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PSOWNN Based Relaying for Power Transformer Protection

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Abstract: This study presents a new, efficient, fast and reliable technique to discriminate internal faults from no fault conditions (inrush condition, normal, over excitation and external faults with CT saturation) in 3 phase transformers. A typical 100 MVA, 110/220 KV, Δ/Y 3 phase transformer connected between a 110 KV source at the sending end and a 220 KV transmission line connected to an infinite bus power system at the receiving end are simulated using PSCAD/EMTDC software. Various types of fault and no fault conditions are simulated and the differential currents are obtained. Wavelet transformation is done on the differential current and the d1 coefficients are obtained. The d1 coefficients are given as inputs to the wavelet based neural network trained by Particle Swarm Optimization (PSO-WNN). The simulation results show that PSO-WNN has very simple architecture, negligible error and provides more accurate results when compared to wavelet combined neural network trained by back propagation algorithm (WNN) and neural network trained by giving 3 phase differential currents as input (ANN). The performance of PSO-WNN based relay is also compared with the conventional harmonic blocking relay. PSO-WNN based relaying provides a high operating sensitivity for internal faults and remains stable for no fault conditions of the power transformers.

Key words: Power transformer, differential protection, harmonic blocking, wavelet transform, neural network, particle swarm optimization

INTRODUCTION

When internal fault occurs in a transformer, immediate disconnection of the faulted transformer is necessary to avoid extreme damage and to protect the power system. Normally, differential protection is employed for power transformers. Transformer differential relay is prone to maloperate during inrush conditions. While an unloaded transformer is energized, high magnetizing inrush current flows on one side of the transformer, it looks likes an internal fault to the differential relay and ends up as spill current and the relay maloperates. Distinguishing inrush current from an internal fault current is one of the most challenging power system problems.

To overcome this drawback, percentage differential relay was implemented. But still percentage differential relays tend to maloperate for inrush currents. One way to combat this problem is to desensitize the relay for a brief period of time, just after switching on. However, this is not desirable, since the probability of insulation failure just after switching on is quite high and the desensitized relay would be blind to faults taking place at that crucial time. The inrush waveform is rich in second harmonics, whereas the internal fault current consists of only fewer amounts of 2nd harmonics. An additional restraint based on the harmonic content of the inrush current was developed to restrain during inrush conditions. The modern transformer relays use either harmonic restraint or blocking. The main drawback of this approach is, during CT saturation, the 2nd harmonic component may also be generated during internal faults and the new low amorphous materials in modern power transformers may produce low 2nd harmonic content in inrush current (Malik *et al*., 1989).

Many researchers then proposed the use of wave shape recognition techniques in differential relays to discriminate internal fault from the inrush current. Rockfeller (1969) proposed a relay to block its operation if the successive peaks of the differential current fail to occur at about 7.5-10 msec. Another principle proposed by Guiliante and Clough (1991) recognizes the length of time interval during which, the differential current is near zero. The relay is blocked for the inrush currents whose low current intervals are >1 quarter cycle and the relay operates for internal faults whose low current intervals are <1 quarter cycle. If the low current intervals last <1 quarter cycle, then the above method will fail to block the relay.

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Subsequently, more reliable protection algorithms based on artificial intelligence techniques like fuzzy, artificial neural networks have been proposed. Nagpal *et al*. (1995) and Zaman and Rahman (1998) have proposed that Artificial Neural Network has proved to be very efficient in power transformer protection in single phase transformers. Moravej and Vishwakarma (2003) has proposed ANN based power transformer protection using Back Propagation Network (BPN) and Radial Basis Function Neural Network (RBFN). Wavelet transform is a powerful tool in the analysis of the transient phenomenon of power transformers because of its ability to extract information from the transient signals simultaneously in both the time and frequency domain unlike Fourier transform, which can give the information in the frequency domain only. Wavelet transforms have been extensively used for analyzing the transient phenomena in a power transformer for distinguishing internal fault currents from inrush currents (Okan *et al*., 2004; Sudha and Jeyakumar, 2007a-c). Peilin and Aggarwal (2001) proposed a classification technique using combined wavelet transform and neural networks. The differential currents are decomposed first using wavelet transform into series of detailed wavelet components and the spectral energies of the wavelet components are employed to train the neural network and detect the fault at 10-15 msec after the occurrence of a fault. Okan *et al*. (2004) proposed a wavelet based ANN approach for transformer protection where the first 10 d1 coefficients after the occurrence of the fault are used for training. The fault detection time is 5 msec i.e. (1/4th of a cycle). Sudha and Jeyakumar (2007a-c) have proposed Wavelet and ANN based relaying using only the first 5 d1 coefficients after the occurrence of the fault for training of 10-20-1 neural network architecture. The maximum fault detection time is 2.5 msec i.e. (1/8th of a cycle) and it also detects fault within 1 msec from the occurrence of the fault i.e. (1/20th of a cycle). To make the neural network architecture simpler and to reduce the error, Particle Swarm Optimization (PSO) technique is implemented to train the neural network.

This study proposes a new PSO-WNN based 3 phase transformer protection algorithm to distinguish internal fault currents from no fault conditions in 3 phase power transformers. The proposed algorithm extracts fault, inrush, normal, over excitation and external fault generated transient signals using Discrete Wavelet Transform (DWT). The signals are then tuned by DWT multi resolution filter bank. The detail 1 coefficients (d1) of the transient signals are obtained by the decomposition using DWT. DWT has considerably reduced the volume of input data of the WNN without any loss of information. The d1 coefficients of transient signals of various fault and no fault conditions are used to train a feed forward neural network. The PSO-WNN architecture has 3 input neurons, 3 first hidden layer neurons, 3 second hidden layer neurons and one output neuron which is trained using PSO algorithm. The trained PSO-WNN based relay clearly classifies internal fault from no fault conditions.

Extensive simulation studies have been conducted using PSCAD/EMTDC software to verify the feasibility of the proposed protection scheme for inrush currents at different voltage closing angles, various types of internal faults such as single phase to ground faults, double phase to ground faults, three phase to ground faults, 2 phase faults and three phase faults, various over excitation cases and various external faults. Analysis reveals that this technique is stable for no fault conditions and is highly sensitive for fault currents. PSO-WNN is compared with ANN, WNN and conventional harmonic blocking relays.

WAVELET TRANSFORM

The Fourier Transform is probably the most popular transform which is used to obtain the frequency spectrum of a signal. But the Fourier Transform is suitable only for stationary signals, i.e., signals whose frequency content does not change with time. The Fourier transform tells how much of each frequency exists in the signal but it does not tell at, which time these frequency components occur.

Signals such as image and speech have different characteristics at different time or space, i.e., they are non-stationary. Transient signals are also non-stationary. To analyze these signals, both frequency and time information are needed simultaneously, i.e., a time-frequency representation of the signal is needed. To solve this problem, the Short-Time Fourier Transform (STFT) was introduced. The major drawback of the STFT is that it uses a fixed window width. The wavelet transform, which was developed in the last 2 decades, provides a better time-frequency representation of the signal than any other existing transforms.

Figure 1 illustrates the implementation procedure of a Discrete Wavelet Transform (DWT), in which the original signal is passed to low-pass (g (n)) and high-pass (h (n)) filters, respectively. At the 1st stage, an original signal is divided into 2 halves of the frequency bandwidth and sent to both high-pass filter and low-pass filter. Then the output of low-pass filter is further divided into half of the frequency bandwidth and sent to the 2nd stage this procedure is repeated until the signal is decomposed to a pre-defined certain level. The set of signals thus,

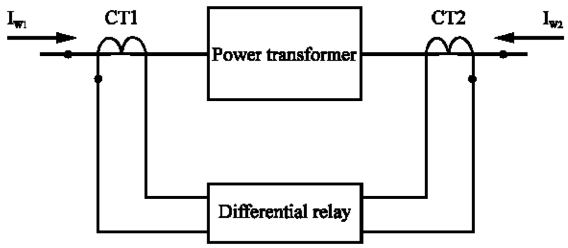

Fig. 1: Differential relay connection diagram

attained represent the same original signal, but all corresponding to different frequency bands. If the original signal is being sampled at Fs Hz, the highest frequency that the signal could contain according to Nyquist's theorem would be Fs/2 Hz. Thus, the band of frequencies between Fs/2 and Fs/4 would be captured in detail1 (d1) coefficient and the band of frequencies between 0 and Fs/4 would be captured in approximation 1 (a1). Then again the signal in a1 is divided into a2 and d2 where the band of frequencies between Fs/4 and Fs/8 would be captured in d2 and the band of frequencies between 0 and Fs/8 would be captured in a2 and so on.

ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Network (ANN) is a mathematical model or computational model based on biological neural networks. It is an exact simulation of a real nervous system. It consists of an interconnected group of artificial neurons and process information using a connectionist approach to computation.

Back propagation algorithm is commonly used for training multi layer FFNN. It can be used to solve complex pattern-matching problems. Network learns a pre-defined set of input-output training pairs by using a2 phase propagate-adapt cycle. The applied input pattern to the 1st layer propagates through each upper layer until an output is generated. This output pattern is compared with the desired output and an error signal is computed for each output unit. The error signals are then transmitted backward from the output layer to each node in the intermediate layer. This process repeats layer by layer. Based on the error signal received, the connection weights are updated to cause the network to converge towards a state that allows all the training patterns to be encoded. After training, when presented with an arbitrary input pattern, the network will respond with an active output if the new input contains a pattern that resembles a trained feature.

PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is an evolutionary optimization technique first introduced by Kennedy and Eberhart in 1995 and has been compared to Genetic algorithms for efficiently finding optimal or near-optimal solutions in larger spaces. Particle swarm optimization method was inspired by the animal social behaviors such as school of fish, flock of birds, etc. and mimics the way they find food sources and prevent from predators. To better understand how it works, consider the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is, but they do know how far the food is in each iteration. An effective strategy to find the food is to follow the bird which is nearest to the food. Particle Swarm algorithm starts with the random initialization of a population of individuals (particles) in the search space and work on the social behaviors of the particles in the swarm. In PSO, single solution is a bird in the search space. Such solutions are called particles. All of the particles have fitness values, which are evaluated by the fitness function to be optimized and have velocities, which direct the flying of the particles. They fly through the problem space by following the current optimum particles.

Each particle keeps track of its coordinates in the problem space, which are associated with the best solution it has achieved so far. This value is called pbest. Another best value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called lbest. When a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest. Suppose that the search space is D-dimensional then the ith particle of the population, which is called swarm, can be represented by a D-dimensional vector $S = (S_1, S_2, \ldots\ldots S_D)$. The velocity of this particle can be represented by another D-dimensional vector $V = (V_1, V_2, \ldots, V_D)$. The best previously visited position of the ith particle is denoted as $P = (P_1, P_2, \ldots, P_D)$. Let g be the index of the best particle in the swarm and let the subscripts denote the iteration number, then the swarm is manipulated according to the Eq. 1 and 2:

$$V_i^{k+1} = WV_i^k + C_1 r_1^k (P_i^k - S_i^k) + C_2 r_2^k (P_g^k - S_i^k) \quad (1)$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \quad (2)$$

where:

W = The inertia weight

C_1, C_2 = Two positive constants called cognitive and social parameters, respectively, also known as learning factors

r_1, r_2 = Random numbers uniformly distributed in (0, 1); i =1, 2,…..N and N is the size of the swarm
K = 1, 2, …. is the current iteration
S^k_i = The current particle (solution)
P^k_i, P^k_g = The pbest and gbest

Parameter selection: The number of particles ranges between 20 and 40. Actually for most of the problems 10 particles is large enough to get good results. The dimension of particles and range of particles are determined by the problem to be optimized. V_{max} determines the maximum change that one particle can take during one iteration. Usually we set V_{max} = 20. The learning parameters C_1 and C_2 are usually set as 2. It can range from (0, 4). The stop condition determines the maximum number of iterations the PSO execute and the minimum error requirement. This stop condition depends upon the problem to be optimized.

Proposed algorithm: The proposed PSO-WNN based relay monitors the transformer differential current and discriminates a fault from no fault condition. The current and voltage signals are obtained from the 3 phase transformer simulated using PSCAD/EMTDC software for different types of fault, inrush, normal, over excitation and external fault with CT saturation. The differential currents of the transformer for various conditions are calculated. Wavelet transformation of the 3 phase differential currents are done using MATLAB software. The d1 coefficients of the signal are obtained and fed to PSOWNN and trained. Internal fault currents are assigned 1 and no fault currents are assigned 0. PSO-WNN based relay accurately distinguishes internal fault current from inrush current, normal, over excitation and external faults. The flowchart of the proposed algorithm is shown in Fig. 2.

Simulation model: A part of power system consisting of a power transformer connected to an alternator and an infinite busbar is modeled using PSCAD/EMTDC software to obtain the required current signals for investigation of the proposed algorithm. A power system consisting of a 110 KV source, three phase 100 MVA, 110/220 KV, 50 Hz, Δ/Y. Transformer connected to an infinite busbar is modeled and simulated as shown in the Fig. 3. Two CT's are installed on the primary and secondary side of the transformer with a ratio of 600:1 and 300:1, respectively. Vector correction is done to the difference of the secondary currents of the 2 CT's and the differential current is calculated. The fundamental frequency of the current is 50 Hz. The current wave-forms generated using PSCAD software have a sampling frequency of 2 Khz. There are 40 samples/cycle.

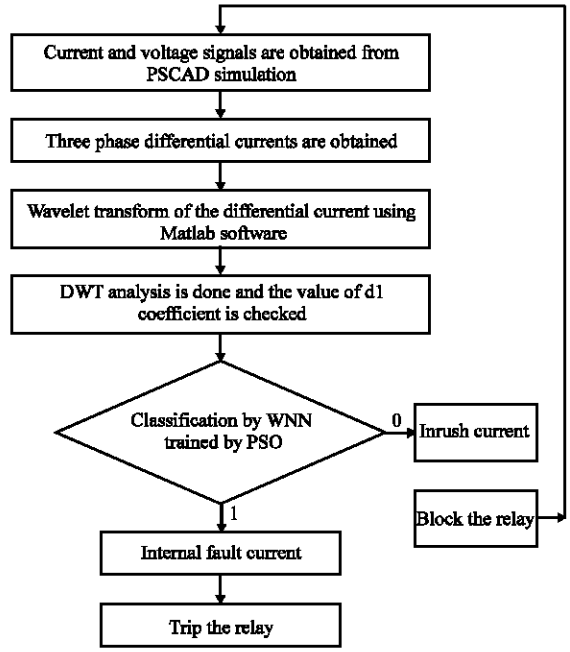

Fig. 2: Flow chart of the proposed algorithm

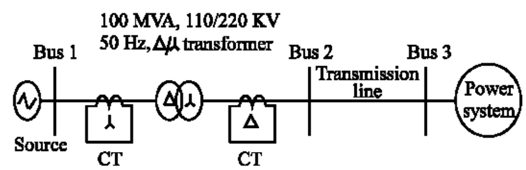

Fig. 3: Simulated power system

Inrush current: The magnetizing inrush current under steady state operating condition is only 1-2% of the transformer rated current. But when the primary of an unloaded transformer is energized, the primary windings of the transformer draw a large magnetizing current which is 10 times greater than the rated current. Due to the slow attenuation of this current, it may take around 10 cycles to settle down.

This current looks like a fault current to the differential relay and the relay maloperates. Inrush current is simulated by energizing the primary and leaving the secondary unloaded. Different cases of inrush currents are simulated by varying the source triggering angle.

Internal fault current: Faults, which occur between the 2 CT's of the transformer are called internal faults. These currents occur due to some short circuit in the transformer windings and cause a large current to flow. The heavy current will damage the power system components, hence, immediate action to isolate the faulty transformer is to be taken. Different cases of fault currents are simulated for single phase to ground faults, double phase to ground faults, double phase faults, 3 phase to ground faults and three phase faults.

External fault current: Differential relays perform well for external faults as long as the CT's do not saturate. When CT's saturate, false differential current appears and cause relay maloperation.

Over excitation: The magnetic flux inside the transformer core is directly proportional to the applied voltage and inversely proportional to the system frequency. Over voltage and/or under frequency conditions can produce flux levels that saturate the transformer core, which cause the relay to maloperate. These abnormal operating conditions can exist in any part of the power system, so any transformer may be exposed to over excitation.

Wavelet transform implementation: The Wavelet transform has been used to analyze the transients in the power transformers. The data obtained from the PSCAD simulations are given to the MATLAB software to calculate DWT coefficients of the signals. There are many types of wavelets such as Haar, Daubechies, Coiflet and symmlet wavelets. In this study, as we are interested in detecting and analyzing low amplitude, short duration, fast decaying and oscillating type of high frequency current signals. Daubechies wavelet of type 6 (DB6) suited well to this type of high frequency current. Therefore, DB6 was used as the mother wavelet. Wavelet decomposition is done on the signal and the DWT coefficients of level 1 of the signal are obtained.

ANN implementation: Neural networks have proved to be very efficient in the field of classification. In this study, back propagation algorithm is used for classifying internal fault current from no fault current in the transformer. The choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems in the construction of neural architecture. ANN with too many neurons will take long training time while ANN with too few neurons may prevent the training process to converge. Several networks by varying the number of hidden layers and the number of neurons were trained and tested. A sample of the test conducted is shown in the Table 1.

The neural network with less number of neurons takes less training time but the error is high. The neural network with 2 hidden layers with 10 neurons in the 1st layer and 20 neurons in the second layer was found to give good performance with less error. Back propagation algorithm is used for training. Tan sigmoid function is chosen to be the transfer function of each node. Total iteration is set to 3000. Error goal is set to 0.001. The learning rate is set to 0.7. The network is trained by giving the samples in the 1st cycle (i.e. 40 samples) after the occurrence of fault for various internal fault and no fault conditions. The trained network is saved and used for testing various cases. The trained neural network accurately identifies an internal fault current for the cases, which are not included in the training set also.

Table 1: Test results for designing ANN architecture

ANN size	Error
5/1	0.12370
10/1	0.04040
18/1	0.05090
12/20/1	0.00429
10/20/1	0.02013

WNN implementation: Wavelet transformation is done on the 3 phase differential currents, which are obtained from the PSCAD simulation. The d1 coefficients obtained from the wavelet transformation are given as inputs to the ANN. As it is combination of wavelet and neural networks, ANN is referred as WNN hereafter. Neural architecture is designed same as in ANN. The network is trained by giving the first 5 sample coefficients after the occurrence of fault for various internal fault and other no fault conditions. The trained network is saved and used for testing various cases. PSCAD simulation was made to run for various cases and the three phase differential currents obtained are given to a moving window of 5 data samples. The 5 data samples in the moving window are tested using the trained neural network. The moving window keeps moving and gets updated with the latest samples and discards the oldest sample. The trained neural network accurately identifies an internal fault current.

PSO-WNN implementation: Particle swarm optimization is used to train WNN and the weights and bias values are updated. The particle swarm optimization concept is initialized with a group of random particles and changes the velocity of each particle towards its pbest and lbest locations at each time step with respect to Eq. 1 and 2.

The objective function or fitness function is given by,

$$f = \sum \sqrt{[(\text{target}) - (\text{actualoutput})]^2} \quad (3)$$

The number of particles in the swarm is taken as 20. The learning parameters C_1 and C_2 are tuned to be 1.75

and 1.75, respectively. The inertia weight is chosen to be 0.9. The maximum search space range is selected as 200.

The objective function for each particle is obtained by updating the weights of WNN as specified by the variables of the particle and finding the mean squared error obtained in WNN training according to Eq. 3. The fitness functions for all particles in the swarm are determined similarly. The particle with lowest fitness function is called as gbest particle and its fitness function is compared with specified accuracy. If the specified accuracy is reached the target is attained and the training is stopped, else, the new velocity and new position of the particles are updated according to Eq. 1and 2. The same procedure is repeated until specified accuracy is reached. Several networks by varying the number of hidden layers and the number of neurons were trained and tested. Test results show that PSO-WNN architecture with three neurons in first hidden layer and three neurons in the second layer and one output neuron gave best performance with less error and simple neural architecture.

ANN based relay: The ANN has three input neurons. Each one for each phase of the three phase differential currents. Forty samples in the first cycle after the occurrence of fault or no fault condition was given as input data for training. It has one output neuron to classify whether it is an internal fault or no fault current. The target output is assigned 1 for internal fault currents and 0 for no fault currents during training.

One twenty cases are simulated using PSCAD software for different internal fault conditions and 75 cases are simulated for various inrush conditions, 25 cases for over excitation, 10 cases for normal varying load conditions and 50 cases for external fault conditions. The 3 phase differential currents are obtained for all the simulated cases. The 3 phase differential currents obtained are given as input for the designed ANN. Figure 4a shows the architecture of the designed ANN for classification of no fault currents and internal fault currents.

WNN based relay: Wavelet transformation is done for the 3 phase differential currents obtained from PSCAD simulation. The WNN also has 3 input neurons, each for the d1 coefficients of each phase of the 3 phase differential currents. Detailed analysis is done in order to decide the No. samples/input data. From the analysis it is inferred that the results are satisfactory and accurate for 5 No. samples/input data itself. Therefore, 5 samples i.e., 1/8th of a cycle after the occurrence of fault or inrush are given as input data for training. The input data given to WNN has been reduced to a great extent. The data

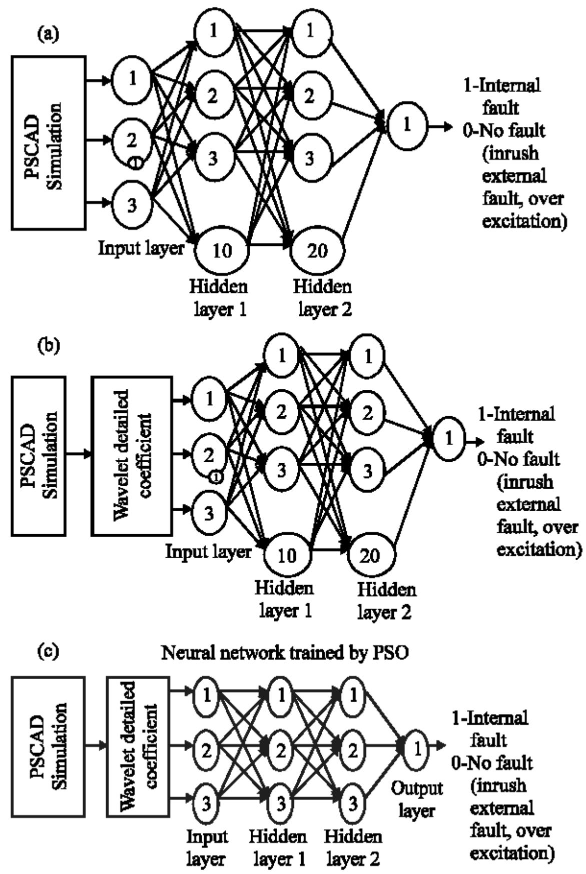

Fig. 4: a) Architecture of the proposed ANN, b) Architecture of the proposed WNN, c) Architecture of the proposed PSO-WNN

reduction contributes a significant role in the reduction of tripping time. The d1 coefficients for the 3 phase differential currents are obtained using wavelet transform and given as input for the designed WNN. The architecture and training cases remains the same as in ANN based relay. Figure 4b shows the architecture of the designed WNN for classification on inrush currents and internal fault currents.

PSO-WNN based relay: PSO-WNN based relay has three input neurons. Each neuron for the d1 coefficients of the each phase of 3 phase differential current. From detailed analysis it is found that 3 neurons in the first hidden layer and 3 neurons in the second layer shows best performance. The first 5 samples i.e., 1/8th of a cycle after the occurrence of fault or inrush are given as input data for training. PSO algorithm is used for training. It has one output neuron to classify whether it is a internal fault or inrush current. The target output is assigned 1 for internal fault currents and 0 for inrush currents during training.

The training cases remains the same as in ANN based relay. Figure 4c shows the architecture of the designed PSO-WNN.

Conventional harmonic blocking relay: The harmonic content of the differential current provides a mean to differentiate internal faults from inrush, external faults or over excitation conditions and thereby restrain or block the relay. In the harmonic restraint, the operating current I_{OP} should overcome the combined effect of the restraining current I_{RT} and the harmonics of the operating current. In harmonic blocking, the operating current is independently compared with the restraining current and the 2nd and 5th harmonics.

Harmonic blocking relay with dual slope of 0.2 and 0.8 is implemented in this paper to compare with the proposed relay. Harmonic blocking for phase A is shown and similarly independent harmonic blocking for phase B and phase C are provided and final trip is generated if anyone of the 3 independent harmonic blocking has trip output 1.

RESULTS AND DISCUSSION

The training and testing simulation results obtained for 100 MVA, 110/220 KV transformer using WNN and PSO-WNN are compared.

Comparison of training of ANN, WNN and PSO-WNN: Training of ANN, WNN and PSO-WNN based differential relay are compared and shown in Table 2.

Though the number of epochs is more for PSO-WNN, the error is nullified and hence, the results are very accurate when compared to ANN and WNN. The architecture is also very simple with less number of neurons in PSO-WNN compared to the architecture of ANN and WNN (Fig. 5a-c).

Comparison of testing of ANN, WNN and PSO-WNN and Conventional relay: For various cases of fault and no fault conditions ANN, WNN and PSO-WNN based relays are tested. Since, the neural network has been trained with all the cases, which cause the maloperation of the relay, the relays work well for all online cases by giving the trip signal during internal fault conditions and blocking the relay for inrush, over excitation, normal and external fault conditions. The testing results are shown in the Fig. 6a-g. The testing results show that the PSO-WNN and WNN based relay gives better performance than ANN based relay as it identifies and discriminates the fault and no fault conditions faster than ANN based relay. But PSO-WNN performs better than ANN and WNN as PSO-WNN identifies and discriminates fault and no fault cases more accurately than other cases and fault detection time is also very less compared to ANN.

Table 2: Comparison table of training WNN and PSO-WNN

Input data	ANN 40 samples 1 cycle	WNN 5 samples 1/8th of cycle	PSO-WNN 5 samples 1/8th of cycle
Architecture	10/20/1	10/20/1	3/3/1
No. epochs	190	79	2000
Error	0.01	0.001	0

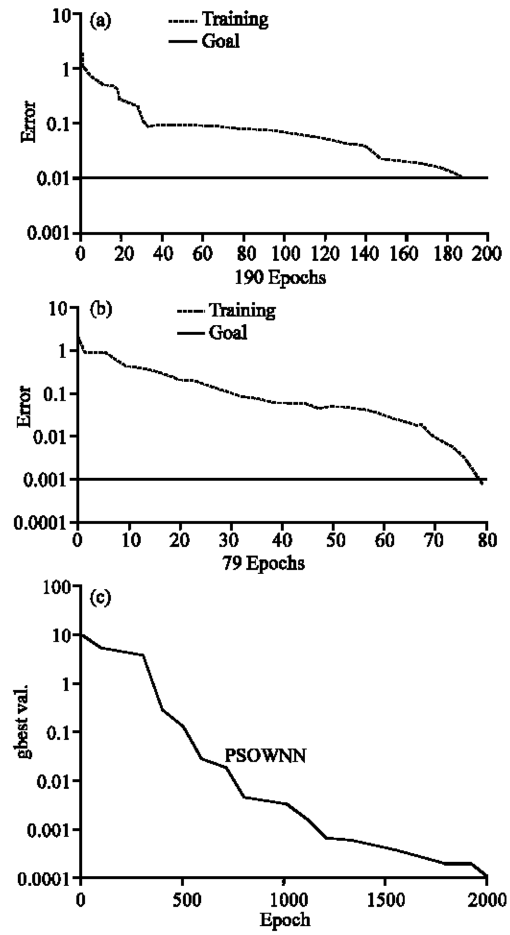

Fig. 5: a) Training of ANN, b) Training of WNN, c) Training of PSO-WNN

Case 1: When an unloaded transformer is energized at t = 0, while AC phases are faulted with a resistance of 10Ω, fault current combined with inrush flows. ANN accurately detects it fast as internal fault within 0.0155 sec (15.5 msec) from the switching time. But PSO-WNN and WNN detects it extremely fast at 0.0025 sec (2.5 msec)

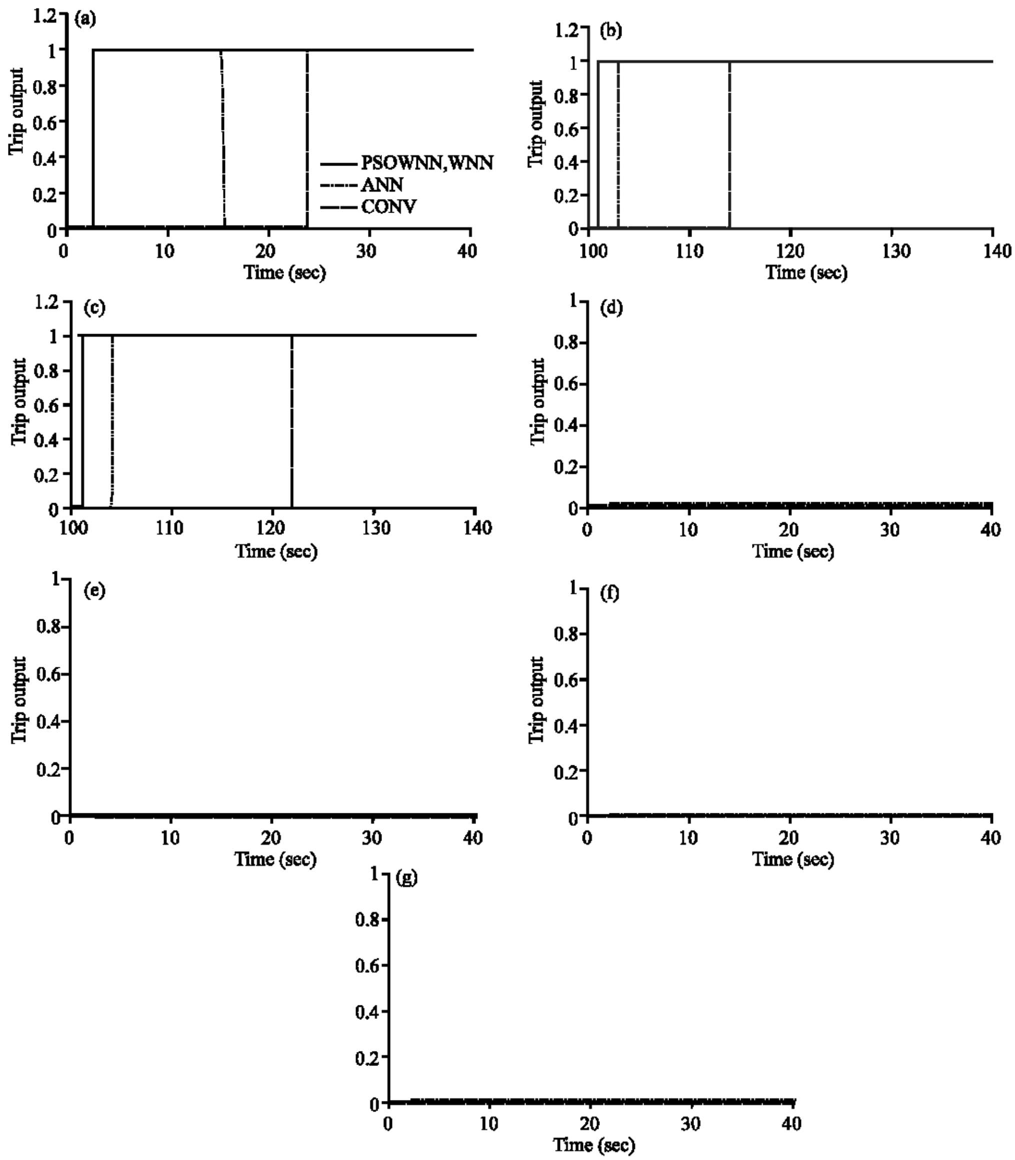

Fig. 6a: Trip output for internal fault with inrush, b) Trip output for internal fault, c) Trip output for internal fault with CT saturation, d) Trip output for inrush, e) Trip output for external fault with CT saturation, f) Trip output for over excitation condition and g) Trip output for normal condition

itself. In this case, PSO-WNN performs very fast by detecting within 1/8th of a cycle with very high accuracy.

Case 2: When a C phase fault to ground with a resistance of 10Ω occurs at 0.1 sec (100 msec). ANN detects it as internal fault at 0.104 sec (104 msec) but PSO-WNN and WNN detects it as internal fault at 0.101 sec (101 msec) itself.

In this case, PSO-WNN performs extremely fast by detecting within 1/20th of a cycle with very high accuracy.

Case 3: When a B phase to ground fault occurs at zero resistance at 0.1 sec (100 msec) CT saturates due to high current. ANN detects it as internal fault at 0.103 sec (103 msec) whereas PSO-WNN and WNN detects, it as internal fault at 0.101 sec (101 msec) itself. In this case, PSO-WNN performs extremely fast by detecting within 1/20th of a cycle with very high accuracy.

Case 4: When an unloaded transformer is energized at t = 0, inrush current flows. ANN, WNN and PSO-WNN takes a delay of 0.0025 sec (2.5 msec) from the switching time for detecting it as no fault condition as the data window size is 5 i.e., 2.5 msec.

Table 3: Comparison table of testing of ANN, WNN, PSO-WNN and conventional relay for various cases

	Output			Detection time (msec)			
Case	ANN	WNN	PSO-WNN	Conv.	ANN	WNN	PSO-WNN
Internal fault at 0 sec combined with inrush	1.0000	1.0000	1.0000	24	15.5	2.5	2.5
	0.9902	0.9989	1.0000				
	1.0000	0.9978	1.0000				
	0.9898	1.0000	1.0000				
	0.9953	0.9924	1.0000				
Internal fault at 100 msec	0.9948	0.9972	1.0000	122	104	101	101
	0.9998	1.0000	1.0000				
	0.9635	1.0000	1.0000				
	1.0000	0.9986	1.0000				
	0.9983	1.0000	1.0000				
Internal fault with CT saturation	0.9884	1.0000	1.0000	114	103	101	101
	1.0000	0.9926	1.0000				
	0.9932	1.0000	1.0000				
	1.0000	0.9963	1.0000				
	0.9976	0.9947	1.0000				
Inrush	0.0538	0.0184	0.0000	20	2.5	2.5	2.5
	0.0253	0.0184	0.0002				
	0.0461	0.0184	0.0000				
	0.0226	0.0184	0.0000				
	0.0347	0.0184	0.0000				
External fault with CT saturation	0.0458	0.0167	0.0000	20	2.5	2.5	2.5
	0.0546	0.0167	0.0000				
	0.0378	0.0167	0.0000				
	0.0227	0.0167	0.0000				
	0.0437	0.0167	0.0000				
Over excitation condition	0.0359	0.0184	0.0000	20	2.5	2.5	2.5
	0.0446	0.0184	0.0000				
	0.0458	0.0184	0.0000				
	0.0249	0.0184	0.0000				
	0.0437	0.0184	0.0000				
Normal condition	0.0231	0.0135	0.0000	20	2.5	2.5	2.5
	0.0197	0.0135	0.0000				
	0.0446	0.0135	0.0000				
	0.0359	0.0135	0.0000				
	0.0226	0.0135	0.0000				

Case 5: When an AC-g fault with 0Ω occurs outside the protected zone, external fault with CT saturation occurs. ANN, WNN a nd PSO-WNN takes a delay of only 0.0025 sec (2.5 msec) from the switching time for detection.

Case 6: When the frequency of the generators at both ends decreases below the rated frequency, over excitation occurs. ANN, WNN and PSO-WNN takes a delay of 0.0025 sec (2.5 msec) from the switching time for detection.

Case 7: When the transformer is operating in normal condition i.e., no fault with rated load. ANN, WNN and PSO-WNN takes a delay of 0.0025 sec (2.5 ms) from the switching time for detecting it as no fault condition.

Table 3 shows the comparison of the testing of ANN, WNN and PSO-WNN and conventional methods for various fault, inrush, over excitation and external fault conditions with respect to its output values and detection time. From the above comparison, it is inferred that though PSO-WNN relay and WNN detects fault extremely faster when compared to other relays, PSO-WNN relay is very accurate with very negligible error. Since the data window size for testing is taken as 5, the ANN, WNN and PSO-WNN based relays have a minimum fault detection time of 2.5 msec at the start, which can be allowed practically. Harmonic restraint usually will not permit tripping for the time approximately equal to the data window length of the estimators (typically one cycle). Conventional harmonic blocking relays shows delayed fault detection.

CONCLUSION

In this study, a new, efficient and reliable PSO-WNN based relay for three phase transformer is proposed and its performance is compared with ANN based differential relay, WNN based differential relay, conventional harmonic blocking relay. Training of WNN based relay is more accurate, has less error and takes lesser No. iterations and volume of input data when compared to ANN based differential relay. WNN based relay has been fine tuned by implementing PSO. Now, PSO-WNN based relay has minimized the error to almost zero and made the neural network architecture very simple. While testing PSO-WNN identifies an internal fault faster than other relays very accurately with 100% accuracy. PSO-WNN based relay is able to detect the fault at 1 msec itself from the fault occurrence i.e., within 1/20th of a cycle with almost 0 error. This is considered to be extremely fast. PSO-WNN based relay has 100% accuracy. The relay also provides high sensitivity for internal fault currents and high stability for inrush currents, normal, external faults with CT saturation and over excitation conditions.

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