Transformer Faults Classification Based on Convolution Neural Network

Original Scientific Paper

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Abstract – *This paper studies the latest advances made in Deep Learning (DL) methods utilized for transformer inrush and fault currents classification. Inrush and fault currents at different operating conditions, initial flux and fault type are simulated. This paper presents a technique for the classification of power transformer faults which is based on a DL method called convolutional neural network (CNN) and compares it with traditional artificial neural network (ANN) and other techniques. The inrush and fault current signals of the transformer are simulated within MATLAB by using Fourier analyzers that provides the 2nd harmonic signal. The 2nd harmonic peak and variance statistic values of input signals of the three phases of transformer are used at different operating conditions. The resulted values are aggregated into a dataset to be used as an input for the CNN model, then training and testing the CNN model is performed. Consequently, it is obvious that the CNN algorithm achieves a better performance compared to other algorithms. This study helps with easy discrimination between normal signals and faulty signals and to determine the type of the fault to clear it easily.*

Keywords: *Machine learning, Transformer, inrush, fault classification, Artificial intelligence, Deep learning, CNN algorithm*

1. INTRODUCTION

The difference between normal signals and faulty signals must be distinguished even when disturbances occur and protective devices should deal with faulty signals to keep continuity of supply [1]. Numerous faults in power systems are unavoidable due to the complex circumstances and a variety of human or natural factors. For more effective power supply restoration and fault cause analysis, fault categorization is crucial [2]. Preventing a costly outage of electrical network system requires efficient fault diagnosis [3].

Artificial intelligent (AI) proved effectiveness in solving many vital challenges [4]. There are different types of faults such as asymmetrical faults (line to ground, line to line, and two- lines to ground) and symmetrical fault. The fault classification by utilizing AI algorithms have received much attention in recent years. However, most of work has been focused on the fault classification problem in power systems [5]. Power transformer is a vital element in power grid. Its failure may affect the continuity of supply of electrical energy to the consumers [6].

Transformers' inrush current can be significant, ranging from five to seven times the rated current [7]. Nowadays, with the development and spread of DL usage, smart grid faults diagnosis based on DL should be considered [8].

Machine learning (ML) techniques have been widely used for power systems faced challenges and achieve good results. ML has been used in solving nonlinear problems (detection, classification, recognition, etc.) [9].

Rao et al. uses ML algorithms in transformer dissolved gas analysis [10]. For the purpose of diagnosing faults in oil-immersed power transformers, a bi-level ML technique with a multi-classification model and a binary imbalanced classification model is suggested; study is made to explain that the inrush current is rich with 2nd harmonic content [11].

For power transformers, differential relays are blocked by using the 2nd harmonic component, and for many researchers, this subject meets a great concern. Therefore, detecting the 2nd harmonic component and fault current wave forms is significant [12-16].

Many researchers had an interest to recognize the current signals using the 2nd harmonic component as transformers' inrush current waveforms includes 62% of 2nd harmonics and 55% of the DC component [17]. The two-instantaneous-value-product algorithm has been used for recognizing fault and inrush currents by extracting the current amplitude variations [18]. Krstivojevic and Milenko presents an algorithm that prevents false tripping of the restricted earth fault relay during the transformer energization [19].

For power transformers, based on adaptive neuro-fuzzy inference systems and discrete wavelet transform, Salama, et al. presented a hybrid algorithm for simulating the faults [20].

Many researchers use MATLAB simulation in modeling and classification. Different types of ANN and their applications are used in solving power systems challenges. ANN used as a classifier by using back propagation method for discrimination between inrush current and the fault current [21].

Both Radial Basis Neural Networks and Back Propagation Neural Networks are frequently employed. The multilayer perceptron, which has at least three layers (input layer, output layer, and hidden layer), is the most common architecture of this computing paradigm [22].

A convolutional neural network (CNN) is a specific category within machine learning. It belongs to a range of ANNs that are utilized for diverse purposes and data formats. CNNs are a type of network structure designed for DL algorithms and are particularly employed for tasks involving pixel data processing, such as recognition tasks [23]. There are further categories of ANNs in DL, but for objects recognition and identification. CNN is the most widely used type of ANNs specialized in classification. The main characteristic of CNN makes it better than standard ANNs for recognition [23]. CNN is an effective tool for recognizing multi-spectrograms that are structured into numerical data for diagnosing faults, eliminating the requirement of selecting the vibration axis beforehand [24]. The proposed ML method uses a CNN framework that performs discrimination between inrush and faulty currents.

Fault detection refers to the requirement of having knowledge about the system's health limited to two possible conditions (normal or abnormal). The normal state indicates that the system is functioning correctly without any worrisome indications. On the other hand, the abnormal state signifies that certain system symptoms fall outside the range of what is considered normal. The system being developed must be capable of identifying and distinguishing between these two states [25].

To prevent undesired tripping due to magnetizing inrush current, a novel approach is introduced for distinguishing internal fault current from inrush current. Transformer inrush currents can reach significant magnitudes, often ranging from five to seven times the rated current of the transformer. The second harmonic component is employed to inhibit the activation of differential relays in power transformers. False triggering of protection systems during inrush situations remains a prominent issue associated with transformer inrush currents.

The main objective of this study is to identify the inrush current and the type of fault based on two methods; variance statistical inference on three phase transformer signal and Fourier analyzers used to analyze the input signal and provide us with second harmonic signal. The peak value of 2nd harmonic input signals of the three phases of transformer. The two methods are used at different operating conditions to train the network.

In this research work, an efficient ML algorithm - which is CNN - is learned to determine the faults conditions and their type. A study is made to explain that the inrush current is rich with 2nd harmonic content and Fourier analyzers are used to analyze the input signal of three phase transformer. The following sections of this research include the ML and Fourier analysis, preparing the dataset of normal and faulty current signals, training the CNN, results and testing of network, comparison with other algorithms and the conclusion.

2. MACHINE LEARNING AND FOURIER ANALYSIS

In this research work, an efficient ML algorithm is learned to determine the faults conditions and their type, this is CNN. CNN includes the pooling, dropout, and fully connected (FC) layers. The phases of the applied ML technique are preparing the dataset of normal and faulty current signals, building the CNN model, splitting the data into train and test, training and testing the model, evaluation, and changing the parameters to enhance the performance [26].

The input layer of CNN is numerical data of current includes the three phases current signals (Red, Yellow, and Blue) each represented by 1041 samples data for variance signal value with a matrix (1041*3) and 1118 samples data for second harmonic signal value with a matrix (1118*3). Some of these data is utilized in the CNN model training and the rest is utilized for testing the proposed model. These parameters taken under different operation condition to train CNN giving different type of current signals (inrush current or different type of faulty current) as the target of CNN that is shown in Table 1.

Table1. The target of CNN

1	Inrush
2	F(A-B)
3	F(A-B-C)
4	F(A-C)
5	F(A-G)
6	F(B-C)
7	F(B-G)
8	F(C-G)
9	F(A-B-G)
10	F(A-C-G)
11	F(B-C-G)

In this study, Fourier analyzers present the 2nd, 3rd and 5th harmonic contents of the transformer input current signals for the current signal model of (normal-inrush-faulty). Peak value of the 2nd harmonic inrush and fault current signals are recorded and some numerical samples of them are selected to be used as an input to the CNN algorithm in order to train it to be ready for the needed fault classification process. Variance statistic values of input signals of the three phases of transformer are used at different operating conditions.

The 2nd, 3rd, and 5th harmonic contents of faulty model are shown in figures 1, 2 and 3 respectively. Table 1 illustrates various harmonic contents.

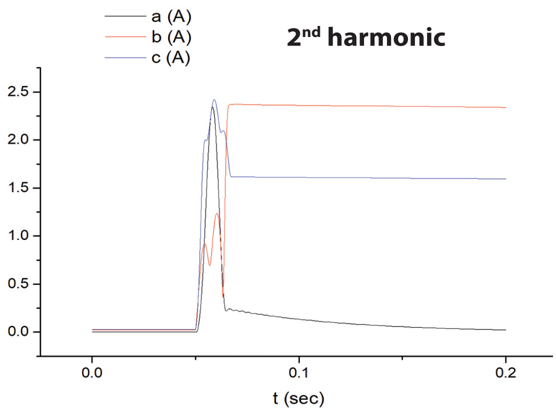


Fig. 1. 2nd harmonic of current signal

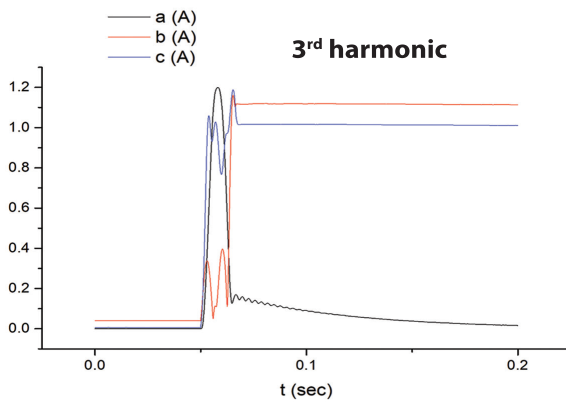


Fig. 2. 3rd harmonic of current signal

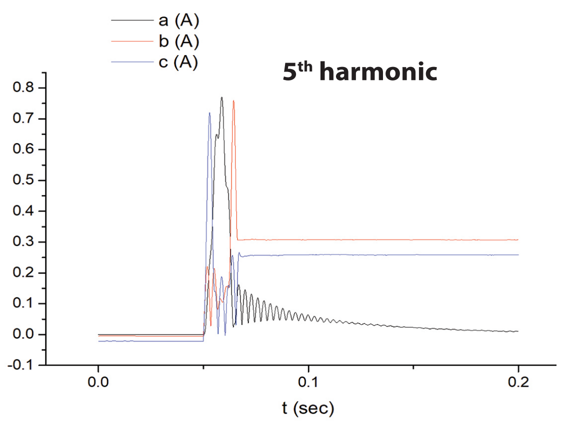


Fig. 3. 5th harmonic of current signal

The data in table 2 confirms that the 2nd harmonic is the dominating harmonic during transformer energization as the greatest value of three different kinds of current is the 2nd harmonic content.

Table 2. Harmonic spectrum

Current type	2nd(A)	3rd(A)	5th(A)
Normal	0.6	0.15	0.1
Inrush	2.4	1.2	0.75
Faulty	(1.5-2.6)	(1-1.5)	(0.25-0.3)

3. DATA SET PREPARATION AND CNN TRAINING

Among the different types of neural networks (others include recurrent neural networks (RNN), long short-term memory (LSTM), artificial neural networks (ANN), etc.), CNNs are easily the most popular. These convolutional neural network models are ubiquitous in the image data space. They work phenomenally well on computer vision tasks like image classification, object detection, image recognition [27].

Input data is processed using sklearn pre-processing function called MinMaxScaler with feature_range = (0, 1). CNN algorithm is used to improve the accuracy of classification. Parameters of this method are adjusted to improve performance where 50 epochs is used with a batch size = 1. a dams optimizer is used and achieves higher performance in most of DL methods. The function "Get dummies" from "pandas" library is used to convert categorical variable of output data into dummy/indicator variables. A sequential CNN model with two dense layers is used with 'relu' activation function for the first input layer and 'softmax' activation function for the second output layer.

A variety of samples of various operation conditions have been chosen and the 2nd harmonic is recorded by Fourier analysis for the three phase current signals. Tables 3 and 4 shows the maximum 2nd harmonic current and variance statistic values respectively for some of these samples under different operating conditions and various current conditions to be input for CNN.

Fig. 4 shows the CNN architecture where it contains an input layer with activation function 'relu', four blocks of hidden layers (convolution / pooling) and FC layers (flatten/dense).

Table 3. Maximum value of 2nd harmonic current

Conditions of operating			Maximum value of 2nd harmonic		
Flux value	Connection of winding	Signal type	I/Ph/ Red	I/Ph/ Yellow	I/Ph/Blue
0.4, -0.2, 0.2	Yg-Yg	Faulty (A-B-C)	2.2	0.0	2.0
0.4, -0.2, 0.2	Yg-Yg	Inrush	0.730	0.010	0.001
0.4, -0.2, 0.2	Y-Y	Faulty (A-B-C)	2.5	2.0	2.0
0.4, -0.2, 0.2	Y-D	Inrush	0.4	0.2	0.3
0.4, -0.2, 0.2	Y-Y	Inrush	0.13	0.13	0.12
0.4, -0.2, 0.2	Y-Y	Faulty (B-G)	0.13	0.12	0.13

0.4, -0.2, 0.2	Y-Y	Faulty (A-B)	2.00	2.00	0.01
0.4, -0.2, 0.2	D-D	Inrush	0.360	0.345	0.054
0.4, -0.2, 0.2	D-D	Faulty (C-G)	0.40	0.35	0.06

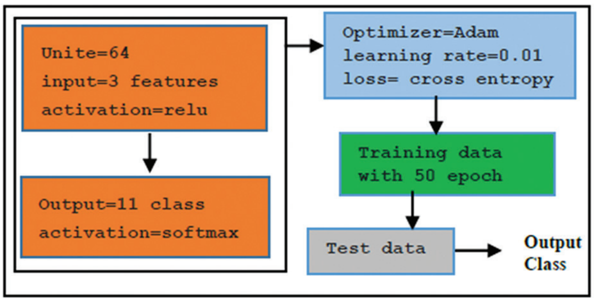
Table 4. Variance value signals

Conditions of operating			variance value		
Flux value	Connection of winding	Signal type	I/Ph/ Red	I/Ph/ Yellow	I/Ph/ Blue
0.4, -0.2, 0.2	Yg-Yg	Inrush	0.00	0.00	0.08
0.2, 0, 0	Y-Y	Inrush	0.003	0.003	0.007
0.4, -0.2, 0.2	Yg-Yg	Faulty (A-B)	0.001	8.03	8.72
0.4, -0.2, 0.2	D-D	Faulty (A-B-C)	11.8	13.2	14.4
0.4, -0.2, 0.2	Y-Y	Faulty (A-C)	8.51	0.01	8.49
0.3, 0, 0	Y-Y	Inrush	0.0017	0.0015	0.0035
0.4, -0.2, 0.2	Yg-Yg	Faulty (B-G)	0.0003	11.005	1.100
0.4, -0.2, 0.2	D-D	Faulty (C-G)	0.01	0.10	0.10
0.6, -0.3, 0.3	D-D	Inrush	0.0002	0.0026	0.0038
0.4, -0.2, 0.2	Y-Y	Faulty (B-C-G)	6.63	6.48	0.21

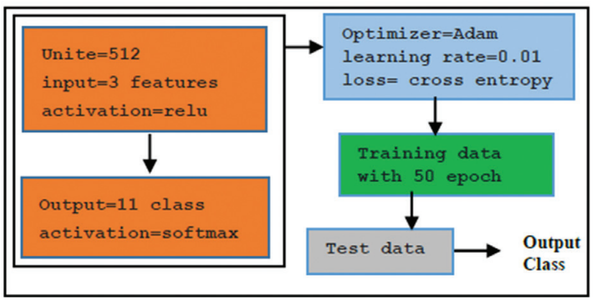
CSV

Split sample to train and test
Each sample contains: [feature1, feature1, feature3, 'target']
Where:
Input= [feature1, feature1, feature3]
Target= one class from 11

Dataset



CNN sequential Model
a) 2nd harmonic model



CNN sequential Model
b) Variance model

Dense Fit model Compile Prediction

Fig. 4. Convolutional neural network architecture

The primary metric for comparing classifiers was the F1-score. F1-score, recall and Precision are computed as shown in the following equations 1, 2 and 3 [24]. Tables 5 and 6 show the parameters of the variance and the 2nd harmonic sequential models respectively.

$$\text{Precision} = \text{Truepositive}/(\text{TruePositive}+\text{FalsePositive}) \quad (1)$$

$$\text{Recall} = \text{Truepositive}/(\text{TruePositive}+\text{FalseNegative}) \quad (2)$$

$$\text{F1\_ score} = (2*\text{Recall}*\text{Precision})/(\text{Recall}+\text{Precision}) \quad (3)$$

Table 5. Variance Sequential Model

Layer (type)	Output Shape	Parameters
dense (Dense)	(None, 512)	2048
dense_1 (Dense)	(None, 11)	5643

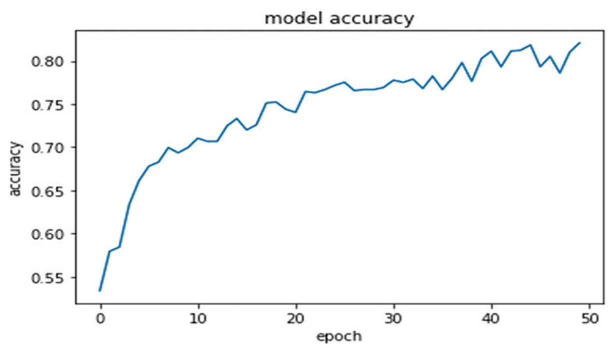
Table 6. Second harmonic Sequential Model

Layer (type)	Output Shape	Parameters
dense (Dense)	(None, 64)	256
dense_1 (Dense)	(None, 11)	715

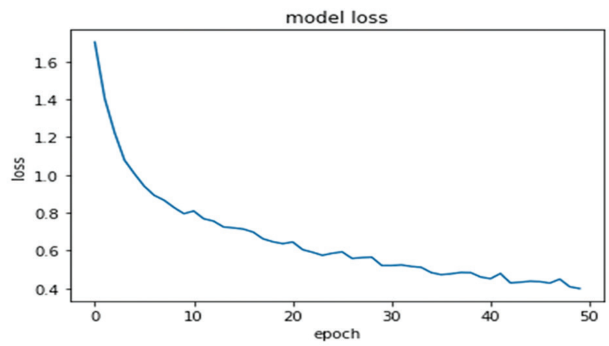
4. RESULTS AND TESTING OF CNN

Different percentages for training and testing are applied and the best results are with training by 60% and testing by 40% of the data for 2nd - harmonic model and with training by 80% and testing by 20% of the data for variance model.

Figs. 5 and 6 shows the accuracy and the loss of CNN model for 50 epochs when training with both variance and 2nd harmonic numerical values.

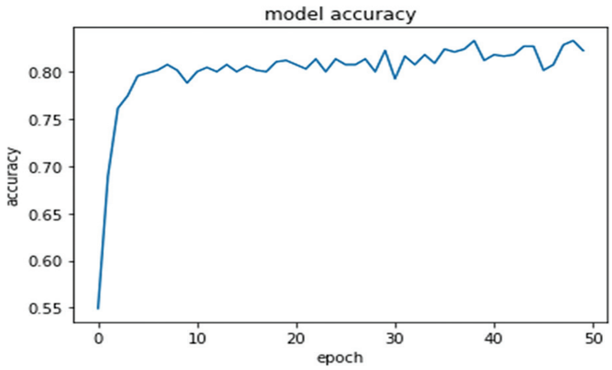


(a)

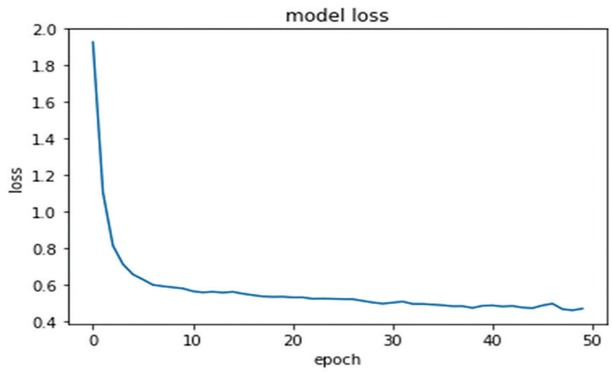


(b)

Fig. 5. Performance of training the CNN model with variance values. (**a**) accuracy and (**b**) Loss



(a)



(b)

Fig. 6. Performance of training the CNN model with second harmonic values. (**a**) accuracy and (**b**) Loss

Two dense layers are applied with specific total parameters equals 7,691 for variance values and equals 971 for 2^{nd} harmonic values. Different optimizers are applied; the best optimizer is a dams. Tables 7 and 8 present the test results of the CNN model with both variance and 2^{nd} harmonic values.

Table 7. Test results of the Sequential Model with variance values

Target	Precision	Recall	f1-score
1	0.96	1.00	0.98
2	0.53	1.00	0.70
3	0.78	1.00	0.88
4	1.00	0.33	0.50
5	1.00	0.73	0.84
6	0.00	0.00	0.00
7	0.86	1.00	0.92
8	0.80	0.44	0.57
9	1.00	0.42	0.59
10	0.67	0.80	0.73
11	0.56	1.00	0.71

The results in Table 7 shows that the recall classifier is better in target classes 1, 2, 3, 7, 10 and 11, while the precision classifier gives better results in target classes 4, 5, 8 and 9.

Table 8. Test results of the Sequential Model with 2^{nd} harmonic values

Target	Precision	Recall	f1-score
1	0.87	1.00	0.93
2	0.82	1.00	0.90
3	1.00	1.00	1.00
4	0.95	1.00	0.74
5	1.00	0.25	0.40
6	0.95	1.00	0.74
7	1.00	0.48	0.65
8	1.00	0.18	0.31
9	0.00	0.00	0.00
10	0.00	0.00	0.00
11	0.00	0.00	0.00

The results in Table 8 shows that the recall classifier is better in target classes 1, 2, 3, 4 and 6, while the precision classifier gives better results in target classes 4, 5, 6,7 and 8. The test results show an accuracy of 83% when using 2^{nd} harmonic signals and 86% with variance signals. The result shows that the sequential CNN model achieves good performance.

5. COMPARISON WITH OTHER ALGORITHMS

In order to rate the proposed CNN model, it is compared with other algorithms that are used for transformer inrush and fault currents classification. Table 9 presents a comparison between the proposed CNN algorithm performance and the performance of other models. The comparison shows that the proposed CNN model achieves a higher accuracy in fault classification than other compared models.

Table 9. Comparison of the proposed model performance with other research works

Model	Proposed CNN model	ANN [29]	Based language ML models [28]	DLNN with auto-encoders (SAE) [30]	Stacked sparse auto encoder DL [31]
Acc.	86%	80.4%	72.3%	71.3%	79.94%

6. CONCLOSION

In this paper, CNN is used to classify transformer faults. Matlab-Simulink is used to simulate the faults at different operating conditions. The current harmonic contents are extracted by using Fourier analysis and become clear that the 2nd harmonic content is the predominant. The accuracy of the CNN model is improved by training with numerical data of variance and 2nd harmonics values. The proposed CNN model achieves an accuracy of 83% when learned with 2nd harmonic values and 86% with variance values. It is obvious that the variance data set yields better performance. A comparison with other techniques is performed and the CNN model presents a higher improved accuracy by about 5.6% more than using ANN.

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