Optimization of identification of non-stationary objects due to information properties and features of models

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Abstract. Constructive approaches, principles, methods of optimal identification of random time series of non-stationary objects with mechanisms of using statistical parameters, dynamic characteristics, specific features, and data patterns are proposed. Models and algorithms for hybrid identification have been developed that combine the capabilities of statistical, dynamic models, and a three-layer neural network. Mechanisms for adjusting model variables are implemented, taking into account the structural complexity, stochasticity of links between the elements of the random time series, ambiguity of dynamics, a large number of variables, the impact of the external environment. In the solutions of optimization problems, probabilistic and soft computing, self-organizing, predictive, adaptive properties of neural networks and dynamic modeling are used. A generalized algorithm for the identification of non-stationary objects is built on the basis of the mechanisms for identifying segments, boundaries, the general interval of element values, the selection of informative elements, and the formation of a training set. A simplified computational scheme for identifying non-stationary objects is implemented on the basis of 4-order orthogonal polynomials, a cubic extrapolation spline function, a linear Kalman filter, and a three-layer neural network. A software complex for identification in the C ++ language in the parallel computing environment "CUDA" has been developed and implemented.

1. Introduction

In technological process control systems, environmental monitoring, navigation, ecology, metrology, information from non-stationary objects of a very large volume is presented in the form of random time series (RTS), which are characterized by highly variable statistical parameters, dynamic characteristics, and the tasks of identification and data processing are carried out under conditions a priori insufficiency, parametric uncertainty [1]. The importance of the optimization problem increases especially even more when considering multidimensional non-stationary objects with mechanisms for extracting useful properties, hidden patterns, specific features of RTS, and adaptation of variable identification models [2].

Constructive approaches, principles, and methods for optimizing the identification and processing of RTS with mechanisms for using statistical parameters, dynamic characteristics, specific features, hidden regularities of non-stationary objects are proposed, which meet the requirements for taking into account the complexity of the structure, stochasticity of connections between components, the ambiguities in dynamics, a large number of variables, and environmental influences. Other features of the developed approaches are the implementation of hybrid identification of non-stationary objects based on combining the capabilities of statistical, dynamic models, neural networks (NN) with mechanisms for
setting variables. The obtained solutions to problems are based on the implementation of probabilistic and soft computing, mechanisms for using self-organizing, predictive, adaptive properties of NN, as well as simulation of non-stationary processes.

2. Main part
For the design of adequate models and algorithms for optimal identification of RTS, a wide range of statistical and dynamic models has been studied, such as trend, autoregression, multivariate regression, adaptive smoothing, sliding dynamic, cognitive, algebraic polynomials, orthogonal-polynomial, linear and nonlinear filters, interpolation and extrapolation spline functions. The efficiency of the mechanisms was investigated according to the criterion of the minimum mean-square error of identification and the characteristics of the gains of dynamic RTS. A multidimensional polynomial Voltaire series has been proposed as a character model for identifying RTS, which allows eliminating the disadvantages inherent in similar models. Below is a methodology for identifying the RTS of non-stationary objects.

2.1. Hybrid identification of non-stationary objects
A finite multidimensional Voltaire series model $H_m[x(n)]$ is given as

$$y_m(n) = H_m[x(n)] = \sum_{n_1, \ldots, n_m \in R_r}^m \sum_{j=1}^r h_m(n_1, \ldots, n_m) \prod_{j=1}^r x(n - n_j),$$  \hspace{1cm} (1)

where $r$ - polynomial dimension, $r \in R_r$; $m$ - polynomial order; $n_j = [n_{j1}, \ldots, n_{jr}]$ - the reference area that is represented $r$-a dimensional lattice of form $R_r = \{\langle n_{j1}, \ldots, n_{jr} \rangle : 0 \leq n_{ji} \leq N_i - 1; i = 1, \ldots, r \}$, where $h_m(n_1, \ldots, n_m)$ is the multidimensional kernel of the model, depending on the arguments $n_j$. Reference area $R_r$ is obtained by lexicographic ordering.

A simplified computational scheme is proposed for the implementation of the polynomial model by representing it in the form of an equivalent matrix form, the elements of which are specified by a vector of the form

$$h^T = [h_1^T, h_2^T, \ldots, h_M^T]$$

with a unique coefficient $L_M = \sum_{m=0}^M C_{n+m-1}^m = C_{n+M}^M$, where $C_n^m$ - number of combinations.

The multidimensional polynomial model is represented in linear form

$$y(n) = h^T x_n^T L_M^T,$$  \hspace{1cm} (3)

where $x_n^T = [L_M^T (x_n^{(2)} - x_n^{(M)})^T]$ - vector of products of input parameter samples.

The minimum root mean square error of identification of the RTS, based on the input parameters represented by the expanded matrix

$$X = \begin{bmatrix} x_1^T \\ \vdots \\ x_l^T \\ \vdots \\ x_l^T \end{bmatrix} = \begin{bmatrix} 1 & \left(x_1^{(2)}\right)^T & \ldots & \left(x_1^{(M)}\right)^T \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \left(x_l^{(2)}\right)^T & \ldots & \left(x_l^{(M)}\right)^T \end{bmatrix}.$$

The following system of equations is solved

$$y = Xh,$$  \hspace{1cm} (4)
where \( h \) – vector of coefficients of the polynomial model; \( X \) – matrix of input parameters; \( \chi_i^T \) – matrix rows, \( i = 1, \ldots, J \).

It is required to obtain estimates of the vector of input parameters taking into account the dynamics of their change. In this regard, equation (4) is transformed into the equation of dynamics

\[
h_{k+1} = h_k + \varphi_k; \quad y_k = X_k h_k + e_k, \quad k \geq s.
\]

The equation allows you to extract the following statistical characteristics of the modeled process:

\[
M\{\varphi_k\} = 0, \quad M\{\varphi_k^T\} = Q\varphi(k); \quad M\{e_k\} = 0, \quad M\{e_k e_k^T\} = R_{e(k)};
\]

\[
M\{h_0\} = \bar{h}_0, \quad M\{(h_0 - \bar{h}_0)(h_0 - \bar{h}_0)^T\} = M_0,
\]

where \( M \) – sign of mathematical expectation.

The components of the equation are defined as

\[
\bar{h}_k = (X_k^{0T} W_k^{-1} X_k^0)^{-1} X_k^{0T} W_k^{-1} y_k^0,
\]

\[
X_0^0 = \begin{bmatrix} X_0^0 \end{bmatrix}, \quad X_k^0 = \begin{bmatrix} 1 & X_k^0 \end{bmatrix}, \quad y_k^0 = (y_{k-1}^0, y_k^T)^T, \quad y_0^0 = (\bar{h}_0^T, y_k^T)^T.
\]

\[
\varphi_k^0 = (e_k^{0T}, e_k^T)^T, \quad e_k^{0T} = \varphi_k^{0T} - X_k^{0T} \varphi_k^{0T}, \quad \varphi_k = (e_k^T, e_k^T)^T, \quad e_0 = \bar{h}_0 - h_0.
\]

\[
M\{\varphi_k^0\} = 0, \quad M\{\varphi_k^0 e_k^T\} = W_k, \quad W_k = \begin{bmatrix} s(e_k^{0T}, e_k^T) & s(e_k^{0T}, e_k^T) \\ s^T(e_k^{0T}, e_k^T) & s(e_k^{0T}, e_k^T) \end{bmatrix},
\]

\[
s(\varphi_k, \varphi_k) = M\{ (\varphi_k - \bar{\varphi}_k)(\varphi_k - \bar{\varphi}_k)^T\}, \quad \bar{\varphi}_k = M\{ \varphi_k \}, \quad \bar{\varphi}_k = M\{ \varphi_k \}.
\]

For what, the least weighted squares method is used. The components of equation (5) are obtained by the following assumptions: there are matrices of the following types of \( W_k^{-1} \) and \( X_k^{0T} W_k^{-1} X_k^0 \): the \( (X_k^{0T} W_k^{-1} X_k^0)^{-1} \) matrix does not exist; the coefficients are obtained in the form

\[
\bar{h}_k = (X_k^{0T} W_k^{-1} X_k^0)^+ X_k^{0T} W_k^{-1} y_k^0,
\]

where "+" - sign of matrix pseudo inversion; the components of the \( \bar{h}_{k+1} \) matrix are defined as

\[
\bar{h}_{k+1} = \bar{h}_{k+1} + K_{k+1}(y_{k+1} - X_{k+1}\bar{h}_{k+1}), \quad \bar{h}_{k+1} = \hat{h}_k + \hat{\varphi}_k,
\]

where

\[
K_{k+1} = \sum_{k=1}^{(1)} \left( \sum_{k=1}^{(2)} \left( X_k^T M_{k+1} X_k + R_{e(k+1)} \right) - X_k^T N_{k+1} \right) = M_{k+1} = p_k + Q\varphi(k); \quad M_{k+1}^0 = p_k + Q\varphi(k);
\]

\[
\sum_{k=1}^{(2)} = X_k^T M_{k+1} X_k^T + R_{e(k+1)} - X_k^T N_{k+1} = \left( X_k^T N_{k+1} \right)^T, \quad N_{k+1} = E\left( (\bar{h}_{k+1} - \bar{h}_k)^T e_k^T \right), \quad p_k = \left( X_k^{0T} W_k^{-1} X_k^0 \right)^-;
\]

\[
p_{k+1} = E\left( (h_{k+1} - \bar{h}_{k+1})(h_{k+1} - \bar{h}_{k+1})^T \right) = M_{k+1} - K_{k+1} \sum_{k=1}^{(1)} = \sum_{k=1}^{(1)}{ }_{k+1}, \quad R_{e(k)} \] - output hybrid model.

For the existence of matrix \( W_k^{-1} \), it is necessary that matrix \( R_{e(k)} \) be non-degenerate. If the matrix \( W_k^{-1} \) is degenerate, then the estimates of the coefficients \( \bar{h}_{k+1} \) are determined in the form
\[ \tilde{h}_{k+1} = \Omega_{k+1}^{(1)} \tilde{h}_k + \Omega_{k+1}^{(2)} y_{k+1}, \quad \text{where} \quad \Omega_{k+1} = \begin{bmatrix} \Omega_{k+1}^{(1)} & \Omega_{k+1}^{(2)} \end{bmatrix}. \]  

(6)

Components \( \Omega_{k+1} \) are calculated as

\[ \Omega_{k+1} = [I - M_{k+1}X_{k,2}^T(X_{k,2}M_{k+1}X_{k,2})^{-1}X_{k,2}] \tilde{h}_{k+1} + M_{k+1}X_{k,2}^T(X_{k,2}M_{k+1}X_{k,2})^{-1} \mu_{k,2} T, \]

where \( X_{i,2} = \mu_{k,2} X_i; \ \Omega_{k+1}^{(1)} \) и \( \Omega_{k+1}^{(2)} \) - determined according to (6); \( \mu_{k,2} \) – non-zero diagonal elements of the matrix \( \mu_k \), which consists of \( q \) columns with numbers \( j_1, j_2, \ldots, j_q \); \( \mu_k \) an orthogonal matrix diagonalizing \( W_k \) with non-zero first diagonal elements \( q_k \); \( q_k \) - rank of matrix \( W_k \).

The algorithms for the identification of RTS based on the polynomial nonlinear Voltaire series have been developed and implemented, which are tested using real data of the technological process of bakery production in the MATLAB PC environment. Identification algorithms based on a polynomial nonlinear model and mechanisms for setting variables by a recurrent expression provide more accurate calculations with a significantly smaller amount of computation.

Table 1 shows the results of comparing the effectiveness of the hybrid identification algorithm of the RTS with the adaptation mechanism (AM), which demonstrates better characteristics than the algorithm without using the adaptation mechanism (WAM).

| Conditional parameters | Algorithms |
|------------------------|------------|
| \( T_p, \ c \)          | 85         | 38         |
| \( g_1(t) \)            | 4.5        | 3          |

For setting the parameter the lag step is set to \( g(s) = 2.5 \).

Figure 1 illustrates the output of the hybrid model identification algorithm in the form of values of controlled variables, which are obtained by taking into account the nature and regularity of input actions and the result of the correction. A graphical comparison of the output indicator of the identification quality \( g(t) \) by algorithms with WAM and without AM is carried out. The algorithm of the hybrid model with AM takes into account changes in the structure and dynamics of a non-stationary object, regulates, and tunes parameters in a wide range.
A generalized algorithm for identifying non-stationary objects has been built and implemented, in which the synthesized mechanisms for identifying segments, boundaries, the total interval of values of each parameter, the selection of informative elements of the RTS, and the formation of a set of training a model [6].

Optimization of RTS identification by the implemented hybrid RTS model is achieved through the following mechanisms: regulation of the size of the input set; choosing an adequate model; segmentation; clustering; formation of an informative set; analysis of coefficients of factors' influence on the effective indicator and elasticity [3,4]. Let us outline the issue of optimization of hybrid identification of non-stationary objects based on the selection of informative elements of the RTS.

2.2. Optimization of identification of non-stationary objects based on mechanisms for selecting informative elements

The peculiarity of the mechanism of selection and formation of an informative set of RTS elements is as follows. The following attributes of the set of informative elements of RTS $x_{j}^{s}$ are set: $x$ - RTS element; $S$ - training set; $j$ serial number of the element in the set; $j = 1, 2, ..., N$; $s$ - serial number of sets, where $s = 1, 2, ..., S$.

It is considered that the element of the input set $x_{j}^{s}$ at the output of the identification algorithm corresponds to the value of the element $y^{s}$, which is represented in the following steps.

Step 1. Initialization of RTS identification parameters.

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

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

Step 1.2. Install: $D_{j} = 0$, $j = 1, 2, ..., N$, where $j$ is the ordinal number of the current element. The amount of the training data set is fixed in the form of the $S$ variable..

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

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

Step 3. Enter the set $x(j) = x_{j}^{i}$ into the $x$ array buffer by the $i$ -parameter of the object.
Step 3.1. Enter a copy of array \( y^* : y(s) = y^* \) into the class buffer.

Step 4. Sort RTS elements in arrays \( x \) and \( y \).

Step 4.1. Form arrays \( x \) and \( y \) in ascending order of numbers of RTS elements.

Step 4.2. Sets the ordinal number of the training dataset, \( s = 1 \).

Step 4.3. If \( s \leq S \), then go to step 4.4, otherwise go to step 5.

Step 4.4. The serial number of the set is set to \( k = s + 1 \).

Step 4.5. If \( k \leq S \), 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. Install: \( k = k + 1 \) and go to step 4.5.

Step 4.8. Install: \( s = s + 1 \) and go to step 4.3.

Step 5. Install: \( s = 1, k = 1 \).

Step 6. If \( s \leq S \), then \( a' = x(s) \) is set to store in the buffer the \( k \)-th segment arrays from the total interval of values of the RTS elements and go to step 7. Otherwise, go to step 11.

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

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

Step 8.1. Segment \( K(i,k) \) is fixed from the total interval of RTS values, \( k \) is the sequence number of the segment; \( i \)-th element in inside \( k \)-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 \( K(i,k) = y(s) \); \( A(i,k) = a' \); \( B(i,k) = x(s) \); \( s = s + 1 \). Go to step 6.

Step 10. Install: \( i = i + 1 \), go to step 2.

Step 11. Stop.

The task of optimizing the identification of RTS was solved using a mechanism for checking the belonging of the values of its elements within the permissible limits. For what, the interval of presentation of the elements of the RTS is determined, which is limited to the left and right portions of \( [y_{left}, r_{right}] \), and also defines the centroid of the element values as \( C_A \).

\[
C_A = \left[ \ldots \int_{z \in Z_1} \ldots \int_{z \in Z_n} \frac{1}{n} \sum_{r=1}^{n} w_r \cdot z_r, \sum_{r=1}^{n} w_r \right] = \left[ y_{left}, y_{right} \right].
\]

(7)

The width of the interval for the presentation of the RTS element is specified as \( [c - s, c + s] \), \( c = (y_{left} + y_{right}) / 2 \); \( s = (y_{right} - y_{left}) / 2 \).

Calculation of the centroid \( C_A \) is related to the problems of minimization and maximization. Suppose that \( z_r = c_r + s_r \) and \( z_r = c_r - s_r \). The two endpoints of the interval: \( y_{left} \) and \( y_{right} \) are found by function \( y(w_1,...,w_n) = \sum_{r=1}^{n} w_r \cdot z_r / \sum_{r=1}^{n} w_r, w_r \in [h_r - \Delta_r, h_r + \Delta_r]; h_r \geq \Delta_r, r = 1, n \).

Let us differentiate the \( y(w_1,...,w_n) \) function with respect to the argument \( w_k \). It is believed that \( \sum_{r=1}^{n} w_r > 0 \), then we get \( \frac{\partial}{\partial w_k} y(w_1,...,w_n) = 0 \).

If \( w_k = y(w_1,...,w_n) \), then \( \frac{\partial}{\partial w_k} y(w_1,...,w_n) = \frac{\partial}{\partial w_k} \left( \sum_{r=1}^{n} w_r \cdot z_r / \sum_{r=1}^{n} w_r \right) = (z_k - y(w_1,...,w_n)) / \sum_{r=1}^{n} w_r, \)
Let us investigate the conditions when \( y(w_1,\ldots,w_n) = z_k \); 
\[
\frac{\sum_{r=1}^{n} w_r \cdot z_r}{\sum_{r=1}^{n} w_r} = z_k.
\]
If \( z_k > y(w_1,\ldots,w_n) \), then as \( w_k \) increases, \( y(w_1,\ldots,w_n) \). If \( z_k < y(w_1,\ldots,w_n) \), then as \( w_k \) decreases, \( y(w_1,\ldots,w_n) \). To solve the problem, we used the Karnik-Mendel algorithm [5]. Let be \( h_r \geq \Delta_r \), \( w_r \geq 0 \), \( r = \overline{1, n} \). The maximum value of \( w_k (k = \overline{1, n}) \) is

\[
h_k + \Delta_k (h_k - \Delta_k).
\]
Function \( y(w_1,\ldots,w_n) \) reaches its maximum value when: \( w_k = h_k + \Delta_k \) for those values of \( k \) for which \( z_k > y(w_1,\ldots,w_n) \); \( w_k = h_k - \Delta_k \) for those values of \( k \) for which \( z_k < y(w_1,\ldots,w_n) \).

Function \( y(w_1,\ldots,w_n) \) reaches its minimum value when: \( w_k = h_k - \Delta_k \) for those values of \( k \) for which \( z_k > y(w_1,\ldots,w_n) \); \( w_k = h_k + \Delta_k \) for those values of \( k \) for which \( z_k < y(w_1,\ldots,w_n) \).

It is assumed that \( z_r = c_r + s_r \), \( (r = \overline{1, n}) \); \( z_r \) are ordered \( z_1 \leq z_2 \leq \ldots \leq z_n \).

The algorithm includes the following steps.

Step 1. Let \( w_r = h_r \) for \( r = \overline{1, n} \). \( y^r = y(h_1,\ldots,h_n) \) is calculated.

Step 2. The definition is \( k(1 \leq k \leq n - 1) \) such that \( z_k \leq y^r \leq z_k+1 \).

Step 3. Let \( w_r = h_r - \Delta_r \) for \( r \leq k \) and \( w_r = h_r + \Delta_r \) for \( r > k + 1 \).

Calculated \( y'' = y(h_1 - \Delta_1,\ldots,h_k - \Delta_k,h_{k+1} + \Delta_{k+1},\ldots,h_n + \Delta_n) \).

Step 4. If \( y^r = y'' \), then the calculations end, and \( y'' \) is the maximum of the \( y(w_1,\ldots,w_n) \) function. If \( y^r \neq y'' \), then go to step 5.

Step 5. We assume \( y^r = y'' \) and go to step 2.

The algorithm requires no more than \( n \) iterations, where one iteration consists of steps 2-5.

The algorithm for determining the minimum of the \( (w_1,\ldots,w_n) \) function is specified by similar procedures for \( z_r = c_r + s_r \), \( (r = \overline{1, n}) \).

Calculated \( y^* = y(h_1 + \Delta_1,\ldots,h_k + \Delta_k,h_{k+1} - \Delta_{k+1},\ldots,h_n - \Delta_n) \). For what, it is assumed that \( w_r = h_r + \Delta_r \), \( w_r = h_r - \Delta_r \), \( r \geq k + 1 \).

The generalized identification algorithm also includes a mechanism for checking the equivalence of RTS segments for each set, i.e. matching \([A(i,k);B(i,k)]\) to \([A(j,q);B(j,q)]\), as well as the formation of an informative training set. The generalized algorithm for the identification of RTS is optimized based on the regulation of the following parameters: \( \{x, y\} \) - sets of pairs, which are represented as arrays of information; \( \{D_j\} \) - the total range of values of the segment element; \( \{A(i,k)\}, \{B(i,k)\} \) - segment boundaries; \( \{K(i,k)\}, \{K(q)\} \) - sequence numbers of the element of each input and output segment.

2.3. Implementation of the generalized algorithm for hybrid identification of non-stationary objects

Mechanisms for optimization of the generalized identification algorithm based on segmentation of the sequence of RTS points have been developed. The RTS sequence segmentation mechanism is assigned the functions of time division and extraction of the RTS property. Each homogeneous segment is defined by the \( M(A,\sigma, D_n) \) model with tuples: \( A \) is the weighting factor of the segment in the RTS sequence, \( D_n \) - variance of segmentation error, \( \sigma \) - identification error.

The generalized algorithm for identifying RTS is investigated in the variants of sequential synthesis of orthogonal polynomials of 4, 5 orders, cubic interpolation and extrapolation spline functions, a linear Kalman filter, and a three-layer NN.
Optimization mechanisms regulate the following parameters: \( n_0 \) – the beginning of the segment; \( W_g, W_t, W_e \) – reference, test and expanding windows; \( m_0 \) – the length of the reference window; \( k_0 \) – the length of the test window; \( e_g, e_t, e_e \) – segmentation errors of the corresponding window; \( s(n:m) \) – section in the sequence of the RTS; \( U_{inp}, U_{hid}, U_{out} \) – the number of neurons in the layers of the network; \( H_g, H_t, H_e \) – the values of the likelihood estimates for the reference, test and expanding windows; \( d \) – distance; \( d(n) \) – threshold for distance estimation.

The effectiveness of the mechanisms of segmentation and training of NN in hybrid identification of RTS was studied under the conditions: when the value \( d(n) < Th \); the test window is attached to the reference window; the test window is shifted by \( d(n) > Th \); segment boundaries are regulated; the parameters of the computational circuits of the structural components of the NN are adjusted. The accuracy of the RTS identification is estimated by the function

\[
F = \sum_{j=1}^{m} \frac{k}{\sum |y_j^i - \hat{y}_j^i|} K_j \cdot m,
\]

where \( m \) – the number of measurements in the training set, \( y_j^i \) – desired value of NN output, \( \hat{y}_j^i \) – modal value of the output of the RTS identification model; \( K_j \) - coefficient of efficiency of training neural network, the value of which is achieved when taking into account the dynamics and properties of nonstationarity of the RTS, regulating the size of the training set [6].

Figure 2 illustrates a graph of the coefficient built depending on the number of RTS segments. The coefficient varies over a certain segment interval within the values of local extrema. The graph also reflects the quasi-stationarity of the process. It has been found that a small number of segments causes an unacceptably high deviation of calculations from the reference characteristics. An excessively large number of segments leads to redundant iterations of the identification algorithm, which slows down NN learning and increases costs.

![Figure 2. Values of the efficiency factor.](image)

In another experimental study, the generalized algorithm for hybrid identification of RTS is considered with a variant of the synthesis of an autoregressive, orthogonal polynomial of the 4th order, cubic extrapolation spline, linear filter, segmentation mechanism. Developed and implemented software modules of the generalized algorithm for identifying RTS, the test results of which are given in table. 2.
Table 2. Results of testing the generalized algorithm for identifying RTS.

| Mechanisms                              | Models and algorithms                  | Number of segments/classes allocated | Identification accuracy in %.
|-----------------------------------------|----------------------------------------|--------------------------------------|-------------------------------|
| RTS segmentation                        | Autoregressive                         |                                      | 78.7                          |
| Modified RTS segmentation               | Orthogonal polynomials                 | 548/19                               | 61.9                          |
| Object identification                   | Spline functions, line filter          |                                      | 82                            |
| Object identification with configuring NN parameters | Three-layer NN                         |                                      | 87                            |
| Identification with parameter setting   | Synthesis of training algorithms for NN, segmentation, identification of RTS, parameter settings | 471/20                               | 97                            |

Developed and implemented a software package (SP) for identification in C++ in the parallel computing environment "CUDA". The PC includes the following functional modules:

- data preprocessing, which performs identification, approximation, filtering, smoothing, contouring, and segmentation of the RTS, determining the boundaries of the RTS segments;
- formation of an informative interval of values of the RTS element for each parameter of non-stationary objects, reduction of the excess number of segments; selection of informative elements, determining the rational size of the informative training set, checking the equivalence and mutual equivalence of elements in the informative set;
- optimization of identification based on mechanisms for selecting informative elements, segmentation, checking whether elements belong to the permitted boundaries, regulating the size of the training set, segment boundaries;
- adaptive training of a three-layer neural network based on mechanisms for setting variable structural components of the network and regulating the boundaries of segments, the interval of values of elements of the RTS.

3. Conclusion

Constructive approaches, principles, methods of optimization of identification of RTS of non-stationary objects with mechanisms of using statistical parameters are proposed, dynamic characteristics, specific features, and hidden patterns in the data that meet the requirements of taking into account the complexity of the structure, stochastic relationships between components, the ambiguity of dynamics, a large number of variables, the impact of the external environment.

Methods for hybrid identification of non-stationary objects based on combining the capabilities of statistical, dynamic models, NN, and variable setting mechanisms are proposed. The mechanisms of probabilistic and soft computing are implemented, which use self-organizing, predictive, adaptive properties of NN, as well as dynamic modeling of non-stationary processes. A SP based on a generalized algorithm for identifying RTS of non-stationary objects has been developed and implemented, which is tested in the MATLAB package environment.

The efficiency of the obtained RTS identification tools has been proved, which have shown themselves with high accuracy, resistance to errors and are less iterative algorithms.

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