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A NOVEL DETECTION AND CLASSIFICATION OF FERRORESONANCE USING WAVELET TRANSFORM AND LVQ NEURAL NETWORK IN DISTRIBUTION NETWORKS

G. Mokryani
Islamic Azad University of Ilkhchi,
Ilkhchi, Iran

M.R. Haghifam
Tarbiat Modarres University, Tehran,
Iran
email:gmokryani@gmail.com

J. Esmaeilpoor
Islamic Azad University of Bukan,
Bukan, Iran

ABSTRACT
A novel method for Ferroresonance detection presented in this paper. Using this method Ferroresonance can be discriminate from other transients such as capacitor switching, load switching, transformer switching. Wavelet transform is used for decomposition of signals and Learning Vector Quantizer(LVQ) Neural Network used for classification. Ferroresonance data and other transients was obtained by simulation using EMTP program. Using Daubechies wavelet transform signals has been decomposed till six levels. The energy of six detailed signals that obtained by wavelet transform are used for training and trailing LVQ Neural Network. Results show that the proposed procedure is efficient in identifying Ferroresonance from other events.

KEY WORDS
Ferroresonance, LVQ Neural Network, EMTP program, Wavelet transform

1. Introduction

Wavelet transform(WT) has been introduced rather recently in mathematics. It is linear transformation much like the Fourier transform, however it allows time localization of differences frequency components of a given signals; Short Time Fourier Transform(STFT) also partially achieves the same goal, but the fixed width windowing function is a limitation. In the case of wavelet transform, the analyzing functions called wavelets, will adjust the time width to the frequency in such a way that high frequency wavelets will be very narrow and lower frequency ones will be broader. In the area of power quality, several studies have been carried out to detect and locate disturbances using the wavelet transform as an useful tool to analyze interferences, impulses, notches, glitches, interruptions, harmonic, flickers, etc. of non stationary signals. [1,2] present an improvement to eliminate the effect of imperfect frequency respond of the filters in WT filter banks, and to better analyze sub-harmonics. [3-8] present a similar approach for harmonics and flicker analysis, respectively. Other similar work using different mother wavelets is presented in [5]. [2] describes harmonic analysis with a trapezoid complex wavelet function and the associated trapezoid WT. [9,10] show a flicker analysis using the Morlet and Gaussian continuous WT. Several works have been developed in many areas with aim of this tool, specially, in the last ten years have been met the potential benefits of applying WT to power systems due to, among other , the interested in analyzing and processing the voltage-current signals in order to make a real time indentification of transients in a fast and accurate way. High impedance fault identification [11-13] is other application area of wavelet transform, for example, [13] presents a comparative analysis for arc fault time location, the author demonstrates that the wavelet approach is strongly affected by the choice of a wavelet family, decomposition level, sample rate and arcing fault behavior. In this paper LVQ network and wavelet transform are used to detection of Ferroresonance form other transient events. LVQ network classifies input vector by a competitive layer for determining the sub-classes, and then composition sub-classes in target classes by linear layer. In spite of Perceptron networks that able to classify only linear distinct vectors, LVQ network can classify every input vectors, only if the competitive layer have enough neurons. In high frequencies, wavelet transform has a good time resolution and a weak frequency resolution. on the contrary, in low frequencies, it has a good frequency resolution and a weak time resolution. This property is useful about signals with high frequencies in short-time domains and low frequencies in long-time domains.

2. Ferroresonance phenomenon

Ferroresonance is a term in witch for description of resonance in a circuit with at least one non-linear inductive element. A Ferroresonance circuit includes series combination of saturable inductor, capacitor and linear resistor. The resonance in witch happens in circuits with saturable reactors is called Ferroresonance. In fact Ferroresonance is a non-linear event, so many ways used to analysis this event are based on time-domain analysis and using EMTP program. Ferroresonance has decaying effects on transformers and other equipments. Some of those effects are as follow: creating high voltages and currents, and disfigurement in voltage and current waveforms. For this reasons, the detection of Ferroresonance from other transients is very important.

In this paper a new algorithm is used for detection of this event. By this algorithm we can predict some possibilities in happening Ferroresonance and so we can face it with making some relays that shown in Fig.1.

3. Obtaining the signals

In order to obtain the signals, a part of a 20kV feeder has been selected in Qeshm island which is illustrated in Fig.1 [14]. These signals include: Ferroresonance, capacitor switching, load switching, and transformer switching signals. The models determined to be simulated by the EMTP program are, p and load frequency model (CIGRE), for line and load respectively, saturable model is used for all transformers. The inductor with hystersis loop of TYPE 96 was used for modeling hystersis loop in EMTP, which was connected to the outlet magnetizing branch of the transformer. The magnetization curve of transformers is illustrated in Fig.3. Feeder information is provided in the appendix. All kind of Ferroresonance that different parameters such as switching types, transformer connection type, hystersis phenomenon, line capacitance feature, line length and load impact which can be influential in the occurance of this phenomenon have been simulated. Fig. 4 illustrates a type of Ferroresonance which has been simulated by the EMTP. Different types of capacitor switching have been obtained through the switching of the two capacitor banks of the feeder in various forms. For example first capacitor bank was firstly switched, then the second one, next both at a time, and other forms can be achieved through the switching of one of the capacitor bank and then by switching a part of the feeder; an example is provided in Fig.5. For simulating different types of load switching, we switch the loads in different arrangements. For example, we firstly switch them one at a time, then two at a time, and other arrangements can be achieved by switching one or two of the loads with a part of the feeder. Thus, different signals are obtained. An example of which is provided in Fig.6. For simulating the transformer switching signals, we switch the transformers in different orders. For example, we switch the transformers one at a time, then two at a time, and different types can be achieved by switching one or two of the transformers with a part of the feeder. Thus, different signals are obtained. An example of which is provided in Fig.7. This way, for each group of signals, 20 types can be obtained. Then we normalize (scale) them in the max-min range (0 to 1). This is very influential in the exact determination of the features and every pattern.

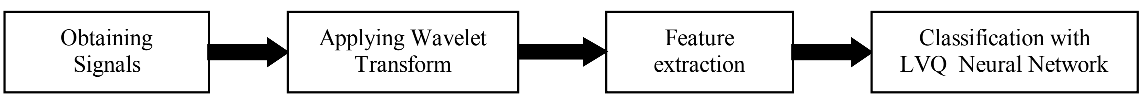


Fig. 1. Proposed algorithm

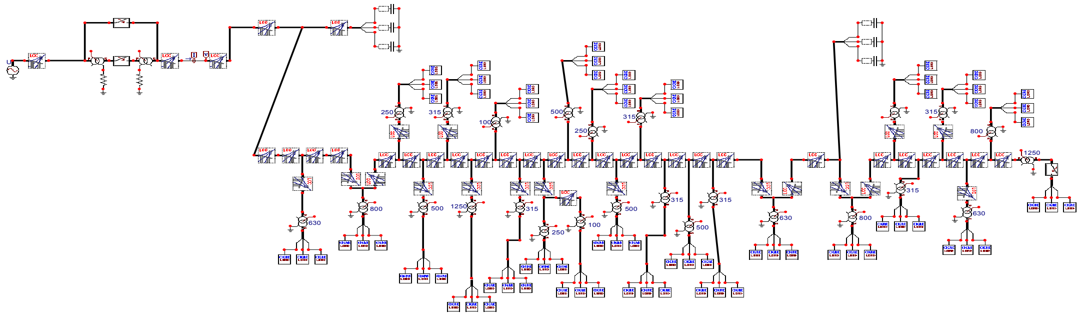


Fig. 2. 20kV Feeder

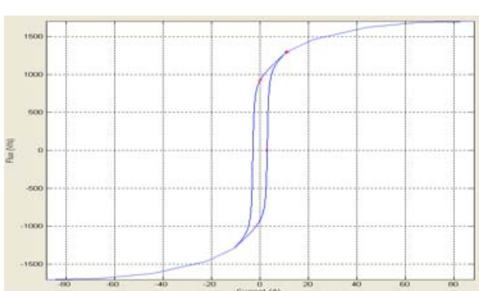


Fig. 3.Magnetizing curve

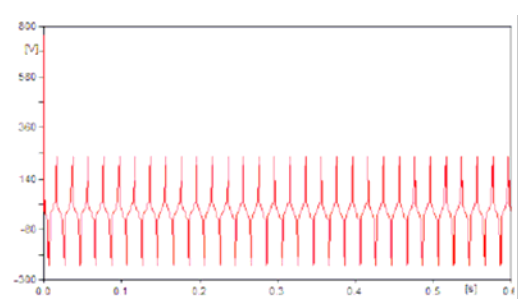


Fig. 4. An example of Ferroresonance

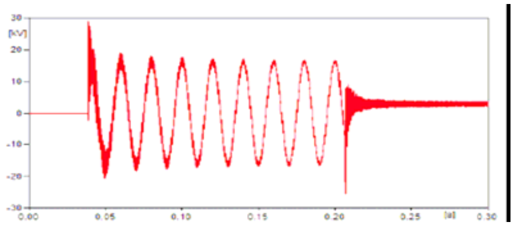


Fig. 5. An example of Capacitor switching

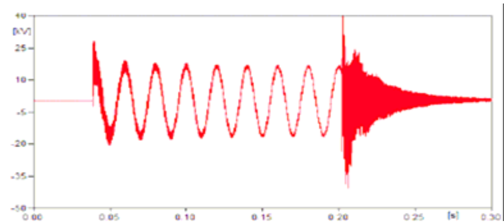


Fig. 6. An example of Load switching

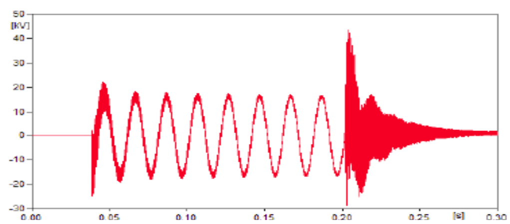


Fig. 7. An example of Transformer switching

4. Wavelet Transform

Wavelet transform (WT) was introduced by J Morlet at the beginning of 1985 and has attracted much interest in the fields of speech and image processing. Applications of DWT in power systems are reported for:

- Power system transients [15].
- Power quality assessment [16].
- Modeling of system component in wavelet domain [17].

In this section an introduction to wavelet transform is presented. More details can be found in [18],[19]. The WT was developed as an alternative to the short time Fourier Transform (STFT) to overcome problems related to its frequency and time resolution properties. More specifically, unlike the STFT that provides uniform time resolution for all frequencies, the DWT provides high time resolution and low frequency resolution for high frequencies and high frequency resolution and low time resolution for low frequencies. The DWT is a special case of the WT that provides a compact representation of a signal in time and frequency that can be computed efficiently. The DWT is defined by the following equation:

$$W(j,K) = \sum_{j} \sum_{k} x(k) 2^{-j/2} \varphi(2^{-j} n - k) \qquad (1)$$

where f(t) is a time function with finite energy and fast decay called the mother wavelet. The DWT analysis can be performed using a fast, pyramidal algorithm related to multi rate filter banks. As a multi rate filter bank DWT can be viewed as a constant Q filter bank with octave spacing between the centers of the filters. Each sub band contains half the samples of the neighboring higher frequency sub band. In the pyramidal algorithm the signal is analyzed at different frequency bands with different resolution by decomposing the signal into a coarse approximation and detail information. The coarse approximation is then further decomposed using the same wavelet decomposition step. This is achieved by successive high pass and low pass filtering of the time domain signal and is defined by the following equations: where y [k] high and y [k] low are the outputs of the high pass (g) and low pass (h) filters, respectively after sub sampling by 2. Down sampling the number of resulting wavelet coefficients becomes exactly the same as the number of input points. A variety of different wavelet families have been proposed in the literature. The choice of mother wavelet plays a significant role in time frequency analysis. It also depends on a particular application. In this work all wavelets available in the Wavelet Toolbox of MATLAB program [20] were used for the decomposition of the signals and the best answer was obtained with Daubechies mother wavelet. It was found to have the most correlation with the decomposed signals and was selected for this procedure.

4.1 Applying Wavelet Transform and feature extraction

The decomposition is done by modifying the wavelet transform through passing the signal via a digital half band low pass filter. This digital half band low pass filter excludes all the signals which are higher than the half of the value of the largest signal frequency. If a signal having nyquist rate(which is twice the largest frequency in the signal) was taken as a sample, the largest frequency present in the signal would be p radian. That is, nyquist frequency in the range of discreet frequency corresponds p (rad/s). After a signal passes through a digital half band low pass filter, according to the theory of nyquist, half of the signals can be excluded, for now the signal has the maximum frequency of p/2 (rad/s). Thus the obtained signal has a length half of that of the original one. This procedure is repeated for 6 times and the signals omitted by the low pass filter at each time, are considered as detail signals. The energies of these detail signals, are the features extracted from the patterns to feed into the neural network. In Fig.8 a Ferroresonance pattern with 6 detail signals and an approximation signal obtained by applying the Db wavelet transform up to six levels is illustrated. According to the definition, the energy of every discreet signal such as x (n) is defined as follows: (N equals the length of the signal)

$$E(x) = \sum_{n=<N>} |x(n)|^2 \quad (2)$$

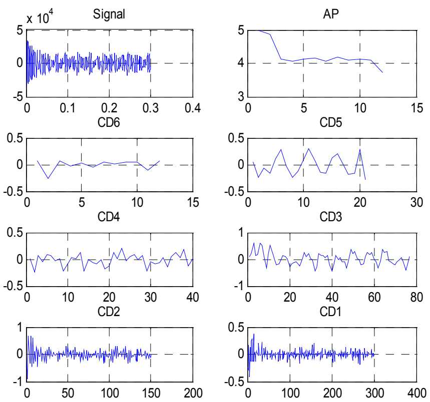


Fig. 8.Decomposition of Ferrosonance by Daubechies mother wavelet

5. LVQ Neural Network

The LVQ network architecture [21] is shown in Fig.9. LVQ network has a first competitive layer and a second linear layer. The competitive layer learns to classify input vectors in much the same way as the competitive layers of

Self-Organizing and LVQ Network described in this chapter. The linear layer transforms the competitive layer's classes into target classifications defined by the user. We refer to the classes learned by the competitive layer as subclasses and the classes of the linear layer as target classes. Both the competitive and linear layers have one neuron per (sub or target) class. Thus, the competitive layer can learn up to S1 subclasses. These, in turn, are combined by the linear layer to form S2 target classes. (S1 is always larger than S2). In Fig.8 P is input vector with R elements and IW1,1 is the weights matrix of neurons in competitive layer . Each row in this matrix is the weights of one neuron. ||ndist|| block computes the distance of input vector P from weight vectors of each neuron. Thus if the number of competitive layer neurons were S1, then IW1,1 is S1 by R matrix. In this case the ||ndist|| output, that determined by n1 in Figure, is an s1 element vector that each element is the distance of input to one neuron. The C block is a competitive function that its output (a1) is a vector with one element equal 1 and others equal 0. the element that equals 1, determines the input subclass. In linear layer, the target class is determined. The neurons number in linear layer is equal to target classes number. The LW2,1 block with elements equal to 1 or 0, is the neurons weight matrix in linear layer. This layer determines the subclasses of each target class. For example, suppose neurons 1, 2, and 3 in the competitive layer all learn subclasses of the input space that belongs to the linear layer target class No.2. Then competitive neurons 1, 2, and 3, will have LW2,1 weights of 1.0 to neuron n2 in the linear layer, and weights of 0 to all other linear neurons. Thus, the linear neuron produces a1 if any of the three competitive neurons (1,2, and 3) wins the competition and output a1. This is how the subclasses of the competitive layer are combined into target classes in the linear layer. We know ahead of time what fraction of the layer 1 neurons should be classified into the various class outputs of layer 2, so we can specify the elements of LW2,1 at the start.

5.1 LVQ Learning Rule

LVQ learning in the competitive layer is based on a set of input/target pairs.

$$\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\} \quad (3)$$

Each target vector has a single 1. The rest of its elements are 0. The 1 tells the proper classification of the associated input. To train the network, an input vector p is presented, and the distance from p to each row of the input weight matrix IW1,1 is computed with the function ||ndist||. The hidden neurons of layer 1 compete. Suppose that the ith element of n1 is most positive, and ith neuron wins the competition. Then the competitive transfer function produces a1 as the ith element of a1. All other elements of a1 are 0. When a1 is multiplied by the layer 2 weights LW2,1, the single 1 in a1 selects the class, k associated with the input. Thus, the network has assigned the input vector p to class k and a2k will be 1. Of course, this assignment may be a good one or a bad one, for tk may be 1 or 0, depending on whether the input belongs to class k or not. We adjust the ith row of IW1,1 in such a way as to move this row closer to the input vector p if the assignment is correct, and to move the row away from p if the assignment is incorrect. So if p is classified correctly:

$$a^2{}_k = t_k = 1$$

we compute the new value of the ith row of IW1,1 as:

$$IW_i^{1,1}(q) = IW_i^{1,1}(q-1) + \alpha(p(q) - IW_i^{1,1}(q-1)) \quad (4)$$

On the other hand, if p is classified incorrectly,

$$a^2{}_k = 1 \neq t_k = 0$$

we compute the new value of the ith row of IW1,1 as:

$$IW_i^{1,1}(q) = IW_i^{1,1}(q-1) - \alpha(p(q) - IW_i^{1,1}(q-1)) \quad (5)$$

These corrections to the ith row of IW1,1 can be made automatically without affecting other rows of IW1,1 by backpropagating the output errors back to layer 1. Such corrections move the hidden neuron towards vectors that fall into the class for which it forms a subclass, and away from vectors that fall into other classes.

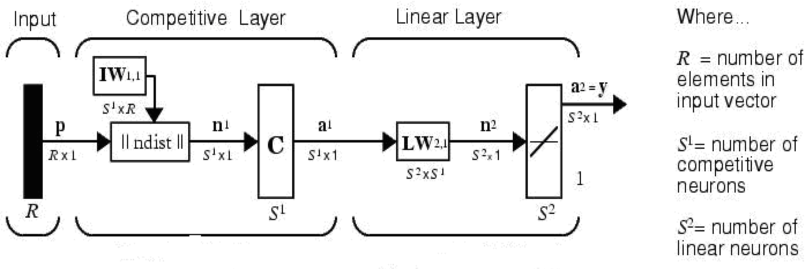


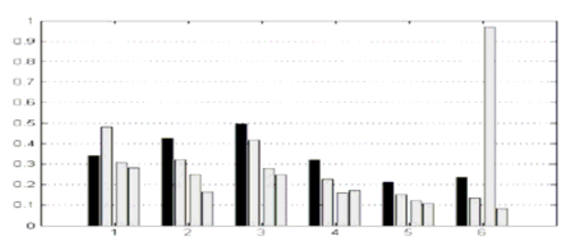
Fig. 9. LVQ Neural Network

6. Simulation Results

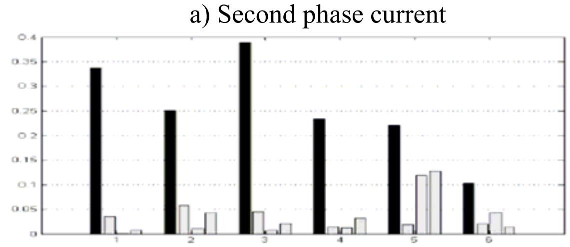
The obtained signals were analyzed by the Daubechies mother wavelet and the energies of the detail signals obtained through the applying wavelet transform up to six levels have been used as the features fed into the neural network. For the LVQ neural network, 8 neurons are determined in the hidden layer, two of which are allocated to Ferroresonance signals and the rest to capacitor switching, load switching, and transformer switching signals. For training the network all four types of signals are used; 15 signals for learning and 10 for testing. Also the learning rate of the neural network is 0.0001 and the number of epochs is selected 250. The Daubechies wavelet transform is enforced in all the three phases of current and voltage signals and the competitive neural network. The results are provided in table1. It should be noted that the currents and the voltages are the primary currents and voltages of the feeder shown in Fig1. By applying the Db1 in the second phase current of the signals, the neural network has the least precisian of 61.66% and by applying the Db2 in the third phase voltage of the signals, neural network shows the most precisian of 95%. The above results can be justified using Fig.10. This Figure compares the average of the components correspondent to the feature vectors extracted by applying Db1 and Db2 in the second phase current and the third phase voltage of signals, respectively.(the rectangles corresponding the Ferroresonance signals are darker.) According to the Figure, the features extracted by applying Db1 in the second phase current are much similar. Thus the precision of algorithm is less in this case. But the features exacted by the applying Db2 in the third phase voltage are least similar. Thus the precision of algorithm is more in this case. The above results can be justified using Fig.11,too. The instantaneous energy of second phase current of signals are much similar. Thus the precision of algorithm is less in this case and the instantaneous energy of third phase voltage of signals are less similar. Thus the precision of algorithm is more in this case.

Table 1. Percentage of NN identification

Signal	WT	Percentage of NN identification
First phase current	Db1	75%
First phase current	Db2	80%
First phase current	Db3	75%
Third phase current	Db2	80%
Second phase current	Db1	61.66%
Second phase current	Db2	83.3%
Second phase current	Db3	83.33%
Second phase voltage	Db6	83.33%
Third phase voltage	Db4	86.65%
Third phase voltage	Db2	95%
Third phase voltage	Db3	90%

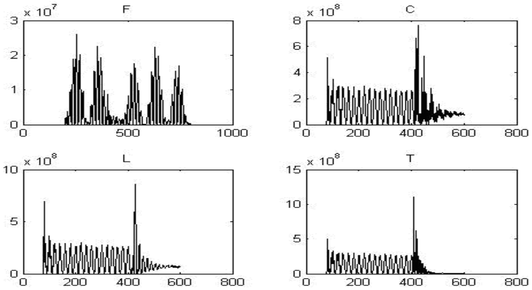


a) Second phase current

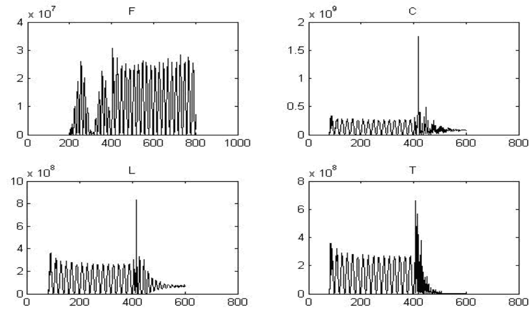


b) Third phase voltage

Fig.10. comparision of the average of the components correspondent to the feature-vectors extracted by applying Db wavelet in second phase current and third phase current of the four groups of the signals when normalized. The four-membered groups from left to right are related to the first to sixth features. In each group, the rectangle respectively refers to Ferroresonance, capacitor switching, load switching and transformer switching



a) Second phase current



b) Third phase voltage

Fig.11. The instantaneous energy of signals (F=Ferroresonance,C=CapacitorSwitching,L=Load switching,T=Transformer switching)

7. Conclusion

The presented algorithm has the highest precision on third phase signal of voltage and lowest precision on the third phase signal of current. One of the main advantages of this algorithm is capability of changing the number of extracted features by changing the number of wavelet transform levels. Also the chosen network has the ability to classifying the nonlinear feature vectors in multi-dimension space. By increasing complexity, only the number of hidden layer neurons should be increased. The applied network has an acceptable precision in the recognition of unused patterns for learning. This fact highlights the practical importance of algorithm.

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Appendix

Table 2 Load data

No.	I_a(A)	I_b(A)	I_c(A)	I_n(A)	Capacity of connected transformers(KVA)
1	115	78	110	90	630
2	295	200	220	165	800
3	40	60	55	0	500
4	200	250	220	0	1250
5	40	40	40	8	315
6	20	25	25	10	250
7	80	50	40	0	100
8	85	40	70	40	500
9	145	130	120	40	315
10	205	180	205	65	500
11	125	100	105	25	630
12	30	60	50	20	800
13	65	55	55	25	315
14	155	140	105	99	630
15	60	55	55	17	250
16	33	57	45	32	315
17	5	20	20	15	100
18	60	65	75	25	500
19	25	65	60	35	250
20	80	85	75	28	315
21	15	15	15	5	100
22	175	130	145	45	315
23	165	175	150	55	800
24	125	150	150	45	1250

A. The data of feeder

R = 0.509 Ω/km, X = 0.3561 Ω/km
Outside Radius of conductor = 0.549 cm

B.Configuration of phases and mechanical data
Height of pole = 12 m
Sag in mid span = 2.32 m

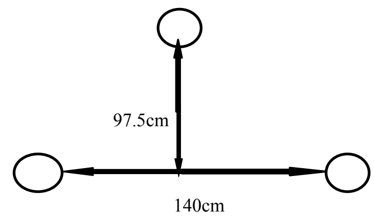

Fig12.Configuration of phases and mechanical data

C.Constant parameters of the CIGRE load model usually considered in the EMTP program are the following:
A = 0.073, B = 6.7, C = 0.74

Table 3 Transformer data

No	S(KVA)	Connection	N_1/N_2	UK%	P_{oc}(W)	In1%	P_{sc}(W)
1	3000	Yd1	63/20kv	14	22410	2.83	151247
2	1250	Dy5	20/0.4kv	6	2100	1.4	16400
3	1000	Dy5	20/0.4kv	6	1750	1.4	13500
4	800	Dy5	20/0.4kv	6	1450	1.5	11000
5	630	Dy5	20/0.4kv	6	1200	1.6	9300
6	500	Dy5	20/0.4kv	6	1000	1.7	7800
7	400	Dy5	20/0.4kv	6	850	1.8	6450
8	315	Dy5	20/0.4kv	6	720	2	5400
9	250	Dy5	20/0.4kv	6	650	2.3	4450
10	100	Dy5	20/0.4kv	6	340	2.6	2150
11	50	Dy5	20/0.4kv	6	210	2.8	1250