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Intelligent Numerical Differential Protection of Power Transformer using DWT and ANN

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***Abstract*—Differential relay is used for transformer protection which is most sensitive and reliable relay. The main objective of differential relaying is to reduce the occurrence and duration of undesirable outages concerned to power transformer. This can be achieved by avoiding false tripping and achieving high operating speed. In order to achieve these objectives digital relay is used which is based on Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN). Earlier digital relays based on Fourier transform was prone to false tripping as it was unable to distinguish between inrush and internal fault current because inrush current is rich in second harmonic component and its magnitude may be high enough as under internal fault condition. Wavelet transform is used for signal processing to extract features from differential current signals in both time and frequency domain. The differential current of the transformer is decomposed into a series of detailed wavelet components. The statistical features (mean, standard and normalized values) of the wavelet components is determined and used to train a feed- forward ANN. Artificial neural network is used for detection and discrimination of faults from normal and inrush condition. Back-propagation algorithm is used to train the artificial neural network.**

Keywords—Discrete Wavelet Transform (DWT), Artificial Neural Network (ANN), Fast Fourier Transform (FFT), Discrete Fourier Transform (DFT)

I. INTRODUCTION

For reliable supply of electrical energy, it is required that there should not be false-tripping of circuit breaker used for power system protection. Power transformer is very costly and dynamic component of power system. So it requires nearly no fault operation. For power transformer protection protective relay should operate immaculately and capriciously in order to reduce the occurrence and period of undesirable outages. This can be achieved by avoiding false tripping and achieving high operating speed of the protective relay. Protective relay include devices that recognize the existence of fault indicates its location and send the trip signal for opening of circuit breaker to disconnect the faulty power system. With the development in the field of digital electronics and signal processing, it is possible to build digital or micro-processor based relays which provide alternative to the electro-mechanical and solid state relays.

A. Challenges to the Differential relaying

In case of power transformer one of the challenging problems in detecting the faults is the high magnetizing inrush current.

A basic differential relay working on the basis of measurement and valuation of currents at the terminals of the transformer cannot prevent tripping during inrush situation, because transformer inrush current is rich in second harmonic component and its magnitude may be as high as in case of internal fault current.

B. Traditional Remedy

To avoid the needless trip by inrush current, along with harmonic restraint logic, a differential logic is used in the fault detection algorithm for the numerical differential protection of transformer. This method exploit the fact that the ratio of the 2^{nd} harmonic to fundamental component of differential current under inrush condition is larger in comparison to that under fault conditions.

C. Problems with Traditional Remedy

The second harmonic restraint principle take long restrain time because the ratio of the amplitude of second harmonic and fundamental are calculated by DFT and it is used to predict whether it is inrush or internal fault current. DFT is not correct if the current is contaminated by harmonics that are not integer multiples of the fundamental. DFT only accounts for frequency analysis but does not give information in the time domain. DFT assumes a periodic signal, inrush current and fault currents are not stationary signals. Also the presence of large quantity of harmonics in the inrush current can cause damage to power factor correction capacitor by exciting resonant overvoltage.

In this paper numerical differential relay is designed using a simulation technique in MATLAB Simulink environment. The design is implemented to protect the power transformer against internal faults and prevent interruption due to inrush currents.

II. TRANSFORMER PROTECTION

In differential protection an internal fault is identified by comparing the electrical conditions like currents or voltages at the terminals of the electrical equipment which is to be protected.

It is based on the fact that during internal fault condition the current entering the electrical equipment is different from that leaving it [6]. Differential relay is capable of detecting very small magnitude of differential current. So it is a sensitive and effective method of protection of power transformer against internal faults.

A. Principle of differential protection

In power transformer differential protection, pair of identical current transformers is fitted at the two ends of transformer. The winding ratios of the two current transformers are such that their secondary currents are equal during external fault or normal situations. Hence the differential current which is the vector sum of secondary currents of the two current transformers will be nearly zero or very less. Such a basic differential relay working on the basis of valuation of currents at the two ends of transformer cannot prevent the trip signal during inrush situation.

B. Inrush current

When a transformer is initially energized, a transient current up to 10 to 15 times greater than the rated transformer current can flow for several cycles. Worst situation happens when the primary winding is switched at the instant of zero-crossing of primary voltage and at the same time, the polarity of the voltage half cycle is same as of the polarity of residual flux in the transformer core. During such start up the core will get saturated and hence the winding inductance will get significantly reduced. In such case the resistance of the primary windings and the impedance of the power line will limit the current. Since saturation occurs for either positive or negative half cycle only, harmonic rich waveforms might be produced.

C. Reason of conflict between inrush and internal fault

During energisation of transformer huge amount of current enters into the primary winding of a transformer but no current flow out of secondary winding [3]. This is like internal fault condition. Since saturation of transformer occurs for either positive or negative half cycles only, harmonic rich waveforms might be produced. Hence there arises a chance of incorrect tripping of the circuit breaker. Therefore it is necessary to distinguish between an internal fault and inrush current condition.

D. Numerical relay

Modern power systems are complex networks. The complexity of these networks demands the relays used for protection to be reliable, secure, accurate and short time decision making. Digital relays are programmable information processors instead of torque balancing devices [3]. In comparison to the conventional non numerical relays that are go-no-go devices and perform only comparison the digital relays has the ability to perform real time computation.

E. Scope for DWT and ANN

Since inrush and fault currents are non-stationary and non-periodic waveforms containing both high frequency oscillations and localized impulses superimposed on the power frequency and current is contaminated by harmonics that are not integer multiples of the fundamental waveform. Therefore wavelets transform which is able to extraction features in both time and frequency domain is suitable method for the feature extraction from the waveforms of power transformer under various situations. As we know, ANN is a good classifier. It has been used for pattern recognition from many years. Also, it has an ability to classify non-linear parameters without any exact mathematical relation between input and output. It uses parallel processing technique, so it is faster and reliable in decision making.

III. WAVELET TRANSFORM AND ARTIFICIAL NEURAL NETWORK

Wavelet Transform deals with building a model for non-stationary signals, with a set of constituents that are small waves, called wavelets [7].

It is defined as

$$W(a,b)=\int f(t)\frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right)d(t) \qquad (1)$$

A. Discrete Wavelet Transform

If the wavelet transform is done in discrete steps it is called discrete wavelet transform (DWT) [7]. Its outcome will be a set of coefficients called wavelet coefficients that depend on the number of discretization step in scale (m) and translation (n).If a_0 and b_0 are the segmentation step sizes for the scale and translation respectively, then scaling and translating parameter will be

$$a = a_0^m \quad \text{and} \quad b = nb_0\, a_0^m$$

$$DWT(m, n) = a_0^{-m/2} \int f(t)\, \Psi(a_0^{-m}t - nb_0)\, dt \qquad (2)$$

(1) Discrete Wavelet Transform and Filter Banks

The DWT is computed by successive low pass and high pass filtering of the discrete time domain signal in one algorithm called the Mallat-tree disintegration. Initially the signal which is to be processed is divided into two halves of the frequency bandwidth and provided to high-pass (H0) and low-pass (G0) filters. Now the outcome of low-pass filter is again divided into two half of the frequency bandwidth and provided to next level. This progression is continued until the filter length becomes equal to length of the signal. Detail coefficients are the outputs of high pass filter and the approximate information are from the low pass filter.

(2) Implementation of Discrete Wavelet Transform

The transformer transient study deals with analyzing short duration, fast decaying current waveforms therefore Daubichies's mother wavelet of level 6 (D6) is used in this paper. The wavelet analysis of various transient current signals obtained from SIMULINK and observation in different conditions like normal, inrush, internal and external fault and over excitation is carried out. The starting sampling frequency is 20 kHz.

B. Artificial Neural Network

"A neural network is a parallel distributed processor made up of simple processing units, which has a natural tendency of storing experimental knowledge and making it available for use". It is similar to the brain in two aspects

1. Knowledge required by the network from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

(1) Multilayer feed-forward ANN

It contains three layers namely input, output and hidden. Each network layer contains processing units called nodes. Each node in a network layer sends its output to all the nodes of next layer. In the input layer the nodes obtain signals from the outside world. The output layer of the neural network serves as an interface that directs info from the neural network's internal processing units to the external world. The input layer transfer signal to hidden layer and the hidden layer transfer the signal to the output layer.

(2) Back propagation training algorithm

It is used to train the feed forward network. BP neural network estimates the non-linear relationship between the input and the output by modifying the weight values internally instead of providing the function expression explicitly. This algorithm looks for minimum of error function in weight space using gradient descent method. A set of weights that reduces error function is considered as solution to the learning problem.

- Training algorithm of back propagation includes four stages [5], i.e.
  1. Weights initialization
  2. Feed forward
  3. Back propagation of errors
  4. Updating the weights and biases

Initialization of weights

Step 1: Weights are initialized to random values between 0 and 1.

Step 2: While stopping condition is false, steps 3-10 are repeated.

Step 3: For each training pair steps 4-9 are performed.

Feed-forward

Step 4: Each input node takes the input signal x_i and transfers that to all nodes in the layer above.

Step 5: Each hidden node ($,z_j, j = 1, \dots .p$) adds the weighted input signals.

$$z_{in_j} = V_{o_j} + \sum_{i=1}^{n}(x_i . V_{i_j}) \quad (3)$$

Applying the activation function

$$Z_j = f(Z_{inj})$$

And this signal is sent to all the units in the layer above

Step 6: Each output unit (y_k, k =1,…..m) sums its weighted input signals.

$$y_{in_k} = W_{o_k} + \sum_{j=1}^{p}(z_j W_{jk}) \quad (4)$$

Applying the activation function to calculate the output signals

$$Y_k = f(y_{ink}) \quad (5)$$

Back-propagation of Errors

Step 7: Every output node ($y_k, k = 1, . m$)obtains a target pattern corresponding to an input pattern.
Error is calculated as follows

$$\Delta_k = (t_k - y_k)f^1(y_{ink}) \quad (6)$$
$$f^1(y_{ink}) = f(y_{ink})(1 - f(y_{ink})) \quad (7)$$

Step 8: Each hidden unit (z_j, j=1,…..,p) sums its delta inputs from units in the layer above.

$$\delta_{in_j} = \sum_{k=1}^{m}(\delta_j W_{jk}) \quad (8)$$

Error term is calculated as

$$\delta_j = \delta_{inj} f1\,(z_{inj}) \quad (9)$$

Where,

$$f1\,(z_{inj}) = (z_{inj})(1 - f(z_{inj})) \quad (10)$$

Updating weights

Step 9: Every output node updates its bias and weights ($Z_j, j = 0, \dots .p$)

The weight correction is given by

$$\Delta W_{jk} = n\delta_k z_j \quad (11)$$

and the bias correction is given by

$$\Delta W_{ok} = n\delta_k \quad (12)$$

Therefore,

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk} + m[W_{jk}(old) - W_{jk}(old - 1)] \quad (13)$$

And

$$W_{ok}(new) = Wok(old) + \Delta W_{ok} \quad (14)$$

Each hidden node updates its bias and weight.

The weight correction term is

$$\Delta V_{ij} = n\delta_j x_i \quad (15)$$

and the bias correction term is

$$\Delta V_{oj} = n\delta_j \quad (16)$$

Therefore

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} + m[V_{ij}(old) - V_{ij}(old - 1)] \quad (17)$$

And

$$V_{oj}(new) = V_o(old) + \Delta V_{oj} \quad (18)$$

Step 10: The stopping condition is analyzed (minimization of the errors).

IV. SIMULATION AND RESULTS

A. TRANSIENT SIGNALS SIMULATION

Various transient signals during different conditions of transformer are simulated in the MATLAB [2].

(1) Normal Operating Condition Case:

In normal case there is no fault and the secondary is connected to a constant load and system parameters are kept constant. A differential current signal of 3 phases in normal condition is shown in Fig. (1)

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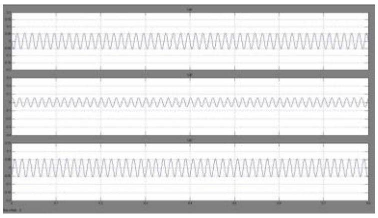

Fig. (1) Differential current signals of 3 phases in normal condition

(2)Inrush Case:

For inrush case simulation, the secondary is opened. Various conditions of inrush are obtained by applying the switching at various angles of source voltage. Here we can observe that inrush is worst when switching is done at 90^o of source voltage. A differential current signal of 3 phases in inrush condition is shown in Fig. (2)

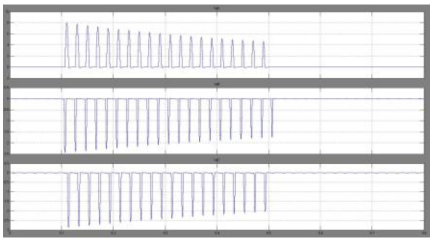

Fig. (2) Differential current signals of 3 phases in inrush condition

(3)Internal Fault Case:

For internal fault simulation the different phases of secondary winding before the current transformer are short circuited with each other. During this condition transformer primary is switched on when source voltage is at 0^o. For LG internal fault simulation any one phase is grounded. For LL fault any two phases are short circuited with each other. Similarly different internal fault conditions are simulated. The fault is applied for one cycle i.e. for 0.02 sec during switching period 0.1 to 0.12 sec. Differential current signals of 3 phases in internal fault condition is shown in Fig. (3)

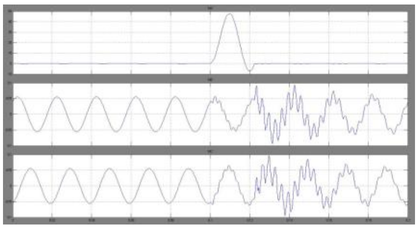

Fig. (3) Differential current signals of 3 phases in internal fault condition

(4) External Fault Case:

For external fault simulation the different phases of secondary winding after the current transformer are short circuited with each other or to ground. During this condition transformer primary is switched on when source voltage is at 0^o. The fault is applied for one cycle i.e. for 0.02 sec during switching period 0.1 to 0.12 sec. Differential current signals of 3 phases in external fault condition is shown in Fig. (4)

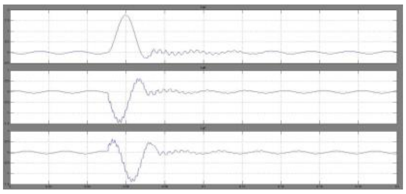

Fig. (4) Differential current signals in external fault condition

(5) Over- Excitation Case:

Over-excitation condition is simulated by connecting the additional load to the present system. Additional load is applied for a period of 0.02 sec at time 0.1 sec with the help of switching circuit that connect the additional load. Differential current signals of 3 phases in Over-excitation condition is shown in Fig. (5)

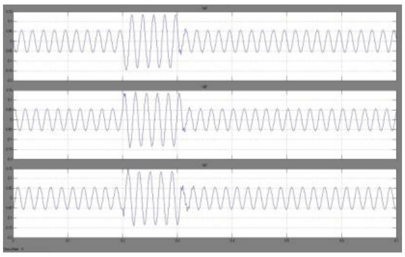

Fig. (5) Differential current signals of 3 phases in over-excitation condition

B. DFT ANALYSIS OF THE TRANSIENT SIGNALS

DFT analysis is performed in order to show the harmonic content in the transient signals. Differential relay based upon second harmonic restraint principle assume that the ratio of second harmonic to fundamental component of differential current under inrush condition is large compared to the ratio under fault condition. This is valid only if the operating time of differential relay will be larger than one cycle period i.e. 20msec. But we are interested in reducing the relay operating time for future smart power system. In such case, the harmonic content of the transient signals differ from conventional values. During DFT analysis we find that if very less transient time is taken into account then the percentage of second harmonic in different fault cases are in the range of inrush current percentage second harmonic.

(1) Normal Condition Case:

FFT analysis of differential current in normal condition is shown in Fig. (6) In this case percentage of second harmonic is very less. Therefore, there is no problem for a common relay operation.

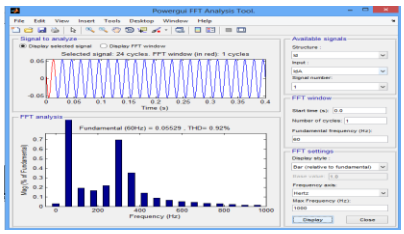

Fig. (6) FFT analysis of differential current in normal case

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(2) Inrush Condition Case:

It is observe that the second harmonic content in inrush case is significant is shown in fig. (7) So, common differential relay will be bond to operate during inrush condition.

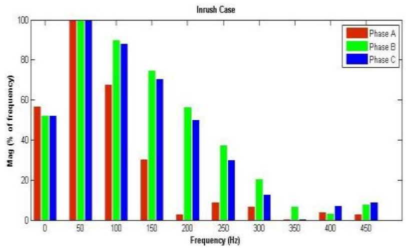


Fig. (7) FFT analysis for Phase A, Phase B and Phase C of differential current signals during inrush case

(3) Internal fault Condition Case:

Here we observe that percentage of second harmonic could be more or nearer to that during inrush case. So, DFT based relay cannot discriminate between inrush case and internal fault case and the relay might give false tripping signal.

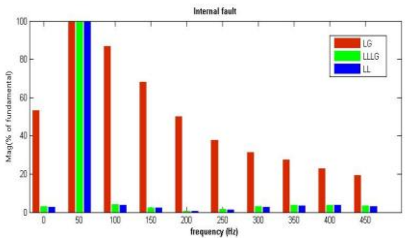


Fig. (8) FFT analysis of differential current signals during LG, LLLG and LL internal fault case

(4) External fault Condition Case:

In this case, percentage of second harmonic is less in comparison to the inrush case.

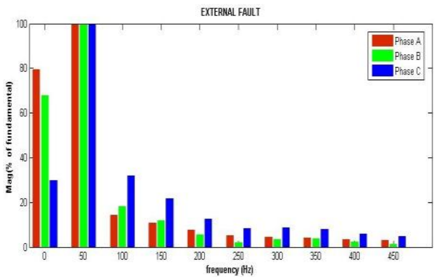


Fig. (9) FFT analysis for Phase A, Phase B and Phase C of differential current signals during external fault case

(5) Over- excitation Condition Case:

Over-excitation causes flow of large current in transformer winding. But the percentage of second harmonic is nearly equal to that under normal case.

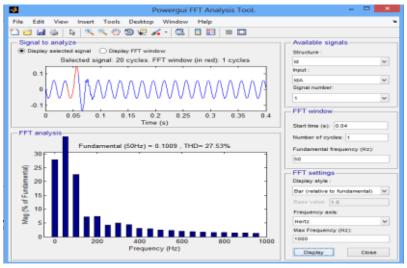


Fig. (10) FFT analysis of differential current signals during over-excitation case

Type of condition	Phase A	Phase B	Phase C
Normal	0.92	0.85	0.88
Inrush	73.08	136.29	127.14
LG fault	72.17	11.32	10.12
LLG fault	152.10	119.91	52.36
LLLG fault	148.27	121.69	108.06
LL fault	152.10	119.91	52.36
LLL fault	148.27	121.69	108.06
External fault	23.04	25.24	47.08
Over-excitation	27.53	25.57	42.38

Table 1 Percentage of second harmonic content in the transient signals during various conditions

C. WAVELET ANALYSIS OF THE DIFFERENTIAL CURRENT SIGNALS

Since inrush and fault currents are non-stationary and non-periodic signals containing both high frequency oscillations and localized impulses superimposed on the power frequency and its harmonics and transformer transient current signals during faults and inrush conditions deals with short duration, fast decaying current signals therefore Daubichies's mother wavelet of level 6 (D6) is suitable for analysis purpose. Wavelet analysis of differential current waveform for all cases is performed up to detail 5 level to obtain the detail coefficients i.e. d1, d2, d3, d4, d5.

(1) Wavelet analysis in Normal case

Wavelet analysis is performed on the differential current signal of power transformer in normal case. Transformer is switched on at 0^o angle of the source voltage. The Fig. 11(a) represents the original differential current signal in normal case while Fig. 11(b) to Fig. 11(d) represent decomposed detail coefficient signals at different levels. This analysis is done for all the three phases. The statistical data i.e. mean, standard and normalized values, are obtained for different detail coefficients. The data of a particular detail coefficient level is first normalized and used to train the ANN. Here we can observe that the frequency of signal decreases as detail level increases and the time for which it is analyzed increases.

Wavelet analysis of phase-A differential current in Normal cases is shown in fig. 11(a) to fig. 11(d)

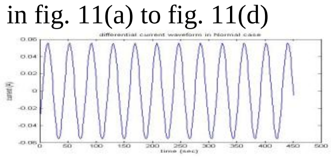


Fig. 11(a) Original signal

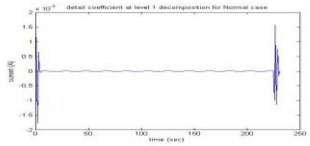


Fig. 11(b) Detail 1

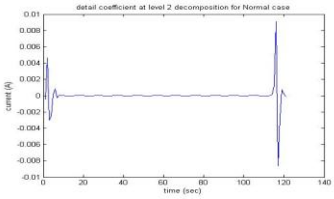


Fig. 11(c) Detail2

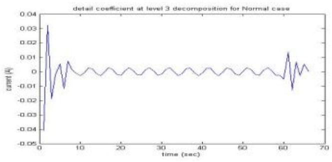


Fig. 11(d) Detail 3

(2) Wavelet analysis in Inrush case

Wavelet analysis is performed on the differential current signal of power transformer in inrush case. Transformer is switched on at 0^o angle of the source voltage [1]. The Fig. 12(a) represents the original differential current signal in inrush case while Fig. 12(b) to Fig. 12(d) represent decomposed detail coefficient signals at different levels. This analysis is done for all the three phases. It is observed in Fig. 12(a) that current get distorted when transformer is switched on at 0^o angle of the source voltage. Here gaps appear along the time of inrush current. We know that "High frequency components are located better in time domain and low frequency components are located better in frequency domain." So, detail coefficients d1, d2 and d3 are visualized better in time domain as they contain high frequency components whereas details d4 and d5 are visualized better in frequency domain as they contain low frequency components. Wavelet analysis of phase-A differential current in Inrush cases is shown in fig. 12(a) to fig. 12(d)

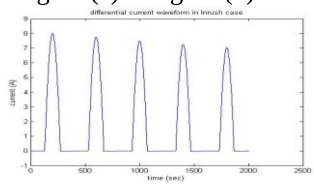


Fig. 12(a) Original signal

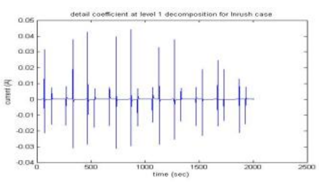


Fig. 12(b) Detail 1

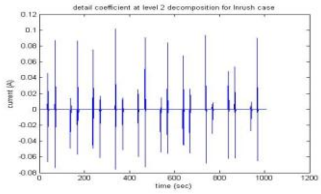


Fig. 12(c) Detail 2

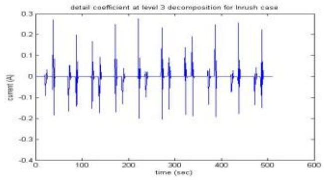


Fig. 12(d) Detail 3

(3) Wavelet analysis in internal fault case

Wavelet analysis is performed on the differential current signal of power transformer in internal fault case. Transformer is switched on at 0^o angle of the source voltage. The Fig. 13(a) represents the original differential current signal during LG fault in internal fault case while Fig. 13(b) to Fig. 13(d) represent decomposed detail coefficient signals at different levels. This analysis is done for all the three phases. Faults are thrown for the period of two cycles of waveform i.e. for the time 0.10 to 0.14 seconds. Fault resistance is varied over 50 Ω to 100 Ω for getting different samples of data. In Fig. 13(a), large frequency distortion can be observed in the differential current waveform during internal fault. This distortion is due to the effect of dispersed inductance and capacitance of transmission system which results in significant second harmonics in internal fault. This poses difficulty in accurate discrimination between internal fault and inrush fault by protection method based on DFT. Also, it can be observed in details d1, d2 and d3 that there are several spikes immediately after fault inception time which rapidly decays to zero within a cycle. But in inrush case these sharp spikes lasts for entire inrush transient period. Similarly results are obtained for other internal fault cases like LLG fault, LLLG fault, LL fault, LLL fault cases.

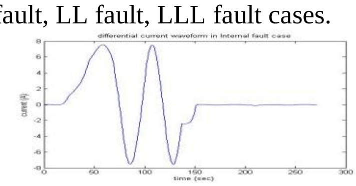


Fig. 13(a) Original signal

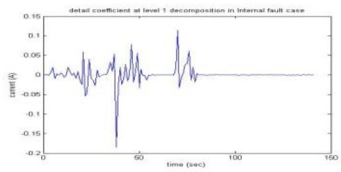


Fig. 13(b) Detail 1

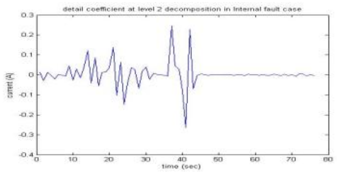


Fig. 13(c) Detail 2

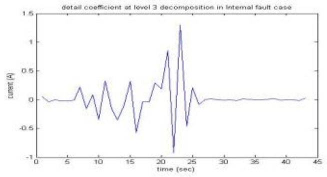


Fig. 13(d) Detail 3

Fig. 13 Wavelet analysis of phase-A differential current for LG Internal fault case

D. ANN MODELLING AND IT'S PERFORMANCE

(1) ANN model

Feed-forward ANN is used for pattern recognition which uses back-propagation algorithm and is able to identify different fault cases very accurately [4]. Sigmoid function is used as activation function whose value lies in the range of 0 to 1.

The statistical data obtained after wavelet analysis of the differential current signal is first normalized in order to get a set of data in the range of 0 to 1. The 3 types of statistical features of each phase and similarly for 3 phases as a whole give a row vector containing 9 data for each fault pattern. These 9 data of each pattern are fed to the 9 input nodes of the ANN for training and testing purpose. The target value is set as 1 for corresponding pattern. Thus modeled ANN has 9 input nodes and 9 output nodes to classify 9 types of faults. The number of nodes in the hidden layer is varied to get satisfactory result.

(2) Performance of ANN

The ANN is trained and tested for the following cases:

- for each detail levels
- for different number of nodes in the hidden layer
- for different momentum factor (m)
- for different learning factor (n)

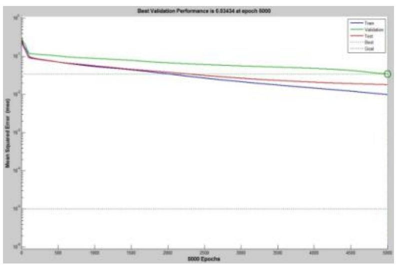


Fig. 14(a) No. of hidden layer nodes= 15

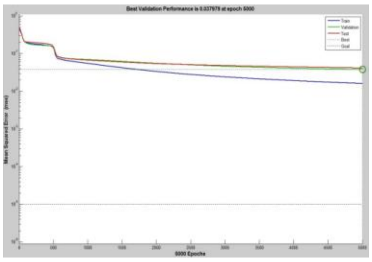


Fig. 14(b) No. of hidden layer nodes= 16
Fig. 14 Performance of ANN for different no. of hidden layer nodes, n= 0.2, m= 0.9

No. of nodes in hidden layer	Mean square error during training after 5000 iterations
10	0.04713
11	0.03680
12	0.09942
13	0.12139
14	0.04715
15	**0.03434**
16	0.03797
17	0.06794
18	0.07287
19	0.06394
20	0.04277

Table 2 Performance of ANN for different no. of hidden layer nodes

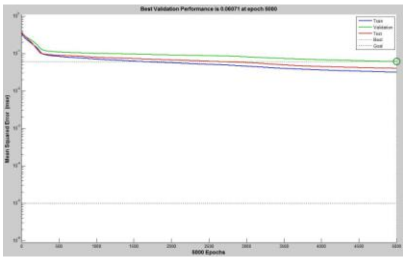


Fig. 15(a) Learning rate, n = 0.1

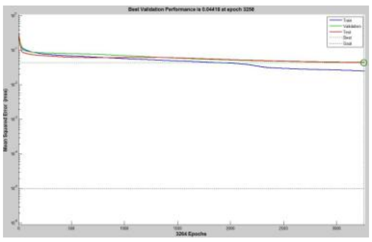


Fig. 15(b) Learning rate, n = 0.3
Fig. 15 Performance of ANN for different learning rate

Learning rate, n	Mean square error during training after 5000 iterations
0.1	0.06071
0.2	**0.03434**
0.3	0.04418
0.4	0.07530

Table 3 Performance of ANN for different learning rate

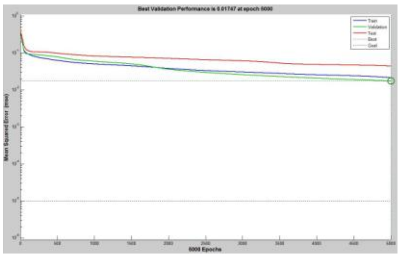


Fig. 16(a) Momentum factor, m = 0.7

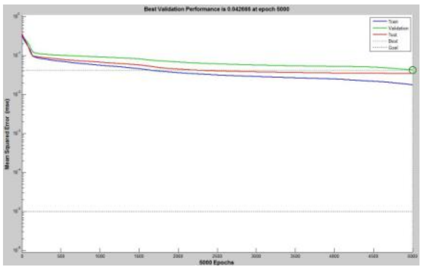


Fig. 16 (b) Momentum factor, m = 0.8
Fig. 16 Performance of ANN for different momentum factor

Momentum factor, m	Mean square error during training after 5000 iterations
0.7	0.06071
0.8	0.04266
0.9	0.03434

Table 4 Performance of ANN for different momentum factor

(3) Best suitable architecture of ANN

Number of input nodes = 9
Number of nodes in hidden layer = 15
Number of output nodes = 9
Momentum factor, m = 0.9
Learning rate, n = 0.2

E. Test result

Line phase	Statistical data	Test data for LG fault		Target	Output	Fault type
Phase A	Mean	0.02891	To FF ANN	0	0.0011	Normal
	Standard	-0.00097		0	0.2364	Inrush
	Norm	0.00705		**1**	**0.8845**	**LG**
Phase B	Mean	0.02937		0	0.0004	LLG
	Standard	0.00235		0	0.0002	LLLG
	Norm	0.24252		0	0.2559	LL
Phase C	Mean	1		0	0.1876	LLL
	Standard	-0.00110		0	0.0002	External
	Norm	0.00692		0	0.0021	Over-excitation

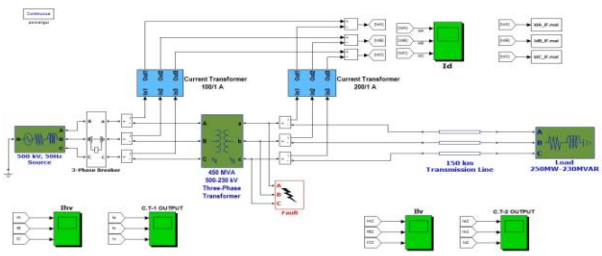
Table 5 Test results corresponding to LG fault

Line phase	Statistical data	Test data for inrush case		Target	Output	Fault type
Phase A	mean	0	To FF ANN	0	0.00001	Normal
	standard	0.03154		**1**	**0.89760**	**Inrush**
	norm	1		0	0.04665	LG
Phase B	mean	0		0	0.02188	LLG
	standard	0.00998		0	0	LLLG
	norm	0.44720		0	0.16187	LL
Phase C	mean	0		0	0.02661	LLL
	standard	0.01418		0	0.06306	External
	norm	0.63528		0	0.00136	Over-excitation

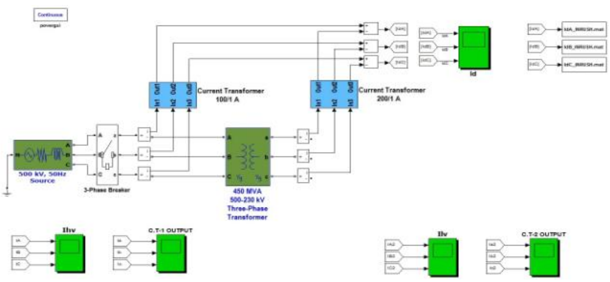
Table 6 Test results corresponding to inrush case

F. SIMULATION DIAGRAM

(1) Internal fault simulation



(2) Inrush case simulation



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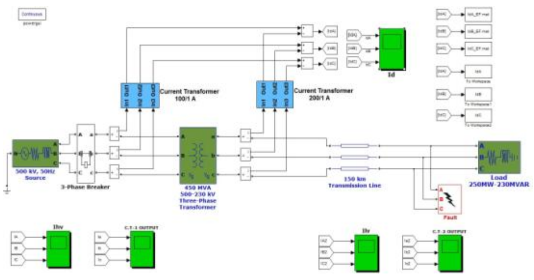
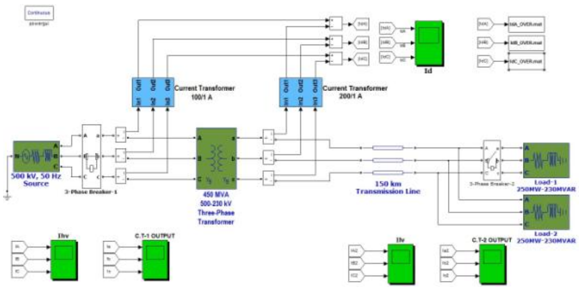
(3) External fault simulation



(4) Over-excitation simulation



V. CONCLUSION

This paper shows that DWT is suitable for extracting the transient differential current signal in both the time and frequency domain. It visualized the high frequency detail components (d1, d2 and d3) better in time domain and lower frequency detail components (d4 and d5) better in frequency domain. Also, it is able to visualize ripples in inrush current which cannot be visualized in time domain. Thus it is able to discriminate inrush current from internal fault current. Pattern recognition neural network in combination with DWT technique satisfactorily identified the different fault patterns. Also the performance of network is found satisfactory i.e. mean square error is within the limit. This numerical relay, based on DWT and ANN, shows very less operating time with desirable accuracy.

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