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NEURAL NETWORK IDENTIFICATION OF ELECTRIC POWER QUALITY INDICATORS OF COMPLEX POWER SYSTEMS

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ABSTRACT

The article reviews and analyzes the existing problems of electric power quality control in complex power systems, attracting attention to the requirements of reference documents on power quality changes. The procedures development of electric power quality indicators of complex power systems is under discussion. This work was carried out comparative modeling of calculations of basic electric power quality indicators by the direct method and neural network technology. An optimal configuration of a neural network for engineering systems for critical applications has been developed. Simulation system allows for a situation of frequency determination at a distorted signal as well as the presence of harmonics, interharmonics, and subharmonics in the signal, and voltage value deviation. The simulation finds that a frequency meter on the basis of a feedforward neural network has the least error.

1. INTRODUCTION

The estimation of quality in the simplest systems involves a problem solution connected with an electric power analysis. This analysis shows if its indicators meet fixed standards. More advanced systems provide a search and identification of malfunctioning nodes being responsible for indicators deterioration. Low-quality electric power, namely the presence of pulse interferences, influences the operation quality of engineering systems for critical applications, the energy supply of which is provided by the corresponding complex power systems.

All requirements for a power supply system are fixed by GOST 32144-2013 [1] which identifies acceptable levels of interferences in an electrical network. They also specify electric power quality, the so-called, electric power quality indicators (EPQI). The analysis

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of electric power is mainly carried out according to five groups of indicators [1]:

1) voltage deviation (failure duration, surge voltage);

2) frequency deviation;

3) voltage fluctuation (voltage fluctuation range, flicker dose);

4) voltage unbalance in a three-phase system (a coefficient in a negative and zero sequence);

5) unsinusoidality of a voltage waveform (a coefficient of voltage waveform distortion, a coefficient of the n-th harmonic voltage component).

In the current GOST on electromagnetic compatibility the following devices are specified as objects of measuring tools:

– for EPQI measurement;

– for EPQI technical control;

– for quality control of electric power;

– for quality analysis of electric power.

We should specify measuring transducers of EPQI separately – measuring tools aiming at generating information in a form is suitable for transmission, further transformation, processing and (or) storage, but not directly seen by an observer.

An identification system has been developed for engineering systems for critical applications. It should be noted that an EPQI identification subsystem can be realized in various ways in terms of its structure:

– EPQI direct calculation;

– EPQI identification via neural network technology.

Each of these ways has its own pros and cons. Direct calculation algorithms are described in the Standard in detail [1]. For the majority of EPQI a calculation algorithm looks like a sequential execution of several operations of the original array transformation of measurements of existing (sometimes instantaneous) voltage values (current).

On the one hand, neural network identification of a net is used for providing an opportunity for approximation on the basis of known measurements results according to which a network is taught. In other words, a taught-in network can identify EPQI values existing between values used for teaching a network and, thus, identify these values in the full range required. On the other hand, a procedure of neural network identification presupposes to do additional calculations before feeding data in a neural network input. Therefore, an algorithm of using a neural network for EPQI identification in a subsystem presupposes the execution of some steps:

- 1. Measurement data accumulation at a time interval during which EPQI values must be identified.

- 2. EPQI characteristics selection. This stage is the most difficult because it requires carrying out signal researches when EPQI change. It is necessary to specify signal characteristics carrying information about the given EPQI, and cut off the very signal component that does not participate in the process of EPQI identification.
- 3. Normalization of characteristics values. This operation leads data to one of the transformations ranges so that they take the most part of it.
- 4. Identification of a normalized output value of a neural network.
- 5. De-normalization of an output value of a neural network. The resulting value is an EPQI value for a signal at a given time interval.

2. LITERATURE REVIEW

Electric power quality assessment is a necessary and obligatory measure for identification in power systems. In accordance with the current GOST [1-4] the following two groups of tasks solved by the subsystem of identification of EPQI are distinguished:

- quality control of electric power - the procedure of verification of conformity of the EPQI with the established values;
- analysis of electric power quality - the procedure of identifying the causes of non-conformity of the EPQI with the established values and the “breakers” with their actual contribution to the deterioration of the quality of electric power.

Researches in the field of the electric power quality in power systems have been carrying out by the Centre of Physical and Engineering Problems of Power Industry of the North since 2004 and have been described in [5–8]. Such control allows us to provide all consumers with proper electric power quality.

Distortions appeared are classified by the acceptable deviation values and standards set in the Russian Federation [1-4]. Reference documents set the frequency of electric power quality control in power systems - once a year and twice for all EPQI, and twice a year for a voltage deviation [4].

The problems connected with the electric power quality stimulated the interest to their solution in the 80s of the last century. A significant contribution to the identification of electric power characteristics was made by domestic scientists: Rod’kin D.I., Mel’nikov N.A., Sokolov V.S., and others.

In papers [9-15], the identification of EPQI of complex power systems is based on the achievements of neurobiology.

To sum up, we can make a conclusion about the practical importance of developing theoretical and practical issues of identifying the states of complex power systems based on the results of parameters monitoring of their physical objects.

3. STUDY OBJECTIVES

For the realization of an engineering system for critical applications, we haven’t defined such an objective as to develop an identification procedure of all EPQI. The objective is to carry out comparative modeling of calculations of basic EPQI according to GOST

32144-2013 by the direct method and neural network technology.

The given Standard specifies the following requirements to frequency identification by the A-class devices:

1. The frequency value should be equal to 10 sec. at each time interval. As the frequency of the alternating current cannot be 50 or 60 Hz sharp at a 10 sec. the time interval, the number of periods can be non-integral. The measured main frequency equals the number of full periods (at 10 sec. time interval) to the general duration of full periods. Frequencies of harmonics and interharmonics should be attenuated in order to minimize the impact of multiple zero-crossings before each evaluation.

2. 10 sec. measurements time intervals shouldn't be exceeded. Intervals exceeding a 10 sec. a time interval is not considered.

3. The frequency measurements error shouldn't exceed ±0.01 Hz. The measurement range shouldn't be narrower than 42.5 ÷ 57.5 Hz.

4. It is possible to use other methods of obtaining equivalent results.

4. THEORY

To build complex energy systems, it is necessary to develop a model of the corresponding power system as a complex measurement object. Such models have a multi-level hierarchical structure and are built using modern methods and modeling tools [16, 17].

To solve the problems of measuring and controlling a power system, some information base has been created that contains many specialized components, the most important of which describe:

- purpose of the power system and work features in different modes and situations;

- model of the power system and its elements;

- methods for determining the estimates of its characteristics and current states [18].

To solve this problem a sequence diagram for EPQI values identification has been developed (Figure1). *Enterprise Architect* 8.0 is used as a software platform of *UML*-modelling.

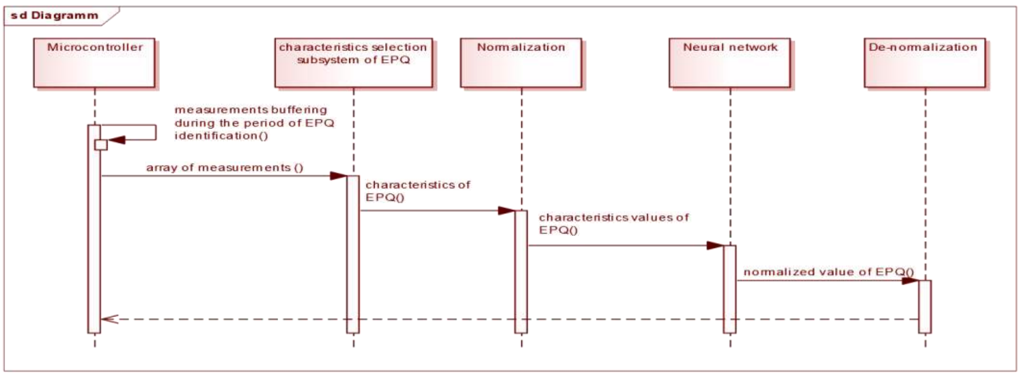

Figure 1: Sequence diagram for EPQI values identification

The microcontroller accumulates measurements during the period of EPQI identification (specified by the Standard), then transmits an array of measurements to the characteristics selection subsystem of EPQI. After that, all indicators are normalized and are fed to a preliminary taught-in neural network. A resulting output normalized value of EPQI is de-normalized and returns to the calling function of the microcontroller.

During the operation of the subsystem of EPQI values identification (Figure2) one can see statuses such as measurements data expectation, EPQI characteristics selection, EPQI values approximation (on the basis of a neural network), EPQI values transmission to the microcontroller which in its turn transmits data to the subsystem of data processing and storage.

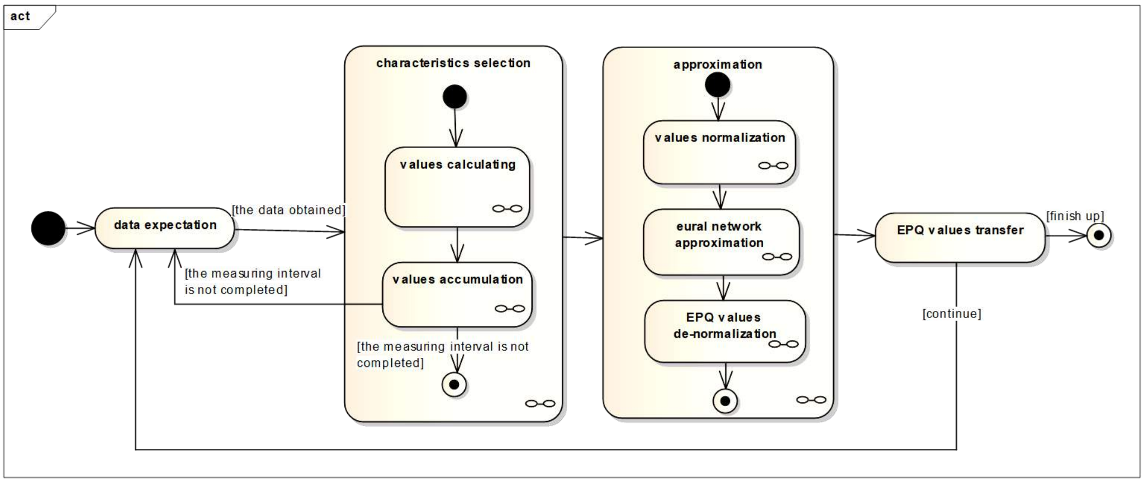

Figure 2: Status diagram of the subsystem of EPQI values identification

It is known that an ideal source of one phase alternative voltage has one signal identified in the form:

$$s(t) = A \cdot \sin(2\pi f t + \varphi), \tag{1}$$

where A – voltage amplitude (≈311 V);

f – voltage frequency (50 Hz);

φ – voltage phase (0°);

t – time (sec.).

It is obvious that under real circumstances all these parameters are not constants.

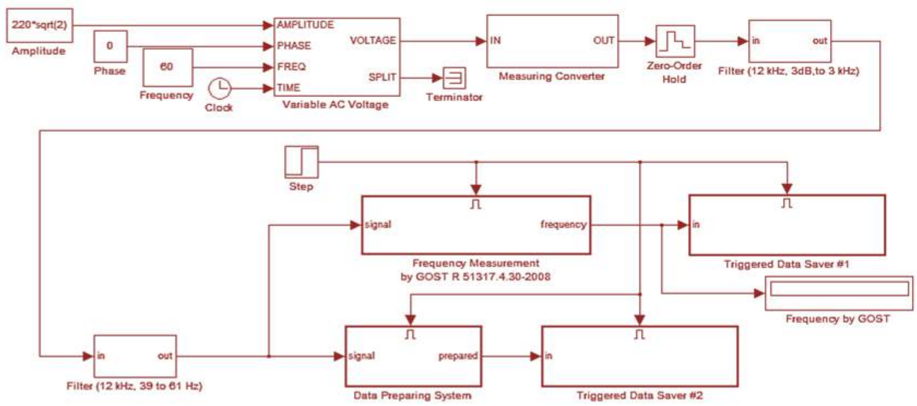

Figure 3: Model used for getting data for neural network training

To solve the identification problem a model used for getting an array of data for neural network teaching has been developed (Figure3).

Main units' description:

Filter (12 kHz, 39 to 61 Hz) is a unit of the band-pass filter with frequency cut off from 39 to 61 Hz and sampling frequency of 12 кHz. This filter suppresses low-frequency and high-frequency signal components beyond the bandwidth of 39÷61Hz. The bandwidth exceeds the measurements range (40÷60 Hz) in order to decrease the influence of the filter amplitude-frequency response discontinuity near intermediate-field regions on the signal amplitude.

Data Preparing System is a subsystem of characteristics selection of a signal carrying frequency data. A distance mean value between zero-crossings by a signal at the measuring interval (10 sec.) is selected as a characteristic due to some additional researches. The calculation of this distance is carried out on the basis of a scheme including three adder units:

– the first adder unit is considered to be a counter of zero-crossings by a signal;

– the second one calculates the number of sampling pulses at the time of two zero-crossings;

– the third adder unit identifies a pulses sum obtained by the second adder unit at the time between the first and second zero-crossing at the measuring interval.

The full model of the given unit is shown in Figure 4

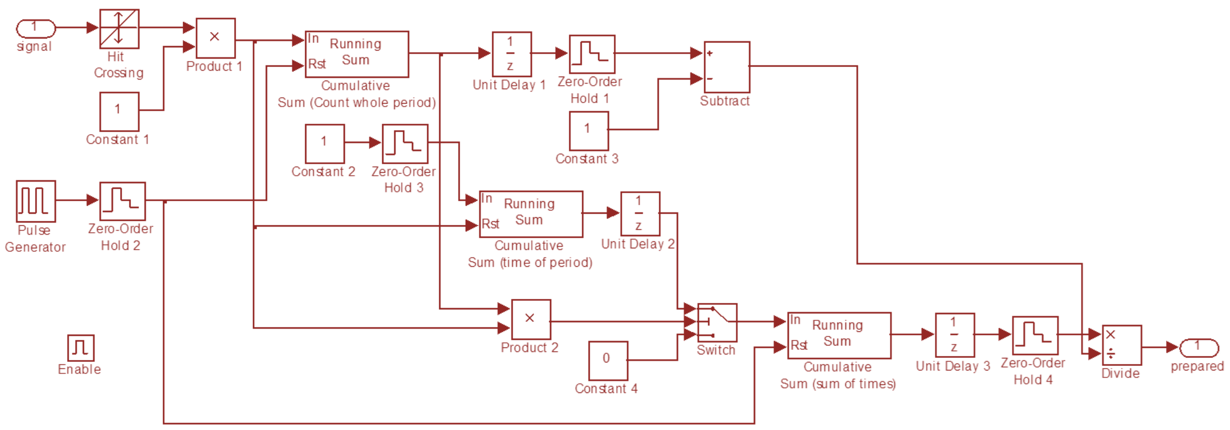

Figure 4: Model of *Data Preparing System* unit

Frequency Measurement is a unit realizing a standard algorithm of frequency calculations. A general algorithm of this unit functioning is similar to that of *Data Preparing System*. There is only one difference: all distance calculations are done between zero-crossings from the negative semi-plane to the positive one (i.e. the signal period duration in samples is calculated), but not between the zero-crossings next (half-period). Moreover, the third adder output is subjected to transformations according to the Equation

(2). It allows us to obtain the following signal frequency value at the unit output:

$$f = \frac{C \cdot f_d}{T_{all}}, \tag{2}$$

where C – number of full periods at the measuring interval;

f_d – sampling frequency, Hz;

T_{all} – duration of all full periods at the measuring interval (it is calculated in repots of sampling frequency).

The unit model is shown in Figure 5.

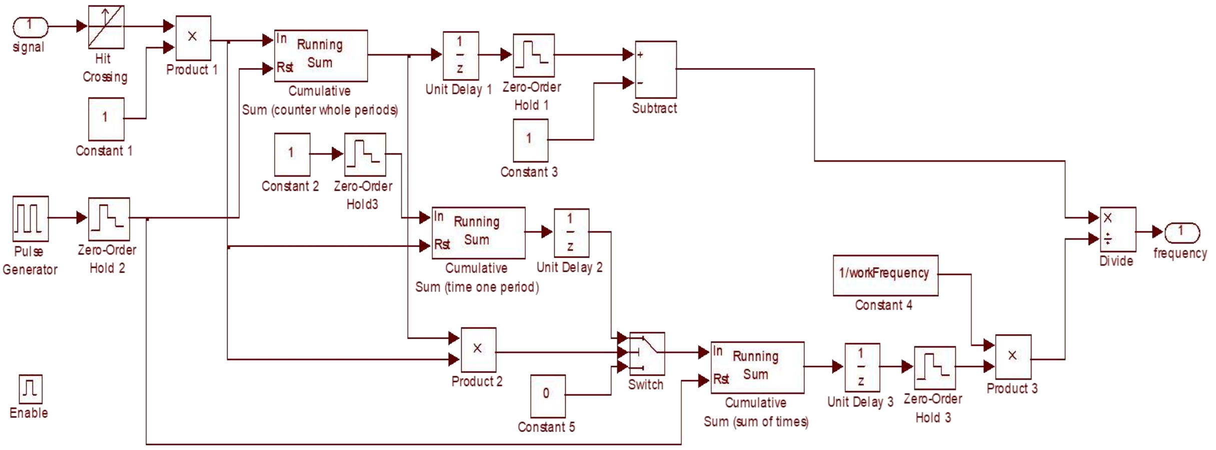

Figure 5: Model of *Frequency Measurement* unit

Triggered Data Saver is a unit of keeping data (Figure 6) providing keeping data according to a control signal

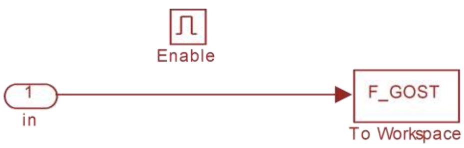

Figure 6: Model of *Triggered Data Saver* unit

The application of *Triggered Data Saver* subsystems allows us to avoid obtaining false data in arrays used for neural network teaching. False data are caused by the settling period of *Filter* unit (12 kHz, 39 to 61 Hz), as during this period signal amplitude is influenced by an attenuated oscillating process, and also by taking into account one false sample at the very beginning of 10 sec. measuring the interval by this model. Subsystems start operating in 10+1/12000 sec. after the model's start. So the modeling time should be equal to more than 20 sec. for obtaining valid results [18].

An optimal configuration has been developed for a neural network. This model (Figure 7) allows us to simulate both a situation of frequency identification at a distorted signal and the presence of harmonics, interharmonics, and subharmonics and voltage value deviation in the signal.

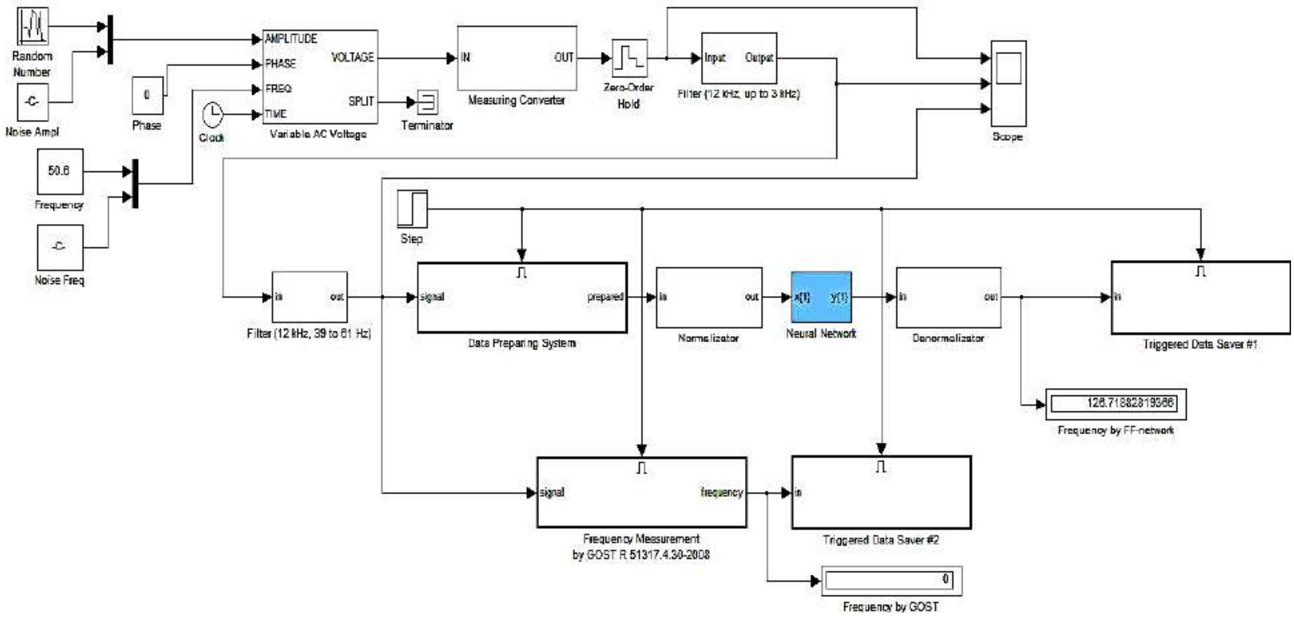

Figure 7: Model of frequency identification work on the basis of a feedforward neural network

Additional units on the scheme:

Normalizator – manages normalization of input values for a neural network (Figure 8).

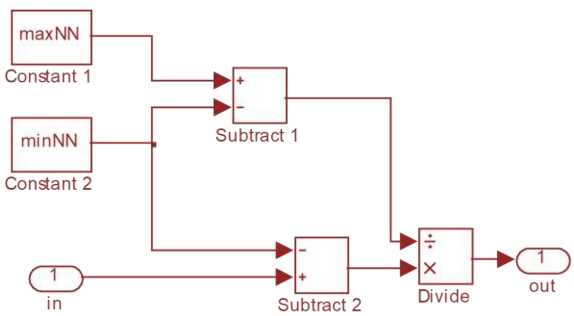

Figure 8: The model of *Normalizator* unit

Denormalizator – manages frequency unnormalized value identification (Figure 9).

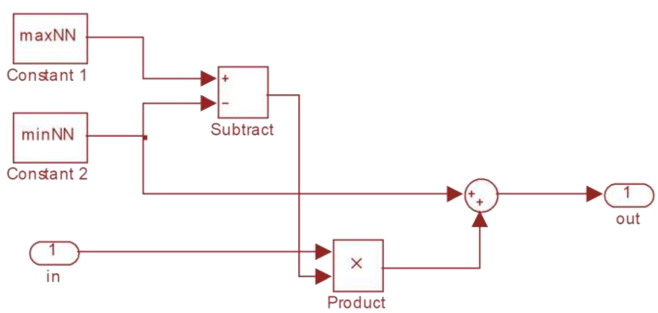

Figure 9: Model of *Denormalizator* unit

5. RESULT AND DISCUSSION

The modeling results are shown in Table 1.

Table 1: Error comparison of frequency identification by neural networks and direct calculation algorithm

Neural network type	Function Matlab	Absolute error, Hz	
		Maximum	Average
Linear network	newlin	1.3989750	0.7099935
Star-type and base network	newrb	0.0024566	0.0006933
Feedforward network	newff	0.0004123	0.0002961
Common and regressive network	newgrnn	0.3266724	0.0573861
Probabilistic network	newpnn	0.6000000	0.2495210
Direct calculation algorithm	-	0.0005258	0.0002588

Simulation results on the frequency band 49 ÷ 51 Hz with a step of 0.2 Hz are:

- The maximum absolute error of the neural network is 0.0004123 Hz (for the direct calculation algorithm - 0.0005258 Hz);

- The average absolute error of the neural network is 0.00016428 Hz (for the direct calculation algorithm, 0.00006456 Hz).

Thus, from the result, a feedforward neural network demonstrates better results against other neural networks. However, the accuracy of the direct calculation algorithm is a little bit higher.

6. CONCLUSION

The identification subsystem has been developed for identifying the electric power quality of complex engineering systems for critical applications. This work was carried out comparative modeling of calculations of basic electric power quality indicators by the direct method and neural network technology. The optimal configuration of a neural network for engineering systems for critical applications has been developed. The study finds that a frequency meter on the basis of a feedforward neural network has the least error.

7. AVAILABILITY OF DATA AND MATERIAL

Data/software source code can be made available by contacting the corresponding authors.

8. REFERENCES

[1] GOST R 32144-2013. Electric power. Electromagnetic compatibility of engineering tools. Standards of electric power quality in general-purpose electric power supply systems.

[2] RF National Standard GOST R 51317.4.7-2008. Electromagnetic compatibility of engineering tools. General manual on tools measurement and harmonic and interharmonic measurements for power supply systems and engineering tools attached to. 01.01.2010. M.: Standartiform, 2009. – PP. 60.

[3] RF National Standard GOST R 53333-2008. Electric power. Electromagnetic compatibility of engineering tools. Electric power quality control in general-purpose power supply systems. 01.07.2019. M.: Standartiform, 2019. – PP. 31.

[4] RD 153-34.0-15.502-2002. Methodological instructions on electric power quality control and analysis in general-purpose power supply systems. Part 2. Electric power quality analysis. 01.08.2002. M.: Energoservis, 2003.-PP.23.

[5] Nefretdinov Yu. M., Yaroshevich V.V., Karpov I.S. Results analysis of monitoring registration of electric power quality indicators. – Vestnik MSTU. – 2014. Vol. 17. №1. – p. 67-76.

[6] Goryunov I.T., Mozgalyov V.S., Dubinsky E.V. Main principles of the system development of electric power quality control, analysis and management // Power stations. 1998. №12.

[7] Sapunov M. Electric power quality issues. Electric engineering news. 2001. №4 (10).

[8] Zhashkova T.V., Volodina E.A. Simulation modelling of the monitoring system of electric power quality indicators – Penza, Modern information technologies, 2012. № 16. – PP. 110-116.

[9] Mikheev M.Yu., Dmitrienko A.G., Zhashkova T.V. Neural network identification of electric power quality indicators. – Penza, International symposium papers «Reliability and Quality», 2009. Vol. 1. – PP. 439-442.

[10] Zhashkova T.V., Syomochkina I.Yu., Lepeshev A.A. The development of a subsystem of neural network identification for determining electric power quality indicators. – Penza, XXI century: Resumes of the Past and Challenges of the Present plus. Scientific Periodical. Series: Engineering Sciences. Information Technologies. – Penza: PenzGTU. 2015. №04 (26). PP. 240-252.

[11] Zhashkova T.V., Murashkina E.N. Power supply control system in AC failure conditions. Modern information technologies: Materials of the International Scientific and Engineering Conference. Issue 16. – Penza: PSTA, 2012. – p. 116-121.

[12] Grishko A.R., Yurkov N.K., Zhashkova T.V. Dynamic optimization of structural elements control of complex systems. XXI century: Resumes of the Past and Challenges of the Present plus: Scientific Periodical. – 2015. - №04 (26). – Penza, 2015. – p. 134-141.

[13] A Lysenko, N. Yurkov, V. Trusov, T. Zhashkova, Ju. Lavendels. Discrete Models in Research of Wave Processes in Rod Structures of Radio-Electronic Means. Applied Computer Systems. – 2018. vol. 23. – Issue 2. – Pp. 135 – 140.

[14] Gemst V.K., Roganov V.R. Technical diagnostics of microprocessor systems of relay protection and automation of electric power systems/lectures. – Riga: Riga Technical Institute, 1983. – PP.72.

[15] Murashkina E.N., Zhashkova T.V. The identification of critical statuses of the monitoring and control system. – Penza, Modern high-tech. 2014. № 5-2. –PP. 62.

[16] M.Yu. Mikheev, T.V. Zhashkova, E.N. Meshcheryakova, K.V. Gudkov, and A.K. Grishko, «Imitation modelling for the subsystem of identification and structuring data of signal sensors» Proceedings of 2016 IEEE East-West Design and Test Symposium, EWDTS 2016, 7807748.

[17] Khodashenas, B. (2015). Nitrate reductase enzyme in Escherichia coli and its relationship with the synthesis of silver nanoparticles. UCT Journal of Research in Science, Engineering and Technology, 3(1),26-32.

[18] K.V. Suslov, N.N. Solonina, A.S. Smirnov «Distributed power quality monitoring» 2014 16th International Conference on Harmonics and Quality of Power (ICHQP), 14399063.

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