Inrush Current Detection Based On Wavelet Transform and Probabilistic Neural Network

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Abstract— In this paper an efficient method for detection of inrush current in distribution transformer based on wavelet transform is presented. This method uses Wavelet Transform (WT) and Probabilistic Neural Network (PNN) to discriminate inrush current from other transients such as capacitor switching, load switching and single phase to ground fault. WT is used for decomposition of signals and PNN for classification. Inrush current data and other transients are obtained by simulation using EMTP program. Results show that the proposed procedure is efficient in identifying inrush current from other events.

Index Terms— Probabilistic Neural Network, inrush current, EMTP program, Wavelet transform

I. INTRODUCTION

A large transient current occurs in an electric circuit when a transformer is switched on. This transient or inrush current depends on various operating conditions, such as the magnitude of the voltage, the switching-on angle, the remanent flux, the i-ϕ hysteresis characteristics of the core, the resistance in the primary circuit, and others. Transformer steady-state exciting current is generally less than 1% of the rated current, but the inrush current may be as high as ten or more times the rated current[1]. Numerous fundamental models for analyzing transformer characteristics exist, such as the network model [2–4], the magnetic model [5], the coupled electromagnetic model [6, 7]. However, in power systems the detection of inrush current is very important. Some techniques have been adopted to identify the magnetizing inrush and internal faults. In [8] a modal analysis in conjunction with a microprocessor-based system was used as a tool for this purpose. In [9] the active power flowing into transformer is used as a discrimination factor which is almost zero in case of energization. In order to extract inrush current and internal fault, three kinds of scheme are currently used [10]. Some schemes make use of the information obtained only from incoming currents of transformer such as method based on the second harmonics restraint principle [11–13]. With development of electrical systems in both capacity and voltage coupled with the wide spread employ of underground cables and growing of non-linear loads, it generates a large amount of second harmonic current in the event of fault. The content of this second harmonic current can be comparable to that produced inrush current. Some methods employ the information achieved from the variation of transformer terminal voltages, such as method based on voltage restraint principle. Other alternative schemes make use of the data achieved from both current and voltage increasing. Wavelet transforms (WT) has been attracted great interest in processing of transient signals such as inrush current [14–16]. However, previous research works on extract inrush current and internal fault of power transformer. In this paper a new inrush current detection method that combines wavelet transform and PNN is presented. Inrush current and other transient data were gathered from a 14-bus IEEE test system. The inrush current phenomenon is introduced in Sections II, a case study and data collection is explained in Section III. Wavelet transform and PNN are introduced in Sections IV and V, respectively. Simulation results are shown in Section VI.

II. INRUSH CURRENT PHENOMENA

When a transformer is energized from a voltage source the peak magnetizing current may achieve a high value and cause a quick dip in the voltage resulting in an unwanted tripping of the differential protective relay. The inrush current is because of temporary transformer core over fluxing at the time of energization. This temporary over fluxing impact is administered by the following factors: the point-on-voltage wave at the instant of energization, the magnitude and polarity of the remanent flux in the transformer core at the instant of energization, the overall resistance of the primary winding circuit, the power source inductance, the inductance of the air core in between the energizing winding and the transformer core. Under steady-state conditions, the core flux density \( B_m \) lags behind the source voltage by 90°. In order to induce one half cycle of the required back EMF, a total change of flux density of \( 2B_m \) is needed. Under normal operating conditions, the leakage inductance of a transformer is small because of the \( B/H \) characteristic of the transformer core material. It has been found that the higher the circuit resistance, the less the number of transient cycles, the time constant and also the magnitude of the first cycle of the inrush current. In practice, the circuit resistance is very small in comparison with the power rating of a transformer, therefore a power transformer has a great primary circuit time constant resulting in a long transient decay.

III. DATA COLLECTION

In order to obtain the signals, a 14- bus IEEE test system has been selected which is illustrated in Fig.1. These signals include: inrush current, capacitor switching, load switching and single phase to ground switching signals. The models determined to be simulated by the EMTP software are, \( \pi \) and load frequency model (CIGRE), for line and load respectively, BCTRAN model is used for all transformers. The inductor with hysteresis loop of TYPE 96 was used for modeling hysteresis loop in EMTP, which was connected to the outlet magnetizing branch of the transformer. The magnetization
curve of the transformers is illustrated in Fig. 2. Feeder information is provided in the appendix. All kind of inrush current that different parameters such as, remanent flux density, the switching angle and the primary winding resistance which can be influential in the occurrence of this phenomenon have been simulated. Fig. 3 illustrates a type of inrush current which has been simulated by the EMTP. Different types of capacitor switching have been obtained through the switching of the three capacitor banks of the feeder in various forms. For simulating different types of load switching, we switch the loads in different arrangements. For example, we firstly switch them one at a time, then two at a time, and other arrangements can be achieved by switching one or two of the loads with a part of the feeder. Thus, different signals are obtained. For simulating the single phase to ground fault, between the break of the conductor and fall to ground, supposed a very short time for achieving to real condition simulation. This way, for each group of signals, 80 types can be obtained. Then we normalize (scale) them in the max-min range (0 to 1). This is very influential in the exact determination of the features and every pattern.

IV. WAVELET TRANSFORM

Wavelet Transform (WT) was introduced by J Morlet at the beginning of 1985 and has attracted much interest in the fields of speech and image processing. Applications of DWT in power systems are reported for:
• Power system transients [17].
• Power quality assessment [18].
• Modeling of system component in wavelet domain [19]. In this section an introduction to wavelet transform is presented. More details can be found in [20]. The WT was developed as an alternative to the short time Fourier Transform (STFT) to overcome problems related to its frequency and time resolution properties. Specially, the DWT provides high time resolution and low frequency resolution for high frequencies and high frequency resolution and low time resolution for low frequencies unlike the STFT that provides consistent time resolution for all frequencies. The DWT is a particular case of the WT that provides a compressed representation of a signal in time and frequency that can be calculated proficiently. The DWT is defined by the following equation:

$$W(j, K) = \sum_j \sum_k x(k) 2^{-j/2} \phi(2^{-j} n - k)$$  \hspace{1cm} (1)$$

Where $\phi(t)$ is a time function with finite energy and fast decay called the mother wavelet. The DWT analysis can be performed using a fast, pyramidal algorithm related to multi rate filter banks. As a multi rate filter bank DWT can be viewed as a constant Q filter bank with octave spacing between the centers of the filters. Each sub band contains half the samples of the neighboring higher frequency sub band. In the pyramidal algorithm the signal is analyzed at different frequency bands with different resolution by decomposing the signal into a coarse approximation and detail information. The coarse approximation is then further decomposed using the same wavelet decomposition step. This is achieved by
successive high pass and low pass filtering of the time domain signal and is defined by the following equations: where $y[k]$ high and $y[k]$ low are the outputs of the high pass ($g$) and low pass ($h$) filters, respectively after sub sampling by 2. Down sampling the number of resulting wavelet coefficients becomes exactly the same as the number of input points. A variety of different wavelet families have been proposed in the literature. The choice of mother wavelet plays a significant role in time frequency analysis. It also depends on a particular application. In this work all wavelets available in the Wavelet Toolbox of MATLAB program [21] were used for the decomposition of the signals and the best answer was obtained with symmlet mother wavelet. It was found to have the most correlation with the decomposed signals and was selected for this procedure. For example decomposition of typical inrush current, capacitor switching, load switching and single phase to ground fault using WT are shown in Figs. 3-6, respectively.

![Fig.3. Decomposition of inrush current by Symmlet mother wavelet](image)

![Fig.4. Decomposition of capacitor switching by Symmlet mother wavelet](image)

![Fig.5. Decomposition of load switching by Symmlet mother wavelet](image)

![Fig.6. Decomposition of single phase to ground by Symmlet mother wavelet](image)

A. Applying Wavelet Transform and Feature Extraction

The decomposition is done by modifying the wavelet transform through passing the signal via a digital half band low pass filter. This digital half band low pass filter excludes all the signals which are higher than the half of the value of the largest signal frequency. If a signal having nyquist rate (which is twice the largest frequency in the signal) was taken as a sample, the largest frequency present in the signal would be $\pi$ radian. That is, nyquist frequency in the range of discrete frequency corresponds $\pi$ (rad/s). After a signal passes through a digital half band low pass filter, according to the theory of nyquist, half of the signals can be excluded, for now the signal
has the maximum frequency of $\pi/2$ (rad/s). Thus the obtained signal has a length half of that of the original one. This procedure is repeated for 6 times and the signals omitted by the low pass filter at each time, are considered as detail signals. The energies of these detail signals are the features extracted from the patterns to feed into the neural network. According to the definition, the energy of every discrete signal such as $x(n)$ is defined as follows: (N equals the length of the signal)

$$E(x) = \sum_{n=1}^{N} |x(n)|^2$$

V. PROBABILISTIC NEURAL NETWORK

Probabilistic Neural Network (PNN) is a type of distance-based ANNs, using a bell shape activation function. This technique makes decision limitations nonlinear and therefore, it can approach the Bayesian optimal [22]. PNN is considered more appropriate to medical application in comparison with traditional back-propagation (BP) neural network since it utilizes Bayesian strategy [23]. The real-time possession of PNN is also vital to our research. In PNN, decision limitations can be changed in real-time as new data become accessible [24]. There is no requirement to train the network over the whole data set. So we can rapidly update our network as more and more patients’ data becomes accessible. The PNN has three layers: the Input Layer, the Radial Basis Layer which assesses distances between input vector and rows in weight matrix, and the Competitive Layer which identifies the class with maximum chance to be correct. The network structure is illustrated in Fig.4, using symbols and notations in [25].

A. Radial Basis Layer

Dimensions of arrays are marked under their names. Vector $b$ is then combined with $||W - p||$ by an element by-element multiplication, represented as “·” in Fig. 4. The result is denoted as $n = ||W - p|| \cdot b$. The transfer function in PNN has built into a distance criterion with respect to a center. In this paper, we define it as

$$\text{radbas}(n) = \exp(-n^2)$$

Each element of $n$ is substituted into (3) and produces corresponding element of $a$, the output vector of Radial Basis Layer. We can represent the $i$-th element of $a$ as

$$a_i = \text{radbas}(||W_i - p|| \cdot b_i)$$

where $W_i$ is the $i$-th row of $W$ and $b_i$ is the $i$-th element of bias vector $b$.

B. Competitive Layer

There is no bias in Competitive Layer. In this layer, the vector $a$ is first multiplied by layer weight matrix $M$, producing an output vector $d$. The competitive function $C$ produces a 1 corresponding to the largest element of $d$, and 0’s elsewhere. $M$ is set to $K \times Q$ matrix of $Q$ target class vectors. If the $i$-th sample in training set is of class $j$, then we have a 1 on the $j$-th row of $i$-th column of $M$.

VI. SIMULATION RESULTS

Using the model system described earlier, the proposed technique is tested using simulated data from the EMTP. The simulations provide samples of currents in each phase on the A-side of the transformer when it is energized or when a fault occurs on the system on the Y-side. Data from the simulations are used as input to the algorithm to identify its response. A total of 300 cases for other transients such as capacitor switching, load switching and single phase to ground fault and 30 inrush cases were simulated to test the various features of the algorithm. Sampling rate of 1.0 kHz has been considered for the algorithm. The obtained signals were analyzed by the sym mother wavelet and the energy of the detail signals obtained through the applying wavelet transform up to six levels have been used as the features fed into the neural network. For the PNN neural network, 16 neurons are determined in the hidden layer, four of which are allocated to inrush current signals and the rest to other transients signals. For training the network all four types of signals are used; 45 signals for learning and 40 for testing. Also the learning rate of the neural network is 0.005 and the number of epochs is selected 500. The sym mother wavelet is enforced in all the three phases of signals. The results are provided in TABLE I. It should be noted that the currents are the primary currents of the feeder shown in Fig.1. By applying the sym 4 in the second phase current of the signals, the neural network has the least precision of 76.66% and by applying the sym 5 in the third phase current of the signals, neural network shows the most precision of 85.33%. The above results can be justified using Fig.8. The instantaneous energy of second phase current of signals are much similar. Thus the precision of algorithm is less in this case and the instantaneous energy of third phase voltage of signals are less similar. Thus the precision of algorithm is more in this case. The above results can be justified using Fig.9, too. This Figure compares the average of the components correspondent to the feature vectors extracted by applying sym 4 and sym 5 in the second phase current and the third phase current of signals, respectively (the rectangles corresponding the inrush current signals are darker). According to the figure, the features extracted by applying sym 4 in the second phase current are much similar. Thus the precision of algorithm is less in this case. But the features exacted by the applying sym 5 in the third phase current are least similar. Thus the precision of algorithm is more in this case.
TABLE I. IDENTIFICATION PERCENTAGE OF PNN

<table>
<thead>
<tr>
<th>Signal</th>
<th>WT</th>
<th>Percentage of NN identification</th>
</tr>
</thead>
<tbody>
<tr>
<td>First phase current</td>
<td>sym 1</td>
<td>81%</td>
</tr>
<tr>
<td>First phase current</td>
<td>sym 2</td>
<td>82%</td>
</tr>
<tr>
<td>First phase current</td>
<td>sym 3</td>
<td>82%</td>
</tr>
<tr>
<td>Second phase current</td>
<td>sym 1</td>
<td>83%</td>
</tr>
<tr>
<td>Second phase current</td>
<td>sym 2</td>
<td>76.66%</td>
</tr>
<tr>
<td>Third phase current</td>
<td>sym 1</td>
<td>83%</td>
</tr>
<tr>
<td>Third phase current</td>
<td>sym 2</td>
<td>83.33%</td>
</tr>
<tr>
<td>Third phase current</td>
<td>sym 3</td>
<td>83.33%</td>
</tr>
<tr>
<td>Third phase current</td>
<td>sym 4</td>
<td>83%</td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td>82.1%</td>
</tr>
</tbody>
</table>

In this paper, the PNN neural network and the wavelet transform have been used to distinguish inrush current from other transients. The presented algorithm has the highest precision on third phase current and lowest precision on the second phase current of the signals. One of the main advantages of this algorithm is capability of changing the number of extracted features by changing the number of wavelet transform levels. Also the network has the ability to classifying the nonlinear feature vectors in multi-dimension space. The algorithm has an acceptable accuracy in the recognition of unused patterns for learning. This fact highlights the practical importance of the algorithm.

REFERENCES


Fig.8. The instantaneous energy of signals 
(I=InrushCurrent,C=CapacitorSwitching,L=Load Switching,T=Transformer switching)

**APPENDIX**

1. **Source parameters**

\[ Z_0 = 0.52 + j 6.65 \, \Omega, \quad Z_1 = 0.32 + j 3.75 \, \Omega \]

2. **Transformer parameters**

Three phase 100.0 MVA, 50Hz, 330/33kV, \( \Delta \)/Y connected windings with earthed neutral with the following parameters:

\( \Delta \)/Y windings

- Wp exc. = 70 kW
- Zp SC. = 30%
- Ip exc. = 0.24% WZ exc. = 6453 kW
- ZZ SC. = 28%
- IZ exc. = 56.25% Wp SC = 312 kW

p, z : stand for positive and zero sequences respectively

W: stands for losses, exc.: stands for excitation

3. **T.L. parameters**

Two cascaded \( \pi \)-sections each with the following parameters:

\[ Z_0 = 1.16 + j 13.3 \, \Omega, \quad Z_1 = 0.665 + j 7.5 \, \Omega \]