Tikrit Journal of Engineering Sciences (2025); 32(2): 1888
DOI: http://doi.org/10.25130/tjes.32.2.24

IRAQI Academic Scientific Journals

ISSN: 1813-162X (Print); 2312-7589 (Online)

Tikrit Journal of Engineering Sciences

available online at: http://www.tj-es.com

TJES Tikrit Journal of Engineering Sciences

Fault Detection and Classification of Power Plant Using Neural Networks

Rawaa J. Hussein [*a], *Khalaf S. Gaeid* [a], *Amin Al-Habaibeh* [b]

a Department of Electrical Engineering, College of Engineering, Tikrit University, Tikrit, Iraq.
b Product Innovation Centre, Nottingham Trent University, UK.

Keywords:
Artificial neural network; Biological neural network; Fault detection and isolation; Machine learning; Power plant.

Highlights:

- *Dual ANNs detect/classify 400kV faults in Iraqi power plants.*
- *MATLAB/Simulink validates ANN accuracy on 87-306 km lines.*
- *Decoding circuits enable precise fault type/location identification.*
- *Phase voltage/current inputs achieve 95%+ fault detection accuracy.*

ARTICLE INFO
Article history:

Received	24 Nov.	2023
Received in revised form	19 Mar.	2024
Accepted	29 May	2024
Final Proofreading	07 Apr.	2024
Available online	31 May	2025

Citation: Hussein RJ, Gaeid KS, Al-Habaibeh A. **Fault Detection and Classification of Power Plant Using Neural Networks**. *Tikrit Journal of Engineering Sciences* 2025; **32**(2): 1888.
http://doi.org/10.25130/tjes.32.2.24

***Corresponding author:**

Rawaa J. Hussein

Department of Electrical Engineering, College of Engineering, Tikrit University, Tikrit, Iraq.

Abstract: This study focuses on the root causes of power station problems that result in system shutdown. A power plant may experience many types of faults, some of which include, for example, line-to-line, double-line-to-ground, and single-line-to-ground. Identifying faults in the 400kV high-voltage transmission line from the Samarra Thermal Power Plant in Iraq is the primary objective of this study using artificial neural networks (ANNs). Recognizing a wide range of electrical power plant faults is an innovative use of artificial neural networks (ANNs) to speed up system recovery. The ANN can perform a wide range of tasks, including pattern recognition, classification, matching, prediction, decision-making, and control; hence, it was selected for this work. This study utilizes two neural networks trained with an input of 8 variables: 3 phases of voltage and 3 phases of current, in addition to the absolute value of the zero sequence for voltage and current. The output for the first artificial neural network (ANN) designed for fault detection will possess a single output; it is for detecting faults only, whereas the second ANN will have five outputs: four of which go to the decoding circuit and the last goes to the fault location detection circuit. Additionally, the MATLAB/Simulink 2022a software is utilized to simulate the Samarra thermal power plant model. The model represents a three-phase power system network comprising two units. The power system has four transmission lines operating at a voltage of 400kV and a frequency of 50Hz. The transmission lines have lengths of 87.10km, 145.00km, 274.00km, and 306.00km.

كشف الأعطال وتشخيصها في محطات الطاقة الكهربائية باستخدام الشبكة العصبية

رواء جاسم حسين ١، خلف سلوم كَعيد ١، امين الحبايبه ٢
١ قسم الهندسة الكهربائية/ كلية الهندسة/ جامعة تكريت / تكريت - العراق.
٢ مركز ابتكار المنتجات/ جامعة نوتنغهام ترينت/ المملكة المتحدة.

الخلاصة
ينصب التركيز الأساسي لهذه الدراسة على الأسباب الجذرية العديدة لمشاكل محطة الطاقة، والتي تؤدي إلى تعطل النظام. قد تواجه محطة توليد الكهرباء العديد من أنواع الأعطال المختلفة، والتي يشمل بعضها خطا إلى خط، وخطا مزدوجا إلى أرض، وخطا واحدا إلى الأرض؛ هذه ليست سوى حالات قليلة. إن العثور على عيوب في خط نقل الجهد العالي ٤٠٠ كيلو فولت في محطة سامراء للطاقة الحرارية هو الهدف الأساسي لهذه الدراسة باستخدام شبكة عصبية اصطناعية (ANN). يعد التعرف على مجموعة واسعة من عيوب محطة الطاقة الكهربائية وإصلاحها استخداما ذكيا للشبكات العصبية الاصطناعية (ANNs). يمكن إنشاء مجموعة واسعة من الطرق، بما في ذلك المنطق الضبابي (FL)، والخوارزمية الجينية، والشبكة العصبية الاصطناعية (ANN)، والانحدار المنطقي، لتحديد، لتحديد العيوب في محطات الطاقة، يمكن إنشاء مجموعة متنوعة من الأساليب، وأبرزها الانحدار المنطقي، والخوارزمية الجينية، والشبكة العصبية الاصطناعية (ANN)، والمنطق الضبابي (FL). نظرا لأن ANN يمكنها أداء مجموعة واسعة من المهام، بما في ذلك التعرف على الأنماط والتصنيف والمطابقة والتنبؤ واتخاذ القرار والتحكم، فقد تم اختيارها لهذا العمل. يتحدث النظام الذكي عن أنواع الفشل الشائعة التي تحدث في أنظمة الطاقة، حتى لو استغرق الأمر الكثير من وقت الحوسبة أثناء التدريب. بالإضافة إلى ذلك، فإنه يقدم فكرة الشبكات العصبية الاصطناعية، أو ANNs، بدءا من شرح النموذج العصبي الأساسي (NN). يذهب إلى مزيد من التفاصيل حول كيفية عمل الخلايا العصبية الاصطناعية (ANN) والخلايا العصبية البشرية (BNN). بالإضافة إلى ذلك، يتم إجراء محاكاة حلقة مغلقة لنظام محطة سامراء للطاقة الحرارية بالكامل باستخدام Simulink / MATLAB 2022a.

الكلمات الدالة: الشبكة العصبية الاصطناعية، الشبكة العصبية البيولوجية، اكتشاف الأخطاء وعزلها، التعلم الآلي، محطة توليد الكهرباء.

1.INTRODUCTION

Electricity is essential in modern lifestyle, necessitating the development of efficient ways for power production. Power plants are classified as either conventional or nonconventional based on energy sources. Conventional energy sources consist of steam, hydroelectric, diesel, and nuclear facilities, whilst nonconventional sources comprise wind, solar, and geothermal energy [1]. Renewable sources provide environmental friendliness by generating a minimum amount of carbon dioxide (CO_2). Prime movers and alternators in generating stations convert energy into mechanical energy and subsequently into electrical energy, which is transmitted to consumers by conductors [2]. Nevertheless, the power system is vulnerable to defects, and in case a fault occurs in any component, it is crucial to have an automated safeguard that promptly identifies the faulty component [3, 4], guaranteeing that the system's undisturbed segment may maintain its usual operation. To avoid any possible harm, it is crucial to rectify the defect within a very short period, often within a fraction of a second [5]. The power system is partitioned into numerous zones, wherein each zone assumes responsibility for one or two distinct system parts to ensure comprehensive protection. The architecture of the protective zones guarantees that every component of the power system is immune to vulnerability [6]. Diverse methodologies are employed to detect and ascertain defects in electrical systems. Artificial neural networks (ANNs) are a potential methodology that can be employed [6]. Artificial Neural Networks (ANNs) are vital in defect identification because they can identify nonlinear patterns and optimize operations. They acquire knowledge from a set of data used for training, necessitating accurate settings customized for particular jobs [7, 8]. For instance, for ANN fault detection to be productive, it is imperative to possess high-quality training data, select pertinent features, and construct an efficient network design [9]. Conventional distance protection is triggered by the impedance, which is the ratio of voltage to current, and determines the distance between the power source and the fault. The relay consists of two coils: one is activated by voltage, resulting in a negative torque, and another is activated by current, resulting in a positive torque [3]. The relay activates when the ratio of voltage to current drops below a predetermined threshold. The characteristic curves (Mho, reactance, or admittance) are employed to depict the anticipated impedance values during regular operation [10]. The present study analyzes the functioning mechanisms of artificial neural networks (ANN) and biological neural networks (BNN). The Samarra thermal power plant model was simulated using MATLAB/Simulink 2022a, depicting a three-phase power system with two modules and four transmission lines (87.10 km, 145.00 km, 274.00 km, and 306.00 km) operating at 400 kV and 50 Hz [11]. Therefore, this study uses ANN to detect grid faults and distance from the power station.

2.CLASSIFICATION OF ANN

Artificial neural networks (ANNs) are algorithmic systems inspired by biological neural networks (BNNs) [10]. Artificial neural networks (ANNs) perform exceptionally in various tasks, including classification, prediction, filtering, optimization, pattern recognition, and function approximation [11]. Artificial neural network algorithms simplify the complex biological nervous system by focusing on key information processing components. Deep learning refers to ANNs with advanced multilayers [12]. An artificial neural network (ANN) can be designed to mimic human brain cognitive processes for specific tasks [13, 14]. The human brain is a large, highly efficient information-processing device capable of executing diverse and intricate signal computations [16, 17]. It possesses the capacity to effectively coordinate these actions to accomplish a particular objective successfully [18-20]. The brain is primarily characterized by its unique ability to process information, accomplished through the coordinated activity of interconnected neurons to solve daily problems [21]. The human brain functions as a neural network, transmitting and receiving signals to perform actions. It conducts online searches, recognizes speech, identifies images, processes language translations, and engages in intuitive activities like eating and biking [22]. The connections between a neuron in the current layer and a neuron in the next layer are determined by an amount that is directly proportional to the negative gradient of the error measure for the specified parameter:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \qquad (1)$$

where w_{ij} is the weight of the connection between a neuron in one layer and a neuron [14, 22]. Supervised learning can be aptly described as the process of learning through using examples. This process involves providing a network with a collection of inputs, denoted as X, together with their corresponding targets, denoted as T. The network calculates an output y = [y1, y2, ...y_m] for each input x = [x1, x2, ... x_n] then compares it to the desired output t = [t1, t2, ... t_m] to calculate an error, E. The network's weights are adjusted according to this discrepancy, which enhances performance [14]. Backpropagation (BP) is still the primary supervised learning algorithm for feedforward networks despite the emergence of alternative algorithms over time. The computed output error is used to update the network weights [15]. There are various error measures, including the summed squared error (SSE). The mean-squared error (MSE) is a commonly used metric in which the sum of squared errors (SSE) between all target and corresponding output values is divided by the total number of outputs:

$$E = MSE = \frac{SSE}{m} = \frac{1}{m}\sum_{k=1}^{m}(t_k - y_k)^2 \qquad (2)$$

where t_k represents the job that determines the mathematical formula for the intended outcome y in an Artificial Neural Network (ANN):

$$y = f(x) + e \qquad (3)$$

The equation above represents e regression model used for continuous value prediction. Binary classification refers to the task of predicting one of two possible outcomes, represented by the values 0 and 1, denoted as $y = [0,1]$. For classification using multiple classes, the variable y is a multiclass one-hot encoded vector represented as $y = [0,0,1, \ldots .0]$. The neuron's output is provided by [16]:

$$y = f(\varphi) = f(\sum_{i=0}^{N_\circ} w_i a_i) \qquad (4)$$

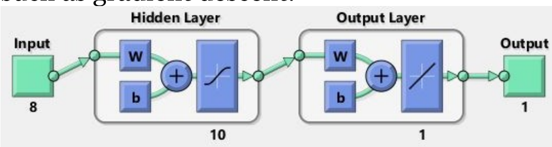
The output of the neuron is represented by the variable y. The function f (φ) is responsible for activating the neural networks. The variable φ represents the signal obtained after processing. The threshold values (polarization) are denoted by $w_i a_i$ [17, 18].

$$\varphi = W^T A \qquad (5)$$

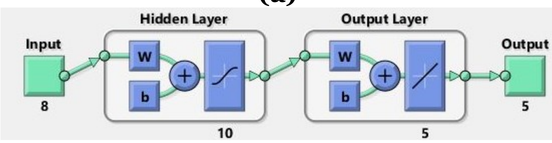
Where

$$W = [w_0\, w_1 .. w_{K_0}], A = [a_0 a_1 \ldots . a_{N_0}]^T \qquad (6)$$

Figures 1 (a) and (b) validate the architecture of the neural network employed in the present research paper. A neural network is composed of two neural networks trained using an input comprising 8 variables: 3 phases of voltage, 3 phases of current, and the absolute value of the zero sequence for voltage and current [19]. The initial artificial neural network (ANN) developed for fault detection will provide a solitary output solely dedicated to fault detection. In contrast, the second ANN will generate five outputs, with four directed towards the decoding circuit and the remaining one directed towards the fault location detection circuit. To enhance network performance, training adjusts weights and biases by employing optimization techniques, such as gradient descent.



(a)



(b)

Fig. 1 (a) The Structure of the First Neural Network (Fault Detection), (b) The Structure of the Second Neural Network (Location and Categories).

3.DETECTION AND CLASSIFICATION BY ANN

Accurately identifying and categorizing defects in a protection strategy is paramount, accomplished by examining transient voltage and/or fault current signals. Artificial Neural Networks (ANN) are mathematical models that draw inspiration from the structure and functioning of biological brain networks. They exhibit adaptive characteristics and can modify their structure throughout a learning phase [23, 24]. Academics have been interested in artificial neural networks, specifically deep neural networks (DNNs) because they comprehend complex nonlinear connections and can tackle nonlinear problems in several domains [25]. The study utilized a Deep Neural Network (DNN), as it can effectively process intricate data related to high-voltage power lines. Deep Neural Networks (DNN) can analyze and extract patterns from data, resulting in continuous performance improvement as they gain experience. Also, it can precisely anticipate probable problems. Automated fault detection can automatically identify flaws. Using DNN achieves enhanced maintenance efficiency and cost reduction [25]. They exhibit greater resilience to fluctuating operational conditions. Neural networks can be constructed and trained to tackle complex issues that are challenging for people or that traditional computing techniques cannot solve [26]. An artificial neural network (ANN) comprises the following components: The components of a neural network include the Input Layer, Hidden Layers, Output Layer, Connections (Weights), and Activation. Functions and their properties Biases are fixed values added to the weighted sum of inputs to each neuron. They help the network in situations where all inputs are zero [25], as can be shown in Fig. 2.

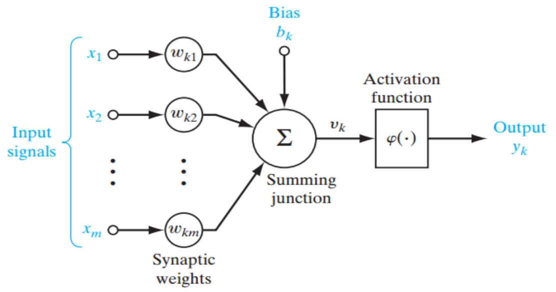


Fig. 2 The ANN's Internal Structure Contents.

Deep Neural Networks (DNNs) have a wide range of practical uses in medical diagnosis [22], signal recognition, and marketing [29, 30]. In this paper, the focus is on using ANN for fault detection, classification, and location.

4.METHODOLOGY OF FAULT DETECTION

Within electrical power systems, breakdowns are an ever-present likelihood, necessitating Network Operators to possess extensive awareness of the condition of their Power System Network, enabling the making of well-informed decisions regarding the necessary corrective measures and repairs to swiftly resolve issues [27-29]. To detect faults effectively, a thorough understanding of their nature, characteristics, and detection methods is essential [27]. Conventional flaw detection relies on parameter settings and voltage and current levels thresholds to disconnect the power grid as protective measures. However, for more advanced and precise defect identification, utilizing artificial neural networks (ANNs) as fault discriminators has been proposed, demonstrating the utilization of Artificial Neural Networks (ANN) as a sophisticated method for identifying faults [22, 29, 30]. The technique is applied to understand the operational principles of Artificial Neural Networks (ANN) in detecting electrical malfunctions [25]. Figure 3 illustrates the approach that employs artificial neural networks (ANN) for fault detection [14].

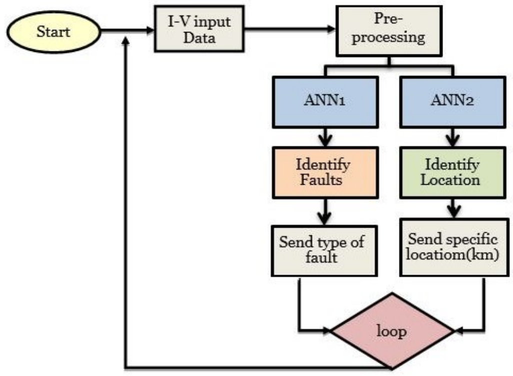


Fig. 3 Artificial Neural Network Algorithm to Fault Detection.

The ANN modeling software includes a training method and testing mechanism. The acquired predetermined data is employed by the training algorithm. The testing algorithm utilizes the training algorithm. The mean square error (MSE) function is used as the performance function. It utilizes the feedforward backpropagation architecture to its advantage. The sigmoid activation function was employed as the activation function. Each artificial neural network (ANN) is trained with 10 neurons in the first hidden layer and 5 neurons in the second hidden layer. The ANN takes 8 inputs and produces a single output. Distinct applications of the identical technique are employed to determine the position and classification. The program employs the delta learning rule and the log sigmoid activation function for learning [15]. The data is divided into three sets: training, testing, and validation. The proportions of data used for each set are 70%, 15%, and 15%, respectively. The output layer was selected to include all three phase values with the ground phase. The input layer was chosen to include the phase values of the voltage and current together with the fault distances [27-29]. The application uses the sigmoid function as its activation function, generating binary data with values 0 and 1. In the sigmoid function equation, the input variable is denoted by "x." The formula for the sigmoid function is:

$$f_{(x)} = \frac{1}{1+e^{-x}} \quad (7)$$

where e is the base of the natural logarithm, and x is the input signal. By utilizing this function, the artificial neural network can generate output values ranging from 0 to 1. Binary classification tasks benefit from this approach since it enables the output to accurately represent the probability of the two potential classes [29, 30].

4.1.An Overview of the Model

The protection technique employs artificial neural networks (ANNs) to conduct classification and diagnostic operations for the ANN protection relay. Variations in current and voltage readings between phases during faults in high-voltage power lines are well-known due to the three-phase electrical system's allocation of electricity, each phase separated by 120 degrees. Figure 4 closed-loop block diagram depicts the simulation of the entire Samarra thermal power plant system using Simulink/MATLAB 2022a [31]. AC sources, known as generating units, are located at both ends of the transmission lines and connected to electrical loads. The system is represented using distributed line parameters, a commonly employed model in the literature that serves as the foundation for analysis.

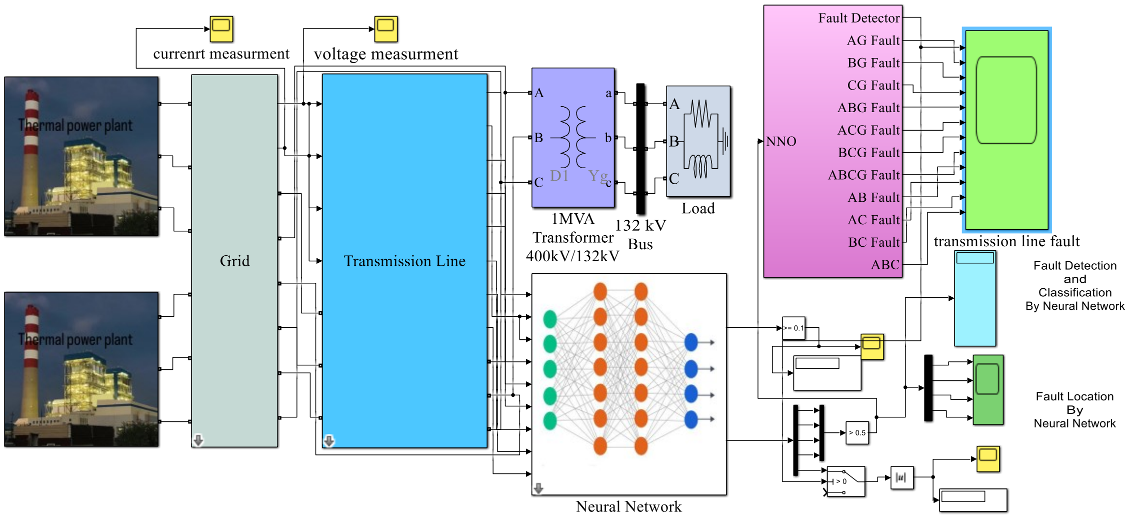


Fig. 4 The Implemented Simulink Model Shows the ANN Fault Detector.

The fundamental components of the present study are 400kV transmission lines, a load system, and a grid-connected thermal power plant located within Samarra. Figure 5 displays a concise Single-Line Diagram illustrating the mechanism. Generating units, sometimes referred to as AC sources, are located at the terminals of transmission lines and connected to electrical loads. The system (PI Networks) utilizes distributed line parameters to indicate its characteristics. According to Fig. 5, if there is a problem in the electrical power plant, the ANN Relay will identify it and transmit a tripping command to the Circuit Breaker (CB) using current and voltage transformers (C.T, P.T) to protect the electrical equipment from harm and fault.

4.2.Results and the Validation

The training dataset consists of fault data, which serves as a benchmark in numerous MATLAB Simulink simulations. The artificial neural network (ANN), specifically deep neurons (DNN), effectively exhibits the ability to recognize these faults accurately. The closed loop block diagram of the Sammara thermal power plant system in Iraq was simulated using Simulink/MATLAB 2022a. Figure 6 illustrates how error decreased with increasing iterations in the training, validation, and testing phases. Figure 6 shows that the greatest validation performance requires 173 loop iterations.

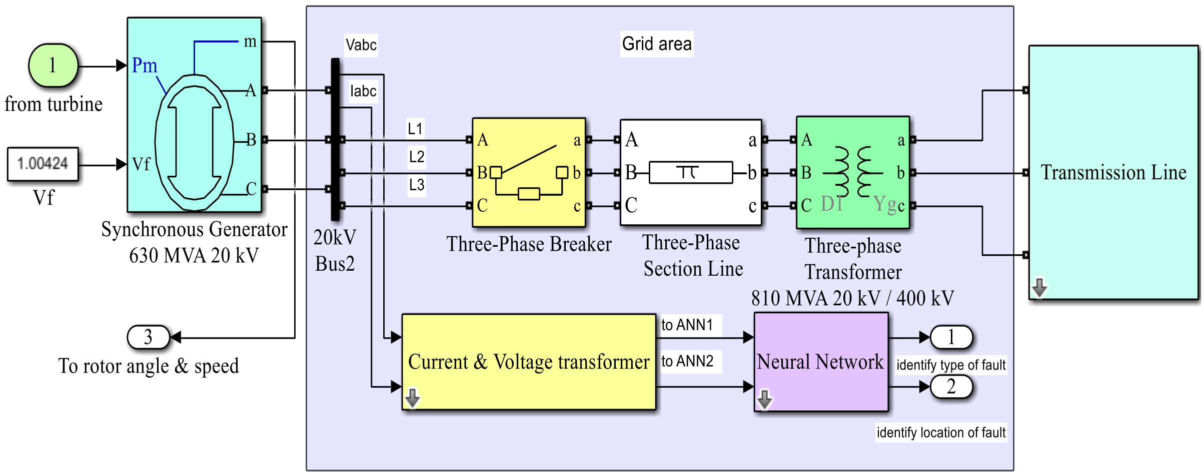


Fig. 5 The Components of the Grid in the Electrical System.

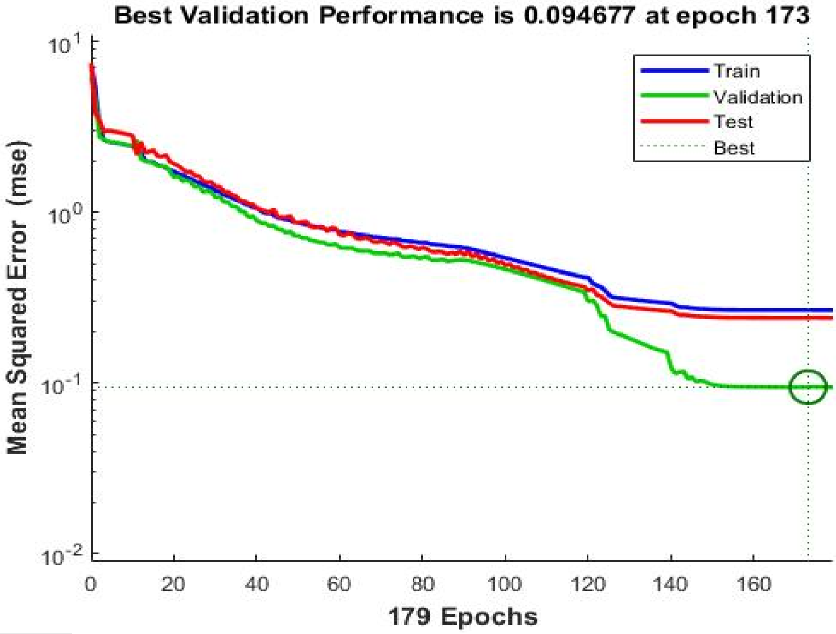


Fig. 6 Performance Graph of Error (MSE) During the Training Process.

Figure 7 displays a defect histogram. Errors yield a value of 1, while the absence of errors yielded a result of 0. The performance at this level was deemed satisfactory (Fig. 7).

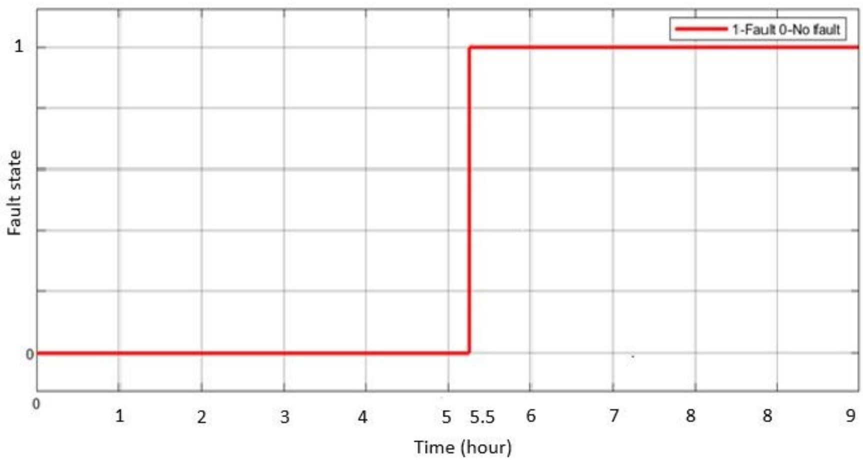


Fig. 7 Performance of Faults in Power System (1 Fault, 0 No-Fault).

Figure 8 displays a plot known as the receiver operating characteristics (ROC) plot. The ROC plot displays the percentage error of the ANN prediction, which indicates the classification model's ability to classify as a function of the acceptable number of false positive classifications. The closer the line was to the left and top sides, the higher the quality of the categorization model. After training, the implemented Artificial Neural Network (ANN) produced only one output. To accurately classify the data, the initial artificial neural network (ANN) was sent to the decoding circuit, where it was converted into a binary input, as depicted in Figure 9. The second ANN, on the other hand, produced a single output that specifies the fault's location. It is critical to point out that Fig. 9 is located in the section related to detecting the type of fault for the system presented in Fig. 4. A decoder circuit's main purpose is to convert the output of an artificial neural network (ANN), which is often encoded or in numerical form, into a specific representation or action. This conversion is particularly common in situations where the output needs to be converted into a practical format for processing or decision-making purposes. The decoder's truth table determines the necessary logic to generate the correct output for each possible combination of inputs. Decoder circuits are widely utilized in various digital system applications, including memory systems and address decoding. Table 1 displays the fault categorization based on Binary Input.

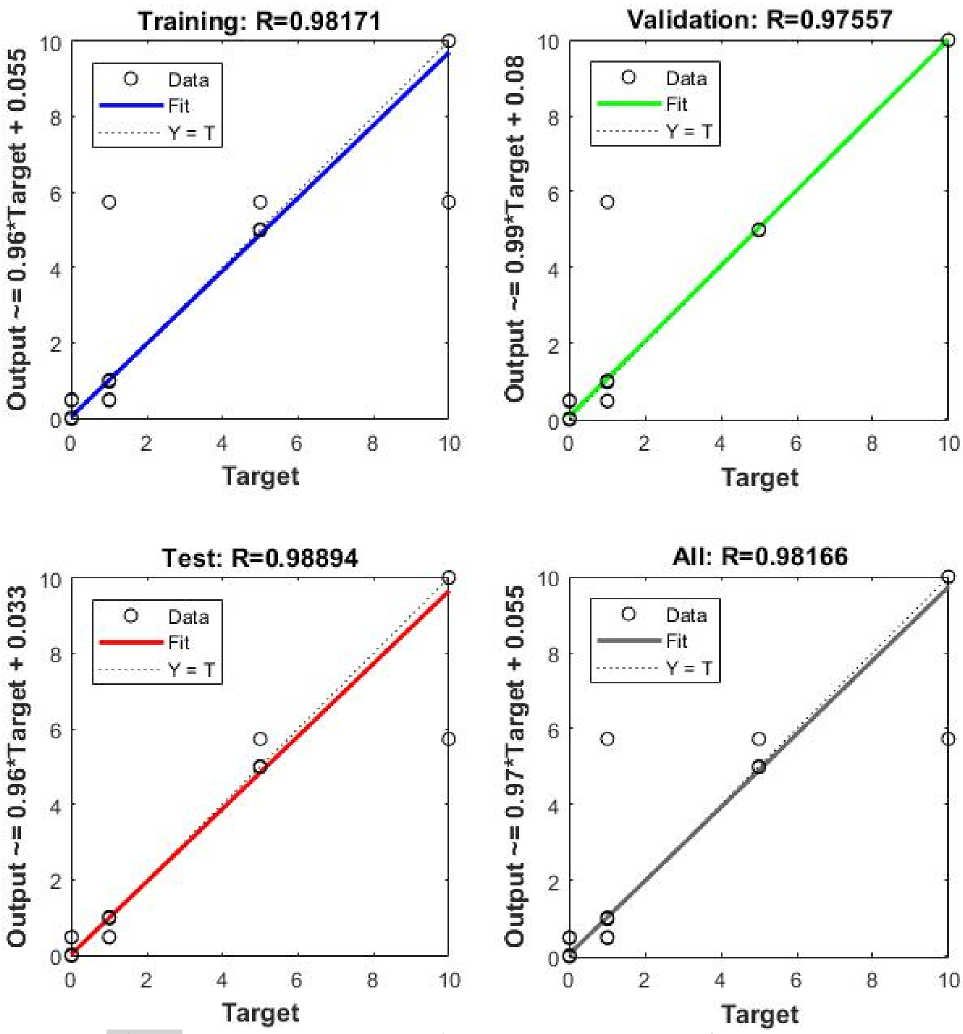


Fig. 8 Receiver Operating Characteristics (ROC) After Training.

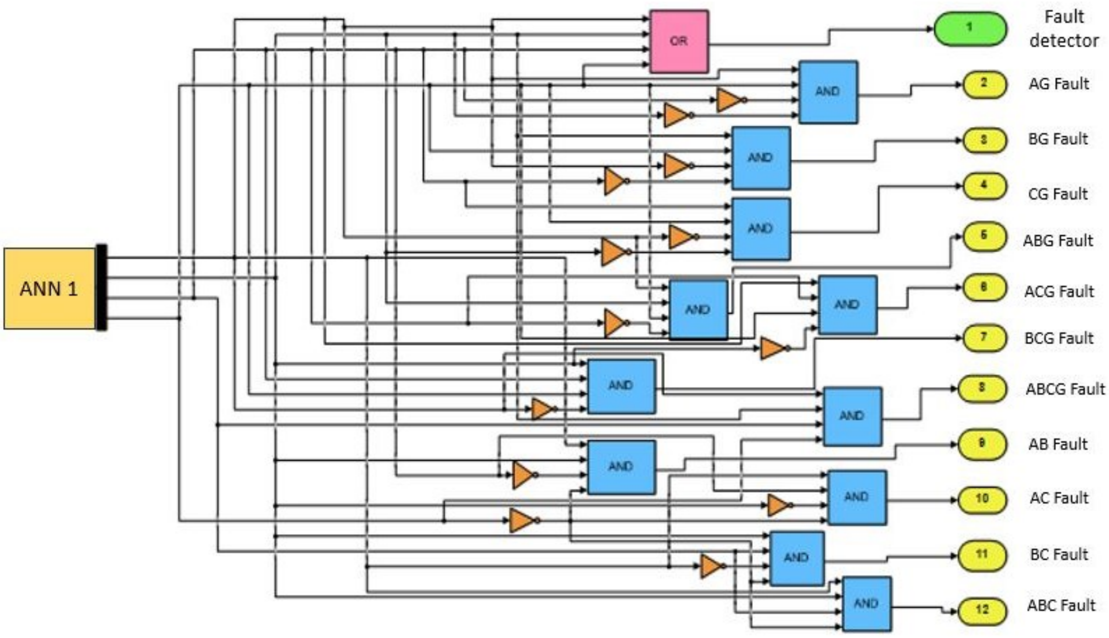


Fig. 9 The Logical Decoding Circuits Show the Type of Fault.

Table 1 An Explanation of How Errors are Classified Using Decoder Logic Circuits.

Decoder Input A	B	C	G	Type of fault (Output)
0	0	0	0	No Fault.
0	0	0	1	No Fault.
0	0	1	0	X
0	0	1	1	Phase C with Ground fault (L.G).
0	1	0	0	X
0	1	0	1	Phase B with Ground fault (L.G).
0	1	1	0	Phase B with Phase C (L.L).
0	1	1	1	Phase B&C with Ground fault (L.L.G).
1	0	0	0	X
1	0	0	1	Phase A with Ground fault (L.G).
1	0	1	0	Phase A with Phase C (L.L).
1	0	1	1	Phase A&C with Ground fault (L.L.G).
1	1	0	0	Phase A with Phase B (L.L).
1	1	0	1	Phase A&B with Ground fault (L.L.G).
1	1	1	0	3Phase (ABC) fault (L.L.L).
1	1	1	1	3Phase (ABC) with Ground fault (L.L.L.G).

The artificial neural network (ANN) utilizes four inputs to detect faults. The training data set was created by considering various combinations of fault conditions and the absence of faults. When there was no issue, the desired outcome was [0 0 0 0]. Unsymmetrical faults consist of phase (A, B, C) with ground (L.G, L.L.G, D.L.G), and phase (A-B, A-C, B-C, A-B-C) known as (L.L, L.L.L). Symmetrical faults in transmission line phases, such as phase (A-B-C) with ground, were also considered. An indication of a high voltage transmission line failure was [1 0 0 1] for the output phase A with the Ground, and so on. Figure 10 illustrates the voltage and current patterns of a Phase A Ground Fault. It is evident that the voltage in Phase A decreased, accompanied by an increase in currents across all phases. To investigate various situations of electrical faults happening on transmission lines, simulation tests were run. These scenarios demonstrated many short-circuit types, including line-ground faults (A-G), contrasting them with the electricity Samarra station's actual fault. These fault categories were investigated for each combination under consideration in Fig. 11. In Fig. 12, the fault occurred on the 400 kV Samarra thermal power plant-Haditha line, which has a length of 306 km. It was an actual electrical fault (the type of fault between phase A and ground), as shown in Figure 12 (a). It was compared with the results obtained from a closed-loop block diagram using Simulink/MATLAB 2022a, as shown in Figure 12 (b). Artificial neural networks were used, showing that the results were very close to the real results.

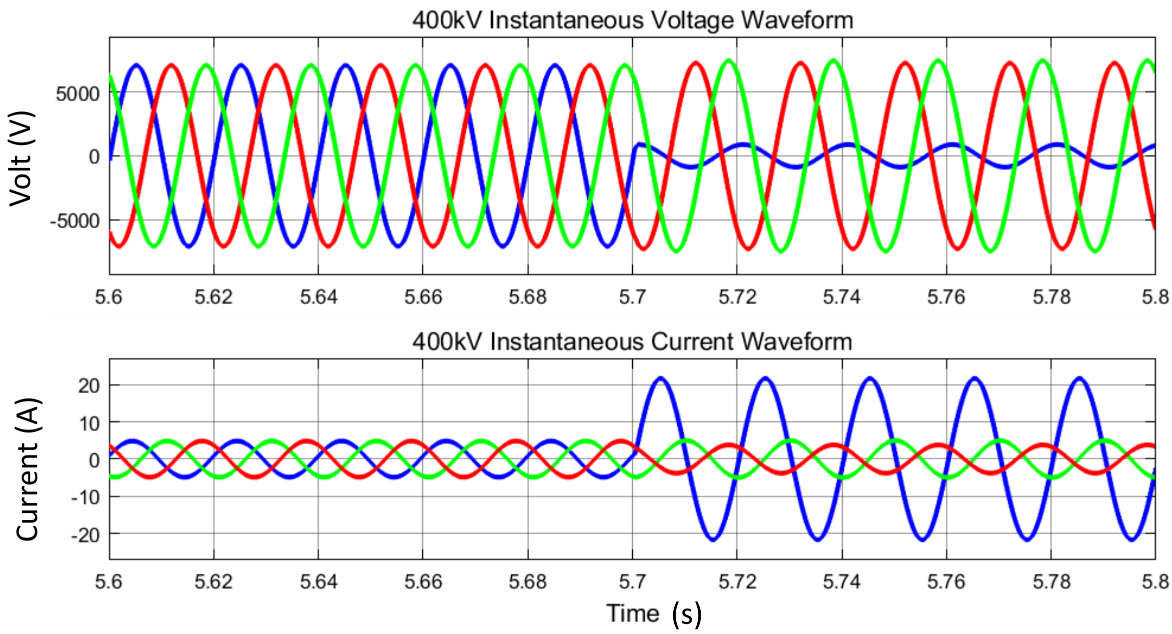


Fig. 10 The Voltage and Current Waveform when the Fault Occurred.

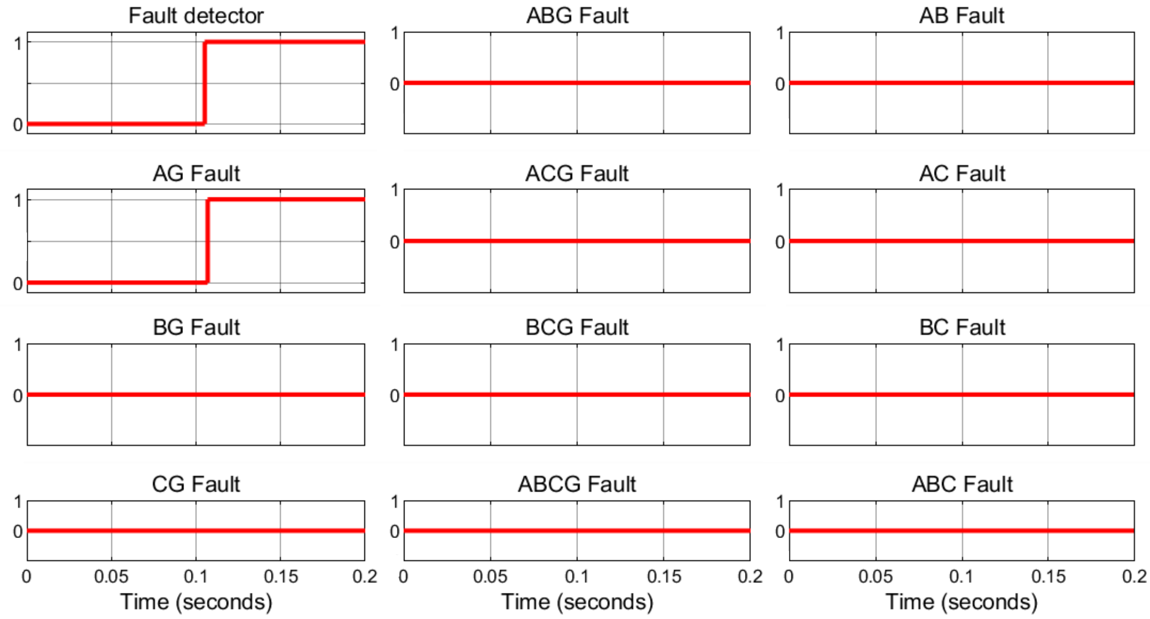


Fig. 11 The Fault that Occurred between Phase A and the Ground.

(a)

(b)

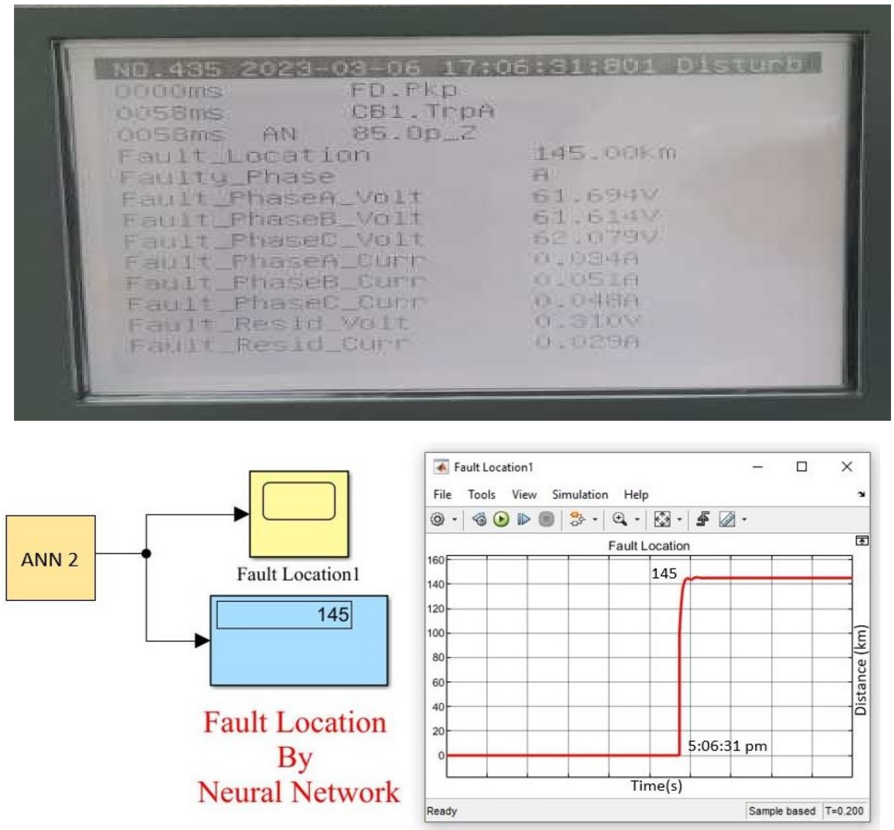


Fig. 12 Fault Location with the Actual System (a) and the Simulated Results (b).

Another type of fault was compared with actual results; Fig. 13 illustrates the voltage and current patterns of the Phase A-B-C Fault. It is evident that the voltage in Phase A-B-C decreased, accompanied by an increase in currents across all phases. This fault is a three-phase fault (A-B-C), and it is being compared to the actual fault occurring at the Samarra power station. The fault depicted in Fig. 14 occurred on the 400 kV Samarra thermal power plant - Taji line, which spans 87 km. It is an authentic electrical fault, namely a phase A-B-C fault, as illustrated in Fig. 14 (a). The results were compared to the closed-loop block diagram created using Simulink/MATLAB 2022a, as depicted in Fig. 14 (b). Artificial neural networks were employed, demonstrating high similarity to the actual results.

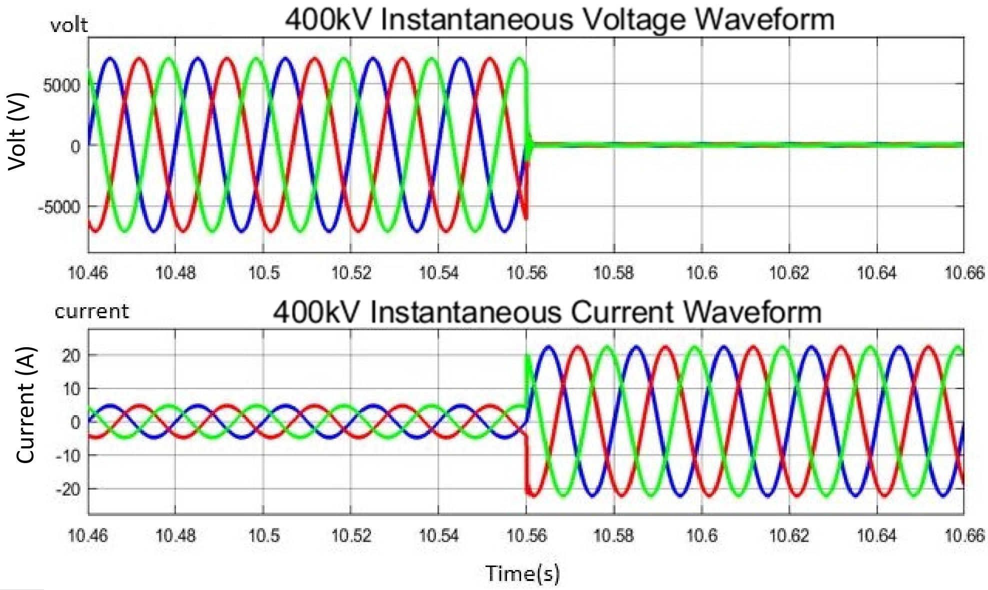


Fig. 13 The Voltage and Current Waveform when the Fault Occurred of Phase A-B-C Fault.

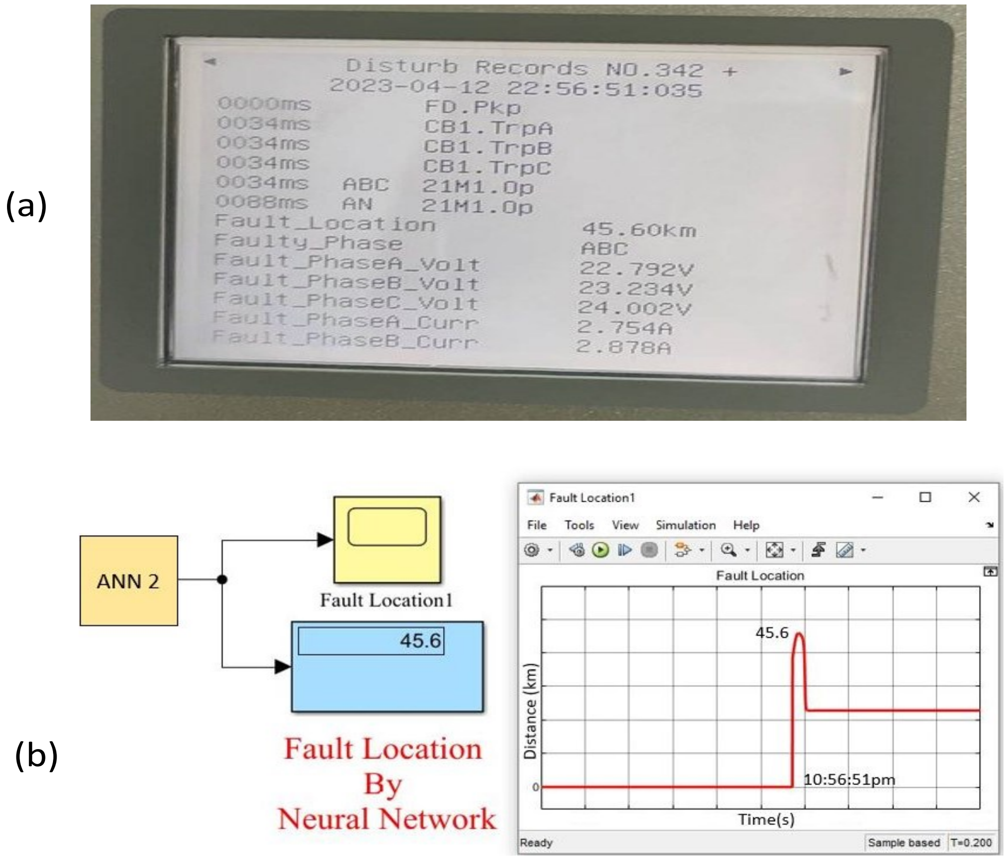


Fig. 14 Fault Location of the Three-Phase Fault (A-B-C) on the Actual System (a) and the Simulated Results (b).

5.SENSITIVITY OF ANN TO MINOR FAULTS

Artificial neural networks (ANNs) may exhibit sensitivity to minor errors, contingent upon aspects such as network architecture, training data quality, and the characteristics of the faults. For instance, the Artificial Neural Network (ANN) was influenced by a 10% alteration in the load whilst utilizing the identical fault data as before. The specified voltage rating for the load was 5000 Volts when the cell was trained at 10% of its rated load. As presented in Fig. 15, the voltage wave and the current wave were affected by the change at the moment of the fault in the (10:05:55 -10:07:01) PM:

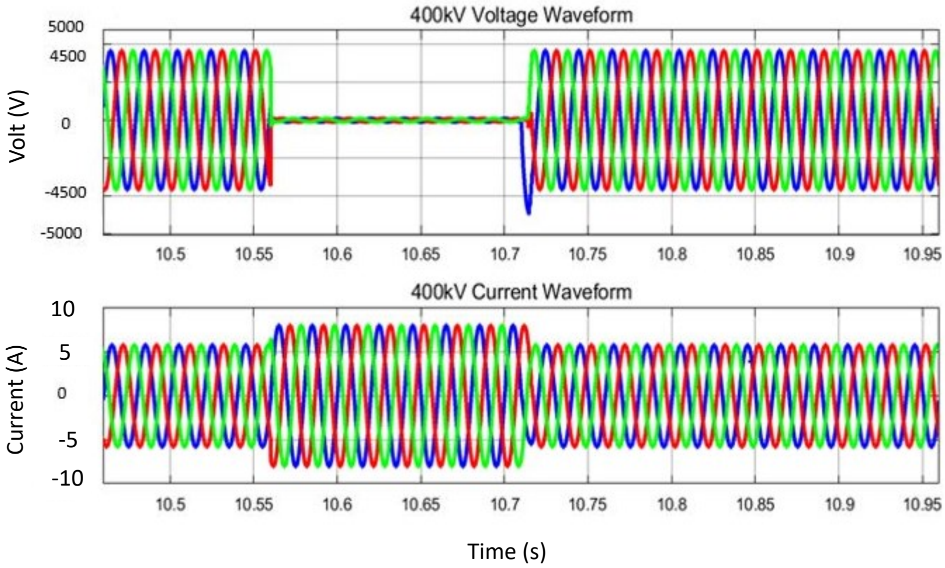


Fig. 15 The Voltage and Current Waveform when the Fault Occurred with Variation in Load Levels of 10%.

As for regression, which is used to solve problems of predicting continuous values, regression plots help understand the relationship between variables and produce predictions based on that relationship. This understanding aids in the decision-making and planning processes while solving problems. Figure 15 depicts the plot that increased from the training process when there was a 10% change in load levels. The R-value, also known as the correlation coefficient, quantifies the magnitude and direction of the association between variables, ranging from -1 to +1.

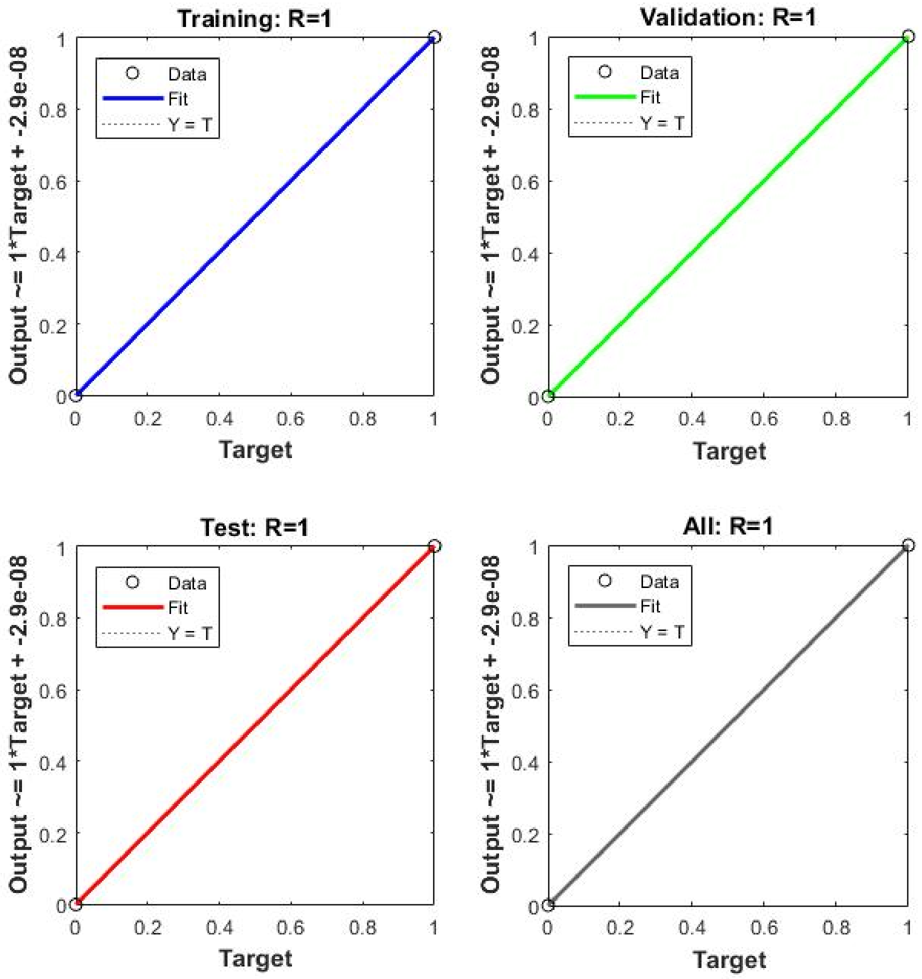


Fig. 16 The Regression Plot between Variables.

6.DISCUSSION AND CONCLUSION

The present study identifies and categorizes malfunctions in electrical transmission lines in power plants using artificial neural networks (ANNs). Samarra Thermal Station in Iraq and its transmission lines were used as the case study for actual data analysis and simulation. The approach uses three-phase currents and voltages obtained from distributors as inputs. A feedforward neural network using the backpropagation algorithm was used to detect and classify defects in each phase. An artificial neural network (ANN) was trained using the actual data from Samarra Thermal Station in Iraq, utilizing actual faults occurring on a 400 kV transmission line. The ANN was trained using currents and voltages obtained from protective relays as inputs. The inputs reduced from 2000 amperes to 1 ampere and from 400 kilovolts to 63.5 volts, respectively. The line lengths considered were 87 km, 145 km, 273 km, and 306 km. The artificial neural network (ANN) training using real fault data yielded detection outcomes that closely resembled conventional line monitoring techniques. The simulation results showed that the provided method can identify and categorize transmission line faults properly and effectively. The system's adaptability was evaluated by performing simulations with varying parameters. The complete Samarra thermal power plant system was modeled in a closed-loop block diagram using Simulink/MATLAB 2022a. In future research, integrating Artificial Neural Networks (ANN) and fuzzy logic will be employed to diagnose and predict transmission failures.

REFERENCES

[1] Naimi A, Deng J, Shimjith S, Arul AJ. **Fault Detection and Isolation of a Pressurized Water Reactor Based on Neural Network and K-Nearest Neighbor.** *IEEE Access* 2022; **10**:17113-17121.

[2] Zare S, Ayati M. **Simultaneous Fault Diagnosis of Wind Turbine Using Multichannel Convolutional Neural Networks.** *ISA Transactions* 2021; **108**:230-239.

[3] Omosanya AJ, Akinlabi ET, Okeniyi JO. **Overview for Improving Steam Turbine Power Generation Efficiency.** *Journal of Physics: Conference Series* 2019; **032040**.

[4] Khan KA, Manir SM, Islam MS, Jahan S, Hassan L, Ali MH. **Studies on Nonconventional Energy Sources for Electricity Generation.** *International Journal of Advanced Research and Innovative Ideas in Education* 2018; **4**(4):229-244.

[5] IEA. **Statistics Report: Key World Energy Statistics 2021.** 2021.

[6] Prasad A, Edward JB, Ravi K. **A Review on Fault Classification Methodologies in Power Transmission Systems: Part—I.** *Journal of Electrical Systems and Information Technology* 2018; **5**(1):48-60.

[7] Heo S, Lee JH. **Fault Detection and Classification Using Artificial Neural Networks.** *IFAC-PapersOnLine* 2018; **51**(18):470-475.

[8] Ibrahim R, Weinert J, Watson S. **Neural Networks for Wind Turbine Fault Detection Via Current Signature Analysis.** *Wind Europe Summit* 2016; Hamburg, Germany: p. 1-7.

[9] Guo M-F, Zeng X-D, Chen D-Y, Yang N-C. **Deep-Learning-Based Earth Fault Detection Using Continuous Wavelet Transform and Convolutional Neural Network in Resonant Grounding Distribution Systems.** *IEEE Sensors Journal* 2017; **18**(3):1291-1300.

[10] Teja ON, Ramakrishna MS, Bhavana G, Sireesha K. **Fault Detection and Classification in Power Transmission Lines Using Back Propagation Neural Networks.** *2020 International Conference on Smart Electronics and Communication* 2020; 1150-1156.

[11] Paithankar YG, Bhide S. **Fundamentals of Power System Protection.** *PHI Learning Pvt. Ltd.* 2022.

[12] Carcangiu S, Montisci A. **A Locally Recurrent Neural Network Based Approach for the Early Fault Detection.** *2018 IEEE 4th International Forum on Research and Technology for Society and Industry* 2018; 1-6.

[13] Altaf S, Ahmad S. **Machine Health Monitoring and Fault Diagnosis Techniques Review in Industrial Power-Line Network.** In: Valdman J, Marcinkowski L, eds. Modeling and Simulation in Engineering-Selected Problems 2020.

[14] Zapar WM, Gaeid K, Mokhlis HB, Al Smadi TA. **Review of the Most Recent Articles in Fault Tolerant Control of Power Plants 2018-2022.** *Tikrit Journal of Engineering Sciences* 2023; **30**(2):103-113.

[15] Abubakar U, Mekhilef S, Gaeid KS, Mokhlis H, Al Mashhadany YI. **Induction Motor Fault Detection Based on Multi-Sensory Control and Wavelet Analysis.** *IET Electric Power Applications* 2020; **14**(11):2051-2061.

[16] Xavier GM, de Seixas JM. **Fault Detection and Diagnosis in a Chemical Process Using Long Short-**

Term Memory Recurrent Neural Network. *2018 International Joint Conference on Neural Networks* 2018; 1-8.

[17] Thakur A, Konde A. **Fundamentals of Neural Networks.** *International Journal for Research in Applied Science and Engineering Technology* 2021; **9**:407-426.

[18] Pattanayak R, Behera S, Parija B. **Classification of Faults in a Hybrid Power System Using Artificial Neural Network.** *2019 IEEE 5th International Conference for Convergence in Technology* 2019; 1-4.

[19] Kumar RR, Cirrincione G, Cirrincione M, Andriollo M, Tortella A. **Accurate Fault Diagnosis and Classification Scheme Based on Non-Parametric, Statistical-Frequency Features and Neural Networks.** *2018 XIII International Conference on Electrical Machines* 2018; 1747-1753.

[20] Yin Z, Zhen Y, Huo C, Chen J. **Deep Learning Based Transformer Fault Diagnosis Method.** *2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering* 2021; 216-219.

[21] Chen M, Challita U, Saad W, Yin C, Debbah M. **Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial.** *IEEE Communications Surveys & Tutorials* 2019; **21**(4):3039-3071.

[22] Kumar KS, Rao AL, Rao MB. **Design, Synthesis, Biological Evaluation and Molecular Docking Studies of Novel 3-Substituted -5- [(Indol-3-Yl) Methylene]-Thiazolidine-2, 4-Dione Derivatives.** *Heliyon* 2018; **4**(9): e00807, (1-26).

[23] Pang Z, Niu F, O'Neill Z. **Solar Radiation Prediction Using Recurrent Neural Network and Artificial Neural Network: A Case Study with Comparisons.** *Renewable Energy* 2020; **156**:279-289.

[24] Bouvier M, Valentian A, Mesquida T, Rummens F, Reyboz M, Vianello E, Beigne E. **Spiking Neural Networks Hardware Implementations and Challenges: A Survey.** *ACM Journal on Emerging Technologies in Computing Systems* 2019; **15**(2):1-35.

[25] Thanakodi S, Nazar NSM, Joini NF, Hidzir HDM, Awira MZK. **Power Plant Fault Detection Using Artificial Neural Network.** *International Conference on Engineering and Technology (IntCET 2017)*; Akdeniz University, Antalya, Turkey: p. 1-11.

[26] Padhy SK, Panigrahi BK, Ray PK, Satpathy AK, Nanda RP, Nayak A. **Classification of Faults in a Transmission Line Using Artificial Neural Network.** *2018 International Conference on Information Technology* 2018; 239-243.

[27] Djalab A, Hafaifa A, Rezaoui MM, Ali T, Sabri N. **An Intelligent Faults Diagnosis and Detection Method Based an Artificial Neural Networks for Photovoltaic Array.** *2019 International Conference on Applied Automation and Industrial Diagnostics* 2019; 1-6.

[28] Mirnaghi MS, Haghighat F. **Fault Detection and Diagnosis of Large-Scale HVAC Systems in Buildings Using Data-Driven Methods: A Comprehensive Review.** *Energy and Buildings* 2020; **229**:110492.

[29] Resmi R, Vanitha V, Aravind E, Sundaram BR, Aswin CR, Harithaa S. **Detection, Classification and Zone Location of Fault in Transmission Line Using Artificial Neural Network.** *2019 IEEE International Conference on Electrical, Computer and Communication Technologies* 2019; 1-5.

[30] Xiao C, Liu Z, Zhang T, Zhang X. **Deep Learning Method for Fault Detection of Wind Turbine Converter.** *Applied Sciences* 2021; **11**(3):1280.

[31] Al Smadi YT, Gaeid KS, Mahmood AT, Hussein RJ. **State Space Modeling and Control of Power Plant Electrical Faults with Neural Networks for Diagnosis.** *Results in Engineering* 2025; **25**: 104582.