Investigate the Effect of Artificial Neural Network Parameters to Improve Fault Distance and Impedance Accuracy

Mohd Syukri Ali *, Ab Halim Abu Bakar*, Nasrudin Abd Rahim* †

*Higher Institution Centre of Excellence (HICoE), UM Power Energy Dedicated Advanced Centre (UMPEDAC), Level 4, Wisma R&D, University of Malaya, Jalan Pantai Baharu, 59990 Kuala Lumpur, Malaysia.

†Renewable Energy Research Group, King Abdulaziz University, Jeddah 21589, Saudi Arabia

E-mail: syukriali@um.edu.my

Abstract. This paper investigates the effect of artificial neural network (ANN) parameters against the ANN accuracy on cable fault location. The investigation is conducted through the fault impedance and distance estimations during the occurrence of high impedance fault (HIF) in the distribution system. The measured three-phase voltage and current signals are utilized and fed into the ANN to estimate the fault impedance and distance. The accuracy of the estimated fault impedance and distance is evaluated with respect to the variation of ANN parameters. Based on the analysis, it shows that more accurate results can be obtained by utilizing the optimal value of ANN parameters.

1. Introduction

Fault is an unbalanced condition or any undesirable circumstances that will create an excessive current that leads to thermal and mechanical damage to the plant that carries it. Besides that, it can cause an extremely high temperature in arcs, which indirectly vaporize any known substances that lead to equipment destruction and fire. The system can become unstable and breakdown due to the fluctuation of the system voltage outside of their acceptable range. It can also cause the three-phase system to become unbalanced thus causing improper operation of the three-phase equipment. Most importantly, the fault will impede the power flow which causes undelivered supply to the intended load.

The occurrence of a fault is inevitable as it can be caused by the natural disaster such as storms, lightning strikes, a fallen tree trunk, animal encroachment and heat cycling. The cable degradation as well can cause the fault as the aging components and broken insulation will expose the cable. It can also be caused by human errors in the forms of accidents or other activities that carried out near to the power system equipment [1].

Fault can be classified into low impedance fault (LIF) and high impedance fault (HIF). Between these two, HIF seldom occurs as compared to LIF. It is reported that around 5% to 10% of all the fault events in the distribution system are caused by HIF. However, the actual percentage could be higher since only HIF events ending in bolted faults are recorded [2]. Even though the occurrence is seldom, but the consequences are more severe than LIF because the fault current produce due to HIF is low and unable to be identified by the conventional overcurrent protection relay [3, 4]. Besides, it is difficult to be detected because of the similarity of the operating current magnitude under normal and faulty
condition. As a result, the fault will be left untreated thus increasing the risk of damage proliferation, outage time and hazard to the equipment and public.

Therefore, it is utmost important to detect and locate the fault as accurate and as fast as possible. Unfortunately detecting and locating the HIF is not an easy task especially for the underground cable due to non-visibility [5]. There are various techniques that have been proposed to detect and locate the HIF. For the HIF detection, it can be categorized into the time domain and frequency domain. In time domain HIF detection, the variation in the magnitude of the voltage and current signals over time is observed [6, 7]. Whereas in frequency domain HIF detection, the characteristic of the voltage and current signals within a frequency range is analyzed [8-10].

To estimate the HIF location, various techniques comprising of the impedance-based method, high frequency traveling wave, analytical formulation, fundamental component-based and knowledge-based methods have been introduced to tackle the HIF localization problem [1, 11, 12]. It is important to properly select the technique and it must be compatible with the distribution network topology. For example, the high frequency traveling wave technique is not suitable for the complex distribution system with lateral branches because it will cause many refractions and reflections from discontinuity points and at the lateral junctions [13]. Recently, knowledge-based method comprising of artificial neural network (ANN) [14, 15], fuzzy logic system (FLS) [16, 17], support vector regression (SVR) [18-21], core vector regression (CVR) [22] and adaptive neuro-fuzzy inference system (ANFIS) [23, 24] is preferable by the researchers to estimate the fault distance.

It was observed that ANN has been utilized to estimate the fault distance and it gives a promising result. However, the relationship between ANN parameters and the accuracy is not yet investigated. As such, in this paper the effect of changing the ANN parameters value comprising of learning rate \((lr)\), momentum constants \((mc)\) and the number of neurons in a hidden layer \((p)\) is conducted. The performance will be evaluated based on the fitness of the estimated fault impedance and distance during the occurrence of the HIF event in the distribution system. In this investigation, a single measurement of three-phase voltage and current waveforms measured at the main substation is utilized and fed into the ANN.

2. Proposed Method

In this paper, ANN is utilized to estimate the fault impedance and distance during the occurrence of the HIF event. The performance of ANN is further enhanced by investigating the effect of varying the value of ANN parameters comprising of learning rates \((lr)\), momentum constant \((mc)\) and the number of neurons in the hidden layer \((p)\). To investigate the effect, the value of each ANN parameters is changed one by one while the other two parameters are fixed. The performance is evaluated based on the fitness value of the estimated fault impedance and distance values.

2.1. Test System

Figure 1 shows a simplified 132/11kV distribution network developed in PSCAD/EMTDC software consisting of 33 nodes. The frequency of the system is 50Hz and the sampling frequency is 4kHz (80samples per one full cycle). Three-phase voltage and current waveforms are measured at the measurement node. In this investigation, different fault impedance values are applied at each node. There are a total of 1089 samples consisting of 11 fault impedance values (from 50Ω to 150Ω in steps of 10Ω), 33 nodes and 3 different types of fault (phase-A-to ground fault, phase-B-to ground fault and phase-C-to ground fault).
Investigate the Effect of ANN Parameters

In this study, the effect of changing the LMB parameters is investigated to observe the performance of ANN to estimate the fault impedance and distance due to the occurrence of HIF event. There are 3 different scenarios related to 3 different LMB parameters. For each scenario, one LMB parameter is varied while the other 2 are fixed. For example, in the first scenario, the value of $lr$ is varied while the value of $mc$ and $p$ are fixed. After obtaining the best value of $lr$, then the value of $mc$ is varied and the value of $lr$ (best value) and $p$ are fixed for the second scenario. In the third scenario by using the best values of $lr$ and $mc$, the performance of ANN is further investigated when the value of $p$ is varied.

In each scenario, the ANN training process is iterated for 100 times and only the lowest average error and maximum error of fault impedance and distance is selected. Then, the best value of LMB parameter is determined based on the fitness for each scenario. The lowest value of fitness is selected as it represents the highest accuracy of the estimated fault impedance and distance. The normalized average error, normalized maximum error and the fitness are calculated as follows:

\[
\text{error} = |\text{estimated-actual}|	ag{1}
\]

\[
\text{average error} = \frac{\sum_{i=1}^{n} \text{error}_i}{n}	ag{2}
\]

\[
\text{norm}\_\text{aver}_k = \frac{\text{average error}_k}{\text{average error}_{\text{max}}}	ag{3}
\]

\[
\text{maximum error} = \max(\text{error}_n).	ag{4}
\]

\[
\text{norm}\_\text{max}_k = \frac{\text{maximum error}_k}{\text{maximum error}_{\text{max}}}	ag{5}
\]
\[ \text{fitness} = \frac{\text{norm\_aver\_imp} + \text{norm\_aver\_dist} + \text{norm\_max\_imp} + \text{norm\_max\_dist}}{4} \]

(6)

where \( n \) represents the total number of samples and \( k \) represent the parameters.

In the first scenario, the value of \( lr \) is varied while the value of \( mc \) and \( p \) are fixed. The value of \( lr \) is varied from 0.1 to 1 in increment by 0.1, while the value of \( mc \) and \( p \) are fixed to 0.5 and 6 respectively. The performance of ANN is evaluated based on the fitness as shown in Figure 2.

The figure indicates the result for fitness, normalized average impedance, normalized maximum impedance, normalized average distance and normalized maximum distance obtained when the value of \( lr \) is varied. The figure shows that the ANN performance varies with respect to the values of \( lr \). It can also be observed that not all the results are the best result for that particular value of \( lr \). For example, when \( lr = 0.4 \), it gives the best result for the normalized maximum impedance, but the rest is not the best results. Therefore, it is important to choose a suitable value of \( lr \) in which it gives a better performance to all the results. As such, the best value of \( lr = 0.7 \) is selected because it gives the lowest value of fitness (0.736)

![Figure 2](image-url)  
Figure 2. The performance of ANN with the variation of \( lr \) values.

Subsequently, the second scenario is conducted in which the value of \( lr \) is set to 0.7 based on the results obtained in the first scenario. The value of \( p \) is fixed to 6. Whereas the value of \( mc \) is varied from 0.1 to 1 in increment by 0.1. Figure 3 shows the results for the variation of \( mc \) values. Based on the results, it can be observed that the lowest fitness value (0.723) is obtained when \( mc = 0.9 \).

![Figure 3](image-url)  
Figure 3. The performance of ANN with the variation of \( mc \) values.
For the third scenario as shown in Figure 4, the value of $p$ is varied in between 3 to 12 (half to double of input data). It is observed that the performance of ANN is improved as the number of $p$ is increasing. However, it should be noted that more training time is required if a greater number of $p$ is utilized. Besides that, the overfitting problem can arise if too many of $p$ is used. In this investigation, it can be observed that the best performance can be obtained if the value of $p=11$ is utilized with the fitness value of 0.078.

It can be concluded that these ANN parameters affect indirectly the performance of ANN. The smallest value of fitness (0.078) is obtained when the value of $lr=0.7$, $mc=0.9$ and $p=11$ is utilized. It should be noted that in this investigation the value of the parameter is set up to 1 decimal point and the analysis is conducted by changing only one parameter at the time. It is expected that more accurate results can be obtained if the value is set up to 3 decimal points for $lr$ and $mc$ and more than one parameter are varied concurrently. Unfortunately, it is difficult to determine the optimal values of these ANN parameters. Therefore, an optimization technique is suggested to be implemented to provide these optimal values.

![Figure 4. The performance of ANN with the variation of p values.](image)

### 4. Conclusion

In this paper, an insight into the significant of ANN parameters is investigated to evaluate the ANN performance. It is observed that higher accuracy can be achieved if the optimal value of ANN parameters is utilized. To justify this hypothesis, a simple distribution network is modeled in PSCAD. Then, the high impedance fault event is simulated at each node with different fault impedance values. A single measurement of measured three-phase voltage and current signals are fed into the ANN to estimate the fault impedance and distance values. The accuracy of the ANN is measured in term of fitness. It is observed that fitness improving if the optimal value of ANN parameters is utilized. In this analysis, it is observed that the best fitness value (0.078) is obtained when the value of $lr$, $mc$ and $p$ are set to 0.7, 0.9 and 11 respectively.

### Acknowledgements

This work was supported by the University of Malaya, Kuala Lumpur under Fundamental Research Grant Scheme (FRGS Grant No: FP093-2018A). The authors also thank the technical and financial assistance of UM Power Energy Dedicated Advanced Centre (UMPEDAC) and the Higher Institution Centre of Excellence (HICOE) Program Research Grant, UMPEDAC - 2018 (MOHE HICOE - UMPEDAC), Ministry of Education Malaysia, RU007-2018 and RU012-2019, University of Malaya.

### References

[1] Filomena AD, Resener M, Salim RH, Bretas AS. Fault location for underground distribution feeders: An extended impedance-based formulation with capacitive current compensation. International Journal of Electrical Power & Energy Systems. 2009;31(9):489-96.
[2] Ghaderi A, Mohammadpour HA, Ginn HL, Shin Y. High-Impedance Fault Detection in the Distribution Network Using the Time-Frequency-Based Algorithm. *IEEE Transactions on Power Delivery*. 2015;30(3):1260-8.

[3] Ali MS, Abu Bakar AH, Mokhlis H, Arof H, Azil Illias H. High-impedance fault location using matching technique and wavelet transform for underground cable distribution network. *IEEE Transactions on Electrical and Electronic Engineering*. 2014;9(2):176-82.

[4] Macedo JR, Resende JW, Bissochi CA, Carvalho D, Castro FC. Proposition of an interharmonic-based methodology for high-impedance fault detection in distribution systems. *IET Generation, Transmission & Distribution*. 2015;9(16):2593-601.

[5] Ghaderi A, Ginn HL, Mohammadpour HA. High impedance fault detection: A review. *Electric Power Systems Research*. 2017;143:376-88.

[6] Sharaf AM, Abu-Azab SI, editors. A smart relaying scheme for high impedance faults in distribution and utilization networks. 2000 Canadian Conference on Electrical and Computer Engineering. Conference Proceedings. Navigating to a New Era (Cat. No.00TH8492); 2000 7-10 May 2000.

[7] Ching-Lien H, Hui-Yung C, Ming-Tong C. Algorithm comparison for high impedance fault detection based on staged fault test. *IEEE Transactions on Power Delivery*. 1988;3(4):1427-35.

[8] Zanjani MGM, Kargar HK, Zanjani MGM, editors. High impedance fault detection of distribution network by phasor measurement units. 2012 Proceedings of 17th Conference on Electrical Power Distribution; 2012 2-3 May 2012.

[9] Yong S, Rovnyak SM. Decision tree-based methodology for high impedance fault detection. *IEEE Transactions on Power Delivery*. 2004;19(2):533-6.

[10] Aucoin BM, Russell BD. Distribution High Impedance Fault Detection Utilizing High Frequency Current Components. *IEEE Power Engineering Review*. 1982;PER-2(6):46-7.

[11] Mora-Flòrez J, Meléndez J, Carrillo-Caicedo G. Comparison of impedance based fault location methods for power distribution systems. *Electric Power Systems Research*. 2008;78(4):657-66.

[12] Gazzana DS, Ferreira GD, Bretas AS, Bettiol A, Carniato A, Passos LFN, et al. An integrated technique for fault location and section identification in distribution systems. *Electric Power Systems Research*. 2014;115:65-73.

[13] Bakar AHA, Ali MS, Tan C, Mokhlis H, Arof H, Illias HA. High impedance fault location in 11 kV underground distribution networks using wavelet transforms. *International Journal of Electrical Power & Energy Systems*. 2014;55:723-30.

[14] Moshtagh J, Aggarwal RK, editors. A New Approach to Ungrounded Fault Location in a Three-Phase Underground Distribution System using Combined Neural Networks & Wavelet Analysis. Electrical and Computer Engineering, 2006. CCECE ’06. Canadian Conference on; 2006 May 2006.

[15] Baqui I, Zamora I, Mazón J, Buigues G. High impedance fault detection methodology using wavelet transform and artificial neural networks. *Electric Power Systems Research*. 2011;81(7):1325-33.

[16] Rafinia A, Moshtagh J. A new approach to fault location in three-phase underground distribution system using combination of wavelet analysis with ANN and FLS. *International Journal of Electrical Power & Energy Systems*. 2014;55:261-74.

[17] Chunju F, Li KK, Chan WL, Weiyong Y, Zhaoning Z. Application of wavelet fuzzy neural network in locating single line to ground fault (SLG) in distribution lines. *International Journal of Electrical Power & Energy Systems*. 2007;29(6):497-503.

[18] Ye L, You D, Yin X, Wang K, Wu J. An improved fault-location method for distribution system using wavelets and support vector regression. *International Journal of Electrical Power & Energy Systems*. 2014;55:467-72.
[19] Thukaram D, Khincha HP, Vijaynarasimha HP. Artificial neural network and support vector Machine approach for locating faults in radial distribution systems. *IEEE Transactions on Power Delivery*. 2005;20(2):710-21.

[20] Shafiullah M, Ijaz M, Abido MA, Al-Hamouz Z, editors. Optimized support vector machine & wavelet transform for distribution grid fault location. 2017 11th IEEE International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG); 2017 4-6 April 2017.

[21] Moloi K, Jordaan JA, Hamam Y, editors. High impedance fault detection technique based on Discrete Wavelet Transform and support vector machine in power distribution networks. 2017 IEEE AFRICON; 2017 18-20 Sept. 2017.

[22] Khorramdel B, Marzooghi H, Samet H, Pourahmadi-Nakhli M, Raoofat M. Fault locating in large distribution systems by empirical mode decomposition and core vector regression. *International Journal of Electrical Power & Energy Systems*. 2014;58:215-25.

[23] Aziz MSA, Hassan MAM, El-Zahab EA. An Artificial Intelligence Based Approach for High Impedance Faults Analysis in Distribution Networks. *International Journal of System Dynamics Applications*. 2012;1(2):44-59.

[24] Barakat S, Eteiba MB, Wahba WI. Fault location in underground cables using ANFIS nets and discrete wavelet transform. *Journal of Electrical Systems and Information Technology*. 2014;1(3):198-211.