e-ISSN 1607-3274 Радіоелектроніка, інформатика, управління. 2019. № 3
p-ISSN 2313-688X Radio Electronics, Computer Science, Control. 2019. № 3

УПРАВЛІННЯ У ТЕХНІЧНИХ СИСТЕМАХ

УПРАВЛЕНИЕ В ТЕХНИЧЕСКИХ СИСТЕМАХ

CONTROL IN TECHNICAL SYSTEMS

UDC 681.513.5

IDENTIFICATION OF THE MATHEMATICAL MODELS OF THE TECHNOLOGICAL OBJECTS FOR ROBUST CONTROL SYSTEMS

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ABSTRACT

Context. The problem of identification of the mathematical models of the technological objects on the basis of which the robust control system is subsequently synthesized has been considered. The methods of identification of the mathematical models of the technological objects for robust control are the target of the research.

Objective. The purpose of the research is to develop recommendations for the existing methods of identifying the mathematical models of the technological objects for robust control to allow the effective application of the robust control systems as well as to increase the energy efficiency of the system as a whole.

Method. The suggested recommendations for the identification of the mathematical models of the technological objects aimed at the further synthesis of robust control are divided into two types – with a known and an unknown area of uncertainty. For the former with the mathematical model which is identified only in the nominal mode the existing methods for identifying the continuous models in accordance with the experimentally obtained data are preferable. Taking the multidimensionality and multiplicity of most technological objects into account, the structure of the model in the space of time variables is recommended. It has been suggested to reduce the area of uncertainty to the additive or multiplicative form for the identification of the mathematical models for which, in addition to the nominal model, identification of the area of uncertainty is stipulated. In this case, several models in different operating object modes are used, while the uncertainty is calculated as the distance between the nominal and other models on the frequency grid with the further approximation of the filters of the preassigned order.

Results. The suggested algorithm for identifying the mathematical models with the area of uncertainty has been implemented and investigated for a production object – the subsystem of the levels of the diagonal extraction plant of a sugar-mill.

Conclusions. The performed experiments have confirmed the efficiency of the proposed calculation of the area of uncertainty of the mathematical models of the technological objects, while the proposed recommendations for the identification of the mathematical models for robust control can be used in practice. Further research is aimed at identifying the area of uncertainty of the closed control systems.

KEYWORDS: identification, production object, robust control, mathematical models, area of uncertainty.

ABBREVIATIONS

AIC – Akaike's information criterion;

AICc – small sample-size corrected Akaike's information criterion;

ARX – autoregressive with external input (model);

BIC – Bayesian information criterion;

Fit – normalized root mean squared error expressed as a percentage;

FPE – Akaike's final prediction error;

LMI – linear matrix inequality;

LossFcn – value of the loss function when the evaluation completes;

MM – mathematical model;

MIMO – multiple input multiple output (model);

MSE – mean squared error;

nAIC – normalized AIC;

OE – output-error (model);

SISO – single input single output (model);

TO – technological object.

DOI 10.15588/1607-3274-2019-3-18

NOMENCLATURE

A, **B**, **C**, **D** are matrices of the state space representation;

$E()$ is expected value;

f is selected function, for example, additive, multiplicative, etc.;

F_{ni} is steam flow in the i-th zone of the sugar mill;

F_c, F_w, F_{dj}, are the flows of chips, feed water and diffusion juice respectively;

$\mathbf{G}(s)$ is matrix of transfer functions;

$\mathbf{G}_0(s)$ is matrix of transfer functions in accordance the nominal object;

$\mathbf{G}^{k*}$, $\boldsymbol{\theta}^*$ are optimal structure and vector of parameters in each structure respectively;

h_i is the level in the i-th zone of the sugar mill;

I, 0 are unit and zero matrices respectively;

$l()$ is a criterion of parametric optimization;

M is the final set of model structures;

N, N_k are the amount of time samples in one experiment and total number of experiments;

$\mathbf{y}(t)$, $\mathbf{y}^k(t)$ are the vectors of the outputs in general and the k-th experiment, respectively;

$\hat{\mathbf{y}}(t)$ is outputs of the model;

$\mathbf{u}(t)$, $\mathbf{u}^k(t)$ are the vectors of the inputs in general and the k-th experiment, respectively;

s is a complex variable;

t is time;

T_s is time-slotting;

T_c, T_w, T_i are the temperature of chips, feed water and chips-juice mixture in the i-th zone respectively;

U is the load on the shafts of the plant;

$\mathbf{W}_1$, $\mathbf{W}_2$ are matrices of transfer functions of filters;

$\Lambda()$ is a criterion of structural optimization;

$\boldsymbol{\varepsilon}()$ is a forecast error vector;

$\boldsymbol{\Delta}_{\mathbf{W}}(s)$, $\boldsymbol{\Delta}(s)$ are weighted and standardized matrix uncertainty, respectively;

$\| \|$ is Euclidean norm.

INTRODUCTION

TOs, including the food industry, are characterized by changes in working conditions due to uncontrolled factors and the evolution of the process. Thereby, requiring a change in the parameters or the structure of the control device it requires constant readjustment of the control system. On the other hand, robust control systems are effective for the objects that function under the conditions of uncertainty of both internal changes in the object itself and the environment. That is, to eliminate the constant readjustment of the control system as well as to reduce the variability of the regulatory variable the application of robust control is justified. One of the problems hindering the introduction of the robust control systems into the manufacturing industry is the lack of a methodological approach to the identification of the MM for robust control.

Depending on the used MM, methods of robust control can be divided into two large groups [1–2]:

– methods that use the nominal MM of the object (2-Riccati approach, loop shaping approach, LMI-approach, nonsmooth-synthesis, and others.);

– methods that use the nominal MM of the object as well as the area of uncertainty which is given in the form of a structural, parametric or mixed structured type (using the Kharitonov's theorem or Lyapunov functions, μ-synthesis, etc.).

Thus, depending on the robust methods used to synthesize the control device, the MM of the object is to describe the nominal operation mode of the TO only – the nominal mathematical model of the TO or a family of the structural or parametric models of the TO – the MM with uncertainties of the TO. The description of the latter is nonunique since the expansion of the area of uncertainty leads to deterioration in the quality of the system in the nominal mode, while the narrowing of the area of ambiguity does not justify the use of a robust regulator. Therefore, the mathematical model of the object is to be adequate to the functioning of the system both in the established and in the transition modes, while its identification is aimed at the further synthesis of the robust regulator.

In the tasks of identifying the MM of the TO two interrelated parts are considered: an invariant part which is common for the TO category; an original part which takes into account the peculiarities of heat transfer and mass transfer processes, etc. In addition, it is necessary to take into account the range of application of the MM, which meets the technological constraints. Meanwhile, the identifiable MMs are to be guided towards inclusion into the decision support subsystem for the purpose of formation of the effective management actions. The diagnostics (assessment of the TO condition) and the specification of the horizon of the MM forecasting are specific tasks that can be solved while identifying the MM of the TO.

The target of the research is the mathematical models of the TO which are used for the further synthesis of the robust control system.

The subject of the research is the methods of identification of the mathematical models of the TO that are aimed at robust control.

The purpose of the research is to develop recommendations for the use of the methods for identifying the mathematical models of the technological objects for robust control which will allow the effective application of the robust control systems and will lead to an increase in the energy efficiency of the system as a whole.

1 PROBLEM STATEMENT

The problem of the research is the fact, that solving the problems of analysis, synthesis and practical use of the robust control systems is based on the adequate MM which should correspond not only to the properties of the TO and the modes of its functioning (situations), but also to the formulation of the problem and methods of its

DOI 10.15588/1607-3274-2019-3-18

solution, with the use of computer technologies in the first place.

It is assumed that information about the system to be modelled is available in the form of input-output data, which could be obtained through identification experiments designed. Then the task is to find the MM TO:

$$\mathbf{y}(t) = \mathbf{G}(s)\mathbf{u}(t) . \qquad (1)$$

The latter describes the operation of a TO on a range of uncertainties:

$$\mathbf{G}(s) = f(\mathbf{G_0}(s), \boldsymbol{\Delta}_\mathbf{W}(s)) \cdot \qquad (2)$$

When solving a problem (1), (2) are used different criteria: parametric identification criteria – for identifying parameters $\mathbf{G}_0(s)$ (for example, MSE, etc.); criterion of optimal approximation in log-Chebyshev sense – for identification of the region of uncertainty.

Thus, the identification of the MM of the TO for robust control requires additional research and systematization.

2 REVIEW OF THE LITERATURE

The problem of identification of the MM of the TO for the construction of control systems is well-known since it raises the compromise issue between the simplicity of the model, which leads to a further simple synthesis of the control system, and an adequate description of the object. Almost all the existing modern identification methods have been considered in [3]. However, the issue of identifying the MM of the TO still remains a creative procedure which requires iterative approach to both the structure of the model and the methods for identifying its parameters. Also problematic is the identification of the closed control systems which are not sufficiently represented in applied scientific literature sources.

During the practical implementation of robust control methods, a problem occurred along with the identification of the nominal MM of the object, the identification of uncertainties [4–11]. Hereby, several problems occur – the choice of the structure of uncertainties and the calculation of the multitude of uncertainties.

In [6–7], when identifying the closed systems, authors suggest using three types of uncertainties: additive uncertainty; uncertainty of Juli; uncertainty based on the v-gap metrics. In [8], the same authors come up with an alternative concept for calculating the boundary of parametric uncertainties for regression models, in particular ARX and OE models. As a result of identification, we obtain a regression model with parametric uncertainty corresponding to a given degree of probability. However, as shown in [6], this approach is not effective for closed systems, since under the subsequent calculations the evaluation of the uncertainties of the object model parameters is shifted.

In addition, the above discussed methods are quite complicated for the tasks of analysis and synthesis of the control system as well as for a maintenance engineer of robust control systems and therefore need simplification, while the methodology is to be based on the system approach to complex systems, the identification of the structure and parameters of the mathematical models of the object.

3 MATERIALS AND METHODS

The main peculiarity of mathematical models that are intended for robust control is the reduction of the accuracy requirements compared to models that are intended for optimal or adaptive control. Given this peculiarity, it is sufficient to apply linear dynamic models with constant coefficients for robust control. In addition, for such models there are well-developed mechanisms of output and application of robust control laws according to different criteria, in particular, H_2-, H_∞-norms of characteristics of a closed or open-loop system.

For the systems of control of the TO, the area of uncertainty of which changes throughout a long period of operation and, therefore, can not be uniquely identified, it is appropriate to apply methods of robust control which use the nominal MM of the object. For TO operating under the conditions of intense internal and external changes, the MM of which can be evaluated experimentally over a short period of time, the use of the robust regulators which are oriented towards the entire area of uncertainty is advisable.

Let us formulate the stages of identification of the mathematical model of the TO with the evaluation of the area of uncertainty according to (1), (2):

– to perform an experiment in accordance with representative input actions (for example, a pseudobinary signal) under different conditions of the object operation:

$$\begin{aligned} &\mathbf{y}^k(t) = \left[\mathbf{y}^k(0), \mathbf{y}^k(T_s), \mathbf{y}^k(2T_s),..., \mathbf{y}^k(NT_s)\right]; \\ &\mathbf{u}^k(t) = \left[\mathbf{u}^k(0), \mathbf{u}^k(T_s), \mathbf{u}^k(2T_s),..., \mathbf{u}^k(NT_s)\right]. \\ &k = 3,4,..., N_k . \end{aligned} \qquad (3)$$

Despite the fact that experimental data has been obtained at corresponding time periods, the MM of the TO is continuous due to the large time constants of the TO and a slight error in transition from discrete to continuous MM.

– to conduct the structural and parametric identification of each experiment:

$$\begin{aligned} &\mathbf{G}^k*(s) = \arg \min_{\mathbf{G}_i^k \in M} \Lambda\left\{\mathbf{G}_1^k(s,\boldsymbol{\theta}*), \mathbf{G}_2^k(s,\boldsymbol{\theta}*),..., \mathbf{G}_M^k(s,\boldsymbol{\theta}*))\right\}; \\ &k = 3,4,..., N_k; \\ &\mathbf{G}_i^k(s,\boldsymbol{\theta}*) = \arg\min_{\boldsymbol{\theta}} l(\boldsymbol{\varepsilon}(t,\boldsymbol{\theta})); \quad i = 1,2,..., M. \end{aligned} \qquad (4)$$

For example M is polynomial models, models in the form of transfer functions of various orders, etc.; $\Lambda()$ is AIC or BIC; $l()$ is a variety of the norm. Note also that the dimension of the vector $\boldsymbol{\theta}*$ is different in each structure.

DOI 10.15588/1607-3274-2019-3-18

– to produce a general sample from (1), to carry out the structural and parametric identification of the nominal model:

$$\mathbf{G}_0{}^*(s) = \arg \min_{\mathbf{G}_i^0 \in M} \Lambda\left\{\mathbf{G}_1^0(s,\boldsymbol{\theta}^*), \mathbf{G}_2^0(s,\boldsymbol{\theta}^*), ..., \mathbf{G}_M^0(s,\boldsymbol{\theta}^*)\right\};$$
$$\mathbf{G}_i^0(s,\boldsymbol{\theta}^*) = \arg\min_{\boldsymbol{\theta}} l(\boldsymbol{\varepsilon}'(t,\boldsymbol{\theta})), \quad i = 1,2,...,M. \tag{5}$$

– to reduce the obtained results to a model with uncertainty of the multiplicative input, output or additive type by means of approximation:

$$\begin{aligned} &\mathbf{G}(s) = \mathbf{G}_0(s)(\mathbf{I} + \boldsymbol{\Delta}_\mathbf{W}(s)); \\ &\mathbf{G}(s) = (\mathbf{I} + \boldsymbol{\Delta}_\mathbf{W}(s))\mathbf{G}_0(s); \\ &\mathbf{G}(s) = \mathbf{G}_0(s) + \boldsymbol{\Delta}_\mathbf{W}(s); \\ &\boldsymbol{\Delta}_\mathbf{W}(s) = \mathbf{W}_1(s)\boldsymbol{\Delta}(s)\mathbf{W}_2(s); \\ &\|\boldsymbol{\Delta}(s)\|_\infty < 1, \end{aligned} \tag{6}$$

where $\mathbf{G}_0(s) = \mathbf{G}_0{}^*(s)$.

To summarize the resulting models to a single $\mathbf{G}(s)$ form with uncertainties one of the structures (4) will be used. The distance between the models of individual samples and the nominal model is calculated as uncertainty in the dynamics of the system on the frequency grid. That is, at each frequency, the forming filters $\mathbf{W}_1$ and $\mathbf{W}_2$ are selected, they are close to the distance value between the models, while the uncertainty value $\boldsymbol{\Delta}$ is considered to be maximal. The choice of the structure of uncertainty (6) can also be performed in accordance with the criterion which is additionally introduced from a plurality of structures, in particular, the mean-square deviation of the final model from the individual on the frequency grid. After receiving the values of W1 and W2 filters on the frequency grid, a dynamic filter of the given order is selected using a method known in the theory of signal processing as log-Chebyshev magnitude design [12]. The order of filters is chosen in advance. It is necessary to note that the final stage is a complicated optimization task [13], which is reduced to linear programming.

4 EXPERIMENTS

Let us consider the acquisition of the MM which describes the level of the chip-juice mixture in the diagonal diffusion plant of the sugar mill. The parametric scheme of the TO is depicted in Fig. 1. The level in the plant (subsystem 2) is a distributed variable according to the length of the plant, but for a robust system of material flow control it is sufficient to use four zones, in each of which the level is described as a linear link with constant coefficients.

Taking into account the material balances of the process, we write the structure of the MM in the space of the state variables:

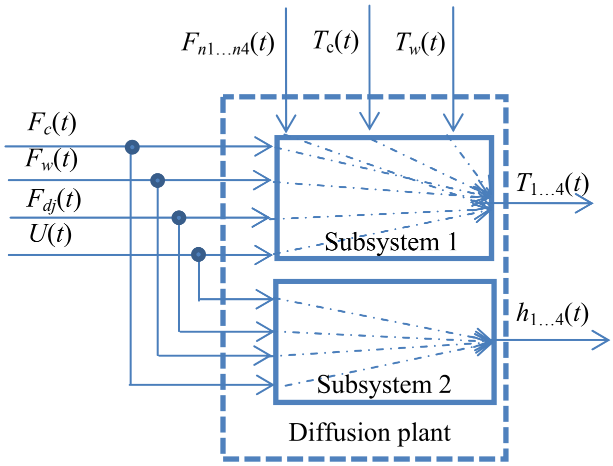

Figure 1 – Parametric diagram of the TO

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\begin{bmatrix}\mathbf{u}(t) \\ \mathbf{z}(t)\end{bmatrix}, \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\begin{bmatrix}\mathbf{u}(t) \\ \mathbf{z}(t)\end{bmatrix}, \end{cases} \tag{7}$$

where the vectors of state coordinates, measured outputs, control and perturbation will be written accordingly:

$$\mathbf{x}(t) = \begin{bmatrix} h_1(t) \\ h_2(t) \\ h_3(t) \\ h_4(t) \end{bmatrix}; \quad \mathbf{u}(t) = \begin{bmatrix} F_c(t) \\ F_w(t) \end{bmatrix}; \quad \mathbf{z}(t) = \begin{bmatrix} F_{dj}(t) \\ U(t) \end{bmatrix};$$
$$\mathbf{y}(t) = \mathbf{x}(t). \tag{8}$$

$$\mathbf{A} = \begin{bmatrix} -a_{11} & a_{12} & 0 & 0 \\ a_{21} & -a_{22} & a_{23} & 0 \\ 0 & a_{32} & -a_{33} & a_{34} \\ 0 & 0 & a_{43} & -a_{44} \end{bmatrix};$$

$$\mathbf{B} = \begin{bmatrix} b_{11} & 0 & -b_{13} & -b_{14} \\ 0 & 0 & -b_{23} & -b_{24} \\ 0 & 0 & -b_{33} & -b_{34} \\ 0 & b_{42} & -b_{43} & -b_{44} \end{bmatrix};$$

$$\mathbf{C} = \mathbf{I}; \quad \mathbf{D} = \mathbf{0}. \tag{9}$$

In (8), (9) the coefficients a_{ij}, b_{ij} of the corresponding **A**, **B** matrices are which require parametric identification. All the variables are measured in deviations.

An experiment has been conducted with pseudo-random input actions to obtain the experimental data for three modes of operation of the TO (3) with the number of experiments $k = 3$.

To identify the parameters (4), we use the non-iteration subspace method with a subsequent refinement of the parameters by means of the forecasting error minimizing method [3]. This method has proven itself to

DOI 10.15588/1607-3274-2019-3-18

be effective for the models that are described in the space of state variables. In addition, the structure of the model can be parameterized by the physical variables of the process. For comparison, three types of models have been chosen – of the 4th order without parametrization of the coefficients, of the 9th order without parametrization of the coefficients and of the 4th order with parametrization of the coefficients according to the form (7), (8). In addition, identification of the parameters with and without regularization has been performed for the first structure of the model. At the same time, evaluation of additional external components is introduced into the first and the third structure.

5 RESULTS

After identifying the coefficients, it has been found that the adequacy of the models is approximately the same. Although, according to certain criteria (Table 1, third column – criteria) the parametric model is worse than nonparametric. However, taking into account the minimum number of evaluated parameters, as well as a slight decrease in the accuracy of the evaluation, finally we choose the MM of the TO which has been obtained on the basis of the parameterized structure (7)–(9). In Table 1, No. 1, 2, 3 show the MM of the TO for each of the three experiments, as well as the criteria for their evaluations, in particular LossFcn; Fit; MSE; FPE; AIC; AICc; nAIC; BIC. Research on the feedback graphs of different models on the identification and verification samples, as well as the transient response curve of identified models, taking into account the confidence intervals of parameters, showed the stability of the obtained models.

To obtain a nominal model, we carry out identification with the same structure and using the same method, but for the combined experimental series of three experiments. Identification results are given in Table 1, Exp. 4. According to the considered criteria, the MM are adequate, in particular, Fig. 2 shows the results of the research of the nominal model on the test sample as well as the normalized mean-square measure of validity of the fitting of the model on the depicted data, which is calculated as follows:

$$\mathrm{Fit} = \frac{\left\|\mathbf{y}(t) - \hat{\mathbf{y}}(t)\right\|}{\left\|\mathbf{y}(t) - E(\mathbf{y}(t))\right\|}. \qquad (10)$$

A conclusion has been reached about the adequacy of the nominal model while the study also revealed a rather narrow confidence interval of parameters, indicating the futility of their use as parametric uncertainties.

Given that the model has many inputs and outputs and the multiplicative structure of a model with uncertainties can be limited and inadequately approximate the range of models, we choose the structure of the model with additive uncertainty. By transferring the obtained models of each experiment into the area of uncertainty, the values of the filter coefficients have been obtained from (6):

$$\mathbf{W}_1(s) = \frac{4.93\cdot 10^{-5}\cdot s^4 + 812.3\cdot s^3 + 2.84\cdot 10^6\cdot s^2 + 3.16\cdot 10^8\cdot s + 1.45\cdot 10^9}{s^4 + 1.81\cdot 10^4\cdot s^3 + 8.08\cdot 10^7\cdot s^2 + 3.30\cdot 10^9\cdot s + 7.05\cdot 10^9}; \quad \mathbf{W}_2 = 1. \qquad (11)$$

Fig. 3 shows a singular Bode diagram of a nominal model, a model with uncertainties, as well as the MM of individual samples. The graph shows that the fitting was successful. Research on random transitive functions of the model with the area of uncertainty confirmed the accuracy of the research performed.

Thus, for multidimensional TOs, it is appropriate to carry out the identification process on models in the space of the state variables, while providing a wide range of possibilities for simulation of the identified systems. Both blackbox type models and parametric models can be used. They can include physical and generalized parameters which reflect only the structure of the main matrices **A**, **B**, **C**, **D**.

6 DISCUSSION

Identification of the mathematical models of objects and systems remains an incorrect task, the regularization of which and subsequent solution are directed towards the purpose of application of the obtained model. For robust control systems, simple linear mathematical models of objects are used, which can be explained by the use of a simple structure of the control system and the control device as well as a well-developed mathematical apparatus for such models.

Nowadays at enterprises the choice of the model structure of the object of control, identification of its parameters, synthesis of the control device and adjustment of its parameters entirely depend on the designer (or programmer) of the TO automation system. Therefore, the quality level of the synthesized control system, its robustness and adaptation to changing the operating conditions are far from their optimal values. On the other hand, if the knowledge on the TO is sufficient, the designer of the control system will successfully select the structure of the simple control system and will adjust its parameters. The programmer of the control device operates the notion of the security of the control system in a wide range of the change in both disturbances and internal changes of the object as well as a given range of the change in the adjustable variable in accordance with the standard operating procedure. For some TOs, the regulator's setting is performed directly on the object without identifying the MM.

Thus, three levels of knowledge about the MM of the TO can be distinguished: the known MM, the poorly known MM and the unknown MM. For the known MM, the control system is to be based on optimal control, for the poorly known MM with due account for the variability of the characteristics of the TO – on robust optimum control, which is to be a part of the higher-level intellectual system. This will secure high quality and energy efficiency of the process where the MM of the TO is an integral part of this system.

DOI 10.15588/1607-3274-2019-3-18

Table 1 – Identification results

№ Exp.	The coefficients of the model	Criteria
1	$\mathbf{A} = \begin{bmatrix} 2.67 & -4.95 & 0 & 0 \\ 5.56 & -115.00 & 209.80 & 0 \\ 0 & 429.20 & -839.50 & -7.86 \\ 0 & 0 & 5.01 & -8.11 \end{bmatrix};$ $\mathbf{B} = \begin{bmatrix} 0.27 & 0 & -0.58 & -0.46 \\ 0 & 0 & 8.83 & 7.43 \\ 0 & 0 & -37.98 & -31.80 \\ 0 & 0.41 & -0.23 & -0.12 \end{bmatrix};$ **C** = **I**; **D** = **0**	LossFcn: 0.0188 MSE: 2.1350 FPE: 0.0203 AIC: 2280.6 BIC: 2365.4 AICc: 2282.3 nAIC: –3.8972 Fit: [82.94;76.24;61.42;62.57]%
2	$\mathbf{A} = \begin{bmatrix} 5.01 & -7.69 & 0 & 0 \\ 13.08 & -5695.00 & 11430.00 & 0 \\ 0 & 5968.00 & -12010.00 & -3.33 \\ 0 & 0 & 6.50 & -8.76 \end{bmatrix};$ $\mathbf{B} = \begin{bmatrix} 0.26 & 0 & -0.57 & -0.58 \\ 0 & 0 & 530.30 & 274.20 \\ 0 & 0 & -558.30 & -289.30 \\ 0 & 0.38 & -0.01 & -0.03 \end{bmatrix};$ **C** = **I**; **D** = **0**	LossFcn: 0.0107 MSE: 1.5511 FPE: 0.0116 AIC: 1994.4 AICc: 1996.1 nAIC: –4.4561 BIC: 2079.2 Fit: [75.71;70.6;56.49;54.62]%
3	$\mathbf{A} = \begin{bmatrix} -71.29 & -78.73 & 0 & 0 \\ 5.45 & -9.58 & 3.28 & 0 \\ 0 & 5.60 & -17.05 & -11.75 \\ 0 & 0 & 15.65 & -22.65 \end{bmatrix};$ $\mathbf{B} = \begin{bmatrix} 5.24 & 0 & 0.05 & -0.09 \\ 0 & 0 & -0.46 & -0.33 \\ 0 & 0 & -0.27 & -0.20 \\ 0 & 0.85 & -0.29 & -0.36 \end{bmatrix};$ **C** = **I**; **D** = **0**	LossFcn: 0.0037 MSE: 1.0650 FPE: 0.0041 AIC: 1455.7 AICc: 1457.4 nAIC: –5.5084 BIC: 1540.4 Fit: [89.47;86.66;82.89;79.71]%
4	$\mathbf{A} = \begin{bmatrix} 3.31 & -5.47 & 0 & 0 \\ 15.28 & -483.40 & 770.70 & 0 \\ 0 & 663.50 & -1102.00 & -2.83 \\ 0 & 0 & 3.62 & -5.28 \end{bmatrix};$ $\mathbf{B} = \begin{bmatrix} 0.31 & 0 & -0.61 & -0.49 \\ 0 & 0 & 24.63 & 20.19 \\ 0 & 0 & -36.81 & -30.21 \\ 0 & 0.27 & -0.12 & -0.10 \end{bmatrix};$ **C** = **I**; **D** = **0**	LossFcn: 0.0228 MSE: [3.0068 2.5891 3.5951] FPE: 0.0246 AIC: 7138.9 AICc: 7139.4 nAIC: –3.7038 BIC: 7245.6 Fit: [76.86 65.72 81.87; 71.1 60.85 75.54; 57.23 46.95 63.3; 58.22 45.45 68.37]%

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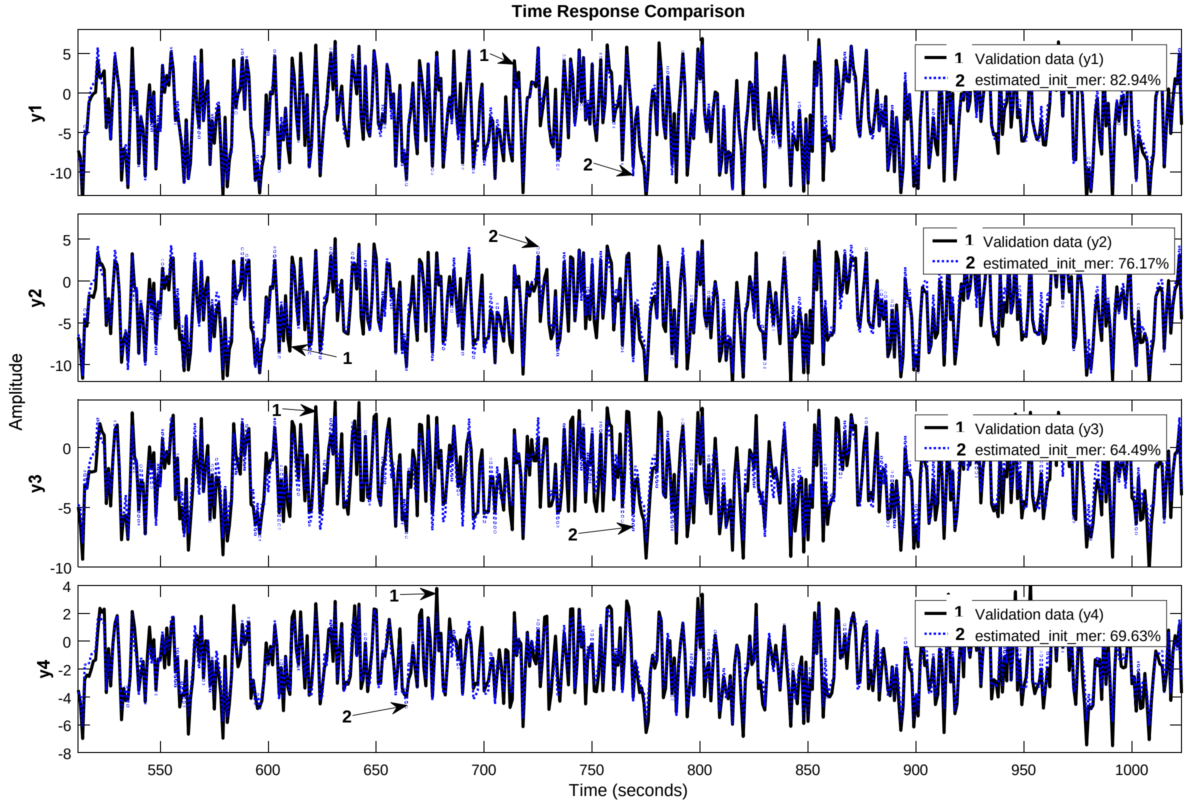

Figure 2 – Comparison of the nominal model on the test sample

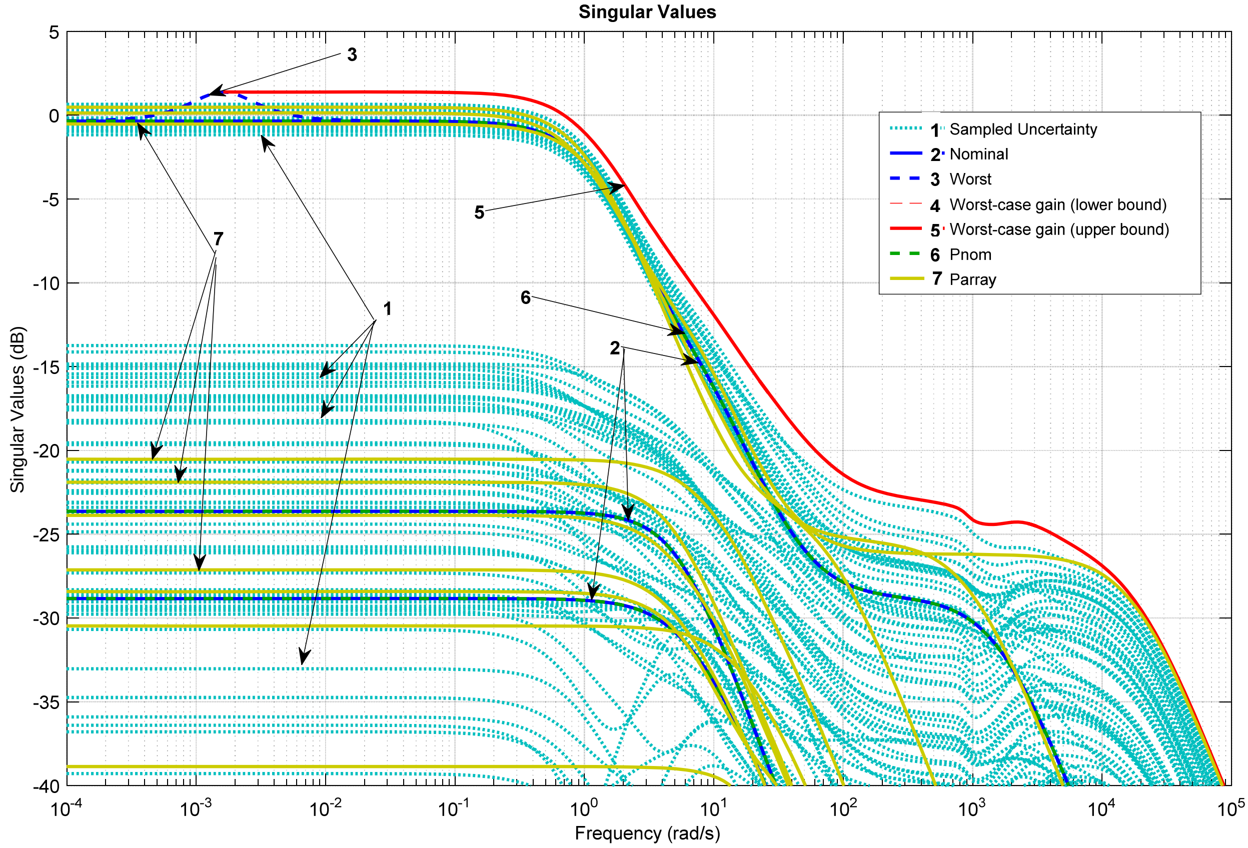

Figure 3 – Singular values plot of MM:
1 – responses randomly sampled from MM; 2 – nominal gain of MM; 3 – the response falling within the uncertainty of MM that has the highest peak gain; 4 – the lowest worst-case gain at each frequency (on the plot is not visible); 5 – the highest gain within the uncertainty at each frequency; 6 – MM with nominal uncertainties; 7 – MM of individual samples

DOI 10.15588/1607-3274-2019-3-18

The structure of the mathematical models of the TO which are aimed at further synthesis of the robust control system is determined in the first place by the designer of the control system who has sufficient knowledge on the operation of the TO. If the knowledge is insufficient, many structures of typical objects of the food industry can be built on the basis of the knowledge of an expert. The choice of the final structure of the mathematical model of the TO is performed on the basis of the criteria given in Table. 1. Parameters of the mathematical models of the TO are calculated after performing an experiment on an object in accordance with the chosen criterion from Table. 1. It should be remembered that the identified MM of the TO is to be observational and manageable.

If the uncertainty of the TO is stationary (that is, the set of uncertainties does not change over a long period of object operation), it can be calculated using the approach which is proposed in this research paper. In addition, experience of experts can be used; in particular, experienced technologists or automation engineers know when and how the transmission factor of an object can change. If the uncertainty of the TO is non-stationary and its calculation is impossible, robust optimum synthesis is performed for the nominal TO model, thus the control system is synthesized according to the criterion of maximum robustness.

CONCLUSIONS

On the basis of the research carried out, the following results were obtained, bearing both **scientific** and **practical significance.**

1. For now, enough MM of the TO, which are determined on the basis of the physical properties of the processes, have been developed. However, their use for the synthesis of robust control is ineffective since the structure of such models is lengthy while the calculated parameters may occur to be far from real values.

2. For robust control of the SISO objects, models can be used in the form of transfer functions which approximate experimental data with aperiodic, periodic or pulsed input actions. The area of uncertainty of the obtained model can be described only approximately within the framework of the experiment performed. Expert data can also be used to refine the area of uncertainty.

3. For MIMO objects, it is recommended to choose the structure of the mathematical model on the basis of the physical properties of the processes to maximally simplify the degree of differential equations. Model parameters are determined on the basis of experimental data. The area of uncertainty of such systems is shaped in the form of a multiplicative or additive structure which includes the model of unaccounted dynamics.

4. Identification by experimental data requires planning of the experiment to gain data informativeness while the obtained mathematical models describe the area of uncertainty only within the framework of the experiment and do not take into account the evolution of the object. Therefore, the mathematical models describing the TO with significant uncertainties are to be divided into two categories:

– determined (calculated) uncertainties;

– undetermined (uncalculated) uncertainties.

Moreover, for the first type of models, the methods of synthesis of the robust optimum regulator are oriented towards the entire area of uncertainty while for the second type – towards the nominal values.

5. For identified MM of closed systems one can calculate the H_∞-norm of the transfer function from the perturbation vector to the vector of regulated outputs, thus evaluating the robust security of the system.

The last position requires in-depth study which is scheduled for **further research**.

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Received 17.03.2019.
Accepted 08.06.2019.

DOI 10.15588/1607-3274-2019-3-18

УДК 681.513.5

ІДЕНТИФІКАЦІЯ МАТЕМАТИЧНИХ МОДЕЛЕЙ ТЕХНОЛОГІЧНИХ ОБ'ЄКТІВ ДЛЯ РОБАСТНИХ СИСТЕМ КЕРУВАННЯ

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АНОТАЦІЯ

Актуальність. Розглянуто задачу ідентифікації математичних моделей технологічних об'єктів, на основі яких в подальшому синтезується робастна система керування. Об'єктом дослідження є методи ідентифікації математичних моделей технологічних об'єктів для робастного керування. Метою роботи є розробка рекомендацій існуючих методів ідентифікації математичних моделей технологічних об'єктів для робастного керування, що дозволить ефективно застосовувати робастні системи керування та призведе до підвищення енергоефективності системи в цілому.

Метод. Запропоновані рекомендації щодо ідентифікації математичних моделей технологічних об'єктів із спрямуванням на подальший синтез робастного керування, поділяються на два види – з відомою і невідомою областю невизначеності. Для перших, математична модель яких ідентифікується лише в номінальному режимі, рекомендується використовувати відомі методи ідентифікації неперервних моделей за експериментально отриманими даними. Враховуючи багатовимірність та багатозв'язність більшості технологічних об'єктів, рекомендується структура моделі в просторі змінних стану. Для ідентифікація математичних моделей, для яких окрім номінальної моделі, передбачається ідентифікація області невизначеності, запропоновано приведення області невизначеності до адитивного або мультиплікативного виду. При цьому використовується декілька моделей в різних режимах роботи об'єкта, а невизначеність розраховується як дистанція між номінальною та іншими моделями на частотній сітці, з подальшою апроксимацією фільтрів заданого порядку.

Результати. Запропонований алгоритм ідентифікації математичних моделей з областю невизначеності реалізований та досліджений для технологічного об'єкта – підсистеми рівнів нахиленої дифузійної установки цукрового заводу.

Висновки. Проведені експерименти підтвердили працездатність запропонованого розрахунку області невизначеності математичних моделей технологічних об'єктів, а запропоновані рекомендації щодо ідентифікації математичних моделей для робастного керування можуть використовуватися на практиці. Подальше дослідження направлено на ідентифікацію області невизначеності замкнених систем керування.

КЛЮЧОВІ СЛОВА: ідентифікація, технологічний об'єкт, робастне керування, математичні моделі, область невизначеності.

УДК 681.513.5

ИДЕНТИФИКАЦИЯ МАТЕМАТИЧЕСКИХ МОДЕЛЕЙ ТЕХНОЛОГИЧЕСКИХ ОБЪЕКТОВ ДЛЯ РОБАСТНЫХ СИСТЕМ УПРАВЛЕНИЯ

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АННОТАЦИЯ

Актуальность. Рассмотрена задача идентификации математических моделей технологических объектов, на основе которых в дальнейшем синтезируется робастная система управления. Объектом исследования являются методы идентификации математических моделей технологических объектов для робастного управления. Целью работы является разработка рекомендаций существующих методов идентификации математических моделей технологических объектов для робастного управления, что позволит эффективно применять робастные системы управления и приведет к повышению энергоэффективности системы в целом.

Метод. Предложеные рекомендации по идентификации математических моделей технологических объектов с направлением на дальнейший синтез робастного управления, делятся на два вида – с известной и неизвестной областью неопределенности. Для первых, математическая модель которых идентифицируется только в номинальном режиме, рекомендуется использовать известные методы идентификации непрерывных моделей по экспериментально полученным данным. Учитывая многомерность и многосвязность большинства технологических объектов, рекомендуется структура модели в пространстве переменных состояния. Для идентификация математических моделей, для которых кроме номинальной модели, предполагается идентификация области неопределенности, предложено сведение области неопределенности к аддитивному или мультипликативному виду. При этом используется несколько моделей в различных режимах работы объекта, а неопределенность рассчитывается как дистанция между номинальной и другими моделями на частотной сетке, с последующей аппроксимацией фильтров заданного порядка.

Результаты. Предложенный алгоритм идентификации математических моделей с областью неопределенности реализован и исследован для технологического объекта – подсистемы уровней наклонной диффузионной установки сахарного завода.

DOI 10.15588/1607-3274-2019-3-18

Выводы. Проведенные эксперименты подтвердили работоспособность предложенного расчета области неопределенности математических моделей технологических объектов, а предложеные рекомендации по идентификации математических моделей для робастного управления могут использоваться на практике. Дальнейшее исследование направлено на идентификацию области неопределенности замкнутых систем управления.

КЛЮЧЕВЫЕ СЛОВА: идентификация, технологический объект, робастное управление, математическая модель, область неопределенности.

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DOI 10.15588/1607-3274-2019-3-18