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Discrimination between inrush and fault currents of transformers using Artificial Neural Network Tools

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ABSTRACT

As a type of new security technique, this paper presents a technique for modeling transformer inrush and fault currents using fitting tools of artificial neural networks (ANN) to discriminate between inrush and fault currents of transformers. Inrush and fault currents are simulated at various winding connections, initial flux, and fault type. MATLAB neural network tool and Simulation package are used to simulate the proposed technique. This paper qualifies an ANN trained to distinguish inrush current and fault type based on multiple statistical inference methods on three phase transformer signals, such as the mean value, standard deviation, and product moment correlation coefficient factor. Use the second harmonic Maximum current of second harmonic signals calculated using Fourier analysis and recorded for three phase signals under various operational circumstances. This information will be used to train and test an artificial neural network. To fit the inputs and targets, a comparison of alternative training methods is done.

1. Introduction

Even when there is a separation, maintaining the supply of power-suppliers is critical. The difference between a normal signal and a faulty signal must be distinguished; if the protection relay trips for a normal signal, there will be a lack of supply. False tripping should be avoided at all costs. Protective equipment should only be used in the event of faulty signals in order to maintain supply [1], Many studies were interested in using the second harmonic as the typical harmonic content of a transformer inrush current to identify current signals [2].

To avoid unnecessary trip caused by the magnetizing inrush current, [3 and 4] presents a new approach for distinguishing internal fault current from inrush current. Inrush currents in transformers can be enormous, ranging from five to seven times the rated current. The power transformers' second harmonic component is utilized to halt relays. Fake protection under inrush situations is one of the most serious issues with transformer inrush currents. Many investigators benefited much from this matter [5]. As a result, revealing the value of the second harmonic component, as well as the maximum value of transformer inrush current and fault current wave patterns, is extremely dangerous [6–8]. The major goal of this research is to determine the inrush current and fault type using many statistical inference methods on three phase transformer signals, such as the mean value, standard deviation, and product moment correlation coefficient factor. Fourier analyzers were utilized to resolve the input signal and generate second harmonic signals. At various operating conditions, the maximum value of the three phases of the transformer's 2nd harmonic input signals is applied.

When a transformer is connected to a power system, the inrush currents improve. When the voltage returns to normal after a line fault, similar inrush currents can occur. The aforementioned statistics for current signals of the three phase transformer were acquired using MATLAB simulation at various operating conditions, and some samples were selected. The maximum value of second harmonic inrush and fault current signals was recorded at various winding connections, beginning flux, and fault types, as well as chosen samples of these signals. The maximum values of the three phases of the transformer's 2nd harmonic input signals are utilized as input to (ANN) to train it with various algorisms and select the best appropriate algorism to use.

An artificial neural network (ANN) was trained using these input signals with the goal of identifying inrush current and fault categories. The Neural Fitting app aids in data selection, network creation, and training. And use regression analysis

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and mean square error to evaluate its performance and discriminate between inrush and fault currents of transformers.

2. Power System Modeling

The power system is depicted in Simulink model [10] in Fig.2, which is represented by a single line diagram in Fig.1. A three phase, 450MVA, 50HZ, (500/230) KV power transformer is included in this model. Transformer primary winding is fed by a three-phase 3000 MVA, 500 KV equivalent source. Different types of winding connection such as (Yg-Yg), (D-D), (Y-Y), (Y-D), (D-Y) are be used to develop-different shapes of inrush current. Hence initial flux affects also the inrush current in each phase of transformer; some of varying initial flux is used to developed different shapes of inrush current. Fourier analyzers were utilized to evaluate the power transformer's input signal and give us with a second harmonic signal.

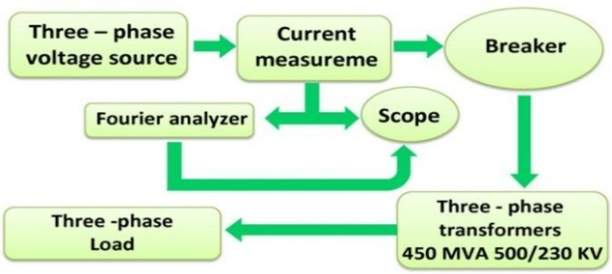

Fig. 1. Picture Model single line diagram

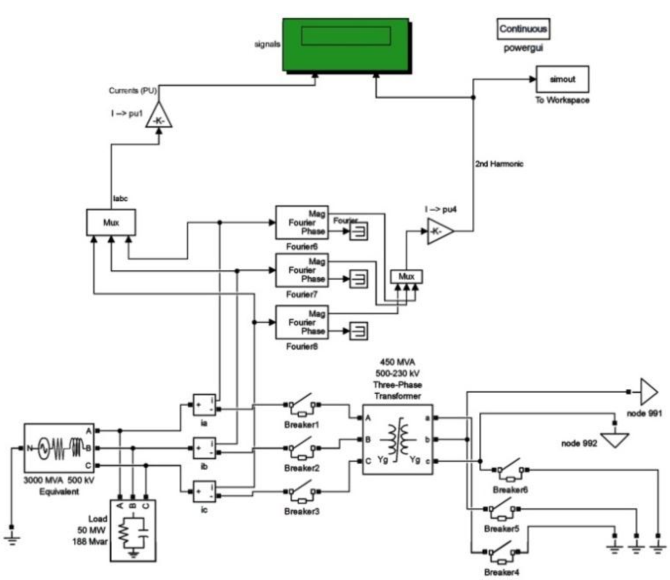

Fig. 2. MATLAB Simulink model for evaluating transformer inrush and fault currents

3. Current Recognition Scheme

Step1. Inrush current and fault current Simulink model. As well as applying some signal statistics under various operating situations.

Step2. Using 2nd harmonic Fourier analysis and recording the maximum 2nd harmonic current for three phase signals at different operating conditions.

Step3. Select data.

Step4. Train network with the data developed with different algorisms.

Step5. Evaluate network performance.

Step6. The network is being tested.

The above scheme is implemented and explained in the following Subsections [12].

3.1. Modeling with inrush and fault current

As stated in [2], the power system modeling with inrush current and defective current is performed in the MATLAB Simulink environment. The model is tested with a variety of beginning flux values, winding connections, and fault kinds. And using statistical inference methods such as the mean value, standard deviation, and product moment correlation coefficient factor on three phase transformer signals. Tables 1, 2, and 3 show how this information was gathered.

Table1: Mean value signals

operating conditions			mean value		
initial flux	Winding connection	current condition	Phase current (A)	Phase current (B)	Phase current (C)
0.4, -0.2, 0.2	Yg-Yg	Inrush	-0.0019	-0.0018	0.7361
0.2, 0, 0	Y-Y	Inrush	-0.1808	-0.1747	0.3555
0.4, -0.2, 0.2	Yg-Yg	Faulty (A-B)	0.0078	-1.0242	1.259
0.4, -0.2, 0.2	D-D	Faulty (A-B-C)	-0.6382	-0.6711	1.3093
0.4, -0.2 ,0.2	Y-Y	Faulty (A-C)	-0.9543	-0.0084	0.9627
0.3, 0, 0	Y-D	Inrush	-0.1141	-0.1298	0.2439
0.4, -0.2, 0.2	Yg-Yg	Faulty (B-G)	0.0106	-0.6033	0.6753
0.4, -0.2, 0.2	D-D	Faulty (C-G)	-0.0781	-0.1315	0.2096
0.6, -0.3, 0.3	D-Y	Inrush	0.0041	-0.0068	0.0026
0.4, -0.2, 0.2	Y-Y	Faulty (B-C-G)	0.1145	-0.5229	0.4085

Table2: Standard deviation value signals

operating conditions			standard deviation value		
initial flux	Winding connection	current condition	Phase current (A)	Phase current (B)	Phase current (C)
0.4, -0.2, 0.2	Yg-Yg	Inrush	0.0107	0.0127	1.051
0.2, 0, 0	Y-Y	Inrush	0.2129	0.1857	0.1665
0.4, -0.2, 0.2	Yg-Yg	Faulty (A-B)	0.0178	2.8199	2.9356
0.4, -0.2, 0.2	D-D	Faulty (A-B-C)	3.4412	3.542	3.8331
0.4, -0.2, 0.2	Y-Y	Faulty (A-C)	2.8621	0.0168	2.8598
0.3, 0, 0	Y-D	Inrush	0.1844	0.2059	0.3901
0.4, -0.2, 0.2	Yg-Yg	Faulty (B-G)	0.0177	3.3242	1.0555
0.4, -0.2, 0.2	D-D	Faulty (C-G)	0.088	0.2815	0.2917
0.6, -0.3, 0.3	D-Y	Inrush	0.0135	0.0231	0.0289
0.4, -0.2, 0.2	Y-Y	Faulty (B-C-G)	2.578	2.5493	0.4552

Table3: Correlation factor signals

operating conditions			Correlation factor		
initial flux	Winding connection	current condition	Phase current (A)	Phase current (B)	Phase current (C)
0.4, -0.2, 0.2	Yg-Yg	Inrush	1	-0.2621	-0.6671
0.2, 0 ,0	Y-Y	Inrush	1	-0.6587	-0.5439
0.4, -0.2, 0.2	Yg-Yg	Faulty (A-B)	1	0.1657	-0.2311
0.4, -0.2, 0.2	D-D	Faulty (A-B-C)	1	-0.3978	-0.5301
0.3, 0, 0	Y-D	Inrush	1	0.9971	-0.9992
0.4, -0.2, 0.2	Y-Y	Faulty (A-C)	1	-0.1378	-1
0.4, -0.2, 0.2	Yg-Yg	Faulty (B-G)	1	-0.2892	-0.5862
0.4, -0.2, 0.2	D-D	Faulty (C-G)	1	-0.0379	-0.2649
0.6, -0.3, 0.3	D-Y	Inrush	1	0.1883	-0.6187
0.4, -0.2, 0.2	Y-Y	Faulty (B-C-G)	1	-0.9843	-0.1512

3.2. Second harmonic Fourier analysis.

A variety of samples have been chosen. Table4 shows the maximum 2nd harmonic current recorded using 2nd harmonic Fourier analysis for three phase signals under various operating conditions.

Table4: the Peak value of 2nd harmonic current

operating conditions			Peak value of 2nd harmonic		
initial flux	Winding connection	current condition	Phase current (A)	Phase current (B)	Phase current (C)
0.4, -0.2, 0.2	Yg-Yg	Inrush	0.73	0.0055	0.0004
0.4, -0.2, 0.2	Y-Y	Faulty (A-B-C)	2.35	2.08	2.1
0.3, 0, 0	Yg-Yg	Inrush	0.66	0.012	0.074
0.4, -0.2, 0.2	Y-D	Inrush	0.395	0.192	0.205
0.4, -0.2, 0.2	Y-Y	Faulty (B-G)	0.131	0.125	0.118
0.4, -0.2, 0.2	Y-Y	Inrush	0.131	0.124	0.118
0.4, -0.2, 0.2	Y-Y	Faulty (A-B)	2	2	0.01
0.4, -0.2, 0.2	D-D	Inrush	0.36	0.345	0.054
0.4, -0.2, 0.2	Yg-Yg	Faulty (A-B-C)	2.19	0	1.91
0.4, -0.2, 0.2	D-D	Faulty (C-G)	0.358	0.349	0.055

3.3. Select data.

The fitting issue is defined using the developed inputs and targets.

The matrix rows that made up the samples were as follows:

-A 1040*3 matrix encoding static data (Ia, Ib, Ic): 1040 samples of three elements is used as input.
-Target is a 1040*5 matrix that represents static data: 1040 samples of 5 elements [Fault (inrush), Fault (a), Fault (b), Fault(c), Fault (g)].
Set 728 for training, 156 for validation, and 156 for testing from these samples.

Set the number of neurons in the hidden layer of the fitting network.

3.4. Training network and training algorism

3.4.1. Training network

Using this information, the network is trained to fit the inputs and targets, starting with the mean values, then the standard deviation values, the correlation factor values, and finally the maximum 2nd harmonic values (Fig. 3). As a result, ANN researches the traits and characteristics of various signals.

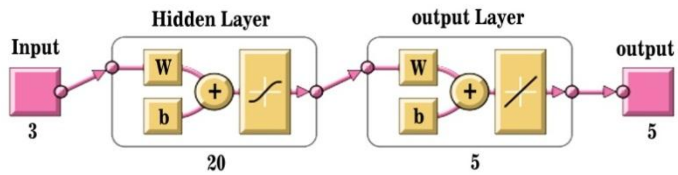

Fig. 3. Training architecture

Given consistent data and enough neurons in its hidden layer, a two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (fitnet) may fit multi-dimensional mapping problems arbitrarily effectively.

3.4.2 Training algorism

Choose one of several algorisms to train the network to fit the inputs and targets, such as:

1- Levenberg Marquardt
2- Bayesian Regularization
3- Scaled Conjugate Gradient

3.4.2.1 Training with Levenberg- Marquardt algorism

This algorism usually necessitates a greater amount of memory but less time.
When generalisation stops improving, as shown by an increase in the mean square error of the validation samples, training automatically terminates. Lower numbers are better, and zero signifies no error, where mean squared error (MSE) is the average squared difference between outputs and targets. Regression the R value indicates the degree of correlation between outputs and objectives; a value of 1 indicates a close association, while a value of 0 indicates a random relationship.
Train with the Levenberg-Marquardt method. (trainlm)

Table5: Results of training with Levenberg-Marquardt algorism

Kind of sample	Samples	MSE	R
Training	781	3.09997e-2	9.24824e-1
Validation	168	3.54662e-2	9.12329e-1
Testing	168	3.07471e-2	9.23417e-1

3.4.2.2 Training with Bayesian Regularization algorism

This algorithm takes longer, but it can provide strong generalization for complex, tiny, or noisy datasets. Adaptive weight minimization causes training to come to an end (regularization).Train using Bayesian Regularization. (trainbr)

Table6: Results of training with Bayesian Regularization algorism

Kind of sample	Samples	MSE	R
Training	781	2.76863e-2	9.32836e-1
Validation	168	0.0000e-0	0.0000e-0
Testing	168	3.08007e-2	9.24538e-1

3.4.2.3 Training with Scaled Conjugate Gradient algorism

This algorithm necessitates a less amount of memory. When generalization stops improving, as shown by an increase in the mean square error of the validation samples, training automatically terminates.

Scaled Conjugate Gradient can be used to train (trainscg).

Table7: Results of training with Scaled Conjugate Gradient algorism

Kind of sample	Samples	MSE	R
Training	781	5.18495e-2	8.68936e-1
Validation	168	5.30483e-2	8.65042e-1
Testing	168	5.64485e-2	8.62804e-1

According to the MSE and R values in table5, table6, and table7, Levenberg–Marquardt is the best algorism for training.

3.5. Evaluates network performance

3.5.1. Performance of mean values training

The following are the results of training networks:
Figure 4 shows the performance of network training with mean values.
At epoch 160, use mean square error to evaluate its performance and yield 0.0637.
The network error Histogram with mean values is shown in Figure 5.
ERORRS = TARGETS – OUTPUTS

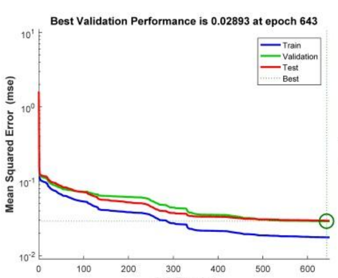

Fig. 4. Performance with Mean values

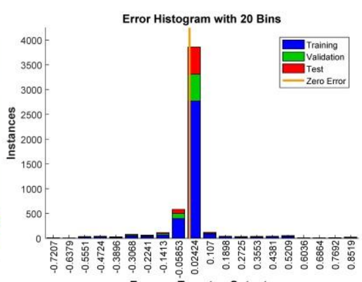

Fig. 5. Histogram with Mean values

3.5.2 Performance of correlation factors training

The following are the results of training networks:
The performance of network training with correlation factors is depicted in Fig. 6.
At epoch 127, performance is 0.0273.
The network error histogram with correlation factors is shown in Figure 7.

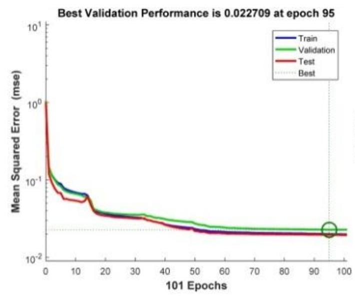

Fig. 6. Performance with Correlation factors

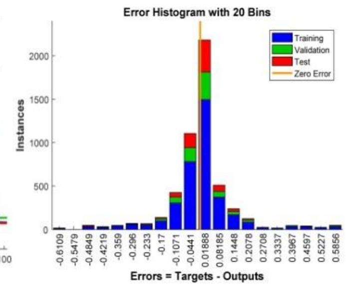

Fig. 7. Histogram with Correlation factors

3.5.3 Performance of standard deviation values training

The following are the results of training networks:
Fig. 8The standard deviation numbers show network training performance.
At epoch 122, performance is 0.01837.
Fig. 9This is a histogram of network error values with standard deviations.

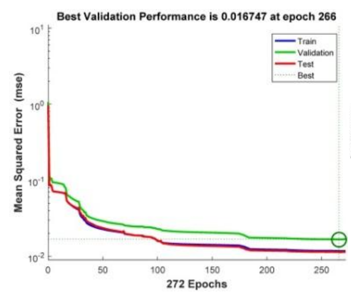

Fig. 8. performance with Standard deviation values

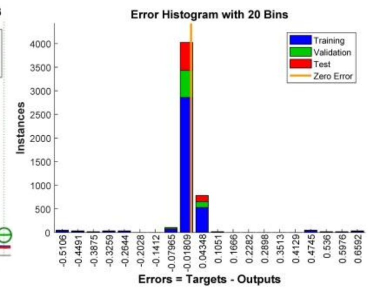

Fig. 9. Histogram of Standard deviation values

3.5.4. Performance of second harmonic values training

The following are the results of training networks:
Figure 10 shows the performance of the network training using second harmonic values.
At epoch 160, performance is 0.03847.
The network error histogram with second harmonic values is shown in Fig. 11.

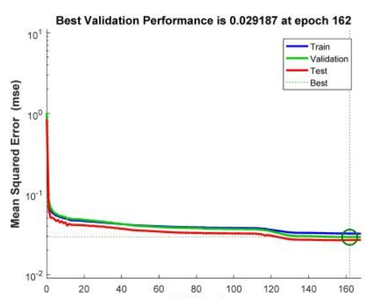

Fig. 10. performance with Second harmonic values

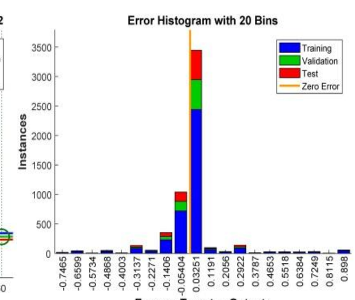

Fig. 11. Histogram with Second harmonic values

3.6. Testing network

Table8: Testing some different selected examples

INPUT			OPERATION	OUTPUT					TARGET					CURRENT CONDITION
IA	IB	IC		IIN	IA	IB	IC	IG	IIN	IA	IB	IC	IG	
0.0178	2.8199	2.94	Standard deviation	0.038	0.36	0.288	0.1	0.11	0	1	1	0	0	FAULT (A-B)
1	**-0.02**	**-0.727**	**Correlation factor**	**0.3**	**0.18**	**0.05**	**0.18**	**0.25**	**1**	**0**	**0**	**0**	**0**	**INRUSH**
-0.714	0.0041	0.912	Mean	0.95	0.018	0.003	0.007	0.01	0	1	0	1	0	FAULT (A-C)
3.44	3.54	3.83	Standard deviation	0.006	0.01	0.05	0.1	0.074	0	1	1	1	0	FAULT (A-B-C)
2.01	1.99	0.018	Second harmonic	0.0025	0.032	0.081	0.26	0.61	0	1	1	0	0	FAULT (A-B)
2.35	2.08	2.1	Second harmonic	0.033	0.035	0.057	0.239	0.632	0	1	1	1	0	FAULT (A-B-C)
1	-0.98	-0.01	Correlation factor	0.95	0.025	0.002	0.01	0.01	0	0	1	1	1	FAULT (B-C-G)

In table 8; Targets and output s are not the same values in most of samples.

4. Conclusion

The current fitting strategy for transformer protection is presented to discriminate between inrush and fault currents of transformers using Artificial Neural Network Tools. Artificial Neural Networks are used to accomplish fault fitting. The neural fitting app aids in the selection of data, as well as the creation and training of the network. And use regression analysis and mean square error to measure its performance. The back propagation algorithm of Levenberg and Marquardt is employed. The defect signal is handled before being sent into the neural network. The network performance reveals that, as proven in this paper, training ANN using standard deviation values yields superior results than training with alternative signal statistics.
The Levenberg-Marquardt algorithm necessitates additional memory, which is a drawback of the neural fitting programme. In most samples, the targets and outputs are not the same values, according to network testing.
The findings of the proposed Transformer current fitting technique are not accurate decision making by ANN, and another technique for transformer current categorization should be adopted.

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