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Spanish Energy Market: Overview Towards Price Forecast

Nicolas Perez-Mora[1,2]*, Miquel L. Alomar[1], Victor Martinez-Moll[1]

[1]University of Balearic Islands, Palma of Majorca 07122, Spain, [2]Sampol Ingeniería y Obras, Palma of Majorca 07009, Spain.
*Email: nperez@sampol.com

ABSTRACT

This paper aims to give an overview of the Spanish Electric Market. This energy market is liberalized and complex due the new and modified rules along time. Due these circumstances the hourly energy prices may vary tremendously. The goal of this work is to analyze in detail the generation technologies, their strategies and energy mix to gain awareness and knowledge to evaluate energy price fluctuations. Two methods are used to forecast in different time horizons: ARIMAX and NARX. Both methods are homologous, using historical energy prices and optionally an explanatory variable. Three options are studied: No explanatory, energy demand and competitive market. Once the models are developed and trained, the results achieved are helpful to understand further changes in the market. These energy forecasts are competent to schedule energy generation and/or consumption.

Keywords: Energy Market, Forecasting, Time Series
JEL Classifications: C5.1, L1.1

1. INTRODUCTION

The amount of liberalized electricity markets is growing steadily worldwide, mainly in Europe. Some of the pioneers in electricity market reform have been successfully operating for more than a decade (Reikard, 2009; Cervone et al., 2014). This is the case of the Spanish Energy Market or "Pool." In the Spanish Energy Market the aggregated electricity power production is balanced in hourly with the demand. The electricity is traded in different markets: The main market "daily" (D) and the 6 regulation markets "intra-daily" (ID). In the daily market the producers and consumer release their bids and offers at 12:00 for next day. The ID markets are regulatory markets to modify previous agreements on energy consumption or generation. These markets take place at: 17:00 (ID #1), 21:00 (ID #2), 01:00 (ID #3), 04:00 (ID #4), 08:00 (ID #5) and 12:00 (ID #6); the generators can release their bids covering each hour from a few hour after the auction time till the end of the auctioned day, as long as that bid modifies a previous bid placed in the daily market (OMEL, 2013).

The energy mix is the result of the counter clockwise auction where the highest price to purchase energy match the cheapest energy offers. This process goes on until the cost of energy offered is the same as the price for purchasing from the demand. The lower and upper boundaries in the auction are 0€/MWh and 180€/MWh, being 40€/MWh an annual average value. Once a break-even point is found, the energy price in an hour will be the same and equal to the last accepted bid in the auction. For any generator to ensure its energy production acceptance in the mix its bid shall be placed at the legal minimum, 0€/MWh even though its retribution would be the final auction price times the generated energy.

For any energy consumer to assure its purchase of energy its offer shall be placed at the legal maximum, 180€/MWh, and again its final cost would be the final auction price times the generated energy. To keep a stable energy system, the grid operator may penalize the generator or the consumer in case that the energy generation is different than the agreed after the energy auction by charging the cost of the deviated energy.

During the last decade there was an increase of renewable energy power plants. This was motivated due the subsidies promoting the construction of green power plants (Monteiro et al., 2013) and the price increase of energy generated from fossil fuels. These boundaries created an scenario where the installation of renewable was profitable business (Monteiro et al., 2013). Such expansion and the policies adopted by many countries to integrate renewable

into the energy generation mix has brought a rearrangement on the energy market (Rubin and Babcock, 2013).

The integration of energy generated by green power plants into electric power system is priority, meaning that this power should be fed into the system in preferential order within the energy mix. In certain cases as solar and wind power its cheap generation cost (if not free) allows renewable energy bids to be placed close to the legal minimum (0€/MWh) on the energy auction which assures its acceptance on the mix.

Nevertheless, the volatility and variability of the renewable resource makes the integration in the grid difficult as the supply and load of electric power must be balanced at every instant. This is a major drawback for technologies harvesting electricity out from volatile resources is the non-continuous availability of the resource. Solar energy depends critically on the variability of irradiance (Flake and Mueller, 2004), typically cloud covers cause rapid changes in the irradiance during the day (Chen et al., 2011) which brings along generation fluctuations. In the same way wind energy generation depends on the wind direction, speed and its variations (Cassola and Burlando, 2012). This dependence on weather conditions may lead to wrong or inaccurate bids from the generators in the energy auction and therefore into penalties from the grid operator. An accurate bid would minimize the penalties for wind and solar generators who have to rely on energy forecasts (Lange and Focken, 2006; Mahoney et al., 2012; Yang et al., 2012; Perez-Mora et al., 2015; Perez-Mora et al., 2016b).

Moreover, this energy variations bring along fluctuations in hourly energy prices. This variations influence as much energy generators as consumers. Therefore, energy prices are required to be forecasted in markets with high renewable energy penetration (Perez-Mora et al., 2016a; Pérez-Mora et al., 2017; 2018). Several forecasting methods have been used for such purpose, a literature survey is presented in (Alfares and Nazeeruddin, 2002).

This paper applies two different approaches to forecast energy hourly prices in different time horizons. The first method is based on auto regressive integrated moving average (ARIMA) and second is based on artificial neural networks (ANN). Both methods can be supported with explanatory variable, in particular, the methods are ARIMA with eXplanatory variable (ARIMAX) and nonlinear autoregressive models with eXogenous NN (NARX). Explanatory variables are related time series to the target time series which have proved to improve accuracy on energy price forecasts. Prove of this accuracy can be found in (Amjady, 2006; Andalib and Atry, 2009; Alomar et al., 2016) for computational models such as in ANN or in (Contreras et al., 2003; Conejo et al., 2005) for regression models such as ARIMA. This work aims to evaluate the forecasting results of both methods without explanatory variable and with two different time series related to the energy price.

This paper is organized as follows: Next section provides an overview of the problem to approach. Section 3 the methodology used to approach the problem is explained. Section 4 presents the results obtained from the methodology and the conclusions from those would be given in Section 5.

2. PROBLEM DESCRIPTION

The energy mix in Spain is shared among different technologies. It is visibly divided between new installations based on renewable technologies and existing installations mainly based on fossil fuels. The power installed and the energy mix of the different technologies on 2016 can be seen on Table 1 (REE, 2016). Biomass, bio-gas, geothermal and marine hydraulic technologies are included under "Other Renewable."

Currently, the total annual energy consumption is 262.8TWh and the maximum demanded power on 2016 was 40.489MW. The demand proceeding from renewable energy sources cover a 41.1% of the total energy consumption. This generation is unstable and changing with time which affects directly on the energy market price.

In this section the main factors affecting the energy price and their causes are described and evaluated.

2.1. Wind Generation

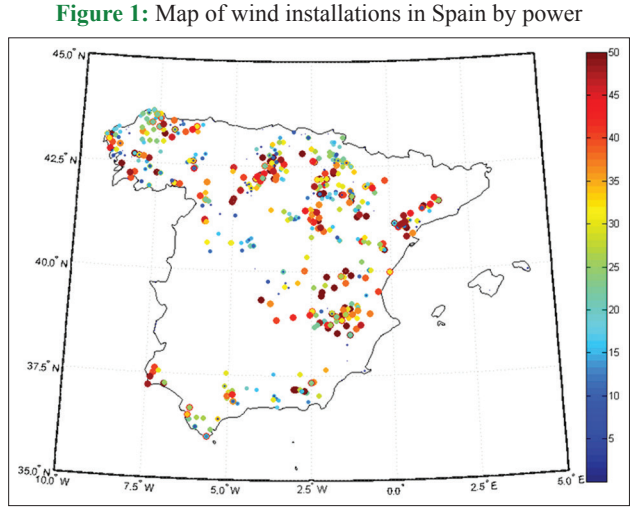
Wind power is a promising technology which has reached market competitiveness without the help of subsidies in the Spanish market.

As shown in Table 1 the installed power is equal to 23.02GW corresponding to a 21.9% of the total energy mix. In Figure 1 the

Table 1: Spanish energy mix on 2016

Technology	Energy (GWh) (%)	Power (MWh) (%)
Hydro power	39.053 (14.9)	20.354 (19.3)
Wind Power	48.927 (18.6)	23.020 (21.9)
Photovoltaic	7.979 (3.0)	4.669 (4.4)
Solar thermal	5.102 (1.9)	2.300 (2.2)
Other renewable	3.451 (1.3)	748 (0.7)
CHP	25.878 (9.8)	6.714 (6.4)
Nuclear	55.546 (21.1)	7.573 (7.2)
Coal	37.038 (14.1)	10.004 (9.5)
Fuel/gas	6.748 (2.6)	2.490 (2.4)
Combined cycle	29.787 (11.3)	26.670 (25.3)
Waste	3.324 (1.3)	754 (0.7)
Total	262.852	105.307

Figure 1: Map of wind installations in Spain by power



wind installation distribution in Spain are shown. The map shows the location and size of the installation in a color-size map, the maximum installed power by law is 50MW.

Wind energy is completely dependent on wind speed, but when the resource is available the generation is considered free. Therefore, the energy producer places energy bids on the market ensuring the energy will be accepted and matched. As the only expense wind power incurs is Operation and Maintenance (O and M), the strategy for bidding usually attempts to cover such costs which generally are under 5€/MWh.

The fact that a great part of the energy share is wind dependent brings an enormous impact on the energy grid and market prices. Wind is a highly variable resource; wind power varies from a minimum of 250MW to a maximum of 17.3GW, reaching peaks of production which may imply over 67% of the total injected power into the grid. Wind power does not necessarily follow the seasons, per se, but an annual trend line. In 2016 wind power was the second energy producer in the Spanish energy mix with a 18.6%.

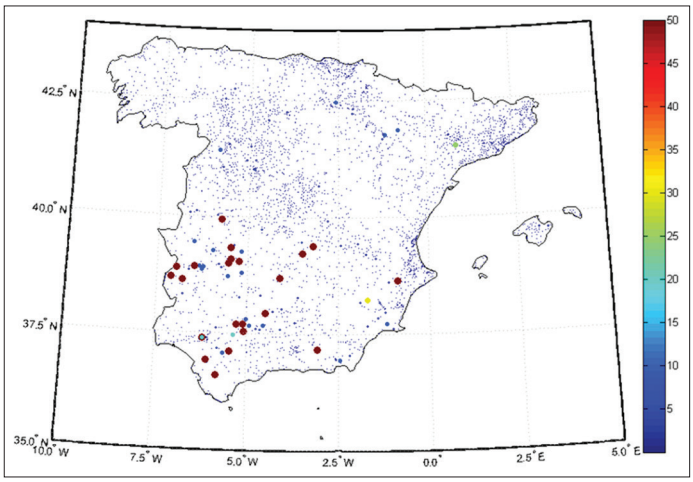
The impact of wind power due its variations is reduced with help of energy forecasters. The main forecasting difficulty is the error in wind speed estimation and the lack of information on wind farm layouts. This disables the use of wind direction to estimate power decrease due shadowing between turbines.

2.2. Solar Generation

Solar power is a common technology in Spain due the high amount of irradiation on the country. Moreover, Spain led worldwide solar power development and installation on the previous decade.

As shown in Table 1 the installed total solar power is equal to 6.97GW which corresponds to a 6.6% of the total energy mix. These figures come from the sum of photovoltaic and solar thermal installations. In Figure 2 the solar installation distribution in Spain are shown. The map shows the location and size of the installation in a color-size map, the maximum installed power by law is 50MW. In Figure 2 solar thermal installations are easily identifiable as they are usually over 40MW.

Figure 2: Map of solar installations in Spain by power



Solar energy is completely dependent on solar irradiation, but when the resource is available the generation is considered free. In the same way as wind producers, solar producers place energy bids on the market ensuring the energy will be accepted and matched. Their strategy for bidding usually attempts the minimum energy market price which is 0€/MWh.

Similarly to wind energy the dependence on climate bring uncertainty to energy market which can be attenuated with energy forecasting.

The importance on forecasting energy generation lies in the markedly difference on generation between stations changing from a 7.5MW of power peck in winter to a 5.600MW of power peck in summer and achieving a maximum of 25% in the total power injected into the grid. It is also important to understand that the solar electricity generation in Spain includes two technologies able to produce electricity:

- Photovoltaic. Ground mounted or in trackers.
- Solar thermal power. Based on concentrated solar power.

It is important to bear in mind that the solar electricity generation coming from photovoltaic is only dependent on the solar irradiation on the panel surface. On the other hand, solar thermal plants generate electricity through a process dependent on solar irradiation and temperature. Additionally, some of these power plants count with an energy storage system.

2.3. Nuclear Power

Nuclear generation is continuous over time. Nuclear power plants generate on its nominal power as long as they are running. This fact is only modified on the times when they start up and shut down to re-charge fuel. As the generators can't be stopped (unless there is a critical situation) this technology bidding strategy is the legal minimum, 0€/MWh. Therefore, it is ensured the offer is accepted and its energy is consumed.

On the Spanish territory there are 7 working nuclear power plants, all of them slightly over 1.00GW nominal power and an extra power plant currently out of duty of 466MW. The total nuclear working power is equal to 7.10GW generating a 21.2% of the total annual demand. In Figure 3 nuclear power plants are shown in the Spanish territory.

2.4. Hydro Power

The hydro power is divided in two groups. The first group are large hydro power constructed years ago. Their nominal power are above 50MW, the installation usually comprise a dam and are fully manageable. They are equipped with backwards pumping, and therefore, the possibility to charge the dam using the pumps. This allows to stabilize the energy demand acting as generator during high demand periods and as consumer during low demand periods.

The second group are smaller installations, always below 50MW, without neither dam or re-charging capacity. The generation of this group of installations are dependent on the water flow passing on the river where they are installed.

In Figure 4 the hydro power installation distribution in Spain are shown. The map shows the location and size of the installation in a color-size map. The total hydro power from both groups is equal to 20.35GW generating a 14.9% of the total annual demand.

The generations strategies of the two groups are completely different. As the first group is regulable they generate when the energy prices are higher to obtain higher profits. On the other hand, the second group is offering energy bids to cover their O and M expenses as they would generate anyway and try to get the energy bid accepted.

2.5. Combined Heat and Power (CHP)

CHP refers to installations which transform fossil fuels into heat and power with high efficiency. These installations are tied to a thermal client to sell the thermal energy as they generate electricity. Therefore, their generation strategies depend on the client's thermal demand as their generation cost differs and so does the energy bid they place on the market.

In Figure 5 the CHP installation distribution in Spain are shown. The map shows the location and size of the installation in a color-size map, the maximum installed power by law is 50MW. CHP power currently installed is equal to 6.71GW generating a 6.4% of the total annual demand. In Figure 5 the location of the power plants are shown in Spain.

2.6. Conventional Thermal Generators

Conventional thermal generator is refereed to an installation which produce power using conventional generation techniques. These installations burn fuel to produce electricity through the movement of a generator. This category includes installations burning fuel such as:

- Coal
- Fuel and gas
- Wastes.

The technologies included here in reference to Table 1 are the above-mentioned fuels plus combined cycle. Conventional thermal generators can generate energy at will since the primary energy used in the combustion is stored nearby the power plant. Therefore, the generation strategies followed depend on the energy market and they generate when the energy prices are high enough to cover expenses and make benefits.

3. METHODOLOGY

This section describes the methodology followed to forecast energy market prices. Accurate energy price forecasts can be obtained using computational models such as NN or ARIMAX. Both forecast model performances may be improved by using a sufficient data series containing relevant information related with the main variable. This information is refereed as explanatory variable.

3.1. ARIMAX

This regression model is fitted with the target time series data. This model may use an extra time series providing information to improve its performance when predicting future values on the target time series. It is composed by an autorregresive model (p), moving average model (q) and differencing degree (D). Mathematically, it can be expressed as: ARIMA (p, D, q).

For ARIMAX forecasting the data is split in training set, 95%; and result comparison set, 5%. The configuration proposed

Figure 3: Map of nuclear installations in Spain by power

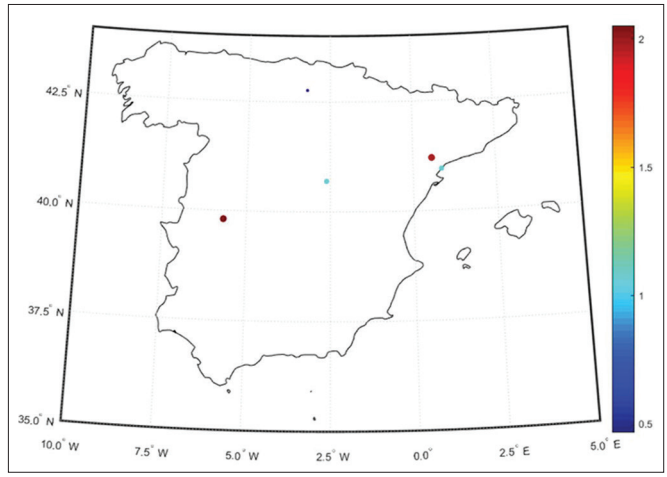


Figure 4: Map of hydro power installations in Spain by power

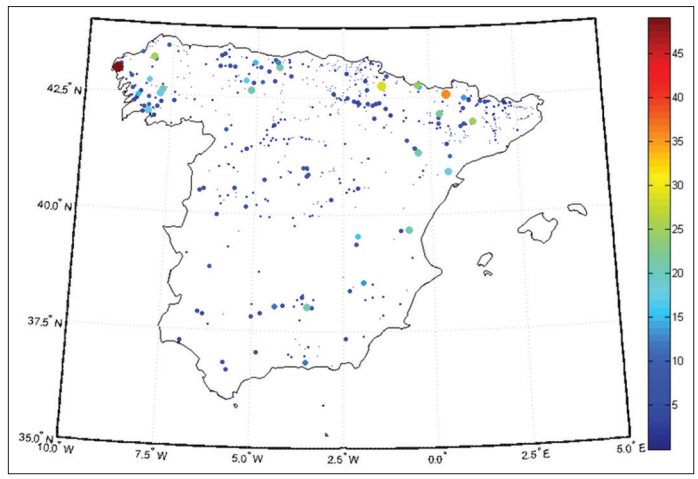
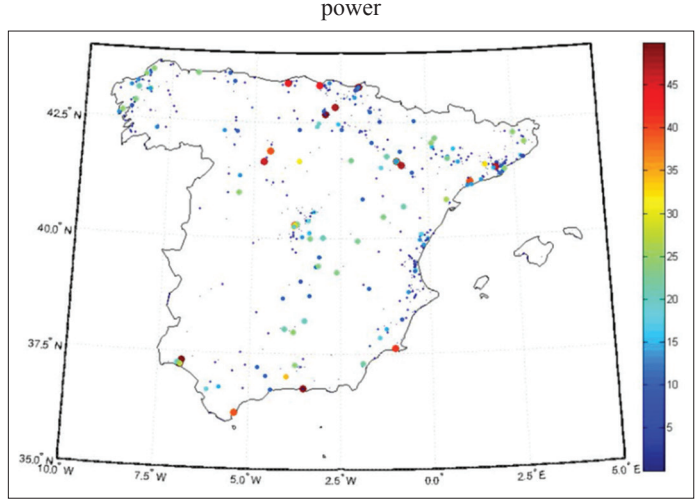


Figure 5: Map of combined heat and power installations in Spain by power



differs from weekday, Saturday and Sunday. The best performing configurations are shown in Table 2; where "MA," stands for vector of non-seasonal moving average coefficients; "SMA," stands for vector of seasonal moving average coefficients corresponding to an invertible polynomial; "AR," stands for vector of non-seasonal autoregressive coefficients; "SAR," stands for vector of seasonal autoregressive coefficients corresponding to a stable polynomial; and "D," stands for integer indicating the degree of the non-seasonal differencing in the time series.

3.2. NARX

The other proposed approach to the problem is using (ANN). These are found to outperform the regression models when it comes to high resolutions (Reikard, 2009). There are several ANN models that approaches forecasting, in this work a NARX model is selected since they outperform other ANN models as multi layer perceptron (Perez-Mora et al., 2015).

NARX model relates the current value of a time series to current and past values of the influencing exogenous series. This approach based on ANN allow to find next values in a time series using past measurements of price and an explanatory variable. These are used as inputs to an autoregressive model with exogenous input (ARX) building like this a NARX recurrent NN. Many NN configurations have been tried out to forecast energy price. The best performing set of configurations are shown in Table 3.

The data is split randomly in three different sets: Training 70%; validation to avoid over fitting 15%; result comparison and testing 15%. The training method used is Lavenberg-Marquardt algorithm. The best performing tried methods and ANN configurations are shown in Table 3. Neurons per layer values correspond to: Input, hidden and output layers. Activation functions stand for: "L" Linear; "ST," Sigmoid Tan-gent and "I" Input layer. The proposed input and feedback delays vary from weekday, Saturday or Sunday but not the configuration.

3.3. Explanatory Variable

To improve the performance of energy price forecast a suitable explanatory variable could be used in both methods. In principle and due the relation between demand and price suggests using the demand as explanatory variable. On the other hand, an as seen in section 2, the demand is not the only factor related with energy price. The energy price is built when matching the energy bids and the demand. Therefore, the price requested in the generation bids is as important as the amount of demand and the price offered for it.

In the energy market it is possible to discern between two kinds of generators: Manageable and not-manageable. The first kind can generate depending on the price and therefore, they match in the energy auction whenever certain economic boundaries are met. On the contrary, the not-manageable power plants are willing to generate no matter selling conditions. This is motivated due the need of most of them to generate that power. These technologies are: Solar, wind and nuclear power. The behavior of the not-manageable power plants affects the final auction price as their energy bids are close to 0€/MWh so the energy is matched.

When considering this fact, another explanatory variable can be considered. This variable is calculated as the energy which is going to be produced regardless economic boundaries is subtracted from the total energy demand. This amount of energy is what is left for manageable generators to match and can be defined as "competitive market" and is defined in equation (1).

$$\text{Competitive Market} = \text{Demand-Solar-Wind-Nuclear} \quad (1)$$

In this work three options are studied to understand the impact of an explanatory variable on forecasts:

1. No explanatory variable
2. Energy demand as explanatory variable
3. Competitive market as explanatory variable.

Pearson correlation study is carried out for the two explanatory variables on the historical values of the year 2016 to find out which one seems more suitable to be used in energy price forecasting. The results of relation between energy price and demand are shown in Figure 6 with a Pearson correlation factor of 0.412. The results of relation between energy price and competitive market are shown in Figure 6 with a Pearson correlation factor of 0.719.

The relation shown for competitive market and energy price is much higher than the relation with the demand. Even the relation is not perfect, and far to be close to 1 (meaning a perfect and direct relation), it is supposed to be a better support in forecasting for both methods and should improve the forecasting accuracy.

3.4. Forecasting Horizon

In this work 6 days ahead are forecasted. The methodology applied is to consider the forecasted days as part of the historical values when forecasting a later day. Therefore, to do the last forecast, 6 days ahead, the target vector would use the historical values plus the last 5 days obtained from forecasts. This methodology will show the impact of forecasted days on future forecasts.

3.5. Error Comparison

To evaluate the forecasting methods performance, the following error metrics are used. The first error metric is mean absolut error (MAE). This error metric shows the deviation of the forecast to the real value as absolute difference. This figure is useful to understand the accuracy of the forecast method. The error metric is expressed in equation (2) in €/MWh.

Table 2: ARIMAX configuration

Variable	Weekday	Saturday	Sunday
AR lags	[1,2,6,24,25,73]	[1:2,5:8,17,21,24]	[1:3,5:7,9,17:21,24]
MA lags	[1:8]	[1:24]	[1:24]
SAR lags	[120,121,194,218,220]	[25,26,32,48:51,68,73,95,97]	[25,26,35:36,43:45,48:50]
SMA lags	[25:29, 46:49]	[25:29, 46:49]	[25:29, 46:49]
D	0	0	0

The second selected metric is mean absolut percentage error (MAPE). This error metric divides the absolute deviation by market upper boundary. As mentioned before the maximum energy price by market definition is 180€/MWh. The error metric is expressed in equation (3) as a percentage and it is useful to understand the impact of the error in further energy strategies.

In equations MAE and MAPE Pr(i) is the real market value, Pf(i) is the forecasted market value and Pmax is the maximum market energy price; all of them measured in €/MWh.

$$MAE = |Pr_{(i)} - Pf_{(i)}| \quad (2)$$

$$MAPE = \left| \frac{Pr_{(i)} - Pf_{(i)}}{Pmax} \right| \quad (3)$$

4. RESULTS

In this section the results from both forecasting methods and the three explanatory variable options are shown and compared. The period under study covers from 1/1/2016 to 31/12/2016. Different time horizons in forecasting are studied covering from 1 to 6 days ahead. To compare both forecasting methods several combinations and configurations of ARIMAX and NARX models have been tried out to obtain the most accurate results but only the best performing are shown.

In Table 4 the results of MAPE for D1, corresponding to 1 day ahead till D6 corresponding to 6 days ahead are shown. In Figure 7 the results for MAE are plotted to visually compare how both methods perform and compete along the time horizon forecasted. It is possible see that ARIMAX method outperforms NARX method. Figure 7 shows how the error increases with the length of time horizon.

5. CONCLUSIONS

In this work an energy market forecasting tool has been developed to obtain hourly market prices. The tool is based on two forecasting methods: ARIMAX and NARX. In both methods a study is conducted to understand the influence in performance of the explanatory variable. The options used are: No explanatory, energy demand or competitive market as explanatory variable.

Table 3: NARX configuration

Variable	Configuration
Neurons per layer	48-24-1
Activation Function	I-ST-L
Gradient	5×10−9
Epochs	200

The forecasting methods are tested in different time horizons, from 1 day ahead to 6 days ahead. This evaluation is done to evaluate the impact on accuracy of time. Once the forecasts are compared with the error figures, the results point that the proposed ARIMAX method outperform NARX is most of the cases. The lower average MAE achieved is 4.78€/MWh given by ARIMAX model in 1 day ahead forecast and using competitive market as explanatory variable. The highest average MAE achieved is 8.19€/MWh given by NARX model in 6 days ahead forecast and using demand as explanatory variable.

The best resulting explanatory variable option is competitive market, followed closely by the no explanatory variable option. On the other hand, using demand as explanatory variable is counterproductive being this the worst option. This fact is due the low correlation between the variable and the target vector (0.41). Despite that competitive market is the best option, these results are obtained with historical values and no forecast error is included or evaluated. In reality, the competitive market variable is a forecasted variable, composed by the forecasts of demand, solar, wind and nuclear energy which are subjected to errors.

In the same way, the results show the influence of the time horizon on forecasting accuracy. The longer the time to the forecasted value the higher the error is. The influence of time is different in the forecasting methods. When comparing the two best performing explanatory variable options, ARIMAX increases the MAE on an average daily base of 0.23€/MWh, meanwhile, NARX increases the error on an average daily base of 0.06€/MWh. Therefore, NARX method is much less sensible to errors in forecasted days. In Figure 7 both error trends are shown. For ARIMAX method the change from one to 2 days ahead forecast is the largest increase of error going from 2.88% to 3.22%.

Figure 6: Correlation between target variable and explanatory variable

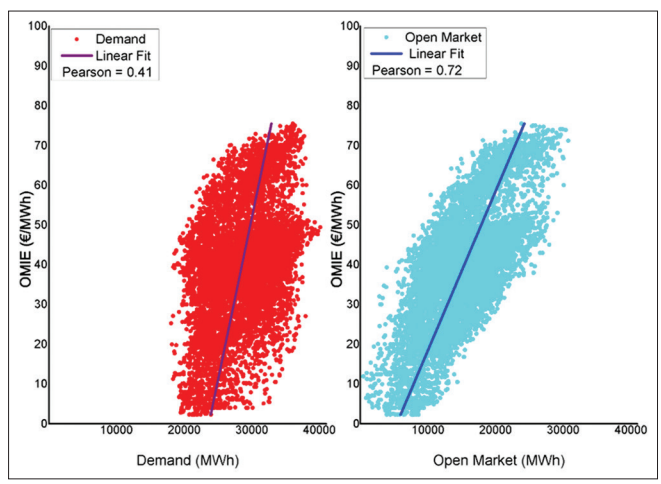
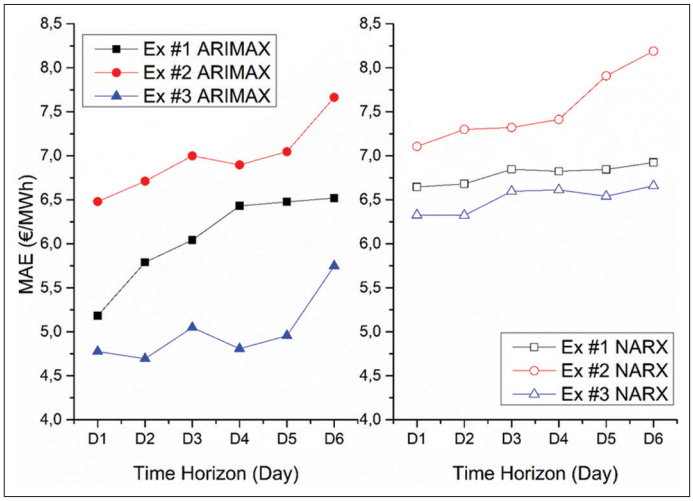


Table 4: MAPE forecasting results

Day Ahead	Ex #1 ARIMAX (%)	Ex #2 ARIMAX (%)	Ex #3 ARIMAX (%)	Ex #1 NARX (%)	Ex #2 NARX (%)	Ex #3 NARX (%)
D1	2.88	3.60	2.65	3.69	3.95	3.51
D2	3.22	3.73	2.61	3.71	4.06	3.51
D3	3.36	3.89	2.80	3.80	4.07	3.66
D4	3.57	3.83	2.67	3.79	4.12	3.67
D5	3.60	3.91	2.75	3.80	4.39	3.63
D6	3.62	4.26	3.19	3.85	4.55	3.70

Figure 7: Mean absolut error of 6 forecasting models



For a practical use on 1 day ahead forecast the no explanatory variable option would, most likely be, the most accurate method. This is motivated due the small error difference between no explanatory and competitive explanatory options (2.88–2.65%) and the fact that the error impact in forecasting the explanatory variable would be avoided. On the other hand, ARIMAX method with no explanatory variable is the most sensible method to time horizon with a daily error increase of 0.27€/MWh.

The results show a better performance of ARIMAX over NARX method in all explanatory variable options. This is due a higher number of occurrences of low errors in ARIMAX method which result on a lower annual error average.

Both methods show accuracy enough to be used as reliable forecasting tool. They show dependence on the time horizon but there is not much effect on accuracy and even mid-term forecast could be considered useful for power generators and consumers.

6. ACKNOWLEDGMENT

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