Integration of Artificial Neural Network in a IEEE 5 BUS System

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Abstract – *The management and the operation of the modern grid is getting more and more complex, especially with the introduction of distributed generation. Grid stability considerations in contemporary power systems are also influenced by the integration of renewable energy, modifications in consumer behavior, and emerging technology. The study of faults impacts in the distribution network is pertinent and important since it helps to increase the efficiency, safety, and dependability of the power system. It allows utilities the ability to react rapidly to problems, improve maintenance procedures, and prepare for the integration of new technologies—all of which are essential for providing consumers with steady and uninterrupted electricity. In the context of Artificial Neural Networks (ANNs), the Levenberg-Marquardt (LM) algorithm is an extensively utilized optimization method and it was used in the MATLAB model proposed. It is generally used to train feedforward neural networks, especially when those networks have several layers and complicated optimization problems. This paper trains a model of LSTM and introduces a fault in an IEEE 5 bus system help to analyze the changes in the system. The data collected from that phase-to- phase voltage fault are computed and train in the proposed model and prove the higher efficiency and ability to detect faults or abnormal disturbances. The simulations are done using MATLAB/Simulink*

***Keywords**: FAULTS; Levenberg-Marquardt Algorithm, IEEE 5 BUS*

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I. Introduction

The world's power system has experienced significant growth over the past few decades, which ultimately resulted in the development of infrastructure in the distribution side [1]. A malfunction in the power system is one of the most significant elements that prevents the uninterrupted flow of electricity and power. A power system fault is any abnormal current flow in one of the parts of a power system. Since some of these defects also result from natural causes that are wholly outside of human control, it is impossible to completely avoid them. Consequently, it's critical to have a cohesive security system that can identify the type of fault, detect any irregular current flow in the power system, and precisely pinpoint where the problem is in the power system. Devices that recognize when a problem occurs and eventually isolate the affected area from the rest of the power system are frequently used to deal with faults. The detection, categorization, and localization of defects are thus some of the significant obstacles for the endless supply of power [2]. There are many different forms of defects, including transient, persistent, symmetric, and asymmetric faults. Each of these fault types has a specific fault detection mechanism, and there is no single method for finding faults of all types. When two or more phases of the power system come into direct contact with one another, a critical event known as a phase-to-phase failure takes place in the electrical network. This kind of fault—often referred to as a "short circuit" or "fault"—can cause serious disturbances in the way the electrical grid functions. Phase-to-phase faults occur in a sharp reduction in the system's typical impedance, which causes an increase in electrical current and the possibility of damage to infrastructure, equipment, and even people. For this study an IEEE 5 BUS system with the implementation of a phase to phase fault was investigated. This investigation will include the ability of artificial neural network to detect fault at the first swing bus. A fault will be implemented and the data gathered from that disturbance will be collected. And then used to be trained in a neural network to effectively with the minimum error the fault.

A. *Artificial neural network*

It refers to a type of information distribution technology that was inspired by how the human brain processes data [3]. It is described as a collection of fundamental neurons that are normally connected in ways that are naturally triggered and layered [4] – [5]. The WT was used to detect single-line-to-ground issues in primary distribution networks by doing a multi-resolution analysis of the current data gathered at the relay point. the distribution network's underground infrastructure must be examined in order to identify the HFC and pinpoint the issue. Training a NN involves fine-tuning different weights that are linked and customized to the dataset and to the neurons. Fig. 1 shows the basic representation of a feedforward ANN.

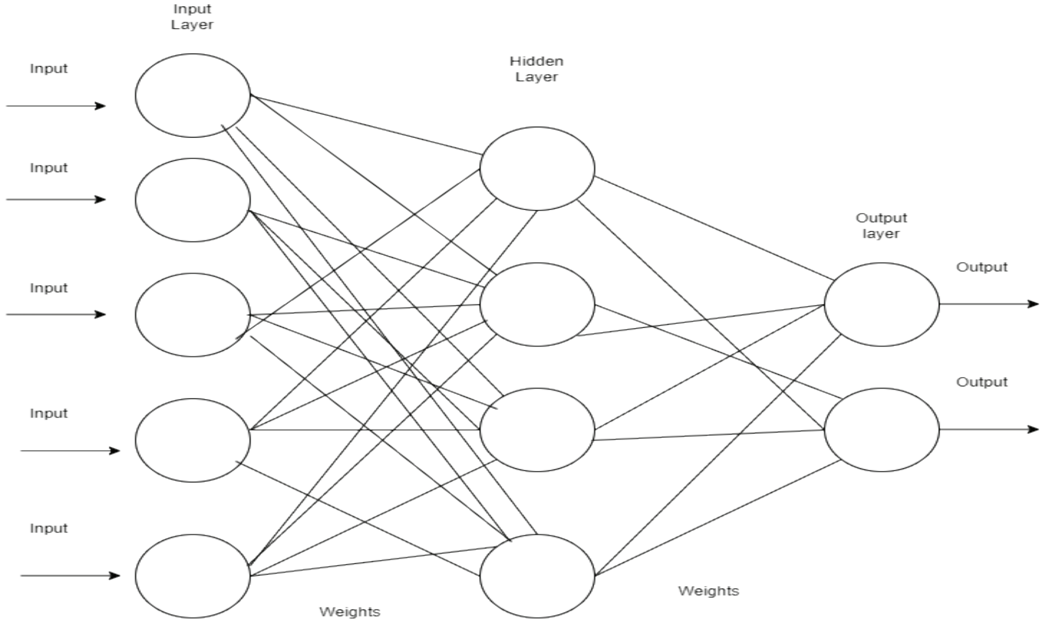


Fig 1. Basic representation of feedforward ANN

By changing the node weights in response to inputs, ANN learns to respond. i.e., a set of information used to train a neural network (NN). The procedure of weight adjustments that are linked to the neurons and specifically designed for the training [7]. By changing the node weights in response to inputs, ANN learns to respond. The back-error-propagation algorithm (BPA) is a simple technique that reduces the error by gradually adjusting the weights of the neuron [8]. Another name for this process is supervised learning. A function that computes the output of 0 N inputs to it might be used to build a basic neuron model (Fig.2 shows the model of a neuron) [9].

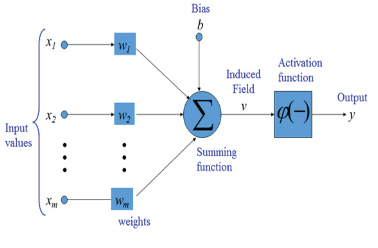


Fig 2. Model of a neuron

The output of the neuron is expressed as:

$$y = f(\varphi) = f(\sum_{i=0}^{No} w_i\, a_i) \qquad (1)$$

where: $w_0 a_0$ represents the polarization, $f(\varphi)$ and y stands respectively for the neuron activation function. The output, φ depicts the summation output signal

$$\varphi = W^T . A \qquad (2)$$

where

$$W = [w_0 w_1 \ldots . w_k] \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

$$A = [a_0 a_{1\ldots\ldots} a_{No}] \qquad (4)$$

Based on the needs of the application, f (), the appropriate activation function is selected.

. The f() represents the robustness of the output function of the input. It can have many different shapes, some of which are as follows:

Step activation function

$$f(\varphi) = \begin{cases} 1\ if\ \varphi \geq 0 \\ 0\ if\ \varphi < 0 \end{cases} \qquad (5)$$

Piecewise Linear Activation Function

$$f(\varphi) = \begin{cases} 1\, if\ \varphi > 1 \\ -1\, if\ \varphi < -1 \\ if\ |\varphi| < -1 \end{cases} \quad (6)$$

Sigmoid Unipolar Activation Function

$$f(\varphi) = \frac{1}{1 - e^{-\beta\varphi}} \quad (7)$$

Sigmoid Bipolar Activation Function

$$f(\varphi) = \tan(\beta\varphi) = \frac{1 - e^{-\beta\varphi}}{1 + e^{-\beta\varphi}} \quad (8)$$

Regarding how a model's neurons are connected, it may generally be divided into two categories: feedforward neural networks and feedback neural networks, often known as recurrent neural networks. The Table I below provides a literature review on related work and gap that have been identified

TABLE I
REVIEW OF PREVIOUS WORKS

Title	Authors	Year	Methodology	Key findings	Limitations
Deep Neural Network with Hilbert–Huang Transform for Smart Fault Detection in Microgrid	Aqamohammadi et al.	2023	LSTM for real-time data analysis	Effective real-time fault monitoring	High memory usage and computational cost
Machine Learning-Based Approach for Fault Detection and Location in Low-Voltage DC Microgrids	Salehimehr et al.	2024	LSTM for analysing temporal patterns in data	LSTM performs well in time-series fault analysis	Longer training times and resource requirements
Fault detection and classification using deep learning method and neuro-fuzzy algorithm in a smart distribution grid	Mbey et al	2023	LSTM combined with CNN for feature extraction	Enhanced fault detection using hybrid model	Requires large dataset for training
Intelligent Fault Detection and Classification Schemes for Smart Grids Based on Deep Neural Networks	Wang and Chen	2022	LSTM networks for sequential data analysis	LSTM effectively detects and classifies faults	Computationally intensive

II. Levenberg-Marquardt Algorithm

With function with multiple inputs and outputs, and the Levenberg-Marquardt (LM) algorithm iteratively locates its minimum. It has been widely embraced across a variety of disciplines and has It has become into a norm for non-linear least-squares issues. The Gauss-Newton method and the steepest descent can both be compared to LM.

Hessian matrix is as:

$$H = J^T J; \ldots\ldots\ldots\ldots\ldots\ (7)$$

where J is the Jacobian matrix containing the network error's first derivative depending on its weights and biases.

Gradient is computed as,

$$G = J^T e; \ \ldots\ldots\ldots\ldots\ldots (8)$$

where e is the vector of weighted and biased network errors.

The complexity of the Jacobian matrix is smaller than what Hessian matrices. Once the algorithm is transfers the matrix into the Newton model will give:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \ \ldots\ldots (9)$$

The equation changes to Newton's method when the scalar quantity μ is 0, and to the gradient descent method when μ is higher. The variables x are weight and bias and I is the identity matrix.

The Bayesian Regularization (BR) algorithm is an additional tool. It reduces the sum of squared mistakes and weights in a linear fashion. To achieve strong generalization abilities at the conclusion after training, the linear combinations are additionally adjusted. Within the LM algorithm, the BR occurs. For the calculation of J, the Jacobian matrix, both use back propagation.

The methodology of the neural network is implemented in three steps:

i. Development of the database: We first implement the neural network and choose the proper architecture. Once it's done we gather the data from the 5 buses on steady condition and faulty conditions. Three timeframes are considered 0.1s,0.6s and 1s. Tables and show the summary of the matrix used to form the database on MATLAB.
ii. Training the matrix implemented and then validation and final testing.

III. Results

IEEE 5 bus system was used to implement the artificial neural network system and see how effective it can be detecting faults on the bus system. The Fig. 3 represents the IEEE 5 bus system developed from Simulink model.

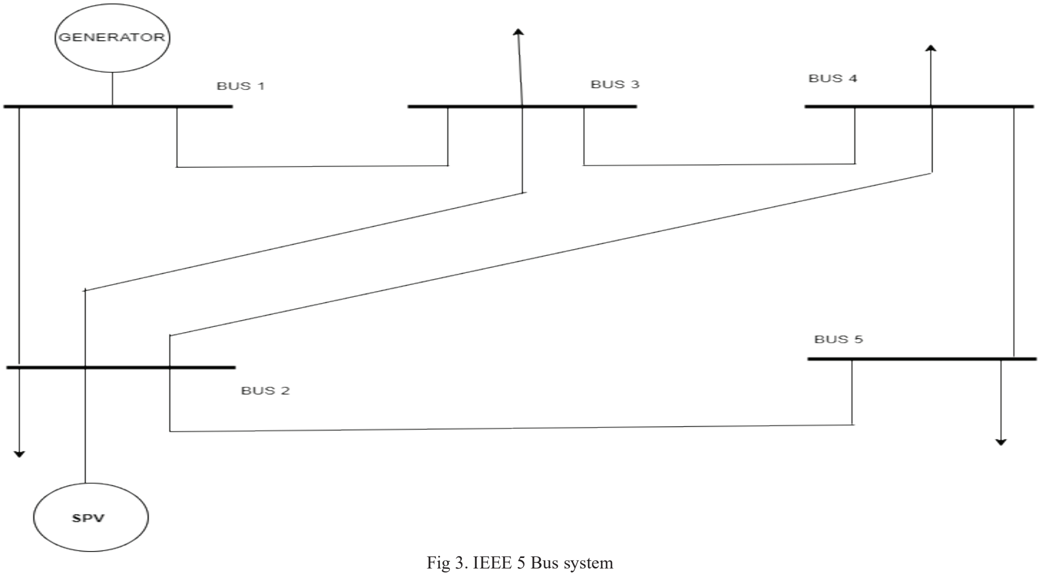


Fig 3. IEEE 5 Bus system

Table II gives the details about the IEEE 5 bus system

TABLE II
IEEE 5 BUS SYSTEM

Bus No	Generation		Load demand	
	MW	Mvar	MW	Mvar
1	0	0	0	0
2	40	30	20	10
3	0	0	45	15
4	0	40	40	5
5	0	0	60	10

This algorithm generates dataset with random voltages which are later on divided and trained 20% of them as depicted in Fig.4. And used 20 other percent for testing. According to standards, if the voltage is above 380V, the system is faulty. Based on that the threshold has been set to 0V. If the voltage reaches that value, the system should detect the fault.

The mean square error from Fig. 2 is $1.3966e^{-20}$ which means that the system works well. The least error, the more effective the data set trained are. Fig. 5 represents Mean Square Error.

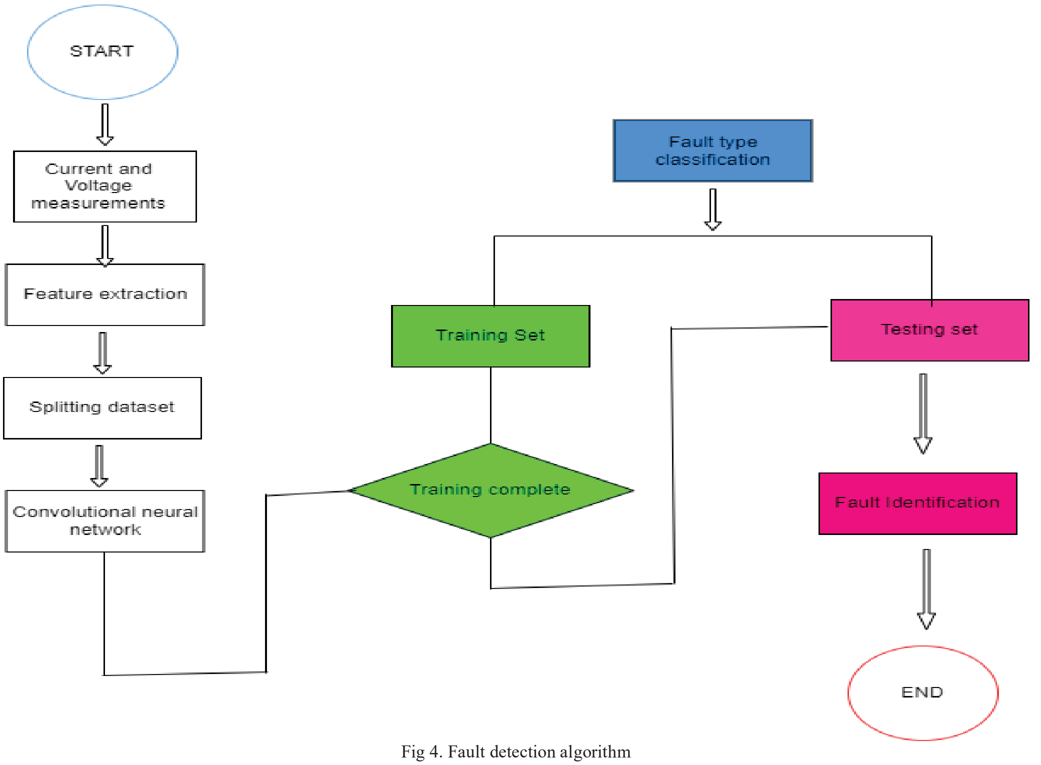


Fig 4. Fault detection algorithm

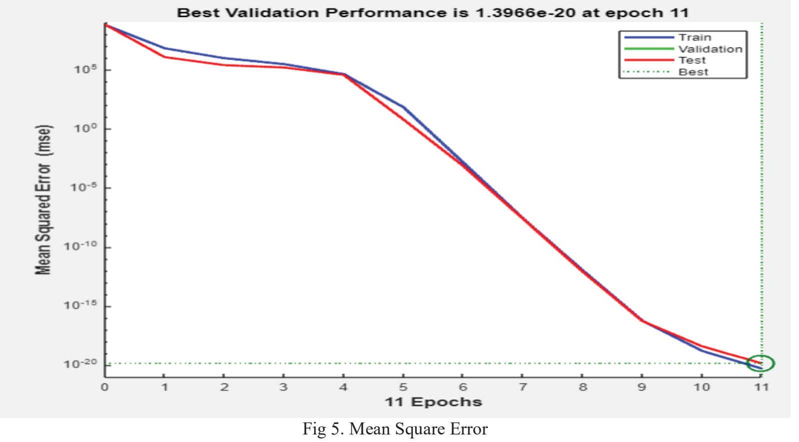
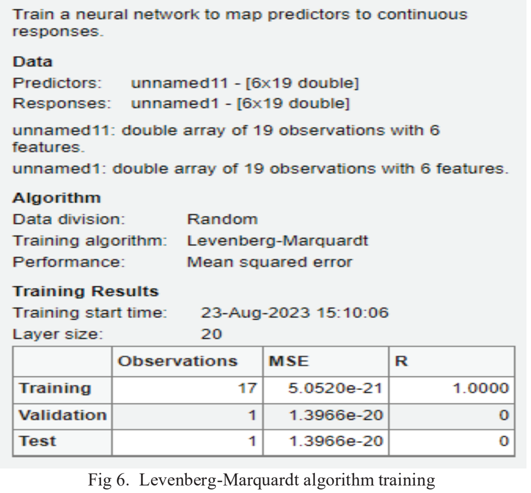


Fig 5. Mean Square Error

Fig. 6 shows that the regression is close to 0 which means that the system is efficient. Levenberg-Marquardt Algorithm was revealed to be a powerful tool when it comes to neural network optimization. 20 layers were used in order to maximise the samples to train and validate.

Table III provides a comparison of an LSTM and CNN, Performance and memory usage were important factors that led to the choice to LSTM architecture



Train a neural network to map predictors to continuous responses.

Data
Predictors: unnamed11 - [6x19 double]
Responses: unnamed1 - [6x19 double]

unnamed11: double array of 19 observations with 6 features.
unnamed1: double array of 19 observations with 6 features.

Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error

Training Results
Training start time: 23-Aug-2023 15:10:06
Layer size: 20

	Observations	MSE	R
Training	17	5.0520e-21	1.0000
Validation	1	1.3966e-20	0
Test	1	1.3966e-20	0

Fig 6. Levenberg-Marquardt algorithm training

IV. Conclusion

An IEEE 5 bus system has been investigated, where a phase-to-phase fault has been implemented in the swing bus. And the Artificial Neural Network system was used to detect the fault with the maximum accuracy.

Within the field of neural networks, the Levenberg-Marquardt algorithm is regarded as a potent optimization method. It is a useful tool for training non-linear models because of its capacity to converge on solutions and traverse complex loss landscapes.

With the Mean Square Error tool, the neural network system trained reveals results close to zero which demonstrates that the system is highly efficient.

This paper contributes to the analysis of faults in the grid using time series data with Long Short Term Memory(LSTM). A brief overview of how data can be acquired via a sensor was provided.

TABLE III
COMPARATIVE ANALYSIS

Parameters	Long Short Term Memory(LSTM)	Convolutional Neural Network(CNN)
Architecture	Recurrent	Convolutional
Suitability	It performs better with time series data where voltage and current measurements are involved	Works well with more local data such as images, videos…
Implementation	Complex	Moderate
Memory Usage	High	Low
Interpretability	Results are far easier to interpret	Low

Appendix

TABLE IV
VOLTAGE MEASUREMENTS BEFORE FAULTS

Time	V1a	V1b	V1c	V2a	V2b	V2c
0.53	12000	-5000	-5000	-0.5	12000	-0.5
0.54	5000	10000	-10000	5000	4000	-0.54
0.55	-12000	10000	0	10000	-10000	0.5

Time	V3a	V3b	V3c	V4a	V4b	V4c
0.53	-380	-400	-400	0	270	-280
0.54	0	-300	0	-100	-120	260
0.55	120	120	120	160	160	120

Time	V5a	V5b	V5c
0.53	-320	-380	320
0.54	200	-300	320
0.55	320	-180	-300

TABLE V
VOLTAGE MEASUREMENTS AFTER FAULTS

Time	V1a	V1b	V3c	V2a	V2b	V2c
0.53	10000	-2000	1000	-13000	-14000	-12000
0.54	-16000	-16000	10000	-10000	-10000	-900
0.55	-16000	-16000	10000	-12500	-12500	-800

Time	V3a	V3b	V3c	V4a	V4b	V4c
0.53	150	150	-400	-200	-200	200
0.54	150	150	-400	0	-120	120
0.55	200	-400	200	-180	-180	180

Time	V5a	V5b	V5c
0.53	100	100	-100
0.54	100	100	-100
0.55	100	100	-600

Conflict of Interest

The authors declare no conflict of interest in the publication process of the research article.

Author Contributions

Thomas Lionel Makosso conceptualised and perfume the analysis. Ali.Almaktoof and Khaled Aboalez edited and reviewed the work. All authors agreed on the final version.

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