Vol. 08, No. 2 (2026) 875-886, doi: 10.24874/PES08.02A.003

Proceedings on Engineering Sciences

www.pesjournal.net

# METHODOLOGY OF APPLICATION OF ROBUST CONTROL SYSTEMS BASED ON NEURAL NETWORK ADAPTATION TO THE OPERATING CONDITIONS OF COMPLEX PRODUCTION PROCESSES

Uvaev Marat Yuryevich [1]
Shikov Alexey Nikolaevich

Received 15.01.2026.
Revised 04.05.2026.
Accepted 20.05.2026.

Keywords:

*Adaptation, Robust control, Multilayer neural network, Technological process, Machine learning, Oil refining*

A B S T R A C T

*The problems and contradictions of modern control systems for high-dimensional technological processes, in particular, petrochemical industries, are due to the main aspects of complexity: multicriticality, multidimensionality, high dynamism, uncertainty of aftereffect and resource constraints on control. To find optimal solutions for controlling such technological processes, it is necessary to enumerate combinations of control actions, while the response time of a number of industries is in a wide range from hours to milliseconds. In such a situation, the development of robust control systems based on neural network adaptation to the operating conditions of complex production processes becomes especially relevant, since it allows, without conducting complex experiments at an industrial facility, to identify the main (not always obvious in advance) factors influencing the target quality indicators and, at the pace of monitoring production processes, select the optimal operating modes of the technological system. Objective: to develop the main provisions and stages of the methodology of precedent adaptation of control device parameters to changing operating conditions of complex production processes. Results: the basics of implementation and stages of the methodology of precedent adaptation of control device parameters to changing operating conditions of complex production processes are presented using the example of petrochemical production. Options for solving two control problems with prediction are described: forecasting disturbing effects on the control object and interpolation of values of optimal control parameters for given disturbances. Practical significance: an option for constructing a hardware and software implementation scheme for the methodology of using robust control systems based on neural network adaptation to the operating conditions of complex production processes, implemented in the infrastructure of an automated process control system of an enterprise, is proposed.*

© 2026 Published by Faculty of Engineering

## 1. INTRODUCTION

As is known, the goal of the synthesis of robust control systems is to find such control laws that would ensure a given mismatch of the parameters of the control object under any operating influences and environmental factors under conditions of a priori uncertainty.

Given that adequate decision-making, even in a relatively simple situation, is usually associated with the lack of

[1] Corresponding author: Uvaev Marat Yuryevich
Email: uvaev_marat@mail.ru

complete certainty, which would allow a deterministic approach to decision-making without resorting to idealization, it becomes clear how relevant it is for modern production systems, where the cost of error in a number of conditions may be unacceptable, to take into account uncertainty factors, which ultimately contribute to increasing the efficiency, reliability and quality of products (Biimyrsaeva et al., 2025).

Classical methods and approaches to solving management problems, developed in the theory of operations research and decision making (Bryson & Ho-Yu-Shi, 2012; Volkova & Kozlov, 2014; Pereira et al., 2025), the theory of automatic control (Kazakov & Mal'chikov, 1983; Besekersky & Popov, 2003), the theory of optimal control, and even the theory of adaptive, invariant, robust and self-organizing systems, require permanent improvement and development, taking into account constantly emerging factors of uncertainty and the characteristics of management objects.

In recent years, there has been a significant increase in the number of studies and publications devoted to the practical application of adaptive and robust methods in various industries. Research in the field of sustainable control (Bhattacharya et al., 2000; Zhou & Doyle, 1999; Morari & Zafiriou, 1989; Mahmoud & Munro, 1989; Calafiore & Dabbene, 2006; Pupkov et al., 2002; Briat, 2015; Sulaimankulova et al., 2025) demonstrates successful examples of the use of robust methods in real production systems. The fundamentals of adaptive and robust control are well developed and described in classical works, such as the works of K. J. Astrom and B. Wittenmark (Åström & Wittenmark, 1990), as well as P. A. Ioannou and J. Sun (Ioannou & Sun, 2012). One of the modern developments in the paradigm of automatic control systems (ACS) is an automatic target designation system, which can only be implemented as an intelligent system (Pozdnyak, 1991). However, intelligent systems at the first stages of their operation under conditions of a priori insufficiency (when there is no information yet or there is little of it) are also required to be robust, which implies the unconditional relevance of methods for synthesizing robust optimal systems. One of them is the method based on the H-theory (Pozdnyak, 1991; Egupov, 2002; Barbu & Sritharan, 1998; Doyle et al., 1989).

At the same time, instability of control under conditions of uncertainty of the control object states and environmental factors, as well as the need for the ACS to function under resource constraints on the time and volume of calculations, suggests a limited applicability of "accurate" control methods. In conditions of increased requirements for the performance and flexibility of control systems, adaptive and robust methods become especially relevant, since Robust control focuses on creating algorithms that ensure the stability and reliability of the system, regardless of the level of uncertainty and changing conditions.

As is known, A generalized closed-loop control system, as the most effective control scheme (according to the criteria of accuracy and speed), is a set of elements connected, in the general case, by nonlinear dependencies (Figure 1) (Bryson & Ho-Yu-Shi, 2012; Besekersky & Popov, 2003).

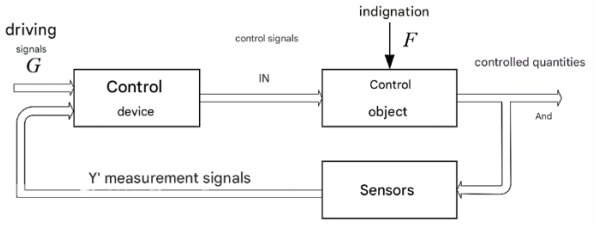



**Figure 1.** Generalized closed-loop control system

With regard to a number of multidimensional technological processes of production, the uncertainty of the relationship between the control results and the characteristics of disturbances makes a predominant contribution to the quality of regulation. At the same time, control based on classical schemes of identification of the control object and forecasting *F*, in a number of cases is complicated by the dimensionality of the problem and restrictions on the speed of generation of control signals *U*. Therefore, there is a need to synthesize an upper-level superstructure that implements recognition of changes in the operating conditions of the ACS and operational parametric synthesis of control devices that are optimal relative to the current combination of G, F and Y. As a result of applying this strategy of adjusting the system to the predicted control conditions, the central task becomes the task of precedent control of the operating modes of the ACS, in which the labor-intensive task of identification is replaced by the operation of selecting a parametrically "close" or similar precedent " *Control conditions →parameters of the control device → parameters of the control object* " based on recognition *F* and the formation of optimal settings *H* for the control device (Figure 2).

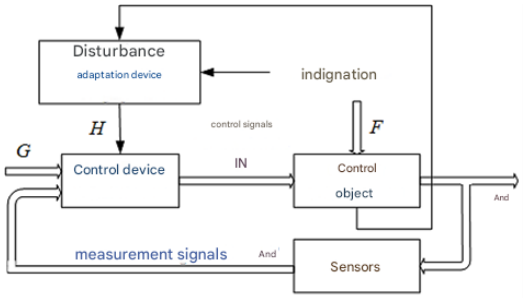



**Figure 2.** Generalized closed-loop control system with adaptation to disturbances and the control object

It is implied that such a methodology of precedent identification of control parameters in practice should promptly identify anomalies in the behavior of the control object or environmental factors and implement adaptation of the control strategy. As is known, the control system can implement adaptation only if it has

memory with non-trivial response logic; in the conditions of complex and high-dimensional control objects, this means that the systems for supporting management decisions must be intelligent.

As a result, it becomes possible, unlike adaptive systems, to design an ACS taking into account the worst-case scenarios, which allows us to guarantee the safe operation of process units even under strong external disturbances, which is important when managing production technological processes for which it is problematic to obtain an analytically specified form of the functional dependence of the input and output signals of the ACS with subsequent clarification of the values of the coefficients included in it.

## 2. MODERN PARADIGMS OF TECHNOLOGICAL PROCESS CONTROL IN ADAPTIVE SYSTEMS

In Figure 3, two main groups of optimal control algorithms are distinguished: universal and specialized. Also, it is necessary to highlight the precedent approach in problem-oriented control systems, when it is not possible to strictly analytically describe the control object, but there is a significant number of control precedents presented in the format { *state; control, disturbances; measurements* }. In this case, various directions of artificial intelligence methods and, in particular, machine learning seem effective.

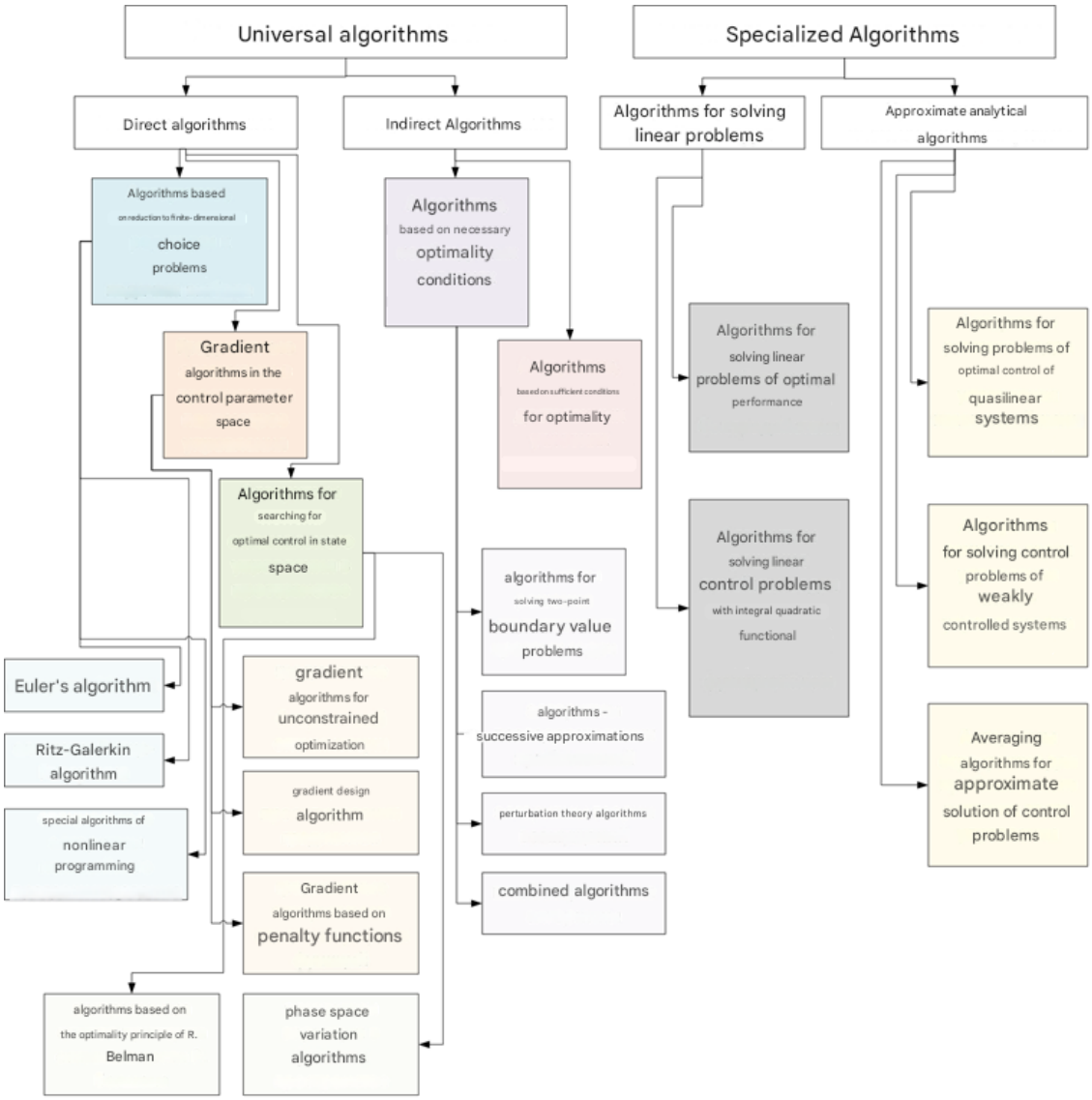



**Figure 3.** Algorithms for solving problems of optimal control of technological processes

This arsenal of methods is used primarily to recognize the state of the control object and optimize the strategy in problem-oriented control systems.

An approximate analysis of adaptive, robust and fuzzy control methods, as well as production technological processes, for example, in petrochemistry and gas processing, causes a pragmatic contradiction, on the one

hand, between the need to increase the reliability, accuracy and efficiency of planning and implementation of control, and on the other hand, an increase in the dimensionality of the state space of modern industries, characterized by an increase in the risks of erroneous control actions in the combinatorial space of possible solutions.

Machine learning technologies are the mainstream in the research areas that allow to parry the above limitations. The use of neural networks (NN) for adaptive control and forecasting of environmental factors in industrial production systems provides a number of key advantages. Neural networks can approximate complex nonlinear dependencies that arise in these technological processes, which is especially important for ensuring the stability and safety of production.

High-performance computers of data centers train neural networks and these results can be replicated and reproduced in various gas processing control processes. The directions of world developments and the functional environment of neural network technologies of machine learning in the field of precedent control are illustrated in Figure 4.




**Figure 4.** Functional environment of neural network technologies of machine learning for management

Most modern NN architectures allow generalizing new input samples with high, but finite reliability due to the fact that information-intensive networks allow approximating a very large number of sample examples (if we do not take into account the convolutional technology, which allows significantly increasing reliability due to recognition invariants) (Xu & Aminian, 2024; Lakshmanan et al., 2022; Khaikin, 2006; Van Veen & Leijnen, 2019)

Architectures such as FixResNeXt-101 (2020), Vit -H/14 (2021), RepVGG-B1 (2021), etc., combined with the ability to decompose training procedures (Deep Learning variations are replacing classical training algorithms) and the use of significant computing power, largely determine the extensive path to success of cloud projects such as ChatGPT - X , Claude - X , Geminu, YandexGPT, Kandinsky 2.1, a wide range of generative architectures, etc.

## 3. METHODOLOGY FOR THE APPLICATION OF ROBUST CONTROL SYSTEMS FOR PRODUCTION PROCESSES BASED ON NEURAL NETWORK ADAPTATION

In the last decade, small-order P, PI and PID process controllers have been actively introduced into the processing industry. The study of the application and adjustment of such controllers has become one of the most relevant areas of the theory of adaptation of linear systems to nonlinear control laws of complex technological processes.

Complex technological processes are understood as multi-parameter and multi-criteria technological processes characterized by instability of the flow, i.e. technological processes, the control of which is carried out according to several parameters with time constraints for the search for optimal control actions. Such processes are widely known in the chemical, metallurgical and other industries in the production of ultra-pure, highly perfect and rare materials (Zyubin, 2004). For example, a common control scheme for oil refining processes with multiple outputs of controlled parameters is a closed loop in Figure 5.

An example of a complex for implementing the control of such a simplified representation of a technological process is the LAB-LABS (linear alkyl benzene and linear alkyl benzene sulfonate) installation for the production of synthetic agents (Figure 6).

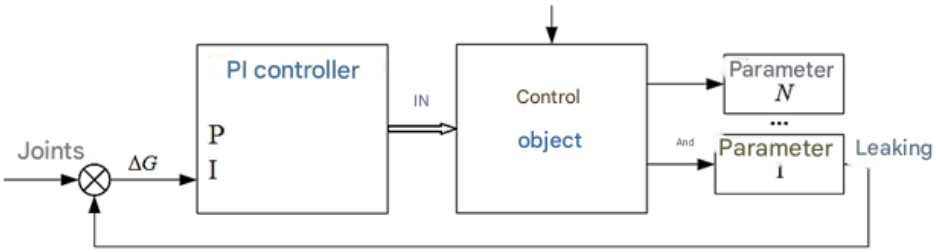



**Figure 5.** The initial process control scheme, in which the error in one of the N controlled parameters is fed to the input of the PI controller



**Figure 6.** Installations of the LAB-LABS complex at the KINEF LLC plant

Separation of hydrocarbon mixtures of complex composition (wide fractions) into simpler and more homogeneous mixtures (narrow fractions) is one of the basic processes of oil refining. Most often, this separation is carried out in rectification columns, where the driving force of the process is the difference in boiling temperatures of the components.

The LAB-LABS complex includes 3 units: for the production of monoolefins , alkylation, and sulfonation (Figure 7).

The parameters of the PI controller of the installation component are calculated for one specific range of change in the value of the integral (multidimensional) characteristic of the input raw material - liquid paraffins. When their composition changes, as well as the composition and temperature variations of benzene, sulfur and alkali, the optimality of product production decreases.

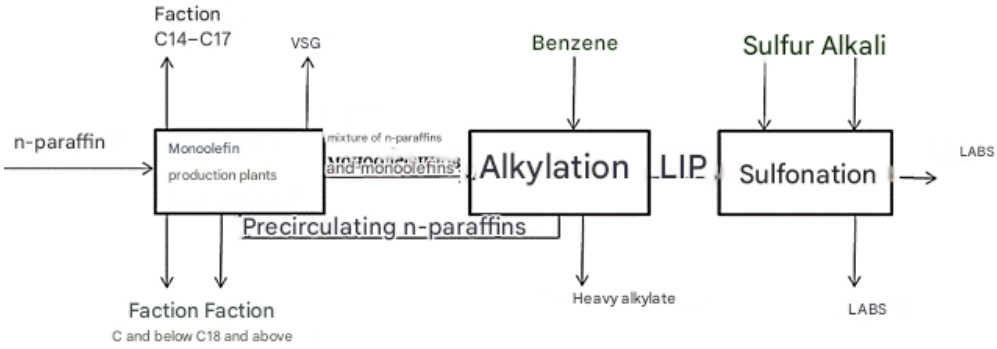



**Figure 7.** Block diagram of LAB-LABS as an object of product yield regulation

In this case, the methodology for using robust control systems for production processes based on neural network adaptation of control parameters (these may not necessarily be the proportional, integral and differential components of the PID controller link) consists of implementing several stages.

1. Formation of a plan for monitoring control variables in various modes of operation of the technological process (including nominal, abnormal) and formation of a table of precedents of the type (Table 1), where $m$ – the number of setting parameters (LABS), $n$ – the number of external environmental factors (temperature, pressure, humidity, …), $l$ – number of control parameters (for PID controller: Kp , Ki and Kd ), number of measured parameters (LABS Na , LABS, alkylate, …), $u$ – number of control quality indicators, N – number of precedents

**Table 1.** Table of precedents of the technological process monitoring plan

| No. | Setting parameters for regulating product yield | Disturbing parameters | Control parameters (device/control algorithm parameters) | Output parameters | Indicators of regulatory quality |
|---|---|---|---|---|---|
| 1 | $g(t)^1{}_1,\ldots,g(t)^1{}_m$ | $f(t)^1{}_1,\ldots,f(t)^1{}_n$ | $k(t)^1{}_1,\ldots,k(t)^1{}_l$ | $y(t)^1{}_1,\ldots,y(t)^1{}_z$ | $q^1{}_1,\ldots,q^1{}_u$ |
| … | … | … | … | … | … |
| $N$ | $g(t)^N{}_1,\ldots,g(t)^N{}_m$ | $f(t)^N{}_1,\ldots,f(t)^N{}_n$ | $k(t)^N{}_1,\ldots,k(t)^N{}_l$ | $y(t)^N{}_1,\ldots,y(t)^N{}_z$ | $q^N{}_1,\ldots,q^N{}_u$ |

The precedent table is essentially an observation protocol in which a combinatorial set of combinations of setting, disturbance, output parameters and control parameters is specified, to which a vector of control quality parameter values corresponds.

$F$ be used as a disturbing influence, control parameters $K_p$ and $K_i$, and the control quality parameters be the areas under the curves of transient processes $Q_1$ and $Q_2$. Then, a correspondence table of optimal values $\{K_P, K_I\}$ to different levels of disturbances $\{F\}$ is formed by means of a table search in the observation protocol (Table 1) for each value $C'$ from the array of variations $\{F\}$, those values of the control parameters $\{K_P', K_I'\}$ *at which the selected indicator of control quality* $Q_1$ or $Q_2$ reaches an extremum (Figure 8).

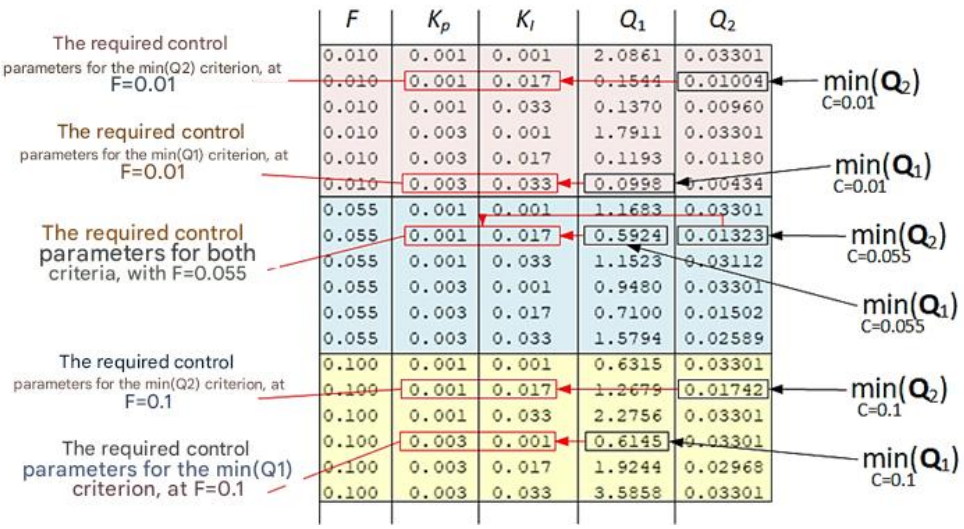



**Figure 8.** An example of a table search for optimal control parameters according to the observation protocol F, for three variations *of* $F$ , two variations of $K_P$ , and three variations of $K_I$

The search and formation of the correspondence table (Table 2) is sequentially implemented in three operations:

1) determination of the block of row indices of one given level of disturbance $F$ (along the left column);
2) determining the index of the row containing the minimum value of the selected indicator $Q_1$ or $Q_2$;
3) reading the required control parameters $K_P$ and $K$ in the found line $I$.

The format of the final table of correspondence between the levels of disturbing effects and the optimal control parameters for the example under consideration is given in Table 2.

Knowing the correspondence table (Table 2) and the values of the disturbing effects $F$, it becomes possible to predictively adjust the parameters of control devices, thereby increasing the efficiency of controlling multidimensional technological processes (Figure 9).

**Table 2.** Format of the table of correspondence of optimal values { K P opt , K I opt } to different levels of disturbing influences { F }, M is the number of levels

| Level of disturbances | Optimal proportional component of PI controller | Optimal integral component of PI controller |
|---|---|---|
| $f^1$ | $K_P^{1opt}$ | $K_I^{1opt}$ |
| $f^2$ | $K_P^{2\ opt}$ | $K_I^{2opt}$ |
| … | … | … |
| $f^j$ | $K_P^{jopt}$ | $K_I^{\ opt}$ |
| … | … | … |
| $f^M$ | $K_P^{Mopt}$ | $K_I^{Mopt}$ |

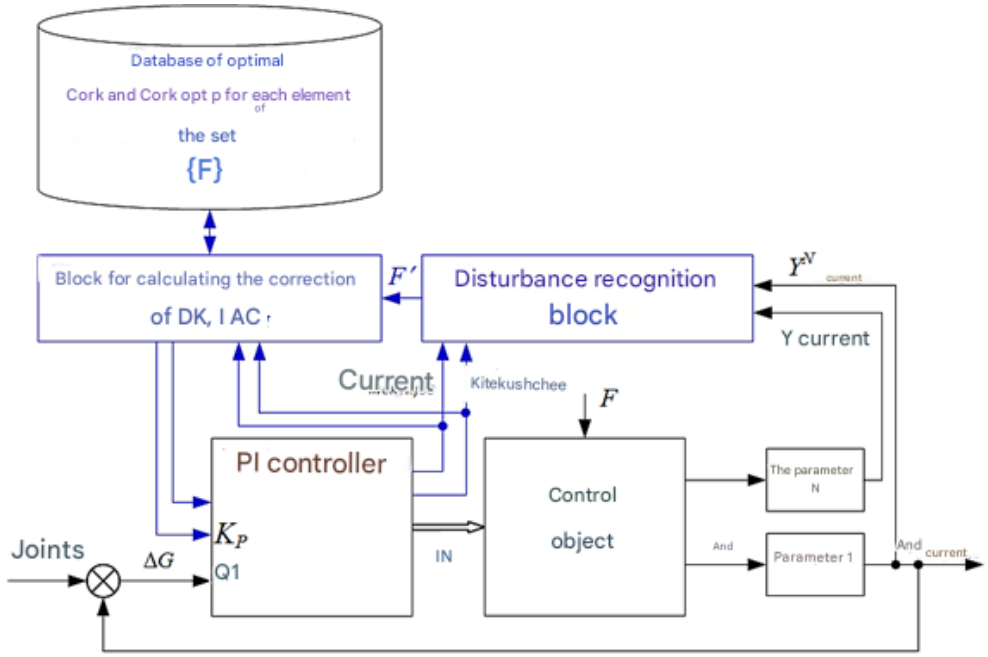



**Figure 9.** Adaptive scheme of robust control of a technological process according to one of N controlled parameters

The described adaptation methodology has two difficulties:

1) to assign optimal control parameters, it is necessary to know the parameters of disturbances before they affect the control object.
2) The stored disturbance levels of the correspondence table (Table 2) may not coincide with the actual levels that arise during the operation of process units. In addition, to obtain data for all possible { F } with a minimum step of change in value corresponding to the control error, a combinatorial set of experiments or an unacceptable observation time of the process may be required.
3) At this stage, the problem of forecasting the values of the disturbing effects F is solved based on the primary measurement outputs Y . Control of technological processes is an inertial process and based on the first discrete values of the output Y it is possible to forecast the level of disturbances with some probability. The training sample is also formed from the observation protocol (Table 1). The forecast is carried out using a multilayer neural network, as the most information-intensive model of pattern recognition (Figure 10).

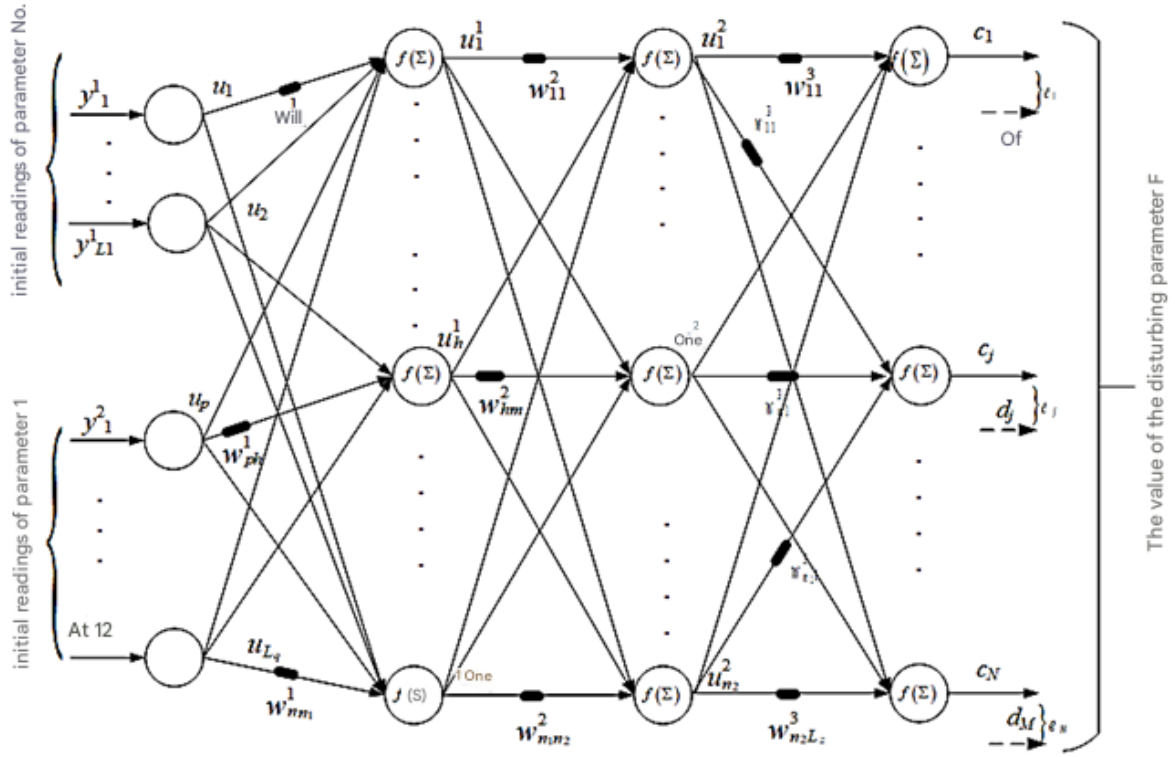



**Figure 10.** NN architecture for mapping sequences of readings of output parameters of a controlled technological process into a set of types of disturbing effects of a vector representation

It is advisable to use either the sigmoid activation function or the hyperbolic tangent as the activation function.

$$f^{[s]}(x)=\frac{e^{\alpha^{[s]}x}-e^{-\alpha^{[s]}x}}{e^{\alpha^{[s]}x}+e^{-\alpha^{[s]}x}}, \qquad (1)$$

since the coding of target vectors in the domain of definition [-1, 1] is most resistant to errors in recording data on the parameters of technological processes in the field of processing.

To train networks of such sizes and dimensions, it is advisable to use the Levenberg-Marquardt neural network training algorithm:

$$w_j(k+1)=w_j(k)+(J_j(k)J_j^T(k)+\chi I)^{-1}J_j(k)(d_j(k)-f(w_j^T(k)x(k))), \qquad (2)$$

where $\chi$ is a scalar parameter; $I$ is the identity matrix; $d_j(k)$ – output of the $j$ -th neuron of the output layer; $J_j(k)=\nabla_{Wj}f\left(w_j^T x\ (k)\right)$ – Jacobian, the matrix of partial derivatives with respect to weights $w_j$ at *the* $k$ -th iteration of training.

The limitation is that the Levenberg-Marquardt algorithm requires the construction of the Jacobian matrix $J$ :

$$(H+\alpha I)\delta=J^{\mathrm{T}}E, \qquad (3)$$

Where $J=\begin{bmatrix}\frac{\partial F(x_1,w)}{\partial w_1} & \cdots & \frac{\partial F(x_1,w)}{\partial w_M}\\ \cdots & \cdots & \cdots\\ \frac{\partial F(x_N,w)}{\partial w_1} & \cdots & \frac{\partial F(x_N,w)}{\partial w_M}\end{bmatrix}$,

$F(x_i, w)$ is the value of the NN output for the i -th input vector $X$ (Marquardt, 1963; Osovsky, 2004; Suratgar et al., 2005; Sousa, 2009).

Formulas for calculating the desired values using a trained network are given in Chapter 2: (2.46) - (2.49). The application of a neural network to predict the values of a disturbing parameter is carried out in accordance with the expression:

$$y_j=f_j^{[3]}\left(\sum_{m=1}^{n_2}w_{mj}^{[3]}\left(f_m^{[2]}\left(\sum_{h=1}^{n_1}w_{hm}^{[2]}\left(f_h^{[1]}\left(\sum_{i=1}^{n}w_{ih}^{[1]}x_i\right)\right)\right)\right)\right), \qquad (4)$$

$f$ is the transfer function of neurons.

4. At the fourth stage of the methodology for applying robust control systems for production processes based on neural network adaptation of control parameters , the problem of interpolating the values of control parameters between known points corresponding to the levels of disturbing effects is solved (Table 2).

In this case, known disturbance values are fed to the input of the neural network during training, and the corresponding optimal control parameters are fed to the output (Figure 11).

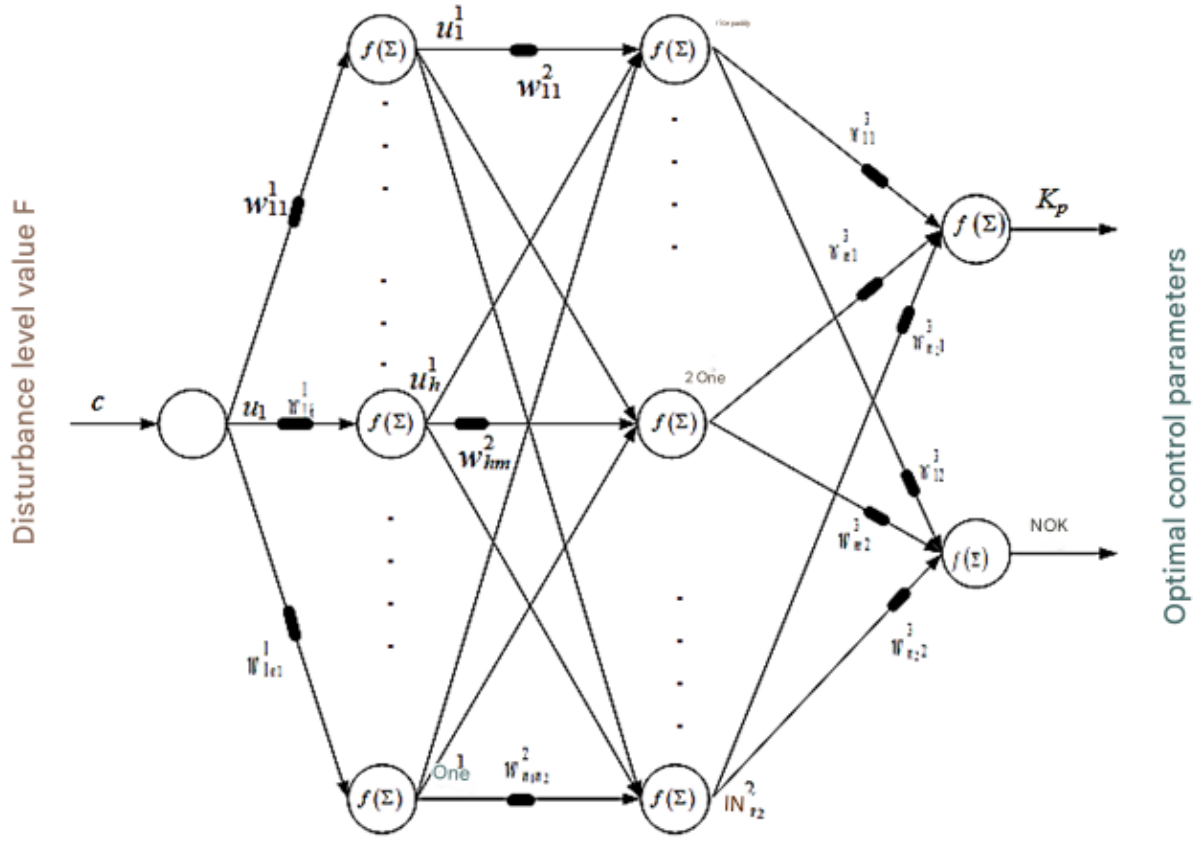



**Figure 11.** NN architecture for interpolation of process control parameter values using the example of two PI controller coefficients

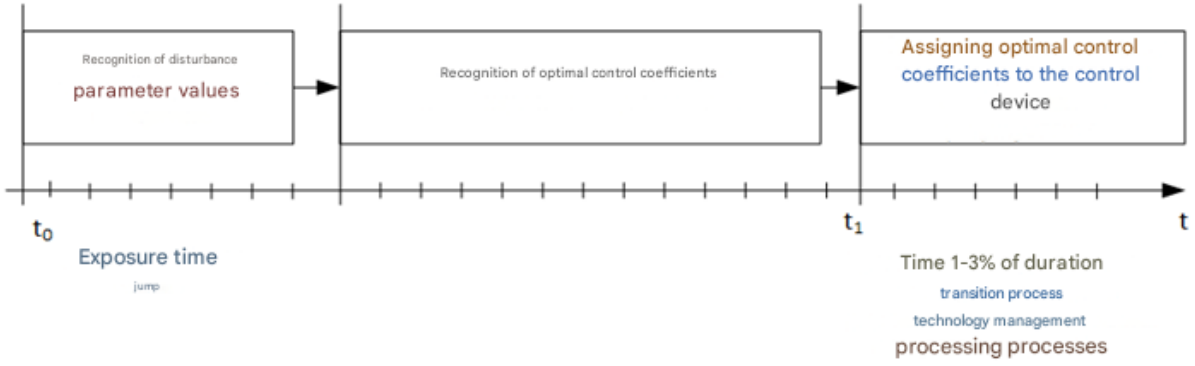



**Figure 12.** Sequence of application of NS for adaptation of the controller to disturbing influences

The algorithm for training the architecture of the interpolating NN, as well as NN№1 for recognizing the shape of the curve, is the pseudo-Newtonian algorithm, or a second-order procedure, in which, in addition to the first, derivatives of the second order are also used.

As a result, the adaptation cycle of the methodology for applying robust control systems for complex production processes looks as illustrated in Figure 12.

A generalized diagram of the hardware and software implementation of the proposed methodology for the application of robust control systems based on neural network adaptation to the operating conditions of complex production processes is shown in Figure 13.

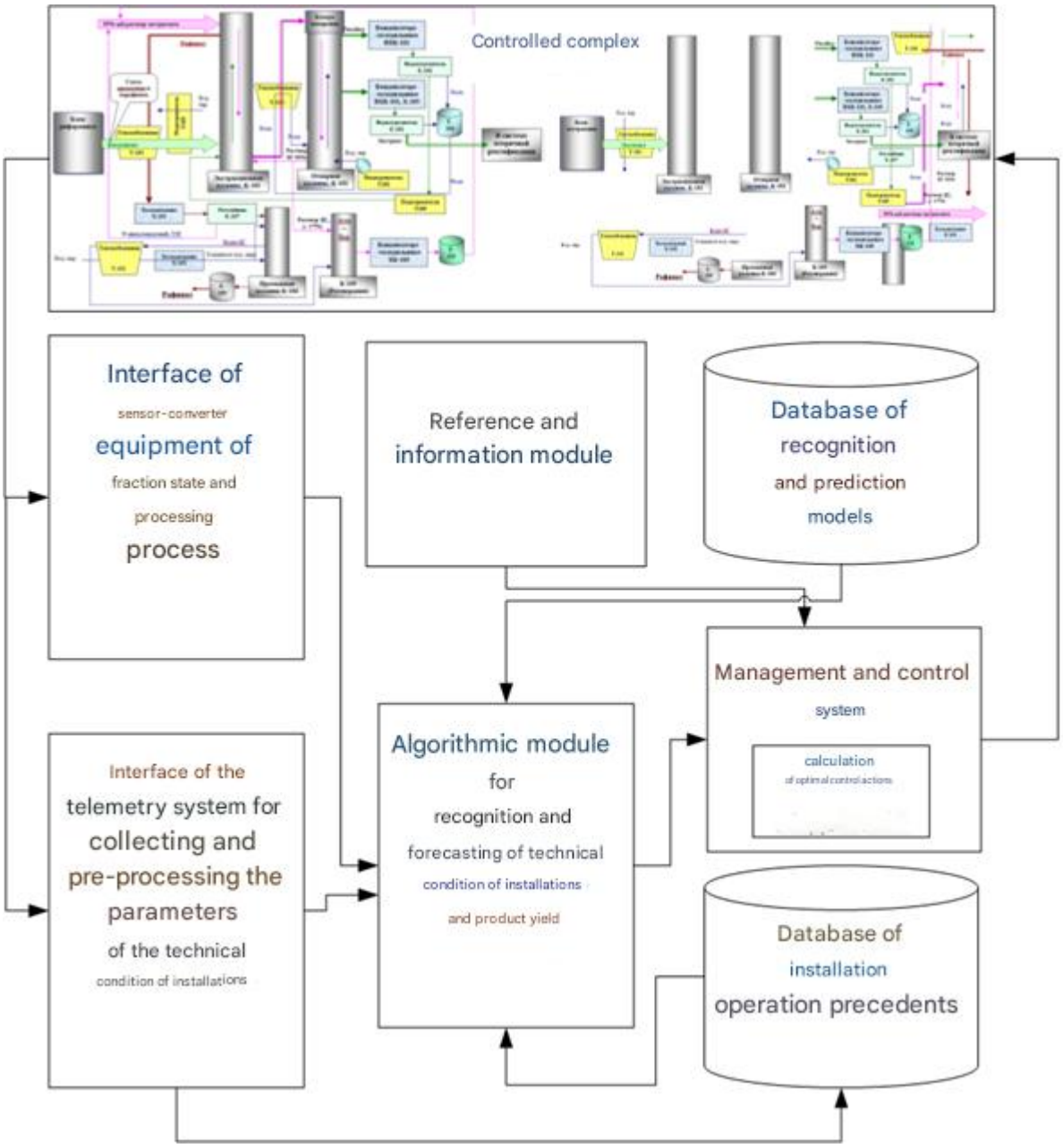



**Figure 13**. A variant of the hardware and software implementation scheme of the proposed methodology for the application of robust control systems based on neural network adaptation to the operating conditions of complex production processes

## 4. CONCLUSION

Given that adequate decision-making, even in a relatively simple situation, is usually associated with the lack of complete certainty, which would allow a deterministic approach to decision-making without resorting to idealization, it becomes clear how relevant it is for modern production systems, where the cost of error in a number of conditions may be unacceptable, to take into account uncertainty factors, which ultimately contribute to increasing the efficiency, reliability and quality of products.

The article describes the application of robust control systems based on neural network adaptation to the operating conditions of complex production processes. The condition for the effectiveness of the methodology is the ability of multilayer NN to generalize when interpolating the control parameters of technological processes in a multidimensional space. Existing algorithms for searching for optimal control coefficients - deterministic gradient and steepest descent schemes, linear and nonlinear programming algorithms, random search schemes and others - when optimizing complex systems require building models of the object and its environment, significant time costs, a large load on computing resources and optimal design groups. In the considered control problem, a strong local dependence of mathematical solutions on changes in the input and output parameters of process units is manifested. The

proximity of solutions is of great importance and can be effectively used in solving problems of extrapolation (interpolation) of the characteristics of the developed sample (or control actions) in conditions of information insufficiency. The task of choosing the optimal model and evaluating the obtained results is significantly complicated by the generalization of any interpolation methods to a multidimensional space, and its solution is impossible without the use of modern computer technologies and software. And the nonlinearity and non-equidistance of interpolation nodes, as applied to a neural network system, under conditions of a finite training sample causes the problem of ensuring a high probability of correct recognition of input samples that were not previously observed, i.e. geometrically parameterized outside the interpolation nodes.

## References:


Åström, K. J., & Wittenmark, B. (1990). *Computer-controlled systems: Theory and design*. Prentice Hall.

Barbu, V., & Sritharan, S. S. (1998). H-infinity control theory of fluid dynamics. *Proceedings of the Royal Society A, 454*(1979), 3009–3033. https://doi.org/10.1098/rspa.1998.0289

Besekersky, V. A., & Popov, E. P. (2003). *Theory of automatic control systems*. Nauka

Biimyrsaeva, E. M., Makyev, S. T., Achilov, A. N., Tolmachev, A. V., & Meteleva, O. A. (2025). Managing quality of high-tech production in the AI economy based on corporate information systems. *Proceedings on Engineering Sciences, 7*(2), 1145–1152. https://doi.org/10.24874/PES07.02B.006

Bhattacharya, S. P., Apellat, & Keel, L. H. (2000). *Robust control: The parametric approach*. Prentice Hall PTR.

Briat, C. (2015). *Linear parameter-varying and time-delay systems: Analysis, observation, filtering & control*. Springer Verlag. https://doi.org/10.1007/978-3-662-44050-6

Bryson, A., & Ho, Y. C. (2012). *Applied theory of optimal control*. Mir.

Calafiore, G. (2006). *Probabilistic and randomized methods for design under uncertainty* (F. Dabbene, Ed.). Springer Verlag. https://doi.org/10.1007/1-84628-095-2

Doyle, J., Glover, K., Khargonekar, P., & Francis, B. (1989). State-space solutions to standard H∞ and H2 control problems. *IEEE Transactions on Automatic Control, 34*(8), 831–847. https://doi.org/10.1109/9.29425

Ioannou, P., & Sun, J. (2012). *Robust adaptive control*. Dover Books.

Kazakov, I. E., & Mal'chikov, S. V. (1983). *Analysis of stochastic systems in state space*. Nauka.

Khaikin, S. (2006). *Neural networks: A complete course* (2nd ed.). Williams.

Lakshmanan, V., Robinson, S., & Munn, M. (2022). *Machine learning design patterns*. BHV-Petersburg.

Mahmoud, M. S., & Munro, N. (1989). *Robust control and filtering for time-delay systems*. Marcel Dekker.

Marquardt, D. (1963). An algorithm for least squares estimation of nonlinear parameters. *SIAM Journal on Applied Mathematics, 11*(2), 431–442. https://doi.org/10.1137/0111030

Morari, M., & Zafiriou, E. (1989). *Robust process control*. Prentice Hall.

Osovsky, S. (2004). *Neural networks for information processing*. Finances and Statistics.

Pereira, T. F., Espuny, M., da Motta Reis, J. S., Rocha, A. B. T., Barbosa, L. C. F. M., Santos, G., & de Oliveira, O. J. (2025). Quality 4.0: Opportunities and challenges for scientific research. *International Journal for Quality Research, 19*(3), 831-846. https://doi.org/10.24874/IJQR19.03-10

Pozdnyak, A. S. (1991). *Fundamentals of robust control (H∞-theory)*. MIPT.

Pupkov, K. A., Egupov, N. D., & Garvilov, A. I. (2002). *Methods of robust, neuro-fuzzy and adaptive control*. Bauman Moscow State Technical University.

Sousa, C. (2009, November 18). *Neural network learning by the Levenberg-Marquardt algorithm with Bayesian regularization (part 1)*. Retrieved from http://crsouza.blogspot.com/2009/11/neural-network-learning-by-levenberg_18.html

Sulaimankulova, Z. Z., Sozinova, A. A., Gevorgyan, A., & Altsybeeva, I. G. (2025). Automatization of quality 5.0 management due to sustainable innovations in the sphere of the internet of things and machine learning. *Proceedings on Engineering Sciences, 7*(4), 2379–2386. https://doi.org/10.24874/PES07.04.025

Suratgar, A. A., Tavakoli, M. B., & Hoseinabadi, A. (2005). Modified Levenberg-Marquardt method for neural networks training. In *WEC'05: The Fourth World Enformatika Conference*.

Van Veen, F., & Leijnen, S. (2019). *The Neural Network Zoo*. Asimov Institute. Retrieved from https://www.asimovinstitute.org/neural-network-zoo

Volkova, V. N., & Kozlov, V. N. (Eds.). (2014). *System analysis and decision making: Dictionary-reference book*. Vysshaya shkola.

Xu, A., & Aminian, A. (2024). *System design. Machine learning. Preparing for a difficult interview*. Piter.

Zhou, K., & Doyle, J. C. (1999). *Essentials of robust control*. Prentice Hall.

Zyubin, V. E. (2004). Creation of control algorithms for complex technological processes. *Automation and Modern Technologies*, (8), 23–31.

**Uvaev Marat Yuryevich**
North-West Institute of Management
RANEPA,
Saint Petersburg
Russia
uvaev_marat@mail.ru
ORCID 0009-0002-9339-7176

**Shikov Alexey Nikolaevich**
Department of Business Informatics,
North-West Institute of Management
RANEPA, Russia, Saint Petersburg
shikov-an@ranepa.ru
ORCID 0000-0002-9942-0907