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# IDENTIFICATION OF MATHEMATICAL MODEL OF TURBINE GENERATOR UNIT IN PRESENCE OF UNCERTAINTY

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*An identification procedure of mathematical model of turbine generator unit in the presence of uncertainty is studied for using in the interconnected robust control automated system. The procedure is based on "worst-case" identification approach. The controlled object is modelled by the matrix transfer function with additive uncertainty. The identification consists of two stages: first is to identify transfer function with nominal parameters with the use of prediction error minimization algorithm, second – to determine weight function in additive uncertainty model using finding the worst-case log-magnitude curve of uncertainties. Identification is performed in active way, determining datasets for each control channel from individual experiments. A linear frequency-modulated signal is selected as the input test disturbance. A simulation model of the controlled object is constructed and the numerical experiment is conducted using the identification procedure.* References 11, figures 7.
***Keywords:*** turbine generator unit, identification, automated control system.

Ensuring the reliability of the turbine generator unit (TGU) in the electric power system is an actual task. One of the ways to solve it is to improve the existing automated control systems and to create new ones based on modern principles. One of the key parts of TGU is its shaft, whose damage can lead to premature decommissioning of the TGU and serious technical accidents [8].

In order to ensure reliable operation and permanent monitoring of the TGU shaft condition, the authors have developed the automated system of interconnected robust control (ACS IR TGU) [2, 3]. As described in [3], ACS IR TGU performs the functions of interconnected robust control of TGU shaft rotation; monitoring of fatigue damage of the shaft material; control of the operation of special equipment related to damping of torsional vibrations of the TGU shaft, namely devices for compensation of torsional oscillations, which are able to create additional torque on certain sections of the shaft line. These functions are proposed to be implemented using separate subsystems, what are reflected in the functional diagram of the automated system, which is given in [3].

The function of controlling the TGU shaft rotation in the system is carried out using an interconnected robust controller, which synthesis procedure is described in [1]. The controller implements interconnected control by coordinating the operation of the automatic turbine speed governor (GOV) and the automatic voltage regulator (AVR) of TGU. The controller also has robustness properties with respect to the following types of uncertainty: unmodeled dynamics due to the linearization of the controlled object model, unaccounted change of the parameters of the controlled object components in relation to different TGU operating modes, as well as the gradual change over time of such parameters relative to the initial technical qualities, determined during the experiments at the factory, as a result of physical deterioration of the technical object.

As shown in [1] by numerical simulation, the result of using such a controller is reducing shaft oscillations relative to the power system and mechanical stresses in its cross sections with robustness of results towards parameter variation of controlled object mathematical model (MM). In the controller synthesis procedure it is used MM with nonparametric additive uncertainty, which includes all types of uncertainty of the considered system. The robust properties of the controller allow achieving the stability and the specified control quality only within the fixed uncertainty boundaries which can change over time due to physical deterioration or modernization of controlled object. For this reason, the controller needs to be reconfigured periodically, subject to significant changes in the MM uncertainty limits of the control object. To apply such an adaptive-robust approach to the design of the control system, which requires periodic readjustment of the robust controller, the control system provides a subsystem for identifying the uncertain model of the controlled object. The subject of these studies is the application of identification methods for systems with uncertainty in the algorithms of the identification subsystem of ACS IR TGU.

The task of identifying uncertain models of controlled objects has arisen in connection with the development of robust control methods. The classical identification methods do not fully meet the needs of robust control problems due to the fact that they can only take in account the signal uncertainty by including additive stochastic noise signals, whereas there are many other types of uncertainty in robust control methods [6]. For example, there are uncertainties due to simplifications of the control model that have non-stochastic nature. And even in the case of stochastic type of signal uncertainties, only the uncertainty boundaries of these signals in specific spaces are required for the synthesis algorithms of robust controllers, and information about the probability distribution of signal error is not used.

The active phase of research on methods for identifying systems with uncertainty came in the 1990s, when robust control methods developed rapidly [7]. These methods have been called "non-stochastic" or "worst-case" identification. A common feature of these methods was that the various noises in the systems models were considered non-stochastic, but limited in some space.

Many tasks remain unsolved today, and methods for identifying models of systems with uncertainty continue to develop, in particular in the way of combination of stochastic and non-stochastic approaches [7], as well as creating methods that optimize experimental design and reduce the computational complexity of algorithms. For example, in [4] new approaches to identification of models with parametric uncertainty have been proposed, the application of which allows to reduce the number and duration of experiments while improving the accuracy of the obtained estimates.

In this paper, algorithms of the identification subsystem of ACS IR TGU are designed based on the worst-case methodology, which most corresponds to the uncertainty type in TGU MM chosen for this study.

**The main results.** In the study the authors use the complete non-linear TGU MM in the form of the combined controlled object (CCO), including generator (G), turbine (T), exciter (E), AVR, GOV, and test electrical system (TES) (Fig. 1). The model was obtained on the basis of the physical principles of the CCO components using the Park-Gorev equations, the detailed description of the model and its parameters is given in [1]. We can express the consolidated mathematical model of CCO as follows:

$$\frac{d}{dt}x(t) = F(x(t)) + Bu(t),$$
$$y(t) = Cx(t) + Du(t), \qquad (1)$$

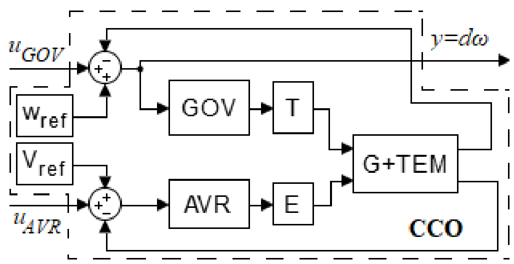


**Fig. 1**

where $x$ is the state vector; $F(x)$ is the nonlinear vector-valued function; $y = \omega - \omega_{ref}$ is the vector of observations: deviation of the generator rotor rotational speed; $B$, $C$, $D$ are the matrices with constant coefficients; $u = \begin{pmatrix} u_{GOV} & u_{AVR} \end{pmatrix}^T$ is the control vector consisting of the control signals of additional stabilizing inputs to GOV and AVR.

For the synthesis of the controller according to the procedure described in [1], the model (1) is linearized around the operating point with fixed values of active and reactive power $P$ and $Q$ corresponding to certain values of the load angle $\theta$ and the generator voltage $V_{ref}$. The order of the linearized model is reduced by the Schur method [9, 10]. The corresponding matrix transfer function $G$ of the linearized CCO system is expressed in the following form:

$$G(s) = C(sI - A)^{-1}B + D = \begin{pmatrix} G^1(s) & G^2(s) \end{pmatrix}. \qquad (2)$$

On the basis of the matrix transfer function $G$ of the CCO linearized system it is formed the CCO model with additive uncertainty:

$$G_{pert}(s) = G(s) + \Delta(s)W(s), \qquad (3)$$

where $G(s) = \begin{pmatrix} G^{(1)}(s) & G^{(2)}(s) \end{pmatrix}$ is the nominal transfer function of the non-perturbed controlled object, $\Delta = \begin{pmatrix} \Delta^{(1)} & \Delta^{(2)} \end{pmatrix}$, $\|\Delta\|_\infty < 1$ is the normalized uncertainty, $\|\bullet\|_\infty$ is the norm in the $RH_\infty$ space, and $W = \begin{pmatrix} w^{(1)} & 0 \\ 0 & w^{(2)} \end{pmatrix}$ is the weight function that also belongs to the $RH_\infty$ space. The additive term $\Delta(s)W(s)$ to the nominal function of the controlled object includes all the types of uncertainty mentioned above.

This description of the controlled object (3) is used for applying the synthesis algorithm of the H∞-suboptimal interconnected robust controller of TGU shaft speed, which reduces the dangerous torsional vibrations of the shaft by coordinating the action of GOV and AVR [1].

The task of identifying the CCO model with uncertainty (3) is to determine the transfer functions $G(s)$ and $W(s)$ from the experimental data, which are presented in the form of time discrete series. Let the system being identified have, in the general case, $Nu$ control inputs ($u_1$, $u_1$, …, $u_{Nu}$) and one output $y$. Suppose we also have a set of parameters ($p_1, p_2, \ldots, p_{Np}$) of the original complete CCO model (1), which are sources of uncertainty and may vary over a range of values. The range of variation of these parameters by virtue of the accepted model should be expressed in the form of nonparametric uncertainty in the CCO model, in other words, the task is to find the limits of nonparametric uncertainty that correspond to the variation of these parameters.

First consider the problem of identification of the nominal transfer function G(s). We will identify the function in the form:

$$G(s)=\left[G^{(1)}(s)\quad \ldots \quad G^{(Nu)}(s)\right],\, G^{(i)}(s)=\left(\sum_{k=0}^{m} a_k^{(i)} s^k\right)^{-1}\sum_{k=0}^{n} b_k^{(i)} s^k,\, i=1\ldots Nu\,. \tag{4}$$

Identification is performed in active way, identifying datasets for each control channel from individual experiments. A linear frequency-modulated signal, also called a "chirp" signal, is selected as the input test disturbance [2]. Identification procedure is carried out by time discrete series using one of the "direct" methods, namely the method of minimizing the prediction error (PEM) [5].

The prediction error minimization method is intended to identify both linear and nonlinear systems [5]. In this method, the output signal is represented as follows:

$$y(k)=\frac{B(q^{-1})}{A(q^{-1})}u(k)+n(k)\,,$$

where $q^{-1}$ is the shift operator and $q^{-1}y(k)=y(k-1)$; $u(k)$ is the input signal, $y(k)$ is the output signal; $n(k)$ is the noise signal; polynomials $A$ and $B$ have the coefficients of the denominator and the numerator of the transfer function $G(s)$ of the system to be identified.

The estimate of the noise signal is expressed by unknown polynomials $F$ and $H$, which are also determined during the identification process:

$$\hat{n}(k\,|\,k-1)=\left(1-\frac{H(q^{-1})}{F(q^{-1})}\right)n(k)\,.$$

Then the estimate of the output signal is expressed as:

$$y(k\,|\,k-1)=\left(1-\frac{H(q^{-1})}{F(q^{-1})}\right)y(k)+\frac{B(q^{-1})}{A(q^{-1})}u(k)\,.$$

The prediction error is equal: $e(k)=y(k)-\hat{y}(k\,|\,k-1)$.

Optimization criterion for finding the coefficients of polynomials A, B, F, H:

$$f(k)=\sum_{k=1}^{N} e_k^2(k)\rightarrow \min\,. \tag{5}$$

In order to minimize the function of the optimization criterion (5), it is advisable to use the Gauss-Newton method [5].

As a result of applying the method for each control channel, we obtain the values of the coefficients $a_k^{(i)}$ and $b_k^{(i)}$ of each element of the nominal transfer function $G(s)$ from (4).

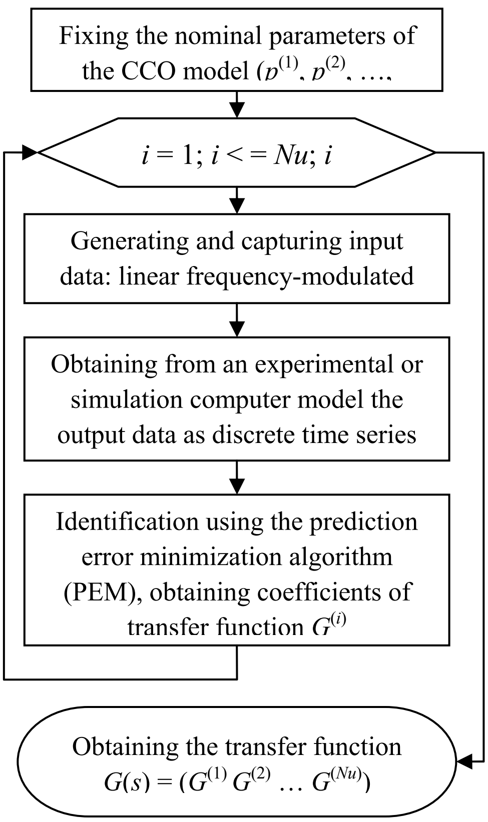


**Fig. 2**

The schematic representation of the identification algorithm of the nominal matrix transfer function of the system is shown in Fig. 2. The identification procedure begins with the fixation of the nominal values of the controlled object varied parameters. Then the cycle starts according to the number of Nu control channels of the system: the input test linear frequency-modulated signal of the fixed frequency range is sent to the input of the current channel of the cycle, the values of input and output signals are registered at time points with the selected step. According to these data, the matrix element of the nominal transfer function corresponding to the current control channel is identified by the PEM method described above. At the end of the cycle, we have a fully identified transfer matrix function of the controlled object.

To determine the weight function $W$, we identify several $G_{pert}$ functions in different modes corresponding to certain parameter values ($p_1$, $p_2$, …, $p_{Np}$) in the neighborhood of nominal values. The parameters can be changed by some regular grid, but if the number of parameters is greater than 2, it can be used a set of randomly generated parameter vectors within the boundaries of their change. Then we construct a set of log-magnitude curve differences, identified with specific parameter values and nominal functions separately for each $i$-th control channel $G_{pert}^{(i)}\big|_{(p_1,\ldots,p_{Np})} - G^{(i)}$, and determine the maximum log-magnitude curve of this family as an upper envelope [9] (Fig. 3).

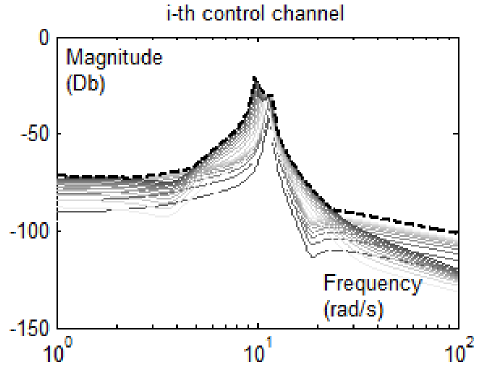


**Fig. 3**

By the determined maximum log-magnitude curves, we restore the minimum-phase transfer functions $w^{(1)}(s)$, by which we build the matrix weight function

$$W(s) = diag\left(w^{(1)}(s) \quad \ldots \quad w^{(Nu)}(s)\right).$$

The identification algorithm of the matrix weight function of the system is shown in Fig. 4.

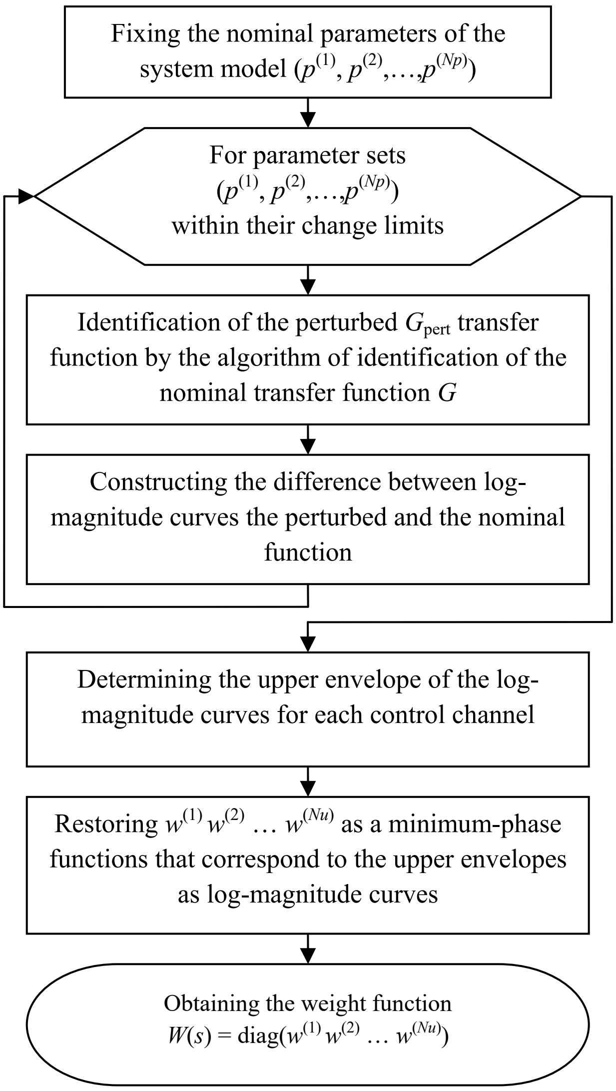


**Fig. 4**

The algorithm starts with fixed CCO nominal parameters, after that the loop executes with the parameters values within their variation range. As already mentioned, these values can be computed both basing on a regular grid or on set of points in the space of parameter values that are uniformly distributed in a limited area. The next step is to determine the parameters of the perturbed transfer function $G_{pert}$ according to the algorithm for identifying the nominal transfer function, shown in Fig. 2. After that we find the difference $G_{pert} - G$ and build the log-magnitude curve of each element of this difference. At the end of the loop we have $Nu$ curves in the graph, an example of such a graph is shown in Fig. 3. For each $i$-th graph we find a discrete set of points in the upper envelope of the family of log-magnitude curves, according to which we calculate the corresponding element of the weight function, solving the Chebyshev approximation problem with the minimax optimality criterion for finding the coefficients of the minimum-phase transfer function to fit the log-magnitude curve [11].

According to the described algorithm, the authors carried out identification of the CCO transfer function of the TGU model consisted of K-200-130 turbine and TGV-200 generator. The sources of uncertainty were fixed as: the coordinates of the system state $x_{nom}$ in the neighborhood of which the equations were linearized and the following parameters of the system: the coefficient $K_{0u}$ of AVR and the resistance of the transmission line $X_{TES}$, which depends on the length of the line $l_{TES}$. Assume that the nominal transfer function of the system $G(s)$ in (1) corresponds to the nominal TGU operating mode, which corresponds to the nominal value of the active power $P_{nom}$ and the value of the reactive power $Q_{nom}$ according to the nominal value of the power factor cos$\varphi_{nom}$. Also, we fix the nominal values of the parameter $K_{0u} = 100$. Range of variation of parameters: $x \in \left[ x|_{P=0}, x|_{P=P_{nom}} \right]$; $K_{0u} \in [50...150]$.

In system (1) there are two input control signals $u_{GOV}$ and $u_{AVR}$ and one output signal $y$. That is, the system has two control channels "$u_{GOV} - y$" and "$u_{AVR} - y$".

As part of the study, using the simulation scheme in the Simulink graphical programming environment of the MATLAB software package, it was generated a set of input data in the form of "chirp" signal and corresponding output data (Fig. 5), by which the nominal transfer function $G(s)$ was identified according to the algorithm shown in the Fig. 3:

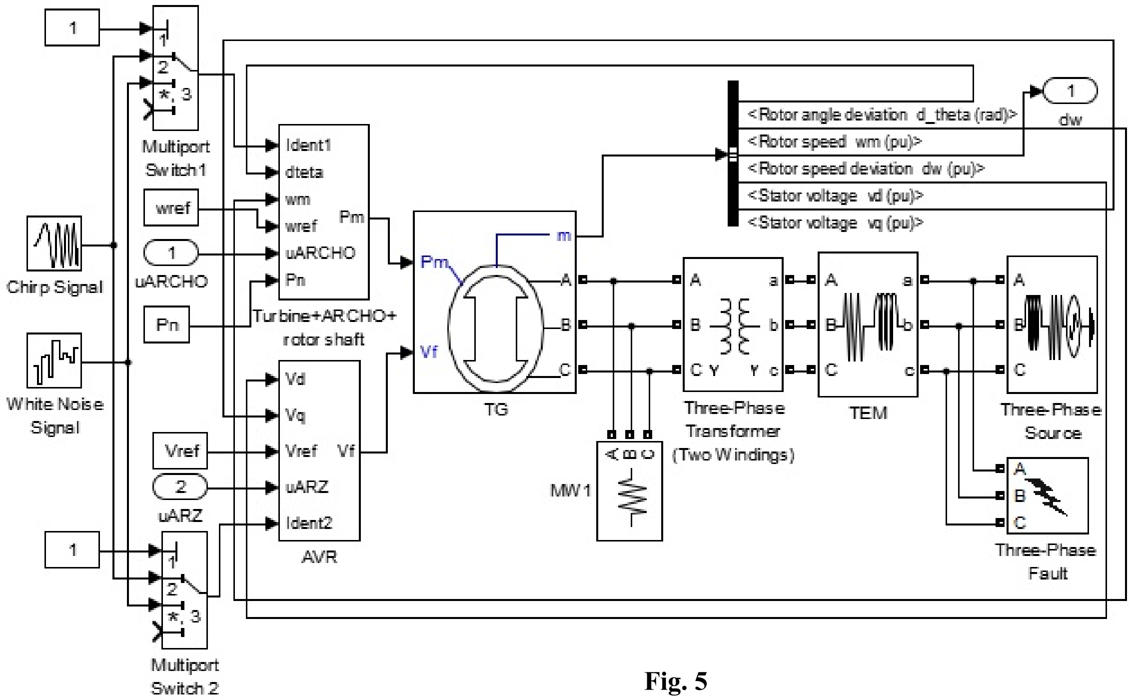


**Fig. 5**

$$G(s) = \left( G^{(1)}(s) \quad G^{(2)}(s) \right), \tag{6}$$

where

$$G^{(1)}(s) = \frac{-0.0001945s^3 - 0.002697s^2 + 2.944s - 3.359}{s^4 + 13s^3 + 185.9s^2 + 1615s + 6321}, \quad G^{(2)}(s) = \frac{0.03354s^3 - 0.8643s^2 - 7.021s - 173.6}{s^4 + 5.627s^3 + 219.9s^2 + 700.1s + 1.125e04}.$$

A comparison of the identified function $G(s)$ with $G_{teor}(s)$ is performed, where $G_{teor}(s)$ was obtained from the TGU complete mathematical model (1) by linearization and order reduction from 14 ($G_{teor14}(s)$) to 4 ($G_{teor4}(s)$) by the Schur method [9, 10]

$$G_{teor14}(s) = \left( G^{(1)}_{teor14}(s) \quad G^{(2)}_{teor14}(s) \right), \tag{7}$$

where
$$G^{(1)}_{teor14}(s) = \frac{\begin{array}{l} 3713s^{10} + 7.966e06s^9 + 2.685e09s^8 + 3.4e12s^7 + 2.235e14s^6 + 3.393e15s^5 + 2.2e16s^4 + \\ +8.406e16s^3 + 1.1e17s^2 + 4.445e16s - 1.018e05 \end{array}}{\begin{array}{l} s^{14} + 3161s^{13} + 2.919e06s^{12} + 1.686e09s^{11} + 1.003e12s^{10} + 7.718e13s^9 + 2.091e15s^8 + \\ +3.413e16s^7 + 4.154e17s^6 + 3.678e18s^5 + 2.218e19s^4 + 8.809e19s^3 + 1.926e20s^2 + \\ +1.116e20s + 1.706e19 \end{array}},$$

$$G^{(2)}_{teor14}(s)=\frac{\begin{array}{l}-2645s^{11}-1.827e06s^{10}+2.892e08s^{9}-5.98e11s^{8}-7.238e13s^{7}-2.917e15s^{6}-4.902e16s^{5}-\\ -3.75e17s^{4}-1.205e18s^{3}-1.06e18s^{2}-1.954e17s+7030\end{array}}{\begin{array}{l}s^{14}+3161s^{13}+2.919e06s^{12}+1.686e09s^{11}+1.003e12s^{10}+7.718e13s^{9}+2.091e15s^{8}+\\ +3.413e16s^{7}+4.154e17s^{6}+3.678e18s^{5}+2.218e19s^{4}+8.809e19s^{3}+1.926e20s^{2}+\\ +1.116e20s+1.706e19\end{array}},$$

$$G_{teor4}(s)=\left(G^{(1)}_{teor4}(s)\quad G^{(2)}_{teor4}(s)\right), \tag{8}$$

where

$$G^{(1)}_{teor4}(s)=\frac{-0.005128s^{3}+0.1142s^{2}+1.297s+1.769}{s^{4}+6.849s^{3}+163.8s^{2}+766.8s+4555},\ G^{(1)}_{teor4}(s)=\frac{0.0007232s^{3}-0.6564s^{2}-28.06s-9.782}{s^{4}+6.849s^{3}+163.8s^{2}+766.8s+4555}.$$

The comparison was performed in the frequency range and showed the equality of the log-magnitude curves of all functions with sufficient accuracy in the operating frequency range. Fig. 6 shows a comparison of log-magnitude curve of the identified function $G(s)$ and those calculated using TGU mathematical models: complete of 14$^{th}$ order and simplified of 4$^{th}$ order.

Then the weighting function $W$ was determined by the given above algorithm shown in Fig. 4 using the input linear frequency-modulated signal. In Fig. 7 log-magnitude curve of $W$ is represented by a dashed line. Using this curve, the minimum-phase functions $w^{(1)}$ and $w^{(2)}$ were restored, which the matrix weight function $W$ consists of:

$$W(s)=diag\left(w^{(1)}(s)\quad w^{(2)}(s)\right), \tag{9}$$

$$w^{(1)}(s)=\frac{1.689e(-06)s^{4}+0.001386s^{3}+0.01571s^{2}+1.009s+2.847}{s^{4}+0.6621s^{3}+231.3s^{2}+70.3s+1.302e04},$$

where

$$w^{(2)}(s)=\frac{3.617e(-05)s^{4}+0.01396s^{3}+0.5976s^{2}+35.36s+36.94}{s^{4}+5.511s^{3}+227.1s^{2}+568.7s+1.251e04}.$$

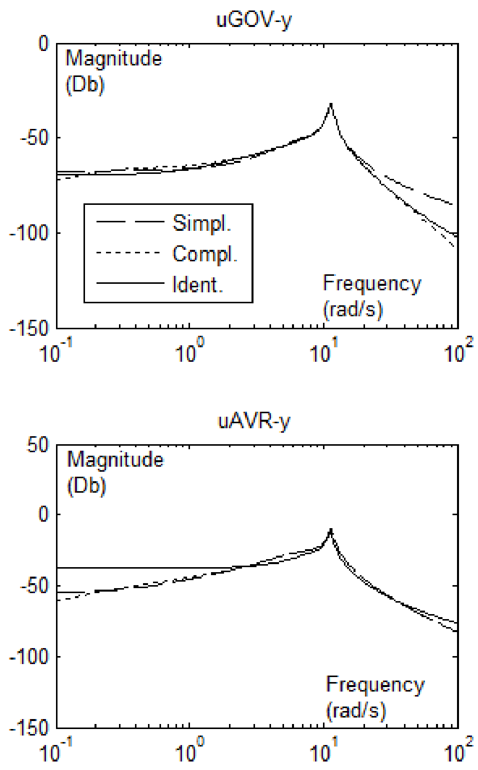


**Fig. 6**

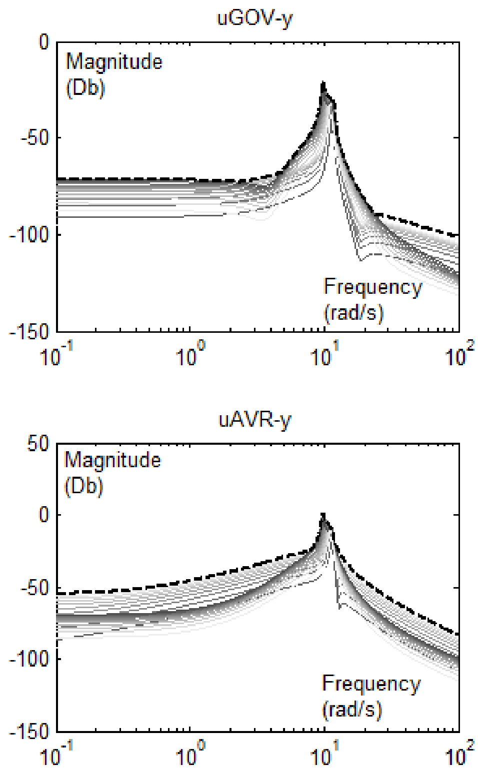


**Fig. 7**

Thus, the above algorithms of determining of the matrix transfer functions $G(s)$ and $W(s)$ can be applied in the operation of the identification subsystem of ACS IR TGU for identification of CCO with uncertainty in form (3) for initial adjustment of the interconnected robust controller as well as for its readjustment during the operation of the control system in the case of a significant change of the boundaries of uncertainty in the CCO MM.

**Conclusions.**

The algorithm for identifying TGU as a controlled object has been developed based on the "worst-case" principle of identifying models of uncertain controlled objects. The simulation has been performed to generate a set of input and output data and to further apply the developed identification procedure. On the basis of these computational experiments, it is shown the approximate equality of log-magnitude curves of the identified nominal COO transfer function of the model with non-parametric uncertainty (3) and the transfer function determined from the complete TGU mathematical model (1) with sufficient accuracy in the range of TGU operating frequencies.

The developed algorithm of identification is intended for use in the identification subsystem of ACS IR TGU.


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## ИДЕНТИФИКАЦИЯ МАТЕМАТИЧЕСКОЙ МОДЕЛИ ТУРБОАГРЕГАТА С НАЛИЧИЕМ НЕОПРЕДЕЛЕННОСТИ

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*Исследована процедура идентификации математической модели турбоагрегата с наличием неопределенности для применения в автоматизированной системе взаимосвязанного робастного управления. Процедура*

*базируется на методологии идентификации "worst-case". Объект управления моделируется матричной передаточной функцией с аддитивной неопределенностью. Идентификация состоит из двух этапов: первый – определение передаточной функции с номинальными параметрами с использованием алгоритма минимизации погрешности прогноза, второй – определение весовой функции в модели аддитивной неопределенности с помощью поиска наихудшего варианта амплитудно-логарифмических характеристик неопределенностей. Идентификация проводится активным способом, определяя наборы данных для каждого канала управления по отдельным экспериментам. Линейно частотно-модулированный сигнал выбирается в качестве входного тестового сигнала. Построена имитационная модель турбоагрегата и проведен численный эксперимент с использованием процедуры идентификации.* Библ. 11, рис. 7.
***Ключевые слова***: турбоагрегат, идентификация, автоматизированная система управления.

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**ІДЕНТИФІКАЦІЯ МАТЕМАТИЧНОЇ МОДЕЛІ ТУРБОАГРЕГАТА З НАЯВНІСТЮ НЕВИЗНАЧЕНОСТІ**

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*Досліджено процедуру ідентифікації математичної моделі турбоагрегата з наявністю невизначеності для застосування в автоматизованій системі взаємозв'язаного робастного керування. Процедура базується на методології ідентифікації "worst-case". Об'єкт керування моделюється матричною передавальною функцією з адитивною невизначеністю. Ідентифікація складається з двох етапів: перший – виявлення передавальної функції з номінальними параметрами з використанням алгоритму мінімізації похибки прогнозу, другий – визначення вагової функції в моделі адитивної невизначеності за допомогою пошуку найгіршого варіанту амплітудно-логарифмічних характеристик невизначеностей. Ідентифікація проводиться в активний спосіб, визначаючи набори даних для кожного каналу керування з окремих експериментів. Лінійно частотно-модульований сигнал обирається в якості вхідного тестового сигналу. Побудовано імітаційну модель турбоагрегата та проведено чисельний експеримент з використанням процедури ідентифікації.* Бібл. 11, рис. 7.
***Ключові слова***: турбоагрегат, ідентифікація, автоматизована система керування.

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