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Ilkhombek Kholiddinov
Ferghana Polytechnic Institute
Doctor of Technical Sciences
https://orcid.org/0000-0002-0120-4043
i.xoliddinov@ferpi.uz
Mashkhurakhon Holiddinova
Ferghana Polytechnic Institute
doctoral student
https://orcid.org/0009-0006-2430-5708
mashhuraxonxoliddinova@gmail.com

Modeling a Block to Determine the Type of Damage to a Power Line Using Matlab

Abstract

This article discusses the modeling of a block for determining the type and location of damage to a power line based on artificial neural networks. A description of the working scheme, the principles of the model and the key stages of neural network training is introduced. The simulation was performed in the MATLAB environment, including Simulink and Neural Network Toolbox, which allowed us to build an accurate and scalable model. Phase voltages and currents, as well as their symmetrical components, were used as input parameters for the analysis.

As part of the research, the architecture of a two-layer neural network with one hidden layer containing 10 neurons using a sigmoidal activation function has been developed. The linear output layer provided prediction of the type of damage and its location. The Levenberg-Marquardt algorithm was used to train the network, which provided a fast and stable solution to the problem. The training was conducted on a large data set containing more than two million observations, divided into training, validation and test samples.

The simulation results demonstrated high accuracy in damage classification, minimal standard deviation, and a stable correlation between model predictions and real data. Graphs and error histograms confirm the stability of the network. The use of artificial neural networks has significantly reduced the diagnostic time and improved the quality of the analysis of emergency modes in 10 kV power lines. The results obtained open up prospects for further implementation of such approaches in the energy industry.

Keywords: *power lines, reliability, modeling, neural networks, type of damage, short circuit*

İlhombek Xoliddinov
Fərqanə Politexnik İnstitutu
texnika elmləri doktoru
https://orcid.org/0000-0002-0120-4043
i.xoliddinov@ferpi.uz
Maşxuraxon Holiddinova
Fərqanə Politexnik İnstitutu
doktorant
https://orcid.org/0009-0006-2430-5708
mashhuraxonxoliddinova@gmail.com

Matlab istifadə edərək elektrik xəttinin zədələnməsinin növünü müəyyən etmək üçün blokun modelləşdirilməsi

Xülasə

Bu məqalədə süni sinir şəbəkələrinə əsaslanan elektrik xəttinin zədələnməsinin növünü və yerini müəyyənləşdirmək üçün bölmənin modelləşdirilməsi müzakirə olunur. İş sxeminin təsviri, modelin iş prinsipləri və sinir şəbəkəsinin öyrənilməsinin əsas mərhələləri təqdim edilmişdir. Simulink və sinir şəbəkəsi Toolbox da daxil olmaqla MATLAB mühitində Simulyasiya aparıldı və bu, dəqiq bir model qurmağa imkan verdi. Analiz üçün giriş parametrləri olaraq faz gərginlikləri və cərəyanları, həmçinin simmetrik komponentləri istifadə edilmişdir.

Tədqiqat, sigmoidal aktivasiya funksiyasından istifadə edən 10 neyrondan ibarət bir gizli təbəqə ilə iki qatlı sinir şəbəkəsinin arxitekturasını inkişaf etdirdi. Xətti çıxış təbəqəsi zərərin növünü və yerini proqnozlaşdırdı. Şəbəkənin tədrisi üçün problemin sürətli və sabit həllini təmin edən Levenberg-Marquardt alqoritmi istifadə edilmişdir. Təlim – təlim, doğrulama və test nümunələrinə bölünmüş iki milyondan çox müşahidədən ibarət böyük bir məlumat silsiləsi üzərində aparılmışdır.

Simulyasiya nəticələri zərərin təsnifatında yüksək dəqiqlik, minimum RMS xətası və model proqnozları ilə real məlumatlar arasında sabit korrelyasiya nümayiş etdirdi. Səhvlərin qrafikləri və histoqramları şəbəkənin sabitliyini təsdiqləyir. Süni sinir şəbəkələrinin istifadəsi diaqnostika müddətini əhəmiyyətli dərəcədə azaltdı və 10 kv gərginlikli elektrik xətlərində təcili rejimlərin analizinin keyfiyyətini yaxşılaşdırdı. Əldə olunan nəticələr enerji sənayesində bu cür yanaşmaların daha da tətbiqi üçün perspektivlər açır.

Açar sözlər: *elektrik xətləri, etibarlılıq, modelləşdirmə, sinir şəbəkələri, zədələnmə növü, qısaqapanma*

Introduction

Power transmission lines (power lines) are key elements of the electric energy system that ensure the transmission of electricity from generators to consumers. The stability and reliability of their operation play a critical role in ensuring uninterrupted power supply (Melnikov, 1975). However, power transmission lines are subject to various types of damage, which can be caused by both internal factors (overloads, equipment malfunctions) and external influences (adverse weather conditions, mechanical damage, short circuits) (Kabashov, 2008).

Diagnosis of damage on power transmission lines is a key task to ensure reliable power supply (Vorkunov, 2013, Kholiddinova, 2024, Kholiddinov, 2024). Modern power transmission lines are characterized by a high length and complexity of infrastructure, which creates additional difficulties in identifying emergency situations. Accurate and fast diagnostic methods are becoming increasingly in demand to prevent prolonged downtime and reduce economic losses (Kholiddinov, 2024). Traditional approaches do not always provide the necessary speed and reliability of analysis, especially in non-standard situations (Kulikov, 2009).

This paper discusses the use of neural networks to develop a model for determining the stage and location of damage. The advantage of neural networks lies in their ability to learn from large amounts of data, identify complex dependencies, and adapt to new operating conditions. MATLAB was chosen as the main environment for simulation and training of neural networks due to its extensive model building capabilities, integration with various analysis tools, and ease of working with big data.

The relevance of the topic is due to the need to improve the reliability of power systems and reduce the time needed to eliminate emergencies. The development of models using neural technologies opens up prospects for the creation of intelligent monitoring and control systems capable of significantly improving the operation of power transmission lines.

Research

Among the most common types of damage to power lines are: single-phase earth faults, which make up a significant part of all damages; interphase faults, leading to serious disruptions to the network; two-phase earth faults and three-phase faults, which often lead to a complete loss of network stability (Vorkunov, 2013).

These malfunctions can cause significant power losses, equipment damage, and power system failures, making their rapid identification and classification one of the most important tasks in the modern electric power industry (Lapina, 2023).

Scientific and practical interest in the problem of diagnosis and classification of damages is explained by the need to minimize the reaction time to a malfunction, reduce the cost of restoration and ensure the safety of operation of power systems. Modern approaches to solving this problem include the use of artificial intelligence methods, systems based on time signal analysis and numerical models (Kholiddinov, 2024; A. Salem, 2023).

The aim of the study is to create and analyze a neural model for classifying the type and location of power line damage based on current and voltage analysis. To do this, the necessary steps were identified, including: collecting and preparing data on emergency modes, building a power line model in MATLAB Simulink, developing a neural network architecture, training and testing the model, analyzing the accuracy and classification of damage.

The electrical network diagram is built using MATLAB Simulink libraries. The main elements of the circuit include: a power source that sets voltage and frequency parameters, power lines that are modeled taking into account active and reactive resistances, loads that represent various types of consumers, nodes and measuring units that are used to monitor currents and voltages at key points in the circuit. Using the library blocks of the Sim Power Systems expansion pack, the power transmission line (its section) is modeled according to the substitution scheme.

When modeling power supply systems, the Three-Phase Fault icon is used (Fig. 1), which simulates a three-phase device that closes the phases to each other, as well as to the ground.:

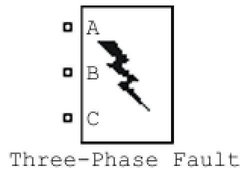


Fig. 1 Three-phase short circuit breaker

The circuit breaker replacement scheme is shown in Fig. 2. The value of the grounding resistance g R is set to 106 ohms if the earth fault is not specified in the block parameters window.

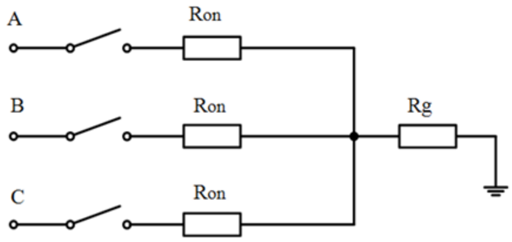


Fig. 2 Three-phase short circuit block replacement circuit

For the model (Fig. 2) using this block, models will be developed for the 12 situations listed in Table 2.

Table 2

Type of malfunction			
AG	AB	ABG	ABC
BG	BC	BCG	ABCG
CG	CA	CAG	Нет

The 8 input and 1 output parameters obtained from them are trained in the NNTool block in the Matlab program (Fig. 3). In this case, the input and output parameters are expressed in a neural network, with 8 parameters used as input values, including phase voltages UA, UB, UC, IA, IB, IC, U0, I0 The number of hidden neurons is 10, and the output parameters are 5: 1) single-phase short circuit to ground, 2) two-phase short circuit to ground, 3) two-phase short circuit, 4) three-phase short circuit, and 5) damage location information.

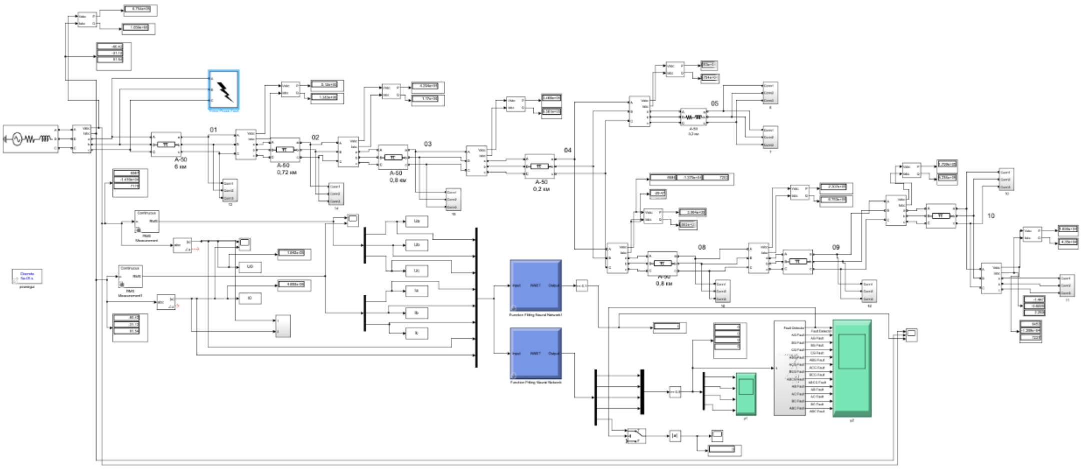


Fig. 3. Electrical network model

This circuit is a comprehensive model of a 10 kV electrical network designed to analyze the condition of the network, locate damage and determine their nature. It is implemented as a flowchart using a modular approach, which allows flexible adaptation and expansion of its functionality. The main elements of the model are the power supply, feeder lines and loads (Q1–Q10), monitoring and measurement units, signal processing units, neural networks, damage classification and localization units.

Neural networks include two neural network processing modules (indicated by blue blocks):

- the first module analyzes the condition of feeder lines (damage detection based on current and voltage data).

- the second module processes data from network nodes (current distribution determination and damage localization).

The damage classification and localization units determine the nature of the damage (breakage, short circuit, etc.) and its location within the feeder line or node. They use the results of neural networks, combining them with the source data. The green blocks in the diagram are responsible for collecting the final data, interpreting it, and providing it to the user.

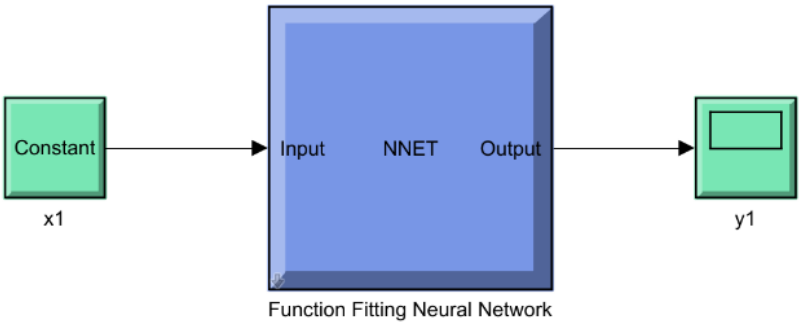


Fig. 4. The developed block for determining the type of malfunction in a neural network

Neural network architecture. The developed block is a multilayer perceptron (feedforward neural network) with one hidden layer and a linear output layer suitable for regression tasks (Fig. 5). The hidden layer consists of 10 neurons using a sigmoidal activation function. The linear activation function of the output layer provides the ability to predict continuous values.

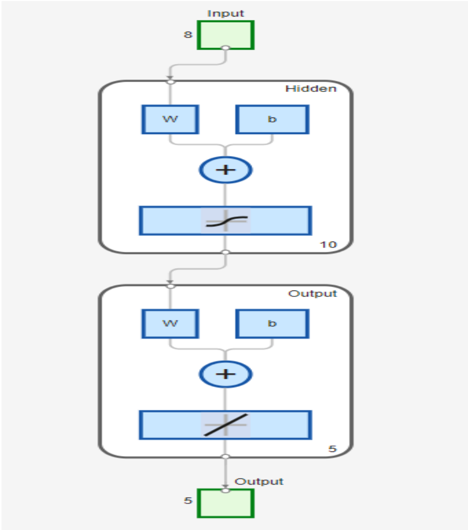


Fig. 5. Neural network architecture

Learning algorithm and stopping criteria. The network was trained using the Levenberg-Marquardt algorithm, which provides a fast and stable convergent solution for problems with a small number of parameters.

The criterion for stopping training was exceeding the set number of validation checks. Training ended on the 574th iteration out of a maximum of 1,000 due to six non-improvements in the error rate in the validation sample.

Arrays of data were used to train the neural network (Fig. 6):

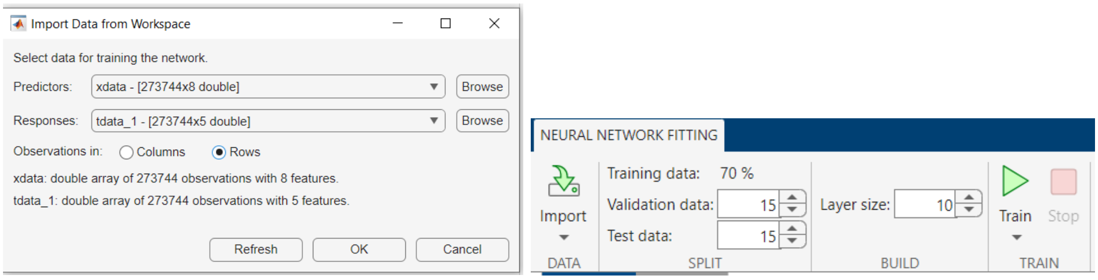
The input data consists of 8 features, and the output consists of 5 (predictors).

Data dimension: 2737144 observations. The data was divided into three parts:

The training sample: 70% (1916,000 observations).

Validation sample: 15% (410,600 observations).

Test sample: 15% (410,600 observations).



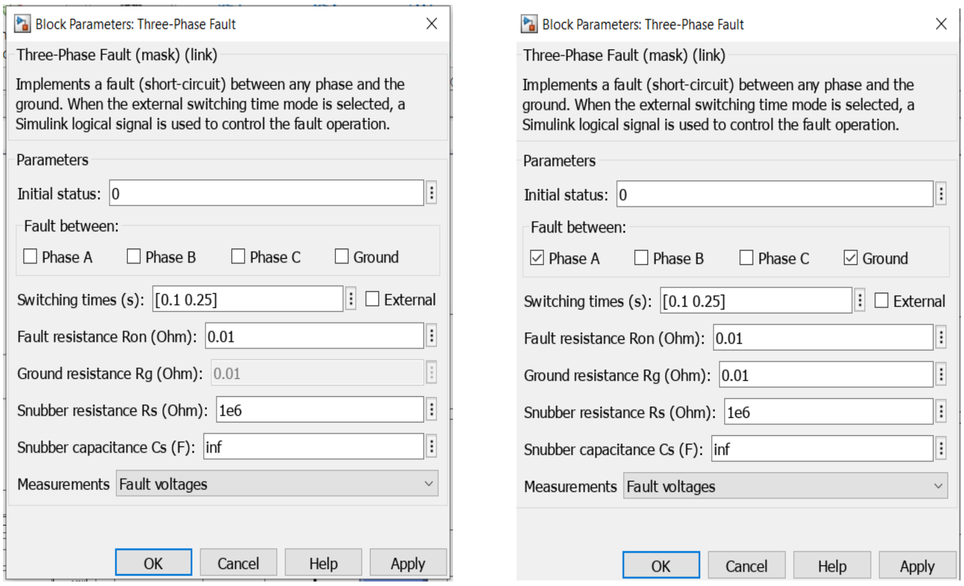
a) b)

6. Arrays of data for network training:

a) dimension; b) data distribution

Learning outcomes. The standard deviation (MSE) for the training, validation and test samples was 2.78×10-3, which indicates a low degree of deviation of the predicted values from the real ones. The coefficient of determination (R) for all samples is 0.7562, which demonstrates a moderate correlation between the input data and the target values.

The chosen neural network architecture showed stable performance, and the error in the test sample turned out to be at the level of the training and validation samples, which indicates the absence of retraining.



a) b)

Fig. 7. The window for setting the short-circuit breaker for the situation:
a) without damage; b) Short circuit of phase A to the ground

The various types of damage listed in the table above are set in the circuit breaker setup window. In Fig. 7,a, the case without damage is considered and the blocks in the model show the result with the values of each line 0 (Fig. 8, a). And another case with damage is considered in Fig. 7,b and Fig. 8,b, where one on the block means that there is damage to phase A. and land.

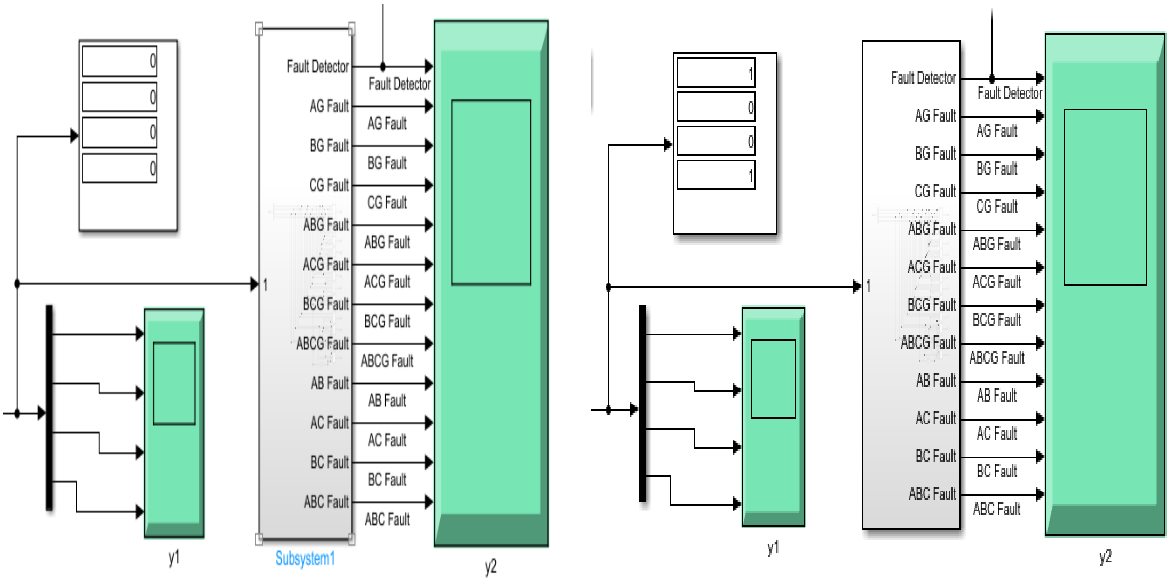
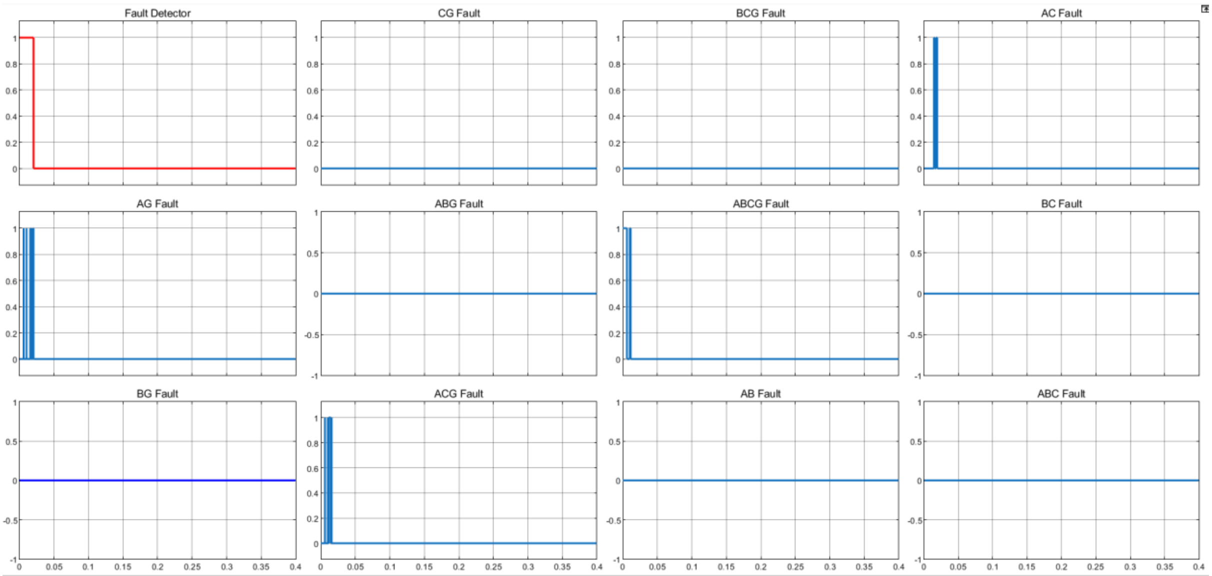
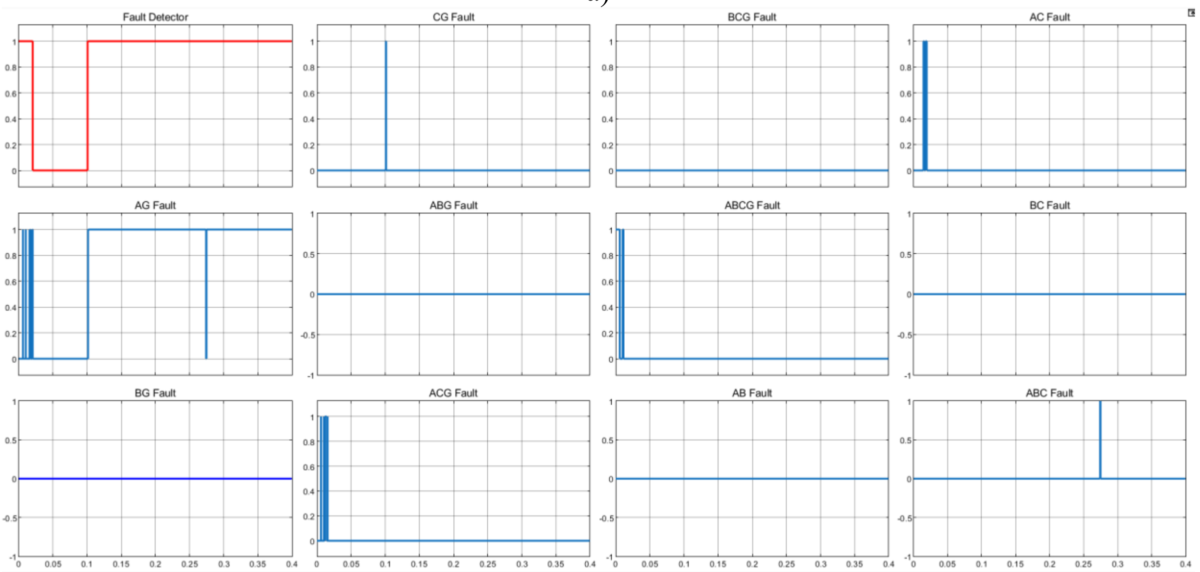


Fig. 8. Fragment of the model section with blocks
a) without damage; b) Short circuit of phase A to the ground

The graphs (Fig. 9) show the operation of the damage detection and classification system. Each subgraph displays temporary changes in indicators reflecting the state of various types of damage in the network.



a)



b)

Fig. 9. Graphs with the results of the type of damage:
a) without damage; b) Short circuit of phase A to the ground

The main Fault Detector indicator shown in the graphs (Fig. 9) demonstrates the system's response to fault detection. Damages are displayed as signals that take the value 1 when a fault is detected, zero – without damage. The remaining subgraphs represent the system response for each type of fault. In Fig. 9,b, the graph shows the occurrence of this type of damage.

All graphs are arranged in the same time interval (0.4 seconds), which allows you to evaluate the performance of the system.

Thus, you can examine each type of damage and see how the blocks work on the model.

Conclusion

The developed model demonstrates high accuracy and stability in determining the type of damage, which is confirmed by the results of modeling in the MATLAB environment. Using the Levenberg-Marquardt algorithm provided fast neural network training on large amounts of data with minimal RMS error values.

The proposed approach makes it possible to significantly reduce the diagnostic time and improve the reliability of power systems. This opens up prospects for further integration of artificial intelligence into power grid management, providing intelligent monitoring and automation of the damage control process.

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