

Lappeenranta University of Technology
School of Energy Systems
Electrical Engineering
Master's Programme in Control Systems

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**DEVELOPMENT OF AN ADAPTIVE CONTROL SYSTEM FOR
AUTOMATIC REGULATION OF VOLTAGE AND REACTIVE
POWER FOR POWER SUBSTATION 500/220/110/10 KV**

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ABSTRACT

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Keywords: Reactive power compensation, voltage control, adaptive control system, artificial neural networks, PID controller.

In this master's thesis the development of an adaptive PID controller for the automatic control system of reactive power compensation units, installed at the high voltage power substation of 500 kV is considered. The control system was designed as adaptive to ensure the required quality of a voltage regulation process in various operating modes of power network, some of which can lead to significantly different behavior of voltage transients.

After studying the current trends in designing various methods of adaptive control, an approach based on the application of artificial neural networks was chosen. This work is intended to investigate whether the application of feedforward artificial neural networks is suitable to solve the problem.

There were created a model of power network and a model of adaptive control system in Matlab Simulink. The first one was used to obtain the training data for artificial neural

network, which adjusts the coefficients of PID controller, and verify the operation of resulted control system.

In general, the designed adaptive control system shows that feedforward artificial neural network can perform a correct identification and provide correct PID coefficients to ensure the required quality parameters of the transition process. As expected, the qualitative functioning of neural network significantly depends on the training data.

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LIST OF SYMBOLS AND ABBREVIATIONS

ACS	Automatic Control System
ANN	Artificial Neural Network
AT	Power Autotransformer
CT	Current Transformer
FL	Fuzzy Logic
FNN	Feedforward Artificial Neural Network
HPP	Hydro Power Plant
IDO	Interregional Dispatching Office
IES	Integrated Energy System
JSC	Joint-Stock Company
PID	Proportional-Integral-Derivative three-term controller
RPC	Reactive Power Compensation
RPCU	Reactive Power Compensation Unit
SCM	System of Computer Mathematics
SDPP	State District Power Plant
SO UPS	System Operator of the Unified Power System
SR	Power Shunt Reactor
SS	Power Substation
SVC	Static VAR Compensator
TL	Power Transmission Line
UES	Unified Energy System
VT	Voltage Transformer

1 INTRODUCTION

1.1 Background

The development of high voltage electrical networks of the unified energy system (UES) of Russia takes place continuously, therefore it is very important to ensure their stable and reliable operation. Important conditions in the complex of measures to achieve these objectives are the ensure of the required transmitting capacity of power lines, the availability of reserves of active power, maintenance of the required quality of electricity. Reactive power compensation (RPC) is also one of the ways to ensure reliable operation of the power system.

For reliable operation of the power system, a balance between generation and consumption of both active and reactive power is required. In contrast to the balance of active power, which must be performed for the power system as a whole, the balance of reactive power must also be maintained at each node of the power grid. Imbalance of reactive power in the nodes leads to deviations in their voltage level from the allowable values. It is the voltage level in the nodes of the electrical power grid that is the main standard indicator for maintaining the balance of reactive power at each time point.

In a power grid significant excess of reactive power may occur when its current generation exceeds consumption. This is due to the load schedules of various electricity consumers. As a result, in some network nodes occur such voltage rises, which may be higher than the acceptable limits, for example dictated by the preservation of the insulating properties of materials used. On the contrary, with excessive consumption of reactive power, lower voltage levels are observed in the nodes, which leads to a violation of the operating conditions of various equipment.

Non-compliance with the requirements for maintenance of reactive power balance can cause such negative consequences as:

- Unacceptable voltage deviations in power networks of different standardized voltage levels. For example, the «leakage» of reactive power to the network of a lower voltage class can lead to an unacceptable voltage level increase in it.
- Reduced transmitting capacity and stability of power transmission through power transmission lines (TL) and transformers, due to their overloading with reactive power flows.
- Increase of active power losses in the power network elements.

- Reduced quality of transmitted electricity.
- Exceedance of permissible limits on reactive power flows to the generators of power plants.

During the day, the active power flows over a power lines can vary significantly. The situation with the reactive power balance is complicated by the fact that some reactive power compensation units (RPCU) installed at substations are not commutated according to the load schedules or have a static operating setting due to various reasons. For example, substation shunt reactors (SR) are designed to consume reactive power generated by overhead or cable transmission lines at low loads or in its idle operating mode. In the mode of transmission of natural power through the line, when the reactive power generated by the its capacitance is consumed by its own inductance, with the SR was not disconnected, a decrease in voltage, transmitting capacity, and an increase in transmission losses throughout of the line will be observed. There is no need for this mode of operation of a SR. Therefore, such SRs are installed with their own power circuit breakers and commutate several times during the daily load schedule. However, such commutations are undesirable because they lead to a decrease in circuit breaker switching resource, voltage surges at the installation site of the SR, switching overvoltage and disturbances affecting the steady-state stability of the transmission mode of the power lines.

All of the problems listed above can be solved by using controlled RPCU. Modern developments of such devices can provide smooth control of voltage and reactive power at their installation site. This raises the question of ensuring the required quality of the corresponding transient processes.

On the other hand, the objectives of the RPC can be divided into solving balance and economic problems. When solving the problem of maintaining a reactive power balance in the nodes the power grid, it is necessary to eliminate the local deficit of reactive power and bring the voltage levels to the required values in the power supply centers. Economic problems are related to the optimization ones. Their solution is associated with a decrease in reduced costs, which forms optimization cost function. The parameters of such a cost function may include active and reactive power losses in the power grid; electricity losses during supply process; voltage level deviations in the power grid nodes, incurring penalty fees; the cost of RPCU installation; the cost of RPCU operation per time unit, caused by its life cycle costs; changes in transmitting capacity of some power equipment, affecting the

profits received by the power grid owners; the cost of generating reactive power at power plants and the excessive consumption of reactive power.

Thus, rational (optimal) compensation of reactive power in electrical power networks is required, which includes a wide range of problems that need to be solved.

1.2 Goals and delimitations

Today, the methods of designing automatic control systems (ACS) are mainly based on proven techniques of classical control theory. Even though classical approaches have good reliability, proven long-term experience of use and analysis mechanisms, they cannot meet all the requirements for control systems, especially when it comes to control complex non-linear and multi-dimensional objects. Compliance with various requirements in the control of such objects requires the use of intelligent adaptive control systems. The application of such ACS will allow to estimate changes in the different parameters of the controlled object; with the necessary speed to identify the actual cause-effect relationships and laws of the system; to control a group of various elements with a wide range of properties that vary over time.

In this work the development of an adaptive controller for the automatic control system of RPCU installed at high voltage substation is considered. The purpose of introducing adaptation into the control system is to ensure the required quality of the voltage regulation process in various operating modes of power network.

Among various methods of adaptive control, an approach based on the application of artificial neural networks (ANN) was chosen. The choice was made based on wide perspectives of such an approach, which allows implementing an adaptive algorithm for controlling an object with the possibility of its creation and re-formation based on an analysis of the operational statistics of the controlled object, the oscillogram archives of previous recorded processes. Also, the use of ANNs can allow the introduction of a specific processes that were not present in the training data because of various reasons but recorded during the operation of the controlled object.

In this work the application of feedforward artificial neural networks (FNN) is discussed. This research is intended to investigate the possibility of using such networks on the example of designing adaptive PID-based control system to solve the posed problems. To verify the concept, only the modes of power TLs commutations were considered. Further

research can be extended to investigate the possibility of using ANNs of other types and architectures, as well as considering other operating modes and processes in power system.

1.3 Structure of the thesis

This thesis consists of three chapters. The first chapter analyzes the current trends in designing adaptive control systems. On the basis this analysis the appropriate approach was chosen, and the adaptive control algorithm was proposed. The second chapter describes the modeling details of the control object and the proposed adaptive control system. The third chapter provides results analysis, which were obtained from the test of modelled adaptive control system.

2 ANALYSIS OF THE CURRENT PROBLEM STATE

2.1 Task description

Main objective. Design and research of an adaptive automatic PID-based control system for reactive power compensation units to maintain a required voltage level on substation buses together with ensuring the required quality of the control transient processes.

Justification of importance of the research. At existing substations, the applied control systems of voltage and reactive power do not take into account the operating modes of electrically close power grid facilities. When changing the circuit-mode parameters of the adjacent grid and power equipment installed at power industry facilities, traditional control systems do not have the ability to provide the required quality of the control process in a wide range of possible changes in a power grid, and the intensity of the influence of reactive power units on voltage levels can vary significantly. As a result, it is possible that the voltage level in the power grid nodes exceeds the permissible limits for the time value which is longer than the value required to ensure the stability of power facilities operation or to avoid damage to equipment in use, for example, to preserve the properties of insulating materials used. Failure to comply with the quality requirements of the control process entails a violation of the equipment and facilities operating modes of various electricity consumers and interested organizations, and as a result, the imposition of fines by various supervisory authorities.

To solve this problem, it is necessary to use the automatic control system, which has the property of adaptability to changes in the power grid. This control system should be able to automatically adapt to the changing behavior of the control object during a time interval sufficient to meet the quality requirements of the control process.

The main tasks to be completed in this work:

1. To carry out an analysis of the state of the issue and current trends in solving the problem.
2. To propose an adaptive control algorithms based on the analysis performed.

3. Perform a simulation of the control object (part of the power grid) in a size which is sufficient to analyze the algorithm operation.
4. Implement the algorithm that meets the main objective and allows to meet the specified requirements for the quality of the control process (overshoot, transition time, control error) in a selected software package.
5. Test the resulted control system by simulation its operation along with control object and draw the conclusions from the data obtained.

The object and subject of the research.

The object of research is the combined behavior of the power facilities, equipment and units which form the grid, high voltage substations with RPCUs installed.

The subject of this research is the automatic control systems for the RPCUs with the adaptability features.

Applied methods.

Research methods are based on the control theory, the theory of electrical circuits, software modeling of electric power facilities and automatic control systems.

2.2 Analysis of the current trends in adaptive control systems design

In preparing the material for this section the literature [1], [2], [3], [4], [5], [6], [7], [8] [9] were used.

2.2.1 Basic concepts.

Automatic control is the process of maintaining the specified value of a physical quantity with a certain degree of accuracy and without human participation[1]. The physical quantity characterizes a technological process or the state of a certain controlled object. In the general case of the control object description it has input and output values. Input values consist of various disturbances (x_{dis}) and control actions (x_{ctrl}), provided by a control system. The output values consist of the control object responses — changes in the selected observable parameters (x_{out}) as shown in Fig. 1. Disturbances cause deviations of the controlled values from the desired values (x_{des}). These deviations are called control errors (x_{err}). Thus, control actions fed to the input of the control object are aimed to eliminate the

control errors. Control actions are formed by a combination of different requirements, laws or algorithms. A control object and a controller forms together an *automatic control system*.

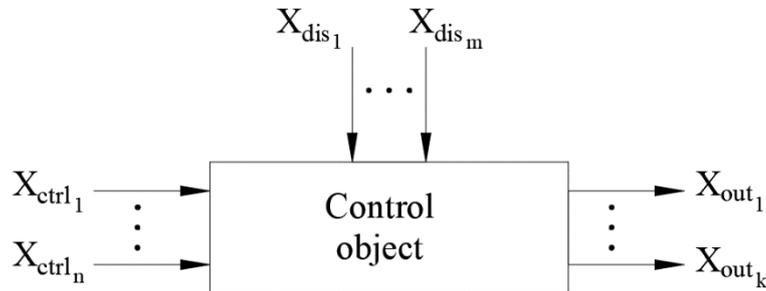


Fig. 1 – Basic representation of a control object.

Control systems are divided into systems of *continuous* or *discrete* control action.

ACSs are dynamic systems, the processes in which are described by differential equations relating the values of the output quantities to the disturbance ones and control actions. The ACS is *linear* if it is described by a linear differential equation with constant coefficients that have a general solution. The linearity of the system allows the independent consideration of disturbances in a ACS. However, real ACSs contain elements with non-linear characteristics. Such systems called *nonlinear*. There are various mathematical methods to simplify the analysis of such systems by reducing nonlinear characteristics to linear ones. The conclusions made for the linear model of ACS are in most cases fairly valid for a real ACS in a certain range of operation of the control object, the range of which depends on the nature of the object's nonlinearity[1].

If the properties of the ACS do not depend on the moment of system behavior consideration, then such a ACS is called *stationary*, otherwise - *non-stationary*. Stationary and non-stationary systems can be linear as well as nonlinear. Changes in the properties of a ACS over time may require monitoring its parameters, which in some cases may lead to a *delay in control signals*. Control actions in an ACS can be formed in two basic ways: by the deviation of the controlled variable from the desired value or by the disturbance signal processing as shown in Fig. 2. The latter is rarely used alone, so there are ACSs that combine these two approaches.

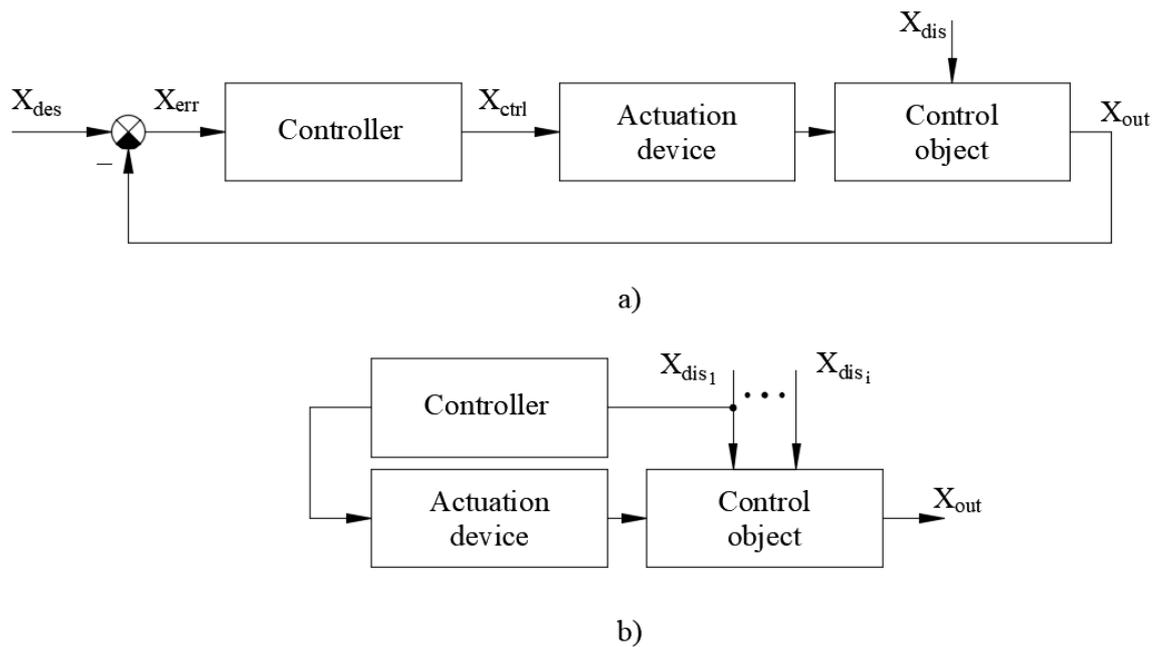


Fig. 2 – Functional diagram of ACS with control action formed by: a) the deviation of the controlled variable from the desired value; b) by the disturbance signal processing.

2.2.2 Types of adaptive control systems.

Adaptive control is a set of methods that allows to synthesize a control system that can change their parameters or structure depending on various changes in the control object, adjusting to them to achieve an optimal control process. However, the parameters of the control object or its state can change in a completely unpredictable way.

Adaptive control systems have a number of classifications[5]:

By the nature of changes in the control system to adapt to various kinds of uncertainties in it, ACSs are divided into:

- Self-tuning controllers. – values of control system parameters change.
- Self-organizing controllers – structure of a control system changes.

By the approach of studying the control object, ACS are divided into:

- Seeking controllers – seeking a certain state of the control object and holding it in it.
 - Extremum-seeking controllers – stabilization of control object operating parameters within certain limits in order to hold a given parameter of the performance function at the extremum point of it.
- Non-seeking controllers – ACS contains a model of real control object.

By the approach of obtaining information, non-seeking systems are divided into:

- Model reference controllers – ACS incorporate a dynamic model of the control object of the required quality. During the operation of such a system, the responses of the reference model and the controlled object are compared, based on which the controller correction is calculated, and its change is made. The example of such an ACS is shown in Fig. 3.

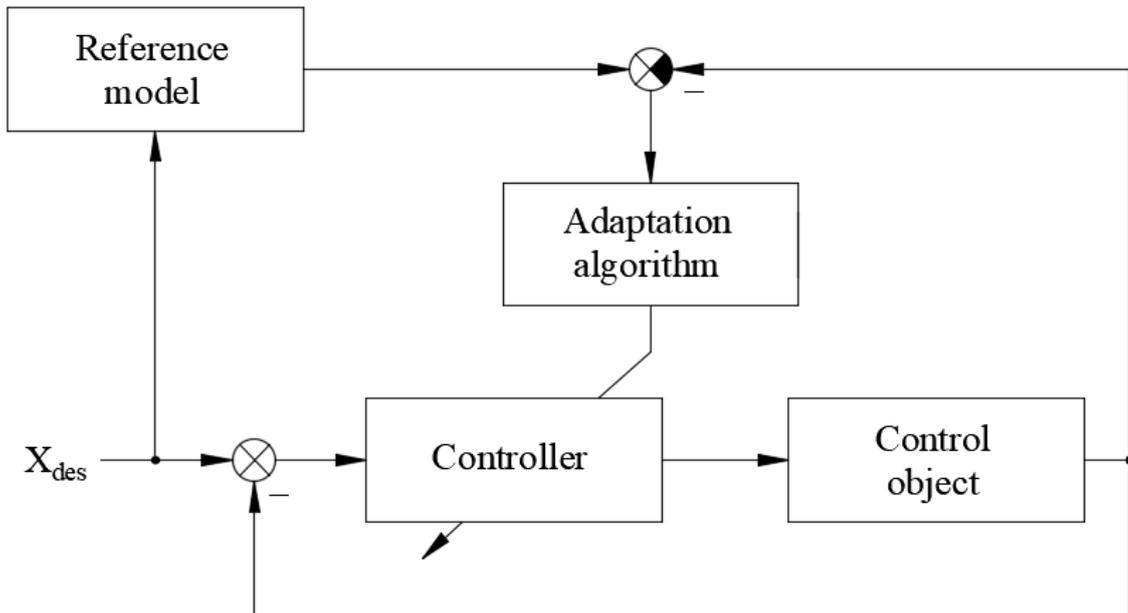


Fig. 3 - Functional diagram of a model reference adaptive controller (MRAC).

- Model identification controllers – identification of the control object state or parameters is performed while the ACS is operating, followed by the controller tune based on the identification performed. The example of such an ACS is shown in Fig. 4.

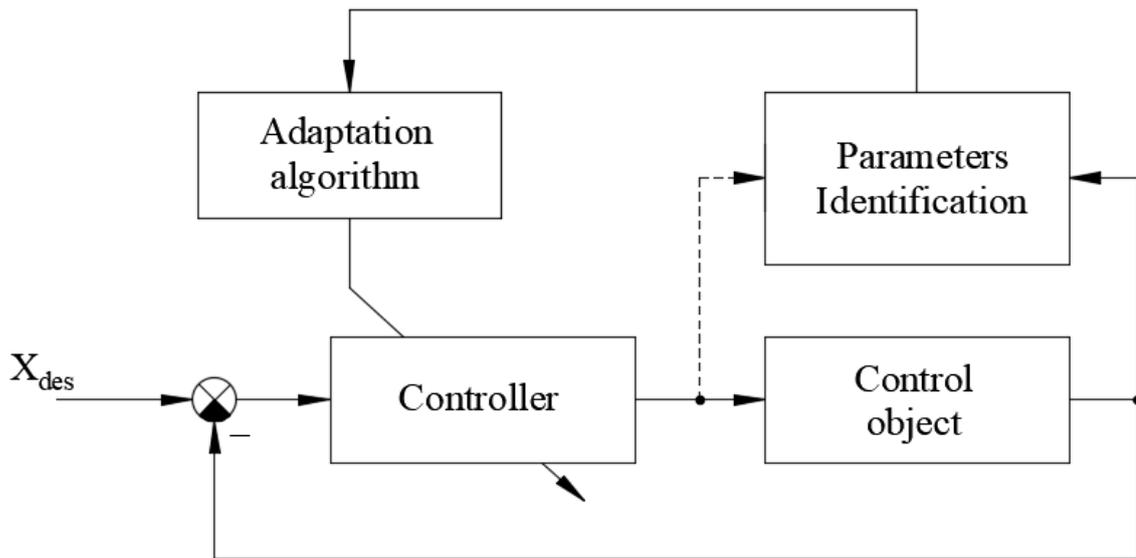


Fig. 4 – Functional diagram model identification adaptive controller (MIAC).

By the approach of identification type, MIACs are divided into:

- Direct identification – identification of the control object parameters is performed based on the measurement of the input (x_{ctrl}) and output signals (x_{out}) of the object.
- Indirect identification – identification of the control object parameters is performed based on the applied test signal (x_{des}) and measured closed loop response signal (x_{out}) of the system.

Self-adjustment of the control system can be performed based on:

- Signal adaptation – the tuning effect is achieved by applying different compensating signals.
- Parametric or structure adaptation – the adaptation effect is achieved by controller parameters or its structure changes.
- Combined adaptation – the combination of the approaches mentioned above.

2.2.3 Artificial neural network based control systems.

Artificial neural network – a mathematical model built on the principle of biological neural networks functioning. ANN is a system of artificial neurons connected and interacting with each other. Mathematically an artificial neuron is a certain nonlinear function « y » of a single argument, which is a linear combination of all input signals x_1, x_2, \dots, x_k as shown in Eq. 1[9]:

$$y = F \left(\sum_{i=1}^k w_i \cdot x_i + b \right) \quad (1)$$

where w_i – weighting factors for each input signal, b – bias term. F – non-linear activation function of the neuron, which is responsible for the result signal value at the neuron output.

Mathematical model of the artificial neuron is shown in Fig. 5.

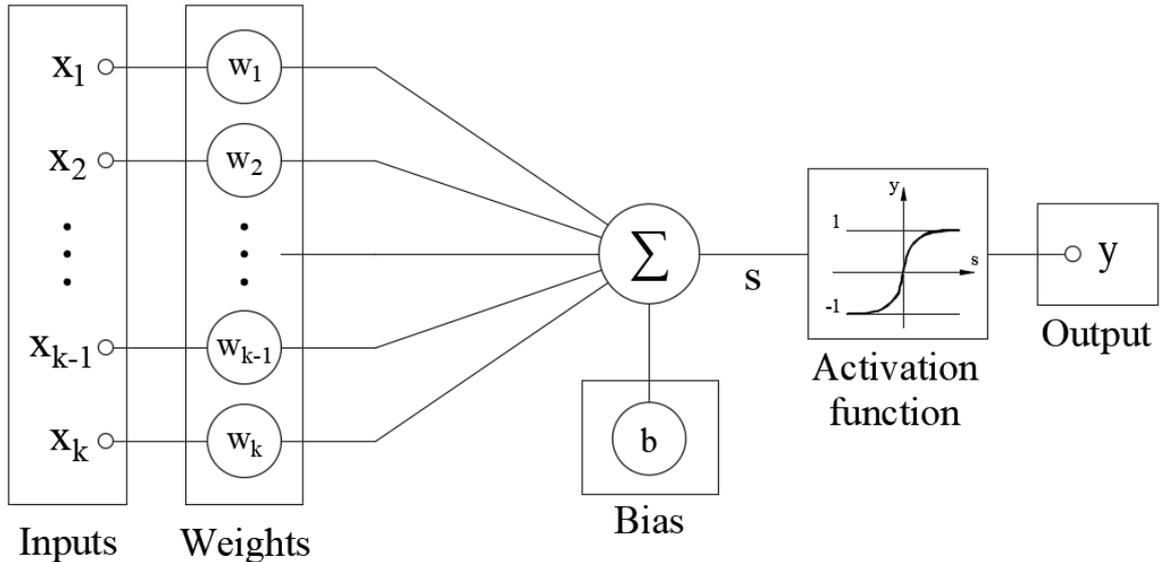


Fig. 5 – Mathematical model of the artificial neuron.

One of the main advantages of mathematical models consisting of a group of such connected neurons is the possibility of its «learning». Quite a lot of problems can be defined as input-output mapping problems, when an algorithm should provide a proper result for a certain input data. In this case learning mechanism consists in the fact that user selects a number of training samples which forms a training data, and then launches the training algorithm, during the operating of which the network automatically adjusts its parameters. Training parameters of ANN to be adjusted are connection weights and bias weights. During the training process, an ANN determines the relationship between input and output in training data, which can be quite complex.

As a result of the training process, the neural network acquires the ability to produce generalizations. The generalization process consists in the fact that the neural network is able to output the correct results for an input data that were not in the training set, were corrupted, noised or partially missed. ANN performs generalization automatically due to its structure and the obtained values of the network parameters during the training process.

The process which is reverse to generalization is called overfitting. Its essence is that an ANN, as training data is processed, begins simply to memorize them. In other words, the model interprets examples from training samples well, but it works relatively poor in other cases that were not presented in training examples.

Mathematically, the process of network learning can be represented as follows. During operation of ANN, it generates an output signal Y in accordance with the input signal X , realizing a certain function $Y = G(X)$. The type of the function G is determined by the network weights and biases, as well as its architecture. Let a solution to a problem be a function $Y = H(X)$ defined by pairs of input-output data $(X_1; Y_1), (X_2; Y_2), \dots, (X_n; Y_n)$ for which $Y_i = H(X_i)$, where $i = 1, 2, \dots, n$. The learning process consists in the search (synthesis) of a function G close to H within a certain desired error function E . An algorithm of the learning process is shown in Fig. 6.

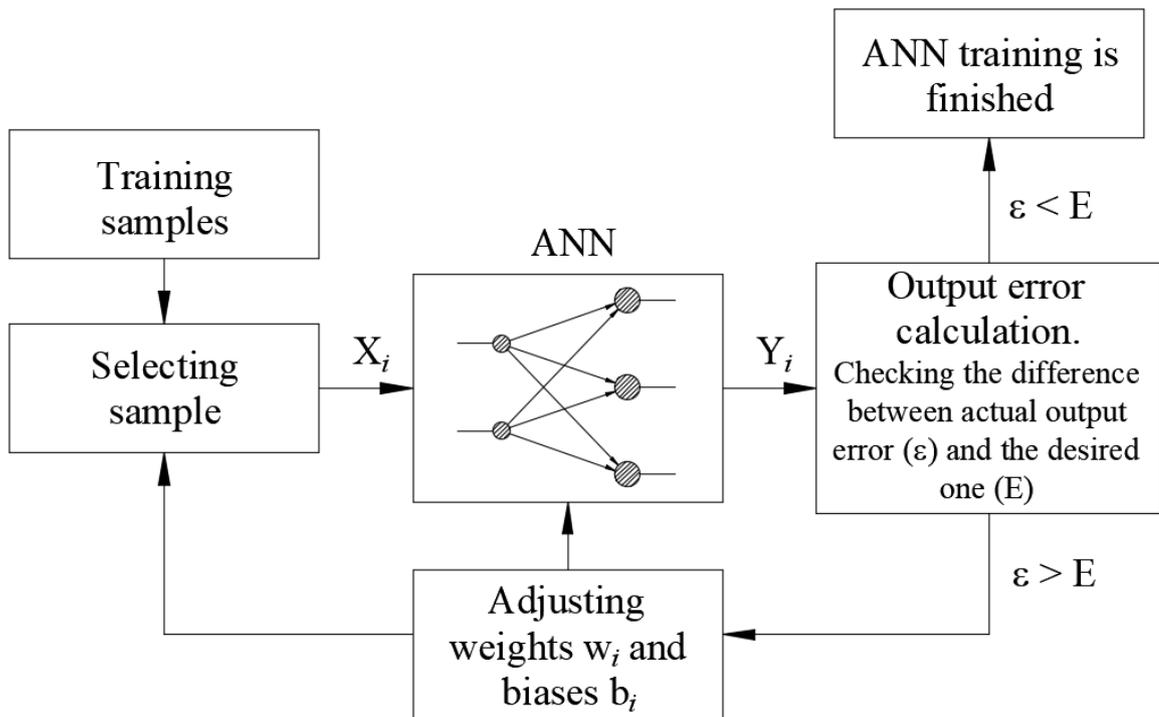


Fig. 6. – ANN training process in the presence of input and desired output data.

Artificial neural networks have a number of basic structures:

- One-layer feedforward artificial neural networks. The example of an ANN with such an architecture is shown in Fig. 7.

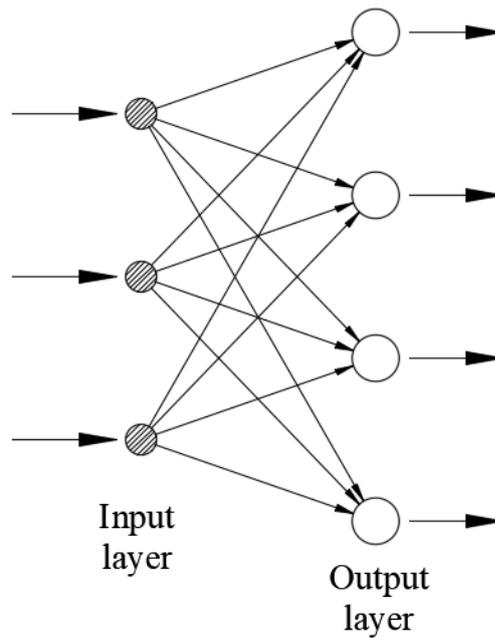


Fig. 7. – The architecture of an one-layer feedforward artificial neural network.

In a network of this type, the arrangement of neurons occurs in layers. There is an input layer of neurons, information from which is transmitted strictly in one direction to the output layer. When determining the number of layers, the input layer is not taken into account, since it does not perform calculations, but only distributes input information to the neurons of the next layer.

- Multi-layer feedforward artificial neural networks. The example of an ANN with such an architecture is shown in Fig. 8.

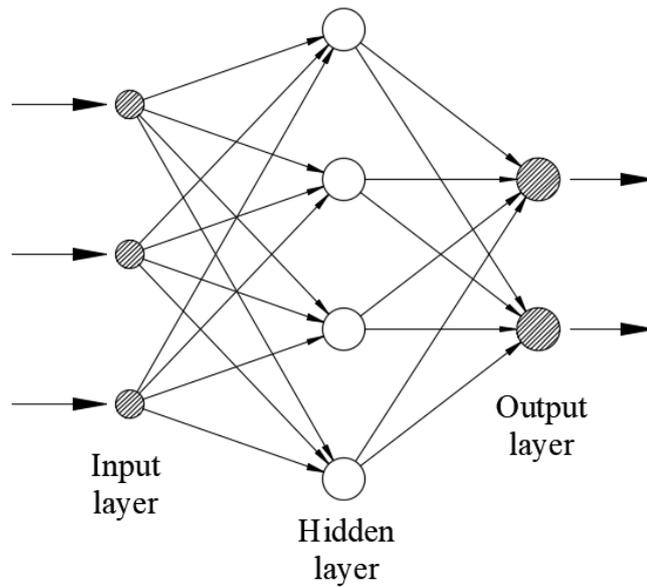


Fig. 8 – The architecture of a multi-layer feedforward artificial neural network.

The networks of this structure are the development of the previous version and contain layers of hidden neurons that mediate between the input and output layers. Each next layer of hidden neurons receives data from the previous layer, converts them considering its own weights and layer size and passes it to the neurons of the next layer. Networks of this structure are able to extract deeper relationships or features in training data than networks of the previous architecture. However, they require more computational power for its training as they have in themselves more parameters to be adjusted.

- Recurrent artificial neural networks. The example of an ANN with such an architecture is shown in Fig. 9.

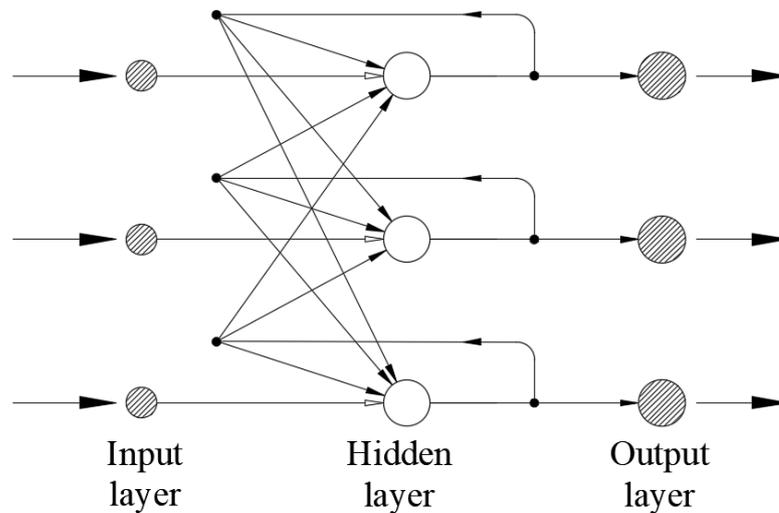


Fig. 9 – The architecture of a recurrent artificial neural network.

The types of feedforward networks discussed above are simple and effective in solving many problems, but they are not available to solve all of them. The main difference between a recurrent network from a feedforward one is the presence of feedback connections between neurons. In addition to the next part of the input data, the neuron receives information about the previous state of the network. Thus, the network implements the ability to memorize. This allows such networks to process a almost an infinite stream of input data, in which not only information is important, but also the order of its feeding.

At the moment, many different architectures of ANNs have been invented, used to solve a variety of problems in many fields of activity. In Fig. 10 the chart of modern different architectures of ANNs is shown.

A mostly complete chart of
Neural Networks

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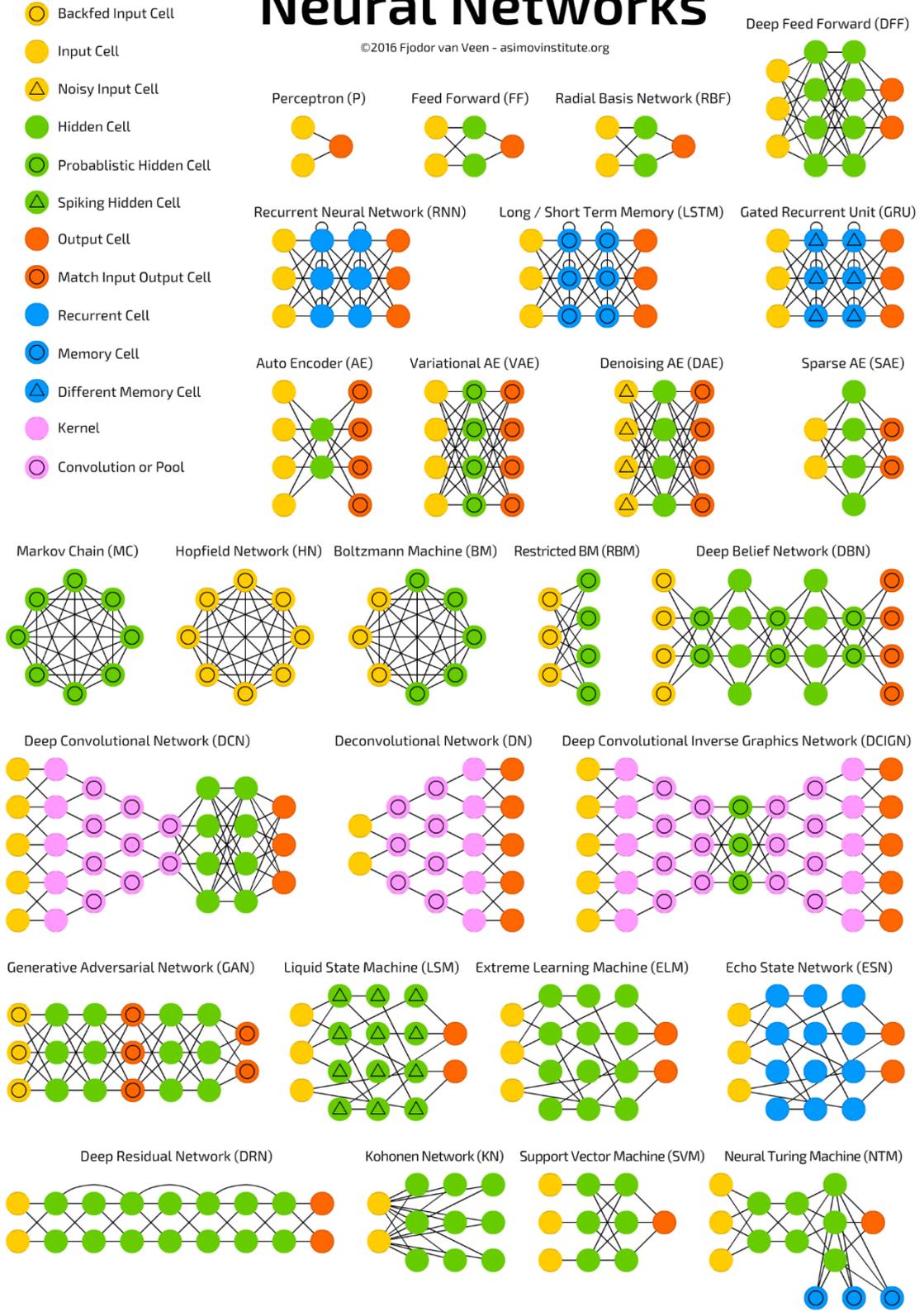


Fig. 10 – A mostly complete chart of ANNs[4].

Returning to adaptive control systems, it should be noted that the use of ANNs for designing such systems is justified by the fundamental properties of neural networks[2]:

1. Signals in multilayer ANNs, as in control systems, propagate in the forward direction.
2. The universal approximation abilities of ANNs are excellent for the formation of nonlinear control algorithms.
3. The learning mechanism gives adaptive properties to neural network control systems.
4. ANNs are capable of parallel signal processing, which makes their use natural for controlling multidimensional objects.

Thus, if for a given nonlinear control object there is an analytical solution to the problem of synthesizing a physically feasible optimal control law, then the ANN with a suitable structure during its training will form this law asymptotically with a sufficient complexity.

When implementing the ANN algorithm in ACS, there are two ways to organize its operation:

- ANN operates in the direct control loop as a controller. The functional diagram of such a control system is shown in Fig. 11

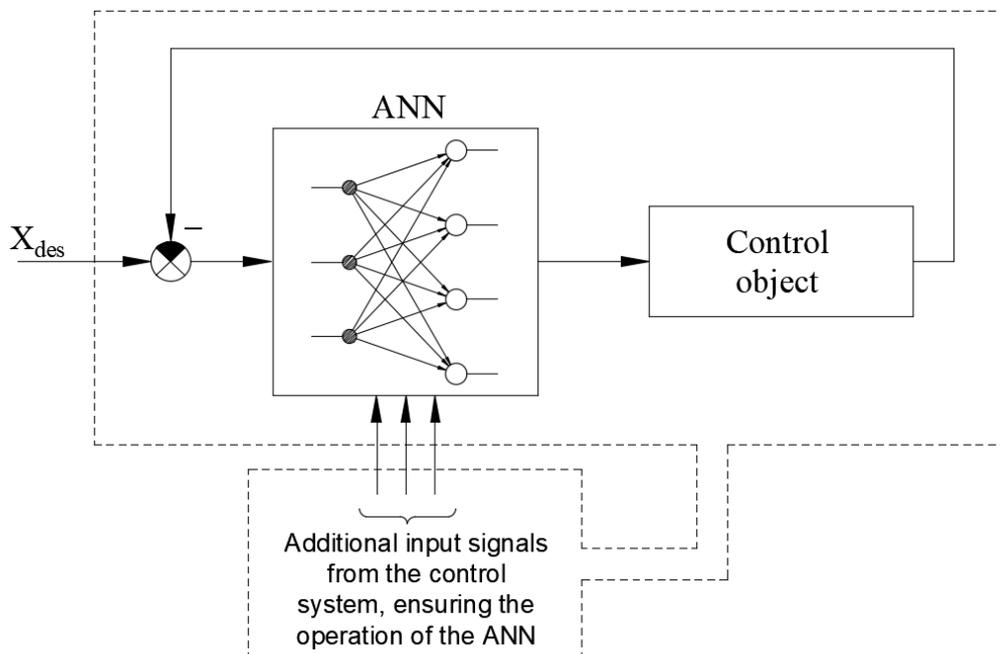


Fig. 11 – The functional diagram of the control system with ANN operating in the direct control loop.

- ANN operates in the outer control loop as an adaptor which tune the controller. The functional diagram of such a control system is shown in Fig. 12

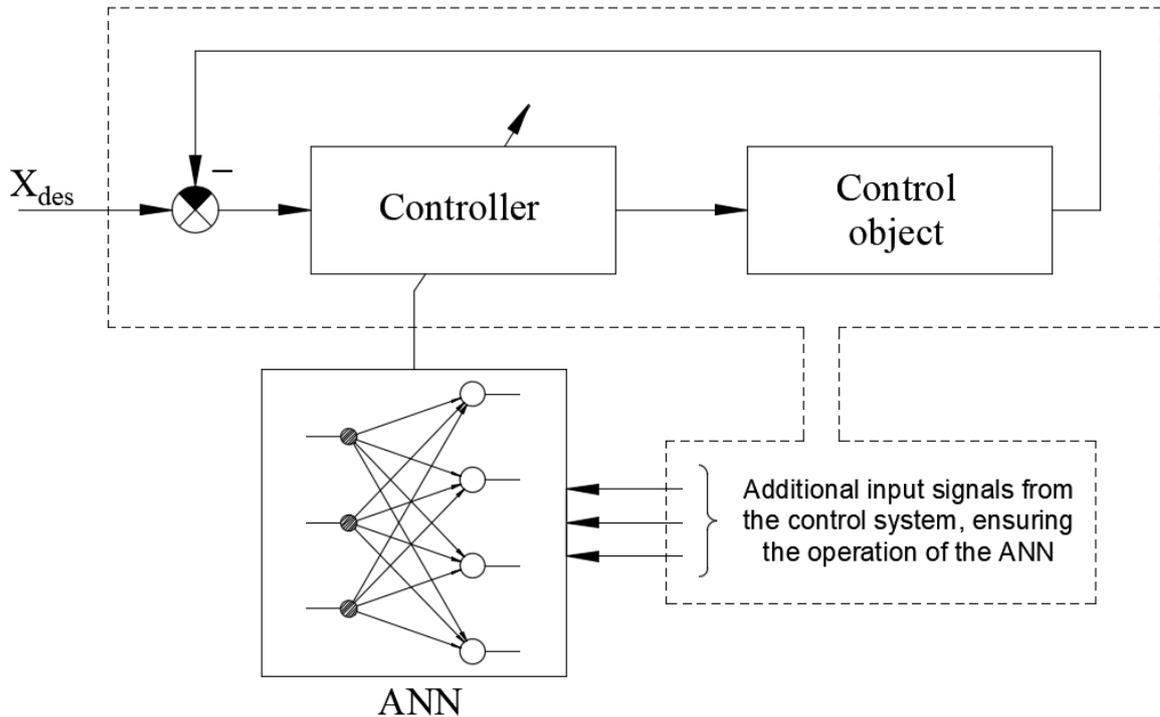


Fig. 12 – The functional diagram of the control system with ANN operating in the outer control loop.

2.2.4 Fuzzy logic based control systems.

When analyzing control objects, it is possible to obtain inaccurate or uncertain information about it. Such processes become extremely difficult to describe using traditional mathematical methods of the control theory, resulting in difficulties in the control algorithms design. When trying to mathematically describe such control objects using various models with the required accuracy, it is found that they often include a lot of empirical parameters, the change of which is possible in a fairly wide range. Identification of these parameters is a challenging task. One way to solve such problems is to apply the concepts and rules of fuzzy logic to from control algorithms.

The control of complex systems often requires the introduction into the control algorithms of decisions based on the experience and intuition of a qualified specialist. In most cases, such a heuristic based control leads to acceptable results, and the higher the qualification of a specialist, the better the results. Thus, there is an approach of designing

control systems based on application of heuristic algorithms and empirical experience using the fuzzy logic theory based, which in its structure is close to natural language.

Fuzzy control is based on the mathematical theory of fuzzy sets. The methods currently developed in the theory of fuzzy control are actively used to design adaptive control systems, in particular for the parametric tuning of PID controllers[6].

The application of the methods of fuzzy logic leads to several mandatory steps: fuzzification, the logical processing of fuzzy variables, defuzzification. Fuzzification procedure – transformation of the input physical quantity into a fuzzy set. The essence of this process is that the range of physical variable variation is assigned to a fuzzy set with some degree of membership. In graphical form, degree of membership of a physical quantity value e is represented as a membership function $\mu(e)$. In the theory of classical sets, a physical quantity can either belong to the set or not, respectively, the degree of membership takes values only either 1 or 0. In the theory of fuzzy sets, membership of a physical quantity to a fuzzy set is characterized by the degree of membership α , the value of which can be any in the range $[0;1]$. The example of assigning of a physical quantity to a fuzzy set with a certain degree of membership is shown in Fig. 13.

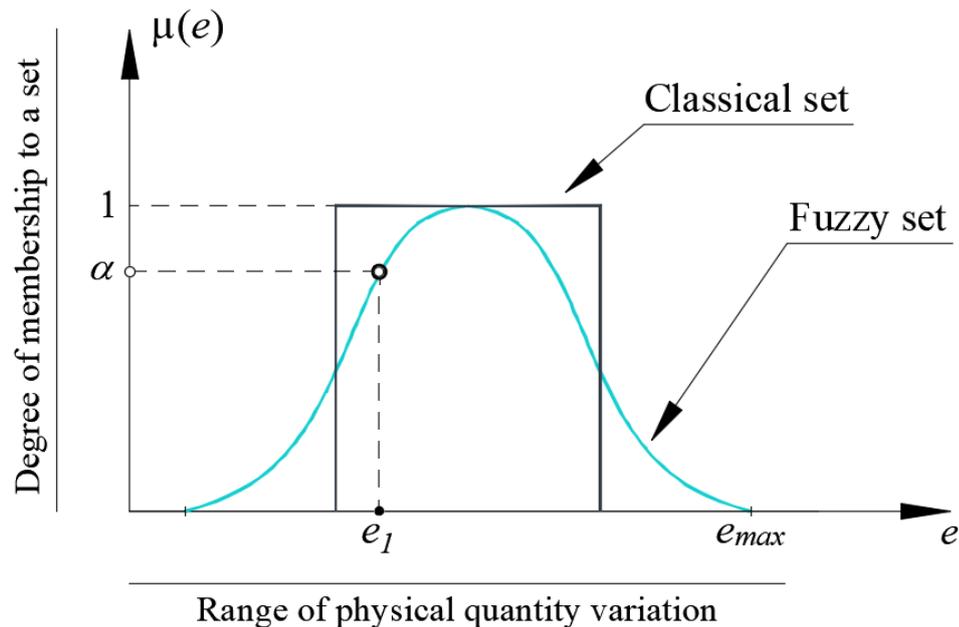


Fig. 13 – The process of assignation of a physical quantity to a fuzzy set with a certain degree of membership α .

The membership of the physical quantity value to a fuzzy set can be given a linguistic form as shown in Fig. 14.

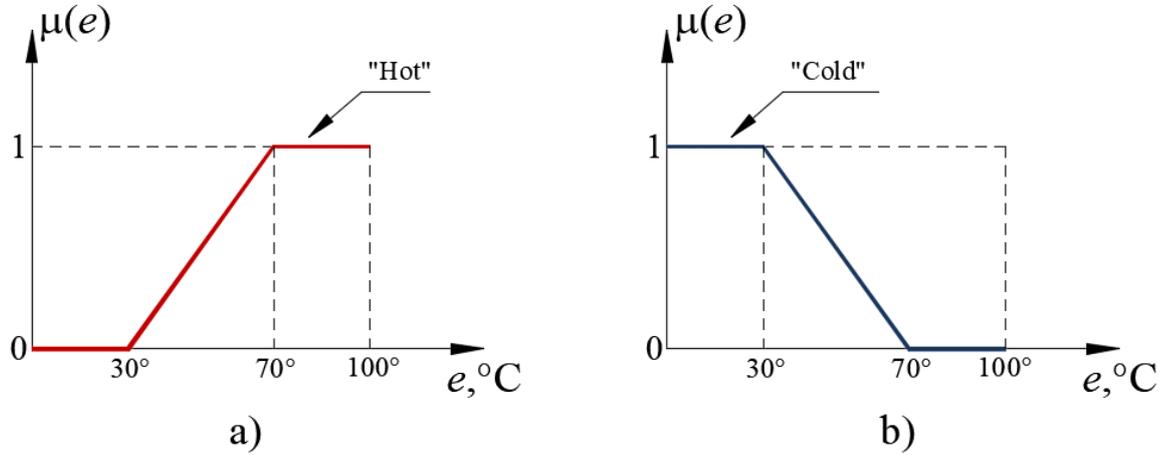


Fig. 14 – Assignment of a linguistic form to a certain fuzzy set: a) linguistic form «Hot»;
b) linguistic form «Cold».

In the theory of classical sets, the fact that a value of a physical quantity belongs to one set precludes the possibility of belonging it to another, while from the position of the theory of fuzzy sets, the value of quantity e_1 belongs to the set «A» with the degree of membership α , and to the set «B» - with the degree β as shown in Fig. 15.

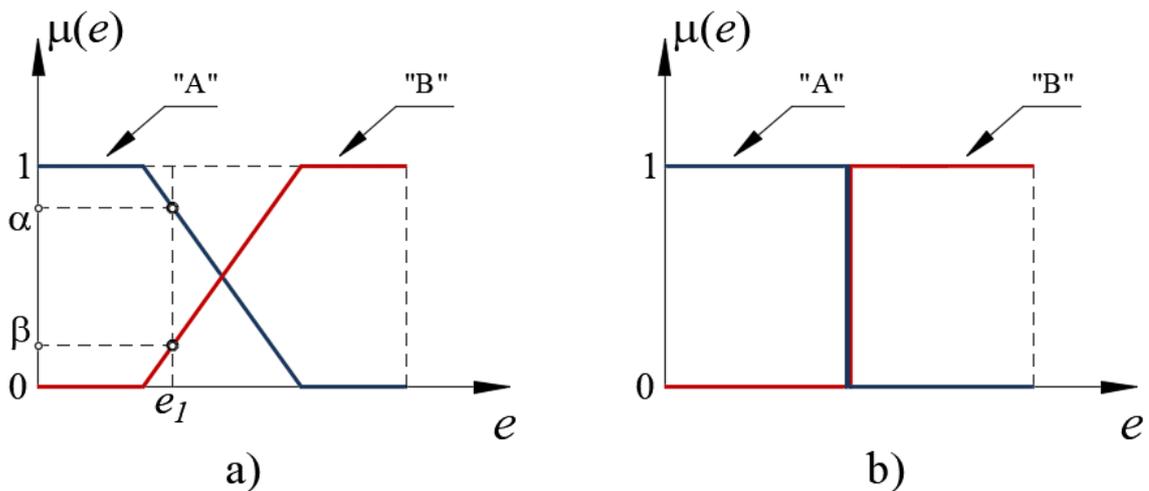


Fig. 15 – Graphical representation of degree of membership in the: a) theory of fuzzy sets;
b) theory of classical sets.

Thus, the boundary between two fuzzy sets is blurred, indefinite, and the transition of a quantity value from one set to another may occur smoothly and without steps. At the same time, in the classical set theory, this transition is carried out stepwise, both sets have a clear boundary between themselves.

As a result, the range of a physical quantity variation is divided into sets (subsets), within each of which the membership function is drawn. For fuzzy sets, there is a system of special linguistic notation: N - negative, P - positive, Z - zero. Linguistic modifications are added to these notations: S - small, M - medium, L - large. There can be any number of such linguistic terms. The example of division the range of quantity variation to the subsets is shown in Fig. 16.

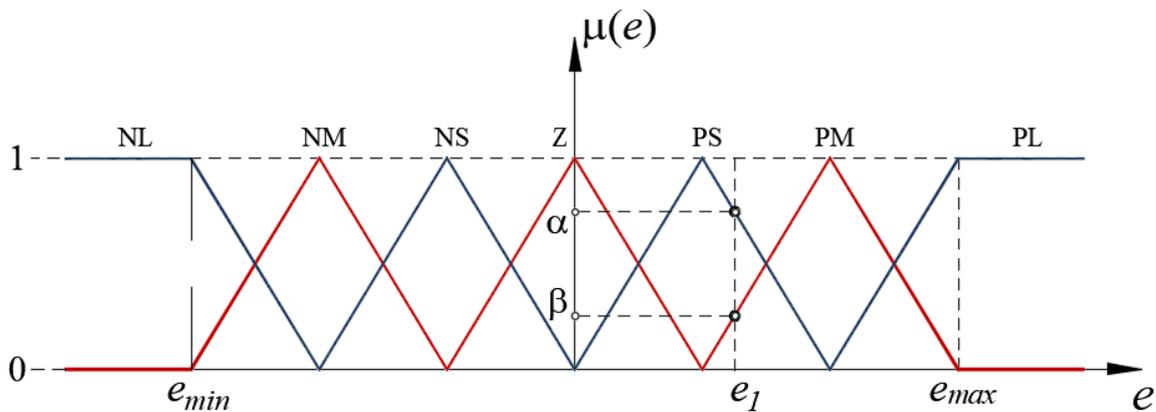


Fig. 16 – The division of the physical quantity e variation range into subsets NL, NM, etc. with drawn membership function $\mu(e)$ of a triangular shape.

The triangular shape of the membership function is the most common, but also trapezoidal and bell-shaped are used. In general, a membership function can be of any shape, depending on the type of problem to be solved.

After the applying the fuzzification procedure to the selected parameters, it is necessary to form fuzzy propositions of the following form: « $p: e = A$ », where « p » is a proposition; « e » is a value of a some physical quantity; « A » is a linguistic variable, which is defined using the corresponding membership function $\mu_A(e)$. Then there is a logical concatenation of fuzzy sentences using logical operations «AND», «OR», «NOT». The classical operations «AND» and «OR» in the theory of fuzzy sets have analogues called the T-norm and S-norm, respectively. In the theory of fuzzy sets, there are an infinite number of ways to define the details of T-norm and S-norm operations, but there are the most commonly used definitions according to Zadeh L., Lukashevich J., Bandler W., Kohout L.[6].

Fuzzy propositions concatenated by logical operators are called conditions, the totality of which determines the totality of conclusions. Together (condition and conclusion) they form fuzzy rules, which are aggregated in a fuzzy rule base $\{R_i\}_{i=1}^n$. A formalized view of such a rule base is shown in Eq. 2[6].

$$\{R_i\}_{i=1}^n = \begin{cases} R_1: \text{If } x_1 = A_{11} \text{ AND } x_2 = A_{12} \text{ AND } \dots, \text{ THEN } y = C_1 \\ \dots \\ R_n: \text{If } x_1 = A_{n1} \text{ AND } x_2 = A_{n2} \text{ AND } \dots, \text{ THEN } y = C_n \end{cases} \quad (2)$$

Where A_{11} , A_{12} , C_1 – fuzzy sets which are defined by corresponding membership functions $\mu_{A_{11}}(x_1)$, $\mu_{A_{12}}(x_2)$, $\mu_{C_1}(y)$ (for R_1 – the first rule in the rule base in Eq. 2).

When analyzing the created rule base, it should be checked for continuity, consistency and completeness.

Thus, the rule base allows us to obtain the final fuzzy value of the variable y , which is expressed using the membership function $\mu_{C_1}(x_1, x_2)$ of the variable y to the fuzzy set C_1 (for R_1 – the first rule in the rule base). The membership function $\mu_{C_1}(x_1, x_2)$ is found as a result of a fuzzy logical operation of implication « \rightarrow » over the fuzzy sets included in the rule R_1 .

For each rule in the base R_i ($i = \overline{1, n}$), using the operations of fuzzy implication « \rightarrow », the local conclusions C_i and the corresponding membership function $\mu_{C_i}(y)$ are derived. Then, using the operation of fuzzy composition « \circ » and aggregation, the general conclusion $C_Y = \bigcup_{i=1}^n C_i$ with the membership function $\mu_{C_Y}(y)$ are derived.

Fuzzy operation of implication and aggregation together form fuzzy inference. Because the fuzzy logical operations of fuzzy inference mentioned above can also be defined differently; therefore, there are different fuzzy inference algorithms. Fuzzy inference algorithms defined by Mamdani M., Sugeno M., Larsen P., Tsukamoto, etc. are widely used.

Thus, the rule base allows us to obtain the final fuzzy value of the variable y , which is expressed using the membership function $\mu_{C_Y}(y)$. The final step is to bring the general fuzzy conclusion to crisp and get the crisp value of the output variable y^* . This procedure is called defuzzification and is performed by various methods. There are several basic methods used: center of gravity (COG), center of area (COA), average maximum.

To illustrate the mechanism of fuzzy inference, which is shown in Fig. 17, let's create a rule base with two rules:

$$\{R_i\}_{i=1}^2 = \begin{cases} R_1: \text{IF } x = A, \text{ THEN } z = B \\ R_2: \text{IF } y = C, \text{ THEN } z = D \end{cases}$$

The input variables took some specific values: x_0, y_0 . The membership functions were derived for them according to fuzzification procedure and the degree of membership $\alpha(x_0), \alpha(y_0)$ were calculated. The implication procedure according to Mamdani M. was performed by «cutting off» the corresponding membership functions $\mu_B(z)$ and $\mu_D(z)$ in the levels $\alpha(x_0)$ and $\alpha(y_0)$. Next, the aggregation of local conclusions B and D by calculating pointwise maximum according to Mamadani M. was performed and the crisp value of z^* was obtained.

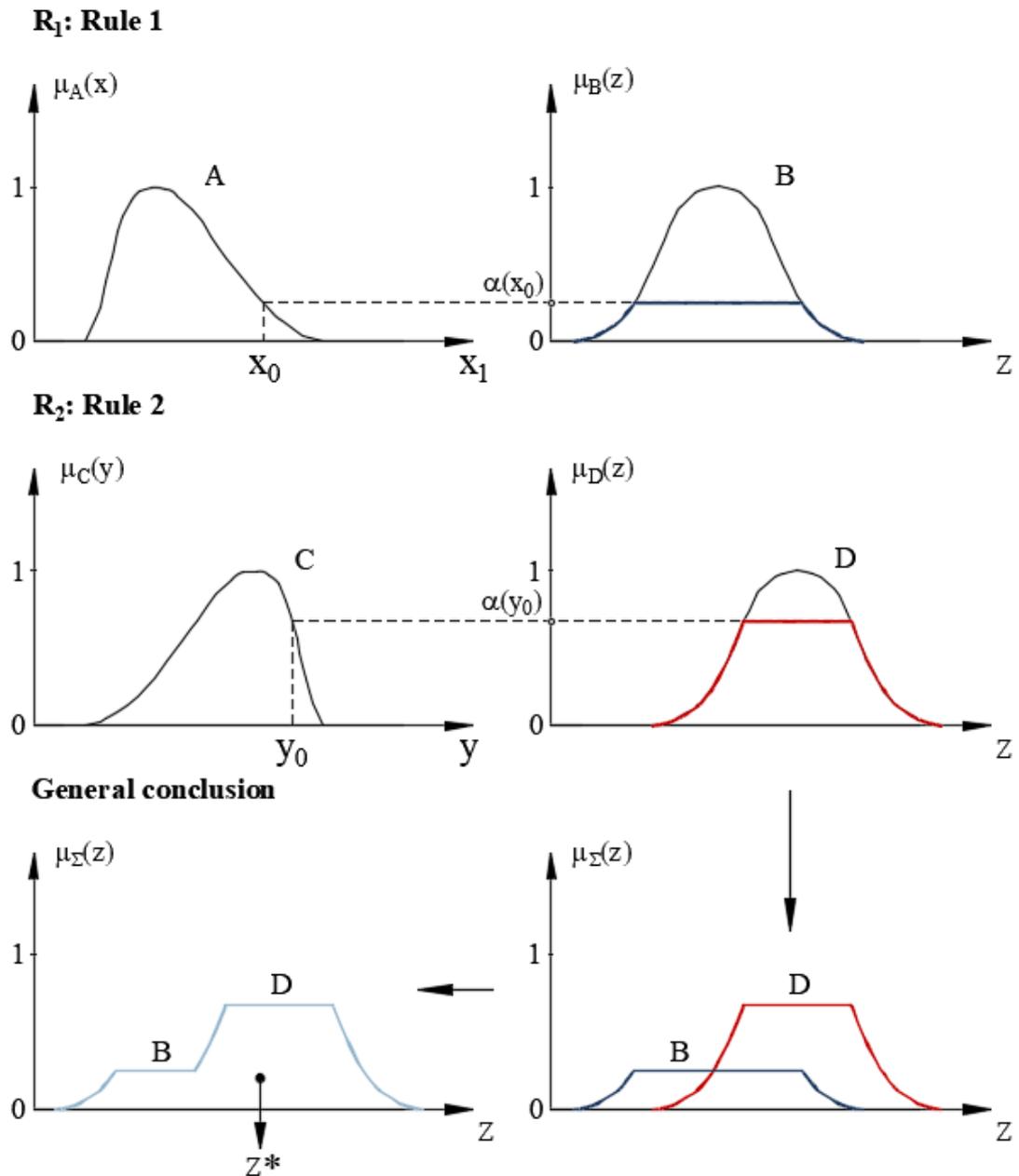


Fig. 17 – The illustration of fuzzy inference algorithm according to Mamdani M.

Thus, fuzzy control requires the selection of membership functions shape, defining a method of fuzzy logical operations processing, fuzzy logical inference derivation, defuzzification procedure etc. The most time-consuming process is the formation of a satisfactory base of fuzzy rules, often requiring empirical knowledge of relevant specialists.

In automatic control systems fuzzy logic have two areas of its practical implementation:

- Fuzzy controller operates in the direct control loop as a signal converter and can implement different transfer function as P-, PI-, PID- or other type of controllers.

The functional diagram of such a control system is shown in Fig. 18.

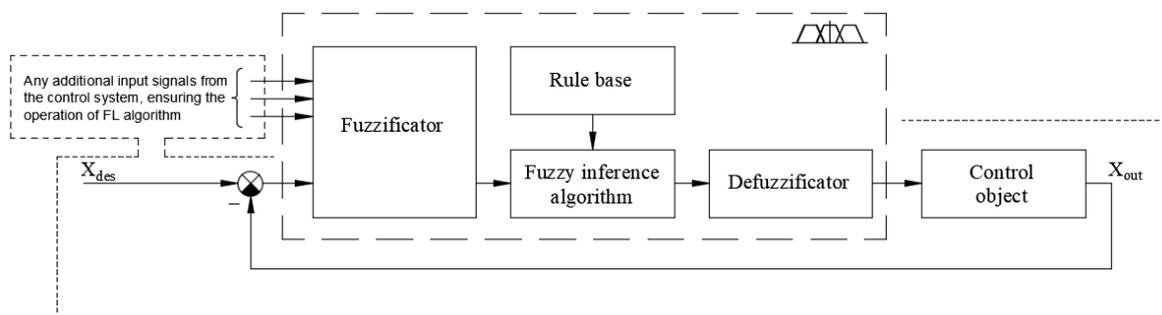


Fig. 18 – The functional diagram of the control system with fuzzy controller operating in the direct control loop.

- Fuzzy logic is used to implement an adaptor which operates in the outer control loop and tune the controller. The functional diagram of such a control system is shown in Fig. 19.

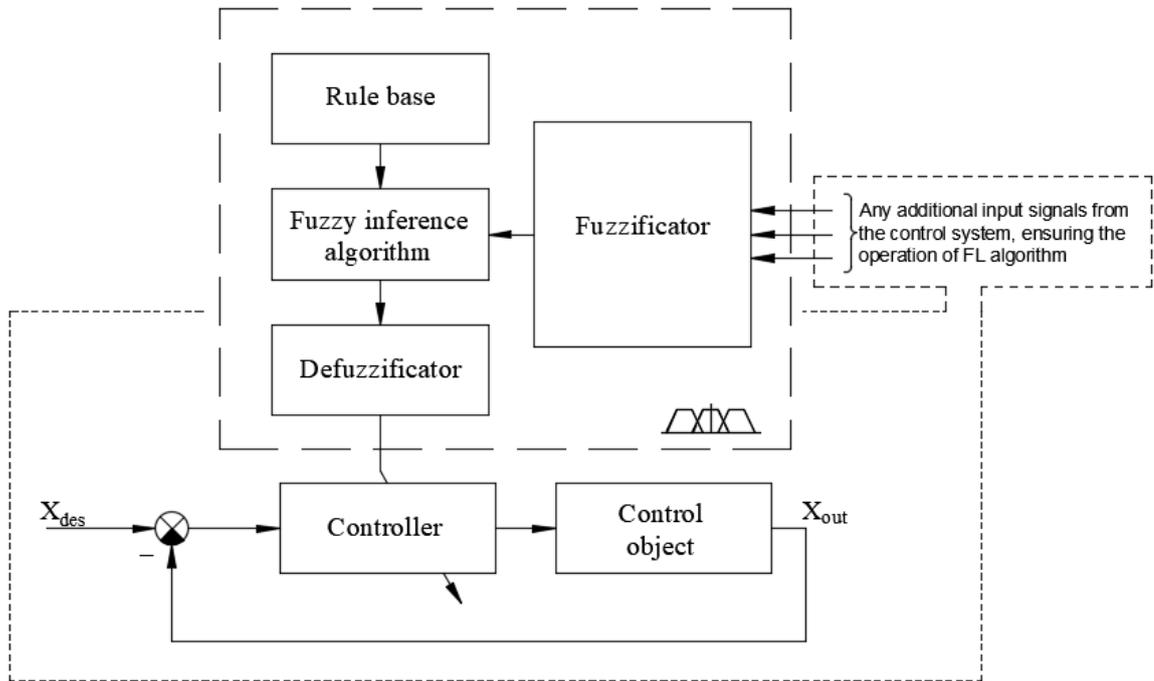


Fig. 19 – The functional diagram of the control system with fuzzy logic based adaptor operating in the outer control loop.

2.2.5 Optimal synthesis based control systems.

The synthesis of the control system is a design problem, with the final goal of achieving the rational structure of the control system, searching and setting the optimal or desired parameters value of its elements which are guaranteed to satisfy control goals[7].

In the problems of optimal synthesis of adaptive control systems, it is required to determine a control algorithm based on the available characteristics and parameters of the control object; carried out analysis of its operation behavior; made mathematical model (if it is possible to make an adequate one) which is capable of being self-adaptive to changing operating conditions and modes of a control object in considered range of its possible variation to meet established control requirements.

As mentioned earlier, adaptive control systems are divided into two main groups: self-organizing and self-tuning. The design of the control algorithm in self-organizing ACSs consists in determining both the controller structure and its parameters. Structural and parametric adaptation takes place as a response to changing operating behaviour of the control object to achieve required control goals (CG) in its each particular state. For optimal synthesis problem this kind of task has obvious complexity and usually requires considerable

computational resources[3]. Therefore it does not widespread implemented. Self-tuning systems have a predetermined structure, it is only necessary to design an algorithm for parametric adaptation.

The problem of adaptive self-tuning ACSs synthesis can be formulated in the following way[6]: Let there be a control object, on which the measured disturbances $Y = Y(t)$, constant disturbances $N = N(t)$ and the control actions $U = U(t)$ are applied. The behavior of the control object depends on a set of unknown parameters ξ . There is a set Ξ of possible values of ξ that defines the class of admissible disturbances and possible control objects. A control goal is set that defines the desired behavior of the control object. It is required to synthesize a control algorithm that uses measured or calculated on their basis values, which are independent of ξ belonging to Ξ and ensuring for each ξ belonging to Ξ the achievement of set control goals.

Control goals express the desired control object state or the behavior of approaching to this state, for example, based on the requirements of a control process quality. To set the control goals, various criterion functions are used: stabilization, tracking, matching the behavior of a control system to a reference model, etc[8]. Control goals are usually set in the form of inequalities at an indefinite or limited noises and external disturbances; in the form of inequalities with a mathematical expectation of disturbance functions if it has a random nature; etc. At the initial stage of the control system operation, the control goals will not be achieved due to a lack of obtained information by the algorithm, so the control goals can be also set in the form of limit inequalities, i.e. they can be achieved asymptotically over time.

An adaptive control algorithm can be divided into a *control algorithm* and an *adaptation algorithm*. The control algorithm, depending on the vector of controller parameters Θ , must ensure the achievement of the control goals for each ξ belonging to Ξ . Adaptation algorithm tunes the vector Θ so the control goals can be achieved for each ξ belonging to Ξ .

Thus, the synthesis problem includes a determination of a control algorithm $U(t)$ and an adaptation algorithm $\Theta(t)$ which ensure the achievement of the control goals. The control object together with the controller form the *main control loop*, and together with the adaptation algorithm block, the *adaptation loop*. The functional diagram of a self-tuning adaptive ACSs according to optimal synthesis problem is shown in Fig. 20.

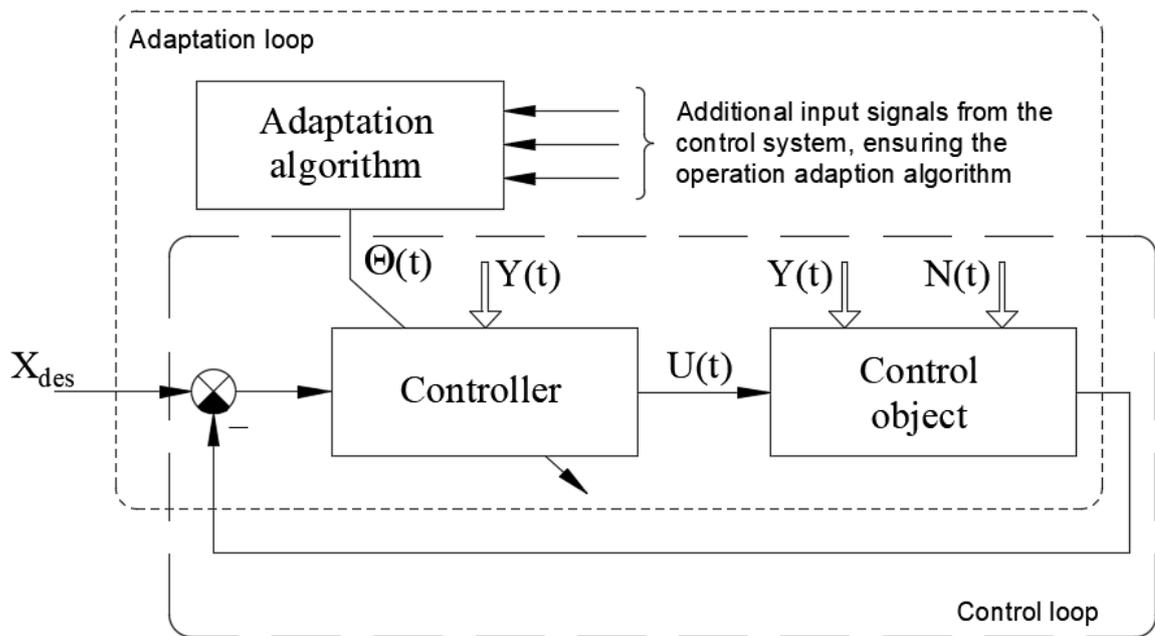


Fig. 20 – The functional diagram of a self-tuning adaptive ACSs according to optimal synthesis problem.

Methods of adaptive ACSs synthesis are distinguished into heuristic and theoretical. Heuristic methods do not allow to strictly substantiate whether the synthesized adaptive control system will be stable in all cases. Theoretical methods are divided into precise and approximate. Some of the commonly used methods for precise synthesis of the main control loop:

- Invariance method – control is performed based on comparison of control system and reference model behavior.
- Modal control method which is based on the desired quality criteria of a control process.
- Methods based on solving of control action optimization problems.

Approximate methods based on synthesis according to a simplified model of a control object. To perform a model simplification methods of system linearization; system order reduction; part neglection of disturbances, etc. are used.

Some of the methods used for synthesis of adaptation loop:

- Gradient based methods.
- Methods based on the application of Lyapunov functions.
- Methods based on the theory of hyperstability.
- Methods based on sliding control.

2.2.6 Conclusions.

Researches conducted so far, offer a wide selection of methods for designing of an adaptive control systems. However, the specifics of particular control task limits the choice of available methods for implementation, since each of them has its own advantages and disadvantages.

Application of ANN based algorithms allows solving a wide range of problems related to obtaining models of complex dynamic non-linear systems, identification, the formation of real-time tunable systems, estimation, pattern recognition, optimization, etc. There are more traditional known methods for solving these problems, but they do not have the required flexibility. The amount of information about the control object required for an ANN operation is minimal. Despite the obvious advantages, the main drawback of the ANNs application is the complexity of their training and substantiation of a control stability.

The application of algorithms, based on fuzzy logic allows to implement a control system where there is a lack of obtainable information about a control object; it is inaccurate, uncertain; or there is no availability to create an adequate mathematical model of a system. Such algorithms make it possible to completely or partially exclude a person from the control loop or accurately simulating heuristic human control algorithms based on its experience and intuition, using the fuzzy logic apparatus and providing acceptable control results. The main drawback of such algorithms is the difficulty in creating a base of fuzzy rules and reconfiguring the control system. Also, there are no ways to determine the optimal set of fuzzy ACSs parameters.

The application of optimally synthesized algorithms is based on the accumulation and processing of an information about the control object operation. Such algorithms do not always have sufficient flexibility and the ability to be synthesized depending on the complexity of the control object, but they allow to answer questions related to the stability and quality of the control process quite confidently.

Based on the research and analysis of various methods for adaptive control systems design, as well as their advantages and disadvantages, in this dissertation, preference is given to developing an adaptive control system based on application of ANN.

3 ADAPTIVE CONTROL SYSTEM DESIGN AND THE EXPERIMENT SET UP

In preparing the material for this section the literature [10], [11], [12] were used.

3.1 Description of the equipment and software used.

This work was performed using the MATLAB software package, offered by The MathWorks Inc.

MATLAB is a system of computer mathematics (SCM) oriented to matrix calculations. This system is one of the most extensive among SCMs and is actually considered as a standard in the field of scientific and technical software[11].

Despite the fact that the system was originally focused on highly specialized matrix calculations, at the moment it has many integrated toolboxes and is a universal integrated SCM for use in personal computer, computer workstation and even supercomputer operating systems.

MATLAB system is based on the C programming language and is a high-level programming language itself.

The modeling tasks in this dissertation were carried out using the Simulink extension – an operating environment that allows to perform a block simulation of various systems. The Simulink environment contains the toolboxes which expand the modeling capabilities and cover large areas of science and technology: modeling of mechanic systems, power systems, signal processing, bioinformatics, etc. Many leading universities and schools around the world have taken part in the development of the libraries.

The bulk of the modeling was done using the Simscape Electrical block library. The Simscape Electrical library, like many other libraries, is focused on modeling specific systems and devices. This library allows to simulate both passive and active electrical devices: power transformers, transmission lines, power electrical sources, etc[10]. The wide functionality of this library allows to perform not only calculations in the time domain, but also various types of resulting systems analysis.

One of the main advantages of the Simulink environment which is widely used in this work is the ability to simulate complex electrical systems by combining imitational and structural modeling approaches, according to which the power circuits of the model were simulated using specialized blocks of the corresponding library, and the control system were

simulated using ordinary blocks of the environment which reflect the algorithm of its work. This allows neglect the electrical circuits and related effects in non-critical places of the model, simplify the model and increase the simulation speed.

3.2 Setting modeling objectives.

3.2.1 Structural elements of the control system to be modelled.

To analyze the possibility of applying the adaptive control system presented in this section for RPC, it is necessary to model the following main components of the system, which is shown in Fig. 21.

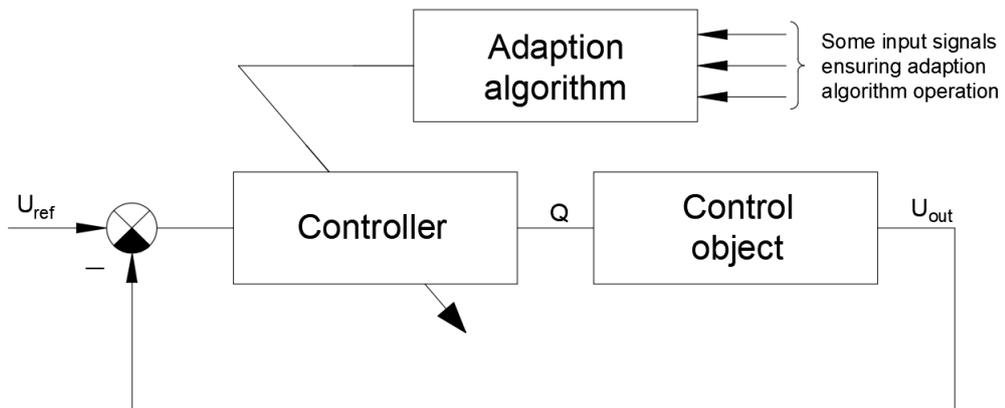


Fig. 21 - General structural diagram of designed adaptive control system.

Control object.

The control object of the system above is a model of the electric power system as shown in Fig. 22, which includes power sources and generator, transmission lines, transformers and load elements.

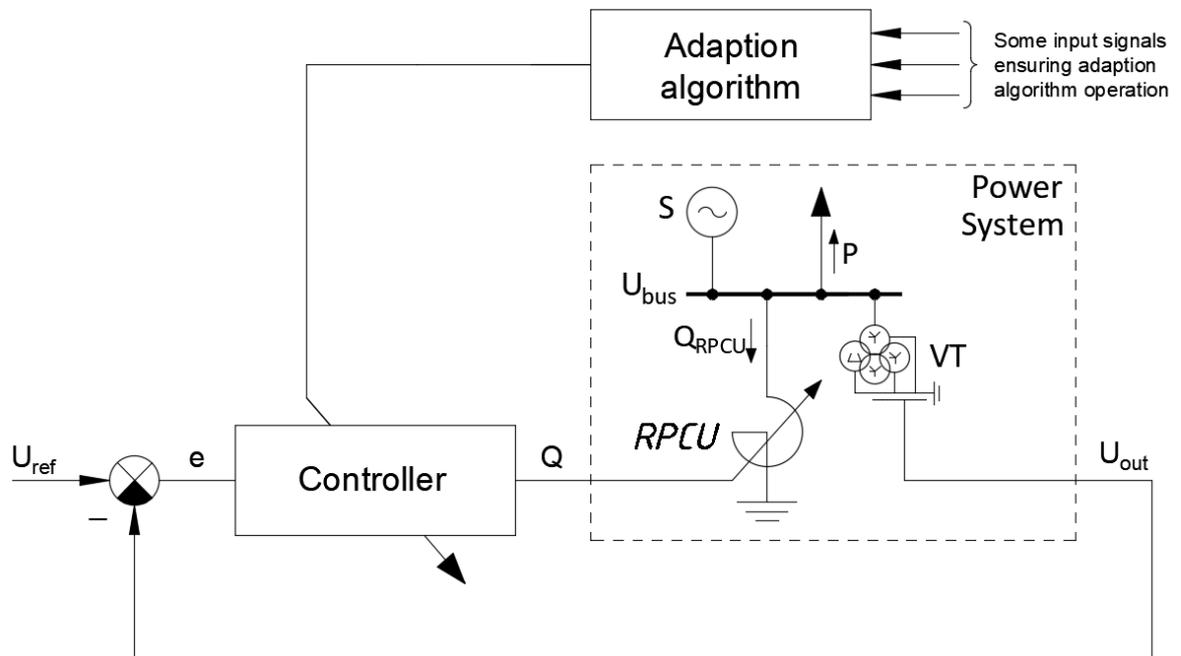


Fig. 22 - Structural diagram of designed adaptive control system with control object represented as a model of power system.

To perform a sufficient simulation of electric power grid operating modes, the model contains elements that expand its behavior and bring it closer to reality: models of generators, turbine and hydraulic units, as well as blocks which models the algorithms of operational automation - automatic excitation control of generators and automatic active power regulators. To perform a commutations during a simulation the models of power circuit-breakers are used.

The controlled elements in the power system model are RPCUs installed on power substation. Normally there can be several RCPUs on a substation. In the model the power substation represented as node with one high voltage bus, so all the system of RCPUs installed on one substation is modelled as one block and the interaction between the particular RCPUs inside the system are not considered. RPCUs affect the current voltage level value on the bus where they are installed by changing the value of reactive power consumption or generation (Q_{RPCU}).

Measuring equipment – voltage (VT) and current (CT) transformers are modelled as ideal and are not affect the control process.

Controller.

In the control loop three-term proportional-integral-derivative (PID) is used as shown in Fig. 23. The control action of the controller is formed by modifying the error signal (e), that is the deviation of measured process variable from the desired setpoint. The error signal is calculated as a difference between the current RMS voltage value (U_{out}) from the desired RMS voltage level (U_{ref}) on the substation bus. In fact, the control action (Q) produced by the controller is the amount of reactive power that must be consumed or generated by RCPU.

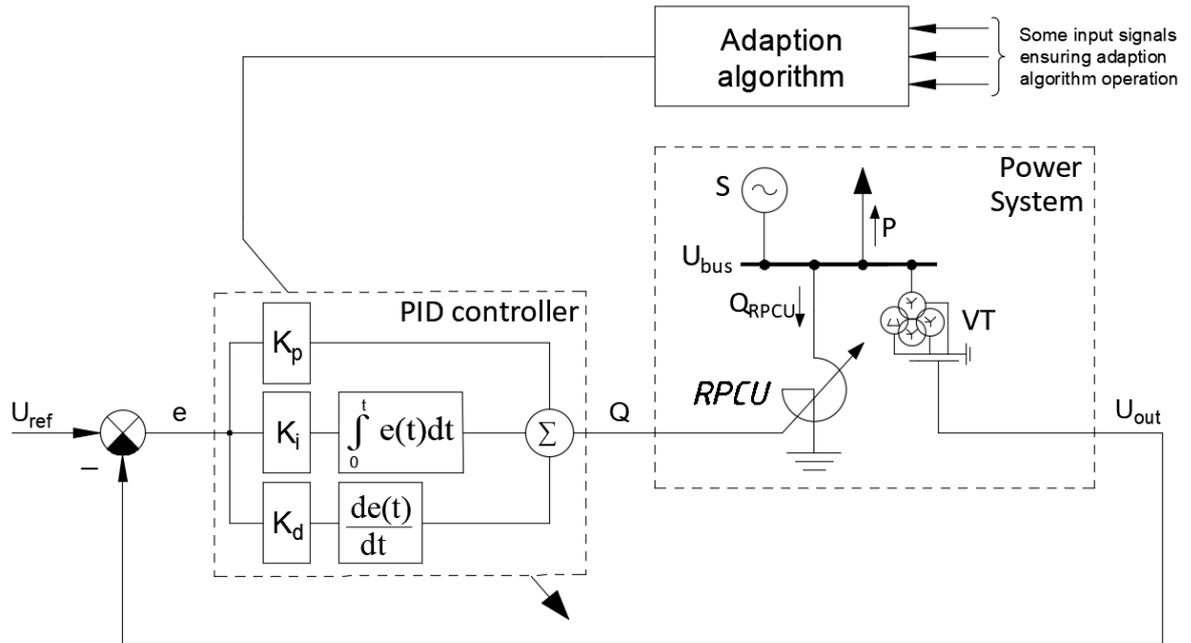


Fig. 23 – Structural diagram of designed adaptive control system with PID controller.

ANN based adaptor.

In this system the adaptor is a mathematical object with adaptability features, that based on a group of input data, tunes the current PID controller coefficients depending on the changes in control object to achieve the required quality of a control transient process.

The adaptor is implemented as a feedforward artificial neural network (FANN). The corresponding input buffers of given depth store the retrospective timeframe of input signals. At each calculation cycle the whole signal timeframe of a given duration and resolution, stored in a particular buffer to the moment, is fed to the corresponding input neurons.

The structural diagram of the adaptive control system with described adaptor block is shown in Fig. 24.

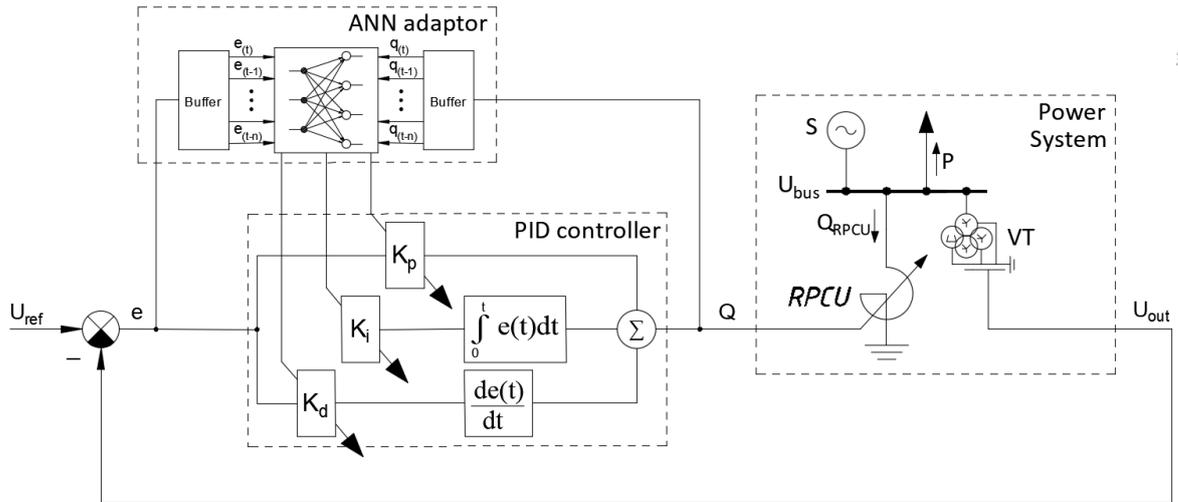


Fig. 24 – Structural diagram of designed adaptive control system with feedforward ANN based adaptor.

3.2.2 The description of scenarios to be simulated.

In this work, the proposed adaptive control system is based on the application of FANN. Thus, in order the the system to obtain adaptability features the neural network must be trained to identify the patterns of considered power grid states. Training should take place on groups of power grid operation modes, in relation to which the system should be self-adapting.

As a group of power system operating modes for FANN training and analysing the details of the control system response to disturbances, such modes as disconnection of one or several transmission lines during the simulation are considered. The disturbances to which the control system should adapt is a steep change in the voltage level on the high volatge bus of a selected substation, caused by the commutation of different transmission power lines in the power system model.

Power transmission lines, that should be disconnected during the simulations can be arranged in order of electrical distance from the selected substation with installed RPCUs.

3.2.3 Testing programme and procedure.

The test object is the adaptive control system shown in Fig. 24.

The testing purpose is to evaluate the parameters of adaptation process of the designed system to the new operating mode of the power system. The experiments were

carried out on the modes included in the training set for FANN as well as on the ones, which were not included in it. There are several parameters to be calculated: the time, that ANN took to obtain solutions with a given error in relation to the duration of the transition process; the overall relative error of the obtained solutions - the deviation of the solutions, produced by the network from the correct ones for a considered power grid operating mode.

The test methods consist of modeling the designed control system and analyzing its behaviour in considered modes and during the applied disturbances. During the experiments the following data were obtained: recorded arrays and timeplots of the power system elements operation and the individual blocks of the model as well, the oscillograms of voltage level transients at the installation site of RCPUs. The obtained results were analyzed and based on the recorded data the parameters of an adaptation process were evaluated.

The composition of the experiments includes simulations of designed control system at a number of power system operating modes included in the training set for FANN, as well as not included in it.

Test procedure: power transmission lines, which are electrically close to the selected substation with installed RCPUs will be disconnected first, then those ones which are distant to it.

3.3 Power system model.

To perform simulations and analyze the adaptive control system operation, mathematical models of the system components, MATLAB software package were used.

3.3.1 General information about the part of a power grid used for modeling.

The control object is a model of electric power system. The model is based on the information and operational data of the power facilities of the integrated energy system (IES) of Siberia region.

The EES of Siberia is located on the territory of the Siberian Federal District, and partially on the territory of the Far Eastern Federal District. The EES of Siberia includes ten regional energy systems.

The Interregional Dispatching Office (IDO) of Siberian region is a branch of joint-stock company «System Operator of the Unified Power System» (JSC «SO UPS»). Affiliates

of JSC «SO UES» provides a supervisory dispatch control of the power systems operating modes of constituent entities of the Russian Federation, that are part of the UES. The dispatch control zone of the Siberian IES includes twelve constituent entities of the Russian Federation.

IES of Siberia is one of the largest energy interconnections of the UES of Russia and borders with the energy systems of such regions as Ural, East; and such countries as China, Mongolia and Kazakhstan.

The Siberian IES includes 103 power plants with a total installed capacity of 51861.09 MW (as at January 1, 2019). Among them, hydro power plants account for 25291.4 MW (48.8%), thermal power plants - 26514.49 MW (51.1%), solar power plants - 55.2 MW (0.1%). The main electric power grid of Siberian IES is formed on the basis of transmission power lines of 110, 220, 500 and 1150 kV voltage classes. The total length of power transmission lines is 101,288 km (as at January 1, 2019) [12]. The displacement map of power facilities of the Siberian IES is shown in Fig. 25.

In the normal operating mode, a power flows of up to 2 million kW passes through the Siberian UES on «Siberia - Ural – Center» transit.

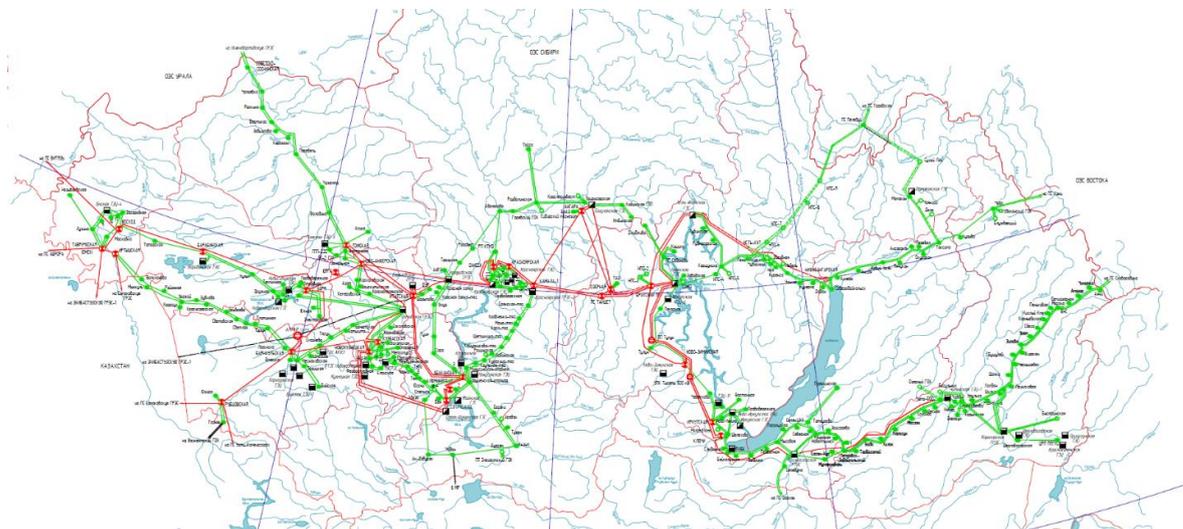


Fig. 25 – Displacement map of power transmission lines, substations and power plants of 220 kV and higher voltage class of the Siberian IES for 2017-2023 years [13].

3.3.2 Part of the Siberian IES to be modelled.

The part of the Siberian IES selected for modeling is shown in Fig. 26. It is circled with circled with a blue line. Power transmission lines of 220 kV voltage class is depicted with a green line, of 500 kV - with a red one.

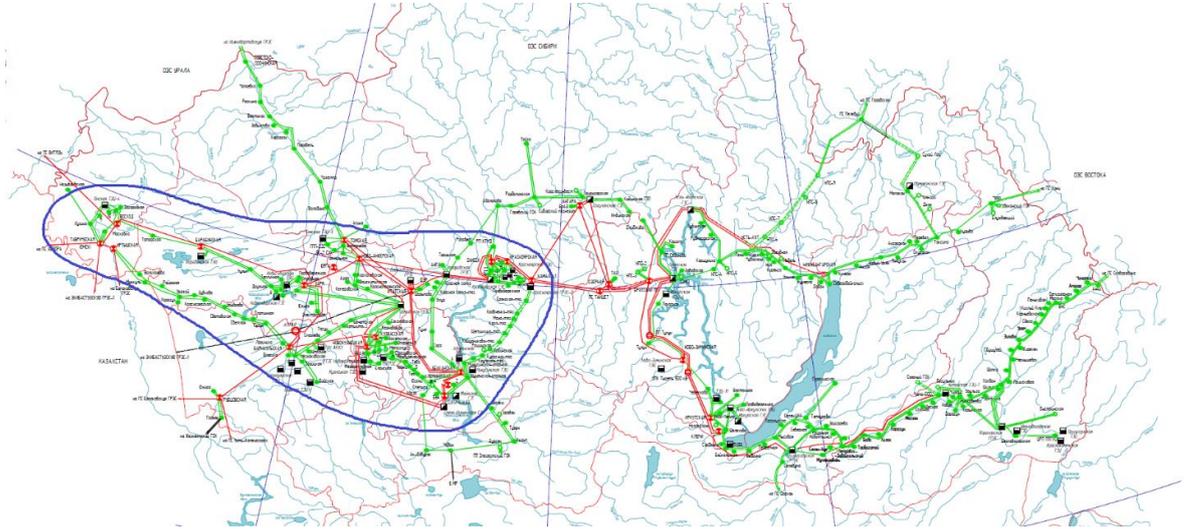


Fig. 26 – The part of the Siberian IES, circled with a blue line and selected for modeling in MATLAB software package.

The selected region of Siberian IES includes both radial and ring topologies of the power grid. The size of the region to be modelled was chosen in way to be able observe an adequate mutual impact of power system elements on each other, and more natural processes in power system model. Power system model was created on basis of 500 kV voltage class power facilities.

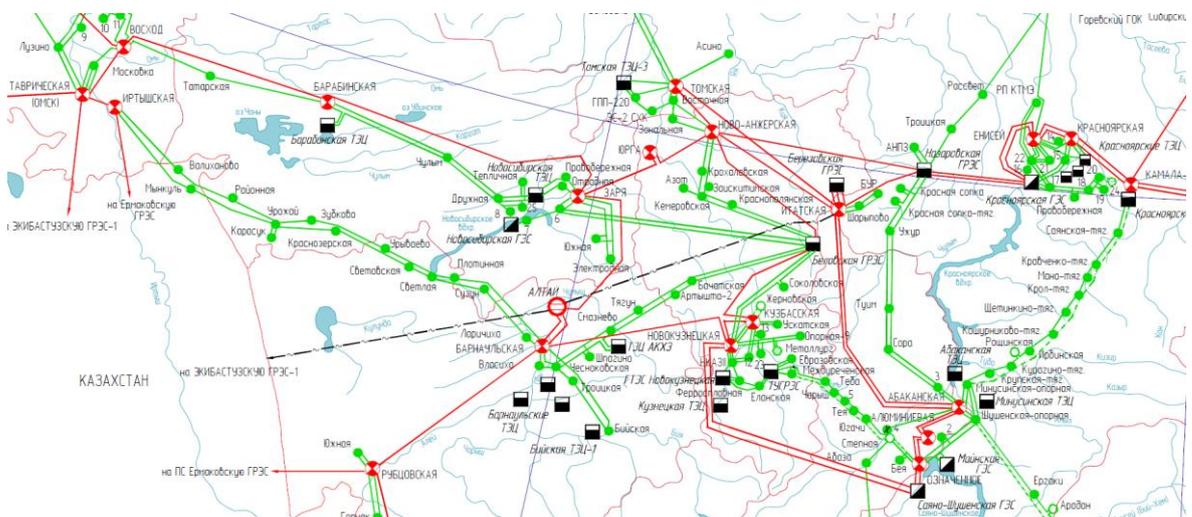


Fig. 27 – Scaled up region of Siberian IES to be modeled.

3.3.3 Topological representation of electrical connections of the selected region.

To obtain data about the parameters related with operating modes of Siberian IES, as well as about some parameters of the power facilities and equipment located in it, RastrWin3 software package was used. RastrWin3 was designed to meet the challenges of calculating, analyzing and optimizing operating modes of electric power systems.

In this software package, the calculation of the operating modes of Siberia IES was performed. There were obtained data about active and reactive power flows by the transmission lines from the operating mode calculation. There were extracted some parameters of power transmission lines, transformers, generators, shunt reactors, etc. from RastrWin3 model of Siberian IES. The topological diagram of electric connections in Siberian IES from RastrWin3 model is shown in Fig. 28.

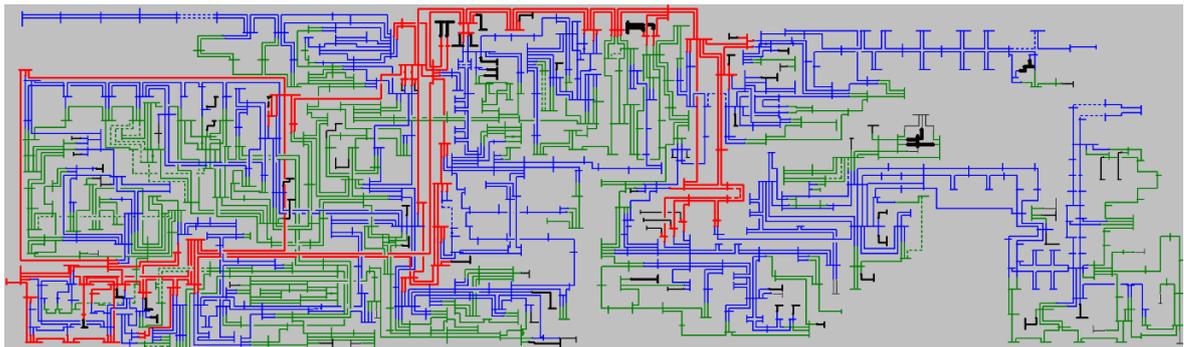


Fig. 28 – The topological diagram about electric connections in Siberian IES from RastrWin3 model.

Siberian IES model in RastrWin3 was reduced according to the region, that was selected for modeling in MATLAB. There were calculated the parameters of the reduced model. The connection diagram of reduced model was drawn in AutoCAD software and is shown in Fig. 29. The reduced model was verified by calculating the balance of power flows in its each node, which were compared with the power flows in original RastrWin3 model.

Abbreviations:

SS - power substation;
 SDPP - state district power plant;
 SDPP - hydro power plant;

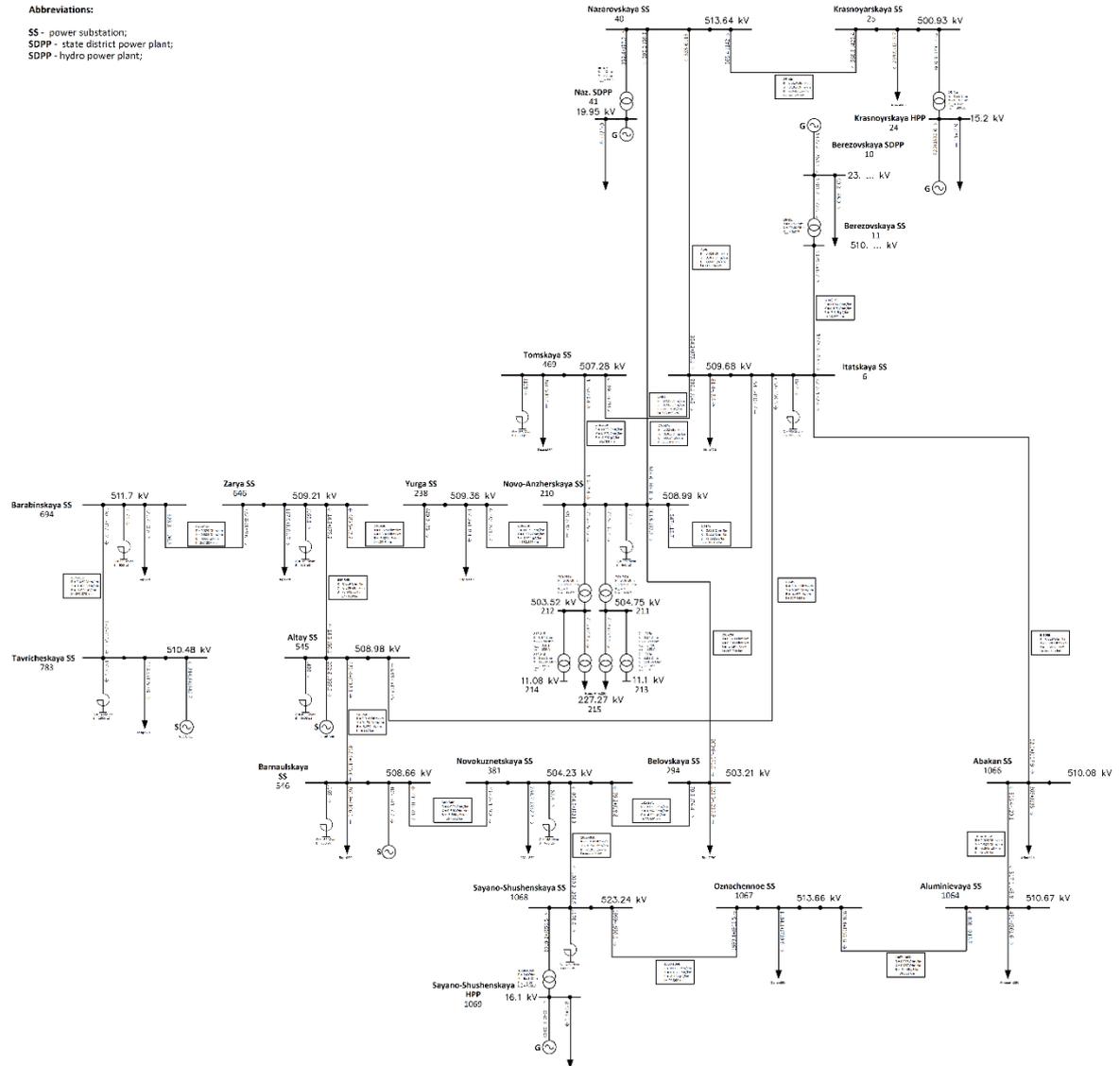


Fig. 29- Connection diagram of the reduced model of Siberian IES for modeling in MATLAB.

3.3.4 Description of power substation with controlled RCPUs installed.

As a process variable which is controlled by the control system, the RMS voltage level measured at the power substation high voltage bus is used. As a power substation where a controlled RCPUs are installed, Novo-Anzherskaya power substation is considered. It is located in the center of the modelled region and can be found in the center of the connection diagram, which is shown in Fig. 29 as well. As for its location on the original topological diagram from RastrWin3 model it is shown in Fig. 30, where it is highlighted with a black box.

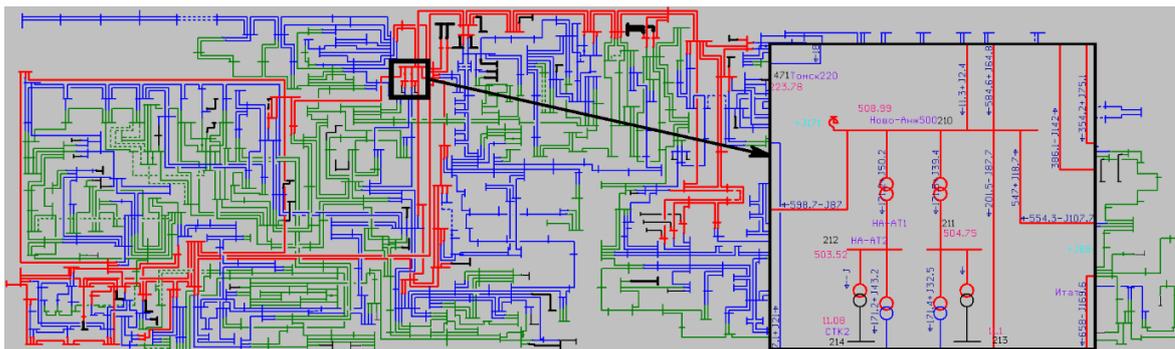


Fig. 30 – The location of the Novo-Anzherskaya power substation on the topological diagram of Siberian IES from RasrtWin3 model.

Novo-Anzherskaya power substation contains four switchgears of different voltage level classes – 500/220/110/10 kV.

Switchgear of 500 kV voltage class is implemented as open-type. It has two busbars connected with circuits. Power transmission lines or transformers are connected to these circuits via two circuit-breakers, so there are three circuit breakers for two connections. The connection scheme is made in accordance to a technical standard[14]. Switchgears of voltage classes 500 and 200 kV are connected via two power autotransformers (AT). Each of power transformers of 500 kV class is consist of three single-phase transformers.

The are 4 reactive power compensation units installed at the substation: 2 power shunt reactors of 180 MVAR nominal power capacity and 2 static thyristor reactive power compensators of 100 MVAR. Each of SR is connected to both busbars but in different circuits. As for static VAR compensators (SVC), they are connected to low voltage side of powers transformers 500/220/10 kV.

Thus, the existing RCPU system of the Novo-Anzherskaya substation has an operational control range of reactive power from -560 MVAR to +200 MVAR («-» – shows reactive power consumption, «+» – reactive power generation). Voltage level, which is measured on the buses of switchgear of 500 kV depends on a control of this RCPU system.

To simplify the overall power system model in MATLAB, Novo-Anzherskaya substation was modelled as single-bus switchgear of 500 kV, and the mentioned above RCPU system was modeled as a single block with the summary control range, since it is not considered the detailed processes of individual elements operation inside the substation in this thesis. The connection diagram of the substation elements inside the switchgear is shown in Fig. 30.

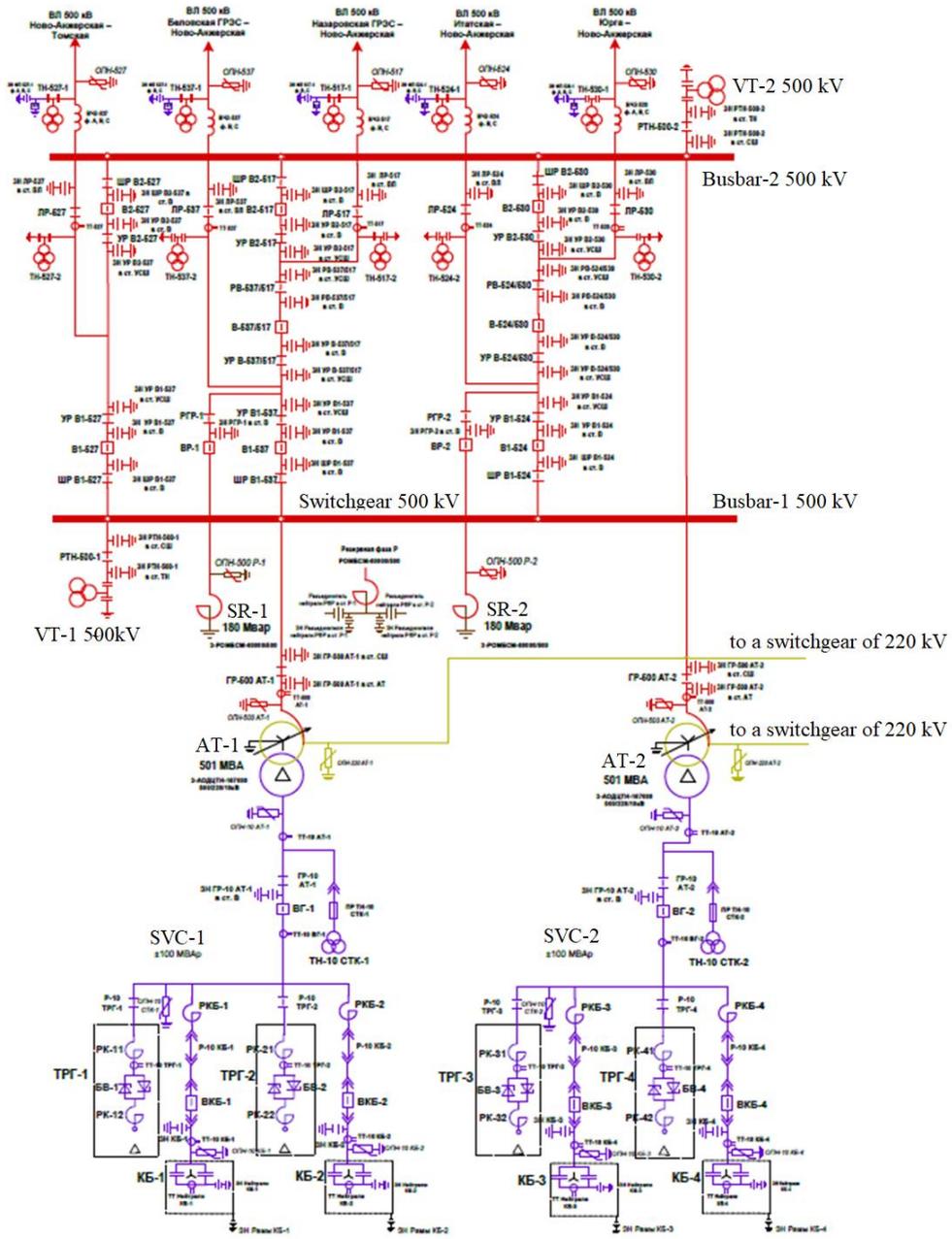


Fig. 31 - Connection diagram of the substation elements inside the switchgear of 500 kV of Novo-Anzherskaya power substation.

3.3.5 Description of the power system model in MATLAB Simulink.

Power system model of Siberian IES in MATLAB Simulink includes 18 power substations (SS) and 4 power plants. The list of power facilities, which are presented in the model is shown in Table 1. Each power facility in the model have its own node number in a

range from 1 to 22. They are named with the original names of the real power facilities of Siberian IES.

Table 1. Power facilities, which are presented in MATLAB Simulink model.

№ of node	Name of power facility	Type	Nominal voltage level, kV
1	Nazarovskaya	SS	500
2	Nazarovskaya	SDPP	20
3	Krasnoyarskaya	SS	500
4	Krasnoyarskaya	HPP	15,75
5	Tomskaya	SS	500
6	Itatskaya	SS	500
7	Berezovskaya	SDPP	24
8	Berezovskaya	SS	500
9	Barabinskaya	SS	500
10	Zarya	SS	500
11	Yurga	SS	500
12	Novo-Anzherskaya	SS	500
13	Tavrisheskaya	SS	500
14	Altay	SS	500
15	Barnaulskaya	SS	500
16	Novokuznetskaya	SS	500
17	Belovskaya	SS	500
18	Sayano-Shushenskaya	SS	500
19	Sayano-Shushenskaya	HPP	15,75
20	Oznachennoe	SS	500
21	Aluminievaya	SS	500
22	Abakan	SS	500

The power system model was built mainly using the blocks of a specialized library for modeling power systems Simscape Electrical. The model layout from MATLAB Simulink is shown in Fig. 32.

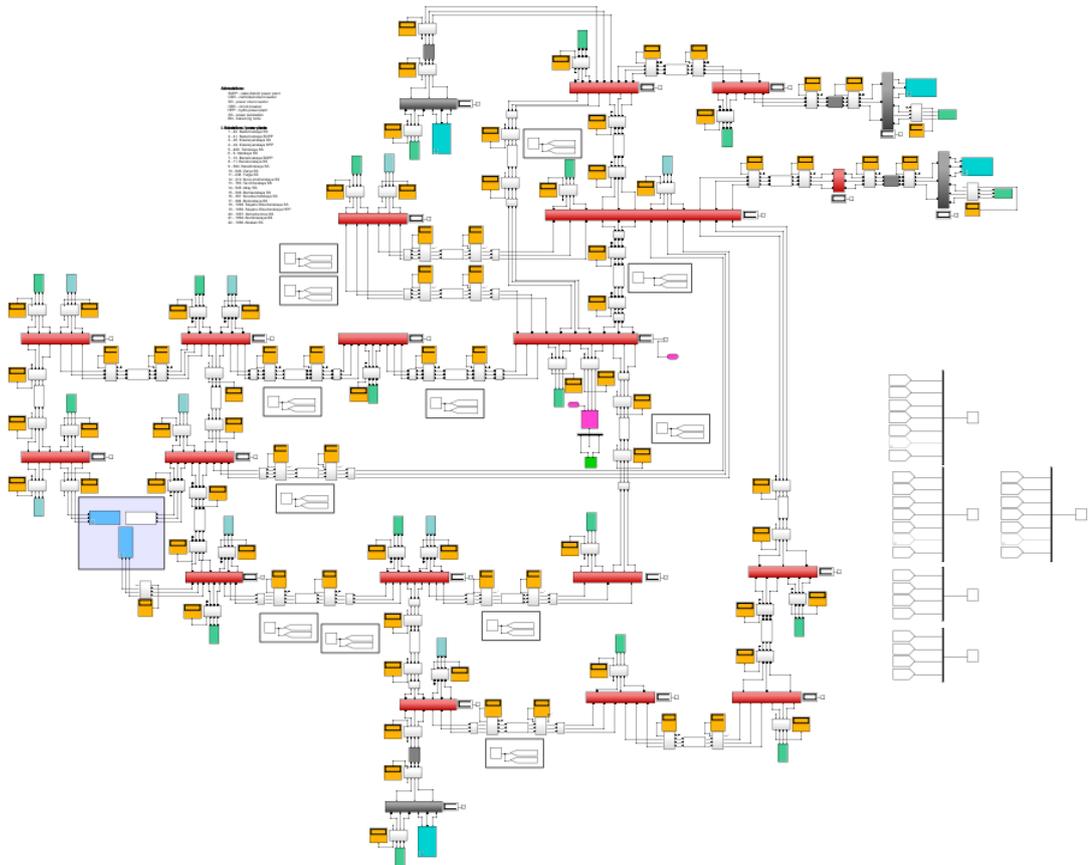


Fig. 32 – The layout of Siberian IES model built in MATLAB Simulink.

The model of Novo-Anzherskaya power substation is located in the center of Fig. 32, its scaled up view is shown in Fig. 33.

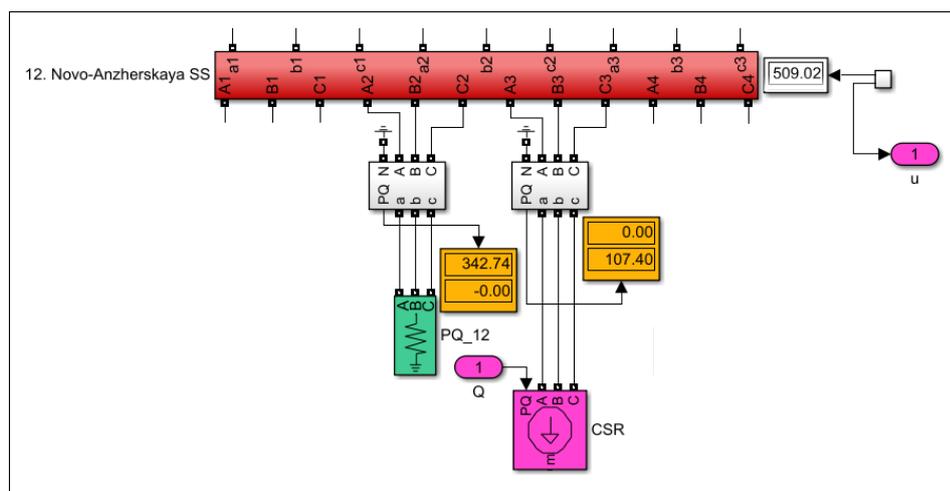
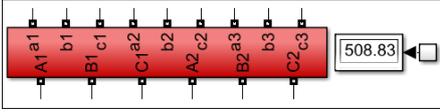
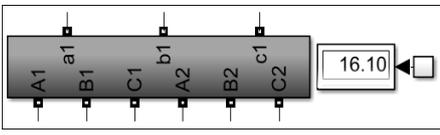
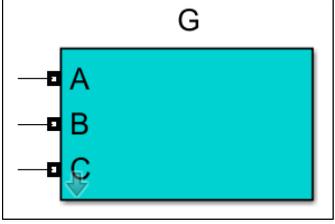
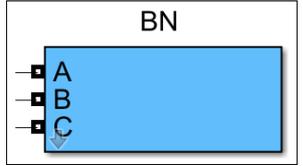
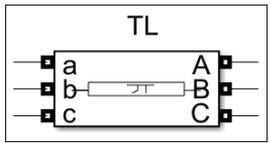
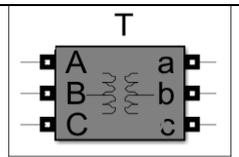


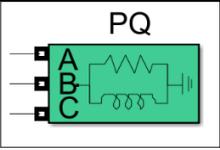
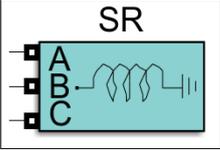
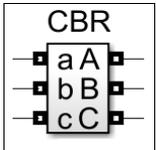
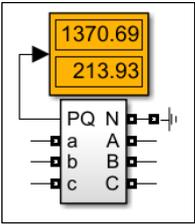
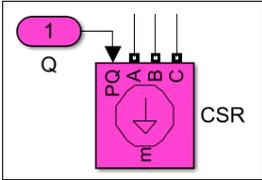
Fig. 33 – The model of Novo-anzherskaya power substation with controlled RCPU system.

To maintain a balance between accuracy and speed of the modeling process, the calculation was performed using the solver «ode1», with a «fixed step» step calculation option enabled and a sampling time of 0.0005 s.

Main blocks, which were created in the model are shown in Table 2.

Table 2. Main blocks of the MATLAB Smulink power system model.

№	Graphical view	Element type	Name	Description
1		Subsystem	Power HV bus	It implements busbars of power substation.
2		Subsystem	Power LV bus	It implements busbars of power plants (HPP, SDPP).
3		Subsystem	Equivalent generator	It implements a group of power plant generators with automatic excitation control and steam or hydro turbines.
4		Subsystem	Adjacent power system	It implements adjacent power system (acts as a balancing node) with controllable phase angles to set desired power generation or consumption.
5		Basic library block	Power transmission line	It implements three-phase power transmission line with lumped parameters.
6		Basic library block	Power transformer	It implements three-phase power

				transformer with two windings.
7		Basic library block	Power load	It implements three-phase active and reactive power load.
8		Basic library block	Power load	It implements three-phase power shunt reactor with static setpoint.
9		Subsystem	Power circuit-breaker	It implements a power circuit-breaker, which commutates power circuits.
10		Subsystem + basic library block «display»	Three-phase power measuring unit	It provides measures of power flows and its direction. The first number shows a value of active power flow in MW and the second one – reactive power flow in MVAR. Positive direction: from «ABC» to «abc».
11		Basic library block	Three-phase controlled load	It implements the controlled RCPU system. It models a reactive power consumption or generation according to a control signal «Q».

Complex models (HPPs, SDPPs, busbars of SS, etc.) were created from the group of basic and specialized library blocks and are presented in the model in a general view as

subsystems to improve the visual model perception, as well as to make easier to monitor real-time parameters of the power system operating mode during simulation (voltage levels and power flows).

The parameters of model elements were set according to a specialized reference books [15] and [16] and were aggregated in separate script files. Missing parameters were calculated based on catalogued data. An example of a section of code from a script file that is responsible for setting the parameters of two-winding power transformer installed on the Nazarovskaya substation is presented below:

```

=====
% Parameters of the power transformers
=====
% T.S - [VA]; T.V1,T.V2 - [V]; T.R1,T.R2 - [pu]; T.x1,T.x2 - [pu];
%-----
%- Nazarovskaya substation -----
% Transformer type: ТП-630000/500
T.S(1,2) = 630e6*2;           % Nominal power
T.V2(1,2) = 20e3;           % Secondary winding nominal voltage
T.R2(1,2) = 0.00103;        % Secondary winding resistance
T.x2(1,2) = 0.07001;        % Secondary winding inductance
T.V1(1,2) = 525e3;          % Primary winding nominal voltage
T.R1(1,2) = T.R2(1,2);      % Primary winding resistance
T.x1(1,2) = T.x2(1,2);      % Primary winding inductance
T.Rm(1,2) = 1260;           % Magnetization resistance
T.Xm(1,2) = 293.36;         % Magnetization inductance
...

```

3.4 Control system model.

As it was mentioned earlier the control system of RPC equipment is formed by modifying the error signal, which is a difference between the current measured RMS voltage level value from the desired one by tunable three-term PID controller. Complete structural diagram of the modeled control system is shown in Fig. 34. It contains four main parts: FANN based adaptor, tunable PID controller, power system model and measurement processing block.

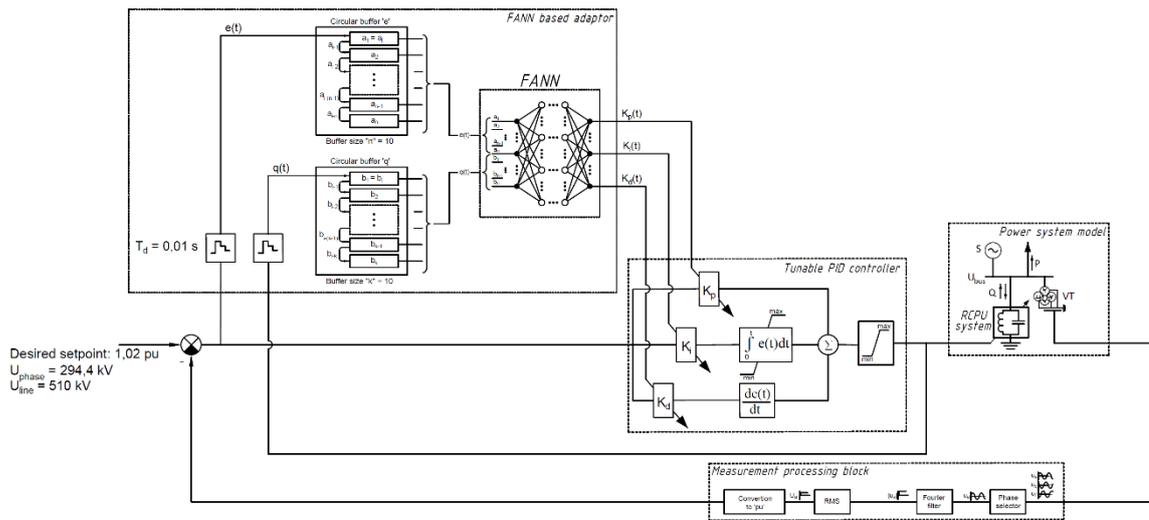


Fig. 34 – Complete structural diagram of the modeled control system.

Let us consider each element individually, except of the power system model. The details of the power system modeling were discussed above.

3.4.1 Modeling of measurement processing block.

The measured and controlled process variable is the voltage level on the high voltage bus of the target substation. The instantaneous voltage values of each phase at each moment of time are measured at the corresponding windings of the voltage transformer. The instrument voltage transformer in the model is ideal, so saturation and voltage loss processes are not considered during simulation. The main phase, which was selected by phase selector to measure voltage levels is phase «A». Using the Fourier filter, the voltage amplitude of phase «A» is extracted and then its RMS value is calculated. Then, the RMS value is converted from the actual values to relative ones and fed to summator to produce an error signal in «pu» units. Desired voltage level setpoint is also set in «pu» units. This value is normally predefined and provided by the system operator for certain substation and certain operational mode of the power system. In the MATLAB model it was set according to the operation mode calculation for Siberian IES in RastrWin3 software.

3.4.2 Modeling of tunable discrete PID controller.

The control system is based on a discrete tunable PID controller, which modifies the produced error signal by its each term and provides a value of current reactive power generation or consumption for RCPU system as its control effect.

The transfer function of the controller in z-plane is shown in Eq 5.

$$G(z) = K_p + K_i \cdot T_s \cdot \frac{1}{z-1} + K_d \cdot \frac{1}{T_s} \cdot \frac{z-1}{z} \quad (5)$$

where K_p – coefficient of proportional term, K_i – coefficient of integrator term, K_d – coefficient of derivative term, T_s – discretization period.

The PID controller operates with a discretization period of 0.01 s. The integral term of the PID controller has a saturation in the form of an upper and lower limits for the output value. It is used to prevent the effect of integral saturation, when the integral component can reach quite big values if the error signal remains its sign for a long time. This can lead to overshoot and increase in regulation time[17].

The output signal of the PID controller also has saturation limits, caused by the limited capabilities of the controlled power equipment to generate and consume reactive power and limited output power of possible mediatory equipment, which implements control action.

The coefficients of the PID controller terms: K_p , K_i , K_d are updated by the command, received from the FANN adaptor at each calculation step with a discretization of 0.01 s, which is the same for the controller.

3.4.3 Modeling of FANN based adaptor.

In preparing the material for this section the literature [6] [11], [18], [19] were used.

Type of the ANN applied.

Adaptor is a mathematical object, which has adaptability features and tunes the current coefficient of PID terms to achieve the required control quality goals is implemented as feedforward artificial neural network. It is the networks of this architecture that are recognized as the most suitable for solving control and identification problems[6]. In the networks of such a type, neurons are combined into layers. They contain neurons of the input and output layers, as well as from one to several hidden layers. Each layer processes a vector

of signals, transmitted from the previous layer. The input layer is used to distribute the input data to the neurons of the next layer - the hidden one. The number of connections between layer neurons can increase the speed at which the network reveals relationships in training data. The variety of FANN can be created depending on the number and dimensions of layers as well as how neurons from the layers are connected. The general structure of a FANN is shown in Fig. 35

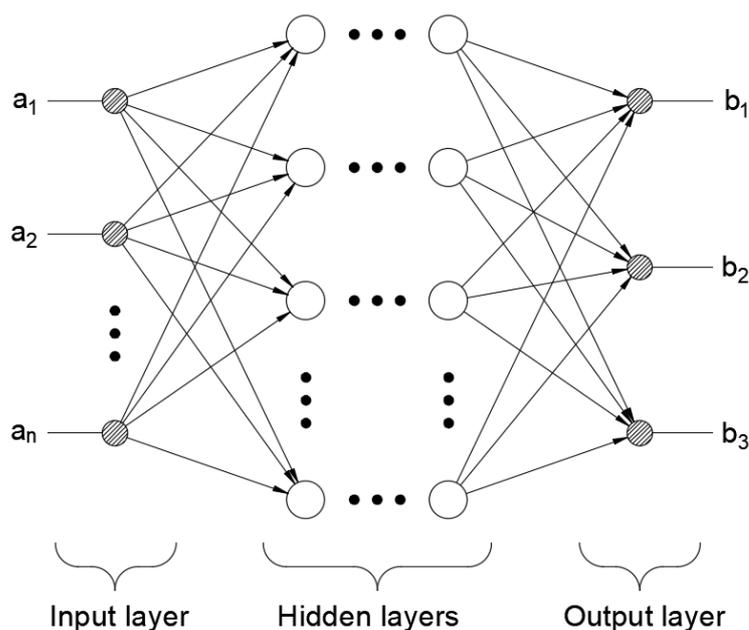


Fig. 35 – Genral structure of a feedforward artificial neural network.

Transfer functions of neurons.

Each neuron in the network can have its own activation function, which is also called transfer function. Normally all the neurons from a particular layer have the same transfer function. As an activation function of hidden layer neurons, the «tansig» function is used, which implements the mathematical transfer function of hyperbolic tangent. The neurons of input and output layers have linear «purelin» activation function, since they only need to distribute the initial and transmit the final data without transformations. An output calculated by the hyperbolic tangent sigmoid transfer from a neuron input can be positive as well as negative. The «tansig» transfer function, applied for hidden neurons, and the «purelin» one, applied for input and output neurons are shown in Fig. 36.

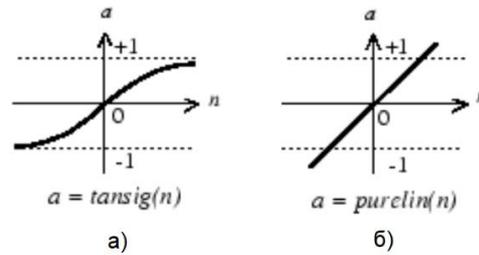


Fig. 36 – Applied neuron transfer functions: a) «tansig»; b) purelin[18].

An activation function is responsible for which neurons will be activated, i.e. which neurons will be able to transmit information to the next neurons. Thus, an activation function determine which information will be transmitted from the current layer to the next one.

FANN architecture.

For most problems, it is recommended to use a neural network with two hidden layers, then gradually increase their number if the network performance with fewer layers is insufficient. An increase in the number of hidden layers with a nonlinear activation function will allow the network to solve complex problems with greater efficiency, to identify more complex nonlinear relationships faster, but at the same time, the required computing resources for its training will increase as well. The network used has two hidden layers.

The number of neurons in the hidden layers usually varies within the range of the number of neurons in the input layer to the number of neurons in the output layer as the layers are arranged from input to output. An increase in the number of neurons in a hidden layer will give the network more flexibility, since the network will be able to optimize more paramters, and therefore to solve more complex problems. If there are too many neurons in the hidden layers, solutions, produced by the network can become uncertain, since during its training such a network will have to optimize more parameters than there are training data vectors that can constrain these parameters. Obviously, a greater number of neurons in hidden layers will also lead to an increase in the required computing resources for network training. At the same time there may be a tendency for a network to be overfitted, when it reveals relationships in the training set too deep, so various disturbances and noises in it are perceived as reliable information. In the network designed the first hidden layer have twenty three neurons, the second one - thirteen. These values are approximately within the number of neurons in the input and output layers.

The number of neurons in the input layer is determined by the dimension of the input data vector, in the output layer - the output one. There are three neurons in the output layer, which form PID controller coefficients at each calculation step: K_p , K_i , K_d . Two groups of signals form the input information, each of which is a vector of ten elements. Input vectors are continuously updating timeframes of 0.1 second time length with a discreteness of 0.01 second. At each calculation step, the current measurement and the nine previous of each group are fed to the corresponding input neurons of the network. Thus, the number of neurons in the input layer is twenty. The designed architecture of a FANN used is shown in Fig. 37

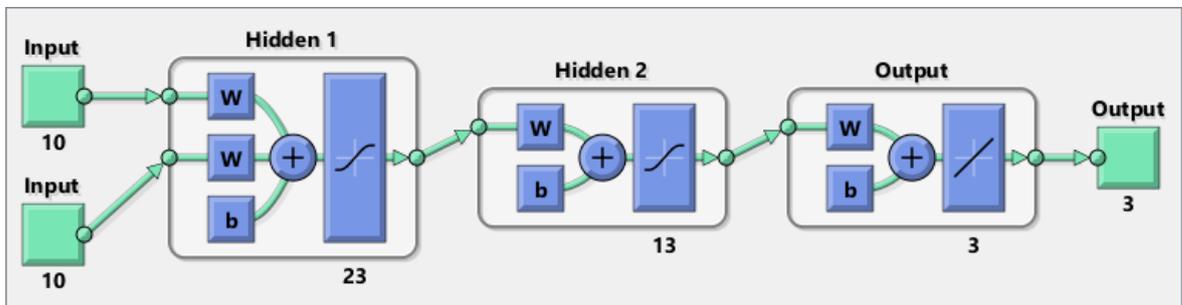


Fig. 37 – Structural diagram of designed FANN architecture.

Each hidden layer neuron contains biases that are also updated during network training. Bias is a weight coefficient, which value is added to a linear combination of all input signal of a particular neuron. The various kinds of relationships in the training data can be expressed as a mathematical function of the input-output dependency. The role of hidden layers is to identify or gradually approximate this function during the training process. The quality of the function approximation depends not only on the number of hidden layers and the number of neurons in them, but also on the presence of bias weights in neurons. Thus, the role of the bias weights roughly is to shift the function curve, produced by the network in the form its weights matrix, so that it would match as close as possible the original input-output dependency function, embedded in the training set.

A neural network with a few hidden layers and with a sufficient number of neurons and biases in them can identify relationships in almost any combination of input and output data. Such a neural network is a general function approximator, capable of constructing dependency function for any finite combination of input and output data with a finite number of discontinuities with a reasonable approximation accuracy[19].

The formation of th input data vectors.

The first group of input data is the timeframe of the error signal $e(t)$, the second one is the timeframe of control action signal $q(t)$. Previous measurements are overwritten with new ones in the corresponding circular buffers used for each group. The explanation diagram of of a circular buffer operation is shown in Fig. 38. The timeplot of the error signal, which is fed to input neurons from the circular buffer «e» is shown in Fig. 39.

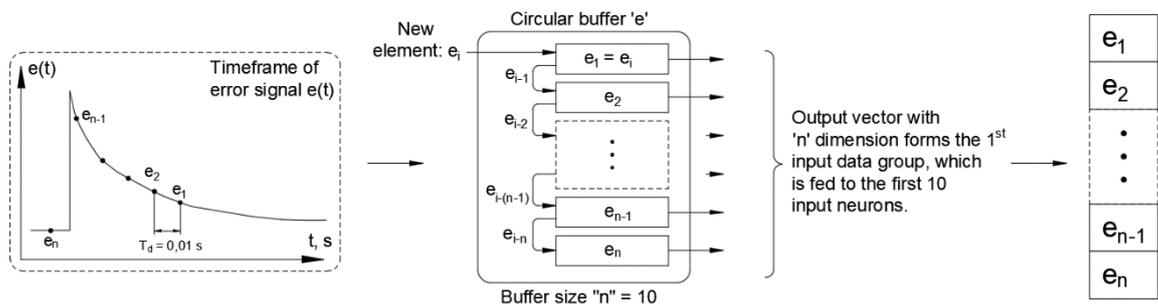


Fig. 38 – The explanation flowchart of the operation of the circular buffer used.

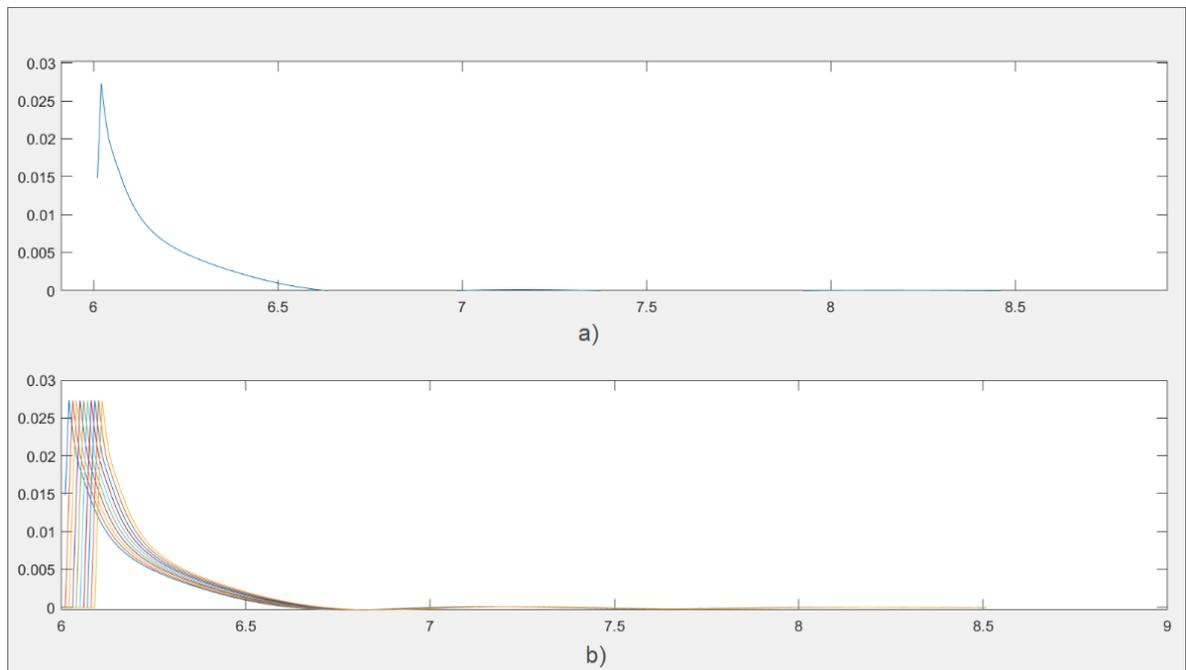


Fig. 39 – Error signal of the control system: a) which is fed to a circular buffer «e»; b) which is produced by the circular buffer «e» and fed to a corresponding input neurons.

It was decided to select the value of 0.01 second as the sampling time of the network operation to match the one of the PID controller. Also, this value provides a trade-off between the affect on the measurement of various noises, the quality of a curve identification and the required computatiона resources for ANN training. The size of the buffers is selected equal to ten elements. An increase in this parameter, as well as a reduce in the sampling time of the control system operation, will result in significantly increased size of the training data arrays, which in turn will require more computing resources and time for network training.

FANN training details.

In order for a network to produce a correct solutions a given task, it is necessary for a network to be familiar with it, so a network should be trained to reveal a certain relationships suitable for a considered problem solving between input and output data in a similar tasks. The process of relationship identification when training set contains input data and the corresponding desired output data, is related to a paradigm of «supervised learning». Also, there are another ANN training paradigms such as «unsupervised learning» and «reinforcement learning». For the considered problem, the methods of «supervised learning» was used, in which a training set is formed as two arrays: input data vectors and the corresponding desired output ones. The output data is posed as desired results, which trained network should produce when was fed with the corresponding input data from the training set. These two arrays implicitly contain the input-output relationships, which network must identify.

Each connection between neurons in a network contains a weight coefficient. When a signal is transmitted from one activated neuron to another, the value of the transmitted signal decreases or increases due to multiplication by the corresponding weight coefficient of the connection between them. Thus, the supervised learning technique involve a process of an ANN weights modification to approximate input-output dependencies by reducing the difference between produced output data and the correct output one for a certain input vectors.

When supervised learning is applied, the corresponding data is fed to the input layer of the neural network, based on the input data and the current values of the weighting factors, the neural network generates the result. This result is compared with the desired output from the training set and the total mismatch error is calculated. Such training method is based on

the method of error correction, i.e. its reduction. Weighting factors are adjusted based on the contribution of each weight to the total error. The contribution of each weight to the total error is calculated as the partial derivative of the total error by the each weight. In a such learning algorithm error values after they were calculated, propagating backward from the output layer to the input one. During an error back-propagation process the partial derivatives are calculated. Therefore this learning algorithm is called as «back-propagation algorithm».

The designed neural network was trained using the back-propagation algorithm of the Levenberg-Marquardt – «trainlm». This algorithm is recommended as the first choice for supervised training. It provides fast solution convergence and high accuracy for training of relatively small feedforward neural networks (about few hundred of weights) in MATLAB. However, it requires more memory for its operation than other algorithms. This algorithm is best suited in solving function approximation problems, to which the considered problem belongs. It has good performance, i.e. allows to obtain lower mean square errors in comparison with other algorithms; and should be applied when the approximation must be quite accurate.

A neural network training process can be described in MATLAB with the following parameters:

- *Network performance.* It represents the average squared error between the network outputs (r_i) and the desired outputs (t_i).

$$mse = \frac{1}{N} \cdot \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \cdot \sum_{i=1}^N (t_i - r_i)^2 \quad (6)$$

- *Magnitude of the gradient of performance.* This parameter decreases as the network reaches a minimum performance during its training.
- *The number of training epochs.* This parameter is increased by one each time the neural network process all training set, consisting of a number of training samples.
- *Number of validation checks.* This parameter represent a number of successive checks when the network performance fails to decrease.

Some of these parameters can be used to automatic stop the training process. It will terminates if the magnitude of the gradient of performance become lower then $1e-5$, the number of validation checks reached the value of six.

Based on pre-formed training data, the network training was performed. Training results are shown in Fig. 40.

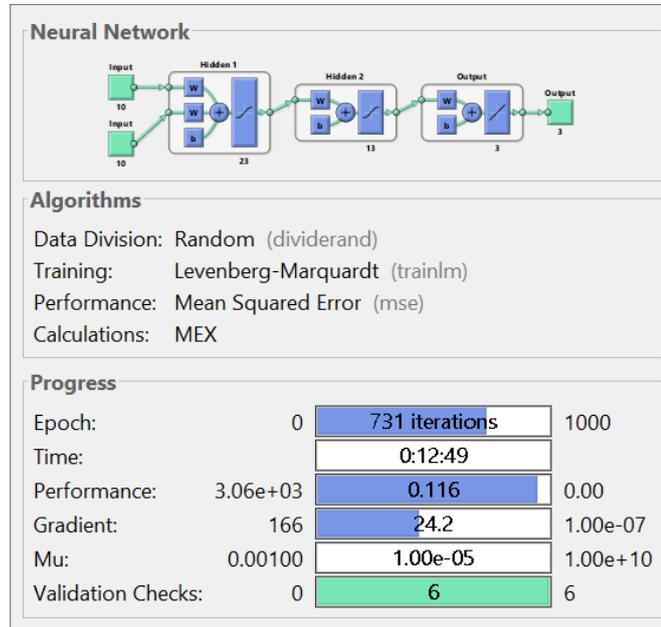


Fig. 40 – Network training options and results.

As it can be seen from the Fig. 40 the training process was stopped due to the reach of the set number of validation checks (six is the default number) at 731 training iteration and with 0.116 performance value obtained.

Also, the results of the network training can be represented with performance plot, which shows the value of the performance function versus the iteration number. It shows performances for training, validation and test sets. All formed training data is divided into three groups with the following percentage: training set – 70%, validation set -15% and test set -15%. For a designed network the performance plot of its training process is shown in Fig. 41.

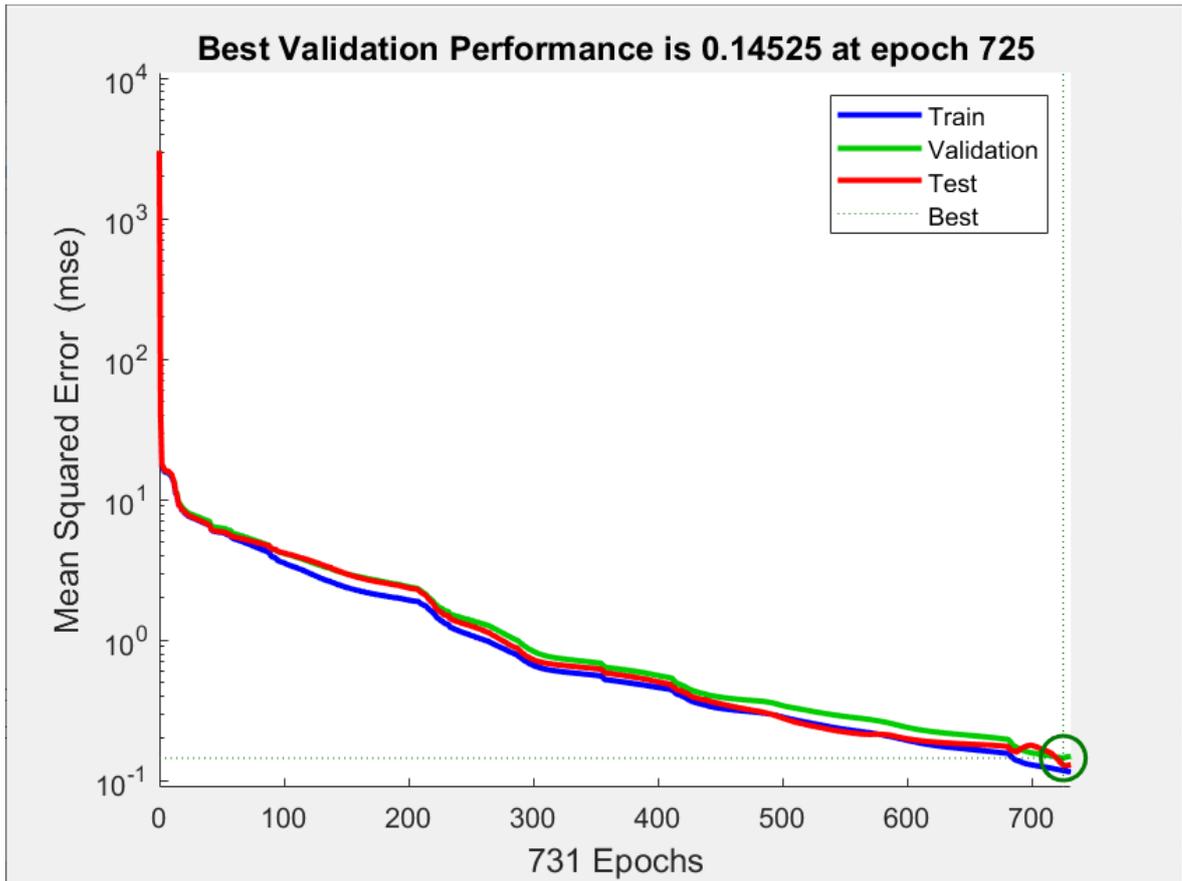


Fig. 41 – Performance plot of a training process of the designed ANN.

Formation of the training data.

The training data was created based on the recorded data of the signals, which are necessary for the FANN operation: control error «e» and the control action «q».

In this work, it was investigated the adaptation of the control system to a new operation mode of the power system, which was caused by the sudden disconnection of different transmission power lines. There is a reason why these modes were considered. Disconnection of various transmission power lines can provide a clear change of transfer function, which describes a power system because they cause changes in power system circuit and reorganization of power flows. So, the training data was formed for these operational modes.

When the transmission line is disconnected, the transfer function of the power system changes as shown in Fig, 42. Since the transfer function has changed, the previous PID controller coefficients cannot provide the required transient process quality in the new

operating conditions of the power system, so they must be changed. In order for the FANN to change the old PID controller coefficients to new ones during a voltage transient, caused by a transmission line commutation, it must determine which new PID controller coefficients should be used. The neural network produces new coefficients based on the learned patterns of changes of the monitored signals («e» and «q») in order to provide the required transient process quality. These signals are fed through special buffers to the network and by analyzing how they changes during the transients it produce new coefficient for a PID controller terms.

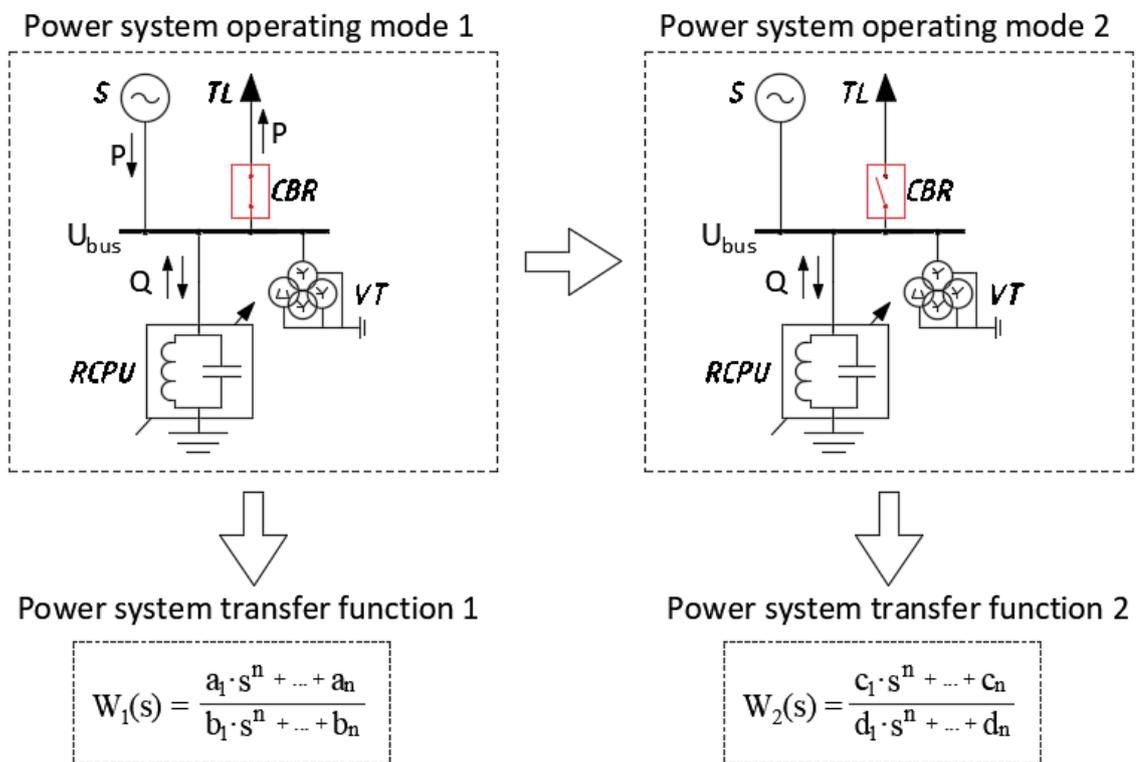


Fig. 42 – The illustration of the power system transfer function change due to the disconnection of power transmission line (TL) via circuit-breaker (CBR).

Thus, the learning sample is formed as follows: the input vectors are the timeframes of signals «e» and «q», the vectors of network desired result are the required PID controller coefficients for the particular behavior of these signals. When disconnecting various transmission lines in the power system, the transient process of voltage change, measured at the bus of considered substation will be different. Therefore, there were selected PID controller coefficients to satisfy the required quality of the transient process for every

considered power transmission line disconnection. Of course, it was considered the disconnection of some lines to form a training array. The network response to a disconnection of lines, which were not included in the training array will be also investigated in the experiments.

The following quality parameters were selected:

- Settling time (t_{settling}) of 1 second;
- Overshoot (os) no more than 1%;
- At the control error (Δ) of no more than 0,01%

Considered quality parameters are shown in Fig. 43.

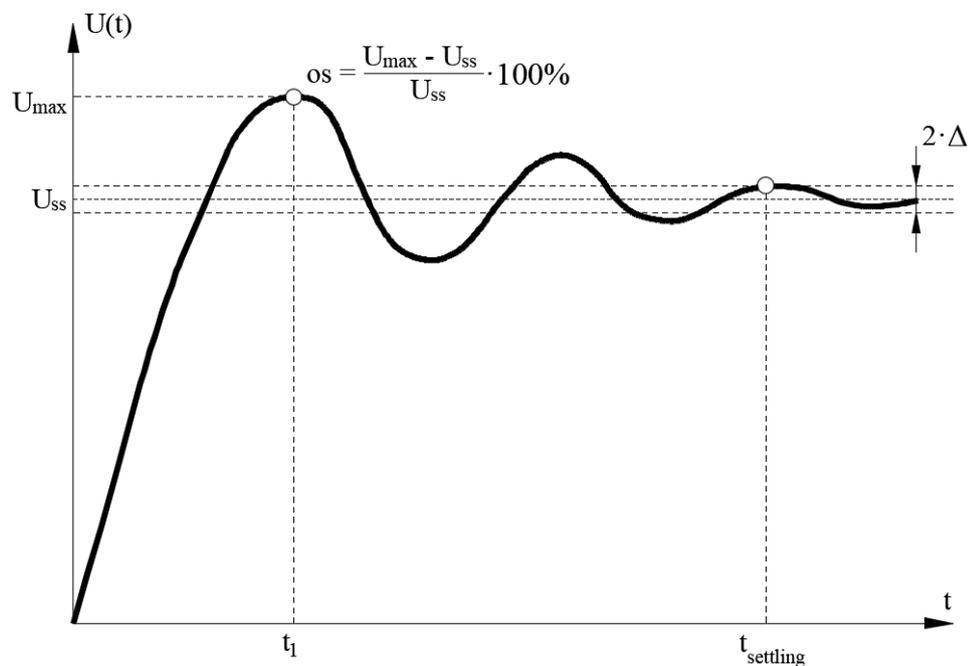


Fig. 43 – Quality parameters of a transient process.

The values of quality parameters we selected as a trade-off between the requirements for power SR control, described in [20] and the amount of computational resources needed for ANN training and the data processing. As the RCPU system to be controlled consists of power SRs and SVCs, there is no clear requirements in a form of technological design standard for a quality of a control process, which should be provided by the combined systems. And which values of control quality parameters should be considered as required, is a specific separate topic to be discussed. However, they can be selected more strictly, which will increase the time needed for the whole work to be done, because of increase in a

data to be processed. The coefficients of the PID controller terms were calculated using the «PID tuner» program extension in MATLAB. The coefficients were calculated for the obtained transfer functions of the power system to satisfy quality goals mentioned above. When one of the transmission lines is disconnected a new transfer function of the control object was identified. Identification was carried out using the «System Identification Toolbox» in MATLAB. It was made based on the recorded graphs of the voltage transient process, measured on the substation bus. The voltage transient process was recorded as a response to applying of test step signal. This step signal was modeled as step switch of the RCPU system to the mode of reactive power consumption from 0 to 360 MVAR. The explanation flowchart of this process is shown in Fig. 44.

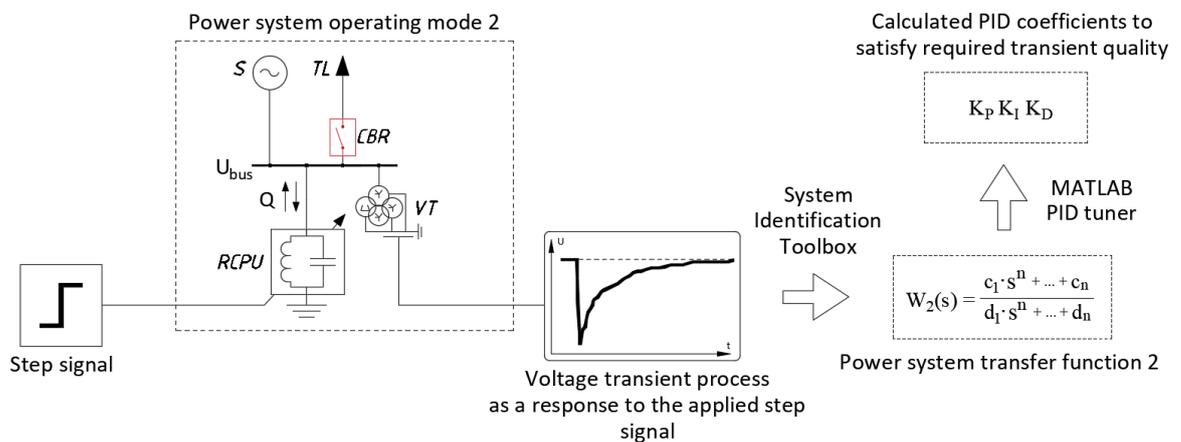


Fig. 44 –The procedure of PID controller coefficients calculation.

The example of measured voltage response and the applied step signal is shown in Fig. 45.

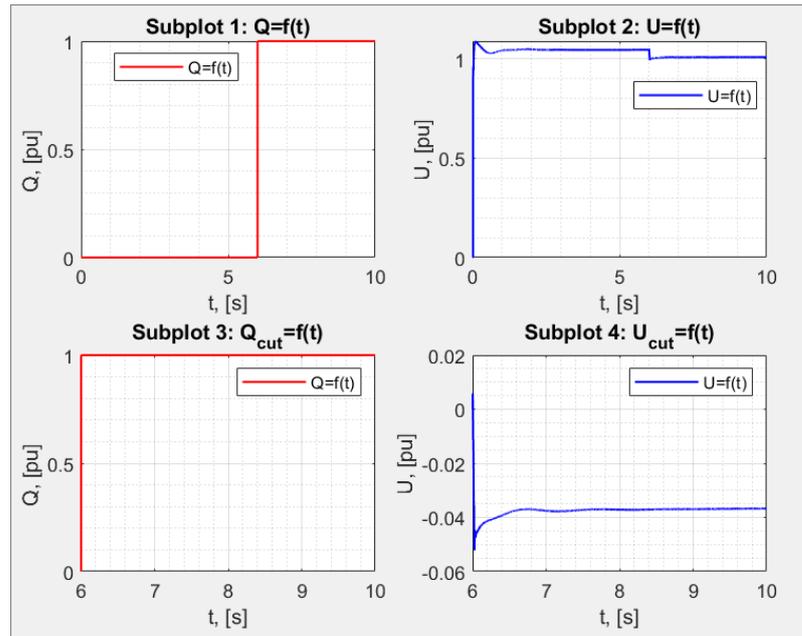


Fig. 45 – The recorded graphs, which are necessary for identification of power system transfer function: «Subplot 1» show test step signal; «Subplot 2» shows the voltage transient as a response; «Subplot 3» and «Subplot 4» show the same curves in cropped and scaled form, ready to be fed into System Identification program.

The «Subplot 1» graph of Fig. 45 shows the switch of the RCPU system to consume of 360 MVAR (1 pu), and the «Subplot 2» graph shows the voltage transient as a response.

Based on the identification results, the control object is described by a 13th-order transfer function. The curve of the measured voltage transient matches with the response from identified transfer function by 96%, as shown in Fig. 46.

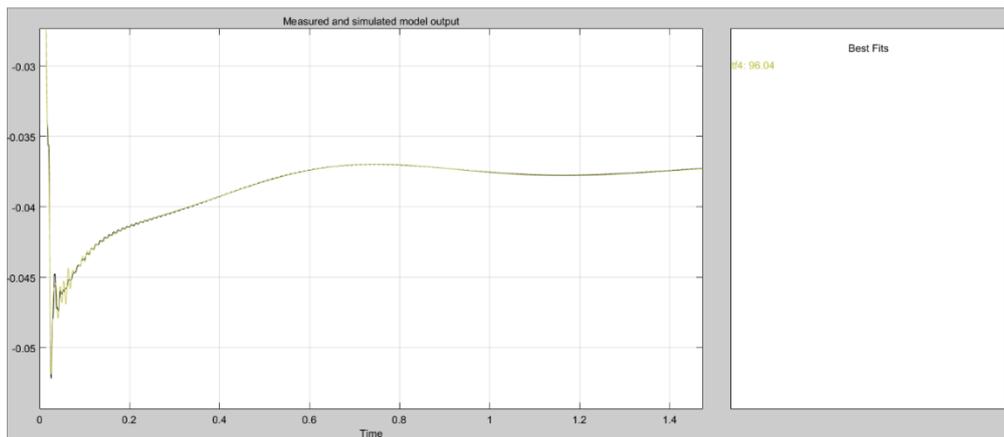


Fig. 46 - Comparison results of the recorded voltage transient curve (black one) caused by the application of test step signal with the response (yellow one) from identified transfer function of the power system.

Thus, when the selected transmission line was disconnected, the voltage transient was recorded, and the corresponding power system transfer function was identified in order to calculate optimal controller coefficients for it.

Next, a series of simulations was performed. The disconnection of each selected transmission line was simulated at various PID controller coefficient. In total, the disconnection of seven different power transmission lines were considered. Each of the disconnection was simulated with eight different sets of PID controller coefficients, while only one of eight set is correct for this disconnection and provides the required quality of the transient process. With this approach to form the training data, the neural network during the learning process is trained how to understand under which transient process pattern which coefficients of the PID controller should be used. A total of 56 different combinations for modelled. Also, one additional simulation with standard PID controller coefficients was performed and included in the training set, when there is no transmission line disconnection. It was made to train the network how it should behave in a steady state operation of the power system. A total of 57 different cases were simulated. The duration of the recorded transients is 2.5 seconds with a sampling of 0.01 seconds, that is, one simulation is recorded as an array with a string of 251 elements. After processing the recorded array in a circular buffer, one training array becomes 10x251 elements. There are 57 training arrays in total, they are combined into a single training set and represent the final array of input training data of 10x14307 elements. The final array of the desired network output, consisting of PID controller coefficients, is an array of 3x14307 elements. The diagram of training arrays formation is shown in Fig. 47.

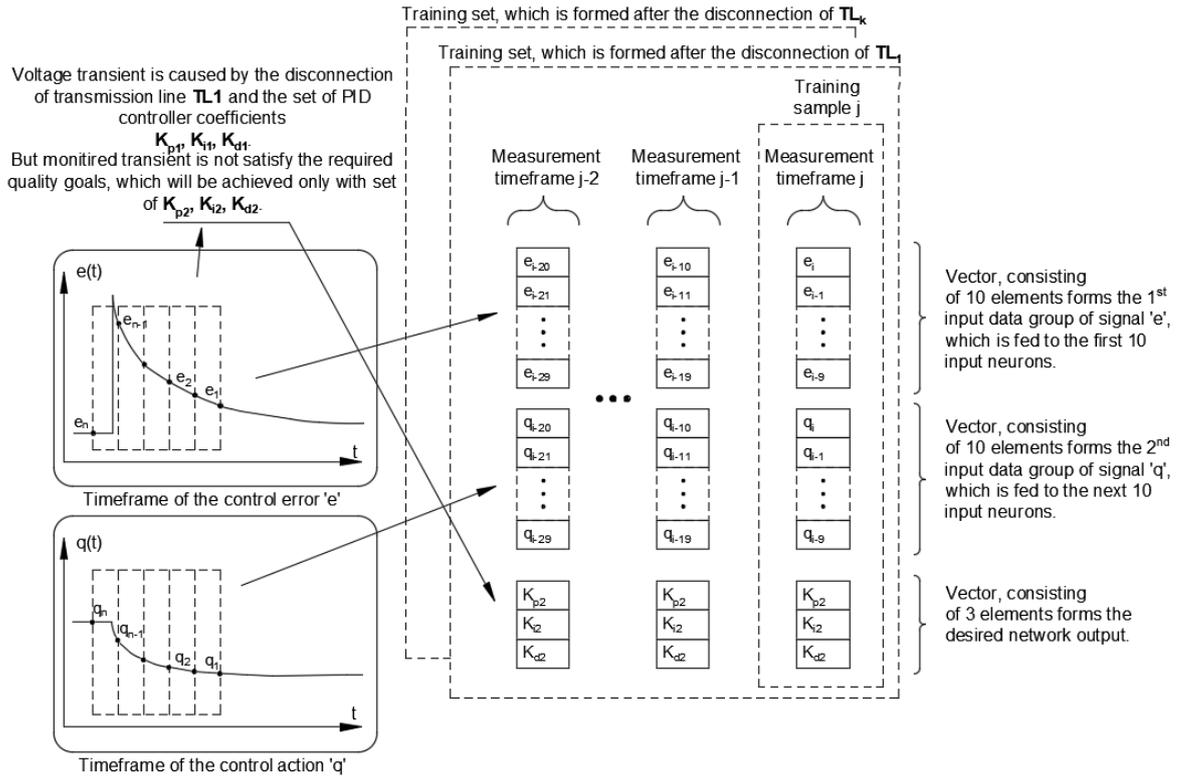


Fig. 47 – The explanation diagram of training data formation.

As it was mentioned above, the training data were divided into three groups: training set - 70%, validation set - 15%, test set - 15%. On the training dataset, the network is trained using the selected training method. Then, on the test data, the trained neural network is used to predict responses, which are compared with the desired network outputs stored in the test set. Finally, on the test data, the trained neural network is objectively and generally assessed if it comply with training data.

The complete model of designed adaptive control system in Matalb Simulink.

After the neural network was created and trained on the formed data in Matlab workspace, it was exported to Matlab Simulink environment for testing purposes to operate as adaptor and tune the PID controller. The complete model of designed control system of reactive power compensation units is shown in Fig. 48.

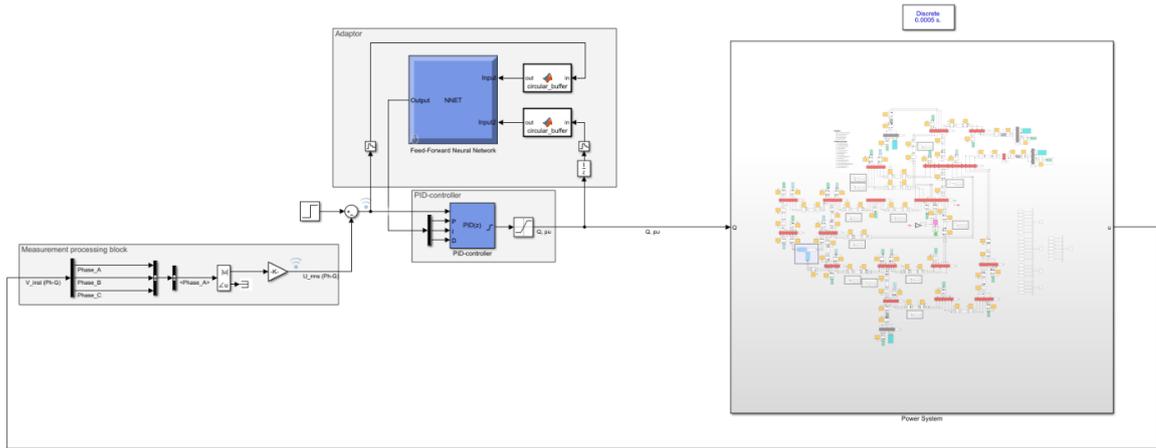


Fig. 48 – The complete model of designed control system of RPCUs.

4 EXPERIMENT RESULTS OF DESIGNED ADAPTIVE CONTROL SYSTEM

Testing of the designed adaptive control system was carried out at power system operating modes, which were considered and included in the training data, as well as at the ones, which were not included in them.

Disturbances, which lead to an appearance of a particular power system mode and cause voltage transients, measured at the installation site of the RCPU system at Novo-Anzherskaya power substation are disconnections of various power transmission lines. The names of transmission lines to be disconnected during the test simulations are shown in Figure 48 with red color.

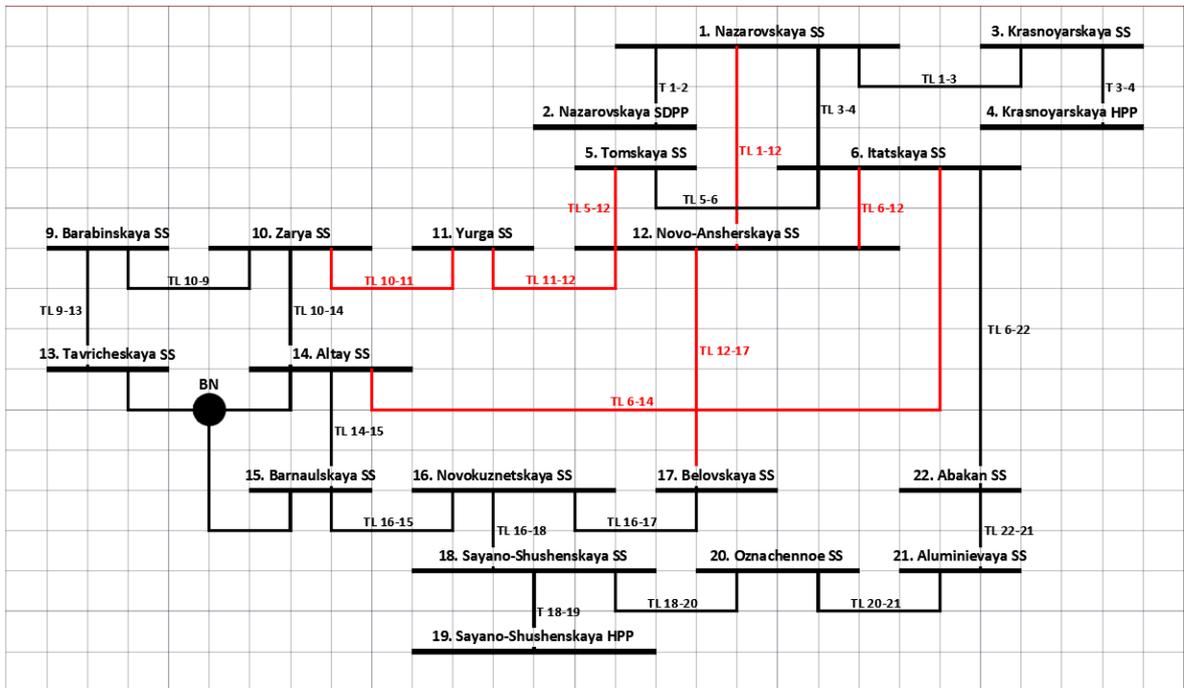


Fig. 49 – The grid diagram of modelled power system with presentation of power transmission lines to be disconnected during the test simulations, marked with red color.

As the results of test simulations, oscillograms of voltage transients measured at the high-voltage busbar of Novo-Anzherskaya power substation, and the time plots of solutions, produced by the FANN based adaptor were recorded. The description of test simulations and the recorded graphs are presented in Appendix 1.

Also, after the simulation data was obtained, the following parameters for performing the analysis of FANN operation were calculated:

- The average time, which is taken by the neural network to asymptotically produce the converged solutions with a given error of its steady-state values (ATPS) in relation to a settling time (ATPSST):

$$atpsst = \frac{1}{3} \cdot \frac{t_p + t_i + t_d}{t_{settling}} \cdot 100\% \quad (7)$$

In relation to the time of the voltage transient to be completely finished (ATPSTT):

$$atpstt = \frac{1}{3} \cdot \frac{t_p + t_i + t_d}{t_{transient}} \cdot 100\% \quad (8)$$

where t_p , t_i and t_d are the times in seconds which were taken by the FANN to asymptotically produce the converged values of respective PID controller coefficients with an error of 0,5% of its steady-state value; $t_{settling}$ is a settling time of a transient process when control error is 0,5%; $t_{transient}$ is the time of the voltage transient to become completely finished, when control error is 0,01%

- The average deviation error (ADE) of the converged PID controller coefficients, produced by the neural network from desired coefficients for a particular operating mode of the power system at the end of solution convergence process:

$$ade = \frac{1}{3} \cdot \sum_{i=1}^3 \left| \frac{\Delta K_i}{K_{i_{desired}}} \right| \cdot 100\% = \frac{1}{3} \cdot \sum_{i=1}^3 \left| \frac{K_{i_{desired}} - K_{i_{result}}}{K_{i_{desired}}} \right| \quad (8)$$

where $K_{i_{result}}$ - the converged value of PID term coefficient (proportional, integral or derivative), produced by FANN; $K_{i_{desired}}$ - the coefficient of PID term, which was calculated for a particular power system operating mode and stored in training data. The convergence process of solutions produced by the FANN is finished when the difference between the produced solutions and the steady-state ones become 0.5%.

4.1 Analysis of the simulation results, based on the data obtained.

Disconnection of the power transmission line «TL 6-12»

When the power transmission line «TL 6-12» is disconnected, the difference between measured RMS voltage value and the desired one become less than 0.5% of the setpoint at

0.38 second from the start of the transmission line commutation process. The settling time with a control error of 0.5% is 0.38 seconds.

After 1 second, the value of measured RMS voltage level reaches the desired value, with a control error less than 0.001% of the setpoint. Thus, the voltage transient process after the 1 second can be considered as completely finished and turned into steady state.

The disconnection of transmission line «TL 6-12» was included in the training data, so it can be concluded that FANN successfully identified patterns of the transient process, caused by the disconnection of transmission line and tuned the coefficients of the PID controller to the new ones.

The average deviation error of the produced PID controller coefficients from the desired ones is 0.14%. The average time, which is taken by the neural network to produce the converged values of PID coefficients is 0,155 second or 40.8% in relation to a settling time, or 15.5% in relation to a duration of the transient process.

Disconnection of the power transmission line «TL 10-11»

When the power transmission line «TL 10-11» is disconnected, the difference between measured RMS voltage value and the desired one become less than 0.5% of the setpoint at 0.1 second from the start of the transmission line commutation process. The settling time with a control error of 0.5% is 0.1 seconds.

After 1 second, the value of measured RMS voltage level reaches the desired value, with a control error less than 0.001% of the setpoint. Thus, the voltage transient process after the 1 second can be considered as completely finished and turned into steady state.

The disconnection of transmission line «TL 10-11» was included in the training data, so it can be concluded that FANN successfully identified patterns of the transient process, caused by the disconnection of transmission line and tuned the coefficients of the PID controller to the new ones.

The average deviation error of the produced PID controller coefficients from the desired ones is 0.84%. The average time, which is taken by the neural network to produce the converged values of PID coefficients is 0,275 second or 275% in relation to a settling time, or 27,5% in relation to a duration of the transient process.

The increased value of ATPS is caused by slower asymptotically approach of K_d coefficient to a desired value in comparison with two other coefficients. Coefficient K_d

approached the desired value with a given error of 0.5% at 0.671 seconds, while two other coefficients – at 0.1 seconds.

Disconnection of the power transmission line «TL 5-12»

The disconnection of transmission line «TL 5-12» was not included in the training data. However, the neural network could identify patterns of the transient process, caused by the disconnection of transmission line and tuned the coefficients of the PID controller to the new ones with an arbitrary well accuracy within the duration of the voltage transient process. But from the oscillograms it can be seen that the values of the PID controller coefficients starts to increase after some time. Despite that fact, a further smooth change in its values will not cause any major problems, because to that time the transient process is finished.

The average deviation error of the produced PID controller coefficients from the desired ones is 5.69%. The average time, which is taken by the neural network produce the converged values of PID coefficients is 0,279 second or 698% in relation to a settling time, or 57,01% in relation to a duration of the transient process.

At the disconnection of this line, there was a quite insignificant disturbance and, as a result, a slight deviation of measured voltage from the desired value, so the value of settling time was extremely short of 0,04 seconds. In comparison to this value of settling time the time, which is needed by FANN to produce correct coefficients seems quite long.

Disconnection of the power transmission line «TL 6-14»

The disconnection of transmission line «TL 5-12» was not included in the training data. However, the neural network could identify patterns of the transient process, caused by the disconnection of transmission line and tuned the coefficients of the PID controller to the new ones. Even though the FANN produced some solutions, they were not optimal, because the disconnection of «TL 6-14» caused such a different and unexpected behavior of the transient process, which were not considered in the training data.

After the disconnection of transmission line TL 6-14, the convergence process of the solutions, produced by the FANN to the desired values has strong (with an amplitude up to 46% of the steady-state value) but short-lived oscillations (duration up to 0.13 second), which was damped after about 30% of the settling time value. So, it can be concluded, that

it was hard for the FANN to identify this power system operating mode and produce the correct values of the PID controller coefficients for it at the first moments of transient process based on learnt patterns.

The average deviation error of the produced PID controller coefficients from the desired ones is 28%. The average time, which is taken by the neural network to produce the converged values of PID coefficients is 0.125 second or 13.2% in relation to a settling time, or 7.813% in relation to a duration of the transient process. Due to the incorrect values of PID controller, there was not achieved the required duration of the transient process. Instead of 1 second, it was resulted in 1.6 seconds.

4.2 Summarizing the results from the obtained data.

The parameters of the FANN operation, which were discussed above were calculated and summarized in table 3.

Table 3. Calculated parameters of the FANN operation for a particular simulation.

Disc. TL	Desired PID controller coefficients			ADE, %	ATPS			Converged values of PID controller coefficients			Time, which is taken by the FANN to produce converged solutions with the error $\Delta=0,5\%$			Settling time $\Delta=0,5\%$	Settling time $\Delta=0,01\%$
	Kp	Ki	Kd		sec.	T _{settling} , %	T _{transient} , %	Kp	Ki	Kd	Tp, sec.	Ti, sec.	Td, sec.	T _{settling} , sec.	T _{transient} , sec.
6-12	0,8367	83,668	0,0021	0,14	0,155	40,8	15,5	0,8369	83,669	0,00209	0,122	0,122	0,221	0,38	1
10-11	0,9821	98,207	0,0025	0,84	0,275	275	27,5	0,99	98,7	0,00247	0,082	0,072	0,671	0,1	1
5-12	1,0576	105,762	0,0026	5,69	0,279	698	57,01	0,992	99,2	0,00248	0,39	0,038	0,41	0,04	0,49
6-14	1,1175	111,751	0,0028	28,01	0,125	13,2	7,813	0,805	80,517	0,00201	0,133	0,111	0,131	0,95	1,6
Average value:				8,67	0,209	257	26,95				0,182	0,086	0,36	0,368	1,023

On the average, the FANN based adaptor provides an error of the PID controller coefficients tuning of about 2-3%, if the identification of a transient pattern was successful. However, its behaviour at the completely unknown situations can significantly increase this error. The average time for the FANN to produce the converged values of the PID controller coefficients is about 0.2-0.3 seconds and about 30% of the duration of the transition process. These values do not demonstrate any major correlations between the operating modes, whether it was included in the training set or not. After that time the neural network is able to produce some converged solutions. So it mostly depends on the designing parameters of the FANN and its operation.

Also, it can be noticed from the graphs of PID controller coefficients variation, caused by FANN operation over the simulation process, they have almost similar variation pattern between one another for each coefficient of PID controller within one simulation.

The designed FANN-based adaptive control system in most modes is able to perform a correct identification and provide the required quality parameters of the transition process. The network's ability to adapt qualitatively significantly depends on the training data, as well as on its accuracy and preprocessing. To reduce the error in the tuning of the PID controller coefficients and to reduce the time of production their converged values with sufficient accuracy, a proper analysis of the operating modes of the control object should be carried out. Training data should include in itself wide range of possible different modes of the control object operation. This will allow the network to approximate its behavior on unknown operating modes better. The training data includes quite accurate measurements of the transients, so the trained neural network was prone to extract some unnecessary relationships in the training data, so it led to oscillations and ripples in solutions convergence process. Therefore, the postprocessing of measurements for a control system and preprocessing of the training data should involve some filtering methods. This allow the network to produce more stable solutions over time and identify more general trends.

SUMMARY

In this work there were designed an adaptive control system of reactive power compensation units control with tunable PID controller and investigated whether it possible to implement an adaptive algorithm, based on the application of feedforward artificial neural network.

The summarized results achieved in this work are as follows:

1. Based on the analysis of current trends in designing of an adaptive control systems, an algorithm for the parametric tuning of the PID controller, based on the application of a trained feedforward artificial neural network, was proposed.
2. There was created an algorithm of training data formation to perform a training of a feedforward neural network to operate as adaptor for PID controller for a particular control object.
3. The real existing part of the Siberian IES was modelled in MATLAB software package as a control object to research its behaviour in different operating modes, create training data arrays and test the designed adaptive control system.
4. There was designed the adaptive control system for automatic control of voltage and reactive power for high-voltage power substation and implemented in MATLAB software package. The system was tested and the simulation of its operation was performed in a various operating modes of the power system.
5. Based on the simulation performed the testing data was obtained and analyzed.

Algorithms and models, which were developed in this dissertation can be used as a basis for creating a software for their practical application in automatic control systems of reactive power compensation units, installed in high-voltage substations.

Further research will be aimed to study the possibility of using other types and structures of artificial neural networks, its after-retraining during the exploitation for a new detected modes; considering a new types of possible disturbances, e.g. short-circuits in power system, and power system operating modes to adapt to.

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APPENDIX 1. Results from the experiments.

For the considered operating modes of the power system, the desired RMS value of the linear voltage in the model on the bus of the Novo-Anzherskaya power substation was set as 509 kV, which in relative units is 1.018 p.u. in relation to the base value of 500 kV.

The oscillograms of voltage and reactive power transients were measured at the high-voltage bus of power Substation Novo-Anzherskaya and at the installation site of the RCPU system respectively.

Disconnection of the power transmission line «TL 6-12»

The power transmission line TL «6-12» connects Itatskaya substation and Novo-Anzherskaya substation.

This transmission line is connected to a bus of high-voltage switchgear of Novo-Anzherskaya power substation; therefore, it can be considered as electrically close to the installation site of the RCPU system.

The disconnection of the transmission line «TL 6-12» was included in the training data. The disconnection of this transmission line occurs at the time of simulation equal to 6 seconds.

The value of active power flow, which is transmitted along the line is about 550 MW and it is directed towards the Novo-Anzherskaya power substation.

The recorded graphs of voltage and reactive power transients during the simulation is shown in Fig. 50

(continues)

APPENDIX 1. (continues)

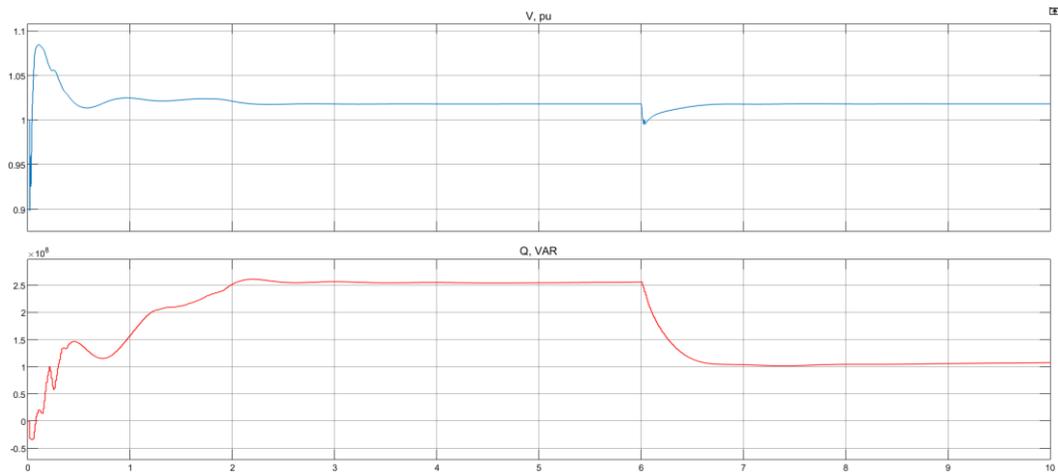


Fig. 50 – The graph of voltage (the blue one) and the RCPU system’s reactive power (the red one) transient at the disconnection of power transmission line «TL 6-12».

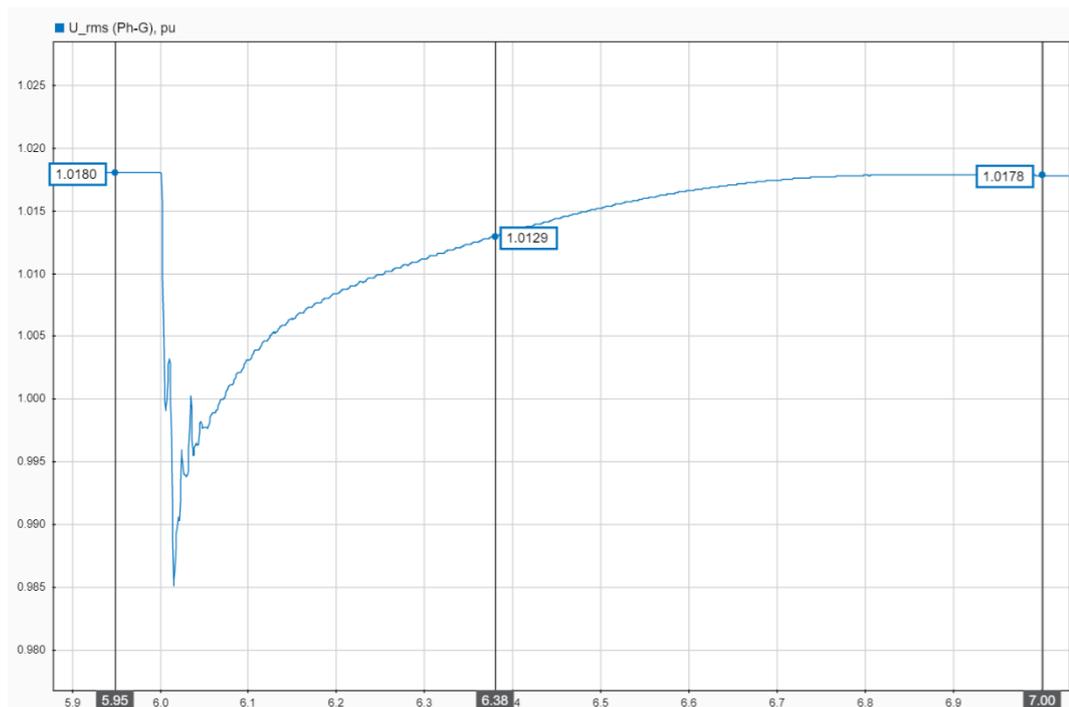


Fig. 51 – Scaled and cropped recorded transient of RMS voltage level, measured at Novo-Anzherskaya power substation at the disconnection of «TL 6-12».

The graphs of solutions, produced by the FANN, which are the coefficients of PID controller terms: proportional, integral and derivative are shown in Fig. 52, 54 and 56 respectively.

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APPENDIX 1. (continues)

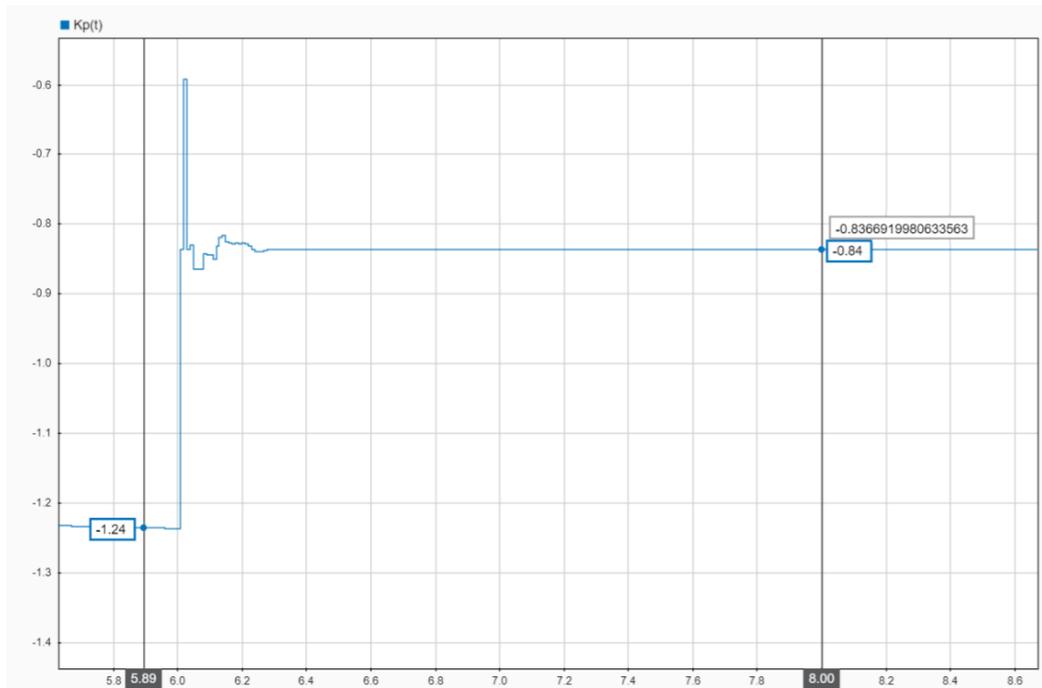


Fig. 52 – Variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 6-12».

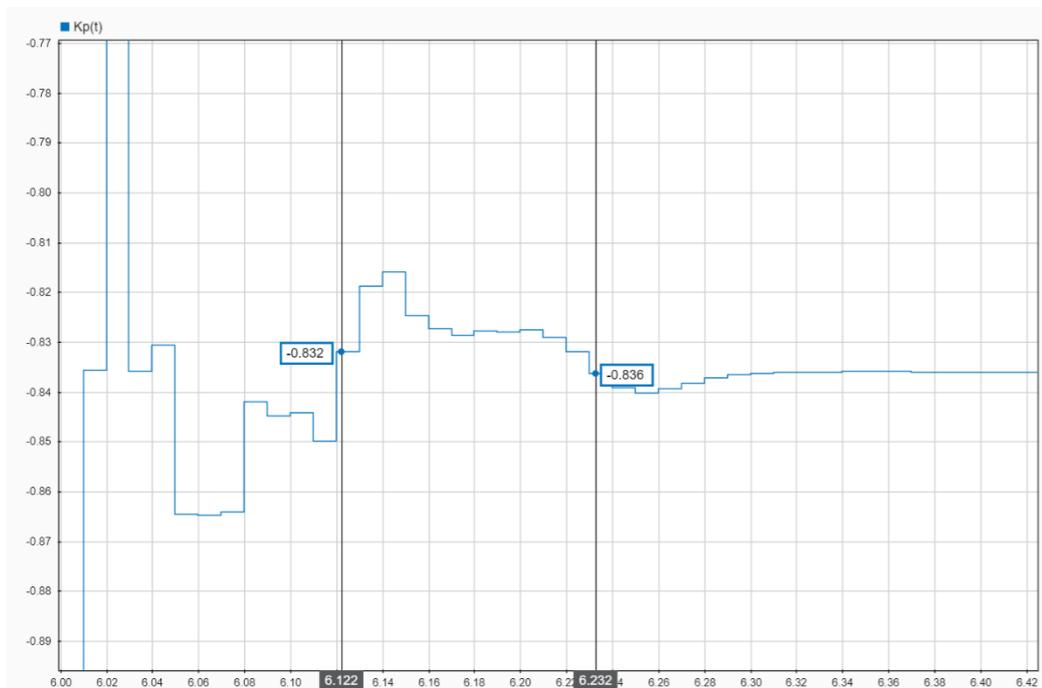


Fig. 53 – Scaled graph of variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 6-12».

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APPENDIX 1. (continues)

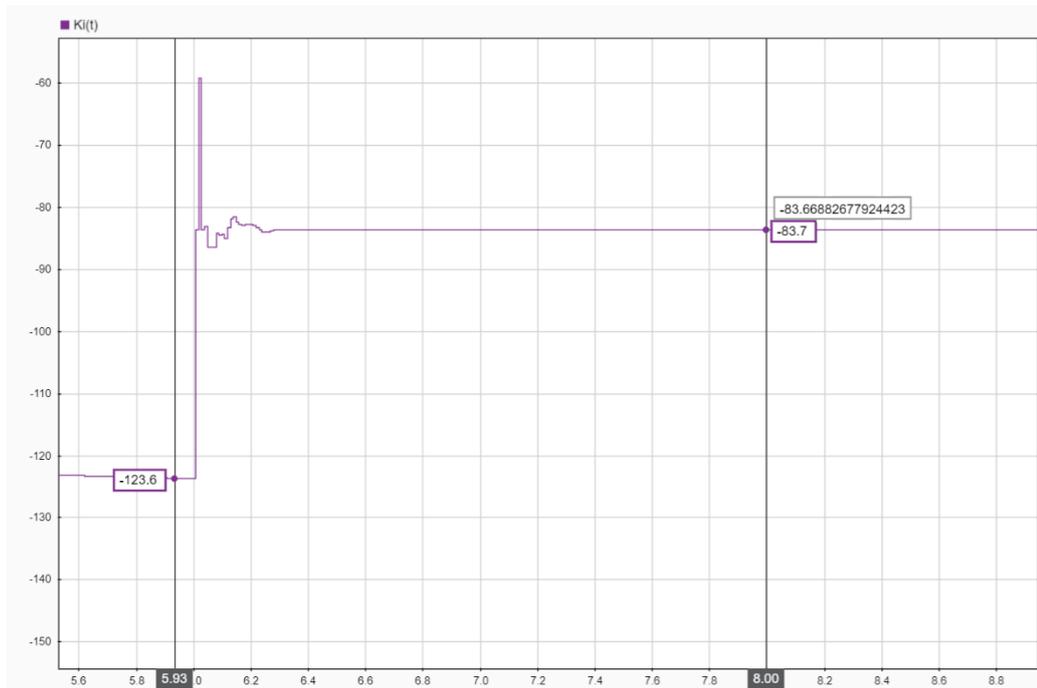


Fig. 54 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 6-12».



Fig. 55 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 6-12».

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APPENDIX 1. (continues)

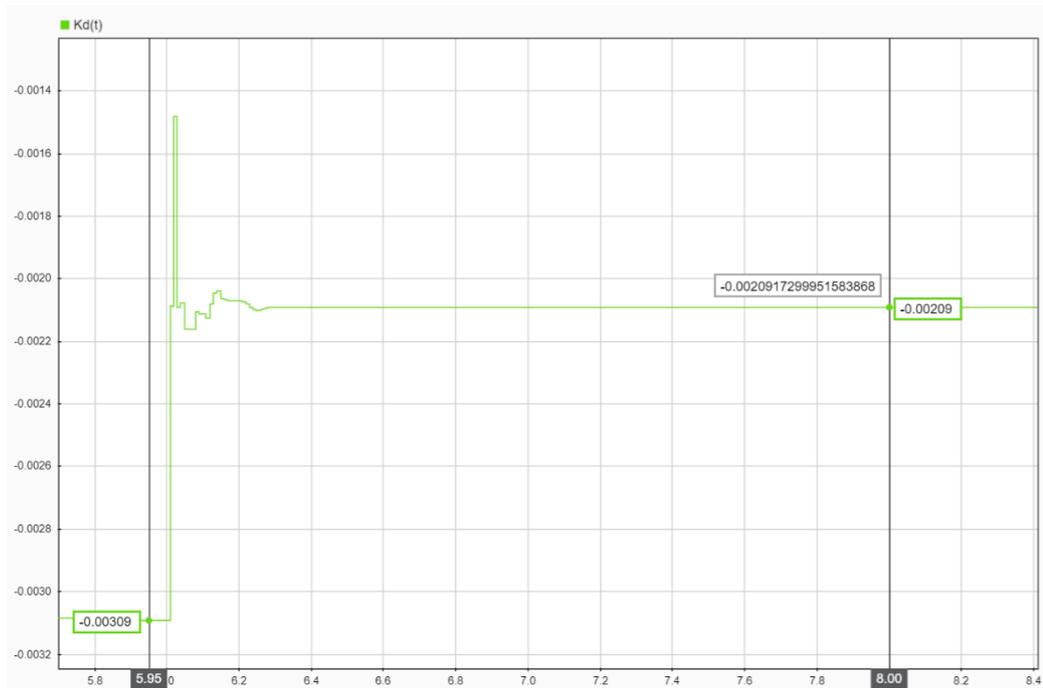


Fig. 56 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 6-12».

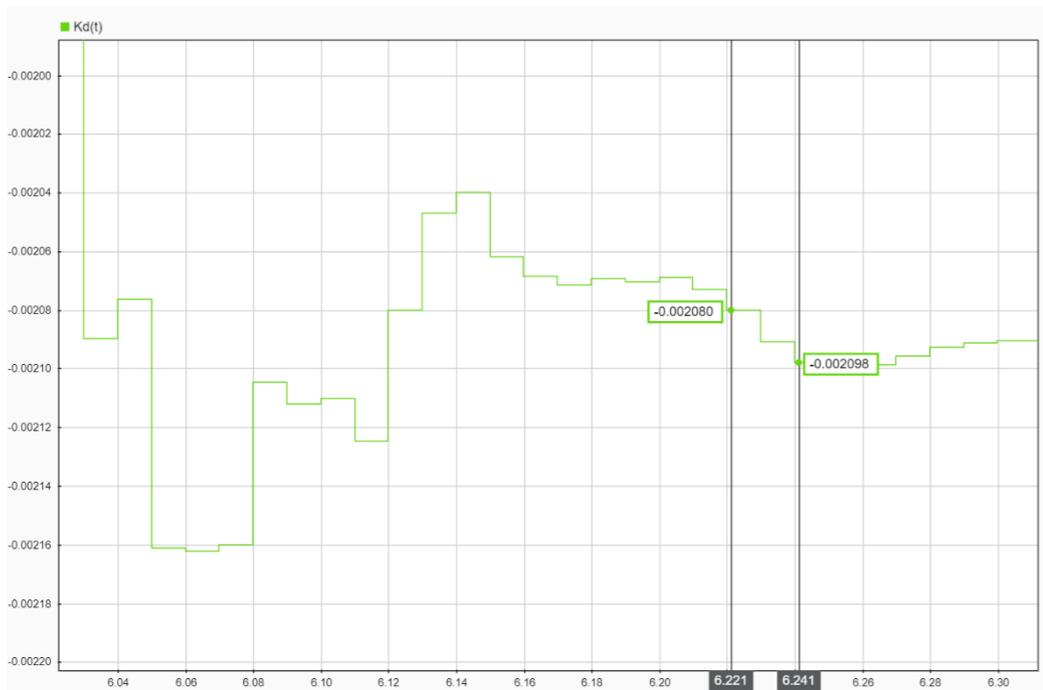


Fig. 57 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 6-12».

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APPENDIX 1. (continues)

Disconnection of the power transmission line «TL 10-11»

The power transmission line TL «10-11» connects Zarya substation and Yurga substation.

Yurga substation is an adjacent to Novo-Anzherskaya power substation; therefore, the transmission line TL «10-11» can be considered as electrically distant to the installation site of the RCPU system.

The disconnection of the transmission line «TL 10-11» was included in the training data. The disconnection of this transmission line occurs at the time of simulation equal to 6 seconds.

The value of active power flow, which is transmitted along the line is about 510 MW and it is directed from the Yurga power substation.

The recorded graphs of voltage and reactive power transients during the simulation is shown in Fig. 58

(continues)

APPENDIX 1. (continues)

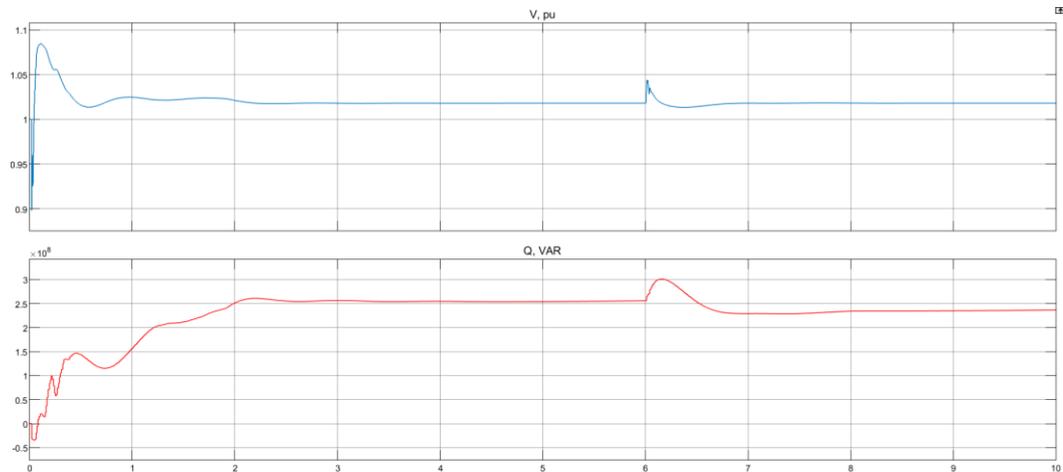


Fig. 58 – The graph of voltage (the blue one) and the RCPU system’s reactive power (the red one) transient at the disconnection of power transmission line «TL 10-11».

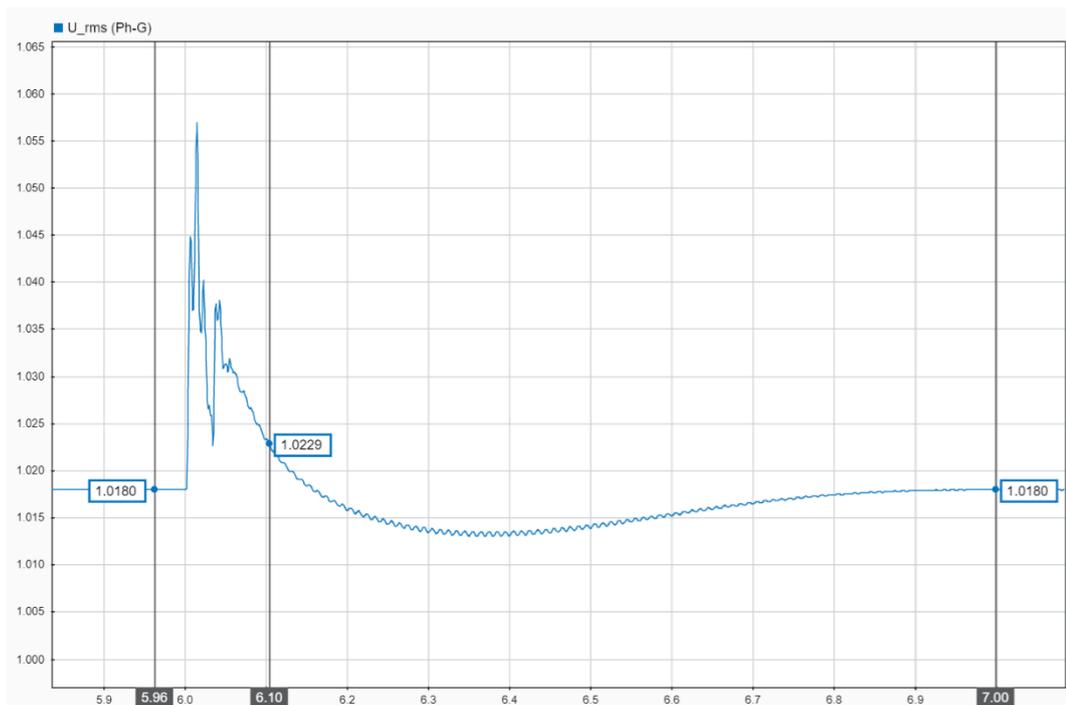


Fig. 59 – Scaled and cropped recorded transient of RMS voltage level, measured at Novo-Anzherskaya power substation at the disconnection of «TL 10-11».

The graphs of solutions, produced by the FANN, which are the coefficients of PID controller terms: proportional, integral and derivative are shown in Fig. 60, 62 and 64 respectively.

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APPENDIX 1. (continues)

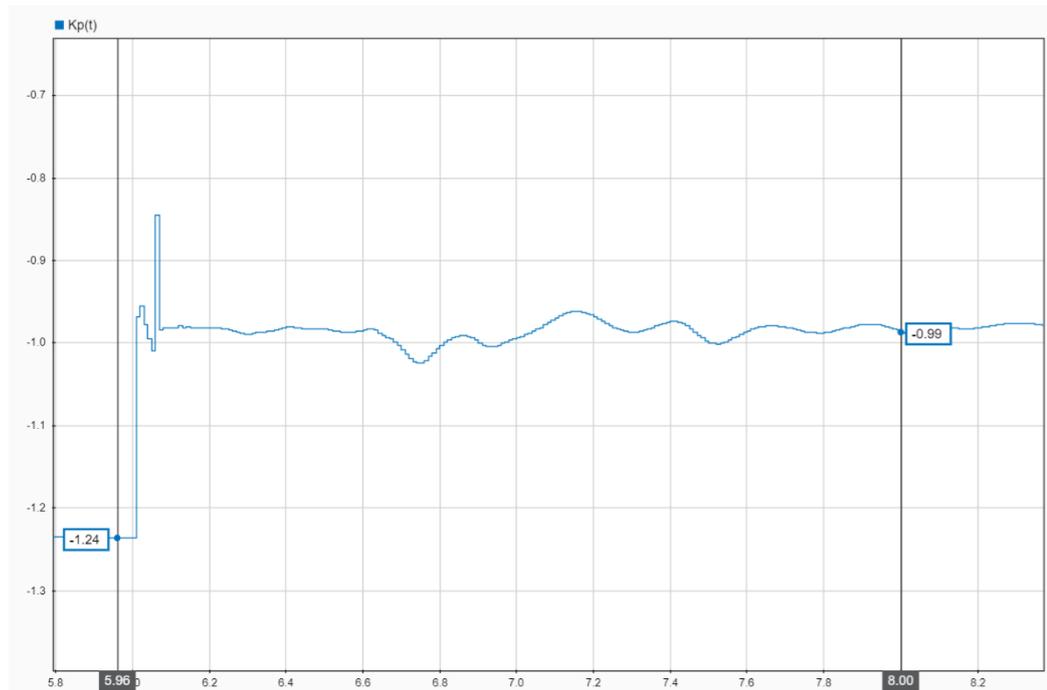


Fig. 60 – Variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 10-11».

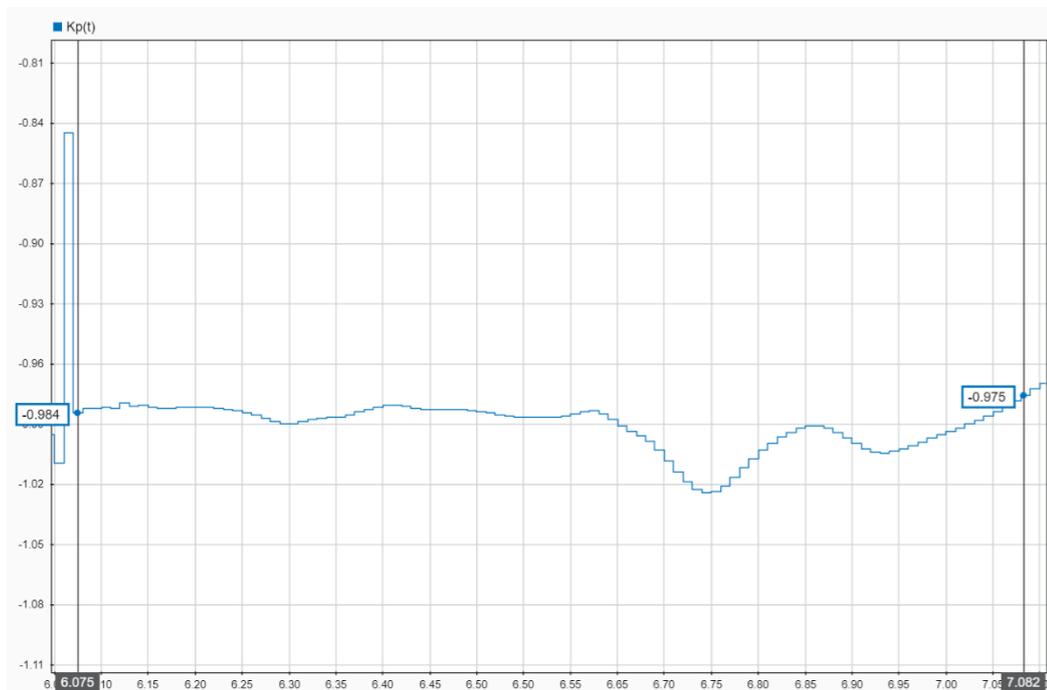


Fig. 61 – Scaled graph of variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 10-11».

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APPENDIX 1. (continues)



Fig. 62 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 10-11».

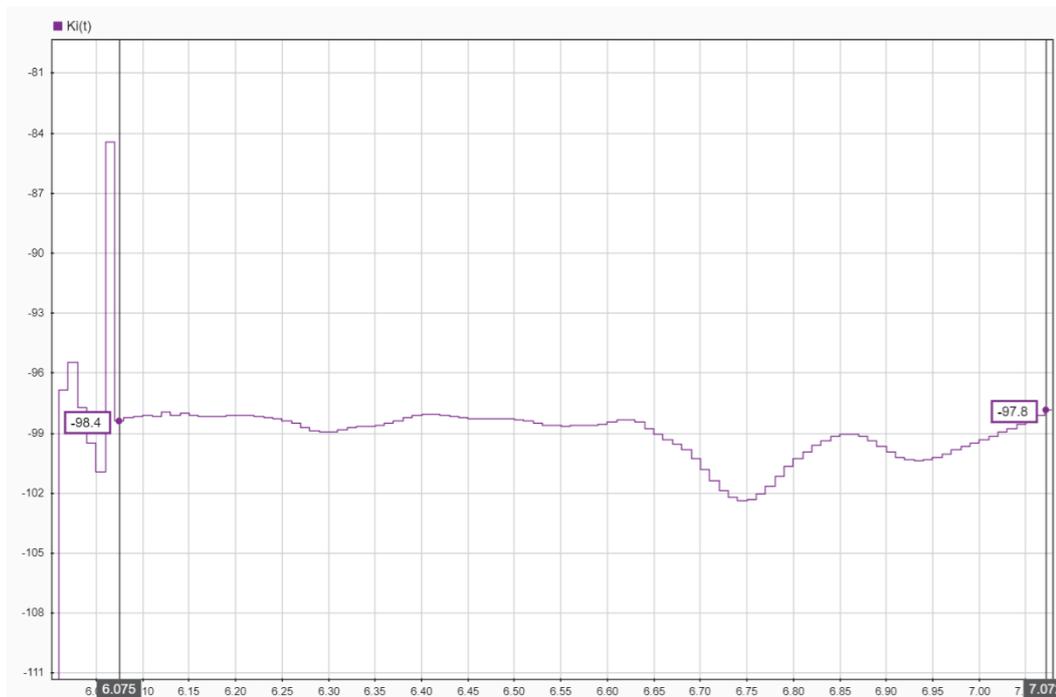


Fig. 63 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 10-11».

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APPENDIX 1. (continues)



Fig. 64 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 10-11».

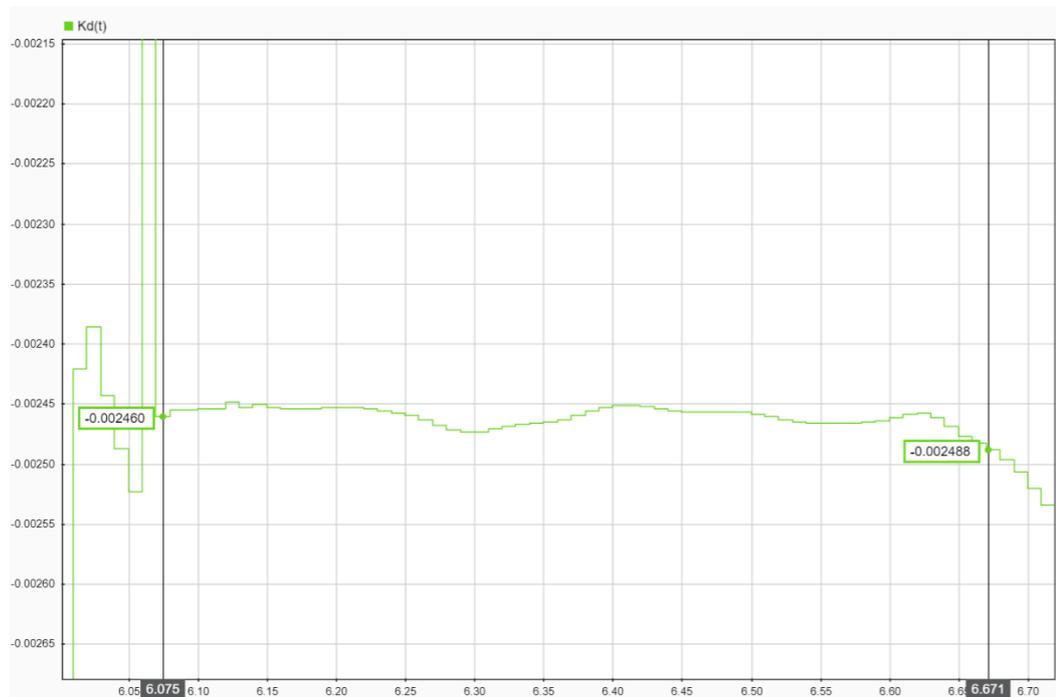


Fig. 65 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 10-11».

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APPENDIX 1. (continues)

Disconnection of the power transmission line «TL 5-12»

The power transmission line TL «5-12» connects Tomskaya substation and Novo-Anzherskaya substation.

This transmission line is connected to a bus of high-voltage switchgear of Novo-Anzherskaya power substation; therefore, it can be considered as electrically close to the installation site of the RCPU system.

The disconnection of the transmission line «TL 5-12» was not included in the training data.

The disconnection of this transmission line occurs at the time of simulation equal to 6 seconds.

The value of active power flow, which is transmitted along the line is about 15 MW and it is directed towards the Novo-Anzherskaya power substation.

The recorded graphs of voltage and reactive power transients during the simulation is shown in Fig. 66

(continues)

APPENDIX 1. (continues)

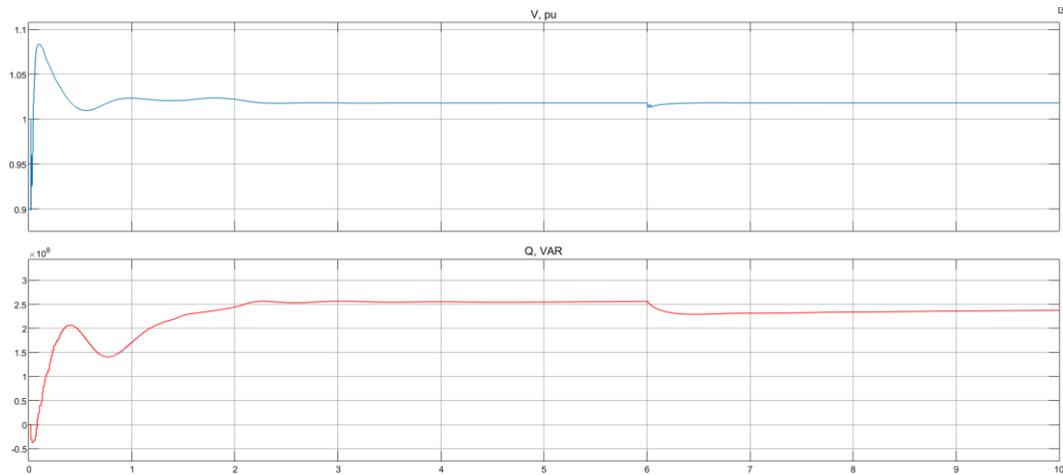


Fig. 66 – The graph of voltage (the blue one) and the RCPU system’s reactive power (the red one) transient at the disconnection of power transmission line «TL 5-12».

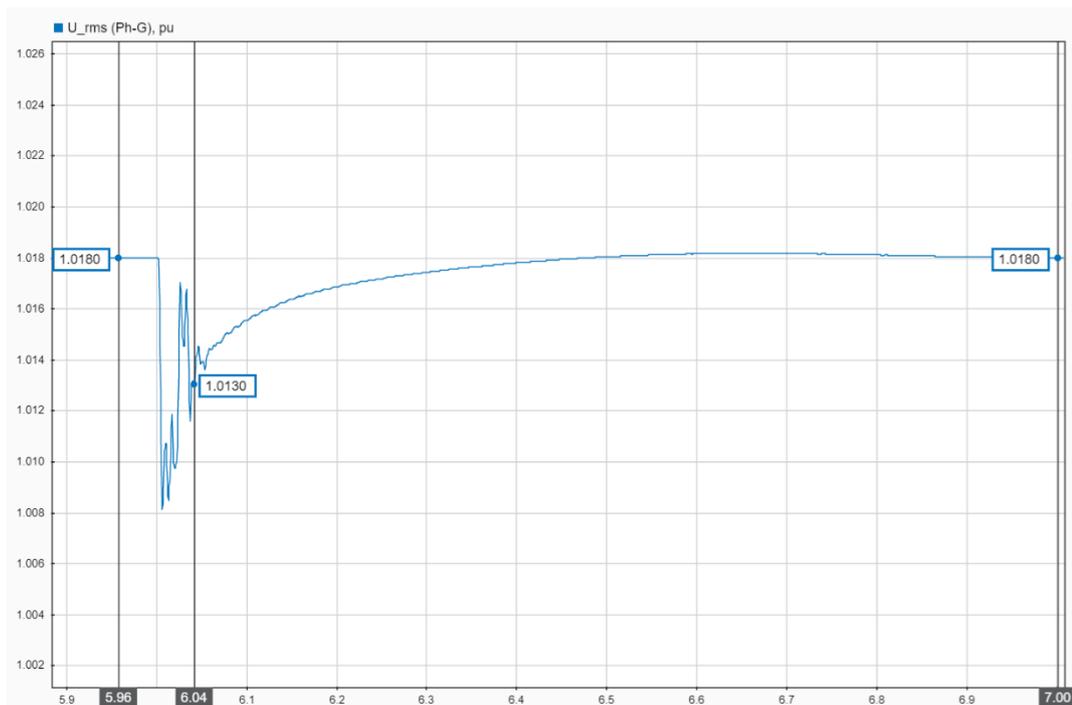


Fig. 67 – Scaled and cropped recorded transient of RMS voltage level, measured at Novo-Anzherskaya power substation at the disconnection of «TL 5-12».

The graphs of solutions, produced by the FANN, which are the coefficients of PID controller terms: proportional, integral and derivative are shown in Fig. 68, 70 and 72 respectively.

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APPENDIX 1. (continues)

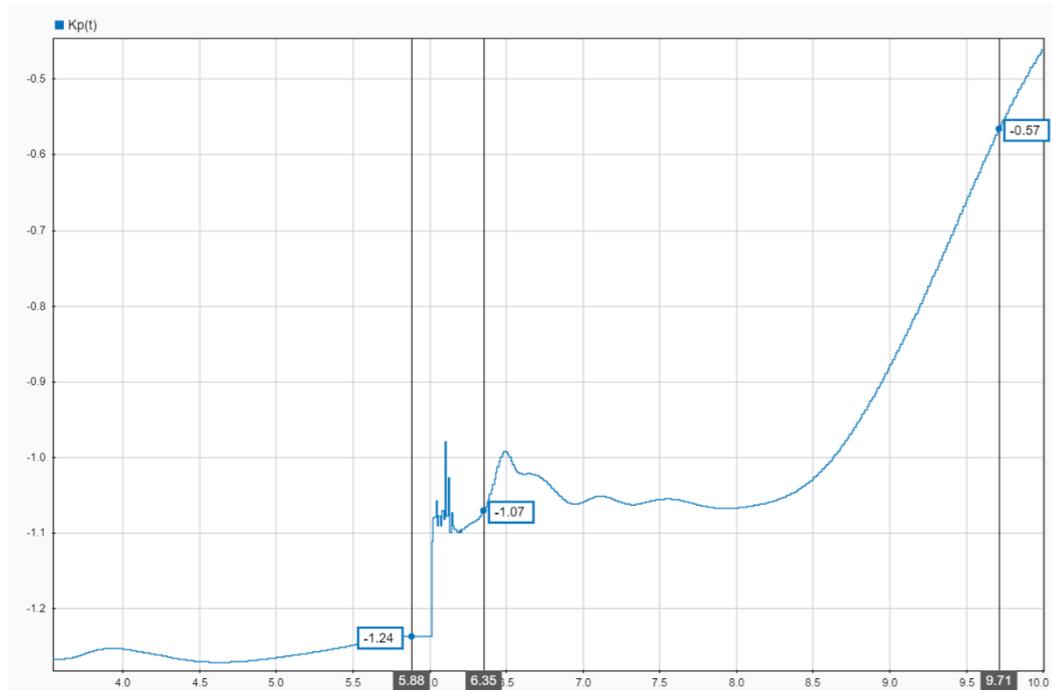


Fig. 68 – Variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 6-12».

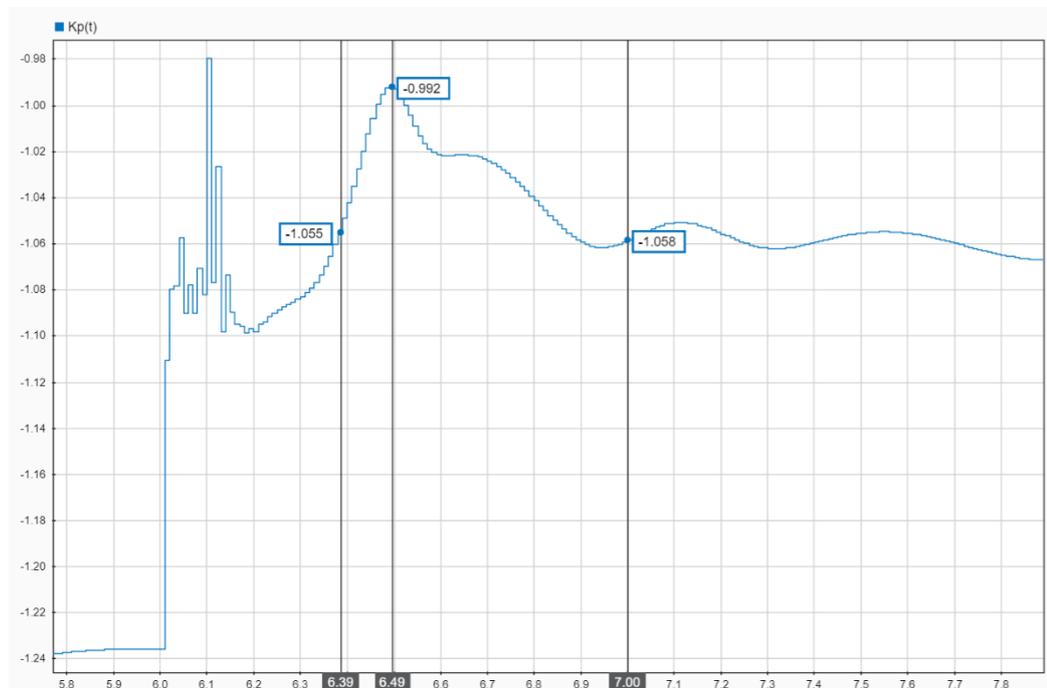


Fig. 69 – Scaled graph of variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 5-12».

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APPENDIX 1. (continues)

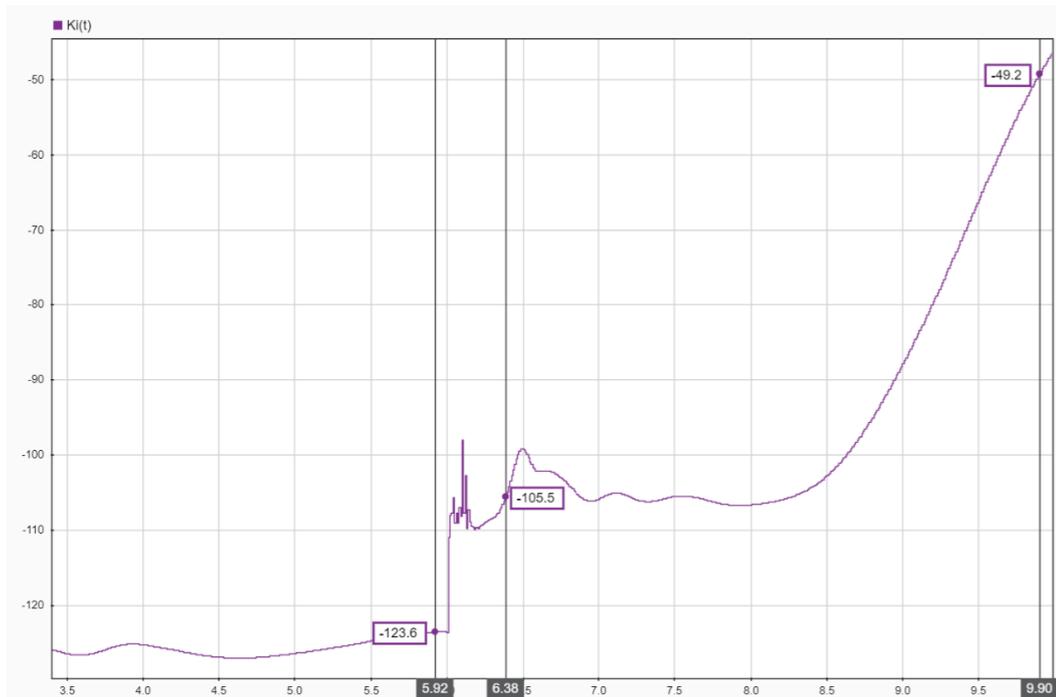


Fig. 70 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 5-12».

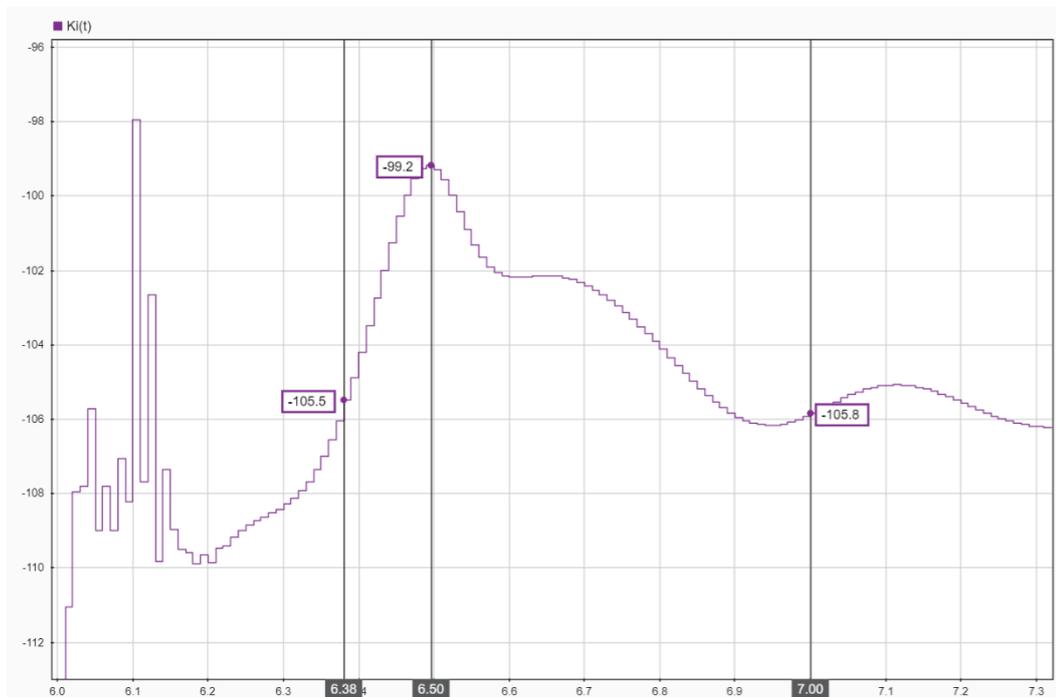


Fig. 71 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 5-12».

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APPENDIX 1. (continues)

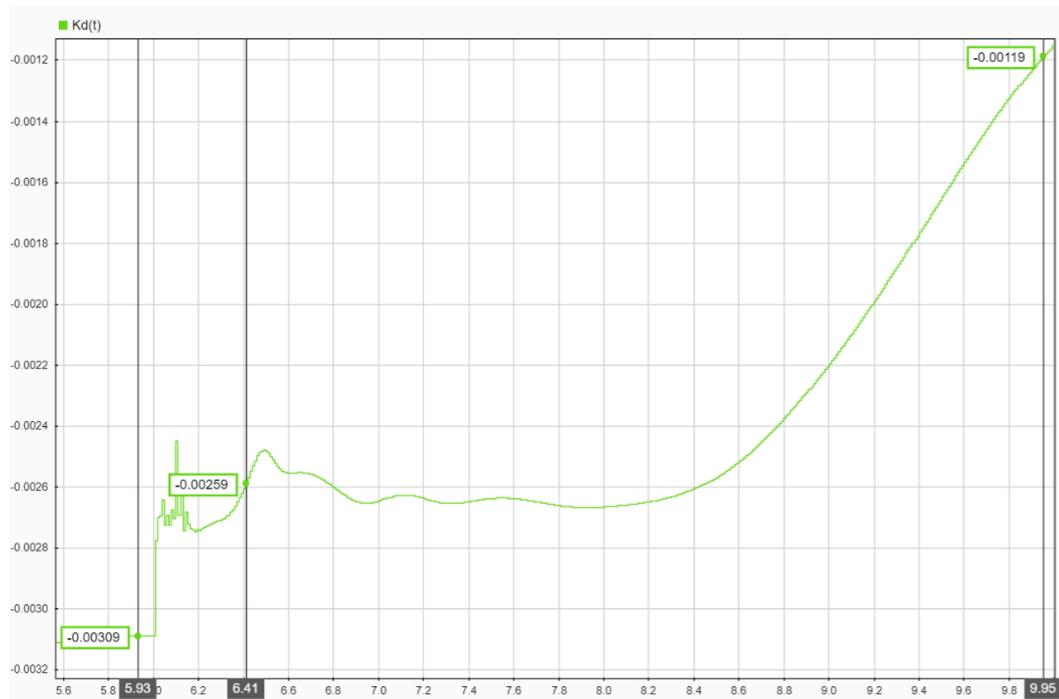


Fig. 72 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 5-12».

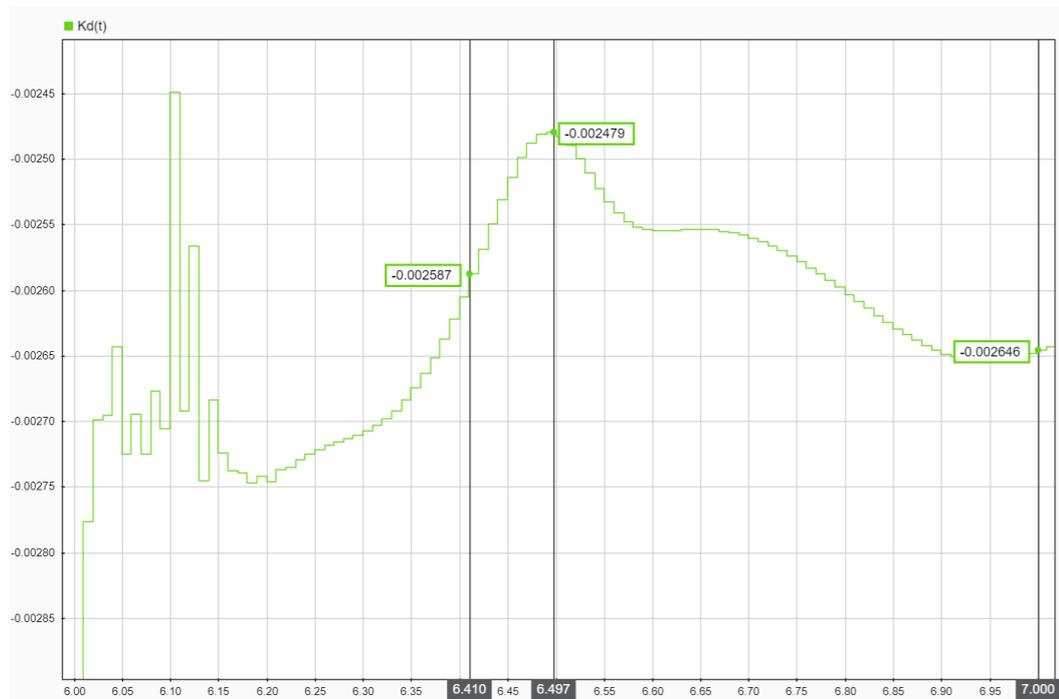


Fig. 73 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 5-12».

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APPENDIX 1. (continues)

Disconnection of the power transmission line «TL 6-14»

The power transmission line TL «6-14» connects Itatskaya substation and Altay substation.

Itatskaya substation is adjacent to Novo-Anzherskaya power substation; therefore, the transmission line TL «10-11» can be considered as electrically distant to the installation site of the RCPU system.

The disconnection of the transmission line «TL 6-14» was not included in the training data.

The disconnection of this transmission line occurs at the time of simulation equal to 6 seconds.

The value of active power flow, which is transmitted along the line is about 700 MW and it is directed from the Itatskaya power substation.

The recorded graphs of voltage and reactive power transients during the simulation is shown in Fig. 74

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APPENDIX 1. (continues)

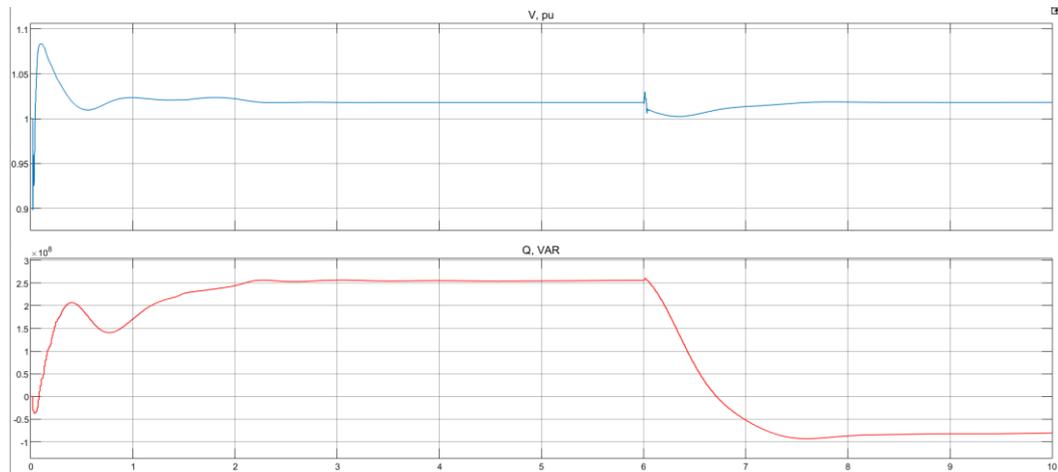


Fig. 74 – The graph of voltage (the blue one) and the RCPU system’s reactive power (the red one) transient at the disconnection of power transmission line «TL 6-14».

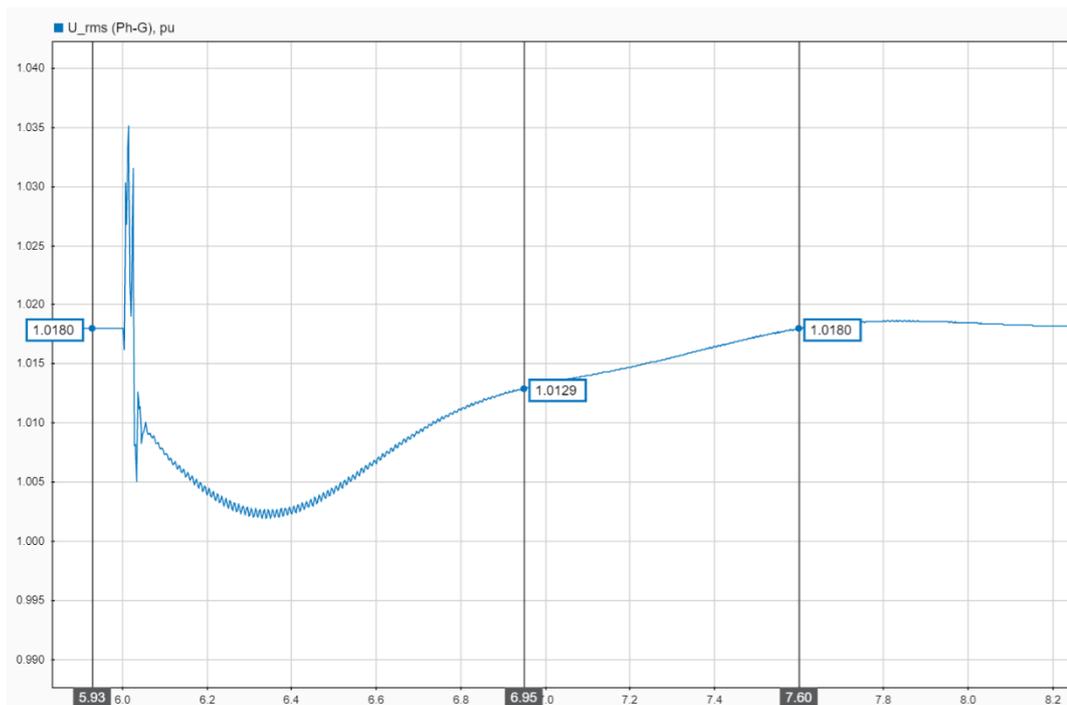


Fig. 75 – Scaled and cropped recorded transient of RMS voltage level, measured at Novo-Anzherskaya power substation at the disconnection of «TL 6-14».

The graphs of solutions, produced by the FANN, which are the coefficients of PID controller terms: proportional, integral and derivative are shown in Fig. 76, 78 and 80 respectively.

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APPENDIX 1. (continues)

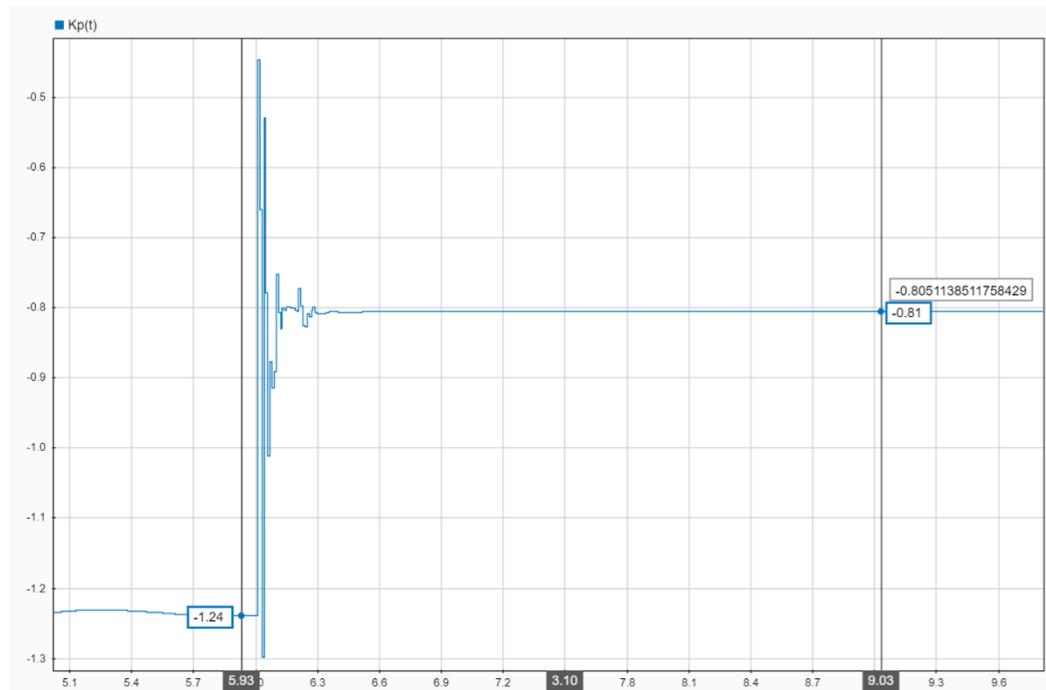


Fig. 76 – Variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 6-14».

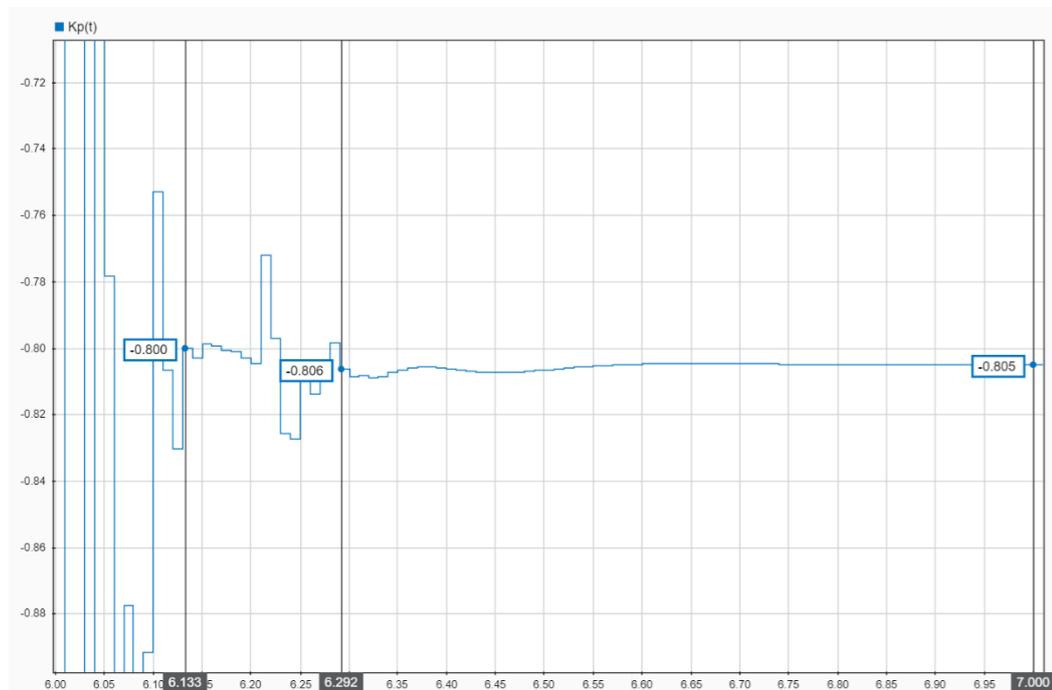


Fig. 77 – Scaled graph of variation of proportional term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 6-14».

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APPENDIX 1. (continues)

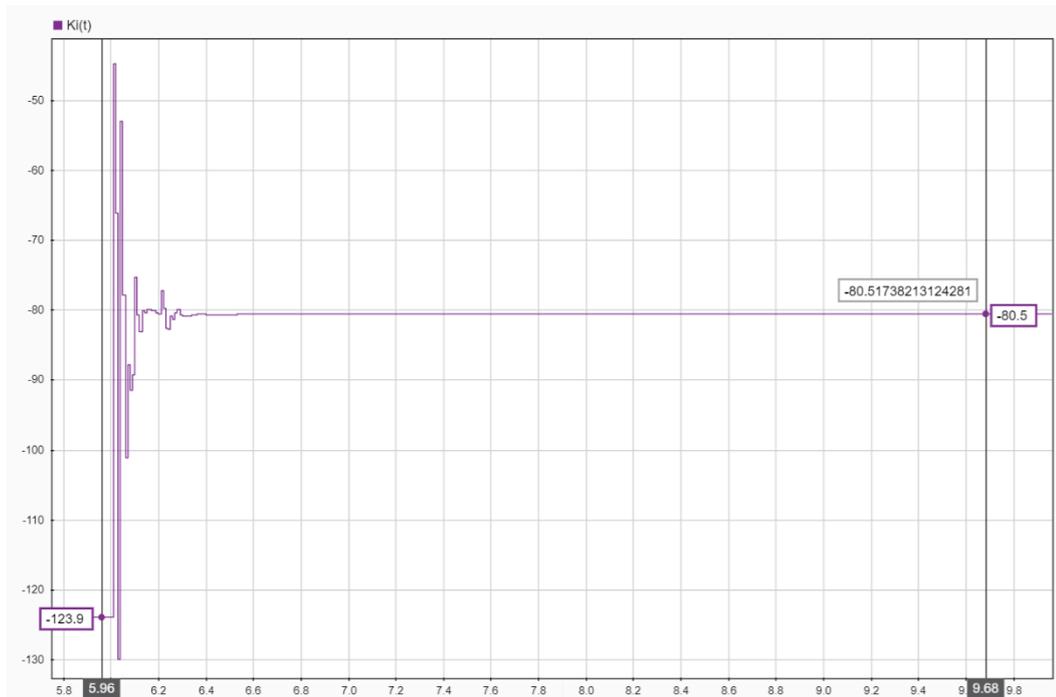


Fig. 78 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 6-14».

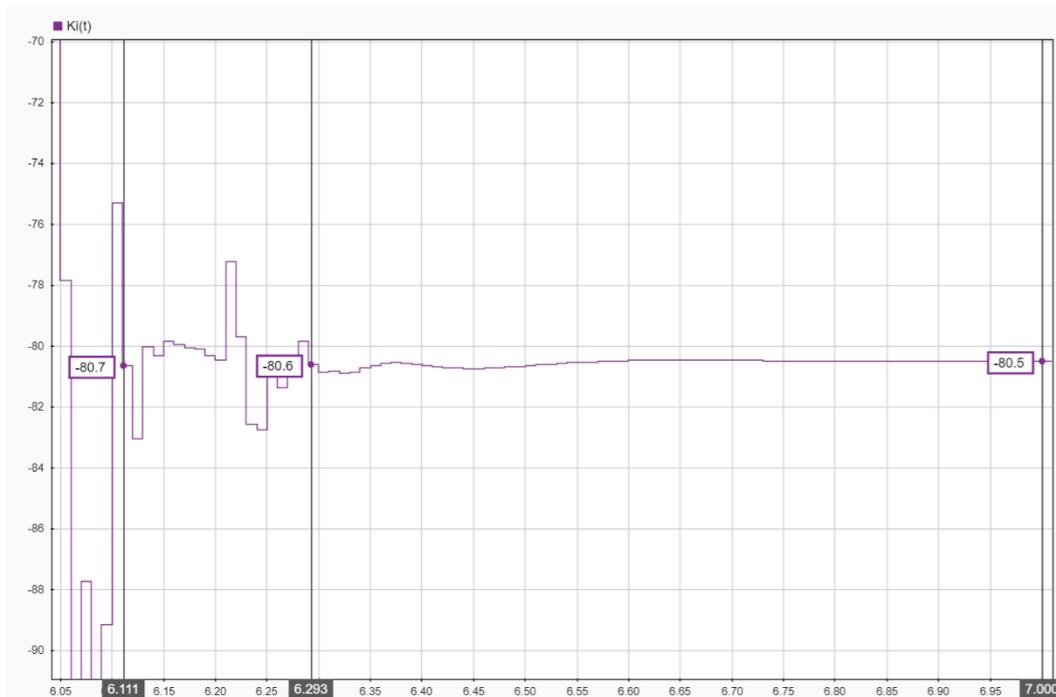


Fig. 79 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 6-14».

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APPENDIX 1. (continues)

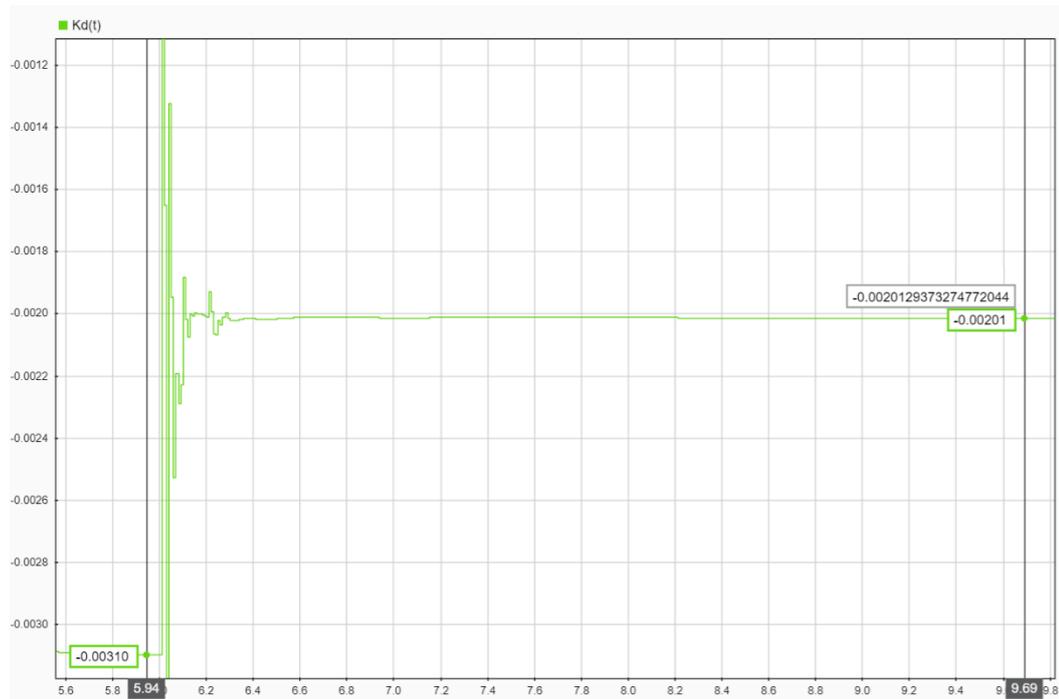


Fig. 80 - Variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of transmission line «TL 6-14».

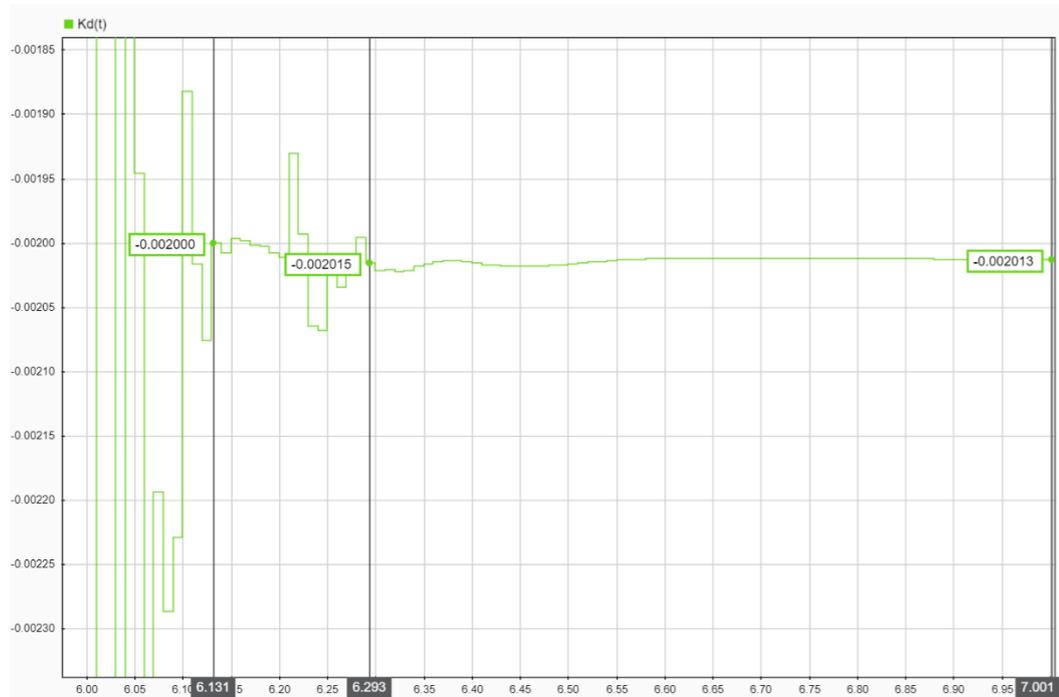


Fig. 81 - Scaled graph of variation of integral term coefficient of PID controller, caused by the operation of FANN adaptor at the disconnection of line «TL 6-14».