DETECTION OF HIGH IMPEDANCE FAULT LOCATION IN 20 KV UNDERGROUND DISTRIBUTION NETWORKS BY DISCRETE WAVELET TRANSFORMATION

[a*]NASER RAHIMI, [b]SAMRAND SHARIFI

[a]*Department of Electrical Engineering, Bonab Branch, Islamic Azad University, Bonab, Iran*
[b]*Department of Electrical Engineering, Boukan Branch, Islamic Azad University, Boukan, Iran*

Email: [a]naser_rahimi_1478@yahoo.com,[b]sa.sh.mn@gmail.com

Abstract. Different designing approaches for detection of the high impedance fault occurrence location are investigated in this paper and the main goal of representing this research is to design a software system for 20 KV distribution networks in Iran. Machine learning for high impedance fault detection, finds the location of fault by feature extraction using discrete wavelet transform and applying partial and approximate coefficients and following that using the multi-class Support Vector Machine classification, provides the possibility of fault estimation. Results are indicative of appropriate performance of system and fault detection accuracy in training and testing states and some problems like uncertainties and relation with actual output, are removed.

Key words: high impedance fault, electrical protection, machine learning, wavelet transform, support vector machine.

1. Introduction

Occuring high ampedance faults in transmission and distribution systems can lead to irreparable faults and therefore it is purposed to first: the place of this occurrence be determined accurately and second: the possibility of predicting it be provided. However it is clear that location of high impedance fault is as a main challenge for current and voltage of network, the greatest impact of this issue and addressing it indicates itself in electrical protection (Akorede and Katende, 2010). Moreover, complexities such as voltage and current levels being heterogeneous and existence of side branches in distribution and transmission system have increased the location of high impedance fault. Ordinary fault which is known as high impedance fault in distribution network will be hardly detectable because of current intrinsic increase which gets form following resistance value limitation (Sedighizadeh et al. 2010). Now a day it is need to a powerful and strong system exist that detect this fault automatically. In most of cases, researchers in recent years were looking for designing this intelligent system, but they have not found convenient tool. It seems that the best tool for making intelligent in this field is artificial intelligence which can detect this fault automatically. But in order to automate the finding this fault, in a few researches the multiple factors such as time, accuracy, and confidence factor of fault occurrence location is considered. Therefore, the importance of research gets raised in terms of finding the fault quickly and accurately.

2. Related systems

Another approach is to apply detection based on electrical components of transmission line. These methods are based on analysis of voltages and currents of beginnings of feeders and are divided to four parts in a general class:

1. presented method in time domain (Kumar, 2014)
2. presented method in frequency domain (Michalik, 2006)
3. presented method in time-frequency domain (Samantaray and Dash, 2009)
4. intelligent combined methods (Bakar et al. 2014)

For systems which are grounded in some points, the angle and domain of unbalanced load current (I_0) is not constant and fault current is variable too. Therefore, over current relays cannot be made sensitive. If a relay can sense only the fault current, its sensitivity increases. In suggested relays by attention to simplicity of measuring the unbalanced load current (I_0), system current (I_N), fault current (I_F), based on equation (1) are calculated and leads to relay operation (Sedighi et al. 2005).

$$I_F = k_1 I_0 + k_2 I_N \tag{1}$$

In which I_0 and I_N are unbalanced load current and neutral wire current respectively and k_1 and k_2 are constant. Considering this issue that these faults are impressible of other physical and environmental factors, a unique technique cannot effectively lead to detect all of them, therefore, some researchers for increasing the reliability of made devices use intelligent techniques or some techniques simultaneously to detect the high impedance (Milioudis et al. 2015).

Lai et al. in 2008 represented a model which includes two variable resistances with serried time and is controlled by EMTP/ATP models. Sharaf in 2004 defines the detection of high impedance fault method in time domain based on low frequencies (third and fifth circulation harmonics patterns). Marek Michalik et al. in 2006 provided a simple and effective method for detecting high impedance in distribution systems by wavelet transformation technique. Samantaray in 2012 introduced an intelligent method for detecting high impedance in power distribution feeders by advanced signal processing techniques such as time-time, time-frequency combined with neural networks.

3. Suggested controllers

Using feature extraction model and classifying by support vector machine as the main cores of intelligent systems are suggested that will be introduced in following.

Three phase voltage signal
Location of fault detection
Feature extraction
Type of fault detection
Classification
Location Multiclass classification
Making decision about fault

3.1 Feature extraction from signal with wavelet transformation

Discrete wavelet transformation is applied as an efficient transformation in feature extraction. After preprocessing of line signal by decomposing to wavelet coefficients, we transform it to different signals. Every stage of this process includes two digital filters and down-sampler with sampling factor of 2. In first filter, g is discrete base wavelet and intrinsically high-pass and h is mirror version of the same wavelets which are intrinsically low-pass.

The output of first order down-sampler for high-pass filters includes partial coefficients D1 and approximate coefficients A1 respectively. The first approximate equation is A1 which is decomposed more than other coefficients. All of the wavelet transformation can be indicated in the form of an equation of low pass filter which satisfies the equation (2) conditions.

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1 \tag{2}$$

In which the H (z) is the z transformation function of filter h and the supplement of high pass filter can be indicated based on equation (3):

$$G(z) = zH(-z^{-1}) \tag{3}$$

A series of filters with increasing length (with index i) can be shown with equation (4):

$$H_{i+1}(z) = H(z^{2^i})H_i(z) \quad i = 0,..., I - 1 \qquad (4)$$
$$G_{i+1}(z) = G(z^{2^i})H_i(z)$$

In which the initial conditions H_0 (z) =1 is considered and two-scale relationship in time domain can be expressed based on equation (5):

$$h_{i+1}(k) = [h]_{-2^i} * h_i(k)$$
$$g_{i+1}(k) = [g]_{-2^i} * h_i(k) \qquad (5)$$

In which the $[h]_{-2}{}^{i}$ and $[g]_{-2}{}^{i}$ are indicator of up-sampling with an m factor and on the other hand K is considered as discrete time of sampling. The base functions and normalized wavelets can be defined as following form:

$$\varphi_{i,l}(k) = 2^{i/2} h_i(k - 2^i l)$$
$$\psi_{i,l}(k) = 2^{i/2} g_i(k - 2^i l) \qquad (6)$$

In which $2^{i/2}$ is the normalized result of inner product. i and l are scale and translate parameters respectively. The decomposition of discrete wavelet transformation can be expressed by equation (7):

$$a_{(i)}(l) = x(k) * \varphi_{i,l}(k)$$
$$d_{(i)}(l) = x(k) * \psi_{i,l}(k) \qquad (7)$$

In which $a_{(i)}(l)$ and $d_{(i)}(l)$ are approximate and partial coefficients with accuracy of i respectively. As result of these calculations, we will be capable of decomposition and rebuilding of signal practically.

3.2 Classification by support vector machines

In soft margin or support vector machine the equations (8) and (9) allow a little deviation from marginal hyper-planes by adding ζ positive parameter.

$$(w \times \mathrm{x}) - \mathrm{b} \leq -1 + \zeta \qquad (8)$$
$$(w \times \mathrm{x}) - \mathrm{b} \geq -1 + \zeta \qquad (9)$$

It can be concluded that support vector machine is an optimum isolation method that output of it is obtained by Bayesian theory. In this set of equation b is the threshold parameter of optimum hyper-plane. The x_i or $\alpha i>0$ training data are called support vectors and SVM finds the hyper-plane in which the distance between support vectors and hyper-plane is maximum. After feature extraction, it is need to fault and its type be classified. To do this we only use the sum of approximate coefficients of first level of second round. This value is divided by sum of approximate coefficient obtained from following equation.

$$AR = \frac{a(HIF)}{a(Normal)} \qquad (10)$$

Based on this value the high impedance fault is divided to one of the following four faults:

1. Single phase line to ground fault in which in average for Iran 20 KV voltage signal the AR of it for one of phases is less than 1 and for other two phases is more than 1.
2. Three phase fault in which the AR of all phases almost is equal.
3. Double phases fault (double line) in which the healthy phase like before has value (AR is almost equal to 1), while change in phase associated with fault have a less than 1 domain and is equal to other phases.

For calculating accurate AR we need to apply an appropriate threshold. This threshold is determined considering the classification output change.

4. Scientific results and simulation

The 20 KV electricity was used as intended overall network. For each type of fault five value of impedance including 60, 70, 80, 90, and 100 will be used for simulation in middle line of each section. Corresponding to occurrence of M cases of fault, 2M feeders is used and finally, a 13 bus distribution network is considered as necessary standard bus in signal analyzing and processing stage. The MATLAB programming environment functions is used for simulation. Some of the values are considered as initial values which are shown in accordance with table 1. The location of fault occurrence is illustrated in figures 1, 2, and 3 for each of two states. The effect of fault signal breaking for one of the faults can be seen in figure 3 that in that fault location the effect of it on impedance is observable. Based on available outputs and considering initial labeling, we can predict the final operation of system in detecting types of quadruple fault. Mechanism of system is clear and is consist of two main phases of fault location detection and detecting type of fault.

Table 1: initializing of different states of high impedance fault occurrence

		Initial values for simulation					
		Fault index	Operation time	Transformation time	Transformation time based on fault index	Cycle number	Fault occurrencesection
resistance	80 ohm resistance	1	0.16 second	10 second	0.08 second	2	Section 12
	70 ohm resistance	1	0.21 second	14 second	0.1 second	2	Section 3
	85 ohm resistance	2	0.15 second	15 second	0.07 second	2	Section 8
	75 ohm resistance	2	0.13 second	13 second	0.06 second	2	Section 4

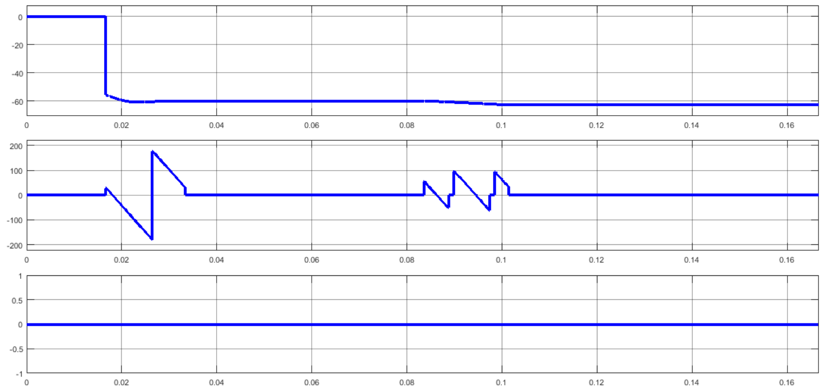

Figure 1: first fault occurrence location

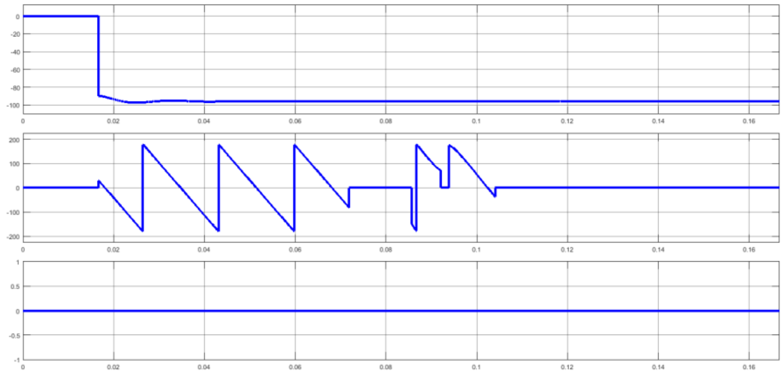

Figure 2: second fault occurrence location

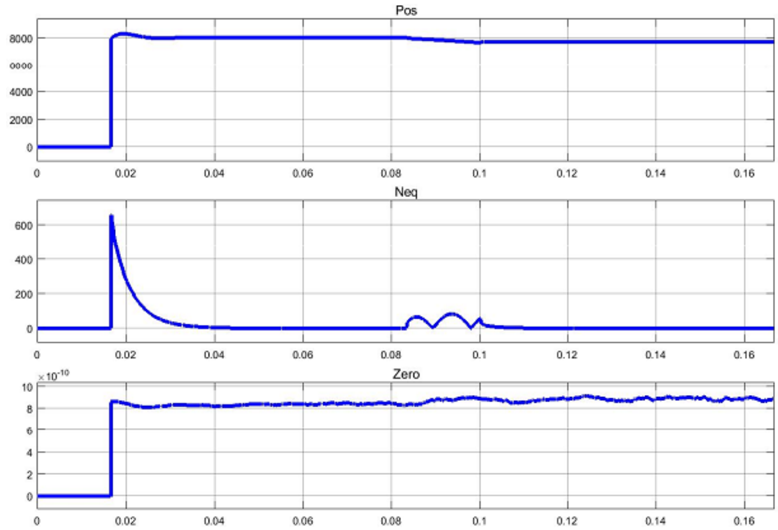

Figure 3: voltage broken signal for one type of fault that have the location and effect of fault on impedance in itself.

The average of absolute difference between features of tested signal and each section of reference data signal can be shown as equation 11:

$$AAD = \frac{a_{i=1}^{n}\left|a \quad d_i(measured) - r_{mi}\right.}{n} \tag{11}$$

In which, m is numbers between 1 to the number of line section. Moreover, n is the number of signals which are between data and $(a \quad d_i(measured))$ the sum of test voltage signals coefficients and finally r_{mi} in database. In table (2) based on inferred value of average absolute difference and definitions that we have based on thresholds about fault and its type, we can estimate the type of fault. In tables (3) and (4), the result of classification in training and testing stages is shown for on time repetition.

Table 2: type of fault estimation for some sample states

impedance	(AR) Approximate rate values		
60 ohm impedance	First value	seconf value	third value
	1.3084	-0.3470	0.9140
	(third type) duoble line fault		
70 ohm impedance	First value	seconf value	third value
	0.9614	0.8935	0.9069

	(second type) three phases fault		
80 ohm impedance	First value	seconf value	third value
	1.6231	1.1318	0.4123
	(first type) single phase fault		
90 ohm impedance	First value	seconf value	third value
	1.3915	-0.1898	1.1645
	(third type) duoble line fault		

Table 3: calculating the accuracy of classes classification for training stage

	First type fault	second type fault	third type fault	forth type fault	accuracy
First type fault	11	1	0	0	91.67%
second type fault	1	12	1	0	86.67%
third type fault	0	0	12	2	85.71%
forth type fault	0	1	2	11	84.62%
	Average fault				**87.16%**

Table 4: calculating the accuracy of classes classification for testing stage

	First type fault	second type fault	third type fault	forth type fault	accuracy
First type fault	6	1	0	0	85.71%
second type fault	0	7	0	0	100%
third type fault	0	0	12	2	71.43%
forth type fault	0	0	1	6	85.71%
	Average fault				**85.71%**

5. Discussion

In most of prior systems which are done to detect and isolate the high impedance fault and its type, the process of detection automating has been less considered and in some cases some researches can be addressed in this field that have automation in detection and generally use feature extraction model and classification. Table 5 shows the comparison of presented method in this paper with other similar methods in early years.

Table 5: comparison with similar methods in early years

Author	Combined algorithm	database	results
Bakar et al.	Feature extraction by wavelet by ranking method	Gathered data of 11 KV Malaysia network	four type fault detection, no accuracy report, no uncertainty addressing, and outputs and their relationship with real labels are not clear
Samantaray	Using classification which is based on decision tree and Kalman filter superposition	Different lines of India including 25 KV and 138 KV	one type of fault Detection from natural state, existing 98% and 88% accuracy for training and testing stages, operation reliability factor of 99% and fast operation
Rafinia et al	Using neural network and fuzzy logic system	Underground 20 KV lines of Iran	Two types fault detection associated with normal state of network, different states of frequency and low studied impedance, no clearance of predictability of testing and training stages
Hong et al.	Wavelet transformation, Clustering K-means methods, genetic algorithm and Support Vector Machine	18 bus 15 KV distribution system	Complexity of algorithmç no training and algorithm testing, low detected fault types, no uncertainty addressing, no clarity of outputs and their relationships with real labels
Suggested method	Feature extraction by wavelet and classification by ranking method and isolation of data for testing and training	Iran 20 KV network	Some fault types detection, resolving uncertainty and convenient generalizability for other network in distribution, 87%and 85% accuracy for testing and training stages in classification

6. Conclusion

In this paper different approaches of intelligent detection of high impedance fault was investigated and accordingly an optimized approach based on feature extraction by discrete wavelet transformation and support vector machine classification is suggested. Some of analysis showed better result than other location of fault and type of fault detection techniques including techniques such as Bakar et al. (2014), Rafinia and Moshtagh (2014), Hong and Huang (2015), Samantaray (2012), which generally have used automation for detecting. Therefore, most of these guidelines or almost all of them are trying to estimate fault in different distribution network including 11 KV, 20 KV, 132 KV, and or 400 KV and tailored to their needs in their country. Simulation and mathematical analysis of suggested algorithm is done in MATLAB programming environment and the results were promising and some of important factors which were neglected in prior other guidelines got investigated. Nevertheless, we need to improve the performance which can lead to optimum high impedance fault detection in future.

References

1. Akorede, M.F. & Katende, J.: *Wavelet transform based algorithm for high-impedance faults detection in distribution feeders*. European Journal of Scientific Research, 41(2), 2010. P. 48-238.

2. Bakar, AH, Ali MS, Tan C, Mokhlis H, Arof H, Illias HA. *High impedance fault location in 11kV underground distribution systems using wavelet transforms.* International Journal of Electrical Power & Energy Systems, 55, 2014. P. 30-723.

3. Hong, Y.Y. & Huang, W.S.: *Locating High-Impedance Fault Section in Electric Power Systems Using Wavelet Transform,-Means*, Genetic Algorithms, and Support Vector Machine. Mathematical Problems in Engineering. 2015.

4. Kumar, A.: *A neural network approach to the detection of incipient faults on power distribution feeders.* Middle-East J. Sci. Res. 20(7), 2014. P. 799-803.

5. Lai T.M., Snider, L.A. & Lo E.: *Wavelet transform based relay algorithm for the detection of stochastic high impedance faults*. Electric power systems research. 76(8), 2006. P. 33-626.

6. Michalik, M., Rebizant, W., Lukowicz, M., Lee S.J. & Kang, S.H.: *High-impedance fault detection in distribution networks with use of wavelet-based algorithm*. IEEE Transactions on Power Delivery. 21(4), 2006. P. 1793-802.

7. Milioudis, A.N., Andreou, G.T. & Labridis, D.P.: *Detection and location of high impedance faults in multiconductor overhead distribution lines using power line communication devices.* IEEE Transactions on Smart Grid, 6(2), 2015. P. 894-902.

8. 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. 55, 2014. P. 74-261.

9. Samantaray, S.R., Dash P.K.: *Adaptive Kalman filter and neural network based high impedance fault detection in power distribution networks.* International Journal of Electrical Power & Energy Systems, 31(4), 2009. P. 72-167.

10. Samantaray, S.R.: *Ensemble decision trees for high impedance fault detection in power distribution network*. International Journal of Electrical Power & Energy Systems, 43(1), 2012. P.1048-55.

11. Sedighizadeh, M., Rezazadeh, A. & Elkalashy, N.I.: *Approaches in High Impedance Fault Detection a Chronological Review*. Advances in Electrical and Computer Engineering. 10(3), 2010. P. 28-114.

12. Sedighi, A.R., Haghifam, M.R., Malik O.P. & Ghassemian, M.H.: *High impedance fault detection based on wavelet transform and statistical pattern recognition*. IEEE Transactions on Power Delivery. 20(4), 2005. P.21-2414.

13. Sedighi, A.R. & Haghifam, M.R.: *Simulation of high impedance ground fault In electrical power distribution systems.* InPower System Technology (POWERCON), 2010 International Conference on 2010 Oct 24, P. 1-7.

14. Sharaf, A.M. & Wang, G.: *High impedance fault detection using low-order pattern harmonic detection.* InProc. Sept. 2004 Elec., Electronic, & Comp. Eng., 2004. ICEEC'04. 2004 Int'l Conf. on 2004 Sep 5 P. 883-886.