FAULT LOCATION OF UNBALANCED POWER DISTRIBUTION FEEDER WITH DISTRIBUTED GENERATION USING NEURAL NETWORKS

Farzad Dehghani
Lorestan Electric Power Distribution Company – IRAN
farzaddehghani81@yahoo.com

Fereydoun Khodnia
Lorestan Electric Power Distribution Company - IRAN
khodnia@barghlorestan.ir

Esfandiar Dehghan
Lorestan Electric Power Distribution Company – IRAN
esf.dehghan1340@gmail.com

ABSTRACT

This paper presents a new fault location method for an asymmetrical and unbalanced distribution feeder in the presence of distributed generations (DGs). In this study, a modified version of IEEE 34-bus test feeder with two fixed speed wind generators is considered. In the proposed method, at first, the type of short circuit is determined using the 3-phase current data that are measured at the substation. Then, to train and test the Artificial Neural Network (ANN), different operating patterns are produced for each type of short circuit. In order to cover the total operating space of the radial distribution network by ANNs; fault location, fault resistance, load of every node and power of DGs are changed in each pattern. For each type of short circuit, three different ANNs are used for estimation of the distance of fault to the substation and the interconnection of DGs. Inputs of the ANNs are 3-phase voltage and current which measured at the substation and the DG buses in pre fault and post fault stages. The results show low estimation error in testing of ANNs. For exact fault location, the estimated fault distance to the substation is compared with the estimated fault distance to the DG buses. Finally, the sensitivity of ANNs to the measuring error of the input data is examined.

INTRODUCTION

Detecting the exact location of short circuit is very complex in distribution networks in comparison with transmission networks due to the load uncertainty, high impedance of short circuit, and the fact that the distribution network is often unbalanced and asymmetrical [1]. The fault location methods are divided in two categories based on measured data as input: 1) the methods which use power frequency component of voltage and current [1-5], 2) the methods that use high frequency components of voltage and current [6]. The first group of methods is divided into four categories: 1) the methods based on measuring short circuit impedance [5], 2) smart methods [1-3], 3) the methods based on analysis of the form of voltage wave [7] and 4) other uncategorized methods [4].

By increasing the application of DGs, distribution networks have changed from one source radial feeders to multiple sources feeders. Consequently, the protection of distribution networks in presence of DGs is more complicated than the past. Moreover, employing the classic methods of fault location in new networks requires some corrections and modifications. Recently, many papers about fault location have been published in presence of DGs [2, 3 and 8].

ANNs are one of the smart methods which have been applied in many cases including the issues related to interpolation, data classification, etc. Zayandehroodi et al. [2] presented a fault location method using RBF ANN in distribution networks in presence of DGs. The authors did not consider fault impedance in their method. Additionally, their represented method is based on assuming a balanced and symmetrical network. Javadian et al. [3] presented another method in which they considered the effect of fault impedance; however they also assumed the distribution network as a balanced and symmetrical one. Furthermore, both above mentioned methods missed the analysis of sensitivity of ANN to measuring error of input data. Brahma et al. [8] represented a relatively comprehensive method based on Thevenin model of DG resources and distribution networks. They used synchronized voltage and current data measured at the substation and the interconnection of DGs. However, in their proposed method, the error of fault location estimation is relatively high in the case of low DGs penetration.

In this study, ANN is used for estimation of the distance between location of short circuit fault and the substation in an unbalanced and asymmetrical distribution network in presence of DGs. First, the type of short circuit is detected using 3-phase current data measured at the substation. Then, for each type of fault, 3 ANNs are trained to estimate the distance of fault to the substation and the interconnection of DGs. The inputs of each ANN are chosen both locally and globally and the achieved results are compared with each other. The global input data includes 3-phase currents and 3-phase voltages which are measured simultaneously at the substation and the interconnection of DGs. To train and test ANNs, the different operating patterns are created in a way that could cover all possible cases during and before short circuit in different locations of distribution network. For this reason, the value of fault resistance is changed in all patterns. For determining exact fault location, the outputs of 3 ANNs are compared with together. Finally, the sensitivity of ANNs to measuring errors of input data is investigated. The studied feeder in this project is a modified version of IEEE 34-bus test feeder with two fixed speed wind generators which is simulated by DIgSILENT power Factory 13.2 software.

PROPOSED METHOD

The scheme of proposed method is shown in Fig. 1. In the proposed method, first the type of fault is detected by the data of 3 phase current measured at the substation [1]. When the normalized current of one or more phase exceeds a defined threshold, this indicates that a short circuit has occurred on the feeder. The normalized current value of each phase of feeder is calculated by dividing the post-fault current to pre-fault current. In the case that an earth fault occurs, the zero sequence current also exceeds its normal value. When the zero sequence current surpasses the defined threshold, this indicates that the earth fault short circuit is occurred in one or more phases [1]. Next step is to train the Fault Distance to Substation Artificial Neural Network (FDSANN) for each type of short circuit, using the data of 3-phase current and 3-phase voltage measured at the substation and the interconnection of DGs. In addition to FDSANN, for each type of short circuit, according to the number of the DG units, Fault Distance to DG Artificial Neural Networks (FDGANNs) are trained to estimate the fault distance to the location of the interconnection of DGs. The FDGANNs use similar inputs to FDSANN. Finally, the exact fault location among the different branches of distribution network is chosen by comparison of the outputs of FDSANN and FDGANNs.

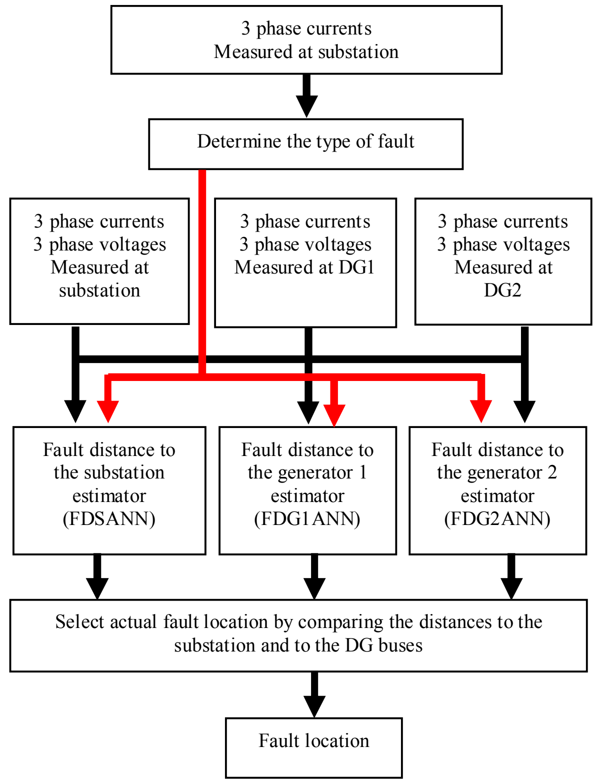

Figure 1. Flowchart of the proposed fault location method.

SIMULATION STUDIES

The proposed method is studied on IEEE 34-bus feeder in presence of two fixed speed wind generators simulated by DIgSILENT Power Factory 13.2 software [9-10]. The IEEE 34-bus network is a long feeder including 3-phase, 2-phase and one phase lines which feed unbalanced spot and distributed loads [1]. Additionally, a capacitor exists on the network. The active power of DGs at normal operation condition of network is 1320 kW equal to 74.6% of total load [10]. The single line diagram of the studied network is shown in Fig. 2. All ANNs use in this study are two layers Perceptron networks in which sigmoid tangent is transfer function of their hidden layer and the linear transfer function is their output layer. To train and test of ANNs, the ANN toolbox of Matlab 2012 software is employed.

Creation of operating patterns

To train and test ANNs, some patterns must be produced that cover all different pre-fault and post-fault conditions of distribution network. For this purpose, 20 short circuits are applied in different operating conditions per kilometer of distribution feeder. In each operating pattern, active power of spot and distributed loads are chosen randomly between 0 to 120% of nominal values. The power factor is chosen randomly between 75 to 95%. At each pattern, the active power of each DG unit is chosen randomly between 0 to 100% of rated power. The location of short circuit on each section is chosen randomly. The fault resistance is chosen randomly between 0 to 50 ohm. All variables are selected randomly with uniform distribution probability. 1632 patterns for A-G short circuit and 1249 patterns for 2-phase and 3-phase faults are produced. The patterns were selected in a way that load flow of network to be converged under normal operating condition. The line between 888 and 890 is not involved in training and testing stages, because of its different voltage (Fig. 2).

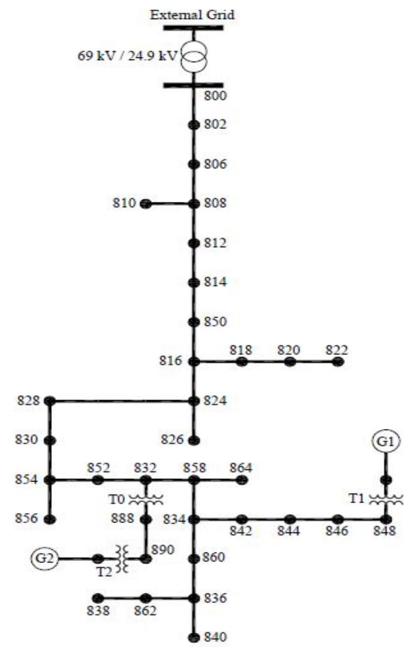

Figure 2. Single line diagram of IEEE 34-bus feeder with two fixed speed wind generators.

Detection of short circuit type and defining fault current threshold

The normalized current for each phase measured at the substation for A-B-G fault on different sections of feeder is shown in Fig. 3, for 1249 patterns. At all patterns, the normalized current of A and B phases is more than threshold ($I_{threshold}$= 3). By the extension of this method to all other types of short circuits, one can detect the fault type. Table 1 shows the detection method of fault type. By studying different types of short circuit and different conditions, the fault detection threshold for each of 3 phases is chosen as I_t=2.76. Moreover, the threshold of zero sequence of current is chosen as I_{t0}= 0.38.

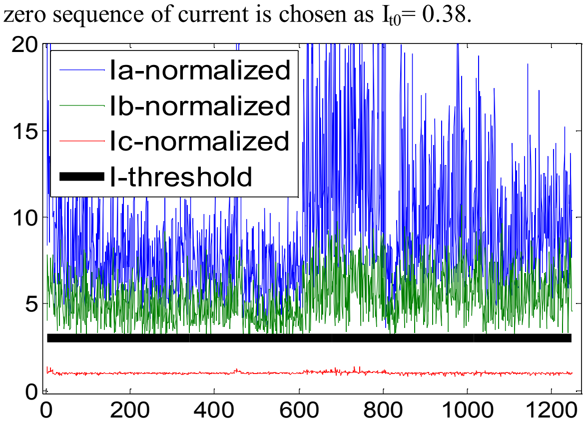

Figure 3. The normalized current for each phase for A-B-G fault on different sections of feeder for 1249 patterns.

Table 1. Determinating of the type of fault

Type of fault	$I_a > I_t$	$I_b > I_t$	$I_c > I_t$	$I_0 > I_{t0}$
A-G	true	false	false	true
B-G	false	true	false	true
C-G	false	false	true	true
A-B	true	true	false	false
A-C	true	false	true	false
B-C	false	true	true	false
A-B-G	true	true	false	true
A-C-G	true	false	true	true
B-C-G	false	true	true	true
A-B-C	true	true	true	-

Testing and training of ANNs

Given that the studied network contains 2 generators as DG units, FDG1ANN and FDG2ANN are trained for estimation of fault distance to DG1 and DG2, respectively. The inputs of ANNs are pre-fault and post-fault voltage and current data measured at the substation and the interconnection of DGs. The ANN is employed off-line for direct estimation of fault location. In fact, each ANN communicates between measured data and the fault distance to the substation or the interconnection of DGs. Phasors of current and voltage are chosen at one cycle before fault stage, to avoid overlapping pre-fault and post-fault data [1]. The post-fault phasors are selected 3 cycles after occurring of the fault to avoid the effect of motor currents [1]. Moreover, the zero sequence of current is employed as the input of the ANN to make it powerful enough to estimate and differentiate the earth faults from the rest. The current and the voltage phasors of DG1 and DG2 are measured at 848 and 890 buses, respectively. The studied ANNs are the feed-forward type which Levenberg-Marquardt is their training method. The amount of estimation error of each ANN is described by the mean square error (MSE) [1]. Each ANN is trained by using 75% of patterns. Afterward, the ANN is tested using the left 25% of the patterns which have not been used for training. The error of ANNs for testing patterns is shown at Table 2 for different types of short circuits and different inputs. As shown in table 2, the test error of ANN for one phase short circuit to the earth is more than the other short circuit types. The least test error belongs to 3 phase short circuit. Moreover, when the inputs of the ANNs are global and measured simultaneously at the substation and the interconnection of DGs, the estimation error is smaller than the condition in which local inputs are employed. Additionally, in condition that the inputs of FDSANN are only local data measured at the substation, and if only the patterns to be used that the total amount of active power of DGs is lower than 25% of total load, the test error is acceptably low, so that FDSANN could estimate fault location by using local inputs alone (Table 2). If the injection percent of DGs increases, the FDSANN estimation error for local inputs will increase. So, in this condition the inputs have to be chosen globally. Furthermore, the FDG1ANN and

FDG2ANN test errors for global inputs are in an acceptable range. The FDSANN outputs of test patterns in compare with real amounts of fault distance to the substation for A-G fault according to global inputs is shown in Fig. 4.

Table 2. Test error of ANNs for all types of short circuits and different inputs.

ANN	ANN inputs measured at:	Penetration ratio of DGs	Test error according of type of faults (MSE %)			
			A-G	A-B	A-B-G	A-B-C
FDSANN	The substation	P_{DG} < %25	0.049	0.0097	0.0084	0.0075
		P_{DG} < %75	0.0915	0.0403	0.0395	0.0366
	The substation, DG1, DG2	P_{DG} < %75	0.032	0.0066	0.0038	0.0026
FDG1ANN	The substation	P_{DG} < %75	0.0808	0.0329	0.0301	0.0277
	The substation, DG1, DG2		0.024	0.0054	0.0041	0.0018
FDG2ANN	The substation	P_{DG} < %75	0.0756	0.0260	0.0254	0.0212
	The substation, DG1, DG2		0.028	0.0071	0.0034	0.0032

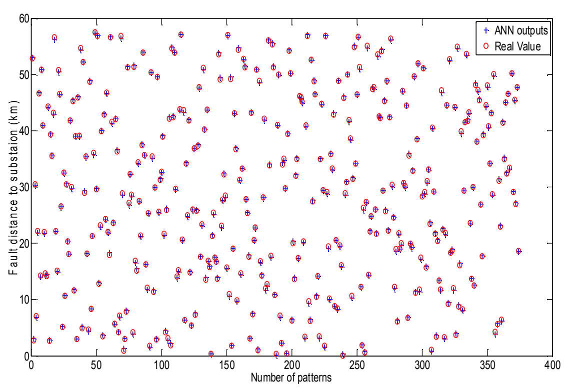

Figure 4. FDSANN outputs and target values for the test patterns of A-G fault.

Determination of exact fault location

A distribution feeder contains numerous branches in which short circuits may occur. For this reason, several situations could happen in which the distance of fault location on different lines of a feeder to the substation are equal, so the FDSANN outputs of all of those lines are equal. Therefore, determining the exact fault location in those cases is not possible using FDSANN alone. In this study, in the explained conditions, the exact fault location and the line in which the fault occurs are detected using FDG1ANN and FDG2ANN outputs and their comparison with that of FDSANN output. Some examples of situations in which the FDG1ANN and FDG2ANN outputs have been used to define exact fault location are shown in Table 3. The line using FDSANN, FDG1ANN and FDG2ANN has been jointly estimated as fault location (marked by red) is chosen as the exact fault location. As it is shown in line 4 of table 3, there is a situation in which all 3 networks indicate 2 common lines as the exact fault location. So, in such a situation the exact fault location could not be defined by our proposed method. In those cases, the real fault location could be determined by using extra equipments like a fault-detector installed on the feeder.

STUDYING SENSITIVITY OF ANNS TO MEASURING ERRORS OF INPUT DATA

The accuracy of each ANN depends on the correctness of electrical values used as inputs. The measuring errors for current and voltage phasors based on IEC standard have to be at the range of -3% to 3% and -5% to 5%, respectively. The measuring errors of input values cause a significant amount of estimation error of each ANN. To overcome this obstacle, each of ANNs that trained before, retrain with error-contained input data. For producing the training and testing patterns which contained measuring errors, voltage and current phasors are multiplied with a random numbers at range of 0.95 to 1.05 and 0.97 to 1.03, respectively. The test error of each ANN for measuring error-contained data is shown in table 4. In condition that ANNs are trained with non-measuring error patterns alone, the test error for the measuring error-contained patterns is high; while, the test error of retrained ANNs is much lower and in an acceptable range (Table 4).

Table 3. Exact fault location for some samples by using outputs of FDSANN, FDG1ANN and FDG2ANN

Type of fault	Fault occurred on line:	Real fault distance to substation (km)	FDSANN output	Candidate lines according FDSANN output	FDG1ANN output	FDG2ANN output	Candidate lines according FDG1ANN output	Candidate lines according FDG2ANN output	Selecting common line as faulty line
A-G	818-820	33.27	33.24	**818-820** 816-824	27.47	22.53	**818-820** 812-814	**818-820** 812-814	**818-820**
A-G	854-852	45.95	45.91	**854-852** 854-856	9.42	4.46	**854-852**	**854-852** 844-846 860-836	**854-852**
A-B	844-846	57.12	57.10	**844-846** 860-836	0.75	4.36	**844-846**	**844-846** 860-836 854-852	**844-846**
A-B-C	836-862	57.47	57.46	**836-862** **836-840**	3.22	4.73	**836-862** **836-840**	**836-862** **836-840**	**836-862** **836-840**

Table 4. Test errors of ANNs for data contained measuring error for global inputs

Type of fault	ANNs trained by data without measuring error			ANNs trained by data contained measuring error		
	FDSANN	**FDG1ANN**	**FDG2ANN**	**FDSANN**	**FDG1ANN**	**FDG2ANN**
A-G	0.531	0.324	0.427	0.041	0.035	0.034
A-B	0.402	0.231	0.355	0.0078	0.0072	0.0091
A-B-G	0.381	0.219	0.302	0.0047	0.0051	0.0048
A-B-C	0.375	0.216	0.321	0.0035	0.0032	0.0041

CONCLUSION

In this paper, a new fault location method was introduced for distribution networks in presence of DGs using ANNs. The proposed method was tested on an asymmetrical and unbalanced distribution network with a low estimation error. The ANN could estimate correctly the distance of fault location to the substation using global inputs. For detecting exact fault location in different branches of distribution feeder, several other ANNs were applied for estimation of fault distance to the interconnection of DGs. Moreover, it was indicated that in condition in which the DG penetration is low, the ANN could estimate the accurate fault location only by using local inputs. Finally, the proposed method was modified in a way that despite existing measuring error in the inputs, the ANN kept its ability to estimate fault location correctly.

REFERENCES

[1] F. Dehghani and H. Nezami, "A new fault location technique on radial distribution systems using artificial neural network", *Electricity Distribution (CIRED 2013)*, 22nd International Conference and Exhibition on, 10-13 June 2013.

[2] H. Zayandehroodi; A. Mohamed; H. Shareef; M. Mohammadjafari, "Determining exact fault location in a distribution network in presence of DGs using RBF neural networks", *Information Reuse and Integration (IRI)*, 2011 IEEE International Conference on, 3-5 Aug. 2011.

[3] S. Javadian, M. Haghifam, and N. Rezaei, "A fault location and protection scheme for distribution systems in presence of dg using mlp neural networks," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2009, pp. 1–8.

[4] R. K. Aggarwal, Y. Aslan, and A. T. Johns, "An interactive approach to fault location on overhead distribution lines with load taps," in *Proc. 6th Int. Conf. Develop. Power Syst. Protect.*, Nottingham, U.K., Mar. 1997,pp. 184–187.

[5] J. Mora-Florez, J. Meléndez, and G. Carrillo-Caicedo, "Comparison of impedance based fault location methods for power distribution systems," lect. Power Syst. Res., vol. 78, pp. 657–666, Apr. 2008.

[6] Z. Q. Bo et al., "Accurate fault location technique for distribution system using fault-generated high-frequency transient voltage signals," *IEEE Proc. Gener. Transmiss. Distrib.*, vol. 146, no. 1, pp. 73–79, Jan. 1999.

[7] S. Lotfifard, M. Kezunovic, and M. J. Mousavi, "Voltage sag data utilization for distribution fault location," *IEEE Trans. Power Del.*, vol. 26, no. 2, pp. 1239–1246, Apr. 2011.

[8] S. M. Brahma, "Fault location in power distribution system with penetration of distributed generation," *IEEE Trans. Power Del.*, vol. 26, no. 3, pp. 1545–1553, Jul. 2011.

[9] W. H. Kersting, "Radial distribution test feeders," in *Proc. IEEE Power Eng. Soc*. Winter Meeting, 2001, vol. 2, pp. 908–912.

[10] R. C. Dugan and W. H. Kersting, "Induction machine test case for the 34-bus test feeder-description," presented at the *IEEE Power Eng. Soc. Gen*. Meeting, 2006.