Forecasting Next-Day Electricity Prices by Time Series Models

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***Abstract*—In the framework of competitive electricity markets, power producers and consumers need accurate price forecasting tools. Price forecasts embody crucial information for producers and consumers when planning bidding strategies in order to maximize their benefits and utilities, respectively. This paper provides two highly accurate yet efficient price forecasting tools based on time series analysis: dynamic regression and transfer function models. These techniques are explained and checked against each other. Results and discussions from real-world case studies based on the electricity markets of mainland Spain and California are presented.**

***Index Terms*—Electricity markets, forecasting, market clearing price, time series analysis.**

I. Introduction

The electric power industry in many countries all over the world 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.

An electricity market usually includes two instruments to facilitate trade among power producers and consumers: the pool, which is an e-commerce marketplace, and a framework to enable physical bilateral contracts. Financial contracts to hedge against risk of price volatility are possible and advisable, but they do not affect the physical operation of the system.

In the pool [power exchange (PX)], power producers [generating companies (GENCOs)] submit generation bids and their corresponding bidding prices, and consumers [consumption companies (CONCOs)] do the same with consumption bids. The market operator (MO) uses a market-clearing tool to clear the market. This tool is normally based on single-round auctions [1], and considers the hours of the market horizon one at a time. A single-round auction is performed every hour to determine the resulting market clearing price in that hour and also the accepted production and consumption bids. Ex post, either repair heuristics or adjustment markets, are used to eliminate physical infeasibilities due to inter-temporal constraints or network congestions.

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Market clearing prices are public information made available by the MO. No other information is usually readily available. For instance, aggregate offer and demand curves are not available in many electricity markets. 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. In the Spanish market, aggregate supply and demand data are only available to the bidders with a three-month delay.

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 [2] and establish a pool bidding technique to achieve its maximum benefit. Similarly, once a good next-day price forecast is available, a consumer can derive a plan to maximize its own utility using the electricity purchased from the pool. If this consumer has self-production capability, it can use it to protect itself against high prices in the pool.

In a medium-term horizon (six months to one year), producers have to find out how much energy to sell through bilateral contracts and how much energy to sell to the pool. Consumers have to make similar decisions on buying energy through bilateral contracts, or from the pool. For this type of portfolio decisions, it is desirable to have available forecasts of price average values over a year horizon. Energy service companies (ESCOs) buy energy from the pool and from bilateral contracts to sell it to their clients. These companies also need good short-term and long-term price forecast information to maximize their respective benefits.

This paper focuses on short-term decisions associated to the pool. Therefore, only the forecasting of next-day prices is considered. This fact implies that, for each day of the week, 24 price forecasts must be computed.

Since next-day price forecasting is a crucial need for producers, consumers and energy service companies, this paper proposes two efficient yet highly accurate next-day price forecasting tools: dynamic regression and transfer function models. They are based on time series analysis and are used to forecast actual prices in the electricity markets of mainland Spain [3] and California [4].

Price forecasting techniques in power systems are relatively recent procedures. In the past, demand was predicted in centralized markets [5]. Competition has opened a new field of study and there are already several techniques in use to forecast prices. Jump diffusion/mean reversion models have been applied by Skantze *et al.* [6] to model electricity prices. Fuzzy regression models that relate prices and demands have been applied to the

Californian market by Nakashima *et al.* [7]. Neural networks are used to predict prices in the England-Wales pool by Ramsay *et al.* [8] and also in California by Gao *et al.* [9] and the Victorian market by Szkuta *et al.* [10]. Finally, techniques based on Fourier and Hartley transforms have been studied by Nicolaisen *et al.* [11].

In current literature, approaches based on time series analysis that forecast successfully next-day electricity prices are rare to find. However, time series analysis has been applied with great success in other areas where the frequency of data is at most weekly, see [12]. This paper proposes two techniques based on time series analysis that produce accurate results with hourly electricity price data.

The remaining of this paper is organized as follows. In Section II, a mathematical description of the models based on time series analysis is given. Section III presents numerical results and Section IV provides several conclusions.

II. Time Series Analysis

In this section, the description of two models based on time series analysis is presented. It is assumed that price values are recorded at fixed time intervals.

The analysis is based on setting up a hypothetical probability model to represent the data. The presented models are selected based on a careful inspection of the main characteristics of the hourly price series. In most competitive electricity markets, this series presents the following:

- high frequency;
- nonconstant mean and variance;
- multiple seasonality (corresponding to a daily and weekly periodicity, respectively);
- calendar effect (such as weekends and holidays);
- high volatility;
- high percentage of unusual prices (mainly in periods of high demand).

These characteristics can be observed in Figs. 1–4 for the pool of mainland Spain and in Figs. 5 and 6 for the Californian one.

Time series analysis can include explanatory variables. In the proposed models, the demand of electricity has been included because, *a priori*, it seems to partly explain the price behavior.

Taking the relationship of these two variables into account, an initial approach to model electricity prices is the use of a *linear regression model*. However, this approach has a serious problem due to the presence of serial correlation in the error that indicates that the model is not appropriate. The drawback of this approach is that it can results in a model that is ineffectual or incorrect and, which is more important, that forecasts with a limited accuracy.

Therefore, it is necessary to develop models that can handle correlated errors. Two such models have been chosen to forecast market clearing prices. These two models have been obtained following a recursive scheme.

An outline of this scheme is as follows.

Step 1) A model is identified assuming certain hypotheses.
Step 2) The model parameters are estimated.
Step 3) If the hypotheses of the model are validated go to Step 3, otherwise go to Step 0 to refine the model.
Step 4) The model can be used to forecast.

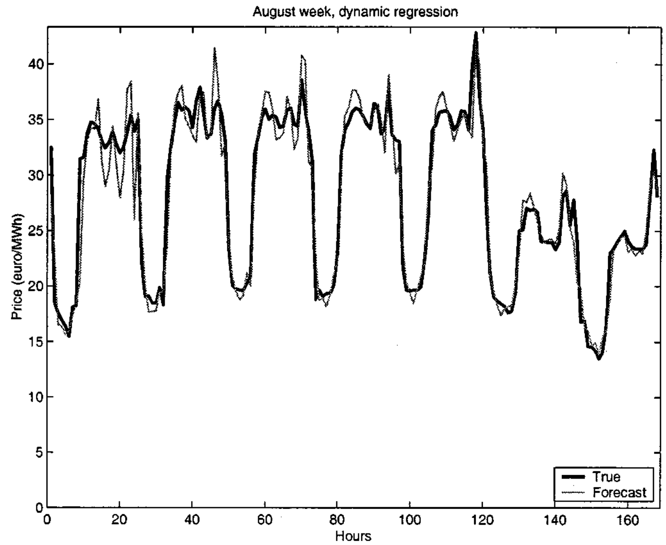

Fig. 1. Forecast of August week in the Spanish market by dynamic regression. Prices in euros per megawatt hour.

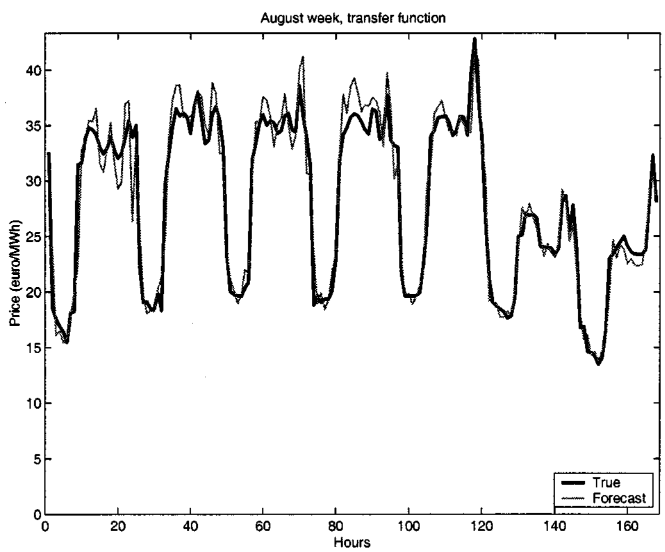

Fig. 2. Forecast of August week in the Spanish market by transfer function. Prices in euros per megawatt hour.

In Step 0, an initial model is built, hypotheses are established, and an initial selection of parameters is chosen.

In Step 1, an estimation procedure is used, based on available data. Good estimators of the parameters can be found by assuming that the data are observations of a stationary Gaussian time series and maximizing the likelihood with respect to the parameters [12].

In Step 2, a diagnostic checking is used to validate the model assumptions. This is carried out by comparing the observed values with the corresponding predicted values obtained from the fitted model. If the fitted model is appropriate, then the residuals (observed values minus predicted values) should behave in a manner that is consistent with the model. To verify this, some techniques such as autocorrelations plots, partial autocorrelations plots, and tests for randomness of the residuals, can be used.

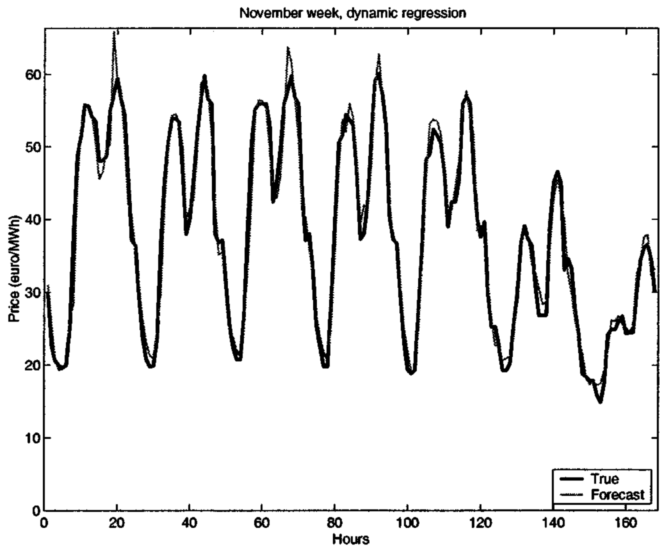

Fig. 3. Forecast of November week in the Spanish market by dynamic regression. Prices in euros per megawatt hour.

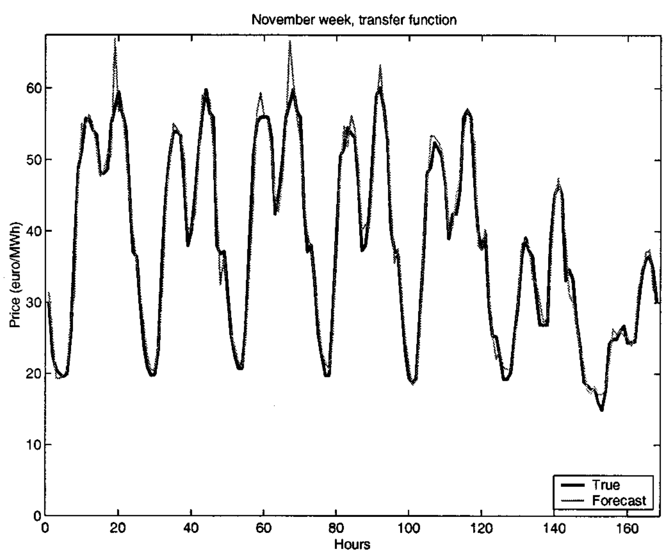

Fig. 4. Forecast of November week in the Spanish market by transfer function. Prices in euros per megawatt hour.

In Step 3, the selected model can be use to predict future values of prices (typically 24 h ahead). Due to this requirement, difficulties can arise because predictions can be less certain as the forecast lead time becomes longer.

Following the above scheme, two models have been selected to forecast market clearing prices: a dynamic regression model and a transfer function model.

A. Dynamic Regression Approach

The first effective technique which is proposed to overcome the serial correlation problem uses a *dynamic regression model* [12]. In this model, the price at hour t is related to the values of past prices at hours $t-1, t-2, \ldots$ and to the values of demands at hours $t, t-1, t-2, \ldots$ This is done to obtain a model that

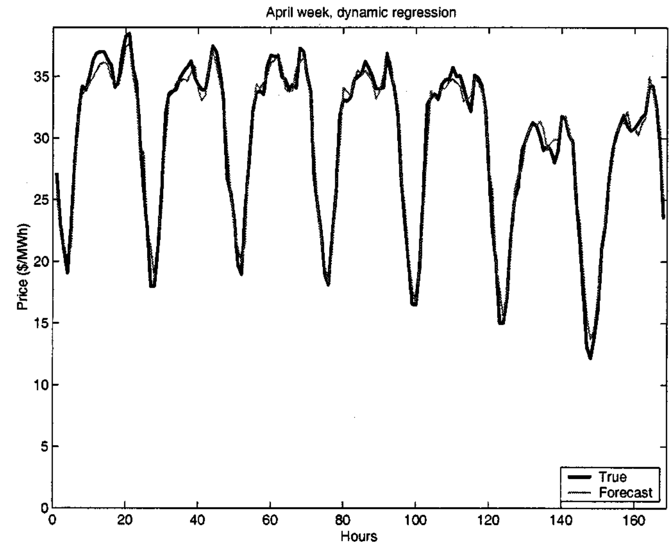

Fig. 5. Forecast of April week in the Californian market by dynamic regression. Prices in dollars per megawatt hour.

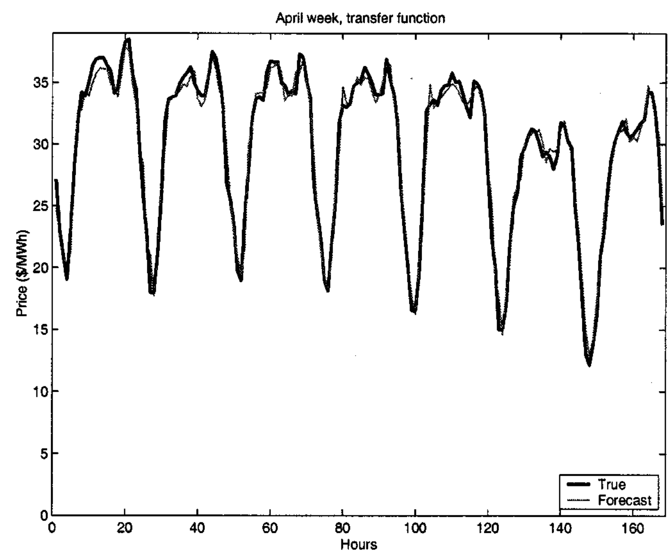

Fig. 6. Forecast of April week in the Californian market by transfer function. Prices in dollars per megawatt hour.

has uncorrelated errors. In Step 0, the selected model used to explain the price at hour t is the following:

$$p_t = c + \omega^d(B)\, d_t + \omega^p(B)\, p_t + \varepsilon_t \qquad (1)$$

where p_t is the price at time t; c is a constant; and d_t is the demand at time t. Functions $\omega^p(B) = \sum_{l=1}^{K} \omega_l^p B^l$ and $\omega^d(B) = \sum_{l=0}^{K} \omega_l^d B^l$ are polynomial functions of the backshift operator $B : B^l z_t = z_{t-l}$, and depend on parameters ω_l^p and ω_l^d, respectively, whose values are estimated in Step 1. Finally, ε_t is the error term. In Step 0, this term is assumed to be a series drawn randomly from a normal distribution with zero mean and constant variance σ^2, that is, a white noise process.

The efficiency of this approach depends on the election of the appropriate parameters in $\omega^d(B)$ and $\omega^p(B)$ to achieve an uncorrelated set of errors. This selection is carried out through Steps 0–2.

In Step 0, all the parameters are set to zero. Then, an inspection of the residuals in Step 2 helps in identifying a set of parameters different from zero to build a refined model in Step 0. After some iterations of this scheme, the series of residuals is checked to validate if it follows a white noise process and, if this checking is passed, final parameters different from zero are selected.

Final selected parameters ω_l^d of function $\omega^d(B)$ in (1) that are different from zero are those corresponding to indexes $l = 0$, 1, 2, 3, 24, 25, 48, 49, 72, 73, 96, 97, 120, 121, 144, 145, 168, 169, 192, and 193. Selected parameters ω_l^p of function $\omega^p(B)$ in (1) that are different from zero are those corresponding to indexes $l = 1$, 2, 3, 24, 25, 48, 49, 72, 73, 96, 97, 120, 121, 144, 145, 168, 169, 192, and 193. Once these parameters are selected, they are estimated in Step 1, as it is indicated in Section III.

B. Transfer Function Approach

A second method is proposed for dealing with serial correlation. It includes a serially correlated error. Such an approach is called *transfer function model* [12]. Specifically, it is assumed that the price and demand series are both stationary (i.e., with constant mean and variance). The general form proposed to model the (price, demand) transfer function is

$$p_t = c + \omega^d(B)\, d_t + N_t \tag{2}$$

where

p_t	price at time t;
c	a constant;
d_t	demand at time t;
$\omega^d(B) = \sum_{l=0}^{K} \omega_l^d B^l$	polynomial function of the backshift operator.

N_t is a disturbance term that follows an ARMA model [12] of the form

$$N_t = \frac{\theta(B)}{\phi(B)} \varepsilon_t \tag{3}$$

with $\theta(B) = 1 - \sum_{l=1}^{\Theta} \theta_l B^l$ and $\phi(B) = 1 - \sum_{l=1}^{\Phi} \phi_l B^l$, both of which being polynomial functions of the backshift operator. Finally, ε_t is the error term.

The model in (2) relates actual prices to demands through function $\omega^d(B)$ and actual prices to past prices through function $\phi(B)$.

Following a recursive scheme (similarly to the dynamic regression approach), the parameters different from zero in $\omega^d(B)$, $\theta(B)$, and $\phi(B)$ are selected.

Final selected parameters different from zero for function $\omega^d(B)$ in (2) are the same as those selected for the dynamic regression model. Selected parameters ϕ_l of function $\phi(B)$ in (2) that are different from zero are those corresponding to indexes $l = 1$, 2, 3, 24, 25, 48, 49, 72, 73, 96, 97, 120, 121, 144, 145, 168, 169, 192, and 193. Due to seasonality, function $\theta(B)$ has been divided into two functions $\theta(B) = \theta_1(B)\theta_2(B)$ where $\theta_1(B) = 1 - \sum_{l=1}^{\Theta} \theta_{1l} B^l$ and $\theta_2(B) = 1 - \sum_{l=1}^{\Theta} \theta_{2l} B^l$. Selected parameters θ_{1l} for the first factor are different from zero for indexes $l = 1, 2, 3, 24$. The only parameter different from zero for the second factor is for index $l = 168$. Once parameters different from zero are selected, they are estimated in Step 1 as it is indicated in Section III.

C. Practical Refinements

Before a final model is identified and its parameters estimated using the available data, the following considerations have to be made.

1) For both models, a logarithmic transformation is applied to the price and demand data to achieve a more homogeneous variance. The resulting models are

$$\log(p_t) = c + \omega^d(B)\log(d_t) + \omega^p(B)\log(p_t) + \varepsilon_t \tag{4}$$
$$\log(p_t) = c + \omega^d(B)\log(d_t) + N_t. \tag{5}$$

2) Due to unexpected or uncontrolled events in the electricity markets, a high frequency of unusual prices can arise. These unusual observations are called outliers in the forecasting literature. As these events are not initially known, a procedure that detects and minimizes the effect of the outliers is necessary. With this adjustment, a better understanding of the series, a better modeling and estimation, and finally, a better forecasting performance is achieved. Additional information for outlier detection and adjustment can be found in [13].
3) To achieve more robust forecasts, another refinement is carried out. If a time series is log-transformed, the estimator of the mean is biased (underestimated). In order to unbias this mean estimate, it is necessary to add half of the variance to the forecast before taking its exponential to eliminate the logarithmic transformation. Additionally, confidence intervals of forecasts should be adjusted to center them around the unbiased mean estimate [14].

In the following section, the performance of the two proposed models (with practical refinements included) is compared.

III. Numerical Results

A. Case Studies

The proposed forecasting models have been applied to predict the electricity prices of both mainland Spain market and the California PX.

For the Spanish electricity market, two weeks have been selected to forecast and validate the performance of the proposed models. The first one corresponds to the third week of August 2000 (from days August 21 to 27), which is typically a low demand week [15]. The second one corresponds to the third week of November 2000 (from days November 13 to 19), which is typically a high demand week [15]. The hourly data used to forecast the first week are from June 1, 2000 to August 20, 2000. It should be noted that to forecast this summer only summer data is used. The hourly data used to forecast the second week are from January 1, 2000 to November 12, 2000.

For the California electricity market, the week of April 3, 2000 to April 9, 2000 has been chosen. It should be noted that this week is prior in time to the beginning of the dramatic price volatility period that is still underway. The hourly data used to forecast this week are from January 1, 2000 to April 2, 2000.

TABLE I
DAILY MEAN ERRORS OF AUGUST WEEK IN THE SPANISH MARKET BY DYNAMIC REGRESSION

Days	1	2	3	4	5	6	7
Mean	8.7%	5.6%	3.9%	4.0%	4.2%	3.8%	5.3%

TABLE II
DAILY MEAN ERORS OF AUGUST WEEK IN THE SPANISH MARKET BY TRANSFER FUNCTION

Days	1	2	3	4	5	6	7
Mean	8.3%	5.4%	4.3%	6.1%	3.7%	3.6%	4.8%

The SCA system [16] has been used to estimate the parameters of the models in Step 1. The parameter estimation is based on maximizing a likelihood function for the available data [12]. A conditional likelihood function (as described in [16]) has been selected in order to get a good starting point to obtain an exact likelihood function (as described in [16]). Also, an option to detect and adjust possible outliers has been selected.

Furthermore, SCA has been used to compute the 24-h forecast. As in the estimation step, the exact likelihood function option and the detection and adjustment of outliers procedure has been selected.

To assess the prediction capacity of the two proposed models, different statistical measures are used. This capacity can be checked afterwards once the true market prices are available. For all three weeks under study, the average prediction error (in percentage) of the 24 h was computed for each day. Then, the average of the seven daily mean errors was computed and called mean week error (MWE). Also, the forecast mean-square error (FMSE) was computed for the 168 hours of each week. This parameter is the sum of the 168 square differences between the predicted prices and the actual ones. An index of uncertainty in a model is the variability of what is still unexplained after fitting the model that can be measured through the variance of the error term in (1) or (3). The smaller σ^2 the more precise the prediction of prices. As the value of σ is unknown, an estimate is required. The standard deviation of the error terms, $\hat{S}_R$, can be used as such an estimate. This estimate is useful when true values of the series are not known.

B. Forecasts

Numerical results with the two proposed models are presented. Figs. 1–6 show the forecast prices for each of the two models and for each of the three weeks studied, together with the actual prices.

Fig. 1 corresponds to the selected week in August for the Spanish market with forecast prices computed using the dynamic regression model (1).

The seven daily mean errors for this week appear in Table I. A good performance of the prediction method can be observed. The daily mean errors are around 4.5% except for the first day (Monday).

Fig. 2 corresponds to the same August week with forecast prices computed with the transfer function model (2).

TABLE III
DAILY MEAN ERRORS OF NOVEMBER WEEK IN THE SPANISH MARKET BY DYNAMIC REGRESSION

Days	1	2	3	4	5	6	7
Mean	5.2%	5.4%	4.9%	4.7%	4.3%	5.6%	5.7%

TABLE IV
DAILY MEAN ERRORS OF NOVEMBER WEEK IN THE SPANISH MARKET BY TRANSFER FUNCTION

Days	1	2	3	4	5	6	7
Mean	5.1%	5.3%	4.6%	5.0%	4.2%	5.4%	5.0%

TABLE V
DAILY MEAN ERRORS OF APRIL WEEK IN THE CALIFORNIAN MARKET BY DYNAMIC REGRESSION

Days	1	2	3	4	5	6	7
Mean	2.6%	3.3%	2.7%	1.9%	2.5%	3.7%	4.0%

TABLE VI
DAILY MEAN ERRORS OF APRIL WEEK IN THE CALIFORNIAN MARKET BY TRANSFER FUNCTION

Days	1	2	3	4	5	6	7
Mean	2.8%	3.3%	2.9%	2.2%	2.3%	3.6%	3.7%

The seven daily mean errors for this week are shown in the Table II.

The same comments stated for the previous model are appropriate for this model, though slightly better predictions are obtained.

Fig. 3 shows the selected November week for the Spanish market with forecast prices computed with the dynamic regression model (1).

The seven daily mean errors for this week appear in Table III. It can be observed that the mean prediction error during the week is around 5%. Also, it can be noted that hours with higher prediction errors are those corresponding to hours with higher prices.

The forecast prices for the transfer function model and their corresponding daily mean errors are shown in Fig. 4 and Table IV, respectively.

The Californian electricity market is considered below. Fig. 5 corresponds to the selected April 2000 week with forecast prices computed with the dynamic regression model (1).

Table V presents the daily mean errors.

In the Californian market better forecasts are obtained using any of the two proposed methods. The daily mean errors are around 3% and spike prices are more efficiently predicted.

Fig. 6 corresponds to the same April week with forecast prices computed using the transfer function model (2).

The seven daily mean errors for this week are shown in Table VI.

Table VII summarizes the numerical results. First column indicates the month, and in parenthesis the times series model used: DR for dynamic regression and TF for transfer function. Second column shows the percentage MWE, the third one

TABLE VII
STATISTICAL MEASURES

	MWE (%)	$\hat{s}_R$	$\sqrt{FMSE}$
August (DR)	5.07	0.088	11.20
August (TF)	5.17	0.082	10.93
November (DR)	5.11	0.089	13.05
November (TF)	4.94	0.087	12.92
April (DR)	2.95	0.056	13.61
April (TF)	2.97	0.055	13.47

presents the standard deviation of the error terms ($\hat{S}_R$), and the forth column shows the square root of the FMSE

$$\sqrt{FMSE} = \sqrt{\sum_{i=1}^{168} (p_t - \hat{p}_t)^2}$$

where $\hat{p}_t$ is the forecast at time t.

The MWE and the FMSE are measured in euro/MWh for the weeks studied in the Spanish market and in $/MWh for the week studied in the California market.

These measures indicate a slightly better performance of the transfer function model. This model is, however, more computationally involved.

All the study cases have been run on a PC Pentium II with 128 Mb of RAM at 600 MHz. Running time, including estimation and forecasting, has been under five minutes for each one of the cases.

To forecast electricity prices, exact demand values are assumed known. Nevertheless, it has been checked that, in the weeks studied, it is not necessary to consider demand as an explanatory variable. If the demand is not considered in the two models, then the forecasted prices are slightly worse, and the standard deviation of the error terms is slightly higher. For example, if $\omega^d(B)$ is set to 0 in the transfer function model (2), and the November week is forecasted (not considering the demand), then the new measure $\sqrt{FMSE}$ is 13.36, just 3.4% larger.

Finally, note that the fitting goodness of a statistical model to a set of data is assessed by comparing the actual values with the corresponding predicted values. If the model is correct, the residuals behave in a manner consistent with the model. In Step 2, this fact has been ensured for the proposed models by checking that the series of residuals follows a white noise process. Histograms of these residuals and autocorrelation and partial autocorrelation functions were used to check that the errors fit the initial hypotheses of the models.

IV. CONCLUSIONS

In this paper, two forecasting models to predict electricity prices have been proposed: dynamic regression and transfer function. Both of them are based on time series analysis. Average errors in the Spanish market are around 5% and around 3% in the Californian market for the weeks under study.

Price predictions obtained for the Spanish and Californian electricity markets are accurate enough to be used by producers and consumers to prepare their corresponding bidding strategies.

However, the following differences between both markets have been observed.

- The Spanish market shows more volatility in general. Reasons to support this fact are: a higher proportion of outliers and a lesser degree of competition. This makes the Spanish market less predictable.
- During peak hours the Spanish market shows even higher dispersion. This fact causes more uncertainty in periods of high demand, producing less accurate forecasts.

In the future, new regulatory frameworks and the introduction of long-term contracts will hopefully change the behavior of day-ahead markets. Their impact on prices is still unknown and it is a relevant subject to future research work.

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