Forecasting Electricity Load and Prices in an Algerian Deregulated Market

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***Abstract*— In a competitive electricity market environment, power producers and consumers need, on one hand, accurate load and/or electricity consumption forecasting tools. These tools will ensure an a-priori knowledge on the amount of energy needed for production. On the other hand, forecasting electricity prices, may play a very important role for producers and consumers when planning bidding strategies, in order to maximize their benefits and utilities, respectively. This paper will address both issues in a newly deregulated Algerian Market, with an analysis of the electricity national demand. An example of electricity demand model will be presented, as well as an attempt to introduce price modelling taking into account that there is only one electricity supplier on the market. Possibilities of price forecasting in a deregulated market may be projected.**

Keywords: Forecasting, electricity Load, electricity price, linear/nonlinear models, time series.

I. Introduction

The electric power industry in many developing countries is moving from a centralized operational approach to a competitive one. The understanding of electric power supply as a public service is being replaced by the notion that a competitive market is a more appropriate mechanism to supply energy to consumers with high reliability and low cost. Algeria is among those countries.

In such competitive environments, prediction become a powerful tool in the seek of higher performances. Indeed, because electrical energy cannot be stored, there exists the unique physical requirement that supply equal demand instantaneously. A valid model (or forecasting tool) for load and/or consumption forecasting, will help to reach this requirement.

On the financial side, a valid prediction of the electricity price, may advantage some companies over others. Producers and consumers rely on price forecast information to prepare their corresponding bidding strategies. If a producer has a good forecast of next-day market-clearing prices it can develop a strategy to maximize its own benefit and establish a pool bidding technique to achieve its maximum benefit. Price forecast is well developed in the American market, where, for example, in the Californian market, aggregate supply and demand curve data are publicly available for the day-ahead market on a three-month delay basis [1].

In the long term, load is an evolving process. With increased economic activity over the last few years, electrical demand has increased considerably. Therefore long term forecasting involves many parameters, such as economic and social ones. In this paper long term will not be treated, and the main goal will be short term forecasting.

In the remaining of the paper, a presentation of five years of Algerian demand data will be presented and analysed, and an example of identification of day types will be shown, Section II. Section III gives an overview of the different techniques that can be used for short term load forecasting. The dependencies and/or correlation with external inputs such as temperature and humidity will be introduced. The actual prediction model used by Sonelgaz is detailed and explained in Section IV-B.

Section V will give an overview on the possible electricity prices forecast and the different techniques that may be used for the Algerian case. An Auto-Regressive (AR) model is constructed and tested for the prediction of the Algerian load or electricity demand. The results are compared to the one obtained by the used method. Finally Section VI, asses the preliminary obtained results, for day type identification as well as for the results of the AR model. Future works that may done, in order to improve the forecasting quality and results, will be enumerated.

II. Primarily analysis of the Algerian electricity demand

Courtesy of Sonelgaz Annaba, we have been generously provided with the last five years of electricity data for the national grid. 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 data points	43796

Figure 1, shows the shape of electricity demand in Algeria in the last five years. The growth in electrical demand is clearly seen. It can be seen that the growth is exponential. To gain initial insight into the nature of the underlying trend a quadratic curve of the form, equation (1) may be fitted to the data [2].

$$d(t) = at^2 + bt + c + \varepsilon(t) \quad (1)$$

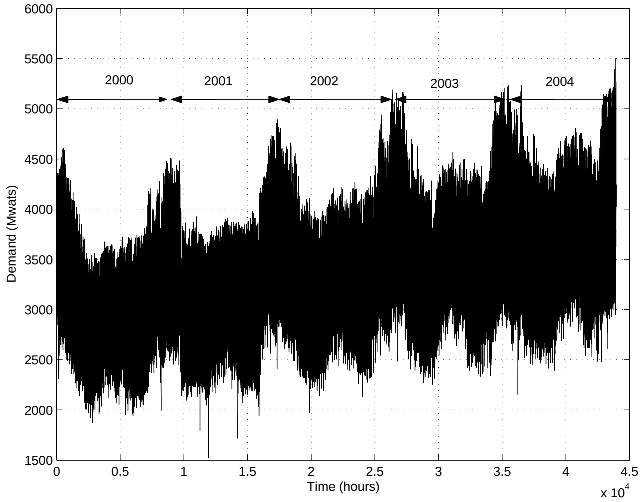

Fig. 1. Load with approximate trend curve

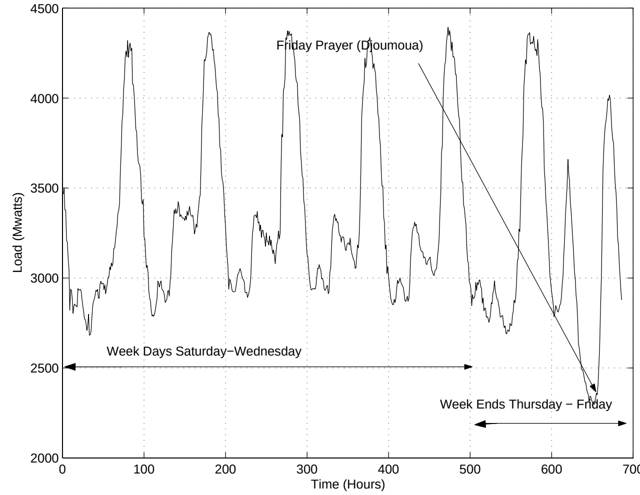

Fig. 2. A typical weekly load

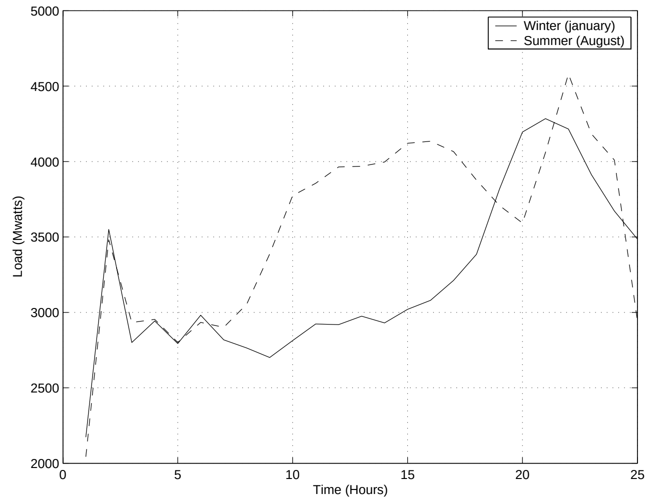

Fig. 3. Typical summer and winter daily Algerian load for a working day

where t is the time in hours since the start of the data (2000), $d(t)$ is the trend at time t, $\varepsilon(t)$ is an error term, and a, b, c are positive coefficients calculated via least squares.

A. Day-type identification

Daily load data can be disaggregated into distinct groups (called day-types) each of which have common characteristics. As can be seen in Figure 2 there is, for example, an obvious difference between the shape of the load on a typical week end day, such as Friday and a working day like Saturday or Sunday due to decreased economic activity and the weekly prier on Friday. Note that having, in Algeria, the week end on Thursday and Friday will not dramatically change the weeks day type as long as it is taken into consideration.

Furthermore, there is a distinct difference between the shape of a typical Winter day and Summer day (Figure 3). A typical Winter working day (saturday) exhibits a high peak at 21pm, in a Summer day (which is the holidays for most people) the peak is a 22pm.

The existence of several different day-types has been shown by several researchers [3], [4], [5]. However, the level of disaggregation 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 [6], the application of a separate load forecasting model for different seasons (for example Summer, Autumn, Winter and Spring) has the advantage that the models need not incorporate seasonal information. Further disaggregation 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 [7] and Mastorocostas *et al.* [8], 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.* [9], and Lertpalangsunti and Chan [10]). In either case the day-types must, however, be identified. The selection of day-types can be guided by analytical techniques.

The self-organising feature map or Kohonen map [11] is the preferable option for day-type identification as the number of day-types is not pre-specified and the proximity of the identif ied daytypes is known. The Kohonen map can be implemented for day-type identification in several different ways (examples are [3], [4], [5]); however differences in the results are insignificant in most cases thus the algorithm used by Hsu and Yang [5] was chosen. The Kohonen map structure is diagrammatically shown in Figure 4 below.

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 $P_k \in R^{1\times n}$, the network calculates the activation of each node by P_k as:

$$a_{i,j,k} = W_{i,j} P_k \tag{2}$$

where $a_{i,j,k}$ and $W_{i,j}$ are the activation of, and weight ($\in$

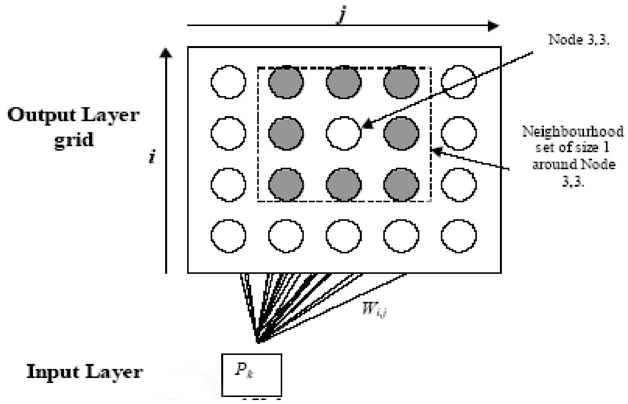

Fig. 4. Kohonen map structure

$R^{1\times n}$) 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 neighborhood. A neighborhood of size N_c around node i, j is defined as nodes $i \pm N_c$ to $j \pm Nc$.

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 [5].

$$Y'(i)_k = \frac{Y(i)_k - minY_k}{maxY_k - minY_k} \qquad i = 1, 2, ..., 24 \qquad (3)$$

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

$$P(i)_k = \frac{Y'(i)_k}{\left(\sum_{j=1}^{24} Y'(i)_k^2\right)^{1/2}} \qquad i = 1, 2, ..., 24 \qquad (4)$$

where $P(i)_k$ is the i^{th} element of P_k. The weights are initialised [5] as:

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

where $\mu_p(1)$ and $\rho_p(1)$ are the 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 [5].

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 [5]. 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 neighborhood are updated as in equation (6).

$$W_{i,j}(m+1) = W_{i,j}(m) + \alpha(m)[P_k - W_{i,j}(m)] \qquad (6)$$

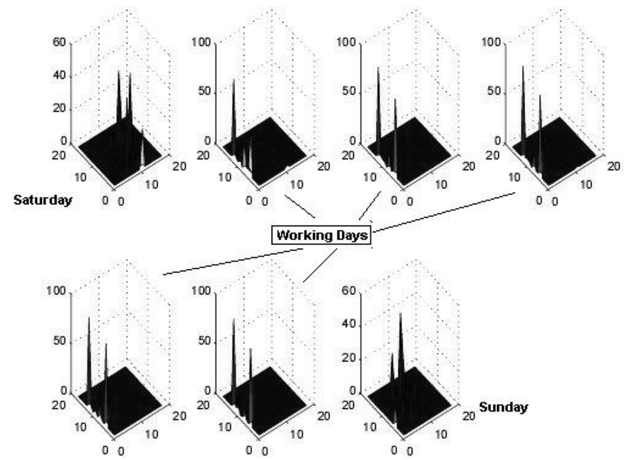

Fig. 5. Weekly day type identification

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 neighbors. In a single iteration all the inputs are presented and the weights adapted. After several iterations, the neighborhood size is reduced by one and so on until zero, i.e. the triggered node only is adapted.

For the present study, the trials used all of the last 3 full years of data, 2000 and 2003. The parameters used for the Kohonen map are similar to those used in [5], for a first try. If needed those parameters will be modified to give better results along the research period.

An example of the results given by a the Kohonen map for the Irish data load [2] is shown in Figure 5, it can be seen that 5 days (week days) gives similar characteristics where, the week end days give different plot shapes. Based on that, the map will be able to filter the type of day from the data and treat it separately in sub-sequent forecast modules. The same approach may be applied for special seasonal days as bank holidays *i.e.,* Christmas.

The previous demonstration shows that, both analytically and with simulation, that day types can be identified. The difference between working and week ends may be captured by the Kohonen map. One of the reasons for that is the fixed spaced occurrence of those days. However, trying to identify bank holidays, especially 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. This will be the target of future research.

III. Load forecasting models

Over the last few decades a number of forecasting methods have been developed falling into two main categories:

- **Linear methods:** well established and proved but limited when dealing with nonlinear functions (the case in load) forecasting).

- **Nonlinear methods:** More suitable to approximate non-linear functions, but still ongoing field of research with the main disadvantage of not having an analytical solution.

A. Linear models (Box-Jenkins)

Box and Jenkins (1970) [12] laid many of the foundations of classical time-series analysis. Their techniques have been used in several load forecasting applications (Di Caprio *et. al.,* [17], Rajukar and Newill [18] to mention a few) and are often used as a baseline for comparison with other newer approaches. Box-Jenkins techniques involve modelling a time-series as a function of previous inputs, output errors and external inputs.

Box and Jenkins suggest several types of models for this purpose. The general form of the Box-Jenkins model is known as the transfer function model and can be expressed as a function of previous values of the time series, external inputs and previous model errors.

$$A(q)x(k) = \frac{B(q)}{F(q)}u(k-\tau) + \frac{C(q)}{D(q)}\epsilon(k) \quad (7)$$

where:

- $x(k)$ is the stationary time series to be modelled at time k,
- $u(k)$ is an external input with delay τ between input and $x(k)$,
- $\epsilon(k)$ is the error in the model at time k, and
- A, B, F, C, D are polynomials in the delay operator q^{-1} such that, for example, A may be expanded as:

  $$A(q)x(k) = (1-a_1q^{-1}-a_2q^{-2}-\cdots-a_{na}q^{na})x(k) \quad (8)$$

  where $a_1, a_2, \cdots, a_{na}$ are the coefficients of the polynomial and na is the order. B, F, C and D can be similarly expanded with coefficients $b_{1,\cdots,nb}, f_{1,\cdots,nf}, c_{1,\cdots,nc}, d_{1,\cdots,nd}$ and orders of nb, nf, nc and nd, respectively. The other models proposed by Box and Jenkins [12] can be derived from Equation (7) by letting F and D equal one with the other variations shown in Table II below.

Box and Jenkins [12] also examined the case where the series to be forecast is seasonal. In order to include the seasonal aspects of the data, Box and Jenkins used the idea of seasonal and non-seasonal operators to adjust the model to take into account the seasonality of the data *e.g.,* day and night, week days week end, seasonal temperature as external inputs ... etc [13].

The next step in the Box-Jenkins procedure involves calculating the orders of the seasonal and non-seasonal AR and MA operators, shown in Table II. The approaches used for identification may be found in many textbook such as [14]. Identification of AR AM parameters for load forecasting may be found in [2].

However as pointed out by Mohamad *et. al.,* [15] Box-Jenkins techniques have the disadvantage that they require a large database for training and are susceptible to errors in that database because of differencing. In addition, as Box-Jenkins techniques assume that the load curve is static they can give large errors when the load curve changes rapidly [15], [16]. Rajurkar and Newill [18] present an ARMAX model in which the coefficients of the model are allowed to change dynamically which allows the load shape to change more rapidly. Another problem with the Box-Jenkins approach is the subjective selection of the model orders, which can result in the wrong model structure being chosen (Chen and Kao [19]). Chen and Kao, to overcome this drawback, propose an automated approach based on repetitively applying a gentle difference algorithm.

TABLE II
BOX-JENKINS MODELS AND ASSOCIATED POLYNOMIALS (F=1, D=1).

Model name	A
AR (Auto Regressive)	$1-a_1q^{-1}-a_2q^{-2}-\cdots-a_{na}q^{-na}$
ARX (AR eXogeneous)	$1-a_1q^{-1}-a_2q^{-2}-\cdots-a_{na}q^{-na}$
MA (Moving Average)	1
MAX (MA eXogeneous)	1
ARMA (ARMA)	$1-a_1q^{-1}-a_2q^{-2}-\cdots-a_{na}q^{-na}$
ARMAX (ARMA eXogeneous)	$1-a_1q^{-1}-a_2q^{-2}-\cdots-a_{na}q^{-na}$
Model name	B
AR (Auto Regressive)	0
ARX (AR eXogeneous)	$b_1q^{-1}-b_2q^{-2}-\cdots-b_{nb}q^{-nb}$
MA (Moving Average)	1
MAX (MA eXogeneous)	$b_1q^{-1}-b_2q^{-2}-\cdots-b_{nb}q^{-nb}$
ARMA (ARMA)	0
ARMAX (ARMA eXogeneous)	$b_1q^{-1}-b_2q^{-2}-\cdots-b_{nb}q^{-nb}$
Model name	C
AR (Auto Regressive)	1
ARX (AR eXogeneous)	1
MA (Moving Average)	$c_1q^{-1}-c_2q^{-2}-\cdots-c_{nc}q^{-na}$
MAX (MA eXogeneous)	$c_1q^{-1}-c_2q^{-2}-\cdots-c_{nc}q^{-na}$
ARMA (ARMA)	$c_1q^{-1}-c_2q^{-2}-\cdots-c_{nc}q^{-na}$
ARMAX (ARMA eXogeneous)	$c_1q^{-1}-c_2q^{-2}-\cdots-c_{nc}q^{-na}$

B. Nonlinear models

There are three factors typically present in short-term electrical load which make non-linear forecasting techniques appealing [2]:

- The non-linear relationship between load and temperature
- The presence of a non-linear auto-regressive relationship in load
- The non-stationarity of the load due to the trend

Many nonlinear approaches were and still are applied to load forecasting. Among these: Parametric nonlinear tech-

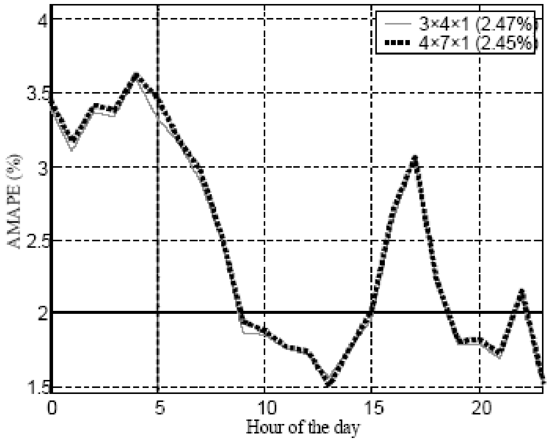

Fig. 6. Short time forecasting for the Irish market

niques, Fuzzy logic and artificial neural networks are among the most popular. An extensive review of most of these techniques are given and explained in [2].

Neural network techniques are black-box modelling techniques. That is, they require no understanding of the physical process underlying the data. The techniques are based on approximating a function via a set of basic processing units called neurons or nodes. Although ANN and nonlinear techniques have been proven very efficient, in most case better than linear ones, their black-box nature limit their understanding. From the authors points of view, investigating linear approaches is compulsory before moving to nonlinear models. However these must remain a target for research, and the seek of better performances.

IV. Examples of load forecasting models

As load forecasting become a crucial issue in deregulated electricity markets, most of the large Electricity producers started a strategy of load forecast a couple of decades ago. Many models and approaches were implemented, among them the ones cited in Section III.

A. Load forecasting for the Irish market

As an example, many approaches from: multi-time scale models, linear models and artificial neural networks gave satisfactory results in Ireland.

On one hand, Figure 6 shows an example of short term forecasting of 24 hour forecast using ANN. It can be clearly seen that the model is outstanding in term of accuracy and peak detection. On the other hand, Figure 7 shows the results for a medium/long term forecast model. It can be clearly seen that the model predicts accurately not only the seasonal aspect of the load, but its exponential trend as well. However, these models were the results of many years of research and experimentations. Both models take into account the weather parameters of the country that affect directly the electricity demand *i.e.,* temperature, wind, humidity ...etc.

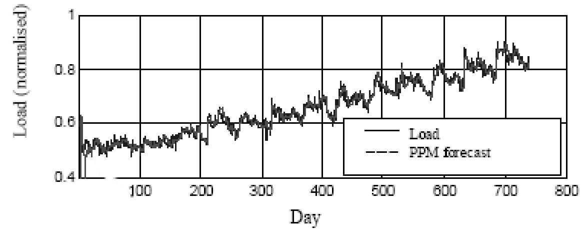

Fig. 7. Long term forecasting for the Irish market

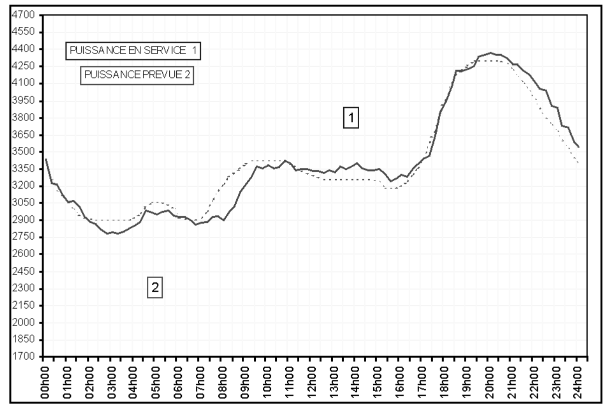

Fig. 8. Actual prediction made for the Algerian market

B. Attempt and perspective for the Algerian market

At the moment, there is not a real strategy to forecast nest day, month or year load at the Algerian company Sonelgaz. The prediction is done only based on the cyclic aspect of the load. The prediction of day $j+1$ is calculated based on the same day of previous week. However, there is an error margin of 50MW and 100MW for the day and the evening peaks respectively, taking into account a temperature factor. The results obtained are not of great quality, see Figure 8. Indeed, the forecasted load is of a flat nature and seem highly linear, able to follow the overall shape of the load, but unable to predict the peaks.

In a first attempt, to build a valid model, a simple linear model of type AR, Table II was chosen as an example. In order to take into account only the past day, 24 regressors were chosen, one for every hour of the day. The overall model structure is given in equation (9).

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + \cdots + a_{24} y(k-24) \quad (9)$$

The model is on its simplest form, not taking into account any of the previous years data, nor the external inputs such as weather, economic and seasonal attribute of the load. Yet, the model, Figure 9, behave better than the actual forecast method Figure 8. However, note that this is only an attempt to show that even the simplest model can match the approximative prediction method used, and should not, in any case considered as valid. The authors believe that obtaining a valid model is only a question of time, efforts and experimentation.

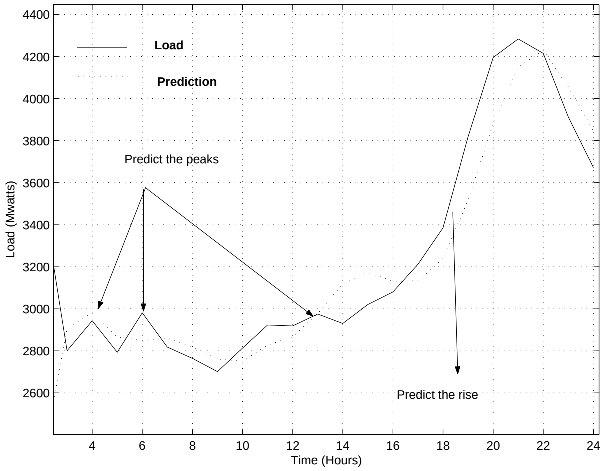

Fig. 9. Response of the simplest AR model for load forecasting

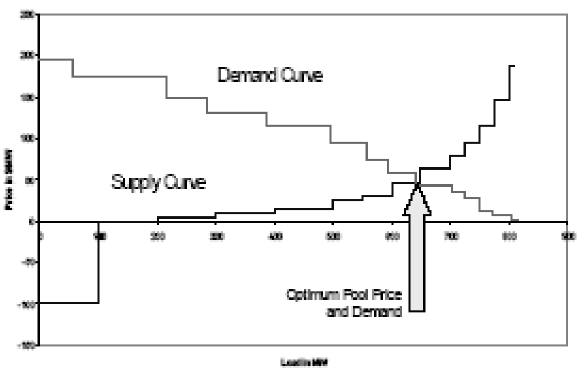

Fig. 10. Intersection of supply and demand curves

V. Electricity price forecasting models

In the electricity market, electrical power plants are dispatched in order of increasing price and consumer demand is supplied until the generation energy sale price equals the consumers energy purchase price [1]. This dispatch process implements the economic theory that the optimum market price is at the intersection of the supply and demand curves Figure 10. The supply curve is the sum of all generator offers to supply electricity and the demand curve is the sum of all demand bids to consume electrical energy. A generator must submit an offer to pool market that lists the amount and price of energy the generator is prepared to sell for every hour. The demand bid is the same only for purchasing energy instead of selling energy. The dispatch process results in a traditional demand curve and a volatile electricity price, which is challenge to forecast.

Forecasting the electricity price may be done, similarly to load, using several techniques and models. Neural networks are used to predict prices in the England-Wales pool by Ramsay *et al.,* [20] and also in California by Gao *et al.,* [21] and the Victorian market by Szkuta *et al.,* [22] In current literature, approaches based on time series analysis

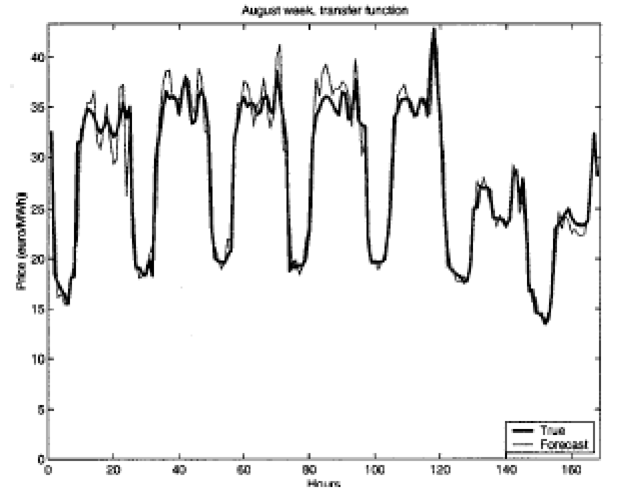

Fig. 11. Forecast of August week in the Spanish market by transfer function. Prices in euros per megawatt hour

that forecast successfully next-day electricity prices are used.

An example for the electricity price accuracy for the spanish market is shown in Figure 11. The figure shows a week ahead of price forecasting [1]. It can be clearly seen that the price follows tightly the weekly aspect of the load (even for a different country load, see Figure 2).

Although, price forecasting is not a primary target for the Algerian market, as the deregulating process is at its infancy, it is always good to have a look at the problem, and the different solutions that may be applied. This will ensure to be one step ahead, when forecasting electricity prices will be an issue.

VI. Conclusions

The importance of load and price forecasting in a deregulated electricity market is paramount in order to achieve a good quality service at a competitive price, this is a win-win situation for, on one hand the producer and on the other hand the customer.

The literature is rich in theories and approaches to build models for load and price forecasting, some were presented in this paper. However, applying those approaches remains more appropriate to certain type of load curves than others. The goal, is to conduct research in order to find the best strategy(ies) to suit the Algerian load curve.

Other parameters must be introduced in order to maximise the accuracy of the model. In the Algerian case, climate parameters such as: temperature, humidity, wind, rainfall ... etc must be taken into consideration. Another problem that must be treated is the several bank holidays based on the lunar calendar as well as the month of Ramhadan, where the load curve is totaly different than the rest of the year.

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