SELECTION AND MANAGEMENT OF DISTRIBUTION TRANSFORMERS USING ARTIFICIAL NEURAL NETWORKS

J. A. Jardini H. P. Schmidt C. M. V. Tahan
PEA - Escola Politécnica - Universidade de São Paulo
CP 61548 - 05424-970 - São Paulo, SP - Brazil
jardini@pea.usp.br

S. U. Ahn
Empresa Bandeirante de Energia
São Paulo, SP - Brazil

CED - Centro de Excelência em Distribuição

This work presents a methodology for distribution transformer rating selection and management. Measured or estimated daily load profiles are used to determine the transformer's loss of life. Loss of life values are obtained for a number of transformers and are stored together with the corresponding load profiles in a database of patterns. The expected loss of life for a transformer not included in the database is obtained by using both classification and interpolation through artificial neural networks.

1. INTRODUCTION

Current practices in Brazil for distribution transformer load management are based on the expected loss of life of the transformer. The loss of life is computed using forecasted demand (kVA) values that are obtained from a statistical correlation between demand and energy (statistical kVA, or kVAs function).

A first improvement to the current methodology was proposed in [1]. Instead of the kVAs function the proposed approach used the transformer daily load profile. However, this procedure was inherently very time consuming from the computational point of view, so further improvements were required. This paper thus represents a second and important extension where the focus is placed on computing time. Detailed loss of life calculations are carried out for a small number of transformers for which the daily load profiles are known. Both the load profiles and the corresponding loss of life values are stored in a database of patterns. The loss of life value for a transformer not included in the database is obtained using the loss of life value of the most similar curve in the database. Therefore, the estimation of a loss of life value consists in a search procedure in the database.

This paper is organized as follows. Section 2 presents the loss of life calculation for a transformer with a known daily load profile. Section 3 presents the loss of life estimation for a given transformer (not included in the database) based on the selection of the best pattern in the database. Various techniques were considered for this selection, namely cluster analysis, euclidean distance and artificial neural networks. The results obtained through each one of these techniques are presented in the same section. Finally, Section 4 presents the conclusions of the paper.

2. LOSS OF LIFE CALCULATION

The loss of life calculation is described in detail elsewhere [1-3] and is summarized below.

2.1 - Daily Load Curve

The transformer daily load curve yields the demand through the transformer at regular time intervals. In this work 15-minute intervals are used, so a daily load curve is made up of 96 pairs of time and demand values. In order to guarantee a representative set of field data, a total of 802 days of measurements were collected from operating transformers from the 3 electricity utilities in the state of São Paulo. A further conversion of demand values in kW to per-unit values was required so as to obtain homogeneous curves. Hence, all measured values were divided by a base demand (D_{base}) equal to the transformer's average demand (monthly energy divided by 720 = 24 * 30). Since each transformer was monitored during 15 days in average, variations were observed from day to day in each transformer. In order to take into account these variations, two daily curves were obtained from the measurements: a mean curve and a standard deviation curve. These curves give the mean and standard deviation values, respectively, in each 15-minute interval for each transformer. Both curves will be collectively referred to as (*m*, *s*) curves. Fig. 1 shows the mean and standard deviation curves obtained for one of the measured transformers.

2.2 - Ambient Temperature

When performing annual loss of life calculations (or its inverse, life expectancy) the annual average ambient temperature is normally used. However, since in some cases the daily load peak occurs at night (when the ambient temperature is lower) and in other cases the peak occurs during the day, the ambient temperature was also represented by daily curves. In this case a mean and a standard deviation curve were defined, which allow for variations observed in ambient temperature in different days. Fig. 2 shows an example of mean and standard deviation curves for ambient temperature.

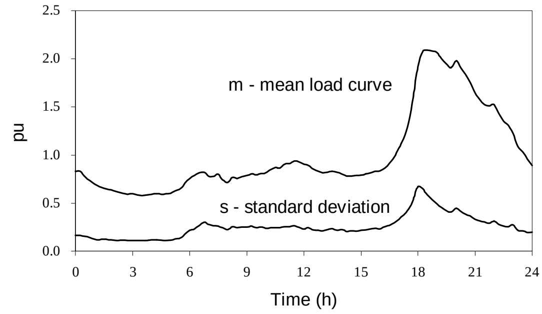

Fig. 1. Mean and standard deviation load curves

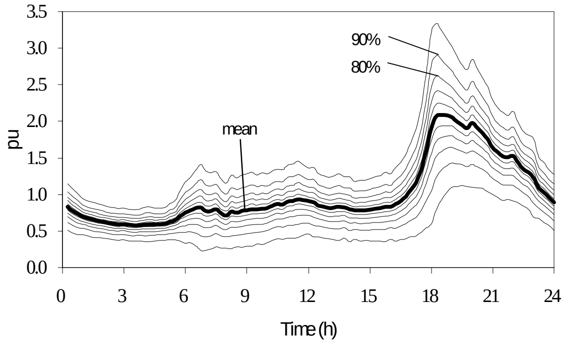

Fig. 3. Set of load curves

2.3 - Probability Associated with Load and Temperature Values

The loss of life of a transformer depends on the effective values of load and temperature in each instant. Values in Figs. 1 and 2 are not suitable for loss of life calculation since they are just average values. For this reason, in the present work, load and temperature are represented by a set of curves that give, in each instant, load and temperature values associated with a probability value. The particular load value at time t

$$L(t) = m(t) + k.s(t) \tag{1}$$

represents a load value that will not be exceeded with probability P, where $m(t)$ is the mean load at time t and $s(t)$ is the corresponding standard deviation. For instance, P = 90% for k = 1.28 when normal (gaussian) distribution of load values is assumed (normal distribution is assumed throughout this work).

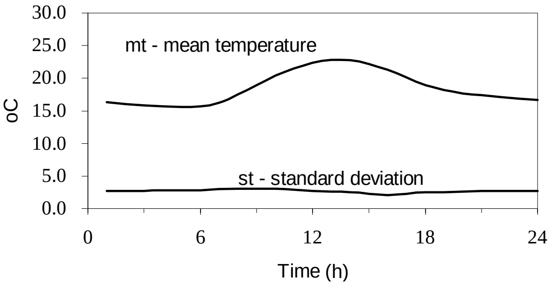

Fig. 2. Mean and standard deviation curves for ambient temperature

Using k as a parameter, the set of 11 load curves represented in Fig. 3 is obtained, which correspond to the following values of P: 2.5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 97.5%. A particular value in the 80% probability curve is interpreted as representing the load value associated with probabilities in the range between 75% and 85%, and therefore it has an associated probability of 10%. It should be noted that in this work it is assumed that the transformer loading remains the same throughout its lifetime. A similar set of 11 curves is obtained to represent the ambient temperature, as shown in Fig. 4.

2.4 - Transformer's Life

By selecting a value for the transformer rating and combining one load curve from Fig. 3 and one ambient temperature curve from Fig. 4, it is possible to obtain the daily temperature curve for the transformer's hot spot, and thus the corresponding loss of life after 1 day of operation [3]. This loss of life value is associated with two probability values, one from the selected load curve and the other from the selected ambient temperature curve.

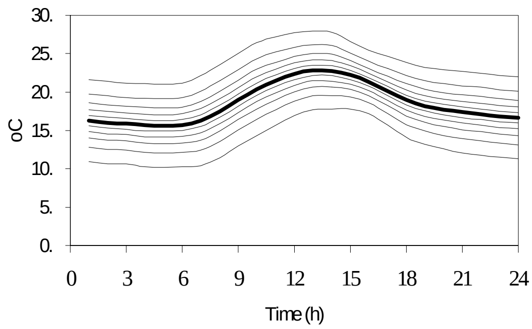

Fig. 4. Set of ambient temperature curves

The total loss of life value can then be obtained by averaging loss of life values obtained through the combination of all load curves (index i) and all ambient temperature curves (index j):

$$Ll_{tot} = \sum_{i,j} Ll_{ij} \cdot Q_i \cdot Q_j \tag{2}$$

where Ll_{tot} is the total loss of life, Ll_{ij} is the loss of life value corresponding to load curve i and ambient temperature j, and Q_i, Q_j are the corresponding probability values. Fig. 5 shows an example of life expectancy calculation as a function of the transformer loading index. The transformer loading index is defined as the ratio between the maximum value of the mean curve in kVA and the transformer rated power in kVA, and it can be varied through a multiplying factor applied to all values in all curves.

This procedure is obviously very time-consuming if applied to each distribution transformer. In the state of São Paulo, only *Eletropaulo Metropolitana* and *Empresa Bandeirante de Energia* (both created from former *Eletropaulo - Eletricidade de São Paulo SA*) account for some 300000 transformers in the distribution network.

3. LOSS OF LIFE ESTIMATION

The life expectancy estimation for a given transformer is based on the comparison of its daily load curve with the daily load curves of sample transformers for which a detailed loss of life calculation was carried out as described in the preceding section. The following techniques were employed:

- classification through Cluster Analysis;
- classification through Euclidean distance;
- classification using the artificial neural network model LVQ (*Learning Vector Quantization*);
- interpolation using the artificial neural network model MLP (*Multi Layer Perceptron*).

The first three techniques fall into the general category of *classification*, whereby a curve (m, s) that is most similar to the load curve (m', s') of the transformer of which the loss of life is to be estimated (testing curve) is selected from the database.

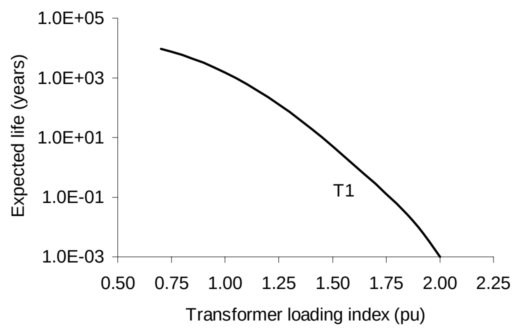

Fig. 5. Expected life as a function of transformer loading index

Once a daily load curve is selected in the database, its associated loss of life value is assigned to the testing curve. In the fourth technique an MLP model is set up and trained with values of load and associated loss of life extracted from the database. Afterwards, while in processing mode, the MLP is capable of producing an estimate for the loss of life given a set of load values. The application of these techniques will be described in greater detail in the following subsections.

3.1 - Load Curve Database of Patterns

For a given daily load curve the 96 mean values were combined with the 96 standard deviation values, yielding a 192-value composite curve. This composite curve was further normalized by dividing all values by the maximum value, so all composite curves possess a maximum value of 1.0. This normalization was required because the relevant feature for the classification procedure is the curve shape (given by the relative values among all time intervals) and not the particular values at each time interval. Fig. 6 shows an example of a normalized composite (m, s) curve.

The classification algorithms were then applied to the normalized composite curves. A value of life expectancy (l) is associated with this curve, thus forming complete (m, s, l) curves. The database is composed of (m, s, l) curves concerning 45 transformers carefully chosen among those available from the measurement set (factors such as the predominant type of consumers - residential, commercial, etc. - were considered for inclusion in the database). These 45 curves will be referred to as *training curves*. The (m, s, l) curves were also obtained for 6 other transformers that were not included in the database (total of 51 curves). The purpose of these 6 new curves is to evaluate the efficiency of each technique employed for estimating the life expectancy and for this reason they will be referred to as *testing curves*.

3.2 - Cluster Analysis

In this case the *FastClus* algorithm was used. This algorithm is part of the *Statistical Analysis System* (SAS) [4]. Let a be the number of curves to be classified, and b the number of categories (clusters) into which the a curves will be classified (b must be specified by the user). In a first step, the algorithm creates the b categories which will accommodate all a curves, using the euclidean distances among the curves. In a second step, a brand new curve that is to be classified (therefore not belonging to the set of the original curves) is assigned to one of the existing clusters through the minimum distance criterion.

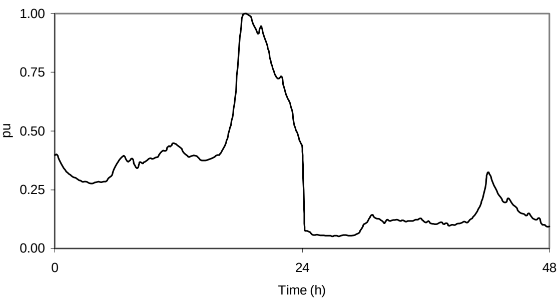

Fig. 6. Normalized composite (m, s) curve

In this work, 45 clusters were created from the 45 training curves (a = b = 45). The 6 testing curves were then classified using the algorithm. Once a category was found for each one of these 6 transformers, the life expectancy curve of the selected category was assigned to each transformer. Fig. 7 shows the daily load curves for transformer T_1 (belonging to the set of 45 training transformers) and transformer T_2 (belonging to the set of 6 testing transformers). Due to the similarity between the daily load curves of transformers T_1 and T_2, the latter was assigned to the same category of T_1. Fig. 8 shows the life expectancy curve of transformer T_1, which was also assigned to transformer T_2, and the true life expectancy curve of transformer T_2 calculated according to subsection 2.4.

As the magnitude of mean values differs considerably from the magnitude of standard deviation values in the load curve (Fig. 1) and the *FastClus* algorithm uses the euclidean distance as classification criterion, other curve compositions aimed at reducing the difference between those magnitudes were studied. Besides the base case (m, s), the following curve compositions were tested:

- (m, ($m+s$));
- (($m+0.525s$), ($m+0.840s$));
- (m, ($m+1.280s$)).

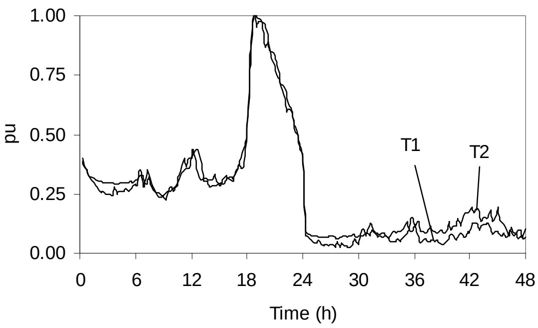

Fig. 7. Classification of the curve of transformer T_2 into the category represented by transformer T_1

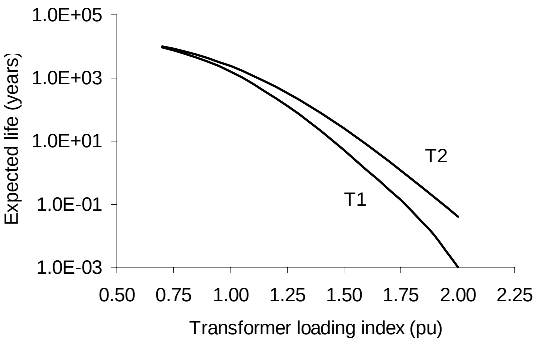

Fig. 8. Comparison between true and assigned life expectancy curves for transformer T_2

As the composite curve is only used to determine the most similar curve to a given curve, the different compositions above did not interfere in the loss of life calculation. In all compositions studied, the classification results were the same as in the base case (m, s).

3.3 - Euclidean Distance

In this case, euclidean distance was also used as criterion for composite curve classification. However, a slight modification was introduced in the computation of the distance, aiming at varying the relative importance of different points in the curve. The modified euclidean distance was defined as follows:

$$ED^2(1,2) = \sum_{i=1}^{96} \alpha_i \left(m_{1i} - m_{2i}\right)^2 + \sum_{i=1}^{96} \beta_i \left(s_{1i} - s_{2i}\right)^2 \qquad (3)$$

where:

$ED(1,2)$	=	Euclidean distance between a training curve (1) and a testing curve (2);
i	=	daily load curve time index
m_{1i}	=	i^{th} mean value of training curve;
m_{2i}	=	i^{th} mean value of testing curve;
s_{1i}	=	i^{th} standard deviation value of training curve;
s_{2i}	=	i^{th} standard deviation value of testing curve;
α_i, β_i	=	weights.

It should be noted that different values for the weights can be used so as to take into account the greater importance of certain periods of the daily load curve, such as the peak period. In the present work, various weight values were selected in order to assess the influence of the weights on the classification results. In all cases the same classification results were obtained.

3.4 - Classification Through Artificial Neural Networks

In this case the *Learning Vector Quantization* (LVQ) algorithm was used [5]. Again, there are two main stages in the application of the algorithm: training and testing. All 45 training curves were used in the first stage, with exceedingly good results as to training time (15 seconds on a 486 Intel-based microcomputer). Once a network is trained, it can be tested through the *Classify* option. Although the available LVQ implementation allows up to 3 refinement levels for the training stage, the first one (LVQ1) was sufficient for achieving good results.

3.5 - Performance Evaluation

Table I shows the processing time required in the testing stage for each one of techniques described in the previous subsections. The machine used is a 486 Intel-based microcomputer.

Table I - CPU time for classification (testing stage)

Operation	CPU time
Loss of life calculation	186 s (1 curve)
FastClus classification	60 s (1 curve)
Euclidean distance classification	0,3 s (1 curve)
LVQ classification	0,03 s (1 curve)

3.6 - Interpolation Through Artificial Neural Networks

In this case, an implementation of the Multi Layer Perceptron (MLP) paradigm using Backpropagation training was used [6]. A 4-layer network was specified, with 192 units in the input layer (96 mean values and 96 standard deviation values), two hidden layers with 12 and

10 units respectively, and the output layer with 14 units. These 14 units represent different life expectancy values for different loading conditions (loading index ranging from 70% to 200% in 10% steps).

A total of 80 normalized curves (see Figure 6) were assembled using available data from 80 operating distribution transformers (1 curve for each transformer). These transformers were carefully selected so as to include typical residential, commercial, industrial and composite load curves. A set of 14 life expectancy values were obtained for each curve through detailed loss of life calculations, using the above loading index values. Out of these 80 curves, 56 curves were used in MLP training and the remaining 24 curves were reserved for MLP testing, thus ensuring that none of the testing curves had been seen by the MLP during its training. As an example, Table II shows the 14 output values regarding the first training vector.

Table II - Output values corresponding to the first training vector

Output variable	Loading index (%)	Output value (life expectancy in years)
1	70	8084.
2	80	5048.
3	90	2800.
4	100	1363.
5	110	581.6
6	120	218.6
7	130	73.07
8	140	21.98
9	150	6.056
10	160	1.558
11	170	0.3810
12	180	0.0900
13	190	0.0200
14	200	0.0040

MLP training was executed using the exponential smoothing algorithm [6]. Table III summarizes the main data regarding MLP training in this case.

Table III - Main data for MLP training

Parameter	Training session				
	1	2	3	4	5
N° of iterations (epochs) performed	500	500	500	500	500
Learning rate	1.0	0.9	0.8	0.7	0.6
Exponential smoothing coefficient	0.2				
Total processing time on a 300-MHz Pentium II based computer (seconds)	118				

Equation (4) was used to compute the evaluation error produced by the MLP for each output variable:

$$error(\%) = \frac{|v_M - v_r|}{v_{\max} - v_{\min}} \cdot 100 \ , \qquad (4)$$

where v_M is the value computed by the MLP, v_r is the reference value (correct output obtained through loss of life calculations) and v_{min}, v_{max} are the minimum and maximum values respectively for the output variable. Table IV shows some statistics regarding the evaluation error produced by the MLP when the 24 testing vectors were presented to it.

Table IV - Error average, standard deviation and distribution considering the testing set (24 vectors)

Output variable	Error average (%)	Error std. dev. (%)	Number of vectors in each error class: 0-2%	2-4%	4-6%	6-8%	8-10%	10-12%	12-14%	14-16%
1	2.25	2.98	17	2	3	1	0	0	1	0
2	2.41	3.12	15	4	2	2	0	0	0	1
3	2.35	3.28	15	5	2	1	0	0	0	1
4	1.95	2.90	17	2	3	1	0	0	1	0
5	1.48	2.11	18	2	3	1	0	0	0	0
6	1.07	1.39	18	5	1	0	0	0	0	0
7	0.75	0.99	21	2	1	0	0	0	0	0
8	0.54	0.80	23	1	0	0	0	0	0	0
9	0.47	0.74	23	1	0	0	0	0	0	0
10	0.45	0.76	23	1	0	0	0	0	0	0
11	0.46	0.78	23	1	0	0	0	0	0	0
12	0.48	0.84	23	0	1	0	0	0	0	0
13	0.51	0.83	23	0	1	0	0	0	0	0
14	0.47	0.80	23	1	0	0	0	0	0	0

Regarding Table IV, the values 23 and 1 in the row corresponding to the 8^{th} output variable mean that this variable was computed with an error equal or less than 2% in 23 testing vectors and with an error between 2% and 4% in 1 testing vector, respectively.

Average errors in the testing set vary approximately between 0.50% and 2.50%, which are considered sufficiently low. Processing times spent by the MLP network are usually negligible; in this case, a total of 0.61 seconds were required to compute the whole 24 vectors (or approximately 0.025 sec for 1 testing vector), using the same computer as specified in Table III.

The results obtained in this testing set were considered very good. For this reason, a decision was made at EBE - *Empresa Bandeirante de Energia* so as to start the implementation of the proposed methodology at production level. The region corresponding to Jundiaí, a medium-size city with 1383 distribution transformers, was chosen for this purpose. Initially, the MLP trained with the 56 selected transformers was used in the processing of these 1383 testing transformers. As to the evaluation error, a small fraction of the testing set were computed with unacceptably large errors, indicating that in this city there might be a few transformers with daily load curves substantially different from the 56 training curves, and so preventing the MLP from exhibiting its generalization capabilities. At present, a new training set specific for this city is being built. This is a difficult task, because significant curve patterns have to be extracted from the set of 1383 transformers, as it was done in the making of the original 56-curve training set. As to the processing time, preliminary results confirm one of the advantages of using the MLP network: 1383 transformers were processed in just 3.24 seconds (or approximately 0.0023 sec per transformer) using the same computer as specified in Table III. Note that in this case the average time required for 1 transformer (0.0023 sec) is approximately 10 times smaller than the corresponding value in the 24-transformer testing set (0.025 sec). This is due to some fixed-time sub-processes within the MLP execution which do not depend on the size of the testing set.

Finally, Fig. 9 shows a qualitative representation of the results obtained with LVQ classification and MLP interpolation in one of the testing transformers.

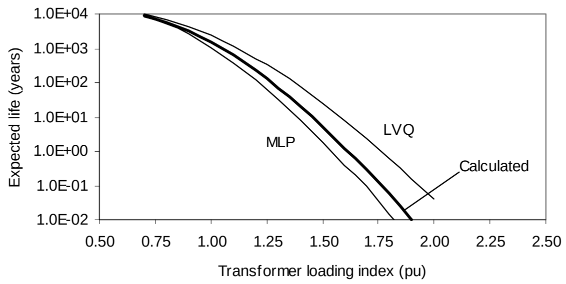

Fig. 9. Life expectancy as a function of transformer loading - results obtained through analytical calculation, LVQ classification and MLP interpolation

4. CONCLUSION

In view of the encouraging results obtained in this work, the proposed methodology [8] is being implemented for distribution transformer management at *Empresa Bandeirante de Energia*. The diagram of Fig. 10 shows the main components of this methodology.

5. ACKNOWLEDGEMENT

The authors acknowledge the support from CED - *Centro de Excelência em Distribuição*, an agreement between *Universidade de São Paulo* and the 4 electricity utilities from the state of São Paulo (*CESP*, *CPFL*, *EBE* and *Eletropaulo*).

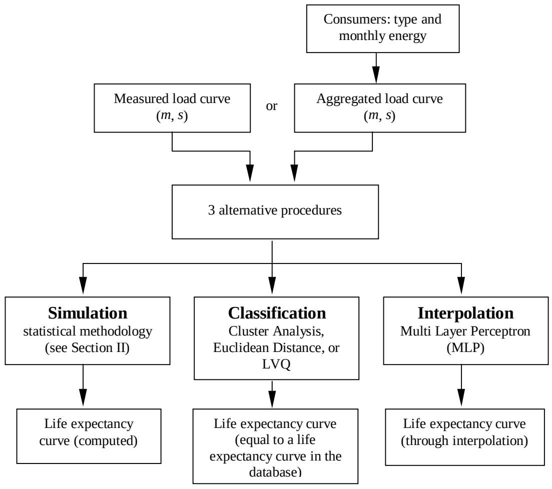

Fig. 10. Transformer life expectancy estimation procedures

6. REFERENCES

[1] J. A. Jardini, C. M. V. Tahan, S. U. Ahn and E. L. Ferrari, “Distribution transformer loading evaluation based on load profile measurements”, *IEEE Transactions on Power Delivery*, vol. 12, no. 4, pp 1766-1770, October 1997.

[2] J. A. Jardini, C. M. V. Tahan, S. U. Ahn and E. L. Ferrari, “Selection of transformers based on economic criteria”, *International Conference on Electricity Distribution - CIRED ’97*, Conference Publication N° 438, pp 6.14.2-6.14.5, IEE 1997

[3] American National Standard Institute - ANSI, “Guide for loading minimal-oil-immersed overhead and pad mounted distribution transformers (rated 500 kVA and less) with 65°C or 55°C average winding temperature rise”, ANSI C.57.91, 1981.

[4] SAS Institute Inc. *SAS/STAT Statistical Analysis System - Guide for Personal Computers Version 6*, 1987.

[5] T. Kohonen et al., *LVQ_PAK - The Learning Vector Quantization Program Package - Version 3.1.* LVQ Programming Team of The Helsinki University of Technology, Laboratory of Computer and Information Science, 1995.

[6] P. D. Wasserman. *Neural Computing - Theory and Practice*, Van Nostrand Reinhold, New York, 1989.

[7] H. P. Schmidt, *Analysis of the voltage stability problem in electric power systems using artificial neural networks.* Ph.D. Thesis, Queen Mary and Westfield College, University of London, UK, 1994.

[8] S. U. Ahn, *Methodology for selection and management of distribution transformers - an ANN approach*. Ph.D. Thesis, Escola Politécnica da Universidade de São Paulo, São Paulo, Brazil, 1997 (in Portuguese).

[9] J. A. Jardini et alii., “Determination of the typical daily load curve for residential area based on field measurements”, *Proceedings of the IEEE*, T & D, Chicago, 1994.

[10] J. A. Jardini et alii., “Residential and commercial daily load curve representation by statistical function for engineering studies purpose”, *International Conference on Electricity Distribution - CIRED ’95*, Brussels, 1995.