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ANN Based Power Transformer Protection

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Abstract: The demand for a reliable supply of electrical energy for the exigency of modern world has increased considerably requiring nearly a no-fault operation of power systems. Power transformers are very expensive and vital components of electric power systems. The crucial objective to mitigate the frequency and duration of unwanted outages related to power transformer puts a high demand on power transformer protective relays to operate effectively. The high demand includes the requirements of dependability associated with no false tripping, and operating speed with short fault detection and clearing time. The second harmonic restrain principle is widely used in industrial application for many years, which uses Discrete Fourier Transform (DFT). This principle often encounters some problems such as long restrain time and inability to discriminate internal fault from magnetizing inrush condition. Hence, Artificial Neural Network (ANN), which has the ability to mimic and automate knowledge, has been proposed for detection and classification of faults in this paper. The Wavelet Transforms (WT) which has the ability to extract information from transient signals in both time and frequency domain simultaneously is used for the analysis of power transformer transient phenomena. The conditions of power transformer to be analysed in a power system are modelled in MATLAB/SIMULINK environment and implemented using LabVIEW software.

Keywords: Power Transformer, Artificial Neural Network, Wavelet Transform, Current Transformer, LabVIEW

I. INTRODUCTION

Protection of large power transformers is a very challenging problem in power system relaying. The key issue lies in discriminating different transformer faults. It is natural that the relay should be initiated in response to internal fault but not to inrush current or over-excitation or external fault current. Early methods were based on desensitizing or delaying the relay to overcome the transients. These methods are unsatisfactory since the transformer may be exposed for a long unprotected time. Yet another method based on the second harmonic content with respect to the fundamental one was introduced, known as harmonic restraint differential protection, which improved security and dependability. However, some researchers have reported the existence of a significant amount of the second harmonic in some winding faults. In addition, the new generations of power transformers use low-loss amorphous material in their core, which can produce inrush current with lower harmonic contents and higher magnitudes. In such cases, some researchers have modified the ratio of second harmonic to fundamental restraining criterion by using other ratios defined at a higher frequency. While other researchers proposed wave comparison and error estimation method, fuzzy logic based techniques, principal component analysis, and correlation analysis method to discriminate internal fault condition from non-fault condition. Power flow through the transformer is also used as an index to detect inrush current. However, all the preceding approaches share the same feature, i.e. they depend on a single index. Furthermore, to choose a proper threshold for discrimination is not easy.

In this paper, Artificial Neural Network is used to improve discrimination between normal, inrush, over excitation, internal fault and external fault conditions and facilitate faster, more secure and dependable protection for power transformers. Inrush and fault currents are non-stationary signals and these fast electromagnetic transients are non-periodic containing both high frequency oscillations and localized impulses superimposed on the power frequency and its harmonics. Therefore wavelet transform is used for the feature extraction from the waveforms of power transformer under various situations. The wavelet transform is a relatively new and powerful tool in the analysis of the power transformer transient phenomenon because of its ability to extract information from the transient signals simultaneously in the time and frequency domain, rather than conventional Fourier Transform which can only give the information in the frequency domain Neural networks on the other hand being a good classifier is used to classify and discriminate the various conditions. The wavelet transform is applied to decompose different current signals of power transformer into a series of detailed wavelet components. The statistical features of the wavelet components are calculated and are used to train a multilayer feed forward neural network designed using scaled conjugate gradient back propagation algorithm to discriminate various conditions

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II. PROPOSED ALGORITHM – SCALED CONJUGATE BACK PROPAGATION ALGORITHM

Scaled conjugate back propagation (Trainscg) learning algorithm is used to train the multi-layer feed forward neural network and is a network training function that updates weight and bias values according to the scaled conjugate gradient method. Trainscg can train any network as long as its weight, net input, and transfer functions have derivative functions. Signals are received at the input layer, it passes through the hidden layer, and reach to the output layer, and then fed to the input layer again for learning. The BP algorithm looks for minimum of error function in weight space using the method of gradient descent. The combination of weights that minimizes the error function is considered to be a solution to the learning problem.
The training algorithm of back propagation involves four stages, i.e.

1. Initialization of weights
2. Feed forward
3. Back propagation of errors
4. Updating the weights and biases

During first stage, i.e. the initialization of the weights, some values are assigned. During feed forward stage each input unit receives an input signal and transmits this signal to each of the hidden units. Each hidden unit then calculates the activation function and sends its signal to each of the output unit. The output unit calculates the activation function to form the response of the network for the given input pattern. During back propagation of errors, each output unit compares its compound activation function with its target value to determine the associated error for that pattern with that unit. Back propagation is used to calculate derivatives of performance with respect to the weight and bias variables. The scaled conjugate gradient algorithm is based on conjugate directions. The trainscg routine may require more iteration to converge than the other conjugate gradient algorithms, but the number of computations is significantly reduced because no line search is performed.

III. POWER SYSTEM MODELLING

The model consists of 3 phase, 50 Hz, 450 MVA, 230kV / 500kV star-star transformer. The power system model with star-star connected transformer is simulated in MATLAB/SIMULINK environment. Three-phase differential current samples are acquired through current transformers connected on both sides of the power transformer. Nonlinearity due to CT saturation and phase compensation conditions is also considered for generating the simulation cases. The simulation cases for different types of internal faults, external faults, over excitation, inrush and normal condition are obtained.

A. Simulation and Results

All the analysis is performed in discrete domain with sampling frequency of 20 kHz. The load is fixed for all situations except for over excitation case. Transformer primary and secondary terminals are connected in star with grounded terminal. The source is star connected with grounded neutral [5]. The simulation diagram is shown in Fig. 1.

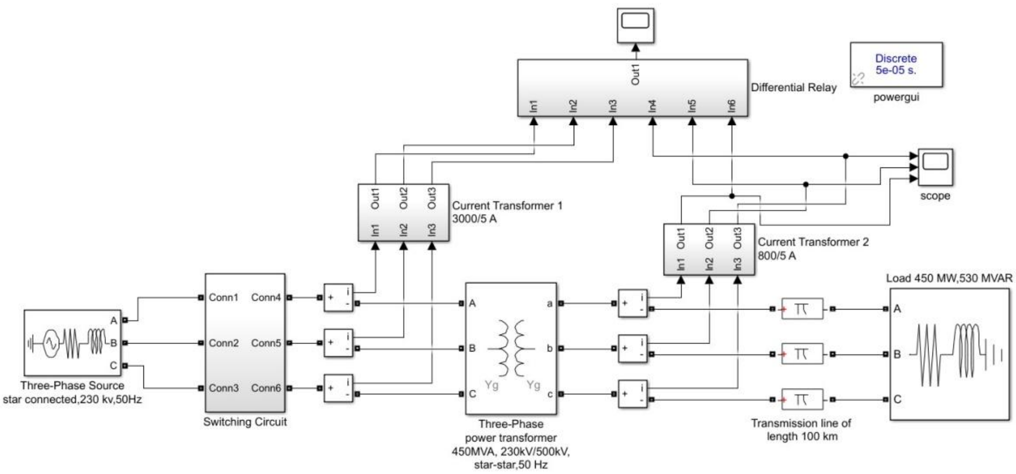

Fig. 1 MATLAB SIMULINK model

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For normal operating condition, the switching circuit connecting the three phase source is switched on at 0.1 sec for all the readings of normal case. For different readings the voltage angle of the source voltage are varied. During the simulation of the inrush condition, the transformer secondary side is kept open and is switched on at 0.1 sec. The various readings are simulated by varying the switching at different angles of the source voltage. The three phase current signals during inrush condition obtained after simulation is shown in Fig. 2. The magnetizing impedance of the transformer drops significantly during the periods of time when the core is saturated, causing high currents that is unipolar in nature (saturation occurs only on the peaks of the positive or negative half cycles). A typical inrush current is unipolar with a slow decay rate. In over excitation case instead of fault, at the same time an additional load is connected to the existing system and the transformer is energized at 0.05 seconds. The switching circuit that connects the additional load is triggered at 0.1 sec. The additional load is of 450 MW and 530 MVAR. The three phase current signals during over excitation condition obtained after simulation is shown in Fig. 3.

During the simulation of internal fault the switching circuit connecting the source and the transformer is activated at 0.05 sec. The switching conditions are kept constant for various readings of the internal fault simulation. The fault transient occurs in between 0.1 to 0.12 sec. The fault resistance is varied for obtaining different set of readings in this situation. The L-G fault occurs in between phase and ground on the secondary side of transformer. The fault occurs inside the protection zone of transformer. In similar situations the L-L, L-L-L, L-L-G and L-L-L-G cases are also simulated and the transient current signals are obtained. The three phase current signals during L-L-G fault obtained after simulation is shown in the Fig. 4. For external fault case all the conditions are same as that of internal fault. The external fault occurs outside the protection zone of transformer among phase A, phase B, phase C and ground on the secondary side of transformer. The three phase current signals during external fault are shown in Fig. 5. Switching occurs at 0.05 sec and the fault duration is from 0.1 to 0.12 sec. The fault exists for a complete cycle.

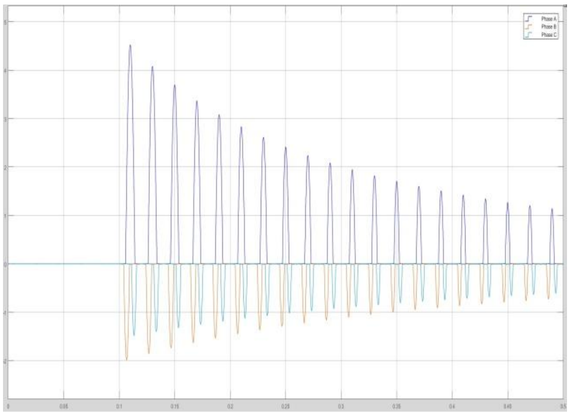

Fig. 2 Inrush condition

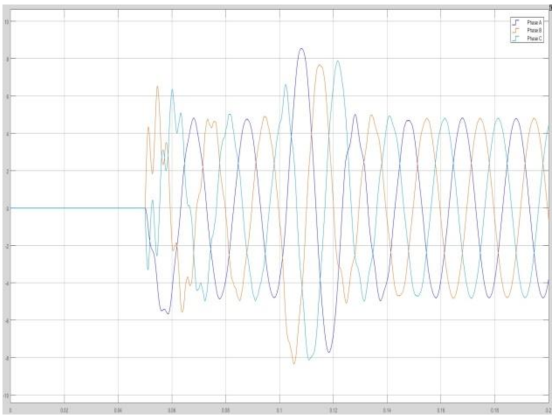

Fig. 3 Overexcitation

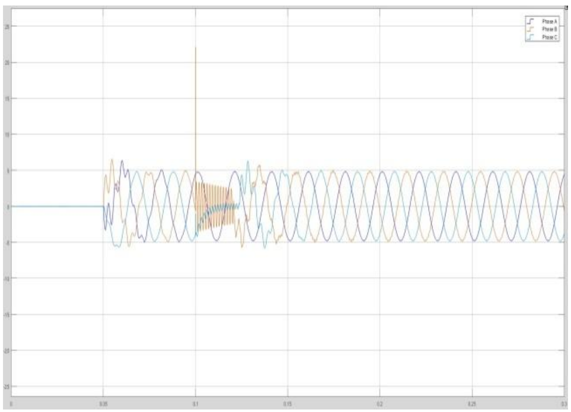

Fig. 4 Internal line-line-ground fault

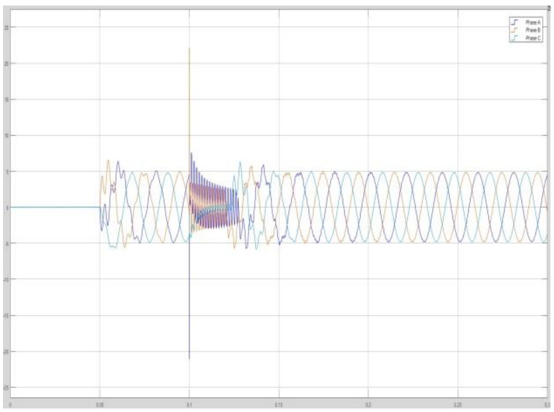

Fig. 5 External fault

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IV. FAULT CLASSIFICATION SCHEME

A. Dataset Generation

Out of a large list of mother wavelets available, the choice of a particular mother wavelet plays an important role in detecting and classifying different types of fault and inrush transients of power transformer. Since the transformer transient study deals with analysing short duration, fast decaying current signals Daubichiess mother wavelet of level 6 (db6) is used. The wavelet analysis of various transient current signals obtained from SIMULINK result in different conditions like normal, inrush, internal fault, external fault and over excitation is carried out. The highest frequency that the signal could content will be 10 kHz as per Nyquists theorem. This frequency is observed at the output of high frequency filter which gives the first detail. Thus the band frequencies between 10 kHz to 5 kHz are captured in detail 1. Similarly the band frequencies between 5 kHz to 2.5 kHz are captured in detail 2 and so on. The Fig. 6 and Fig. 7 represent the decomposed detail coefficient signals in different levels during internal fault and inrush conditions respectively.

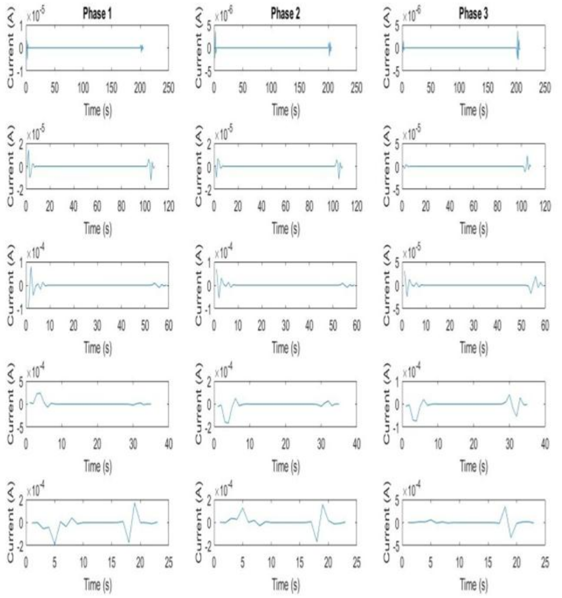

Fig. 6 Wavelet analysis of inrush condition

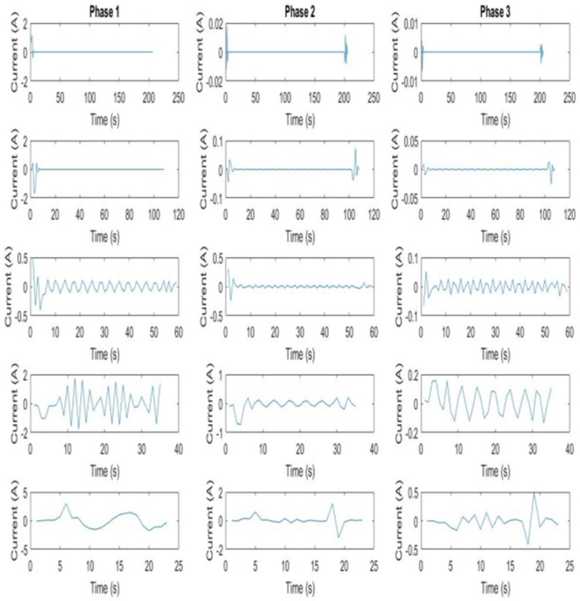

Fig. 7 Wavelet analysis of internal fault LG condition

The statistical data obtained from the decomposed signals of wavelet analysis at level 1 to 5 are used to train and test the ANN. The training and testing data are statistical features like mean, standard deviation and norm (root mean square value) of the decomposed detail coefficients in various levels. The data obtained after statistical analysis are normalized before training or testing by dividing the maximum value of data of a row with other data. There are three type of statistical feature for each phase and similarly for three phases as a whole gives a row vector containing 9 data. Hence for each corresponding faults we get certain 9 data which are fed to the input nodes of the ANN i.e. 9 input nodes.

B. Implementation of ANN

Neural network toolbox is used for training, validation and testing of the neural network. Scaled conjugate gradient back propagation (trainscg) algorithm is used to train the ANN. The activation functions used in the ANN are of sigmoid type in hidden layer and softmax function in output layer. ANN based power transformer protection is used for distinguishing faulty signal from the normal signal and is an effective fault classifier. The fault classification is done by the hidden layers of the neural network. The ANN is trained and tested for each level of detail coefficients i.e. for both high frequency and low frequency constituents, by taking their statistical features. Using this proposed system, nine different types of transformer operating conditions are classified and therefore 9 nodes are present at the output for indicating the type of the fault. The architecture of the ANN consist of one hidden layer, 16 nodes in hidden layer, 9 nodes in input layer and 9 nodes in output layer . The nodes in output layer indicate the particular fault.

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C. Testing performance

The test data is given to the trained ANN network, and the result obtained gives us the output which indicates the fault occurring. The graph represents the probability of the fault occurring, so higher the magnitude of the probability then the more the chance of the fault occurring. Y axis represents the magnitude of probability of fault occurrence.

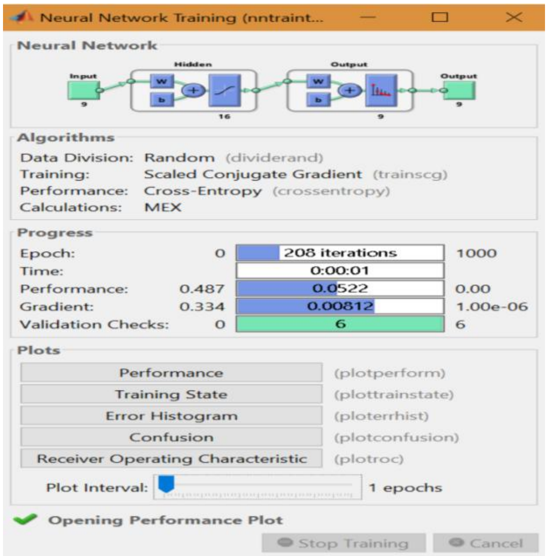

Fig. 8 Network training

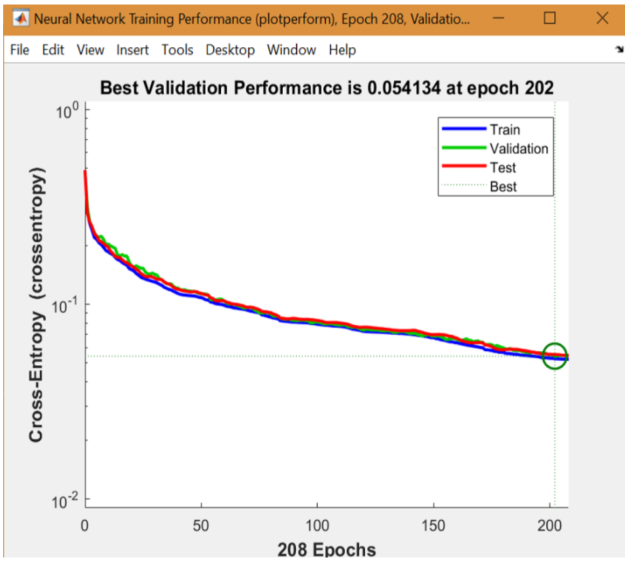

Fig. 9 Performance plot

Fig. 10 Internal L-L fault detected waveform

Fig. 11 Over excitation detected waveform

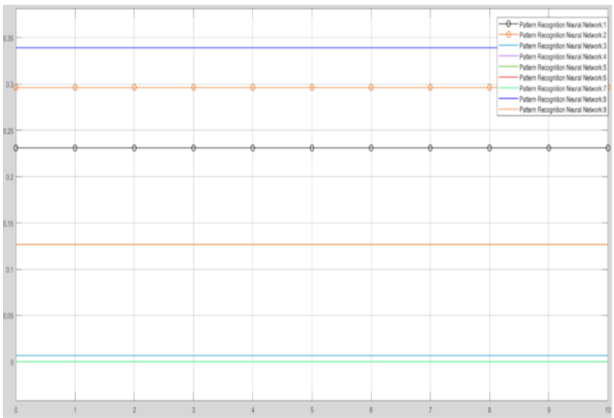

Fig. 12 External fault detected waveform

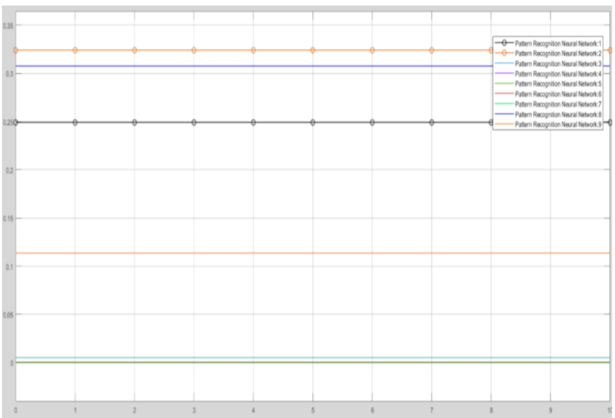

Fig. 13 Inrush detected waveform

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Fig. 14 Internal L-G fault detected waveform

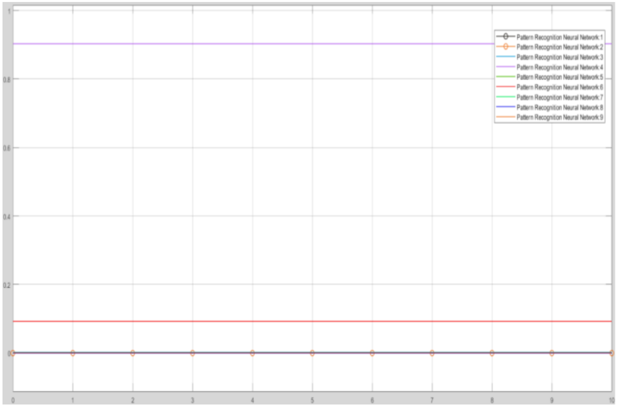

Fig. 15 Internal L-L-G fault detected waveform

TABLE I NOTATIONS IN THE GRAPH

Pattern recognition neural network: 1	Normal
Pattern recognition neural network: 2	Inrush
Pattern recognition neural network: 3	Internal LG fault
Pattern recognition neural network: 4	Internal LLG fault
Pattern recognition neural network: 5	Internal LLLG fault
Pattern recognition neural network: 6	Internal LL fault
Pattern recognition neural network: 7	Internal LLL fault
Pattern recognition neural network: 8	External fault
Pattern recognition neural network: 9	Over excitation

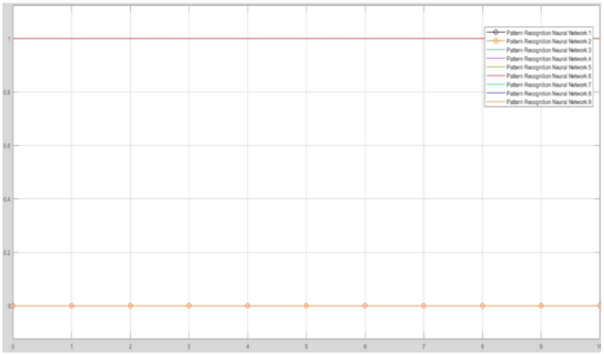

Fig. 16 Internal L-L fault detected waveform

The output is the classification and recognition of the various faults occurring in the transformer. When the output probability of the pattern is high, then that pattern is recognized i.e. that fault is recognized which is given to the relay for tripping action. Hence, the proposed protection scheme is an effective fault classifier.

V. ANN IMPLEMENTATION IN LABVIEW

LabVIEW is a general purpose programming language used for developing projects graphically. Neural nets are parallel processors and they have data flowing in parallel lines simultaneously. LabVIEW has the unique ability to develop data flow diagrams that are highly parallel in structure. So, LabVIEW seems to be a very effective approach for building neural nets. After the proper training of ANN, the weights obtained are used in the testing of ANN in LabVIEW environment. The input data formed after wavelet analyses are used for the same.

A. Block Diagram Implementation

The block diagram contains the actual program part of LabVIEW. After building the front panel, codes are added by using graphical representations of functions to control the front panel objects. The block diagram contains the graphical source code. Front panel objects appear as terminals on the block diagram and these terminals are entry and exit ports that exchange information between the front panel and the block diagram. The data that entered into the front panel controls enter the block diagram through the control terminals. After the functions complete their calculations in the block diagram, the data flow to the indicator terminals, where they exit the block diagram, re-enter the front panel, and appear as front panel indicators. The structure for the implementation of the proposed protection scheme is shown in the Fig 17.

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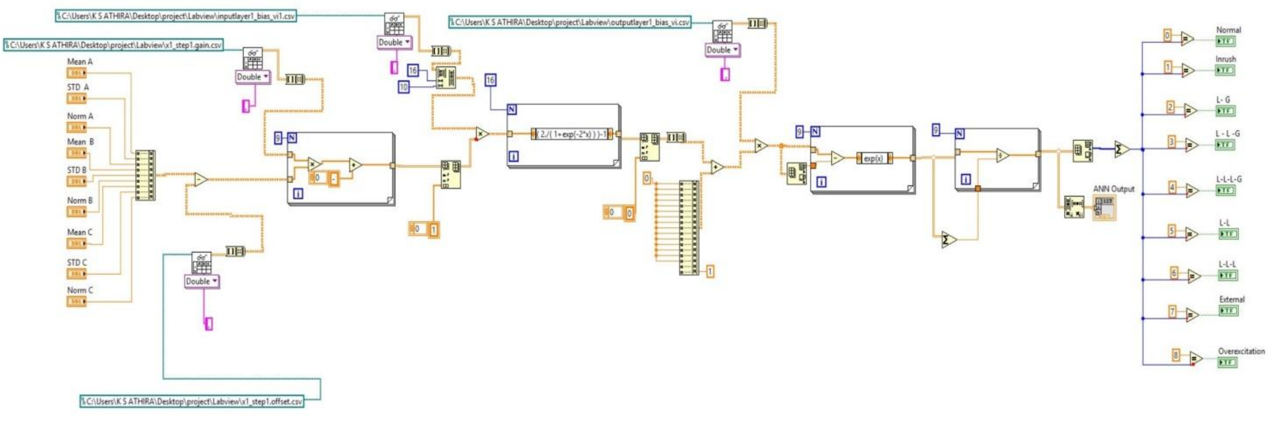

Fig. 17 Block diagram for the implementation of ANN

B. Results

The front panel constitutes one part of the program in which the GUI is developed. LabVIEW utilizes a powerful Graphical User Interface (GUI). The Front panel acts as the user interface and the front panel view indicates the operating condition of the power transformer. When a fault occurs, depending on the fault, corresponding LED turns on. The detection of various operating conditions of a power transformer is shown in the Fig. 18, Fig. 19, Fig. 20 and Fig. 21 respectively.

Figure 18 Detection of inrush condition

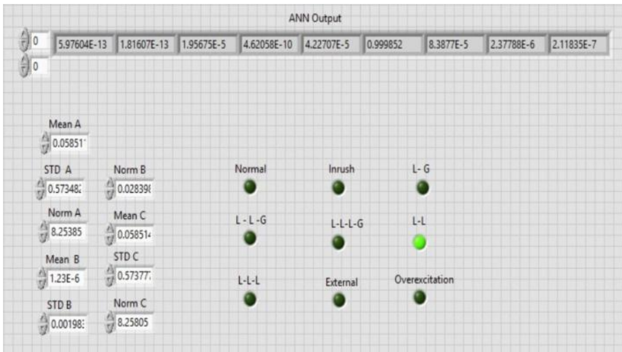

Figure 19 Detection of internal line - line fault

Figure 20 Detection of external fault

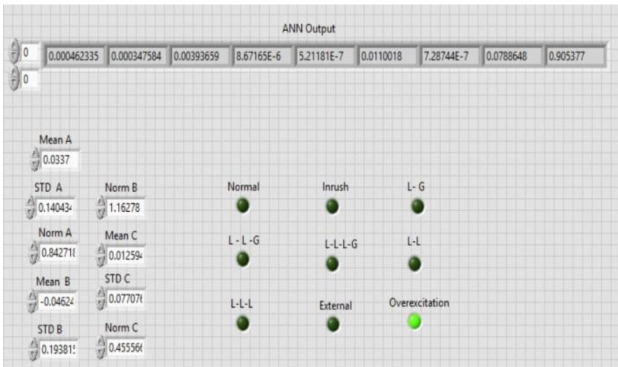

Figure 21 Detection of over excitation condition

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VI. CONCLUSION

From the study and analysis carried out in this paper, the performance of neural networks has been found to surpass the performance of conventional methods, which need accurate sensing devices, costly equipment and an expert operator or engineer. Neural network based algorithm has more adaptability. The simulation results obtained show that the new algorithm is more reliable, efficient, accurate and faster. The classification ability of the ANN in combination with advanced signal processing technique opens the door for smart relays for power transformer protection with very less operating time and with desirable accuracy. Artificial Neural Network (ANN) has been equipped with distinctiveness of parallel processing, nonlinear mapping, associative memory, offline and online learning abilities. The wide uses of ANN with its conquering outcomes make it an effective diagnostic mean in electric power systems.

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