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Power Plant Fault Detection Using Artificial Neural Network

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Abstract. The fault that commonly occurs in power plants is due to various factors that affect the system outage. There are many types of faults in power plants such as single line to ground fault, double line to ground fault, and line to line fault. The primary aim of this paper is to diagnose the fault in 14 buses power plants by using an Artificial Neural Network (ANN). The Multilayered Perceptron Network (MLP) that detection trained utilized the offline training methods such as Gradient Descent Backpropagation (GDBP), Levenberg-Marquardt (LM), and Bayesian Regularization (BR). The best method is used to build the Graphical User Interface (GUI). The modelling of 14 buses power plant, network training, and GUI used the MATLAB software.

INTRODUCTION

In power plants, faults occur due to various factors such as lightning, equipment damage, trees, animals, natural disasters and humans [1]. There are two types of faults that can occur in a power plant. The first fault is symmetrical fault which happened when the lines link together simultaneously, also known as three phase balanced fault. This is a short circuit condition that has equal fault current and phase, but for unsymmetrical faults, there is an equal fault current and phase. Examples of unsymmetrical faults are single line to ground fault, line to line fault and double line to ground fault.

This paper used the intelligent method which is an Artificial Neural Network (ANN) to diagnose and solve the types of fault in a simple power plant networks. There are many methods that can be developed to detect the faults in power plants such as Logic Regression, Genetic Algorithm, Artificial Neural Network (ANN) and Fuzzy [12] Logic (FL). For this paper, the ANN has been used because it has functions such as, to perform pattern recognition, pattern classification, pattern matching, prediction, decision making, and control. It is an intelligent system even though it requires an abundance of computation training time.

Literature Review

A fault in an electrical system is usually an inevitable problem which poses a great threat to the continuity of the electricity supply. Most certainly, faults in an electrical system will lead to a condition known as short circuiting. When a fault unexpectedly occurs, it will result in a heavy current flow through the equipment and almost certainly will cause damage to the equipment and interrupt the supply of electricity. In power plants, a fault can normally occur due to various factors such as lightning, equipment damage, tree, animal, natural disaster and human. There are two types of faults which can occur in a power plant, namely symmetrical or unsymmetrical fault.

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An unsymmetrical fault is best defined as an unbalanced fault, which does not have equal value of fault current and phase. Some examples of unsymmetrical faults which have a high probability of occurring in a power plant include single line to ground fault, line to line fault and double line to ground fault [2]. When lines link together simultaneously, this leads to a condition which is known as a three phase fault or more commonly, symmetrical faults. This is an example of a short circuit condition that has an equal value of fault current and phase. With a 120° displacement among them, the current in each line will be equivalent in magnitude. Based on previous research, this type of fault is the most common and most favorite to occur in a power plant system. In faults that occur in transmission line, roughly 5% are symmetric [3].

TABLE 1. The characteristic of algorithms

Training Methods	Characteristic
Gradient Descent Back Propagation	Slow response, but can be used in incremental mode training.
Levenberg-Marquardt	Faster training for network of moderate size. It has memory reduction feature for use when the training is large.
Bayesian Regularization	Improve generalization capability. More adaptive and robust BP network.

Table 1 shows the comparison between training methods and characteristic. There are three types of training methods has been considered and compared which are Gradient Descent Back Propagation, Levenberg Marquardt, and Bayesian Regularization.

TABLE 2. Related works

References	Objectives	Methodology	Results
[4]	To implement a complete scheme for distance protection	• Back propagation Neural Network training method	• Fast evaluation of errors obtained.
[6]	Comparative purpose to model the thermodynamic process of a coal-fired power plant.	• Back propagation Neural Network • Radial Basis Neural Network Training method • Bayesian Regularization	• BPNN is found to be better model than RBNN for plant performance analysis. • BPNN with BR is more appropriate for this application.
[3]	To determine the suitability and the applicability of artificial neural network for detecting quality river's water based on algae composition.	• Multi-layered Perceptron Network. • Bayesian Regularization • Levenberg Marquardt • Gradient Descent Back propagation	• Bayesian Regularization produces the best result with a high accuracy percentage as compared to the other methods.
[1]	To diagnose the fault occur in power plant using trained artificial neural network.	• Multi-layered Perceptron Network. • Back Propagation Neural Network.	• The simulation output is similar to the desired output. • BPNN is capable to recognize the pattern very well.
[8]	To supply electricity at the least possible cost with a constant service quality.	• Feedforward and Back Propagation	• Significance of feedforward ANN and Back Propagation training algorithm has been clearly demonstrated.

METHODOLOGY

The software that is used in this paper is MATLAB software. This software is chosen because it has a neural network tool that is suitable for this research. There are several flowcharts to explain the research workflow. It contains some work to execute the study of power plant fault detection and artificial neural network as a method to diagnose.

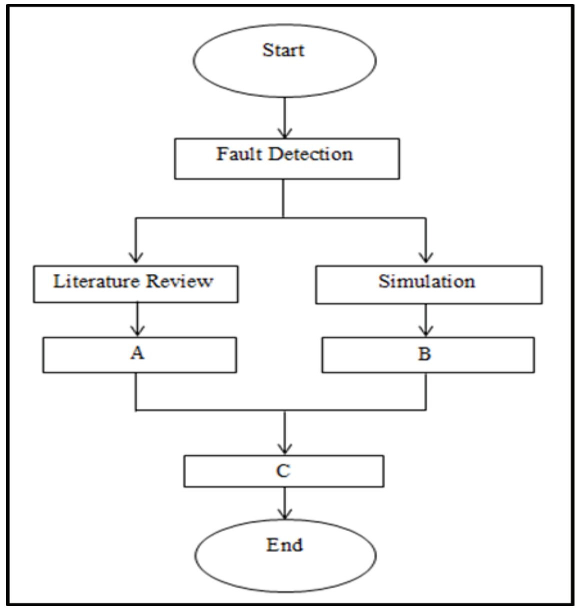

FIGURE 1. Methodology flow chart

Figure 1 shows the overall flowchart of methodology from the beginning of this research until the final stage. This research is subdivided into two processes which are literature review and simulation. The two processes explained in details in Fig. 2-3 respectively. The combination of the two processes will be interpreted in part C that is shown in Fig. 4.

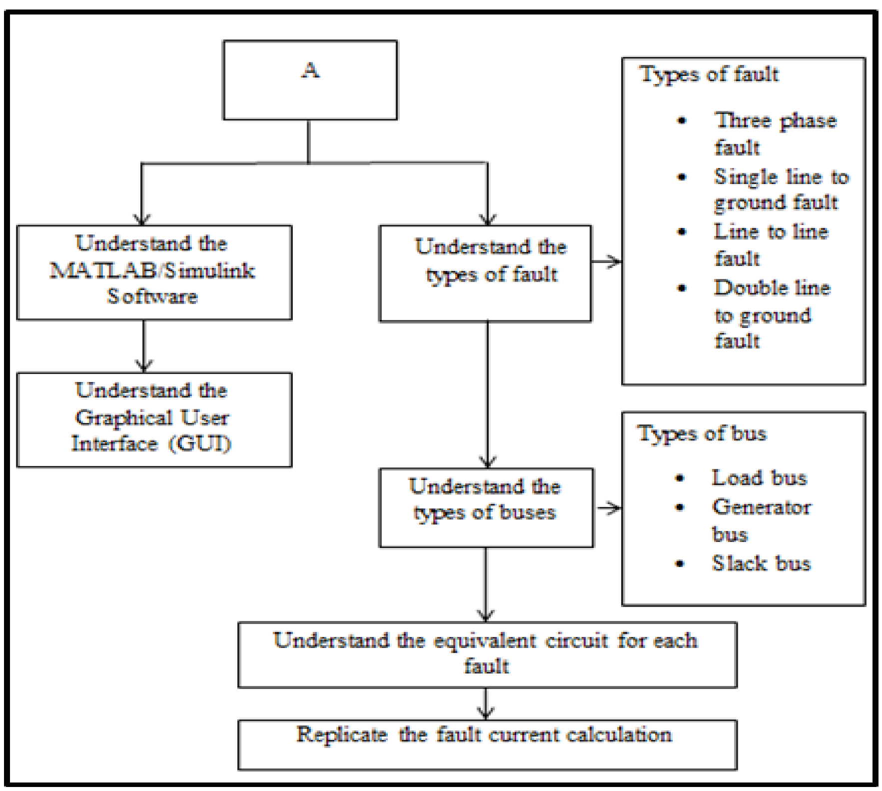

FIGURE 2. Literature review flow chart

Figure 2 shows the literature review flow chart that studies and explains all the processes in this research. There are several terms that needed to study and understood in this research such as fault analysis, bus analysis and MATLAB software.

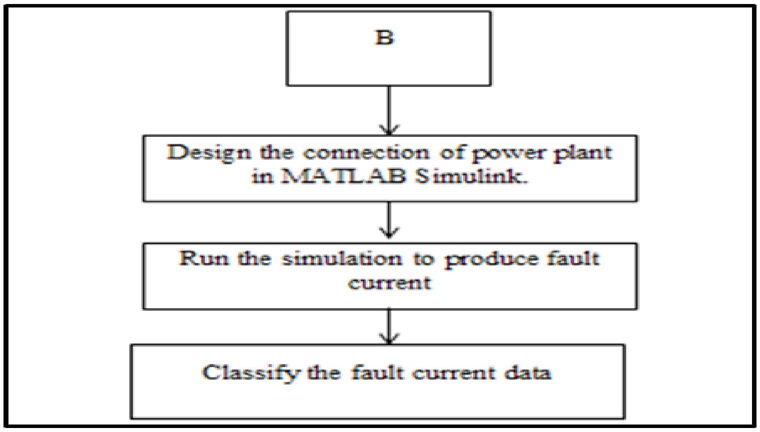

FIGURE 3. Simulation flow chart

Figure 3 shows the simulation flow chart by using MATLAB software. The fault current data collected from the simulation and is classified according to the type and location of faults.

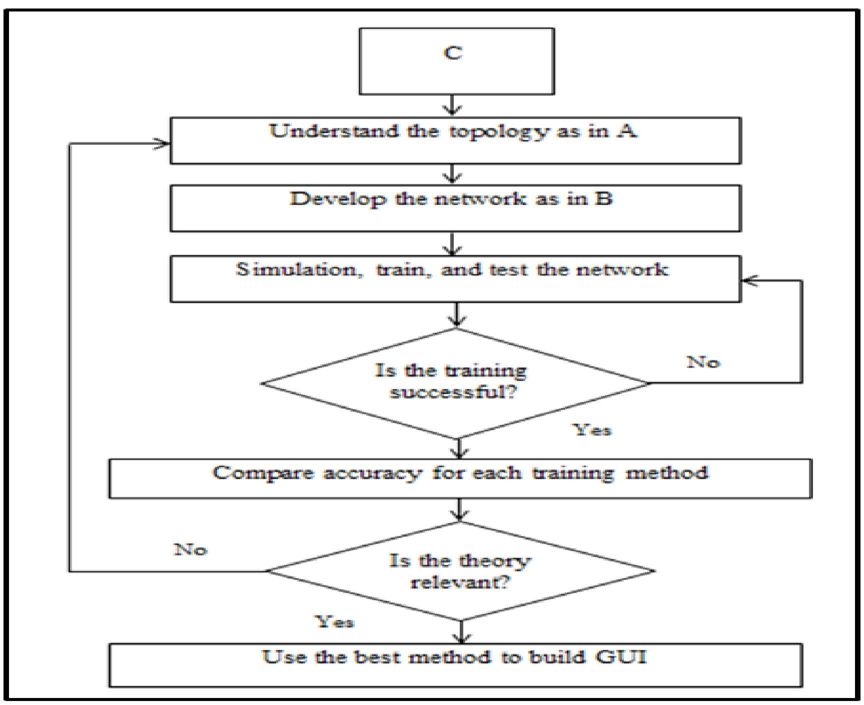

FIGURE 4. Flow chart of part C

Figure 4 shows the next step that is needed to be carried out to complete this research, after the combination of processes in part A and part B. When the training of the network is successful, the network was applied to the power plant for fault detection. Based on the simulation analysis, the conclusion of this research has been carried out.

RESULTS AND DISCUSSION

In this paper, the 14 buses system was built using MATLAB [11] software following the IEEE standard such as in Fig. 5. The types of fault were set in 14 buses system to obtain the fault current.

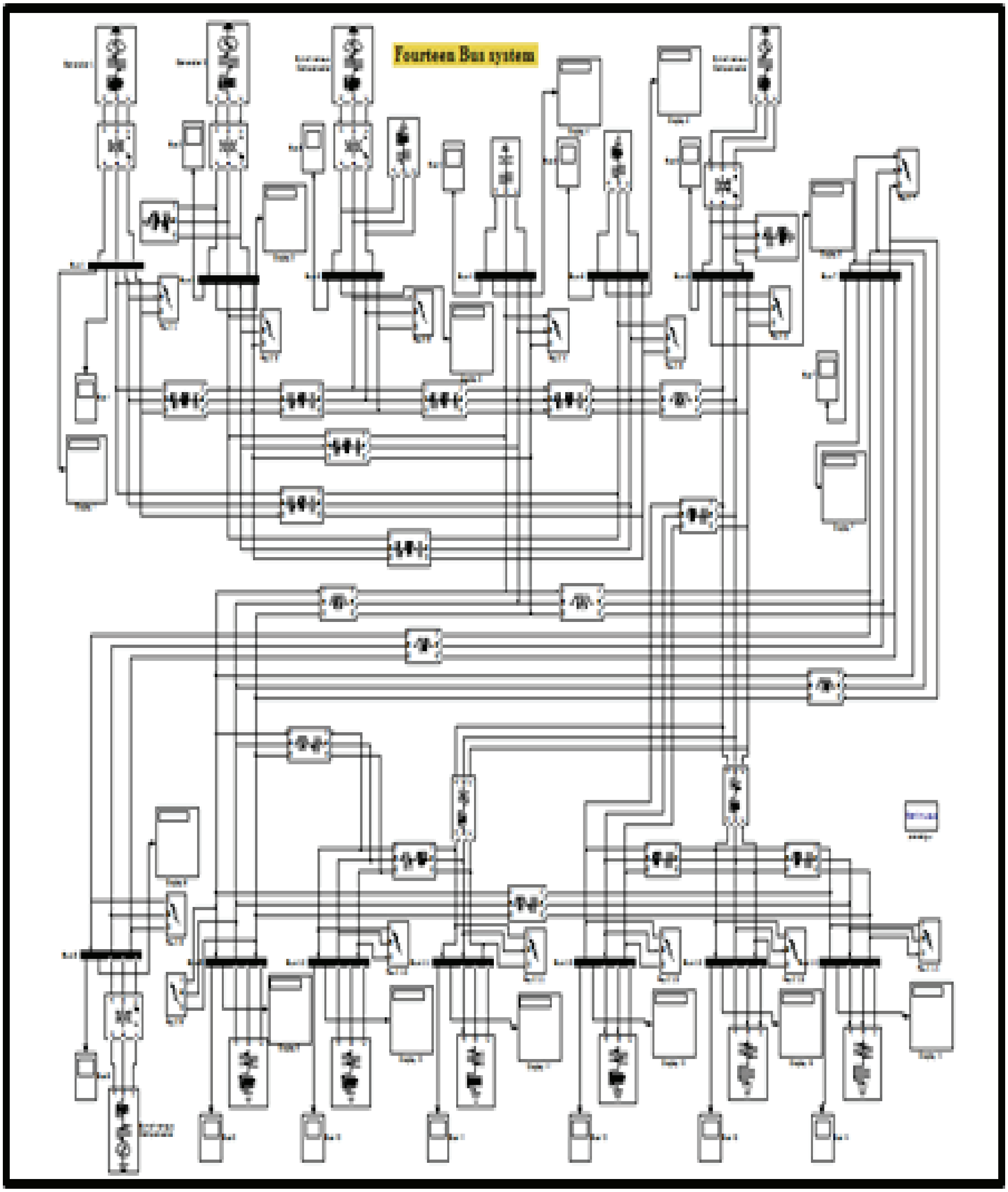

FIGURE 5. 14 buses system

The data given in Table 3 is on 100 MVA base.

TABLE 3. Line data-14 bus systems

From Bus	To Bus	Line Impedance (pu)		Susceptance (pu)
		Resistance	Reactance	
1	2	0.01938	0.05917	0.02640
1	5	0.05403	0.22304	0.02190
2	3	0.04699	0.19797	0.01870
2	4	0.05811	0.17632	0.02640
2	5	0.05695	0.17388	0.01700
3	4	0.06701	0.17103	0.01730
4	5	0.01335	0.04211	0.00640
4	7	0	0.20912	0
4	9	0	0.55618	0
5	6	0	0.25202	0
6	11	0.09498	0.1989	0
6	12	0.12291	0.25581	0
6	13	0.06615	0.13027	0
7	8	0	0.17615	0
7	9	0	0.11001	0
9	10	0.03181	0.0845	0
9	14	0.12711	0.27038	0
10	11	0.08205	0.19207	0
12	13	0.22092	0.19988	0
13	14	0.17093	0.34802	0

In this simulation, there was 1350 data of fault current collected. Then, the fault current was classified based on their type and location. The performance of the fault could be summarized based on the percentage of occurrence of fault in the power plant as shown in Fig. 6.

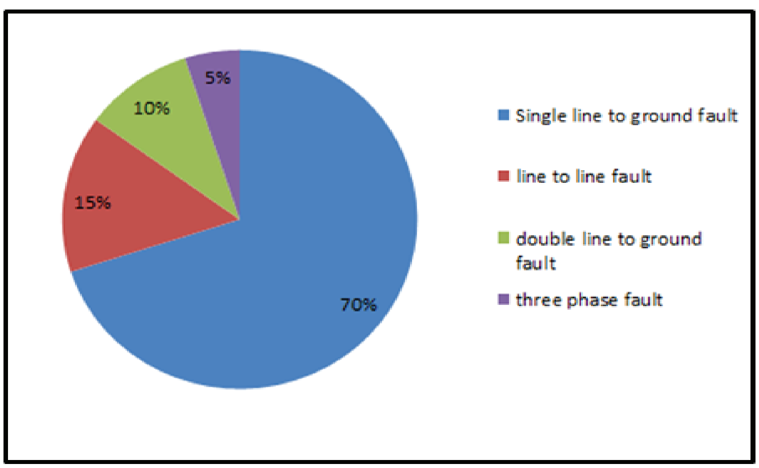

FIGURE 6. Fault occurrence percentage

Fig. 6 shows the percentage of fault occurrence in power system according to fault type. Single line to ground fault have higher percentage than the others fault which commonly occur in power plant due to lightning and storm damage at the power plant. For training the network, fault current act as the input on the network while types of fault are outputs. The network had been trained using three types of methods which are Gradient Descent Backpropagation, Levenberg Marquardt and Bayesian Regularization.

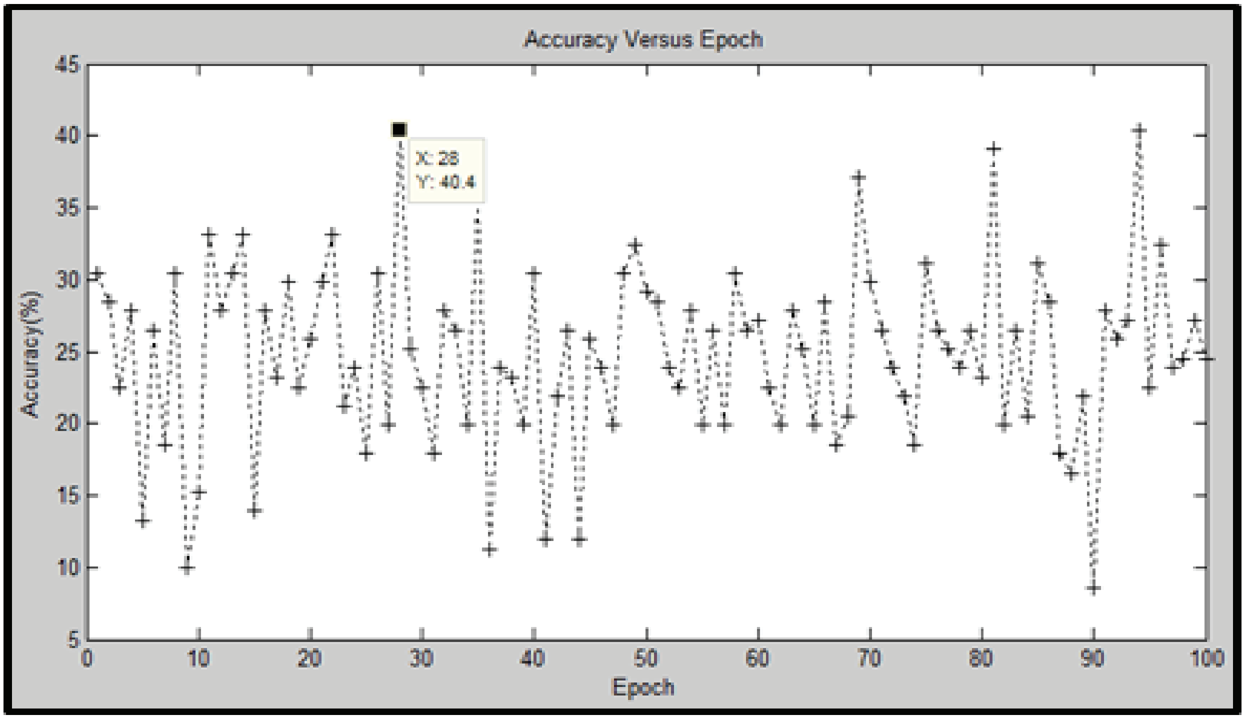

FIGURE 7. Accuracy (%) versus epochs (GDBP)

The simulation of network training is undergoing by using Gradient Descent Backpropagation (GDBP) is shown in Fig. 7. The result of the network training shows the highest accuracy point obtained is 40.4% which is when iteration is at 28.

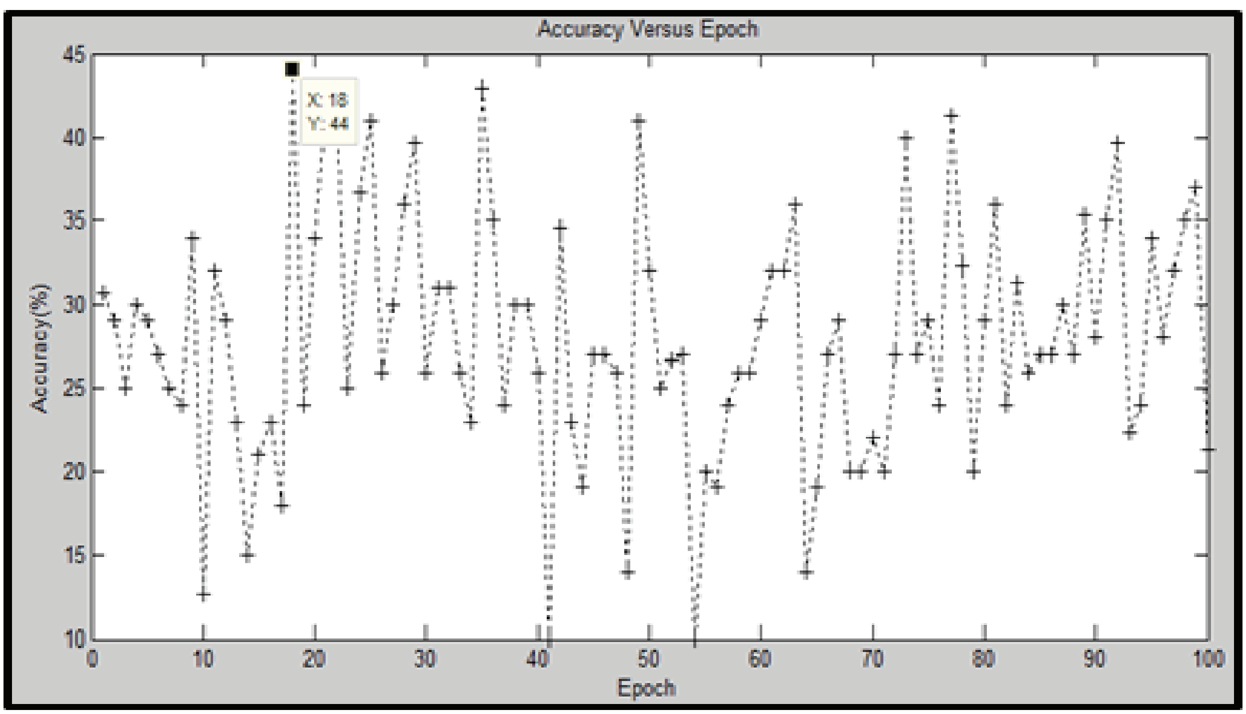

FIGURE 8. Accuracy (%) versus epochs (LM)

Fig. 8 shows the Levenberg Marquardt method is used to train the MLP network. It shows that the highest accuracy point achieved was 44%, which is at an iteration of 18. The last method used to train the MLP [9-10] network is the Bayesian Regularization method. The result is shown in Fig. 9.

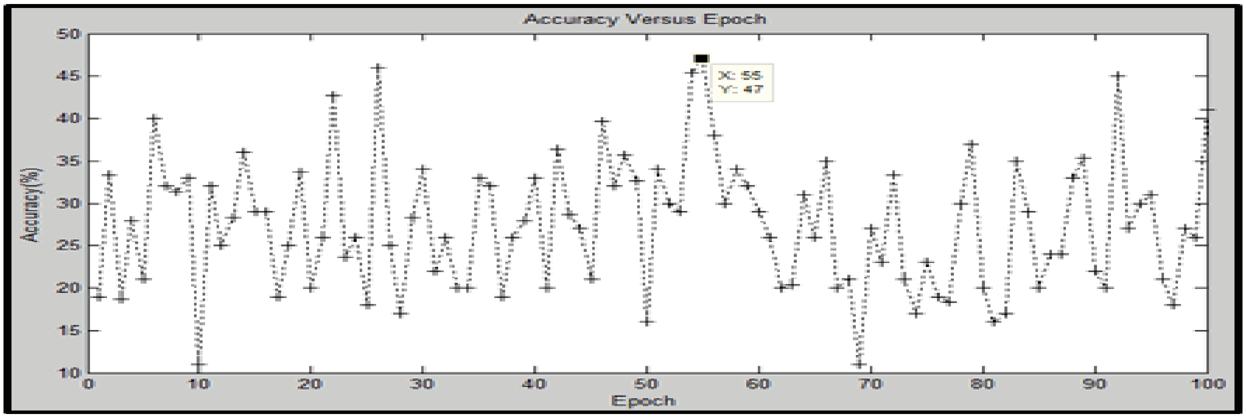

FIGURE 9. Accuracy (%) versus epochs (BR)

Fig. 9 shows the relationship between the accuracy of network training and the iteration of training. At an iteration of 55, the highest accuracy point was achieved which is 47%.

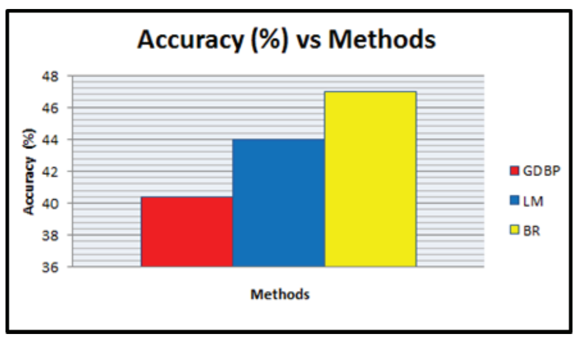

FIGURE 10. Accuracy (%) versus methods

Fig. 10 shows the comparison of the accuracy of the network between the methods. Bayesian regularization methods have highest accuracy compared to the other methods because this method improves the generalization capability. Besides that, BR is a more adaptive and robust network.

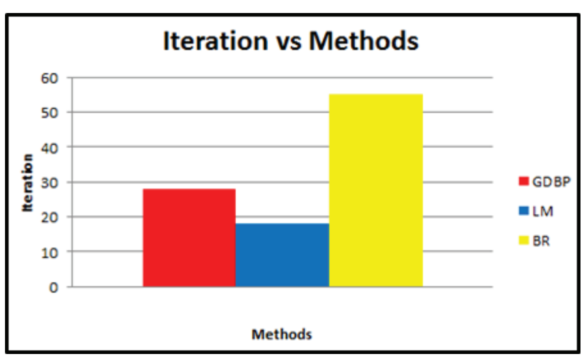

FIGURE 11. Iteration versus methods

Fig. 11 shows the comparison of iteration between three methods which are GDBP, LM, and BR. It shows how fast the method trains the network. Levenberg Marquardt shows the fastest iteration than the other methods because it has faster training characteristic for networks of moderate size. Besides that, it has a memory reduction feature for use when the training is large.

TABLE 4. Results for performance analysis of the MLP network

Methods	Accuracy (%)	
	Max	Epoch
GDBP	40.4	28
LM	44	18
BR	47	55

Based on Table 4, the highest accuracy obtained of network training is by using Bayesian Regularization, but Levenberg Marquardt shows the fastest fault detection which is at the 18th iteration. The graph indicates that this type of training method suffers from a slow convergence rate because the search for global minima may become trapped at local minima and the algorithm can be sensitive to the user selectable parameters [4]. The purpose of the trying three different methods is to find the most accurate and fastest method. Therefore, the best method for fault detection is Levenberg Marquardt. The weight of this method has been carried out. All of this weight has been used in coding to build Graphical User Interface (GUI) [17-18].

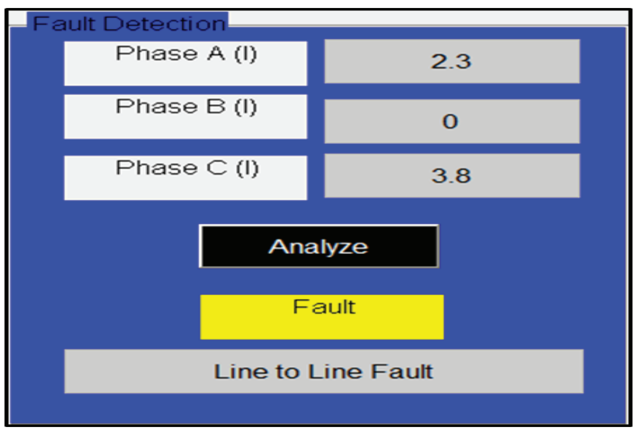

FIGURE 12. Graphical User Interface (GUI)

Fig. 12 shows the interface that is used to detect the fault. It consists of a fault current that should be inserted before analyzing the types of fault. The result shows the types of fault that occur in power plant. The results obtained in GUI validates with results from [7] which proves that the coding and the system is true. The system must use 14 buses system, the same data and parameters of transformers, generators and line to ensure a more accurate result.

TABLE 5. Validation data in GUI [5]

Fault Current (A)			Result
Ia	Ib	Ic	
0.9241	0.1635	0.1635	Single Line to Ground Fault
1.2586	1.2586	1.2586	Line to Line Fault
1.9552	1.9552	0.2312	Double Line to Ground Fault
0.9945	0.9945	0.9945	Three Phase Fault

Based on the results shown in Table 5, when the values of Ia, Ib and Ic are entered into the GUI, results obtained are the same as expressed in [7]. This shows that the GUI system applied is satisfactory to IEEE standards.

CONCLUSION

There are four types of faults that can occur in a power system which are single line to ground fault, line to line fault, double line to ground fault, and three phase fault. The Artificial Neural Network (ANN) is a suitable method for fault detection in a power plant. There are three types of training methods used in this project which are Gradient Descent Back propagation, Levenberg Marquardt and Bayesian Regularization. Based on the result, Levenberg Marquardt is the best method for detecting faults because it had a higher accuracy and faster time detection. In this paper, the simulation of power plant fault detection using Artificial Neural Network has been carried out. However, further studies of this paper can be done in certain areas. The study of power plant fault detection using Artificial Neural Network [13-16] needs to be extended with larger power plant systems. Besides this, this paper needs to be extended to the hardware implementation level.

REFERENCES

1. M. Aifaa, Fault diagnosis in power plant using artificial neural network, Universiti Teknologi Malaysia, Johor, 2008.
2. Y. K. Hung, Fault identification in power distribution system using fuzzy logic, Universiti Teknologi Malaysia, Johor, 2009.
3. N. A. M. Isa, F. R. Hashim, F. W. Mei, D. A. Ramli, W. M. W. Omar and K. Z. Zamli, "Predicting quality of river's water based on algae composition using artificial neural network," in IEEE International Conference on Industrial Informatics (Institute of Electrical and Electronics Engineers, Piscataway, NJ, 2006), pp. 1340-1345.
4. E. B. M. Tayeb, American Journal of Engineering Research **2**, 69-75 (2013).
5. P. Manke and S. Tembhurne, International Journal of Computer Science **9**, 520-256 (2012).
6. D. A. Ramli, J. M Saleh, F. R. Hashim and N. A. Mat Isa, "Multilayered perceptron (MLP) network trained by recursive least squares algorithm," *Computers, Communications, & Signal Processing with Special Track on Biomedical Engineering, 2005. CCSP 2005. 1st International Conference on,* pp. 288-291, 2005.
7. M. F. Ismail, "Toolbox for power system fault analysis using MATLAB," Universiti Malaysia Pahang, 2011.
8. F. R. Hashim, J. J. Soraghan and L. Petropaulakis, "Multi-Classify Hybrid Multiyared Perceptron (HMLP) Network for Pattern Recognition Applications," *Artificial Intelligence Applications and Innovations,* 381, pp. 19-27, 2012.
9. J. Adnan, N. G. N. Daud, A. S. N. Mokhtar, F. R. Hashim, S. Ahmad, A. F. Rashidi and Z. I. Rizman, Journal of Fundamental and Applied Sciences **9**, 417-432 (2017).
10. I. M. Yassin I, R. Jailani, M. Ali, M. S. Amin, R. Baharom, A. Hassan, A. Huzaifah and Z. I. Rizman, International Journal on Advanced Science, Engineering and Information Technology **7**, 215-221 (2017).
11. B. Nawi, B. Sulaini, Z. A. R. Mohd, A. Z. Shamsul and I. R. Zairi, Journal of Applied Environmental and Biological Sciences **5**, 166-173 (2015).
12. M. F. A. Latip, M. K. A. M. Udin, M. M. Othman, I. M. Yassin, Z. I. Rizman, N. Zaini, M. N. Hidayat, N. Aminuddin, S. H. Herman, H. Saad and M. H. F. Rahiman, International Journal of Advanced and Applied Sciences **4**, 159-163 (2017).
13. A. Zabidi, I. M. Yassin, H. A. Hassan, N. Ismail, M. M. A. M. Hamzah and Z. I. Rizman, Journal of Fundamental and Applied Sciences **9**, 768-778 (2017).
14. F. R. Hashim, N. G. N. Daud, K. A. Ahmad, J. Adnan and Z. I. Rizman, Journal of Fundamental and Applied Sciences **9**, 493-502 (2017).
15. F. R. Hashim, J. Adnan, M. M. Ibrahim, M. T. Ishak, M. F. M. Din, N. G. N. Daud and Z. I. Rizman, Journal of Fundamental and Applied Sciences **9**, 1-10 (2017).
16. I. M. Yassin, A. Zabidi, R. Jailani, M. S. A. M. Ali, R. Baharom, A. H. A. Hassan and Z. I. Rizman, International Journal on Advanced Science, Engineering and Information Technology **7**, 215-221 (2017).
17. F. D. M. Fauzi, T. Mulyana, Z. I. Rizman, M. T. Miskon, W. A. K. W. Chek and M. H. Jusoh, International Journal on Advanced Science, Engineering and Information Technology **6**, 489-494 (2016).
18. M. T. Miskon, Z. I. Rizman, W. A. K. W. Chek and F. D. M. Fauzi, Journal of Applied Environmental and Biological Sciences **4**, 108-114 (2014).