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Broken Conductor Detection on Power Distribution Feeder

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Abstract – *An irregular activity on electric power distribution feeder, which does not draw adequate fault current to be detected by general protective devices, is called as High impedance fault (HIF). This paper presents the algorithm for HIF detection based on the amplitude of third and fifth harmonics of current, voltage and power. It proposes an intelligent algorithm using the Fuzzy Subtractive Clustering Model (FSCM) to detect the high impedance fault. The Fast Fourier Transformation (FFT) is used to extract the feature of the faulted signals and other power system events. The effect of capacitor bank switching, non-linear load current, no-load line switching and other normal event on distribution feeder harmonics is discussed. The HIF and other operation event data were obtained by simulation of a 13.8 kV distribution feeder using PSCAD. It is evident from the outcomes that the proposed algorithm can effectively differentiate the HIFs from other events in power distribution feeder.* ***Copyright © 2013 Praise Worthy Prize S.r.l. - All rights reserved.***

Keywords: *FFT, High Impedance Faults, Subtractive Clustering, TSK Fuzzy Modeling*

Nomenclature

ANFIS	Adaptive Neural Fuzzy Inference System
DC	Direct Current
DFT	Discrete Fourier Transform
DST	Discrete S-Transform DST
DTT	Discrete Wavelet Transform
DWT	Discrete Time–Time Transform
FFT	Fast Fourier Transform
FSCM	Fuzzy Inference System
HIF	High Impedance Fault
TSK	Takagi Sugeno-Kang
WPT	Wavelet Packet Transform
RMSE	Root Mean Squared Error
I_i V_i P_i	The amplitude of i harmonics of current, voltage and power
P_i	The new potential value i-data
P_i*	The potential value data as cluster center
x_1*	The cluster center of data
β	The weight i- cluster center
r_i	The distance between cluster center
η	A positive constant and is called the squash factor

I. Introduction

A High Impedance Fault (HIF) is a weird event and difficult to detect on electric power distribution feeder.

A high impedance fault is generated due to a faulty high impedance object or during an unnecessary electrical contact made by a main circuit conductor, which limits the current flow below the level of detection for the protective devices. Generally the resultant level of fault current will be lesser than the normal current (approximately 10 to 50 A) of the electric power distribution feeder [1].

The failure to detect HIF results in adverse consequences such as, electric shock to human and probable fire accidents, which might cost human lives and assets. HIF does not usually pose any risk to the electric power distribution feeder; however, the protection against them desirable. Significant number of studies has been conducted since early seventies related to HIFs for identifying features in the current or voltage waveform, which might facilitate the detection of HIF [1].

HIF has many characteristics, the most two characteristics are the low current and arcing. The gaps created due to looseness of contact with the ground or the object that has been grounded. Furthermore, air gaps might also appear in the ground (soil) or in the grounded objects such as, concrete, trees etc. As soon as the air gap breaks down, a high potential is generated in a short distance and the sustainable current level in the arc is not adequate to be detected consistently by standard methods.

Few other electrical events also behave like the HIF (capacitor bank operation, air switching operation, nonlinear load and starting induction motor), therefore, the algorithm proposed to detect HIF should have ability to discriminate HIF from other normal events in power distribution system. Most of the detection methods require extensive computation in the reprocessing stage for feature extraction of the input signals. Then a strategy is applied to obtain detection parameters.

During the past decades, protection engineers and researchers have tried to find a complete solution to this type of fault.

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The fault has many characteristics like presence of harmonics and high frequency components due to the arcing, detection techniques aim to identify useful features of HIF from the pattern of the voltage or current signals associated. A lot of detection algorithms have been proposed to detect HIF, some of these have used frequency-based to extract relevant features of the harmonic components [2][3][4][5][6] other have utilized time–frequency-based features to examine the transient phenomena of HIFs signals in both the time and frequency domains [7][8][9][10][11][12][13][14][15], the extracted features usually can be obtained after process the signals with one of methods of signal processing like discrete Fourier transform (DFT), discrete wavelet transform (DWT) and some other time–frequency analysis methods such as discrete S-transform (DST), discrete time–time transform (DTT)[14] and the wavelet packet transform (WPT)[15].

A method for detecting HIF based on the nonlinear behaviour of current waveforms has been presented in the research work [12], which employs a wavelet multi-resolution signal decomposition method to extracting features and an adaptive neural fuzzy inference system (ANFIS) for identifying and classifying purposes. Similarly, wavelet transform and principal component analysis are employed for extracting and selecting features [16]. Moreover, classification is carried out by fuzzy inference system and input membership functions are adjusted by a genetic algorithm. In [11] the author uses (ANFIS) as a classifier to detect HIF.

The ratio of harmonics amplitude (2^{nd}, 3^{rd}, 5^{th}, 7^{th}, 9^{th} and 11^{th}) to the fundamental harmonic amplitudeare uses as features of HIF. And in [17] a 'feature' or 'diagnostic' vector are formed by a group of foremost key harmonic signals, rather than a single dominant harmonic signal. In this paper, fast Fourier transform (FFT) is employed to extract the vector, which comprises the third and fifth harmonics of the voltage, current and power signals. Fuzzy subtractive clustering model (FSCM) is used as a classifier. Fuzzy systems have two useful properties and capabilities: (i) potential of approximating any complex nonlinear system and (ii) model determination, through the input-output data (learning process). Fuzzy system is adaptive and depends on input output data rather than on a classical method, so the resulting scheme is valuable, efficient and capable of reflecting changes in high impedance fault behaviors. Fuzzy Subtractive Clustering Model (FSCM) is a special class of fuzzy systems which is used in this paper.

II. Fuzzy Modeling Basedon Subtractive Clustering

Takagi, Sugeno and kang (TSK fuzzy system) has introduced fuzzy subtractive clustering system [18],[19].

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 feature space 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 pre-specified 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 method to identify rules is that, the resulting rules are heavily modified to the input data as against the fuzzy inference system, where they are created devoid of clustering. This minimizes the challenges of combinatorial explosion of rules, with high dimensional input data.

The TSK fuzzy system is a efficient method to producing from a given input-output data set. 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:

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

where xj (j [1, n], n is the number of inputs) 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 [20].

Assume a group of m data points in an N-dimensional space. The data points are normalized, without losing generalization. In this algorithm, a potential Pj is allotted to each data points zj= (xj, yj), based on its location to all other data points:

$$p_i = \sum_{j=1}^{M} e^{-\alpha\left\|x_i - x_j\right\|^2} \quad (2)$$

where:

$$\alpha = \frac{\gamma}{r_a^2} \quad (3)$$

Pj represents the potential value i-data as a cluster center;
α is the weight between i-data to j-data;
xi and xj are the data point;
γ is variables;
$ra$is a positive constant known as cluster radius.

Subsequent to the calculation of the prospective of all the data points, the point with the maximum prospect is selected as the center for a cluster. Let $x1$ and $P1*$ be the center of the first cluster and its potential value. The potential of each data point $x1*$ is recalculated as follows:

$$p_i = p_i - p_k^* \zeta \tag{4}$$

$$\zeta = e^{-\beta \left\| x_i - x_i^* \right\|^2},\ \beta = \frac{4}{r_b^2},\ r_b = \eta r_a \tag{5}$$

pj is the new potential value i-data.
pi* is the potential value data as cluster center.
x_1* is the cluster center of data.
β is the weight i- cluster center.
ri is the distance between cluster center.
η is a positive constant and is called the squash factor.

After recalculating the prospects of all data by (2), the data point with the maximum outstanding prospect is chosen as the second cluster center. Normally, after obtaining the kth cluster center, the prospect of all the data points are recomputed as follows:

$$p_i = p_i - p_k^* e^{-\beta \left\| x_i - x_k^* \right\|^2} \tag{6}$$

where P^*k is potential value and x^*k is the center of the kth cluster. The process of acquiring new cluster center and recalculating potential repeats in relation to squash factor together with the accept ratio, reject ratio and influence range. A fraction of the potential of the first cluster center is set by the accept ratio, above which another data point will be accepted as a cluster center. However the potential is set by the reject ratio, as a fraction of the potential of the first cluster center, under which a data point will be rejected as a cluster center.

By the end of clustering, a adequate number of cluster centers and cluster sigma is produced. The initial number of rules and antecedent membership functions are determined by this information and then fuzzy inference system of TSK model is identified.

III. System Modeling

III.1. Model of Distribution

A 13.8 kV distribution feeder was performed in PSCAD/ EMTDC. Two networks are studied in the proposed algorithm (a) radial distribution network and (b) meshed network. Figs. 1(a) and (b) represent the two proposed systems, respectively. The network includes 30kV / 10MVgenerator that connects to the transformer with 30/13.8 kV and 10 MV. The simulation involves producing different types of HIF and normal event signals under linear and no-linear loads with various loading operational conditions. The sampling rate chosen is 12.8 kHz. Fig. 2(a) shows HIF fault current signal under linear load and Fig. 2(b) depicts HIF fault current signal under no-linear loads. The fault has created at 0.2 s. Under linear loading condition, the signal of HIF comprises higher harmonic components compared with the signal before the fault (Fig. 2(a)). Thus, the distinguish HIF from other normal operations, in this cases, is easy. However, in case of HIF under nonlinear loading condition, the signal before and during the HIF comprises higher harmonic components (Fig. 2(b)).

Consequently, it becomes hard to differentiate HIF from other normal condition under nonlinear loading condition 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 is like for those that HIF in frequency domain.

III.2. 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 two DC sources, Vn and Vp, which signify the inception voltage of air in soil and/or between distribution line and trees. The two varying resistors, Rn and Rp, were employed to signify the fault resistance, irregular values enables to simulate an asymmetric fault currents. The fault current flows towards the groundif the phase voltage is higher than the positive DC voltage Vp, however,when the line voltage is less than the negative DC voltage Vn, thenthe fault current reverses. No fault current flows when values of the phase voltage between Vp and Vn. The Fig. 3 illustrates a simplified model of HIF [21].

IV. Detection Algorithm

The detection algorithm includes three important parts: data preparation, features generation and classification. Data preparation part is described in simulation section. The rest parts are described below.

IV.1. Features Generation

On the modeled distribution system, different operation conditions have been simulated by using PSCAD/ EMTDC. The simulated data then were transferred to MATLAB to complete the rest algorithm.

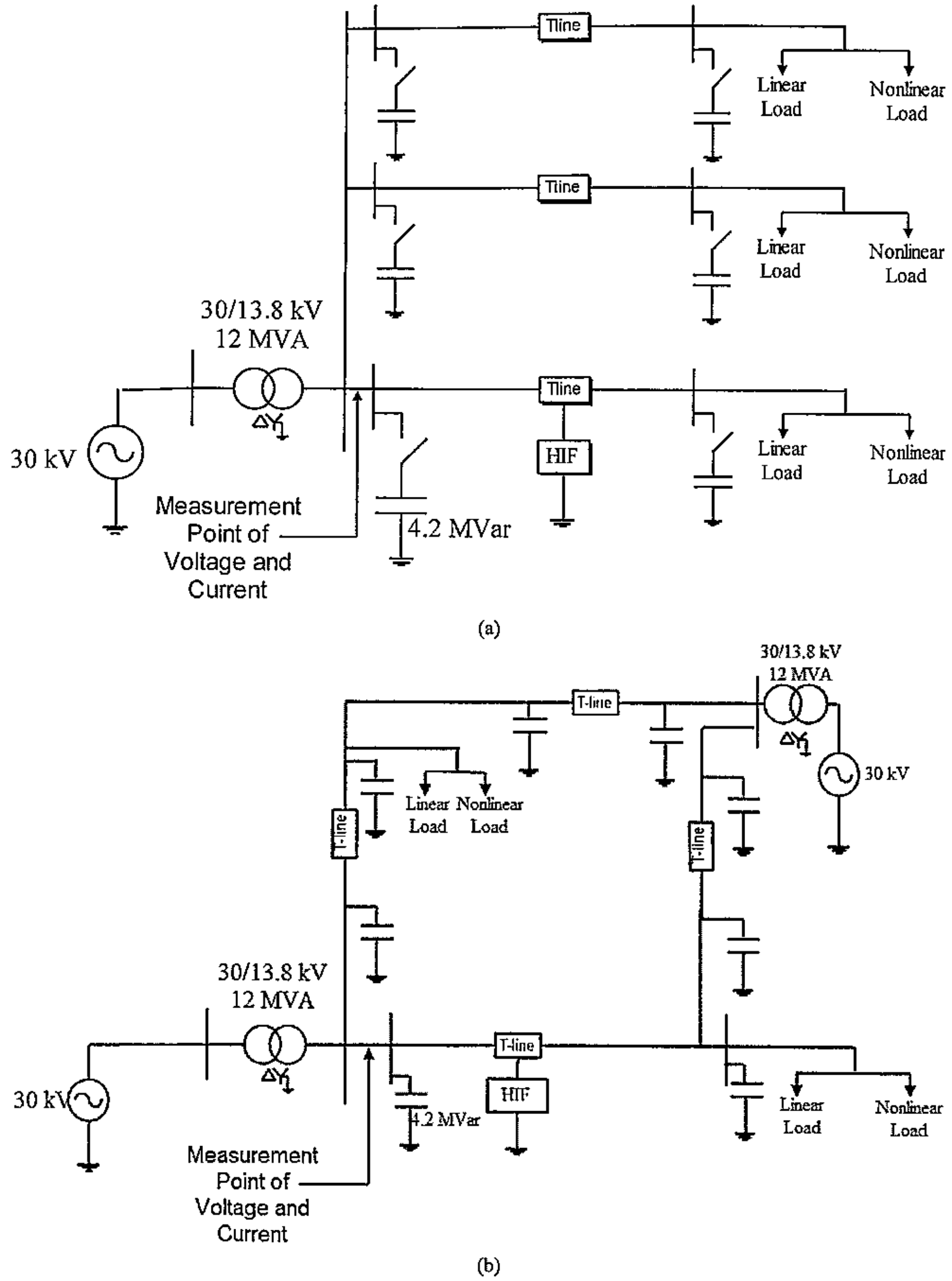
The main goal of algorithm is to discriminate between HIFs and other similar waveforms. In this algorithm, there are three types of feature are investigated to detected HIF faults:

- The amplitude of third and fifth harmonics of current, voltage and power.(Type 1) $[I3\ V3\ P3\ I5\ V5\ P5]$
- The ratio of third and fifth to the fundamental of current, voltage and power. (Type 2):

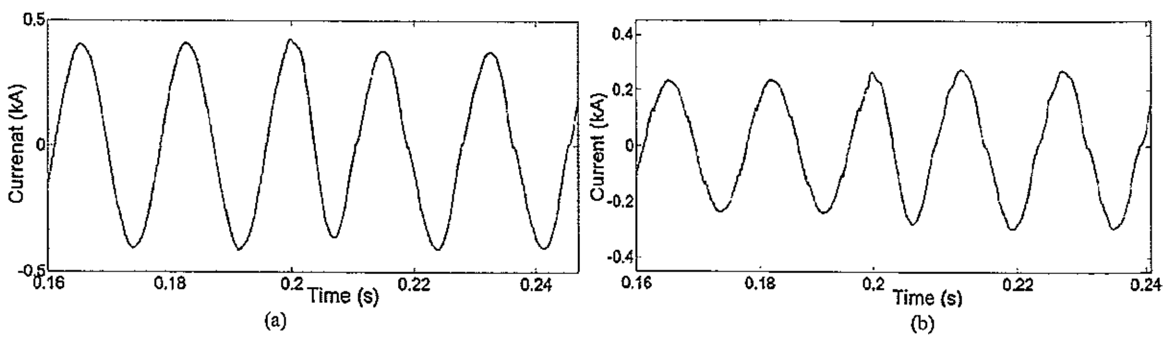
$$[I3/I_f\ \ V_3/V_f\ \ P3/P_f\ \ I5/I_f\ \ V5/V_f\ \ P5/P_f]$$

- The ratio of harmonics amplitude (2^{nd}, 3^{rd}, 5^{th}, 7^{th}, 9^{th}and11^{th}) to the fundamental harmonic amplitude of current. (Type 3):

$$[I2/I_f\ \ I3/I_f\ \ I5/I_f\ \ I7/I_f\ \ I9/I_f\ \ I11/I_f]$$



Figs. 1. Graphic Diagram of the Simulated 13.8kV Power System (a) Radial network (b) mesh network



Figs. 2. HIF fault current signal (a) under linear load. (b) under nonlinear load

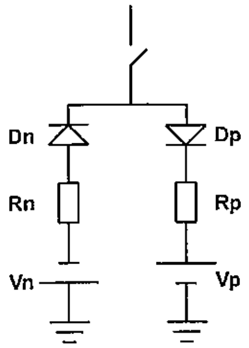
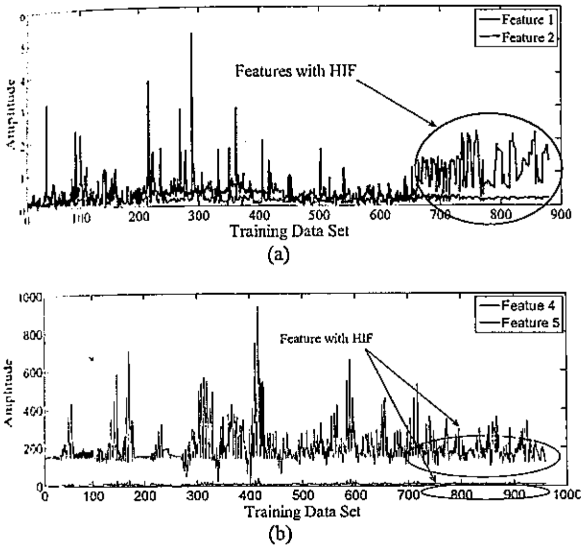


Fig. 3. Model of HIF



Figs. 4. Relation between Feature (a) Feature F1 against F2 (b) Feature F4 against F5

where I_f, V_f and P_f are the fundamental of current, voltage and power. Features from HIF and other events signals of diverse operating conditions of the power distribution networks are extracted by a Fast Fourier Transform (FFT) method.

After the process of fault inception, the features are extracted for 6 cycle fault current signal. The HIF and other events (current, voltage) signals are produced from the power distribution network models.

The relationship among the features is illustrated in Figs. 6(a), (b), each plot represent relation between two features, of which few features are distinctive, while some are overlapped. The plots provide information related to the capability of the extracted features for classification in raw feature form, for using those features as inputs to the designed FSCM.

IV.2. Classification

Cluster analysis is an exploratory data analysis tool so that different objects classify into groups, if two objects was belonging to the same group, the degree of association between them will be maximal, and minimal otherwise.Given the above, cluster analysis can be used to form structures in data without offering an interpretation. In other words, cluster analysis simply discovers structures in data without clarifying why they exist. Clusters in fuzzy logic are created using input-output training data, and using information of cluster to generate FSCM that gives the best describing to the behavior of data using a minimum number of rules. The rules divide themselves based on the fuzzy features associated with each of the data clusters

In this study, subtractive clustering fuzzy logic is used as the classifier to serve for the fuzzy classification. Six extracted features are used to generate fuzzy inference system.

V. Simulation

V.1. Data Preparation

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

A) Preparing the Clustering Data and,

B) Rules generation.

A) Preparing the Clustering Data

Fuzzy inference system based on subtractive clustering needs classifying the training data into two data sets:

a) An input data set which has values for the six inputs [F1, F2, F3, F4, F5, F6] represent either the amplitude of third and fifth harmonic of current, voltage and power, the ratio of third and fifth to the fundamental of current, voltage and power or the ratio of harmonics amplitude (2nd, 3rd, 5th, 7th, 9th and 11th) to the fundamental harmonic amplitude of current. 1440 input data points were selected from frequency domain 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 zero for other normal event in power system. 1440 output data points, corresponding to the selected input points. These points were placed into a single output data set.

The 160 input and output data points which are different from the training data are remained and are used for testing purpose.

B) Rules Generation for FSCM

Fuzzy Subtractive Clustering Model (FSCM) supposes the centers of cluster in a set of data.It considers each data point is a possible to be center of cluster then a measure of the likelihood that each data point would define the cluster center is calculated.

The algorithm that based on the density of neighboring data points has three important steps:

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

2) To determine the new cluster and the location of its center, all data points are removed from the surroundings of the first cluster center (as determined by radii).

3) The above procedures continue until all data located within radii of a cluster center.

The value of radii is between 0 and 1 which determines the influence of cluster center's range in each of the data dimensions, supposing the data enters within a unit hyperbox. If radii value is small, FSCM will produce few large clusters. best value for radii is often between 0.2 and 0.5. In this application, the value of the radii is 0.2.This was shown to result higher processing speeds and fewer membership functions, without reducing accuracy. the FSCM based system is generated using a certain MATLAB functions that available with fuzzy logic toolbox. This function extracts a set of rules that model the data behavior.

VI. Results

In this study, first order TSK fuzzy approach based on subtractive clustering was used to detect high impedance fault. The process of model building using subtractive clustering was carried out by making of clusters in the data space and translation of these clusters into TSK rules.

There have been 1440 training cases which were selected to train the network. The training sets included 360 HIF cases and the rest are non-fault cases. The FSCM has one output, the output is one when the system detect HIF case and is zero when other cases. Three types of feature are investigated. The FSCM is trained with various groups of inputs to check the influence on classification rate. The training and testing data sets are used to calculate the classification rate of FSCM for both the radial distribution and mesh networks.

Fig. 5 show the HIF classification rate of FSCM using three types of features extracted from FFT. The x-axis of Fig. 5 shows the radial distribution and mesh networks with three types of feature, and the y-axis of the Fig. 5 shows the percentage HIF classification rate. FSCM with feature type 1 provides up to 93.12%classification rate for radial network and 95.48% classification rate for mesh network.

Also, FSCMwith feature type 2 provides up to 73.89% and 65.48% classification rate for radial network and mesh network respectively. And it provides only 84.37% and 70.34% classification rate with feature type 3. It is found that fuzzy subtractive with feature type 1 gives better classification rate result.

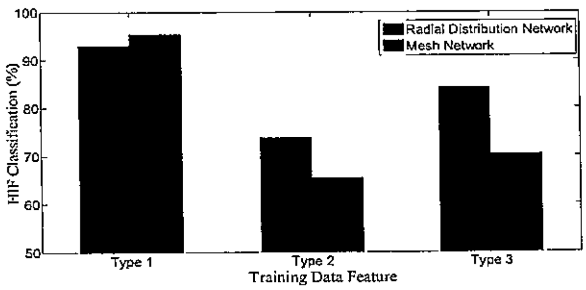


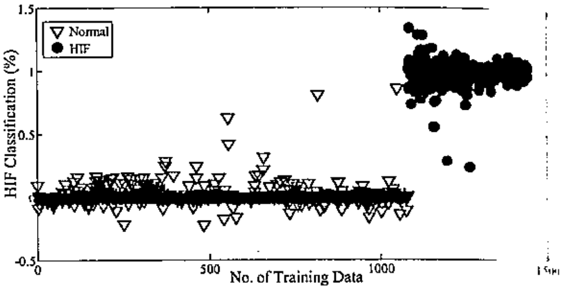
Fig. 5. The HIF classification rate of fuzzy subtractive

Figs. 6 shows output of the FSCM to the training data with feature type 1. For radial network, Fig. 6(a) it is obvious that the HIF detection is successful to detect 85% of the fault cases and 95.83% for non-fault cases.

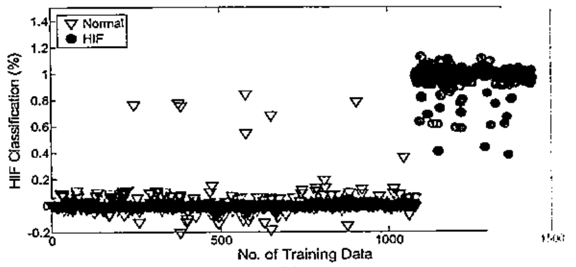
The classification rate over all cases is 93.12% and the RMSE value of the model of training case is 0.0697.

Also for mesh network, Fig. 6(b) the FSCM has succeeded to detect 91.38% of the fault cases and 96.85% for non-fault cases.

The classification rate over all cases is 95.48% and the RMSE value of the model of training case is 0.0810. The system is trained properly and has categorized different cases effectively.



(a)



(b)

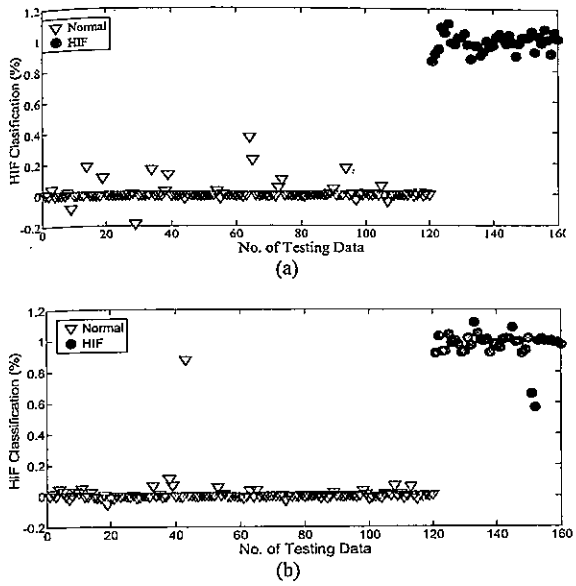
Figs. 6. Output of the subtractive clustering fuzzy system (a)Radial Network (b)Mesh Network

To evaluate the suitability of proposed algorithm, test data cases were fed to the FS and the obtained output is shown in Figs. 7(a), (b). It shows that the proposed method could classify different input categories successfully and reliably. It is found that the proposed algorithm is capable to categorize 98.75% and 98.12% for radial and mesh network respectively. Results of the testing phase, which demonstrates that the algorithm is reasonably reliable.

Also two aims are chosen to test the HIF detection algorithm. The first one is to test the impact of input feature sets of training data that are used to train the FSCM. The second aim deals to find the effect of the percentage of input training set on the FSCM classification rate performances.

VI.1. The Effect of Input Feature Sets

The first aim deals to investigate the impact of input feature set on the classification rate of the FSCM, various feature sets are tested.



Figs. 7. Output of the subtractive clustering fuzzy system
(a) Radial Network (b)Mesh Network

These sets are mentioned in Table I, and Table II displays the classification rate of the presented algorithm for each of them.

TABLE I
DESCRIPTION OF FEATURE SET

	Feature type	No. of feature
FS1	[I3, V3, P3, I5, V5, P5]	6
FS2	[I3, V3, I5, V3]	4
FS3	[I3, P3, I5, P5]	4

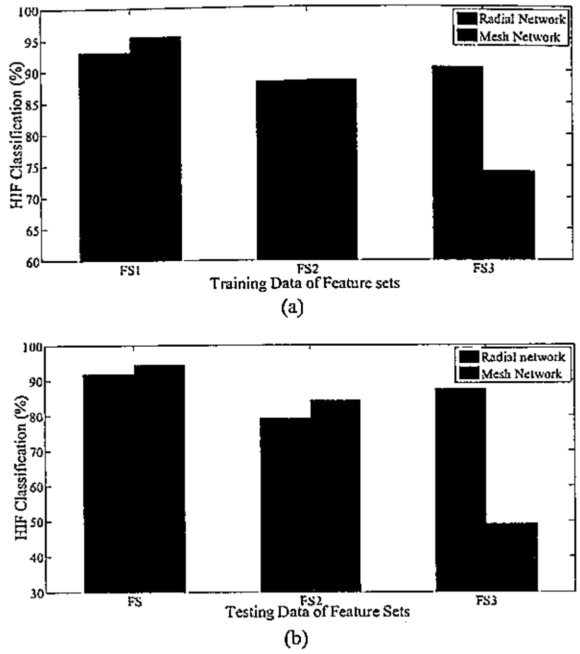
TABLE II
THE CLASSIFICATION RATE FOR EACH FEATURE SET

Feature set	Radial network		Mesh network	
	RMSE	Classification rate	RMSE	Classification rate
FS1	0.0697	93.12	0.0810	95.48
FS2	0.1828	88.29	0.1332	88.49
FS3	0.1254	90.48	0.1431	74.11

It is noticeable that the feature sets of FS1 have more characteristic information than the other feature set, as appeared in average classification rate. Also, it can be conclusion that the feature of the FS1 has shown good results. Figs. 8(a), (b) show the classification rate for the different training and testing feature set.

VI.2. The Effect of Number of Training Data Set

In this stage, the FSCM is trained with different number of training data set to get the best classification rate. Figs. 9 (a), (b) show the HIF classification rate of FSCM with input training data set (FS1) that has different number of training data set. The maximum classification rate with training data set is 98.81% for radial network and 98.33% for mesh network respectively. And FSCM with testing data set provides up to 98.75% and 98.12% classification rate for radial network and mesh network, respectively.

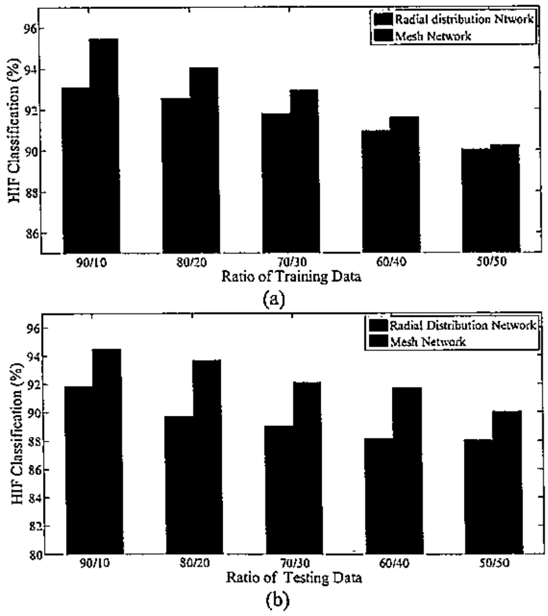


Figs. 8. The classification rate for the different training and testing feature set. (a) Training Data (b) Testing Data

VII. Discussion

In the presented algorithm, a investigation was made between three types of features to get best classification rate for HIF detection in power distribution feeder. From the results obtained, it was found that the feature of type1 provides better results compared with other features.

Also with using 90% training and 10% testing data sets to train and test the FSCM has given a good classification rate result.



Figs. 9. HIF classification rate with different number data set
(a) Training Data (b) Testing Data

VIII. Conclusion

FSCM to detect and classify HIF was presented in this research studies. An effort has been made for classification the HIF from other event in distribution system under linear and nonlinear loads. In this paper, the harmonic of current, voltage and power of the HIF and other events are used as an input vector of FSCM.

The harmonics of current, voltage and power were computed using FFT and different features like (type1, type2 and type3) were extracted and used for training and testing theFSCMfor HIF classification. The obtained classification rate of HIF using FSCM is more than 93% for radial network and more than 95% for mesh network.

Thus, the presented algorithm is accurate and fast to identify HIF that may be extended to protect a power distribution network.

References

[1] M. Sedighizadeh, a. Rezazadeh, and N. I. Elkalashy, "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] 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.

[4] 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.

[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] 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.

[7] 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.

[8] 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.

[9] 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.

[10] M. . Sedighi, A.R., Haghifam, M.R., Malik, O.P., 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.

[11] Sulaiman, M., Adnan H. Tawafan, High impedance fault detection on power distribution feeder, (2012) *International Review on Modelling and Simulations (IREMOS)*, 5 (5), pp. 2197–2204.

[12] 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.

[13] 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.

[14] P. K. Samantaray, S.R., Panigrahi, B.K., Dash, "High impedanc fault detection in power distribution networks using tim frequency transform and probabilistic neural network," *IE Generation, Transmission & Distribution*, vol. 2, no. 2, pp. 261–270, 2008.

[15] N. Ghaffarzadeh and B. Vahidi, "A New Protection Scheme fc High Impedance Fault Detection using Wavelet Pack Transform," *Advances in Electrical and Computer Engineerin*, vol. 10, no. 3, pp. 17–20, 2010.

[16] O. P. Haghifam, M.-R.; Sedighi, A.-R.; Malik, "Development of fuzzy inference system based on genetic algorithm for hig impedance fault detection," *Generation, Transmission & ...*, vo 153, no. 3, pp. 359–367, 2006.

[17] S. Saleem and A. Sharaf, "A fuzzy ARTMAP based hig impedance arc fault detection scheme," in *Electrical an Computer Engineering,2008. CCECE 2008. Canadia Conference on*, 2008, pp. 871–876.

[18] M. Tagaki, T., Sugeno, "Fuzzy identification of systems and it application to modeling and control.pdf," *IEEE Transactions o systems, Menand Cybemetics 15*, pp. 116–132, 1985.

[19] M. Sugeno and G. T. Kang, "Structure identification of fuzz model," *Fuzzy Sets and Systems*, vol. 28, no. 1, pp. 15–33, 1988.

[20] Chiu SL, "fuzzy model identification based on clust estimation.pdf," *journal of intelligent and fuzzy systems*, vol. 2 pp. 267–278, 1994.

[21] T. Lai, L. Snider, and E. Lo, "Wavelet transform based rela algorithm for the detection of stochastic high impedance faults," *International Conference on Power Systems Transients*, vol. 1 no. 1, pp. 1–6, 2003.

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