ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

UDC 004.032.26:681.5.015.5. **doi: 10.32620/reks.2024.4.15**

Serhii VLADOV[1], Anatoliy SACHENKO[2,5], Victoria VYSOTSKA[3], Yevhen VOLKANIN[1], Dmytro KUKHARENKO[4], Danylo SEVERYNENKO[3]

[1] Kharkiv National University of Internal Affairs, Kharkiv, Ukraine
[2] West Ukrainian National University, Ternopil, Ukraine
[3] Lviv Polytechnic National University, Lviv, Ukraine
[4] Kremenchuk Mykhailo Ostrohradskyi National University, Kremenchuk, Ukraine
[5] Kazimierz Pulaski University of Radom, Radom, Poland

THE RELIABLY STABLE NEURAL NETWORK CONTROLLERS' SYNTHESIS WITH THE TRANSIENT PROCESS PARAMETERS OPTIMIZATION

*The **subject of this paper is to develop** a method for synthesizing stable neural network controllers with optimization of transient process parameters. The **goal** is to develop a method for synthesizing a neural network controller for control systems that guarantees the closed-loop system stability through automated selection of Lyapunov function with the involvement of an additional neural network trained on the data obtained in the solving process the integer linear programming problem. The **tasks** to be solved are: study the stability of a closed-loop control system with a neural network controller, train the neurocontroller and Lyapunov neural network function, create an optimization model for the loss function minimization, and conduct a computational experiment as an example of the neural network stabilizing controller synthesis. The **methods** used are: a neural network-based control object simulator training method described by an equations system taking into account the SmoothReLU activation function, a direct Lyapunov method to the closed-loop system stability guarantee, and a mixed integer programming method that allows minimizing losses and ensuring stability and minimum time regulation for solving the optimization problem. The following **results** were obtained: the neural network used made it possible to obtain results related to the transient process time reduction to 3.0 s and a 2.33-fold reduction in overregulation compared to the traditional controller (on the example of the TV3-117 turboshaft engine fuel consumption model). The **results** demonstrate the proposed approach's advantages, remarkably increasing the dynamic stability and parameter maintenance accuracy, and reducing fuel consumption fluctuations. **Conclusions.** This study is the first to develop a method for synthesizing a stabilizing neural network controller for helicopter turboshaft engines with guaranteed system stability based on Lyapunov theory. The proposed method's novelty lies in its linear approximation of the SmoothReLU activation function using binary variables, which allowed us to reduce the stability problem to an optimization problem using the mixed integer programming method. A system of constraints was developed that considers the control signal and stability conditions to minimize the system stabilization time. The results confirmed the proposed approach's effectiveness in increasing engine adaptability and energy efficiency in various operating modes.*

Keywords: *optimization; controller; neural network; Lyapunov function; mixed integer programming.*

1. Introduction

Motivation. Modern control systems increasingly use neural network approaches to ensure adaptability to the changing external influences and the parameters of control objects [1]. One critical task in this area is the synthesis of controllers, which can guarantee the entire control system's stability under various external and internal disturbances [2]. This approach requires powerful optimization methods and consideration of the transient process specifics that determine the dynamic characteristics of systems [3]. Achieving a compromise between stability and the quality of transient processes is vital for designing neural network controllers [4]. Guaranteed stable controllers using neural networks technologies synthesis is of particular importance in critical systems such as aviation [5], energy [6], and robotic [7] systems. These systems require high reliability and can quickly adapt to changing conditions. However, standard approaches often do not correctly provide the quality of transient processes, leading to decreased operational efficiency and safety. In this context, methods that simultaneously provide guaranteed stability and optimization of transient process development are becoming an urgent scientific and practical task.

State of the art. Neural network controllers are a promising development in the automatic control systems (ACS) field due to their ability to train and adapt under uncertainty. Researchers [8, 9] have considered deep neural networks used for the controller's synthesis, which improves the dynamic characteristics of the control systems. Research [10, 11] has shown that the recurrent and convolutional architectures provide high accuracy for modelling and controlling complex dynamic objects, such as robotic manipulators and autonomous vehicles. However, neural network-based approaches often face overfitting and insufficient interpretability.

Currently, the control system's stability ensures that the problem is of primary importance, which has been emphasized in previous studies [11, 12]. Methods based on Lyapunov theory and guaranteed stability allow us to obtain strict criteria for designing controllers [13, 14]. However, many analyzed methods, for example, [12, 14], do not consider the nonlinear nature of complex objects, which limits their application in highly dynamic systems. A previous study [15] highlighted the need to integrate classical approaches with modern machine learning methods to ensure guaranteed stability of control systems.

The optimization of transient processes is also an essential aspect of research. The researchers [16, 17] used gradient descent and evolutionary computation algorithms to minimize overshoot and transient time. These studies focused on the selection of parameters by neural network controllers considering the systems' dynamic characteristics. However, a significant part of existing solutions is focused on the problem's specific classes and do not have universality, which limits their practical application.

Researchers [18, 19] have considered the possibility of hybrid approaches that combine neural networks and classical methods. These systems allow us to achieve a compromise between adaptability and stability. However, most of them are at the laboratory testing stage [19, 20], indicating the need for further research to create applied solutions for critical control systems.

Despite significant advances in the development of neural network controllers [8–12], the problem of integrating stability methods into neural network training remains unresolved. In particular, approaches based on Lyapunov theory [13, 14] require accurately defining Lyapunov functions to analyze closed-loop system stability. Traditional methods [14] for finding such functions are excessively computationally complex or do not scale to high-dimensional systems. One promising idea is to use an additional neural network to perform an automated search for

Lyapunov function [21, 22]. However, training such a network requires structured data [16, 18], which entails solving the integer linear programming (ILP) adjoint problem and ensuring the correctness of the obtained data and physical interpretability.

The developing methods for generating training data for a neural network approximating

Lyapunov function problem considering the stability limitations remain relevant. The issues of selecting the optimal neural network architecture, training algorithms, and interpretation of the results remain open. Modifying the research approach involves hybrid methods in which the stability problem is reduced to the sequential integration of the ILP and neural network models. This approach requires approximation errors and computational complexity impact analysis on stability guarantees, which makes it promising but requires additional research.

Objective and Approach. Based on the above, the research **goal** is to improve the approach to the neural network controller's synthesis for control systems to ensure the guaranteed stability of closed systems by automated search for Lyapunov function using an additional neural network trained on data obtained by solving an integer linear programming problem. The research **objective** is control systems with neural network controllers operating under dynamic and nonlinear influences. The research **subject** includes methods and algorithms for the guaranteed stable neural network controller's synthesis, including Lyapunov function used, neural network models, and integer linear programming methods.

Structure of the article. The article is structured as follows: introduction, sections “Materials and methods of research”, “Case study”, “Discussion”, conclusions, and references. The introduction substantiates the research' relevance, the existing research overview provides in the research area, highlights unresolved issues, and formulates the research' aim. In the section “Materials and methods of research”, a method for modeling a closed-loop control system using neural networks is developed. This method guarantees the system' stability based on Lyapunov function, minimizes the stabilization time, and complies with the constraints on the control signals. In addition, the parameter optimization process is implemented through mixed integer programming with linear approximation of the SmoothReLU activation function. The section “Case study” presents the computational experimental results using the example of synthesizing a neural network stabilization controller for a simplified fuel consumption model of helicopter turboshaft engines. It is shown that neural controller use significantly improves the fuel regulation quality of helicopter turboshaft engines, providing a reduction in the transient process time and a decrease in overshoot by 2.33 times compared to the traditional approach. The section “Discussion” presents a discussion of the results obtained, highlights their limitations, and develops prospects for further research. The conclusions present the main results of the research.

2. Materials and methods of research

This research proposes a method to develop a robust and stable neural network controller using the nonlinear

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

object' closed discrete control system (Figure 1) optimization concept [23, 24] based on Lyapunov function [21] using mixed integer programming (MIP) to approximate the activation function and ensure system stability by satisfying Lyapunov conditions. Training is performed using the error's backpropagation method using a direct neural emulator [25].

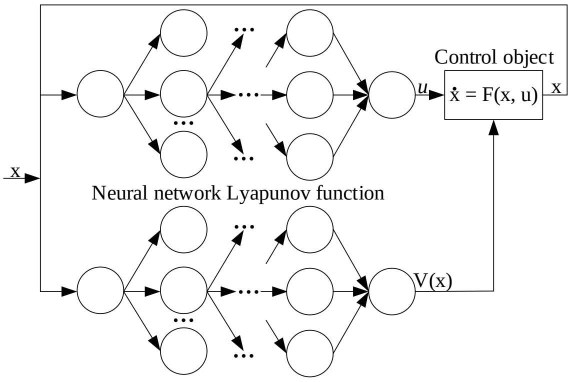

Fig. 1. Scheme of the closed neural network control system

In the first stage, the control object simulator training [26] is performed and implemented on a neural network, which is described as follows:

$$x_{t+1} = f(x_t, u_t) - \Theta(x_t, u_t) - \Theta(x^*, u^*) + x^*, \quad u_{min} \leq u_t \leq u_{max}, \tag{1}$$

where x_t is the state vector of the control objects at time t; u_t is the value of the control signals at time t; u_{min} and u_{max} are the lower/upper limits of the objects' control signals; x^* is the systems equilibrium point in the phase space; u^* is the control value at this point; Θ is a direct propagation neural network with the SmoothReLU activation function, developed by this group of authors in [27]:

$$f(x) = \begin{cases} x, & \text{if } x > 0, \\ \dfrac{1}{1 + e^{-\gamma \cdot x}}, & \text{if } x \leq 0. \end{cases} \tag{2}$$

To represent the SmoothReLU activation function as an inequalities system with binary variables and constraints, we can use the functions' parts linear approximation method to activate the corresponding branch through binary variables. It is assumed that $z \in \{0, 1\}$ is a binary variable, where z = 1 if x > 0, and z = 0 if x ≤ 0. Then, the constraints for branch activation are represented as:

$$x - M \cdot (1 - z) \leq 0 \text{ at } z = 1,\ x > 0, \quad x + M \cdot z \geq 0 \text{ at } z = 0,\ x \leq 0, \tag{3}$$

where M is a large positive number that limits the x range. For output y, enter:

$$y \geq x \cdot z, \quad y \leq x \cdot z + M \cdot (1 - z), \quad y \geq \frac{1}{1 + e^{-\gamma \cdot x}} \cdot (1 - z), \quad y \leq \frac{1}{1 + e^{-\gamma \cdot x}} + M \cdot z. \tag{4}$$

The constraints system is reduced to the form y = f(x), where

$$\begin{cases} x > 0 \Rightarrow z = 1, y = x, \\ x \leq 0 \Rightarrow z = 0, y = \dfrac{1}{1 + e^{-\gamma \cdot x}}. \end{cases} \tag{5}$$

Thus, based on [21, 27], the neural network is represented as an algebraic equalities and inequalities system, describing each neuron taking into account (3)–(5), which allows for the SmoothReLU linear approximation branches using mixed integer constraints.

In this case, the neural network controller is expressed as follows:

$$u_t = r(x_t) = \Theta_r(x_t) - \Theta_r(x^*) + u^*, \tag{6}$$

where Θ_r is the neural network at the core of the controllers.

This form of equations (1) and (6) representation guarantees the fulfilment of the conditions at the equilibrium point. According to Lyapunov's theory [12, 21, 22], a system is considered stable if a function is strictly positive and decreases at all points except the equilibrium state. Therefore, Lyapunov function must satisfy the following requirements:

$$V(x[t]) > 0 \forall x[t] \in S, x[t] \neq x^*, \tag{7}$$

$$V(x[t + 1]) - (x[t]) < 0 \forall x[t] \in S, \tag{8}$$

$$V(x^*) = 0, \tag{9}$$

where x_t is the state of the control objects at time t, x^* is the equilibrium state, and S is the initial condition region in which the system is stable.

Lyapunov function is represented by the neural network Θ_V as:

$$V(x_t) = \Theta_V(x_t) - \Theta_V(x^*) + R\|x_t - x^*\|_1, \tag{10}$$

where R is a matrix with full rank, and $R\|x_t - x^*\|_1$ allows us to satisfy (7). For $x_t = x^*$, this equation enables us to satisfy requirement (9).

To train the neural controller and the neural network Lyapunov function, it is necessary to form data based on points found in the phase space S limited region that violate conditions (7) and (8) to the greatest extent. The finding of such point is reduced to solving the ILP problem, that is, optimizing the following objective functions:

$$\max_{x[t]\in S}\left(\varepsilon|R\|x_t - x^*\|_1| - V(x_t)\right),$$
$$\max_{x[t]\in S}\left(V(x[t+1]) + (\varepsilon - 1)\cdot V(x_t)\right). \quad (11)$$

The obtained points are used to train the neural networks, and these points should minimize the detected violations:

$$L_1 = \max_{x[t]\in S}\left(\varepsilon|R\|x_t - x^*\|_1| - V(x_t)\right),$$
$$L_2 = \max_{x[t]\in S}\left(V(x[t+1]) + (\varepsilon - 1)\cdot V(x_t)\right). \quad (12)$$

A system is modeled from each point found with a sampling step dt for the interval $t_m > t_r$ to control the regulation time t_r. The points recorded after t_r are compared with the equilibrium point to calculate the stabilization error, which is minimized in the learning process. The proposed method encourages the neural network controller to reduce the regulation time. According to [19, 21], the criterion is expressed as follows:

$$L_3 = x[i] - x^*, \quad (13)$$

where x[i] is the state at the discrete i-th step from the simulation start, and i is the discrete step number from the required control time to the simulation end.

The general loss function looks like this:

$$L = (L_1)_l + (L_2)_l + (L_3)_l. \quad (14)$$

Thus, by minimizing (14), the neural networks of Lyapunov function and the neurocontroller are trained. The resulting closed system will be stable in the local area with the confirmed Lyapunov function, and the regulation time will be minimized.

Then, the optimization problem for minimizing L is expressed as follows:

$$\min_{\Theta_V,\Theta_r,R}(L_1 + L_2 + L_3), \quad (15)$$

in which the expression represents the objective function:

$$L(\Theta_V,\Theta_r,R) = \max_{x[t]\in S}(\varepsilon|R\|x_t - x^*\|_l| -$$
$$-V(x_t)) + \max_{x[t]\in S}(V(x[t+1]) + (\varepsilon - 1)\cdot \quad (16)$$
$$\cdot V(x_t) + (x[i] - x^*).$$

The constraint on the neural networks $\Theta_V(x_t) - \Theta_V(x^*) + R\|x_t - x^*\|_1$ for all $x[t] \in S$ ensures that Lyapunov function is approximated correctly, given its behaviour in the phase space. The constraint on the control signal $u_{min} \le u_t \le u_{max}$ for all t values limits the possible values of the control signal. The systems' state constraints are represented as $\|x_t - x^*\|_1$, where x^* is the systems' equilibrium point, and S is the initial conditions domain. Lyapunov conditions $V(x[t]) > 0\ \forall\ x[t] \in S$, $x[t] = x^*$ and $V(x^*) = 0$ ensure that the system is stable in the initial conditions domain.

To minimize the objective function (16), it is advisable to use the MIP method [28], which allows the objective function $L(\Theta_V, \Theta_r, R)$, to be minimized while considering the constraints. The problem is transformed into a linear representation that includes binary variables for activating the SmoothReLU activation function branches, approximating Lyapunov conditions, and controlling constraints. The objective functions' (16) final MIP model is represented as:

$$\min_{\Theta_V,\Theta_r,R,\xi_1,\xi_2,\xi_3}(\xi_1 + \xi_2 + \xi_3) \quad (17)$$

subject to the constraints given in Table 1.

Table 1

Constraints applied in the MIP model

No.	Constraints
1	$\xi_1 \ge \varepsilon|R\|x_t - x^*\|_l| - V(x_t), \forall x[t] \in S$
2	$\xi_2 \ge V(x[t+1]) + (\varepsilon - 1)\cdot V(x_t), \forall x[t] \in S$
3	$V(x_t) = \Theta_V(x_t) - \Theta_V(x^*) + R\|x_t - x^*\|_1$
4	Conditions on z for the SmoothReLU
5	Control signal constraints $u_{min} \le u_t \le u_{max}$
6	Stability conditions: $V(x[t]) > 0$, $V(x^*) = 0$

Model (17) with constraints (Table 1) is passed to a MIP solver (e.g., Gurobi, CPLEX), which will find the Θ_V^*, Θ_r^*, R^* optimal values.

The proposed method leverages a neural network-based control object simulator, where the system dynamics and equilibrium are modeled using MIP. The SmoothReLU activation function is linearized using binary variables to represent activation branches, which ensures a piecewise algebraic description. Stability is guaranteed via Lyapunov function trained alongside the neurocontroller to minimize stabilization time and ensure compliance with system constraints. The optimization process minimizes a composite loss function reflecting stability, control signal constraints, and regulation time, which is solved using the MIP to determine the optimal parameter.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

3. Case study

The research conducted a computational experiment as a neural network stabilizing controller synthesis example for the helicopter turboshaft engines (TE) simplified fuel consumption model [29]. Solving the problem of the TE fuel consumption control is essential for increasing the efficiency and operational effectiveness [30, 31]. In this context, neural network methods allow the synthesis of adaptive controllers capable of effectively stabilizing helicopter TE operations, considering complex nonlinear dependencies. According to [32, 33], the simplified model of the helicopter TE fuel consumption simplified model is represented as:

$$\tau \cdot \frac{dG_T(t)}{dt} + G_T(t) = K_T \cdot P(t) + a \cdot G_a(t), \qquad (18)$$

where K_T is the specific fuel consumption per unit of power (kg/(W·s)), P(t) is the current engine power (W), $G_a(t)$ is the volumetric air flow rate (kg/s), a is an empirical coefficient taking into account additional losses, τ is the time constant of the fuel supply systems, reflecting the inertia of fuel supply regulation. These parameters were determined analytically using a helicopter TE universal mathematical model [34] based on the parameters recorded on board the helicopter by standard sensors [27]: gas-generator rotor speed (n_{TC}), free turbine rotor speed (n_{FT}), and gas temperature in front of the compressor turbine (T_G^*).

The computational experiment used a TV3-117 TE [35], which is a part of the Mi-8MTV helicopter power plant. The initial engine parameters (n_{TC}, n_{FT}, T_G^*) were obtained exclusively from the flight data recorded during the helicopter flight tests. The data were collected using the D-2M and D-1M sensors and 14 pairs of T-101 thermocouples. The recording was performed during 256 s of the actual flight at a frequency of 1 measurement per second [36]. Based on (18) and using the analytical expressions from [34], the fuel consumption values were obtained and subsequently normalized using z-normalization [37, 38] as follows:

$$z(G_T)_i = \frac{G_T^{(i)} - \frac{1}{N} \cdot \sum_{i=1}^{N} G_T^{(i)}}{\sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(G_T^{(i)} - \frac{1}{N} \cdot \sum_{i=1}^{N} G_T^{(i)}\right)^2}}, \qquad (19)$$

where N = 256.

The normalized fuel consumption values (Table 2) form a training dataset homogeneous according to the Fisher-Pearson [39, 40] and Fisher-Snedecor [41, 42] criteria at the strict significance level of α = 0.01 [43, 44] (Table 3).

Thus, based on the fuel consumption values (Table 2), it is necessary to synthesize a controller to ensure minimum fuel consumption while the transient process time should not exceed 5 seconds [45, 46]. To confirm stability, Lyapunov neural network function was constructed. For the system, using the backpropagation method with an adaptive training rate [47], a stabilizing controller and the control objects' (helicopter TE) neural network simulator were obtained, presented in the form of a direct propagation neural network with adaptive elements [47] (Figure 2).

Table 2

The training dataset fragment

No.	G_T value	No.	G_T value	No.	G_T value
1	0.973	…	…	…	…
2	0.982	110	0.979	213	0.976
…	…	…	…	…	…
36	0.988	143	0.980	242	0.983
…	…	…	…	…	…
71	0.975	182	0.967	256	0.980

Table 3

Results of homogeneity assessment of the training dataset

Parameter	The Fisher-Pearson criterion		The Fisher-Snedecor criterion	
	Calculated	Critical	Calculated	Critical
G_T	6.028	6.635	4.932	5.12

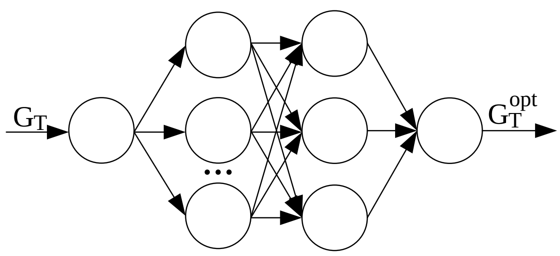

Fig. 2. Refined proposed feedforward neural network

Using the ILP, Lyapunov neural network function was obtained, as shown in Figure 3. Figures 4 and 5 show the diagrams of transient processes according to the simplified TE fuel consumption model.

The diagrams (Figures 4 and 5) show the helicopter TE-normalized fuel consumption transient processes depending on time (0…5 seconds). The traditional controller is characterized by a slow transient process, where the normalized value reaches 0.63 in 2 seconds and asymptotically approaches 1.

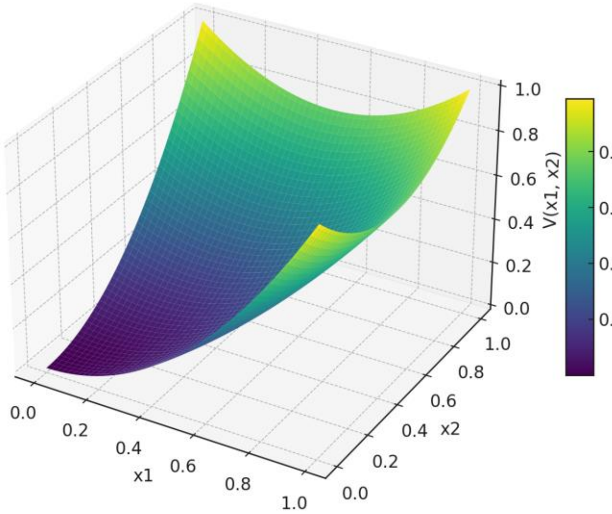

Fig. 3. Diagram of the neural network Lyapunov function surface

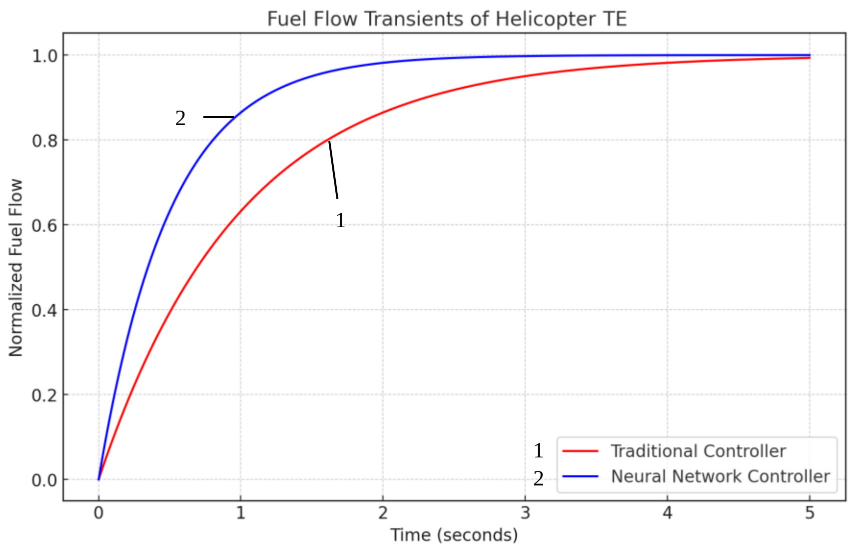

Fig. 4. Diagrams of transient processes with regulation time optimization:
"red curve" (1) is the traditional controller use; "blue curve" (2) is the neural network controller use

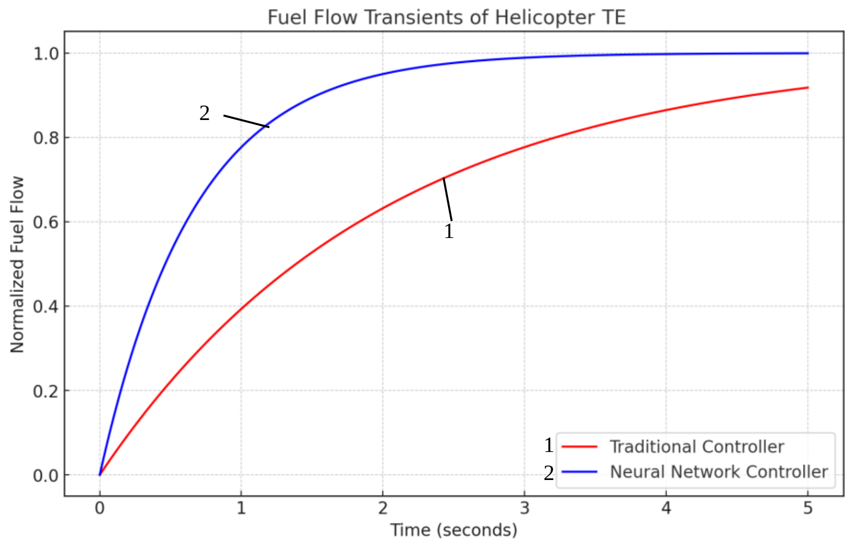

Fig. 5. Diagrams of transient processes without regulatory time requirements:
"red curve" (1) is the traditional controller use; "blue curve" (2) is the neural network controller use

The neural network controller demonstrated a faster transient process, reaching 0.78 by 2 s and stabilizing at 1 by 3 s. The results show the advantages of the neural network approach, including reduced regulation time, improved dynamic stability, and more accurate maintenance of set parameters, which are critical for helicopter TE control under variable load conditions. According to Figures 4 and 5, the overshoot value for transient processes was calculated as the difference between the normalized fuel consumption maximum value and its steady-state value [48] (G_T = 1.0). For the traditional controller, the maximum fuel consumption value reached 1.105, corresponding to an overshoot of 10.5 %, while for the neural network controller, the maximum value was 1.045, corresponding to an overshoot of 4.5 %. These data show that the neural network controller, according to the proposed approach, improves the regulation quality by 2.33 times with less overshoot, thereby reducing fluctuations in fuel consumption during transient processes.

The proposed model evaluates the neural network controller quality using the following traditional metrics: accuracy [49, 50], Precision [50, 51], Recall [51], and F1 score [51, 52], which are defined as follows:

$$\begin{gathered} \text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \\ \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \\ \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \\ \text{F1} - \text{score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \end{gathered} \tag{20}$$

In the context of the helicopter TE fuel consumption model, TP (True Positive) reflects cases in which the model correctly predicts the need to increase fuel consumption with increasing load, TN (True Negative) is a correct prediction of maintaining or decreasing consumption with an unchanged or decreasing load, FP (False Positive) characterizes erroneous predictions of increasing fuel consumption when there is no need, and FN (False Negative) is the missed cases when the model does not record the need to improve fuel consumption with increasing load.

Figures 6 and 7 show the Accuracy and Loss metrics as the model was trained over 200 epochs.

The accuracy diagram (Figure 6) shows that the metric for the training dataset (blue curve) gradually increased from 0.5 to 0.992, reaching convergence by the 200th epoch. The accuracy of the test dataset (orange curve) increased, but at a slightly slower rate, reaching a value of approximately 0.975. In the loss plot (Figure 7), the curve for the training dataset (blue) starts at 0.02 and decreases exponentially to 0.005, indicating successful model optimization. The loss for the test dataset (orange curve) also decreased, but at a slower rate, reaching a value of approximately 0.006. Both graphs demonstrate successful convergence of the model with improved accuracy and reduced loss during training.

In the helicopter TE simplified fuel consumption model context, the obtained metrics Precision = 0.983, Recall = 0.999, and F1-score = 0.991 indicate the models' high quality in predicting fuel consumption or identifying certain issues, such as possible malfunctions or optimal engine operating modes.

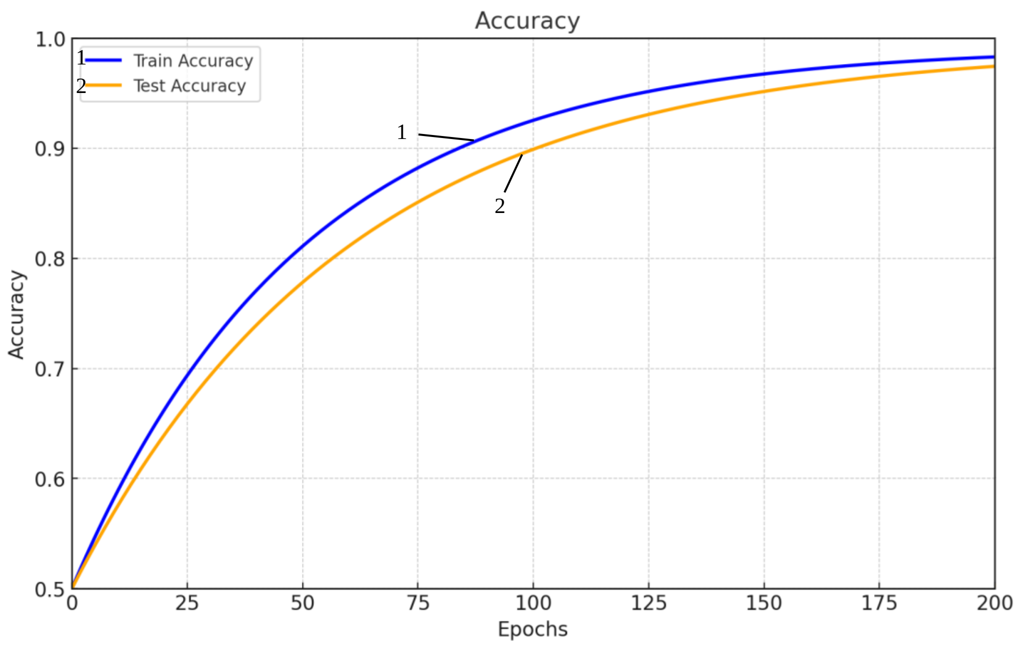

Fig. 6. The accuracy metric: “blue curve” (1) is the accuracy on training dataset; “orange curve” (2) is the accuracy on the test dataset

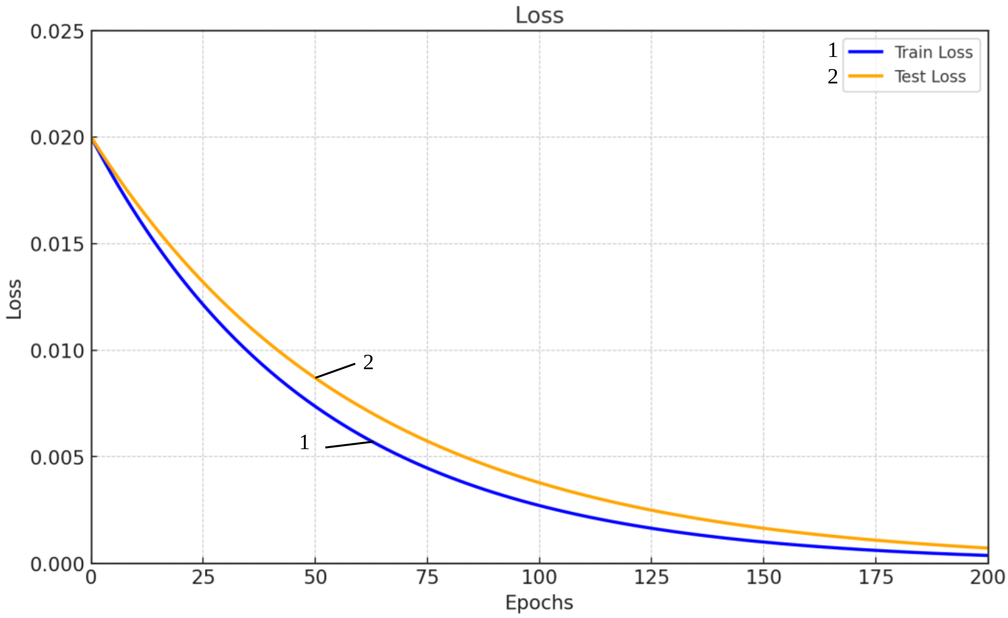

Fig. 7. The loss metric: "blue curve" (1) represents the loss on training dataset; "orange curve" (2) represents the loss on the test dataset

Precision = 0.983 indicates that the model correctly classified almost all positive cases, minimizing false positives, and recall = 0.999 demonstrates that the model effectively identified nearly all positive events without missing significant cases. The F1-score = 0.991 confirms that the model's balance between Precision and Recall is optimal, providing high accuracy and recall in predictions.

4. Discussion

A method that uses a neural network to model a control object and synthesizes a neural controller with guaranteed system stability was further developed. The proposed process is based on the SmoothReLU activation function linear approximation using binary variables and Lyapunov theory to ensure stability. A constraint system was developed, including constraints on the control signals and the fulfilment of stability conditions, which were reduced to an optimization problem using mixed integer programming. The result is a neural controller that minimizes stabilization time and meets all specified system conditions.

The results show that using neural networks to synthesize a stabilizing controller for helicopter turboshaft engines and the simplified fuel consumption model can effectively solve the problems of increasing energy efficiency and operational effectiveness. The neural network methods allow the creation of adaptive controllers that stabilize helicopter turboshaft engine operation, taking into account complex nonlinear dependencies, which is confirmed by the system's Lyapunov function construction for the system and the backpropagation method with an adaptive training rate successful application.

The results showed that, unlike the traditional controller, the neural network demonstrates faster fuel consumption regulation with minor fluctuations and smaller overruns, significantly improving the dynamic stability and accuracy of maintaining specified parameters under changing loads. The results obtained for the model quality labels (Precision = 0.983, Recall = 0.999 and F1-score = 0.991) confirm the high efficiency of the neural networks in predicting fuel consumption and identifying faults or optimal engine operating modes with minimization of classification errors.

The main limitations of the obtained results are related to simplifications and assumptions in the helicopter TE fuel consumption model, which may affect the generalizability and accuracy of the proposed neural controller under real operating conditions. The simplified model does not consider all the complexities and variations of natural engine dynamics, such as detailed thermodynamic processes or the influence of external factors such as weather conditions [53, 54]. Although the neural controller showed faster regulation time and improved regulation quality compared to traditional controllers, metrics such as Precision, Recall, and F1-score may not fully reflect possible rare cases or extraordinary operating conditions. In addition, the flight test data used to record over a limited period (256 seconds) with a fixed set of sensors may introduce a particular bias into the training dataset, which reduces the generality of the controllers in broader operating scenarios.

Despite the significant improvement in control quality (more than 2 times) during the optimization process, it depends on the selected parameters and training

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

conditions, which may not be universal for other types of engines [55, 56] or fuel consumption models [57]. The computational complexity of neural network training, especially considering the time required for optimization and the MIP use, may pose a scalability problem in more complex systems.

Prospects for further research include the development of more complex and accurate models of helicopter TE fuel consumption that consider all the physical and thermodynamic aspects of engine operation in various operating modes [52, 53]. Another critical area is the proposed neural controller integration with natural onboard control systems [58, 59], optimizing its operation under changing external factors, such as weather conditions or engine loads [60]. Further research may consider hybrid methods that combine neural network approaches with classical control algorithms [61, 62] to improve the stability and adaptability of systems under dynamically changing operating conditions.

4. Conclusions

The closed discrete control system's stability-ensuring method has been further developed, which differs from the existing ones in that, based on Lyapunov function, the regulation time is minimized and the specified constraints are satisfied. At the same time, a control object simulator was developed based on a neural network, and it describes the system dynamics considering the control constraints and the SmoothReLU activation function. The control object's developed neural network simulator training is performed by the error backpropagation method through a direct neural emulator, which allows simulating of the system' behavior in various modes with an accuracy of more than 99 %, taking into account nonlinearities and dynamic changes, and also ensures high adaptability to changing control conditions.

The results of the computational experiment on the stabilizing neural network controller synthesis for a helicopter turboshaft engine fuel consumption model are presented. The developed neural controller demonstrated advantages over a traditional controller, including a reduction in the transient process time to 3 s, an increase in dynamic stability, and a decrease in overshoot to 4.5 % (compared to 10.5 % for a traditional controller). Accuracy = 0.992, Precision = 0.983, Recall = 0.999, and F1-score = 0.991 confirmed the model's high accuracy and reliability in predicting fuel consumption and identifying optimal engine operating modes.

Contributions of authors: conceptualization, methodology – **Serhii Vladov;** formulation of tasks, analysis **– Serhii Vladov, Victoria Vysotska;** development of model, software, verification **– Serhii Vladov, Yevhen Volkanin, Dmytro Kukharenko;** analysis of results, visualization **– Anatoliy Sachenko**, **Victoria Vysotska;** writing – original draft preparation, writing – review and editing **– Anatoliy Sachenko**, **Victoria Vysotska, Danylo Severynenko.**

All the authors have read and agreed to the published version of this manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest regarding this research, whether financial, personal, authorship, or otherwise, that could affect the study and its results presented in this paper.

Financing

This study was conducted without financial support.

Projects information

Project 0123U104884 "Theoretical and applied aspects of the development of the aviation sphere" is implemented within the Agreement framework between the Government of Ukraine and the Government of the French Republic regarding official support for the aviation safety and civil protection unified system creation in Ukraine to improve the helicopter flight safety used in Ukraine' state aviation. This project aims at developing mathematical and software support systems for optimizing control processes and increasing efficiency and safety in the aviation industry. In particular, the project includes the active development of the helicopter TE onboard neural network control systems. For example, the project developed a helicopter TE three-channel control system model, which, unlike the existing ones, includes a channel for controlling the free turbine rotor speed and software modules for adaptive control by separating the engine parameters and the fuel metering unit, which made it possible to improve the quality indicators of control channels up to 60 %.

Project 0123U104884 "Theoretical and applied aspects of the development of the aviation sphere" is closely related to project 187/0012 "Information system development for automatic detection of misinformation sources and inauthentic behaviour of chat users" through the common methods of data analysis, machine learning, and intelligent systems development. Approaches to creating algorithms to analyze big data, neural network models, or identify anomalies can be adapted for aviation tasks and to monitor information reliability in chats.

Project 187/0012 aims to create innovative solutions applicable to both public communications and specialized industries, including aviation, where the reliability of information is critical to flight safety. Project 187/0012 develops machine learning and natural language processing (NLP) algorithms for analyzing text messages, classifying data sources, and predicting disin-

formation likelihood. Particular attention is paid to models' creation oriented toward application in the aviation sector, including the information analysis flows on aircraft technical conditions, the disinformation risks predicting, the cybersecurity of aviation networks, and the identification of false messages that may affect flight safety. Information flow visualization tools are being developed to monitor the spread of unreliable information and its impact on operational activities.

Data Availability

Data are contained in the article.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods in their work.

Acknowledgments

The Ministry of Internal Affairs of Ukraine supported the research entitled "Theoretical and applied aspects of the development of the aviation sphere", under Project No. 0123U104884. The research was carried out with the grant support of the National Research Fund of Ukraine, "Information system development for automatic detection of misinformation sources and inauthentic behaviour of chat users", project registration number 187/0012 from 1/08/2024 (2023.04/0012). Also, we would like to thank the reviewers for their precise and concise recommendations that improved the presentation of the results obtained.

References

1. Zhang, Y., Yao, Q., Luo, B., & Chen, N. Robust control of uncertain asymmetric hysteretic nonlinear systems with adaptive neural network disturbance observer. *Applied Soft Computing*, 2024, vol. 167, part B, article no. 112387. DOI: 10.1016/j.asoc.2024.112387.

2. Chu, Y., Zhou, C., Hou, S., Chen, H., & Fei, J. Self-organizing feature selection fuzzy neural network-based terminal sliding mode control for uncertain nonlinear systems. *ISA Transactions*, 2024, vol. 154, pp. 171–185. DOI: 10.1016/j.isatra.2024.09.007.

3. Li, A., Swensen, J. P., & Hosseinzadeh, M. Provably-stable neural network-based control of nonlinear systems. *Engineering Applications of Artificial Intelligence*, 2024, vol. 138, article no. 109252. DOI: 10.1016/j.engappai.2024.109252.

4. Chen, J., Mei, J., Hu, J., & Yang, Z. Deep neural networks-prescribed performance optimal control for stochastic nonlinear strict-feedback systems. *Neurocomputing*, 2024, vol. 610, article no. 128633. DOI: 10.1016/j.neucom.2024.128633.

5. Vladov, S., Yakovliev, R., Hubachov, O., & Rud, J. Neuro-Fuzzy System for Detection Fuel Consumption of Helicopters Turboshaft Engines. CEUR Workshop Proceedings, 2024, vol. 3628, pp. 55-72. Available at: https://ceur-ws.org/Vol-3628/paper5.pdf. (accessed 11.10.2024)

6. Sayeh, K.F., Tamalouzt, S., Sahri, Y., Lalouni Belaid, S., & Bekhiti, A. Artificial intelligence-based direct power control for power quality improvement in a WT-DFIG system via neural networks: Prediction and classification techniques. *Journal of the Franklin Institute*, 2025, vol. 362(1), article no. 107401. DOI: 10.1016/j.jfranklin.2024.107401.

7. Zhang, Y., Xu, Z., Chen, J., Zhao, L., Wang, X., & Hua, C. Neural networks-based composite learning control for robotic systems with predefined time error constraints, *Neurocomputing*, 2024, vol. 608, article no. 128414. DOI: 10.1016/j.neucom.2024.128414.

8. Shipman, W. J., & Coetzee, L. C. Reinforcement Learning and Deep Neural Networks for PI Controller Tuning. *IFAC-PapersOnLine*, 2019, vol. 52, iss. 14, pp. 111–116. DOI: 10.1016/j.ifacol.2019.09.173.

9. Ding, Y.-X., Cheng, S., Huang, Y.-T., & Hong, D.-Y. Deep PID Neural Network Controller for Precise Temperature Control in Plastic Injection-moulding Heating System. *IFAC-PapersOnLine*, 2022, vol. 55, iss. 27, pp. 114–119. DOI: 10.1016/j.ifacol.2022.10.497.

10. Merabet, A., Kanukollu, S., Al-Durra, A., & El-Saadany, E. F. Adaptive recurrent neural network for uncertainties estimation in feedback control system. *Journal of Automation and Intelligence*, 2023, vol. 2, iss. 3, pp. 119–129. DOI: 10.1016/j.jai.2023.07.001.

11. Huang, J.-C., Zeng, G.-Q., Geng, G.-G., Weng, J., Lu, K.-D., & Zhang, Y. Differential evolution-based convolutional neural networks: An automatic architecture design method for intrusion detection in industrial control systems. *Computers & Security*, 2023, vol. 132, article no. 103310. DOI: 10.1016/j.cose.2023.103310.

12. Bonassi, F., & Scattolini, R. Recurrent Neural Network-based Internal Model Control design for stable nonlinear systems. *European Journal of Control*, 2022, vol. 65, article no. 100632. DOI: 10.1016/j.ejcon.2022.100632.

13. Quilles-Marinho, Y., Oliveira, R.C.L.F., & Peres, P.L.D. Output-feedback control design for Takagi-Sugeno fuzzy systems through Lyapunov functions depending polynomially on the states. *Fuzzy Sets and Systems*, 2025, vol. 499, article no. 109156. DOI: 10.1016/j.fss.2024.109156.

14. Fu, H., Xie, W., & Kao, Y. Adaptive sliding mode control for uncertain general fractional chaotic systems based on general Lyapunov stability. *Chinese Journal of Physics*, 2024, vol. 92, pp. 1361–1372. DOI: 10.1016/j.cjph.2024.05.032.

15. Quin, F., Weyns, D., & Gheibi, O. Reducing large adaptation spaces in self-adaptive systems using classical machine learning. *Journal of Systems and Software*, 2022, vol. 190, article no. 111341. DOI: 10.1016/j.jss.2022.111341.

16. Rivas, J. M., Gutiérrez, J. J., Guasque, A., & Balbastre, P. Gradient descent algorithm for the optimisation of fixed priorities in real-time systems. *Journal of Systems Architecture*, 2024, vol. 153, article no. 103198. DOI: 10.1016/j.sysarc.2024.103198.

17. Xue, Y., Wang, Y., & Liang, J. A self-adaptive gradient descent search algorithm for fully-connected neural networks. *Neurocomputing*, 2022, vol. 478, pp. 70–80. DOI: 10.1016/j.neucom.2022.01.001.

18. Agulhari, C. M., & Peres, P. L. D. Stability analysis and control synthesis of hybrid time-varying linear systems using a discretisation-based approach. *Journal of the Franklin Institute*, 2024, vol. 361, iss. 7, article no. 106815. DOI: 10.1016/j.jfranklin.2024.106815.

19. Fagundes, A. S., Gomes da Silva, J. M., Jr., & Jungers, M. Stability analysis of sampled-data control systems with input saturation: A hybrid system approach. *European Journal of Control*, 2024, vol. 75, article no. 100890. DOI: 10.1016/j.ejcon.2023.100890.

20. Albea, C., & Seuret, A. Time-triggered and event-triggered control of switched affine systems via a hybrid dynamical approach. *Nonlinear Analysis: Hybrid Systems*, 2021, vol. 41, article no. 101039. DOI: 10.1016/j.nahs.2021.101039.

21. Sachenko, A., Kochan, V., Turchenko, V., Tymchyshyn, V., & Vasylkiv, N. Intelligent nodes for distributed sensor network. *Proceedings of the 16th IEEE Instrumentation and Measurement Technology Conference (IMTC/99)*, Venice, Italy, 24–26 May 1999, pp. 1479–1484. DOI: 10.1109/IMTC.1999.776072.

22. Hertneck, M., & Allgöwer, F. Robust dynamic self-triggered control for nonlinear systems using hybrid Lyapunov functions. *Nonlinear Analysis: Hybrid Systems*, 2024, vol. 53, article no. 101485. DOI: 10.1016/j.nahs.2024.101485.

23. Ocheretnyuk, N., Voytyuk, I., Dyvak, M., & Martsenyuk, Y. Features of structure identification the macromodels for nonstationary fields of air pollutions from vehicles. *Proceedings of International Conference on Modern Problem of Radio Engineering, Telecommunications and Computer Science*, Lviv, Ukraine, 21–24 February 2012, p. 444.

24. Dyvak, M., Pukas, A., Oliynyk, I., & Melnyk, A. Selection the “saturated” block from interval system of linear algebraic equations for recurrent laryngeal nerve identification. *Proceedings of 2018 IEEE Second International Conference on Data Stream Mining & Processing (DSMP)*, Lviv, Ukraine, 2018, pp. 444–448. DOI: 10.1109/DSMP.2018.8478528.

25. Zhang, Z., Li, C., Zhang, W., Zhou, J., & Liu, G. An FPGA-based memristor emulator for artificial neural network. *Microelectronics Journal*, 2023, vol. 131, article no. 105639. DOI: 10.1016/j.mejo.2022.105639.

26. Han, C., Qin, K., Lin, B., Shi, M., Li, Z., & Liu, Q. Neural network-based distributed consensus tracking control for uncertain Euler–Lagrange systems over directed topologies. *Neurocomputing*, 2024, vol. 608, article no. 128383. DOI: 10.1016/j.neucom.2024.128383.

27. Vladov, S., Scislo, L., Sokurenko, V., Muzychuk, O., Vysotska, V., Osadchy, S., & Sachenko, A. Neural Network Signal Integration from Thermogas-Dynamic Parameter Sensors for Helicopters Turboshaft Engines at Flight Operation Conditions. *Sensors*, 2024, vol. 24, article no. 4246. DOI: 10.3390/s24134246.

28. Mayadunne, S., Rajagopalan, H. K., & Sharer, E. A multi-step mixed integer programming heuristic for warehouse layout optimisation. *Supply Chain Analytics*, 2024, vol. 8, article no. 100088. DOI: 10.1016/j.sca.2024.100088.

29. Gurrola Arrieta, M. de J., Botez, R. M., & Lasne, A. An Engine Deterioration Model for Predicting Fuel Consumption Impact in a Regional Aircraft. *Aerospace*, 2024, vol. 11, iss. 6, article no. 426. DOI: 10.3390/aerospace11060426.

30. Pasieka, M., Grzesik, N., & Kuźma, K. Simulation modeling of fuzzy logic controller for aircraft engines. *International Journal of Computing*, 2017, vol. 16, iss. 1, pp. 27–33. DOI: 10.47839/ijc.16.1.868.

31. Vladov, S., Shmelov, Y., & Yakovliev, R. Method for Forecasting of Helicopters Aircraft Engines Technical State in Flight Modes Using Neural Networks. *CEUR Workshop Proceedings*, 2022, vol. 3171, pp. 974–985. Available at: https://ceur-ws.org/Vol-3171/paper70.pdf (accessed 16.10.2024)

32. Zheng, X., Zeng, H., Wang, B., Wen, M., Yang, H. & Sun, Z. Numerical simulation method of surge experiments on gas turbine engines. *Chinese Journal of Aeronautics*, 2023, vol. 36, iss. 3, pp. 107–120. DOI: 10.1016/j.cja.2022.08.007.

33. Sheng, H., Chen, Q., Li, J., Jiang, W., Wang, Z., Liu, Z., Zhang, T., & Liu, Y. Research on dynamic modeling and performance analysis of helicopter turboshaft engine's start-up process. *Aerospace Science and Technology*, 2020, vol. 106, article no. 106097. DOI: 10.1016/j.ast.2020.106097.

34. Avrunin, O., Vladov, S., Petchenko, M., Semenets, V., Tatarinov, V., Telnova, H., Filatov, V., Shmelov, Y., & Shushlyapina, N. *Intelligent automation systems*, Novabook: Kremenchuk, Ukraine, 2021, pp. 144–160. DOI: 10.30837/978-617-639-347-4.

35. Catana, R. M., & Dediu, G. Analytical Calculation Model of the TV3-117 Turboshaft Working Regimes Based on Experimental Data. *Applied Sciences*, 2023,

vol. 13, iss. 19, article no. 10720. DOI: 10.3390/app131910720.

36. Vladov, S., Shmelov, Y., & Petchenko, M. A Neuro-Fuzzy Expert System for the Control and Diagnostics of Helicopters Aircraft Engines Technical State. *CEUR Workshop Proceedings*, 2021, vol. 3013, pp. 40–52. Available at: https://ceur-ws.org/Vol-3013/20210040.pdf (accessed 20.10.2024)

37. Pasieka, M., Grzesik, N., & Kuźma, K. Simulation modeling of fuzzy logic controller for aircraft engines. *International Journal of Computing*, 2017, vol. 16, iss. 1, pp. 27–33. DOI: 10.47839/ijc.16.1.868.

38. Rusyn, B., Lutsyk, O., Kosarevych, R., Kapshii, O., Karpin, O., Maksymyuk, T., & Gazda, J. Rethinking Deep CNN Training: A Novel Approach for Quality-Aware Dataset Optimization. *IEEE Access*, 2024, vol. 12, pp. 137427–137438. DOI: 10.1109/access.2024.3414651.

39. Kim, H.-Y. Statistical Notes for Clinical Researchers: Chi-Squared Test and Fisher's Exact Test. *Restorative Dentistry & Endodontics*, 2017, vol. 42, article no. 152. DOI: 10.5395/rde.2017.42.2.152.

40. Benaceur, A., & Verfürth, B. Statistical Variational Data Assimilation. *Computer Methods in Applied Mechanics and Engineering*, 2024, vol. 432, article no. 117402. DOI: 10.1016/j.cma.2024.117402.

41. Paliy, I., Sachenko, A., Koval, V., & Kurylyak, Y. Approach to Face Recognition Using Neural Networks. *Proceedings of the 2005 IEEE Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, Sofia, Bulgaria, 2005, pp. 112–115. DOI: 10.1109/IDAACS.2005.282951.

42. Cosenza, P., Fauchille, A.-L., Prêt, D., Hedan, S., & Giraud, A. Statistical Representative Elementary Area of Shale Inferred by Micromechanics. *International Journal of Engineering Science*, 2019, vol. 142, pp. 53–73. DOI: 10.1016/j.ijengsci.2019.05.012.

43. Stefanovic, C. M., Armada, A. G., & Costa-Perez, X. Second Order Statistics of -Fisher-Snedecor Distribution and Their Application to Burst Error Rate Analysis of Multi-Hop Communications. *IEEE Open Journal of the Communications Society*, 2022, vol. 3, pp. 2407–2424. DOI; 10.1109/ojcoms.2022.3224835.

44. Rusyn, B., Lutsyk, O., Kosarevych, R., Maksymyuk, T., & Gazda, J. Features Extraction from Multi-Spectral Remote Sensing Images Based on Multi-Threshold Binarization. *Scientific Reports* 2023, vol. 13, article no. 19655. DOI: 10.1038/s41598-023-46785-7.

45. Bezobrazov, S., Golovko, V., Sachenko, A., Komar, M., Dolny, R., Kasyanik, V., Bykovyy, P., Mikhno, E., & Osolinskyi, O. Deep multilayer neural network for predicting the winner of football matches. *International Journal of Computing*, 2020, vol. 19, iss. 1, pp. 70–77. DOI: 10.31891/1727-6209/2020/19/1-70-77.

46. Berko, A., Alieksieiev, V., & Holdovanskyi, V. Determination-based correlation coefficient. *CEUR Workshop Proceedings*, 2024, vol. 3711, pp. 198–224. Available at: https://ceur-ws.org/Vol-3711/paper12.pdf (accessed 28.10.2024)

47. Vysotska, V., Lytvyn, V., Nazarkevych, M., Vladov, S., Yakovliev, R., & Yurko A. Training Neural Network Method Modification for Forward Error Propagation Based on Adaptive Components. *CEUR Workshop Proceedings*, 2024, vol. 3711, pp. 138–168. Available at: https://ceur-ws.org/Vol-3711/paper9.pdf (accessed 28.10.2024)

48. Vladov, S., Bulakh, M., Vysotska, V., & Yakovliev, R. Onboard Neuro-Fuzzy Adaptive Helicopter Turboshaft Engine Automatic Control System. *Energies*, 2024, vol. 17, iss. 16, article no. 4195. DOI: 10.3390/en17164195.

49. Cherrat, E. M., Alaoui, R., & Bouzahir, H. Score fusion of finger vein and face for human recognition based on convolutional neural network model. *International Journal of Computing*, 2020, vol. 19, iss. 1, pp. 11–19. DOI: 10.47839/ijc.19.1.1688.

50. Vladov, S., Yakovliev, R., Vysotska, V., Nazarkevych, M., & Lytvyn, V. The Method of Restoring Lost Information from Sensors Based on Auto-Associative Neural Networks. *Applied System Innovation*, 2024, vol. 7, iss. 3, article no. 53. DOI: 10.3390/asi7030053.

51. Morozov, V. V., Kalnichenko, O. V., & Mezentseva, O. O. The method of interaction modeling on basis of deep learning the neural networks in complex IT-projects. *International Journal of Computing*, 2020, vol. 19, iss. 1, pp. 88–96. DOI: 10.47839/ijc.19.1.1697.

52. Komar, M., Sachenko, A., Golovko, V., & Dorosh, V. Compression of network traffic parameters for detecting cyber attacks based on deep learning. *Proceedings of the 2018 IEEE 9th International Conference on Dependable Systems, Services and Technologies (DESSERT)*, Kyiv, Ukraine, 2018, pp. 43–47. DOI: 10.1109/DESSERT.2018.8409096.

53. Zhang, C., & Gümmer, V. The potential of helicopter turboshaft engines incorporating highly effective recuperators under various flight conditions. *Aerospace Science and Technology*, 2019, vol. 88, pp. 84–94. DOI: 10.1016/j.ast.2019.03.008.

54. Li, Y., Zhang, J., & Xuan, Y. The influence of helicopter rotor-fuselage flow interaction on temperature fields in forward flight. *Applied Thermal Engineering*, 2017, vol. 116, pp. 488–499. DOI: 10.1016/j.applthermaleng.2016.12.114.

55. Sagin, S., Madey, V., Sagin, A., Stoliaryk, T., Fomin, O., & Kučera, P. Ensuring Reliable and Safe Operation of Trunk Diesel Engines of Marine Transport Vessels. *Journal of Marine Science and Engineering*,

2022, vol. 10, iss. 10, article no. 1373. DOI: 10.3390/jmse10101373.

56. Sagin, S. V., Sagin, S. S., Fomin, O., Gaichenia, O., Zablotskyi, Y., Píštěk, V., & Kučera, P. Use of Biofuels in Marine Diesel Engines for Sustainable and Safe Maritime Transport. *Renewable energy*, 2024, vol. 224, article no.120221. DOI: 10.1016/j.renene.2024.120221.

57. Baranovskyi, D., Bulakh, M., Myamlin, S., & Kebal, I. New Design of the Hatch Cover to Increase the Carrying Capacity of the Gondola Car. *Advances in Science and Technology Research Journal*, 2022, vol. 16, 186–191. DOI: 10.12913/22998624/156205.

58. Baranovskyi, D., Myamlin, S., Bulakh, M., Podosonov, D., & Muradian, L. Determination of the Filler Concentration of the Composite Tape. *Applied Sciences*, 2022, vol. 12, iss. 21, article no. 11044. DOI: 10.3390/app122111044.

59. Xu, Q., & Zhang, Y. Event-triggered nonlinear information fusion preview control of a two-degree-of-freedom helicopter system. *Aerospace Science and Technology*, 2023, vol. 140, article no. 108474. DOI: 10.1016/j.ast.2023.108474.

60. Gopmandal, F., & Ghosh, A. LQR-based MIMO PID control of a 2-DOF helicopter system with uncertain cross-coupled gain. *IFAC-PapersOnLine*, 2022, vol. 55, iss. 22, pp. 183–188. DOI: 10.1016/j.ifacol.2023.03.031.

61. Kazi, S. R., Thombre, M., & Biegler, L. Globally Convergent Method for Optimal Control of Hybrid Dynamical Systems. *IFAC-PapersOnLine*, 2024, vol. 58, iss. 14, pp. 868–873. DOI: 10.1016/j.ifacol.2024.08.446.

62. Zhao, H., & Guo, W. Coordinated control method of multiple hybrid energy storage systems based on distributed event-triggered mechanism. *International Journal of Electrical Power & Energy Systems*, 2021, vol. 127, article no. 106637. DOI: 10.1016/j.ijepes.2020.106637.

Received 09.10.2024, Accepted 18.11.2024

СИНТЕЗ НАДІЙНО СТІЙКИХ НЕЙРОМЕРЕЖЕВИХ РЕГУЛЯТОРІВ ІЗ ОПТИМІЗАЦІЄЮ ПАРАМЕТРІВ ПЕРЕХІДНОГО ПРОЦЕСУ

С. І. Владов, А. О. Саченко, В. А. Висоцька, Є. Є. Волканін, Д. В. Кухаренко, Д. Северинeнко

Предметом вивчення в статті є розробка методу синтезу стійких нейромережевих регуляторів із оптимізацією параметрів перехідного процесу. **Метою** є розробка методу синтезу нейромережевого контролера для систем управління, що гарантує стійкість замкнених систем через автоматизований підбір функції Ляпунова із залученням додаткової нейронної мережі, навченої на даних, отриманих у процесі розв’язання задачі цілочислового лінійного програмування. Завдання: дослідження стійкості замкненої системи управління з нейромережевим регулятором, навчання нейрорегулятора та нейромережевої функції Ляпунова, створити оптимізаційну модель мінімізації функції втрат, провести обчислювальний експеримент як приклад синтезу нейромережевого стабілізуючого регулятора. Використовуваними методами є: метод навчання симулятора об'єкта керування на основі нейронної мережі, що описується системою рівнянь з урахуванням функції активації SmoothReLU, прямий метод Ляпунова для гарантування стійкості замкненої системи, метод змішаного цілочислового програмування, яка дозволяє мінімізувати втрати та забезпечити стійкість і мінімальний час регулювання для розвязання оптимізаційної задачі. Отримані такі **результати.** Застосування нейронної мережі дозволило отримати результати, пов’язані із зменшенням часу перехідного процесу до 3,0 секунд та зниженням перерегулювання у 2,33 рази порівняно з традиційним контролером (на прикладі моделі витрати палива газотурбінного двигуна ТВ3-117). **Висновки.** У роботі вперше розроблено метод синтезу стабілізуючого нейромережевого регулятора для газотурбінних двигунів вертольотів із гарантованою стійкістю системи на основі теорії Ляпунова. Новизна методу полягає у використанні лінійної апроксимації функції активації SmoothReLU із застосуванням бінарних змінних, що дозволило звести задачу забезпечення стійкості до задачі оптимізації методом змішаного цілочислового програмування. Розроблено систему обмежень, яка враховує сигнал регулювання та умови стійкості, що забезпечує мінімізацію часу стабілізації системи. Отримані результати підтверджують ефективність запропонованого підходу для підвищення енергоефективності двигунів та їхньої адаптивності до змінних режимів роботи.

Ключові слова: оптимізація; регулятор; нейронна мережа; функція Ляпунова; змішане цілочислове програмування.

Владов Сергій Ігорович – канд. техн. наук, начальник відділу організації наукової діяльності, Харківський національний університет внутрішніх справ, Кременчуцький льотний коледж, Харків, Україна.

Саченко Анатолій Олексійович – д-р техн. наук, проф., директор Науково-дослідного інституту інтелектуальних комп'ютерних систем, Західноукраїнський національний університет, Тернопіль, Україна; Радомський університет імені Казімежа Пуласького, Радом, Польща.

Висоцька Вікторія Анатоліївна – д-р техн. наук, доц., проф. каф. інформаційних систем та мереж, Національний університет «Львівська політехніка», Львів, Україна.

Волканін Євген Євгенович – канд. техн. наук, зав. каф. електронних комунікацій, радіотехніки та авіоніки, Харківський національний університет внутрішніх справ, Кременчуцький льотний коледж, Харків, Україна.

Кухаренко Дмитро Володимирович – канд. техн. наук, доц., доц. каф. комп'ютерної інженерії та електроніки, Кременчуцький національний університет імені Михайла Остроградського, Кременчук, Україна.

Севериненко Данило – асп. каф. інформаційних систем та мереж, Національний університет «Львівська політехніка», Львів, Україна.

Serhii Vladov – Candidate of Technical Sciences, Head of the Scientific Activity Organization Department, Kharkiv National University of Internal Affairs, Kremenchuk Flight College, Kharkiv, Ukraine,
e-mail: serhii.vladov@univd.edu.ua, ORCID: 0000-0001-8009-5254, Scopus Author ID: 57204826154

Anatoliy Sachenko – Doctor of Technical Sciences, Professor, Director of the Research Institute for Intelligent Computer Systems, West Ukrainian National University, Ternopil, Ukraine; Kazimierz Pulaski University of Radom, Radom, Poland,
e-mail: as@wunu.edu.ua, ORCID: 0000-0002-0907-3682, Scopus Author ID: 35518445600

Victoria Vysotska – Doctor of Technical Sciences, Associate Professor, Professor at the Information Systems and Networks Department, Lviv Polytechnic National University, Lviv, Ukraine,
e-mail: victoria.a.vysotska@lpnu.ua, ORCID: 0000-0001-6417-3689, Scopus Author ID: 24484045400

Yevhen Volkanin – Candidate of Technical Sciences, Associate Professor, Associate Professor at the Department of Electronic Communications, Radio Engineering and Avionics, Kharkiv National University of Internal Affairs, Kremenchuk Flight College, Kharkiv, Ukraine,
e-mail: volkanin@ukr.net, ORCID: 0000-0003-3507-1987, Scopus Author ID: 59296447700

Dmytro Kukharenko – Candidate of Technical Sciences, Head of the Department of Computer Engineering and Electronics, Kremenchuk Mykhailo Ostrohradskyi National University, Kremenchuk, Ukraine,
e-mail: dkuch100@gmail.com, ORCID: 0000-0002-2845-6881, Scopus Author ID: 57105553800

Danylo Severynenko – Postgraduate of the Information Systems and Networks Department, Lviv Polytechnic National University, Lviv, Ukraine,
e-mail: danylo.y.severynenko@lpnu.ua, ORCID: 0000-0002-1708-316X.