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The method of multi objective design of nonlinear electromechanical tracking systems based on neural network controller using hybrid metaheuristic optimization algorithm

***Problem**. Most research on the design of nonlinear electromechanical tracking systems has been conducted using typical proportional-differential controllers, but there is no methodology for designing nonlinear electromechanical tracking system based on neural network controller to meet different requirements that are imposed on the operation of the system in different modes. **Goal.** To develop the method of multi objective design of nonlinear electromechanical tracking system based on neural network controller to satisfy different requirements that are imposed on the operation of the system in various modes. **Methodology.** The designed nonlinear electromechanical tracking system based on neural network controller implements the dynamics of a reference model by training a neural network controller for a given model of a nonlinear control object. Multi objective design of the reference model reduces to solving a vector nonlinear programming problem, in which the components of the vector objective function are direct different requirements that are imposed on the operation of the system in various modes. The solution to the vector nonlinear programming problem is calculated using a hybrid heuristic optimization algorithm, incorporating particle swarm optimization and stochastic sequential quadratic programming. **Results**. The results multi objective design of two-mass nonlinear electromechanical tracking systems based on neural network controller in which different requirements that are imposed on the operation of the system in various modes were satisfied are given. Based on the results of modeling and experimental studies it is established, that with the help of synthesized neural network controllers, it is possible to improve of quality indicators of two-mass nonlinear electromechanical tracking system in comparison with the system with standard regulators. **Scientific novelty.** For the first time the method of multi objective design of nonlinear electromechanical tracking systems based on neural network controller to satisfy different requirements that are imposed on the operation of the system in various modes is developed. **Practical value.** From the point of view of the practical implementation the possibility of solving the problem of multi objective design of nonlinear electromechanical tracking systems based on neural network controller to satisfy different requirements that are imposed on the operation of the system in various modes is shown.* References 43, figures 8.

Key words: **nonlinear electromechanical tracking system, neural network controller, multi objective design, computer simulation, experimental research.**

***Проблема**. Більшість досліджень по проєктуванню нелінійних електромеханічних систем стеження виконані на основі використання типових пропорційно диференційних регуляторів, але відсутня методологія проєктування нелінійних електромеханічних систем стеження на основі нейромережевого контролеру для задоволення різноманітних вимог, які пред'являються до роботи системи у різних режимах. **Метою** роботи є розробка методу багатокритеріального проєктування нелінійних електромеханічних систем стеження на основі нейромережевого контролеру для задоволення різноманітних вимог, які пред'являються до роботи системи у різних режимах. **Методологія**. У спроєктованих нелінійних електромеханічних систем стеження на основі нейромережевого контролеру реалізується динаміка еталонної моделі в результаті навчання нейромережевого контролеру для заданої моделі нелінійного об'єкта управління. Багатокритеріальне проєктування еталонної моделі зводиться до вирішення проблеми векторного нелінійного програмування, в якій компонентами цільової векторної функції є різноманітні вимоги, які пред'являються до роботи системи у різних режимах. Вирішення проблеми векторного нелінійного програмування обчислюється за допомогою гібридного евристичного алгоритму оптимізації, що включає оптимізацію роєм частинок і послідовне стохастичне квадратичне програмування. **Результати**. Наведено результати багатокритеріального проєктування двомасової нелінійної електромеханічної системи стеження на основі нейромережевого контролеру, в якій були задоволені різноманітні вимоги, які пред'являються до роботи системи у різних режимах. На основі результатів моделювання та експериментальних досліджень встановлено, що за допомогою синтезованих нейромережевих контролерів можна підвищити якісні показники двомасової нелінійної електромеханічної системи стеження у порівнянні із системою зі стандартними регуляторами. **Наукова новизна**. Вперше розроблено метод багатокритеріального проєктування нелінійних електромеханічних систем стеження на основі нейромережевого контролеру для задоволення різноманітних вимог, які пред'являються до роботи системи у різних режимах. **Практична значимість**. З точки зору практичної реалізації показана можливість вирішення задачі багатокритеріального проєктування нелінійних електромеханічних систем стеження на основі нейромережевого контролеру для задоволення різноманітних вимог, які пред'являються до роботи системи у різних режимах.* Бібл. 43, рис. 8.

Ключові слова: **нелінійна електромеханічна система стеження, нейромережевий контролер, багатоцільове проєктування, комп'ютерне моделювання, експериментальні дослідження.**

Introduction. Most existing electromechanical tracking systems are based on DC motors due to their low cost and ease of design and setup [1, 2]. Furthermore, brushless DC motors are also becoming widespread in modern electromechanical tracking systems [3]. Despite the need for a valve commutator for the windings of a brushless DC motor, the subsequent control algorithms are equivalent to those of a brushed DC motor. Due to the rapid development of converter technology, modern electromechanical tracking systems are also designed on the basis of AC motors – synchronous or asynchronous – due to their higher reliability despite their higher cost [4, 5].

Electromechanical tracking systems are often installed on a moving base, which imposes additional requirements for compensating for disturbances when the moving base moves over rough terrain. The use of permanent magnet synchronous motors for such systems instead of traditional hydraulic motors, together with modern control systems instead of standard regulators, allows for a more than tenfold increase in the control accuracy of such electromechanical tracking systems.

Electromechanical tracking systems have different accuracy requirements for various operating modes. Therefore, the design of electromechanical tracking systems is a multi objective problem [6–8].

The potential accuracy of electromechanical tracking systems is often limited by the presence of nonlinear friction characteristics on the drive motor and working mechanism shafts, as well as elastic elements between the drive motor and working mechanism shafts, which lead to uneven movement up to the so-called «stick-slip» solution when moving at low speeds. Therefore, existing electromechanical tracking systems use standard proportional-differential controllers, which limits the potential accuracy of such systems. Often, it is the operating accuracy of systems in these modes that determines their potential accuracy of electromechanical tracking systems.

When driving at high speeds and with high acceleration, the dynamic characteristics of electromechanical tracking systems are limited by the maximum voltage of the on-board network and the maximum torque of the actuator motor [9, 10].

In addition, the parameters of electromechanical tracking systems, firstly, are not known precisely and, secondly, can change significantly during operation, therefore the designed electromechanical tracking system must be robust [11, 12].

The presence of complex nonlinear dependencies, uncontrolled disturbances and interference, uncertainties in parameters, and possibly the structure, models of the control object and external disturbances in electromechanical tracking systems complicates the implementation of traditional control strategies, since both modern, in particular the theory of adaptive and optimal control, and classical control theory are largely based on the idea of linearization of systems.

Currently, neural networks controllers based on artificial neural networks (ANN) are widely used to control various objects, which make it possible to effectively control complex nonlinear objects under conditions of uncertainty. Most research on the design of nonlinear electromechanical tracking systems has been conducted using typical proportional-differential controllers, but there is no methodology for designing neural network control by nonlinear electromechanical tracking system to meet different operating requirements in different modes.

The goal of the work is to develop the method for multi objective design of nonlinear electromechanical tracking systems based on neural network controller to satisfy different requirements that are imposed on the operation of the system in various modes. This goal proposed to achieve based on hybrid metaheuristic optimization algorithm.

Problem statement. Recently, ANN has become a very promising alternative to classical methods of constructing control systems for nonlinear objects. Neural network control technologies allow us to overcome many of the challenges that arise when working with nonlinear objects or objects of unknown structure and that are intractable using conventional adaptive control methods. The ability of ANN to implement complex nonlinear control laws is due to the use of sigmoid activation functions or other nonlinear functions for neurons in hidden layers.

The ability of ANN to self-learn allows the use of neural controllers even in conditions of significant uncertainties, while for the implementation of traditional adaptive control methods, a necessary condition is the presence of a large amount of a priori information about the control object. The high performance and reliability of neural controllers is due to the high degree of parallelism of ANNs. The ease of implementation of neural networks on modern computing hardware and their ability to learn make them particularly attractive for controlling complex nonlinear systems in real time.

The diagram of the neural network system with a reference model is shown in Fig. 1.

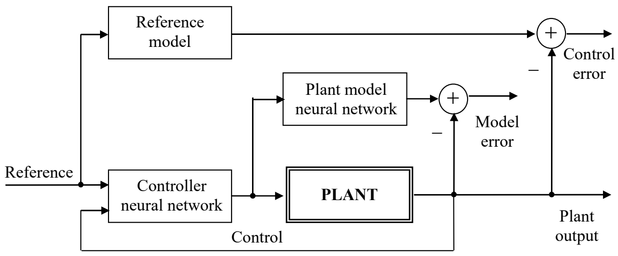


Fig. 1. Diagram of the control system with a reference model

Let us consider a mathematical model of a nonlinear control object of an electromechanical tracking system in the form of a state space adopted in classical control theory

$$z(k+1)=\boldsymbol{\Psi}[z(k),\boldsymbol{u}(k),\boldsymbol{\varphi}(k)], \quad (1)$$

$$\boldsymbol{y}(k)=\boldsymbol{F}[z(k),\boldsymbol{u}(k),\boldsymbol{\varphi}(k)], \quad (2)$$

where $\boldsymbol{z}(k)=[z_1(k),z_2(k),...,z_{k_z}(k)]^T$ is the system state vector; $\boldsymbol{u}(k)=[u_1(k),u_2(k),...,u_{k_u}(k)]^T$ is the vector of input signals $\boldsymbol{y}(k)=[y_1(k),y_2(k),...,y_{k_y}(k)]^T$ is the vector of output; $\boldsymbol{\Psi}[\cdot]$, $\boldsymbol{F}[\cdot]$ are some static nonlinear functions; $\boldsymbol{\varphi}(k)$, $\boldsymbol{\phi}(k)$ are the process noise and measurement noise, respectively.

Model (1), (2) takes into account the presence of nonlinear friction characteristics on the shafts of the drive motor and the working mechanism, as well as elastic elements between the shafts of the drive motor and the working mechanism.

Process noise also includes uncertainties in the control object model and external influences.

Let us write a mathematical model of a nonlinear control object of an electromechanical tracking system (1), (2) in the form of a Nonlinear Autoregressive-Moving Average (NARMA) – model

$$y(k)=f\begin{bmatrix} y(k-1),...,y(k-n_y),u(k-1),..., \\ u(k-n_u),e(k-1),...,e(k-n_e) \end{bmatrix}+e(k), \quad (3)$$

where $y(k)\in R^{M\times 1}$ is the output signal of the object; $u(k)\in R^{N\times 1}$ is the input signal of the object; $e(k)\in R^{M\times 1}$ is the measurement error; $f\ [\cdot]$ is the nonlinear transformation function:

$$f:\boldsymbol{R}^{(k_yM+k_uN+k_eM)\times 1}\to \boldsymbol{R}^{M\times 1},$$

where n_y, n_u, n_e are the orders of magnitude of the delay in the output and input signals of the object and the measurement error, respectively.

Representations of objects as NARMA models play a fundamental role in the study of nonlinear objects using ANN. It is important to consider a generalization of model (3) that takes into account various types of nonlinearities in input and output variables.

The NARMA neural network controller uses a NARMA model of the controlled object. When synthesizing the controller in question, a discrete nonlinear model of the nonlinear controlled object is constructed as NARMA model in the form

$$y(k+d)=N\begin{bmatrix} y(k),y(k-1),...,y(k-n+1), \\ u(k),u(k-1),...,u(k-m+1) \end{bmatrix}, \quad (4)$$

where $y(k)$ is the model output; d is the number of prediction cycles; $u(k)$ is the model input.

At the identification stage, a neural network is constructed for the NARMA model. This procedure is similar to the identification procedure described above with a predictive controller.

If it is necessary to design a tracking system that ensures movement along a given trajectory

$$y(k+d)=y_r(k+d). \quad (5)$$

Then the controller calculates the control in the following form:

$$u(k+1)=\frac{y_r(k+d)-f\begin{bmatrix} y(k), y(k-1),..., y(k-n+1), \\ u(k-1),...,u(k-m+1) \end{bmatrix}}{g\begin{bmatrix} y(k), y(k-1),..., y(k-n+1), \\ u(k-1),...,u(k-m+1) \end{bmatrix}}. \quad (6)$$

After the network is created, it is trained using the trainlm function, which corresponds to the Levenberg-Marquardt algorithm. Currently, genetic algorithms and hybrid heuristic algorithms are widely used to train neural networks, which allow finding a global optimum.

Multi objective design of reference model. When operating electromechanical tracking systems, the following accuracy requirements are typically imposed in various modes. The range of control objects angles with a stepwise input. The time it takes to process the specified control object angles with a stepwise input.

This time typically characterizes the system's response time when transferring the control object's position and when compensating for large errors during initial positioning. Limitations on reducing this time are the energy limitations of the drive motor's rotation speed and torque.

The minimum rate of increase and decrease of the controlled object's angles with a linearly varying input signal is. Typically, limitations are set on the roughness of the working element's motion at low guidance speeds. The main limitations here are the nonlinear friction characteristics on the drive motor and working mechanism shafts. These limitations often determine the potential accuracy of the electromechanical tracking system.

Error in processing harmonic changes in the set angles of the controlled object and set frequencies [13, 14]. These requirements are typically based on the accuracy of compensation for disturbances acting on the electromechanical tracking system mounted on a moving base as it moves over rough terrain [15, 16]. All these requirements must be satisfied using a single neural network controller. Naturally, it is necessary to take into account the uncertainties in the controlled object [17–19]. The neural network controller implements the system's dynamics.

Let's consider a nonlinear electromechanical tracking systems based on neural network controller with a reference model shown in Fig. 1. Using an object's neural controller, the system dynamics defined by the reference model are implemented for a given model of the control object [20–22]. Naturally, the reference model is defined as an NARMA system [23–25]. To train the NARMA model with a reference model, it is first necessary to design a reference model in NARMA model form.

We introduce the vector $\boldsymbol{\chi}$ of the reference model's parameter in the state space form (1), (2) adopted in classical control theory [26, 27]. Then, for a given value of the desired vector $\boldsymbol{\chi}$ of the reference model's parameters, the performance indicators that are imposed on the electromechanical tracking system in various operating modes can be calculated. We introduce the vector objective function

$$\boldsymbol{F}(\chi)=[F_1(\chi), F_2(\chi)...F_m(\chi)]^T, \quad (7)$$

in which the components of the vector target function $F_i(\boldsymbol{\chi})$ are direct quality indicators that are presented to the system in various modes of its operation such as the time of the first matching, the time of regulation, overshooting, etc. To calculate the vectors objective function (7), the initial nonlinear electromechanical tracking system (1), (2) based on neural network controller (6) is modeled in various modes of operation, with different input signals [28–30].

Then, the process of training the reference model (1), (2) in the NARMA model form (6) is reduced to minimizing the vector objective function (7) with respect to the desired vector $\boldsymbol{X}$ of reference model parameters.

Hybrid heuristic optimization algorithm. This multi objective nonlinear programming problem (7) is solved on the basis on hybrid heuristic optimization algorithm, which includes multi-swarm stochastic multi-agent optimization algorithms and stochastic sequential quadratic programming optimization algorithms [31–33].

For this purpose minimum for multi objective nonlinear programming problem (7) desired parameters vector X calculated by multi-swarm stochastic particle swarm optimization algorithm in following procedure [34–36]. Particle i swarm j movement described by

$$x_{ij}(t+1)=x_{ij}(t)+v_{ij}(t+1), \quad (8)$$

where

$$\begin{aligned} v_{ij}(t+1) &= w_j v_{ij}(t)+c_{1j}r_{1j}(t)H(p_{1j}-\varepsilon_{1j}(t))\times\ldots \\ &\ldots\times[y_{ij}(t)-x_{ij}(t)]+c_{2j}r_{2j}(t)H(p_{2j}-\varepsilon_{2j}(t))\times\ldots \\ &\ldots\times[y_j^*(t)-x_{ij}(t)], \end{aligned} \quad (9)$$

where $x_{ij}(t)$, $v_{ij}(t)$ are position and velocity vectors components of the particle i of the swarm j for multi objective nonlinear programming problem (7) minimum for desired parameters vector $\boldsymbol{\chi}$ calculated.

This optimization algorithm (8), (9) works effectively at initial stages of iterations, when movement speeds have significant values. When entering quasi-stationary range of multi objective nonlinear programming problem (7) motion speeds tend to zero. To speed up global optima calculating process in stationary range, it is advisable second-order methods used based on second derivatives. One of simplest and quite effective second-order optimization methods is sequential quadratic programming algorithm. The of the initial parameters values of desired parameters vector $\boldsymbol{\chi}$ obtained with optimization algorithm (8), (9) help are initial values for refining solutions in quasi-stationary range.

To calculate multi objective nonlinear programming problem (7) minimum for desired parameters vector $\boldsymbol{\chi}$ by stochastic sequential quadratic programming optimization algorithms formulated minimization problem with quadratic objective function [37–39]

$$\begin{aligned} &\boldsymbol{H}_r(\boldsymbol{X}_{ij}(t))\rangle+\frac{1}{2}\boldsymbol{d}_{ijx}^T(t)\boldsymbol{H}_{ijx}(\boldsymbol{X}_{ij}(t))\boldsymbol{d}_{ijx}(t)+\ldots \\ &\ldots+\boldsymbol{J}_{ijx}^T(t)\boldsymbol{d}_{ijx}(t). \end{aligned} \quad (10)$$

Jacobian matrices $\boldsymbol{J}_{ijx}(t)$ and Hessian matrices $\boldsymbol{H}_{ijx}(t)$ components along vector $\boldsymbol{X}$ calculated from particle i of swarm j movement velocities $v_{ij}(t)$ and accelerations $a_{ijx}(t)$, which calculated based on velocities $v_{ij}(t)$

$$a_{ijx}(t+1) = v_{ij}(t+1) - v_{ij}(t). \qquad (11)$$

During stochastic sequential quadratic programming optimization algorithms process (10) step size $d_{ijx}(t)$ calculated, which used to calculated multi objective nonlinear programming problem (7) minimum by desired parameters vector $\boldsymbol{X}$

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ijx}(t) d_{ijx}(t). \qquad (12)$$

Simulation results. Let us now consider the dynamic characteristics of the nonlinear electromechanical tracking system with the designed neural network controller. The design of neural network controller is implemented in the Neural Network Toolbox application package of the MATLAB system.

The parameters adopted for neural network controller design for nonlinear electromechanical tracking system are: rated voltage of the drive motor U_n=27 V rated motor current; I_n=31 A; armature winding resistance of the motor R_a=75 mΩ; motor design factor c_f=0.062; moment of inertia of the motor rotor J_r=27·10^{-5} kg·m^2; electromagnetic time constant of the armature chain T=4.5·10^{-3}; power amplifier transmission coefficient k=27; gear ratio of the kinematic coupling device N=377; dry friction moments in the motor bearings M_b=0.15 N·m; frictional torque on the working mechanism shaft M_s=200 N·m; load moment of inertia J_m=250 kg·m^2; transmission element stiffness coefficient c=3·10^5 N·m; gap between the teeth of the drive and driven gears σ=1,5′.

One of the most demanding operating modes of the system is the mode of processing specified rotation angles of the actuator with a stepwise input signal. This mode largely determines the speed of processing the reference values and compensating for disturbances. Figure 2 shows the implementations of the state variables of the nonlinear electromechanical tracking systems based on neural network controller in this operating mode.

Figure 2 shows the following state variables: *a*) plant rotation angle $\varphi(t)$; *b*) plant rotation speed $\omega_p(t)$; *c*) elastic moment $M_e(t)$; *d*) motor speed $\omega_m(t)$; *e*) motor current $I_m(t)$; *f*) voltage on the motor circuit $U_m(t)$. As can be seen from these figures, the main limitation is the on-board network voltage, which changes practically in a relay manner from the minimum to the maximum value. Note that this operating mode approximately corresponds to a maximum-speed controller, which approximately implements the minimum transient process time. Thus, the use of a neural network controller allows for a more than 2-fold reduction in the system's transition time in this operating mode of the nonlinear electromechanical tracking system.

Another stressful operating mode is the low-speed guidance mode. In this mode, friction nonlinearities on the actuator and working mechanism shafts are most pronounced, resulting in uneven movement of the working element in the «stick-slip» mode. Technical requirements for electromechanical tracking systems in this mode typically impose restrictions on the unevenness of the working element's motion at low, creeping speeds. Figure 3 shows the implementation of the state variables of an electromechanical tracking system in this operating mode. Figure 3 shows the same state variables as in Fig. 2.

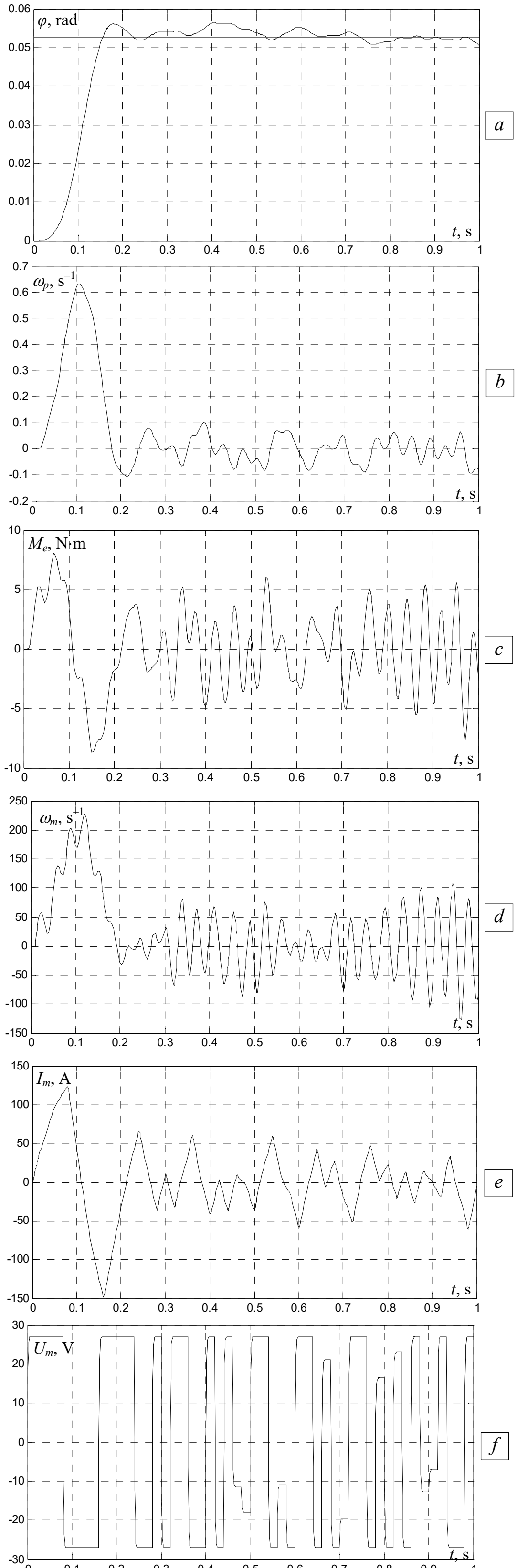


Fig. 2. Transition process when working out angle

As can be seen from these figures, the movement of the working element is accompanied by oscillations at a frequency of approximately 6 Hz and stops. Note that for many electromechanical tracking systems, the requirement for uneven movement of the working element at low, creeping speeds determines the potential accuracy of the electromechanical tracking system in one of its most critical operating modes. One of the system's stressful operating modes is high-speed movement. This mode determines the system's response time when firing behind fast-moving targets and also defines the system's key technical characteristics in this mode.

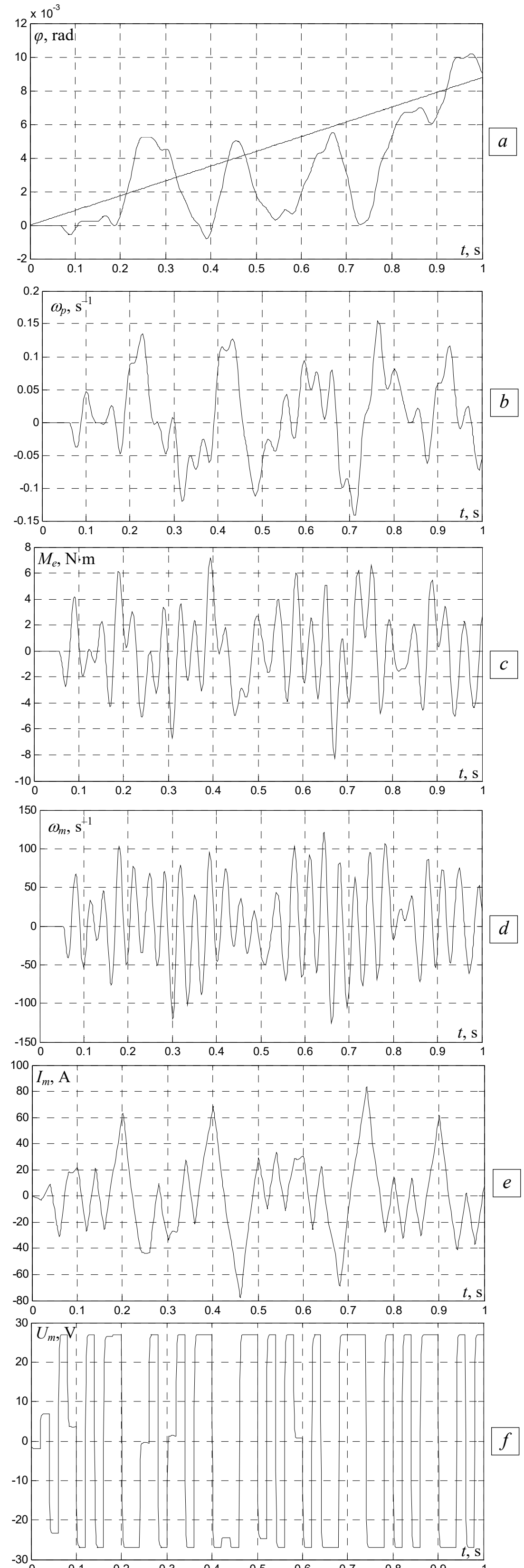


Fig. 3. Transition process during guidance at low speeds

Figure 4 shows the implementation of the state variables of an electromechanical tracking system in this operating mode. Figure 4 shows the same state variables as in Fig. 2. As can be seen from Fig. 4,*a*, the system exhibits a steady-state velocity error. As can be seen from Fig. 4,*b*, even when moving at high speed, the system exhibits «stick-slip» sections where the velocity becomes zero, resulting in uneven motion of the controlled object. In this case, the control voltage, as can be seen from Fig. 4,*f* changes practically according to the relay law from the minimum to the maximum voltage of the motor.

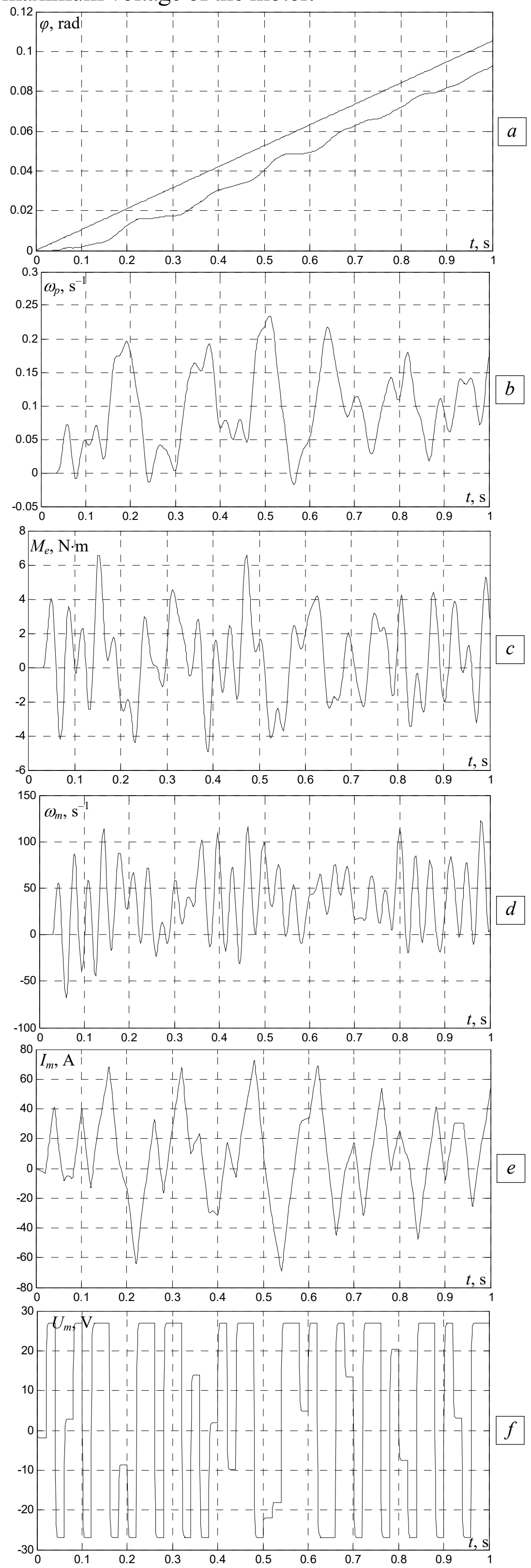


Fig. 4. Transition process during guidance at high speeds

In conclusion, we note that similar results can be obtained with vector control of permanent magnet synchronous motor [40] or induction motor [41–43].

Experimental research. To conduct experimental studies of the effectiveness of the designed neural network controller a laboratory setup for a two-mass electromechanical tracking system was developed, the schematic of which is shown in Fig. 5.

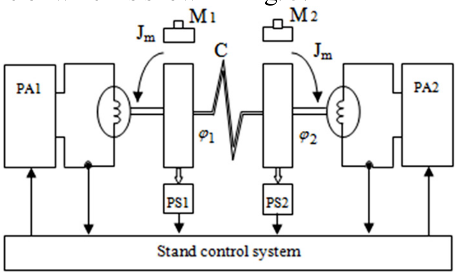


Fig. 5. Laboratory setup for a two-mass electromechanical tracking system

The setup consists of two motors M1 and M2, the shafts of which are connected by an elastic coupling. The diagram shows the power amplifiers PA1 and PA2 and motor position sensors PS1 and PS2. Figure 6 shows the appearance of the laboratory setup.

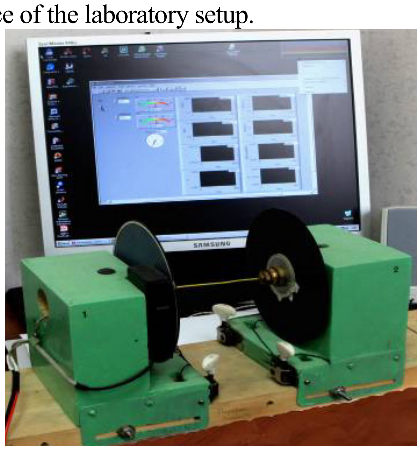
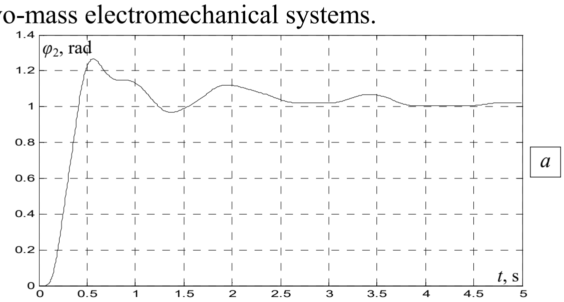


Fig. 6. The appearance of the laboratory setup

Let's consider experimental transient processes in the mode of working element rotation angle testing. In this operating mode, the limitations on state and control variables are most pronounced. Figure 7 shows the realizations of the state variables of the electromechanical servo system in this operating mode.

The following state variables are shown in Fig. 7: *a*) the angle $\varphi_2(t)$ of the second motor; *b*) the speed $\omega_1(t)$ of the first motor; *c*) the elastic moment $M_e(t)$; *d*) the voltage $U_1(t)$ on the chain of the first motor.

As can be seen in Fig. 7,*b*, the second motor's rate of change transiently reaches a limit. As can be seen in Fig. 7,*c*, the first motor's rate of change transiently doubles, which is typical for forcing transient processes in two-mass electromechanical systems.



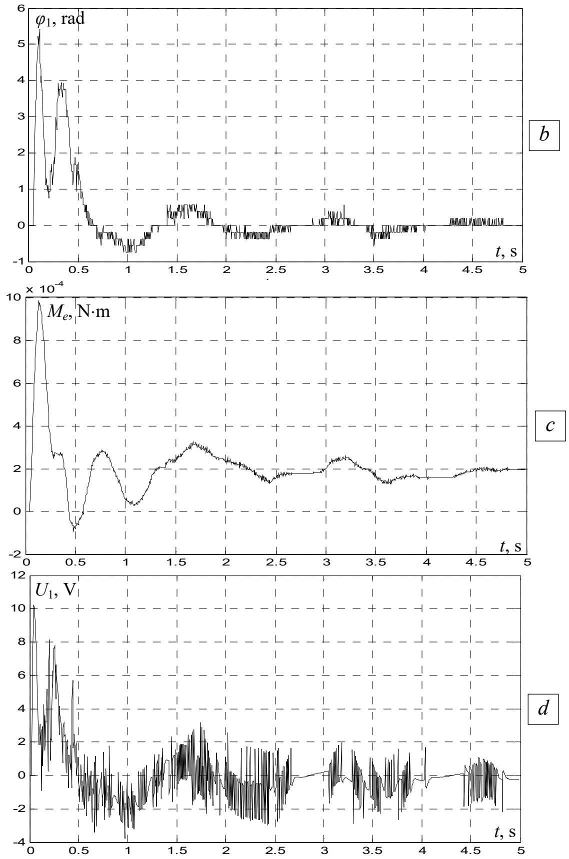


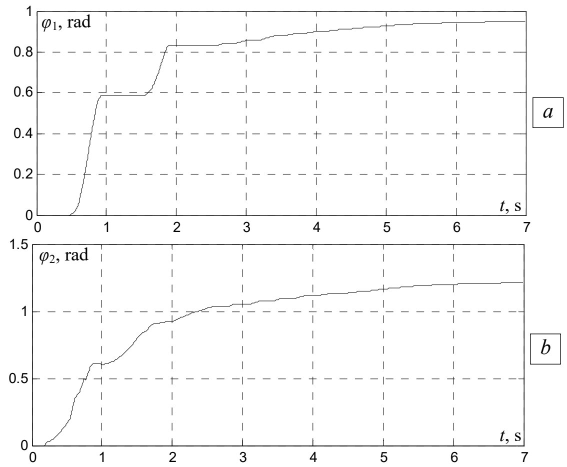
Fig. 7. Experimental transient processes during the development of large rotation angles

Let us now consider the experimental transient processes in the low-speed mode of the working element.

Figure 8 shows the realizations of the state variables of the electromechanical servo system in this operating mode.

Transient processes in the mode of movement of the working element at low speed: *a*) the angle $\varphi_1(t)$ of rotation of the first motor; *b*) the angle $\varphi_2(t)$ of rotation of the second motor; *c*) the speed $\omega_1(t)$ of the first motor; *d*) the speed $\omega_2(t)$ of the second motor; *e*) the moment of elasticity $M_e(t)$; *f*) the voltage $U_1(t)$ on the anchor chain of the first motor.

The nature of the transient processes in this low-speed operating mode is largely determined by the presence of nonlinear friction relationships on the shafts of the drive motor and the operating element.



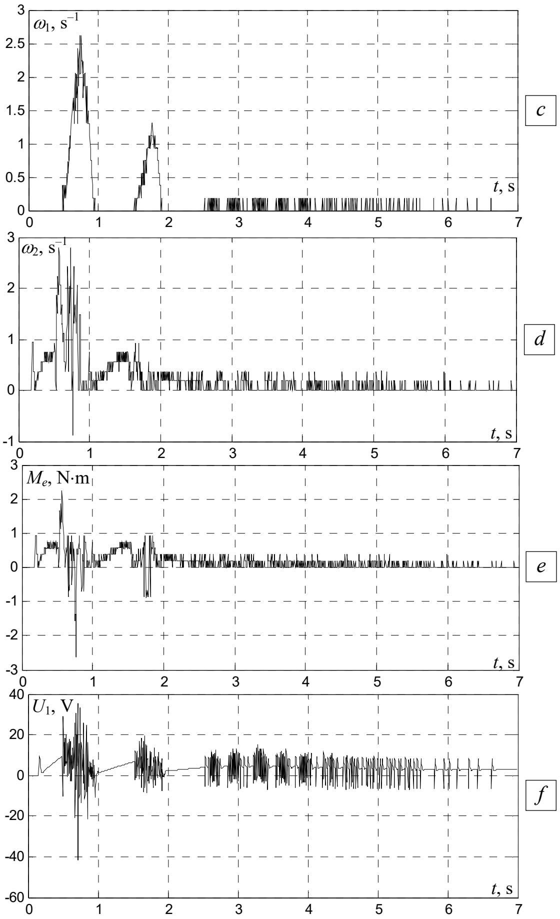


Fig. 8. Transient processes in the mode of movement of the working element at low speed

The transient process of the second motor exhibits characteristic stops and, naturally, zero speeds at those points in time when the elastic moment between the shafts of the drive motor and the operating element does not exceed the dry friction moment on the shaft of the operating element.

Conclusions.

1. For the first time the method of multi objective design of nonlinear electromechanical tracking system based on neural network controller is developed, which allows to satisfy different requirements that are imposed on the operation of the system in various modes.
2. The new solution method of reference model multi objective design problem for nonlinear electromechanical tracking system based on neural network controller is formulated as vector nonlinear programming problem solution, in which the components of the vector objective function are different requirements that are imposed on the operation of the system in various modes.
3. The new solution method of vector nonlinear programming problem is developed based on hybrid heuristic optimization algorithm, incorporating particle swarm optimization and stochastic sequential quadratic programming, which allows to reduce the computation time.
4. Based on the results of modeling and experimental studies of designed two-mass nonlinear electromechanical tracking system based on neural network controller it is established, that with the help of designed neural network controller, it is possible to reduce the control error the angle of rotation of the shaft of the second motor more than 2 times in comparison with the system with standard regulators.
5. Based on the results of modeling and experimental studies of designed two-mass nonlinear electromechanical tracking system based on neural network controller it is established, that designed control system is robust. When the moment of inertia of the working mechanism is varied by a factor of two, either upward or downward, relative to the average value adopted during the multi-criteria design of the reference model, the dynamic characteristics of the designed system with a neural network controller change only slightly compared to the dynamic characteristics of a system with standard controllers.
6. It is planned to practically realization of developed method of multi objective design of nonlinear electromechanical tracking system based on neural network controller to satisfy different requirements that are imposed on the operation of the system in various modes of real electromechanical tracking system.

Conflict of interest. The authors declare that they have no conflicts of interest.

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