ARIMA Models to Predict Next-Day Electricity Prices

Javier Contreras, *Member, IEEE*, Rosario Espínola, *Student Member, IEEE*, Francisco J. Nogales, and Antonio J. Conejo, *Senior Member, IEEE*

***Abstract*—Price forecasting is becoming increasingly relevant to producers and consumers in the new competitive electric power markets. Both for spot markets and long-term contracts, price forecasts are necessary to develop bidding strategies or negotiation skills in order to maximize benefit. This paper provides a method to predict next-day electricity prices based on the ARIMA methodology. ARIMA techniques are used to analyze time series and, in the past, have been mainly used for load forecasting, due to their accuracy and mathematical soundness. A detailed explanation of the aforementioned ARIMA models and results from mainland Spain and Californian markets are presented.**

***Index Terms*—ARIMA models, electricity markets, forecasting, market clearing price, time series analysis.**

I. Introduction

ELECTRICITY markets are becoming more sophisticated after a few years of restructuring and market competition. They usually incorporate two instruments for trading: the pool, and bilateral contracts. In the pool, the producers submit bids, consisting of a set of quantities at certain prices, and the consumers do likewise. There is an operator that clears the market and announces the set of clearing prices for the next day. On the other hand, the companies also want to hedge against the risk of daily price volatility using bilateral contracts.

For both cases, predicting the prices of electricity for tomorrow or for the next 12 months is of the foremost importance for electric companies to adjust their daily bids or monthly schedules for contracts.

In the pool, market clearing prices are publicly available in the www, as it is the case of the day-ahead pool of mainland Spain (www.omel.es), the Californian pool (www.calpx.com), or the Australian national electricity market (www.nemmco.com.au). With a good next-day price forecast, a producer can develop an appropriate strategy to maximize its own benefit, or a consumer can maximize its utility [1], [2].

For the medium-term, spanning from six months up to one year, producers need to know how much of their energy can be sold via bilateral contracts. By means of a reliable daily price forecast, producers or energy service companies are able to delineate good bilateral contracts, or financial ones.

Manuscript received October 12, 2001. This work was supported in part by the Ministry of Science and Technology (Spain) and the European Union through grant FEDER-CICYT 1FD97-1598.

The authors are with the E.T.S. de Ingenieros Industriales, Universidad de Castilla—La Mancha, 13071 Ciudad Real, Spain (e-mail: Javier.Contreras@uclm.es; Rosa.Espinola@uclm.es; FcoJavier.Nogales@uclm.es; Antonio.Conejo@ uclm.es).

Digital Object Identifier 10.1109/TPWRS.2002.804943

Therefore, an accurate price forecast for an electricity market has a definitive impact on the bidding strategies by producers or consumers, or on the price negotiation of a bilateral contract.

Auto Regressive Integrated Moving Average (ARIMA) models have been already applied to forecast commodity prices [3], [4], such as oil [5] or natural gas [6]. In power systems, ARIMA techniques have been used for load forecasting [7], [8] with good results. Currently, with the restructuring process that is taking place in many countries, simpler Auto Regressive (AR) models are also being used to predict weekly prices, like in the Norwegian system [9].

In addition, Artificial Neural Networks (ANN) techniques, that have been widely used for load forecasting, are now used for price prediction [10]–[13]. In particular, Ramsay *et al.* [11] have proposed a hybrid approach based on neural networks and fuzzy logic, with examples from the England-Wales market and daily mean errors around 10%. Also, Szkuta *et al.* [12] have proposed a three-layered ANN with backpropagation, showing results from the Victorian electricity market, with daily mean errors around 15%. Finally, Nicolaisen *et al.* have presented Fourier and Hartley Transforms [13] as "filters" to the price data inputs of an ANN. Stochastic models of prices, as in [14], are also competing with traditional time series models in order to predict daily or average weekly prices [15].

This paper focuses on the day-ahead price forecast of a daily electricity market using ARIMA models. That is, this paper provides ARIMA models to forecast today the 24 market clearing prices of tomorrow. These models are based on time series analysis and provide reliable and accurate forecasts of prices in the electricity market of mainland Spain [16] and California [17].

The remainder of the paper is organized as follows. In Section II, a general methodology to build an ARIMA model for price forecasting and the final models for the Spanish and Californian markets are provided. Section III presents numerical testing results, and Section IV states some conclusions.

II. ARIMA Time Series Analysis

ARIMA processes are a class of stochastic processes used to analyze time series. The application of the ARIMA methodology for the study of time series analysis is due to Box and Jenkins [18].

In this section, the description of the proposed ARIMA model and the general statistical methodology are presented. The general scheme is as follows:

```
Step 0) A class of models is formulated
assuming certain hypotheses.
```

```
Step 1) A model is identified for the observed data.
Step 2) The model parameters are estimated.
Step 3) If the hypotheses of the model are validated, go to Step 4, otherwise go to Step 1 to refine the model.
Step 4) The model is ready for forecasting.
```

In Sections II-A–E, each step of the above scheme is detailed.

A. Step 0

In this step, a general ARIMA formulation is selected to model the price data. This selection is carried out by careful inspection of the main characteristics of the hourly price series. In most of the competitive electricity markets this series presents: high frequency, nonconstant mean and variance, and multiple seasonality (corresponding to daily and weekly periodicity, respectively), among others. If p_t denotes the electricity price at time t, the proposed general ARIMA formulation is the following:

$$\phi(B)p_t = \theta(B)\varepsilon_t \tag{1}$$

where p_t is the price at time t, $\phi(B)$ and $\theta(B)$ are functions of the backshift operator B: $B^l p_t = p_{t-l}$, and ε_t is the error term. Functions $\phi(B)$ and $\theta(B)$ have special forms. They can contain factors of polynomial functions of the form $\phi(B) = 1-\sum_{l=1}^{\Phi}\phi_l B^l$ and/or $\theta(B) = 1-\sum_{l=1}^{\Theta}\theta_l B^l$, and/or $(1-B^S)$, where several values of ϕ_l and θ_l can be set to 0. For example, function $\phi(B)$ could have the following form:

$$\phi(B) = \left(1-\phi_1 B^1 - \phi_2 B^2\right)\left(1-\phi_{24}B^{24}-\phi_{48}B^{48}\right) \times \left(1-\phi_{168}B^{168}\right)(1-B)(1-B^{24}). \tag{2}$$

It should be noted that this example does not correspond to a standard ARIMA formulation, as presented in [18]. However, the model in (1) is sufficiently general to include the main features of the price data. For example, to include multiple seasonality, factors of the form $\left(1-\phi_{24}B^{24}\right)$, $\left(1-\phi_{168}B^{168}\right)$, and/or $\left(1-\theta_{24}B^{24}\right)$, $\left(1-\theta_{168}B^{168}\right)$, and perhaps $(1-B^{24})$, $(1-B^{168})$, can be included in the model.

Finally, certain hypotheses on the model must be assumed. These hypotheses are imposed on the error term, ε_t. In Step 0, this term is assumed to be a randomly drawn series from a normal distribution with zero mean and constant variance σ^2, that is, a white noise process. In Step 3, a diagnosis check is used to validate these model assumptions, as explained in Section II-D.

B. Step 1

A trial model, as seen in (1), must be identified for the price data. First, in order to make the underlying process stationary (a more homogeneous mean and variance), a transformation of the original price data and the inclusion of factors of the form $(1-B^S)$ may be necessary. In this step, a logarithmic transformation is usually applied to the price data to attain a more stable variance. And, to attain a more stable mean, factors of the form $(1-B)$, $(1-B^{24})$, $(1-B^{168})$, may be necessary, depending on the particular type of electricity market, as explained at the end of this section.

After the underlying process is accepted as being stationary, the structure of functions $\phi(B)$ and $\theta(B)$ in (1) must be selected. In a first trial, the observation of the autocorrelation and partial autocorrelation plots (see Appendix A) of the price data can help to make this selection. In successive trials, the observation of the residuals obtained in Step 3 (observed values minus predicted values) can help to refine the structure of the functions in the model.

C. Step 2

After the functions of the model have been specified, the parameters of these functions must be estimated. Good estimators of the parameters can be computed by assuming the data are observations of a stationary time series (Step 1), and by maximizing the likelihood with respect to the parameters [18].

The SCA System [19] is used to estimate the parameters of the model in the previous step. The parameter estimation is based on maximizing a likelihood function for the available data [18]. A conditional likelihood function is selected in order to get a good starting point to obtain an exact likelihood function, as described in [19]. Also, an option to detect and adjust possible unusual observations (called outliers in the forecasting literature) is selected. 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 [20].

D. Step 3

In this step, a diagnosis check is used to validate the model assumptions of Step 0. This diagnosis checks if the hypotheses made on the residuals (actual prices minus fitted prices, as estimated in Step 1) are true. Residuals must satisfy the requirements of a white noise process: zero mean, constant variance, uncorrelated process and normal distribution. These requirements can be checked by taking tests for randomness, such as the one based on the Ljung-Box statistic, and observing plots, such as the autocorrelation and partial autocorrelation plots.

If the hypotheses on the residuals are validated by tests and plots, then, the model can be used to forecast prices. Otherwise, the residuals contain a certain structure that should be studied to refine the model in Step 1. This analysis is based on a careful inspection of the autocorrelation and partial autocorrelation plots of the residuals (see Appendix A).

E. Step 4

In Step 4, the model from Step 2 can be used to predict future values of prices (typically 24 hours ahead). Due to this requirement, difficulties may arise because predictions can be less certain as the forecast lead time becomes larger.

The SCA System is again used to compute the 24-hour forecast. Likewise, the exact likelihood function option and the detection and adjustment of outliers procedures are selected.

As a result of these five steps, the final models for the Spanish and Californian electricity markets for the year 2000 are shown in (3) and (4), respectively. See Appendix B for details

$$\begin{aligned}&\left(1-\phi_1B^1-\phi_2B^2-\phi_3B^3-\phi_4B^4-\phi_5B^5\right)\\&\times\left(1-\phi_{23}B^{23}-\phi_{24}B^{24}-\phi_{47}B^{47}-\phi_{48}B^{48}\right.\\&\quad\left.-\phi_{72}B^{72}-\phi_{96}B^{96}-\phi_{120}B^{120}-\phi_{144}B^{144}\right)\\&\times\left(1-\phi_{168}B^{168}-\phi_{336}B^{336}-\phi_{504}B^{504}\right)\log p_t\\&\quad=c+\left(1-\theta_1B^1-\theta_2B^2\right)\left(1-\theta_{24}B^{24}\right)\\&\quad\quad\times\left(1-\theta_{168}B^{168}-\theta_{336}B^{336}-\theta_{504}B^{504}\right)\varepsilon_t\end{aligned}\tag{3}$$

$$\begin{aligned}&\left(1-\phi_1B^1-\phi_2B^2\right)\\&\times\left(1-\phi_{23}B^{23}-\phi_{24}B^{24}-\phi_{47}B^{47}-\phi_{48}B^{48}\right.\\&\quad\left.-\phi_{72}B^{72}-\phi_{96}B^{96}-\phi_{120}B^{120}-\phi_{144}B^{144}\right)\\&\left(1-\phi_{167}B^{167}-\phi_{168}B^{168}-\phi_{169}B^{169}-\phi_{192}B^{192}\right)\\&\times(1-B)(1-B^{24})(1-B^{168})\log p_t\\&\quad=c+\left(1-\theta_1B^1-\theta_2B^2\right)\\&\quad\quad\times\left(1-\theta_{24}B^{24}-\theta_{48}B^{48}-\theta_{72}B^{72}-\theta_{96}B^{96}\right)\\&\quad\quad\times\left(1-\theta_{144}B^{144}\right)\\&\quad\quad\times\left(1-\theta_{168}B^{168}-\theta_{336}B^{336}1-\theta_{504}B^{504}\right)\varepsilon_t.\end{aligned}\tag{4}$$

Note that, as mentioned in Step 0, the proposed formulation extends the standard ARIMA model by including more than two factors in (3) and (4), and a special polynomial structure of the overall function.

It also should be noted that model (3) needs the previous 5 hours to predict the next hour, whereas (4) just needs the previous two hours. Also, the model in (3) does not use differentiation, and the one in (4) uses hourly, daily and weekly differentiation: $(1-B)(1-B^{24})(1-B^{168})$. This is related to the stationary property of the series, and it can be traced by inspecting the autocorrelation and partial autocorrelation plots. (See Appendix A).

III. Numerical Results

A. Case Studies

The ARIMA models in (3) and (4) have been applied to predict the electricity prices of mainland Spain and Californian markets, respectively.

For the Spanish electricity market, three weeks have been selected to forecast and validate the performance of the ARIMA model. The first one corresponds to the last week of May 2000 (from May 25th to 31st). The second one corresponds to the last week of August 2000 (from August 25st to 31th), which is typically a low demand week. The third one corresponds to the third week of November 2000 (from November 13th to 19th), which is typically a high demand week. The hourly data used to forecast the first week are from January 1st to May 24th, 2000. The hourly data used to forecast the second week are from June 1st to August 24th, 2000. The hourly data used to forecast the third week are from September 1st to November 12th, 2000.

For the Californian electricity market, the week of April 3rd to 9th, 2000 has been chosen. This week is prior in time to the beginning of the dramatic price volatility period that took place afterwards. The hourly data used to forecast this week is from January 1st to April 2nd, 2000.

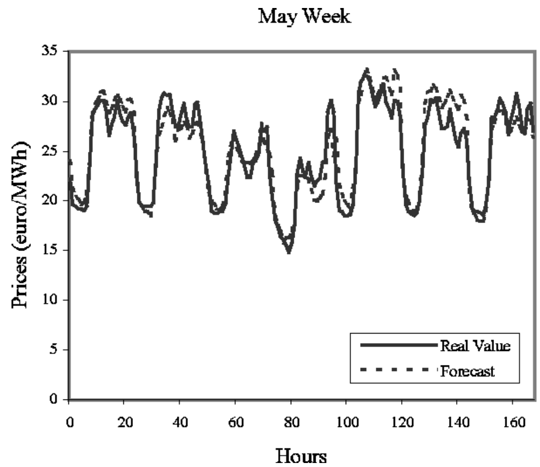

Fig. 1. Forecast of the selected week of May in the Spanish market. Prices in euro/MWh.

TABLE I
DAILY MEAN ERRORS OF THE SELECTED WEEK OF MAY IN THE SPANISH MARKET

Days	1	2	3	4	5	6	7
Mean	4.73%	4.13%	3.71%	6.84%	6.09%	6.96%	3.41%

All the study cases presented in this section use the ARIMA models (3) and (4), corresponding to the Spanish and Californian markets, respectively.

B. Forecasts

Numerical results with the ARIMA models are presented. Figs. 1–4 show the forecasted prices resulting from the ARIMA models for each of the four weeks studied; three for the Spanish electricity market, and one for the Californian market, together with the actual prices.

Fig. 1 corresponds to the selected week in May for the Spanish market.

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 5%.

Fig. 2 corresponds to the selected week in August for the Spanish market.

The seven daily mean errors for this week appear in Table II. The daily mean errors are around 8%. Note that the third day experienced an unusual increase in the price.

Fig. 3 corresponds to the selected week in November for the Spanish market.

The seven daily mean errors for this week appear in Table III. The daily mean errors are around 7%.

Fig. 4 corresponds to the selected week in April for the Californian market.

The seven daily mean errors for this week appear in Table IV. The daily mean errors are around 5%.

To verify the prediction accuracy of the ARIMA model, different statistical measures are utilized.

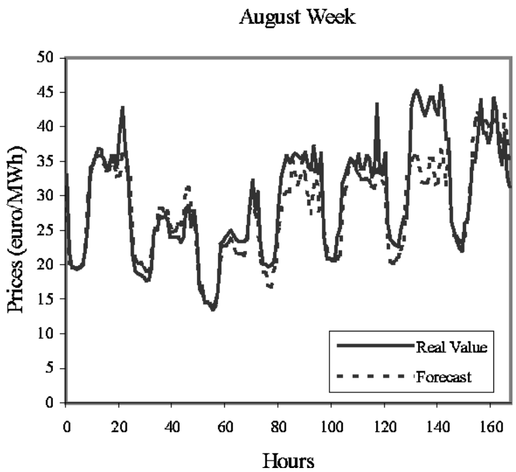

Fig. 2. Forecast of the selected week of August in the Spanish market. Prices in euro/MWh.

TABLE II
DAILY MEAN ERRORS OF AUGUST WEEK IN THE SPANISH MARKET

Days	1	2	3	4	5	6	7
Mean	4.34%	7.99%	4.57%	10.81%	6.12%	17.34%	6.05%

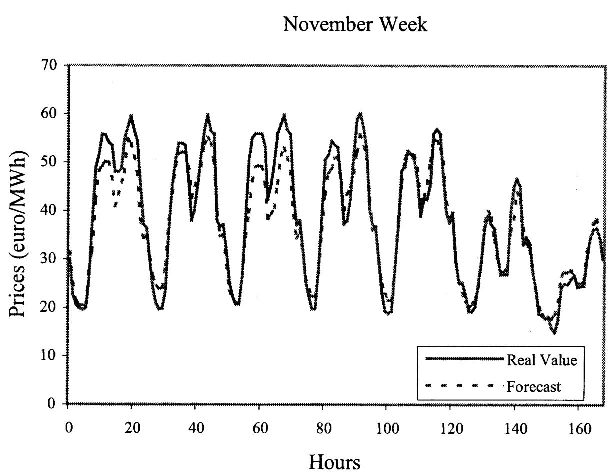

Fig. 3. Forecast of the selected week of November in the Spanish market. Prices in euro/MWh.

TABLE III
DAILY MEAN ERRORS OF THE SELECTED WEEK OF NOVEMBER IN THE SPANISH MARKET

Days	1	2	3	4	5	6	7
Mean	9.01%	8.14%	10.46%	7.08%	5.35%	5.08%	6.1%

For the four weeks under study, the average prediction error of the 24 hours is computed for each day. Then, the average of the daily mean errors is calculated: Mean Week Error (MWE). Finally, the Forecast Mean Square Error (FMSE) for the 168 hours of each week is derived.

An index of uncertainty in any of the models is the variability of what is still unexplained after fitting the model. That can be measured through the variance of the error term: σ^2. The smaller σ^2, the more precise the prediction of prices is. Since the value of σ is unknown, an estimate is used. The standard deviation of the error terms, $\hat{s}_R$, can be used as such an estimate. This estimate is useful when the true values of the series are unknown.

Tables V and VI present the numerical results as follows. The second column of both tables shows the percentage Mean Week Error (MWE), the third one presents the standard deviation of

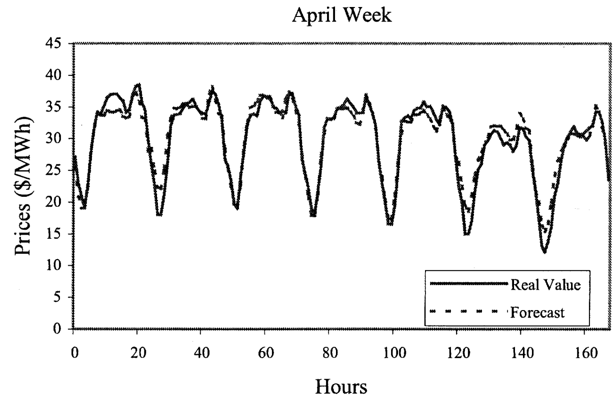

Fig. 4. Forecast of the selected week of April in the Californian market. Prices in $/MWh.

TABLE IV
DAILY MEAN ERRORS OF APRIL WEEK IN THE CALIFORNIAN MARKET

Days	1	2	3	4	5	6	7
Mean	4.35%	6.17%	2.6%	2.53%	3.57%	8.46%	7.44%

TABLE V
STATISTICAL MEASURES WITHOUT EXPLANATORY VARIABLES

	MWE (%)	$\hat{s}_R$	$\sqrt{FMSE}$
January (Spain)	12.06	0.106	71.98
February (Spain)	8.05	0.106	36.77
March (Spain)	11.28	0.104	71.75
April (Spain)	19.37	0.104	61.51
May (Spain)	4.99	0.083	19.91
June (Spain)	9.97	0.061	81.14
July (Spain)	9.39	0.067	42.59
August (Spain)	8.17	0.092	48.13
September (Spain)	12.01	0.097	70.82
October (Spain)	13.63	0.097	80.33
November (Spain)	7.32	0.098	47.51
April (California)	5.01	0.060	21.19
August (California)	15.65	0.121	469.85
November (California)	13.6	0.074	393.23

TABLE VI
STATISTICAL MEASURES WITH EXPLANATORY VARIABLES

	MWE (%)	$\hat{s}_R$	$\sqrt{FMSE}$
January (Spain)	9.97	0.106	64.72
February (Spain)	8.13	0.107	45.10
March (Spain)	10.5	0.105	71.57
April (Spain)	14.68	0.102	45.24
May (Spain)	7.75	0.082	33.25
June (Spain)	10.8	0.061	80.99
July (Spain)	8.83	0.066	41.80
August (Spain)	9.39	0.092	49.35
September (Spain)	10.72	0.097	65.50
October (Spain)	13.69	0.094	77.57
November (Spain)	9.88	0.098	73.73
April (California)	5.21	0.060	21.82
August (California)	21.03	0.123	674.58
November (California)	13.68	0.074	397.27

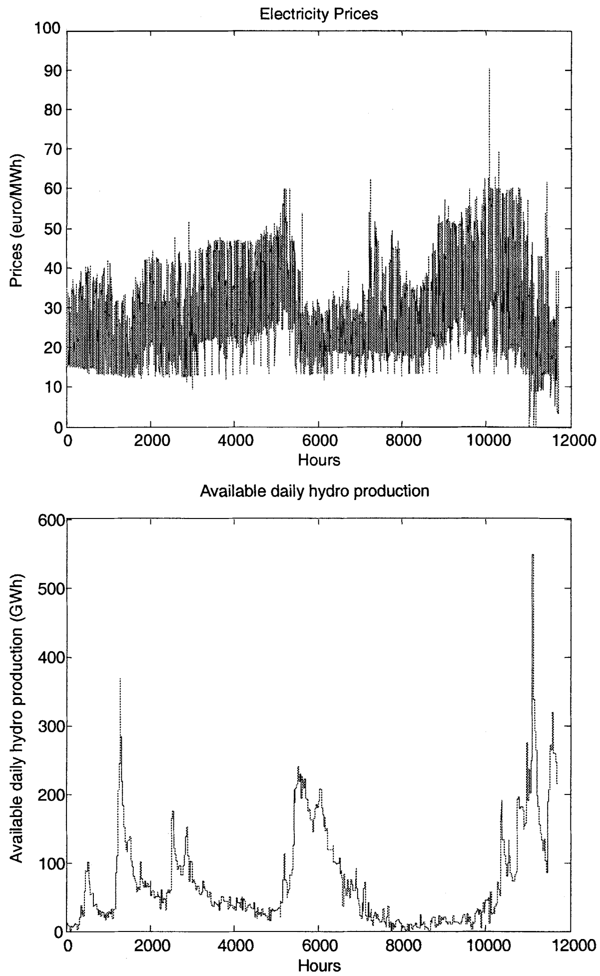

Fig. 5. Electricity prices vs. available daily hydro production: September 1999 to December 2000 in the Spanish market.

the error terms $(\hat{S}_R)$, and the fourth column shows the square root of the Forecast Mean Square Error (FMSE):

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

where p_t and $\hat{p}_t$ are the actual and forecasted prices, respectively. Note that prices, $\hat{s}_R$, and $\sqrt{\mathrm{FMSE}}$ are measured in euro/MWh and \$/MWh in the Spanish and Californian markets, respectively.

In addition to the four weeks under study, and for the sake of completion, Table V shows the statistical measures for the last week of the first ten months of the year 2000 in Spain, and November, in which the third week is selected. The end of November and the whole month of December are highly unstable, as seen in Fig. 5, and the ARIMA model hypotheses are not met. Table V also shows the week of April 3rd to 9th, the week of August 21st to 27th, and the week of November 13th to 19th, 2000. Note that, after April 2000, this market experienced high spikes that provoked its collapse at the end of 2000. Table VI presents results with the inclusion of explanatory variables to the model, such as: (i) demand and (ii) available daily production of hydro units. In the Californian market, only the

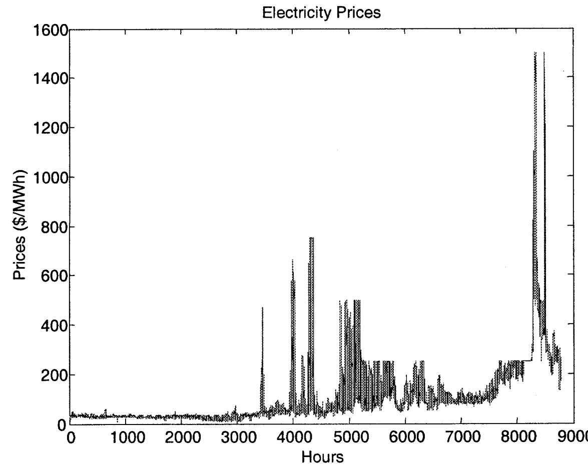

Fig. 6. Electricity prices: January to December 2000 in the Californian market.

demand is considered. Fig. 6 shows the prices from January to December 2000 in the Californian market.

To illustrate the effect of explanatory variables, Fig. 5 shows hourly data of both electricity prices and available hydro production from September 1999 to December 2000 in the Spanish market. From this figure, it is observed that the dramatic decrease in prices that took place in January, April and November–December 2000 was coincidental with a measurable increase in available hydro production. In November 2000, the increase was so dramatic, that prices plummeted down, reaching zero for some hours. That explains why the price forecast with explanatory variables improves during January and April, but not in November.

Outlier detection add-ons have been tested, but discarded. If the outliers were considered in the ARIMA model, then the forecasted prices would be slightly better, and the standard deviation error terms slightly lower, but the computational time involved would increase dramatically.

The following differences between both markets have been observed:

- Spanish market: It shows more volatility in general. Its ARIMA model needs data from the previous 5 hours and does not use differentiation to attain a stable mean.
- Californian market: Price predictions are better before the collapse. This could be due to the fact that the Californian market shows less volatility in that period. Its ARIMA model needs data from the previous 2 hours and needs three differentiations.

All the study cases have been run on a DELL Precision 620 Workstation with two processors Pentium III with 1 Gb of RAM at 800 MHz. Running time, including estimation and forecasting, is under five minutes for each case.

IV. Conclusion

This paper proposes two ARIMA models to predict hourly prices in the electricity markets of Spain and California, respectively. The Spanish model needs 5 hours to predict future prices, as opposed to the 2 hours needed by the Californian model. These differences may reflect different bidding structures and ownership.

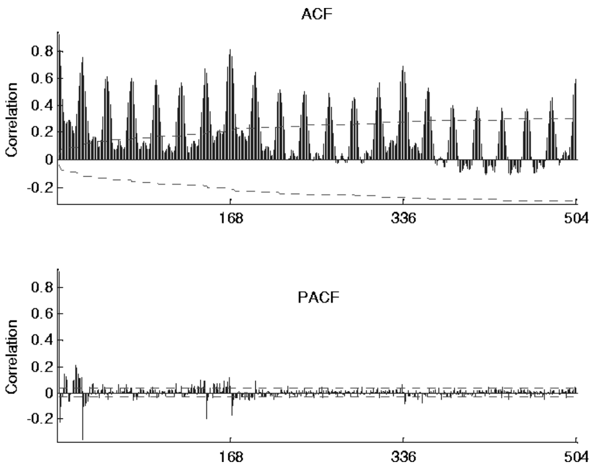

Fig. 7. ACF and PACF: The first three weeks of January 2000 in the Spanish market.

Average errors in the Spanish market are around 10% with and without explanatory variables, and around 5% in the stable period of the Californian market (around 11% considering the three weeks, and without explanatory variables). In Spain, explanatory variables are only needed in months with high correlation between available hydro production and price. In any other month, the effect is cancelled out. For both markets, these are reasonable errors, taking into account the complex nature of price time series and the results previously reported in the technical literature, in particular from Artificial Neural Networks.

APPENDIX A

The correlation and autocorrelation functions, ACF and PACF respectively, are basic instruments necessary to identify ARIMA models in stationary series [19].

The observation of the autocorrelation and partial autocorrelation plots of the price data and the residuals helps to build the models (3) and (4). Fig. 7 shows the ACF and PACF functions of the logarithmic transformed price data for the first three weeks of January 2000 of the Spanish market. For instance, according to Fig. 7, terms of the form $\left(1-\phi_{168}B^{168}\right)$ or $\left(1-\theta_{24}B^{24}\right)$ appear in models (3) and (4). The first term means that there is an exponential decline at the value 168 in the ACF, and a peak in the PACF at the same value. This corresponds to an AR model. The second term means that there is a peak at the value 24 in the ACF, and an exponential decline in the PACF at the same value. This corresponds to an MA model. A similar line of reasoning plus experience and technical intuition lead to the complete form of models (3) and (4).

APPENDIX B

For illustrative purposes, Table VII shows the estimated parameter values for the ARIMA models (3) and (4).

These values correspond to a Wednesday in May for the Spanish market, and to a Wednesday in April for the Californian market, both models without explanatory variables. The estimated values are very similar for other forecasted days.

TABLE VII
ESTIMATED PARAMETER VALUES OF THE SPANISH AND CALIFORNIAN ARIMA MODELS

SPANISH MARKET		CALIFORNIAN MARKET	
Parameters	Estimate	Parameters	Estimate
c	–0.0052	c	–0.00015
ϕ_1	0.5432	ϕ_1	0.447
ϕ_2	0.8373	ϕ_2	0.206
ϕ_3	–0.4174	ϕ_{23}	0.0625
ϕ_4	–0.0271	ϕ_{24}	–0.0193
ϕ_5	0.0243	ϕ_{47}	–0.0095
ϕ_{23}	0.0384	ϕ_{48}	–0.3013
ϕ_{24}	0.4165	ϕ_{72}	–0.021
ϕ_{47}	0.0532	ϕ_{96}	–0.0581
ϕ_{48}	0.004	ϕ_{120}	–0.0698
ϕ_{72}	0.0196	ϕ_{144}	–0.2739
ϕ_{96}	0.019	ϕ_{167}	0.0222
ϕ_{120}	–0.003	ϕ_{168}	–0.5922
ϕ_{144}	0.1474	ϕ_{169}	0.0595
ϕ_{168}	0.3342	ϕ_{192}	–0.0681
ϕ_{336}	0.2873	θ_1	0.9326
ϕ_{504}	0.2661	θ_2	0.0291
θ_1	–0.0941	θ_{24}	0.7752
θ_2	0.6998	θ_{48}	–0.2376
θ_{24}	0.1607	θ_{72}	0.2386
θ_{168}	0.2304	θ_{96}	–0.0053
θ_{336}	0.1726	θ_{144}	–0.2713
θ_{504}	0.2232	θ_{168}	0.0248
		θ_{336}	0.5082
		θ_{504}	0.0007

ACKNOWLEDGMENT

We are grateful to Mr. B. Lattyak, from SCA, and Dr. D. J. Pedregal from the Universidad de Castilla—La Mancha for their help and advice.

REFERENCES

[1] J. M. Arroyo and A. J. Conejo, "Optimal response of a thermal unit to an electricity spot market," *IEEE Trans. Power Syst.*, vol. 15, pp. 1098–1104, Aug. 2000.

[2] A. J. Conejo, J. Contreras, J. M. Arroyo, and S. de la Torre, "Optimal response of an oligopolistic generating company to a competitive pool-based electric power market," IEEE Trans. Power Syst., to be published.

[3] E. Weiss, "Forecasting commodity prices using ARIMA," *Technical Analysis of Stocks & Commodities*, vol. 18, no. 1, pp. 18–19, 2000.

[4] M. Chinn, M. LeBlanc, and O. Coibion. The predictive characteristics of energy futures: Recent evidence for crude oil, natural gas, gasoline and heating oil. presented at UCSC Working Paper #409. [Online]. Available: http://people.ucsc.edu/~chinn/energyfutures.pdf

[5] C. Morana, "A semiparametric approach to short-term oil price forecasting," *Energy Economics*, vol. 23, no. 3, pp. 325–338, May 2001.

[6] W. K. Buchananan, P. Hodges, and J. Theis, "Which way the natural gas price: An attempt to predict the direction of natural gas spot price movements using trader positions," *Energy Economics*, vol. 23, no. 3, pp. 279–293, May 2001.

[7] G. Gross and F. D. Galiana, "Short-Term load forecasting," *Proc. IEEE*, vol. 75, no. 12, pp. 1558–1573, December 1987.

[8] M. T. Hagan and S. M. Behr, "The time series approach to short term load forecasting," *IEEE Trans. Power Syst.*, vol. 2, pp. 785–791, Aug. 1987.

[9] O. B. Fosso, A. Gjelsvik, A. Haugstad, M. Birger, and I. Wangensteen, "Generation scheduling in a deregulated system. The norwegian case," *IEEE Trans. Power Syst.*, vol. 14, no. 1, pp. 75–81, Feb. 1999.

[10] H. S. Hippert, C. E. Pedreira, and R. C. Souza, "Neural networks for short-term load forecasting: A review and evaluation," *IEEE Trans. Power Syst.*, vol. 16, pp. 44–55, Feb. 2001.

[11] A. J. Wang and B. Ramsay, "A neural network based estimator for electricity spot-pricing with particular reference to weekend and public holidays," *Neurocomputing*, vol. 23, pp. 47–57, 1998.

[12] B. R. Szkuta, L. A. Sanabria, and T. S. Dillon, "Electricity price short-term forecasting using artificial neural networks," *IEEE Trans. Power Syst.*, vol. 14, pp. 851–857, Aug. 1999.

[13] J. D. Nicolaisen, C. W. Richter Jr., and G. B. Sheblé, "Price signal analysis for competitive electric generation companies," in *Proc. Conf. Elect. Utility Deregulation and Restructuring and Power Technologies*, London, U.K., Apr. 4–7, 2000, pp. 66–71.

[14] J. Valenzuela and M. Mazumdar, "On the computation of the probability distribution of the spot market price in a deregulated electricity market," in *Proc. 22nd Power Ind. Comput. Applicat. Int. Conf.*, Sydney, Australia, May 2001, pp. 268–271.

[15] F. J. Nogales, J. Contreras, A. J. Conejo, and R. Espínola, "Forecasting next-day electricity prices by time series models," *IEEE Trans. Power Syst.*, vol. 17, pp. 342–348, May 2002.

[16] J. González and P. Basagoiti, "Spanish power exchange and information system design concepts, and operating experience," in *Proc. 21st Power Ind. Comput. Applicat. Int. Conf.*, Santa Clara, CA, May 1999, pp. 245–252.

[17] F. Albuyeh and Z. Alaywan, "Implementation of the California independent system operator," in *Proc. 21st Power Ind. Comput. Applicat. Int. Conf.*, , Santa Clara, CA, May 1999, pp. 233–238.

[18] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time Series Analysis Forecasting and Control*, Third ed. Englewood Cliffs, NJ: Prentice-Hall, 1994.

[19] L. Liu and G. P. Hudak, *Forecasting and Time Series Analysis Using the SCA Statistical System*: Scientific Computing Associated, 1994.

[20] A. Pankratz, *Forecasting With Dynamic Regression Models*. New York: Wiley, 1991.

Javier Contreras (M'98) was born in Zaragoza, Spain, in 1965. He received the B.S. degree in electrical engineering from the University of Zaragoza, Spain, in 1989, the M.Sc. degree from the University of Southern California, Los Angeles, in 1992, and the Ph.D. degree from the University of California, Berkeley, in 1997, respectively.

Currently, he is Associate Professor at the Universidad de Castilla—La Mancha, Ciudad Real, Spain. His research interests include power systems planning, operations and economics, and electricity markets.

Rosario Espínola (S'02) received the B.S. degree in statistics from Universidad de Granada, Spain, in 1999. She is currently pursuing the Ph.D. degree at Universidad de Castilla—La Mancha, Ciudad Real, Spain.

Her research interests include planning and economics of power systems, forecasting, and time series analysis.

Francisco J. Nogales received the B.S. degree in mathematics from Universidad Autónoma de Madrid, Spain, in 1995, and the Ph.D. degree in mathematics from Universidad Carlos III de Madrid, Spain, in 2000.

Currently, he is Assistant Professor of statistics and operations research at the Universidad de Castilla—La Mancha, Ciudad Real, Spain. His research interests include planning and economics of power systems, optimization, and forecasting.

Antonio J. Conejo (S'86–M'91–SM'98) received the B.S. degree in electrical engineering from the Universidad P. Comillas, Madrid, Spain, in 1983, the M.S. degree in electrical engineering from Massachusetts Institute of Technology, Cambridge, in 1987, and the Ph.D. degree in electrical engineering from the Royal Institute of Technology, Stockholm, Sweden, in 1990.

Currently, he is Professor of electrical engineering at the Universidad de Castilla—La Mancha, Ciudad Real, Spain. His research interests include control, operations, planning, and economics of electric energy systems, as well as optimization theory and its applications.