A Method to Identify Inrush Current Based on Deep Convolutional Neural Networks

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Abstract. In this paper, the deep convolutional neural network (CNN) is proposed as the core classifier to discriminate between the magnetizing inrush and the internal fault of power transformers. Two novel CNN structures, A8-Net and A5-Net, are proposed considering the influence of the features and quantities of the inrush current and the internal fault current waveform image data on the classification effect. Parameters of the CNN structures can be automatically trained from the dataset. Relaying signals for various operating conditions, consisting of internal faults and magnetizing inrush, have been obtained by modelling the three-phase transformer in PSCAD/EMTDC. Half of the dataset is used to train the CNN classifier and the rest are used to evaluate the performance of the proposed algorithm. Experimental results at various testing configurations indicates the efficiency and robustness of the proposed CNN classifier. Even with heavy interferences, the proposed method can still remain stable and functional.

Introduction

Power transformers are the core component in electrical power systems and of high strategic importance. Their reliable and stable functionality is vital to the entire power generation and transmission. Therefore, the protection of power transformers should be efficient and reliable. Generally, the power transformer should be monitored carefully and regularly in order to detect the early evidence of the electrical failure and prevent the following losses. Furthermore, differential relaying technique is used to protect the power transformers by comparing the value of differential current with no-load value. Due to the sudden switching operation or the recovery from external fault, magnetizing inrush occurs in transformer. The transient magnetizing inrush current is a major drawback to the differential relaying because it results in false tripping. Magnetizing inrush current may reach as high as 10 times of the full load current which leads to high differential current and cause the relay to operate [1]. Therefore, there is a strong demand for the effective discrimination between internal faults and inrush current.

Conventionally, the second harmonic restraint method are implemented to avoid maloperation and unnecessary tripping against magnetizing inrush condition [2]. Generally, the operation criteria of the differential protection can avoid maloperation from internal faults. However, when inrush currents occur, existing differential protection using the method of identifying the second harmonic component in differential current does not always function correctly. The methods based on second harmonic component detection assume that the second harmonic components in the inrush current are more than 15% of the fundamental harmonic. However, as the improvement of the transformer capacity and transmission line length, the capacitance of the system may lead to a rich harmonic internal fault current. Meanwhile, the harmonic component of inrush current is becoming smaller than before due to the development of large capacity transformers and the low saturation flux density of the
Therefore, it is more and more difficult to achieve satisfied discrimination between internal fault and magnetizing inrush current by using harmonic component detection method. In order to solve the above problem and improve the discrimination accuracy, many identification methods have been proposed to distinguish inrush current from internal fault current. Since discriminating internal faults from inrush current is essentially a classification problem, differential currents are classified into several categories including internal faults, inrush current, and etc. By training the obtained data, a classifier can be obtained. New testing data can be sorted into the correct categories by the classifier. By treating the differential current waveform as one dimensional data, methods and tools that are employed by pattern recognition can be applied in inrush current detection, for example, principle component analysis (PCA) [5], decision tree [6-8], and support vector machine (SVM) [9].

More recently with the developments in artificial neural network (ANN) [10-12], their application for protection of power transformer is become more and more popular. In [13], the author proposed a hidden Markov based model to discriminate between fault and magnetizing inrush. Development of ANN also enhances the scope of waveform identification approach. ANN approach is faster, robust and easier to implement than the conventional waveform approach. ANN has already been used in the power system protection due to its good generalization ability and learning stability. Most of the author used multilayer feedforward neural network with back propagation learning technique [17,18]. In [10], the author firstly reconstructed the saturated current signals using a recurrent ANN, followed by applying the Elman training method using a Stuttgart neural network simulator. In [12], Tripathy and colleagues introduced probabilistic neural networks to classify all possible operating conditions of the power transformers, such as baseline, over-excited, magnetizing inrush, sympathetic inrush, external fault, and internal fault.

In this paper, another type of neural network, convolutional neural network (CNN) is investigated for the protection of power transformer. A CNN based algorithm with higher novelty and efficiency to discriminate between the transformer internal fault and inrush current is proposed. In differential relaying protection scheme, the CNN is utilized as classifier to discriminate between magnetizing inrush and internal fault of power transformer. Since the parameters of the CNN structures need to be automatically trained from the dataset, it is crucial to formulate a dataset with strong diversity, extensibility and robustness. Relaying signals for various operating conditions, consisting of internal faults and magnetizing inrush, have been obtained by modelling the three-phase transformer in PSCAD/EMTDC. Half of the dataset is used to train the CNN classifier and the rest are used to evaluate the performance of the proposed algorithm. In this paper, emphasis is placed on the detection of magnetizing inrush and internal fault of power transformer which is crucial in differential protection scheme. The inrush current identification model and basic CNN knowledge are illustrated in Section 2. In Section 3, the data simulated from a three-phase transformer model is formulated for CNN. Two novel CNN structures, namely A8-Net and A5-Net, are trained and tested in the Section 4. The classification accuracy of the proposed deep convolutional neural network is compared with the harmonic restraint method and SVM based classifier. The paper is concluded in the Section 5.

Deep Convolutional Neural Network

Artificial neural networks are motivated by the learning capabilities of the human brain which consists of neurons interconnected by synapses. In fact, at least theoretically, they are able to learn any given mapping up to arbitrary accuracy [14]. In addition, they allow to easily incorporate prior knowledge about the task into the network architecture. As result, in 1989, LeCun et al. introduced convolutional neural networks (CNN) for application in computer vision tasks [15]. The CNN has shown excellent performance in many machine learning problems, and many of which are basically classification problems. For example, CNN can be used to classify different images by identifying which image is a car and which one is a cat.
CNN is a neural network with specialized connectivity structure. It stacks multiple stages of feature extractors. Layers at higher stages compute more global, more invariant features. CNN takes the measured data, such as one-dimensional signal or images, directly as input. Instead of handcrafted features, convolutional neural networks are used to automatically learn a hierarchy of features which can then be used for classification purposes. This is accomplished by successively convolving the input data with learned filters to build up a hierarchy of feature maps. In contrast to traditional multilayer perceptions such as SVM, parameters of deep convolutional neural networks, such as filter entries and value of shared weights between connected layers, can be trained automatically by using mathematical methods, such as gradient descent for parameter optimization combined with error back propagation. Features learned by CNN are more generic and intrinsic to represent the nature of the original signal than the previous methods such as ANN and SVM. This is the reason why CNN obtains much better performance than the traditional methods in many application fields.

**Inrush Current Identification Model**

The waveforms of inrush current and internal fault current show completely different visual modes in both time and frequency domain, and have strong local geometric features. These local visual modes change differently as the operating state of the transformer changes. How to effectively extract and abstract these visual modes into distinguishable features is the key to distinguish inrush current from internal fault current. In this paper, inrush current identification is modeled as an image classification system using CNN shown in Figure 1. Image data representing the time and frequency domain information of the current waveforms is input into the image classification system, and the criteria for waveform classification are obtained by feature extraction and classification of the system.

![Figure 1. The frame of the classification system.](image)

**The Architecture and Principle of CNN**

\[ x^1 \rightarrow \omega^1 \rightarrow x^2 \rightarrow \cdots \rightarrow x^{L-1} \rightarrow \omega^{L-1} \rightarrow x^L \rightarrow \omega^L \rightarrow z \]  

(1)

The above Equation(1) illustrates how a CNN runs layer by layer in a forward pass. The input is \( x^1 \), usually a data vector or matrix. It goes through the processing in the first layer, which is the first box. We denote the parameters involved in the first layer's processing collectively as a filter \( \omega^1 \). The output of the first layer is \( x^2 \), which also acts as the input to the second layer processing. This processing proceeds till all layers in the CNN has been finished, which outputs \( x^L \). One additional layer, however, is added for backward error propagation, a method that learns good parameter values in the CNN. Let's suppose the problem at hand is a classification problem with \( C \) classes. A commonly used strategy is to output \( x^L \) as a \( C \) dimensional vector, whose \( i \)-th entry encodes the prediction (posterior probability of \( x^1 \) comes from the \( i \)-th class). To make \( x^L \) a probability mass function, we can set the processing in the \((L-1)\)-th layer as a softmax transformation of \( x^{L-1} \) (the distance metric and data transformation note). In other applications, the output \( x^L \) may have other forms and interpretations. The last layer is a loss layer. \( t \) is the corresponding target (ground-truth) value for the input \( x^1 \), then a cost or loss function can be used to measure the discrepancy between the CNN prediction \( x^L \) and the target \( t \). For example, a simple loss function could be although more complex loss functions are usually used. This squared l2 loss can be used in a regression problem. Equation (2) explicitly models the loss function as a loss layer, whose processing is modeled as a box with parameters \( w_L \). Some layers may not have any parameters, that is, \( \omega_i \) may be empty for some \( i \).
The softmax layer is one such example. Typical convolutional neural networks are consist of several basic components, including convolutional layer, non-linearity layer, feature pooling and subsampling layer, and fully connected layer.

\[ z = \frac{1}{2} \| f - x^t \|_2 \]  

(2)

**Dataset Formulation for CNN**

The parameters of deep convolutional neural networks, such as filter entries and shared weights between connected layers, are automatically learned from the dataset. This indicates that the quality of the dataset directly affects the quality of the trained classifier, thereby affects the efficiency of the power transformer protection. High quality dataset should ensure the following several requirements: amount, diversity and robustness. Since there is no such public dataset for the differential relaying protection, a dataset is specially designed in this paper. A three-phase power transformer is simulated by using PSCAD/EMTDC software, various training and testing signals under different operating conditions are generated for CNN training and testing.

PSCAD/EMTDC v4.6 is used to model a 400kV/220kV three-phase double-winding transformer to realize the simulation of the following four conditions: no-load closing, turn-to-turn fault of the primary winding during operation, turn-to-ground fault of the primary winding in operation and no-load closing on turn-to-turn fault of the primary winding. The three-phase transformer is composed of three single-phase transformers in YD1 mode. The current transformer ratio of the primary side is 220:1, and the current transformer ratio of the secondary side is 400:1. The basic parameters of the simulation system are shown in Table 1, inrush current and internal fault simulation system are shown in Figure 2 and Figure 3 respectively.

![Figure 2. Three phase transformer inrush current simulation system.](image-url)
$Z_1 = 0.8715 \, \text{[ohm]} + j9.9615 \, \text{[ohm]}$

Figure 3. Three phase transformer internal fault simulation system.

Table 1. The basic parameters of the simulation system.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated capacity</td>
<td>315MVA</td>
</tr>
<tr>
<td>Rated voltage ratio</td>
<td>400kV/220kV</td>
</tr>
<tr>
<td>Frequency</td>
<td>50Hz</td>
</tr>
<tr>
<td>Magnetizing current</td>
<td>0.1% rated current</td>
</tr>
<tr>
<td>Air core reactance</td>
<td>0.2p.u.</td>
</tr>
<tr>
<td>Knee voltage</td>
<td>1.17p.u.</td>
</tr>
<tr>
<td>Zero sequence impedance</td>
<td>1.7430+j19.9230Ω</td>
</tr>
<tr>
<td>Positive sequence impedance</td>
<td>0.8715+j9.9615Ω</td>
</tr>
</tbody>
</table>

Typical simulation results of four conditions are shown in below.

Figure 4. Typical simulation results of (a) inrush current, (b) inrush current with turn-to-turn fault current, (c) turn-to-ground fault current, (d) turn-to-turn fault current.
The simulation data of 18975 three-phase transformers were sorted out, of which 9488 groups were used for training, and the remaining 9487 groups were used for testing. The simulation data statistics are shown in Table 2.

Table 2. Three phase transformer simulation data.

<table>
<thead>
<tr>
<th>Current type</th>
<th>Variables</th>
<th>Number of groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inrush current</td>
<td>1. Switching angle: 0°~165°, interval: 1°</td>
<td>9075</td>
</tr>
<tr>
<td></td>
<td>2. Source impedance: ±20%, ±10%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. Remanence: −1~1p.u., interval: 0.2p.u.</td>
<td></td>
</tr>
<tr>
<td>Turn-to-ground fault current</td>
<td>1. Fault location from winding headend: 1%~100%, interval: 1%</td>
<td>3300</td>
</tr>
<tr>
<td></td>
<td>2. Fault inception angle: 0°~165°, interval: 5.16°</td>
<td></td>
</tr>
<tr>
<td>Turn-to-turn fault current</td>
<td>1. Short turn ratio: 0.1%~10%, interval: 0.1%</td>
<td>3300</td>
</tr>
<tr>
<td></td>
<td>2. Fault inception angle: 0°~165°, interval: 5.16°</td>
<td></td>
</tr>
<tr>
<td>Inrush current with turn-to-turn fault current</td>
<td>1. Switching angle: 0°~165°, interval: 16.5°</td>
<td>3300</td>
</tr>
<tr>
<td></td>
<td>2. Remanence: −0.5, 0, 1p.u.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. Short turn ratio: 0.1%~10%, interval: 0.1%</td>
<td></td>
</tr>
</tbody>
</table>

Implementation of CNN Based Algorithm and Result Analysis

Proposed CNN Structure: A8-Net and A5-Net

The structural design of A8-Net refers to the design idea of AlexNet [16], which is widely used in image classification and recognition. Since AlexNet's structure and parameter design are for processing massive (million-level) complex images (face, human pose, etc.), that is different from the differential current curve. The image of the differential current is relatively simple and the number of data sets is about ten thousand. Therefore, this paper has optimized inrush current identification problem based on AlexNet. The dimensional properties of the convolutional layer, the pooling layer and the fully connected layer are adjusted, and the last layer softmax is reduced from 1000 classifications to 4 classifications (inrush current, turn-to-ground fault current, turn-to-turn fault current, inrush current with turn-to-turn fault current). Under the premise of ensuring feature extraction and classification efficiency, the training and testing efficiency of A8-Net has been significantly improved due to the reduction of the number of parameters of the entire network.

![Diagram of A8-Net](image)

C1–C5: Convolutional layers; F1–F3: Fully connected layers

Figure 5. Architecture of A8-Net.

The design idea of A5-Net is to compress the network structure and reduce the number of parameters of the network under the premise that the recognition accuracy is as consistent as possible
with A8-Net, and further improve the efficiency of the convolutional neural network. Compared with A8-Net, the depth of A5-Net has changed from 8 layers to 5 layers, network parameters are reduced by up to 50%, net size is reduced by 50%, and training speed is increased by two times, which significantly improves network training. And the efficiency of testing makes the whole network more suitable for the differential protection system.

![Architecture of A5-Net](image)

**Test and Result Analysis**

In the Table 3, the accuracy and corresponding number of false positive and false negative of A8-Net on the three-phase transformer are illustrated. The accuracy can be calculated from the number of false positive and false negative by using the Equation (3) and (4).

\[
\text{Classification Error Rate} = \frac{(\text{No. FalsePositive} + \text{No. FalseNegative})}{\text{Total number of test cases}} \times 100\% \quad (3)
\]

\[
\text{Classification Accuracy} = (1 - \text{Classification Error Rate}) \times 100\% \quad (4)
\]

For the same set of tests, the sum of the number of false positives and false negatives must be equal. That is because in a closed test set (the test set contains all the test possible results), the false positive data for one category must be the false negative data for the other category. As can be seen from Table 3, A8-Net achieves very good classification accuracy on three-phase transformer simulation data. Most of the current curve images are correctly classified, only a very few are classified into the incorrect category. The accuracy rate has reached more than 99%.

<table>
<thead>
<tr>
<th>Current type</th>
<th>Test number</th>
<th>False positive</th>
<th>False negative</th>
<th>Classification accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inrush current</td>
<td>4537</td>
<td>10</td>
<td>8</td>
<td>99.60%</td>
</tr>
<tr>
<td>Turn-to-ground fault current</td>
<td>1650</td>
<td>3</td>
<td>4</td>
<td>99.58%</td>
</tr>
<tr>
<td>Turn-to-turn fault current</td>
<td>1650</td>
<td>5</td>
<td>8</td>
<td>99.21%</td>
</tr>
<tr>
<td>Inrush current with turn-to-turn fault current</td>
<td>1650</td>
<td>5</td>
<td>3</td>
<td>99.53%</td>
</tr>
<tr>
<td>Total classification accuracy</td>
<td></td>
<td></td>
<td>3</td>
<td>99.52%</td>
</tr>
</tbody>
</table>

In addition to the longitudinal analysis of inrush current identification algorithm proposed in the test data set, this paper also compared A8-Net and A5-Net classification algorithm with traditional second harmonic restraint method, support vector machine (SVM) based classification algorithm and
back-propagation neural network (BP) based classification algorithm. Table 4 shows the comparison results of classification accuracy.

Table 4. Comparison results of classification accuracy between different methods.

<table>
<thead>
<tr>
<th></th>
<th>A5-Net</th>
<th>A8-Net</th>
<th>Second harmonic restraint method</th>
<th>SVM</th>
<th>BP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification accuracy</td>
<td>98.6%</td>
<td>99.5%</td>
<td>70.0%</td>
<td>88.7%</td>
<td>89.2%</td>
</tr>
</tbody>
</table>

As can be observed, the proposed method A5-Net and A8-Net can outperform the traditional method significantly especially on the practically measured data. Under typical magnetizing inrush and internal fault condition, for some of the current curves, the ratio of the second harmonic is quite high which makes the harmonic restraint method lose its efficiency. Meanwhile, the SVM based method is more sensitive to noise and unpredicted disturbances. All these evidences prove that the CNN based classification algorithm can efficiently deal with the noise and disturbance which makes it simpler and robust than the conventional digital filtering algorithms. The adoption of the CNN method can ensure the efficiency and robustness of the whole system.

Summary

A novel algorithm to discriminate between the transformer internal fault and inrush current is proposed in this paper. The algorithm is based on the convolutional neural network and two new structures, namely A5-Net and A8-Net, are trained and tested to deal with the classification problem. The data simulated from a three-phase transformer model is adopted in the training and testing procedure. From the experimental results, we can conclude that the proposed algorithm can achieve a state-of-the-art classification accuracy and more complicated neural network structure can always ensure a better performance. The proposed algorithm is independent of the harmonics contained in differential current which is quite suitable for the modern power transformers that use high-permeability low coercion core materials. Due to the strong robustness and strong anti-interference capability of the deep convolutional neural network, the proposed method can deal with the data with noise or disturbance more efficiently than the traditional method. As the deep learning and artificial intelligence techniques keep developing, more and more techniques will be applied to deal with the big data problem in the global power systems.

References


