A Novel Transformer Protection Method Based on Hilbert Huang Transform and Artificial Neural Network

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Abstract

This paper presents the application of Hilbert-Huang Transform (HHT) and artificial neural network (ANN) for fault detection on transformers. The combined procedure, Emprical mode decomposition (EMD) and Hilbert transform, is called the Hilbert-Huang Transform (HHT). The ANN is designed and trained using feed forward propagation algorithm. The input features of the ANN are extracted from the frequency and aplitude of IMFs by applying the Hilbert transform. Simulation results of the proposed method for fault detection on tranformers proveto be effective.

1. Introduction

The quality of electric power has become substantial issue for electric power utilities. To improve power quality, one has to know about the sources of power system disturbances and the actual causes behind them. The previous work on power transformer protection has included other approaches, among these are transformer inductance during saturation, artificial neural networks, flux and voltage restraints and fuzzy logic [1-4].

Wavelet transform [5] has been proposed to detect and classify various type of power quality disturbaces. Although wavelet transform has the capability to exract features from the signal in both frequency and time domain and has been applied in the detection and classification of power quality, it exhibits some disadvantages. Such as [6] computation, sensitivity to noise level and the dependency of its accuracy on the chosen basis wavelet. A combined wavelet transform and probabilistic neural network (PNN) approach for disturbance waveform classification has been proposed by Gaing [5]. In this approach, the time duration of each disturbance are taken as features of the network.

Mishra et al. [7] has proposed the S-transform approach for feature extraction in disturbance waveform classification. Phase contours and the frequency of the S-matrix of the signal are used as features for the network.

Classification is another major task. The body of literature concerning the application of Artificial Neural Network has implemented power systems [8-10], data analysis, modeling, and diagnostic classification [11]. ANN based approach can detect normal, magnetizing inrush, and over excitation currents by recognizing their wave shapes from the fault current wave shapes. Zhao [12] used a feed-forward neural network (FFNN) with sigmoidal nonlinearities for model development. In [13], Moravej suggested using a feed forward neural network to discriminate between magnetizing inrush and fault currents and the result shows that FFNN can be an alternative method in achieving the goal.

The various stages involved in the network development are data generation, feature extraction, and network training. Firstly, the current signals are decomposed into several Intrinsic Mode Function (IMFs) using the Empirical Mode Decomposition (EMD). The algorithm to obtain Intrinsic Mode Functions (IMFs) is explained in Section 2. The next step is the feature extraction from IMFs, which is explained in Section 3. The Hilbert Transform introduced by Huang et al. [14] is used for feature extraction.The cases for simulation that are used in this paper is generated by PSCAD and explained in detail in Section 4. After the extracted features are presented to the neural network for training, then the network is tested with the test data to assess the capability of the network.

2. Emprical Mode Decomposition

The emprical mode decompostion process is useful for analyzing natural signals, which are most often non-linear and non-stationary. The decomposition is an iterative algorithm that operates on a signal to refine and extract the IMF.

The algorithm to extract an IMF as follows:

1. Find the upper and lower envelopes by connecting all the maxima and all the minima.
2. Take the mean of the two envelopes ($y(t)$) and subtract it from the original signal ($x(t)$). Let us call the resulting signal $h_1(t)$
3. If the new signal $h_1(t)$ satisfies the following conditions of IMF's:
    a. The number of extreme and the number of zero crossing must either be equal or differ at most by one.
    b. At any point, the mean value of the envelope defined by the local maxima and the local minima is zero.

    Then,$z_1(t)$ is the first intrinsic mode function. If not, it is treated as the original signal and steps (1) - (3) are repeated to get component $z_{11}(t)$.

4. The above process that is repeated i times to get $z_{1i}(t)$ becomes the first IMF and is known as IMF1. Then IMF1 is separated from $x(t)$ and let $r_1(t)$be such that:

$$r_1(t) = x(t) - z_{1i}(t)$$

5. Take the signal $r_1(t)$ as the original signal and repeat the steps (1)-(4) to obtain the second IMF.

The above procedure is repeated n times and thus n IMFs are obtained. The stopping criterion for the decomposition process occurs when $r_n(t)$ becomes a monotonic function from which no more IMF can be extracted.

3. Feature Extraction Using Hilbert Transform

In this paper, Hilbert Transform (HT) has been used for feature extraction. Hilbert Transform transforms the real data sequence into an analytical signal which has a real part that contains original data and an imaginary part that contains the Hilbert transform. The imaginary part is a version of the original part with a 90^o phase shift. One important property of the hilbert transformed series is that it has the same frequency content and amplitude as the original signal. Also, phase information of the hilbert transformed series depends on the phase of the original signal.

Theinstantaneous frequency and amplitude of IMF's can be calculated by using the Hilbert Transform. The Hilbert Transform of a real values time domain signal $x(t)$ is another real values time domain signal, denoted by$\hat{x}(t)$. The resulting analytical signal is $z(t) = x(t) + j\hat{x}(t)$.

The real-valued function x(t) defined as:

$$\hat{x}(t) = H[x(t)] = \int_{-\infty}^{\infty} \frac{x(\tau)}{\pi(t-\tau)} \qquad (1)$$

The Hilbert Transform of a signal effectively produces an orthogonal signal that is phase shifted by 90^0 from the original signal.

In terms of x(t) and $\hat{x}(t)$,

$$A(t) = [x^2(t) + j\hat{x}^2(t)] \qquad (2)$$

$$\theta(t) = tan^{-1}\left[\frac{\hat{x}(t)}{x(t)}\right] \qquad (3)$$

Where $\theta(t)$ is the instantaneous phase signal of $x(t)$.

And the "instantaneous frequency" is given by:

$$f_0 = \frac{1}{2\pi t} tan^{-1}\left[\frac{\hat{x}(t)}{x(t)}\right] \qquad (4)$$

4. Simulation of the Power System

Simulation is performed on the delta-wye transformer with ratings of 315 MVA and 400/220 kV. Different situations that result in a transformer inrush current are simulated. In the first case, the transformer is energized at no load. The no load energization is a common source of inrush current in the power system network because it takes place when the transformer is returned to the circuit after either an unwanted outage (trip) or a wanted outage (scheduled maintenance outage). 13 no-load inrush current signals are generated by adjusting the energization breaker's switching angle between 0-360 degrees in increments of 30 degrees.

In the second case, the transformer is energized while connected parallel to an operating transformer. The inrush current that is induced in the transformer energized is called the sympathetic inrush. Similarly, 13 sympathetic inrush current signals are generated by adjusting the breaker's energization switching angle between 0-360 degrees in increments of 30 degrees. The effect of residual flux in the transformer core is simulated to induce transformer saturation current, as recommended by the PSCAD user's manual. The residual flux is imitated in the simulation environment by connecting a parallel voltage source to the main input voltage source through a breaker. The two sources are operating 180 degrees apart for two different periods. The residual-flux voltage source will inject a current into the transformer in the period prior to the energization of the transformer from the main input voltage source. The value of the injected current reflects the value of the residual flux in the transformer core prior to energizing the transformer. Therefore, the magnitude of the residual flux can be controlled by regulating the instances of the opening of the breaker supplying the current, which reflects the residual flux, to the transformer core and by controlling the operating voltage of the flux-injecting source. Thus, to obtain all the possible values of the residual flux in the transformer core, adjusting the angles of the related breaker varying between 0-360 degrees in increments of 30 degrees and the operating voltage of the flux-injecting source is varied between 10-80% of the rated voltage value of the main voltage source energizing the transformer. The internal fault of the power transformer is simulated using the special transformer internal fault module available in the PSCAD library. The internal fault of the transformer is simulated by shorting the transformer turns at different sections, like 5%, 15% and 80%, of the total transformer turns through a breaker that connects the transformer shorted turns to the ground. Different internal fault signals are generated by closing the shorting breaker at different switching angles varying between 0-360 degrees of the voltage source cycle.

Table 1 summarizes the cases simulating the conditions on which the different transformer inrush current and internal fault current signals are obtained.

Table 1. Cases simulated in PSCAD

Internal fault current	Inrush current (residual flux effect)	Sympathetic inrush current	No-load inrush current
Portion of turns shorted are: 5%, 15%, 25%, 40%, and 50%.	104 signals 8 different voltage levels of the residual flux source 10-80% of the rated main voltage source	13 samples	13 samples
78 signals	130 signals		
208 differential current signals			
60 Hz frequency			
load of 285+j13728 MVA			

5. Feature Extractions and Neural Network

In Figure1, the no load inrush current is shown at a switching angle of zero for the input source voltage waveform. If the switching angle is zero, the induced transformer inrush current is at a maximum because the starting flux at this instance would be maximum (if the voltage is *sin* signal then the flux is a *cos* signal).

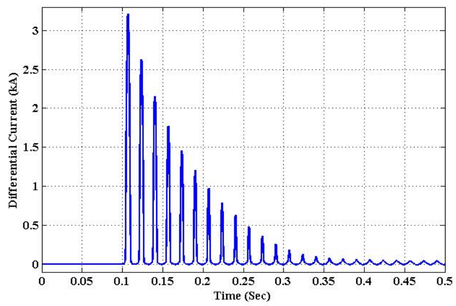

Fig. 1. Sample signal of transformer no-load current

The internal fault signal generated at zero degree-switching angle and at 5% of the transformer turns shorted is shown in Figure 2.

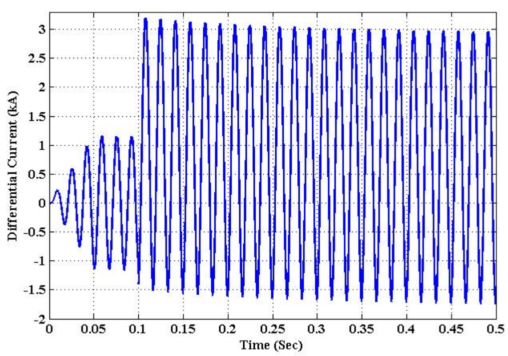

Fig. 2. Sample signal of transformer internal fault at phase (a)

EMD (no-load current signal) is decomposed into 4 IMFs plus residue, as shown in Figure 3. EMD (internal fault) is decomposed into 5 IMFs plus residue, as shown in Figure 4.

The features of the disturbance signals are extracted by applying the Hilbert Transform to the IMFs obtained from the EMD. The first three IMFs are considered for feature extraction because most of the frequency contents lies in first three modes. The extracted features are standard deviation of the amplitude, energy distribution, and standard deviation of the phase.

Feed forward neural network is used for fault identification and classification purposes in this paper. Feed forward is the first and simplest type of artificial network. One of the shortcomings of this network is that it takes long time for training.

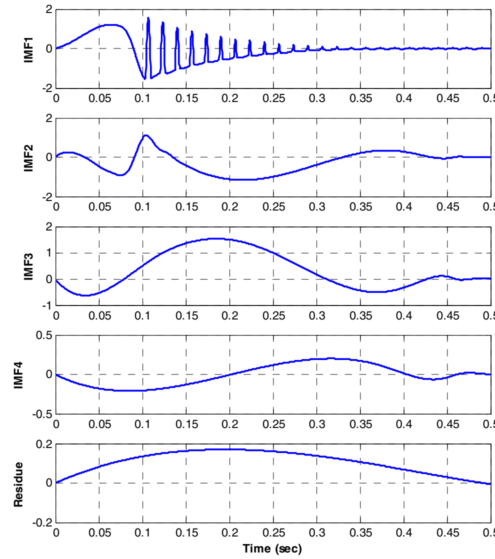

Fig. 3. Intrinsic mode functionsof transformer no-load current signal

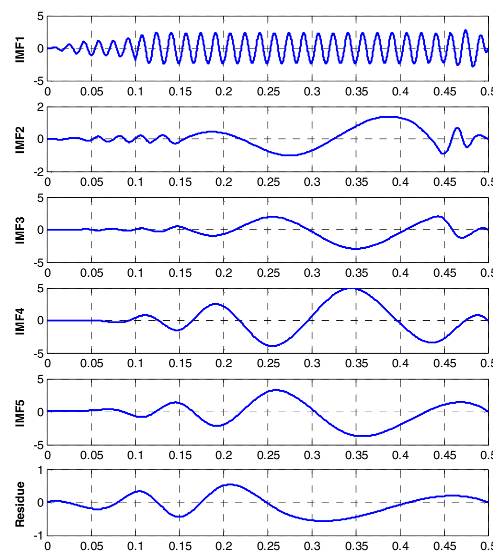

Fig. 4. Intrinsic mode functions of transformer internal fault at phase

The architecture of the artificial neural network is shown in Figure 5. The network has an input layer, a hidden layer, and an output layer. The extracted features from IMFs are presented to the neural network for training. After training, the network is tested with the test data to assess the capability of the network. In total, a set of 208 signals are generated. Neural network is trained with a data set of 125 patterns consisting of 47 internal fault currents and 78 inrush currents. The remaining data of 83 patterns are used for testing the neural network.

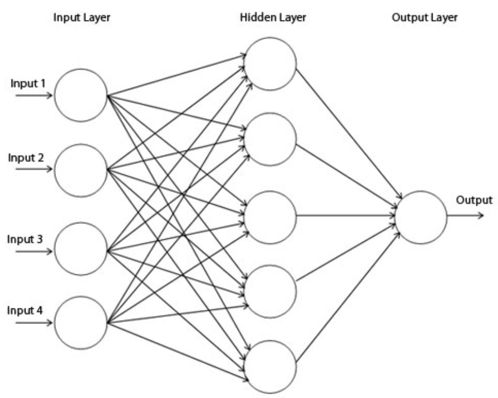

Fig. 5. Architecture of artificial neural network.

The maximum classification efficiency of the method with the neural network was calculated as 92.85% shown in Figure 6. The method is failed to locate some of the inrush current.

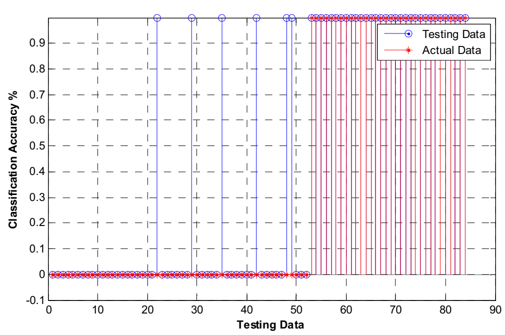

Fig. 6. Performance of ANN on testing data (92.85%)

In this trial, the training time is about 6.3msec and testing time is about 6.0msec for 125 training and 83 testing scenarios.

6. Conclusions

As previously mentioned, set of 208 signals are generated in total. Neural network is trained with a data set of 125 patterns consisting of 47 internal fault currents and 78 inrush currents. The remaning data of 83 patterns are used for testing the neural network. EMD is performed with Hilbert –Huang Transform to extract the features of energy distribution, standard deviation of amplitude and standard deviation of the phase. The first three IMFs are considered for the feature extraction because most of the frequency contents lie in first three modes. The efficiency of the method with the neural network is 92.85%.

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