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IDENTIFICATION OF INRUSH CURRENT AND INTERNAL FAULT CURRENTS IN A TRANSFORMER USING SELF ORGANIZING MAPS

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ABSTRACT

Differential protection of a transformer is used in protecting the transformer windings against internal faults based on the simple property that the ratio of currents entering and leaving the transformer is equal to the inverse of the transformation ratio. This ratio is affected by either internal faults or inrush currents during transformer magnetization. In order to avoid mis-operation of a transformer differential protection relay due to inrush current, a distinction must be made between the inrush current and internal fault currents. This paper aims at using Self Organizing Maps to distinguish between the currents without delving into the particular differences in the properties of the 2 currents.

Keywords: *Inrush Currents, Internal Fault, Self Organizing Maps, Transformers, Kohonen Map*

1. INTRODUCTION

Differential protection scheme for a transformer is one of the most reliable methods for over-current protection but the similarity between internal faults in the transformer and the inrush current during the initial magnetization process can cause over-current differential relays to operate wrongly. This need has been strongly highlighted [1]

Current industrial relays employ harmonics to discriminate between the inrush current and fault current but current transformer saturation and possible line capacitance from high tension lines connected to the transformer make it hard to segregate this harmonic component. Several researchers have come up with several methods aimed at segregating the two currents. One method is the use of the spectral energy of the fault and inrush currents to discriminate between them [2]. The method uses the hyperbolic S-transform to convert the signals to phase space and then compare their spectral energies. Other methods used the symmetrical components [3]. The method takes advantage of the negative sequence current components which are present in fault currents but not in magnetizing current. The main advantage of this is that it can work in over-flux and CT-saturation conditions. A new technique that's popular is the use of Discrete Wavelet Transform [4-6]. These utilize the wavelet transform to extract energy distribution characteristics from the current which form the distinguishing factor between inrush and internal fault currents. Still another popular approach is the use of the Jiles-Atherton model [7]. The measured parameters of voltage and current are used to calculate the transformer parameters as per the Jiles-Atherton model and then optimize them using another method, mostly artificial intelligence, to distinguish the parameters when the transformer is under a fault or inrush current after being energized. An interesting approach is adopted in [8] where the instantaneous inductance of the transformer is used in discriminating between inrush current and internal fault currents. These techniques show the different properties of inrush current and fault current that can be used in distinguishing between them.

In another development, a study was carried out to present an effective technique for detection of inrush current in distribution transformer based on wavelet transform. By utilizing this technique, inrush current can be discriminate from other transients such as single phase to ground fault, load switching as well as capacitor switching. LVQ (Learning vector Quantizer) is employed in classification while wavelet transform is utilized for

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signals decomposition [9]. Simulation by the use of EMTP can have the capacity to generate inrush current as well as other transients. The findings of this study demonstrated that the suggested protocol is effective in establishing inrush currents from other events. This study is almost identical with what is being proposed in this paper. In this study, SOM (Self-organizing maps) are utilized in classification while the described study above employs LVQ for classification.

In another study, optimal bayes classifier was employed to create a technique for discriminating non-fault from fault events [10]. The Prony approach was utilized in extracting the modal parameter of the current waveform. The fault was discriminated from the switching case by feeding the FFD (Fundamental frequency damping) as well as the ratio of the second HA (Harmonic amplitude) over the FHA (fundamental harmonic amplitude) to the classifier.

A new technique for discerning internal faults (IF) from inrush currents (IC), using DT (decision trees) in an attempt to protect power transformer has been proposed [11]. Internal faults as well as the differential current of one cycle are taken as DT inputs with matching output as "1" for internal fault conditions and "0" for inrush current. The decision trees are trained with IF as well as IC wit broad discrepancies in operating parameters of the PN (power network) and offers precise outcome in discriminating IC from IF. The findings of this study demonstrates that the suggested decision trees based algorithm was discovered to robust as well as accurate in the protection of power transformer. Although all these proposed methods look somewhat similar, none of the studies has proposed the use of Self Organizing Maps in indentifying inrush currents from internal faulty currents in a transformer. This paper aims at coming up with a simple means of trying to aggregate the various properties of the 2 currents and distinguishing them simply by using self organizing maps which would be able to capture the various differences between the currents.

2. SELF ORGANIZING MAPS

Normal computation technologies that simply automate mathematical formulae have the main disadvantage of taking comparatively long time to produce results mainly because they are exact methods. Artificial Neural Networks can be defined as a class of mathematical algorithms designed to solve a specific problem [12]. Basically they are parallel computational models comprised of densely interconnected adaptive processing units. An extremely important and human characteristic of ANN is their adaptive nature, where learning by experience replaces programming in solving problems.

Self Organizing Maps (SOM) is a special class of artificial neural networks that are used to classify data based on the similarities and differences. They use the unsupervised learning algorithm where the data to be classified is fed into the network and based on some maximization or minimization function, the variables are arranged among the neurons depending on the relative weights to the objective functions.

2.1 Kohonen Maps

The Kohonen network is probably the closest of all artificial neural networks architectures and learning schemes to the biological neuron network. As a rule, the Kohonen type of net is based on a single layer of neurons arranged in a two-dimensional plane having a well defined topology. Kohonen Maps are self-organizing systems applied to the unsupervised problems (cluster analysis and data structure analysis). In Kohonen maps similar input objects are linked to the topological close neurons in the network. Basically, the neurons have as many weights as the number of responses in the target vectors and learn to identify the location in the ANN that is most similar to the input vectors; the weights of the net are updated on the basis of the input object, i.e. the network is modified each time an object is introduced and all the objects are introduced for a certain number of times (epochs) [13]. An example of the structure of a Kohonen map with dimension 5x5, built for a dataset described by *p* variables is shown in the Fig. 1 [14].

2.2 Cp_Ann

Counter propagation Artificial Neural Networks (CP_ANNs) are very similar to the Kohonen Maps and are essentially based on the Kohonen approach, but combines characteristics from both supervised and unsupervised learning, i.e. CP-ANNs can be used to build both regression or classification models. Classification consists in finding a mathematical model able to recognize the membership of each object (sample) to its proper class on the basis of a series of measurements (the classes must be defined a priori). To do so, an output layer is added to the Kohonen ANN [13]:

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After the training process accomplished, the complete set of the training vectors is once more run through the KANN. In this last run the labeling of the neurons excited by the input vector is made into the table called top map. The top-map shows the various weights and the variables arranged according to their weightings as calculated in the CP_ANN net. Similarly, weighted variables are clustered in the same neuron and in the same neighborhood of other similarly weighted neurons.

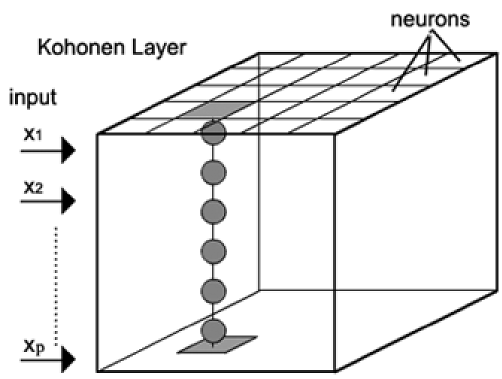

Fig 1. Kohonen Ann Structure

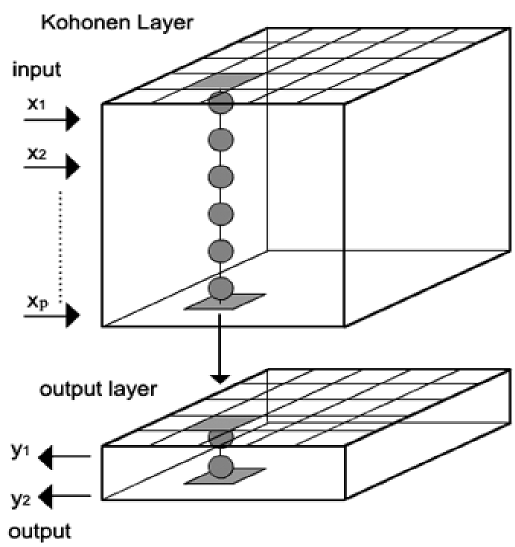

Fig 2. Cp_Ann Structure

Artificial Neural Networks have already found use in the identification of fault currents before in the identification of the type of transformer fault from the current measurements in [15].

3. SYSTEM STUDIED

The system used in the simulation was developed in Matlab-Simulink with a 2000MVA 220kV Generator, A 3-phase breaker, a 450MVA 220kV/500kV transformer and a linear load of 250MW. The four winding configurations of D-D, D-Y, Y-Y, Y-D were also considered while the internal faults simulated were winding to ground and winding to winding. The sampling rate was 3.2 kHz with each cycle containing 64 samples running for a period of 0.04s. The system model shown in fig.10.it is in the Appendix-1.

4. RESULTS AND DISCUSSION

4.1 Inrush Current Simulation

The system model was used to simulate inrush current for the various winding connections. The various line currents resulting from 2054 samples taken were as shown in Fig 3.

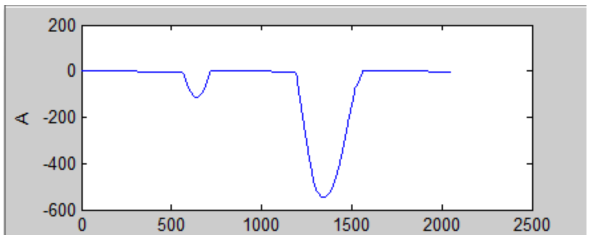

Fig 3.1 Inrush current with D-D connection

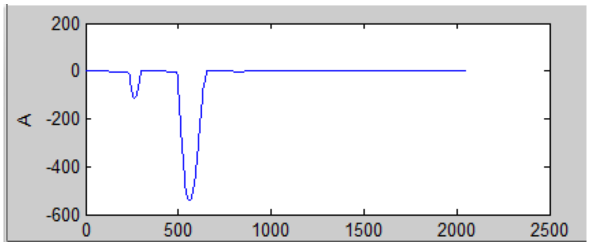

Fig 3.2 Inrush current with D-Y connection

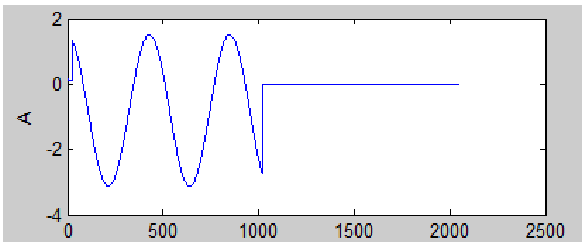

Fig 3.3 Inrush current with Y-Y connection

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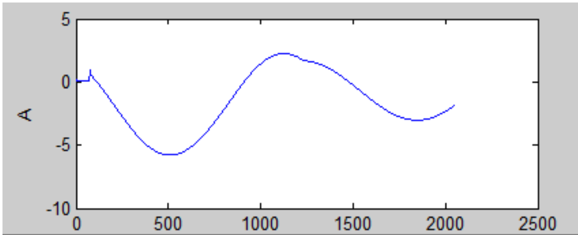

Fig 3.4 Inrush current with Y-D connection

Fig. 3 Inrush Currents for Various Connections

4.2 Fault Current Simulation

Similarly, the line currents with an internal line-to-ground and line-to-line fault were simulated. To simulate the internal faults, a fault was connected to the primary side of the transformer and the 2 fault conditions simulated for the 4 connections with 3000 samples for a period of 0.04s giving the results as shown in Fig. 4.

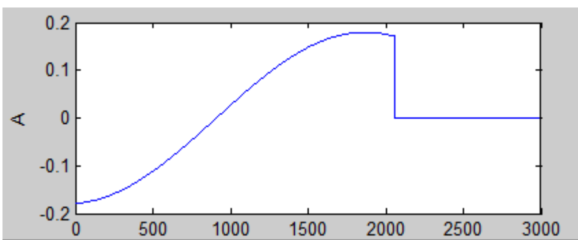

Fig 4.1 Fault current, line-ground fault, D-D connection

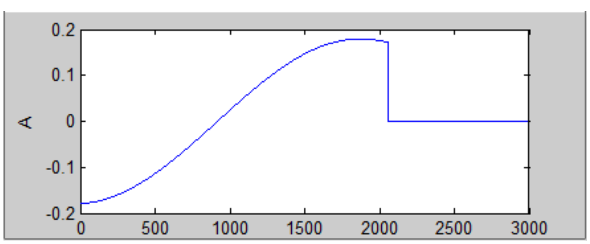

Fig 4.2 Fault current, line-ground fault, D-Y connection

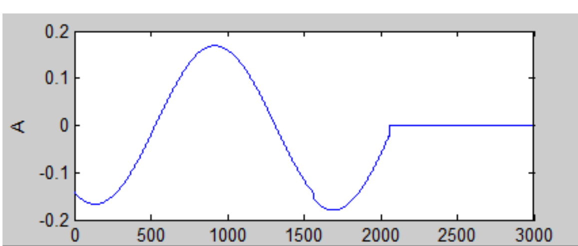

Fig 4.3 Fault current, line-ground fault, Y-Y connection

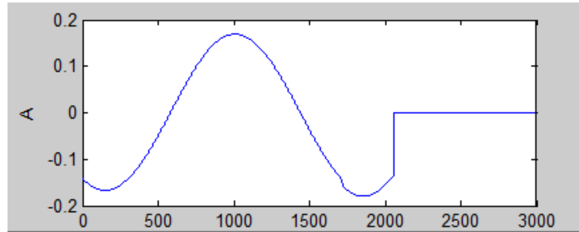

Fig 4.4 Fault current,line-ground fault, Y-D connection

Fig.4 Fault Currents for Line-Ground Faults

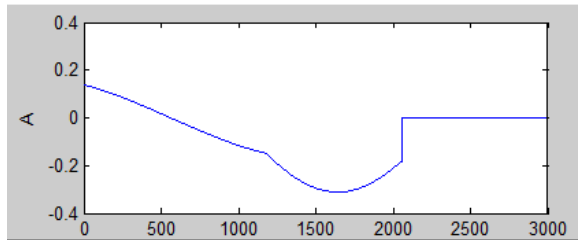

Fig 5.1 Fault current, line-line fault, D-D connection

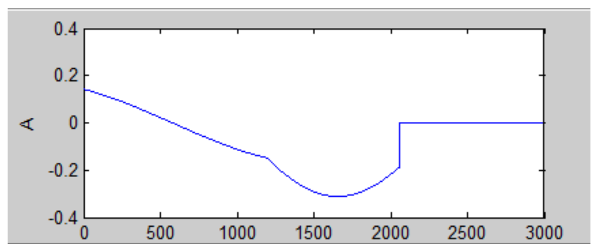

Fig 5.2 Fault current, line-line fault, D-Y connection

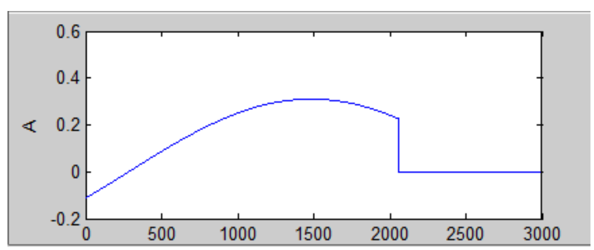

Fig 5.3 Fault current, line-line fault, Y-Y connection

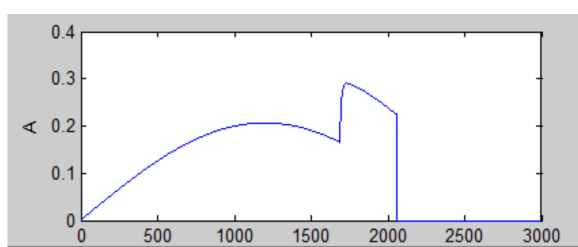

Fig 5.4 Fault current, line-line fault, Y-D connection

Fig.5 Fault Currents for Line-Line Faults

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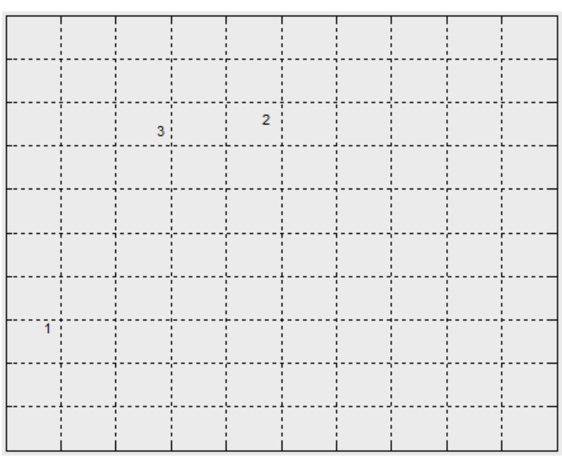
From the fault currents, it's clear that the fault current is affected by the connection of the transformer but the determining factor seems to be the primary winding configuration. The secondary winding has some visible effect but the primary winding has a greater impact on the fault current. The healthy phases carry the load current as the effect on the faulted phases (shown in Fig. 4 and Fig. 5) seems muted to only some harmonics introduced into the line current.

The inrush current is of a very high magnitude which distorts the graph but they die out quickly. The current seems to have a frequency affected by the transformer parameters and the connection of the transformer. A Y-connected primary transformer seems to be affected less by the inrush current as compared to the D-connected primary transformer.

4.3 Cp_Ann Classification

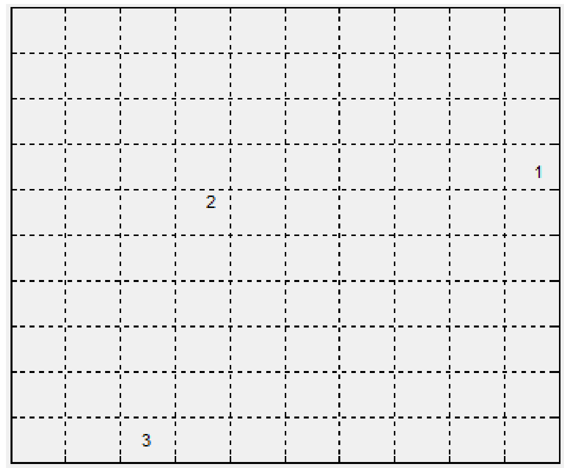
With the data from the inrush and fault currents, the currents were then fed into the CP_ANN model and classified. The training method was Back Propagation with a toroidal architecture. The artificial neural network used had 10 neurons on each side making 100 neurons and was trained for 20 epochs. The training was done for each transformer connection to see whether the CP_ANN would be able to classify the various currents. The resulting top map from each simulation is shown below:



Legend: 1-Inrush; 2-line-ground; 3-line-line

Fig.6. SOM top-map for D-D connection

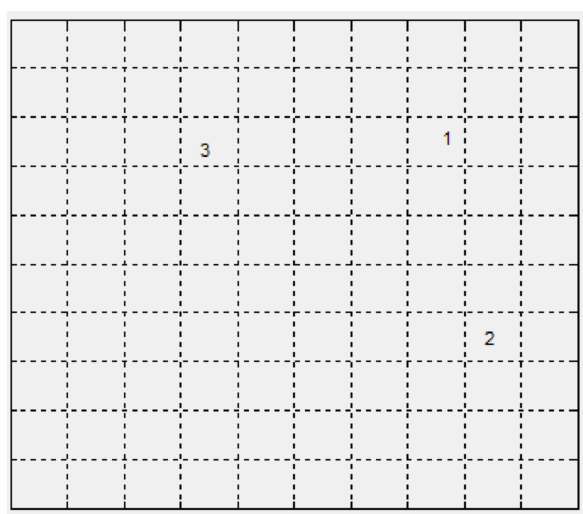
As figure 6 above indicates, the inrush current is distinguished from two fault currents separately**.** Number 1 in this figure indicates inrush current while number 2 and 3 indicate fault currents. The3 currents (inrush as well as the 2 fault currents) form a triangular pattern if connected together.



Legend: 1-Inrush; 2-line-ground; 3-line-line

Fig.7. SOM top-map for D-Y connection

As figure 7 above shows, the inrush current is distinguished from two fault currents separately**.** 1 in this figure indicates inrush current while 2 and 3 indicate fault currents. A triangular pattern is formed when the 3 currents are connected to one another.



Legend: 1-Inrush; 2-line-ground; 3-line-line

Fig.8. SOM top-map for Y-Y connection

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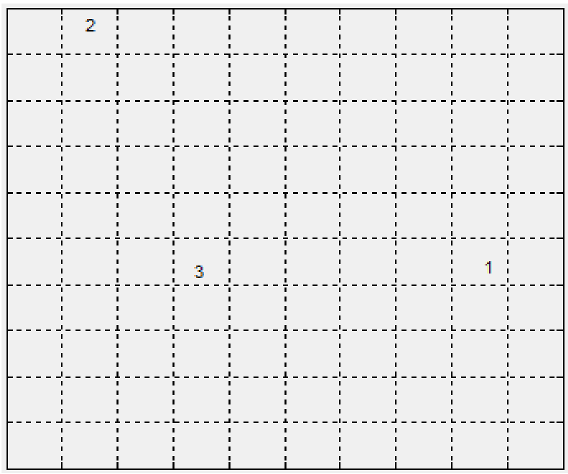
As figure 8 above exhibits, the inrush current is discriminated from two fault currents separately**.** Number 2 and 3 in this figure indicate fault current while number 1 shows fault currents. All the three currents form a triangular pattern.



Legend: 1-Inrush; 2-line-ground; 3-line-line

Fig.9. SOM top-map for Y-D connection

As figure 9 above demonstrates, the inrush current is discriminated from two fault currents separately**.** Number 1 in this figure indicates inrush current while number 2 and 3 indicate fault currents. The three currents form a triangular pattern if joined together.

From the various connections, the CP_ANN was able to classify the inrush and two fault currents separately in different neurons with separate weights. It shows that for any connection, the inrush and fault currents for various fault configurations have different characteristics. Of interest was the fact that the arrangement of the 3 currents on the top-map followed a distinct triangular pattern which indicates that the inrush and fault currents are similar and the magnitude and phase is what affects them depending on the transformer connection.

5. CONCLUSION

From the simulations, it's clear than artificial Neural Networks, and particularly CP_ANNs can classify inrush and fault currents in a transformer. This was demonstrated and the classification was seen to be functional independent of the transformer connection or the fault current waveform.

This is important as artificial neural networks do not compute mathematical relations but simply change weights depending on the input variables. It means that a transformer at the manufacturer could have its top-map for various inrush and fault conditions simulated at manufacture and the differential protection relays to be used can have the same top-map configuration in order to distinguish between inrush current and internal faults currents for the particular transformer. This would save on computational times by the differential relay which would mean faster times in relay operation without affecting sensitivity or causing mis-operation.

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APPENDIX-I

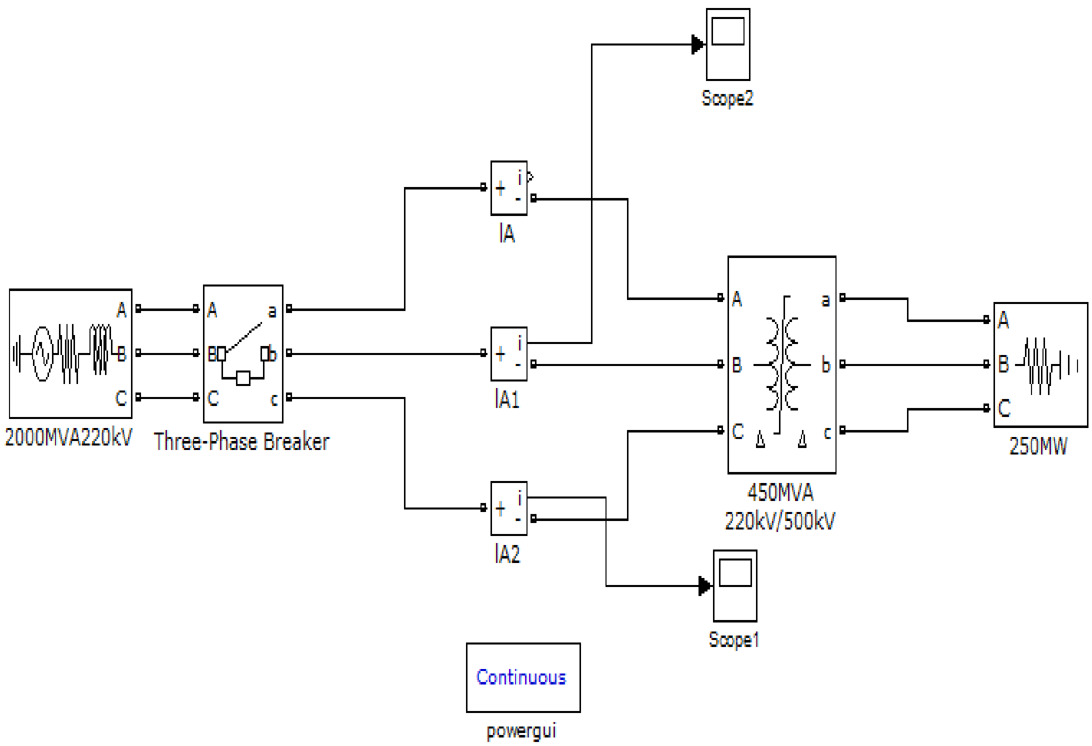

Fig.10. System Model