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Fault Location of Doukan-Erbil 132kv Double Transmission Lines Using Artificial Neural Network ANN

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ABSTRACT

Transmission lines are generally subjected to faults, so it is advantageous to determine these faults as quickly as possible. This study uses an Artificial Neural Network technique to locate a fault as soon as it happens on the Doukan-Erbil of 132kv double Transmission lines network. CYME 7.1-Programming/Simulink utilized simulation to model the suggested network. A multilayer perceptron feed-forward artificial neural network with a back propagation learning algorithm is used for the intelligence locator's training, testing, assessment, and validation. Voltages and currents were applied as inputs during the neural network's training. The pre-fault and post-fault values determined the scaled values. The neural network's performance was evaluated, and tests were run. Line-to-ground faults were examined. The study demonstrates how effective, rapid, and precise this method is at locating faults. The neural network's performance was examined, and tests were run on it. The overall performance of the mean square error in the trained network execution was 0.11792 at 35 epochs. The correlation coefficient at the entire target was 0.99987 percent of an error on the Doukan-Erbil double transmission lines.

Keywords: Fault Location, Mean Square Error, Single Phase to Ground Fault, Artificial Neural Network, Power Transmission Lines

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موقع أعطال خطوط النقل المزدوجة في دوكان – أربيل 132 ك.ف باستخدام الشبكة العصبية الاصطناعيةANN

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الخلاصة

بشكل عام ، تتعرض خطوط النقل للأعطال ، لذلك من المفيد تحديد هذه الأعطال في أسرع وقت ممكن. تناقش هذه الدراسة كيفية تحديد موقع الخطأ بمجرد حدوثه على شبكة خطوط النقل المزدوجة في دوكان – أربيل 132 كيلو فولت باستخدام تقنية الشبكة العصبية الاصطناعية. استخدمت CYME 7.1–Programming / Simulink المحاكاة لنمذجة الشبكة المقترحة. يتم استخدام شبكة عصبية اصطناعية متعددة الطبقات معدة لخوارزمية تعلم الانتشار الخلفي لتدريب محدد الذكاء واختباره وتقييمه والتحقق منه. تم تطبيق الفولتية والتيارات كمدخلات أثناء تدريب الشبكة العصبية. تم تحديد القيم المقاسة بواسطة قيم ما قبل الخطأ وما بعده. تم تقييم أداء الشبكة العصبية وإجراء الاختبارات عليها. تم فحص عيوب الخط إلى الأرض. توضح الدراسة مدى فعالية وسرعة ودقة هذه الطريقة في تحديد الأعطال. تم فحص أداء الشبكة العصبية وإجراء الاختبارات عليها. كان الأداء الإجمالي لمتوسط الخطأ التربيعي في تنفيذ الشبكة المدربة 0.11792 في 35 حقبة وكان معامل الارتباط عند الهدف بأكمله 0.99987 في المائة من الخطأ على خطوط النقل المزدوجة دوكان – أربيل.

الكلمات الرئيسية : موقع الخطأ ، متوسط الخطأ المربع ، أحادي الطور إلى خطأ الأرض ، الشبكة العصبية الاصطناعية، خطوط نقل الطاقة

1. INTRODUCTION

An electric power system consists of electricity generation, transmission, and distribution. Electricity is sent across transmission lines to the far big load centers. The number of transmission lines and their total length have increased considerably due to the rapid development of electric power systems over the past few decades **(Džafić, 2013).** These transmission lines are vulnerable to faults due to lightning, short circuits, damaged equipment, wrong operation, human error, overload, and aging**. (Ignatius, 2020)**. Many electrical faults result in mechanical damage, which needs to be fixed before the line can be used again. The restoration process can be expedited if the fault location can be identified or reasonably estimated **(Džafić, 2013).** When a transmission line fault occurs, the voltage at the fault location immediately reduces to a minimal value **(Ignatius, 2020)**. The fault location estimate is important in power system engineering to quickly resolve issues and resume power supply with the least disruption.
The power equipment's safety and customer satisfaction depend on this. Numerous techniques have been employed to estimate faults' location, including line impedance-based numerical methods, traveling wave methods, and Fourier analysis **(Dashtdar, 2019).** Transmission line faults are classified into series and shunt faults. While shunt faults are more frequent, especially single line-to-ground faults and double line-to-ground faults **(Davis, 2012).** The location of faults on overhead electric power transmission lines is

imperative for rapid clearance of faults on transmission lines **(Elnozahy, 2019).** The paper's objective is to locate a fault that uses an artificial neural network to find a fault when it happens on the Doukan-Erbil network of 132 kV double transmission lines. The network is modeled and simulated in the programming Simulink environment of CYME 7.1.
The phase voltages and currents were used as inputs for the neural network during training, and its performance was assessed as well, as a test was carried out. A back propagation neural network technique is investigated and used for a fault locator. Voltages and currents signals of the line and fault are shown to operate. Neural networks can be created and trained to solve specific issues that humans or traditional computing techniques find challenging. **(Zhao, 2009)**.
The objectives of this paper can be listed as follows:

- Determine fault location as fast as possible by simulating faults using ANN.
- Determine and fix the fault distance to assist the maintenance team in quickly restoring service and reducing interruption duration and revenue loss.
- Inspired by the 132kV double transmission lines model, which is more complex than single Transmission lines because of the mutual effect.

2. METHODOLOGY

2.1. Modelling the Three-Phase Transmission Line System

The transmission line 132 KV from Doukan –Erbil double transmission line is the model. The line is 98.5km long, and the single-to-ground (SLG) was used to model multiple fault locations along the line of different fault resistance; a fault simulator was employed. Distributed parameters were used to model the line, and these parameters were taken from electrical directories. The line and the CYME 7.1 -Programming Simulink was simulated using ANN-Toolbox in MATLAB/Simulink. **Fig. 1** depicts the line model used to create the training and test data sets **(Gaurav, 2020)**. The voltage and current samples at terminal A were measured with three-phase V-I measuring blocks **(Ignatius, 2017)**.
The CYME Power Engineering software is a collection of programs that includes an analysis module, a network editor, and user-customizable model libraries from which you can select the most potent solution. The modules offered include numerous cutting-edge programs and sizable libraries for either transmission/industrial or distribution power network analysis. Designed to help engineers to handle the complexity of electrical systems. We obtained feature data after simulating fault points on transmission lines at different distances or per kilometer length. Enter this feature data into Artificial Neural Network (ANN) **(Ayyagari, 2011). Fig. 2** is the flowchart for the analysis and fault location.

2.2 The Artificial Neural Network

One of the fundamental ideas behind the successful usage of neural networks in any discipline is their learning or training, which is used to choose the parameters to produce the desired result. Supervised and unsupervised learning processes are the two fundamental learning processes that can be used to train an artificial neural network **(Singh, 2014).** The backward propagation technique is used in supervised learning to iteratively modify network weights to reduce the error between a given set of input data and their corresponding target values **(Hagh, 2005)**. This process, commonly used in electric power transmission lines fault locators, was employed in this study. The input-output pairs used to train the neural network are obtained before the training process by using physical measurements and performing some simulations **(Demuth, 2000)**.

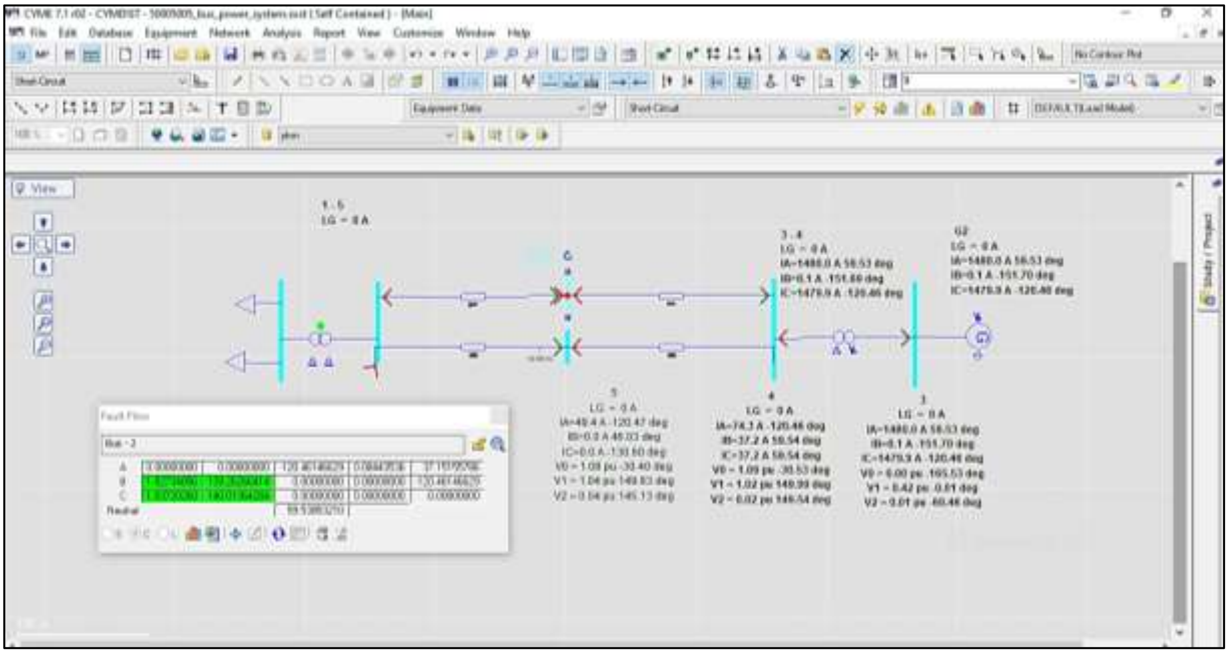

Figure 1. Model to locate the fault

The neural network is taught to adjust its values based on the error (e) between the outputs and the targets. On the other hand, the correlation between the inputs and the goal values is unknown in unsupervised learning. With the help of training data set with known input values, neural networks are developed. It is critical to pick the correct selection of examples to train effectively. A resemblance principle is typically used to select these samples. The feed-forward neural network's supervised learning method is depicted in **Fig. 3.**

$$e = \text{Error }\% = \frac{ANN\ output - Actual\ Fault\ locate}{length\ of\ Actual\ Fault\ locate} * 100 \quad (1)$$

where

"*ANN output*" is the ANN fault locator's output in kilometers. "*Fault location*" is the distance to the transmission line fault (km). The output of a back propagation neural network (BPNN) is sent back into the input to determine how the weight values should change. One of the main justifications for using back propagation methods is eliminating the restriction. The error is determined for each iteration and each point by starting at the last step and transmitting the calculated error backward. The neural network's back-error-propagation algorithm uses randomly selected weights to feed back a pair of inputs and then calculate the output.

The developer's training data set contains all possible input-output combinations. Thus, the weights are updated with the new ones after each step, and the procedure is repeated. This procedure is repeated until the network converges for the specified targets at the predetermined error tolerance. **Fig. 3** helps to explain the full back-propagation procedure. In addition to being used for error functions (other than the sum of squared errors), the back error-propagation approach is also useful for calculating Jacobian and Hessian matrices. Every network layer adopts this complete process and does it in the opposite direction

(Hayati, 2007). The errors in each iteration of the proposed algorithm are calculated using the Mean Square Error (MSE) method. **Fig. 4** explains the BPNN idea.
The algorithm of BPNN is as follows **(Jamil and Sharma, 2015).**

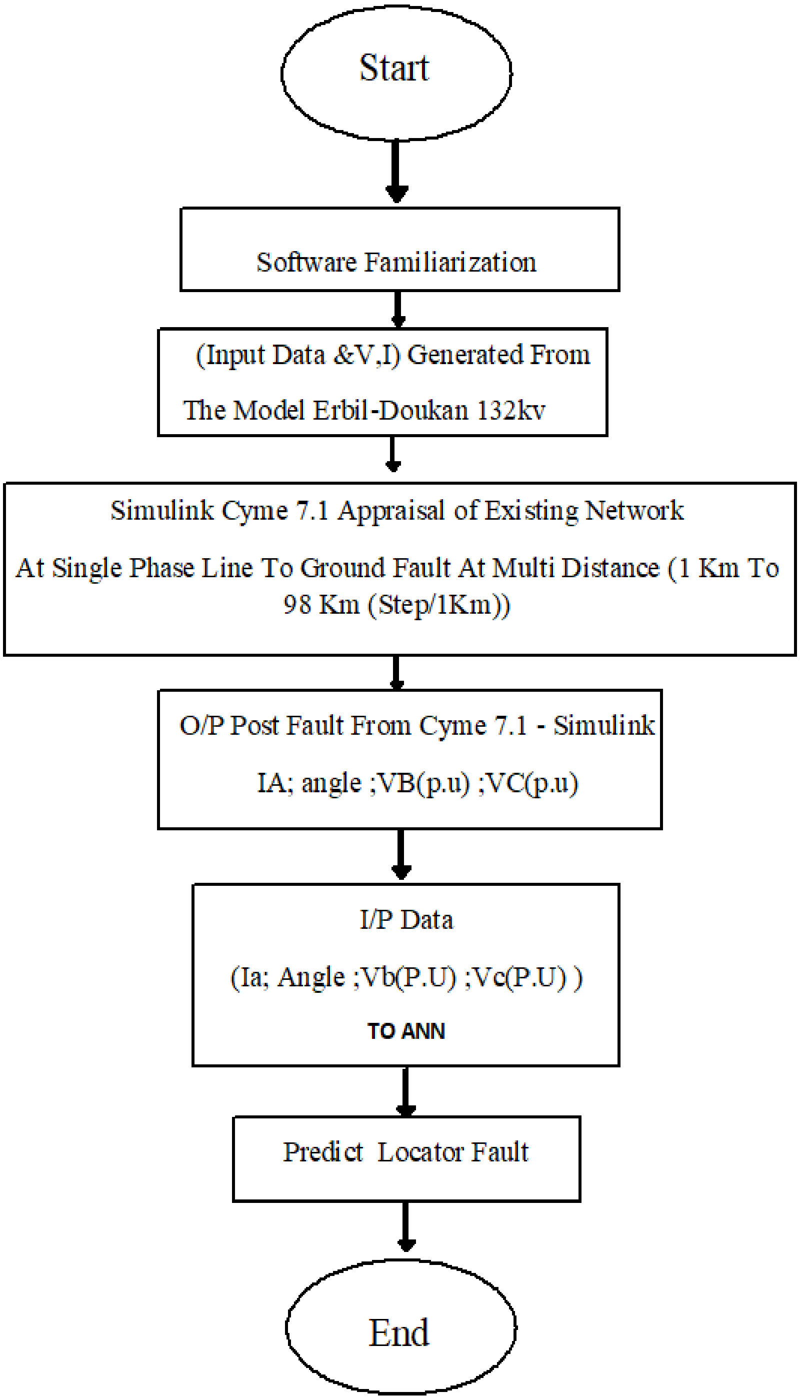

Figure 2. Flow chart representing the proposed algorithm for fault location

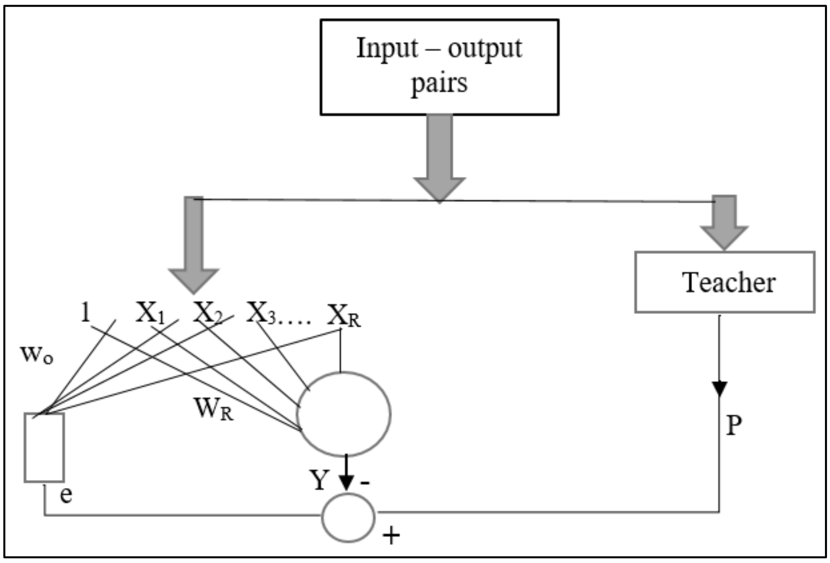

Figure 3. An illustration of the supervised learning scheme, P is the desired output; y is the output at the layer for training; 'e' Error between the outputs and the targets.

1. Forward propagation

$$a_j = \sum_i^m w_j i^{(1)} x_i \tag{2}$$

$$z_{j=} f(a_j) \tag{3}$$

$$y_{j=} \sum_i^m w_k j^{(2)} z_j \tag{4}$$

2. Output difference

$$\delta_k = y_k - t_k \tag{5}$$

3. Back-propagation for hidden layers

$$\delta_{j\,=}\ (1 - \ Z_j{}^{(2)}) \sum_{k=1}^{k} W_{kj} \tag{6}$$

where:
a_j: weighted sum of inputs
w_{ki}: weight associated with the connection
x_i: inputs
z_j: activation unit of (input) that sends a connection to unit j
δ_k: derivative of error at kth neuron
y_i: ith output
y_k: activation output of unit k
t_k: corresponding target of input
δ_j: derivative of error w.r.t to a_j
4. First- and second-layer weights compute the error gradient.
5. The prior weights are updated
The *MSE* for each output in each iteration is calculated by

$$MSE = \frac{1}{N}\sum_{1}^{N}(E_{i-}E_{o})^2 \qquad (7)$$

where
N is the quantity of iterations.
E_i is the actual output.
E_o is the output of the model.
Fig. 4 depicts every stage of the algorithm. It illustrates the whole architecture of the back propagation-based ANN.

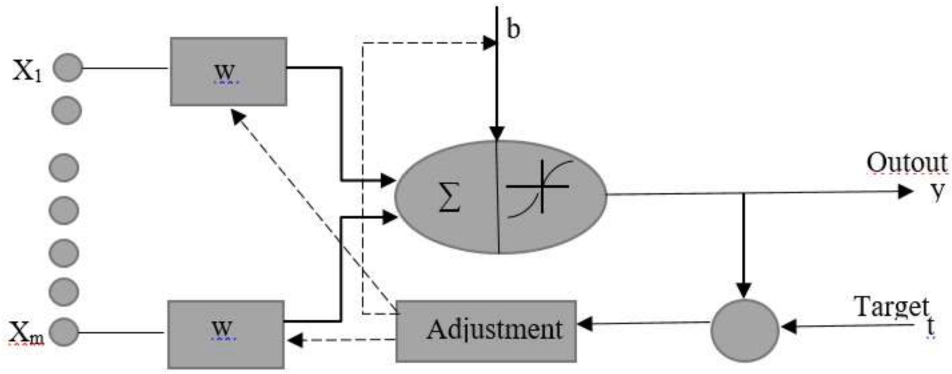

Figure 4. Artificial neural network

2.3 ANN Model Analysis

One or more hidden layers of sigmoid neurons are frequently seen in feed-forward networks, followed by an output layer of linear neurons. The network can learn nonlinear interactions between the input and output vectors thanks to its several layers of nonlinear transfer function neurons. The linear output layer is most frequently applied to situations involving nonlinear regression or function fitting.
In this study, the ANN minimizes error using the gradient-descending approach and the back-propagation learning algorithm. Levenberg-Marquardt's (Trainlm) optimization methodology-based architecture was chosen for the training method's optimization. Choosing the right number of hidden neurons for a back-propagation network is challenging. With more hidden neurons, back-propagation network prediction accuracy rises. The network cannot learn very well, and training accuracy suffers if the hidden layer's neuron count is low. If the number of neurons is huge, training time increases, and the network results are ineffectively fitting. The total number of iterations necessary to attain a desirable convergence rate relies on the following criteria **(Gaurav, 2020).**
• The neural network's size.
• Network structure.
• The problem under investigation.
• The method of learning used.
• The training/learning set's size.

2.4 Design Procedure of the ANN Fault Locator

The following steps comprise the planning process for the ANN fault locator:

1. Development of an appropriate training data collection that accurately depicts the events the ANN needs to learn.
2. Deciding which ANN structure is best for a certain application.
3. Training the ANN
4. Using test patterns, the trained ANN is evaluated until its performance is satisfactory. The structure of back-propagation ANN is shown in **Fig. 4.**

Four different fault types can happen in a power system: single-line-to-ground fault, line-to-line fault, double-line-to-ground fault, and three-phase fault. A good technique for locating transmission line faults is the Artificial Neural Network (ANN). Gradient Descent Backpropagation, Levenberg-Marquardt, and Bayesian Regularization are the three training method types used in this research. According to the results, the Levenberg-Marquardt approach, which had greater accuracy and was quicker to define fault sites, is the best for finding faults. This paper simulates the operation of a fault locator for power plants using an artificial neural network.

3. RESULTS AND ANALYSIS

3.1 Analysis of Training Performance of the Neural Network

Following several tests using neural networks in various topologies, the 4-4-1-1 was selected since it performed satisfactorily. The network's training performance plot is displayed in **Fig. 5**. It was apparent from the training performance plot in **Fig. 5** that the neural network's 4-4-1-1 Configuration enabled it to train successfully. At 35 epochs, the trained network's total mean square error (MSE) is 0.11792. The trained neural network was consequently selected as the best for locating the defect. In ANN-based algorithms, training is the most crucial component. The training of networks for fault location is supervised, meaning the network is also shown the output corresponding to each input. The next step was to test the neural network's performance once trained. Two techniques were used to assess the performance.

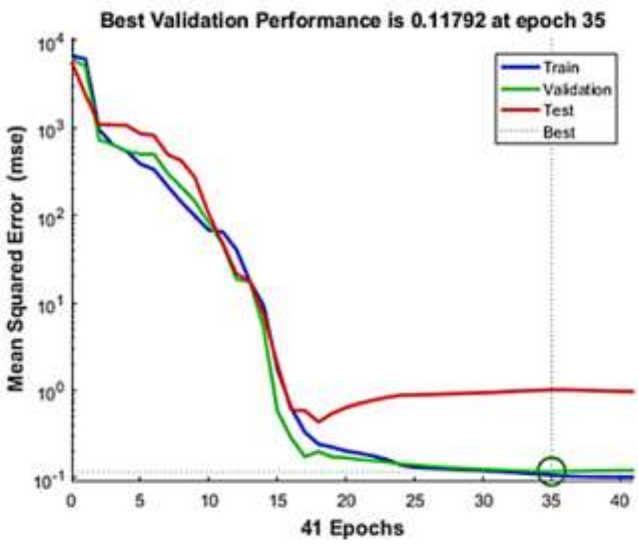

Figure 5. The mean-square error performance of the network to locate the fault

3.1.1 The regression plot

The best linear regression that connects the targets and outputs was shown to create the regression plot. It demonstrates how well the neural network's goal can follow changes in output. In **Fig. 6**, the regression plot is displayed. The correlation coefficient (r), which ranges from zero (no correlation at all) to one (perfect correlation), is a measurement of how well the neural network's objectives can track variations in the outputs. Testing and validation had correlation coefficients of 0.99964 and 0.99994, respectively, whereas the training procedure had a coefficient of 0.99994. It is clear from these data that the correlation is very good.

3.1.2 Creating a separate set of data to analyze the Network's performance

The second step in testing involves producing a unique set of data that is used to gauge how well the trained neural network performed. This step is referred to as the test set. The fault site varied across all 98 samples, but the neural network's ability to identify the presence of a defect was rather strong; as a result, the neural network had the highest level of precision.

3.2 Analysis of Testing Performance of the Neural Network

The Neural Network Toolbox, a part of Matlab software, was used to set up the ANN topologies, train them and obtain the appropriate weights. Results gained from the CYME-Programming Simulink environment simulations were used as input vectors for the ANN-learning algorithm. ANN instruction three groups of inputs were created: a training set, which contained 70% of the data; a validation set, which contained 15% of the data; and a testing set, which contained 15% of the data **(Demuth, 2000)**.

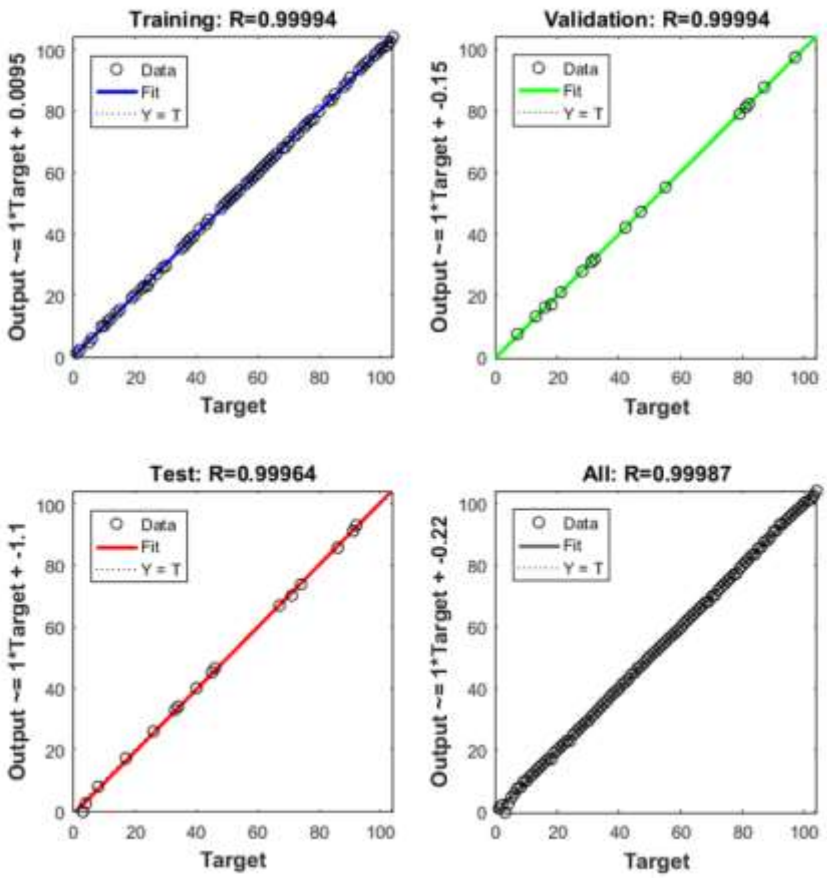

Figure 6. Regression plot of the network with 4-4-1-1 Configuration

The ANN received a random input of the training and validation data sets. The net input in the network's first layer results from multiplying the input by the weight and bias. The weight must be extremely low if the input is large to keep the transfer function from being saturated. Normalizing the inputs before applying them to the network is a typical procedure.

In most cases, the data set's input and target vectors go through the normalization stage. This ensures that the network output always falls within a normalized range. When the network is used in the field, the output can be reverse-transformed to return to the units of the original target data. Most of the network-building tools, including the multilayer ones as feed-forward nets, automatically allocate processing tasks to the inputs and outputs of the network. These functions transform the specified input and target values into more suitable for network training. In this instance, preprocessing and post-processing were carried out automatically. The ANN was created as depicted in **Fig. 7.**

The Training State diagram of the network is presented. In this chart, the errors are observed. Which was in improvement mode in this plan, and the faults reached 0.001 in 41 epochs, as shown in **Fig. 8.** The model is used to simulate locating faults at different distances (1, 2, 3, 4 to 98 km). Fault location is changed for each fault-making kilometer, and thus the voltage, current, and angle changes for each fault location, and per phase line, we obtained feature data. An input matrix (98 × 4) was obtained, as shown in **Table 1**.

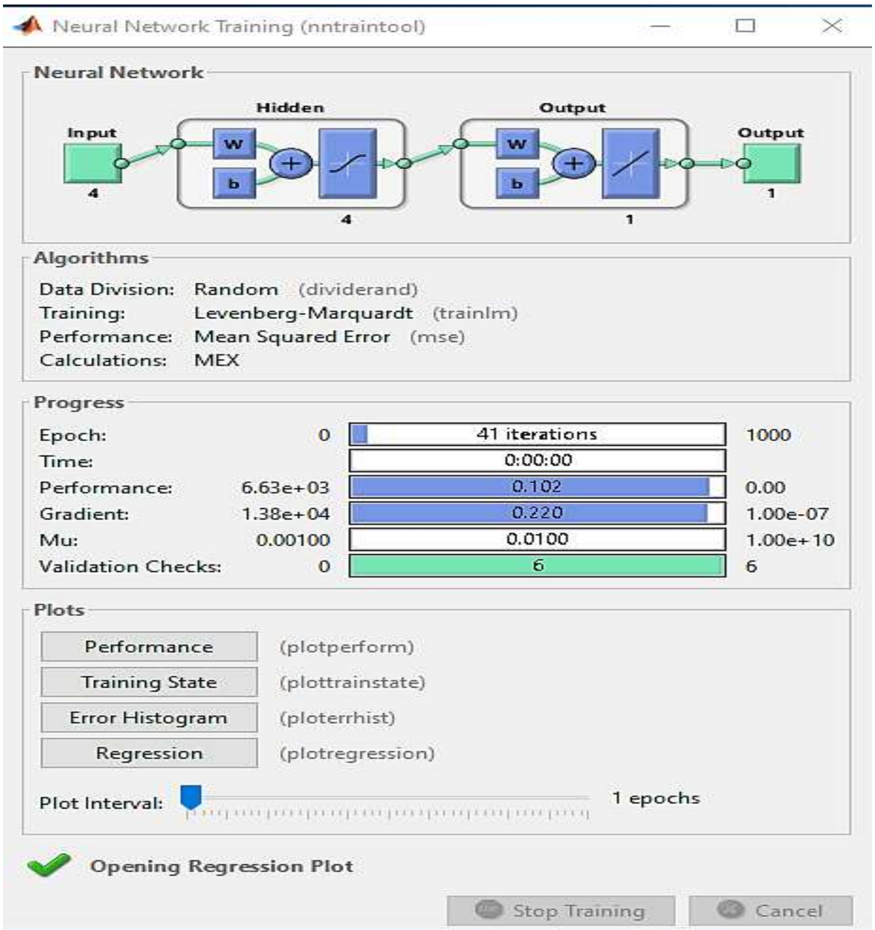

Figure 7. Developed ANN model in Simulink to locate the fault

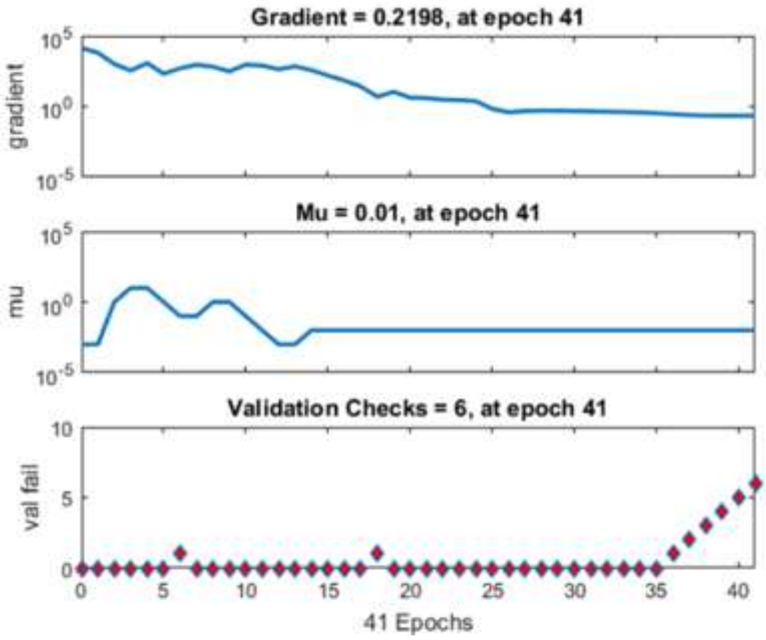

Figure 8. Training state diagram of neural networks to locate the fault

And the entered feature data to ANN_Toolbox distance obtained an output matrix (98×1). While using the associated distances as a target matrix. After numerous trays of varying the number of neurons, hidden layers, and activation functions, the structure of 4- 4-1-1 is used with transfer functions which gave the Overall correlation accuracy performance of 0.99987. Gradient Descent Back Propagation, Levenberg-Marquardt, and Bayesian Regularization provide the most accurate structure for the ANN locator training methods utilized in this research. According to the results, the Levenberg-Marquardt approach, which had greater accuracy and was quicker to define fault sites, is the best one for finding defects.

5. CONCLUSIONS

This work on applying an Artificial Neural Network to locate transmission line faults was completed successfully. The Doukan –Erbil double transmission line was used as a case study. The transmission line was simulated by applying CYME Power Engineering software Simulink- environment. Phase voltage and current values were used as the network's inputs during neural network training. The work's training data set was a simulation. The effect results showed that they are very accurate in performing. The Artificial Neural Networks Toolbox was heavily utilized during the training and analysis of the neural network performance. The value was scaled in relation to the values before the fault, considering faults of the single line-ground variety. Results were obtained for locating faults and were accurate at 0.9987 in performing. These results show that the neural network is an efficient method for locating faults on the transmission lines. The correlation coefficient, in this case, is %99.9, which indicates excellent correlation. The next stage is to design Artificial Neural Network to simulate other types of faults, such as the line to line faults, double-line-to-ground faults, and three-phase faults also uses an Artificial Neural Network for fault diagnosis to choose the proper ANN for each type of fault.

Table 1. A Case Study

INPUT DATA				$\text{Error }\% = \frac{\text{ANN distance} - \text{Actual distance}}{\text{length of Actual distance}} * 100$		
I line - phase A	Ø (IlineA)angle (degree)	V line phase B (P.U)	V line phase C (P.U)	Actual distance (km)	ANN distance (km)	% Error
7649.114	-82.6684	0.968652	1.002432	98	97.90269	-0.099291724
6535.411	-81.7987	1.001794	1.031982	95	94.99916	-0.00087924
5357.183	-50.8705	1.041916	1.065028	90	90.10488	0.116527986
4631.177	-50.2881	1.069429	1.086562	85	84.93711	-0.073991921
4153.254	-49.894	1.089084	1.101543	80	80.04165	0.052063144
3828.596	-49.6146	1.103592	1.112433	75	75.07616	0.1015526
3607.889	-49.4114	1.114536	1.120572	70	70.02058	0.029398573
3463.771	-49.2625	1.122882	1.126747	65	64.93776	-0.095760526
3380.839	-79.155	1.129234	1.131436	60	60.02471	0.041182561
3351.058	-79.0811	1.133969	1.134938	55	54.98605	-0.025363873
3371.692	-79.0369	1.137316	1.137429	50	49.96287	-0.0742691
3444.646	-49.0206	1.139383	1.139	45	45.00968	0.02151144
3576.924	-49.0335	1.140175	1.13966	40	40.08174	0.204358584
3782.411	-79.0795	1.139575	1.139334	35	35.05959	0.17025236
4085.893	-79.1674	1.137303	1.137824	30	30.06911	0.230362764
4531.792	-49.3132	1.132804	1.134734	25	24.97557	-0.097728089
5204.419	-49.5487	1.125	1.129272	20	19.91224	-0.438797009
6281.5	-49.9412	1.111643	1.119733	15	15.00979	0.065259236
8207.511	-50.66	1.08739	1.101833	10	9.948116	-0.518844723
12482.62	-82.2791	1.036484	1.061181	5	4.922519	-1.549625046
22879.64	-86.2593	0.943675	0.963054	1	1.000953	0.095283227
Overall % Error = % 0.243384475						
From All Results, the Overall correlation is % 99.987. It is an excellent Result						

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Appendix A

The study case used in this paper is to determine locate fault as quickly as possible from the Doukan-Erbil 132kv. shown in **Table 1A**, Generation and load data, and transmission line data are shown in **Tables 2A and 3A (Salih et al., 2022).**

Table1A. Generation and load demands data for (Erbil –Doukan power system)**(Salih et al., 2022)**

BUS NO.	BUS Names	Pgeneration (MW)	Qgeneration (MVAR)	Pload (MW)	Qload (MVAR)
1	DOkHPG	248	84.2	0	0
2	Koya	0	0	19.4422	9.4163
3	Bawajy	0	0	11.4366	5.5390
4	Bakur	0	0	75.4816	36.5574

Table 2A. Transmission line data for (Erbil –Doukan power system)**(Salih et al., 2022)**

From bus	To bus	Length (km)	R(p.u)	X(p.u)	B(p.u)
Dok HPG	Koya	34.5	0.0146	0.055131	0.024802
Koya	Bawajy	4.5	0.001907	0.007191	0.003235
Koya	Bakur	60	0.025422	0.09588	0.043134
DokHPG	Bakur	98.5	0.0474668	0.181659	0.063771

Table 3A. Transmission lines parameters for (Erbil –Doukan power system)**(Salih et al., 2022)**

Type	Type (Details)	R0 Ohm/km	X0 Ohm/km	R1 Ohm/km	X1 Ohm/km	$\beta x10^{-6}$ Ohm/km
LARS	Single Circuit-Single Lark Conductor	0.3275	1.231	0.147	0.428	2.66
LARD	Double Circuit-Single Lark Conductor	0.378	1.28	0.147	0.4	2.87