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Article

Application of an Artificial Neural Network for Detecting, Classifying, and Making Decisions about Asymmetric Short Circuits in a Synchronous Generator

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Abstract: Fast and accurate detection of emerging faults in synchronous generators, which have found wide application in power and transport systems, contributes to ensuring reliable operation of the entire system. This article presents a new approach to making accurate decisions on the continuation of the operation of damaged generators in accordance with the requirements of IEEE standards. The necessity of limiting the duration of operation of the generator in conditions of asymmetric short circuits in the stator windings is substantiated. The authors of the article, based on an artificial neural network in the Matlab software environment, have developed a model for detecting, classifying, and making quick and accurate decisions about the operation of the generator in the event of asymmetric short circuits in the stator windings of the generator. This makes it possible to simulate the operation of the generator at various parameters. Prior to training the neural network, the database formed by phase current and voltage signals was analyzed by various features. The neural network was trained using the back-error-propagation algorithm. The output 10 neurons of the network showed the state of the phase windings of the stator. The recorded information of the output neurons was evaluated, in terms of meeting the requirements of the IEEE standard, and decisions were made about continuing or interrupting the generator operation. Tests of the effectiveness of the model showed that it could achieve the desired result at step 49, and the calculated accuracy was 99.5833%. The results obtained can be successfully used in the development of high-speed and highly reliable diagnostic systems and control and decision-making systems for generators for various purposes.

Keywords: neural network; synchronous generator; asymmetric mode; short circuit; decision-making; classification

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1. Introduction

Synchronous generators, an alternating current electricity source, are widely used in power (thermal, hydro, nuclear and other stations) and transport systems (cars, airplanes, diesel locomotives). Increasing the requirements for the production and quality of electricity poses new challenges to the power system operating with different capacities. These problems need urgent solutions. To ensure the sustainable development of society, in addition to traditional energy systems, renewable energy and diesel or gasoline generators that provide non-stationary power supply occupy a special place. Synchronous machines have high energy indicators, in particular, high efficiency, a high power factor, high quality of generated energy, and the ability to withstand overload in the power network. Despite the noted indicators, synchronous generators can be in various abnormal modes and become faulty.

A damaged generator or one operating in an abnormal mode affects the stable operation of the system and leads to a decrease in its performance, additional losses of electricity, and sometimes the occurrence of emergency situations in the system. Abnormal operating modes in the generator may occur due to the following circumstances:

- Inefficient operation of the control system used;
- Defective operation of the relay protection;
- Lack of diagnostics or its defective functioning.

The generator control system must be flexible, i.e., capable of processing signals from a large number of objects, and be fast-acting and economical.

In [1], the authors propose a new generator control unit based on the structure of a dual digital signal processor. The proposed generator control unit provides high-quality power supply in a wide frequency range. In [2], it is proposed to use a predictive controller with an adaptive model to control the generator. This solution allows signal levels to be automatic adapted to changes in the facility. The simulation tests carried out by the authors confirmed the expediency of using the considered control system in turbogenerators. Assuming that renewable energy sources will be dominant in the future, the authors of the article [3] propose an improved approach for evaluating high-voltage DC power supply systems. In particular, using the impedance-based method, it became possible to ensure stable control of a synchronous generator of a high-frequency DC transmission system. A comprehensive analysis of the control of power transmission generators in renewable energy sources is presented in [4]. In [5], based on the study of the results of modeling the distribution network, a method for assessing stability is presented. The possibility of applying the Popov criterion in the distribution network is revealed [6].

There are various types of relay protection used to protect the generator, which, however, are expensive and destructive [7–16]. For this reason, an important problem is the timely detection of emerging failures during the operation of the generator and making decisions on its further operation. Clear information about the working condition of the synchronous generator, when timely revealed, will prevent unexpected repairs of its individual elements, preventive measures, and settings.

The causes of malfunctions and abnormal operating modes of a synchronous generator are mainly electrical or mechanical [17,18]. The distribution of malfunctions or their occurrence in abnormal modes is shown in Figure 1. The sum of the causes of malfunctions and their occurrences in abnormal modes is represented by 100% and the percentage ratios of electrical and mechanical causes of their occurrence are given.

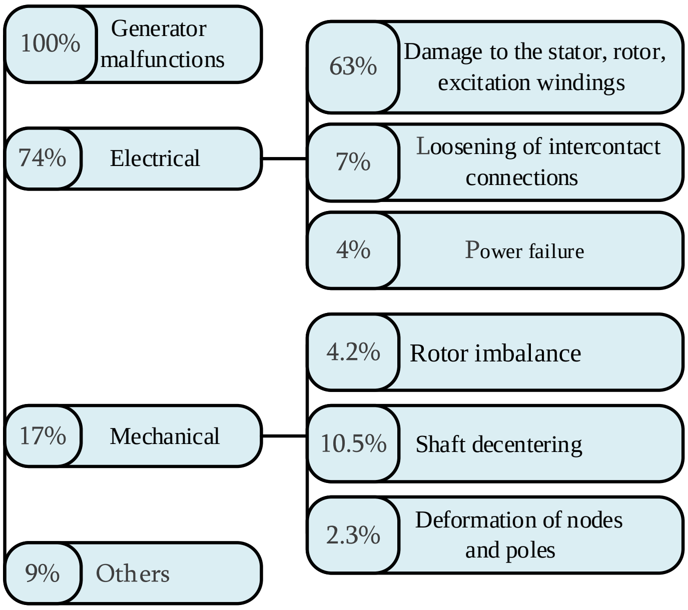


Figure 1. Distribution of the causes of malfunctions or their occurrence in abnormal modes of the generator.

The operation of a synchronous generator in abnormal modes is accompanied by the flow of overcurrents and the appearance of overvoltages, which lead to [19]:

- Violation of synchronism, loss of excitation, which leads to overheating of individual generator units;
- Asymmetry of phase currents, which leads to overheating of the rotor and mechanical vibration;
- An increase in voltage with a decrease in load, which leads to insulation breakdown.

Considering that the predominant part of the causes of malfunctions and occurrences in abnormal operating modes of the generator are electrical, the known works carried out in this direction are analyzed.

Damage to the insulation of the generator windings leads to inter-turn short circuits, the detection of which is devoted to a number of scientific papers [20–26].

The applied significance of the localization of the consequences of inter-turn short circuits is substantiated in [20,21]. In [22], inter-turn short circuits were detected by means of indicators modeled for a specific fault, and in [23,24], to prevent short circuits, an algorithm was proposed for monitoring insulation aging in online and offline modes, respectively. Using the extended Kalman filter [25], a fast and reliable method for detecting inter-turn short circuits is proposed in [26]. Based on the estimation of the form of the harmonic component of the voltage signal applied to the stator windings of the generator, an analytical method for detecting, classifying, and localizing internal faults is proposed [27].

In [28] the possibilities of improving fault detection of a single-pole synchronous generator were considered. Inter-turn short circuits in the excitation winding were detected during the operation of the generator based on an algorithm for analyzing data signals about the magnetic field of scattering.

The works devoted to the detection of excitation current loss are worthy of attention [29,30].

In a series of failures of synchronous generators, the key is the loss of excitation, since this affects both generators and electrical networks [29]. The traditional method of detecting the loss of excitation is accompanied by a drop in speed. To avoid this, [29] used the discrete wavelet transform. This makes it possible to detect the loss of excitation and classify the logic of various failures both in normal operating modes and under power fluctuations. A new method for detecting excitation loss and correcting its shortcomings is proposed [30], which uses a combined circuit based on the derivative of the voltage at the terminals and the angle of the derivative of the generator power. The proposed strategy makes it possible to improve the safety of the excitation loss relay.

In [31], a mechanism for detecting unfavorable oscillations and faults that appear in the generator based on monitoring the output signal created by the system is presented. Data processing and evaluation of changes in the behavior of system characteristics was carried out on the basis of a neural network.

The neural network has also been also used to monitor and diagnose the generator in operation [32]. In this case, the input parameters of the neural network are the stator and rotor currents, and the output shows the operating state of the generator. The neural network is trained for all possible operating conditions of the generator [32].

During operation, a three-phase synchronous generator may be in an asymmetric mode. The asymmetric mode of the phases is accompanied by the occurrence of reverse sequence currents in the armature, which lead to the occurrence of undesirable and emergency dangerous phenomena [33,34]:

- Increase in losses in the damping winding and massive parts of the rotor;
- Significant fluctuations;
- Voltage asymmetry;
- Violation of the sinusoidality of currents and voltages.

Asymmetric modes in a three-phase generator mainly occur in cases of connection to the network of a powerful single-phase consumer, as well as phase breakage and single-phase or two-phase short circuit [35,36].

In [37] the faults appearing in the generator were classified by estimating the phase-shift angle between the reverse sequence voltage at its terminals and the current on the neutral wire. The proposed method makes it possible to distinguish between internal and external malfunctions.

An analysis of well-known works devoted to the identification of malfunctions and abnormal operating modes occurring in a synchronous generator shows that the predominant part of them is aimed at detecting and localizing damage to the insulation of the stator and rotor windings and the excitation winding and, as a result, the resulting interphase short circuits. At the same time, various methods and means are used to achieve this goal, which are mainly applicable to particular situations. In some works, attention is drawn to the identification of emerging malfunctions in power transmission lines [38,39]. The presented approaches do not have the ability to react and detect the location and type of short circuit occurring simultaneously in different phases, and the fact of a short circuit is signaled at the output of the network. This makes it impossible to make accurate decisions about the further operation of the generator, as well as to evaluate the quality indicators of electrical energy.

In the known works, there is no possibility of making accurate decisions on the further operation of the generator in case of short circuits during its operation in accordance with IEEE standards [40,41]. Meanwhile, non-compliance with the standard leads to heating of the rotor and the occurrence of vibration, which can cause various kinds of accidents.

This article discusses the issues of fast and accurate decision-making on the detection, classification, and further operation of the generator based on an artificial neural network in the event of an asymmetric short circuit in the stator winding.

In synchronous generators used at hydroelectric power plants, during acceleration, when the pressure of the water flow increases, the voltage in the circuits increases and large voltages and currents arise, causing interphase short circuits or short circuits between the phase and the case. In addition to the above, such short circuits in the synchronous generator also occur due to mechanical influences, in particular, when bearings are damaged. It is also noteworthy that in a diesel or gasoline generator, in the event of a failure of the control mechanism of the motor being started, during acceleration, the same phenomena occur as in hydro generators. The results obtained by us have a specific application in hydrogenerators and diesel generators. The results obtained in the work were tested on a 2.85 kW synchronous generator, which is used in mini-hydroelectric power plants and diesel generators. All tests were carried out without load, by simulating short circuits. The results of the simulation tests confirm the viability of the proposed model and the possibility of detecting and classifying simultaneously occurring short circuits, as well as the possibility of their application for decision-making in accordance with current standards.

The remainder of this paper is organized as follows. The Section 2 contains comments on changes in the characteristics of asymmetric short circuits that occur during the operation of the generator, as well as an analysis of the necessary requirements for their detection. The dynamics of changes in phase currents and voltages, in the case of various kinds of short circuits, and an algorithm for training an artificial neural network are presented. The Section 3 presents experimental results on the detection and classification of asymmetric short circuits occurring in the stator winding of the generator. A block diagram of decision-making for the operation of the generator in the case of its operation in an unsymmetric mode is proposed.

Comments and suggestions on the results of the study are given in the Section 4.

2. Materials and Methods

2.1. Requirements for the Evaluation of Asymmetric Short Circuits

Due to the occurrence of an asymmetric short circuit in the stator windings of the generator, the load between the phases is distributed unevenly. In practice, as a result of the operation of the relay protection, the damaged section is turned off, but this may have a negative impact on the further operation of the generator. In order to avoid sudden changes in the electromagnetic moment and the appearance of shock currents, it is necessary to limit the operation of the synchronous generator in conditions of load asymmetry. In addition, according to the current standard, the operation of a three-phase generator in the case of an unbalanced load is permissible if the current in the phases does not exceed the nominal value and the deviation of the phase currents does not exceed 10% [40].

In practice, the most common causes that disrupt the normal operation of the generator in both energy and transport systems are short circuits:

- Single-phase, occurs in phases;
- Two-phase, occurs between phases;
- Two-phase short circuit on the neutral wire, occurs between the phase and the neutral wire.

In Figure 2 a schematic representation of single-phase and two-phase, as well as the neutral wire of two-phase short circuits, is shown.

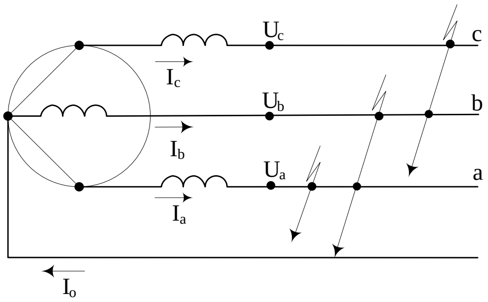
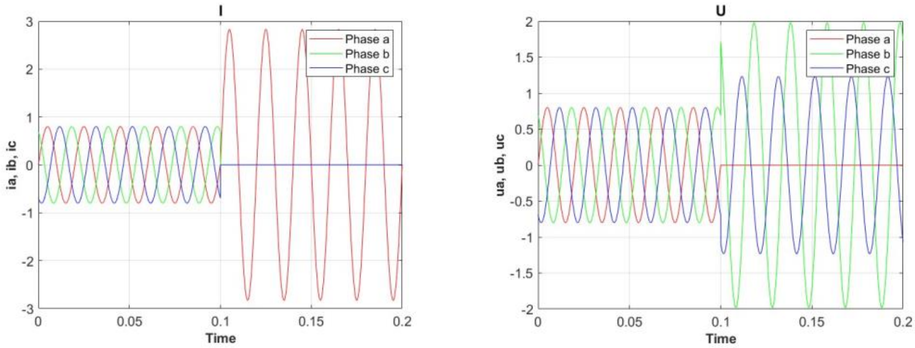


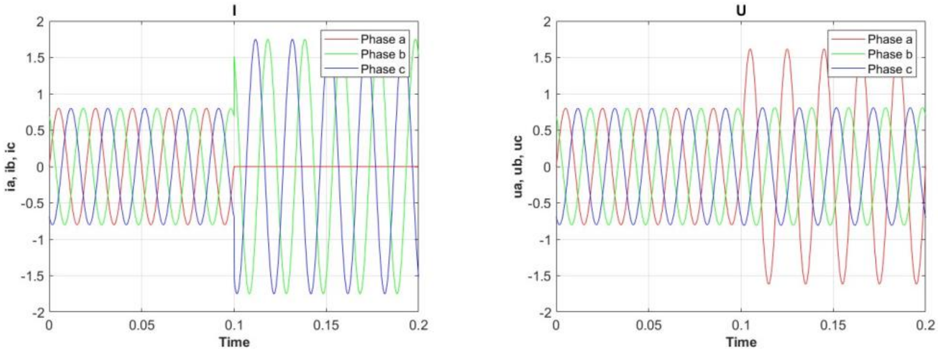
Figure 2. The scheme of single-phase, two-phase, and also the neutral wire of two-phase short circuits.

For the short-circuit cases shown in Figure 2, the dynamics of changes in phase current and voltage signals are shown (Figures 3–5). It is impractical to implement short circuits on the original generator. For this reason, mathematical equations of a three-phase generator are used to obtain dependencies, which take into account changes in the characteristics caused by a short circuit.



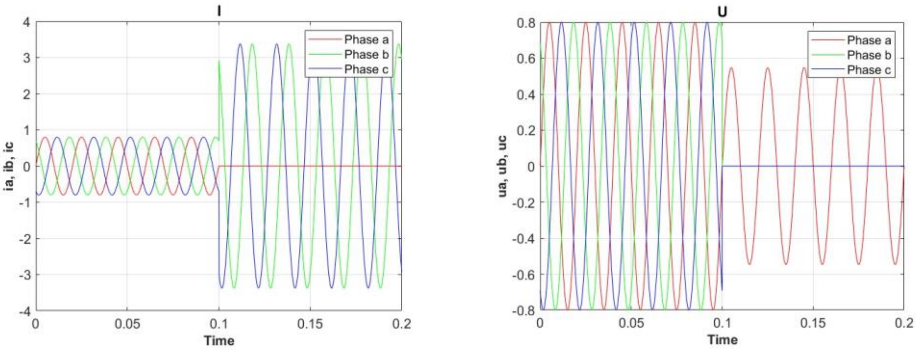
(**a**) (**b**)

Figure 3. Images of changes in signals of corresponding (**a**) currents and (**b**) voltages during a short circuit in phase a.



(**a**) (**b**)

Figure 4. Images of changes in the signals of (**a**) currents and (**b**) voltages in the case of a short circuit between phases b and c.



(**a**) (**b**)

Figure 5. Images of changes in the signals of (**a**) currents and (**b**) voltages in the case of a short circuit between phases b and c on a neutral wire.

The reactive resistance of the generator was much greater than the active resistance, for this reason, the current flowing through the winding was inductive in nature. As a result, the short-circuit current vector lagged behind the EMF vector by almost 90°. It turns out that the initial value of the winding short-circuit current will depend on the position of the poles relative to the stator winding in which the EMF is induced. It is known that sudden asymmetric short circuits cause transients that lead to abrupt changes in the electromagnetic moment and the appearance of shock currents [42].

The above comment shows that the model for detecting and classifying asymmetric short circuits must meet the following requirements:

- Quick response to all damages and malfunctions that occur in the generator due to a short circuit;
- Determination of the damaged place and decisionmaking on the further operation of the generator, taking into account the dynamic changes that have arisen.

To meet these requirements, it is advisable to develop a high-speed and highly reliable model using an artificial neural network, which can be implemented using simple actions.

2.2. The Use of an Artificial Neural Network to Detect Asymmetric Short Circuits

An artificial neural network has become widely used for solving control and diagnostics problems and improving the monitoring of electromechanical systems due to its increased speed in processing large amounts of data, ability to solve nonlinear problems, and ability to self-organize and self-train, as well as its high reliability and accuracy [43–45]. The main disadvantage of using an artificial neural network is the lack of clear instructions for choosing the type of network and architecture [46].

To detect and make decisions in the case of asymmetric short circuits in the generator windings, the currents and voltages of a, b, c phases are used as input signals, and information about the type of fault and its location is used as an output signal. Information about the serviceability of the generator or the type of malfunction, which is determined by the value of the phase voltage and current, is output to the network output.

In this work, in order to build an artificial neural network, the features of data processing required to determine the type and location and make further decisions in case of asymmetric short circuits occurring in the generator are taken into account. The back-error-propagation algorithm was used to train the neural network [47,48]. The block diagram of the neural network training is shown in Figure 6.

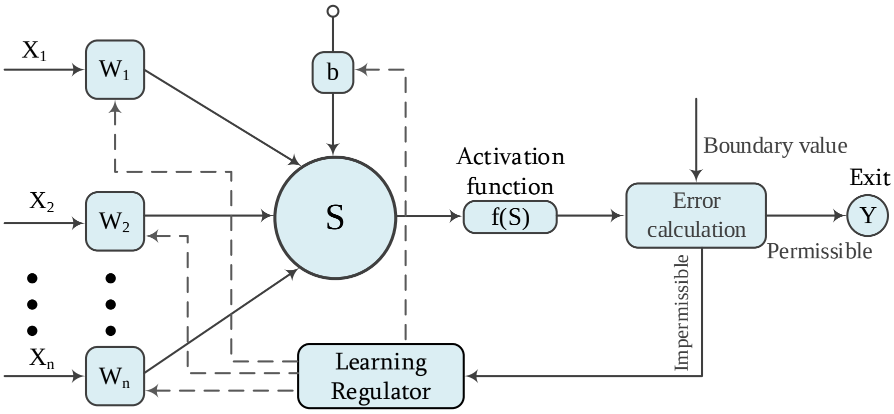


Figure 6. Block diagram of the neural network training.

An algorithm for training an artificial neural network.

1. The desired learning error E_d is set;
2. The values of the weighting w_{ij}^k and threshold b_j^k coefficients of the network are generated randomly;
3. The output values of all neurons are calculated:

$$S_j^k = f\left(\sum w_{ij}^k S_i^{k-1} - b_j^k\right)$$

where w_{ij}^k is the i-th weight coefficient of the j-th neuron of the k-th layer; $x_1, x_2, \ldots, x_j$, $\ldots x_n$ is the input signal; b_j^k is the threshold of the j-th neuron of the k-th layer; S_i^{k-1} is the output vector of the $k - 1$st layer:

For the current layers, the ReLU function is used as the neuron activation function f (Figure 7), and the softmax function is used for the output layer (Figure 8).

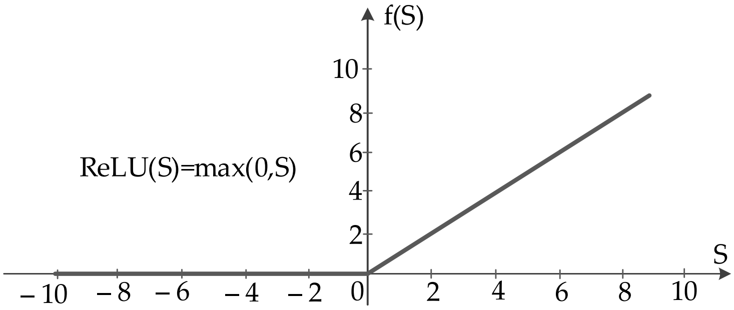


Figure 7. Activation function ReLU.

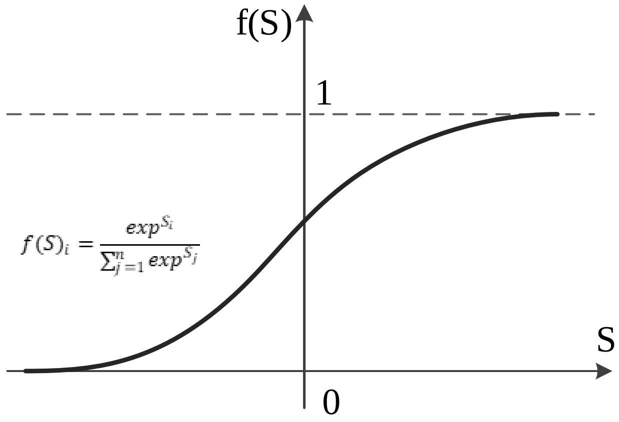


Figure 8. Activation function softmax.

4. The errors of neurons of the output and hidden layers are calculated. In this article, cross-entropy loss is used, which is defined as follows:

$$CE = -\sum_i^c t_i \log(p_i), \quad p_i = f(s)_i$$

   where t_i is the truth label and p_i is the softmax probability for the i class;
5. The weights and thresholds of neurons are changed for each layer;
6. The total error of the neural network is calculated;
7. If the total error is greater than the allowable one, then go to step 3; otherwise, the algorithm is terminated.

Based on the described algorithm, a simulation model has been developed, the results of which are presented in detail.

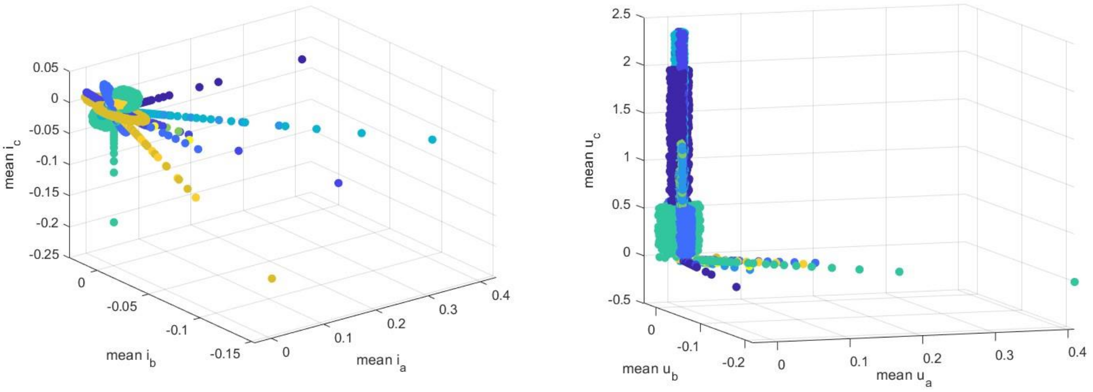
3. Results

3.1. Detection and Classification of Asymmetric Short Circuits

The model implemented in the MATLAB software environment makes it possible to:

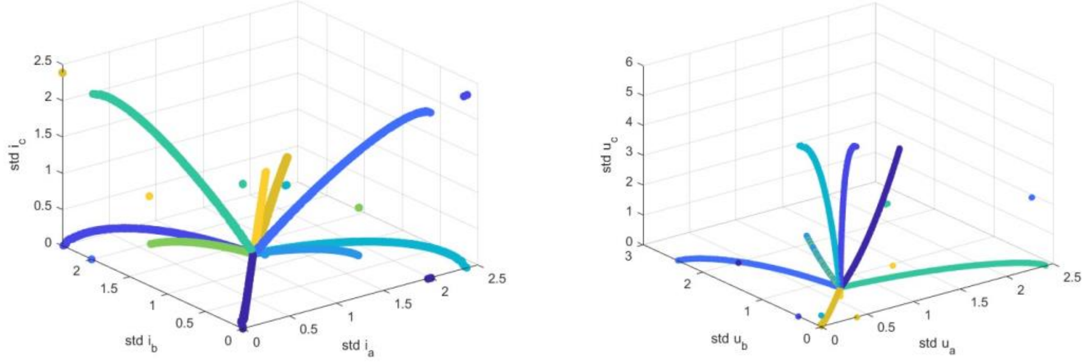
1. Simulate the operation of the generator under various parameters;
2. Generate:
   - Short circuits in phases a, b, and c;
   - Two-phase short circuits ab, bc, and ac;
   - Short circuit to neutral in phases ab, bc, and ac;
3. Detect the type of short circuit and the location;
4. To make decisions on the further operation of the generator in case of an asymmetric short circuit.

For the generator under consideration, data were collected in the frequency range from f = 45 Hz to 65 Hz and for a period of time $t = 0 \ldots 0.5$ s, in the mode of 100 arbitrary short circuits at various points in time, and also in normal operating mode, i.e., without short circuits. Thus, as a result, 20,000 data were collected, which were further processed according to various features: average value, root-mean-square deviation, variation, skewness, kurtosis, fast Fourier transform in the amplitudes of the first-, second-, and third-order harmonics. The graphical dependences of the phase current and voltage signals, processed according to these characteristics, are shown in Figures 9–16.



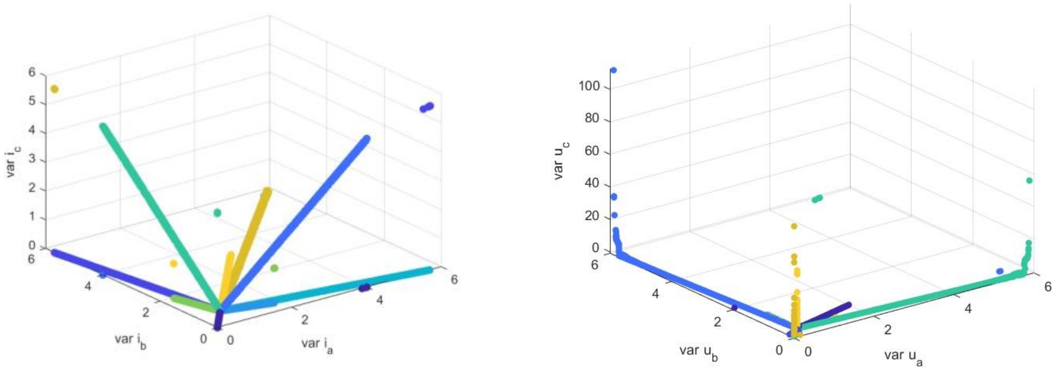
(**a**) (**b**)

Figure 9. Dependence of average values of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.



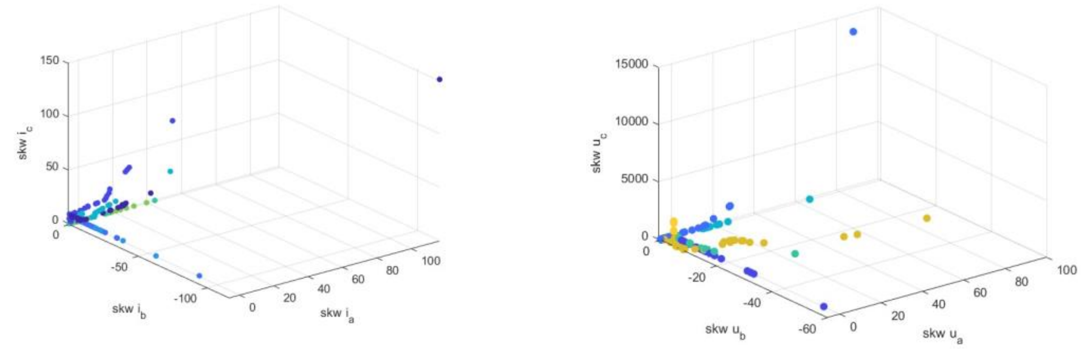
(**a**) (**b**)

Figure 10. Dependence of the root-mean-square deviations of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.



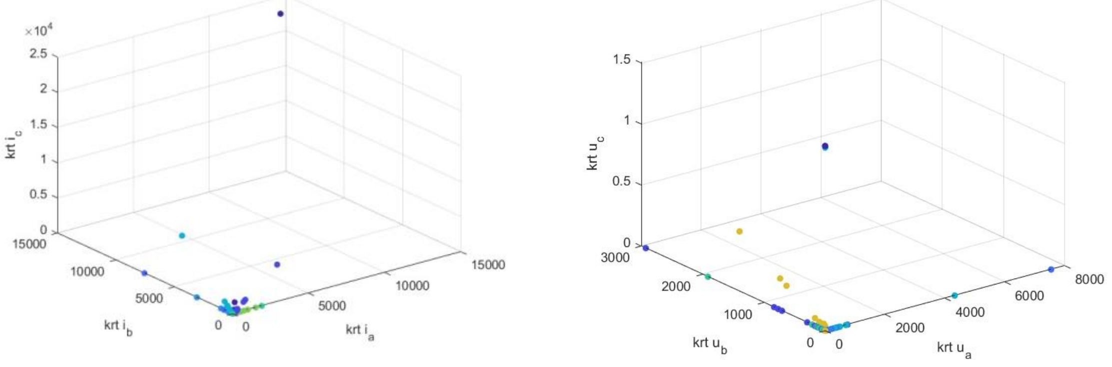
(**a**) (**b**)

Figure 11. Dependence of variation of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.



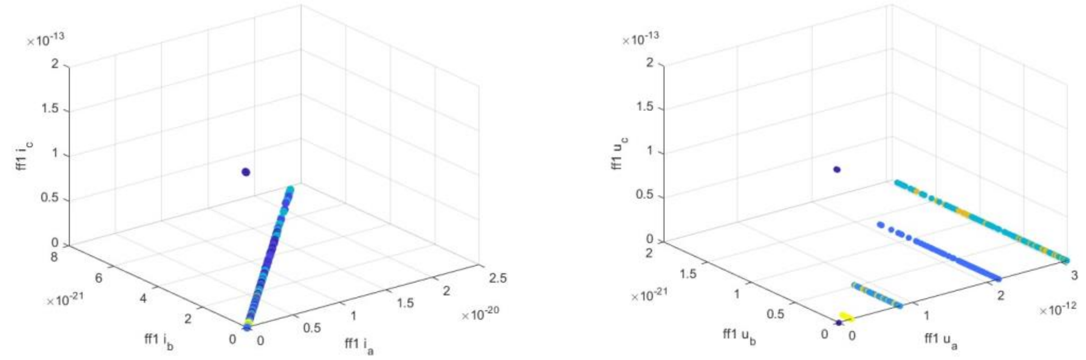
(**a**) (**b**)

Figure 12. Dependence of skewness of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.



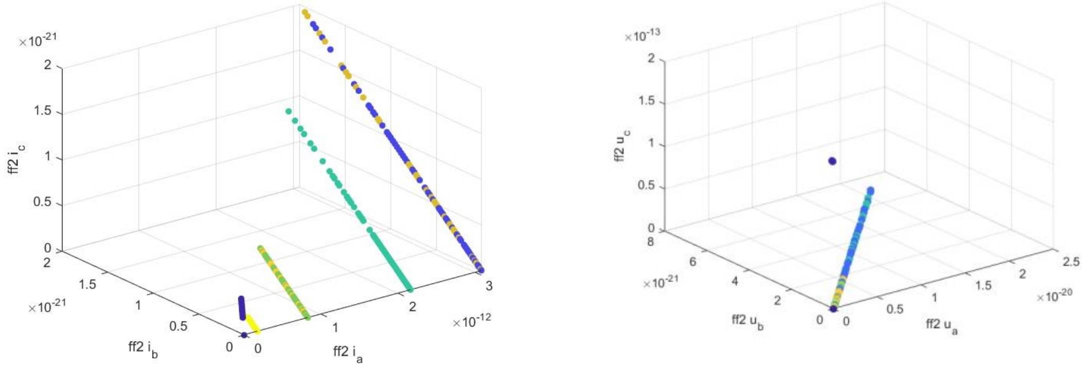
(**a**) (**b**)

Figure 13. Dependence of the kurtosis of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.



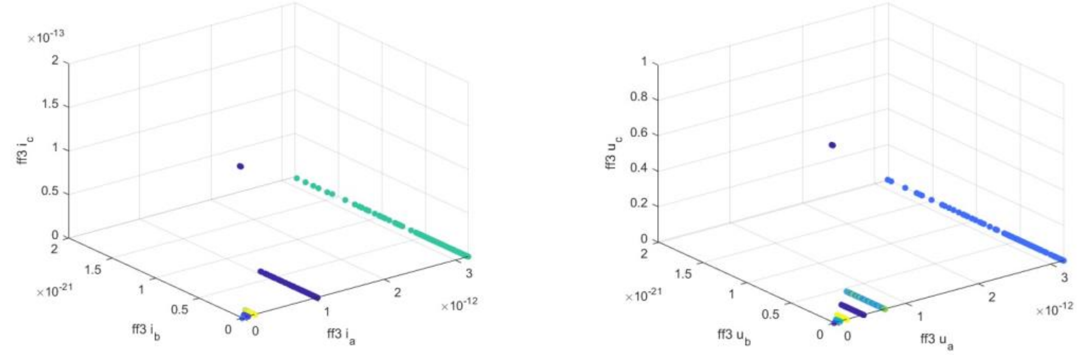
(**a**) (**b**)

Figure 14. Dependence of the first-order harmonic amplitude of the fast Fourier transform of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.



(**a**) (**b**)

Figure 15. Dependence of the second-order harmonic amplitude of the fast Fourier transform of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.



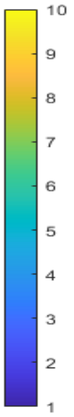
(**a**) (**b**)

Figure 16. Dependence of the third-order harmonic amplitude of the fast Fourier transform of the (**a**) currents i_a, i_b, i_c and (**b**) voltages u_a, u_b, u_c.

The analysis of the obtained dependencies (Figures 9–16) shows that the best features for which the phase separation is clearly visible are average values, root-mean-square deviation, and variations. They were used to train a neural network.

Table 1 shows the names of dependencies' colors, as shown in Figures 9–16.

Table 1. Color assignments of the characteristics shown in Figures 9–16.

 10	without short circuit
9	a short circuit in the neutral phase ca
8	a short circuit in the neutral phase bc
7	a short circuit in the neutral phase ab
6	a short circuit in the ca phase
5	a short circuit in the bc phase
4	a short circuit in the ab phase
3	a short circuit in phase c
2	a short circuit in phase b
1	a short circuit in phase a

Considering that data is multidimensional and has a non-linear decision boundary, the fully connected feed-forward neural network architecture was chosen for further work. The artificial neural network created in the MATLAB software environment consists of 3 layers, the structure of which is shown in Figure 17. The number of input neurons was 48. It was obtained by processing according to the above eight different features (mean, std, var, sk, krt, fft1, fft2, fft3) of the phase currents i_a, i_b, i_c and the voltages u_a, u_b, u_c of the generator. The second layer consisted of 30 neurons. The number of output neurons was 10, which yielded classes corresponding to the numbers from 1 to 10, as shown in Table 1. The softmax function converts a z vector of size 10 into a vector σ of the same size, where each order of the resulting vector σ_i in the range from 0 to 1 are real numbers whose sum is 1. As a result, the presence of a short circuit or its absence is revealed.

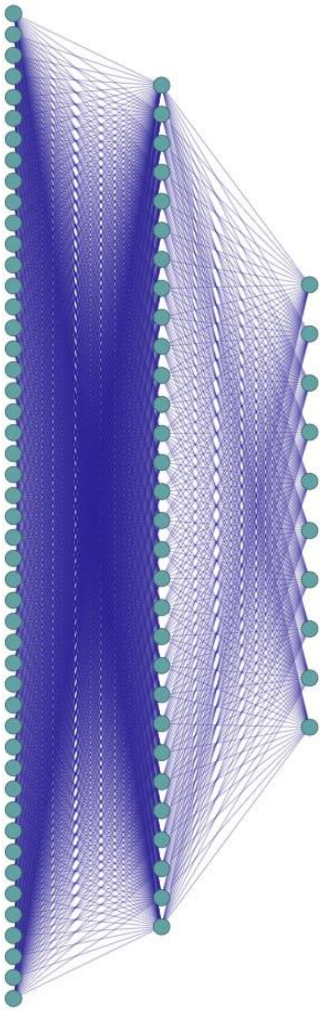


Figure 17. Neural network structure.

The neural network learning process is shown in Figure 18. The collected data is divided into two parts, training and validation, with a ratio of 70% and 30%, respectively. Training data was used to train the model, and during the training process, the accuracy of the model was evaluated using validation data. That is, the model was trained according to training data, and tested according to validation data. This approach allowed us to get a more accurate model.

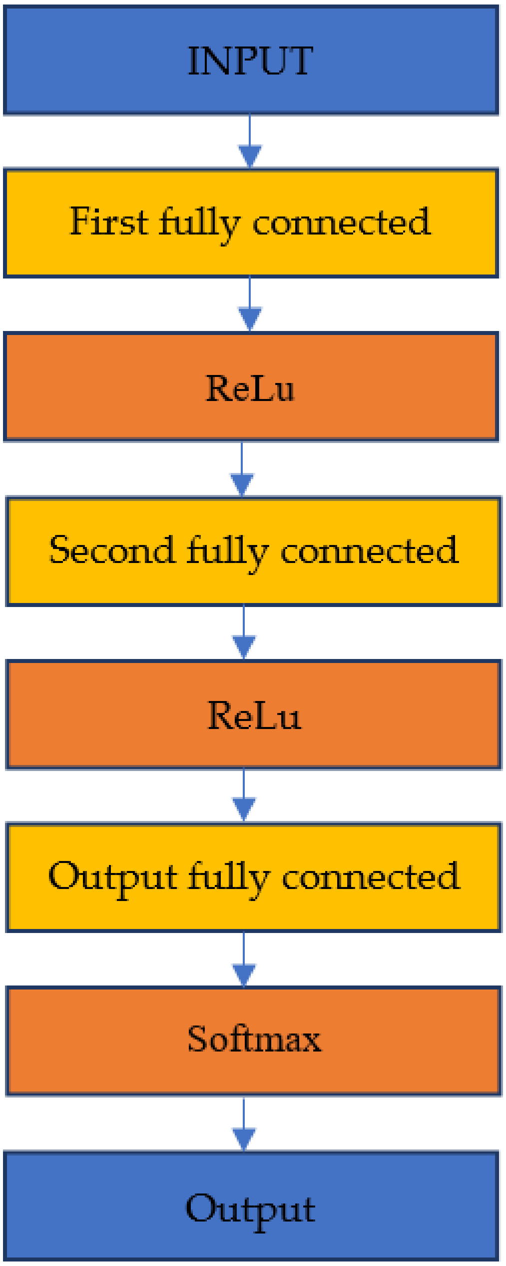


Figure 18. Neural network training process.

The effectiveness of the neural network training was evaluated by the error received at the end of training, which in this case, turned out to be 0.004 (Figure 19).

To check the performance of the neural network, a confusion matrix was used, which is in the form of a square matrix where the column represents the actual values and the row depicts the predicted value of the model, and vice versa. The confusion matrix can be visualized using the heatmap function, as illustrated in Figures 20 and 21. Validation data (30% of 20,000) were used as the input data of the model. With the help of this matrix, it is possible to track how the model confuses any class with any other class, that is, how it is mistaken. Diagonal blue cells show correctly classified cases.

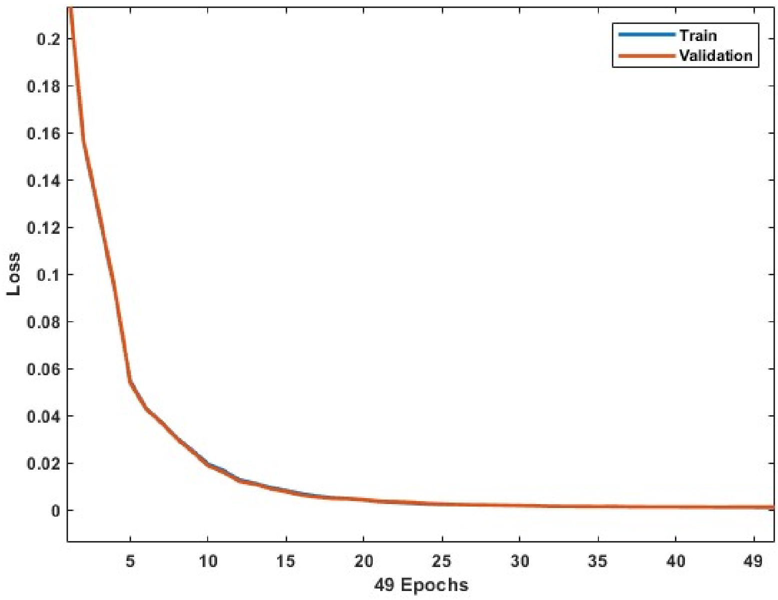
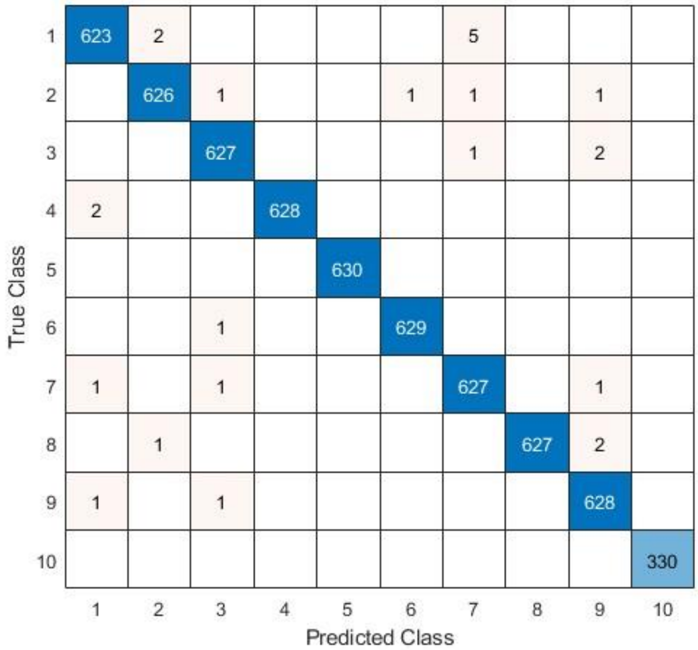
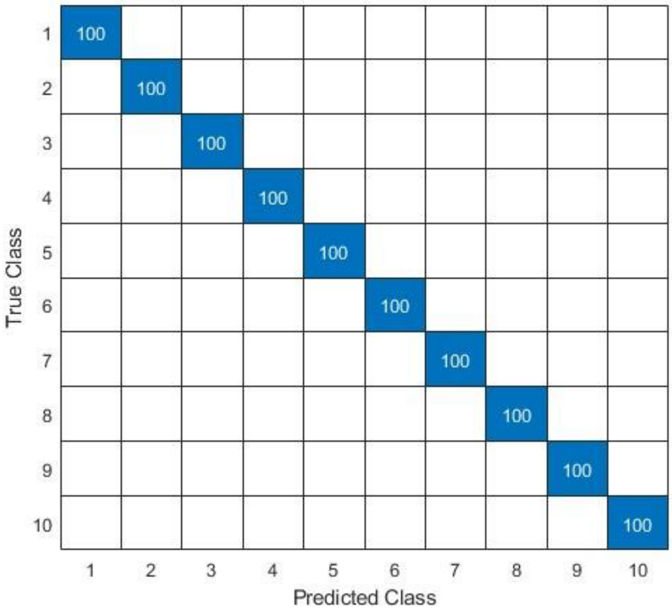


Figure 19. The training performance.



	1	2	3	4	5	6	7	8	9	10
1	623	2					5			
2		626	1			1	1		1	
3			627				1		2	
4	2			628						
5					630					
6			1			629				
7	1		1				627		1	
8		1						627	2	
9	1		1						628	
10										330

Figure 20. Confusion matrix of validation data.



True Class \ Predicted Class	1	2	3	4	5	6	7	8	9	10
1	100									
2		100								
3			100							
4				100						
5					100					
6						100				
7							100			
8								100		
9									100	
10										100

Figure 21. Confusion matrix of unknown data.

From Figure 20, it follows that the data from the first class, 623, were correctly guessed by the model, the second was confused with the second class, and the fifth with the seventh class.

To evaluate the performance of the model, arbitrary data unknown to the model were collected, 100 data from each class. The confusion matrix built on the basis of these data is shown in Figure 21. It can be seen that the model correctly recognized the classes and does not confuse them with other classes.

The developed neural network model can be used in the diagnostic system that detects short circuits and prevents further failures.

3.2. Making Decisions about the Operation of the Generator in Case of a Phase Short Circuit

The result of detecting the type and location of a phase short circuit is a necessary but insufficient condition for protecting a synchronous generator from negative modes. Taking into account this circumstance, a model of decision-making about the operation of the generator is proposed. The basis for the construction of this model is a neural model of the classification of phase short circuits and the current requirements of the standards for the generator.

The Matlab/Simulink environment was chosen for its powerful engineering system modeling tools, which are used for the simulation of complex generator faults. To make decisions based on the results obtained at the output of the neural network, a simple and high-precision system was developed in the Matlab/Simulink environment, the structural scheme of which is shown in Figure 22.

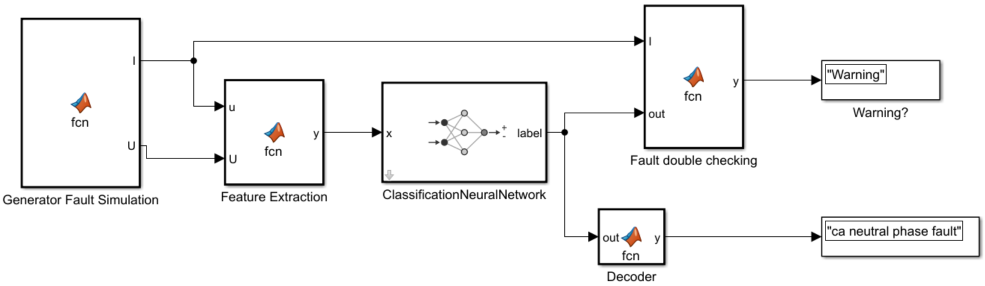


Figure 22. Block diagram of the decision-making system about the operation of the generator in the case of an asymmetric load.

The data received at the output of the neural network classification were transferred to the "decoder" and "fault double checking" blocks. The signal received in the decoder block was decoded and signaled a phase short circuit. In the "fault double checking" block, the degree of asymmetric load distribution in the phases was estimated. To make a decision on the further operation of the generator, the compliance of the values of the phase currents with the requirements of the standards was checked.

$$i_a < i_N, i_b < i_N, i_c < i_N \tag{1}$$

$$\frac{(max(i) - min(i))100\%}{min(i)} < 10\% \tag{2}$$

If any of the conditions were not met, then a signal was generated to turn off the generator, otherwise it continued to work.

4. Discussion

In this paper, the most common malfunctions occurring in a synchronous generator are considered in a logical sequence, as well as studies aimed at their detection and prevention. The hypotheses presented in well-known works are analyzed and appropriate comments on their applicability are provided. An in-depth analysis of well-known works in this direction has shown that they are mainly aimed at solving individual particular problems, which limits their applied significance. A significant part of the work is devoted to monitoring the generator, diagnostics, and detection of defects. Meanwhile, in the case of defects detected and abnormal operating conditions resulting from this, the primary task is to make decisions on the further operation of the generator that meet the requirements of current standards. It is known that in a three-phase generator, asymmetric short circuits mainly occur as a result of single-phase, two-phase, three-phase and neutral wire short circuits, from which follows the strategy of implementing the idea presented in this article. Within the framework of this article, the authors have developed and proposed, for further use, a model based on an artificial neural network about the type of short circuits in the generator windings, detecting their location, and making decisions about their further operation. The tests were carried out in the Matlab software environment based on the selected generator. The signals of phase currents and voltages were processed by different features, which make it possible to form an objective representation of the phase characteristics. The use of the SoftMax activation function for the output layer of the neural network made it possible, in the case of various short circuits, to immediately fix and freely transfer them to the decode block.

From the practical evaluation of the results obtained, it follows that:

1. The developed model for detecting and classifying defects in the generator has high operation speed and accuracy. This is due to the complex processing of the collected data on the mean value, mean square deviation, and features of variation. In this case, during the training process, it was established that the network should be trained for 1000 cycles. However, the network trained for 49 cycles, the learning process was suspended, and the accuracy was 99.5833%;
2. The model for detecting and classifying phase short circuits in a synchronous generator has high performance, which is confirmed by the results shown by the confusion matrix built for various data;
3. In the event of asymmetric operating modes, the decision-making model for the further operation of the generator makes it possible to increase the efficiency of the system.

Unlike the well-known works, where the detection of phase short circuits of a synchronous generator and their classification are considered in power transmission lines [38,39], the model developed for this study is applicable to the stator windings of synchronous generators used in various fields. In addition, the proposed model makes it possible to simultaneously evaluate short circuits in all phases. The specific application of the results obtained was considered for generators used in hydroelectric power plants and diesel or gasoline installations for stationary power supply, taking into account the phenomena that occur during their acceleration.

Analysis of the obtained results shows that a neural network model built to detect and classify phase short circuits can be exported and placed in real controllers. This will expand the application of the results obtained and, in addition, build controllers with various modifications. The presented comments give reason to conclude that the obtained results have wide development possibilities; in particular, they can be applied to the diagnosis of various electrical machines and the development of intelligent systems that provide high reliability and control speed.

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