1. Skander BOURAGHDA, 2. Zoubir CHELLI 3. Mohcen BECHAOUAT

ORCID: 1. 0000-0001-7306-6359; 2. 0000-0003-0656-861X and 3. 0000-0002-0434-4324

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Artificial neural networks based detection of power transmission line faults

Wykrywanie usterek zasilania w liniach przesyłowych przy zastosowaniu sztucznych sieci neuronowych

Abstract. *As manufacturing, transportation, distribution, and usage systems improve, so does the requirement for a dependable power supply. It is crucial to continue providing customers with high–quality, safe electricity in order to satisfy these demands. The biggest danger to the uninterrupted supply of energy is electrical system failures. Electric power system faults are an inevitable issue. Therefore, to limit damage and disturbance to the electrical system, a well–coordinated protection system must be installed to quickly identify and isolate problems. The proper functioning of protective relays depends on the identification of defects in electrical networks. When a fault occurs in a transmission line, the fault current is always greater than the rated load current. Several methods and conventional numerical techniques have been used and proposed for the detection of faults. In this paper, artificial intelligence has been used, namely artificial neural networks (ANN). We develop a program, under the Matlab environment, based on the method of ANN using the sampled values of signal currents & voltages. These allow us to detect different types of shunt faults in transmission lines.*

Streszczenie. *Wraz z udoskonalaniem systemów produkcji, transportu, dystrybucji i użytkowania, wzrasta również zapotrzebowanie na niezawodne zasilanie. Aby sprostać tym wymaganiom, konieczne jest ciągłe dostarczanie klientom wysokiej jakości, bezpiecznej energii elektrycznej. Największym zagrożeniem dla nieprzerwanego zasilania są awarie systemów elektrycznych. Awarie systemów elektroenergetycznych są nieuniknionym problemem. Dlatego też, aby ograniczyć uszkodzenia i zakłócenia w systemie elektrycznym, należy zainstalować dobrze skoordynowany system automatyki zabezpieczeniowej, aby szybko identyfikować i izolować problemy. Prawidłowe działanie przekaźników zabezpieczeniowych zależy od identyfikacji usterek w sieciach elektrycznych. Gdy w linii przesyłowej wystąpi awaria, prąd zwarciowy jest zawsze większy niż znamionowy prąd obciążenia. Do wykrywania usterek zastosowano i zaproponowano kilka metod i konwencjonalnych technik numerycznych. W tym artykule zastosowano sztuczną inteligencję, mianowicie sztuczne sieci neuronowe, mianowicie ANN. Opracowujemy program w środowisku Matlab, oparty na metodzie ANN, wykorzystujący próbkowane wartości prądów i napięć sygnału. Pozwalają nam one wykrywać różne rodzaje usterek bocznikowych w liniach przesyłowych.*

Keywords: ANN, Fault detection, Transmission line, Power system.
Słowa kluczowe: ANN, wykrywanie usterek, linia przesyłowa, system zasilania

Introduction

In power systems, high–voltage transmission lines are vital links that achieve the essential continuity of service from generating plants to end users. The transmission line is exposed to the environment and the possibility of experiencing faults is generally higher than that on other main components. Line faults are the most common faults, they may be triggered by lightning strokes, trees may fall across lines, fog and salt spray on dirty insulators may cause the insulator strings to flash over, and ice and snow loadings may cause insulator strings to fail mechanically [1, 2, 3, 4, 5].

Over the past two decades, extensive research has been conducted on transmission line protection, with a particular focus on fault detection and location. Transmission lines are critical components of power systems, and their reliable operation is essential for maintaining uninterrupted electricity supply. When a fault occurs on an electrical transmission line, it is crucial to quickly detect the issue and accurately pinpoint its location. This enables utility operators to carry out necessary repairs efficiently and restore power with minimal delay. The speed and accuracy of fault detection and location directly impact the reliability and quality of power delivery. Prolonged fault identification times can lead to extended outages, increased operational costs, and potential damage to equipment, all of which can negatively affect the overall stability of the power grid. As a result, advancements in fault detection and location technologies have become a key area of interest, aiming to enhance the resilience and efficiency of modern power systems. [6]. Therefore, accurately locating faults on transmission lines is a critical requirement, especially in the case of permanent faults. Precise fault location not only minimizes the time required for repair crews to identify and address the issue but also significantly reduces outage durations, ensuring a quicker restoration of power supply. This is particularly important for maintaining the reliability and stability of the power grid, as prolonged outages can lead to operational inefficiencies, increased costs, and customer dissatisfaction. Advanced fault location techniques and technologies are essential for modern power systems, enabling utilities to enhance their response capabilities and improve overall service quality [7].

Once an occurrence of fault is happened in the transmission network, a fault detection and location systems estimate the fault location of transmission lines, then a transmission line protection system isolates the fault region from the entire transmission network by cutting the power feeding at some relaying points around the fault region [7]. Various methods of fault detection and location have been developed in the past, some of which use data from one line terminal and some of which use data from two or more line terminals [1, 8, 9].

During the last decade a number of fault detection and location algorithms have been developed, including the steady state phasor approach [10, 11], the differential equation approach and the traveling–wave approach [11]. Many successful applications of ANNs to power systems have been demonstrated, including security assessment, load forecasting, control, etc [5, 12]. Recent applications in protection have covered fault diagnosis for electric power systems, transformer protection and generator protection [13, 14]. Various approaches have been published describing applications of ANNs to fault detection and location in transmission lines [15–18].

In this paper, we develop a program, under the Matlab environment, based on the method of ANN using the sampled values of signal currents & voltages. These allow us to detect different types of shunt faults in transmission lines.

This paper is structured to provide a comprehensive overview of the design, implementation, and performance of an ANNs–based fault detector for power transmission lines. It begins with an Introduction that highlights the importance of fault detection and the role of ANNs in addressing this challenge. The Design Process of the ANNs Fault Detector section outlines the steps involved in developing the ANNs, including data collection, feature selection, and network architecture. The Inputs & Outputs of the ANN section details the electrical parameters used as inputs and the fault classifications generated as outputs. The Learning Algorithm of the Artificial Neural Networks section explains the supervised learning approach, such as backpropagation, used to train the ANNs. The Test Results Obtained by the ANNs section presents the detector's performance in identifying specific fault types, including Single Phase to Ground Fault (L–G), Double Phase Fault (L–L), and Three–Phase to Ground Fault (L–L–L–G). Finally, the Conclusion summarizes the findings, emphasizes the ANN's effectiveness, and suggests directions for future research and practical applications.

Design process of the ANN fault detector

The design process of the ANN fault detector goes through the following steps:

1. Preparation of a suitable training data set that represents cases the ANN needs to learn.
2. Selection of a suitable ANN structure for a given application.
3. Training the ANN.
4. Evaluation of the trained ANN using test patterns until its performance is satisfactory.

Inputs & outputs of the ANN

Let us denote by I_a, I_b&I_c the line currents and V_a, V_b&V_c the voltages of phases a, b & c. The homopolar current and voltage are denoted, respectively, by I_o&V_o. The fault detector uses as inputs to the ANN the instantaneous values sampled at a frequency of 2 [kHz] of the signals of the currents I_a, I_b, I_c&I_o and the voltages V_a, V_b, V_c&V_o at the bus S. The sampled current and voltage values are normalized to reach the input level (±1) of the ANN. A moving window of 7 samples of length 3 [ms] for each signal is used as input to the ANN to define the state of the line whether it is faulty or non–faulty situation.

The number of input neurons to the network is 56 (7 samples for each of the 8 signals). The output layer has a single neuron to define the state of the line. The output is indexed with the value 1 to indicate the presence of a fault or 0 for the no–fault situation.

After various tests, a number of 16 neurons in the hidden layer was chosen giving the best results. The sigmoid transfer function was employed in the hidden layer and the output layer. Figure 1 shows the architecture of the ANN fault detector.

Power System under Consideration

Figure 2 presents the network considered in this study, to evaluate the performance of the proposed fault detector. The transmission line is 420 [kV] and 150 [km] long, supplied from both ends by the GS and GR sources. The line is represented by distributed parameters taking into account the dependence of these parameters on the frequency.

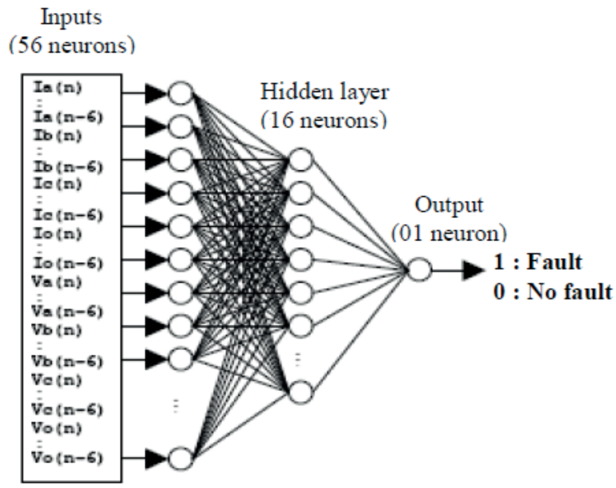

Fig. 1. Architecture of the ANN fault detector

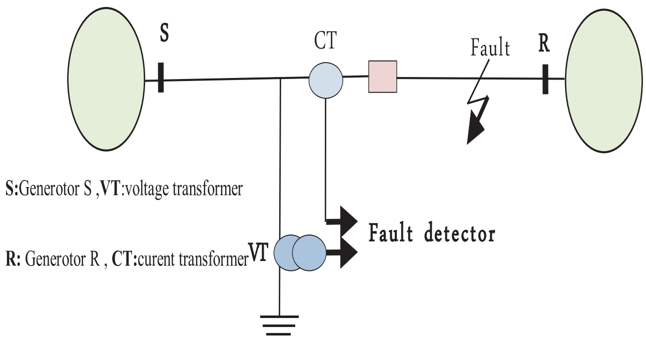

Fig. 2. System under study

Learning Algorithm Of The Artificial Neural Networks

Artificial neural network is an interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist approach to the computation. Transfer function in the ANN is an important key element to invoke the nonlinear relationships that maps the input (s) to the output (s). In the process of learning the neural network presented with pairs of input and output data then is taught (?) how to produce the output when the corresponding input is presented. Through iterative training procedure the network's weights are adjusted by the error signal in a way that the network output tries to follow the desired output as close as possible [19, 20].

The learning procedure continues until the error signal is close to zero or below a predefined value. The sum of the errors over all the training samples can be considered as a kind of network performance measure, which is a function of free parameters of the system. Such function can be visualized a multidimensional error surface where network free parameters serves as coordinates. During the course of learning the system gradually moves to a minimum point along an error surface. The error surface is determined by the network architecture and the cost function.

Data generated from the transmission line system are collected, trained and tested. The detection of a fault situation in the system is the first step. Following that is the investigation of the fault class and finally location of the faulty zone to be isolated.

In this paper the error back propagation learning algorithm is used. It is extremely important to train ANN well and test them properly. The ANN is trained with various patterns corresponding to different fault types and conditions, at various locations of the transmission line L_f and different fault resistances Rf. During training, different structures (number of neurons in the hidden layer) with different parameters (momentum term, learning rate and transfer functions) are evaluated to determine the optimal network structure to produce good learning and to have the best results during testing. Table 1 gives the values of the network and fault parameters used to generate the dataset for ANN training.

After training, the output of the RNA is sketched in Figure 3

Table 2. Various cases study for power sharing controls.

PARAMETERS	DIMENSIONS	LEARNING
Fault location Lf	[km]	3; 40; 80; 120; 147
Angle occurrence of fault θ_f	[°]	0; 45; 90
Fault resistance Rf	[Ω]	0; 20; 40; 100
Power of sources	[GVA]	9; 20; 40; 100
Source voltage	[pu]	0.9; 1.1
Source angles	[°]	– 20; 0; + 20

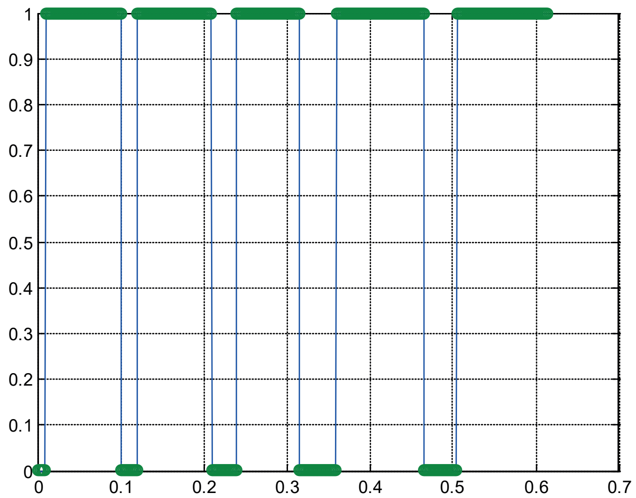

Fig. 3. Output of the ANN

From this figure we notice that we have a good learning that will lead us to good test results. The learning performance curve is given by Figure 4. We notice that the learning is in the order of 10^{-15}. Thus, it can be considered zero.

Discussion

After training, the ANN of the detector is tested with patterns not seen during training to satisfy the detector performance. During testing, the ANN uses the values of the weights and biases from the final training. The neural fault detector was tested with new conditions and for each type of shunt fault on the electrical network.

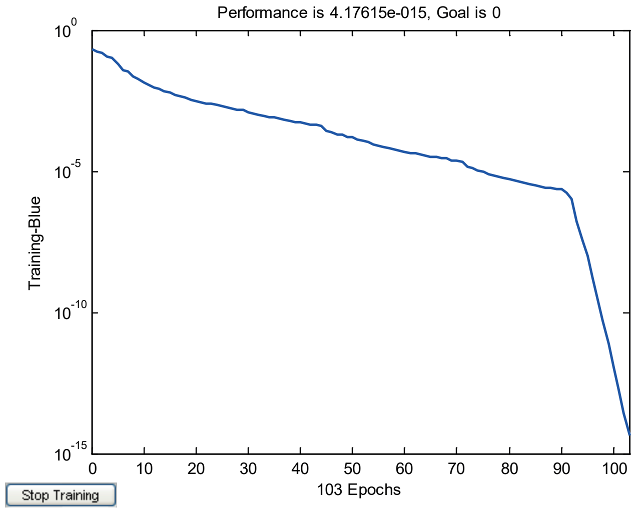

Fig. 4. learning performance of the ANN

Single Phase to Ground Fault (L–G)

For instance, a Single Phase to Ground Fault (L–G) was simulated, involving a shunt fault between phase B and earth at time t=28 ms. The simulation results, as depicted in Figure 5, demonstrate the ANN's ability to accurately detect and classify the fault. The graphical data in Figure 5 shows the system's response over a 70–millisecond timeframe. The first graph represents the raw voltage or current signal, oscillating between +5 and –5 units, with significant changes occurring at t=28 ms. The second graph displays a filtered or scaled version of the signal, ranging between +2 and –2 units, which helps isolate the fault characteristics. The third graph indicates the fault detection flag, with values peaking at 0.5 units, confirming the ANN's successful identification of the fault. These results underscore the ANN's effectiveness in detecting faults under diverse conditions, showcasing its potential for real–time fault detection and enhancing the reliability of electrical networks. The simulation results are given in figure 5.

Double Phase Fault (L–L)

To further evaluate the performance of the ANN–based fault detector, a Double Phase Fault (L–L) was simulated, involving a fault between phases B and C at time t=30 ms. The results of this simulation are illustrated in Figure 6. The graphical data in Figure 6 captures the system's response over an

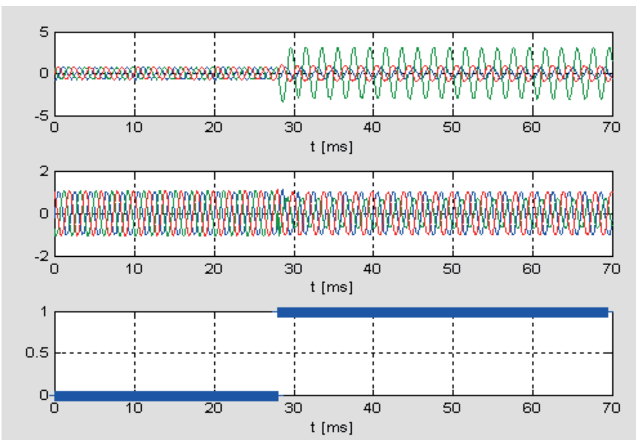

Fig. 5. Current and voltage waveforms and the ANN output for the b–g fault

80–millisecond timeframe. The first graph depicts a high–amplitude waveform oscillating between +5 and –5 units, likely representing the raw voltage or current signal during the fault. The second graph shows a lower–amplitude signal ranging between +2 and –2 units, which may correspond to a filtered or scaled version of the original signal. The third graph displays a normalized signal peaking at 0.6 units, potentially indicating the fault detection flag or a control signal triggered by the fault. These results demonstrate the ANNs capability to accurately detect and classify double–phase faults, further validating its robustness and reliability in identifying complex fault conditions in electrical networks.

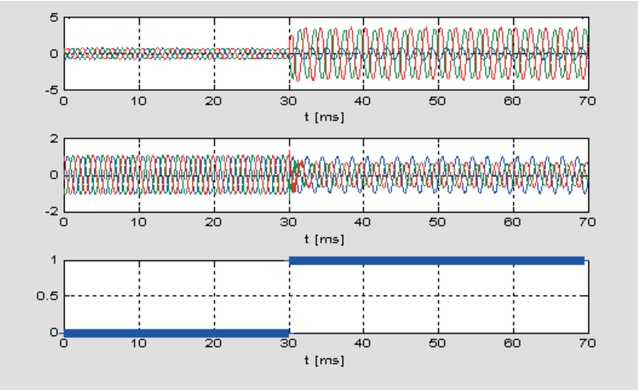

Fig. 6. Current and voltage waveforms and the ANN output for the b–c fault

Three–Phase to Ground Fault (L–L–L–G)

Figure 7 characterizes the results obtained for a Three–Phase to Ground Fault (L–L–L–G), which involves a fault occurring simultaneously on phases A, B, and C at time t=30ms. The graphical data in Figure 7 illustrates the system's response over a 70–millisecond timeframe. The first graph shows a high–amplitude waveform oscillating between +5 and –5 units, representing the raw voltage or current signal during the fault. The second graph displays a lower–amplitude signal ranging between +2 and –2 units, likely corresponding to a filtered or scaled version of the original signal. The third graph presents a normalized signal peaking at 0.5 units, which may indicate the fault detection flag or a control signal activated by the fault. These results highlight the ANN's ability to accurately detect and classify severe fault conditions, such as three–phase–to–ground faults, further demonstrating its effectiveness in ensuring the reliability and stability of electrical networks under complex fault scenarios.

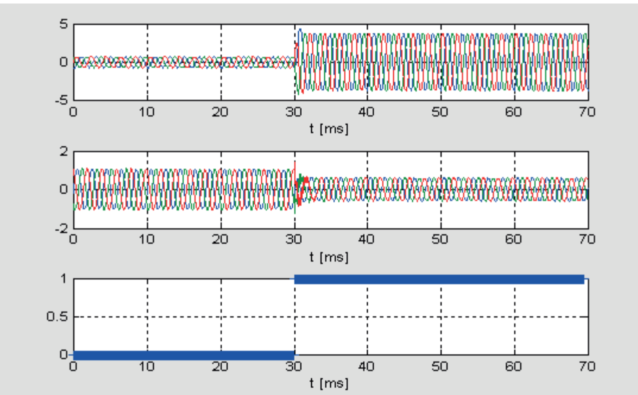

Fig. 7. Current and voltage waveforms and the ANN output for the a-b–c-g fault

To demonstrate the stability of the ANN output both in the absence of a fault and during a fault condition, a Single Phase to Ground Fault (L–G) was simulated between phase A and ground, occurring between t=30 ms and t=50ms. The detection results are illustrated in Figure 8. The graphical data in Figure 8 shows the system's response over a 70–millisecond timeframe. The first graph represents the raw voltage or current signal, oscillating between +5 and –5 units, with noticeable disturbances occurring between t=30 ms and t=50ms. The second graph displays a filtered or scaled version of the signal, ranging between +2 and –2 units, which helps isolate the fault characteristics. The third graph indicates the fault detection flag, with values peaking at 0.5 units during the fault interval, confirming the ANN's ability to accurately detect and classify the fault. These results highlight the ANN's stability and reliability in distinguishing between normal operation and fault conditions, further validating its effectiveness for real–time fault detection in electrical networks.

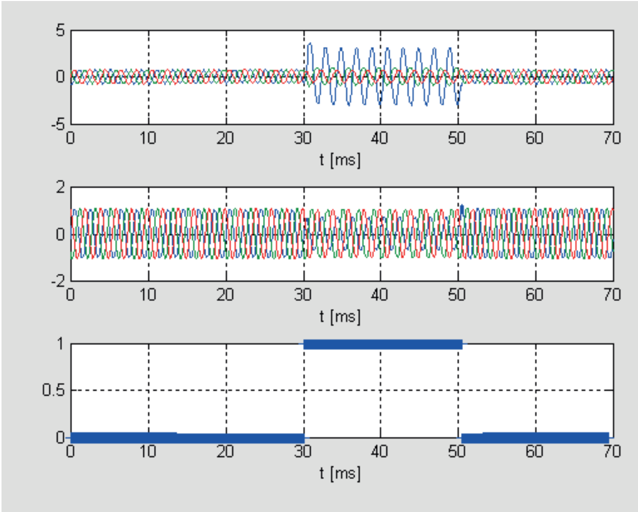

Fig. 8. Current and voltage waveforms and the ANN output for the a-g fault

The results clearly demonstrate that the fault detector is capable of producing accurate responses in both the presence and absence of a fault. It is important to note that the ANN output value '0' corresponds to the state of the line without a fault, while the value '1' indicates the presence of a fault. The test results for various types of faults highlight the stability of the ANN's output and its ability to rapidly transition when the 7–sample window shifts from a fault state to a fault–free state. This rapid and reliable transition underscores the ANN's effectiveness in real–time fault detection and its potential to enhance the robustness of power system monitoring and protection.

Conclusion

In this work, we have utilized ANNs for fault detection in electrical networks. ANNs are well–suited for this task due to their ability to learn complex patterns and adapt to dynamic system conditions. By leveraging MATLAB as a simulation and implementation platform, we have developed an ANNs–based fault detection system capable of identifying various types of faults that may occur in electrical networks. The results demonstrate that the ANN method is highly effective in detecting faults, including single–phase–to–ground (L–G), double–phase (L–L), and three–phase–to–ground (L–L–L–G) faults, with high accuracy and reliability. This approach not only enhances the speed and precision of fault detection but also contributes to improving the overall stability and efficiency of power systems. The success of this method highlights the potential of ANNs as a powerful tool for real–time fault detection and diagnosis in modern electrical networks.

***Authors**: Dr. Skander BOURAGHDA. Presently he is Assistant Professor in Department of Electronics, University Center of Tipaza, Algeria. His fields of interest are Power Quality, Power System, FACTS, Power Electronic.*
E-mail: skander21440@yahoo.fr
Dr. Zoubir CHELLI. Presently he is Associate Professor in Department of Electrical Engineering, University of Mohamed-Cherif Messaadia of Souk Ahras, Algeria; Electrotechns and Renwable energy Laboratory (LEER). His fields of interest are Power Quality, Power System, FACTS, Power Electronic.
E-mail: zoubir.chellir@univ-soukahars.dz
Pr. Mohcen BECHAOUAT. Presently he is Full Professor in Department of Automation and Electromechanics, Faculty of Science and Technology, University of Ghardaia, Ghardaia, Algeria. His fields of interest are Renwable energy, Power Electronic.
E-mail: bechouat.mohcene@univ-ghardaia.edu.dz

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