International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:2, No:10, 2008

Day Type Identification for Algerian Electricity Load using Kohonen Maps

Mohamed Tarek Khadir, Damien Fay, and Ahmed Boughrira

***Abstract*—**Short term electricity demand forecasts are required by power utilities for efficient operation of the power grid. In a competitive market environment, suppliers and large consumers also require short term forecasts in order to estimate their energy requirements in advance. Electricity demand is influenced (among other things) by the day of the week, the time of year and special periods and/or days such as Ramadhan, all of which must be identified prior to modelling. This identification, known as *day-type identification*, must be included in the modelling stage either by segmenting the data and modelling each day-type separately or by including the day-type as an input. Day-type identification is the main focus of this paper. A Kohonen map is employed to identify the separate day-types in Algerian data.

***Keywords*—**Day type identification, electricity Load, Kohonen maps, load forecasting.

I. INTRODUCTION

IN common with many countries, the electricity market in Algeria is currently being deregulated. This deregulation places the onus on the new energy suppliers, generators and the grid operator to produce accurate short-term forecasts (up to 7 days ahead on an hourly basis) of their energy requirements.

The forecasted energy requirements are typically reconciled with the actual energy requirement by purchasing (or selling) the difference on the spot market at an expensive price (or at a loss). In such competitive environments, prediction becomes a powerful tool in seeking better performances. Short term forecasts are also required by the national grid operator to determine the optimal power stations to turn on (known as the *unit commitment problem*) and to determine the *spinning reserve* (the amount of excess production required to guarantee quality of supply).

However, the design and validity of a given model is, often, severely subject to a good understanding and a-priori knowledge of the real load behaviour [2]. In the case of short term load forecasting, it is proven that the day types or daily habits of consumers for different periods of time, such as working days, weekends, special holidays, etc affect heavily the load shape [3]. Different prediction models may then be designed for each day type. Kohonen networks are proven to be efficient for self-organisation and associative memory [4], and so are employed in this paper in order to identify these day types [5], [6].

In the remainder of the paper, an overview of the Algerian load data is given, as well as a brief overview on the Kohonen map. Results for Algerian load data are presented in Section V.

M.T. Khadir is with the Laboratoire de Recherche en Informatique (LRI), University Badji Mokhtar Annaba, Algeria (e-mail: Khadir@lri-annaba.net).
D. Fay is with the department of Mathematics, National University of Ireland, Galway (e-mail: damien.fay@nuigalway.ie).
M. Boughrira is with the "departement Dispatching", Sonelgaz, Annaba Algeria (e-mail: ahmed_b66@msn.com).

II. OVERVIEW OF ALGERIAN ELECTRICITY DEMAND

The range and time-scale for the available data is given in Table I.

TABLE I
DATA, TIME-SCALE AND RANGE

Range	Saturday 1st January 2000 until Friday 31st December 2004
Timescale	hourly
Number of Points	43796

Electrical demand in Algeria from 01/01/2000 to 31/12/2004 is shown in Fig. 1. As can be seen there is an upward trend in the data reflecting increased economic activity over this period.

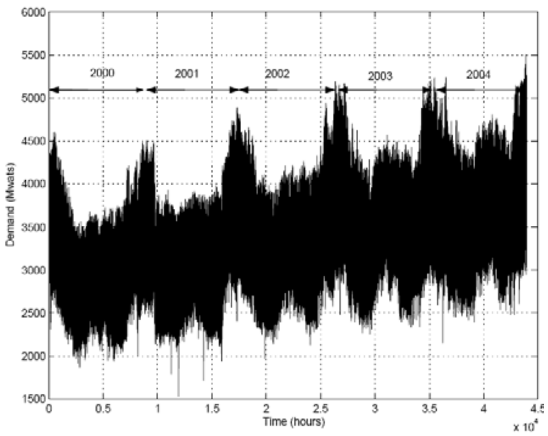
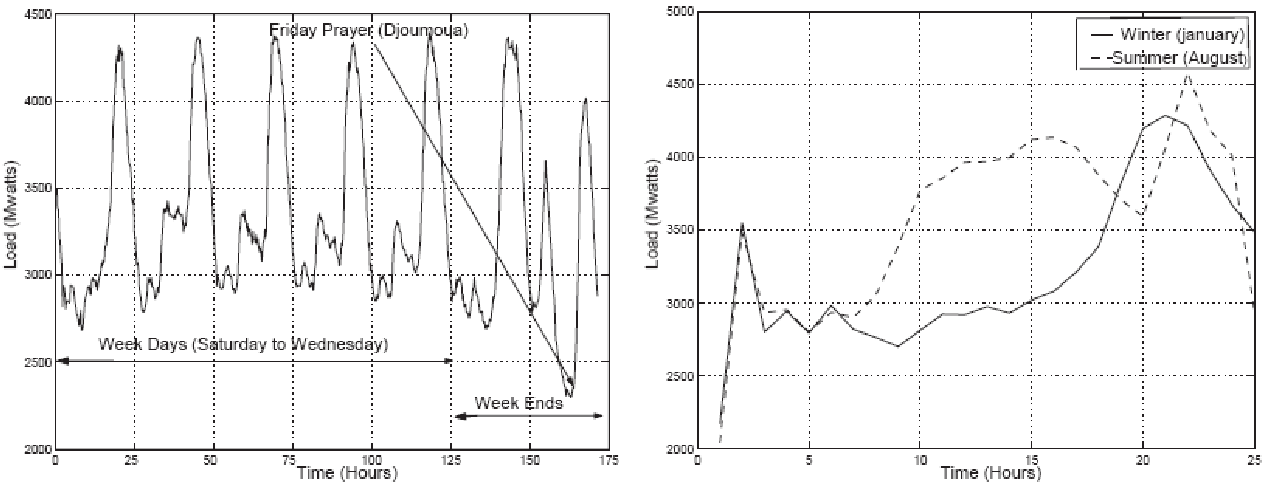


Fig. 1 Algerian electricity load 2000-2004



(a) Weekly load

(b) Summer and winter working days

Fig. 2. Typical daily Algerian load

III. Day-Type Identification

Daily load data can be disaggregated into distinct groups (called day-types) each of which has common characteristics. As can be seen in Fig. 2(a) there is, for example, an obvious difference between the shape of the load on a typical weekend day, such as Friday and a working day like Saturday or Sunday due to decreased economic activity and the weekly religious prayer on Friday. Note that in Algeria the weekend is on Thursdays and Fridays. Furthermore, there is a distinct difference between the shape of a typical winter day and summer day (Fig. 2(b)). A typical winter working day (Saturday) exhibits a high peak at 9pm; in a summer day (which is a holiday for most people) the peak is at 10pm. In all cases the day-types must, however, be identified.

The existence of several different day-types has been shown by several researchers [7], [8], [6]. However, the level of desegregation in day-type selection is, to a large extent, subjective and dependant on the judgement of the forecaster. As pointed out by Hubele and Cheng [9], the application of a separate load forecasting model for different seasons (for example Summer, Autumn, Winter and Spring) has the advantage that the models do not need to incorporate seasonal information. Further desegregation of the load by day of the week (for example Summer Sunday, Winter Sunday, Summer Monday etc.) reduces further the amount of information that the model need incorporate. Such approaches have been implemented successfully by Srinivasan et al [10] and Mastorocostas *et al.* [11], to mention but a few. Where a single model is used for all the data, the day-type information is often incorporated as an additional input (two examples are Chen *et al.* [12], and Lertpalangsunti and Chan [13]). In either case the day-types must, however, be identified. The selection of day-types can be guided by analytical techniques.

IV. Kohonen Map for Day-Type Identification

The self-organising feature map or Kohonen map [14] would appear ideal for day-type identification as the number and similarity between day-types is not known *a priori*. The Kohonen map can be implemented for day-type identification in several different ways (examples are [7], [8], [6]); however differences in the results are insignificant in most cases thus the algorithm used by Hsu and Yang [6] was chosen. The Kohonen map structure is diagrammatically shown in Fig. 3.

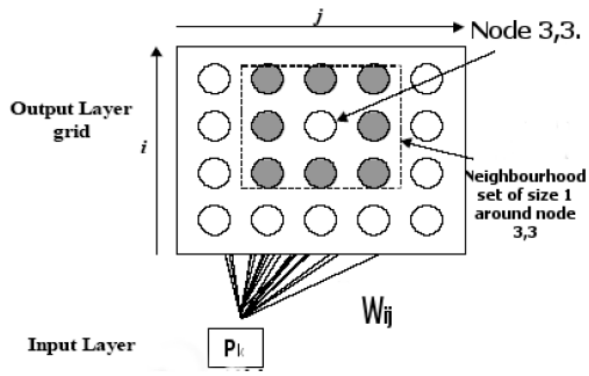


Fig. 3. Kohonen map structure

The network consists of a grid of output nodes connected to the inputs via a set of weights. When presented with the k^{th} input vector P_k R^{ixn}, the network calculates the activation of each node by P_k as:

$$a_{i,j,k} = W_{i,j} P_k \tag{1}$$

where $a_{i,j,k}$ and $W_{i,j}$ are the activation of, and weight ($R^{1\times n}$) connecting P_k to, node *i, j* respectively. P_k is said to be mapped onto the node with the highest activation. After several inputs have been presented, similar inputs are mapped to the same or adjacent nodes, *i.e.,* within a small neighbourhood. A neighbourhood of size N_c around node *i, j* is defined as nodes $i \pm N_c$ to $j \pm N_c$.

P_k for the current study is formed in two steps. Initially, the daily load curve is extracted from each day to give a set of load curves that have a minimum value of zero and a maximum value of one[6].

$$Y'(i)_k = \frac{Y(i)_k - minY_k}{maxY_k - minY_k} \qquad i = 1, 2, ..., 24 \qquad (2)$$

where $Y'(i)_k$ and $Y(i)_k$ are the i_{th} elements (hour) of the load curve Y'_k $R^{1\times 24}$, and actual load Y_k $R^{1\times 24}$ of day k respectively. The load curves are then normalised to give them unity length:

$$P(i)_k = \frac{Y'(i)_k}{\left(\sum_{j=1}^{24} Y'(i)_k^2\right)^{1/2}} \qquad i = 1, 2, ..., 24 \qquad (3)$$

where $P(i)_k$ is the i^{th} element of P_k. The weights are initialised [6] as:

$$W_{i,j} = \|[\mu_P(1), \mu_P(2), \cdots, \mu_P(24)] + 5u[\rho_P(1), \rho_P(2), \cdots, \rho_P(24)]\| \qquad (4)$$

where $\mu_P(1)$ and $\rho_P(1)$ are the sample mean and standard deviation of $P(i)$ over all k, u is a uniformly distributed random number in the range -0.5 to 0.5 and $W_{i,j}$ is normalised to unit length as in [6].

The weights are not initialised randomly but initialised around the mean of the inputs as the inputs are all similar and thus restricted to a small portion of the space [6]. During training the inputs are presented one by one and the weights of the triggered node (the node to which the inputs is mapped) and nodes in its neighbourhood are updated as in equation (5).

$$W_{i,j}(m+1) = W_{i,j}(m) + \alpha(m)[P_k - W_{i,j}(m)] \qquad (5)$$

Where α is the adaptation gain, with $0 < \alpha < 1$, and m is the iteration number. This has the effect of increasing the activation of the triggered node and its neighbours. In a single iteration all the inputs are presented and the weights adapted. After several iterations, the neighbourhood size is reduced by one and so on until zero, *i.e.*, the triggered node only is adapted.

V. Simulation and Results

For the present study, the trials used full years of data of 2003 and 2004. The kohonen map was trained using the following parameters:

- An initial neighbourhood size of $N_c = 4$,
- Adaptation gain equal to 0.002,
- Total number of iteration $m = 10$ and
- A Grid size 18×18 (324 in total).

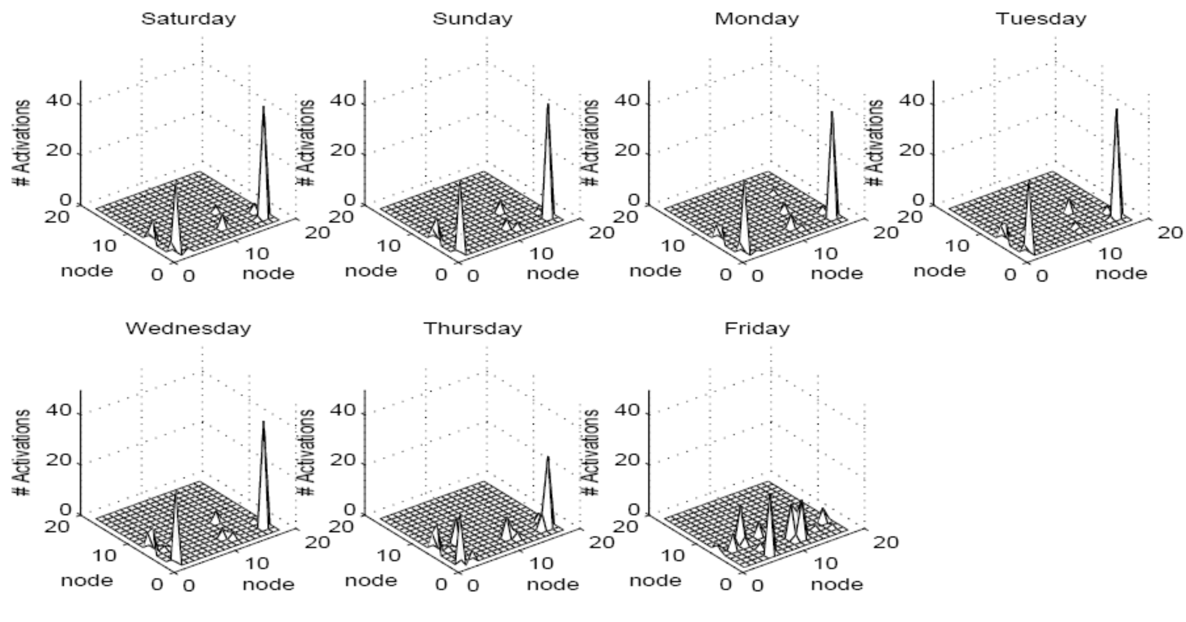


Fig. 4. Weekly day type identification

These values are similar to those used by Hsu and Yang [6]. It should be noted that the technique was found to be quite robust to a change in the parameters values for the used Kohonen map (cited above). However, if needed, those parameters will be modified to give better results along the research period.

The value of α affects the rate at which the network adapts to each input; if the value is too large the network overreacts to each input while the network will not converge if the value is too small. The value of α may be adapted from iteration to iteration however in simulations conducted by the author little difference was found; this was also the case reported by Hsu and Yang [6]. As was found by Hsu and Yang [6], a wide range of values from .001 to .007 was found to give satisfactory results. Fig. 4 shows a plot of the number of nodes activated by inputs of various types, in the trained Kohonen map. It can be seen that weekdays activate roughly the save map nodes where, the weekend activate different nodes. The difference is most predominant for Fridays that excites the Kohonen map in the most particular manner. This was expected as Friday coincides with the weekly prayer occurring from 12 to 2:30 pm depending on the season, and affecting the load by a consumption drop. The larger peaks further apart from right to left, represent the day types for winter and summer respectively.

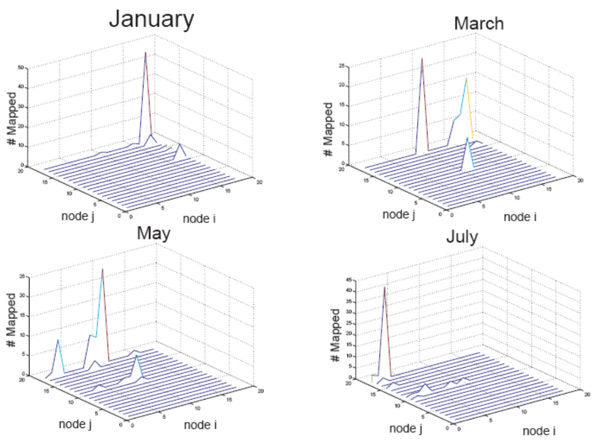


Fig. 5. Seasonal effect on triggered nodes

This was identified when analysing the map behavior for each month of the analysed years. Fig. 5, shows clearly that winter months triggers nodes on the right hand side of the map, whereas summer months triggers nodes on the left hand side. summer and winters days are therefore clearly identified. The successive months from September to august will trigger nodes further away from the right hand side of the map until reaching the extreme left hand side. Note, that Octobers and Novembers, might excite a wider area of the map as these months may contain, days exhibiting both the characteristics of winter and summer days.

This is even more clearly shown for January (a Winter month) and August (a Summer month), Fig. 6. As for the smaller peaks they represent weekends and special day types, *i.e.*, days of bank or religious holidays, weekends, Ramadhan, etc. where the load behaves differently than other summer or winter mapped days.

An interesting issue is the month of fasting (Ramadhan), where the habits of the population changes dramatically, *i.e.* less working hours, same habits for working or weekdays, new dining hours, etc. For the month of Ramadhan 2003, Fig. 7, there are no clear distinction between weekends and weekdays given by the Kohonen map. The only difference noticed is the split of the weekdays into two distinct groups. However, the national bank holiday (1st of November) is clearly picked out.

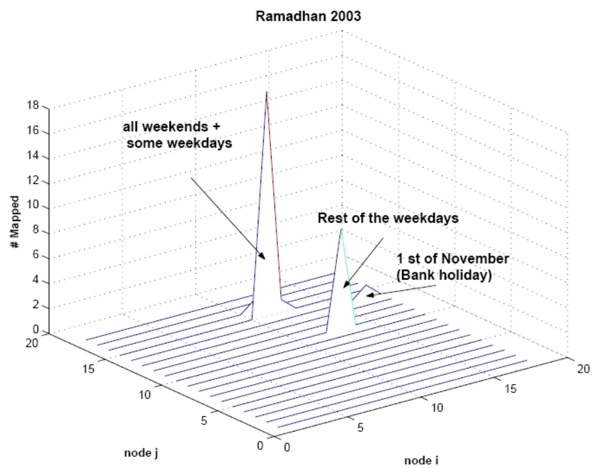


Fig. 7. Kohonen map behavior for Ramadahn

VI. Conclusion

The previous demonstrations, Sections V and IV, show that day types for Algerian electricity load, are successfully identified using Kohonen MAP. Indeed the map captured:

- the difference between working days and weekends,
- the difference between summer and winter days, and
- all of the national bank holidays (these days follows the Gregorian calendar).

One of the reasons for this success, is the fixed spaced occurrence of those day types. However, trying to identify religious bank holidays, will be more laborious as it doesn't follow the Gregorian calendar. Indeed, religious bank holidays as well as ramadan follow the lunar calendar, in which a year is 10 to 11 days shorter than the Gregorian one. Despite that, the map showed clearly the distinct effect of the month of Ramadhan where the load behavior is totally different than the rest of the days, and is not, or poorly, affected by the weekend weekdays habits. Identifying Ramadhan or other religious bank holidays as special day types, stand as a solid challenge.

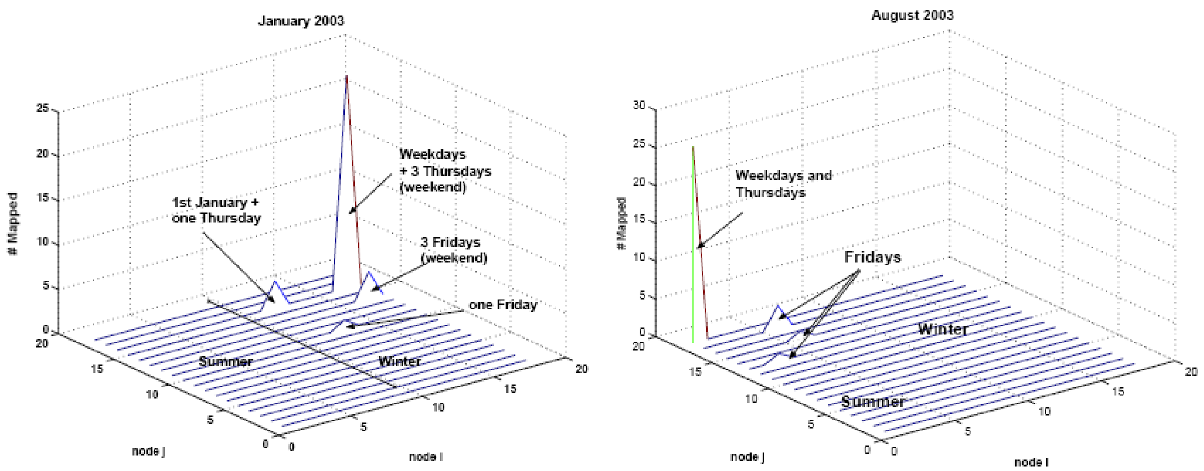


Fig. 6. Day type identification for summer and winter months

ACKNOWLEDGMENT

Courtesy of Sonelgaz (Societe Algerienne d'Electricite et de Gaz) Annaba, we have been generously provided with five years of electricity data for the national grid.

REFERENCES

[1] Francisco J. Nogales, Javier Contreras, Antonio J. Conejo and Rosario Espnola, 2002, Forecasting Next-Day Electricity Prices by Time Series Models, *IEEE Transactions on Power Systems*, Vol. 17(2), pages 342-348.

[2] Sharif S.S. and Taylor J.H., 2002, Real-Time Load Forecasting by Artificial Neural Networks, *IEEE Power Engineering Society Summer Meeting*, Vol 1, pp 496-501.

[3] Fay, D., 2004, *A strategy for short-term load forecasting in Ireland*, Ph.D Thesis, Dept. of Electronic Engineering, Dublin City University, Ireland.

[4] Magali, R., Meireles, G., Paulo, E., Almeida, M. and Sim¨oes, M.G., 2003. A comprehensive review for industrial applicability of artificial neural networks *IEEE Transactions on Industrial Eletronics,* Vol 50 (3), pp 585-60.

[5] Fay, D., Ringwood, J.V., Condon, M. and Kelly, M. 2003. 24-hour electrical load data - a sequential or partitioned time series? *Journal of Neurocomputing*, Vol 55, (3-4), pp 469-498.

[6] Hsu, Y.Y. , Yang, C.C., 1991, Design of artificial neural networks for short-term load forecasting Part I: Self-organising feature maps for day type identification, *IEE Proceedings-C*, 138(5), page 407-413.

[7] Muller, H., Petrisch, G., 1998, Energy and load forecasting by fuzzyneuralnetworks. In: Jurgen, H., Zimmermann, H.J., *eds., Proceedings, European Congress on Intelligent Techniques and Soft Computing*, Aachen, Germany, September 1998. Aachen: Elite foundation, 1925-1929.

[8] Bretschneider, P., Rauschenbach, T., Wernstedt, J., 1999, Forecast using an adaptive fuzzy classification algorithm for load, *6th European Congress on Intelligent Techniques and Soft Computing, Vol.3*, pp 1916-1919.

[9] Hubele, N.F., Cheng, C.S., 1990, Identification of seasonal short-term forecasting models using statistical decision functions, *IEEE Transactions on Power Systems*, 5 (1), 40-45.

[10] Srinivasan, D., Tan, S. S., Chang, C. S., Chan, E. K., 1999, Parallel neural network-fuzzy expert system for short-term load forecasting: system implementation and performance evaluation, *IEEE Transactions on Power Systems*, 14 (3), 1100-1106.

[11] Mastorocotas P.A., Theocharis, J.B., Bakirtzis, A.G., 1999, Fuzzy modelling for short term load forecasting using the orthogonal least squares method, *IEEE Transactions on Power Systems*, 14 (1), 29-35.

[12] Chen, S.T., Yu, D.C., Moghaddamjo, A.R., 1992, Weather sensitive short-term load forecasting using non-fully connected artificial neural network, *IEEE Transactions on Power Systems*, 7 (3), 1098-1104.

[13] Lertpalangsunti, N., Chan, C.W., 1998, An architectural framework for the construction of hybrid intelligent forecasting systems: application for electricity demand prediction., *Engineering Applications of Artificial Intelligence*, 11, 549-565.

[14] Kohonen , T., 1990, The self-organising map, *Proceedings IEEE*, 78 (9).