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Detection and Diagnosis of electrical faults in Samarra thermal power station using ANN based model.

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Abstract

The paper investigates thermal power plant malfunctions, including line-to-line, double line-to-ground, and single line-to-ground faults leading to system downtime. The research focuses on utilizing Artificial Neural Network (ANN) as an intelligent tool for fault diagnosis in electrical power plants. Among various fault detection methods like Logic Regression, Genetic Algorithm, and Fuzzy Logic, the paper chooses ANN for its pattern recognition, classification, matching, prediction, decision-making, and control capabilities. Despite requiring extensive computational training, ANN is considered an intelligent system. The last part provides a concise overview of electrical stations, particularly thermal power plants, explores common fault types and introduces ANNs with explanations of the fundamental neuron model. It elaborates on human neuron (BNN) and artificial neuron (ANN) operations, providing examples of ANNs in fault detection from previous literature.

Introduction:

In our modern society, electricity has become an essential part of daily life, driving the need for efficient power generation methods [1]. Power stations, categorized into conventional and nonconventional sources, meet this demand. Conventional sources include nuclear, diesel, steam, and hydroelectric plants, while nonconventional sources encompass wind, solar, and geothermal energy [2]. Renewable sources offer eco-friendliness, emitting minimal CO2. Despite this, turbomachinery-based thermal plants, reliant on fossil fuels, remain dominant, contributing to about 80% of global electricity generation [3], [4]. These plants employ various technologies and mechanisms to convert mechanical energy into electrical power [6]. However, the power system, comprising generators, transformers, and transmission lines, is prone to faults, necessitating rapid detection and isolation. Artificial Neural Networks (ANNs) play a vital role in fault detection, leveraging their ability to identify non-linear correlations and automate processes. ANNs learn from training data to optimize their configurations, requiring precise feature selection and network architecture design for effective fault detection[1]. On the other hand, nonconventional sources include wind power, solar radiation, and energy derived from naturally replenished sources encompassing geothermal heat, the sun's rays, rain, waves and tides [2]. These are considered non-conventional because they have not been extensively utilized in our daily lives until now. Renewable energy sources hold a significant advantage over fossil fuels due to their environmental friendliness. Renewable energy sources produce minimal CO2 emissions, making them less polluting and more ecologically sustainable.

Turbomachines are still being utilized by extensive energy producers despite the increasing spotlight on environmentally friendly and cost-effective technological advances in energy. These producers heavily rely on fossil fuels as the primary source of energy generation, which remains a versatile and dominant energy source on a global scale [3], [4]. Turbomachinery-based thermal power plants, which rely on various fuel sources, account for around 80% of the world's electricity generation. These facilities can employ a range of technologies, including internal combustion, nuclear, gas turbine, or steam power systems [3]. A power plant employs a primary mechanism connected to a generator in order to produce electrical power. This primary mechanism, whether it is a steam or water turbine, transforms energy from an external source converting mechanical energy. The primary mechanism's mechanical energy is then transformed into electrical energy throughout the generator.

The produced electricity is then sent to various users through conductors [3], [4]. The generators, transformers, transmission lines, and distribution lines that make up the system that supplies electricity, are vulnerable to faults. In power systems, when an abnormal condition arises, such as voltage, current, or phase angle exceeding preset limits, it is termed as a fault. It is essential to have an automated protection mechanism that quickly separates the damaged element in order to handle component problems. By doing this, it is ensured that the system's unaffected portion may carry on as usual.

In order to avoid any harm, faults must be cleared quickly—within a few microseconds. Extended short circuits can cause damage to important parts of the system and provide a fire risk because of high short circuit currents that could propagate throughout the system. Desynchronization between generators within a power plant or between many power plants can also result from a reduction in system voltage[6], Every unit of device and component in the power system has its own protection approach. These tactics include protecting transformers, bus bars, transmission lines, generators, and other components. The power system is split up into many zones, each zone in being responsible for protecting one or, in certain situations, two system components, in order to provide complete protection [7]. No part of the power system is left exposed due to the protection zones' design, which ensures total coverage. Artificial Neural Networks (ANNs) are one of the techniques used to identify and isolate electrical system defects [8], This is the major goal of the investigation. ANNs are very helpful for finding non-linear correlations and automating procedures.

ANNs learn to create the desired output by assigning various weights to different inputs through data-driven training. To tailor them to the specific issue at hand, it is necessary to ascertain precise configurations for the quantity of neurons and training level needed. It should be emphasized that the effectiveness of an ANN in fault detection relies on the quality and representativeness of the training data, the appropriate selection of features and the efficacy of the network architecture design [9], [10].

Related Works

a. At [11], The study utilizes a feed-forward artificial neural network with a back propagation algorithm for fault classification [12] Figure 1. The neural network is trained using extracted instantaneous voltage and current values. The classifier's performance is evaluated using the Mean Square Error (MSE).

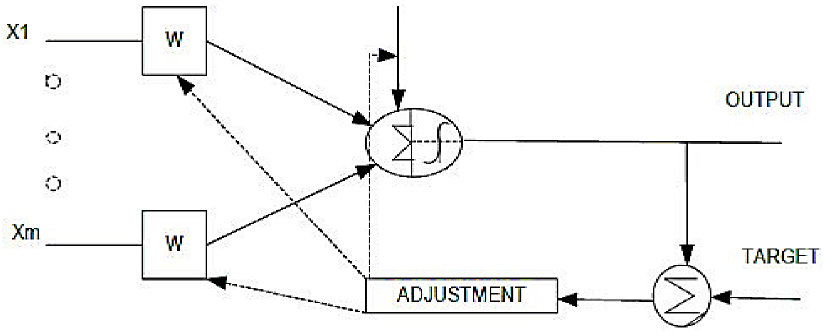

Fig.1 *Back-Propagation Artificial neural network architecture [11].*

The Mean Squared Error (MSE) for each output is computed in every iteration as follows:

$$MSE = \frac{1}{N}\left(\sum_{1}^{N}(E_i - E_0)^2\right) \qquad (7)$$

b. At [13], this study utilizes an artificial neural network with back propagation to classify transmission line faults. MATLAB models the transmission line, extracting voltage and current magnitudes for classifier training and testing. The neural network has one layer with eight neurons. Figure 2 presents a matrix where rows show predicted outputs, columns show target values and the diagonal section indicates observation counts and their percentage impact.

Fig.2 *Confusion Matrix for artificial neural network classifier [13].*

c. At [14], the study looks at a technique that uses artificial neural networks (ANN) to identify a model of wind turbine dynamics. The method first constructs a Luenberger observer, which uses a time-invariant gain vector L, (Φ − LH) to place the eigenvalues of the observer state transition matrix at predetermined points on the unit circle |z| < 1. Both measured and unmeasured states are estimated using this observer, regarding the nonlinear element.

By applying a Luenberger observer, the system's observer model can be defined in the following manner [14]:

$$X^\wedge(t) = AX^\wedge + Q^\wedge(X^\wedge, u) + G(y - CX^\wedge) \quad (11)$$

$$y^\wedge(t) = CX^\wedge(t) \quad (12)$$

d. At [15], the study utilizes a feed-forward ANN with a back-propagation algorithm to develop the fault detector and classifier. MATLAB with SIMPOWER systems Toolbox is used to simulate and model the transmission lines, Figure 3 displays a representation of the model utilized to generate training and testing datasets. Table 1 shows the results of faults in electrical lines.

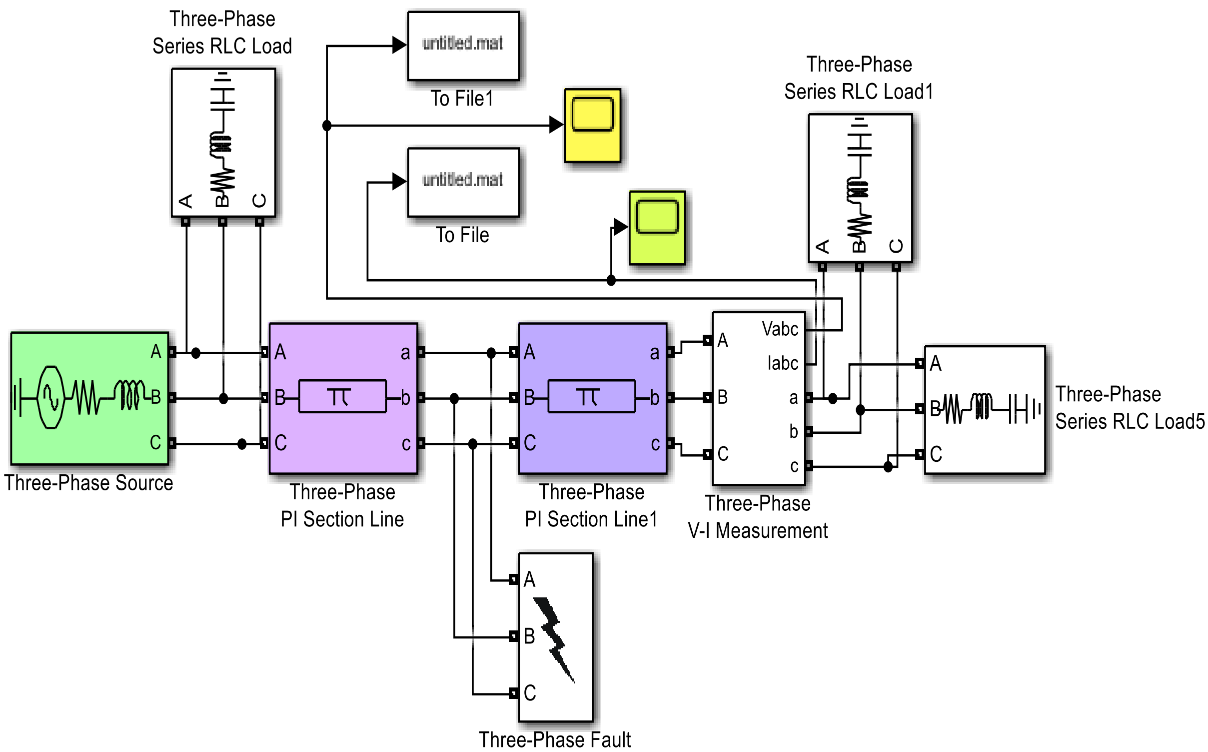

Fig.3 *Snap of the studied model in SIMPOWER systems [15].*

e. After conducting extensive simulations to analyse output errors and network performance, a single hidden layer with 10 neurons, an input layer with 6 neurons, and an output layer with 1 neuron make up the selected network architecture.

Table1: The inputs are provided to the Artificial Neural Network (ANN) for different fault scenarios when the (R) is set to 1Ω [15].

Case	*Input Vector*	

No.	Va/Va (pf)	Vb/Vb(pf)	Vc/Vc(pf)	Ia/Ia (pf)	Ib/Ib (pf)	Ic/Ic(pf)	Type Fault
1	0.571	1.052	1.023	39.3	1.18	1.28	A-Ground
2	0.770	0.463	0.227	0.69	30.4	0.57	B-Ground
3	0.92	1.098	0.785	-0.6	0.94	3.12	C-Ground
4	1.15	-1.07	0.99	57.0	32.5	1.00	A-B
5	0.99	0.49	0.79	1.00	55.7	19.0	B-C
6	0.69	0.99	0.70	71.3	1.00	22.1	A-C
7	1.223	0.528	1.076	64.8	37.5	0.86	A-B-G
8	0.982	0.211	0.792	0.78	55.4	12.8	B-C-G
9	0.554	1.021	0.689	70.9	0.83	24.3	A-C-G
10	1.000	1.000	1.000	1.00	1.00	1.00	No-Fault

f. At [16], this study builds new temporal recurrent graph neural network models for fault diagnostics, classifies fault type/phase, and pinpoint's fault location using cutting-edge graph learning techniques. The block diagram of the fault detection method in Figure 4 shows that another benefit of the proposed strategy is that it uses voltage signals rather than current signals, which eliminates the need to place relays on every line of the distribution system.

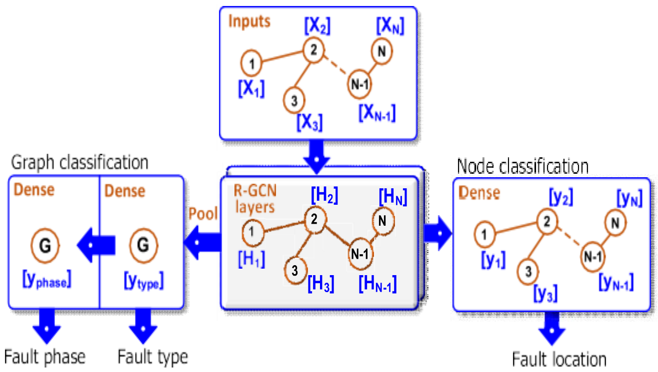

Fig.4 *Block diagram of the suggested fault diagnostic system [16].*

Classification of Faults

Classification encompasses the perception and division of concepts and objects as well as the categorization process as a whole. By classifying the things, we may establish relationships between them that might not be apparent when analysing them all at once. Furthermore, the act of classifying things allows us to arbitrarily determine the relative values of various objects [6]. Faults in a power system might be categorized as conducting route failures or insulation failures. Failures in the insulation can result in short circuits that could damage the equipment in the power system.

Most problems with transmission and distribution lines are the result of switching surges, overvoltage from lightning strikes, or contact between external conducting items and overhead wires [17].

Overvoltages resulting from lightning or switching surges can trigger flashovers on insulator surfaces, resulting in short circuits. Additionally, insulators may be punctured, fractured, or accumulate foreign particles such as soot or dirt, which diminish their insulation capability and lead to flashovers. Short circuits can also occur when tree branches or other conductive objects fall onto overhead lines. Furthermore, faults can occur when birds make contact with a phase wire, the earth wire, or the metallic supporting structure [6], [17]. When conductors break, the path for electrical conduction is disrupted, leading to an open circuit. If the fractured conductor falls to the ground, it results in a short circuit. Failures at connection points in cables or overhead lines can also lead to disruptions in the conduction path [18]. An imbalanced electrical system due to the loss of one or two phases can result in uneven currents, producing harmonic effects that rapidly heat up rotating machinery.

Problems in testing or maintenance procedures, improper connections, malfunctions in protective devices, and switching problems can all cause circuit breakers to trip. These problems may also be caused by the usage of inferior system components or bad system designs. As a result, reducing the likelihood of these errors requires improvements in system architecture, the use of premium parts and materials, and the adoption of better operating and maintenance procedures [19].

Thermal Power Plant:

Steam power stations, also known as steam power plants or thermal power stations, are large-scale electricity generation facilities that produce electrical energy by converting the conversion of steam's thermal energy into mechanical energy, then energy for electricity [20]. These power stations are commonly used to generate electricity on a significant scale and are an essential part of the world's power generation infrastructure [21]. The basic principle of a steam power station involves the following steps:

1. Fuel Combustion: A boiler burns a fuel source, comparable to coal, oil, or natural gas, for their energy needs to achieve high-temperature combustion gases.

2. Boiler: The combustion gases transfer their thermal energy to water in the boiler, creating steam. Typically, the boiler is made up of tubes that are filled with water that are subjected to heat by the gases produced by combustion.

3. Steam Turbine: Steam from the boiler's high-pressure output enters a steam turbine. High-speed rotation of the turbine rotor is brought on by the expansion and conveying of the energy of the steam as it transmits through the turbine blades.

4. Generator: A generator, which is attached to the revolving turbine shaft, transforms the mechanical energy of the turbine's revolution into power that is electrical. The generator has a structure made up of wire coils that spin under a magnetic field to generate an electric current

5. Condenser: In a condenser, low-pressure steam that has just exited a turbine is converted back into water. Heat is released during the condensation process, which is typically

transmitted to a cooling medium like a cooling tower or river water nearby.

6. Feedwater Pump: A feedwater pump then pumps the condensed water from the condenser back to the boiler, where it is subsequently heated and condensed into steam. This cycle repeats to sustain continuous power generation.
7. Power Distribution: The generated electrical energy is then sent to a transformer, which steps up the voltage to a higher level for efficient transmission over long distances through power lines. The electricity is then distributed to homes, industries, and various consumers through the electrical grid [22] [20], [21]. Figure 5 explains the layout of the Thermal Power Plant.

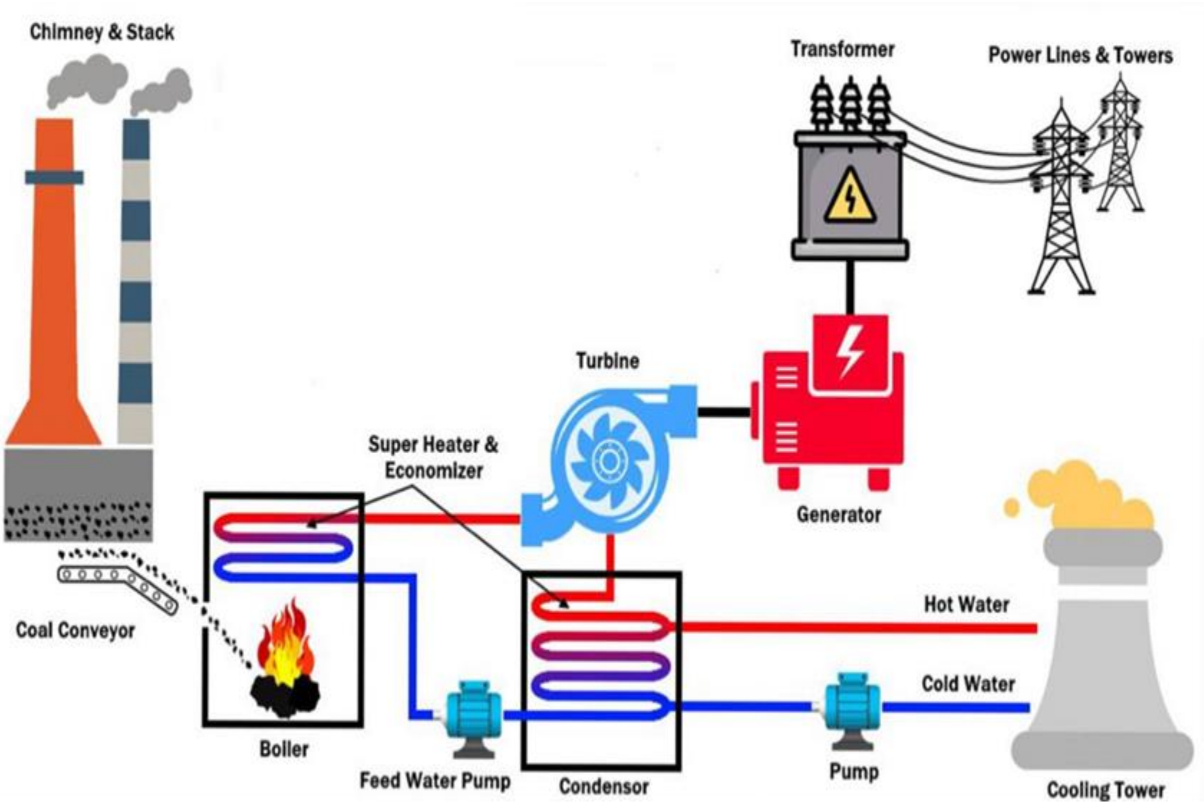

Fig.5 *Layout of thermal power plant [20].*

Fault diagnostic methods

The techniques for locating errors vary depending on a number of variables, including the kind of system, data that is available, domain knowledge, and the level of accuracy that is required. Different strategies can be combined or adjusted to fit specific requirements or applications [23]. Figure 6 provides an illustration of this.

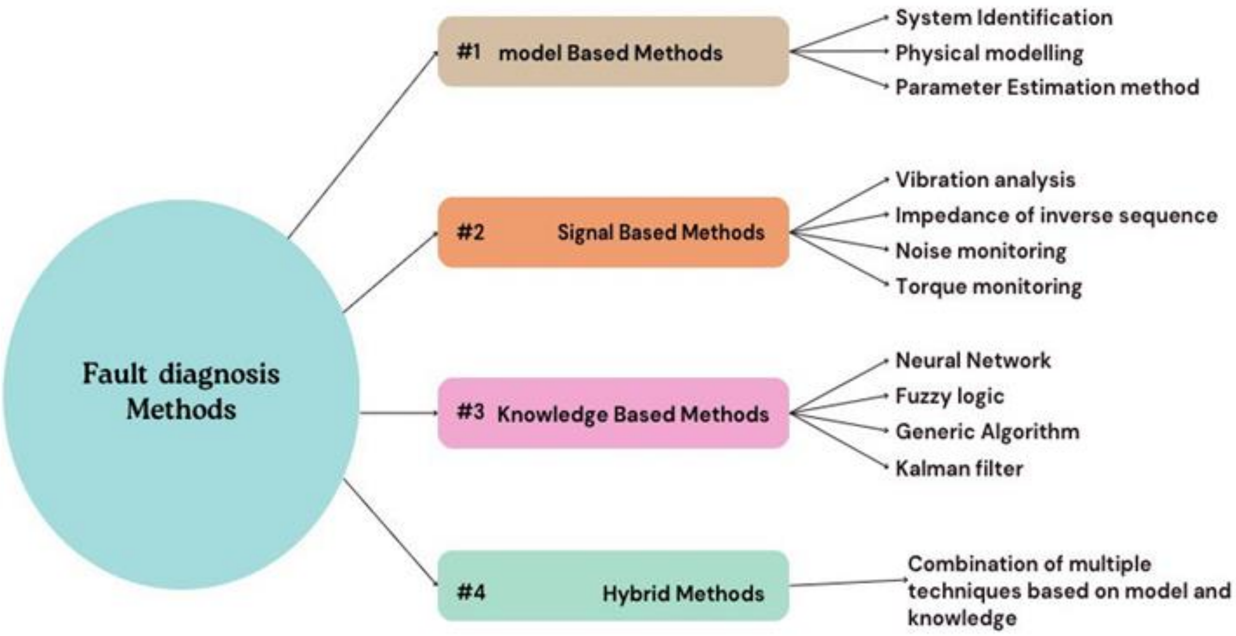

Fig.6 *Classification of different fault diagnosis methods [23].*

Classification of Neural Networks

This was at the beginning of the 1940s when two mathematicians, Walter Pitts and Warren McCulloch, came up with a basic mathematical framework that aimed at copying human brain operations. By so doing, they set the stage for further research into neural network applications in artificial intelligence. These are multi-input, multi-output systems composed of artificial neurons constituting neural networks. Converting data coming to them into useful output is their main objective. A typical neural network has an input layer, an output layer and one or more hidden layers where each neuron is connected to affect others [24]. Through in-depth dataset analysis, neural networks may identify intricate patterns in sizable data sets and comprehend the relationships between different data parts. They can identify complex patterns in huge datasets thanks to this ability [11], [25].

The output of the neuron is given by:

$$y = f(\varphi) = f(\textstyle\sum_{i=0}^{N_\circ} w_i a_i) \quad (1)$$

$$\varphi = W^T A \quad (2)$$

$$\text{Where} \quad W = [w_0\, w_1 \ldots\ldots w_{K_0}], A = [a_0 a_1 \ldots\ldots a_{N_0}]^T \quad (3)$$

In the equation $w_0 a_0$ represent the threshold values (polarization), f (φ) is the activation function of the neuron, φ is the input signal, and y is the output of the neuron.

One major advantage of integrating Neural Networks (NNs) in classification tasks is their capacity to comprehend intricate non-linear patterns. Additionally, since the data dictates the best model, NNs do away with the requirement for predestined models. But there are numerous and commonly dangers to watch out for, such overfitting—a phenomena in which a neural network model performs well on training data but badly on newly received information. It is advised to use caution when selecting the right structure and configuration settings for the NN model in order to handle these problems[24] [25]. Sometimes the information being collected is separated into three subsets: training, validation, and test data. The accuracy of the test set results indicates how well the classifier can predict, while the validation set ensures that the model does not overfit the training set. In our suggested technique, we suggest a two-step segmentation process. The first classification algorithm uses signal power documentation to identify faults, and the second classifier is made to categorize specific types of defects in the system [26].

Artificial Neural Network

In reaction to biological neural networks (BNNs), algorithmic systems known as Artificial Neural Networks (ANNs) were built. They are exceptionally good at finding solutions to issues in a variety of fields, including function approximation, pattern recognition, categorization prediction, selection, and optimization [25]. ANNs simplify this complexity and focus on key aspects for efficient information processing Deep learning encompasses artificial neural networks (ANNs) characterized by intricate multilayer structures [27]. ANNs, like artificial neural networks, have the capacity to mimic the human brain's approach to executing specific tasks [28].

An ANN's internal structure consists of the following elements:

1. **Input Layer:** The input data is supplied into the network's first layer here.
2. **Hidden Layers:** The layers where computing occurs are situated in between the input and output layers. The number of neurons in each hidden layer and the total number of hidden layers varies based on the intricacy of the issue.
3. **Output Layer:** The computed output is generated at the last layer of the network, here. The type of problem determines how many nodes are in the output layer. In a regression problem [29].
4. **Connections (Weights):** Via connections with corresponding weights, every neuron in one layer is connected to every other neuron in the layer below.
5. **Activation Functions:** To provide non-linearity to the network and enable it to recognize intricate links in the data, activation functions are added to each neuron's output. The sigmoid, tanh, ReLU (Rectified Linear Unit), and SoftMax are examples of common activation functions.
6. **Bias Neurons:** These are extra neurons in every layer (apart from the input layer) that provide the network the capacity to move the activation function curve, improving data fitting [30].

An illustrative instance of the human brain functioning as a neural network, which sends and receives signals to facilitate human action's function is explained in the modeling of the biological neural network and its mathematical simulation can be shown in Figure 7 [31].

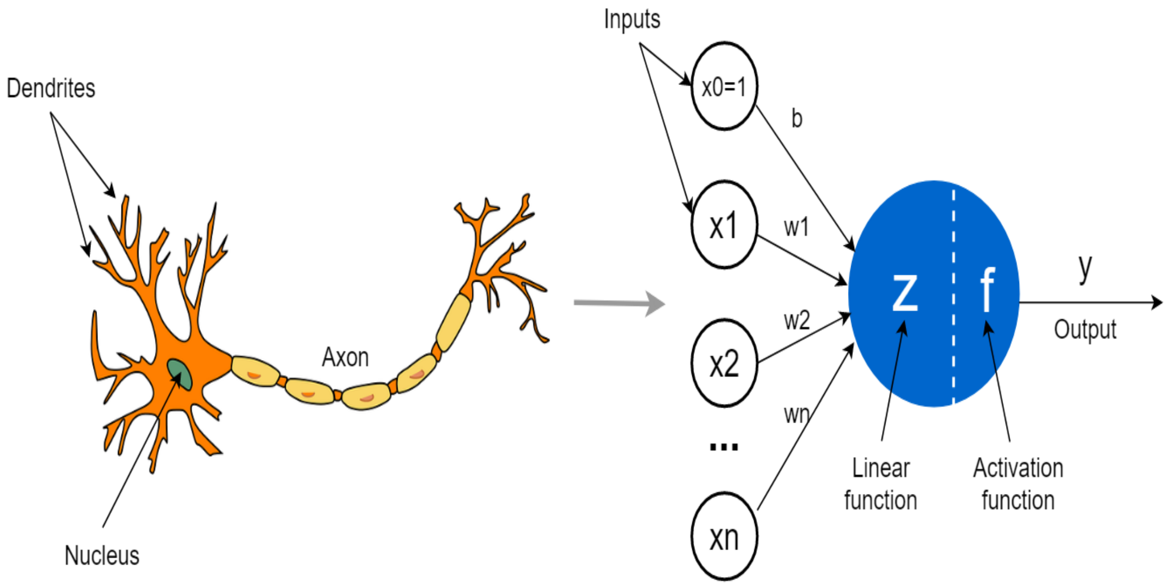

***Fig.7** Biological and artificial neural network [31].*

The connection between a neuron in the current layer and a neuron in the next layer depends on an amount that is proportionate to the negative gradient of the error measure concerning that specific parameter:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \qquad (4)$$

w_{ij}: The weight of the connection between a neuron in one layer and a neuron in the next is expressed [31].

Fault detection with the classification of ANN

Detecting and categorizing issues within a protective system is of utmost importance. This can be accomplished by examining transient voltage or fault current data. Artificial Neural Networks (ANNs) are mathematical models inspired by biological neural networks. They exhibit adaptability and can modify their configuration during a learning process [2]. The ability of ANNs to understand complex nonlinear relationships and their use in resolving nonlinear problems in several domains have captivated scientists. ANNs provide more resilience and noise resistance than traditional power system engineering methodologies [30]. The impact of shifting operational conditions is less on them. When faced with tough issues that are beyond the capabilities of people or traditional computational techniques, neural networks can be trained and developed to tackle them [10]. An advanced ANN structure for fault detection and classification in power system models is shown in Figure 8. Through the input layer's data feeding and analysis of the output, the system is able to classify the type of defect, pinpoint its exact position, and ascertain whether a fault is there [30].

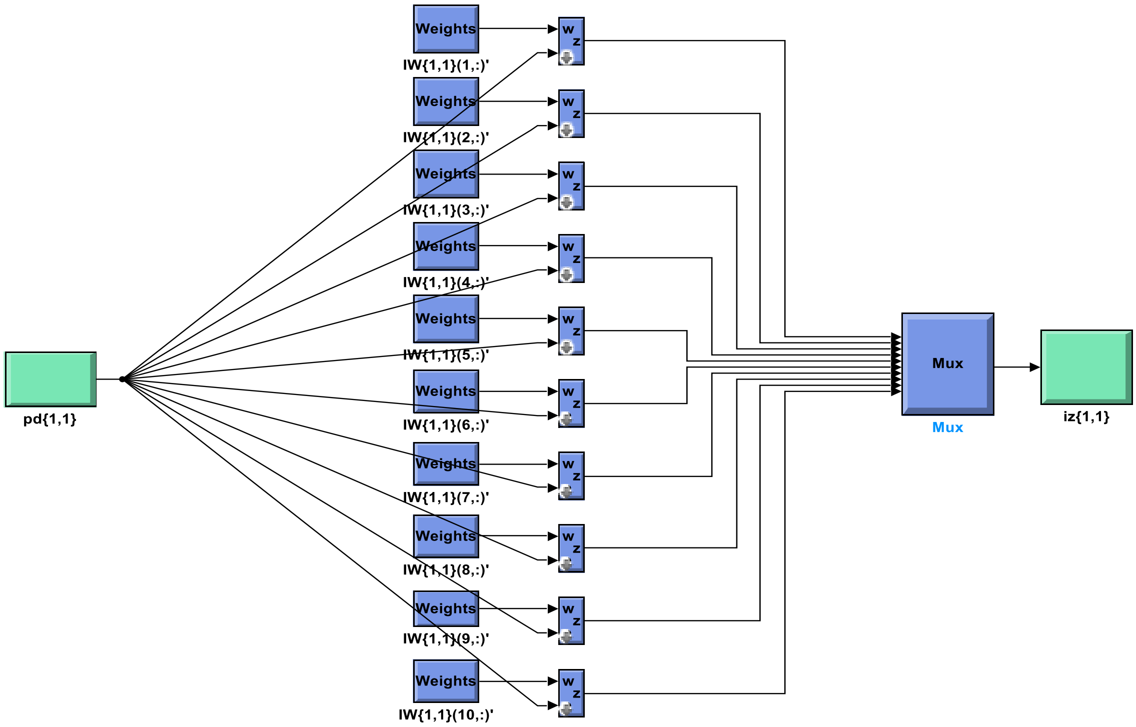

Fig.8 *Overview of the ANN in MATLAB Simulink.*

The neural network used for fault detection and location is depicted in Figure 9. It consists of two layers.

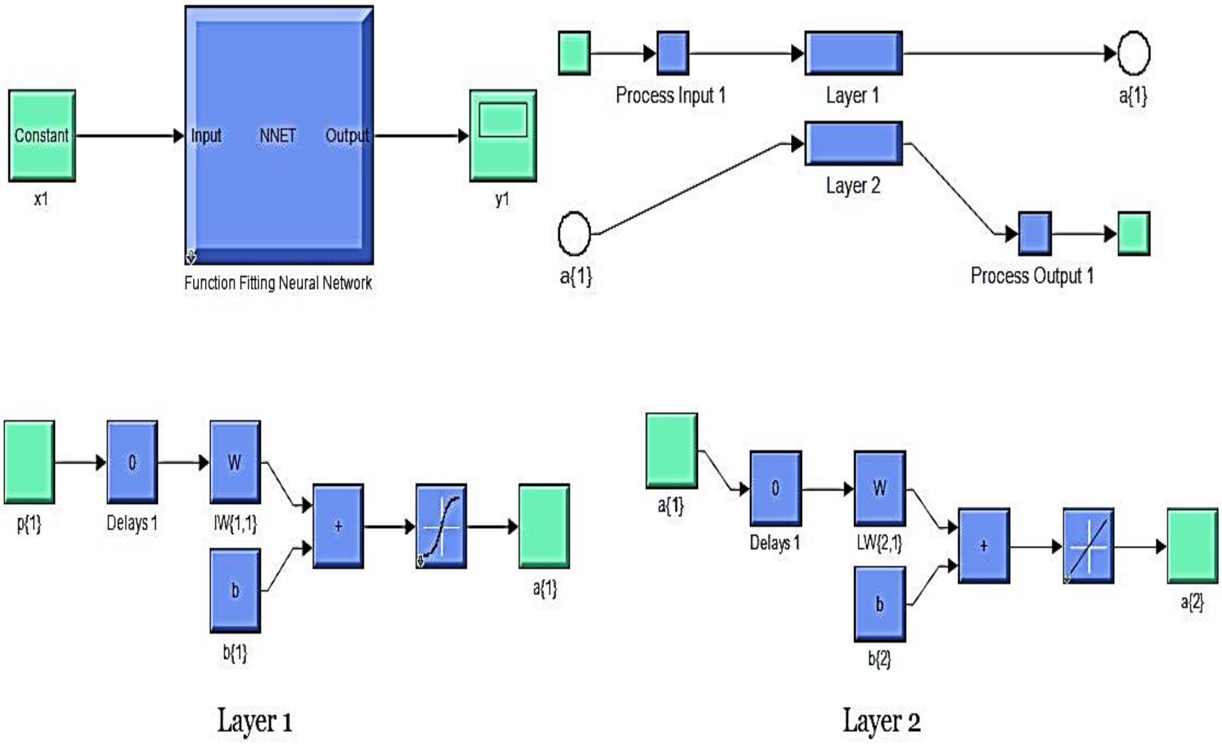

Fig.9 *MATLAB Simulink's overview of the ANN [32].*

For training, testing, and validation, the proportion of data utilized is 70%, 15%, and 15%, respectively. For the input layer, phase values of the voltage and current with fault distances were selected, and for the output layer, all three phase values with the ground phase were selected. In this application, the sigmoid function is utilized as the activation function. Binary data ([0,1]) can be output using the sigmoid function. "x" represents the net input in the sigmoid function equation.

Case study

The 400kv transmission lines, load system, and thermal power plant with grid comprise the system that serves as the basis for this research. Artificial Neural Networks (ANNs), particularly Deep Neural Networks, are used in the protection strategy to carry out the diagnostic and classification tasks of the ANN protection relays. The values of voltages and currents that are used as input to the ANN are the same as those taken from the measurement transformers pt, ct. The voltage is converted from 400 kV to 63.5 Volts, and the current values are from 2000 Amperes to 1 Amper. A simplified Single Line Diagram explaining the mechanism is shown in Figure 10 Situated at both ends of the transmission lines and connected to electrical loads are generating units, also known as AC sources.

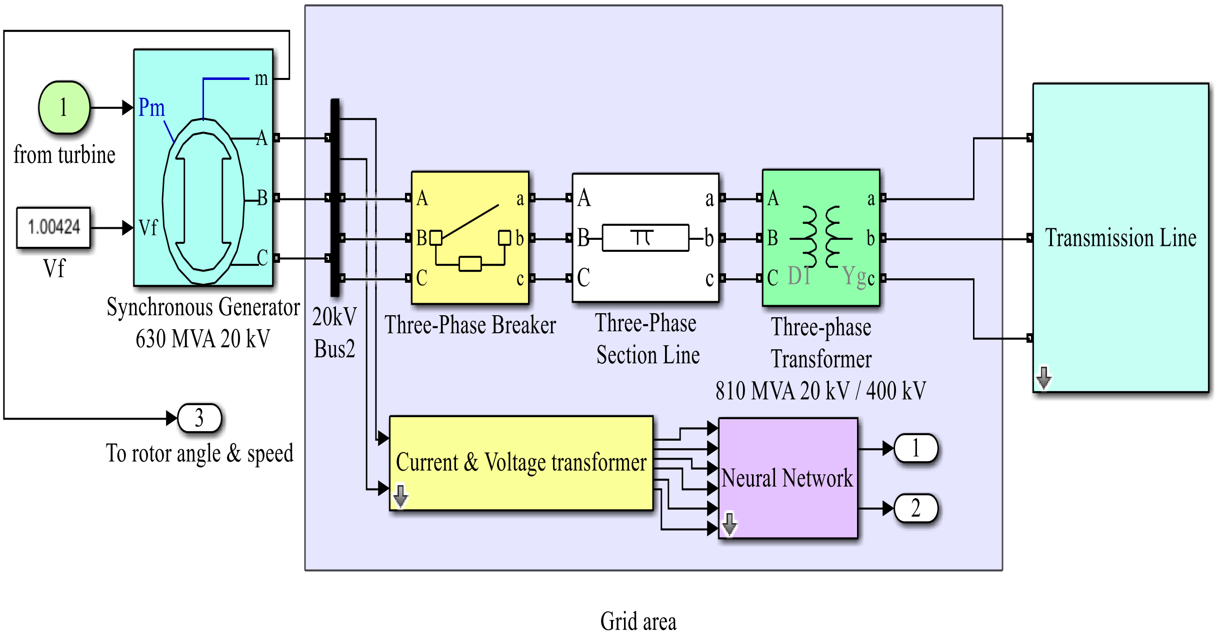

Fig.10 *Overview of thermal power plant and ANN in MATLAB.*

As seen in 9, in the event that an electrical power plant malfunctions, the ANN Relay will detect the malfunction and send a tripping order to the Circuit Breaker (CB) to safeguard the electrical equipment from damage and failure.

Fault detection mechanism: The artificial neural network provides the outputs to the logical decoding circuits so that the diagnosis may be made precisely and selectively after training the neural network to identify the fault and its location, enter all the data, and ensure the process's success shown in Figure 11.

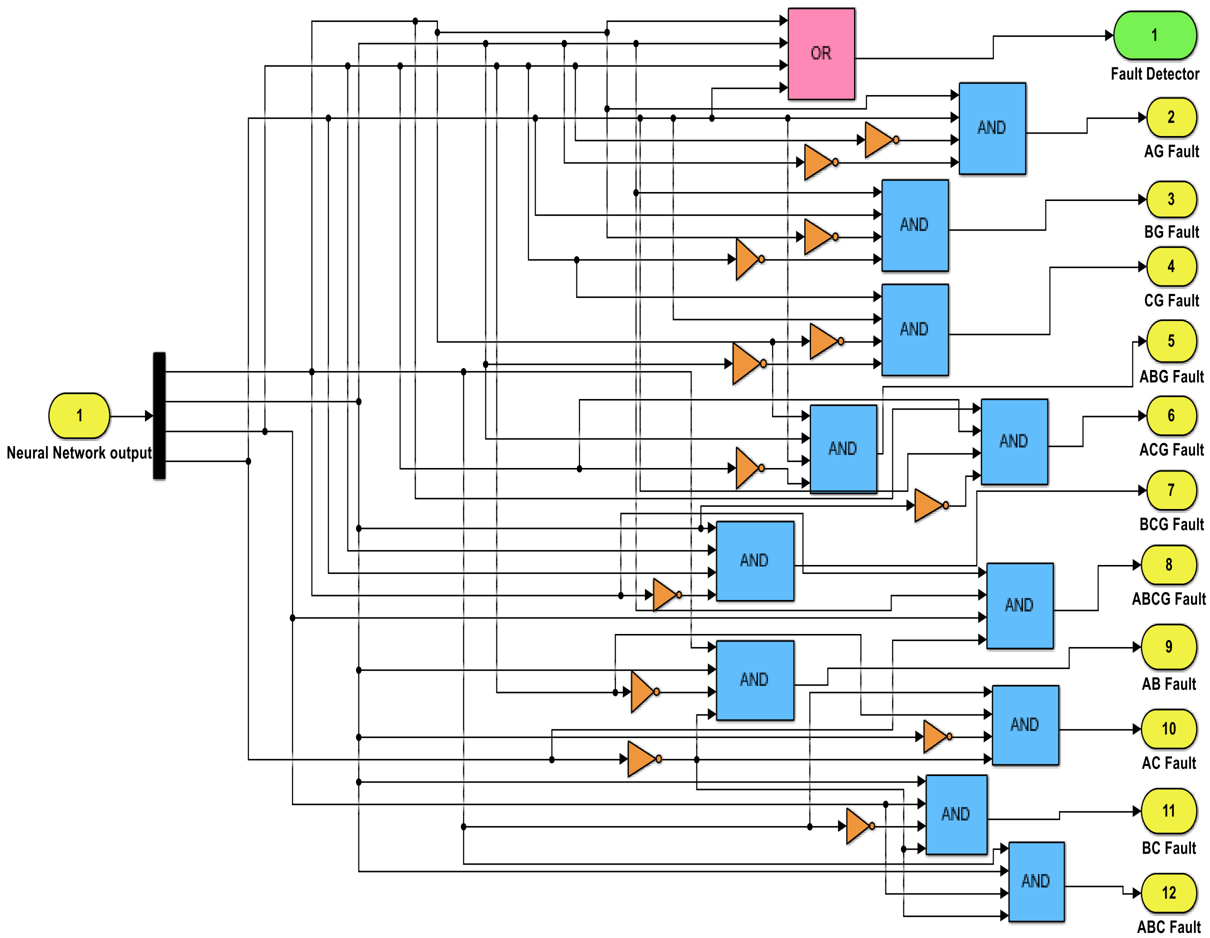

Fig.11 *The logical decoding circuits.*

It is important to pay attention to the decoder's logic diagram and the mechanisms it uses. A combinational logic circuit known as a decoder converts binary data from input lines into a single output line. The fundamental idea is to generate product terms for each output using AND gates, and then combine these product terms into the final output lines using OR gates. The logic required to produce the right output for every combination of inputs is determined by the truth table of the decoder. Memory systems, address decoding, and many other digital system applications make extensive use of decoder circuits [33], Table 2 presents the fault classification according to Binary Input [34].

Table 2: explains how the faults are classified using decoder logic circuits.

Decoder input				*Type of fault*
A	*B*	*C*	*G*	
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).*

To prove this, Figure 12 and Figure 13 show how the fault is detected through the digital outputs. The number 0101 indicates that the fault occurred in phase B with the ground, in addition to Figure 9 representing the output of the model Figure 11.

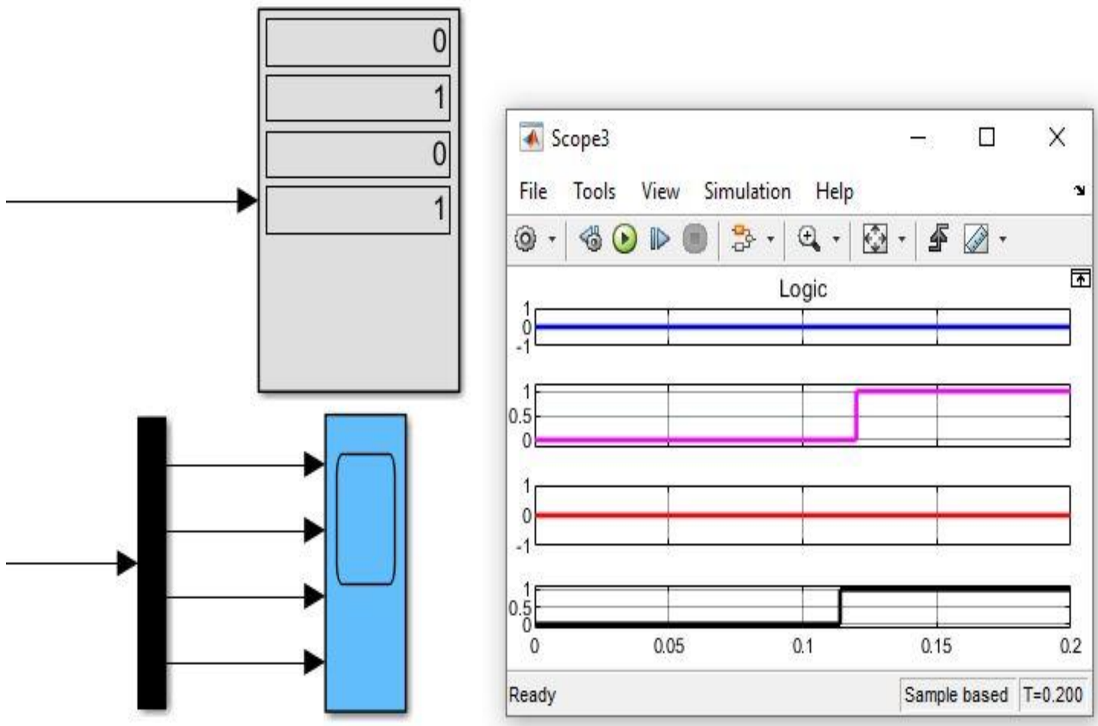

***Fig.12** displays the decoder circuit's output for a fault diagnosis [11].*

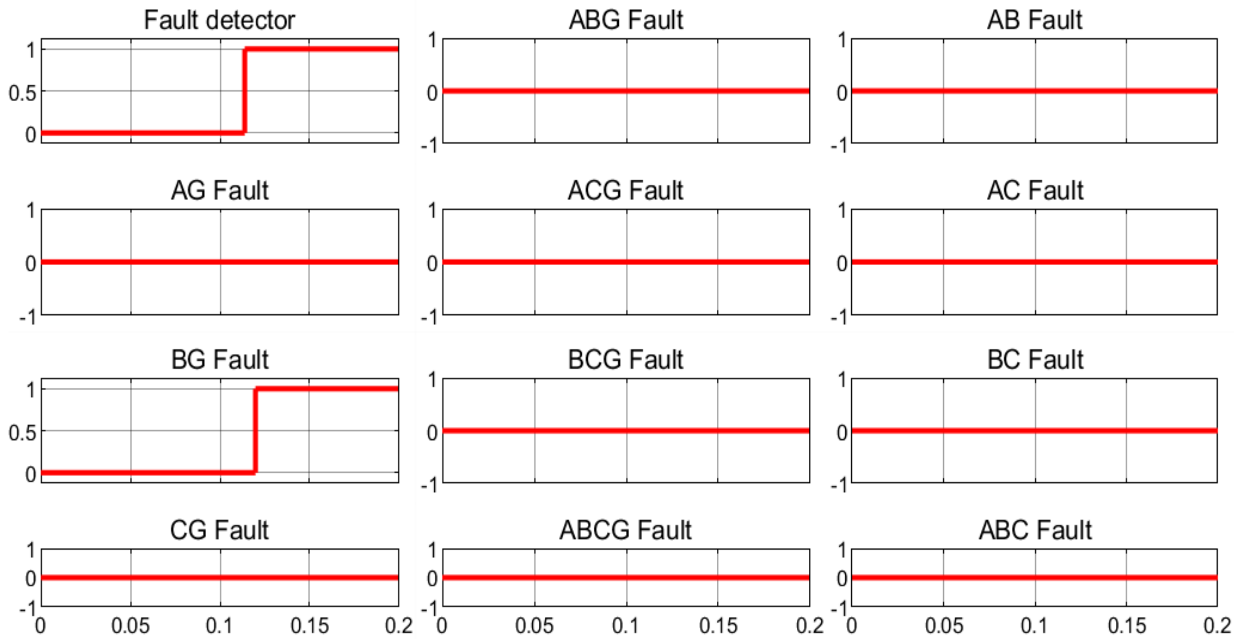

Fig.13 *displays the detection of phase B with Ground fault.*

The study applied an experimental approach at the Samarra thermal station, where an artificial neural network (ANN) was trained using real faults from 400 kV transmission lines. The ANN utilized currents and voltages from protective relays as inputs, with values scaled down from 400 kV to 63.5 Volts for voltage and from 2000 Amperes to 1 Ampere for current. Additionally, line lengths (87km, 145km, 273km, 306km) were included. The ANN training utilized actual fault data, yielding detection results comparable to established line monitoring methods Figure 14.

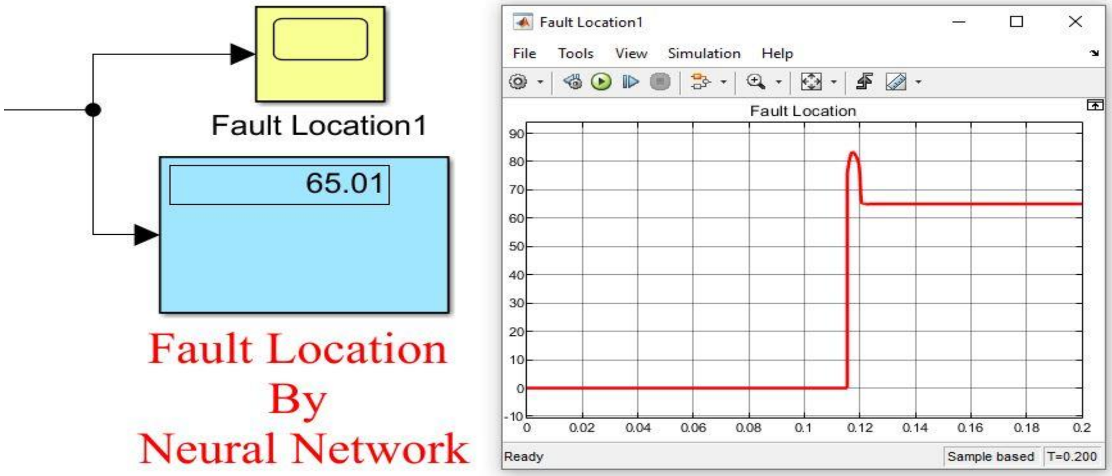

Fig.14 *Shows the artificial neural network's outputs compared to the actual outcomes.*

Conclusion

This paper focuses on employing artificial neural networks for defect detection and classification on electrical power transmission lines. The proposed method takes as inputs the three-phase currents and voltages of the feeders from the Samarra Thermal Power Plant. For the purpose of analysing each of the three process stages, the feed-forward neural network and the back propagation algorithm have been used to identify and classify the error. A thorough examination with different counts of hidden layers has been carried out to confirm the neural network selection. According to the simulation results, the current neural network-based technique is effective at identifying and categorizing transmission line defects with respectable performances.

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