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Research paper

Comparative Analysis of Wavelet Based Algorithms for Protection of Power Transformer

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Abstract

The main theme of this paper is to protect the transformer from unnecessary tripping due to inrush current and to overcome drawbacks in traditional frequency transform based protection schemes. In this method, Inrush and Internal fault currents are simulated and Protection of power transformer is presented using a time-frequency transform. Pre-processing is done using Continuous Wavelet Transform for decomposition of signals. Preprocessed signals are used to train Artificial Neural Network architecture using Multi Layer Perceptron, Particle Swarm Optimization Techniques. Results are compared and better classification combination is chosen.

Keywords*: inrush current, internal fault current, wavelet, Artificial Neural Network, Multi layer perceptron and Particle swarm optimization*

1. Introduction

In electrical power transmission design, there are several factors need to be contemplate to satisfy the demandsof electricity consumers. Electrical power system, encounters faults at different times due to severalundesired conditions like short circuit, over current, surges, high temperatures etc.The power systems engineer in his design shouldinclude preventive measures in order to prevent any devastating occurrences due to thefaults that the system may experience at any inclined time.[3]
Second harmonic restraint relay had already been implemented to protect the Transformer from second harmonics in inrush current but the second harmonics will be present in internal faults which resembles in mal operation.Hence further processing done on Wavelets and with Artificial Neural Networks based
algorithms for the discrimination of inrush and internal fault currents to get rid ofmaloperation.[1]

1.1. Inrush currents

When a transformer power supply is interrupted suddenly orswitched on immediately,transformercore is over fluxing temporarily at the time ofenergization, due to this averyhigh peak in magnetizing currenti.e.doubling effect is achieved as shown in Fig.1.It results an unwanted tripping of the differential protective relay.[3]

Temporary over fluxing phenomenon is decided by the factors:
i. The point-on-voltage at the time of switching or energization.
ii. The magnitude and polarity of the remnant flux in the transformer core at the instant ofenergization, the overall resistanceof the primary winding circuit
iii. The power source inductance, the inductance of the air core in between the energizing winding and the transformer core.[4]

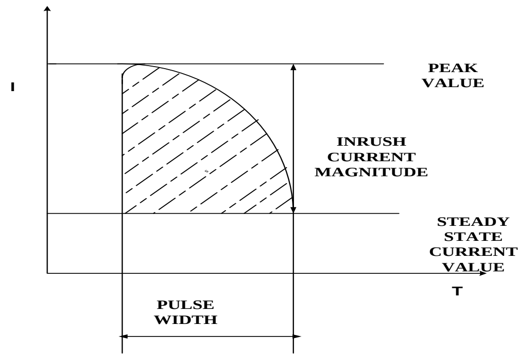

Fig.1:Inrush Currents

1.2. Internal fault currents

Internal faultsoccurring insidethe transformer tank, includes the short circuit between the phase winding, single-phase inter-turn short circuit, single-phase ground short circuit, its turn to turn short circuitproblems etc. are harmfulbecause the high temperature electric arc short-circuit currents will not only damage the winding insulation, burning core, but will also heat the insulating materials which will cause decomposition of transformer oil producing large amounts of gas causingthe transformer tank explosion.[3]

2. Continuous wavelet transform

Harmonic restraint relay which is used to protect transformer from inrush currents in which differential current is divided into fundamental and second harmonic components, but the second harmonic component will present in internal faults too, hence the further discrimination is needed.
Wavelets has ability to accomplish the local analysis i.e. to analyze a localized area of the larger signal.[5]The Wavelet Transform utilizes mother wavelet functions, and performs the decom-

position of signalinto weighted set of the scaled wavelet functions.In various applications, continuous wavelet transform functions are used for compact support as mother wavelet.
CWT was developed to overcome resolution problem.CWT uses interior products to measure the identity betweencurrent signal and examiningfunction.In Fouriertransform,examining functions are complex exponentialswaveforms ,$e^{j\omega t}$.The resulting FT is a function of single variable, ω.InCWT,the examiningfunction is a wavelet. CWT compares the any signal to shifted and compressed or stretched versions ofthe wavelet.By estimating the current signals with wavelets at different scales and positions.The equation shown in (1) is a real valued continuous wavelet transform function.[1]

$$C(scale, position)= \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt \cdots \qquad (1)$$

3. Methodology

Inrush current signals at various switching angles and Internal fault current signalsat various conditions i.e LG,LLand LLGare simulated. For these current signals CWT is done and then RMS coefficients are obtained.ANN is trained byusingmultilayer perceptron, Particle Swarm Optimizationby giving RMS Coefficients as input.Finally, inrush and internal fault current classification is done as shown in Fig.2

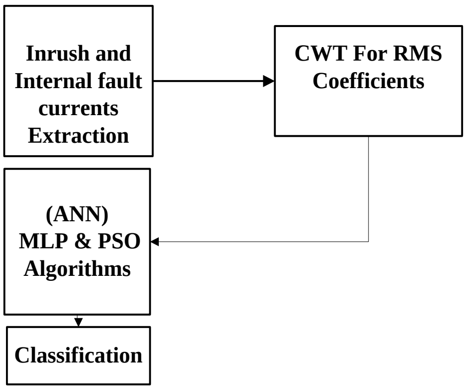

Fig.2: Block diagram

3.1. Extraction of Inrush Currents

Two timecontrolled switches and BCTRAN transformer modelareusedas shown infollowing Fig.3.Purpose is to get subsequent energization to obtain magnetizing inrush signals as shown in Fig.4

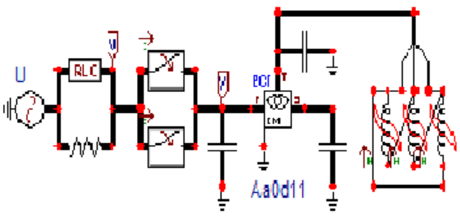

Fig.3: Modeling of transformer for inrush extraction

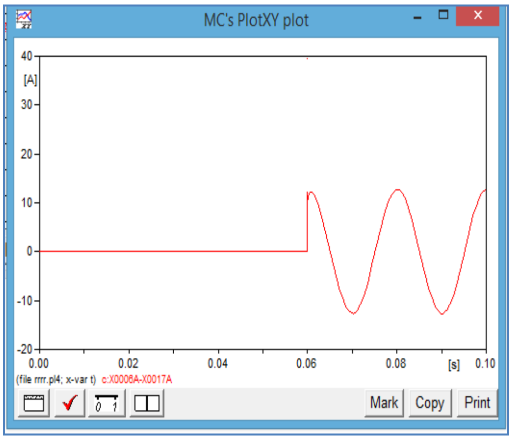

Fig.4: Simulation of Inrush Currents in ATP

3.2. Extraction of internal faultcurrent

LG,LLG,LLLG faults are been created in the Power Transformer using the BC TRAN transformer model in ATP as shown in Fig.5.Internal Fault current is simulated as shown in Fig.6

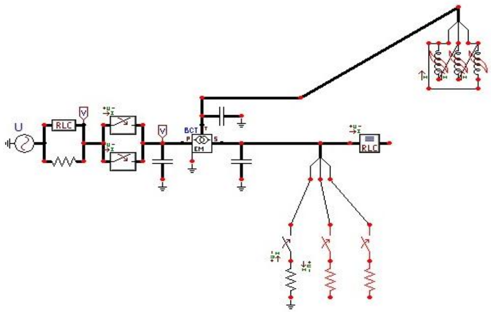

Fig.5: Modelling of power transformer for fault current

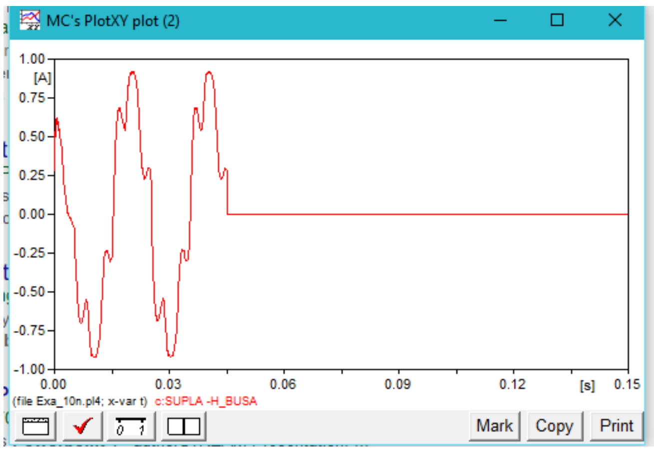

Fig.6: Simulation of Internal Fault Currents in ATP

3.3. Extraction of RMS Coefficients

For the simulated inrush and internal fault current signals continuous wavelet Transform is done and then RMS coefficients are obtained. These extracted coefficients are given as input data to ANN by using multilayer perceptron and Partial swarm optimization for training.

4. Wavelet based algorithms

4.1. Multilayer Perceptron

Back propagation algorithm is an Artificial Intelligence tool used in most common in training a network. MLP with ‘x’ hidden layers, ‘y’ hidden nodes and ‘z’ outputs has (x*y) +y+(y*z)+z weights and biases. Output values are evaluated by input neurons with processed hidden neurons and with activatedsigmoid functions.

Algorithm

Step1: Intialize Input and output values in between 0 and 1

Step2: Number of neurons in hidden layer lies between the rangel< m< 2l

Step3: {V} constitutes the weights between input neurons and hidden neurons and {W} constitutes the weights between hidden to output layer. Initialize the weights between the values -1 to 1

Step4:Trainingdata:present one set of inputs and outputs. Inputs to input layer is $[I]_I$ and output to input layer is $[O]_I$

$$[O]_I = [I]_I \tag{2}$$

Step5: Enumerate the inputs to hidden layer by multiplying weights as Inputs to hidden layer $[I]_H$

$$[I]_H = \{V\}^T [O]_I \tag{3}$$

Step6:The hidden layer neurons assess the output to the hidden layer by sigmoid function is

$$[O]_H = (1/(1+\exp(-I_H)) \tag{4}$$

Step7:Enumerate the input to the output layer by multiplying weights as

$$[I]o = \{W\}^T [O]_H \tag{5}$$

Step8: The output of output layer is computed by sigmoid function as

$$[O]o = (1/(1+\exp(-I_O)) \tag{6}$$

Step9: Evaluate the error as difference between MLP output and desired output;

$$e = \text{target} - \text{actual output} \tag{7}$$

Step10: Find $[d] = [T_K - O_o]O_o (1-O_o)$ (8)

Find matrix $\{Y\}= [O]_H< d >$;d=delta (9)

Step11: Attain $\{W\}=\eta \{Y\}$ (10)

Step12: Attain $[e] = \{W\} [d]$ (11)

$[d^*] = e_i (O_{Hi}) (1- O_{Hi})$ (12)

$\{X\} = [O]^I< d^*>= [I]_I<d *>$ (13)

Step13:Attain$\{V\}=\eta \{X\}$ (14)

Step14: For Weight updation

$$\{V\}new = \{V\}old + \{\Delta V\} \tag{15}$$

$$\{W\}new = \{W\}old + \{\Delta W\} \tag{16}$$

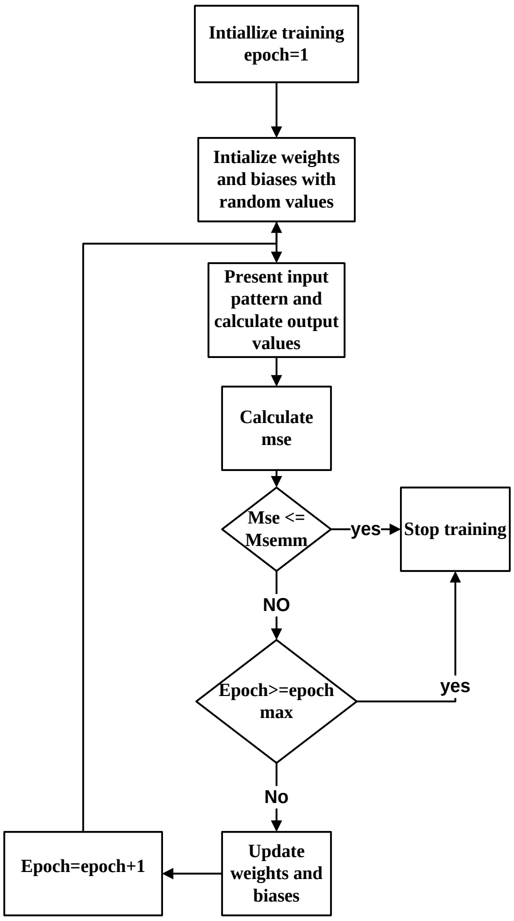

Fig.7: Flow chart of Multi-Layer Perceptron

4.2. Particle Swarm Optimization

Particle Swarm Optimization is an artificial intelligence based on the collective behavior of the decentralized, self-organize systems.[9].Generations (iterations) are done until the optimized solution is obtained from the particles. A flock of particles are taken for the optimization of certain objective function, In this context, the particles are the RMS coefficients of inrush and internal fault currents at various conditions and the objective function is taken as the discrimination of the two features i.einrush and internal fault currents.[9]

In this perspective of the iterations, with respect to particles for the respective neural network are initialized. Each particle knows its best value so far called pbest and its position. Moreover, each particle knows the best value in the group best among bests. Each particle tries to modify its position according to the current value .

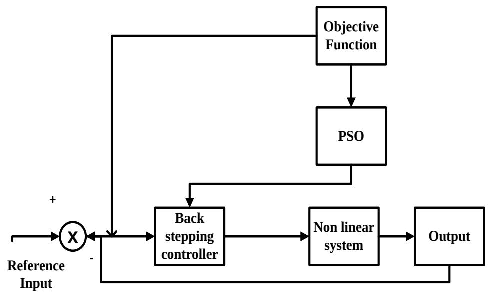

Fig.8: Block diagram of Particle Swarm Optimization

As shown in Fig.8, Basic operation of the PSO in which objective function discrimination is given to the particle swarm block and the back stepping controller, the controller which used for designing and stabilizing the controls for the class of non linear systems.

By considering and comparing with the reference input, the closed loop process will be continued until the error is minimized, with an contemplate classification rate and with an optimized solution.[9]

5. Results ofwavelet based algorithms

For comparative analysis, ANN is trained using wavelet based multilayer perceptron and Particle swarm optimization by changing number of iterations and number ofhidden neurons to obtain least Mean squared Error

5.1. Wavelet based Multilayer perceptron

ANN is trained using multilayer perceptron by using 5 hidden neurons in each hidden layer where two hidden layers are used to obtain least Mean squared Error by changing number of Iterations

Table.1: MLP with 5 neurons in each hidden layer

Iterations (Epochs)	Learning rate	No of Hidden neurons	MSE
500	0.56	10	0.0278
5000	0.56	10	0.0164
10000	0.56	10	0.0021
15000	0.56	10	0.0019
50000	0.56	10	0.0005

Table.2: MLP with 10 neurons in each hidden layer

Iterations (Epochs)	Learning rate	Neurons in Hidden layer (Noofhidden layers=2)	MSE
500	0.56	[5 5]	0.34021
5000	0.56	[5 5]	0.25258
10000	0.56	[5 5]	0.24289
15000	0.56	[5 5]	0.23081
50000	0.56	[5 5]	0.17010

In Table.1 It is observed that as number of iterations are inreased then Mean square error is decreased.
ANN is trained using multilayer perceptron by using 10 hidden neurons in each hidden layer where two hidden layers are used to obtain least Mean squared Error by changing number of Iterations
In Table.2 It is observed that as number of iterations and hidden neuronsare increased , Mean square error is decreased more than the 5 number of hidden neurons

5.2. WaveletbasedParticleswarmOptimization

ANN is trained by choosing Particle Swarm Optimization parameters with Number of masses as 30,Number of training samples as 150 and Gravitational constant as 1 by using 10 hidden neurons to obtain least Mean squared Error by changing number of Iterations
Table.3 PSO with 10 hidden neurons
In Table.3 It is observed that as number of iterations are increased then Mean square error is decreased which is better than Multilayer perceptron with 10 hidden neurons.

Table.3 PSO with 10 hidden neurons

Iterations (Epochs)	Learning rate	Neurons in Hidden layer (Noofhidden layers=2)	MSE
500	0.56	[10 10]	0.17011
5000	0.56	[10 10]	0.04123
10000	0.56	[10 10]	0.05030
15000	0.56	[10 10]	0.03762
50000	0.56	[10 10]	0.00513

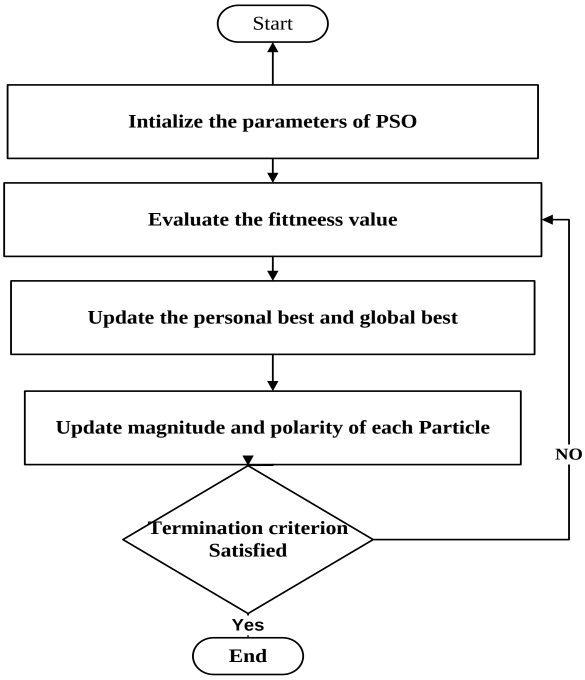

Fig.9: Flow chart of Particle Swarm Optimization

ANN is trained by choosing Particle Swarm Optimization parameters with Number of masses as 30, Number of training samples as 150 and Gravitational constant as 1by using 20 hidden neurons to obtain least Mean Square Error by changing number of Iterations

Table.4: PSO with 20 hidden neurons

Iterations (Epochs)	Learning rate	No of Hidden neurons	MSE
500	0.56	20	0.0034
5000	0.56	20	0.0014
10000	0.56	20	0.0011
15000	0.56	20	0.0009
50000	0.56	20	0.0001

In Table.4 It is observed that as numbers of iterations are increased Mean square error is decreased better than Multilayer perceptron with 20 hidden neurons.

6. Conclusion

In the Present work, Inrush and Internal fault currents are extracted in simulation environment using ATP/EMTP software. The Current signals are being preprocessed using CWT and RMS coefficients of preprocessed signals fed to ANN architecture for training using Multilayer Perceptron and Partial Swarm Optimization algorithms. Mean square errors for desired classification, in case of normal and fault currents compared. It is observed that wavelet based Particle Swarm Optimization technique gives the high level of classification rate with less Mean square error.

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