i^s = K(i,k)$, where y_i^s is the sequence number of the segment in the s-th set by feature i; $\mu_{i,k}(x_i)$ is the membership function (MF) of the i-th RTS carrier.

The issues of choosing the type of membership function, determining the boundaries of the membership function, and the common interval of supports of the corresponding sets are investigated. The trapezoidal model of the MF, the rules for estimating the parameters $\mu_{i,k}(x_i)$ in the form are considered:

$$\mu_{i,k}(x_i) = \begin{cases} 0, \ \ if \ \ x_i \leq 0{,}5(A(i,k) + B(i,k-1)), \\ \dfrac{x_i - 0{,}5(A(i,k) + B(i,k-1))}{0{,}5(A(i,k) - B(i,k-1))}, \ if \\ 0{,}5(A(i,k) + B(i,k-1)) \leq x_i \leq A(i,k), \\ 1, \ if \ A(i,k) \leq x_i \leq B(i,k), \\ \dfrac{0{,}5(A(i,k+1) + B(i,k)) - x_i}{0{,}5(A(i,k+1) - B(i,k))}, \ if \\ B(i,k) \leq x_i \leq 0{,}5(B(i,k) + A(i,k+1)), \\ 0, \ if \ \ 0{,}5(B(i,k) + A(i,k+1)) \leq x_i. \end{cases}$$

П - shaped membership function are defined as $\mu_{i,k}(x_i) = \mu_{i,k_S}(x_i)\mu_{i,k_Z}(x_i)$.

The values of the parameter $\mu_{i,k_S}(x_i)$ for S-shaped, $\mu_{i,k_Z}(x_i)$ for Z-shaped membership function are evaluated according to the following conditions:

$$\mu_{i,k_S}(x_i) = \begin{cases} 0, \quad if \ x_i < 0{,}5(A(i,k) + B(i,k-1)); \\ \dfrac{1}{2} + \dfrac{1}{2}\cos\left(\dfrac{x_i - A(i,k)}{0{,}5(A(i,k) - B(i,k-1))}\pi\right), \\ if \ 0{,}5(A(i,k) + B(i,k-1)) \leq x_i \leq A(i,k); \\ 1, \quad if \ x_i > A(i,k); \end{cases} \qquad \mu_{i,k_Z}(x_i) = \begin{cases} 1, \quad if \ x_i < B(i,k); \\ \dfrac{1}{2} + \dfrac{1}{2}\cos\left(\dfrac{x_i - B(i,k)}{0{,}5(A(i,k+1) - B(i,k))}\pi\right), \\ if \ B(i,k) \leq x_i \leq 0{,}5(B(i,k) + A(i,k+1)); \\ 0, \quad if \ x_i > 0{,}5(B(i,k) + A(i,k+1)). \end{cases}$$

For each training set, the compliance of the membership function parameters is checked. The correspondence of the parameters $\mu^0(x^s)$ and $\mu^1(x^s)$ to the common interval of values of the RTS element requires the following condition to be met: $\mu^0(x^s) = \max \mu_{i,k}(x_i)$; $\mu^1(x^s) = \max \mu_{i,k}(x_i)$.

Output y_i^s is represented by the rule $y^s = \begin{cases} 1, & \mu^1(x^s) > \mu^0(x^s); \\ 0, & \mu^1(x^s) \leq \mu^0(x^s). \end{cases}$

If there is a maximum correspondence of the parameter $\mu^1(x^s)$ to the total range of values of the MF element, then the segment $K(i,k) = 1$ is fixed. Otherwise, $K(i,k) = 0$. A mechanism for adaptive learning of a three-layer NN is proposed.

Mechanism of variables adaptation in teaching a three-layer NN.

The activation functions of a three-layer NN are defined as

$$\varphi^{(3,1)}\left(w^{(3,1)},x^{(3,1)}\right)=\sum_{j=1}^{2} w_j^{(3,1)}x_j^{(3,1)}+w_0^{(3,1)}\ ;\quad \psi^{(3,1)}(x)=\begin{cases}0, & if\ x<0,\\ 1, & if\ x\geq 0;\end{cases}\quad \varphi_j^{(2,i)}\left(w^{(2,i)},x^{(2,i)}\right)=\min_j\left(w^{(2,i)},x^{(2,i)}\right),\quad i=1,2\ ;$$

$$\psi^{(2,i)}(x)=\max_j \varphi_j^{(2,i)}\left(w_j^{(2,i)},x_j^{(2,i)}\right),\ i=1,2\ ,$$

where $\psi^{(\eta,i)}(x)$ is the activation function of the i -th neuron of the η -th layer of the NN; $\varphi_j^{(\eta,i)}=f(w^{(\eta,i)},x^{(\eta,i)})$ - function of the postsynaptic potential of the j -th output of the i -th neuron in the η -th layer of the network; $w^{(\eta,i)}$ – weight coefficients of the input $x^{(\eta,i)}$, the i -th neuron in the η -th layer of the network.

The weight coefficients $w^{(\eta,i)}$, i -th neuron, in layer η are determined by the following conditions:

$$w_j^{(\eta,i)}=\begin{cases}0,\ if\ \eta=2, i=1, K(p,q)=0, j=z(p,q),\\ p=1,2,...,N, q=1,2,...,k_p,\\ 0,\ if\ \eta=2, i=2, K(p,q)=1, j=z(p,q), p=1,2,...,N,\\ q=1,2,...,k_p,\\ 1,\ if\ \eta=2, i=1, K(p,q)=1, j=z(p,q), p=1,2,...,N,\\ q=1,2,...,k_p,\\ 1,\ if\ \eta=2, i=2, K(p,q)=0, j=z(p,q), p=1,2,...,N,\\ q=1,2,...,k_p,\\ 0,\ if\ \eta=2, i=1,2, j=0,\\ 0,\ if\ \eta=3, i=1, j=0,\\ 1,\ if\ \eta=3, i=1, j=1,\\ -1,\ if\ \eta=3, i=1, j=2,\end{cases}$$

where $z(p,q)=q+\sum_{v=1}^{P-1}k_v$.

The mechanism for setting the parameters of the NN structural components was developed on the basis of the conjugate gradient optimization method. Various NN models, methods for calculating the weights of neurons, interneuronal connections, choosing an appropriate activation function, NN architecture, and searching for global and local extrema have been studied [35-40].

The NN learning optimization mechanism based on the conjugate gradient method represents modifications of gradient descent with a computational scheme for setting the weights of interneuron connections in the form $\Delta w_{ij}^{(q)}=\eta\frac{\partial E}{\partial w_{ij}}$, where $\Delta w_{ij}^{(q)}$ is the value of the change in the weights of connections between the i -th neuron of the ($q-1$)-th layer and the j -th neuron of the q -th layer;

η is the coefficient that determines the learning rate of the NN, $0<\eta<1$.

The change in the weights of connections between neurons are defined as $\Delta w_{ij}^{(q)}=-\eta\delta_j x_i$, where δ_j is the error value of the j -th neuron in layer q ; x_i is the value of the i -th input signal for the j -th neuron of layer q .

To adjust neuron offsets, x_i is replaced by "1". The error value of the residual type in the output layer of the NN is estimated as $\delta_i=(f_{i,k}(S))'(f_{i,k}-y_{i,k})$, where $y_{i,k}$ is the required output of the NT; $f_{i,k}$ is the actual output value of the k -th neuron for the i -th set of training data; $(f_{i,k}(S))'$ is the value of the derivative of the activation function of the k -th neuron for the i -th set.

The output errors of the hidden layers are estimated as $\delta_i^{(q)}=(f_i^{(q)}(S))'\sum_j w_{ij}\delta_j^{(q+1)}$, where $\delta_i^{(q)}$ is the error of the i -th neuron in the q -th layer of the NN; $\delta_j^{(q+1)}$ - error of the j -th neuron in the $(q+1)$ -th layer of the NN; w_{ij} - weight of interneuron connections.

The value of the error of the first layer of the NN proportionally affects the value of the errors of neurons in the next layer. The change in the error value of the output NN layer for the k-th set of training data determines the network learning rate. When the activation function of the NN is given as a sigmoid $f(S)=\frac{1}{1+e^{-aS}}$, a is a constant, then its derivative is given as $f'(S)=af(S)(1-f(S))$. The value of errors in the activation function of the i-th neuron is determined as

$$\delta_i = af_{i,k}(1-f_{i,k})(f_{i,k}-y_{i,k}), \tag{1}$$

which for the q - th NN layer is calculated as

$$\delta_i^{(q)} = af_i(1-f_i)\sum_j w_{i,j}\delta_j^{(q+1)}. \tag{2}$$

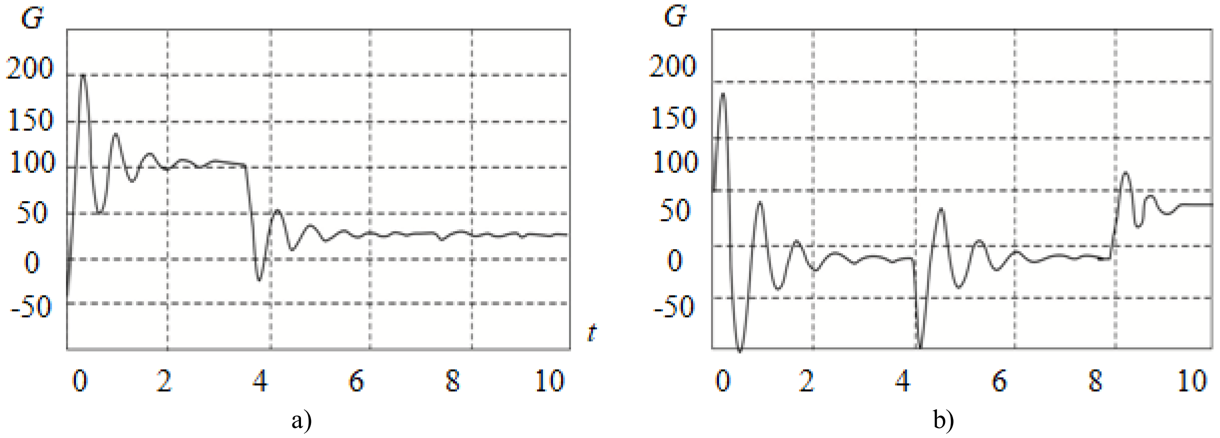
Setting the values of the weights of interneuronal connections is performed according to the computational scheme

$$w_{ij}(t+1)=w_{ij}(t)-\eta\delta_j x_i+\alpha\Delta w_{ij}(t-1), \tag{3}$$

where η and α are the inertia coefficients given in the interval $[0,1]$.

The obtained expressions (1)-(3) reflect the peculiarity of the proposed approach to improving the computational schemes of the NN components.

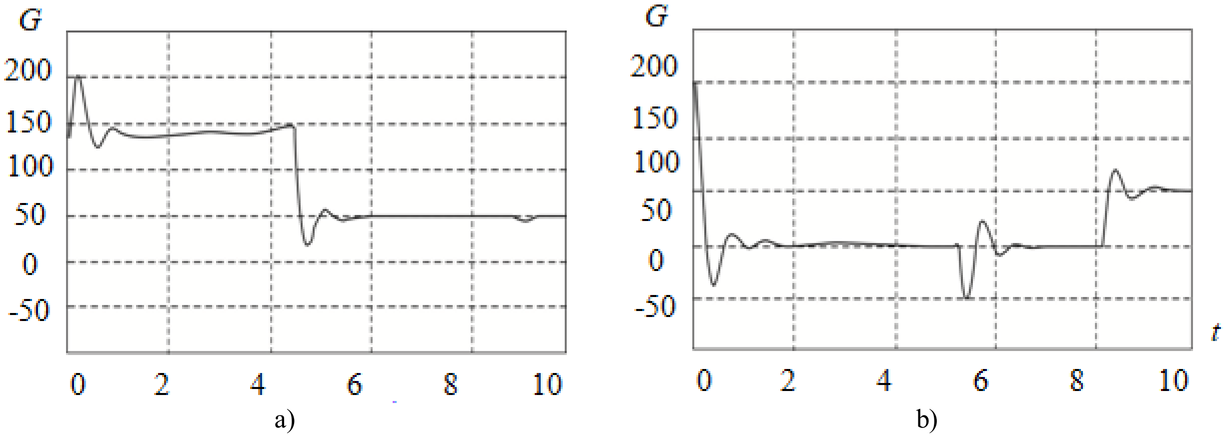
In figure 1 shows graphs of the output values of the non-stationary object approximator without the use of control mechanisms and parameter settings for the jumps of the specified input signal and the obtained output result according to the statistical and neural network models.



a) b)

Fig. 1. Graphs of the RTS approximator a) according to the statistical model; b) based on NN.

In figure 2 illustrated the results of the approximation of the dynamic and neural network models of a non-stationary object with the tuning algorithm for the output process.



a) b)

Fig. 2. Graphs of the RTS approximator with the algorithm for setting the model parameters: a) according to the statistical model; b) based on NN.

A mechanism for retranslating the properties of the RTS, dynamic identification models on the NN, instead of complex nonlinear recurrent dependencies, is proposed.

The learning algorithm of the NN includes the following computational schemes: setting the parameters of the structural components of the NN; providing a dialogue with the formed databases and knowledge bases; extraction and use of statistical, specific characteristics, dynamic properties of information; computational schemes of NN structural components. Thanks to the implementation of these computational schemes, the algorithm acquires additional advantages, as well as the possibility of significant expansion due to the synthesis of smoothing and filtering algorithms for sharp jumps, random bursts in the RTS dynamics.

The generalized identification algorithm is based on the use of a matrix data representation model, and the knowledge base involves the synthesis of integer matrices of the following types: matrix Q, which specifies the description of an object parameter with k - attribute characteristics in the form of a sequence $z_1,..., z_m$; a difference matrix R that specifies the results of splitting (segmentation) of the RTS for clustering; matrix I, which defines the description of the object parameter with informative characteristics in the form of $z^*_1,..., z^*{}_m$; matrix E that defines the estimates of the dynamic characteristics of the RTS.

The matrix model is given in interval form. Informative features z_j^* $(j \in \{1,2,..., m\})$ are allocated for each parameter of the identification model in the form of one row of the matrix Q. The results are compared with the row elements of matrix Q.

For what, from the set of rows of the matrix R, one column matrix R' is formed, in which non-informative elements of the RTS are marked, as well as placed as an element of the matrix Q. A binary diagnostic test matrix T is formed, the columns of which are compared with the column of the matrix Q. In each row of the matrix T, informative features are marked with a "+" sign.

The matrix model is synthesized with the implication matrix (U), in which various criteria, rules, conditions, and patterns are specified to identify features in an informative data set composed of different parameters. The learning algorithm with network parameter tuning includes the following steps.

Step 1. The weight coefficients of neurons w are set, where k is the weight index of the j-th neuron in the i-th layer of the network.

Step 1.1. The output O_n of the network is calculated and the value $E_{\max}$ of the network error function is determined.

Step 2. Sequence numbers of the presented training data sets are registered.

Step 3. The total value of the network error function is calculated for the input sets of training pairs $\bar{x} = \bar{x}^n$, $\bar{y} = \bar{y}^n$.

Step 4. The neuron weight coefficients w_{ijk} are adjusted. The weights are corrected in the direction from the last layer to the first.

Step 5. The value of the network error function E is corrected.

Step 6. If $E > E_{\max}$, then go to step 2.

Step 7. If $n < N$, then counting $n = n+1$ go to step 3.

Step 8. Finish.

It is proved that the generalized learning algorithm of the NN with parameter tuning with a strong variation of the elements of the RTS becomes more stable and converges 4-5 times faster than the algorithms built on the basis of typical computational schemes for learning the NN..

3. Conclusions

Scientific and methodological foundations for optimizing the identification and processing of data of non-stationary objects with mechanisms for setting the informative range of values of the RTS elements, the size of the training data set based on the segmentation of the RTS, adaptive learning of the NN, the formation of a database and a knowledge base have been developed.

A generalized algorithm has been developed that synthesizes mechanisms for setting the boundaries of RTS segments, selecting an informative data set, calculating feature equivalence coefficients, and adaptive learning of the neural network. High-precision tools for identification of RTS and data processing, adaptive learning of the NN in real time have been obtained.

The algorithms have transparent structures, are error tolerant, and address the shortcomings of highly iterative algorithms. The properties of the NN and non-stationary objects are effectively emulated, as a result of which the accuracy of the RTS forecasting increases to the required level and becomes less expensive.

A generalized RTS identification algorithm has been developed and implemented in the MATLAB package environment. The mechanisms for setting the informative interval of RTS values, adaptive segmentation, adjusting the size of the NN training set, neurons in layers, coefficients of interneuronal connections, network architecture, functional dependence "input-output" are implemented.

The efficiency of algorithms for identification, RTS segmentation, adaptive learning of the NN has been studied and the results obtained have been compared with the efficiency of the traditional NN learning algorithm.

A software package for identifying RTS has been developed to predict the technical and economic indicators of annual power consumption by enterprises in the industrial zone of the Samarkand region, which is represented by the following functional modules for data pre-processing, filtering, smoothing, RTS segmentation; definition of segment boundaries, the informative interval of parameters.

References

1. Yu. V. Vizilter, Image processing and analysis in machine vision tasks: A course of lectures and practical exercises, Moscow: Fizmatkniga, 672, (2010).
2. D. V. Shashev, Information-measuring equipment and technologies, Tomsk, 544 – 550 (2016).
3. I.I. Jumanov , S.M. Xolmonov, Optimization of identification of non-stationary objects due to information properties and features of models, *IOP Conf. Series: Materials Science and Engineering* **1047**(1), 012064 (2021)
4. G. M. Popova and V. N. Stepanov, Automation and telemechanics, **1**, 131-142 (2004)
5. O.I. Djumanov , S.M. Kholmonov, Optimization of learning the neuronetworking data processing system for non-satinary objects recognition and forecasting, *4th International Conference on Application of Information and Communication Technologies* **2010**, 5612037 (2010)
6. S. V. Kuleshov, Yu. A. Aksenov and A. A. Zaitseva, “Innovative Science,” **5**, 82-86 (2015)
7. D.O. Isroilovich, X.S. Maxmudovich, Effective recognition of pollen grains based on parametric adaptation of the image identification model, *International Conference on Information Science and Communications Technologies* **2020**, 9351486 (2020)
8. I.I. Jumanov, O.I. Djumanov, R.A. Safarov, Recognition and classification of pollen grains based on the use of statistical, dynamic image characteristics, and unique properties of neural networks, *11th World Conf. “Intelligent System for Industrial Automation* **1323**, 170-179 (2020). doi: 10.1007/978-3-030-68004-6_22
9. V.G. Ivanova, A.I. Tyajev, Cipher signal processing and signal processors, PGUTI, Samara (2017)
10. J.I. Ibragimovich, D.O. Isroilovich, S.R. Abdullayevich, Optimization of identification of micro - objects based on the use of characteristics of images and properties of models, *Int. Conf. on Information Science and Com. Tech.* **93**, 51483 (2020). doi: 10.1109/ICISCT50599.2020.9351483
11. N.A. Borisenko, S.B. Orexov, Application of wavelet - transformations for the analysis of ECG and RVG signals, *Injenernaya Fizika* **5,** 9-12 (2002)
12. I.I. Jumanov, R.A. Safarov, L.Ya. Xurramov, Optimization of micro-object identification based on detection and correction of distorted image points, *AIP Conference Proceedings* **2402**, 070041 (2021)
13. A. Boucher, P. Hidalgo, M. Thonnat, J. Belmonte, C. Galan *2nd European Symposium on Aerobiology*, Vienna (Austria) (2000)
14. I.I. Jumanov, O.I. Djumanov, R.A. Safarov, Recognition of micro-objects with adaptive models of image processing in a parallel computing environment, *Journal of Physics: Conference Series* **1791**(1), 012099 (2021)
15. A.K. Tsytsulin, Sh.S. Fahmi, E.I. Kolesnilov, S.V. Ochkur, Functional interchange of transmission rate and complexity of the coder continuous signal, *Information Technology* **4**, 71–77 (2011)
16. Jumanov, I., Safarov, R., Optimization of the Processing of Images of Pollen Grains Based on the Use of Their Specific Characteristics and Geometric Features, AIP Conference Proceedings, **2637**, 040016 (2022)
17. J. Turan, L. Ovsenik, A. Kolesarova, 2010 Video surveillance systems, *Acta Electrotechnica et Informatica* **10**, 46–53 (2010)
18. Jumanov, I., Djumanov, O., Xolmonov, S., Mechanisms of image recovery optimization in the system for recognition and classification of micro-objects, AIP Conference Proceedings, **2686**, 020009 (2022)
19. Z. Xu, U. Bagci, A. Mansoor, et. al. 2015 *Medical Physics* **42**, 3896-3910 (2015)
20. I.I. Jumanov, R.A. Safarov, O.I. Djumanov, Mechanisms for using image properties and neural networks in identification of micro-objects, 16th IEEE Int. Conf. on Application of Information and Communication Technologies, AICT 2022 - Proceedings, (2022). doi: 10.1109/AICT55583.2022.10013633
21. R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classification, John Wiley & Sons, New York (2001)
22. A.S. Durai, A.E. Saro, M. Phil, *GVIP Journal* **6**, 122-128 (2006)
23. Yu.Ye. Voskoboynikov, Wavelet filtering of signals and images, NGASU, Novosibirsk (2015)

24. H.A. Borisenko, A.D. Fertman, Automated analysis of experimental data using wavelet-transformation, *Pribori i Texnika Eksperimenta* **2**, 28-34 (2003)
25. C.M. Costa, S. Yang, Counting pollen grains using readily available, free image processing and analysis software, *Annals of Botany* **104**, 1005–1010 (2009)
26. G.Y. Larina et. al., Automated identification of images of pils grains with similar textural features modern trends in the development of science and technology, *2nd International Scientific and Practical Conference*, Belgorod (2015)
27. K. Blatter, Wavelet analysis, Fundamentals of Theory, Technosfera, Moscow (2004)
28. D.D. Kosheleva, A.V. Doronina, Fourier Transform and Fast Fourier Transform, *Innovasii. Nauka. Obrazovaniye* **38**, 626-632, (2021)
29. BM Kruglikov, New Directions in Pattern Recognition and Time Series of Discrete Data, *Internauka* **185**, 16-23 (2021)
30. D. Forsayt, D. Pons, Computer vision. Modern approach, Vilyams (2004)
31. R. Baldock, J. Graham, Image processing and analysis. A practical approach, Oxford University Press, New York (2000)
32. Ya. Furman, Introduction to contour analysis and its applications to image and signal processing, Fizmatlit, Moscow (2002)
33. S Mallat, A wavelet tour of signal processing, Academic Press (1999)
34. A.A. Jarkix, V.A. Kvashenko, Comparison of the representation accuracy of Gaussian wavelets of different orders, *Bulletin of the Murmansk State Technical University* **24**, 218−223 (2009)
35. V.I. Volovach, M.V. Shakurskiy, A Method for Increasing the Speed of Cipher Filters Based on the Moving Discrete Fourier Transform, *Elektrotexnicheskiye i informasionniye kompleksi i sistemi* **3**, 20-22 (2010)
36. S.V. Shvidchenko, D.A. Bezuglov, Synthesis of algorithms for discrete wavelet analysis of image fragments under a priori uncertainty on a random background, *Uspexi sovremennoy radioelektroniki* **5**, 031-038 (2013)
37. G.M. Popova, V.N. Stepanov, *Automation and telemechanics* **1**, 131-142 (2016)
38. B. Verma, M. Blumenstein, S. Kulkarni, *Journal of Intelligent Systems* **9**, 39-54 (1999)
39. A.V. Chernov, *Fast Method for Local Image Processing and Analysis* **9**, 572-577 (1999)
40. M.M. Almahrouq, A.I. Bobrovsky et al., Precision, speed and complexity of devices for image coding by control points, *Inf. Tech., Mechanics and Optics* **16**, 678–688 (2016)