Journal of Advances in Computer Research
Quarterly pISSN: 2345-606x eISSN: 2345-6078
Sari Branch, Islamic Azad University, Sari, I.R.Iran
(Vol. 7, No. 1, February 2016), Pages: 101-116
www.jacr.iausari.ac.ir

Load and Harmonic Forecasting for Optimal Transformer Loading and Life Time by Artificial Neural Network

S.Mohammad Bagher Sadati✉[1], **Jamal Moshtagh**[1], **Abdollah Rastgou**[2]

1) Department of Electrical and Computer Engineering, University of Kurdistan, Sanandaj, PO Box 416, Kurdistan, Iran.

2) Faculty of Electrical and Electronics, Kermanshah Branch, Islamic Azad University, Kermanshah, Iran.

bagher_sadati@yahoo.com; j.moshtagh@uok.ac.ir; abdollah.rastgo@gmail.com

Received: 2015/05/10; Accepted: 2015/08/02

Abstract

Proper operations of transformer have several issues such as; preventing of unscheduled removal's, increasing of reliability and continues supply of consumer demand. This result would be obtained that load and harmonic orders of sensitivity transformer at intervals appropriate for next hours and days is predicted to by selecting optimal utilization coefficient, reduction life of transformer is prevented. A possible solution for load and harmonic orders forecasting is implementation of heuristically algorithm and method such as Artificial Neural Network (ANN). In this paper, firstly relationship between transformer loss and life and effect of harmonic on its, is evaluated. Then by ANN method, load and harmonic orders of 400KVA distribution transformer is predicted. Then by using of existing standards and programs written in MATLAB environment, Load ability or optimal utilization coefficient and life of transformer is calculated.

Keywords: *Artificial Neural Network. Transformer Loss and Life, Load Ability, Harmonic Orders.*

1. Introduction

Transformers are one of the most important and strategic equipment in distribution systems, so that the end of 2014 in Iran about 594000 set by 104618 MVA capacities are installed [1]. Proper operations of transformer can be caused preventing of unscheduled removal's, increasing of reliability and continues supply of consumer demand.

Transformers are normally designed and built for utilizing at rated frequency and prefect sinusoidal loads. The significance of harmonics in power systems and distribution networks has increased substantially due to the use of solid state controlled loads and other high frequency producing devices. Increase in load current harmonic content causes additional losses in the coils and thus, overall network losses growth and also hot spot temperature growth and the useful life reduction in transformers.

Temperature rise of transformers due to non-sinusoidal load currents was discussed in IEEE Transformer Committee in March 1980. This meeting Recommended providing a standard guidance for estimation of the loading capacity of the transformers with distorted currents. Finally, a standard IEEE C57-110 entitled "recommended procedure for determination of the transformer capacity under non-sinusoidal loads". The aim in publishing this standard was providing a procedure for determination of the capacity of a transformer under non- Sinusoidal loads. This procedure determines the level of decreasing the rated current for risen harmonic [2].However; unfortunately this Standard is not implemented in IRANs Power Distribution system and annual due to not defining of optimal utilization coefficients, many distribution transformers is damaged.

In [3-6], transformer losses relations and the impact of harmonics on transformer losses are expressed. A suitable model of transformer in harmonic conditions is presented. Also the losses of an oil-filled transformer with simulation in MATLAB/SIMULINK environment under a sample harmonic load have been calculated. In [7-11], the oil-filled transformer derating under harmonic condition by using Finite Element Method has been calculated.

Also in [12], transformers life relations and the impact of harmonics on transformer life are expressed, and then the useful life of two oil-filled transformers has been calculated according to their loading measurements. Also, Load ability of transformers in different environmental temperature has been calculated. In addition in [13], a distribution transformer life has been estimated using two dimensional finite element method. Results show that with increasing in current THD and harmonics, the transformer useful life will be decreased drastically.

Also many papers have been focused on neural networks for load forecasting. In [14] compare of two techniques i.e. artificial neural networks (ANN) and fuzzy logic (FL) for short term load forecasting is done. The simulation results clearly are shown that the ANN model produces significantly better results than FL method. A multi-layer perceptron ANN, based on a back propagation algorithm with loads, data concerning the type of day, time of the day and weather data as inputs, has been proposed for forecasting the day-ahead load consumption [15-16]. Results proved to be satisfactory with reasonable errors in terms of Mean Absolute Percentage Error (MAPE). In [17] several different models, which use different input variables as follows, have been presented:

1- Forecast with Load (F_L)
2- Forecast with Load and Working/non-Working (F_L_W)
3- Forecast with Load, Working/non-Working and Day of the week (F_L_W_DW)
4- Forecast with Load, Working/non-Working and Month (F_L_W_M)

Result shown that the most accurate model is F_L_W_M, which uses the following variables: load profile, workability and month.

For influence of real-time electricity market on short-term load, a model to forecast short term load is established by combining the artificial neural network with the adaptive neural fuzzy inference system (ANFIS) [18]. The experimental evaluations have demonstrated calculation accuracy, strong practicability, feasibility, and effectiveness of the proposed load forecasting scheme.

In [19] is dedicated to tackle the problem of energy consumption forecasts, using ANN, based in a 18 months long comprehensive set of data obtained from monitoring the energy consumption of 93 real households with a 15 mn granularity, in Lisbon. The paper introduced the ANN technique for modeling energy consumption for a random day, the next hours (until 3th day), using a Boolean metering system. The energy consumption and electric load profiles have been determined using several weeks, including both weekdays and weekend. Support Vector Machines (SVM) and neural network techniques are surveyed in [20], along with an exploration of the effects of combining the two techniques for purposes of load forecasting. The authors conclude that a combination of the two results in better performance than using each individually.

In [21] is present a practical neural network-based ensemble model for day-ahead building-level electricity load forecasting and show that it outperforms the previously established best performing model, SARIMA (Seasonal Auto Regressive Moving Average), by up to 50%, in the context of load data from half a dozen operational commercial and industrial sites. However, the comparisons are made only with SARIMA model, which is a linear statistical model, which may not be capable of capturing high nonlinearity of the building-level electricity load.[22] is applied a Self-Recurrent Wavelet Neural Network (SRWNN) forecasting engine for electricity load prediction of micro-grids. Moreover, the Levenberg-Marquardt (LM) learning algorithm is implemented to train the SRWNN.The proposed method improves the forecast accuracy for highly volatile and non-smooth time series of micro-grid electricity load.

In [23], a model based on three levels has been presented for short-term load forecasting in micro grids: a pattern recognition to classify with SOM (self-organizing map), a clustering with k-means algorithm, and finally an MLP model for each of the clusters obtained in the clustering process. The model produces low errors compared to other simple models that are not specialized by means of classification and clustering. The capability of the hybrid quantized Elman neural network (HQENN) model for short-term load forecasting is studied in [24]. For the structure, the quantum map layer is employed to address the quantized load pattern mismatch between the input layer and the hidden layer. Result is shown that the proposed approach employing the quantum techniques can provide a higher accuracy of the short term power load forecasting.

In [25], the hybrid networks which is a combination of neural network with stochastic learning techniques such as Back Propagation (BP) Algorithm, genetic algorithm (GA), particle swarm optimization (PSO) etc. which has been successfully applied for short term load forecasting is discussed thoroughly.

According to many studies about the effects of harmonics on transformers and Load forecasting with ANNs every year, but hasn't been research for determining of optimal utilization coefficient of transformer by forecasting load and harmonic orders. In this paper for forecasting load; times, electrical load and are pervious and present temperature information are good inputs for proposed ANNs. So the rest of the paper is organized as follows. Section 2 and 3 discusses about transformer losses and life in harmonic condition, respectively. Artificial Neural Networks and proposed method is defined in section 4. In section 5, Electrical load of a 400 KVA transformer that installed in the MAZANDARAN distribution company, by using C.A.8310 Power Analyzer for four days, is measured. In Section 6 the general trend of calculation of optimal utilization coefficient and life of transformer based on ANNs is defined. In this section by load and harmonic forecasting with ANNs the life and load ability of transformer is calculated. Also we report our result in section 7.

2. Transformer losses in harmonic load

Transformer losses consist of no-load or core losses and load losses. This can be expressed by equation 1[2-4].

$$P_T = P_{NL} + P_{LL} \tag{1}$$

Where, P_{NL} is no-load loss, P_{LL} is load loss, P_T is total loss. No-load loss is due to the induced voltage in core. Load losses consist of ohmic loss, eddy current loss, and other stray loss, or in equation form:

$$P_{LL} = P_{dc} + P_{EC} + P_{OSL} \tag{2}$$

Where, P_{dc} is loss due to load current and dc resistance of the windings, P_{EC} is winding eddy loss, P_{OSL} is other stray losses in clamps, tanks, etc. Pdc is calculated by measuring the dc resistance of the winding and multiplying it by the square of the load current. The stray losses can be further divided into winding eddy losses and structural part stray losses. Winding eddy losses consist of eddy current losses and circulating current losses, which are considered to be winding eddy current losses. Other stray losses are due to losses in structures other than windings, such as clamps, tank or enclosure walls, etc.

The total stray losses are determined by subtracting dc losses from the load losses measured during the impedance test. In many references, total starry losses are 30% of load losses.

$$P_{TSL} = P_{EC} + P_{OSL} = P_{LL} - P_{dc} = 0.3 \times P_{LL} \tag{3}$$

Most power systems and distribution networks, the harmonic distortion of the system voltage is well below 5% unless there is excessive harmonic loading or a resonance condition. The frequency of the applied voltage is predominantly fundamental or designs frequency, so the no-load loss should be close to the design values. Load current harmonics passing through the transformer do not significantly affect the no-load losses of the transformer. The losses components get affected by the harmonic load current are the I2R loss, winding eddy current loss and the other stray loss [2-4].

If the rms value of the load current is increased because of harmonic component, the I^2R loss will be increased accordingly. Winding eddy current loss in the power frequency spectrum tends to be proportional to the square of the load current and the square of frequency. Under harmonic loads, eddy current loss of windings multiply by harmonic loss factor i.e. F_{HL}. Other stray loss in the core, clamps, and structural parts will also increase at a rate proportional to the square of the load current. The studies of manufacturers and other researchers have shown that the eddy current loss in bus bars, connecting and structural parts increase by a harmonic exponent factor of 0.8 or less. Under harmonic loads, other stray losses multiply by harmonic loss factor of stray loss i.e. $F_{HL\text{-}STR}$ [8-10]. So transformers losses in harmonic load are expressed by below equation.

$$P_{LL} = \sum_{h=1}^{h=\max} \left(\frac{I_h}{I_1} \right)^2 \times \left[P_{dc} + F_{HL} \times P_{EC} + F_{HL-STR} \times P_{OSL} \right] \tag{4}$$

$$F_{HL} = \frac{\sum_{h=1}^{h=\max} h^2 \left(\frac{I_h}{I_1} \right)^2}{\sum_{h=1}^{h=\max} \left(\frac{I_h}{I_1} \right)^2} \tag{5}$$

$$F_{HL-STR} = \frac{\sum_{h=1}^{h=\max} \left[\frac{I_h}{I_1} \right]^2 h^{0.8}}{\sum_{h=1}^{h=\max} \left[\frac{I_h}{I_1} \right]^2} \tag{6}$$

3. Transformer losses of life in harmonic load

The heat generated within a transformer as a result of copper and core losses has to be dissipated away to keep the temperature rise within permissible limit for the class of insulation employed. Particularly, temperature of the hot spot of winding is a critical parameter. If the temperature rise goes beyond the permissible value, in order to preserve the insulation from deterioration, the load of transformer must be reduced or an auxiliary transformer is used.

The heat generated by the active parts of transformers such as windings, core, and also the heat generated by the eddy current in the inactive parts such as tank, yoke support parts, arm, and screw leads to temperature rise of the different parts of the transformer.

According to the IEEE standard, the permissible temperature of different parts of a transformer puts limit on the dimensions of transformer and this influences the loading capability and the operating conditions. Different cooling systems can be used based on the structure, capacity, and environment conditions of transformer.

So far, many researches have been done to estimate transformer life time that base on these researches is estimation of life time of transformer's insulation. The life time of transformer's insulation under electrical, mechanical, thermal and chemical stresses is reduced. But, thermal stresses have most influence [27-28]. In fact, reduction of transformer's life time is due to increase of temperature of hot spot of winding. Also, this temperature is impressed by harmonics and environment temperature [29]. Following equations show the way of life time calculation of transformer [2]:

$$\theta_{TO} = \theta_{TO-R} \left(\frac{P_{LL} + P_{NL}}{P_{LL-R} + P_{NL}} \right)^{0.8} \tag{7}$$

$$\theta_g = \theta_{g-R} \times \left(\frac{P_{LL}}{P_{LL-R}} \right)^{0.8} \tag{8}$$

$$\theta_H = \theta_{TO} + \theta_g + \theta_A \tag{9}$$

$$F_{AA} = \exp\left(\frac{15000}{383} - \frac{15000}{\theta_H + 273} \right) \tag{10}$$

$$\mathrm{Re}\mathit{al\ Life} = \frac{30}{F_{AA}} \tag{11}$$

In above equations, θ_g ,$\theta_{g\text{-}R}$,θ_{TO} ,$\theta_{TO\text{-}R}$,θ_A , θ_H ,F_{AA} are conductor hot spot temperature rise with respect to oil temperature, nominal conductor hot spot temperature rise with respect to oil temperature, oil temperature rise with respect to ambient temperature, nominal oil temperature rise with respect to ambient temperature, ambient or environment temperature, temperature of winding's hot spot, relative age factor, loss of life in percent and per-unit of life, respectively.

Real life time of a distribution transformer that its insulations have been dried well and average thermal mutation of windings is 65 degree, has been considered 30 years.

4. Artificial Neural Networks Overview

In recent years, much research has been conducted on the application of artificial intelligence techniques to load forecasting problems [26]. However, the models that have received the most extensive attention are undoubtedly the ANNs, cited among the most powerful computational tools ever developed. Fig. 1 presents an outline of a simple biological neural and an ANNs basic element. ANN models operate like a ‘‘black box’’, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previous data. ANN models can handle large and complex systems with many interrelated parameters. They simply seem to ignore excess data that are of minimal significance and concentrate instead on the more important inputs [30]. Several types of neural architectures are available, among which the multi-layer back propagation (BP) neural network is the most widely used. As Fig. 2 reveals, a BP network typically employs three or more layers for the architecture: an input layer, an output layer, and at least one hidden layer. The computational procedure of this network is described below:

$$Y_j = f\left(\sum_i w_{ij} X_{ij}\right) \qquad (12)$$

Where Y_j is the output of node j, f the transfer function, w_{ij} the connection weight between node j and node i in the lower layer and Xi the input signal from the node i in the lower layer.

The BP algorithm is a gradient descent algorithm. It tries to improve the performance of the neural network by reducing the total error by changing the weights along its gradient. The BP algorithm minimizes the square errors, which can be calculated by:

$$E = \frac{1}{2}\sum_p \sum_j [O_j^p - Y_j^p]^2 \qquad (13)$$

Where E is the square errors, p the index of pattern, O the actual (target) output and Y the network output.

The BP algorithm is based on a steepest descent technique with a momentum weight/bias function, which calculates the weight change for a given neuron. It is expressed as follows [31]: let $\Delta w_{ij}^p(n)$ denote the synaptic weight connecting the output of neuron i to the input of neuron j in the p_{th} layer at iteration n. The adjustment $\Delta w_{ij}^p(n)$ to $w_{ij}^p(n)$ is given by:

$$\Delta w_{ij}^p(n) = -\eta(n)\frac{\partial E(n)}{\partial w_{ij}^p} \qquad (14)$$

Where $\eta(n)$ is the learning rate parameter. By using the chain rule of differentiation, the weight of the network with the BP learning rule is updated using the following formulae:

$$\begin{aligned}\Delta w_{ij}^{p}(n) &= \eta(n)\delta_j^{p}(n)X_i^{p-1}(n) + m(n)\Delta w_{ij}^{p}(n-1)\\ \Delta w_{ij}^{p}(n+1) &= w_{ij}^{p}(n) + \Delta w_{ij}^{p}(n)\end{aligned} \tag{15}$$

Where $\delta_j^{p}(n)$ is the nth error signal at the j_{th} neuron in the p_{th} layer, $X_i^{p-1}(n)$ is the output signal of neuron i at the layer below and m is the momentum factor. The constant terms of □ and m are specified at the start of the training cycle and determine the speed and stability of the network. In brief, the procedure to set up a BP network is:

1. Select input and define output variables.
2. Determine layer(s) and the number of neurons in hidden layers. No hard rule is available for determining them, which may depend on trial and error.
3. Learning (or training) from historical data. Learning is the process by which a neural network modifies its weights in response to external inputs in order to minimize the global error. The equation that specifies this change is called the learning rule.
4. Testing. When a neural network is well trained after learning, the neural networks are processed via a test set containing historical data that the network has never seen. If the testing results are in an acceptable range, the network can be considered as fully trained. The next step can then be performed.
5. Recalling. Recalling refers to how the network processes a driving force from its input layer and creates a response at the output layer. Recalling does not do any learning and expects no desired outputs.

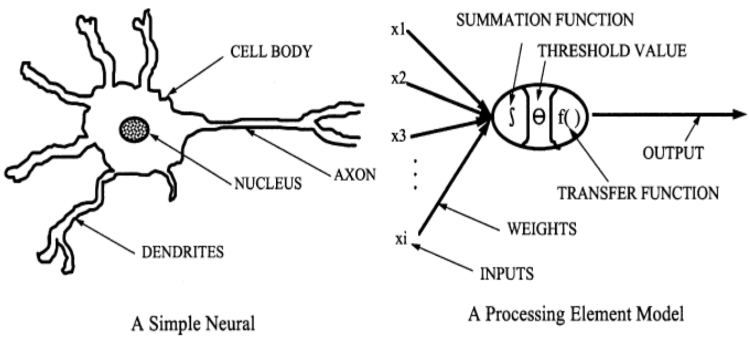

Figure 1. A simple neural vs. a PE model

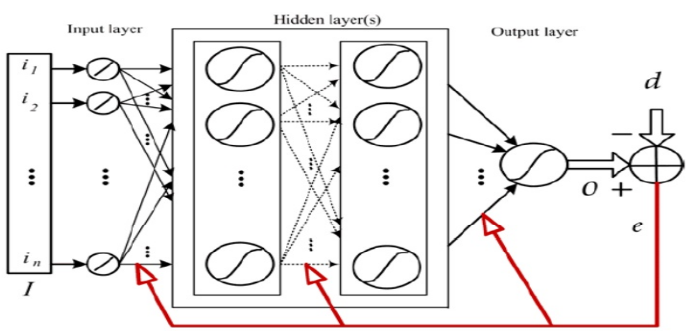

Figure 2. Back Propagation networks

For forecasting load; times, electrical load and weather information are good inputs. Time information divided to season, day and peak hours. Load information contain pervious electrical load and peak loads. Also future and pervious temperature, humidity and etc are weather information. So temperature has an effective role in electrical demand and two inputs in ANNs are pervious and present temperature. Actually at first by an ANNs weather is predicted.

A Block diagram of the proposed neural network in this paper is shown in figure 3. Neural networks designed for this purpose, a network with three layers is assumed. The first layer is the input layer. Second layer is hidden layer so that initially starts by small number of neurons for determination of hidden layer neurons and then gradually increase it until the end of the teaching process. The appropriate number of neurons in the hidden layer is selected based on the teaching and learning outcomes. The third layer is the output layer.

Training is done on a daily and results are determined for each hour of the next days. In each day, load is forecasted for tomorrow and this information is stored by NNs. When actual load is accessed, difference between actual and forecasted loads per hour is calculated and neural network weights are updated regularly based on the latest information. For example electrical load of second day are consider as pervious load inputs for load forecasting of third day. When actual third load is accessed new weight in this stage by forecasting and actual third load is obtained and prediction of four days with new weight and related inputs is done.

Transfer functions in hidden and output layers are sigmoid and linear, respectively. Learning rate is 0.5 and the number of repetitions for training of network is selected 600. The criterion for stopping training of neural network based on the error produced by NNs is defined. For identification of errors, absolute percentage error (APE) and the mean absolute percentage error (MAPE) are defined. So that:

$$APE = \frac{\left|Load_{forecast} - Load_{actual}\right|}{Load_{actual}} \times 100$$
$$MAPE = \frac{1}{N_h}\sum_{N_h} APE \qquad (16)$$

In the above equation, N_h is the hours of prediction period. If MAPE calculated is more than 3%, others teaching is needed. This process is continued until all the MAPE obtained for weight training is less than 3%.

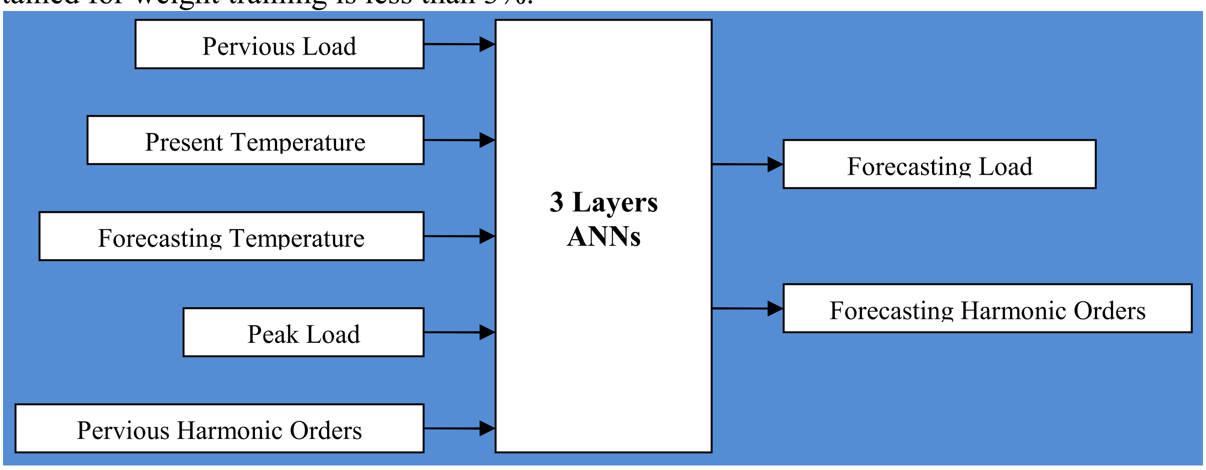

Figure 3. Block diagram for proposed ANNs

5. Measurements and Experimental Tests

In order to sample the transformer load a power analyzer C.A8310 is used. Some of various ability of this device is as fallow:

1. store the three phase current and voltage waveforms
2. measure the rms value of phase and line voltage and current
3. measure the active and reactive and apparent power of each phase
4. measure the voltage and current harmonic order up to 25th order
5. measure the THD_v and THD_i

The device was installed in the output of 400 KVA oil-field transformers for four days and data have been recorded with time interval 1 hour. The transformer feed a commercial area in the city of sari. Power Log software has been used to transfer the data stored in the instrument to the laptop. Fig. 4 shows 400 KVA distribution transformers. Fig. 5 shows the C.A8310 power analyzer. Fig 6 and 7, effective value of current of one phase and orders of its harmonics in 400 kVA transformer have been shown, respectively.

Figure 4. The picture of 400 kVA distribution transformer

Figure5. Power analyzer C.A8310

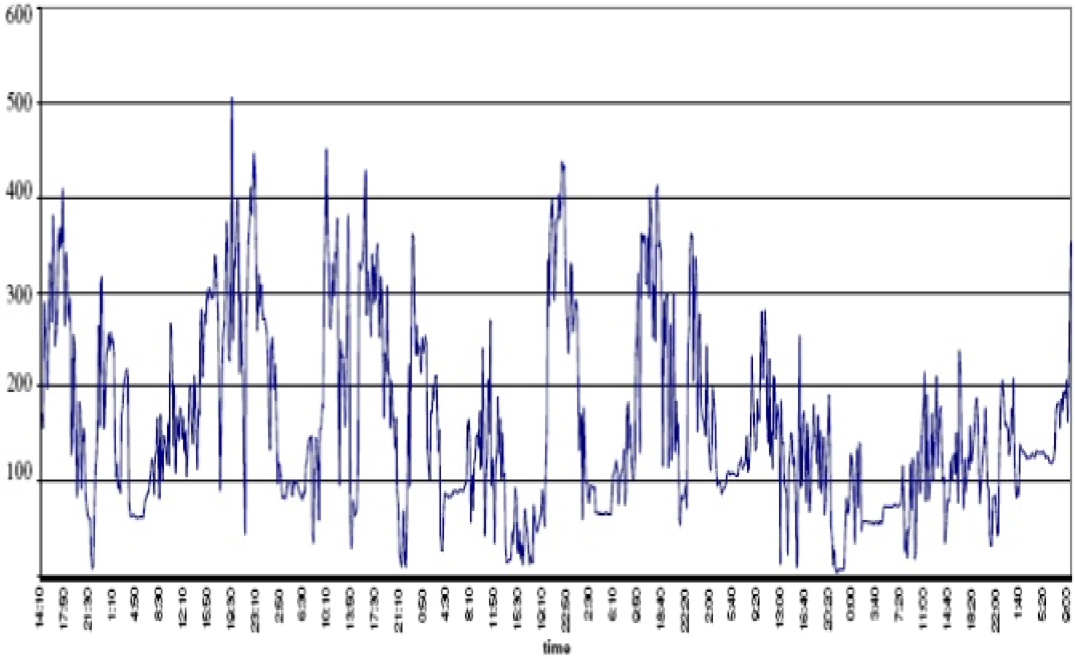

Figure 6. Sampled effective current in one phase of 400 kVA transformer

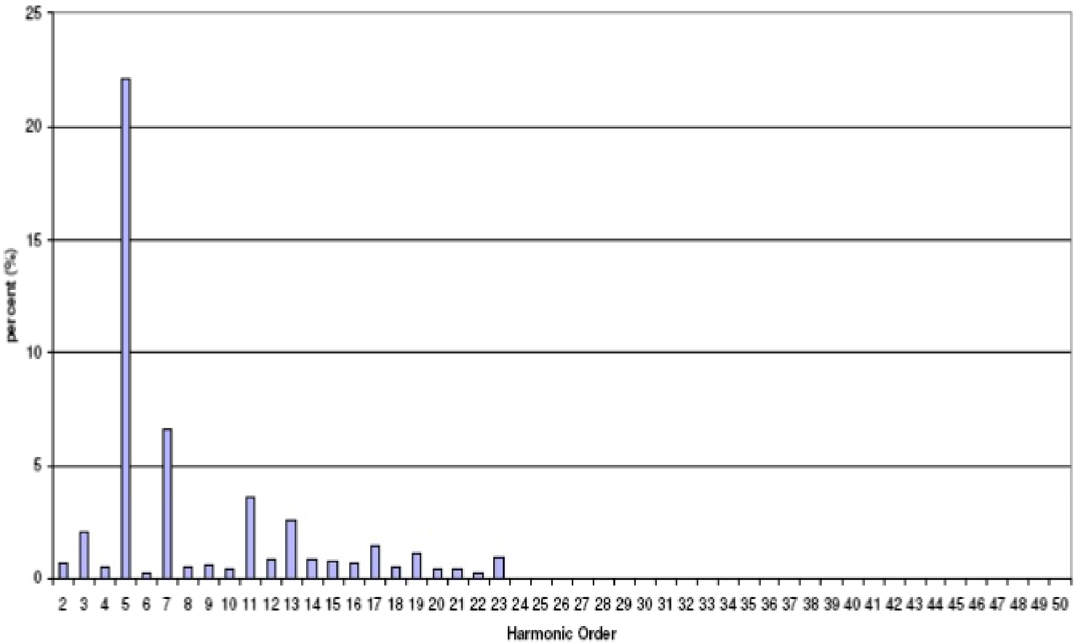

Figure 7. Harmonic content of sampled effective current of 400 kVA transformer

6. Determination of optimal load ability and life of transformer

In this section the optimal utilization coefficient and life of 400 kVA transformer is calculated. Figure 8 shows the process of doing it, completely.

By using power analyzer, the values of the temperature, load current and most effective harmonic order (i.e. harmonics third, fifth, seventh and eleventh) of transformers are recorded for four days. Then by using of ANNs, Load current and harmonic orders and temperature is predicted for next days.

Result of load current forecasting for next day, with ANNs has been shown in table 1. Also after forecasting of harmonic orders, required harmonic factor (F_{HL} , F_{HL_STR}) for calculating optimal utilization coefficient and life , is obtained. Table 2 has been shown this harmonic factor. Table 3 has been shown technical specifications of 400 KVA transformers.

Since load and harmonic order is measured and forecasted with time interval 1 hour therefore life and optimal utilization coefficient is calculated the same time. Also transformer losses in harmonic condition are calculated in this time. Table 4 has been shown how to calculate the transformer losses (for 4 PM i.e. peak time) in harmonic condition. Also transformer losses during one day have been shown in table 5. We can see that harmonic orders and their amplitude have direct effect on t increasing of loss of transformers and its important effect is on eddy loss windings.

Optimal operation coefficient and life of the transformer under these loads are calculated by a program written in MATLAB environment. For example figure 9 shows the transformer life. According with figure optimal load ability of transformer – without life reduction- is 0.96 p.u.We can see if the transformer is used in this situation at Full Load life of is reduced about 11 years. Table 6 shows optimal load ability of transformer during the one day. Also nominal life of transformer at full load and harmonic situations has been shown in figure 10.

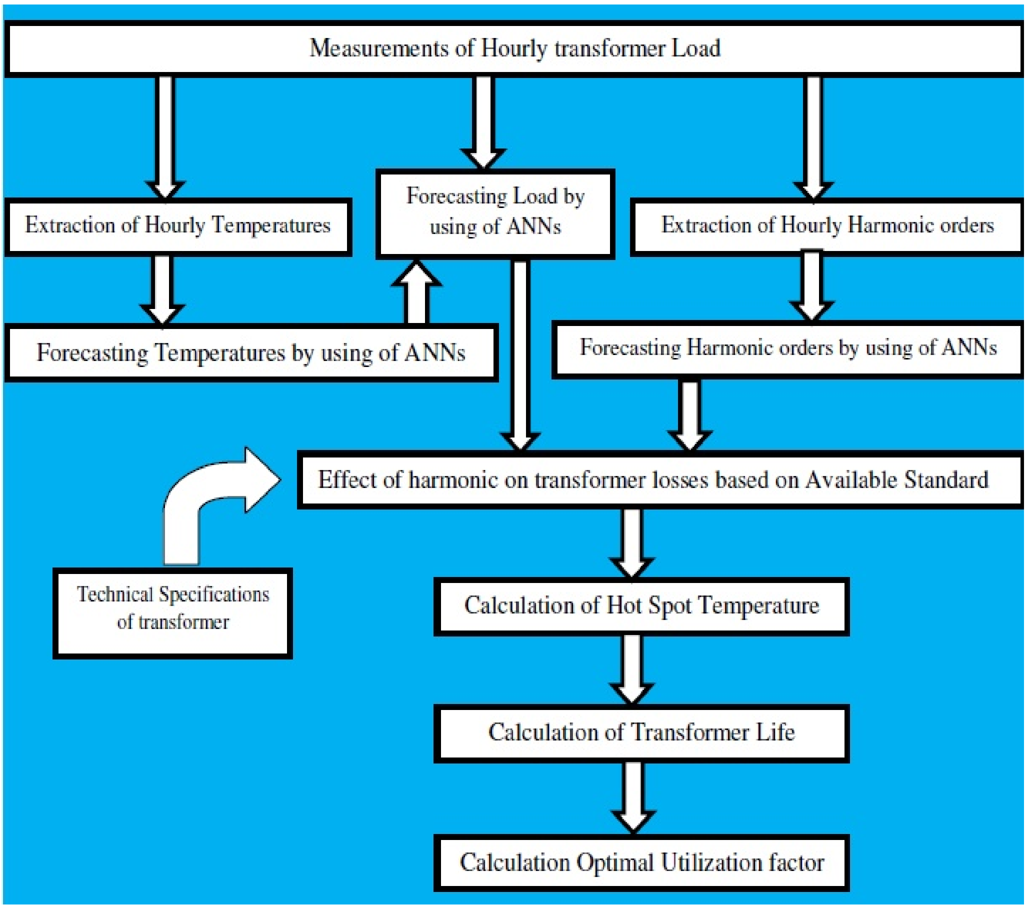

Figure 8. The general trend of calculation of optimal utilization coefficient and life of transformer

Table 1. Forecasting load (Ampere) during one day by using of ANNs

Time	Forecasting load	Time	Forecasting load	Time	Forecasting load
00:00	378.33	08:00	223.40	16:00	461.27
01:00	350.55	09:00	218.66	17:00	430.17
02:00	323.14	10:00	256.50	18:00	428.11
03:00	278.53	11:00	330.55	19:00	423.83
04:00	270.47	12:00	364.39	20:00	353.56
05:00	272.52	13:00	374.44	21:00	348.68
06:00	252.18	14:00	398.26	22:00	407.82
07:00	226.53	15:00	422.60	23:00	417.32

Table 2. Harmonic factor calculation during one day after forecasting harmonic order with ANNs

Time	F_{HL}	F_{HL-STR}	Time	F_{HL}	F_{HL-STR}	Time	F_{HL}	F_{HL-STR}
00:00	2.539	1.145	08:00	2.411	1.198	16:00	2.574	1.148
01:00	3.513	1.175	09:00	2.631	1.089	17:00	3.245	1.176
02:00	2.301	2.123	10:00	2.742	1.349	18:00	3.017	1.169
03:00	3.541	1.865	11:00	2.178	1.202	19:00	3.561	1.132
04:00	2.632	1.370	12:00	2.641	1.212	20:00	3.212	1.686
05:00	2.765	1.544	13:00	3.133	1.143	21:00	3.076	1.254
06:00	3.223	1.422	14:00	3.078	1.324	22:00	3.423	1.187
07:00	2.790	2.211	15:00	2.984	1.119	23:00	2.783	1.053

Table 3. 400 KVA transformer technical specifications

Power(KVA)	I_1(A)	I_2(A)	P_{NL}(w)	P_{SC}(w)	$R_{dc1}(\Omega)$	$R_{dc2}(\Omega)$	θ_{TO-R} (^{o}c)	θ_A (^{o}c)	θ_{g-R} (^{o}c)
400	11.55	577	850	6450	5.41	0.0022	60	40	5

Table 4. The losses of 400 KVA transformer in peak load time (4 PM)

The Kind of Loss	Rated Losses (watt)	Loss under Harmonic Effective Current (watt)	Harmonic Loss factor	Harmonic Loss (watt)
P_{NL}	850	850	-	850
P_{dc}	4515	3970.35	-	3970.35
P_{EC}	638.55	561.52	2.574	1445.36
P_{OSL}	1296.45	1140.06	1.148	1308.78
P_T	7300	6521.94	-	7574.50

Table 5. Transformer losses (watt) during one day

Time	Harmonic losses	Time	Harmonic losses	Time	Harmonic losses
00:00	6346.46	08:00	4090.06	16:00	7574.50
01:00	6384.50	09:00	4020.97	17:00	7502.27
02:00	6232.12	10:00	4769.20	18:00	7344.18
03:00	5731.94	11:00	5553.61	19:00	7521.18
04:00	4960.48	12:00	6249.53	20:00	6749.01
05:00	5152.95	13:00	6558.85	21:00	6237.57
06:00	4896.36	14:00	7073.52	22:00	7256.10
07:00	4807.13	15:00	7191.40	23:00	6149.98

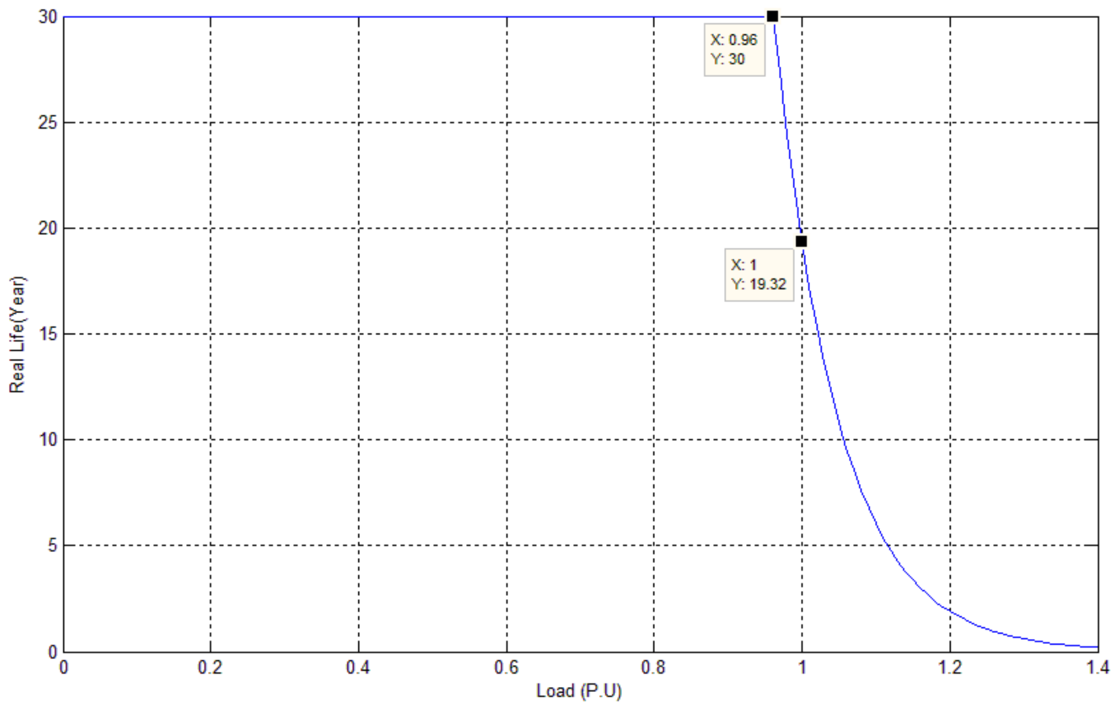

Figure 9. The 400 kVA transformer life time versus loading by forecasting load and harmonic orders with ANNs

Table 6. Transformer optimal utilization coefficient (OUC) during one day

Time	OUC	Time	OUC	Time	OUC
00:00	0.96	08:00	0.96	16:00	0.96
01:00	0.93	09:00	0.96	17:00	0.93
02:00	0.90	10:00	0.94	18:00	0.94
03:00	0.88	11:00	0.96	19:00	0.92
04:00	0.94	12:00	0.95	20:00	0.90
05:00	0.92	13:00	0.94	21:00	0.93
06:00	0.92	14:00	0.94	22:00	0.93
07:00	0.88	15:00	0.94	23:00	0.96

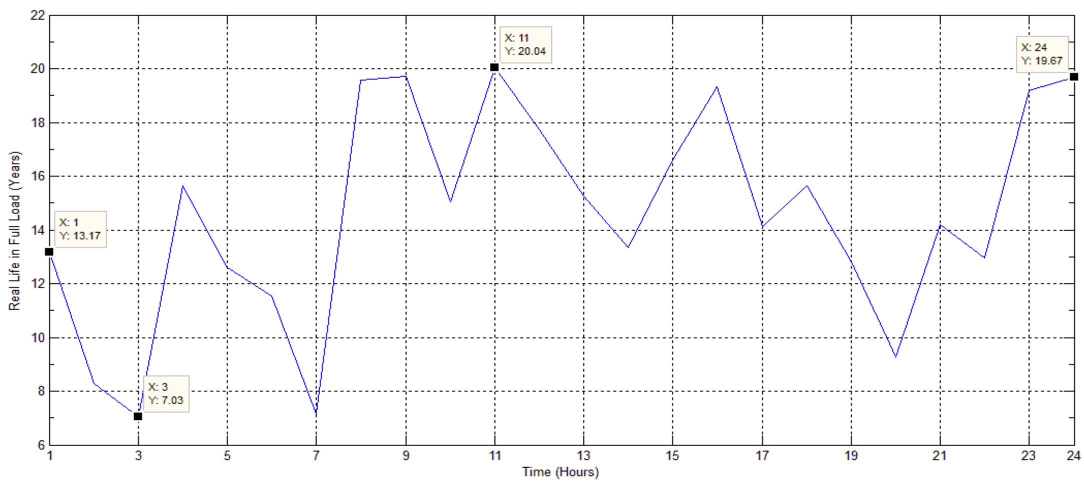

Figure 10. Nominal life of transformer at full load and harmonic situation

7. Conclusion

Harmonic in power system have a lot of negative results, including increasing losses and decreasing efficiency of equipments. So, investigation of the effects of harmonics on expensive network equipment, especially transformers is necessary. So, measuring of transformers load (especially in spring and summer) for extracting harmonic and calculating transformer losses, life and optimal utilization factor is very important. Also for proper operations are better that prediction of transformer load and harmonic order is done.

In this paper a multi-layer perceptron ANN, based on a back propagation algorithm, has been proposed for forecasting the day-ahead load consumption of transformer. Then By forecasting of 400 KVA transformer load and harmonic orders – using ANNs- and a suitable algorithm its losses and life and optimal utilization coefficient (OUC) of transformer in a 24-hour period is calculated.

Result is shown that transformer losses increase in presence of harmonics. These losses is caused temperature in different parts of transformer increasing, especially its hot spot and increase of this temperature can reduce useful life time of transformer's insulations and OUC.

Also results shown that amplitude current had direct impact on increasing losses. But In addition to amplitude current, harmonic orders affect on optimal utilization coefficients of transformers. For example at the 4 PM i.e. peak time, amount of current and losses of transformers is maximum. But at this time due to the low harmonic factors, OUC is very appropriate. As can be seen at 3 and 7 AM, despite of low current, because of high harmonic factors, the OUC is minimum amount.

References

[1] http://amar.tavanir.org.ir/pages/project/generation/week/94/1.pdf

[2] IEEE Std C57.110-1998, “IEEE Recommended Practice for Establishing Transformer Capability when Supplying Non sinusoidal Load Currents”, IEEE Publication, Piscataway, NJ, USA, 1998.

[3] S. B. Sadati, A. Tahani, M. Jafari, and M. Dargahi, Derating of transformers under Non-sinusoidal Loads, In proceedings of 11th IEEE International Conference on Optimization of Electrical and Electronic Equipment, Brasov, Romania, pp. 263-268, 2008.

[4] S .B. Sadati, A. Tahani, B. Darvishi, M. Drgahi, and H.Youefi, Comparison of Distribution Transformer Losses and Capacity under Linear and Harmonic Loads, In Proceedings of 2nd IEEE International Power and Energy Conference, Johor Bharu, Malaysia, pp. 1265-1269, 2008.

[5] Amit Gupta and Ranjana Singh, Evaluation of Distribution Transformer Losses Under Harmonic Loads Using Analytical and Simulation Methods, international Journal on Emerging Technologies, PP. 90-95, 2011.

[6] S. B. Sadati, B. D. Motevali, M. Dargahi, and M. Yazdani-Asrami, Evaluation of Distribution Transformer Losses and Remaining Life considering Network Harmonic, Based on Analytical and Simulation Methods, Australian Journal of Basic and Applied Sciences (AJBAS), Vol. 4, No. 10, pp. 5291-5299, 2010.

[7] Asaad A. Elmoudi, EVALUATION OF POWER SYSTEM HARMONIC EFFECTS ON TRANSFORMERS Hot Spot Calculation and Loss of Life Estimation, Doctoral Dissertation, Helsinki University of Technology, Department of Electrical and Communications Engineering, 2006.

[8] M. B. B. Sharifian, J. Faiz, S. A. Fakheri and A. Zraatparvar, Derating of Distribution Transformers for Non-Sinusoidal Load Currents Using Finite Element Method, In Proceedings of IEEE ICECS, pp. 754-757, 2003.

[9] M. B. B. Sharifian, and J. Faiz, Derating of a distribution transformer for non-linear loads, European Transactions on Electrical Power (ETEP), Vol. 16, pp. 189-20, 2006.

[10] M. Yazdani-Asrami, M. Mirzaie and A. Shayegani Akmal, Calculation of Transformer Losses under Non-Sinusoidal Currents Using: Two Analytic Methods and Finite Element Analysis, World Applied Science Journal (WASJ), Vol. 9, No. 8, pp. 889-897, 2010.

[11] M. Yazdani-Asrami, M. Mirzaie and A. Shayegani Akmal, Investigation on Impact of Current Harmonic Contents On the Distribution Transformer Losses and Remaining Life, In Proceedings of IEEE 2nd Power and Energy Conference, Malaysia, pp. 689-694, 2010.

[12] S. B. Sadati, M. Yazdani-Asrami, and M. Taghipour, Effects of Harmonic Current Content and Ambient Temperature on Load Ability and Life Time of Distribution Transformers, International Review of Electrical Engineering (I. R. E. E.), Vol.5, pp. 1444-1451, 2010.

[13] M. Yazdani-Asrami, M. Mirzaie, A. Shayegani Akmal, and S. Asghar Gholamian, Life Estimation of Distribution Transformers Under Non-Linear Loads Using Calculated Loss by 2D-FEM, Journal of Electrical Systems (JES), Vol. 7, No. 1, pp. 12-24, 2011.

[14] A. Badri, Z. Ameli, A.Motie Birjandi, “Application of Artificial Neural Networks and Fuzzy logic Methods for Short Term Load Forecasting, 2nd International Conference on Advances in Energy Engineering (ICAEE), ELSEVIER, 2012.

[15] A. Bagnasco, M. Saviozzi, F. Silvestro, A. Vinci, S. Grillo, E. Zennaro, “Artificial Neural Network Application to Load Forecasting in a Large Hospital Facility, International Conference on Probabilistic Methods Applied to Power Systems (PMAPS),2014.

[16] Anju Bala, N. K. Yadav, Narender Hooda, “Implementation of Artificial Neural Network for Short Term Load Forecasting, Current Trends in Technology and Science, Volume: 3, Issue: 4, 2014.

[17] Luis Hernández, Carlos Baladrón, et al, “Artificial Neural Network for Short-Term Load Forecasting in Distribution Systems, Energies journal, pp 1576-1598. 2014.

[18] 18- J. P. Rothe□, A. K. Wadhwani and S. Wadhwani. “Artificial Neural Network and ANFIS Based Short Term Load Forecasting in Real Time Electrical Load Environment, International Journal of Current Engineering and Technology, Vol.4, No.3, pp 1939-1944, 2014.

[19] Filipe Rodrigues, Carlos Cardeira, J.M.F.Calado, “The daily and hourly energy consumption and load forecasting using artificial neural network method: a case study using a set of 93 households in Portugal”, The Mediterranean Green Energy Forum, ELSEVIER, 2014.

[20] A.S. Ahmad, M.Y. Hassan, M.P. Abdullah, H.A. Rahman, F. Hussin, H. Abdullah, R. Saidur, A review on applications of ANN and SVM for building electrical energy consumption forecasting, Renewable and Sustainable Energy Reviews, pp102–109, 2014.
[21] Jorjeta G. Jetcheva, Mostafa Majidpour, Wei-Peng Chen, Neural network model ensembles for building-level electricity load forecasts, Elsevier Journal of Energy and Buildings, pp. 214–223, 2014.
[22] Hamed Chitsaz, Hamid Shaker, Hamidreza Zareipour, David Wood, Nima Amjady, Short-term Electricity Load Forecasting of Buildings in Microgrids, Elsevier Journal of Energy & Buildings , 2015.
[23] Luis Hernandez, Carlos Baladron, Javier M. Aguiar, Belen Carro, Antonio Sanchez-Esguevillas, Jaime Lloret, "Artificial neural networks for short-term load forecasting in micro grids environment, Elsevier Journal Energy, 2014.
[24] Penghua Li, Yinguo Li , Qingyu Xiong , Yi Chai , Yi Zhang , "Application of a hybrid quantized Elman neural network in short-term load forecasting, Elsevier Journal of Electrical Power and Energy Systems, pp. 749–759, 2014.
[25] Arjun Baliyana , Kumar Gauravb , Sudhansu Kumar Mishrac," A Review of Short Term Load Forecasting using Artificial Neural Network Models, International Conference on Intelligent Computing, Communication & Convergence, Procedia Computer Science, pp. 121-125, 2015.
[26] Kalogirou SA. Applications of artificial neural networks in energy systems: A review. Energy Conversion and Management; vol. 40, pp 1073–1087, 1996.
[27] M. I. Samesima, J. W. Resende, and S. C. Araujo, "Analysis of transformer loss of life driving nonlinear industrial loads by the finite elements approach", IEEE Thirtieth IAS Annual Meeting of Industry Applications Conference, pp.2175 – 2179, 1995.
[28] L. Pierrat, R. J. Resende, and J. Santana, "Power transformers life expectancy under distorting power electronic loads", Proceedings of the IEEE International Symposium on Industrial Electronics, pp.578 –583, 1996.
[29] A. Elmoudi, M. lehtonen , Hasse Nordman, "Effect of Harmonics on Transformers Loss of life", IEEE conference record of the International Symposium on Electrical Insulation ,11-14 June, pp.408-411, 2006.
[30] Kalogirou SA. Applications of artificial neural networks in energy systems—a review. Energy Conversion Manage, pp. 1073–87, 1999.
[31] Che-Chiang Hsu, Chia-Yon Chen, Regional load forecasting in Taiwan–applications of artificial neural networks, Energy Conversion and Management , volume 4, pp 1941–1949, 2003.