High Impedance Fault Detection on Power Distribution Feeder Using Subtractive Clustering Fuzzy System

الكشف عن خطأ مقاومة عالية في مغذي توزيع الطاقة باستخدام طريقة الطرح التجميعي للمنطق المضبب

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ABSTRACT

A novel algorithm based on discrete wavelet transform DWT and subtractive clustering fuzzy inference system is presented to detect high impedance fault. As HIFs detection is usually very difficult using the common over current devices, both frequency and time data are needed to get the exact information to classify and detect no fault from HIF. Discrete wavelet transform is utilized for decomposing typical current, voltage and power of high impedance fault current signals. A specific comparison is made among many types of features of the voltage signal, current signal and power signal. The effect of switching of capacitor bank, switching of no-load line, linear and non-linear load current, and harmonics of other normal event on distribution system is presented. Simulation of a 13.8 kV distribution system using PSCAD were done to obtain the HIF signals and other operation event signals. The proposed method shows that it is more convenient for HIF detection in distribution systems with ample varying in operating cases.

KEYWORDS:
Discrete Wavelet Transform, Power distribution faults, High Impedance Fault, Fuzzy Subtractive Clustering Model

الخلاصة

عرض خوارزمية جديدة باستخدام تحويل المويجات منفصلة وطريقة الطرح التجميعي للمنطق المضبب للكشف عن خطأ مقاومة عالية. وبما أن كشف خطا المقاومة العالية عادة ما يكون صعبا جدا باستخدام الأجهزة المعروفة والموجودة حاليا، في هذا البحث ، كلا من معلومات التردد و الزمن لاشارات الفولتية والتيار استخدمت للحصول على المعلومات الدقيقة يمكن من خلالها تصنيف واكتشاف خطأ الممانعة العالية عن باقي الاشارات في منظومة القدرة ، يتم استخدام تحويل المويجات منفصلة لتحليل نماذج اشارات التيار ، والجهد والقدرة المؤخوذة من اجهزة القياس. يتم إجراء مقارنة محددة بين أنواع كثيرة من الصفات لإشارة الجهد، وإشارة التيار وإشارة الطاقة. تم اخذ تاثير المتسعات ، وحالة الحمل و اللا حمل ، وكذلك الاحمال الخطية و غير الخطية لمنظومة القدرة ، وباقي الظروف الطبيعية التي تحدث بالمنظومة ومناقشتها. تم عمل محاكاة لنظام توزيع قدره 13.8 كيلوفولت باستخدام استخدام برنامج PSCAD للحصول على إشارات الخطا وإشارات أحداث التشغيل الأخرى. وتظهر الطريقة المقترحة أنه أكثر ملاءمة للكشف عن خطا الممانعة العالية في أنظمة التوزيع مع وفرة متفاوتة في حالات التشغيل.

1 INTRODUCTION

Detection of high impedance faults in distribution systems is very hard. It often occurs in power distribution systems and, in general, cannot operate common protection devices because of high impedance, which prevents the fault to draw high current values, at the fault point. These types of faults usually occur, when a distribution line and high impedance surfaces make loose contact or the conductors touch a high impedance object like trees[1]. The primary objective in detection of HIF , in contrast with low impedance faults, is not for the protection of the devices, but to provide public safety and prevent flammable risks because of the electric arcing[2]. HIFs are divided into two types: the passive faults and the active ones. Passive HIFs do not make an electric arc. They are very dangerous to human and animal life since there is no statement of the energisation case of the conductor. Active high impedance faults are usually pursued by arc and draw currents less than the protection devices set [3]. Generally, fault currents are reduced over time until the arc is completely extinct [3]. Most of the methods utilized for detection of HIFs take advantage of fault signals that produce harmonic and non-harmonic components because of the arcing. While sometimes the detection system cannot gather enough data to make sure that fault has occurred because the electric arc may vanish before that. Few other electrical events (switching of capacitor bank, operation of air switching, starting of induction motor and nonlinear load) also behave like the HIF [4].

During the last years, researchers and protection engineers have tried for finding a complete solution for these types of faults. The fault possesses many features, like high frequency components and presence of harmonics. A lot of detection algorithms have proposed for detection HIF, some of these algorithms have utilized frequency-based algorithm in extraction of features of the harmonic components in relevance [2][5–8]. Others have used time–frequency-based characteristics for examination events of the transient operations of HIF signals in each of the frequency domain and time domain [3][9–17]. In the research work [14], A method of detection HIF based on the nonlinear current behaviour waveforms using wavelet multi-resolution signal decomposition method had proposed to extract features. Similarly, principal component analysis and wavelet transform are employed in extracting and selecting features [13]. In [17] the author uses (ANFIS) as a classifier for detection HIF. The 3rd harmonic, magnitude and angle, for the 3 phase current signals are selected to be input vector. And in [18] The 3rd and 5th harmonic components of the current, voltage and power signals are employed to create feature vector which uses in the input of the Fuzzy ARTMAP Network. This paper represents a HIFs detection method that includes capturing the voltage and current signals produced in a distribution conductor under HIF and non-fault cases. Discrete wavelet transform is utilized to extract features vector. The findings obtained from this research relate to a typical 13.8-kV, where the known Power Systems CAD PSCAD software is used to attain the faulted signals. A representation of HIF model is involved in this simulation. The system generalization is then tested on presence of HIF signal within a range of various non-fault and fault cases faced in real.

2 SYSTEM STUDIED

HIF Simulation

In the past, several HIF models have been presented based on Emanuel arc model. These models have been analyzed by researchers to select the best model for HIF. A simplified Emanuel model proposed in 2003 comprises a pair of DC voltage sources, the inception voltage of the arcing between the conductor and high impedance abject is represented by Vp and Vn. While fault resistance, Rp and Rn, are modeling by suing two varying resistors, unequal values of fault resistance permit for asymmetric fault currents to be simulated.

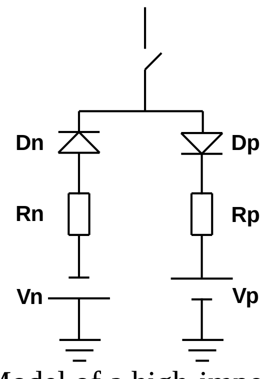


Figure 1: Model of a high-impedance faults.

Distribution System Model

Two 13.8 kV distribution networks were simulated using PSCAD. The first network comprises three distribution radial networks and the second network represent mesh network. Figure 1 illustrates the schematic diagrams. The 30 kV and 10 MV generator connects to the 10 MV transformer with 30/13.8 kV. The voltage of distribution network is 13.8 kV. The linear, nonlinear loads with various loading events and switching capacitor are stimulated. The nonlinear loads are represented by 6-pulse rectifier. The selected sampling rate is 12.8 kHz[19].

Figure 3 illustrates the waveform of HIF current signal under linear and nonlinear loads. The fault has occurred at 0.2 sec. Under linear loading conditions, the HIF signal comprises more harmonic components in contrast with the signal before the fault (Figure 2a). Thus, in these cases, it is easy to distinguish HIF from other normal operations. However, when HIF is under nonlinear loading conditions, the signal before and during the HIF has comprised higher harmonic components (Figure 2b). Consequently, it becomes hard to differentiate HIF from other normal conditions under nonlinear loading conditions and this is a crucial problem in power distribution network. Additionally, it is mandatory to examine the reliability of any HIF method, due to the transient event generated by capacitor bank switching, which produces harmonics like for those that HIF in frequency domain. Many capacitor energisation events have been considered while studying the distribution system.

3 DISCRETE WAVELET TRANSFORM (DWT)

Discrete Wavelet Transform (DWT) was developed by Mallat [20]. It is a computationally effective way and a common tool to execute time localization from a given signal at the various frequency components. Using DWT, time and frequency resolution of a signal is achieved through the use

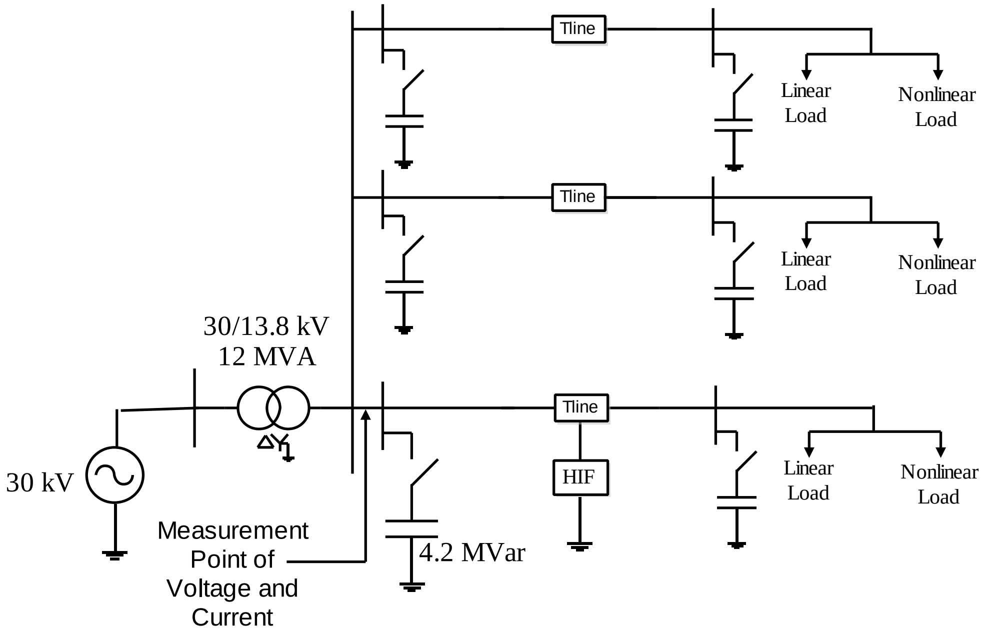
mother wavelet. The most important characteristic of the mother wavelet is that the time intervals are long for low frequency components, whereas the time intervals are short for high-frequency components. The DWT is defined as:

$$DWT\,(m,n) = \frac{1}{\sqrt{a^m}} \sum_k x\,[n] g\left(a^{-m} n - k\right) \tag{1}$$

where x(n) represents the input signal, g(n) is mother wavelet, The result is geometric scaling (i.e. $1\,,\ \frac{1}{a}\ ,\ \frac{1}{a^2},.....$) and translation by $0\ ,\ n\ ,\ 2n,.....$

The DWT generates as many wavelet coefficients as there are samples in the original signal, using filter systems. The decomposition procedure begins when a signal passes into these filters. High pass filter output is the detail signal while Low pass filter output is the approximation signal.

Many Wavelet Transform applications for analyzing transient signals of power system have been published



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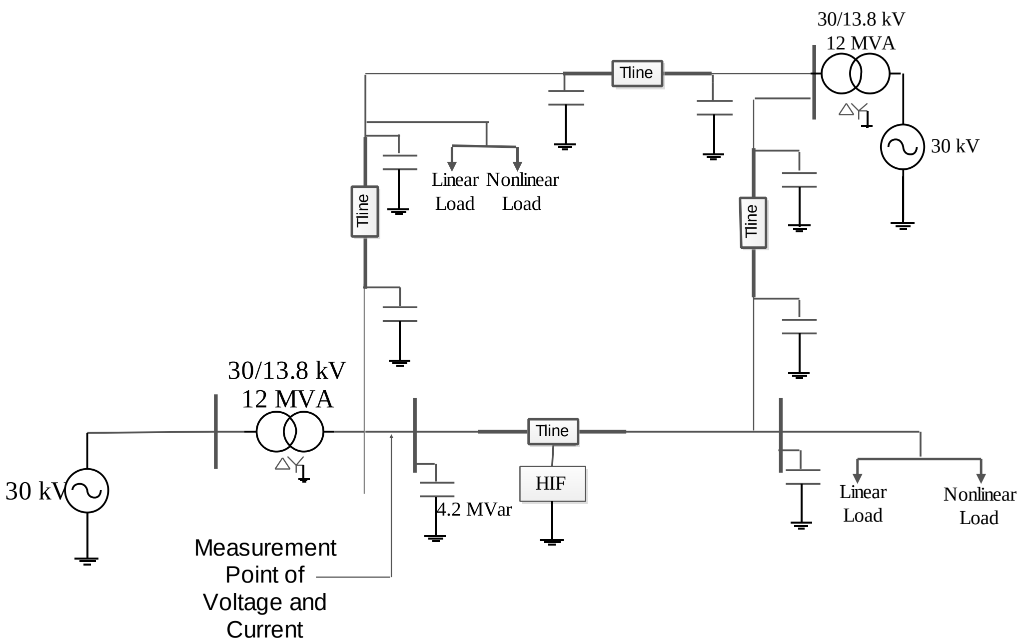

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Figure 2: 13.8kV Distribution Power System Simulation (a) radial network (b) mesh network

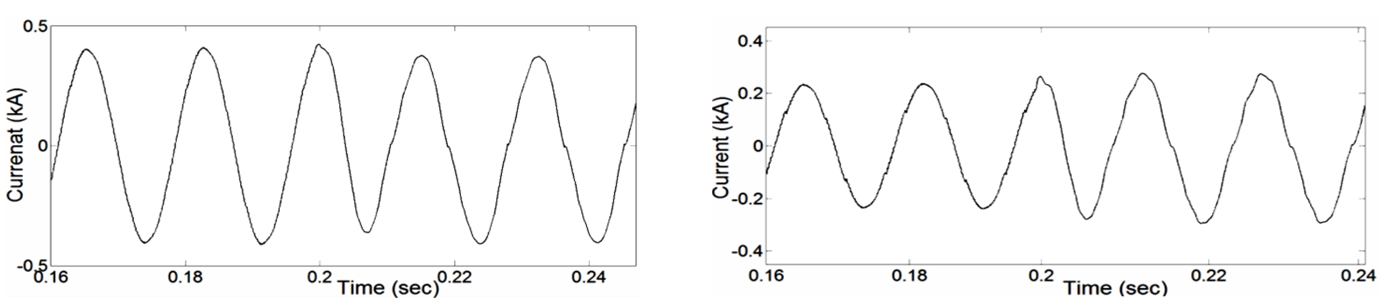

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Figure 3: HIF current signal (a) HIF current signal under linear load (b) HIF current signal under nonlinear load.

lately in the literature. Applications of Wavelet transform for distribution network fault detection are improved by some motivating researches and studies. In this paper, different operation conditions have been simulated by using PSCAD/ EMTDC. The current and voltage signals generated in time domain for each case are analyzed using a wavelet transform. Daubechies wavelet Db6 is selected as the mother wavelet, where it has presented best classification result for fault analysis in distribution systems. According to this sampling time, the signal is analyzed into 7 stages. Figure 4 depicts implementation of the tree structure of 7 analysis stages for DWT and shows the frequency bands range for coefficients up to 7th levels, g[n] represents the high pass filters whilst, h[n] represents the low pass filters, and the arrows indicate to the down sampling process.

4 FUZZY RULE BASE CLASSIFIER SYSTEM

Takagi, Sugeno and kang (TSK fuzzy system) has introduced fuzzy subtractive clustering system. This model is fast, a one-pass algorithm, which is efficient in ascertaining the amount of the clusters and cluster centers in a set of data. The quantity of data points in the feature space and recognized regions in the space of feature with huge quantity of data points form FS clustering. The center for a cluster is represented by the point and in accordance with the maximum number of neighbours. The data points in a predefined fuzzy radius are then confined (separated), and a new point, with the highest number of neighbours is searched by the algorithm. This process is continued until all the data points are inspected. A significant benefit for employing a subtractive way for identifying rules is that, the resulting rules are heavily modified to the data entry as against the fuzzy inference system, where they are created devoid of clustering. It minimizes the combinatorial explosion challenges of rules, with high dimensional input data.

The TSK fuzzy system is an efficient method to produce fuzzy rules based on a data set of the input-output pair. This model comprises rules with fuzzy sets in the antecedents and crisp function (generally is a polynomial in the input variables) in the subsequent part. The TSK model contains of IF-THEN rules of the following form:

$$\begin{aligned} &IF\ x_1 is\ A_{1k}\ and\ x_2 is\ A_{2k},\ \ldots\ldots,\ and\ x_n is\ A_{nk} \\ &THEN\ y^k = P_0^{\,k} + P_1^{\,k} x_1 + P_2^{\,k} x_2 + \ldots. + P_n^{\,k} x_n \end{aligned} \tag{2}$$

where xj is jth input, yk is the consequent of the kth rule, A jk and Pjk is the MF and regression parameter in the kth rule, respectively. Initially, the rule extraction method employs the subtractive clustering function, to ascertain the amount of antecedent membership functions and rules; later it employs linear least squares estimation to establish the consequent equations of all the rules. This function retorts a FIS structure, which comprises a set of fuzzy rules to encompass the feature space [21].

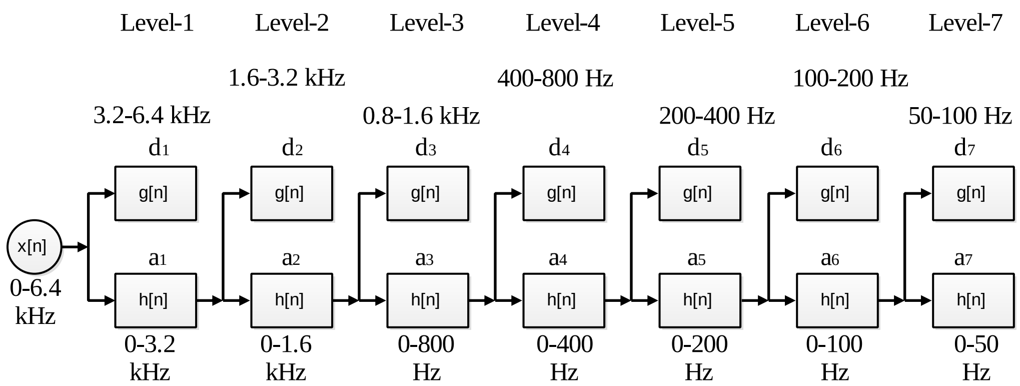


Figure 4 the tree structure of 7 analysis stages for DWT and shows the frequency bands range for coefficients up to 7th levels

5 THE PROPOSED METHOD

The proposed FSCM -based method for classification and detection of HIF will be developed based on the following two important parts: features generation and Data preparation.

Features Generation

Different operation conditions (HIF and non-fault cases) have been simulated by using PSCAD/ EMTDC, on the modelled distribution system. The simulated data were then transferred to MATLAB to complete the rest of the algorithm. The main goal of algorithm is to discriminate between HIFs and other similar waveforms.

In this study, the process of feature extraction is prepared to attain the highest accuracy of classification, with major data, which can represent the most important properties of the problem. Many investigations and comparisons are made between the performance of FSCM with different types of features, like standard deviation (STD), root mean square (RMS), mean, energy and mean of energy of each frequency bands (coefficients and signals) levels. The proper features extracted vector (FSCM input) are established as follows:

$$STD = \sigma^2 = \sqrt{\left(\frac{1}{n-1} \sum_{i=1}^{n} \left(x_i - \frac{1}{n} \sum_{i=1}^{n} x_i \right)^2 \right)} \tag{3}$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} |x_i|^2}{n}} \tag{4}$$

$$MEAN = \frac{\sum_{i=1}^{n} x_i}{n} \tag{5}$$

$$ENERGY = \sum_{i=1}^{n} x_i^2 \tag{6}$$

$$MeanENERGY = \frac{\sum_{i=1}^{n} x_i^2}{n} \tag{7}$$

where “x” is the data vector and “n” the number of elements in that data vector.

Data Preparation

Building a fuzzy inference system with fuzzy subtractive (FSCM) involves two steps:

A) Clustering Data Preparation and,

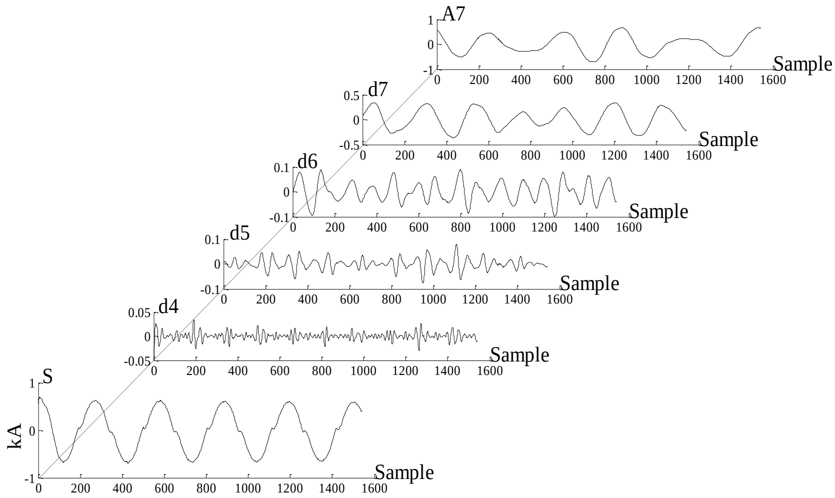
B) Rules generation.

A) Clustering Data Preparation for FSCM

It is essential to divide training data into two data sets as follows, to generate FSCM clustering-based fuzzy inference system:

a) An input data set which has values for the 15 inputs represent the7th level of approximation coefficients and four levels (4th, 5th, 6th and 7th) of detail coefficients of the (current, voltage and power) signal. 1440 input data points were selected from time–frequency plane of current, voltage and power signals. These points were placed into a single input data set.

b) An output data set which has values for the one output (1 or 0). The output of FSCM either 1 for high impedance fault occurs or 0 for other normal event in power system. 1440 output data points,



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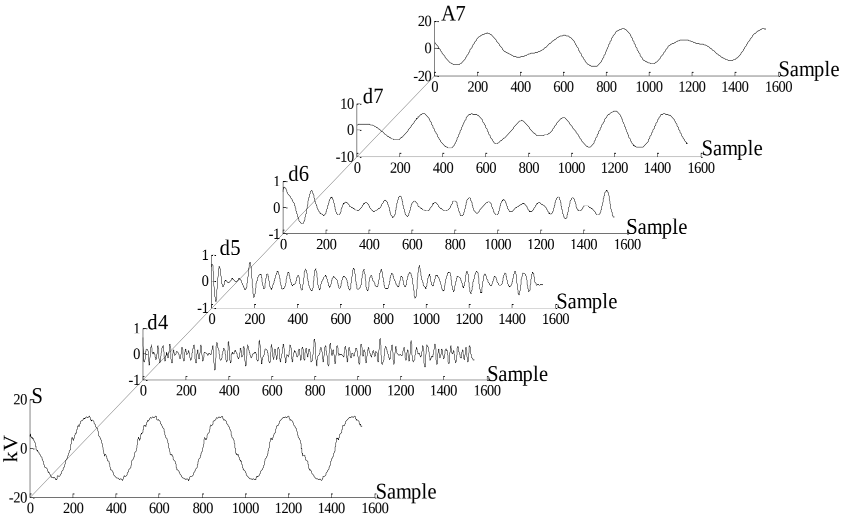

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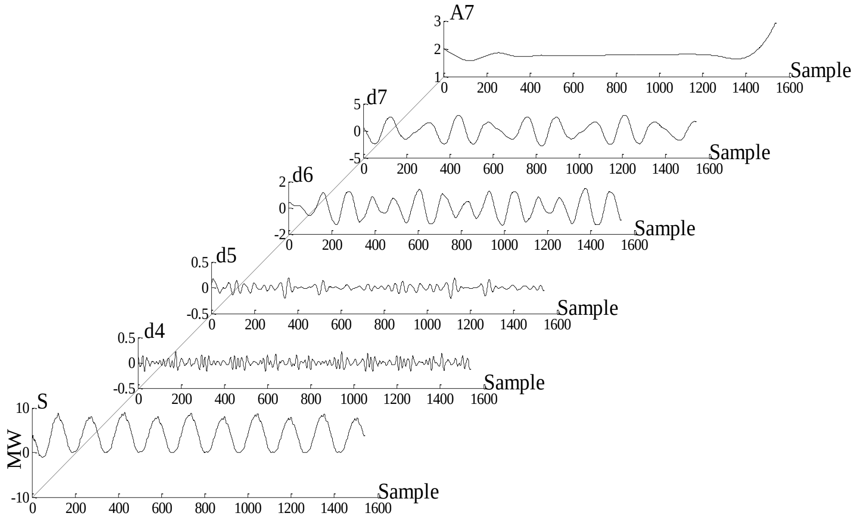

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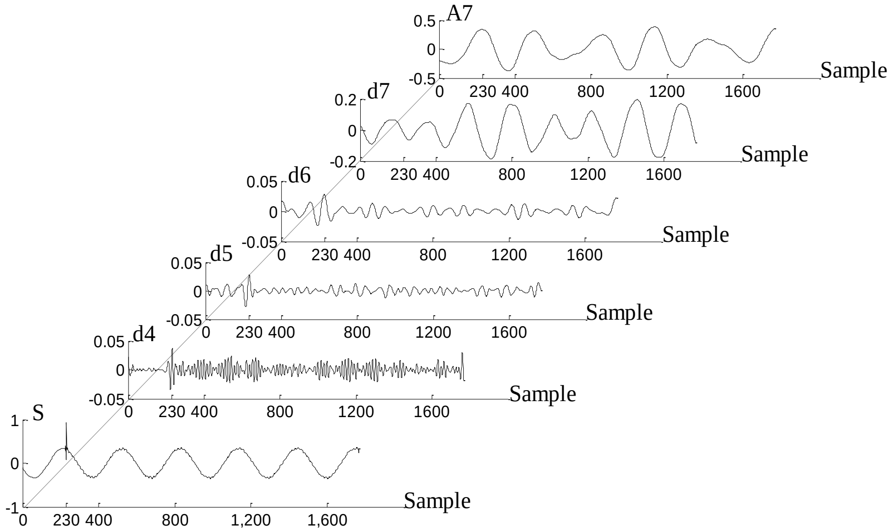
Figure 5: decomposing signal under a HIF condition and their detail coefficients at levels 4, 5, 6 and 7 and approximate coefficient at level 7 using db6. a) current signal b)Voltage signal c) power signal



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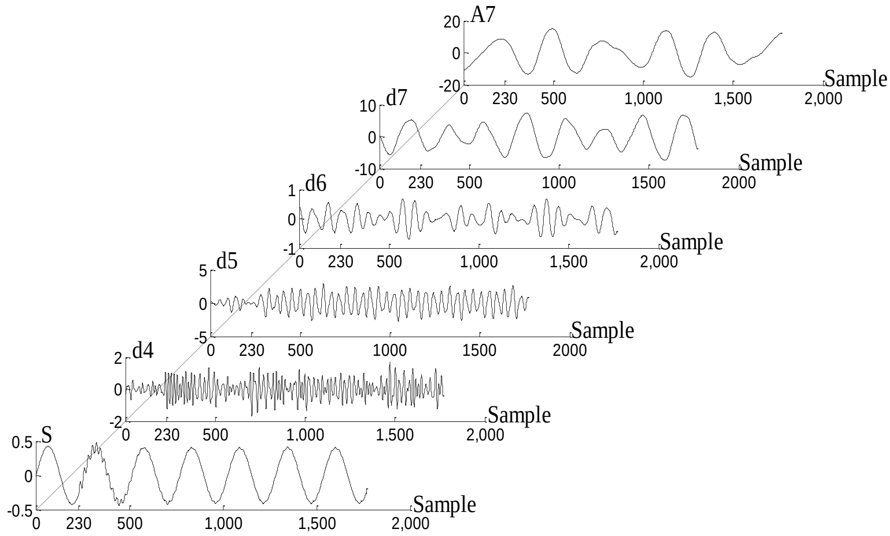

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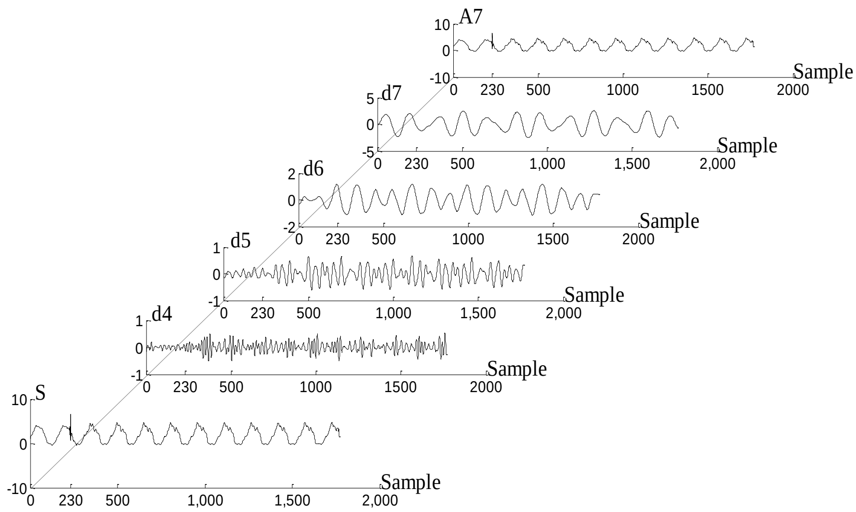

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Figure 6:decomposing signal under capacitor switching condition and their detail coefficients at levels 4, 5, 6 and 7 and approximate coefficient at level 7 using db6 a) current signal b)Voltage signal c) power signal

related with the number of the chosen input points. These points were placed into a single output data set.

The remaining 160 pairs of input and output data points (dissimilar from the training data), will be employed to test the algorithm.

B) Rules Generation for FSCM

The cluster centers in a set of data are estimated by the fuzzy subtractive clustering algorithm. Each data point is assumed as a potential cluster center by the algorithm and a level of the probability is computed so that, each data point could delineate the cluster center, depending on the density of neighboring data points. The algorithm has three important steps:

1) The data point with the highest potential to be the first cluster center is chosen.

2) All data points from the first cluster center region are removed (as determined by radii), for determining the next cluster and its center location

3) These steps are repeated till the complete data is in radii of a cluster center.

The variable of radii is a vector of entries between 0 and 1, which designates the range of influence of a cluster center in each of the data dimensions, assuming that the data falls within a unit hyper-box. Generally small radii values result in identifying a few large clusters, particularly, the best values for radii ranges between 0.2 and 0.5. For this application, the chosen value for all the radii was 0.2. This was found to result in fewer membership functions and higher processing speeds, without sacrificing accuracy.

6 RESULTS

After the decomposing process, figure 5 depicts voltage, current and power decomposing signal under a HIF condition and their detail coefficients at levels 4, 5, 6 and 7 and approximate coefficient at level 7 using db6. The effect of the arc period clearly appears by high transient frequencies which are seen in the Wavelet levels D4 and D5. While figure 6 appears the behavior of decomposition signal under capacitor operation switching conditions (no fault). Any increasing or decreasing in the values of current doesn't effect on the method developed results because of the high frequency part of the signal show only within a short period of time, at the instant of capacitor switching.

There have been 1440 training cases which were selected to train the network. Numbers of features in each input vector are 15 features which represent the energy of the four levels (4th, 5th, 6th and 7th) of detail coefficients and 7th level of approximation coefficients of the (current, voltage and power) signal. The training sets included 360 HIF cases and the rest are non-fault cases. The subtractive clustering fuzzy system has one output, the output is one when the system detect HIF

case and is zero when other cases. Different combinations of inputs are used to train and test fuzzy subtractive, to assess the influence on classification rate. The rates of classification are computed on the training and testing data sets.

Table 1 illustrates output of the FSCM to the training data with different type of features, standard deviation (STD), root mean square (RMS), mean, energy and mean of energy of each frequency bands (coefficients and signals) levels. It is found that FSCM with STD feature gives better classification rate result for radial network, its provides up to 92.15% classification rate for training data of radial network. While FSCM with Mean feature gives better classification rate result for mesh network its provides up to 95.83% classification rate for training data of mesh network. It is obvious that the system is trained properly and has categorized different cases effectively. figure 7 show the HIF classification rate of FSCM using five types of features.

To evaluate the suitability of proposed algorithm, test data cases were fed to the FSCM and the obtained output is shown in Table 2. It shows that the proposed method could classify different input categories successfully and reliably. FSCM with STD feature are capable of categorizing 85.62% classification rate for testing data of radial network. FSCM with Mean feature are able for classifying 95.25% classification rate for testing data of mesh network. Results of the testing phase demonstrate that the algorithm is reasonably reliable.

Table 1: FSCM response to training data

FSCM	STD (%)	RMS (%)	Mean (%)	Mean energy (%)	Energy (%)
Radial network	**92.15**	91.875	90.34	88. 3	88.33
Mesh Network	94.65	95.62	**95.83**	95.69	95.69

Table 2: FSCM response to testing data

FSCM	STD (%)	RMS (%)	Mean (%)	Mean energy (%)	Energy (%)
Radial network	**85.625**	90	90.625	88.75	88.75
Mesh Network	93.125	95.62	**95.25**	90.62	90.62

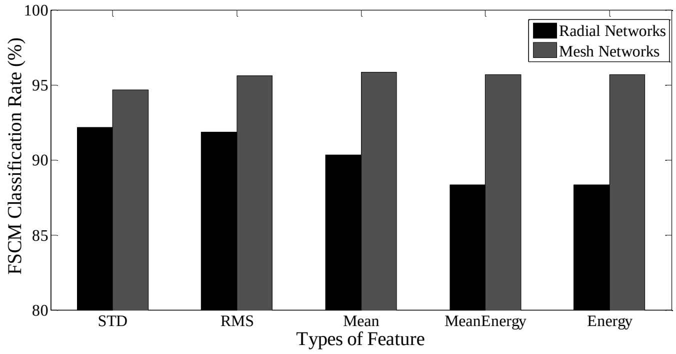

Figure 7 : the classification rate for the different type of features.

Furthermore, three goals, selection of proper mother wavelet, examine the impact of percentage input training set on the classification rate performances of the fuzzy subtractive and the effect of number of training data, are tested to validate the method of detection HIF.

Proper mother wavelet

Appropriate selection of the mother wavelet represents a major part for detection various types of signal transients. The selection relies on the application nature. Daubechies and Reverse biorthogonal families mostly used For detection of small amplitude, fast decaying, short period and oscillating types of signals, (e.g. db2, db3 etc. and rbio2.7, rbio3.7 etc.). Also, smoothness and wideness of mother wavelet relies on its number. So many investigations were done to select the proper wavelet class and its number.

After many investigations, the db6 mother wavelet was chosen. The selection is based on the following reasons:

- As alternatives, 29 forms of wavelets were utilized in training FSCM, involving: Daubechie, Symlets, Coiflets, Biorthogonal and Discrete Meyer (dmey). figure 8 is shown the percentage of classification rate for each type of mother wavelet for mesh network.
- The standard used to choose the better mother wavelet was the percentage of classification rate figure 8
- A total of 1440 tests were performed. Simulation results show a high average accuracy of 92.15 % and 95.83% for the radial and mesh network respectively, that justifies why db6 mother wavelet was selected.

Impact of input feature sets

Various feature sets are investigated to study the impact of input feature set on the classification rate of the fuzzy subtractive. Table 3 illustrates these sets, whereas the Table 4 tabulates the classification rate of the proposed method for each of the sets.

Table 3Table 3 Input Feature Set Types

Feature type		No. of feature
FS1	the energy of the four levels of (current, voltage and power) signal	15
FS2	the energy of the four levels of (current and voltage) signal	10
FS3	the energy of the four levels of (current and power) signal	10

Table 4: The Classification Rate of Input Feature Set Types

Feature set	Classification rate for radial network	Classification rate for mesh network
FS1	92.15	95.83
FS2	85.9028	85.625
FS3	76.5278	71.2500

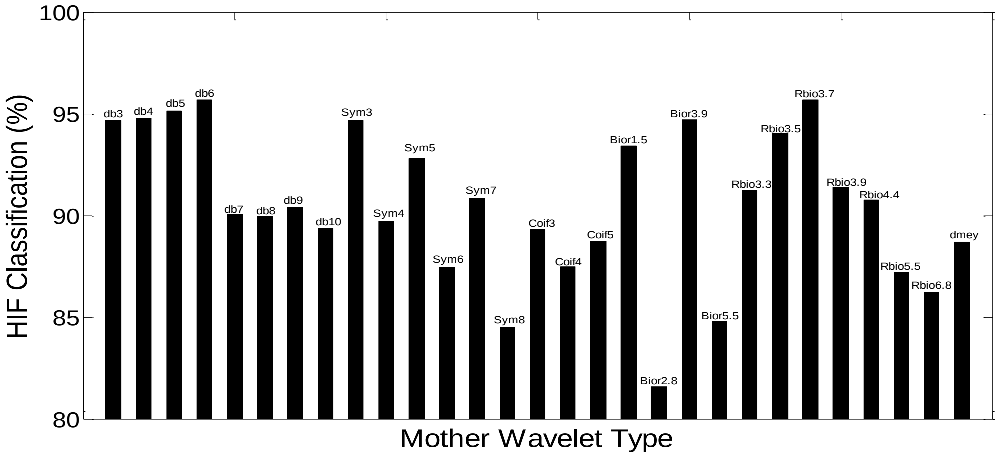

Figure 8: the better mother wavelet

It is evident that generally the FS1feature sets contain more selective information as against other feature sets, as exposed in average classification rate. Also, it can be concluded that the features of the FS1 has shown good results. figure 9 depicts the classification rate for the different feature set.

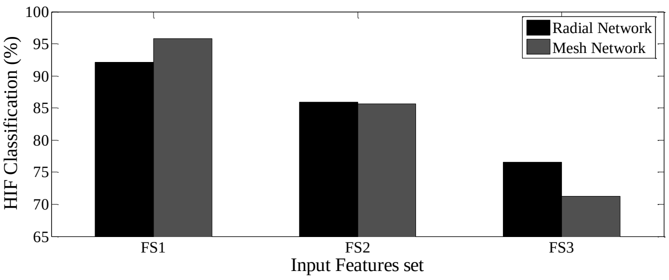

Figure 9: classification rate for the different feature set.

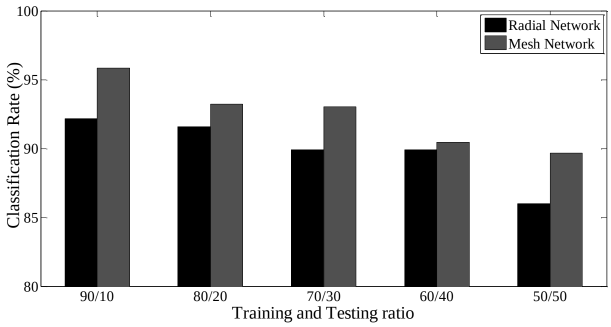

Figure 10: the HIF classification rate of fuzzy subtractive with input training data set (FS1)

The effect of number training data

The proposed fuzzy subtractive is trained and tested with 1600 stimulated cases.Various combinations of inputs are used to test the fuzzy subtractive, to assess the influence on classification rate. The rate of classification is computed on the training and testing data set. In this stage, the fuzzy subtractive is trained with different number of training data set to get the best classification rate of the fuzzy subtractive. Figure 10 shows the HIF classification rate of fuzzy subtractive with input training data set (FS1) that has different number of training data. The maximum classification rate is 92.15% and 95.83% for radial and mesh network, respectively with 90% of training data and classification rate is reduced with others percentage training

7 DISCUSSION

A qualitative comparison was made among five types of feature for HIF detection in power distribution feeder, in the proposed algorithm. Based on the outcomes, it was found that the STD feature for radial network and Mean feature for mesh network provides better results compared with other features. Also the features FS1give the best classification rate, for radial distribution network is 92.15% and 95.83% for mesh network compared with 85.90% and 76.52% for both features of FS2 and FS3 for radial network while 85.62% and 71.25% for both features of FS2 and FS3 for mesh network, respectively. Also with using 90% training and 10% testing data sets to train and test the fuzzy subtractive has given a good classification rate result.

8 CONCLUSIONS

This study has presented the fuzzy subtractive clustering for HIF detection and classification. An effort has been made to classify the HIF from other event in distribution system under linear and nonlinear loads. In this paper, four levels (4th, 5th, 6th and 7th) of detail coefficients and 7th level of approximation coefficients of the (current, voltage and power) signal is selected to be extracted features using wavelet transform and different features like (FS1, FS2 and FS3) were computed and used to train and test the fuzzy subtractive clustering for HIF classification. HIF classification rate is more than 92%, from obtained fuzzy subtractive clustering with using STD of details coefficients of current, voltage and power feature for radial network and more than 95% obtained for mesh network. Ultimately, the proposed approach is quick and precise in identifying HIF and can be extended to guard huge power distribution networks.

9 REFERENCES

[1] Sedighizadeh, A. Rezazadeh, "Approaches in high impedance fault detection - a chronological review," Advances in Electrical and Computer Engineering, vol. 10, no. 3, pp. 114–128, 2010.

[2] B. Aucoin And B. Russell, "Distribution high impedance fault detection utilizing high frequency current components," IEEE Trans. Power Apparatus And Systems, vol. pas-101, no. 6, pp. 1596–1606, 1982.

[3] P. K. Samantaray, S.R., Panigrahi, B.K., Dash, "High impedance fault detection in power distribution networks using time-frequency transform and probabilistic neural network," IET Generation, Transmission & Distribution, vol. 2, no. 2, pp. 261–270, 2008.

[4] A. V. Mamishev, B. D. Russell, And C. L. Benner, "Analysis of high impedance faults using fractal techniques," IEEE Transactions on Power Systems, vol. 11, no. 1, pp. 435–440, 1996.

[5] R. P. Russell, B.D., Mehta, K., Cinchali, "An arcing fault detection technique using low frequency current components performance evaluation using recorded field data," IEEE Trans. Power Deliv, vol. 3, no. 4, pp. 1493–1500, 1988.

[6] E. M. Emanuel, A.E., Cyganski, D., Orr, J.A., Shiller, S., Gulachenski, "High impedance fault arcing on sandy soil in 15 kv distribution feeders: contributions to the evaluation of the low frequency spectrum," IEEE Trans. Power Delivery, …, vol. 5, no. 2, pp. 676–686, 1990.

[7] W. Kwon and G. Lee, "High impedance fault detection utilizing incremental variance of normalized even order harmonic power," IEEE Trans. Power Deliv, vol. 6, no. 2, pp. 557–564, 1991.

[8] S. Lien, K.Y., Chen, S.L., Tzong, C.J.L., Guo, Y., Lin, T.M., Shen, "Energy variance criterion and threshold tuning scheme for high impedance fault detection," IEEE Trans. Power Deliv, vol. 14, no. 3, pp. 810–817, jul. 1999.

[9] A. G. Lai, L.L., Styvaktakis, E., Sichanie, "Application of discrete wavelet transform to high impedance fault identification," Proc. Int. Conf. Energy Management and Power Deliveivery, pp. 689–693, 1998.

[10] J. A. Lazkano, A., Ruiz, J., Aramendi, E., Gonzalez, “Study of high impedance fault detection in levante area in spain,” Proc. Int. Conf. Harmonics and Quality of Power, pp. 1011–1016, 2000.
[11] M.Sedighi, Haghifam, Malik, Ghassemian, “High impedance fault detection based on wavelet transform and statistical pattern recognition,” IEEE TRANS. POWER DELIV, vol. 20, no. 4, pp. 2414–2421, 2005.
[12] t. m. Lai, L. A. Snider, E. Lo, And D. Sutanto, “High-impedance fault detection using discrete wavelet transform and frequency range and rms conversion,” IEEE Trans. Power Deliv, vol. 20, no. 1, pp. 397–407, jan. 2005.
[13] O. P. Haghifam, M.-R. Sedighi, A. R. Malik, “Development of a fuzzy inference system based on genetic algorithm for high-impedance fault detection,” Generation, Transmission & …, vol. 153, no. 3, pp. 359–367, 2006.
[14] A. Etemadi and M. Sanaye-Pasand, “High-impedance fault detection using multi-resolution signal decomposition and adaptive neural fuzzy inference system,” Generation, Transmission & …, vol. 2, no. 1, pp. 110–118, 2008.
[15] S. H. Michalik, M., Lukowicz, M., Rabizant, W., Lee, S.J., Kang, “New ann-based algorithms for detecting hifs in multigrounded mv networks,” IEEE Trans. Power Deliv, vol. 23, no. 1, pp. 58–66, 2008.
[16] N. Ghaffarzadeh And B. Vahidi, “A New protection scheme for high impedance fault detection using wavelet packet transform,” Advances in Electrical and Computer Engineering, vol. 10, no. 3, pp. 17–20, 2010.
[17] Sulaiman, M., Tawafan, A. H., & Ibrahim, Z.. Detection Of High Impedance Fault Using A Probabilistic Neural-Network Classfier. Journal of Theoretical and Applied Information Technology, 53(2), 180–191, 2013, ISSN: 1992-8645.
[18] M. S. Abdel Aziz, M. A. Moustafa Hassan, and E. A. Zahab, “Applications of anfis in high impedance faults detection and classification in distribution networks,” 8th IEEE Symposium on Diagnostics for Electrical Machines, Power Electronics & Drives, pp. 612–619, sep. 2011.
[19] S. Saleem and A. Sharaf, “A Fuzzy artmap based high impedance arc fault detection scheme,” In Electrical And Computer Engineering,2008. CCECE 2008. Canadian Conference on, 2008, pp. 871–876.
[20] Adnan Hasan Tawafan, "Detection of high impedance fault of power distribution network uing intelligent fuzzy systems" ph.D. thesis , University Teknikal Malaysia Melaka, 2014.
[21] T. Lai, L. Snider, And E. Lo, “Wavelet transform based relay algorithm for the detection of stochastic high impedance faults,” International Conference on Power Systems Transients, vol. 1, no. 1, pp. 1–6, 2003.
[22] S. Mallat, “A Theory for multiresolution signal decomposition: the wavelet representation,” Pattern Analysis And Machine Intelligence, IEEE …, vol. i, no. 7, pp. 674–693, 1989.
[23] Chiu S. L, “Fuzzy model identification based on cluster estimation,” Journal of Intelligent and Fuzzy Systems, vol. 2, pp. 267–278, 1994.