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High impedance fault detection: Discrete wavelet transform and fuzzy function approximation

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Abstract

This paper presents a method including a combination of the wavelet transform and fuzzy function approximation (FFA) for high impedance fault (HIF) detection in distribution electricity network. Discrete wavelet transform (DWT) is used in this paper as a tool for a signal analysis and after studying different types of mother signals, detailed types and feeder signal, the best case is selected. In the next step, the DWT is used to extract the features. The extracted features are used as the FFA Systems inputs. The FFA system uses the input-output pairs to create a function approximation of the features. The FFA system is able to classify the new features. The combined model is used to model the HIF. This combined model has the high ability to model different types of HIF. In the proposed method, different kind of loads including nonlinear and asymmetric loads and HIF types are studied. The results show that the proposed method has high capability to distinguish between no fault and HIF states accurately.

Keywords*: High Impedance Fault, Fuzzy Function Approximation, Wavelet Transform, Distribution Network, Arc Fault.*

1. Introduction

Safety is one of the important issues in distribution electricity networks. Lack of security in the power network may lead to damage to humans and equipment. The prevention is the best solution to avoid the harmful events. The HIF is one of the issues that results in death and financial damages. The HIF occurs when a conductor contacts with the ground or high impedance object. As the impedance of the current path is high, the current value in this type of fault is low and usually ranges from 0A to 100A [1]. Hence, by the conventional over current relay, it is not possible to detect this kind of fault; it is treated as a normal load current raise.

The HIF can occur in two forms. In the first form, a conductor breaks and falls to the ground. In the second form, an electrical conductor is not disconnected but only is to be connected to a high impedance object (such as tree branches and leaves). The HIFs are usually associated with an electric arc, which may cause a fire. Due to the nonlinearity nature of the fault, the HIF current contains various frequency harmonic components including low and high frequency components. It should be noted that other network components have also broad frequency harmonics. Therefore, the HIF should be studied precisely. The researchers have performed several HIF experiments and have studied the associated voltage and current to obtain models that are to be used in the simulations. As the HIF has a random nature and the fault current is influenced by many parameters, developing a model that covers all conditions is difficult. However, since the developed model is based on practical experiments, the researchers considered some aspects of the HIF characteristics.

The first model of HIF was introduced in1985. In this model, the HIF was modeled by a single resistor in the fault location [2]. After five years, with respect to the presence of ARC in the HIF, an arc based model is presented [3]. In this model, the HIF is presented in anti-parallel two diodes, each one is in series with a DC voltage source and series impedance. The two diodes as well as the voltage sources show the diode voltage threshold. The series impedance also controls the current. Three years later, branch impedances were replaced with two nonlinear resistors [4]. Also in 2005, the arrangement of fixed and variable resistors in two half cycles were presented [5]. In addition to the electrical aspects for HIF modeling, the dynamical aspects of the HIF arc are used. This is possible by using the dynamical relationships of electrical arc [6,7]. Also, a combinational method which uses the both aspects were employed in [8]. In this reference, a dynamical relationship is considered for a variable resistor placed in a path out of the diodes routs. The advantage of this method is that the arc model results are close to the practical experiments. Also, in this model, the routes of the two diodes can represent the non-similarity between positive and negative half cycle of high impedance fault in [9], two voltage sources with random value were used to create random characteristics for the HIF current.

Researchers have proposed various methods for the detection of the HIF. These methods usually start by measuring available signal at the feeder and preparing them for analysis. Then, the signal processing tools are for feature extraction and obtaining discriminative. The latter has been used to discriminate between normal and HIF situations. Finally, the fault classification is performed using simple or intelligent algorithms. References [10] and [11] used discrete Fourier transform to find the voltage signal harmonics and feeder current. In order to extract frequency feature of the HIF, some signal processing tools such as Fourier transform and Kalman filter have been utilized. Also, the magnitude of the harmonics was founded through using Kaman filter [12]. In the power system, time-frequency based methods are used. This leads to more use of the wavelet transform. This fact is due to the time varying behavior of the power system phenomena especially HIF. The wavelet transform based methods were for analysis the measured signal in [13,14].

After extracting features, the HIF should be distinguished from normal operating conditions. Sequential algorithms such as described in [15] to check the appropriate features, if the feature exceeds the threshold value, it means that the HIF has been occurred. Intelligent methods such as artificial neural network (ANN), perform classification the training data. In [12,16,17] different methods of training, the ANN was used in HIF detection. A combination of the ANN and sequential algorithm was used in [18] and the method employed in [14] is based on the a neuron-fuzzy method.

In this paper, firstly the signal is decomposed using DWT. In the next stage, the wavelet output is used to find appropriate features for classification. In order to consider the more realistic case, a combined model of the HIF is used. In the classification stage, an FFA intelligent method for is presented.

In this paper, firstly the wavelet transform and FFA are briefly explained. Then, the proposed method is provided. After that, the component modeling is described. Finally, the simulation results and discussion are described.

2. Wavelets for signal analysis

The wavelet analysis is a signal-processing tool that has successful applications in various fields especially in power engineering. Some applications of the wavelet are in the field of power quality [19], power system protection [20], power system transient [21].

Unlike Fourier transform, the wavelet analysis is able to provide simultaneous time and frequency information. Hence, it is a useful tool for analysis of transient signal that contains high frequency and low frequency components. There are two discrete and continuous wavelet transforms. The DWT is used to process digital data. The DWT for the function x is given by:

$$DWT(m,k) = \frac{1}{\sqrt{a_0^m}} \sum_n x[n].\, g[\frac{k - n a_0^m}{a_0^m}] \qquad (1)$$

Where x[n] is a digital signal, g is the mother wavelet, a0 and k are scale factors, respectively. Also n and m are real numbers.

The DWT can be implemented by using a multistage filter with the mother wavelet as the low pass filter and high pass filter [22]. The center frequency is varied by changing the scale and time shift in the mother wavelet. This shows that the wavelet transform can suitably extract unwanted transient signals and frequency components of a waveform. There are different types of mother wavelets, which can extract specific features of the signal. It should be noted that the selection of the mother wavelet is important in feature extraction. This selection depends on the type of application. Suitable mother wavelet should have a greater difference between the normal and faulted output signal. As a result, the suitable mother wavelet creates a better output. With regards to the specifications of the mother wavelet, several mother wavelets are considered as the suitable ones. In order to find

the most suitable mother wavelet, several mother wavelets can be examined.
The DWT is considered as a multistage filter with mother wavelet, which acts as the high pass and low pass filter. The output of the low pass filter gives the details of the low-frequency component of the signal. In addition, the output of the high pass filter gives the details of the high-frequency component of the signal. To obtain more details from the input signal, we can change the mother wavelet or levels of detail. This analysis called multi-resolution analysis shown in figure 1.

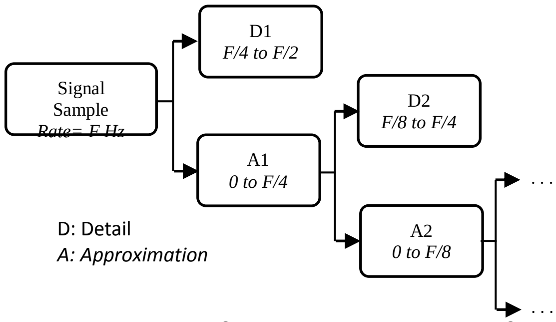


Figure 1. Diagram of multi-resolution analysis of wavelet.

3. Fuzzy system for approximation of function

The FFA is a method for nonlinear system modeling. Some types of fuzzy system are written as a closed nonlinear formula. These closed formulas simplify the fuzzy system computation. In addition, the fuzzy system can be treated an approximation of a function using the closed formula. It is very important to choose suitable number of fuzzy rules in design of fuzzy systems. Because choosing many fuzzy rules will complicate the fuzzy system, which may not be needed for the problem. On the other hand, choosing limited number of fuzzy rules, may lead to incorrect result. The important notion of employing fuzzy system for approximation function is to use mapped if-then fuzzy based on the output Mamdani fuzzy system according to
(2). The specification of this fuzzy system is given in [23].
In (2), the input-output pairs create if-then rules. This equation presents an the FFA, where F is the function approximation,(x_i, y_i) are input-output pairs as training data, n is number of training data, m is input data dimension, x is input variable, x_i is input training data, y_i is output training data and parameter σ is the standard deviation of the Gaussian membership function.

$$F(x) = \frac{\sum_{i=1}^{n} y_i * exp(-(\frac{(x-x_i)^2}{\sigma^2}))}{\sum_{i=1}^{n} exp(-(\frac{(x-x_i)^2}{\sigma^2}))} \qquad (2)$$

In this equation by choosing a suitable value for the parameter σ in the fuzzy system, it is possible to adapt any n-pairs input with any precision. If the number of pairs of input - output is large, then the function will have a better approximation. Smaller σ results in smaller adaptive error and the less F(x) smoothness. If F(x) is not being smooth, it is possible not to generalize it for the paired that do not lie in the set, not in a learning set. So σ should be chosen carefully to balance adaption popularities [23].

4. Proposed HIF detection methodology

The proposed method for identifying the HIF is based on DWT and FFA. In the first step of the proposed method, the feeder signal (voltage or current) is measured and then stored with 100 kHz sampling frequency for the duration of one second. In the next step, the signal processing is performed with DWT through choosing the best mother wavelet and details. Then, the features are built using the output of DWT. These features can discriminate between the no fault and HIF states. In the last step, the HIF classification is performed by FFA and training data. Figure 2 shows this process briefly.

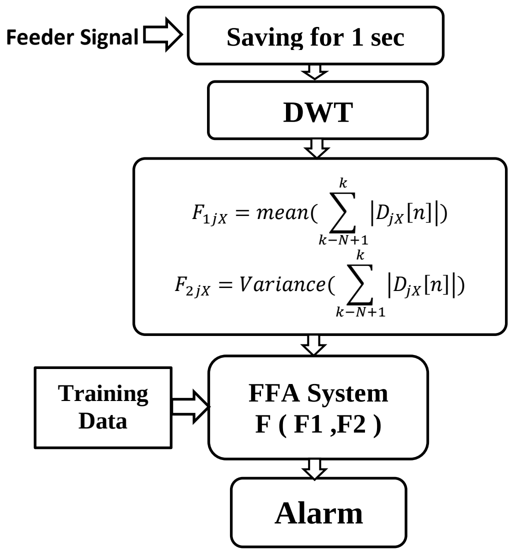


Figure 2. Process of HIF detection using DWT &FFA.

It is worthwhile to note that both voltage and current signals are examined separately, then after investigating the result, it will be decided which of these signals should be used in the simulation.
In the above algorithm, the following questions should be answered:

1- Which one of the measured signals provides the best accuracy?

2- Which one of the mother wavelet and what level of detail provides the best accuracy?

3- How to create the discriminating features using the wavelet output?

4- How does FFA the classify the HIF?

In response to the first question, it should be noted that, in this paper, phase voltage, phase current and summation of all phases voltage have separately been examined and simulated. From the results, the signal that creates the highest detection accuracy, is selected as an appropriate signal.

In response to the second question, it should be noted that in this paper, 17 types of mother wavelet ('db2','db4', 'db5', 'db8','db14','db20', 'sym5', 'sym8', 'coif4', 'bior2.6', 'bior5.5', 'bior6.8', 'rbio2.2', 'rbio3.1', 'rbio3.3', 'rbio4.4') and seven levels of details for all types of measured signal have been separately investigate. Among them, each one that has the highest detection accuracy, is selected as an appropriate mother wavelet and details.

The response to the third question is given in the following. As, the output of the wavelet is not the number and it is a function discrete of variables. Thus, this cannot be considered as the input of an intelligent algorithm or classification algorithm. Therefore, the appropriate input signal should extract features from the output of the wavelet, which expresses the desired behavior of the signal. In this paper, firstly, summation absolute detail (SAD) is taken from the output wavelet. The SAD calculated as follows [24]:

$$SAD_{jX}[k] = \sum_{k-N+1}^{k} \left| D_{jX}[n] \right| \qquad (3)$$

In (3), D_{jx} is the detail of the wavelet output at Level j for Signal X, k and N are real numbers. Next, two features of output wavelet are extracted. These two features for signal X at level j are the mean and variance denoted by F_{1jx} and F_{2jx}. The two features used as inputs of the classification system. These two features calculated as:

$$F_{1jX} = mean(SAD_{jX}[k]) \qquad (4)$$

$$F_{2jX} = variance(SAD_{jX}[k]) \qquad (5)$$

In response to the fourth questions is that as FFA needs input-output pairs as the training data for the FFA. These pairs are the mean and variance of SAD output for no fault and HIF cases, respectively. The value of output pairs the HIF case is one, and value of output pairs for no fault and normal load situations is zero. Expanding (2) for the two inputs (n=2) yields.

$$F_{HIF} = F(F_1, F_2) = \frac{\sum_{i=1}^{n} y_i * exp(\frac{-(F_1-F_{1i})^2}{\sigma_1^2}).exp(\frac{-(F_2-F_{2i})^2}{\sigma_2^2})}{\sum_{i=1}^{n} exp(\frac{-(F_1-F_{1i})^2}{\sigma_1^2}).exp(\frac{-(F_2-F_{2i})^2}{\sigma_2^2})} \qquad (6)$$

$$y_i = \begin{cases} 1 & for\ HIF \\ 0 & for\ NF \end{cases}$$

Where F_{HIF} is the FFA of HIF, n is the number of training data, F_1& F_2 are input features, F_{1i}& F_{2i} are input training data, y_i is output training data and parameter σ is the standard deviation.

In (6), y_i is also equal to one for HIF training data and equal to zero for no fault. Thus, if the function F (F_1, F_2) is equal to one for the new data of features, this represents the occurrence of HIF in the network. Alternatively, if the function F (F_1, F_2) is equal to zero, for it means that the network is working normally.

5. Component modeling and system under study

The study system in this paper is a radial distribution network as shown in figure 3. The parallel feeders are connected to a 63 kV slack bus via a63/20 kV substation transformer and the system frequency is 50 Hz. The parallel feeders (lines) have different lengths. Lines lengthare10, 20 and 30km.To have a better accuracy, the π model is used for the lines.

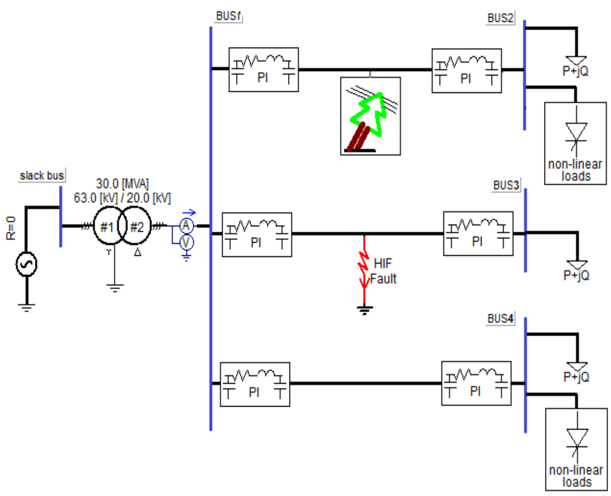


Figure 3. Single line diagram of the MV network under study.

Different loads for consumers in the buses are also used. The different loads are:

- Constant power (with different Power rating and different Power Factor)
- Induction machine (with constant and random torque)
- Electric arc furnace
- Load switching

- Thyristor load (3-Phase, 1-Phase, fixed angle, random angle, R&L load)
- Asymmetric loads (R & L & C)

In addition to different electrical loads, normal operating states are simulated such as capacitor bank switching, saturation transformer and change the situation the tap changer.

In this paper, a combined HIF model is employed in the simulation. This model combines the dynamical relationship arc and electrical model. In this model, the HIF is represented by anti-parallel two diodes, each one is in series with a DC voltage source and series dynamic resistors. The dynamic model of a dynamic resistor depends on the HIF currents. This model is shown in figure 4.

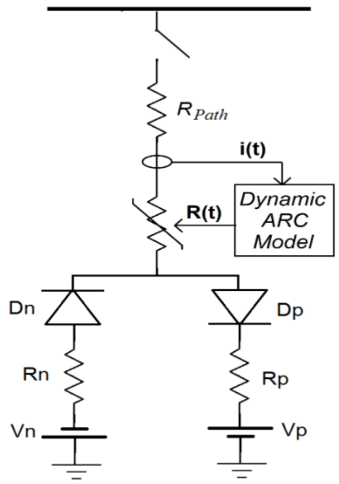


Figure 4.The combined model of HIF.

In figure 4, the dynamic resistance of arc model is calculated from the following equations [25]:

$$g = \int \frac{1}{\tau}(G - g)\,dt \tag{7}$$

$$G = \frac{|i|}{u_{st}} \tag{8}$$

$$u_{st} = (u_0 + r|i|)l \tag{9}$$

$$R = \frac{1}{g} \tag{10}$$

Where, g is the time-varying arc conductance, G is the stationary arc conductance, τ is time constant, i is the arc current, u_0 is constant voltage parameter per arc length, r is resistive component per arc length and l is the arc length [25].

The used model in this paper can satisfy several features of the behavior of HIF. For example, to create an asymmetry in the positive and negative half-cycle the two routes diodes are modeled differently. In order to create the random behavior for the HIF, the randomness in the resistance value or in the value of source voltage or even dynamic parameters such as the length of the arc are modeled. With the available parameters of the combined HIF model, many HIF models can be simulated. In this paper, some of the discrepancies in the used model are:

- Path resistance
- Dynamic parameters (l, r, u_0)
- Random variation of the dynamic parameter around their nominal values
- Resistor and voltage source in parallel branches.(R_n,R_p,V_n, V_p)
- Random variation resistor and voltage source around their nominal values
- Location and phase of the HIF fault

The reason of using of different changes in model parameters, is to create various features of HIF that are to be justified by the real situations.

6. Simulation and data analysis

In this section, the simulations and data analysis are given based on the proposed method. The simulation has two distinct parts. In the first part, the simulation of the HIF is performed based on the proposed method and models of the component introduced in Sections 4 and 5, respectively. The schematic diagram of the process of the application of the proposed algorithm is given in figure 5.

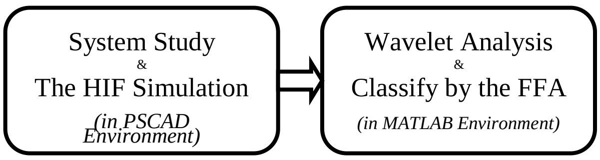


Figure 5.The schematic diagram of the execution of the proposed algorithm.

The number of systems running in PSCAD is 100. Among the total runs of 100, 50% is devoted for the no fault and 50% for the HIF case.

6.1. HIF simulation

In this section, some typical currents of the HIF model simulation in this paper, have been investigated. Figures 6 to 8 show typical current of HIF model for different cases. Also, figure 9 shows the voltage-current characteristic of one type of the HIF models.

In figure 6, constant amplitude of current HIF is seen. This is due to the constant parameters. Also, the parameter values routes of the two diodes are identical, the positive and negative half cycles are symmetric. But, in figure 7, the arc length parameter randomly is randomly changed. Hence, the random behavior in amplitude of current HIF can be observed and even in the current amplitude, it reaches to zero.

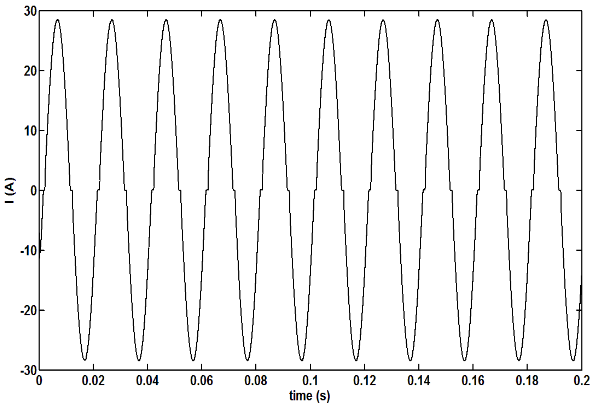


Figure 6. A typical current of HIF with constant amplitude.

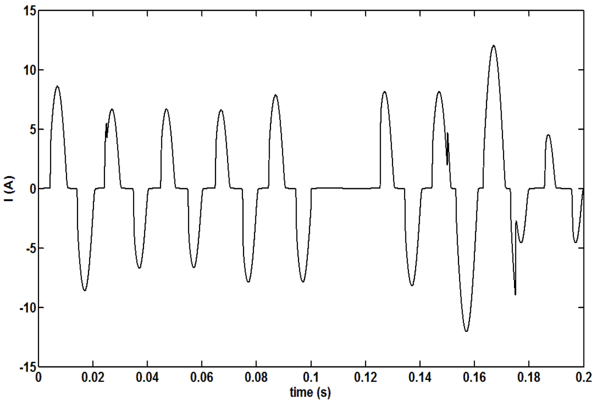


Figure 7. A typical current of HIF with random behavior.

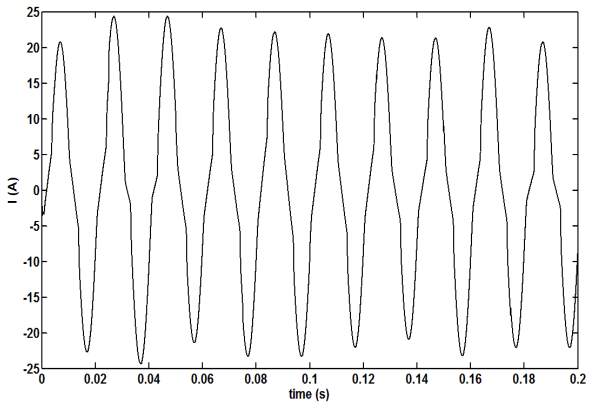


Figure 8. A typical current of HIF with randomness and asymmetry behavior.

In figure 8, the value of DC voltage parameters in the two diodes route change randomly and asymmetrically. Hence, in the current of the HIF model, the random behavior and asymmetry in the two half cycles can be seen easily. These figures demonstrate some are capabilities of the combined model.

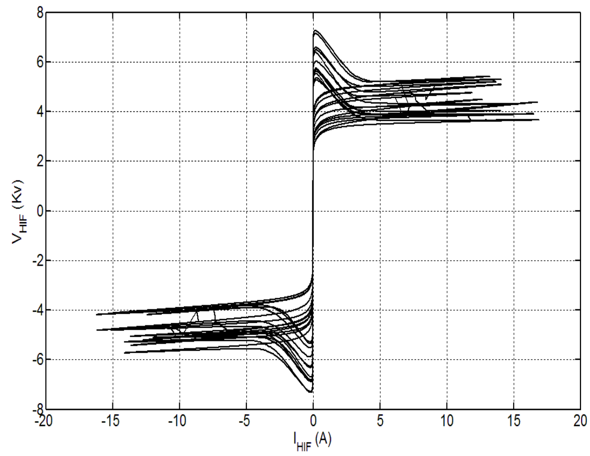


Figure 9. A typical voltage current characteristic of HIF with random behavior.

6.2. Wavelet analysis of the proposed method

At the beginning of this section, the discrimination between normal situation and HIF case is investigated. Then, the features are constructed using DWT output. Finally, the results of the algorithm analyzed.

6.2.1. Output of DWT

For different electrical network events and different measured signals or mother wavelet, the wavelet output can vary dramatically. For example, several wavelet outputs for no fault work and HIF event for phase voltage with mother wavelet db14 are examined.

Figure 9 shows the detail parts of the wavelet output for the case of switching load. As can be seen in this figure, the detailed output wavelet has a non-zero value for a short time period and for the rest of the time, its value is equal to zero. Wavelet detailed outputs in figure 10, belongs to the case of the saturation transformer. Comparing with the previous figure shows that the details in figure 9 output are smaller and have a repetitive jumps and smaller value and for Detail 4. The value is nearly zero (except in the beginning of the time).

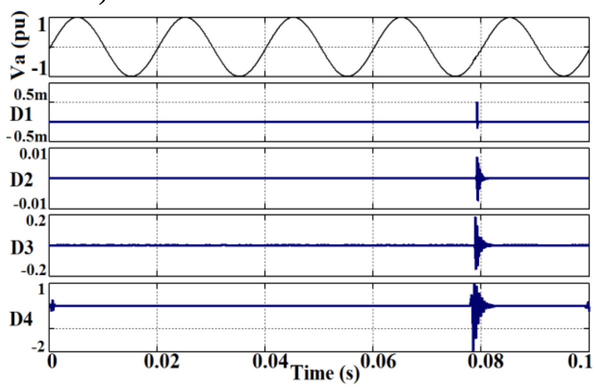


Figure 9. DWT details for switching load.

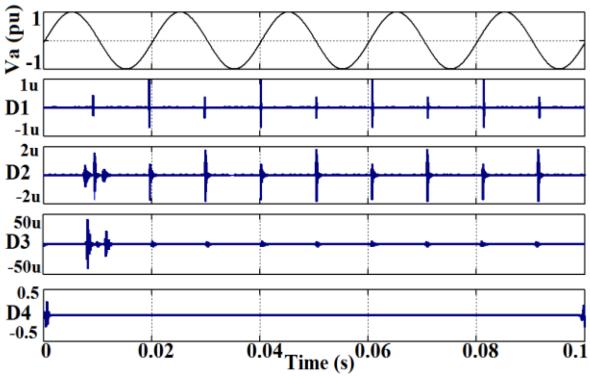


Figure 10. DWT details for saturation Transformer.

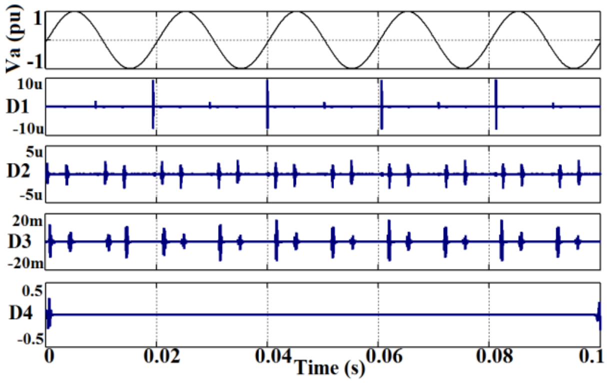


Figure 11. DWT details for electric Arc furnace.

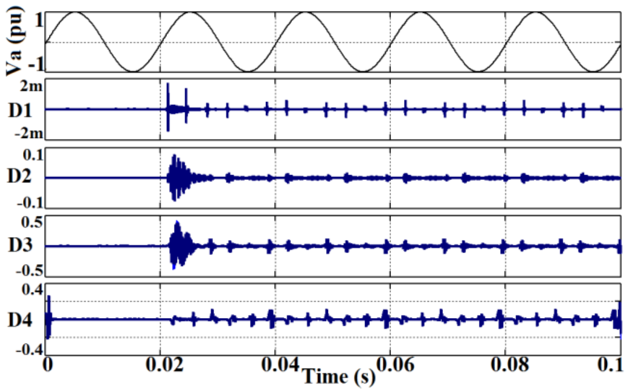


Figure 12. DWT details for thyristorload.

Also, figure 11 shows the wavelet detailed outputs for the case of electric arc furnace. The details behavior seen in figure is similar to the transformer saturation case. However, the case of the thyristor load (shown in Figure 12) has a different behavior.

The wavelet detailed outputs for the case of the diode load is illustrated figure 13. As this figure indicates there is an asymmetry in the first three details and small value in Detail 4. For the case of HIF, the wavelet Detail outputs are given in figure 14. In this figure, the amplitude of Detail 4 is greater than the corresponding detail in the previous cases. This issue helps us to find a discriminative feature to distinguish between no fault work and HIF case.

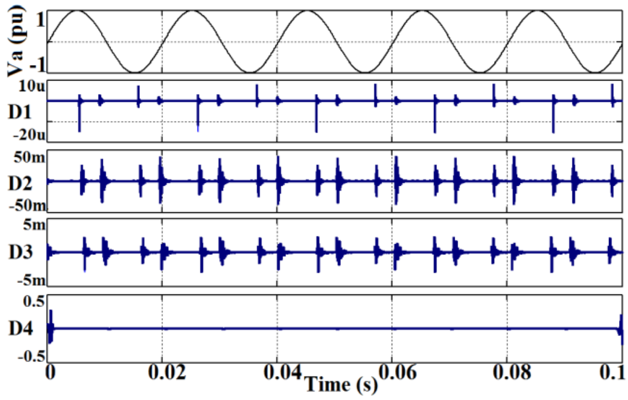
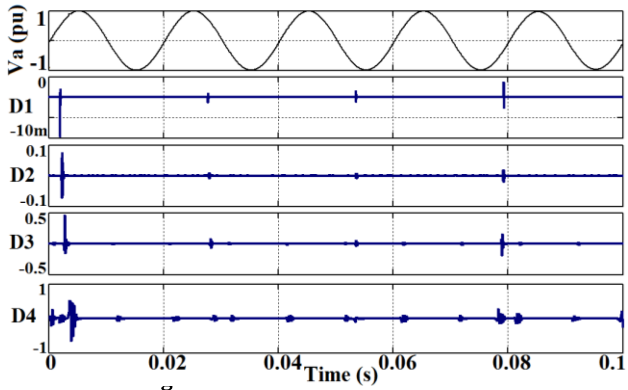


Figure 13. DWT details for Diode load.



6.2.2. Feature extraction from the output of DWT

As stated previously, the output of DWT is not an integer number. Hence, at first, the value of SAD is computed from the output wavelet. If for example in (3), let X to be V_a (voltage of Phase a), j to be 4 and mother wavelet to be, db14, then $SAD_{4Va}$is computed and the result is shown in figure 15. The values of SAD_{4Va} in figure show several of no fault work and several HIF cases.

The values of SAD are the difference between no fault and several HIF cases. But, it should be noted that this visual interpretation of the extract feature needs to be converted a mathematical form. According to figure 15, that amount SAD of HIF case is larger than amount SAD for no fault. But, it is not always true. Also, for the HIF case, that abrupt change SAD of HIF is more than the no fault, and again it is not always the case. The two main differences in the outputs of SAD, mean and variance have chosen as the extracted feature for distinguishing between the normal working situations and HIF cases. Generally, these two features are can be different which depends on the type of mother wavelet, detail and measurement signals.

To select the best of two features, they are drawn in two-dimensional coordinates for normal working and HIF cases as shown. For example, if two features (F1,F2) extracted from the output wavelet of the sum of three voltage phase by mother wavelet Demy and Detail 6, then figure 16 shows two features relative to each other.

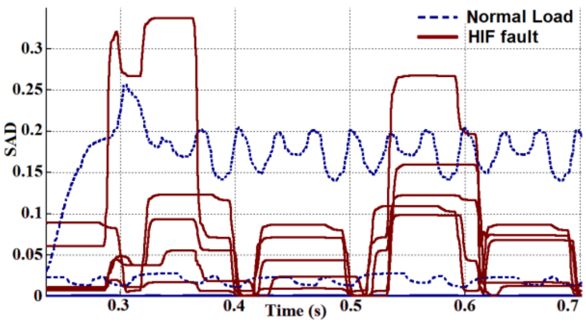


Figure 15. SAD for several cases.

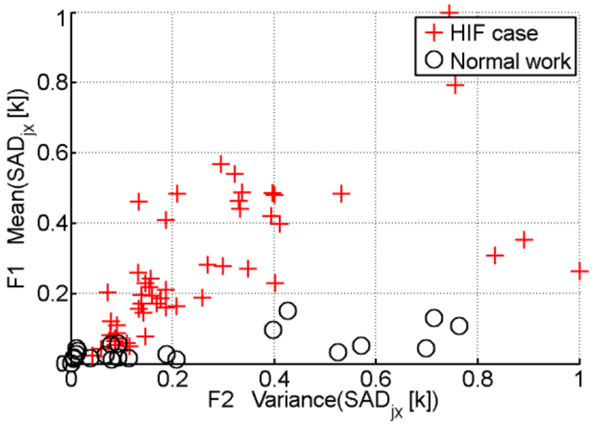


Figure 16. F1 versus F2 using (Vabc) with Mother WT demy and detail 6.

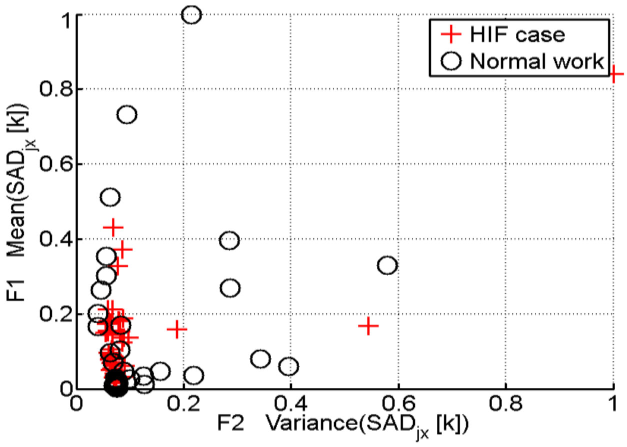


Figure 17. F1 versus F2 using Va with Mother WT db14 and detail 7.

Also, figure 17 shows two features from the output wavelet of Va by db14 mother wavelet and Detail 7. In figure 16 for most of the cases, the features corresponding to the normal working cases are closer to the coordinates. By changing the mother wavelet and the signal type, this closeness can be varied. In general, as a better discriminative criterion is made, the better is feature will be selected.

6.3.1. Result analysis and discussion

In order to find the best features as the different features, the two factors of $F1_{jx}$ and $F2_{jx}$ are determined and classified from 17 mother wavelets, 7 detailed levels including voltage, current and sum of the voltage feeder for three phases were performed and classified. The accuracy of results is different for each type. In the FFA system, 80 input-output pairs for training and 20 input-output pairs for testing were considered. Some of the results of the simulation for 833 cases are given in table 1.

Table 1.The best detection using WT &FFA.

Row	Feeder Signal	Mother WT	Detail	Accuracy (%)
1	Vabc	Demy	D6	94.19
2	Vabc	Rbio3.3	D4	93.93
3	Vabc	Sym5	D5	93.16
4	Vabc	Bior5.5	D5	92.97
5	Vabc	Coif4	D5	92.85
6	Vabc	Bior6.8	D5	92.83
7	Vabc	Sym8	D5	92.80
8	Vabc	Demy	D5	92.73
9	Vabc	Bior2.6	D4	92.64
10	Vabc	Db14	D5	92.40
⋮	⋮	⋮	⋮	⋮
39	Vx	Rbio2.2	D7	89.83
⋮	⋮	⋮	⋮	⋮
103	Ix	Db5	D5	83.51
⋮	⋮	⋮	⋮	⋮
833	Vx	Db8	D1	52.79

According to these results, it can be seen that the best classification accuracy is 94.19%, which is a correct diagnosis. In the best classification for the case of the sum of three-phase voltage, the used mother wavelet is 'Demy' with Detail 6.

This means that to have better accuracy in the proposed algorithm, firstly the three phase voltages should be measured. Then, some of the measured voltages are used as the inputs for the wavelet transform. In the next step, the wavelet transform with Demy mother wavelet is employed. After that, the value of SAD is computed according to (3) to compute Detail 6. Then, the features of F1 and F2 are computed using (4) and (5). Finally, the two features are applied to the FFA as the inputs.

With choosing a suitable mother wavelet, detailed level in the result shows the proposed method is able to discriminate between no fault and HIF cases with high accuracy.

6.3.2. Implication issues

Implication issues for the proposed algorithm show that the findings based on the phase voltage has less accuracy compared with the findings based on three-phase voltage. Nevertheless, still the phase voltage based results has high accuracy as much as 89.83%, which is acceptable. The use of phase current does not yield an accuracy as high as the previous ones and the use of the phase current is not recommended for detection the HIF.

7. Conclusion

In this paper, a new HIF detection method based on the combination of FFA and DWT, is proposed. This method is an alternative method for diagnosing of HIF from no fault case. In this method, the feature is extracted using wavelet output. By investigating different mother wavelets, feeder signals and detail types, the base case is selected.

In the proposed method, the FFA system is used for classification. The FFA system uses training data to perform classification. The 80 training data used in this paper. The FFA system is able to perform classification accuracy.

In addition, an accurate combined model used to model the HIF. This combined model has the high ability to model different types of HIF. In order to study the performance of the proposed method for different types of HIF case and different normal working conditions such as thyristor load and arc furnace were examined. The obtained results have a very good accuracy as high as 94.19%. This indicates that the proposed algorithm has correct performance under different operating conditions in the electricity distribution networks.

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نشریه هوش مصنوعی و داده کاوی
دانشگاه شاهرود

تشخیص خطای امپدانس بالا به کمک تبدیل موجک گسسته و تقریب‌گر تابع فازی

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چکیده:

در این مقاله یک روش از ترکیب تبدیل موجک و تقریب‌گر تابع فازی (FFA) برای تشخیص خطای امپدانس بالا (HIF) در شبکه توزیع برق پیشنهاد شده است. در این روش برای تجزیه سیگنال اندازه‌گیری شده از تبدیل موجک گسسته (DWT) استفاده می‌شود که با بررسی انواع موجک مادر، انواع سیگنال فیدر و انواع سطح جزئیات بهترین حالت انتخاب می‌شود. مرحله بعد با استفاده از خروجی موجک اقدام به ساخت شاخص می‌گردد که این شاخص‌ها به عنوان ورودی سیستم تقریب‌گر تابع فازی مورد استفاده قرار می‌گیرند. تقریب‌گر تابع فازی با استفاده از زوج‌های ورودی – خروجی تابعی از شاخص‌ها را تقریب می‌زند، سپس تقریب‌گر تابع فازی توانایی کلاس‌بندی برای یک شاخص جدید را خواهد داشت. مدل استفاده شده برای خطای امپدانس بالا یک مدل ترکیبی می‌باشد که قابلیت بالایی برای مدل کردن انواع خطای امپدانس بالا دارد. روش پیشنهادی برای انواع بارهای غیرخطی و نامتقارن و انواع HIF مورد بررسی قرار گرفته است. نتایج نشان داده است که روش پیشنهادی توانایی بالایی در تمایز دادن حالت کار عادی شبکه و رخداد خطای امپدانس بالا را دارد.

کلمات کلیدی: خطای امپدانس بالا، تقریب‌گر تابع فازی، تبدیل موجک، شبکه توزیع.