The Journal of CPRI,
Vol. 10, No. 2, June 2014 pp. 245-252

High Impendance Fault Detection in Distribution System under Distributed Generation

Manohar Singh*

Conventional power distribution systems are radial in nature, characterized by a single source feeding a network of downstream feeders. Location of faults in such power networks is very challenging when fault resistance is quite high. In distribution systems, fault location algorithms primarily utilize the fault current amplitude for deciding the nature and location of the faults. However, the distribution systems become radial nature when distributed generation sources are connected with them. Under such circumstance mere magnitude of fault current is not sufficient to locate and classify the fault on the power feeders. Additional fault informations are required for identification of faults in the interconnected power distribution systems.

This presented paper suggests a novel algorithm, which can detect the high impendence fault based on transient behavior of fault currents. The proposed algorithm utilizes the transient energy content of the high impendence fault signals for detecting the faults in the distribution networks. The PSCAD/EMTDC software is used for simulation for the faults in the power network under study.

Keywords: *Transient energy, Distributed generation, Discrete wavelet transform, High impendence fault.*

1.0 INTRODUCTION

In the last decades, electric power systems undertook several modifications toward a more decentralized energy system paradigm, allowing the increase of distributed generation *(DG)* penetration in the power networks at low voltages. Connection of new *DG* fundamentally alters the distribution network operation and creates a variety of impacts on protective relaying, reclosing and distribution automation *(DA)* which is based on feeder terminal unit *(FTU)*. Currently distribution automation solution based on feeder terminal unit *(FTU)* has been successfully applied in urban distribution networks. In these schemes the *FTU* are installed on the disconnect switches and plays the role of the over-current fault detector. The fault informations such as over-current fault states and over-current amplitudes are sent by *FTU* to the master system. There after the master system performs fault location, isolation and restoration function by utilizing the appropriate actions.

Conventional power distribution systems are radial in nature with unidirectional flow of power from one end to another. Penetration of new DG energy sources causes bidirectional flow of the fault currents on the feeders of the distribution systems. In order to detect the correct location and nature of the faults on the power feeders under such circumstance both the magnitude and direction of the fault currents required.

*Engineering Officer Grade-3, Power System Division, Central Power Research Institute, Bangalore-560080. Mobile: +91 9632940855, Email: manoharsingh@cpri.in

The detection and location of high impedance faults *(HIF)* in power distribution systems *(PDS)* is a great challenge for the power community [1]. This is due to highly non-linear nature of fault signals which are utilized by fault detection and location algorithms. *HIF* are low current faults and are very difficult to be detected by conventional overcurrent relays. Moreover, the nature of HIF may similar to normal load currents which were varying due to normal load change. This poor magnitude of fault currents may lead to the failure of existing over current based protection schemes. Mostly *HIF* faults in the distribution systems are due to broken conductors or its contact with poorly grounded objects, like trees, vehicles and wood fences. In order to analysis the impact of *HIF* on the fault detection techniques, several studies have been made in the past and are available in the literature [2]–[3]. This paper discusses a new fault detection and location scheme for investigation of *HIFs* in feeders with *DG* for reduction of the restoration time. The proposed methodology is based on the use of particular features of *HIF* and artificial neural networks *(ANN)*. This paper is organized in different sections. Section-1 discusses the general introduction regarding the detection of *HIF* in the distribution systems. In section-2, the *HIF* fault model used in this study is presented. In the section-3, the impacts of distributed generation in *PDS* are discussed. In the section-4, a brief introduction to *ANNs* is presented. Section-5, presents brief introduction on *ANN*. Results are discussed in section-6 of this paper. Finally the conclusions and future scope of work are discussed at the end of the paper.

2.0 HIF MODELLING

In this paper, a *HIF* is modeled to very similar to real faults. The proposed *HIF* model also takes into account the existence of an electric arc at the fault point. Electric arc has a voltage/current nonlinear relation and might show an asymmetric behavior of the positive half cycle with respect to the negative cycle. This model is illustrated in Figure 1 [4].

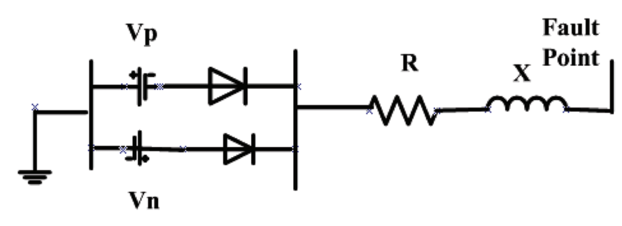


FIG. 1 HIF MODEL

The *HIF* is modeled with two absolute DC sources in series with diodes. During the positive half cycle, the current flows through V_p and during the negative, though V_n. These voltage values are maintained constant during the simulations. The harmonic content generated by the fault are functions of the voltage difference $V_n - V_p$ and the relation *XL/R*.

3.0 DISTRIBUTED GENERATION IMPACTS

The addition of new generation units to the power distribution feeders has significant impact on the overall operation of these systems. As it is a new source of power inside the system, the main change introduced by the addition of *DG* in *PDS* is the loss of its radial characteristic.

The addition of *DG* changes the original power flow, making a modification in the protection systems settings necessary. Thus, the protection equipment that has protection routines and settings for a specific circuit could work improperly [5]. For detection of faults on the radial feeder, the magnitude of the fault signals are sufficient. But in case of bidirectional angle information of the fault signals are also required for detection of the faults in the *PDS* under *DG* penetration [6].

4.0 DISCRETE WAVELET TRANSFORM

Discrete wavelet transform is found to be useful in analyzing transient phenomenon such as that associated with faults on the transmission lines. Multi-Resolution Analysis *(MRA)* [7] is one of the tools of Discrete Wavelet Transform *(DWT)*, which decomposes original signal typically non-stationary signal into low frequency signals called approximations and high frequency signals called details, with different levels or scales of resolution. It uses a prototype function called mother wavelet [8], [9]. At each level of multiple decomposition, approximation signal is obtained by convolving signal with low pass filter followed by dyadic decimation, whereas detail signal is obtained by convolving signal with high pass filter followed by dyadic decimation. The decomposition tree is shown in Figure 2.

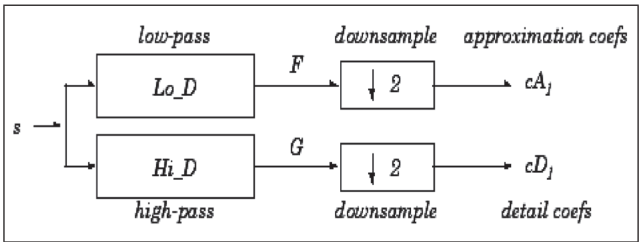


FIG. 2 WAVELET TRANSFORM *(MRA)*

The *DWT* maps the one dimensional time domain signal f (t) into two dimensional signals as:

$$f(t) = \sum_k c_j(k)\Phi(t-k) + \sum_k \sum_j d_j(k)\psi(t-k)^{2-j} \qquad ....(1)$$

Where c_j, d_j are approximate and detail coefficient respectively; ϕ *(t)* and ψ(t) are scaling and wavelet functions respectively and *J* is the decomposition level [9].

5.0 NEURAL NETWORKS

The feasibility of using artificial neural network *(ANN)* for transmission line protection has been confirmed. *ANN* consists of highly distributed interconnections of nonlinear processing elements and can be considered as an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data. Neural networks are used for both regression and classification. In regression, the outputs represent some desired, continuously valued transformation of the input patterns. In classification, the objective is to assign the input patterns to one of several categories. *ANNs* possess excellent features such as generalization capability, noise immunity, robustness and fault tolerance [10]. Therefore, the decisions made by *ANN* based relaying algorithm will not be seriously affected by variations in system conditions. For this, neural network for a particular application must be trained. There are different training algorithms for feed-forward networks [11]. All of these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance function. The gradient is determined using a technique called back propagation which involves performing computations backwards through the network.

A variation of back propagation algorithm is called Levenberg-Marquardt *(LM)* algorithm and is used for neural network training [12]. Since this algorithm is one of the fastest methods for training moderate-sized feed forward neural networks. The *LM* algorithm which updates the weights is expressed as:

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \qquad ....(2)$$

Where J is the Jacobian matrix that contains first derivatives of network errors with respect to the weights and biases, e is a vector of network errors, $J^T J$ is an approximation of Hessian matrix, the gradient is $J^T e$ and μ is a scalar affecting the performance function.

6.0 THE IMPLEMENTATION OF PROPOSED METHODLOLIGY

The use of transient energy of higher harmonics is used to detect HIF in this research paper. During simulation it is seen that transient energy of harmonics corresponding to fault signals have unique aspects due to the occurrence of HIFs. Its value is obtained by discrete wavelet transform decomposition using multiple resolution analysis (MRA) of simulated fault current signals [13].

The proposed scheme utilizes fault current signals which are obtained from Current Transformers (CT's) connected on the faulty feeders. Flow chart of the methodology is shown in Figure 3. In this flow chart the discrete wavelet transform of the fault signals are performed to extract the transient energy content which is further utilized for the detection of the faults on the distribution feeders.

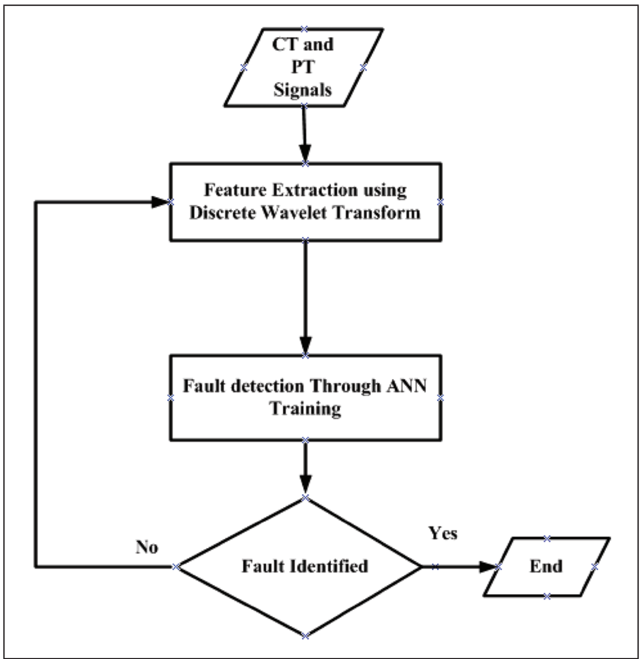


FIG. 3 FAULT DETECTION ALGORITHM

6.1 Network Simulation

The training data sets for an *ANN* were obtained from network simulation of a typical distribution system as shown in Figure 4. The test power network consists of a conventional synchronous machine connected to a transmission on which the faults are detected. A wind mill is connected at remote end of the transmission line. The performance of the proposed fault detection algorithm is tested for remote end connected distributed energy resources. The control feedback control system of wind mill is also shown in the Figure. The details of networks data are available in the PSCAD simulation software.

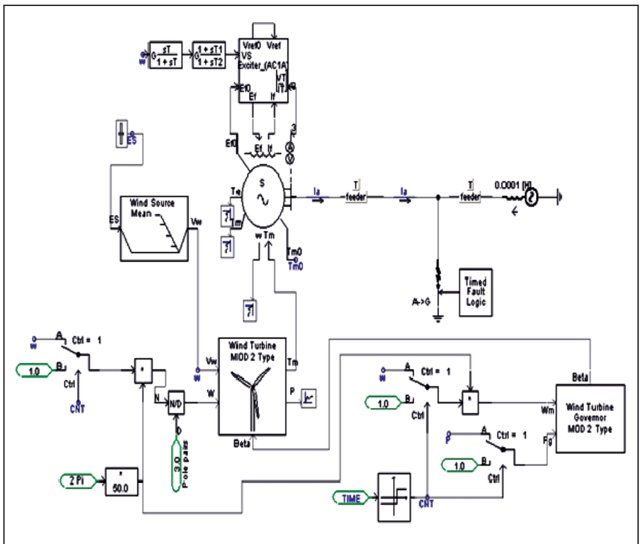


FIG. 4 DISTRIBUTED GENERATION MODEL

Digital simulations were performed using an electro-magnetic transient program PSCAD/EMTDC [14] for different types of faults, fault location, fault resistance and fault inception angle. Conditions considered for training pattern data generation is shown in Table 1.

TABLE 1	
SYSTEM PARAMETERS USED FOR GENERATION OF TRAINING PATTERNS	
Fault type	a-g, b-g, c-g, a-b, b-c, c-a, a-b-g, b-c-g, c-a-g, a-b-c and a-b-c-g
Fault resistance (Ω)	0 10 , 20 , 50 , 100
Fault inception angle (0')	0, 45, 90, 135, 180, 225, 270, 315 and 360

For each simulated case the faults were applied in 10 different locations in each feeder. Of these 10 positions, 8 were used in the ANN training process while the other 2 were used as test cases for the trained ANN model. The conditions for the test case generation are listed in Table 2.

Simulated waveforms for single line ground fault current for the fault on the transmission are shown in Figure 5 below.

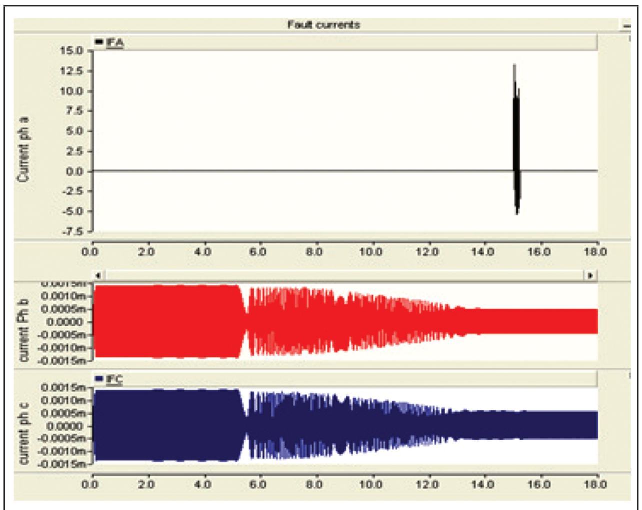


FIG. 5 SIMULATED THREE PHASE FAULT

TABLE 2	
SYSTEM PARAMETERS USED FOR GENERATION OF TESTING PATTERNS	
Fault type	a-g, b-g, c-g, a-b, b-c, c-a, a-b-g, b-c-g, c-a-g, a-b-c, a- b-c-g
Fault resistance (Ω)	5 Ω, 30 Ω, 55 Ω, 80 Ω, 105 Ω, 135 Ω ,155Ω
Fault inception angle (0’)	0, 60, 120, 180, 240, 300, 360

6.2 Feature extraction

The feature extractor is used to extract the feature for the raw fault signals. The processes data obtained from the feature extractor are input signals that is used in the next processing block (*ANN* training) [15]. The input current signals are captured at 5 KHz sampling frequency. These input patterns obtained from the feature extractor are the transient energy of harmonics of discrete three phase fault current samples. Discrete wavelet transform is used for feature extraction. *DB 4* is used as mother wavelet (change in transient energy of decomposed coefficients for fault samples is clearly observable at db-4 mother wavelet) and level 2 decomposition is used for feature extraction using multiple resolution analysis (MRA).In Figure 6 below the details coefficients of harmonics of fault current and healthy current are shown.

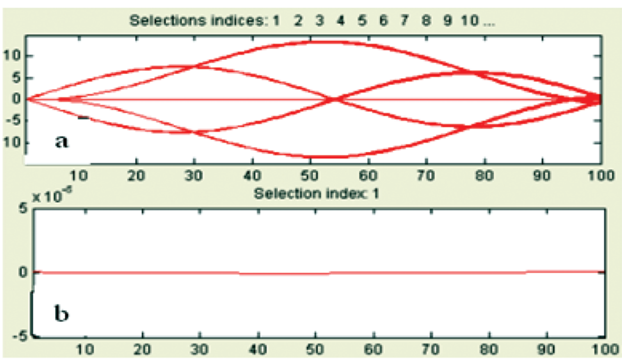
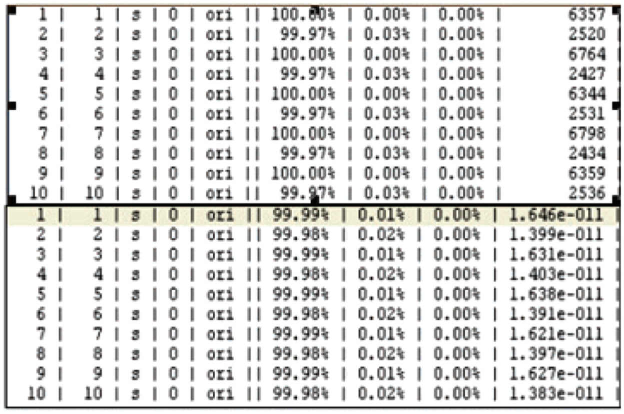


FIG. 6 DETAILED COEFFICIENTS (A) FAULTY PHASE (B) HEALTHY PHASE

Figure 7 shows the value of transient energy of higher harmonics for fault signal and healthy signals. From Figure 7 it is clearly observable that magnitude of transient energy for fault is quite higher than the non-fault signals due the presence of higher frequency transient signals.



1	1	s	0	ori	100.00%	0.00%	0.00%	6357
2	2	s	0	ori	99.97%	0.03%	0.00%	2520
3	3	s	0	ori	100.00%	0.00%	0.00%	6764
4	4	s	0	ori	99.97%	0.03%	0.00%	2427
5	5	s	0	ori	100.00%	0.00%	0.00%	6344
6	6	s	0	ori	99.97%	0.03%	0.00%	2531
7	7	s	0	ori	100.00%	0.00%	0.00%	6798
8	8	s	0	ori	99.97%	0.03%	0.00%	2434
9	9	s	0	ori	100.00%	0.00%	0.00%	6359
10	10	s	0	ori	99.97%	0.03%	0.00%	2536
1	1	s	0	ori	99.99%	0.01%	0.00%	1.646e-011
2	2	s	0	ori	99.98%	0.02%	0.00%	1.399e-011
3	3	s	0	ori	99.99%	0.01%	0.00%	1.631e-011
4	4	s	0	ori	99.98%	0.02%	0.00%	1.403e-011
5	5	s	0	ori	99.99%	0.01%	0.00%	1.638e-011
6	6	s	0	ori	99.98%	0.02%	0.00%	1.391e-011
7	7	s	0	ori	99.99%	0.01%	0.00%	1.621e-011
8	8	s	0	ori	99.98%	0.02%	0.00%	1.397e-011
9	9	s	0	ori	99.99%	0.01%	0.00%	1.627e-011
10	10	s	0	ori	99.98%	0.02%	0.00%	1.383e-011

FIG. 7 TRANSIENT ENERGY CONTENT

The input patterns (training and test patterns) are normalized to [+1,-1] before passing to the *ANN* training module. The main advantage of normalization is to avoid attributes in greater numeric ranges that dominate which are in smaller numeric ranges.

6.3 Design of Fault Classifier Unit

The major issue in the design of *ANN* architecture is to ensure that when choosing the number of hidden layers and number of neurons in the hidden layers, its attribute for generalization is well maintained. In this respect, since there is no parametric/theoretic guidance available, the design has to be based on a heuristic approach [16]. The selected structure of the *ANN* unit is shown in Figure 8. Hyperbolic tangent function was used as activation function for the neurons in the hidden layers [17]. Pure linear function is the activation function for the neurons of the output layer.

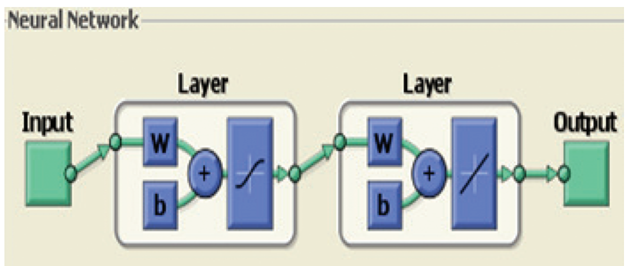


FIG. 8 NEURAL NETWORK STRUCTURE

The *ANN* output layer consists of 4 neurons. Four outputs of the scheme corresponding to each phases and neutral of the system. Based on the fault type that might occur on the system, each of the network outputs should be either 0 or 1.The the numbers of hidden neurons are 15.

Figure 9 shows the training graph obtained with the Levenberg-Marquardt algorithm while training the neural network, of the proposed fault identifier scheme. From Figure 9, it is seen that the error rapidly converges to the desired level and the training has stopped after 99 iterations,

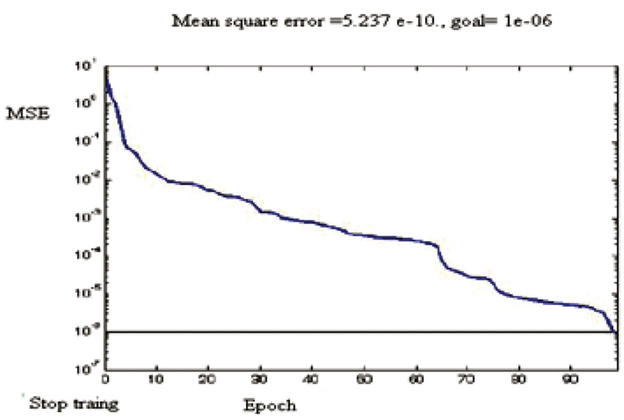


FIG. 9 MSE REDUCTION DURING TRAINING OF FAULT CLASSIFIER

after reaching the set desired *MSE* of 1e-06. The performance of a trained network can be measured to some extent by the errors on the training, validation and test sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets. The *MSE* is reduced to order of e-10 even though goal is e-06. Figure 10 shows only one of the four graphical outputs provided by regression analysis. The network outputs viz phase 'a' is plotted versus the targets as open circles. The best linear fit is indicated by a solid line. Output of regression line 1 indicates fault is detected.

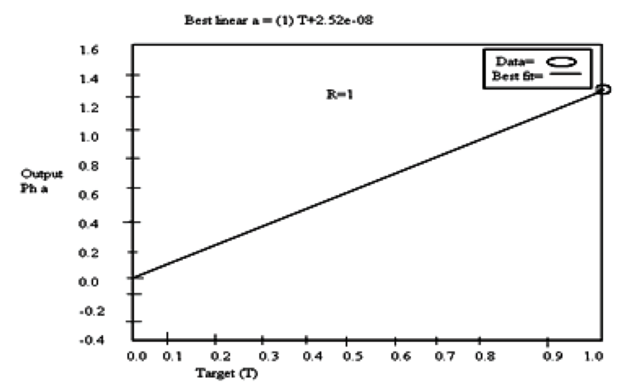


FIG. 10 REGRESSION ANALYSIS FOR PHASE A-G FAULT

The result of fault detection on different phases of a distribution feeder is tabulated in Table 3. The proposed protection scheme is independent of fault current magnitude. Training of extracted feature is provided with ANN. Then trained structure is tested for different simulated fault samples. It is observed that fault is detected with high accuracy. The effect of non-linear nature of fault resistance on the fault detection has little effect since non-linear feature of fault is used for fault detection.

TABLE 3

TEST RESULT OF FAULT DECTOR

Fault Type	**Fault Location**	**Fault inception angle**	**Fault Resistance**	**ANN Output**			
				Phase a	**Phase b**	**Phase c**	**Neutral**
a-g	10	90	10	0.9870	0.0030	0.0056	1.0350
b-g	15	45	0	0.0230	1.2040	-0.035	0.9750
c-g	20	0	50	0.0560	0.5600	1.035	0.8900
a-b	25	135	20	0.9560	1.4608	0.4572	0.3567
b-c	30	225	100	0.3300	1.2403	1.2670	0.2980
ac-g	35	270	10	0.8976	-0.369	1.2640	0.9378
abc-g	40	45	20	1.2075	1.1562	0.9672	0.8452

As discussed above, the fault classifier gives the output 1 when there is sufficient high transient energy content in the input signal. From the Figure 7, it is clear that the transient energy content of a fault phase is very high as compare to the non-faulty phases. The fault classifier maps the high transient content near to 1 and low transient energy content near to 0.

7.0 CONCLUSION

In this paper research paper a novel fault detection methodology for power distribution feeders with distribution generation is proposed. The proposed scheme is capable to lead precise fault detection and location estimations for both linear and non-linear HIF faults.

The proposed scheme is based on the signature extraction using the wavelet theory and training the ANNs structure. In the proposed fault detection scheme the transient energy content of the high frequency component of faulty signal are utilized for training the ANN structure. Based upon the level of input, the ANN differentiates the fault as per their nature and location. In the proposed fault detection scheme direct magnitude of the fault currents are not utilized and hence it is immune to the impact of HIF on the fault location algorithms.

REFERENCES

[1] B. Bhalja and R. P. Maheshwari, “Philosophy of protection for multi-terminal and double-circuit lines,” In Proc. Int. Conf. on Computer Applications in Electrical Engineering Recent Advances, Roorkee, India, Sept. 28–Oct. 1, 2005, pp. 582–588.

[2] C. G. Wester, “High impedance fault detection on distribution systems,” In Proc. 42nd Rural Electric Power Conference, 1998, pp. c5–1–5.

[3] C. L. Benner and B. D. Russel, “Practical high-impedance fault detection on distribution feeders,” IEEE Transactions on Industry Applications, vol. 33, no. 3, pp. 635–640, May. 1997.

[4] F. G. Jota and P. R. S. Jota, “High-impedance fault identification using a fuzzy reasoning system,” In Proc. of IEE Generation, Transmission and Distribution, vol. 145, no. 6, pp. 656–661, Nov. 1998

[5] Zhang Chao, JiJian-ren, et al. “Effect of distributed generation on relay protection and automation of distribution network,” East China Electric Power, vol.34, pp.23-26, Sep.2006.

[6] Kim C.H., Aggarwal, R., “Wavelet transforms in Power systems,” IET Power Engineering Journal, vol. 15, pp. 193-200, Aug. 2001.

[7] S. G. Mallat, “A theory for multi-resolution signal decomposition: The wavelet representation,” IEEE Trans. Pattern Anal. Mach. Intell., vol.11, no. 7, pp. 674–693, Jul. 1989.

[8] C. S. Burrus, R. A. Gopinath, and H. Guo, Introduction to Wavelets and Wavelet Transform: A Primer. Englewood Cliffs, NJ: Prentice-Hall, 1998.

[9] D. Das, N.K. Singh and A.K.Sinha, “A Comparison of Fourier transform and wavelet transform methods for detection and classification of faults on transmission lines”, In Proc. of IEEE Power India Conf., 2006.

[10] S. J. Huang and C. T. Hsieh, “High-impedance fault detection utilizing a Morlet wavelet transform approach,” IEEE Trans. Power Delivery, vol. 14, no. 4, pp. 1401–1410, Oct. 1999.

[11] S. J. Lee, M. S. Choi, S. H. Kang, B. G. Jin, D. S. Lee, B. S. Ahn, N. S. Yoon, H. Y. Kim, and S. B. Wee, “An intelligent and efficient fault location and diagnosis scheme for radial distribution systems,” IEEE Transactions on Power Delivery, vol. 19, no. 2, pp. 524–532, Apr. 2004.

[12] A. E. Emanuel, D. Cygansky, J. A. Orr, S. Shiller, and E. M. Gulachenski, “High impedance fault arcing on sandy soil in 15kv distribution feeders: Contributions to the evaluation of the low frequency spectrum,”

IEEE Trans. on Power Delivery, vol. 5, no. 2, pp. 676–686, Apr. 1990.

[13] M. E. Baran and I. El-Markaby, "Fault analysis on distribution feeders with distributed generators," EEE Transactions on Power Systems, vol. 20, no. 4, pp. 1757-1764, Oct. 2005.

[14] D. T. W. Chan and X. Yibin, "A novel technique for high impedance fault identification," IEEE Trans. Power Delivery., vol. 13, no. 3, pp. 738–744, Jul.1998.

[15] S. Ebron, D. L. Lubkeman, and M. White, "A neural network approach to the detection of incipient faults on power distribution feeders," IEEE Trans. Power Delivery., vol. 5, no. 2, pp. 905–914, Apr. 1990.

[16] H.Khorashadi-Zadeh, "Artificial neural network approach to fault classification for double circuit transmission lines," In Proc. of IEEE Transmission and Distribution Conf., pp.859-862, 2004.

[17] MATLAB 7.1 User's Guides for SimPower System, Wavelet Toolbox and Neural Network Toolbox.