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# Transmission Line Fault Isolation Using Artificial Intelligence via Neural Networks

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**Abstract**: Transmitting a bulk amount of power from one place into another is normally performed using transmission lines. The increase of these transmission lines in different areas with different conditions usually leads to developing faults in these lines. Hence, it becomes of high interest in locating the line faults to maintain system stability and resume normal power flow operation. Knowing the current and voltage data is mainly the key point in locating the network faults. In this paper, a transmission line fault isolation technique using Artificial Intelligence (AI) via Artificial Neural Networks (ANNs) is presented. The current and voltage values of faults in different areas of transmission lines are studied and identified. The identification of the fault location is performed utilizing the ANN backpropagation algorithm. Based on the data provided by the ANN, a designated circuit breaker is used to isolate the fault and avoid system instability. The proposed technique is investigated by performing a comparison with recently related published work while clearly seeing the advantages of the new approach.

**Keywords:** Power transmission line, Fault detection and isolation, Bus systems, Artificial intelligence

## Introduction

One of the most important procedures and operations that must be carried out to protect an electrical network equipment and affect its stability safety is the prompt and accurate detection of faults and isolating them from the network (Barik, et al., 2018). In a network, there are multiple types of faults that may occur in transmission lines. Faults may be characterized as a Short Circuit Fault: (AG (phase A to Ground), BG (phase B to Ground), CG, ABG, BCG, CAG, AB, BC, CA, ABC, and ABCG) or an Open Circuit Fault (Silva et al., 2006). One of the most commonly used methods is using a relay that reads the current value on the transmission line and then gives a command to the circuit breaker to trip if the current exceeds a predetermined threshold value (Piesciorovsky & Schulz, 2017; Costa, Monti, & Paiva, 2017). Accordingly, the most important relay used in the protection of transmission lines is the distance relay.

The relay is designed to trip the circuit breaker in the event of a fault which is divided into multiple zones, each with its specific impedance. Its operation principle relies on measuring the impedance of the transmission line, which is read when a fault occurs (Lotfifard et al., 2010). A non-unit protection distance relay (a global short-circuit protection scheme) is also used for long transmission systems. In this relay, supplementary currents and relay terminals receive current values from the current transformers (CTs) and voltage values from the voltage transformers (VTs).

This aids in monitoring the apparent impedance, which serves as a practical indicator of the physical boundary settings for the several stepped zones, including the first, second, and third zones (Venkatanagaraju et al., 2021). The work in this paper is divided into different sections. Section II illustrates some of the previous studies for fault identification using neural networks, as will be the focus of this paper. Then, Section III explains the proposed methodology while outlining the process of building the neural network, training it, and testing its performance using MATLAB simulations. Section IV presents results and analysis of the proposed method performance as compared with some of the other related techniques. As a final section, Section V presents the conclusion of this paper.

## Literature Overview

Power system protection has been recently considered as an imprtatnt research subject area (Ali et al., 2024). Different AI methods have been used in system modeling and optimizaton (Alsmadi et al., 2024). Many research studies have used neural networks to identify and classify faults in transmission lines. A group of researchers, in 2015, used a neural network in two stages.

In the first stage, the ANN was used to determine the presence or absence of a fault, with a single output representing “1” for fault presence and “0” for no fault. In the second stage, the neural network was used to identify the type of fault. The outputs represent each phase that experience some faults. For example, if a fault occurred in phase A to ground, then the output would be represented as 1001 (Leh, at al., 2020).

Recently, Kumari et al. used a neural network technique to identify faults in a transmission line that was 100 km long with a specific load at its end (Kumari, et al., 2023). There was one output for the neural network, which means there would be 1 output in the presence of a fault and 0 output in the absence of a fault. In 2021, Bishal et al. used neural networks to study faults in a transmission line, in which their neural network was used to trip a circuit breaker in the event of a fault. The system used in this study consisted of 1 circuit breaker, 1 load, and 1 transmission line (Bishal, et al., 2021). Khoa et al. (2022) also recently presented a paper with performance comparison of impedance-based fault location methods for transmission lines (Khoa, et al., 2022).

As a matter of fact, many researchers presented different methodologies in developing improved power system protection techniques for transmission lines fault elimination. As so, Mukherjee et al. recently published an exhaustive review presenting several methodologies while mentioning the highlights and shortcoming of each method (Mukherjee et al., 2021). However, in spite of the many algorithms developed, no method can provide acceptable results for all kinds of networks, as proved by the many different methods presented early. In this paper, we will present a different ANN technique for transmission line fault isolation and elimination with some advantages over the existed methodologies investigated in this paper.

## Methodology

Artificial Neural Networks technology is a modern technique that excels in dealing with linear and mainly nonlinear problems and effectively handles massive amounts of information. In power systems, ANNs can be extensively and efficiently used in fault detection due to the infinite number of transmission lines and their various types, which results in a vast amount of information within the system. ANNs are characterized by their speed, high responsiveness, and high reliability based on their training (Jamil, Sharma, & Singh, 2015). The work in this paper is proposed as laid in Figure 1. In this section, we will present the main methodology parts as to where and how the ANN has been employed.

#### Back Propagation (BP)

The Back Propagation Neural Network (BPNN) is a technique that calculates weight adjustments by propagating errors from the output layer back to the input layer. Unlike two-layer artificial neural networks, the BPNN overcomes the limitation of producing similar outputs for similar inputs. The algorithm iteratively selects random weights, feeds input pairs, computes the output, updates the weights, and repeats this process for the entire training dataset until the network converges within a predefined error tolerance (Saeed, et al., 2020).

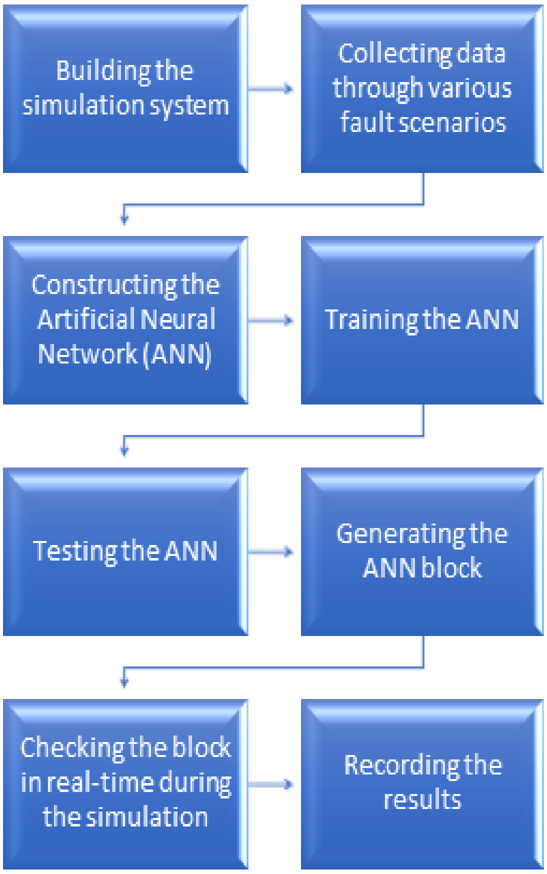


Figure 1. Proposed methodology

The widely-known iterative BP algorithm, used in this research, can handle various error functions. In each iteration, the proposed algorithm utilizes the Mean Square Error (MSE) following a reverse process through each layer in the network (Saeed et al., 2020). The total number of iterations required for the algorithm converging and the time taken for training to reach a predefined error level depend on some factors such as; structure and size of neural network, complexity of the problem being addressed, learning method, and size of the input and output datasets. These factors collectively influence the convergence and training time of the algorithm.

The effectiveness and optimal performance of a trained artificial neural network and the most suitable learning method can be evaluated by testing the final network using a designated testing dataset. This testing dataset, which is typically provided by the developer, forms an integral part of the network development process.

**System Modelling of Transmission Lines**

A 3-phase system consisting of transmission lines, with different lengths and various loads at the end of each line, was constructed using MATLAB software. Figure 2 illustrates the system configuration used in this research. The system includes a generator with a capacity of 20 MVA and a voltage of 3.3 KV. Table 1 provides the details of the system transmission lines (TL) and corresponding loads. The transmission line system was constructed using the MATLAB software, and the values for the transmission lines were adapted. Considered faults were assumed at different locations along the transmission lines, with 10 different locations for each transmission line. The current and voltage values were recorded only at the generator side.

Table 2 represents a sample of the current and voltage values recorded during phase-to-ground faults on different transmission lines. The voltage and current values were utilized by the RMS block in MATLAB as a training data set for the neural network. The circuit breaker that should trip, in case of a fault, is the output of the neural network. For example, if a fault occurs on line 1, this line should be isolated from the network at the feeding side. This means that the circuit breaker CB1 should be opened.

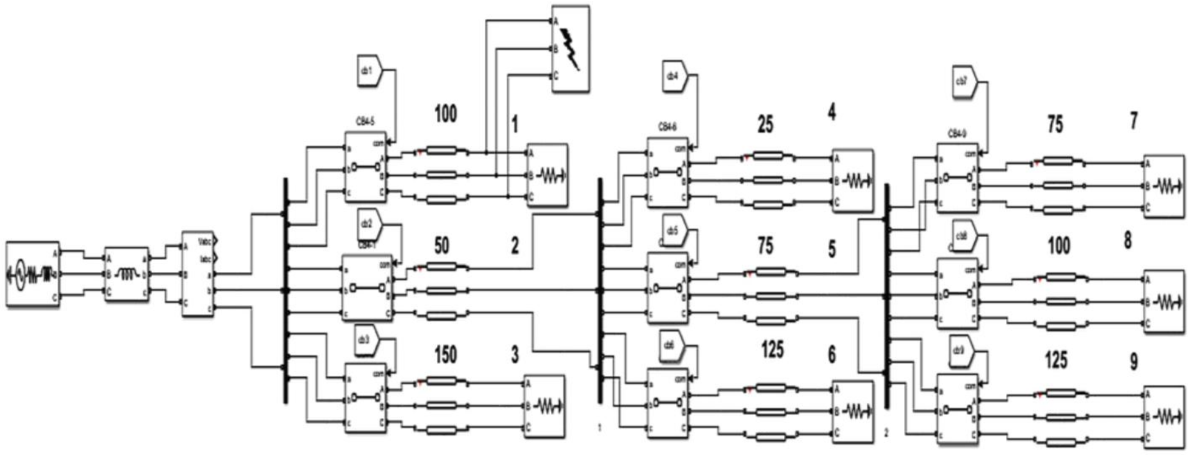


Figure 2. System configuration with a generator of a capacity of 20 MVA and a voltage of 3.3 KV.

Table 1. Considered transmission line with its corressponding loads

| Transmission Line | Distance [km] | load | Power [kw] |
|---|---|---|---|
| 1 | 100 | 1 | 50 |
| 2 | 50 | 2 | ---- |
| 3 | 150 | 3 | 50 |
| 4 | 25 | 4 | 100 |
| 5 | 75 | 5 | ---- |
| 6 | 125 | 6 | 100 |
| 7 | 75 | 7 | 500 |
| 8 | 100 | 8 | 500 |
| 9 | 125 | 9 | 500 |

Table 2. Current and voltage samples during phase-to-ground faults

| TL | $V_{AG}$ | $V_{BG}$ | $V_{CG}$ | $I_A$ | $I_B$ | $I_C$ |
|---|---|---|---|---|---|---|
| 1 | 0.6 | 0.6 | 0.6 | 37 | 37 | 37 |
| 2 | 0.5 | 0.5 | 0.5 | 71 | 71 | 71 |
| 3 | 0.65 | 0.65 | 0.65 | 23 | 23 | 23 |
| 4 | 0.5 | 0.5 | 0.5 | 50 | 50 | 50 |
| 5 | 0.6 | 0.6 | 0.6 | 33 | 33 | 33 |
| 6 | 0.64 | 0.64 | 0.64 | 21 | 21 | 21 |
| 7 | 0.65 | 0.65 | 0.65 | 19 | 19 | 19 |
| 8 | 0.67 | 0.67 | 0.67 | 13 | 13 | 13 |
| 9 | 0.68 | 0.68 | 0.68 | 10 | 10 | 10 |

**Training and Testing**

In this part, and after having prepared the necessary data for training the neural network off-line, we obtained 12800 samples that were fed into the network. In this set of data, each sample contained 6 inputs representing voltage and current values, and 9 outputs representing the circuit breaker numbers that should open in case of a fault. Figure 3 shows the neural network used in the training operation where 2 hidden layers have been employed. Training with the considered data, a mean square error of 0.003098 was achieved as shown in Figure 4.

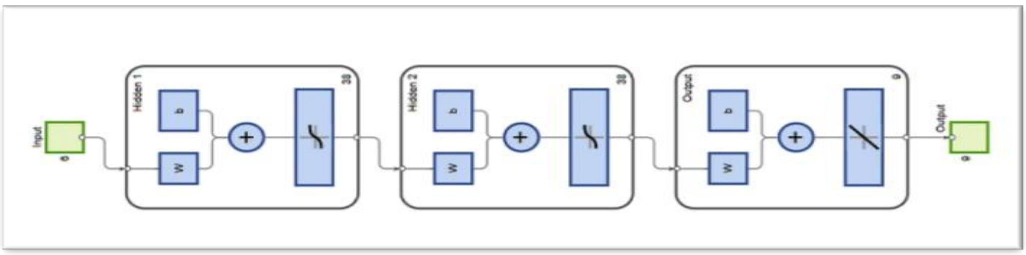


Figure 3. Training process of the ANN with two hidden layes

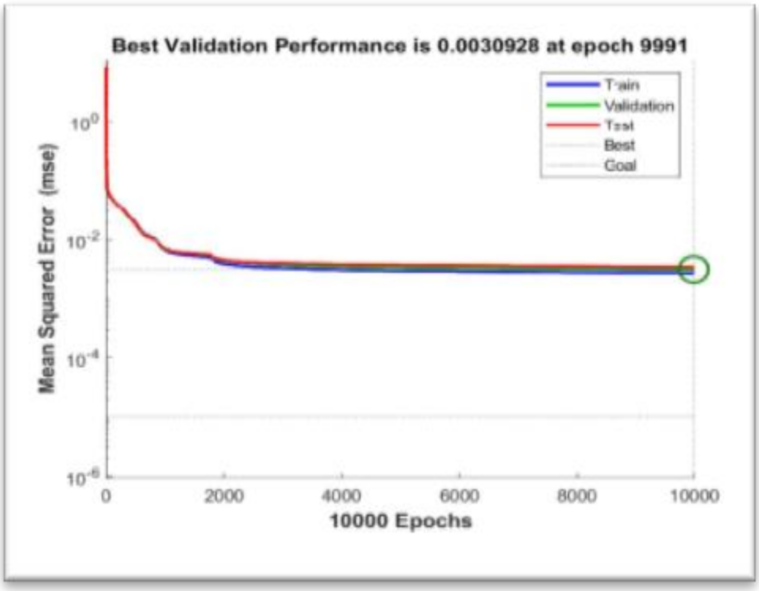


Figure 4. Mean square error convrgence.

## Results and Discussion

Now that the training process was completed, a real-time application within the simulation was performed for this network. This was done by using a certain command to create a new block that contains inputs for current and voltage values, and an output for the circuit breaker number that should open during a fault. In this block, the incoming current and voltage values were processed according to the training that had been conducted previously.

A signal was taken from the block output to each circuit breaker, and the trip command was to be issued to the circuit breaker in case of a fault occurrence. Accordingly, Figure 5 represents the current curves at the generator side in the absence of the ANN assistance for all three phases, A, B, and C. As observed, a significant increase in the current values during a fault on Line 1. Figure 6 on the other hand, shows the current curves when the ANN is used and the circuit breaker is activated.

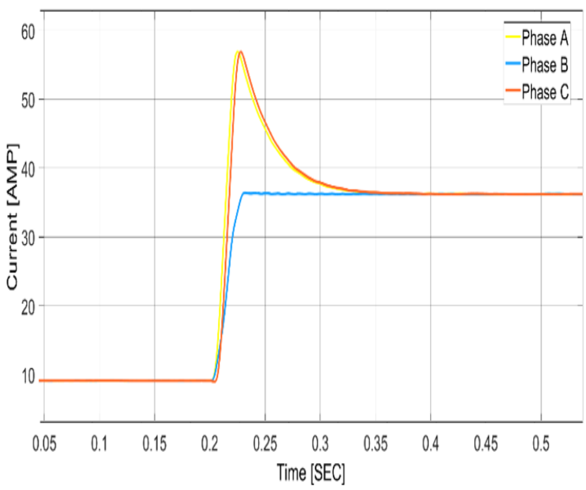


Figure 5. Generator 3-phase currents without using ANN for Line 1.

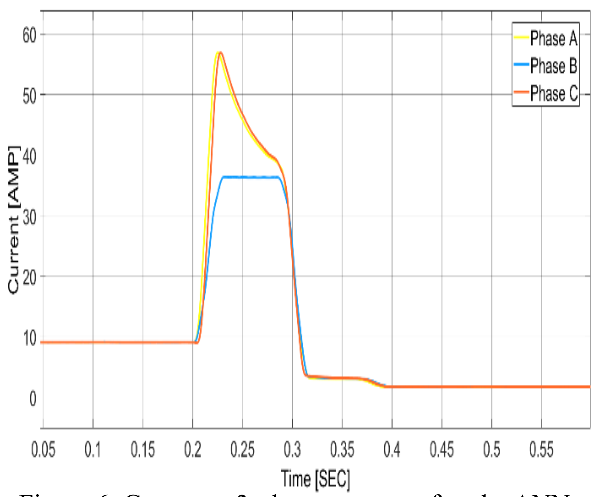


Figure 6. Generator 3-phase currents after the ANN implementation for Line 1.

Figures 7 and 8 represent respectively the current values in the absence and presence of the neural network during another fault on Line 8. Using a delay of 0.1 second, we can observe the isolation of the faulted area and the network returning to its normal state

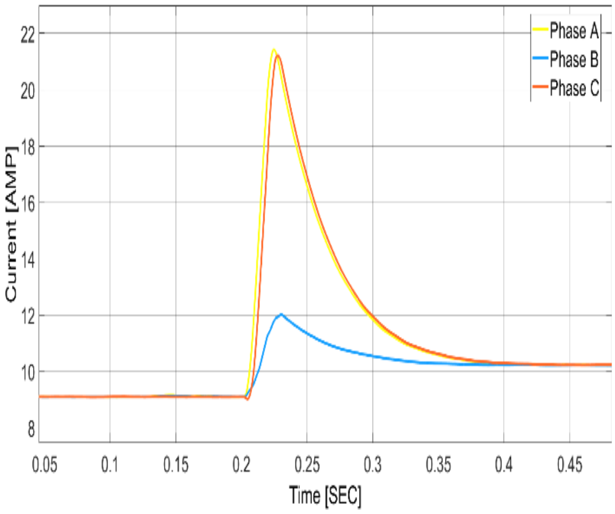


Figure 7. Generator 3-phase currents without using ANN for Line 8.

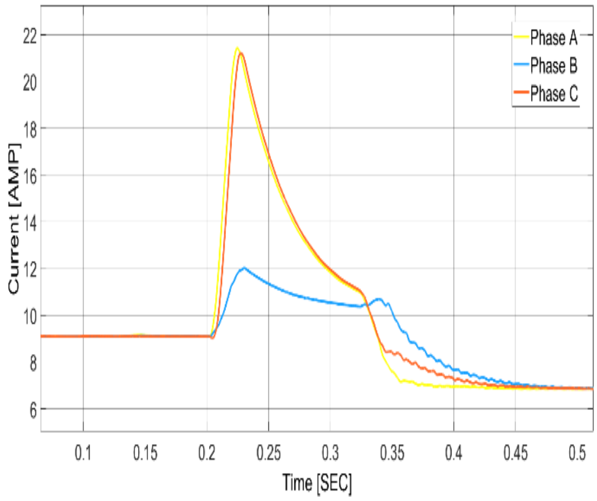


Figure 8. Generator 3-phase currents after the ANN implementation for Line 8.

To investigate the potentiality of the proposed method, a comparison of performance with different approaches published recently was made as shown in Table 3.

Table 3. Proposed approach performance comparison with different approaches

| **Proposed method** | **No of inputs** | **Description** | **No of outputs** | **Descripton** | **Utilization of output ports** | **Number of devices used in the Network** |
|---|---|---|---|---|---|---|
| | 6 | 3- phase voltage<br>3- phase current | 9 | Fault location | Signal for tripping the circuit breaker responsible for isolating the line based on the fault location. | 7 loads<br>1 generator<br>9 transmission line<br>9 CB |
| [8] | 6 | 3- phase voltage<br>3- phase current | 1 | Fault detection | ----- | 1 load 1 transmission line<br>1 generator 1 transformer |
| [9] | 6 | 3- phase voltage<br>3- phase current | 1 | Fault detection | Signal to the circuit breaker present in the system. | 2 loads 1 transmission line<br>1 generator 1 transformer<br>1 CB |
| [7] | 6 | 3- phase voltage<br>3- phase current | 1<br>4 classification # | Fault detection and classification | ------ | 2 generators<br>1 transmission line |

## Conclusion

In this research, a transmission line fault isolation was investigated utilizing ANN. The methodology was based on the current and voltage values from a single line location in the network, which could potentially reduce the need for the use of current and voltage transformers for protection purposes in the future, which in this case, the issue becomes a centralized fault control. The current and voltage values' locations were read and fed into the ANN, which used the back-propagation algorithm. The data was analyzed and accordingly a command was The data the circuit breaker to open and isolate the fault from the network. Even though the three-phase system fault was the focus in this research, however, the same method can be applied to other types of faults as well. In comparison, it was found that the proposed method provides relatively superior results with larger databases.

## Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

## Conflict of Interest

* The authors declare that they have no conflicts of interest

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