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Comparison of ANN Based Power Transformer Protection and WNN Based Power Transformer Protection

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Abstract: This study compares Artificial Neural Network (ANN) based power transformer protection and Wavelet combined Neural Network (WNN) based power transformer protection for classification of internal fault current and inrush currents in three phase power transformers. A typical 100 MVA, 110/220KV, Δ/Y three phase power transformer connected between a 110KV source at the sending end and a 220KV transmission line connected to an infinite bus power system at the receiving end were simulated using PSCAD/EMTDC software. The generated data were used by the MATLAB software to test the performance of the proposed technique. The simulation results obtained show that the WNN based algorithm is faster, more reliable and accurate when compared to ANN based algorithm. It provides a high operating sensitivity for internal faults and remains stable for inrush currents of the power transformers.

Key words: Power transformer, differential protection, magnetizing inrush current, wavelet transform, neural networks

INTRODUCTION

When transformer internal fault occurs, immediate disconnection of the faulted transformer is necessary to avoid extreme damage and to protect the power system. Normally differential protection is used for fault detection in transformers. Inrush conditions produce false differential currents that could cause relay maloperation. Transformer differential relay is prone to maloperate during inrush conditions. Earlier attempts were made to prevent the maloperation of the differential relay by:

- Introducing an intentional time delay in the differential relays.
- Desensitizing the relay for a given time to override the inrush condition.
- Adding a voltage signal to restrain or to supervise the differential relay.

It was recognized that the information obtained from the harmonic content of the differential current is used to differentiate the internal fault form the inrush current. It was recognized that the inrush current contains second harmonics which is at least 20% of the fundamental component. The main drawback of this approach is during CT saturation, the second harmonic component may also be generated during internal faults and the new low-loss amorphous materials in modern power transformers may produce low second harmonic content in inrush current (Liu *et al.*, 1989).

Many researchers have proposed the use of wave shape recognition techniques in differential relays to discriminate the internal fault from the inrush currents (Rockerfeller, 1969). Fuzzy logic techniques have been implemented for reliable protection (Myong Chul *et al.*, 2003). Artificial Neural networks have been applied to single phase power transformer protection to distinguish internal faults from magnetizing inrush currents (Nagpal *et al.*, 1995; Zaman and Rahman, 1998). ANN based harmonic restraint differential protection of power transformers is been implemented. Signals are sampled at the sampling rate of 16 samples per cycle (Moravej and Vishwakarma, 2003). But the time taken to detect an internal fault is 13ms which is more than 3/4th of a cycle. Wavelet transforms have been extensively used for analyzing the transient phenomena in a Power transformer for distinguishing internal fault currents from inrush currents (Ozgonenel *et al.*, 2004; Sudha and Jeyakumar, 2007). Wavelet transform combined with Artificial Neural Network (ANN) have been implemented for this purpose (Mao and Aggarwal, 2001; Ozgonenel, 2005; Valsan and Swarup, 2007). A new wavelet and ANN based three phase transformer protection algorithm to distinguish inrush currents from internal fault currents in three phase power transformers is been proposed (Sudha and Jeyakumar, 2007).

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This study compares Artificial Neural Network (ANN) based power transformer protection and Wavelet combined Neural Network (WNN) based power transformer protection for classification of internal fault current and inrush currents in three phase power transformers.

Extensive simulation studies have been conducted using PSCAD/EMTDC software to compare the performance of WNN and ANN based relays for various 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, two phase faults and three phase faults and various internal fault combined with inrush.

Analysis reveals that WNN distinguishes inrush current from a fault condition more accurately and faster than ANN. WNN identifies an internal fault within 1ms from the fault occurrence i.e., 1/20th of a cycle.

Transformer differential protection: For protection of the three phase transformer, percentage restraint differential relays have been in use for several years. Figure 1 shows the connection diagram of the differential relay.

Differential element compares an operating current with the restraining current. If an operating current exceeds the restraining current the relay operates and generates the tripping signal.

$$Iop > SLP.Irt \qquad (1)$$

Where,

Iop = The operating current
Irt = The restraining current
SLP = The slope of the percentage differential characteristics.

The phasor sum of the currents entering the protected element gives the operating current, Iop

$$Iop = Iw1+Iw2 \qquad (2)$$

Where, Iw1 and Iw2 are the primary and secondary currents of the transformer.

Operating current is directly proportional to the internal fault current and reaches zero for other operating conditions.

The restraining current, Irt is given by,

$$Irt = k\,(|Iw1|+|Iw2|)$$

Where, k is a compensation factor usually taken as 1 or 0.5.

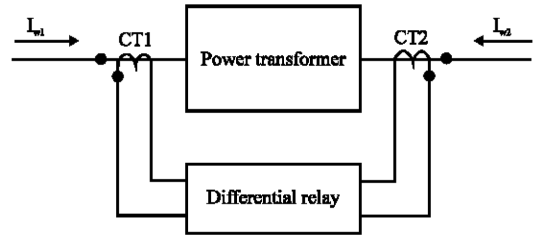

Fig. 1: Differential relay connection diagram

When CTs reproduce primary current correctly, differential relays work well. If one or both of the CTs saturate at different levels, difference in current appears in the differential relay and leads to maloperation of the relay.

Magnetizing inrush current: The magnetizing inrush current in the transformer results from the following causes:

- Any drastic change in magnetizing voltage.
- Energization of a transformer.
- Occurrence of an external fault.
- Voltage recovery after clearing an external fault.
- Out of phase synchronizing of a connected generator

This magnetizing current creates an imbalance between the currents at the transformer terminals and hence the differential relays sense it as a false differential current. The differential relay should not operate for the false differential currents and remains stable for inrush conditions.

Many approaches were used in earlier days to identify internal fault from inrush conditions. The methods are of two categories:

- Harmonics to restraint or block
- Wave shape identification

MATERIALS AND METHODS

Wavelet transform: The Fourier Transform is probably the most popular transform used to obtain the frequency spectrum of a signal. But the Fourier Transform is only suitable 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 two decades, provides a better time-frequency representation of the signal than any other existing transforms.

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 two decades, solves the above problem to a certain extent and provides a better time-frequency representation of the signal than any other existing transforms.

In contrast to STFT, which uses a single analysis window, the Wavelet Transform uses short windows at high frequencies and long windows at low frequencies. This results in multi-resolution analysis by which the signal is analyzed with different resolutions at different frequencies, i.e., both frequency resolution and time resolution vary in the time-frequency plane without violating the Heisenberg inequality.

Figure 2a shows the time-frequency tiling in the time-domain plane and Fig. 2b shows the tiling in frequency-domain plane. It is seen that Fig. 2a does not give any frequency information and Fig. 2b does not give any time information. Similarly Fig. 2c shows the tiling in STFT and Fig. 2d shows the tiling in Wavelet Transform. It is seen that STFT gives a fixed resolution at all times, whereas Wavelet Transform gives a variable resolution.

Figure 3 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 first stage, an original signal is divided into two 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 cut in half of the frequency bandwidth and sent to the second stage; this procedure is repeated until the signal is decomposed to a pre-defined certain level. The set of signals thus attained represent the same original signal, but all corresponding to different frequency bands.

Neural networks: The ANN is an exact simulation of a real nervous system. A multi layered Feed Forward Neural Network (FFNN) consists of an input layer, an output layer and one or more hidden layers between its input and output layer. Each layer consists of certain number of neurons. Back propagation algorithm is commonly used for training multi layer FFNN. It can be used to solve complex pattern-matching problems.

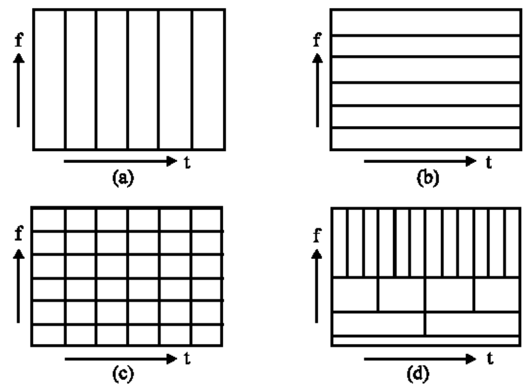

Fig. 2: The time-frequency tiling for (a) Time-domain (b) Frequency-domain (c) STFT and (d) DWT

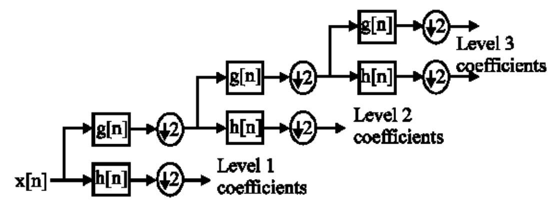

Fig. 3: Block diagram of filter analysis

Network learns a pre-defined set of input-output training pairs by using a two phase propagate-adapt cycle. The applied input pattern to the first 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 toward 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 the feature the individual units learn to recognize during training.

Comparison of ANN based differential relay and WNN based differential relay

ANN based relay algorithm: The flowchart of the ANN based relay algorithm is shown in Fig. 4 and is explained in steps.

Step 1: The current and voltage signals are obtained from the three phase transformer using PSCAD/EMTDC software for different types of fault and inrush currents.

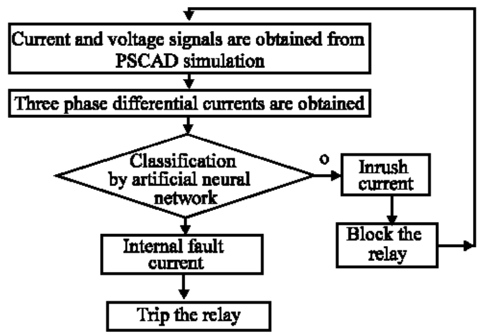

Fig. 4: Flowchart of the ANN based relay algorithm

Step 2: The differential currents of the transformer are calculated.

Step 3: The differential currents of the transformer for different fault and inrush currents are fed to ANN and trained.

Step 4: ANN based relay distinguishes internal fault current from inrush current.

WNN based relay algorithm: The flowchart of the WNN based relay algorithm (Fig. 5) and is explained in steps.

Step 1: The current and voltage signals are obtained from the three phase transformer using PSCAD/EMTDC software for different types of fault and inrush currents.

Step 2: The differential currents of the transformer are calculated.

Step 3: Wavelet transform of the three phase differential currents are obtained using MATLAB software.

Step 4: The detail coefficients of the signal are obtained.

Step 5: The d1 coefficients of different fault and inrush currents are fed to ANN and trained.

Step 6: WNN based relay distinguishes internal fault current from inrush current.

Power system simulation: 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 100MVA, 110/220KV, 60 Hz, Δ/Y Transformer connected to an infinite busbar is modeled and simulated (Fig. 6).

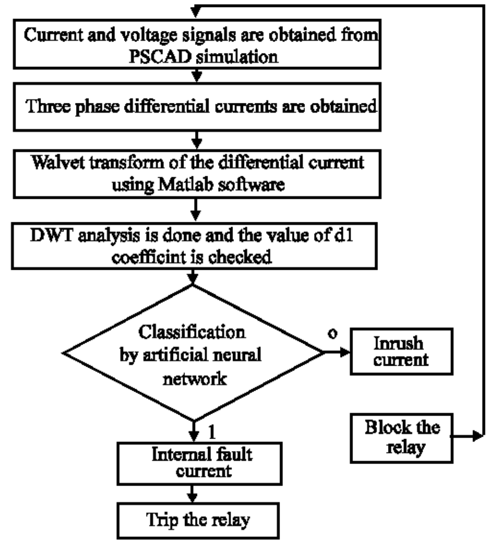

Fig. 5: Flowchart of the WNN based relay algorithm

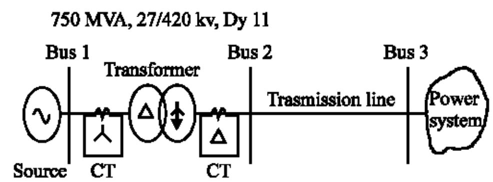

Fig. 6: Simulated power system

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 ten 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.

Internal fault current: Faults which occur between the two 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 inrush currents and fault currents are simulated. 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.

Different cases of fault currents are simulated for single phase to ground faults, double phase to ground faults, double phase faults, three phase to ground faults and three phase faults. The fundamental frequency of the current is 50 Hz.The current waveforms generated from the faults using PSCAD software have a sampling frequency of 2 KHz. There are 40 samples/cycle.

Implementation of wavelet transform: 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 1of the signal are obtained.

Implementation of neural network: Neural networks have proved to be very efficient in the field of classification. In this study, back propagation algorithm is used for classifying inrush and internal fault currents 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 (Table 1).

The neural network with less number of neurons takes less training time but the error is high. The neural network with two hidden layers with ten neurons in the first 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 for various cases. 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 for the cases which are not included in the training set also.

Table 1: Test results for designing ANN architecture

ANN size	Error
6/1	0.1237
10/1	0.0404
18/1	0.0509
12/20/1	0.00429
20/10/1	0.02013

Table 2: Analysis for no. of samples/input data

Cycle	No. of samples/input data	Results1
1/8	5	Not accurate
1/4	10	Not accurate
1/2	20	Not accurate
1	40	accurate

ANN based relay: The ANN has three input neurons one for each phase of three phase differential current. The fundamental frequency of the differential current is 50 Hz. Time period of 1 cycle is 20 m. The current waveforms generated from the faults using PSCAD software have a sampling frequency of 2 KHz. There are 40 samples/cycle. Detailed analysis was done in order to decide the No. of samples/input data (Table 2).

From the analysis it is inferred that the results are not satisfactory, not accurate for 5, 10, 20 No. of samples/input data. For input data of 40 samples, the results were accurate. Therefore, 40 samples i.e., samples in 1 cycle after the occurrence of fault or inrush are given as input data for training. It has one output neuron to classify whether it is a fault or inrush current. The target `output is assigned 1 for internal fault currents and 0 for inrush currents during training. 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.

One hundred ten cases are simulated using PSCAD software for different fault conditions and 110 cases are simulated for different inrush conditions.

Totally 220 cases are simulated. The three phase differential currents are obtained for both the fault and inrush conditions and given as input for the designed ANN.

WNN based relay: Wavelet transformation is done for the three phase differential currents obtained from PSCAD simulation. The WNN has three input neurons. Each one for the d1 coefficients of the each phase of three phase differential current. Detailed analysis was done in order to decide the no. of samples/input data. From the analysis it was inferred that the results are satisfactory and accurate for 5 No. of samples/input data itself. Therefore, 5 samples i.e., 1/8th 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

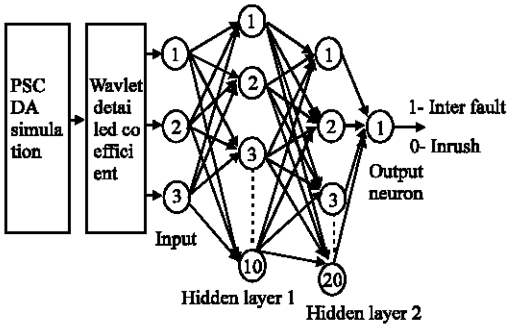

Fig. 7: Architecture of the proposed WNN

reduction contributes a significant role in the reduction of tripping time. 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.

One hundred ten cases are simulated using PSCAD software for different internal fault conditions and 110 cases are simulated for different inrush conditions. Out of 110 cases, 90 cases are used for training and 20 cases for testing both fault and inrush conditions.

Totally 220 cases are simulated. The three phase differential currents are obtained for both the internal fault and inrush conditions. The d1 coefficients for the three phase differential currents are obtained using wavelet transform and given as input for the designed WNN. Figure 7 shows the architecture of the designed WNN for classification on inrush currents and internal fault currents.

RESULTS AND DISCUSSION

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

Comparison of training of ANN and WNN: Training of ANN and WNN based differential relay are compared (Table 3).

From the above comparison it is clear that the WNN based differential relay shows better performance when compared to ANN based differential relay during training. WNN shows best performance for an input data of the samples in 1/8th of cycle itself. i.e., 5 sample coefficients. Whereas ANN shows best performance for an input data of the samples in 1 cycle. i.e., 40 samples. The volume of data has got reduced to a great extent and the fault detection time has also got reduced. The No. of epochs has got reduced to 79 in WNN. The training time has also got reduced drastically to 17.9 sec from 281 sec. Figure 8a shows the training of ANN and Fig. 8b shows the training of WNN.

Table 3: Comparison table of training ANN and WNN

	ANN	WNN
	40 samples	5 samples
	1 cycle	1/8th cycle
No. of epochs	190	79
Training time	281secs	17.9secs
Accuracy	99%	99%

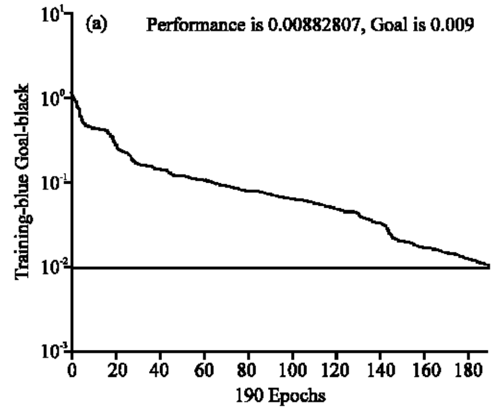

Fig. 8a: Training of ANN

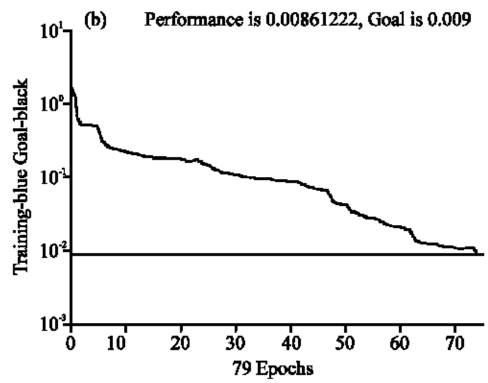

Fig. 8b: Training of WNN

Comparison of testing of ANN and WNN: Both ANN and WNN based differential relays were tested for various inrush conditions, fault conditions, inrush combined internal fault conditions and for various special cases which cause conventional differential relays to maloperate. 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 moving data window is linked to the trained neural network. The trained neural network tests the data in the moving window and gives trip signal accurately for internal fault current very fast even for the cases which are not included in the training set also.

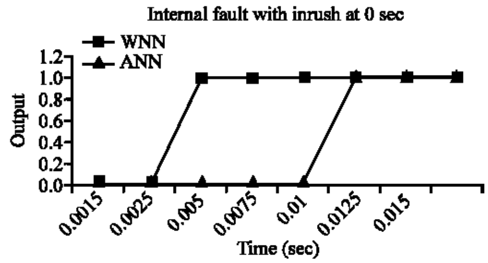

Fig. 9a: Trip output for internal fault with inrush

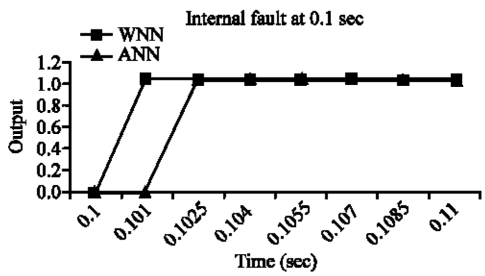

Fig. 9b: Trip output for internal fault

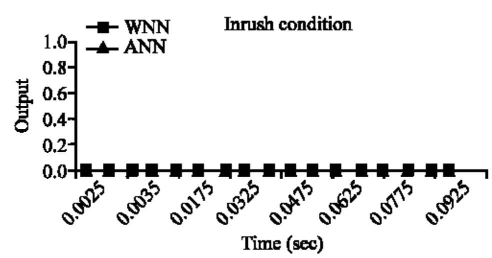

Fig. 9c: Trip output for inrush

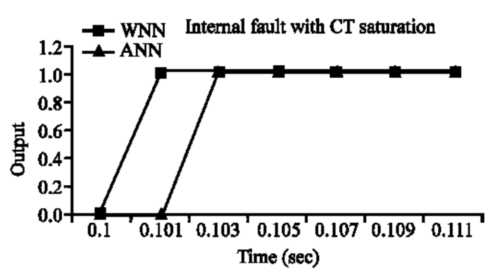

Fig. 9d: Trip output for internal fault with CT saturation

Case 1: When an unloaded transformer is energized at t = 0 while BC phases are faulted with a resistance of 25 Ω, fault current combined with inrush flows.

ANN accurately detects it fast as internal fault within 0.01s (10ms) from the switching time. But WNN detects it extremely fast at 0.0025 s (2.5 m) itself. WNN performs extremely faster than ANN (Fig. 9a).

Table 4: Comparison table of testing of ANN and WNN for various cases

		Time (s)	
Case	Output	ANN	WNN
Internal fault combined with inrush	1	0.01	0.0025
Internal fault at 0.1 sec	1	0.1025	0.101
Inrush	0	0.0025	0.0025
Internal fault with CT saturation	1	0.103	0.101

Case 2: When a B phase fault to ground with a resistance of 20 Ω occurs at 0.1 s (100 ms).

ANN detects it as internal fault at 0.1025 s (102.5 ms) but WNN detects it as internal fault at 0.101 s (101 ms) itself. In this case WNN performs extremely fast by detecting within 1/20th of a cycle (Fig. 9b).

Case 3: When an unloaded transformer is energized at t = 0, inrush current flows.

ANN detects it as inrush current at 0.0025 s (2.5 ms) from the switching time, WNN also detects it as inrush current at 0.0025 s (2.5 ms) itself (Fig. 9c).

Case 4: When a A phase to ground fault occurs at zero resistance at 0.1 s (100 ms) CT saturates due to high current.

ANN detects it as internal fault at 0.103s (103ms) whereas WNN detects it as internal fault at 0.101s (101ms) itself (Fig. 9d).

From comparison it is inferred that WNN performs faster than ANN and also performs extremely faster than ANN for special cases. WNN is more reliable than ANN. Fault detection time is very less (Table 4).

CONCLUSION

In this study, performance of ANN based differential relay and WNN based differential relay of three phase transformers are compared. Training of WNN based relay is more accurate, has less error and takes lesser no. of iterations, volume of input data and training time when compared to ANN based differential relay. While testing WNN distinguishes internal fault from magnetizing inrush current faster than ANN and more accurately. WNN based relay is able to detect the fault at 1ms itself from the fault occurrence i.e., within 1/20th of a cycle. This is considered to be extremely fast. The relay also provides high sensitivity for internal fault currents and high stability for inrush currents.

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