Journal of Intelligent Systems and Internet of Things
Vol. 18, No. 02, PP. 122-129, 2026
DOI: https://doi.org/10.54216/JISIoT.180209

Fault Monitoring in Transmission Lines Using Modular Neural Networks in Simulated Smart Grids

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Abstract

The transmission of energy is one of the main tasks of Electrical Engineering. Transmission lines are used for this purpose, which are susceptible to various problems such as short-circuit, overload, open circuit, and complex faults. From the perspective of smart grids, one of the open challenges is to have autonomous systems that allow the detection, classification, and location of faults in transmission lines. On the other hand, Artificial Neural Networks are computational tools used in classification and control tasks to be applied to different plants and systems. There are several ways to solve problems using ANNs; one is modularity. This strategy consists of dividing the problem into components that are easier to classify. In this way, a modular system is proposed that is composed of three ANNs: One for detection, one for classification, and one more for the location of faults in transmission lines. A simulation model of a three-phase electrical power system was built using Simulink MATLAB, employing a data transmission approach typical of smart grids. Supervised learning and WEKA software were used for network training. Databases were created using the potential difference and line current, as well as the ground fault impedance. The database was developed through cases and mathematical models, and the performance of the networks was evaluated in the simulated model. The results show that the proposed model allows the identification of all cases presented in the test stage (100%), which is a better performance than a single neural network (81.25%) that is responsible for detecting, classifying, and locating faults.

Received: March 07, 2025 Revised: June 01, 2025 Accepted: July 10, 2025

Keywords: Modular Artificial Neural Networks; Transmission Lines; Power system failures; Smart Grids

1. Introduction

Within electrical power systems, one of the main tasks is to transport energy to users. Transmission lines are a particularly essential element in this task since they are the elements that allow the conduction of energy between different points. Transmission lines are susceptible to failures that prevent the transmission of electrical energy; among them are short-circuit, overload, open-circuit, failure between coil turns, and complex faults [1].

Given the current technological progress and its permeability in society, which requires the continuous consumption of electrical energy, it is crucial to study the events associated with the grids. This is reflected in the goal of multiple smart grid systems to maintain a reliable supply [2]. Smart grids are an application of Industry 4.0 [3] and society 5.0 [4] where electrical variables must be constantly monitored for the improvement of generation, transmission, distribution, and consumption processes [5]. These types of systems depend mainly on the use of communication and information exchange mechanisms [6], such as the Internet of Things (IoT), and automatic control systems based on decision-making [7]. Incorporating systems based on Artificial Intelligence (AI) is one of the open and most important challenges in the field [8].

Thus, to avoid the adverse effects caused by damage to transmission lines, there are various tools for detecting, classifying, and locating faults. Among them are Artificial Neural Networks (ANN), such as feed-forward [9]. An example of this is proposed [10] for the classification of failures. The purpose is the classification of faults using current and phase voltage signals as inputs for the neural networks. Or the system for fault diagnosis based on a Long Short Term Memory ANN [11], which uses the electric current and the potential difference in the lines. These solutions are characterized by focusing on the detection, classification, or location of faults. That is, these solutions are not capable of performing all three tasks at the same time.

The problem of detecting, classifying, and locating faults in transmission lines using ANNs can be addressed through the perspective of modular systems. This type of system divides the problem into components, so the overall solution comes from the interaction of all the modules. This approach has proven successful in other applications of ANNs, such as robot control [12], where the modules solve tasks, such as avoiding obstacles or identifying areas. In addition, modular ANNs have some characteristics as high learning capacity, flexibility in using different data types, capacity to manage nonlinear models, and complex models [13].

Research questions that this article seeks to answer are as follows: Does a modular AAN system allow detection, classification, and localization of faults in transmission lines? Can a non-modular model solve this problem? Thus, in this research, it is proposed to create a modular model for the detection, classification, and location of faults in transmission lines using a simulated environment and the smart grid approach through remote sensing. The results are compared with a non-modular model trained to fulfil the three tasks. To do this, feed-forward neural networks trained by backpropagation and a database coded from the mathematical model of the transmission lines are used.

Thus, section two of this article presents the methodology used for the creation of the modular model and the tests conducted. Section three shows the results obtained in the simulation environment. The discussion is addressed in the fourth section, and in the last section, the conclusions of the research are presented.

2. Methodology

The objective of this work is to create a modular model based on ANNs for the detection, classification, and location of faults in transmission lines. In addition, it seeks to verify that a feed-forward ANN cannot conduct these three tasks. All this is evaluated in a virtual environment, where a model is created oriented to the requirements of a smart grid with remote sensors.

The first step was to build a computational model of the transmission lines (see Figure 1). The model includes a three-phase generator, line voltage of 13.8kV RMS and frequency of 60Hz, a delta (primary) - star (secondary) transformer with a power of 10kVA and a ratio of 13.8kV/138kV. The second transformer has a star (primary) and delta (secondary) configuration, with the same power rating as the first and a ratio of 138kV/13.8kV. A sensor is used to measure phase-to-ground voltages and phase currents. The transmission lines resistance was 16.075Ω, inductance of 21.675H, and negligible capacitance. A load (8kW consumption) is included at the end of the model. Finally, data produced by the sensors is transmitted through a communication model to be processed by the neural network.

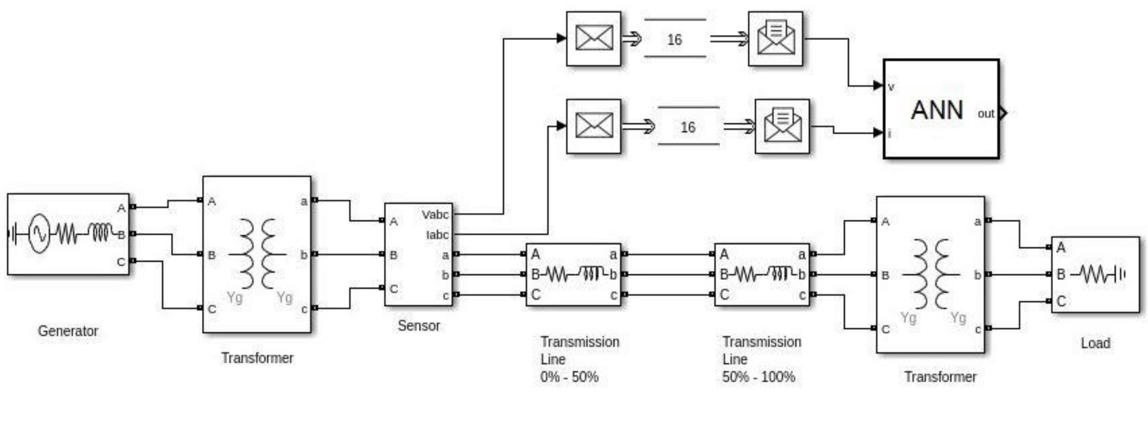

Figure 1. Transmission line model used. It contains a three-phase generator, two transformers, two blocks that simulate half of the transmission line, as well as a three-phase current-voltage sensor and a resistive load. The data from the sensors is transmitted to the neural network for processing.

Three neural networks were created for the detection, classification, and location of faults. In the case of a neural network for detection, phase currents were used as inputs. In all three cases, binary values are used for the electric current, with a value of 0 when the current is less than or equal to 5A and 1 when this threshold is exceeded. Seven different models of neural networks were evaluated, all with feed-forward architecture and trained using Weka with a supervised learning algorithm (learning rate 0.3, momentum 0.2, max epochs 500, cross-validation 10 folds). Four models were configured with a two-layer topology, while three models were set up with a three-layer topology. Feed-forward ANNs were chosen because the system solves a classification task, and the databases are not time series.

For the classification neural network, eleven faults were established: Single-phase fault in each phase (A, B, and C), two-phase fault (AB, BC, and CA), two-phase ground fault (ABG, BCG, and CAG), three-phase fault (ABC), three-phase ground fault (ABCG). In addition, a fail-free state and a read-error state are set. Phase currents with binary values are used as inputs, as in the previous network. Additionally, phase impedance (Z_f) with binary values is used. The same neural network models used for the detection network were evaluated, using the classification percentage as a discrimination metric.

In the case of the location network, phase currents and voltages are used as input. The output has four states: Failure in the first half of the line, failure in the second half of the line, no failure, and error. The same architecture as in the case of the previous two networks was evaluated, using the percentage of correct classification as the metric for selecting the model.

Finally, a non-modular model with a feed-forward neural network was created. Seven different models of neural networks (4 two layers and 3 two layers) were evaluated. The network had as inputs the three lines' voltages and the three line currents, in addition to the phase impedance value. The value of the seven inputs is binary, and twenty-four output situations were obtained to cover the cases of detection, classification, and localization with a single network.

For the validation of trained networks, cross-validation with ten folds is used. The training process is replicated ninety times for each model. The percentage of correct answers was used as a variable for the selection of the final model.

The two control models were programmed: modular and non-modular. To do this, function blocks were used for the programming of artificial neural networks. These components were also used for the categorization of input signals such as phase impedance, voltages, and line currents. The faults were simulated in the transmission line model with two transformers and a generator. The modular and non-modular models were compared by simulating the 128 possible states, which are a consequence of the combination of the seven proposed binary inputs.

3. Results

In the proposed modular scheme, the networks operate under a distributed and no centralized scheme. That is, the three networks operate independently by classifying at the same instant of time. The database design and common inputs allow the task to be performed properly; avoiding inconsistent instances (see Figure 2).

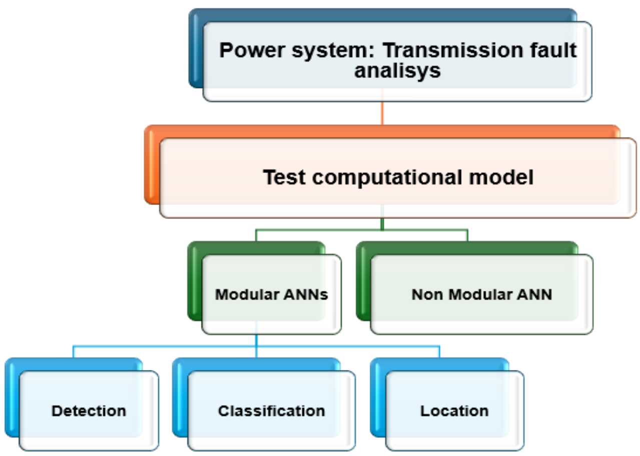

Figure 2. Experimental configuration. A modular and non-modular architecture for power transmission fault analysis was evaluated in a simulated scenario. The modular ANN was divided into 3 ANNs for detection, classification, and location tasks, respectively.

Regarding the neural network for fault detection, the model with the highest percentage of classification during training was chosen. In this case, a two-layer network was used, with two neurons in the input layer, two neurons in the output layer, and a sigmoidal tangential transfer function (see Figure 3).

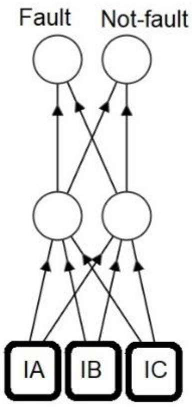

Figure 3. Neural network for fault detection. It is powered by all three-phase currents.

In the case of the neural network, the model with ten neurons in the input layer and thirteen neurons in the output layer was used to classify the type of failure (see Figure 4).

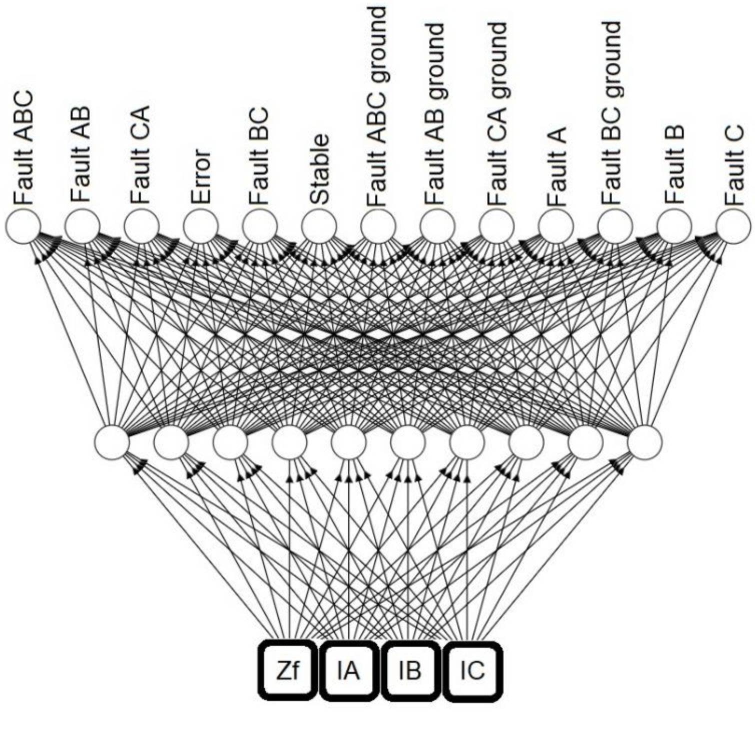

Figure 4. Neural network for fault classification. It has as inputs the three-phase currents and the impedance to ground.

Regarding the faulty location task, a multilayer model of ten neurons was used in the input layer, five in the hidden layer, and four in the output layer (Figure 4).

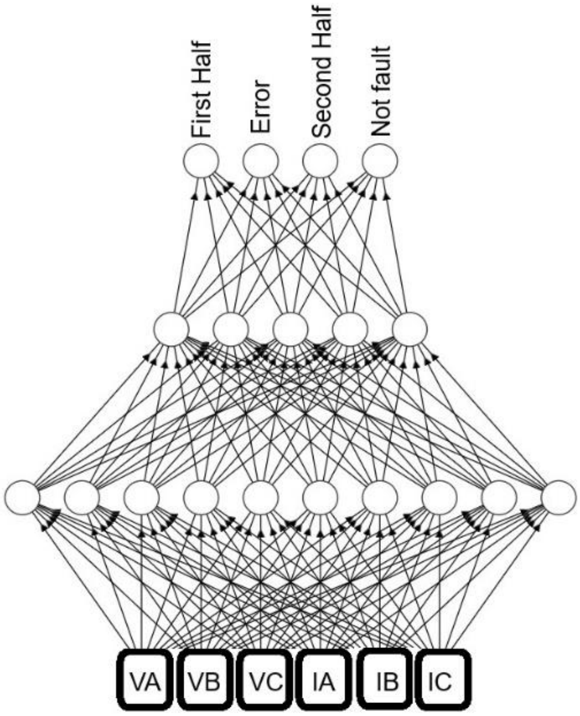

Figure 5. Neural network for fault location. It uses phase currents and voltages as inputs. Identify in which of the two halves the fault is located.

For the non-modular network, the best topology was configured by six neurons in the input layer and twenty-four neurons in the output layer (Figure 5).

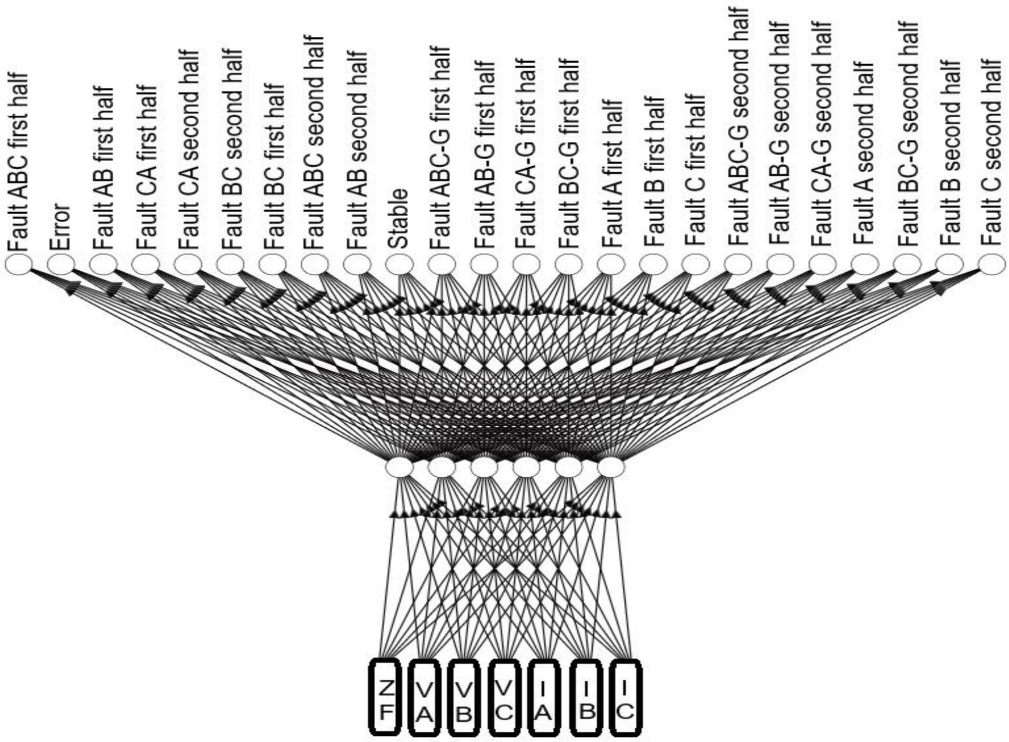

Figure 6. A non-modular network is used for the detection, classification, and location of faults in the power system. It uses phase currents and voltages, as well as the value of the impedance to ground.

By checking the 128 possible states in the simulated environment, the results of the modular model establish a 100% classification in each of the three networks that make it up (see Figure 7). For the non-modular model, the percentage of success in the simulation was 81.25%.

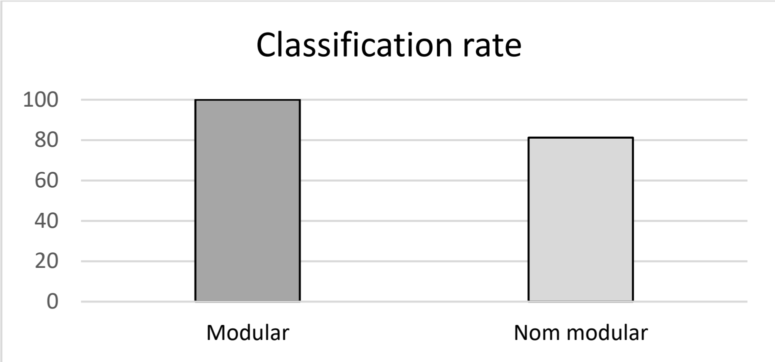

Figure 7. Results of the test stage in the simulator for the modular and non-modular models.

Table 1: Matrix confusion for modular and non-modular architecture

Task	Correct	Wrong
Detection	128	0
Classification	128	0
Location	128	0
Non-modular	104	24

4. Discussion

The result of this research is the proposal of a modular model based on feed-forward neural networks to solve the tasks of detection, classification, and location of faults in a transmission line. The test environment was Simulink software. To do this, it was compared with a feed-forward neural network model trained to classify all three tasks at the same time.

These results are consistent with what has been presented in the literature on the subject. For example, the accuracy of our ANN for classification faults (see Figure 14). In this case, [14] report that they obtained an efficiency of 98% in the analysis of transmission line failures. For their part, [15] mention that networks trained through Back Propagation reach 97.3% in the fault classification task. In both cases, the ANNs do not include the detection and localization of faults.

One ANN cannot fully solve the problem of the three classification tasks due to the divergence of the solution spaces [16]. It is, therefore, necessary to use techniques to divide tasks into various classification sub-systems. This is what the modular system represents, where there is a network that independently solves each task.

Although this technique is not the only one to avoid divergence of the solution spaces, it is one of the simplest to apply. It is based on the divide and conquer strategy, which reduces the complexity of the solution spaces. If the tasks are independent, i.e., the interaction between the modules does not exist or is reduced, the training produces the appropriate results, as shown in this case.

The proposed system needs a compatible IoT technology to operate in real time, reduce data loss, and increase the reliability of monitoring processes. We propose to use MQQT, which allows scalability, low bandwidth consumption, and low cost for implementation [17]. The protocol is compatible with system components (sensors, data processing modules, interfaces) and is suitable for the required latency [18] produced by the long distances involved in transmission lines.

Finally, what we presented is a total proposal for monitoring through neural networks, which not only allows the detection and classification of faults. This model detects the section where the fault is located (first or second half of the transmission line). This reduces repair and maintenance times in power systems. This approach is fully compatible with the needs of smart grids, where remote real-time data acquisition schemes are employed [19] and control systems that determine actions to ensure the proper functioning of the grid [20], and it is scalable for data models with more instances [21].

6. Conclusion

The proposed modular system of artificial neural networks allows for solving the problem of detection, classification, and location of faults in transmission lines. This allows constant monitoring of electricity networks to verify their correct operation. This approach is important from the perspective of smart grids, Industry 4.0, and Society 5.0. As future research, modular architecture will be reached using time series analysis and a real-time learning algorithm, which increases the discrimination capabilities.

Funding: "This research received no external funding"

Conflicts of Interest: "The authors declare no conflict of interest."

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