Neural Network Control of the Mobile Robotic Platform's Adhesion Force

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Abstract
This paper focuses on the advancements in mobile robotics, specifically on universal robotic platforms that have versatile applications in different technological environments and settings within industrial facilities. These platforms exhibit the capability to navigate complex terrains on horizontal surfaces and even ascend vertically on walls and ceilings, making them autonomous and adaptable tools for performing intricate operations in challenging and hazardous areas. The primary challenge addressed in this research pertains to the precise control of adhesion when these robotic platforms traverse inclined planes. To tackle this issue, the authors have developed and analyzed an intelligent adhesion control system. This system harnesses the principles of neural network control to stabilize the required adhesion force for safe and efficient platform movement across varying surface inclinations. The obtained computer simulations results confirm the high effectiveness of the proposed intelligent system.

Keywords [1]
Mobile robotics, universal robotic platform, intelligent adhesion control, neural network control system, NARMA-L2 controller, computer simulation

1. Introduction

The integration of robotic systems and complexes across diverse sectors of human activity has experienced significant growth in recent years [1, 2]. Nowadays, robots of various types play a pivotal role in numerous processes, spanning from closed production cycles in heavy industries and metallurgy to customer service and cargo delivery. The adoption of robotic solutions yields substantial advantages, notably the elimination of costly human labor, a significant boost in productivity, accuracy, and operational speed, as well as a reduction in risks to human life and health when executing tasks in hazardous and detrimental environments [3, 4]. Furthermore, the utilization of robots helps mitigate errors arising from operator fatigue and human factors [5].

In the monograph of T. Braunl [6] the mobile robots and robotic complexes are singled out as a distinct and widely utilized class of robotic systems. Also, the studies of researchers O. Tosun et al. [7] confirm that these systems excel in tasks such as monitoring, inspection, reconnaissance, as well as facilitating the movement of equipment and tools to execute labor-intensive operations in challenging and inaccessible locations. Their true effectiveness is witnessed through their ability to operate in fully automatic modes [8, 9]. For instance, mobile robots developed by M. Sorour [10] and B. Ross et al. [11] have proven to be highly effective in painting tasks as well as paint removal from various surfaces. Moreover, notable advancements have been made in the research of Z. -W. Mao et

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al. [12] at the development and successful application of mobile welding robotic complexes capable of autonomously tracking and performing large fillet welding seams in narrow spaces. Additionally, robots proposed by D. Souto, et al. [13] and M. Cardona et al. [14] for complex cleaning and inspection of diverse objects' surfaces have gained widespread usage.

As the studies of such researchers as M. Karimi, et al. [15], and V. Mazur [16] show, the universal mobile robotic platforms (UMRP) exhibit even higher levels of efficiency. Their modular structure enables the integration of various propulsion systems and diverse sets of technological tools, enabling them to undertake a wide range of tasks across different environments and conditions. These platforms demonstrate their adaptability on horizontal surfaces with intricate terrains, underwater environments, as well as vertical and inclined surfaces of various types [17]. Consequently, their versatility contributes to a considerable increase in task performance speed and a reduction in the costs associated with diverse technological operations [18]. Nevertheless, the development of such UMRPs presents considerable challenges for designers in creating highly efficient intelligent control systems. These control systems must possess a modular structure to automate the control processes of diverse propulsion devices (for moving above water and underwater, as well as maneuvering on horizontal and inclined surfaces) and various working tools (for welding, monitoring, inspection, painting, cleaning, etc.). As recent studies show, it is most advantageous to develop such control systems based on the methods and approaches of artificial intelligence [19, 20]. For instance, fuzzy control systems prove highly effective in navigating different types mobile robots capable of moving on inclined surfaces [21]. Moreover, researchers M. Algabri, et al. [22] proposed an optimized fuzzy controller for mobile robot navigation that allow avoiding random obstacles when moving in unknown environments. Neural network (NN) control is also widely utilized, which is confirmed by a number of its successful applications [23, 24]. In particular, R. Garcia-Hernandez, et al. [23] developed methods of decentralized neural control and successfully applied it to various mobile robots. Besides, H.A. Mayer [24] designed an approach to ontogenetic teaching of mobile autonomous robots with dynamic neurocontrollers.

Significant emphasis should be placed on the adhesion force control system (AFCS) when the platform navigates across different types of inclined surfaces. This system holds paramount importance as it directly influences the safety of movement on inclined and vertical surfaces. Moreover, precise control of the adhesion force can greatly enhance the overall efficiency of the motion control system by enabling the optimal distribution of loads. Thus, the development of an intelligent system for precise control of the adhesion force will solve one of the important automation tasks of the universal mobile robotic platform.

The primary objective of this research is to develop and investigate an intelligent system for stabilizing and automatically controlling the adhesion force of a universal mobile robotic platform.

2. Structure of the Generalized Hierarchical Control System for the UMRP

Due to the intricate and multifaceted nature of the universal mobile robotic platform, a hierarchical control system with multiple levels is essential. The hierarchical multi-level control approach encompasses distinct levels, including the highest, strategic, tactical, and executive levels of control. The highest level entails the human operator and the human-machine interface [25]. At this level, the operator is responsible for making informed decisions regarding specific technological operations, tasks, movements, or maneuvers of the UMRP. These decisions are based on comprehensive assessments of the environment, prevailing conditions, external disturbances, and other relevant factors [26, 27]. Furthermore, in order to facilitate decision-making, the operator can utilize embedded simulation models to conduct preliminary simulations of specific situations. These simulations enable the operator to predict the behavior of the UMRP as well as the state of the environment, aiding in informed decision-making processes.

At the strategic level of control, upon receiving specific commands or control goals from the highest level, it is necessary to plan the sequence of technological operations, tasks, or movements. This involves transforming them into a series of elementary actions or subtasks. Depending on the nature of the operation, various control algorithms can be employed at this level [26]. The strategic level then generates commands for the tactical level, which is responsible for executing specific actions or basic operations. The primary objective of the tactical control level is to convert the commands received from the strategic level into control programs that dictate the coordinated functioning and movement of the executive mechanisms and actuators at the executive level of control. These programs define sequences of desired values for the generalized controlled coordinates of the UMRP's primary executive mechanisms [26].

The executive level of control comprises the executive mechanisms, actuators, and the sensory system. Additionally, it includes automatic control subsystems that, through appropriate control inputs, determine the desired values for the platform's generalized controlled coordinates received from the tactical level [26]. The sensory system plays a crucial role in providing feedback and gathering comprehensive information about the state of the UMRP and its surrounding environment.

Fig. 1 illustrates the basic structure of the generalized hierarchical control system for the UMRP, with the following notations being used: HMI is the human-machine interface; CATO1, CATO2, …, CATO*l* are the control algorithms of the 1st, 2nd, …, *l*th technological operations; CMPD1, CMPD 2, …, CMPD*n* are the control modules of the 1st, 2nd, …, *n*th propulsion devices; CMTT1, CMTT 2, …, CMTT*m* are the control modules of the 1st, 2nd, …, *m*th technological tools; $\mathbf{U}_{SS}$ is the vector of sensory system outputs; $\mathbf{U}_{SL}$ is the vector of control signals for the strategic level; $\mathbf{U}_{TL}$ is the vector of control signals for the tactical level; $\mathbf{U}_{EL}$ is the vector of control signals for the executive level; $\mathbf{X}_{R}$ is the vector of controlled and technological variables of the UMRP.

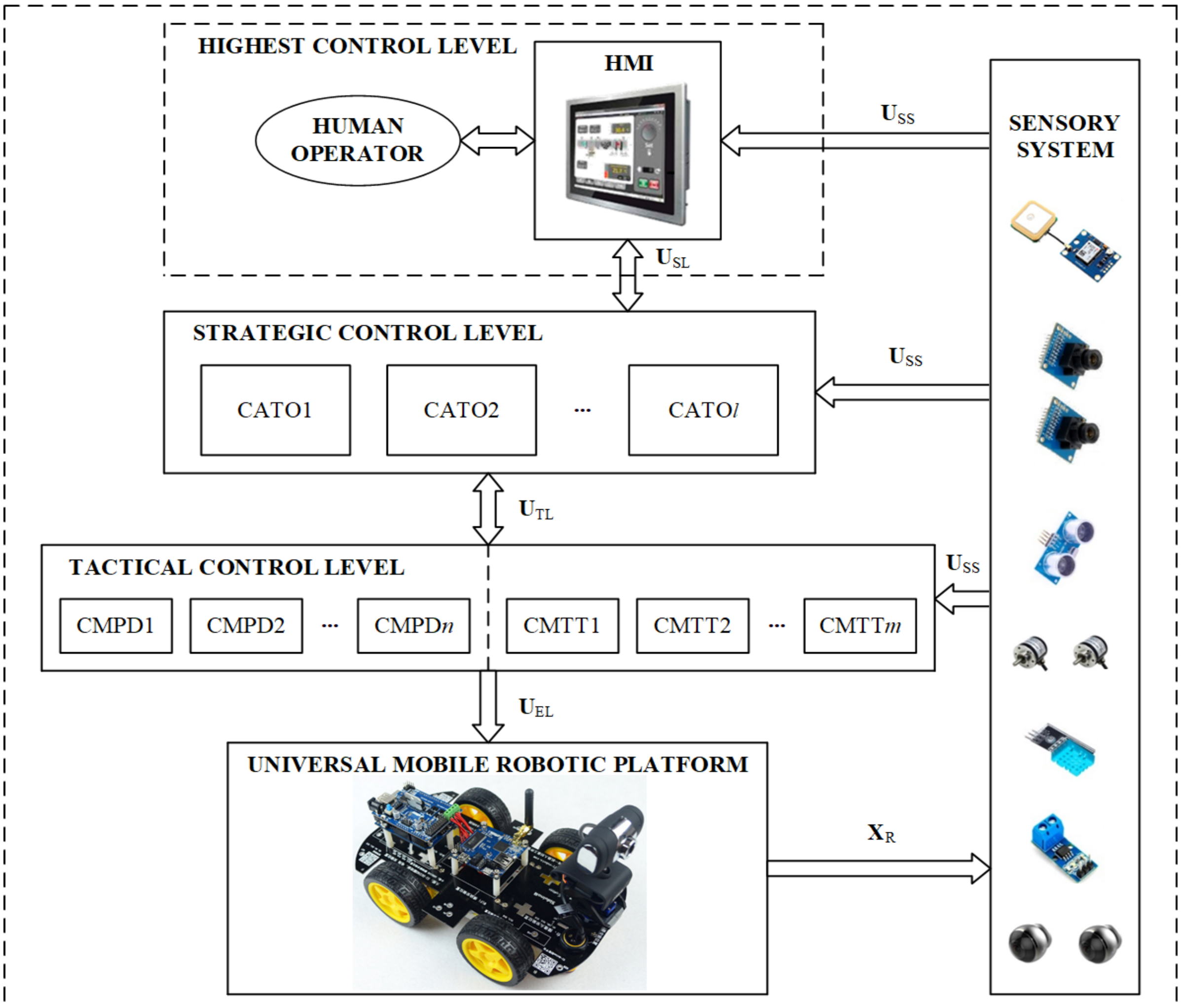

Figure 1: Structure of the Generalized Hierarchical Control System for the UMRP

Within this hierarchical control system, at the highest level the operator utilizes a dedicated human-machine interface to relay control signals $\mathbf{U}_{SL}$ to the strategic control level, while also receiving signals $\mathbf{U}_{SS}$ regarding the platform's state and environmental conditions from the sensory system.

In turn, the strategic level incorporates a collection of *l* control algorithms (CATO1, CATO2, …, CATO*l*) designed to facilitate control over a range of technological operations (such as inspection, ultrasonic diagnostics, welding, painting, rust removal, cleaning, etc.) achievable with the robotic platform. Furthermore, different combinations of propulsion devices and technological tools available on the mobile platform can be employed for executing these technological operations. Additionally, the control system allows for the inclusion of new control algorithms at the strategic level to accommodate novel types of technological operations.

To facilitate direct control over diverse propulsion devices (such as wheeled, caterpillar, propeller, gravity-based, walking, etc.) and technological tools (including manipulators, video cameras, welding machines, cleaning cutters, and more) during the execution of various operations, the system incorporates corresponding control modules (CMPD1, CMPD2, …, CMPD*n*, CMTT1, CMTT2, …, CMTT*m*) at the tactical control level. When introducing new propulsion devices or technological tools to the UMRP, it is necessary to design and integrate the relevant control modules into the system's tactical control level beforehand. These control modules, possessing a complex structure, are responsible for the coordinated control of all executive mechanisms, drives, and actuators associated with specific propulsion devices and technological tools. Lastly, dedicated stabilization and automatic control subsystems are employed at the executive level (depicted directly on the UMRP in Fig. 1) of this system to govern the variables of individual drives and actuators. These subsystems operate as subordinate control systems to the tactical-level control modules.

Among the numerous propulsion devices and working tools utilized by the mobile robotic platform, the adhesion device (AD) holds notable significance. Its incorporation expands the scope of tasks and technological operations, enabling work in challenging and inaccessible locations on inclined and vertical surfaces (such as sheer walls and ceilings). The AD can be realized based on diverse physical principles, including magnetic, electromagnetic, propeller, vacuum, and others, depending on the tasks and operational conditions. Consequently, for the effective utilization of various types of adhesion devices on the UMRP across different operating modes, the development of a suitable universal control module is imperative. Subsequently, we delve into the development of a functional structure, control algorithms, and key components of the adhesion device control module, specifically focusing on the specialized adhesion force control system.

3. Structure of the Control System for the UMRP's Adhesion Force

The primary objective of the adhesion device on the mobile robotic platform is to generate the required adhesion force on inclined or vertical surfaces, ensuring the platform's safe and effective movement while conducting necessary technological operations. While it is possible to maximize the adhesion force in all operating modes to securely hold the UMRP, this approach would result in heightened energy consumption by the adhesion device and introduce substantial resistance to the propulsion devices. Consequently, overall efficiency of the UMRP and the performance of specific operations would be significantly diminished. Therefore, to achieve optimal utilization of the adhesion device while conserving energy, it is imperative to implement a flexible control system for the adhesion force that adapts to different platform movement modes, diverse technological operations, and various influencing factors. Simultaneously, the AFCS is responsible for determining the desired (preset) adhesion force and ensuring its automatic maintenance and stabilization. Various parameters heavily influence the set value of the adhesion force, including the surface inclination angle, friction coefficient of the working surface, total mass of the robotic platform, technological tools, and the traction force exerted by the propulsion devices. Furthermore, it is essential for the control system structure to be universally applicable to any type of adhesion device.

Considering the aforementioned conditions and specific characteristics, as well as the intricacy of mathematically describing the process of the platform moving on various types of inclined surfaces, it is advisable to develop the adhesion force control system using artificial intelligence principles [28, 29]. This system should comprise two levels of control: tactical and executive. At the tactical level, the desired adhesion force value between the platform and the surface is determined based on parameters such as the surface inclination angle, friction coefficient, and traction force of the propulsion devices. On the other hand, the executive level focuses on the automatic control of the adhesion force, ensuring the stabilization of the desired value in the presence of various disturbances.

After analyzing various methods and approaches in artificial intelligence, it is concluded that developing the tactical-level subsystem to determine the desired adhesion force using fuzzy or neuro-fuzzy models is most appropriate [9, 30, 31]. Fuzzy and neuro-fuzzy systems allow effective generalization of expert knowledge and experimental data, formalization of human thought processes, creation of linguistic models for complex phenomena, and approximation of nonlinear multidimensional relationships [32]. These systems can be synthesized based on expert assessments and subsequently easily optimized using experimental data or simulation models based on effective algorithms [33-35]. Furthermore, the executive-level subsystem for automatic control of the adhesion force should be designed with a neural network controller [36]. Neural network controllers enable effective training based on experimental models and provide precise control over complex nonlinear systems in the presence of uncertain disturbances [37, 38]. Considering these factors, the basic structure of the two-level adhesion force control system for the UMRP is established, as depicted in Fig. 2.

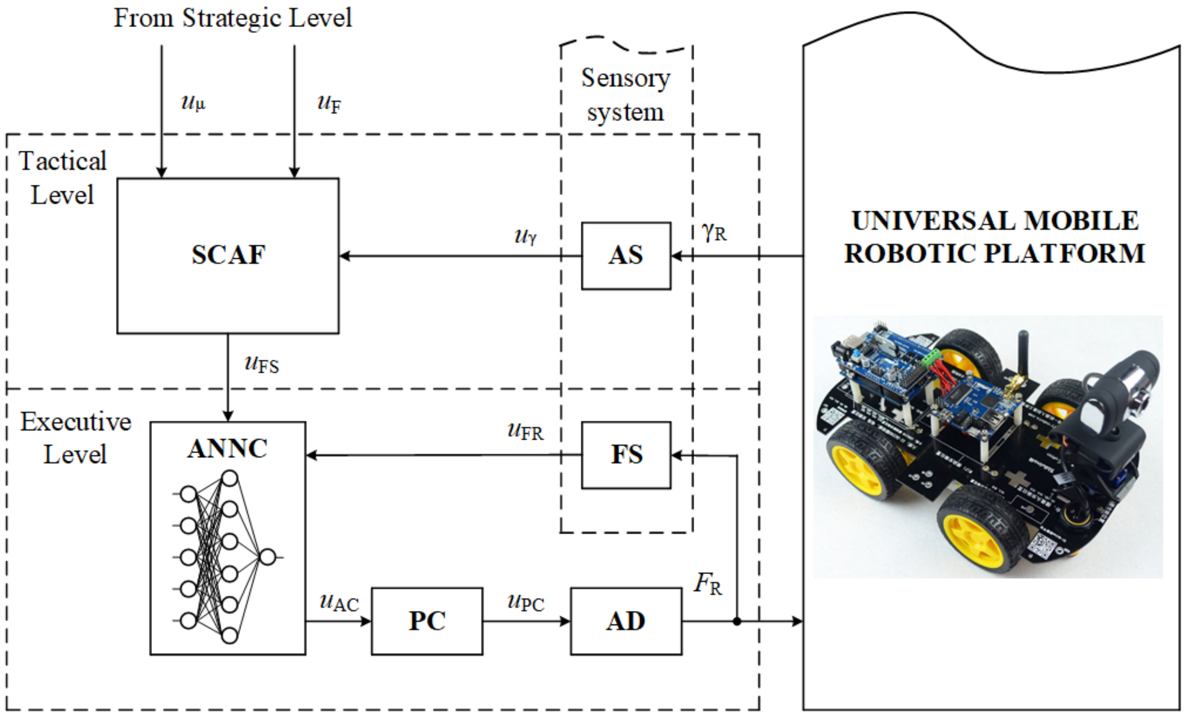

Figure 2: Structure of the two-level control system for the UMRP's adhesion force

In Fig. 2, the following notations are used: SCAF is the subsystem for calculating the UMRP's adhesion force set value; ANNC is the adhesion neural network controller; AS and FS are the angle and force sensors; PC is the power converter; u_μ is the signal indicating the current value of the coefficient of friction of the contact parts of the UMRP and the working surface; u_F is the signal indicating the current value of the traction force of the UMRP propulsion devices; u_γ is the signal indicating the current value of the angle of inclination of the working surface; u_{FS} is the SCAF output signal which corresponds to the set value of adhesion force; u_{FR} is the FS output signal which corresponds to the real value of adhesion force; u_{AC} is the ANNC output control signal; u_{PC} is the PC output signal; γ_R is the current value of the angle of inclination of the working surface; F_R is the adhesion force real value.

As depicted in Fig. 2, the SCAF operates at the tactical level and calculates the set value of the adhesion force using signals such as the current coefficient of friction u_μ, the current traction force of the UMRP propulsion devices u_F, and the current angle of inclination of the working surface u_γ. The signals u_μ and u_F are obtained from the strategic level of control, while the signal u_γ is acquired from the angle sensor measuring the working surface's inclination. The current coefficient of friction is determined through experimentation or preset by the operator, taking into account the type and material of the working surface. The current traction force of the UMRP propulsion devices is provided by the platform's propulsion device control system. Subsequently, the SCAF employs a fuzzy inference engine with a predefined rule base or a neuro-fuzzy system (previously trained) to calculate the signal u_{FS}, which represents the required value of the adhesion force.

At the executive level, the adhesion force stabilization is achieved through the implementation of the neural network controller. The ANNC compares the signal u_{FS} received from the SCAF with the force sensor signal u_{FR}. Utilizing its embedded algorithm based on a neural network, the ANNC autonomously controls the adhesion force of the UMRP. The output control signal u_{AC} generated by the ANNC is amplified by a power converter and directly applied to the adhesion device. It is important to note that the ANNC needs to be trained beforehand for a specific adhesion device, utilizing training data, simulation, or experimental models.

In this paper, the processes of developing and researching the effectiveness of the executive-level neural network subsystem are considered in detail.

4. Development of the Neural Network Subsystem for Stabilization and Automatic Control of the UMRP Adhesion Force

The neural network subsystem for stabilization and automatic control of the UMRP adhesion force (Fig. 2) has two inputs (u_{FS}, u_{FR}) and one output (u_{AC}). Analyzing various types of neural network controllers, we can say that in this case, the most appropriate is the development of the adhesion force control system based on the NARMA-L2 controller [39]. This controller has a fairly high efficiency in controlling complex nonlinear plants with a relatively simple processes of designing and further implementation [40, 41]. NARMA-L2 controller uses the nonlinear autoregressive with moving average model of control process [39]. For the synthesis of this controller it is necessary to construct a discrete nonlinear model of the control process as auto regressive model with moving average. The control signals of this controller are generated as follows:

$$\begin{aligned} u_{\mathrm{AC}}(k+1) = & \frac{u_{\mathrm{FS}}(k+d)}{g\left[u_{\mathrm{FR}}(k), u_{\mathrm{FR}}(k-1), \ldots, u_{\mathrm{FR}}(k-n+1), u_{\mathrm{AC}}(k-1), \ldots, u_{\mathrm{AC}}(k-m+1)\right]} - \\ & - \frac{f\left[u_{\mathrm{FR}}(k), u_{\mathrm{FR}}(k-1), \ldots, u_{\mathrm{FR}}(k-n+1), u_{\mathrm{AC}}(k-1), \ldots, u_{\mathrm{AC}}(k-m+1)\right]}{g\left[u_{\mathrm{FR}}(k), u_{\mathrm{FR}}(k-1), \ldots, u_{\mathrm{FR}}(k-n+1), u_{\mathrm{AC}}(k-1), \ldots, u_{\mathrm{AC}}(k-m+1)\right]}, \end{aligned} \tag{1}$$

where d is the number of prediction cycles; $g(\cdot)$ and $f(\cdot)$ are the nonlinear operators.

The equation (1) is used when $d \geq 2$. The functional diagram of the control process and structure of the neural network controller NARMA-L2 are shown in Fig. 3 and Fig. 4, respectively. Blocks of delay lines DL memorize the corresponding input and output sequences. The dual-layer neural networks form the estimations of nonlinear operators and calculates the control signal in the form (1).

The procedure of the synthesis of this controller represents the process of control plant identification and designing of the controller in the form of the neural network NARMA-L2-model (Fig. 4).

The control plant identification process for NARMA-L2 controller is conducted in the following way. Various control signals are sequentially applied to the control plant within predetermined operating ranges in terms of amplitude and time. Herewith, the ranges of change of the control signal in amplitude and time are set taking into account the real dynamic characteristics and operating conditions of the plant. Moreover, in most cases, it is advisable to apply random control signals within the established limits. These control signals, as well as the output response of the plant, are recorded and form a training sample with the required number of lines. At this point, the identification process is considered complete, and this generated sample can be used to train the neural network controller.

The development of this subsystem must be carried out directly for a specific type of adhesion device, since the neural network controller must be correctly trained on a specific simulation model.

In this paper, an electromagnetic adhesion device was chosen for research, which allows the robotic platform to move along inclined and vertical ferromagnetic surfaces. This device uses an electromagnet with the possibility of smooth control to create the required value of the adhesion force to the ferromagnetic surface. The mathematical model of the adhesion device of this type is presented in detail in the paper [42]. This device is applied to the robotic platform with a maximum mass (with equipment) of 90 kg and is capable of developing a maximum adhesion force of 6000 N. In the identification process of the control plant (electromagnetic adhesion device) for the NARMA-L2 controller, the training sample of 10,000 points was formed. The dynamics of changes in the input and output signals of the electromagnetic adhesion device as a control plant in the identification process is shown in Fig. 5. In the process of synthesizing the considered neural network controller, the following parameters were chosen: the number of neurons of the hidden layer is 9, the number of delay elements at the model input is 2, the number of delay elements at the model output is 3.

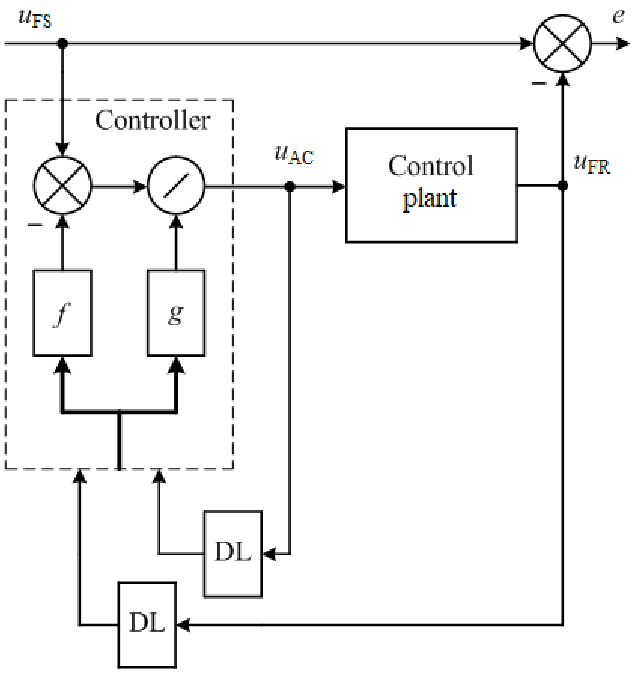

Figure 3: Functional diagram of the control process with the NARMA-L2 controller

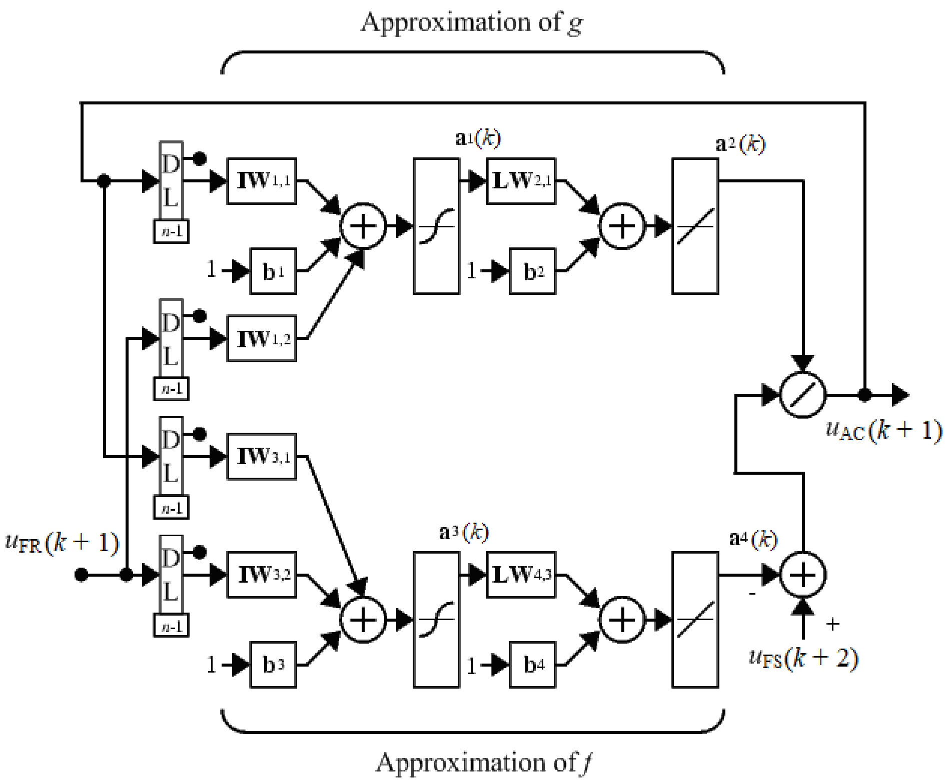

Figure 4: Structure of the neural network NARMA-L2 controller

The dynamics of the training error change and the testing on the validation and testing samples are shown in Fig. 6. The number of training cycles was 200. Training of the neural network was conducted using the obtained training sample with 10,000 points and the Levenberg-Marquardt training algorithm [43, 44]. At the same time, the given sample was divided into three different sub-samples for training, validation and testing in the following proportions: 70%, 15% and 15%. The results of the neural network training, validation and testing are shown in Fig. 7-9.

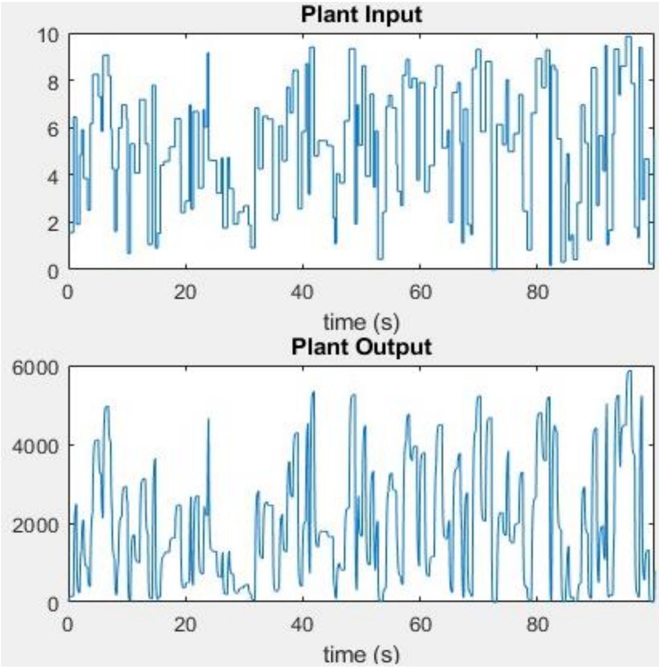

Figure 5: Dynamics of changes in the input and output signals of the electromagnetic adhesion device as a control plant in the identification process

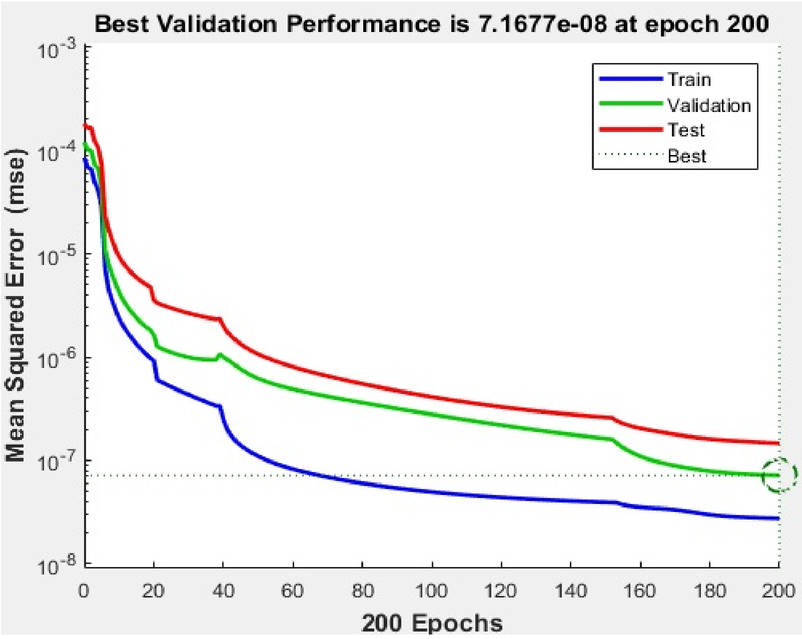

Figure 6: Dynamics of the training error change and the testing on the validation and testing samples

As can be seen from Fig. 7-9, the trained neural network has a sufficiently high accuracy, which makes it possible to ensure the stabilization of the set value of the adhesion force of the robotic platform by the NARMA-L2 controller with a sufficiently high efficiency. To confirm the performance and efficiency of the developed adhesion force stabilization subsystem based on the neural network controller, the Fig. 10 shows the transients of automatic control of the adhesion force value in case of an accidental change in the set point. In turn, the following designations are adopted in Fig. 10: 1 is the given adhesion force value, which comes from the tactical level subsystem; 2 is the real value of the adhesion force, which is provided by the neural network subsystem of the executive level. Based on Fig. 10 we defined the quality indicators of transients of the adhesion force automatic control based on the developed neural network stabilization subsystem. The given quality indicators are presented in Table 1.

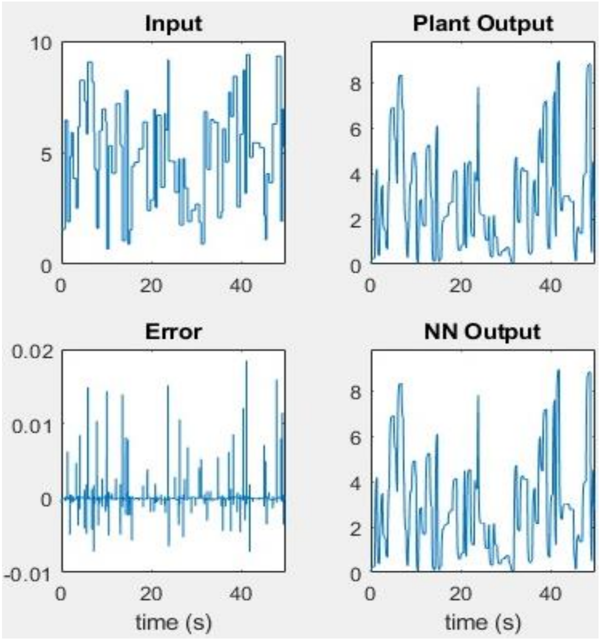

Figure 7: The NARMA-L2 neural network training results

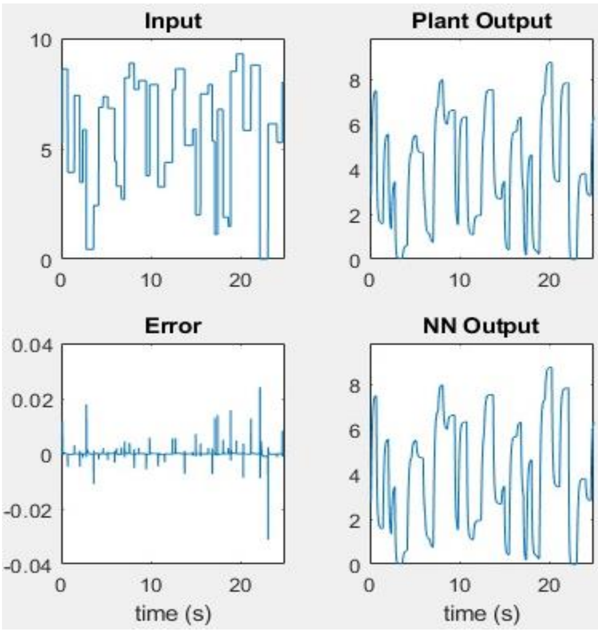

Figure 8: The NARMA-L2 neural network validation results

As can be seen from Fig. 10 and Table 1, the developed automatic control subsystem based on the trained NARMA-L2 neural network controller has sufficiently high indicators of control quality in case of random changes in the set values of the adhesion force. In particular, the maximum overshoot value and the maximum control time are 59.12% and 0.625 seconds, respectively, at the largest jump (1^{st} step) in the adhesion force set point. Moreover, when working out each set value, the subsystem provides a zero static error in the adhesion force automatic control. In general, we can conclude that the developed neural network subsystem has a sufficiently high accuracy and speed of the adhesion force control, as well as, at the same time, a sufficiently large overshoot value. This fully satisfies the requirements for the adhesion force automatic control systems of universal robotic platforms, since a large overshoot value does not seriously affect the quality of control, energy efficiency, reliability and overall performance. The main requirements of systems of such type are high accuracy and speed, which, in general, provides reliable adhesion to the working surface.

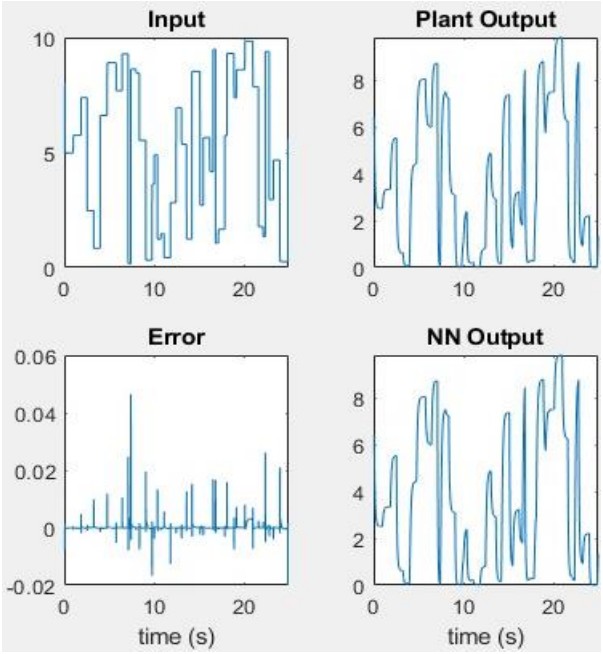

Figure 9: The NARMA-L2 neural network testing results

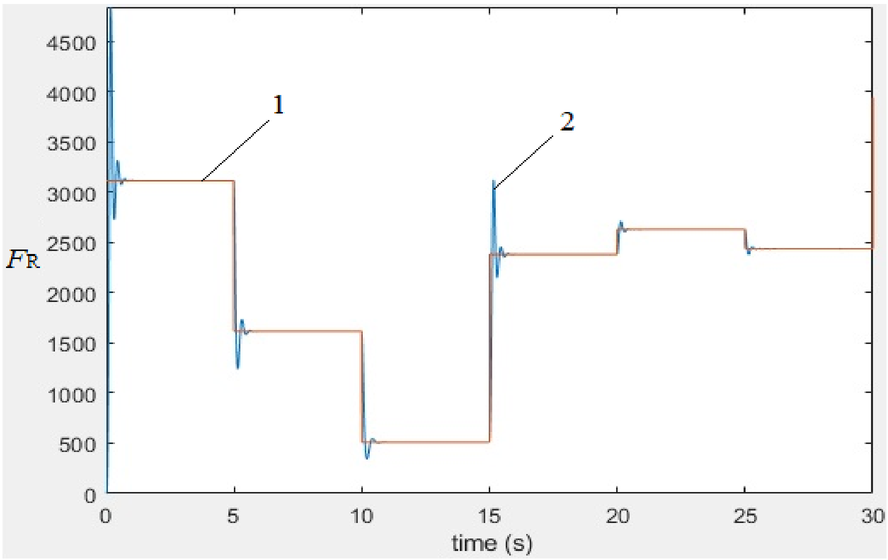

Figure 10: Transients of automatic control of the adhesion force value in case of an accidental change in the set point

5. Conclusions

This work focuses on the development and investigation of an intelligent system for the automatic control of adhesion in the universal mobile robotic platform. The proposed system for adhesion automatic control in the universal mobile robotic platform adopts a two-level structure, consisting of tactical and executive levels of automatic control. It leverages the principles of artificial intelligence to enable adaptable automatic control of the adhesion force, considering different platform movement modes, various technological operations, and other influencing factors. The tactical-level subsystem plays a key role in determining the required adhesion force based on real-time measurements of surface inclination, friction coefficient, and propulsion device traction force.

Table 1
Quality indicators of transients of the adhesion force automatic control subsystem

Step number	Set value, N	Step time, s	Control time, s	Overshoot, %
1	3140	0	0.625	59.12
2	1620	5	0.536	25.91
3	510	10	0.514	16.89
4	2410	15	0.612	39.47
5	2680	20	0.352	35.82
6	2460	25	0.265	32.14

The executive-level subsystem is developed on the basis of the neural network and allows implementing proper stabilization and automatic control of the UMRP adhesion force. In particular, the NARMA-L2 neural network controller is designed and trained on the previously obtained training data that gives the opportunity to provide effective automatic control of the adhesion force value at different values of input and disturbing actions. In turn, the development of this subsystem is carried out for the electromagnetic adhesion device, which allows the robotic platform to hold and move along inclined and vertical ferromagnetic surfaces due to the smooth control of the electromagnet. The obtained simulation results in the form of transients of the adhesion force automatic control during the random changes in the set values show that the developed control subsystem based on the trained NARMA-L2 neural network controller has sufficiently high quality indicators of control. Namely, the proposed executive-level subsystem provides a sufficiently high accuracy and speed of the adhesion force automatic control (the maximum overshoot and the maximum control time are 59.12% and 0.625 seconds, respectively, at the zero value of the static error).

The developed executive-level subsystem based on the NARMA-L2 neural network controller can be successfully applied in practice for real universal mobile robotic platforms of various types, sizes and configurations that move on inclined surfaces. In particular, this version of the system can be used not only for electromagnetic adhesion devices, but also for other types of devices: propeller, vacuum, etc. Herewith, it will first be necessary to train the NN controller for the selected clamping device and UMRP with specific parameters on a simulation model with further adjustment on a real plant.

Further research should be conducted towards the optimization of the proposed intelligent system of the adhesion control, development of its software and hardware as well as performing experimental studies on real universal robotic platforms when carrying out various technological operations.

6. Acknowledgements

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7. References

[1] E. Garcia, et al. The evolution of robotics research. In IEEE Robotics & Automation Magazine, Vol. 14, No. 1, 2007, pp. 90-103. DOI: 10.1109/MRA.2007.339608.
[2] R. Duro, et al. (Eds). Advances in intelligent robotics and collaborative automation. River Publishers, Aalborg, 2015. DOI: https://doi.org/10.13052/rp-9788793237049
[3] B. Siciliano, O. Khatib. Springer handbook of robotics. Springer, 2016.
[4] X. Han, et al. Trend of Intelligent Robot Application Based on Intelligent Agriculture System, 2021 3rd International Conference on Artificial Intelligence and Advanced Manufacture (AIAM), Manchester, United Kingdom, 2021, pp. 205-209, doi: 10.1109/AIAM54119.2021.00050.
[5] S. Santhosh. Innovative methodology and designing of intelligent mobile robots computer vision with genetic algorithm SLE mechanism and advanced sensors in managing disaster, 2014 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2014], Nagercoil, India, 2014, pp. 1692-1697, doi: 10.1109/ICCPCT.2014.7054895.
[6] T. Braunl. Embedded Robotics. Mobile Robot Design and Applications with Embedded Systems. Third Edition. Berlin Heidelberg: Springer-Verlag, 2008.

[7] Mobile Robotics: Solutions and Challenges. Proceedings of the Twelfth International Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines / Edited by O. Tosun, H. L. Akin, M. O.Tokhi, G. S. Virk. Istanbul, Turkey, 2009.

[8] M. Taranov, et al. Simulation of robot's wheel-mover on ferromagnetic surfaces. Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications: Proceedings of the 2017 IEEE 9th, International Conference, Vol. 1, 2017, pp. 283-288. DOI: 10.1109/IDAACS.2017.8095091

[9] Y. P. Kondratenko, J. Rudolph, O. V. Kozlov, Y. M. Zaporozhets, O. S. Gerasin, Neuro-fuzzy observers of clamping force for magnetically operated movers of mobile robots, Technical Electrodynamics, 5 (2017), 53-61, (in Ukrainian). DOI: 10.15407/techned2017.05.053.

[10] M. Sorour. RoboPainter – A detailed robot design for interior wall painting. 2015 IEEE International Workshop on Advanced Robotics and its Social Impacts (ARSO), Lyon, France, 2015, pp. 1-6. DOI: 10.1109/ARSO.2015.7428214.

[11] B. Ross, J. Bares, C. Fromme. A Semi-Autonomous Robot for Stripping Paint from Large Vessels. The International Journal of Robotics Research, 2008. pp. 617-626.

[12] Z. -W. Mao, J. -l. Pan, H. Zhang. Mobile welding robot system based on rotating arc sensor applied for large fillet welding seam tracking. 2010 Sixth International Conference on Natural Computation, Yantai, China, 2010, pp. 394-397. DOI: 10.1109/ICNC.2010.5583304.

[13] D. Souto, et al. A New Type of Robot for Underwater Non-magnetic and Complex Hull Cleaning. Robotics and Automation: Proceedings of IEEE International Conference, Karlsruhe, Germany, 2013, pp. 3394-3399.

[14] M. Cardona, J. Cerrato, E. García. Design and Simulation of a Mobile Robot for Pipeline Inspection. 2022 IEEE Central America and Panama Student Conference (CONESCAPAN), San Salvador, El Salvador, 2022, pp. 1-6. DOI: 10.1109/CONESCAPAN56456.2022.9959592.

[15] M. Karimi, et al. ReMoRo; A mobile robot platform based on distributed I/O modules for research and education. 2015 3rd RSI International Conference on Robotics and Mechatronics (ICROM), Tehran, Iran, 2015, pp. 657-662, DOI: 10.1109/ICRoM.2015.7367861.

[16] D. Maia, A. Coelho, M. Ricardo. Obstacle-aware On-demand 5G Network using a Mobile Robotic Platform, 2022 18th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), Thessaloniki, Greece, 2022, pp. 470-473, doi: 10.1109/WiMob55322.2022.9941633.

[17] D. Canelon-Suarez, Y. Wang, N. Papanikolopoulos. Omnibot: A Small Versatile Robotic Platform Capable of Air, Ground, and Underwater Operation. 2020 International Conference on Unmanned Aircraft Systems (ICUAS), Athens, Greece, 2020, pp. 1742-1747, DOI: 10.1109/ICUAS48674.2020.9214021.

[18] K. Shabalina, A. Sagitov, E. Magid. Comparative Analysis of Mobile Robot Wheels Design. 2018 11th International Conference on Developments in eSystems Engineering (DeSE), Cambridge, UK, 2018, pp. 175-179, DOI: 10.1109/DeSE.2018.00041.

[19] C.C. Aggarwal. Artificial Intelligence. Springer International Publishing, 2021. DOI 10.1007/978-3-030-72357-6.

[20] L.U. Emaletdinova, A.N. Kabirova. Neural fuzzy controller to control the angle of heel and the course of the unmanned aerial vehicle. Dynamics of Systems, Mechanisms and Machines (Dynamics), 2016, pp. 1-5.

[21] Y. P. Kondratenko, A. V. Kozlov, Parametric optimization of fuzzy control systems based on hybrid particle swarm algorithms with elite strategy, in Journal of Automation and Information Sciences, 51, 12 (2019), New York: Begel House Inc., 25-45. DOI: 10.1615/JAutomatInfScien.v51.i12.40

[22] M. Algabri, et al. Optimization of Fuzzy Logic Controller using PSO for Mobile Robot Navigation in an Unknown Environment. Applied Mechanics and Materials, Vols. 541-542, 2014, pp. 1053-1061.

[23] R. Garcia-Hernandez, et al. Decentralized Neural Control: Application to Robotics. Studies in Systems, Decision and Control, Vol. 96, Springer International Publishing, 2017.

[24] H.A. Mayer, Ontogenetic teaching of mobile autonomous robots with dynamic neurocontrollers. International Journal of Computing, Vol. 3, Issue 1, 2004, pp. 38-45.

[25] Y. P. Kondratenko, O. V. Kozlov, O. S. Gerasin, A. M. Topalov, O. V. Korobko. Automation of control processes in specialized pyrolysis complexes based on Web SCADA Systems. Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS): Proceedings of the 9th IEEE International Conference. Bucharest, Romania, volume 1, 2017, pp. 107-112, DOI: 10.1109/IDAACS.2017.8095059.

[26] R. Jabłoński, T. Březina, (Eds.). Mechatronics. Recent Technological and Scientific Advances. Springer-Verlag Berlin Heidelberg, 2012.
[27] P. T. H. Sen, et al. A New Tracking Control Algorithm for a Wheeled Mobile Robot Based on Backstepping and Hierarchical Sliding Mode Techniques, 2019 First International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP), Bangkok, Thailand, 2019, pp. 25-28, doi: 10.1109/ICA-SYMP.2019.8646288.
[28] A. Shevchenko, M. Vakulenko, M. Klymenko. The Ukrainian AI Strategy: Premises and Outlooks, in: Proceedings of the 12th Int. Conf. on Advanced Computer Information Technologies, ACIT 2022, Sep. 26-28, 2022, pp. 511-515. doi: 10.1109/ACIT54803.2022.9913094
[29] Knight, K., Zhang, C., Holmes, G., Zhang, M.-L. (Eds.). Artificial Intelligence. Second CCF International Conference, ICAI 2019, Xuzhou, China, August 22-23, 2019, Proceedings, Springer Singapore, 2019. DOI 10.1007/978-981-32-9298-7.
[30] L.A. Zadeh, A.M. Abbasov, R.R. Yager, S.N. Shahbazova, M.Z. Reformat (Eds.), Recent Developments and New Directions in Soft Computing, STUDFUZ 317, Cham: Springer, 2014. DOI 10.1007/978-3-319-06323-2.
[31] Y.P. Kondratenko, O.V. Kozlov, Mathematical Model of Ecopyrogenesis Reactor with Fuzzy Parametrical Identification, in: Lotfi A. Zadeh, et al. (Eds.), Recent Developments and New Direction in Soft-Computing Foundations and Applications, Studies in Fuzziness and Soft Computing, Vol. 342, Berlin, Heidelberg: Springer-Verlag, 2016, pp. 439-451. doi.org/10.1007/978-3-319-32229-2_30.
[32] J. M. Mendel, Uncertain Rule-Based Fuzzy Systems, Introduction and New Directions, Second Edition, Springer International Publishing, 2017.
[33] Y. P. Kondratenko, A. V. Kozlov. Generation of Rule Bases of Fuzzy Systems Based on Modified Ant Colony Algorithms, Journal of Automation and Information Sciences, 51, 3 (2019), New York: Begel House Inc., 4-25. DOI: 10.1615/JAutomatInfScien.v51.i3.20.
[34] O. Kozlov, G. Kondratenko, Z. Gomolka, Y. Kondratenko, Synthesis and Optimization of Green Fuzzy Controllers for the Reactors of the Specialized Pyrolysis Plants, in: Kharchenko V., Kondratenko Y., Kacprzyk J. (eds) Green IT Engineering: Social, Business and Industrial Applications, Studies in Systems, Decision and Control, Vol 171, Springer, Cham, 2019, pp. 373-396. https://doi.org/10.1007/978-3-030-00253-4_16
[35] O. Castillo, P. Melin, An Approach for Optimization of Intuitionistic and Type-2 Fuzzy Systems in Pattern Recognition Applications, in: 2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), New Orleans, LA, USA, 2019, pp. 1-5, doi: 10.1109/FUZZ IEEE.2019.8858951.
[36] D. Wang, et al. Neural optimal tracking control of constrained nonaffine systems with a wastewater treatment application. Neural Networks, Vol. 143, 2021, pp. 121-132.
[37] M. Lungu, R. Lungu. Neural network based adaptive control of airplane’s lateral-directional motion during final approach phase of landing. Engineering Applications of Artificial Intelligence, Vol. 74, 2018, pp. 322-335.
[38] J. Kern Molina, et al. Development of a neural controller applied in a 5 DOF robot redundant, in IEEE Latin America Transactions, vol. 12, no. 2, pp. 98-106, 2014, doi: 10.1109/TLA.2014.6749524.
[39] K. S. Narenda, S. Mukhopadhyay. Adaptive Control Using Neural Networks and Approximate Models. IEEE Transactions on Neural Networks, Vol. 8, 1997, pp. 475-485.
[40] B. Ullah, et al. Speed Control of Separately Excited DC Motor Using NARMA-L2 Controller. 2022 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP), Jakarta, Indonesia, 2022, pp. 43-47. DOI: 10.1109/ICT-PEP57242.2022.9988795.
[41] F. Fourati, S. Baklouti, H. Moalla. NARMA-L2 neural control of a bioreactor. 2015 4th International Conference on Systems and Control (ICSC), Sousse, Tunisia, 2015, pp. 504-509. DOI: 10.1109/ICoSC.2015.7153307.
[42] O.V. Kozlov Optimal Selection of Membership Functions Types for Fuzzy Control and Decision Making Systems. Proceedings of the 2nd International Workshop on Intelligent Information Technologies & Systems of Information Security with CEUR-WS, Khmelnytskyi, Ukraine, IntelITSIS 2021, CEUR-WS, Vol-2853, 2021, pp. 238-247.
[43] C. Kanzow, N. Yamashita, M. Fukushima. Levenberg–Marquardt methods with strong local convergence properties for solving nonlinear equations with convex constraints. Journal of Computational and Applied Mathematics, Vol. 172, Iss. 2, 2004, pp. 375-397.
[44] Y. Todorov, et al. Fuzzy-neural predictive control using Levenberg-Marquardt optimization approach. 2013 IEEE INISTA, 2013, pp. 1-5. DOI: 10.1109/INISTA.2013.6577624.