ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ, СИСТЕМНИЙ АНАЛІЗ ТА КЕРУВАННЯ

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METHOD AND ALGORITHMS OF NONLINEAR DYNAMIC PROCESSES IDENTIFICATION

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МЕТОДИКА ТА АЛГОРИТМИ ІДЕНТИФІКАЦІЇ НЕЛІНІЙНИХ ДИНАМІЧНИХ ПРОЦЕСІВ

Purpose. Increasing accuracy of dynamic models of the complex nonlinear processes for solution of the tasks for these processes control.

Methodology. Structural-parametric identification of nonlinear dynamic processes including the identification of the model structure based on selection by non-shift criterion, as well as self-reactance identification of the optimum structure model by the regularity criterion through the whole sampling of experimental data.

Findings. The algorithms of global and local optimization of nonlinear dynamic process models realizing the procedure of structural-parametric identification by their structural and self-reactance optimization were developed, which allows getting the models of extra accuracy.

Originality. The method of identification of nonlinear dynamic processes consisting of procedures for estimation of the state and characteristics of the process, as well as their structural-parametric identification, was offered. It allows, unlike the known of methods, to fulfil the identification of these processes in the batch mode by structural-parametric and in real-time mode by self-reactance optimization of their models.

Practical value. The results of the research can be used while developing algorithms for controlling complex nonlinear processes based on their complex estimation and identification.

Keywords: *method, algorithm, identification, nonlinear process, model*

Introduction. To manage complex control objects (CO), which are characterized by nonstationarity, nonlinearity and stochasticity, it is relevant to solve the problems of identification and forecasting that allows improving the management quality of such CO due to increase of accuracy of estimation of their condition and mathematical model.

Among such complex CO there are: mobile objects, technological processes of ore-preparation (crushing and grinding), telecommunication systems, etc.

Problem definition. Identification of the process as a dynamic system consists in receiving or specifying the mathematical model of this process using experimental data; the model is expressed by means of one or another mathematical apparatus.

The process of structural-parametric identification includes the definition of the structure, estimation and optimization of CO model parameters. The first two operations are solved by generating (by means of basic functions) pretending models of various complexity and setting up their parameters with the subsequent selection of the best of them according to the chosen criteria (the optimum structure). The operation of determination of the optimum parameters is solved applying the known methods of optimization by specifying values of parameters received earlier according to the criteria of regularity through all sample of the initial data [1].

To implement the approaches considered above to the work [2], the compositional method of CO structural-parametric identification has been offered; it consists of the following:

1) formation of an identification problem with a choice of methods and criteria of structural (global) optimization, methods of constraint accounting, a model structure type; basic functions and methods of parametric optimization;

2) identification of the CO model structure based on the composition of the methods of global optimization which contain the generation of pretending model structures (basic functions), and methods of local optimization for parametric education of basic functions, and also selection of the best models according to the criteria of structural optimization;

3) identification of parameters of optimum structure model by its lead-through with the methods of local parametric optimization according to the criteria of regularity through the entire data sample.

Objectives. Development and estimation of the efficiency of the identification methods and algorithms of nonlinear dynamic processes realizing the composition method of structural-parametric identification of the complex CO.

Main research. ***Identification technique.*** The identification technique of nonlinear dynamic processes (Fig. 1) is offered based on the composition method.

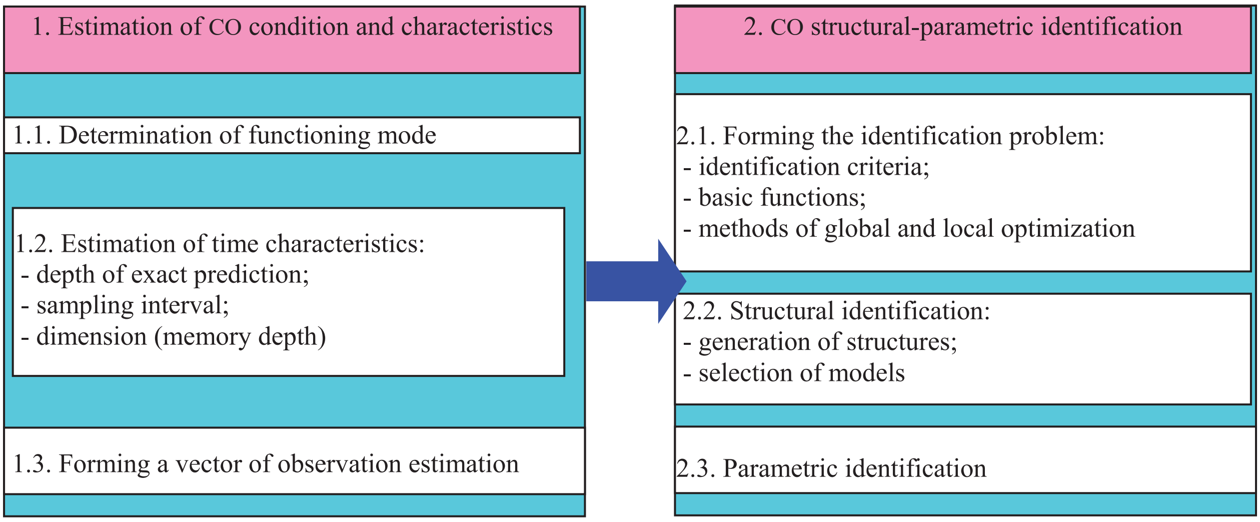

Fig. 1. The identification technique of nonlinear dynamic process

This technique consists of stages of estimating the CO condition and characteristics and its structural-parametric identification.

The estimation of the CO condition and characteristics includes:

a) the procedure of the CO functioning mode definition, containing:

- the qualitative analysis of the time signal type, its range, correlation function and wavelet transform;

- calculation of correlation entropy, being the evaluation of the Kolmogorov entropy and characterizing the CO functioning mode [3];

b) the procedure of estimating the CO temporary characteristics, containing:

- calculating the correlation interval of predictability (forecast depth) of the process, being the assessment of the interval of exact forecasting of the CO condition [3];

- determining the equivalent time of a delay in the CO by mutual correlation functions of the CO channels;

- selecting the sampling period by the value of correlation interval of predictability and interval of correlation;

- calculating the correlation dimension of an attractor, which characterizes the Hausdorff dimension [3];

- determining the dimension of attractor nesting (dimension of phase space – memory depth) of the CO by the correlation dimension of the attractor;

c) formation of the CO condition vector estimation.

The structural-parametric identification of the CO includes:

a) formation of the identification problem which is carried out with selection of:

- types of criteria of structural-parametric identification;

- basic functions;

- the structural (global) optimization method;

- methods of parametric optimization defined by selection of basic functions.

The above-described selection is carried out at the stage of designing the control system for the nonlinear dynamic process and is based on aprioristic (theoretical and experimental) data;

b) structural identification carried out by means of the method composition of global and local optimization by generating the structures of the pretending models (basic functions with their structural characteristics) and selecting the best of them according to the criterion of structural optimization;

c) parametric identification consisting of determining the model parameters of the optimum structure by its lead-through with the method of local parametric optimization according to the criterion of regularity.

Identification algorithm. The error value $J_{рег}$ (criterion of regularity) is the criterion of parametric identification of the CO model. Its physical sense means that it defines the difference between the values of the output of the CO optimum structure model and the real output of the CO. Therefore, redefinition (adaptation) of the optimum parameters of the CO optimum structure model occurs in real time (Fig. 2).

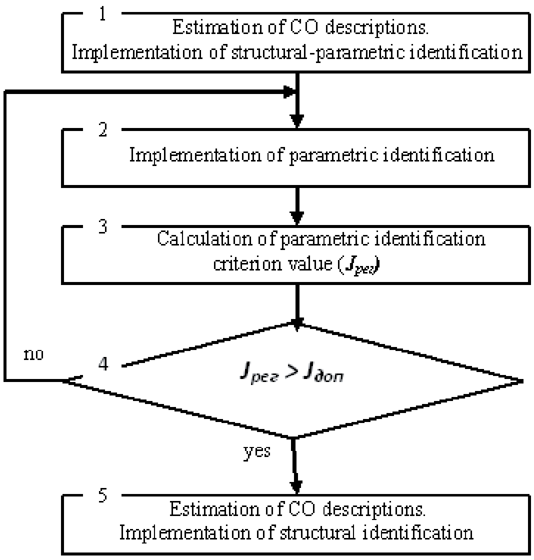

Fig. 2. The scheme of the structural and parametric identification algorithm

If the value of error $J_{рег}$ for optimum values of parameters is higher than the admissible error ($J_{рег} > J_{доп}$), it means that the CO model optimum structure determined earlier is not the same any more (for example, due to the change of the CO functioning mode). Therefore, it is reasonable to consider an error $J_{рег}$ while making a decision about the need of proceeding to the estimation of the CO characteristics and its structural identification (Fig. 2).

Otherwise, (if the error $J_{рег} \le J_{доп}$) the CO model parametric identification continues to be carried out in the real time mode.

Given this, steps 1, 5 of the algorithm in Fig. 2 are carried out in an automated mode and steps 2–4 – in an automatic one.

The generalized scheme of structural identification using the global optimization methods is as follows: direct random search (DS) and genetic algorithm (GA) [4] and basic functions in the form of Feed forward neural networks (FFNN), neural networks (NN) with radial basis function (RBF), as well as adaptive neuro-fuzzy inference system (ANFIS) [5] is given in Fig. 3.

The algorithm of global optimization using the DS method is carried out as follows:

Step 1. Formation of the initial points. Definition of structural characteristics of the model is carried out; they include the type of basic function, amount of neurons in the hidden layer, the type of activation (membership) functions of the hidden layer, as well as the type of the parametric optimization algorithm. Each point represents a vector of structural characteristics. At that, the options for the DS work are adjusted: conditions for stopping of the DS algorithm, choice of methods, means and properties of the search.

Step 2. Calculation of the value of the structural optimization criterion for the initial conditions. Using the local optimization algorithms of basic functions, the values of CO model output are determined; they are used to calculate the values of the structural optimization criterion.

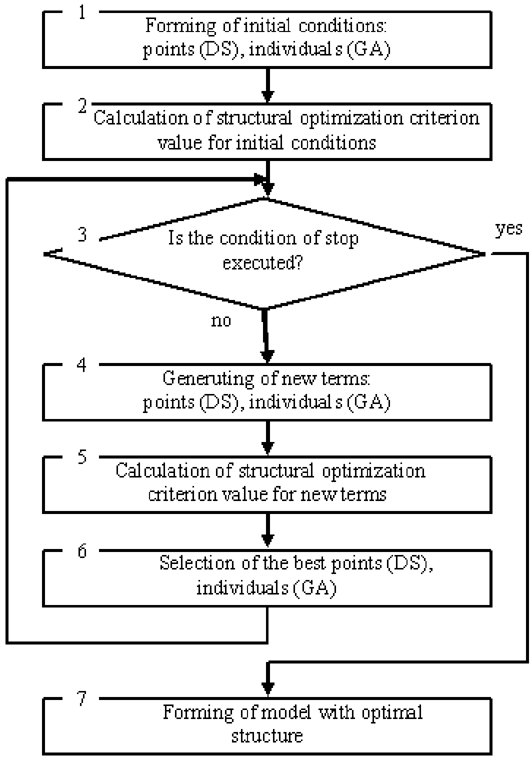

Fig. 3. Scheme of structural identification algorithm

Step 3. Is the algorithm of the stop condition fulfilled? If it is, then the transition to *Step 7* occurs, otherwise one proceeds to *Step 4*. At that, the DS stop conditions are the following:

- the number of iterations reaches the specified maximum value;
- the size of a cell (a point) is smaller than the preset value;
- the total number of calculations of the objective function values reached the maximum preset value;
- the distance between the point found in a successful poll, and the point found in an unsuccessful poll will be smaller than preset value;
- changes in the objective function for one successful poll and the subsequent successful poll will be less than the value preset.

Step 4. Generation of new points occurs due to the search methods adjusted in *Step 1.*

Step 5. Calculation of the criterion value for new points occurs similar to the calculations at *Step 2*.

Step 6. Selection of points with the best criterion values, which are entered in the new sequence of the search. Further, the transition to *Step 3* occurs.

Step 7. Formation of optimum structure model. The values of the best points (structural characteristics) corresponding to the extremum of the criterion are determined using the DS algorithm. The model of the optimum structure is formed.

The algorithm of global optimization using the GA is carried out analogously to the DS:

Step 1. Formation of the initial individuals. Each individual represents a vector with elements in the form of structural characteristics. At this stage, the adjustment of the GA options is carried out; they are stop conditions, the population size as well as formation of the genetic operators (mutation, selection, crossing-over, migration, etc.)

Step 2. Calculation of the criterion value of the structural optimization for the initial conditions.

Step 3. Here the GA stop conditions are the following:

- the number of generations reaches the preset value;
- the preset operating time of the algorithm has run out;
- the criterion value of the best individual of the current population reaches the extremum;
- there is no improvement of the criterion in the sequence of the generations following one another; the length of the sequence is set at *Step 2;*
- there is no improvement for the criterion within the preset time interval.

Step 4. Generation of new individuals occurs due to the genetic operators adjusted at *Step 1.* First, the selection of parents is fulfilled, and then the crossing-over of parents occurs followed by crossing and probabilistic mutation of the descendants. Here the share of the individuals migrating from one population to another is defined.

Step 5. Calculation of the criterion value for new individuals occurs.

Step 6. Selection of individuals with the best criterion values for new population.

Step 7. The values of the best individuals (structural characteristics) corresponding to the criterion extremum are determined using the GA. The model of the optimum structure is formed.

The generalized scheme of the parametric identification algorithm using the basic functions in the form of FFNN, NN RBF and ANFIS is given in Fig. 4.

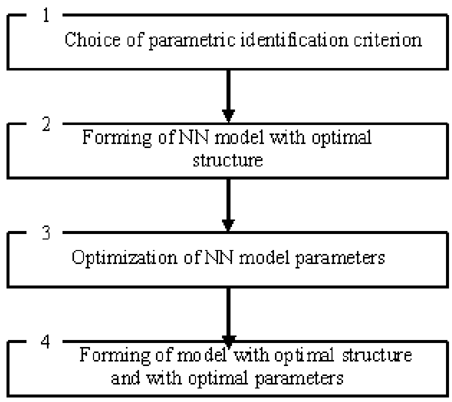

Fig. 4. The scheme of the parametric identification algorithm

The algorithm of local optimization using the basic FFDD function is carried out as follows:

Step 1. Selecting the type of the parametric identification criterion.

Step 2. Formation of the optimum structure model. The FFNN development with the following structural characteristics: memory depths, the size of the hidden layer, the function of neurons activation of the hidden and output layers as well as the parametric optimization method. The option adjustment for NN training is performed: conditions of training halt, formation of arrays of the training and test data, functions of one-dimensional search, etc.

Step 3. Optimization of the model parameters (NN training) by determining the values of the weighting coefficients according to the method of parametric optimization selected at *Step 2.* Training halt conditions are:

- the number of cycles (epochs) of training has reached the maximum preset value;
- the error has decreased to the preset level;
- time of training has reached the maximum preset value;
- the level of the error excess of the test selection in comparison with the training has reached the maximum preset value.

Step 4. Formation of the optimum structure model with optimum values of parameters corresponding to the minimum of the parametric optimization criterion (weighting coefficients of communication of input and output layers).

The algorithm of local optimization using the basic NN RBF function is carried out similarly to FFNN:

Step 1. Selection of the parametric identification criterion.

Step 2. Formation of the optimum structure model. Choice of structural characteristics of NN RBF: depths of memory, the maximum size of the hidden layer, functions of neuron activation of the hidden (RBF) layer, functions of neuron activation of the output layer, as well as the parametric optimization method. Options are adjusted for NN training; they are training halt conditions, choice of deviation value (an influence parameter), etc.

Step 3. Training halt conditions are as follows:

- the error has decreased to preset level;
- the number of neurons of the hidden layer has reached the maximum preset value.

Step 4. Formation of the optimum structure model with optimum values of the RBF parameters of neurons of the hidden layer and weighting coefficients of the output layer.

The algorithm of the local optimization using the ANFIS basic function is carried out as follows (Fig. 4):

Step 1. Selection of the parametric identification criterion.

Step 2. Generation of a Sugeno-type structure with selection of the following structural characteristics: depths of memory, functions of membership and the number of rules for decomposition at inputs.

Step 3. Training halt conditions are:

- the quantity of cycles (epochs) of training has reached the maximum preset value;
- the error has decreased to the preset level.

Step 4. Formation of the optimum structure model with the optimum values of parameters for membership functions.

Modelling. Let us consider the development of the intellectual predicting model of the complex CO by an example of the process of ore large-sized crushing (LSC), the output coordinate of which is the content in shredded ore of class +100 mm Γ_{+100}.

$$J_{регККД} = \frac{\left\| \Gamma_{+100B}[k+n] - \widehat{\Gamma}_{+100B}[k+n] \right\|}{\left\| \Gamma_{+100B}[k+n] \right\|}, \tag{1}$$

where k, n are the current time step and depth of the forecast; Γ_{+100B}, $\widehat{\Gamma}_{+100B}$ are the experimental values and values recei-ved according to the model of the CO output.

As the structural optimization criterion, the criterion of unbiasedness of the type was used

$$J_{смККД} = \frac{\left\| \widehat{\Gamma}_{+100A}[k+n] - \widehat{\Gamma}_{+100B}[k+n] \right\|}{\left\| \Gamma_{+100}[k+n] \right\|}, \qquad (2)$$

where $\widehat{\Gamma}_{+100A}$, $\widehat{\Gamma}_{+100B}$ are the values of the CO output received according to the model during its training by the training A and test B samples.

To identify the LSC process as the input signals, the experimental temporary sequences of the weighted average of input ore fineness and rigidity was used, as well as the operating influence – the size of a crusher opening.

Herewith, according to the dynamic properties of the LSC process, the depth of the forecast was $n = 3$ time steps (for compensation of delay and time to produce and realize the control actions), and the memory depth made 4 time steps. The measurement error of the LSC process variables did not exceed 10%, and the size of realization was $N = 60$ time steps (ore portions).

The DS and GA were applied during the identification as global methods of optimization. At the same time, the basic functions in the form of NN were used: cascade FFNN, NN RBF and ANFIS.

The results of global optimization of the LSC process model structure are given in Fig. 5, 6.

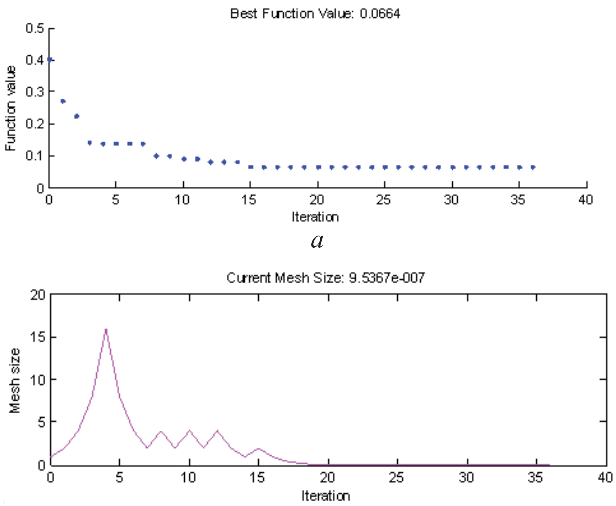

Fig. 5. Global optimization of the model structure using the DS: the convergence process (a) and the search space size (b)

The GA had a single-point crossing, selective choice of parents and formation of new population with replacement; the DS algorithm was an adaptive step of search and complete search around the current iteration. The number of iterations for the DS (for the GA generations) was limited at the level of 100 while the size of the search space for the DS (for the GA it was the size of the GA population) was 30.

With the global optimization, the following structural characteristics of the model were used (varied):

1) the basic function type including cascade FFNN, NN RBF and ANFIS;

2) the number of neurons in the hidden layer;

3) the type of activation functions (for FFNN) and membership (for ANFIS) of the hidden layer;

4) the algorithm type of the parametric optimization (for FFNN and ANFIS).

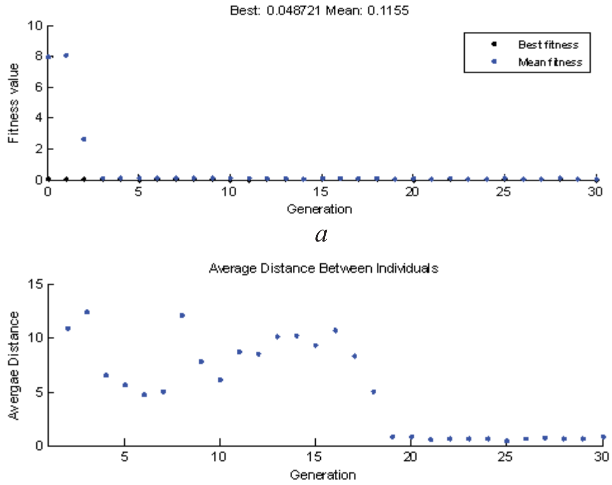

Fig. 6. Global optimization of the model structure using the GA: the convergence process (a) and the population size evolution (b)

As a result of modelling (Fig. 5, 6), it has been established that the GA has a higher speed of convergence (the GA goes to the area of optimum decisions at the first generations, whereas the DS does after 15 iterations). The DS algorithm revealed the higher response speed (4.2 s on iteration at 10.6 s on generation in the GA). The convergence of the GA algorithm is higher than that of the DS algorithm (the criterion values (2) were 0.048 and 0.066 accordingly).

In general, it has been established that the basic functions in the form of FFNN cascade correspond to the minimum of the unbiasedness criterion (2) for the LSC process. At that, the number of neurons in the hidden layer makes 26, the activation function of the hidden layer is sigmoid and that of the output layer is linear, the algorithm of NN training is based on the Levenberg-Marquardt method.

As a measure of parametric identification accuracy of the optimum structure model, the regularity criterion was used (1); its value for the model of the LSC process was 0.0357.

The adequacy of the received intellectual predicting model of the LSC process was checked by nonparametric criterion of signs. It has been established that the developed model with the identified structure and parameters is relevant to the significance level of 0.01 to the LSC process dynamics.

The search time of optimum decisions at the global optimization of the LSC process on a PC with a Pentium IV processor made 4…12 min that is much less than the periodicity of change of the functioning modes of ore-preparation processes which take several hours. The time of the NN parametric optimization of the LSC model does not exceed 3 s, and the time of calculations according to it makes up to 10 ms per forecast cycle. In general, the realization of the algorithms suggested does not bring any temporary restrictions regarding their use in the control system of the LSC process.

Conclusions. The identification technique of nonlinear dynamic processes consisting of procedures to estimate conditions and characteristics of the process and its structural-parametric identification has been suggested. Unlike the known one, it allows carrying out the identification of these processes in a batch mode by structural-parametric optimization and parametric optimization (in a real time mode) of their models by.

The algorithms of global and local optimization of the nonlinear dynamic process model have been developed; they realize the procedure of the structural-parametric identification by their structural and parametric optimization that allows receiving models of the improved accuracy.

Time expenditures on identification and calculation of the model do not impose any temporary restrictions on their realization in the process control system.

The further studies are to be directed at the development of algorithms of difficult process control using the techniques and identification algorithms suggested.

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Мета. Підвищення точності динамічних моделей складних нелінійних процесів для розв'язання задач керування цими процесами.

Методика. Структурно-параметрична ідентифікація нелінійних динамічних процесів, що включає ідентифікацію структури моделі на основі селекції за критерієм незміщеності, а також параметричну ідентифікацію моделі оптимальної структури за критерієм регулярності у всій вибірці експериментальних даних.

Результати. Розроблені алгоритми глобальної та локальної оптимізації моделей нелінійного динамічного процесу, які реалізують процедуру структурно-параметричної ідентифікації шляхом їх структурної та параметричної оптимізації, що дозволяє отримувати моделі підвищеної точності.

Наукова новизна. Запропонована методика ідентифікації нелінійних динамічних процесів, що складається з процедур оцінки стану та характеристик процесу, а також їх структурно-параметричної ідентифікації. Це дозволяє, на відміну від відомих методик, виконувати ідентифікацію цих процесів у пакетному режимі шляхом структурно-параметричної, а в режимі реального часу – параметричній оптимізації їх моделей.

Практична значимість. Результати досліджень можуть бути застосовані при розробці алгоритмів керування складними нелінійними процесами на основі їх комплексної оцінки та ідентифікації.

Ключові слова: *методика, алгоритм, ідентифікація, нелінійний процес, модель*

Цель. Повышение точности динамических моделей сложных нелинейных процессов для решения задач управления этими процессами.

Методика. Структурно-параметрическая идентификация нелинейных динамических процессов, включающая идентификацию структуры модели на основе селекции по критерию несмещенности, а также параметрическую идентификацию модели оптимальной структуры по критерию регулярности для всей выборки экспериментальных данных.

Результаты. Разработаны алгоритмы глобальной и локальной оптимизации моделей нелинейного динамического процесса, которые реализуют процедуру структурно-параметрической идентификации путем их структурной и параметрической оптимизации, что позволяет получать модели повышенной точности.

Научная новизна. Предложена методика идентификации нелинейных динамических процессов, которая состоит из процедур оценки состояния и характеристик процесса, а также их структурно-параметрической идентификации. Это позволяет, в отличие от известных методик, выполнять идентификацию этих процессов в пакетном режиме путем структурно-параметрической, а в режиме реального времени – параметрической оптимизации их моделей.

Практическая значимость. Результаты исследований могут быть использованы при разработке алгоритмов управления сложными нелинейными процессами на основе их комплексной оценки и идентификации.

Ключевые слова: *методика, алгоритм, идентификация, нелинейный процесс, модель*

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