HIGH IMPEDANCE FAULT LOCATION – CASE STUDY USING WAVELET TRANSFORM AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This paper presents a high impedance fault (HIF) location method in distribution systems. The estimation of the HIF location is carried out by using an artificial neural network (ANN). The ANN inputs are both three phase currents and its energy of the Wavelet Coefficients obtained during the HIF. The Wavelet mother function used was Daubechies 48. The ANN was trained and the performance of the proposed HIF location was evaluated by using a HIF modeled with two series time-varying resistances controlled by the Transient Analysis of Control Systems (TACS) of the Alternative Transient Program (ATP). Actual data obtained from several staged HIFs in different soil types on Energisa utility (a Brazilian distribution system) were used to adjust the HIF model.

INTRODUCTION

High impedance faults in distribution lines are short-circuits that cannot be easily detected, located and cleared by conventional protective devices due to their low fault current magnitudes. This kind of fault occurs when an energized conductor of the primary network falls in a surface with high resistive value, as well as trees or sand. When a HIF happens, energized conductors may fall within reach of personnel and, as the arcing often accompanies these faults, it further poses a fire hazard [1]. As a consequence, the energized conductor on the ground surface can pose public danger, as well as risk of fire due to the probable arc ignition. The damage derived from HIF concerns people, animals, and properties rather than electrical equipment of the network [2].

The difficulty of detecting HIFs is determined by the configuration of the distribution network and by the loads connected to the system. A reliable HIF diagnosis is essential to avoid dangerous consequences for both people and power system equipment. In order to reach success in these purposes, a method should be developed and evaluated with actual and simulated data, in which are necessary an accurate system modeling, and a HIF model which represents typical characteristics observed in actual HIFs, such as: buildup, shoulder, nonlinearity, and asymmetry.

A brief review of the fault location techniques can be found in [3]. Recently, several works have been done for fault diagnosis in distribution systems. Some of them are based on conventional methods [4], monitoring of voltage imbalances [5], traveling waves [6]. The latest techniques involve the use of ANNs [7, 8] and Wavelet Transform (WT) [9]. The ANNs present high capacity for learning and generalization, besides velocity and robustness in the diagnosis.

In order to adjust the HIF model with a typical HIF on Energisa utility, a Brazilian distribution system, as well as develop and evaluate the proposed HIF location method, several HIF experiments were staged, taking into account dry and wet contact surfaces: grass, crushed stone, sand, pavement, and local soil. The current and voltage waveforms in each stage were captured by digital fault recorders (DFRs) at both HIF location and far from 1 and 11 km. The HIF simulations were carried out on ATP [10] by using the power system model of the Energisa utility where the HIFs were staged.

The HIF locator is based on ANN where the input database was built with the post-fault current with its energy of the Wavelet Coefficients. The Neural Network Toolbox from MATLAB® was used for ANN construction and knowledge. Good results were obtained at HIF location evaluation.

FIELD EXPERIMENTS SUMMARY

In order to collect HIF data to assist the development of HIF modeling and database building, staged fault tests were performed on a distribution feeder at Energisa, in Boa Vista town. Fig. 1 depicts the structure built for the tests, whose main features were:

- HIF tests were done on seven different kinds of contact surfaces: grass, crushed stone, pavement, asphalt, sand, tree and local soil;
- A two-meter transition pole was placed between the common pole and the fault point, where the potential and current transformers were installed;
- A 13.8 kV conductor coming from the common pole was connected to the transition pole and to an insulating rod;
- An insulating scaffold was placed in order to enable security for the responsible technician;
- Isolation and signalizing of the testing area;

- A 15360 Hz sampling frequency DFR was installed at the fault point and configured in order to enable the measurement, recording, and viewing of the events to be generated in the tests;
- Other DFRs were installed far 1 and 11 km from the fault point.

Fig. 1 – Structure to stage HIF.

HIF MODELING

In order to choose a HIF model, the characteristics of the phenomenon must be represented adequately. Although these methods represent the nonlinear and the asymmetry characteristics of HIFs well, they do not embrace the other characteristics, such as buildup, shoulder, and intermittence [12]. This work used the model proposed by [11], which simulates the characteristics by employing two time-varying resistances controlled by TACS in ATP.

In this model, the first resistance (R_1) represents the characteristics of nonlinearity and asymmetry (it has the same characteristics at every cycle of the signal), while the second resistance (R_2) represents the characteristics of buildup and shoulder (it only has influence at the beginning of the signal). In order to obtain R_1 and R_2behaviour, 32 points for the V-I characteristic (obtained from voltage and current waveforms) for one cycle in the steady state were considered (Fig.2).

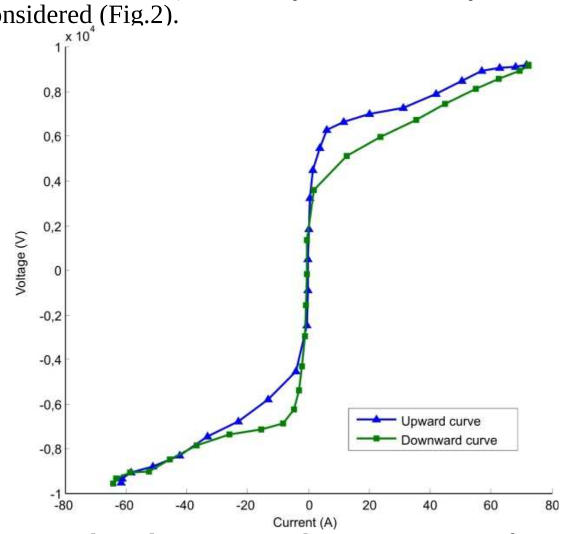

Fig. 2 –The voltage-current characteristic curve for one cycle in the steady state of HIF on the local soil.

If the faulted branch voltage is in $v_n \leq v(t) < v_{n+1}$, the corresponding current is obtained by:

$$i(t) = i_n + \frac{i_{n+1} - i_n}{v_{n+1} - v_n} \cdot (v(t) - v_n) \qquad (1)$$

The resistance R_1 will be estimated by Law of Ohm using $v(t)$ and $i(t)$. The resistance R_2 is calculated considering only the maximum absolute value of voltage and current because the buildup and shoulder characteristics. The steps to compute R_1 and R_2 are as follows:

1. Obtain the total resistance $R(\tau)$ by dividing $v(\tau)$ by $i(\tau)$;
2. Obtain $R_2(\tau)$ by subtracting $R_1(\tau)$ from $R(\tau)$;
3. Obtain R_2 applying the method of least squares.

SIMULATIONS

Database Building

A variety of situations were considered to form a set of 180 different test cases for sand as contact surface used in the experiments. The simulation variables chosen are summarized in the Table I. HIF between one phase and ground were simulated [11].

TABLE I – Simulation Variables

Simulation variables	Test set
Load condition (%)	25, 50, 75, 100
Fault location (Bus)	10, 23, 30, 35, 44, 49, 50, 56, 63
Fault location (km)	5.76, 14.86, 15.96, 18.56, 9.86, 11.66, 4.56, 10.26, 17.06
Inception angle (°)	88, 89, 90, 91, 92
Contact surface	Sand

System Modeling

The proposed method was developed in order to be used in a real 13.8kV distribution feeder of Energisa. To make the modeling, the utility provided data about the chosen feeder, such as: the power of transformers, the wire and poles characteristics, the distances between line sections, and the loads. The feeder is illustrated in the Fig. 3.

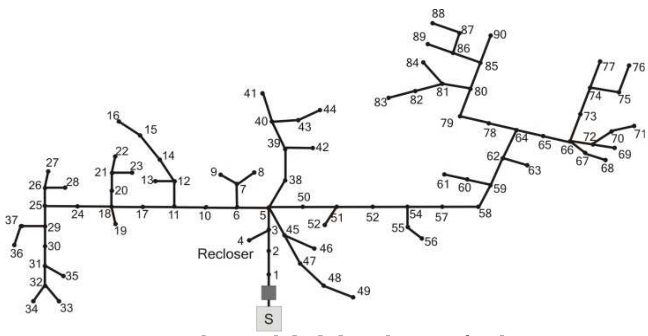

Fig. 3 – The modeled distribution feeder.

In order to model the system, some considerations were necessary. For instance, the distribution feeder was modeled and simulated by using the ATP. The skin adopted was 0.33 and the ground resistivity 350 Ω.m. A constant impedance load model has been adopted with a power factor of 0.955, a distributed parameters model has been used to all line sections composed by 4 AWG wires. The loads were concentrated into 90 buses.

APPLYING THE WAVELET TRANSFORM

It is well known that currents with HIF are non-stationary signals. Therefore, a suitable way to extract information regarding the frequency contents of HIF currents is to apply the discrete Wavelet Transform (DWT). By using the Wavelet Transform the non-stationary signals are analysed within different frequency ranges by means of dilating and translating of a single function named mother wavelet [13]. According to Mallat's algorithm, the DWT uses high-pass (*h*) and low-pass (*g*) filters to divide the frequency-band of the input signal into high- and low frequency components (wavelet and scaling coefficients). This operation may be repeated recursively, feeding the down-sampled low-pass filter output into another identical filter pair, decomposing the signal into scaling (*s*) and wavelet (*w*) coefficients for various scales.

The major drawback of non-redundant transforms such as the DWT is their non-invariance in time and space [14]. In this way, the detection and location of HIF is carried out through the Maximal Overlap Discrete Wavelet Transform (MODWT), a time invariant transformation, where scaling and wavelet coefficients are obtained in similar way as the DWT.

The coefficients of the scale *g* and wavelet *h* filters are associated with the selected mother wavelet. With regard to the HIF location, it was verified that long mother wavelets provided an accurate identification of the fault point. Therefore, the wavelet Daubechies with 48 filter coefficients (db48) was used in this paper.

According to the Parseval theorem, the energy of a signal can be decomposed in terms of the energy of both wavelet and scaling coefficients at the first scale [15], as follows:

$$\sum_{k=1}^{k_t} |i(k)|^2 = \sum_{k=1}^{k_t} |w(k)|^2 + \sum_{k=1}^{k_t} |s(k)|^2 \qquad (2)$$

Where: $\sum_{k=1}^{k_t} |v(k)|^2$ is the energy of the current *i*, $\sum_{k=1}^{k_t} |w(k)|^2$ the wavelet coefficient energy and $\sum_{k=1}^{k_t} |s(k)|^2$ the scaling coefficient energy.

Some features of the transients of HIF can be identified through the analysis of their energy. The signal energy can be decomposed in terms of the wavelet and scaling coefficient energies at the first scale, the features of the transients can be identified through the analysis of the wavelet coefficient energies at this scale, when the wavelet coefficients are predominantly influenced by frequency components regarding the transients.

The one-cycle wavelet coefficient energy (ε) of a signal (voltage or current), at the first scale, can be computed as follows:

$$\varepsilon(k) = \sum_{n=k-\Delta k+1}^{k} w^2(n) \qquad (3)$$

since k ≥ Δk; Δk is the amount of coefficients in one of the fundamental power frequency. The one-cycle wavelet coefficient energies of MODWT of the HIF currents were evaluated in this paper for HIF location.

HIF LOCATOR

Among the existing architecture types for ANNs, the multi-layer perceptron network (MLP) was selected because of its simplicity and adequacy to solve properly the fault location problem. The resilient back propagation (RPROP) algorithm was used for ANN training [16]. In this case, the neuron weights are calculated by means of the partial derivative sign in each iteration, improving the learning process. The *Neural Network Toolbox* of MATLAB® was used for all ANN operations and development.

According to [17], the energy of wavelet coefficients characterize strong indicators for disturbances diagnosis. This reasoning was extended to HIF. Thus, the input database chosen for the selected ANN were the normalized post-fault current and the normalized wavelet coefficients energy of the current for the phase with fault. Thus, there was obtained an idea of the current behavior in time domain with post-fault current samples; well as the incidence of transient, with the advent of energy.

In the pre-processing step, 80% of the database were chosen for ANN learning, in which 70% were used in training set and 30% were used in validation set. The remaining 20% of the database were designated for the methodology test. For training network, each input database variable was grouped in three samples, in a process known as windowing. Thus, the necessary number of inputs for the used ANN was 12 (4 variables for 3 samples). The activation function for input layer was logarithmic. It was also chosen the hidden layer adoption, whose activation function was hyperbolic tangent. With regarding the training process, a maximum of 30000 epochs was used to achieve the minimum root mean square (RMS) error. However, in the best result, the training process was stopped with 5221 epochs with an error of 0.0173. The architecture 12-50-20-1 presented the best result.

The test set was divided in files with registers with COMTRADE standard, in which all current energies were computed and submitted to the ANN. The most frequent location estimated by the ANN for each file is the normalized HIF location.

A success rate of 93% for the HIF location were obtained in the test set, providing the correct identification of the protection zone on which the HIF occurred.

CONCLUSION

A distinctive importance of the proposed method was the staged faults in a real distribution feeder, with a field tests build. The work was performed by both simulated and actual data.

The adoption of wavelet coefficients energy for the current with fault was satisfactory. The used Wavelet was Daubechies 48 (db48).

A success rate of 93% in high impedance fault location was achieved. The obtained results for high impedance fault location based on artificial neural network attest the efficiency and effectiveness of the proposed method.

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