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Research and Development of Algorithmic Transport Control Systems

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ABSTRACT

The necessity of a systematic approach is shown when considering the problems of transport systems management. The effectiveness of the algorithmic approach is shown for the creation of an automated system for identification and optimization of management processes for complex systems. Experimental statistical methods are proposed for solving the problem in the field of complex systems for the development of modeling control algorithms.

The necessity of an algorithmic approach to the development of a methodology for creating an information reference system in the field of transport is shown.

The developments are investigated by algorithmic mathematical models of processes in the transport system.

KEYWORDS: *Algorithmic systems, control of complex systems, mathematical models, performance criteria, regression equation, active experiment methods, Taylor series, communications operator*

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Technical progress in the transport system and the associated intensification of production dictate new problems in the management of sectors of the national economy, which are presented in the form of complex systems.

Complexes of tasks are methods of analysis and synthesis of complex systems, since they solve the problems of determining the behavior of an object and predicting it, forming criteria for the efficiency of transport objects and optimizing its modes. This opportunity gives us an algorithmic approach to the construction of mathematical models of complex systems [1,2].

The methods of mathematical description and modeling of production processes considered in the literature provide a solution to a wide range of practical problems. However, they refer only to discrete production processes and do not cover a significant number of continuous production processes common in the national economy.

If discrete production processes observed in transport are characterized by the following features: 1) operating on individual parts, semi-finished products, units, etc., from which the product is ultimately assembled, and 2) the possibility of dividing the production process into separate elementary acts, called operations, then the class of continuous production processes is devoid of these features.

A systematic analysis of complex systems encountered in practice shows that solving problems of operational and high-quality control of them necessitates identifying information flows, forming a control algorithm, centralizing control, developing a modeling algorithm and objectivity criteria, taking into account such factors as the randomness of deviations from the planned modes of operation, multidimensionality, poor observability, poor controllability, unsteadiness of subsystems, lack of technical means of quality control of processed products, etc.

The multidimensionality of the elements of the system is one of the features in determining the complexity of the system [3]. Production processes existing in transport are multidimensional and, being elements of a complex system, have their own characteristics. However, the multidimensionality of the elements of a complex system, when forming performance criteria, can lead to contradictory situations, which dictates the need for a compromise decision. Presence of elements at the input $\vec{X}$ and at the output $\vec{Y}$ of vector quantities allows you to use the methods of vector optimization.

A priori estimates of some technological processes have shown that the level of their observability and controllability is very low and is within 18% -40% of the total state space. Consequently, from the classification point of view, we can say that the processes in transport are related to weakly observable, poorly controlled and non-stationary processes, in which quasi-stationarity areas can be identified at short time intervals.

For these processes, it is advisable to study the object as a converter of information. At the same time, the main attention is paid to the relationships associated with the paths of information passage through their possible transmission channels in order to achieve greater dynamism and efficiency of control.

So, let *T*- be a fixed subset of real positive numbers (the set of considered moments of time), X, U, Y, Z - sets of any nature. The elements of the indicated sets will be called as follows: $t \epsilon T$ - moment of time; $x \epsilon X$ - input, $u \epsilon U$- control, $y \epsilon Y$ - output signals, $z \epsilon Z$- state. In the subsequent states, input, output and control signals will be considered as functions of time, and their values at time *t* will be denoted *z(t), x(t), y(t)*respectively [4,5].

Due to the fact that the main production processes are complex, that is, with many input and output variables, the task is to build a mathematical model for a multidimensional object A_t^*. It can be formulated as follows: according to the results of experimental-statistical observations, it is necessary to find an estimate of the object operator that is optimal in some sense. In this case, the requirement is imposed that the estimate is close to the true A_t^*. value in the sense of some criterion, that is, the requirement for the proximity of the vector random function at the output of the model must be fulfilled $Y^*(t)$:

$$\vec{Y}^* = A_t^*\{x_1(t),\dots,x_n(t)\} = \vec{A}_t^* \vec{X}^*(t)$$

to the vector output variable of the object $\vec{Y}(t)$:

To determine the optimal operator by the criterion of the minimum mean square of the error in this case, the loss function, which depends on the output variables of the object $\vec{Y}(t)$ and the model $Y^*(t)$, and not on the operator, should take the form:

$$\beta[Y(t), Y^*(t)] = \sum W_i [Y_i(t) - Y_i^*(t)]^2,$$

where the weights are determined by the significance of each of the output variables $y_i(t) (i = 1,2, \dots, m)$

In the case of determining mathematical models under normal operating conditions, to determine the optimal estimates of operator A_t^* by the criterion of the minimum mean square of the error, the basic equation for the observation time *T* can be represented as a system of integral equations, including auto and cross-correlation functions of the variables under consideration [5,6].

The main mathematical apparatus for processing the results of observations when using methods of planning an experiment is regression analysis. The regression analysis procedure consists in estimating the regression coefficients using the least squares method (OLS), followed by statistical analysis of the resulting regression model.

In this case, the mathematical description is presented in the form of a segment of the Taylor series:

$$Y = \beta_0 + \sum_{i=1}^{L} \beta_i x_i + \sum_{i=j}^{L} \beta_{ij} x_{ij} + \sum_{i=1}^{L} \beta_{ii} x_{ii}^2 + \dots$$

Using the results of the experiment, it is possible to determine only the sample regression coefficients b_0, b_i, b_{ij}, b_{ii}, which are only estimates for the theoretical regression coefficients β_0, β_i, β_{ij}, β_{ii}.

The regression equation obtained from experience is written

$$\hat{Y} = b_0 + \sum_{i=1}^{L} b_i x_i + \sum_{i=j}^{L} b_{ij} x_i x_j + \sum_{i=1}^{L} b_{ii} x_{ii}^2 + \dots$$

where $\hat{Y}$ is the output predicted by the equation.

Following the established tradition in many fields of science, we will evaluate the properties of complex systems using numerical characteristics. Each of the numerical characteristics used to assess the properties of a complex system must satisfy at least the following requirements: 1) be a value that depends on the process of the system's functioning, which, if possible, is simply calculated based on the mathematical description of the system; 2) give a visual representation of one of the properties of the system; and 3) allow, within the limits of the possible, a simple approximate estimate based on experimental data. One of the main properties of a complex system that characterizes its quality of work is the efficiency indicator. Under the indicator of the effectiveness of a complex system, we mean a numerical characteristic in the form of an efficiency criterion (CE).

For production processes, the problem of multicriteria optimization is formulated as follows: Let the process parameters be described by an "n" dimensional input vector $\vec{X}$) (vector of parameters) $\vec{X} = \{x_1, x_2, \dots x_n\}, \vec{x} \in \vec{X}$, and the quality of functioning is estimated by a π dimensional vector - function Y (efficiency vector) [6,7].

$Y(x) = \{Y_1(x), Y_2(x), \dots Y_\pi(x)\}$whose components are given real functions of the variable *X*.

The optimal solution is a certain value of the vector X from the set of possible solutions $X(x^* \in X)$, which gives a combination of the levels of the selected parameters $x_1, x_2, \dots x_n$which corresponds to a certain optimum of the efficiency vector Y.

Let us consider the problems of algorithmic control of complex systems in the transport system. The problem of algorithmic construction of mathematical models can be formulated as follows: according to the results of the experiment, it is necessary to find the optimal, in a sense, an estimate of the object operator A_t^*. In this case, the requirement of closeness of the vector random function at the output of the model $\vec{y}^*(t) = A_t^* X(t)$to the vector output variable of the object $\vec{Y}^*(t)$should be highlighted.

The algorithm provides for the possibility of obtaining the best estimate $A_t$in the sense of the minimum mean square of the error for any number of input variables in the class of all possible operators.

Let us give an algorithm for constructing a static model of a control object under normal operating conditions [7].

Let there be a linear correlation between *Y*and $x_1, x_2, \dots x_n$

$$y = a_0 + a_1 x_1 + a_2 x_2 + \dots + a_n x_n$$

The model building algorithm is as follows:
1. Variables of equation (1) are normalized.
2. Coefficients of paired correlations between process variables are calculated.
3. A system of normal equations is compiled.
4. By solving the system of normal equations, the values of the standardized regression coefficients are obtained.
5. For practical use of the resulting model, it is necessary to return to the natural scale.
6. Calculate the multiple correlation coefficient.
7. Calculate the residual variance.
8. Calculate the calculated value of the Fisher criterion.
9. The model is considered adequate if

$$F_{payment.} > F_{table}$$

Where $F_{table}$is the tabular value of the Fisher criterion for the selected significance level of n degrees of freedom.

10. The significance of the coefficients of the multiple regression equation is assessed by *t* - ratio.

Coefficient $\alpha_j$differs significantly from zero if $t_j > t_{table}$ at the selected significance level and the number of degrees of freedom. When $t_j > t_{table}$, the coefficient α_j differs insignificantly from zero, and in this case the jth variable is excluded from consideration.

If the regression equation does not adequately describe the process (which is established by clause 9), then proceed to the construction of a nonlinear regression model.

In this case, the regression equation looks like this:

$$y = b_0 + \sum_{j=1}^{n} b_j x_j + \sum_{j=1}^{n} b_{jj} x_j^2 + \sum_{k=1}^{n} \sum_{l=1}^{k-1} b_{kl} x_k x_l \quad (2)$$

To simplify the solution of the problem of determining the coefficients of the last equation, all its second-order terms are considered as new variables:

$$y = b_0 + \sum_{j=l}^{n} a_j x_j + \sum_{\rho=n}^{m} b_\rho x_\rho$$

where: $m = n + q$,

q - the number of terms in the last sum of equation (2)

$$q = C_n^2 = \frac{n(n-1)}{2}$$

Further, the procedure for determining the coefficients of equation (2) completely coincides with the above procedure (1-10). Nonlinear equation (2) is considered as a linear equation with $2n + C_n^2$ 2 with input variables [8].

As mentioned above, when constructing mathematical models by methods of active experimentation, the relationship equations between *Y* and X can be implemented in the form of Taylor series. It is most convenient to look for this connection in the class of linear functions. If the resulting model does not satisfy the conditions of adequacy, then go to plans of a higher order.

In other words, the communication operator must be sought in the class of nonlinear functions.

The proposed algorithm makes it possible to reliably evaluate and refine the unknown parameters of linear models and can serve as a tool for automated processing of experimental results.

Linear type models

$$y = в_a + в_1 x_1 + в_2 x_2 + \cdots + в_L x_L$$

where *L* is the number of independent variables, are the simplest approximating functions.

The algorithm performs the following sequence of calculations:

1. The average values are calculated for the rows of the planning matrix.
2. Line-by-line variances are determined.
3. The hypothesis about the homogeneity of the sample estimates is tested.
4. The variance of the reproducibility of the mean value of the function is estimated.
5. The hypothesis about the significance of the difference between the maximum and minimum values of the optimization parameter is tested using the Student's *t*-test.
6. This difference is considered significant if $t_{payment.} > t_{table}$ for the significance level and degrees of freedom *f*=kmax+kmin.
7. The coefficients of the regression equation are calculated.
8. The variance of the regression coefficients is estimated.
9. The significance of the coefficients of the regression equation is checked using the Student's t-test. The coefficient is significant if $t_{payment.} > t_{table}(f1, \alpha\ \ )$
10. The residual variance is estimated.
11. Testing the hypothesis about the adequacy of the representation of the response surface by the linear regression equation is carried out according to the Fisher criterion [9].

Adequacy check according to the chosen method is possible if the number of significant coefficients of the regression equation is at least one less than the number of rows of the planning matrix.

When these two values are equal, it is necessary to reduce the dimension of the polynomial by discarding one of its terms. It is proposed to discard the term of the normalized equation with the minimum, in absolute value, coefficient, i.e. this contributes less to the increase in residual variance.

If the linear model turns out to be inadequate, then go to higher-order models (for example, second-order plans):

$$y = в_0 + в_1 x_1 + \cdots + в_m x_m + в_{12} x_1 x_2 + \cdots$$
$$+ в_{(m-1)m} x_{(m-1)} x_{m+} + в_{11} x_1^2 + \cdots$$
$$+ в_{mm} x_m^2 + \cdots \qquad (3)$$

Nonlinear designs, unlike linear ones, do not simultaneously satisfy several optimality criteria. Therefore, in each case, it is necessary to choose the plan that best suits the research objectives. Items 6 and further for the Hartley plan with five factors will have the following meanings:

1. The coefficients of the regression equation are calculated:
2. The variance of the regression coefficients is estimated.
3. The covariance of the regression coefficients is calculated.
4. The proportion of the variance of the response function due to the linear terms of the regression equation is calculated.
5. The significance of this fraction of the variance from zero is checked.
6. To assess the significance of the group of coefficients at the terms of the second order, the

proportion of the variance of the response function caused by them is calculated:

7. The significance of the variance associated with terms of the second order from zero is checked.
8. The residual variance is estimated.
9. The hypothesis about the adequacy of the representation of the response surface by the nonlinear regression equation according to Fisher's criterion is tested.

One of the main sources of increasing production efficiency is improving the quality and productivity of technological equipment [10,11].

For the effective functioning of the system, it is necessary to fulfill a number of conditions of a general and special nature, set forth in the form of general system requirements, as well as requirements for information, software, technical and organizational types of support.

System-wide requirements contain a number of conditions to ensure the effective functioning of the system as a whole.

The software must contain programs that implement the functions of monitoring and controlling processes based on microprocessor technology.

The technical support of the system, on the one hand, must be sufficient for the implementation of all information, control and auxiliary functions of the system, and on the other hand, it must have minimal hardware redundancy.

The organizational support of the system should be presented in the form of operating instructions, including the form of the system and the regulations for its operation in the form of descriptions of the functional, technical and organizational structures of the system, as well as instructions and regulations for the operating personnel on the operation of the system.

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