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FORECASTING HOURLY PRICES IN THE PORTUGUESE POWER MARKET WITH ARIMA MODELS

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This work would not be possible without the full support of my
father, who believed in me all the time, even when I did not.
This is for him

I would like to thank my family (my mother, my sisters and my aunt), for understanding the effort made during the execution of this work, not questioning even once the long time I did not spend with them, especially during these last nine months. Their concern became part of my motivation so that I could finish this piece of my research.

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ABSTRACT

As power markets became a recent worldwide phenomenon, electricity prices' forecast is a new subject for investigators. Due to the electricity's particularities, a power market has some very specific rules that must be understood before one begins its study.

This empirical research presents a comparative study between two forecasting methods of the day-ahead hourly electricity prices in the Portuguese power market: a complete hourly time-series analysis and an hour-by-hour approach, each one for a Summer and an Autumn seasons.

My purpose is to check if an exhaustive hourly analysis would improve significantly the energy price forecasts accuracy and, if so, would the additional computing time offsets this improvement. As it is common in energy prices empirical research, we use ARIMA models. To select the models on a first stage, the Mincer-Zarnowitz regression was considered. On a second stage, to compare the models and select the best one in terms of predictive ability, the Harvey-Newbold encompassing test was applied.

Some evidence was found that, in accordance to Cuaresma *et al.* (2004), analysing each hour separately produced better results than considering the complete time series, although the time taken to estimate the models can be an issue for short term predictions.

The ARIMA models that captured the weekly effect encompassed the others and produced more accurate forecasts.

Key words: Electricity Market; Time-series analysis; Energy price; Price forecast.

JEL classification: C53; E37

PREVISÃO DE PREÇOS HORÁRIOS NO MERCADO PORTUGUÊS DE ELECTRICIDADE COM MODELOS ARIMA

RESUMO

Com a transformação dos mercados de electricidade num fenómeno mundial, a previsão de preços de electricidade tornou-se num novo tema de estudo para os investigadores. Devido às particularidades da electricidade, um mercado eléctrico tem regras muito específicas que têm que ser compreendidas antes de se iniciar o seu estudo.

Este trabalho experimental apresenta um estudo comparativo entre dois métodos de previsão dos preços horários de electricidade para o dia seguinte: uma análise da série horária completa e uma aproximação hora a hora, cada uma delas para um período de Verão e de Outono.

O meu objectivo é verificar se uma análise horária exaustiva melhora significativamente a precisão das previsões dos preços de energia e, caso tal se verifique, se o tempo adicional requerido compensa esta melhoria. Como tem sido comum em estudos empíricos sobre preços de energia, utilizámos modelos ARIMA. Para seleccionar os modelos foi considerada a regressão de Mincer-Zarnowitz numa primeira fase. Num segundo momento, para comparar os modelos e seleccionar o melhor no que respeita à capacidade preditiva, o teste de Harvey-Newbold foi aplicado.

Encontrámos evidências de que, de acordo com Cuaresma *et al.* (2004), analisar cada hora separadamente conduz a melhores resultados do que considerar a série temporal completa, embora o tempo requerido para estimar os modelos seja relevante para previsões de curto-prazo.

Os modelos ARIMA que captaram o efeito semanal englobavam os outros e produziram previsões mais precisas.

Palavras-chave: Mercado eléctrico; Análise de séries temporais; Preços de energia; Previsão de preços.

Classificação JEL: C53; E37

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ABBREVIATIONS' LIST

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIK	Akaike Information Criterion
AR	Autoregressive
BG	Breusch-Godfrey
CBMC	Contractual Balance Maintenance Costs
CCGT	Combined Cycle Gas Turbine
EDP	Energias de Portugal
ERSE	Entidade Reguladora dos Serviços Energéticos
EU	European Union
FCST	Final Costumers' Sales Tariff
GW	Gigawatts
GWh	Gigawatts-hour
HN	Harvey-Newbold statistical test
KW	Kilowatts
KWh	Kilowatts-hour
LRS	Last Resource Supplier
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCP	Market Clearing Price
MCV	Market Clearing Volume
MIBEL	Iberic Electricity Market
MW	Megawatts
MWh	Megawatts-hour
NPV	Net Present Value
OMEL	Spanish pole of MIBEL, responsible for the spot market management
OMI	Iberic Market Operator
OMIP	Portuguese pole of MIBEL, responsible for the forward market management
ORP	Ordinary Regime Production

PACF	Partial Autocorrelation Function
PPA	Power Purchase Agreements
REN	Redes Energéticas Nacionais
RMSE	Route Mean Square Error
SIC	Schwarz's Information Criterion
SRP	Special Regime Production

1. INTRODUCTION

In the Summer of 2008 I decided to do some research on a theme which I've been working with in the company I work in: develop and propose a price forecasting model for the Portuguese Power Market.

Although several approaches have been proposed in the past two decades, forecasting energy prices is a recent research subject. As I will mention below, the market liberalization around the world started effectively in the early 90s. In Portugal, as the total liberalization occurred just in 2007 (although the regulated market has been existing simultaneously), only recently the market is reaching such a maturity that some inference can be made from historical electricity prices.

Even in a country where both the liberalized and regulated market exist simultaneously, price forecasting is highly important for companies. This is valid either in retail where they have to maximize their margin or in production where a plant should guarantee that its production is bought in the market whenever they intend to sell it. Risk management is also an important reason to be accurate in electricity price forecasting.

1.1 Power Markets' Description

Ever since electricity was discovered and eventually became available to the large public, a certain market model or, to be more precise, a certain kind of structure was implemented in the countries, having as main goals:

- To deliver electricity to every consumer;
- To guarantee the security of supply;
- To practise "reasonable prices".

Due to this "heavy" social component, the vertically integrated companies appeared as the natural kind of structure mentioned above. The four activities (Production, Transmission, Distribution and Retail Supply) were usually owned by a single company, which was, most of the times, state owned. As traditionally, in each country the vertically integrated companies had the monopoly of electricity business (from generation, passing through transmission and distribution (Weron, 2006) and ending up in the retail business), neither the economic nor the energetic efficiency were the state owner's primary goal. In many cases, as electricity should be available to everyone, tariffs did not reflect the real production marginal cost. Furthermore, there were no incentives to build more efficient power plants because price was not a strategic issue.

Therefore cost minimization was the "market engine": a central operator decided centrally which plants should or should not be operating in order to minimize total system costs while, simultaneously, the entire demand must be satisfied (Conejo *et al.*, 2005).

In the late eighties and early nineties, liberalization seemed to be the best solution for the inefficiencies of the existing markets, supported by a vertically integrated player and over the last two decades, a considerable number of countries embraced the liberalization of their power markets. The main purposes were (Weron, 2006):

- To promote efficiency gains;
- To stimulate technical innovation;
- Lead to efficiency on investment.

Thus *"In most countries, a cost minimization paradigm has been replaced by a profit maximization one"* (Conejo *et al.*, 2005: 435) where producers and retailers' bids reflect their most efficient and profitable choices.

There was not a unique market model created all over the various countries, but different, although sometimes similar, power markets have been brought to life: the two main liberalized market models are called Power Exchanges and Power Pools and finding the differences between them is not a clear task.

According to Weron (2006) a Power Pool consists in a one sided auction, where generators (the plant owners) bid their supply offers, which are matched with the forecasted demand. Because these offers consist in a pair Volume/Price, the intersection point settles the Market Clearing Price (MCP) and the Market Clearing Volume (MCV). No offers can be made outside the market.

The great differences from Power Pools to Power Exchanges are: firstly, bilateral contracts are allowed (in the later ones) and secondly, a two sided auction takes place. Producers place their supply offers, which are sorted by their production marginal cost (sorting the different technologies by its marginal cost is called the "Merit Order") and distributors and/or retail suppliers place their demand offers, according to the demand they predict from their costumers. Again, MCP and MCV came out of the demand and supply curve intersection.

A bilateral transaction is no more than a direct agreement between a producer and a retail supplier, in which they agree to transact a certain amount of energy, in a given period in the future, at a pre-settled price. The Market Operator should be informed of each bilateral contract established, as well as the Independent System Operator, so that the physical requirements needed for a secure transaction can be satisfied (to guarantee there would be no grid constrains).

With more competition in the power markets, a price decrease would be expected. Although some argue that, on average, electricity prices fell, since the liberalization process started, this position deserves two comments under a consumer's point of view: according to Weron (2006) net electricity prices have generally decreased, but the new taxes imposed on the prices have in many cases reversed the effect and the prices paid by some consumer groups do not necessarily reflect the costs of producing and transporting electricity. In regulated power markets, industrial costumers often subsidize retail consumers.

Another main issue of the liberalization process is how to guarantee the security of supply, since this is the most important preliminary condition to participate in the market. Incentives were created to lead producers to invest in new generation and the best-known one is the capacity payment.

In a market where different players compete for efficiency (both economic and energetic) investment decisions prefer some technologies instead of others (these decisions are due to intensiveness of capital, production marginal cost, construction time, ... (Weron, 2006)) or could be driven by price expectations (low expectation of power prices can be a reason to delay some investment decisions in new generation).

The Capacity Payment, usually supported in the installed capacity, is a payment to guarantee that no under capacity occurs in the market at any time, meeting the hourly demand. It is a payment to guarantee the release of the necessary load to the system and reserve the required extra capacity.

The retail sellers (who sell the electric energy to the end-user consumer) need to guarantee the necessary energy to meet their obligations. This amount of energy equals the required energy in a peak hour plus a reserve margin. This is why capacity payments exist.

Established the difference between Power Pools and Power Exchanges, I will focus my work, from now on, on the later, because the market I purpose to study is a Power Exchange[1].

Although Power Markets share some characteristics with capital markets, the MCP formation process is quite different especially due to one particular feature of the underlying asset: the instantaneous nature of electricity is responsible for the creation of a brand new mechanism of Market and, thus, for the development of a new research area.

Although electricity is a commodity, it is not an ordinary one since it has a huge difference from oil or gas: it can not be stored. Every hour, every minute, every second, *"The physical laws that determine the delivery of power across a transmission grid require a synchronized energy balance between the injection of power at generating points and the off take at demand points (plus some allowance for transmission losses)"* (Bunn and Karakatsani, 2003: 3). The System Operator has the miraculous task of keeping production and consumption in balance, to avoid sudden voltage fluctuations. If there is a positive fluctuation in demand or a production unit get off the system suddenly, the System Operator, in order to satisfy the continuously required demand, has to call for generators with extra capacity that are able to inject quickly energy into the system. This monitoring is of most importance as one easily knows that the final consumer doesn't realise all of this sensitivity while consuming electricity.

At a given hour of a day, day-ahead prices are settled in an auction. Actually, 24 prices are settled, resulting from the 24 two-sided auctions between generators (producers) and retailers (suppliers), one for each hour of the next day. Prices and energy volume are required from the players until 9:00 am Portuguese time (10:00 am Spanish time) and are known about one hour later. This occurs after the clearing is done

[1] The detailed explanation of the Iberian Power Market functioning mechanisms, and especially, the Portuguese one, is presented in APPENDIX A.

by the Market Operator and the System Operator verifies that the physical conditions are satisfied (generating capacity, transmission and distribution constraints).

Each player bids one or more offers for each hour of the next day (a pair of price (€/MWh) and energy (MWh)). A generator bid strategy is related with its generating mix and the corresponding production marginal cost of each plant. On the other side, suppliers' strategies are more related with the energy they expect their clients will consume, which they are obliged to guarantee.

For each hour, the Merit Order is settled according to the producers' bids. This constitutes the supply curve (actually, it is more like a supply "step by step growing line"). Likewise, demand curve is a "step by step decreasing line". The point in which both curves do intercept settles the MCP and MCV for the given hour.

With this auction mechanism, the most expensive technology (the one with higher marginal cost) that satisfies the demand, settles the price for the hour. So, technologies with low marginal costs are guaranteed in seeing their production sold, as long as there is enough demand and the plant is available.

After the MPC from the daily market, there are six intra daily markets, which function is to allow those suppliers who were out of the daily market, to meet the obligations with their costumers. Anyway, the purpose of this study is the MCP and not the later adjustments' markets.

1.2 Electricity prices' particularities

As mentioned above, one issue related the electricity prices behaviour, is the fact that electricity can not be stored.

Actually, there is one way of storing electricity: to produce electric energy by hydroelectric means, the water used is, in many cases, stored in a reservoir. However, the electricity produced through hydroelectric resources has not the same importance in different regions. In Scandinavia, for example, *"when the level of the water reservoirs (...) is low, the prices are less influenced by temperature"* (Weron and Misiorek, 2008: 18) suggesting the large dependence between prices and hydroelectric production on this region. On the opposite side is the California Market (which is divided in 26 zones), where *"hydroelectric power represents a relatively small fraction of total electricity generation, compared to nuclear and fossil-fuelled generators."* (Knittel and Roberts, 2005: 794).

The non-storability of electricity is of huge importance because it justifies a completely new approach in analyzing, modelling and forecasting techniques regarding electricity prices: it implies that inventories can not be used to arbitrage prices across time, not allowing the link between expectations and spot prices (Knittel and Roberts, 2005; Cuaresma *et al.*, 2004).

Extreme volatility is also a very important consequence of the non-storability and the "threaten" for capacity constrains. In some cases, this can show a time-varying structure (Nogales *et al.*, 2002; Bunn and Karakatsani, 2003). Daily volatilities of 29% (Huisman and Mahieu, 2003) are quite common and may reach 50% in extreme scenarios (Weron and Misiorek, 2008). Annualised values of 200% are not surprising (Bunn and Karakatsani, 2003).

Another point we must care is the capacity constraints. Together with non-storability, this leads to the inelasticity of the electricity supply (Huissman and Mahieu, 2003; Knittel and Roberts, 2005). The demand is also extremely inelastic (at least at short time) as consumers pay a fixed price, being indifferent or ignoring the wholesale price (Knittel and Roberts, 2005; Weron and Misiorek, 2008).

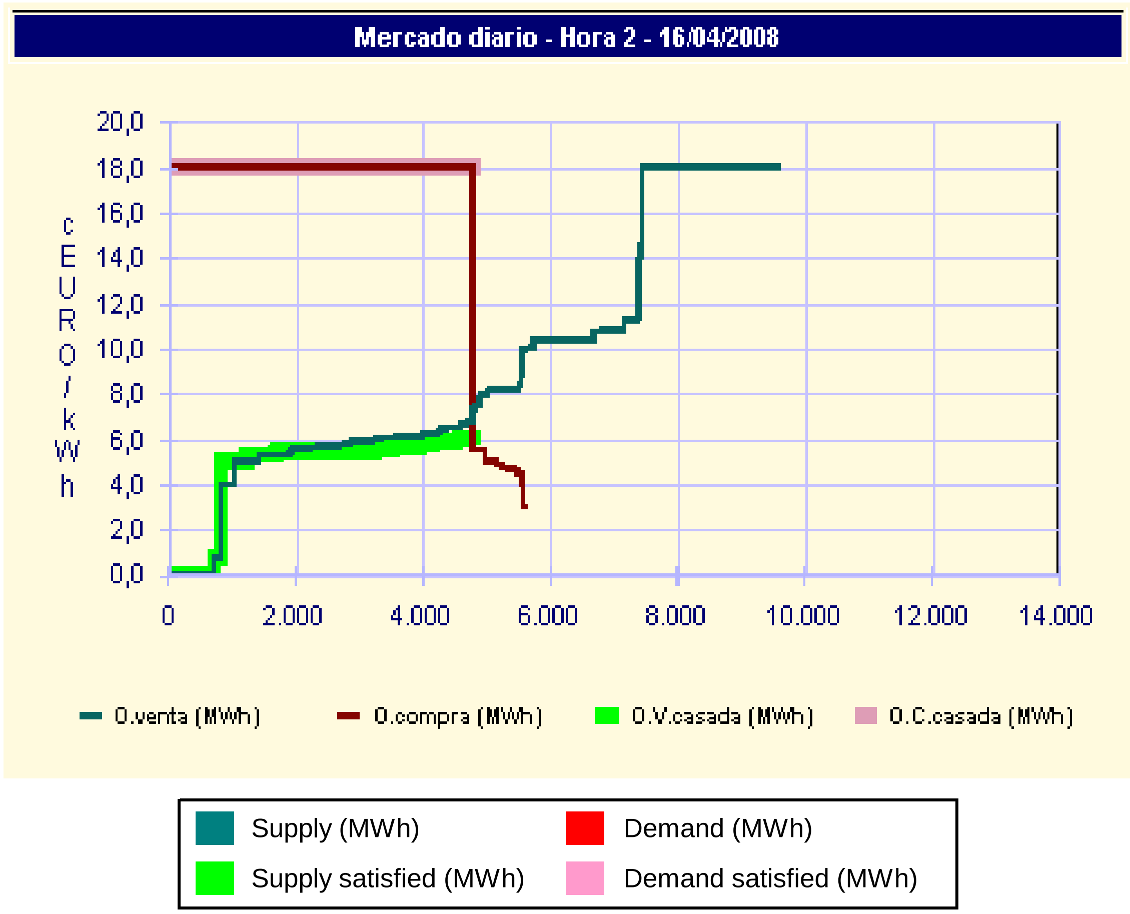
The presence of sudden "*and frequent extreme jumps in prices that die out rapidly*" (Huisman and Mahieu, 2003: 425) is another consequence of the demand and supply behaviour. These jumps, usually called spikes, are of unknown frequency and magnitude. This erratic behaviour tends to revert quickly to a long-term equilibrium mean, and fluctuate around it (Huisman and Mahieu, 2003). This process is called mean-reversion and is another feature of electricity prices.

Seasonality is another important feature of electricity prices, at different levels: intra-daily, weekly and seasonal (Bunn and Karakatsani, 2003), which is complemented by a calendar effect, such as weekends and holidays (Nogales *et al.*, 2002).

Such a proper time-series behaviour may be explained (among other reasons) by the different technologies getting into the system (with different efficiencies and production costs) at different price levels, which will settle the MCP (Bunn and Karakatsani, 2003; Weron, 2006).

On Figure 1 we can see the market curves for Portugal for hour 2 of April 16, 2008. The extreme inelasticity of demand is clearly seen. The inelasticity of supply is not that notorious:

Figure 1: Supply and demand of energy for Portugal - hour 2 of April 16, 2008



"Another distinguishing feature of electricity markets is the potential for suppliers to exercise market power" [2] (Knittel and Roberts, 2005: 794). This oligopolistic nature is characterized by a few dominant players, even in markets where it seems to exist enough competitors to produce lower prices (Bunn and Karakatsani, 2003).

The presence of negative prices can actually happen in power markets, as for some generators may be more profitable to pay so that a plant would not get off the system for one or two hours (which would increase the production marginal cost due to the start up cost).

In MIBEL that is not allowed as the minimum bid level allowed is 0 €/MWh.

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[2] In a report published in May 2009, by the Portuguese Competition Authority about the gross prices' formation in Portugal in the second semester of 2007, the Authority concludes that there were evidences that support that EDP Produção (the main electrical company in Portugal in the gross market) in more than 80% of the hours was indispensable to satisfy at least 25% of the demand (and in 22% of the period EDP was necessary to supply more than half of the demand)

Based on this brief introduction, the main purposes of this thesis are: forecasting the day-ahead electricity prices for the Portuguese Power Market through ARIMA models, and comparing two different approaches. A first one in which the complete hourly prices time-series is used to forecast short-term prices through a selected ARIMA model and a second one where the price of each hour is independently forecasted leading to 24 independent analysis (and forecasts) of the 24 daily prices.

Electricity prices in the Portuguese Power Market, have not yet been studied before (also because no more than 3 years passed since the complete market opening)

We will use the Mincer-Zarnowitz regression and the Harvey-Newbold statistical test to enrich the study bringing a new perspective to the results as the forecasts were set against the real values and the models were compared to each other before selecting the best one.

To perform an hour-by-hour analysis (after Cuaresma *et al.* (2004)), intended to bring some accuracy to the forecasts as we could treat each one of the 24 price series as a "regular" time-series while the complete time-series had to take into account previous forecasts in order to get new forecasts.

The thesis is organized as follows. Next section presents the literature review with the most important conclusions resulting from the econometric approaches done on the subject. Section 3 describes the ARIMA models used in this study, for the complete time-series analysis and the hour-by-hour analysis. Section 4 discusses estimation results and compares out-of-sample evaluation for an Autumn and a Summer period. Finally, section 5 presents some concluding remarks.

2. LITERATURE REVIEW

Although being a recent research subject the study of the electricity prices' series throughout the world (only possible after the markets' deregulation) has produced several diversified papers in the last fifteen years.

Because each market has its own rules, not every detail in each study can be blindly applied to all markets. Even so, because all power markets share a kernel of important characteristics (mentioned above), the methods and the conclusions already published can be generally applied to the liberalized markets.

As the scientific papers related with the Portuguese energy market are very sparse or do not exist, and due to the main objective of this thesis, forecasting the energy prices in the Portuguese market, the analysis of prior research is oriented for the econometric tools already used to forecast energy prices considering different time frequency and/or different markets.

Nogales *et al.* (2002) presented two forecasting tools, based on time-series analysis, with similar econometric background: dynamic regression and transfer function models applied to the hourly price series in the Californian and Spanish markets. In both models a single fundamental was used: the demand. They found that the Spanish prices were less predictable as the daily mean error was about 5% against a 3% one for the Californian prices.

Huisman and Mahieu (2003) tried a different econometric approach: taking into account the mean-reversion, high volatility and the extreme spikes of electricity prices, a three states' regime-switching model was proposed. The daily spot price (the average of the 24 hourly prices in each day) was decomposed as the sum of a deterministic and a stochastic component, in which mean-reversion can be separated from spike periods. Three markets' data were used for comparison purposes (APX from The Netherlands, LPX from Germany and Telerate UK Power Index).

Contreras *et al.* (2003) suggested two kinds of ARIMA methodologies to forecast day-ahead prices in the Californian and Spanish markets again: a pure ARIMA model and an ARIMA model with two exogenous explanatory variables: the demand and the available daily production of hydro units. The average daily mean error in the Spanish market was about 10% while in the Californian market was about 11%.

A summary of the research done on the power markets was made by Bunn and Karakatsani (2003) in a working paper where the fundamentals of power markets and the behaviour of electricity prices have been organised and explained.

Cuaresma *et al.* (2004) based their empirical study on the hourly prices of the LPX market. The methods applied include AR and ARIMA models, with time-varying intercept or jumps (ARIMA). They concluded that "*an hour-by-hour modelling strategy for electricity spot-prices improves significantly the forecasting abilities of linear univariate time-series models*" (Cuaresma *et al.*, 2004: 105)

Guirguis and Felder (2004) studied historical electricity prices from two New York State areas to conclude about the forecasts' improvement of GARCH models when compared to other techniques such as dynamic regression, transfer-function models and exponential smoothing.

Conejo et al. (2005) compared the three time series' methods they had worked on before (ARIMA, dynamic regression and transfer function) with neural networks and wavelets. The demand was considered as exogenous variable but not always improved the forecasts' accuracy. Transfer function and Dynamic regression presented the best predictions on the PJM Interconnection.

Knittel and Roberts (2005) presented a comparative study of several forecasting methods applied to electricity prices (a mean-reverting process (AR), Jump-diffusion, ARMA with time-varying intercept (ARMAX), EGARCH or ARMAX with temperature as exogenous variable). ARMAX, EGARCH and Jump-diffusion were among the models with the best performances suggesting a malleable statistical behaviour of electricity prices, the presence of spikes and time-varying high volatility. The data consisted of hourly prices from California.

Nogales and Conejo (2006) returned with a detailed analysis of the electricity hourly prices' forecast through transfer function analysis. Demand data was used as the unique explanatory variable for forecasting in the PJM Interconnection.

Huisman, Huurman and Mahieu (2007) proposed a very different approach. In this paper *"hourly prices cannot be seen as a pure time series process"* (Huisman and Huurman, 2007: 242) as time-series models assume the information is available in each time step and not every 24 time steps. To forecast the price for hour 23 of the next day, we just know the prices until hour 24 of the previous day and not the one from hour 22 of the next day. A panel-data analysis is suggested in which the prices of 24 cross-sectional hours vary from day to day. Three data sets were compared: APX, EEX from Germany and PPX from France.

Silva (2007), in her Master Thesis, provided a comparative study of statistical models to predict electricity prices. She studied short-term forecasts both for daily and monthly prices. For the day-ahead prices forecast, SARIMA models and GARCH models were tested while for the next-month prices forecast, the approach was made through SARIMA models, SARIMA with intervention effects and GLS (Generalised Least Squares) models. The OMEL Spanish prices were the working data. The GARCH model was the one that performed better.

Weron and Misiorek (2008) compared several forecasting tools ending up for concluding that, although not being unanimous, a semiparametric approach (an Auto

Regressive model calibrated with a smoothed nonparametric maximum likelihood estimator) had a better performance than AR, Regime-Switching or Mean-reverting jump diffusions models. Californian and Nord Pool’s hourly prices constituted the working data.

Bunn and Karakatsani (2008) came up with an exhaustive study of the UK market. After realizing that stochastic models were incomplete (good for modelling but not so good for forecasting) and that the existing models are more concerned about the autoregressive effects than price’s reaction to fundamentals, a large comparative study of models, with a large number of explanatory variables was suggested. Time-varying parameters, either a Regression or Autoregressive, were the most accurate.

No more than twenty years ago, worldwide liberalized power markets only existed as projects and nice political intentions. When they boomed, several econometric tools found in electricity prices a new object to test their own reliability. Much more work on the subject will be produced in the coming years, as the existing markets will eventually be getting into their maturity. As we will see in the next sections, this work is also a contribution for comparing two energy prices forecasting techniques.

3. METHODOLOGY

3.1 Models and frequency data

Following several power markets’ researchers (Contreras *et al.* (2003), Cuaresma *et al.* (2004), Conejo *et al.* (2005)), I have the purpose to build a model which will able to forecast the 24 day-ahead electricity prices. For this purpose, and according to the literature review, a great number of options came up. The reasons that led me to forecast electricity prices through ARIMA models come in the next paragraphs.

As it is explained in APPENDIX A, both the Portuguese and the Spanish markets are related (even physically) so, predicting prices for these markets should be an interesting study (probably an idea for future research). Anyway, as some work has already been done on the Spanish market, which exists since 1998 (Contreras et al. 2002 and 2003) and no public work has been published about the Portuguese market (at least in the econometric point of view), I decided to concentrate on the Portuguese case.

After some research, and based on the literature review, I realized the large number of different approaches which had already been applied to the subject (Simple regressions, GARCH-type models, ARIMA models, ARIMA models with exogenous variables, Jump-diffusion models, Markov-processes' models, exponential smoothing, transfer-function models, neural network models, etc...).

While looking for fundamentals that are significant to predict the hourly electricity prices, a restricted number of variables always appeared: temperature, level of the reservoirs and demand. However, two main problems arise when these variables are included: in an hour-forecasting model, we need both hourly-basis historical data and forecasts for the explanatory variables, which may not be available or may have a considerable error component. The more fundamentals we include in the model, the larger error component we may get (Weron, 2006). For example, if we think about hourly temperature forecasts for the next 30 days, we realize the enormous potential error in perspective, besides the difficulties in getting access to historical hourly data. With demand, although historical information is freely available, the greatest problem is due to its forecast[3]. Furthermore, pure time series models are more appropriate to describe the behaviour of power markets than of financial markets, due to the "normal" seasonality, which occurs with the electricity prices (Weron, 2006).

Based on this, I decided do not include any of these fundamentals in the estimated models. I assumed that general fluctuations in demand and temperature are already incorporated in historical prices; otherwise, as we forecast the price for each hour of the 30 days-ahead, we would have to include 720 point forecasts (30 x 24) per fundamental variable included in the model.

The unique variables I added to the standard ARIMA model are three dummy variables, which have been included one-by-one separately. The first dummy captures the weekend effect (being 1 on Saturdays and Sundays and 0 on working days), the second dummy captures the holiday effect (being 1 on holidays, if not a weekend, and 0

[3] In the Portuguese Competition Authority's report published in May, 2009, it is explained that the demand forecast relies, among other things, in the forecast of eolic energy production which is highly volatile once it depends directly from the wind speed and direction in each hour.

otherwise) and the third dummy grouped the previous two (being 1 on weekends and holidays and 0 on the remaining days).

I also considered to exclude weekends (because prices are much different from the remaining weekdays) and to include a dummy variable to capture the effect of each one of the four seasons. However, I did not realise any of these changes. It seemed to me that, excluding weekends would change the prices relation pattern in such a way that some important inference could be lost in the process. Including a variable to reflect the seasonal effect seemed useless once it would only make sense in a large sample (more than a year) so that the seasonal cycle could be captured.

My initial idea was also to include a volatility analysis to the Portuguese electricity hourly prices and so, to include the possible ARCH effects in the model. Guirguis and Felder (2004) concluded that GARCH models performed better than other statistical ones and Knittel and Roberts (2005) found evidence of an “inverse leverage effect” in electricity prices. Because this is not a closed research, my next step in this investigation will be to test the significance of ARCH effects and to analyze the electricity prices considering conditional heteroskedastic models. Anyway, I performed the log-transformation to the data in order to prevent some time-varying volatility.

One of the improvements of this work is that it considers the complete time-series analysis at once but also analyses each hour separately (hour-by-hour analysis). Cuaresma *et al.* (2004) concluded that an hour-by-hour analysis performed more accurate forecasts than if one considers the complete hourly time-series at once. Furthermore, in each case, the kind of prediction should be different. As Huisman, Huurman and Mahieu (2007) refer, if we consider the real hourly price formation process, the complete series is not a “normal” time-series once we do not know the value of an observation at each time step, but all the 24 at once every 24-length cycle. This impacts directly the forecasts’ method and consequently, its quality.

By using the complete series, prediction must be obtained day-by-day and we must use forecasts in order to produce new forecasts. For example, to forecast the price for the hour 24 of the next day, we don not know the prices of the first 23 hours of that day. So, we should run the model in order to get the forecast price for hour 1, and then we use that forecast to forecast the price for hour 2, and so on. When we get the forecasting for hour 24, the previous 23 observations are not real values but forecasts.

The hour-by-hour analysis has the advantage of eliminating this issue. Because we consider 24 separate time series, one for each hour, when we will perform the forecast of the hour 24 of the next day, we only use the series of prices of hour 24 from previous days. Thus, we know the real value of past observations and no forecasts are needed to perform a new forecast. In the *EViews* program, in the former case we must perform a dynamic forecast every 24 observations for the whole 720 forecasting period, and in the later one, we can perform a static forecast for the whole 30 observations of the forecasting period, for each one of the 24 models. I performed both so I could compare which one produces best results.

3.2 Estimation and forecasting periods

In terms of sample size, and from the information we could get, there is not one best standard estimation period. Nogales and Conejo (2006) used only 61 days (in a complete time series approach which completes 1,464 observations), Weron and Misiorek (2008) used a 9 months sampling period, Bunn and Karakatsany (2008) used almost 10 months (300 days) and Knitell and Roberts (2005) considered 29 months (21,216 observations). Based on this, I decided to consider a 6 months sampling period in order to get forecasts for the next 30 days. More than that seemed to be excessive: I thought that it would not improve the model' performance once it would capture price relations too far from the present time (in dynamic markets, where the production mix is changing regularly, it is expected that the price relation over time becomes dynamic too).

As some researchers evaluated their models in different periods, usually in the more stable and more volatile ones (Weron and Misiorek, 2008; Nogales et al., 2002), the same methodology was adopted. We selected two 30-days forecasting periods, the first in the Autumn of 2008 and the other in the Summer of 2009 (actually it wasn't exactly a Summer season, since June is a half-Spring and a half-Summer period).

Therefore, the sample is partitioned in two distinct parts: the first part of the sample (6 months) is retained for the ARIMA parameters estimation while the remaining part (1 month) is considered as the forecasting period. In each part of the sample, we considered two distinct periods: April-September (A-S) and December-May

(D-M) for the parameters estimation and Autumn and Summer for the forecasting evaluation as one can see in table 1.

Table 1 Sampling periods

Analysis	Period	Estimation sample	#	Period	Forecasting sample	#
Complete time-series	A - S	From 1-4-2008 to 30-9-2008	4392	Autumn	From 1-10-2008 to 30-10-2008	720
	D - M	From 1-12-2008 to 31-5-2009	4368	Summer	From 1-6-2009 to 30-6-2009	720
Hour by-hour	A - S	From 1-4-2008 to 30-9-2008	183	Autumn	From 1-10-2008 to 30-10-2008	30
	D - M	From 1-12-2008 to 31-5-2009	182	Summer	From 1-6-2009 to 30-6-2009	30

Parameters for the conditional mean equation are therefore estimated based on 6 months information (corresponding roughly to 183 and 182 observations in the hour-by-hour analysis and to 4,392 and 4,368 in the complete time-series analysis, for the A-S and D-M periods, respectively). These parameters are used to estimate the hourly conditional mean. To estimate the ex-ante out-of-sample predictive power of the models, the estimated parameters are used to forecast the hourly day-ahead conditional mean for the forecasting month (corresponding to 30 observations in the hour-by-hour case and 720 observations in the complete time-series analysis).

In the Autumn forecasting, there was some risk in considering an estimation period that began only 9 months after the Portuguese market's opening. It may not have reached the required maturity level in order to produce a meaningful model. Anyway, some authors did not consider any "maturity-lag" at all (Cuaresma *et al.*, 2004; Knittel and Roberts, 2005) and I decided to estimate the model based on that sample.

In the Summer case, the estimation period begins more than one year after the market opening. Thus, the market was at a different stage of maturity.

Another methodological issue was to decide if the estimating period would evolve over time. Most researchers applied the "Rolling Window" and the "Jackknife" methods. The "Rolling Window" method consists in, at each estimation step, to move one observation forward the calibration sample. The sample dimension remains unchanged. In the "Jackknife" method, only the ending observation would move forward at each step and the starting observation is the same at each step. So, the estimation sample dimension increases with time. The third option consists in keep the sampling period unchanged at every step: we estimate the model with a sample until a certain day, and use that same model to forecast the prices for all the days of the forecasting period. I decided for this third option.

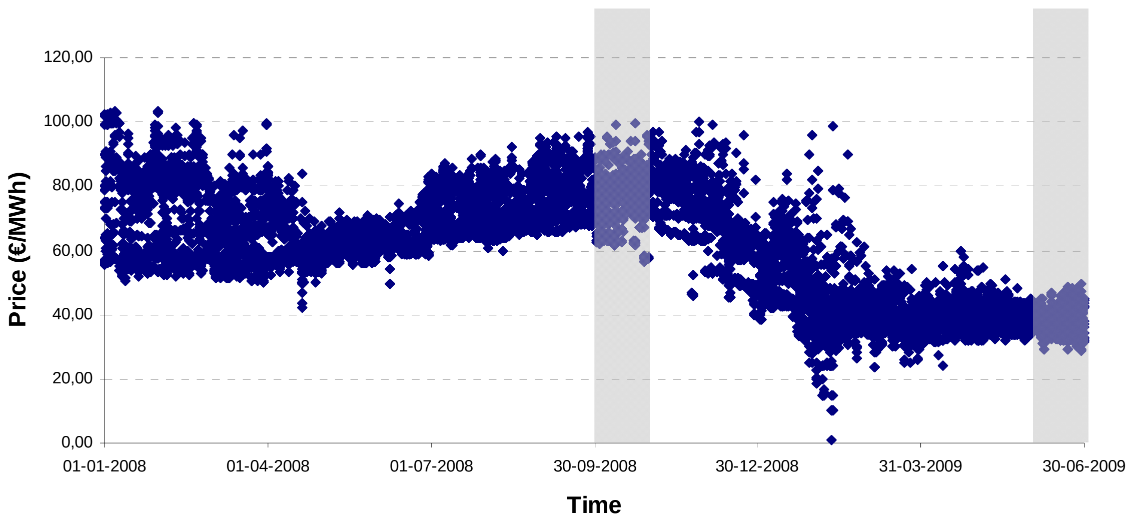
I started by applying all the three methods but I abandoned this idea for one main reason: some researchers (but not all) who used one of the two dynamic samples, usually made forecasts for longer periods (50 days or more) than the one I used (30 days). I believe that, in 30 days, the price relation through the days doesn't change so dramatically that one needs to re-estimate the model at every time step.

Therefore, I decided to keep the forecasting period in a medium-size period (it seemed to me that 30 days fulfilled this condition) and to keep the model constant while forecasting through the 30 steps of the test sample.

As one can see in Figure 2, electricity prices behaved regularly in the OMEL during the two estimation periods (A-S and D-M).

Actually, there were not many values that one might consider as spikes: in fact there was only one extreme value (jump) in the sample, on February 2, 2009, on hour 5: the price reached 1 €/MWh (the average price from January to June 2009 was 40.88 €/MWh) as it can be seen in Figure 2. This observation was not deleted from the sample as jumps must be taken into account while working with electricity prices. If a larger number of jumps were observed in the sample, they should be treated carefully because, as Weron (2006) argues, one should be careful in handling the anomalous prices (usually spikes). Although one does not want to bias the price prediction with an outlier, the fact that spikes are actually important in power markets makes them non-excludable and so, they require a special attention.

Figure 2: The Portuguese electricity hourly prices - January 1, 2008 to June 30, 2009



The grey areas in Figure 2 are the forecasting periods: the Autumn one (October 2008) and the Summer one (June, 2009).

The only change performed on the series was the one in the missing hour in March (at the Spring's starting) and the extra hour in October (when the Autumn starts). In the first case, I added one hour with the average price of both the previous and the following prices. In the second case, the 25th price of the day was eliminated to the series.

3.3 Econometric approach

In order to stabilize the variance and to reduce the heteroskedasticity impact on estimation results, the workable series are the natural logarithm of electricity spot prices.

Either in the complete time-series analysis or in the hour-by-hour analysis, I had to guarantee that the series was (at least) covariance stationary. To check the existence of a unit root and to test the stationarity of the series, the Augmented Dickey-Fuller (ADF) was performed. In the test equation, trend and intercept were included so that the test could capture not only the stochastic trend but also the deterministic trend of the series. An automatic lag length selection has been applied by using Schwarz's Information Criterion (SIC) (more demanding than the Akaike Information Criterion (AIC) in what the number of estimated parameters are concerned).

When the null hypothesis of the ADF's test applied to the electricity log-prices was not rejected, a first difference was computed and with this transformation, the new series became stationary. By the inspection of the estimated Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), in some cases a seasonal differentiation is suggested and computed. However, this procedure is adopted only when, after performing a first order regular differentiation, the series remained non-stationary.

We expected that some seasonal behaviour might occur, specially a weekly effect, and by the ACF and PACF inspection, most of the analysed series seemed to confirm this suspicion. Thus, based on the estimated autocorrelation functions we use ARIMA and/or SARIMA models for each considered period.

In the complete time-series analysis, a few times 24-length cycle emerged, while in the hour-by-hour analysis, a 7-length cycle was dominant (in the hour-by-hour analysis, the weekly effect is more evident than in the complete-time series where the daily cycle dominates).

In order to capture the weekly seasonal effect that SARIMA model could not capture and/or to capture the possible holiday effect**,** the three dummy variables mentioned earlier have been included in each one of the models separately.

After estimating the models, an autocorrelation residual analysis was performed based on Breusch-Godfrey LM serial correlation test. The test decision should point to a white noise process to assure that the estimated model was able to capture the observed linear dependency in the time-series data.

At this point, I had 2 groups of models (covering the A-S and D-M periods) each one divided in 25 subgroups: one for each of the 24 hours of the day and one for the complete time series' analysis. A total of 507 models were estimated as several models have been considered for each one of the 25 subgroups, due to the Autocorrelation and Partial Autocorrelation functions appearance.

After estimation, the models' selection began. The first criterion was to exclude any model with at least one pair of coefficient estimates with correlation greater than 0.7 (Murteira, 2000). This prevented that a small change in the estimation sample might cause a large difference in the model's coefficients estimates (butterfly effect). By imposing this limitation, the number of candidate models diminishes to 339 models.

On the next selection step, the Mincer-Zarnowitz regression equation is estimated. The observed hourly electricity price from the Autumn and Summer 30-days forecasting period is the dependent variable in a linear regression having the forecasted values as the unique independent variable; intercept is also included in the regression. The purpose is to select from each one of the 50 subgroups, the 5 models with the highest coefficient of determination (R^2) resulting from the Mincer-Zarnowitz regression. If in a subgroup there are less than 5 models, all of them are selected. At this step, 208 models remained after the Mincer-Zarnowitz regression was applied.

At this point, the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) have been computed for the

208 selected models. The main reasons to compute these measures were to compare the hour-by-hour results with the ones resulting from the complete time series' analysis and to compare this empirical study's results with the ones from previous studies.

To select the best model from each one of the 50 subgroups resulting from the Mincer-Zarnowitz regression, the final criterion is the Harvey-Newbold (Harvey and Newbold, 2000) encompassing test. This test compares at once one single model (that we represent by model A, for example) with all the others, indicating if model A is better than the remaining ones. The test is based on a linear regression where the forecasting errors from model A is the dependent variable and the differences between the forecasting errors of model A and the ones resulting from the other models constitute the explanatory variables. In the null hypothesis, we state that model A encompasses the rest of the models under comparison against the alternative that at least one of the other models encompasses model A too. There are as many HN test results as models under comparison.

As the final criterion is the Harvey-Newbold test, the best scenario was to accept the null hypothesis in one of the forecasting models test and to reject it for all the rest of the models. Unfortunately, it might happen that none of the models encompasses all the others. In this case, the models selection is based on the highest *p*-value associated with the HN test result. Another possible scenario (and more plausible) is that several models encompass the remaining ones. If this is the case, the one that is more distant from the "rejection point" is chosen.

At this point 50 models were selected and Table 2 concludes about the number of models selected in each step.

Table 2: Number of models selected

	# - Start	**# - Correlations < 0.7**	**# - Top 5 Mincer-Zarnowitz R^2**	**# - Best models according to HN**
Complete time-series	8	6	6	2
Hour-by-hour	499	333	202	48
Total	507	339	208	50

4. EMPIRICAL STUDY

4.1 THE DATA

As we referred before, the sample used for parameters estimation is partioned in two different periods (from April 1, 2008 to September 30, 2008, A-S period, and from December 1, 2008 to May 31, 2009, D-M period) corresponding roughly to 183 and 182 observations in the hour-by-hour analysis and to 4,392 and 4,368 observations in the complete time-series analysis, for the A-S and D-M periods, respectively.

Table 3 shows the electricity spot prices descriptive statistics for the two estimation samples when the complete time-series analysis is considered. Tables 4 and 5 show the electricity spot prices' descriptive statistics for the hour-by-hour analysis. The grey areas in the Jarque-Bera statistical test column indicate the hourly prices series where the normality assumption can be assumed (for 5% significance level).

Table 3: Descriptive Statistics for the Portuguese electricity spot prices (complete hourly series)

Estimation period	Mean	SD	Skewness	Kurtosis	Jarque-Bera
From 1-4-2008 to 30-9-2008	68.42	8.58	0.53	2.76	213.93
From 1-12-2008 to 31-5-2009	45.17	12.58	1.10	3.95	1039.64
	56.80	10.58	0.82	3.36	

In average, the prices were much higher in the period April-September (with an average difference greater than 20€/MWh) as 2008 was an extreme year in what concerns the electricity prices (Table 3). In terms of prices normality distribution, the hypothesis is rejected for both periods according to the Jarque-Bera test.

Table 4: Descriptive statistics for the Portuguese electricity spot prices over period April 1, 2008 to September 30, 2008

Hour	Mean	SD	Skewness	Kurtosis	Jarque-Bera
1	66.76	6.01	0.08	2.70	0.90
2	64.30	5.44	0.12	2.61	1.60
3	63.77	5.57	0.69	5.91	78.90
4	63.04	4.93	0.10	2.92	0.37
5	62.34	4.62	-0.07	2.48	2.24
6	62.08	4.54	-0.17	2.36	4.00
7	62.78	4.91	0.02	2.11	6.01
8	64.88	5.95	0.57	3.13	10.05
9	65.40	5.94	0.28	2.99	2.41
10	68.62	7.58	0.08	2.48	2.28
11	71.96	8.67	0.12	2.09	6.76
12	72.80	8.76	0.06	2.10	6.23
13	74.21	9.15	0.00	2.10	6.18
14	73.53	9.29	0.02	1.97	8.16
15	71.17	8.74	-0.08	2.08	6.72
16	70.88	8.72	-0.06	2.33	3.57
17	70.39	9.12	0.01	2.52	1.77
18	70.11	9.48	0.09	2.50	2.17
19	69.44	8.91	0.19	2.32	4.62
20	68.53	8.43	0.19	2.20	5.98
21	69.8	9.64	0.44	2.21	10.51
22	73.77	9.52	0.55	2.33	12.66
23	72.35	8.29	0.30	2.53	4.40
24	69.07	7.00	0.21	2.62	2.52
Average	68.42	7.47	0.16	2.57	

In what concerns the hour-by-hour analysis, the average electricity spot price is also higher during the April-September period for the daily 24 hours. The normality assumption only stands in 14 hourly price series of this period. The same assumption is always rejected for the 24 hourly series of the December-May period as one can see in Table 5.

Table 5: Descriptive statistics for the Portuguese electricity spot prices over period December 1, 2008 to May 31, 3009

Hour	Mean	SD	Skewness	Kurtosis	Jarque-Bera
1	45.5	11.56	1.30	4.08	59.79
2	41.92	10.92	1.22	3.69	48.91
3	39.54	10.36	1.04	4.69	54.24
4	37.45	9.16	0.69	4.86	40.51
5	36.48	8.97	0.35	5.33	44.93
6	36.85	8.42	0.67	4.89	40.97
7	39.05	7.43	1.06	4.82	58.82
8	42.7	9.13	0.95	3.76	31.65
9	44.07	10.47	0.88	3.18	23.86
10	45.88	10.96	0.90	3.22	24.80
11	47.65	10.62	0.82	2.82	20.50
12	47.43	10.68	0.86	2.74	23.09
13	47.15	10.82	0.97	2.89	28.93
14	46.27	10.75	1.04	2.87	32.69
15	44.88	11.19	1.13	2.95	38.44
16	44.69	11.58	1.10	2.97	36.79
17	44.32	11.67	1.08	2.91	35.61
18	44.76	12.09	0.99	2.73	30.01
19	48.06	16.01	1.15	3.17	40.38
20	53.12	18.07	0.76	2.34	21.01
21	55.28	16.43	0.55	2.19	14.21
22	54.25	11.64	0.65	2.35	15.87
23	49.52	11.31	0.88	2.50	25.51
24	47.19	12.01	1.13	3.05	38.75
Average	45.17	11.34	0.92	3.38	

4.2 ESTIMATION AND FORECASTING RESULTS

The empirical results are shown in several tables. They are based on the information settled at the end of the first step before any selection criterion being applied. So, the results reflect the characteristics of all the 507 models mentioned above.

4.2.1 Complete time-series analysis

4.2.1.1 Stationarity

Based on the Augmented Dickey-Fuller (DF) test we concluded that both series are non-stationary. For the D-M series, a first regular differentiation was performed while for the A-S series, a first regular differentiation or a seasonal differentiation were enough to transform the series into a (weakly) stationary one.

Table 6: Stationarity of the complete time-series

Period	#	First difference	Seasonal difference (24)	Stationary series
April-September (A-S)	1	1	1	0
December-May (D-M)	1	1	0	0
Total	2	2	1	0

4.2.1.2 Estimation models

A total of 8 models were estimated in the complete time series analysis, 6 for the A-S period and 2 for the D-M period (Table 7).

Non seasonal models in the complete time series analysis refer to any model where the maximum lag in the autoregressive or moving average terms is lower than 24.

Five seasonal models refer to the A-S period while only one refers to the D-M period. Thus, 6 out of the 8 estimated models had at least one seasonal (daily) coefficient. This suggests the strong daily relationship between hourly electricity prices.

Table 7: Autoregressive and Moving Average lags per period for the complete time series analysis

Period	#	SAR(24)	SMA(24)	SAR(24) and SMA(24)	Seasonal models	Non seasonal models
April-September (A-S)	6	4	0	1	5	1
December-May (D-M)	2	1	0	0	1	1
Total	8	5	0	1	6	2

SAR: Seasonal Autoregressive, SMA: Seasonal Moving Average.

4.2.1.3 Dummy variables

First, I recall what the three dummy variables represent: *Dummy* is 1 on weekends and holidays and 0 otherwise, *Weekends* is 1 on weekends and 0 otherwise and *Holidays* is 1 on holidays and 0 otherwise.

The estimated coefficients for the dummy variables were statistically significant in just two of the 8 models and both for the A-S period as one can see in table 8.

Table 8: The dummy variables in the complete time-series analysis

Period	Dummy	Weekends	Holidays
April-September (A-S)	1	1	0
December-May (D-M)	0	0	0

According to Table 9, although the estimated coefficients for the dummy variables representing both weekend and holiday effects, in one case, and the weekend effect in the other case, are statistical significant in seasonal models, no relevant conclusion can be taken as the cycle length represents one day (not one week).

Table 9: The relation between dummy variables and seasonality in the complete time series analysis

	Seasonal models			Non seasonal models		
Period	Dummy	Weekends	Holidays	Dummy	Weekends	Holidays
April-September (A-S)	1	1	0	0	0	0
December-May (D-M)	0	0	0	0	0	0

4.2.1.4 The best model

For the A-S period, 4 models out of 6 reached the end of the process. The models with the dummy variables were among the best 4 and 3 of these models had a significant seasonal (daily) lag.

After performing the HN test[4] (see the MS* row on table 10) the conclusions pointed to the rejection of the null hypothesis in spite of the model being considered; thus, none of the models encompassed the others. Due to these results, and based on the criteria defined before, the best model is the one with the HN test *p*-value closer to the significance level at 5%, which is, according to Table 10, model number 2. This model is a SARIMA $(1,0,0)(1,1,0)_{24}$ with no dummy variables. This is the best forecasting model for the 30-days in the Autumn season.

[4] The test values are obtained using EVIEWS 5.1-based custom software.

Table 10: The Harvey-Newbold test's results for the A-S period on the complete time series analysis

Statistics of the test	Test value 1	P-value 1	Test value 2	P-value 2	Test value 3	P-value 3	Test value 4	P-value 4
F standard	72.375	0.000E+00	7.400	6.592E-04	17.192	5.093E-08	16.286	1.210E-07
F1	56.501	0.000E+00	6.524	1.557E-03	15.289	3.145E-07	14.479	6.846E-07
F2	39.675	0.000E+00	5.922	2.813E-03	12.550	4.391E-06	11.991	7.545E-06
MS*	44.465	0.000E+00	6.004	2.594E-03	12.968	2.935E-06	12.369	5.231E-06

Next table presents the error forecasting measures resulting from the selected model.

Table 11: The error forecasting measures for the best model of the A-S period on the complete time series analysis

Model	MAE	RMSE	MAPE
SARIMA $(1,0,0)(1,1,0)_{24}$	3,87	5,10	5,15%

Based on MAE, RMSE and MAPE results (MAE and RMSE are measured in €/MWh whenever they appear in this document), we conclude that the values are in line with the ones from previous studies.

In Summer forecasting period, 2 models rested in the final step: ARIMA (0,1,1) and SARIMA $(0,1,0)(1,0,0)_{24}$. None of them has a significant dummy variable.

The MS* line from Table 12 shows the HN test results. Model number 2, a SARIMA $(0,1,0)(1,0,0)_{24}$, emerged as the best model.

Table 12: The Harvey-Newbold test's results for the Summer period on the complete time-series analysis

Statistics of the test	Test value 1	P-value 1	Test value 2	P-value 2
F standard	295.784	0.0000	0.132	0.7161
F1	277.980	0.0000	0.124	0.7244
F2	130.653	0.0000	0.124	0.7244
MS*	159.396	0.0000	0.124	0.7245

The common forecasting accuracy measures for the best model are presented in table 13. The results are slightly higher than the ones I expected. For example, the value for MAPE (9%) is higher than the expected 7%-7.5%.

Table 13: The error forecasting measures for the best model of the Summer period on the complete time-series analysis

Model	MAE	RMSE	MAPE
SARIMA $(0,1,0)(1,0,0)_{24}$	3,39	4,45	9,02%

Surprising was the fact that the MAPE for the Summer forecasting period was much higher than the one in the Autumn season. However, these results are in line with the ones of Contreras et al. (2003).

One final point to refer is that these results were achieved with a daily dynamic forecasting, which means that, in each day, the forecasting procedure for the next day is based on forecasts for that same day and not on real data. For example: to forecast hour 10, hours 1, 2, ..., 9 are forecasts and not real values as they are not known at the forecasting moment.

4.2.2 Hour-by-hour analysis

Hour-by-hour analysis is also conducted in four steps: Stationarity of the series, Estimation models, Dummy variables and Best model selection.

4.2.2.1 Stationarity

Based on the Augmented Dickey-Fuller tests and Table 14 results, we can conclude that most of 24 hourly series are non-stationary in spite of the A-S or D-M period being considered. In the D-M period, 23 hourly series are non-stationary, while in the April-September period all the series are non-stationary. The necessary transformation to achieve the stationarity of the series is not always the same, but in 90% of the series, a first regular differentiation was enough. In three cases, it was necessary a regular and a seasonal differentiation to produce stationary transformed time series and in just one case, a seasonal differentiation turned the series into a stationary one.

Table 14: Stationarity of the hourly time series

Period	#	First difference	Seasonal difference (7)	First difference and seasonal difference (7)	Stationary series
April-September (A-S)	24	22	1	1	0
December-May (D-M)	24	21	0	2	1
Total	48	43	1	3	1
	%	89.6%	2.1%	6.3%	2.1%

4.2.2.2 Estimation models

Based on Table 15 results, we conclude that from the 499 estimated models in the hour-by-hour analysis, 277 are used to forecast the electricity prices for the Summer period while the remaining 222 models produce the Autumn prices forecasts.

Table 15: Autoregressive and Moving Average lags per period on the hour-by-hour analysis

Period	#	SAR(7)	SMA(7)	SAR(7) and SMA(7)	Seasonal models	Non seasonal models
April-September (A-S)	222	68	55	66	189	33
December-May (D-M)	277	41	54	95	190	87
Total	499	109	109	161	379	120
				%	76.0%	24.0%

SAR: Seasonal Autoregressive, SMA: Seasonal Moving Average.

In spite of the period being considered, April-September or December-May, more than 75% of the estimated models had at least one (weekly) seasonal component (189 and 190 models, representing 85% and 69%, respectively). Thus, the seasonal component of the Portuguese electricity prices is stronger in the hour-by-hour analysis when compared to the complete time series approach.

4.2.2.3 Dummy variables

Table 16 refers to the presence of the dummy variables in the estimated models. From 499 models, 202 include a dummy variable (40.5%) whose estimated coefficient is statistically significant. This number reflects the importance of these variables as they complement the weekly behaviour (and/or holiday effect) on the prices series.

Table 16: The impact of dummy variables on the hour-by-hour analysis

Period	#	Dummy #	Dummy %	Weekends #	Weekends %	Holidays #	Holidays %	Total #	Total %
April-September (A-S)	222	26	11.7%	22	9.9%	16	7.2%	64	28.8%
December-May (D-M)	277	59	21.3%	41	14.8%	38	13.7%	138	49.8%
Total	499	85	17.0%	63	12.6%	54	10.8%	202	40.5%

Analysing each one of the three binary variables, the most representative is the *Dummy* which refers to the weekend and holiday effects (it is included in 17% of the estimated models). The weekend effect comes next with *Weekends* representing roughly 12.5% and *Holidays* comes lastlty, included in 11% of the models. This decreasing frequency of the dummy variables (from *Dummy* to *Holidays*) occurs either in the A-S or in the D-M periods.

As one can see (Table 16), the presence of these variables is more significant in the December-May period where almost 50% of the estimated models include a dummy variable, while in the April-September period that percentage reduces to 29%.

The hour-by-hour analysis results in a larger percentage of statistically significant dummy variables coefficients when compared to the complete series analysis. This can be explained by the fact that the hour-by-hour analysis considers 24 time-series, one for each hour: because in each one of the series, each observation corresponds to one unique day, different hours of the day have different dummy coefficients. In the complete time series analysis, the 24 hours of each day are considered in the same series. Thus, the dummy coefficient is the same for the whole 24 prices and so, this analysis might reduce its explanatory power.

In order to analyse the dummy variables effects in the seasonal and non-seasonal models, we aggregated the results in Tables 17 and 18.

Table 17: The dummy variables/seasonality relation in the hour-by-hour analysis

Seasonal models										
Period	**#**	**Dummy**	**%**	**Weekends**	**%**	**Holidays**	**%**	**Total**	**%**
April-September (A-S)	189	23	12.2%	19	10.1%	14	7.4%	56	29.6%
December-May (D-M)	190	40	21.1%	22	11.6%	31	16.3%	93	48.9%
Total	379	63	16.6%	41	10.8%	45	11.9%	149	39.3%

Within the seasonal models, more than 39% include a dummy variable. The weekend and holiday effect *Dummy* variable is the most frequent (it is included in 63 models, representing 16.6%). The holiday effect comes next with 11.9% of the models and finally the weekend effect appears in 10.8% of the models. *Dummy* is also the most frequent in both periods, but *Weekends* and *Holidays* switch positions: Weekends are more important than Holidays in the April-September period, but the opposite takes place in the second period. The dummy variables appear more often in December-May: 93 models representing almost 49%, against 29.6% for the April-September period.

Proceeding with the non-seasonal models (table 18), we conclude that the frequency of the *Holidays* dummy variable decreases when compared to its presence in the seasonal models (from 11.9% to 7.5%). The number of models with *Dummy* variables (weekends and holidays effects) increases slightly from 16.6% to 18.3% but the strong increase comes from *Weekends* dummy variable that appears in 18.3% of the models (versus 10.8% in the seasonal ones).

We expected this result as seasonal coefficients that previously captured the weekly effect, overpassed the *Weekends* coefficient. With no seasonal coefficients, the weekly effect should be captured through the *Weekends* variable.

Table 18: The dummy variables/non-seasonality relation in the hour-by-hour analysis

Non seasonal models									
Period	**#**	**Dummy**	**%**	**Weekends**	**%**	**Holidays**	**%**	**Total**	**%**
April-September (A-S)	33	3	9.1%	3	9.1%	2	6.1%	8	24.2%
December-May (D-M)	87	19	21.8%	19	21.8%	7	8.0%	45	51.7%
Total	120	22	18.3%	22	18.3%	9	7.5%	53	44.2%

Again, dummy variables are more often in the December-May period, with 51.7% of the models against less than 25% for the April-September period. This difference is higher than the one from seasonal models.

Comparing the frequency of the dummy variables in seasonal and non-seasonal models, they are more important in the later ones (as expected) with 44.2% of the models including a dummy variable against 39.3% in the seasonal models.

4.2.2.4 The best models

Tables 19 and 20 show, for each hour, the best model selected according to the HN statistical test for the Autumn and Summer periods, respectively, as well as the MAE, RMSE and the MAPE for the selected model.

Table 19: The error forecasting measures of the selected models for the Autumn period accordingly the HN test on the hour-by-hour analysis

Hour	Model (according to HN test)	MAE	RMSE	MAPE
1	SARIMA $(3,1,0)(1,0,1)_7$ D	3.63	4.96	5.03%
2	SARIMA $(3,1,0)(0,0,1)_7$	4.58	5.98	6.62%
3	SARIMA $(0,1,2)(0,0,1)_7$	4.45	5.37	6.51%
4	ARIMA (3,1,4)	4.02	4.93	6.04%
5	ARIMA (0,1,3)	4.05	4.71	6.14%
6	ARIMA (0,1,2)	3.98	5.08	6.12%
7	ARIMA (3,1,4)	3.94	5.02	5.89%
8	SARIMA $(0,1,1)(1,0,1)_7$	4.62	5.27	6.20%
9	SARIMA $(2,1,3)(0,0,1)_7$	4.95	6.11	6.62%
10	SARIMA $(0,1,1)(1,0,1)_7$	3.20	3.78	4.18%
11	SARIMA $(3,1,4)(1,0,1)_7$	1.99	2.40	2.53%
12	SARIMA $(0,1,1)(1,0,1)_7$	2.30	3.05	2.94%
13	SARIMA $(0,1,1)(1,0,1)_7$	2.40	3.40	3.07%
14	SARIMA $(4,1,0)(1,0,0)_7$	2.47	3.27	3.19%
15	SARIMA $(3,1,0)(0,0,1)_7$	3.14	3.88	4.13%
16	ARIMA (6,1,0)	2.45	3.17	3.12%
17	SARIMA $(0,1,1)(1,0,1)_7$	2.35	2.87	3.05%
18	SARIMA $(0,1,2)(010,1)_7$	2.64	3.70	3.47%
19	SARIMA $(0,1,2)(1,0,1)_7$	3.16	4.06	4.15%
20	SARIMA $(0,1,2)(0,0,1)_7$	3.63	4.49	4.48%
21	SARIMA $(4,0,0)(0,1,1)_7$	4.26	5.05	4.77%
22	SARIMA $(1,1,2)(0,1,1)_7$	3.51	4.37	4.06%
23	SARIMA $(0,1,1)(1,0,1)_7$ H	2.42	2.88	2.97%
24	SARIMA $(4,1,0)(0,0,1)_7$	2.73	4.16	3.51%
	Average	3.37	4.25	4.53%

D - Dummy variable   W - Weekends variable   H - Holidays variable

Table 20: The error forecasting measures of the selected models for the Summer period accordingly the HNB test on the hour-by-hour analysis

Hour	Model (according to HN test)	MAE	RMSE	MAPE
1	ARIMA (5,1,0)	1.88	2.33	4.87%
2	SARIMA $(3,1,0)(1,0,1)_7$	1.57	1.91	4.38%
3	SARIMA $(4,1,3)(1,0,1)_7$	1.96	2.62	5.62%
4	SARIMA $(4,1,3)(1,0,1)_7$	1.56	2.18	4.67%
5	ARIMA (4,0,0)	1.32	1.73	4.01%
6	SARIMA $(0,1,3)(1,0,0)_7$	1.54	1.96	4.67%
7	SARIMA $(0,1,1)(1,0,1)_7$ W	1.16	1.41	3.40%
8	SARIMA $(0,1,4)(1,0,1)_7$	1.74	2.12	5.11%
9	SARIMA $(0,1,1)(1,0,1)_7$ H	1.99	2.83	5.46%
10	SARIMA $(4,1,0)(1,0,1)_7$	1.81	2.14	4.77%
11	SARIMA $(3,1,0)(1,0,1)_7$ D	2.07	3.09	5.07%
12	SARIMA $(3,1,0)(0,1,1)_7$	1.99	2.49	4.89%
13	SARIMA $(3,1,0)(0,1,1)_7$	2.07	2.67	5.00%
14	SARIMA $(2,1,0)(1,0,1)_7$	2.07	2.63	5.13%
15	SARIMA $(4,1,4)(1,0,1)_7$	2.30	2.75	5.81%
16	SARIMA $(3,1,0)(1,0,1)_7$	2.15	2.72	5.39%
17	SARIMA $(2,1,1)(1,0,1)_7$	1.83	2.32	4.52%
18	SARIMA $(3,1,4)(1,0,1)_7$	1.96	2.39	4.85%
19	SARIMA $(2,1,1)(1,0,1)_7$	1.98	2.43	5.00%
20	ARIMA (6,1,0) W	2.45	2.99	6.10%
21	ARIMA (6,1,0) D	1.97	2.55	4.99%
22	ARIMA (0,1,1)	1.67	2.07	4.21%
23	ARIMA $(0,1,1)(1,0,0)_7$	1.68	2.34	3.90%
24	SARIMA $(0,1,1)(1,0,1)_7$	2.08	2.75	5.07%
	Average	1.87	2.39	4.87%

D - Dummy variable   W - Weekends variable   H - Holidays variable

As one can see in Tables 19 and 20, the seasonal models dominate the non seasonal ones, as SARIMA models represent about 79% of the models either in the Autumn or Summer seasons (19 out of 24). Thus, analysing the selected 48 models, if we consider the seasonal ARIMA coefficients and the dummy variables, we get 40 (out of 48) models in which the weekly effect has a considerable impact to explain the variations on the Portuguese electricity prices.

5. CONCLUSIONS

The main purpose of this thesis was to select the best ARIMA models to forecast the day-ahead electricity prices for the Portuguese Power Market by comparing two different approaches. A first one in which the complete hourly prices time-series is used and a second one where the price of each hour is independently forecasted leading to 24 models (and forecasts) for the 24 daily prices.

The sample used was divided in two different periods (from April 1, 2008 to October 30, 2008 and from December 1, 2008 to June 30, 2009). Each one was partitioned in two distinct parts: the first one (6 months - from April 1, 2008 to September 30, 2008 and from December 1, 2008 to May 31, 2009 corresponding roughly to 183 and 182 observations in the hour-by-hour analysis and to 4,392 and 4,368 observations in the complete time-series analysis, for the first and second periods, respectively) was retained for the ARIMA parameters estimation while the remaining part (1 month) was considered as the forecasting period.

To determine the ex-ante out-of-sample predictive power of the models, the estimated parameters have been used to forecast the hourly day-ahead conditional mean for the forecasting month (corresponding to 30 observations in the hour-by-hour case and 720 observations in the complete time-series analysis). Two distinct 30-days forecasting periods have been also considered: from October 1, 2008 to October 30, 2008 (Autumn) and from June 1, 2009 to June 30, 2009 (Summer).

The models' selection was based on two major criteria: the R^2 from the Mincer-Zarnowitz regression and the Harvey-Newbold encompassing test.

In accordance to Cuaresma *et al.* (2004), a first important conclusion is that analysing each hour separately produced better forecasting results than considering the complete time series approach. As one can see in the next summary table, the value of the forecasting accuracy measures resulting from the best models is lower for the hour-by-hour approach:

Table 21: Forecasting accuracy measures for the complete time series analysis and the hour-by-hour analysis

Approach	Forecasting season	MAE	RMSE	MAPE
Complete time series	Autumn	3.87	5.10	5.15%
	Summer	3.39	4.45	9.02%
	Average	3.63	4.78	7.09%
Hour-by-hour time series	Autumn	3.37	4.25	4.53%
	Summer	1.87	2.39	4.87%
	Average	2.62	3.32	4.70%

The hour-by-hour results are in line with the ones of previous research and an average MAPE of 4.70% seems to be a good result, especially if we consider that we are computing this measure for a 30-days period. However, these results are not directly comparable as the rolling window or the "Jackknife" methods are not applied, which can lead to worse results, and the forecasting period is 30 days, not always coincident with the one-week forecasting period, the most common one in the previous research.

In terms of results, Summer forecasts perform worse when compared to the Autumn ones (a result that was not expected *a priori*).

In the Autumn analysis, a seasonal component was included in roughly 80% of the 24 hours analysed. I conclude that the weekly effect was very significant in most of the hours.

MAPE results are worse during the night and in the early morning hours – the average is 6.13% that compares with 3.57% for the rest of the hours. In the night period the seasonal coefficients were not always statistically significant and it can partially explain the worse forecast accuracy.

For the Summer period the seasonal effect is statistically significant in the same 79% (19 out of 24) while the dummy variables appear in two non seasonal models. When the dummy variables are also considered, only three models were left out, with no weekly effect.

MAPE performs uniformly throughout the day, with an average value of 4.87%. Summer models perform better than the Autumn ones during the night and early morning (a more pronounced seasonal behaviour might explain this improvement) but worse on the remaining hours.

As we referred before, the hour-by-hour analysis led to better results when compared to the ones resulting from the complete time-series approach, but the processing time is also very different: while the complete time series analysis was performed in three hours, the hour-by-hour estimation process took almost one week. This raises the question of accuracy versus time. However, while for the Autumn period the MAPE results are not strongly different, 5.15% versus 4.53%, for the Summer period a decrease from 9.02% to 4.87% can be a considerable result, when the complete and hour-by-hour analyses are compared.

Therefore, I conclude that, because the hour-by-hour analysis performed better, it is worthwhile to do it, even taking more time, because the forecast improvement can be very significant. This also makes sense as we are forecasting 30 days and less than one week of work produces more than three weeks of forecasts. This procedure can definitely be optimized in order to reduce the computing time and to turn the estimation process more efficient.

This study has some limitations that must be referred.

Concerning the estimation period, six month was the chosen sample length but no other lengths were tested and thus, alhough this period seemed to be the most balanced one (in terms of including the right amount of information), there might be a chance that some other sample length is better.

Although the log-prices were computed in this process, our concern was much more focused on specify the model(s) correctly, in terms of the residuals serial correlation, than on the ARCH effects.

The time taken to estimate the models (in the hour-by-hour analysis) is another point in which we must work on.

Because of these limitations, for a future research, the study of the electricity prices volatility, through ARCH effects, should be carefully looked as some evidence was found that time-varying volatily models produced good electricity prices forecasts (Guirguis and Felder (2004), Knittel and Roberts (2005)).

Another issue that requires a deeper investigation in the hour-by-hour analysis is the link between the price level of the hour in study and the baseload of the previous day. To consider the baseload of the previous day as a fundamental should be an interesting approach.

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REN – Redes Energéticas Nacionais – www.ren.pt

APPENDIX A

Brief description of the iberic electricity market
Portuguese case

INDEX

1. Historical context

Historically, the electricity business in Portugal has been owned, until nearly 2 years ago, by a single operator (EDP) who produced (the majority) and sold the electricity in the existing regulated market at a tariff previously settled by ERSE (the Portuguese energy sector regulator), under government's approval. The tariff remunerates the different activities of the Value Chain, from the moment electricity is produced until it reaches the final consumer (Production, Transmission, Distribution and Supply), as well as it incorporates the predicted (and verified) deviations relative to previous years and includes general economic interest costs (energy efficiency measures, costs with renewable energy, ...).

In 2005, through the Ministers' Council Resolution number 169/2005, following the recommendations of the Directive 2003/54/EC of the European Parliament, the Portuguese government, in order to position the country in the front line of the new energy challenges, established some strategic goals to define what the Energy Business in Portugal should be, concerning mainly the diversification of primary energy sources, a greater environmental preoccupation, the competition promotion, etc...

In 2006 the Law-Decree number 29/2006, adapted the strategic orientations of Directive 2003/54/EC and Resolution number 169/2005.

Still in 2006, Directive 2006/32/EC of the European Parliament settled the guidelines to practise a more rational use of energy and energy services, in order to raise the level of energetic efficiency within the Union. The directive anticipates the consequences of such guidelines:

- Reduction of the primary energy consumption;
- CO_2 emissions reduction as well as other greenhouse gases (and thus, to prevent dangerous climate changes);
- To save energy (about 9%) in a cost-efficiency perspective;
- To reduce Union's energetic dependence from abroad.

These were not just intentions as the EU purposed some practical measures to promote, in final consumers, the rational use of energy and services such as an easier access to information, to establish energy audits among consumers or to proceed to a detailed metering and billing.

Also in 2006, the Law-Decree number 172/2006 settled the procedures for licensing the ordinary regime production, Transmission and Distribution grid concessions and electricity commercialization.

Besides the fact that it legislated what was predicted in the Law-Decree number 29/2006, these new Law-Decree proposals are in line with the energy sector liberalization intention (which results from the Directive 2003/54/EC that establishes the common rules for the internal electricity market) as well as with the iberic electricity market functioning (after the agreement between Portugal and Spain on October 1, 2004).

This was the context in which the need/will to build a liberalized market in Portugal came up, in line with what was being done in the rest of Europe and with the need to join Spain in this process, believing that free competition would lead to a price reduction. So, the rise of the Portuguese Electricity Market was deeply connected to the rise of the Iberic Electricity Market (MIBEL).

2. MIBEL's formation

MIBEL exists, in an operational and formal way, as an iberic market with a common platform for the Portuguese and Spanish operators since July 1, 2007. Through this first decade of the 21st century, Portuguese and Spanish' governments revealed their interest in building a common electricity market, but difficulties of several orders turned the process into a long and winding road. The issues were operational, political or economical ones.

Operationally, some key questions emerged as the electricity transmission between both countries (interconnection), which was necessary to develop, the possibility of buying electricity in one country and selling it in the other, or the efforts between Portugal and Spain to develop a legal framework that would allow market's negotiation and operation.

About the political questions, and being a recently born project, it required a careful monitoring by the political players, as well as to continue the agreements sequence already on the run. The political instability in Portugal between 2001 and 2005 (4 governments in 4 years) delayed the MIBEL's process for a while.

Lastly, some economical questions were raised concerning the passage from a regulated market to a liberalized one. A few important issues came up:

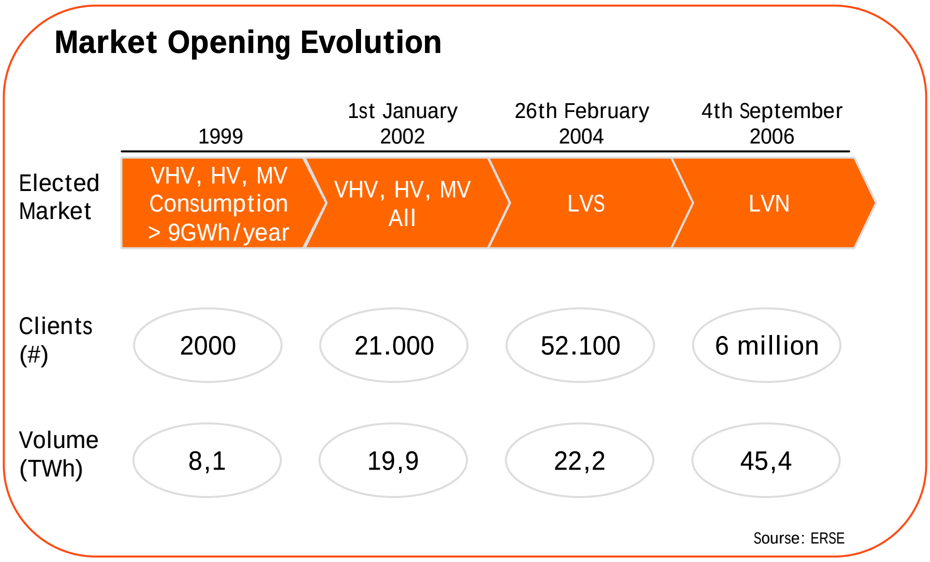
- Both the Portuguese and the Spanish electricity market had always been regulated and the sudden passage to the liberalized market could bring a cost escalation to the final consumer because the tariff did not always reflect the real production costs. A model was then created in which both the regulated and the liberalized markets co-exist (one regulated market per country and one liberalized market per country);
- Most of the electrical producers in Portugal had an electricity sales' agreement with a pre-established return on capital for a considerable period. These were the PPA (Power Purchase Agreements). With the market's opening, energy bids would be made in the market and so, companies would be exposed to market risk (and the PPA would be broken);

In order to get a time window to allow the adaptation to the new market model, having as a goal the creation of OMI (Iberic Market Operator), two operators were created, each one responsible for the management of an organized market:

- OMEL, the Spanish pole, responsible for the management of the spot market (daily and intra-daily);
- OMIP, the Portuguese pole, responsible for the management of the forward market.

The beginning of MIBEL's spot market happened on the January 1, 1998, just for the Spanish market. The derivative's market began on the July 3, 2006.

Figure 3: The Market opening evolution



3. The Regulated Market

3.1 The Value Chain

Although MIBEL's overture became a reality, the regulated market, either in Portugal or in Spain continues to exist.

The regulated market in Portugal is settled in the additive principle in which the different activities of the sector are additively incorporated in the tariff: Production, Transmission (Very High Voltage), Distribution (High Voltage, Medium Voltage and Low Voltage) and Supply. The liberalization in Portugal occurred on the first and the fourth sectors of the Value Chain (Production and Supply): any of these activities could be practised through a licence. Transmission and Distribution were not liberalized once they are natural monopolies: they remained regulated activities.

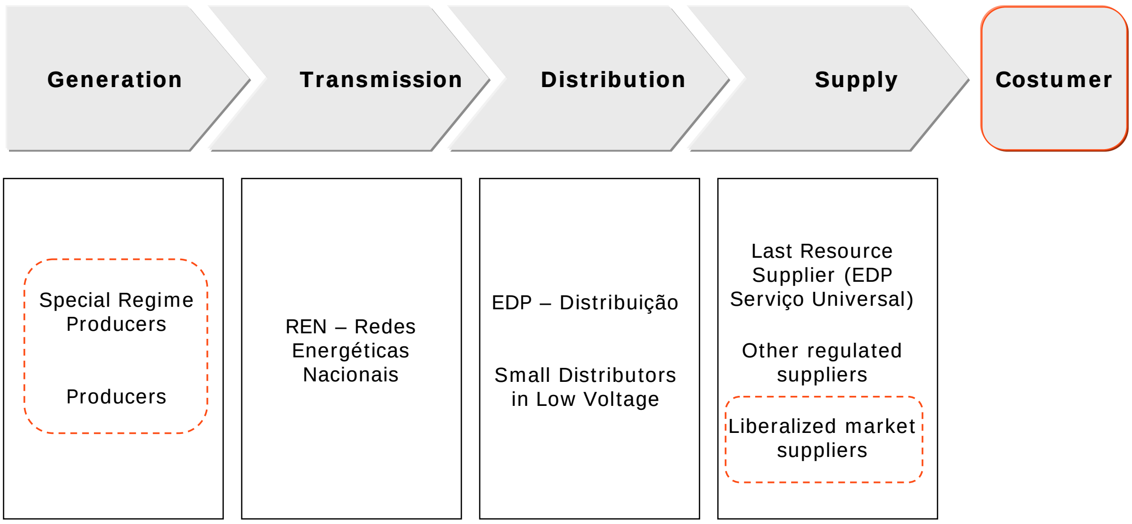
Electricity's transmission is operated by REN (Redes Energéticas Nacionais) while Distribution is made by EDP Distribuição, a company of the group EDP created for that effect.

There are several ways in which suppliers can get the electricity (spot market is just one of them):

- Through spot market (OMEL);
- Through forward market (OMIP or Auctions);
- Through Bilateral Contracts

The Value Chain can be resumed as follows:

Figure 4: The Value Chain



At the same time there is the Technical system's management which consists in the inclusion of the grid's technical constrains, to check if the quantities resulted from the market bids are technically possible, in order to guarantee the system's availability.

The Last Resource Supplier (LRS) is the supply company of the Portuguese regulated market. That role is delivered to EDP Serviço Universal.

3.2 The Regulated Tariff

Once just Production and Supply were liberalized, the Final Costumers' Sales Tariff (FCST) in Portugal can be divided in 3 parts:

– Access Tariff;
– Energy Tariff;
– Commercialization Tariff.

The Access Tariff includes the regulated activities paid by all final consumers of electricity in Portugal, either they are in the regulated market or in the liberalized market. It includes all the sector's activities that were not liberalized and adjustments of negative (or positive) balances from previous years or structural changes:

– Transmission's Grid Use Tariff;
– Distribution's Grid Use Tariff;
– System's Global Use Tariff.

This Access Tariff is the part of the FCST that allows competition: all suppliers have free access and in the same conditions to the transmission and distribution grids (as long as they get a licence).

The clients that remained in the regulated market have included on their Tariff the Energy Tariff and the Commercialization Tariff. For the costumers from the liberalized market the energy cost is the one that results from the agreement with the supplier (which should result from the supplier's forecast of the market price) being the commercialization margin at the supplier's responsibility.

One note to say that the System's Global Use Tariff is the part of the FCST that reflects the way regulator found to include the adjustments of energy costs that result from the additional costs of the energy acquired to the special regime producers, energy costs limitations, etc...

3.3 Tariff deficit and deviations

Economic efficiency defends that each one of the Tariff's component should reflect the costs it has to remunerate. In the market, the final energy price results from the bid and offer curves and so, the value of energy should reflect the production marginal cost of electric energy. Meanwhile, sometimes the value of the Energy Tariff does not reflect the cost of production. There are two main reasons that contribute to this difference between the value expressed in the regulated tariff and the real cost of energy:

- Tariff deficit;
- Adjustments

The technical concept of "Tariff deficit" consists in the assumption, by the regulator, in the moment when the regulated tariff is proposed, that the proposed value of the energy tariff is not enough to cover the costs of production. A deficit is created which will be recovered through the tariff in the five following years.

The concept of "Deviation" results when, by the end of the year the regulator realizes the energy tariff was not enough to cover the real costs resulting from the market or, on the other side, generated a positive balance once it forecasted the cost of energy higher than it actually was. The additional cost (or positive balance) is included (or discounted) in the tariff in the two following years.

Deficit and Deviation with a negative balance differ only about the moment in time they are calculated (the former is calculated before the beginning of the year while the later is calculated by the end of the year). Both represent a negative balance with energy acquisition that final consumers will have to pay in the future, more or less spread through time, but that constitutes, in both cases, an accumulated debt. A deviation with positive balance leads to a discount in the following years in order to proceed to the adjustment.

2008 was an atypical year concerning the evolution of commodities' prices, and electricity was no exception. Once the formation of the FCST wouldn't incorporate a mechanism of control to face extreme fluctuations of market's energy prices, Law-Decree 165/2008 came to fulfil that gap, allowing that a payment of a deviation that occurred in an extreme year could be made in a longer period (maximum 15 year). The deviation that occurred in 2008 will be paid in 15 years, beginning in 2010.

Without this Law-Decree, the cost of electricity for the final costumer in the regulated Portuguese market would increase about 42% in 2009.

3.4 SRP (Special Regime Production)

Special Regime Production (SRP) was the name given to a certain kind of electricity production that is environmentally friendly and, in some cases, more efficient than the ordinary regime production. The SRP status reflects the goals settled in 2005 (environmental concerns and primary energy sources diversification). In common language, the SRP includes the sources of renewable production together with the cogeneration:

- Eolic energy; Mini-Hydro (small dam with no more than 30 MW of installed capacity), Solar energy, Biomass and biofuels, ...
- Cogeneration is a process of energy production that has as an output the production of (at least) 2 different kinds of energy. Usually, together with electricity, there is a heat production. That is why a cogeneration is almost always associated with an industrial facility that uses the heat in some part of its process. Due to this "synergy", global efficiency is about 80%. Gas is the most common raw material (produces less CO_2 than the usual sources of energy like fuel or coal).

These technologies are protected in the Portuguese market in two different ways:

- They are the first to satisfy the demand among all the production technologies in Portugal. So, electricity produced by a SRP facility has a guaranteed consumption;
- The electricity produced is paid through a "protected" tariff (obviously higher than the regulated tariff) that tries to translate to a price the country's benefits for its use.

So, the energy produced by SRP is remunerated (in many cases) above the production marginal costs. The SRP does not get into the market to form the hourly energy price. The fact that the Last Resource Supplier (LRS) is obliged to buy all SRP (article 49 from the Law-Decree number 29/2006), reduces the amount of energy to be bought in the market in each hour. So, the offer curve is pushed and this effect causes a reduction of the price resulting from the market.

The additional cost with the SRP, which is incorporated in the access tariff, is the difference between the value paid by the energy produced under SRP and the resulting market clearing price (MCP).[5]

The production by special regime means in 2008 in Portugal, as well as its installed capacity is represented in the following figures:

Figure 5: SRP in Portugal in 2008 (MWh)

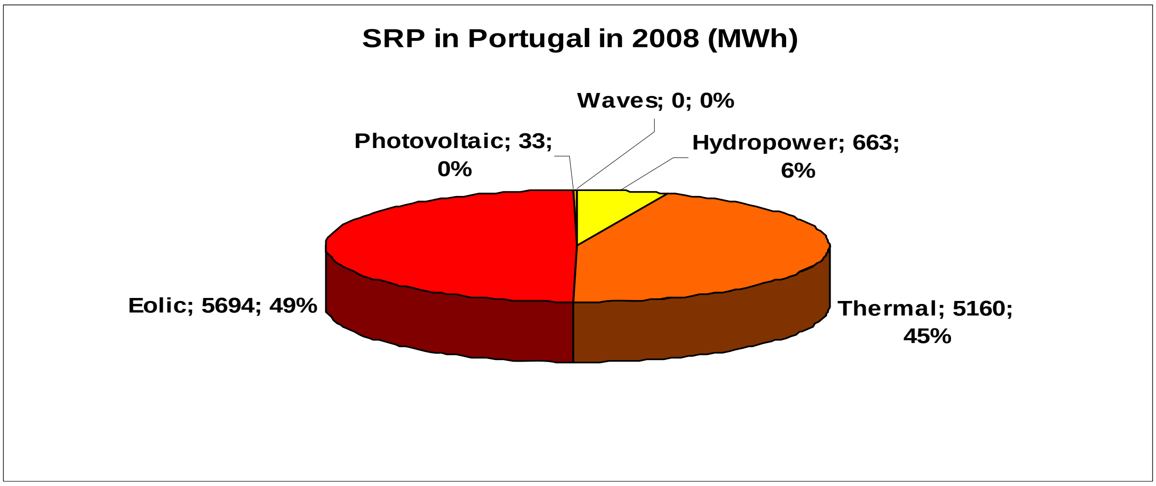
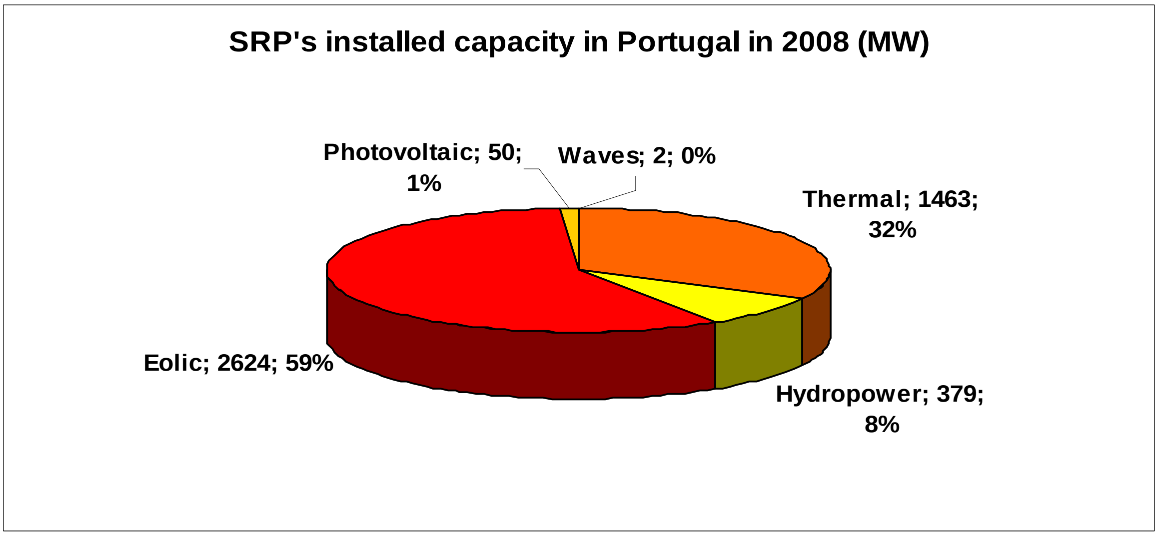


Figure 6: SRP's installed capacity in Portugal in 2008 (MWh)



[5] In the 2009 report published by the Portuguese Competition Authority about the gross prices' formation in Portugal in the second semester of 2007, the Authority draw the attention for the fact that the MCP decrease due to the introduction of SRP in the Portuguese generation should be taken into account when calculating the SRP's additional cost.

3.5 From PPA to CBMC

Before the liberalized market's overture, existed in Portugal an energy acquiring system called Power Purchase Agreement (PPA)

Under the PPA system, producers received, on one side, an availability payment, which covered the fixed costs (O&M), depreciations and the return on capital at a suitable rate, and on the other side, the variable cost they had with the energy production.

This payment was updated with inflation and adjusted by the real deviations verified in the facility's availability when compared to the contracted availability. No matter how much energy was produced in the facility, costs were always satisfied.

The end date of each PPA would go from 2007 (Tunes' Power Plant) until 2027 (Frades' Hydroelectric Power Plant).

With the Portuguese and Spanish governments' commitment in promoting MIBEL, it was not sustainable the existence of a system in which 58% of the satisfied demand was made through Plants under the PPA regime (being 41% owned by EDP). If we joined to these 58% the 20% of SRP, we can see the difficulty in creating a market (in production) to satisfy no more than 25% of the energy needs. Such "distortions" where not in line with the Union's directives of the market's liberalization. Contractual Balance Maintenance Costs (CBMC) were then proposed to replace PPA.

The CBMC had some advantages:

- The plants' market NPV under the PPA was maintained (with the assumptions revised every year from 2007 until 2017);
- To bring liquidity to the market;
- To have European Union's endorsement;

The difference between the accorded NPV under the PPA and the NPV of future cash flows in the market is the CBMC's base, and, once the first 10 years of the CBMC assumed an annual assumptions' revision, producers guaranteed the previously agreed return for that period.

After 2017, no more revisions will occur, as a fixed income will take place until the end of the CBMC in 2027.

4. The Liberalized Market

4.1 The Market

It was mentioned above that the spot market began operating in 1998 while the forward market began in July 2006.

Each daily hour electricity price results from demand and offer market curves. So, in one day, there is not just one single price of the underlying asset but 24 different (or not) prices, one for each hour. In a pool we have 24 demand curves and 24 offer curves. Offer bids are given by producers while the demand bids are settled by distributors and suppliers.

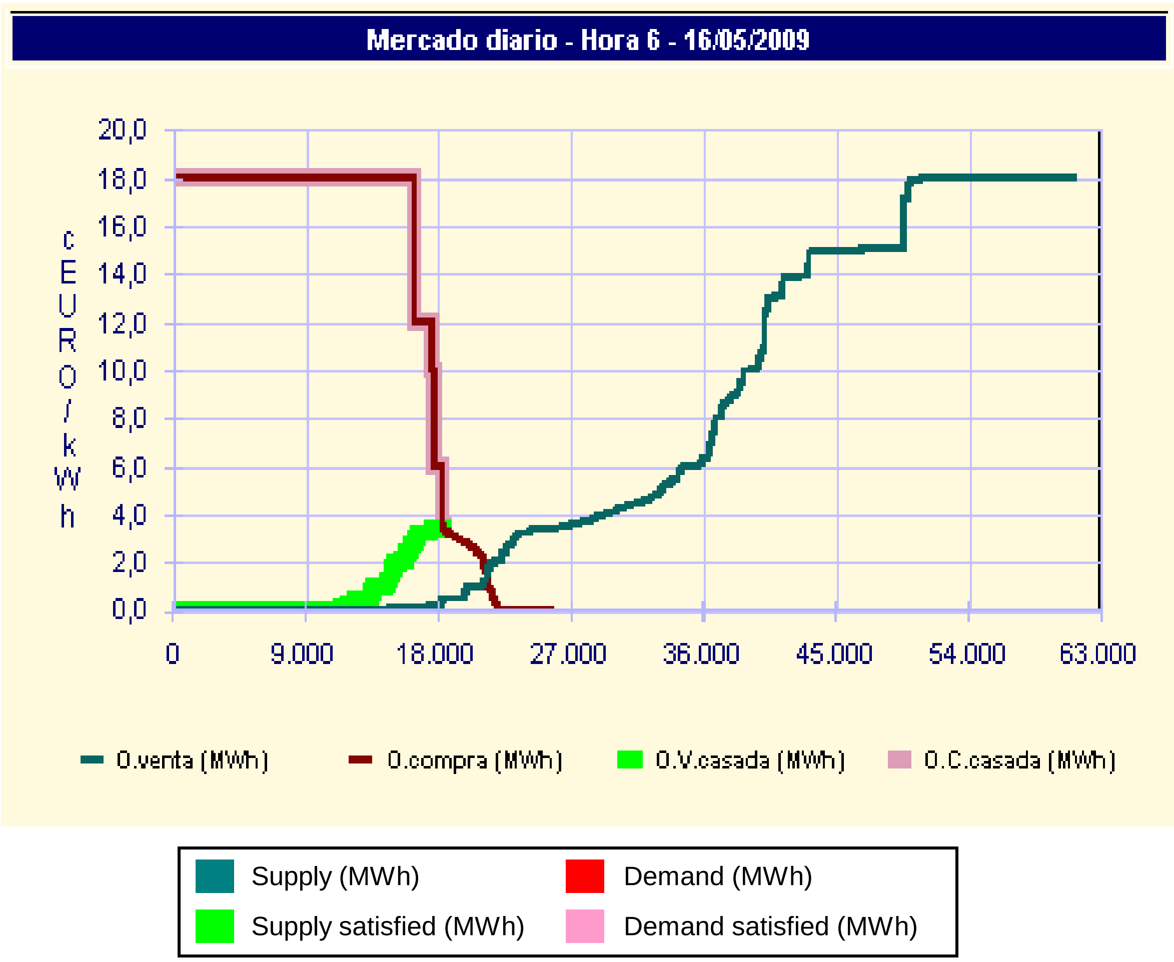
MIBEL has some particularities relating with either the underlying asset or the price formation process:

- The contract size is 1 MWh of electrical power for one single hour of the following day. Per day, there are 24 resulting prices from the daily market session;
- Bids are made until 10:00 a.m. from the previous day (Spanish hour – 9:00 a.m. Portuguese hour) in the daily market session. The hourly prices are published at 11:00 a.m. that same day (the previous one). *Baseload* is the name given to the arithmetic mean of the hourly prices for each MWh from the daily market session;
- After the daily market session, there are six adjustments sessions called intraday sessions (to match demand and supply more precisely);
- Suppliers and distributors put their demand bids while producers send their offer bids to the market. Each bid is an array of quantity-price. For each hour the day, the MCP is the result of both demand and offer curves and all the electricity provided that hour is negotiated at the MCP (it is a marginal price system);
- Bids in Portugal and in Spain began in a common platform. While interconnection is not congested (the capacity to bring electricity cross borders), Portuguese and Spanish prices are the same;

– When the interconnection is congested (either in the Portugal-Spain way or the reverse) *market-split* occurs and the bids from each country take place inside the bounds of its own borders;

– Besides the pool[6], there are bilateral contracts made between producers and suppliers - this energy is not traded in the market. Anyway, the market operator must be informed of each contract's characteristics (amount of energy, price, periodicity, ...).

Figure 7: Supply and demand of energy for MIBEL - hour 6 of May 16, 2009



[6] Although the name Pool is not correctly attributed to MIBEL, because, as it was mentioned in the introduction, MIBEL is a Power Exchange, I'll refer to MIBEL in the common language as it is used by the market players.

4.2 Installed capacity and Generation mix

The Generation mix in both countries differs in several aspects: in 2008, the installed capacity in Portugal was about 14.915 GW while in Spain this number was much higher: 89,944 GW. The following figures reflect such capacity's distribution:

Figure 8: Installed capacity in Portugal in 2008 (MW)

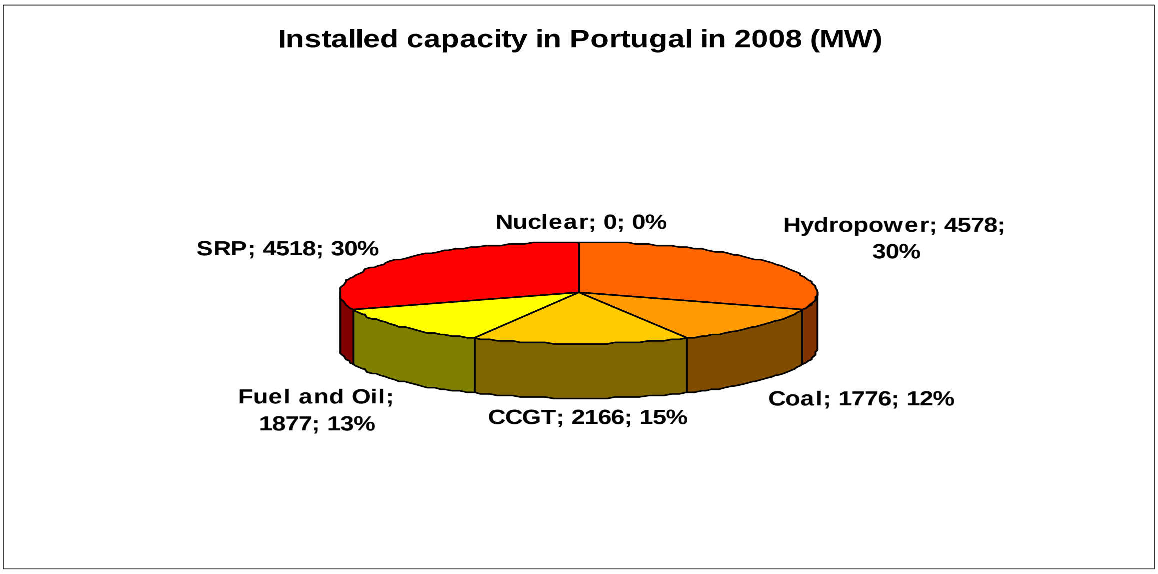
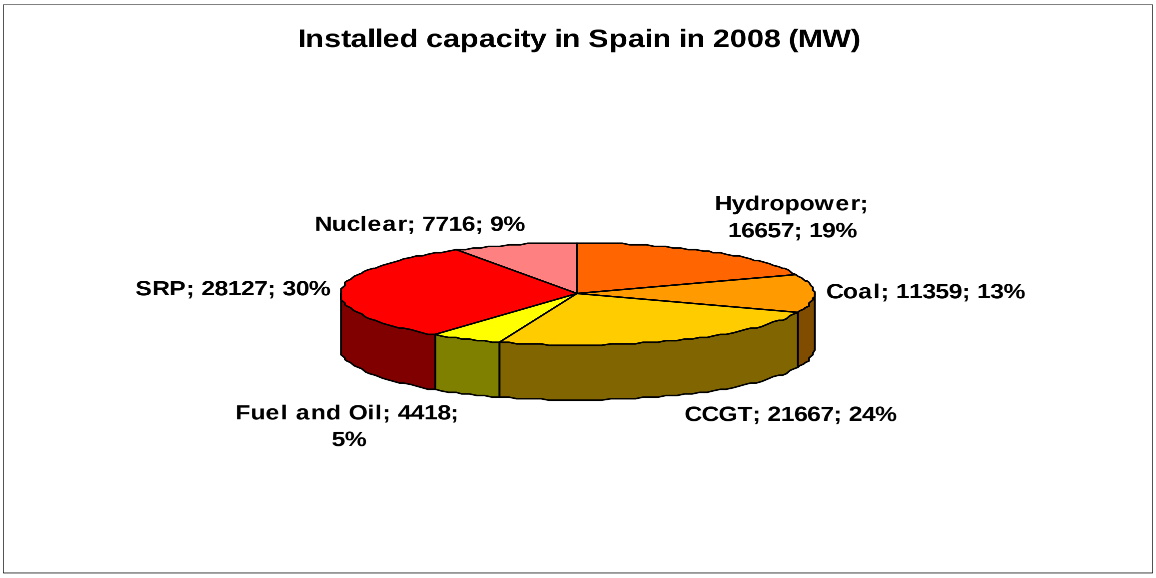


Figure 9: Installed capacity in Spain in 2008 (MW)



The installed capacity generates a certain distribution in power production:

Figure 10: Production in Portugal in 2008 (GWh)

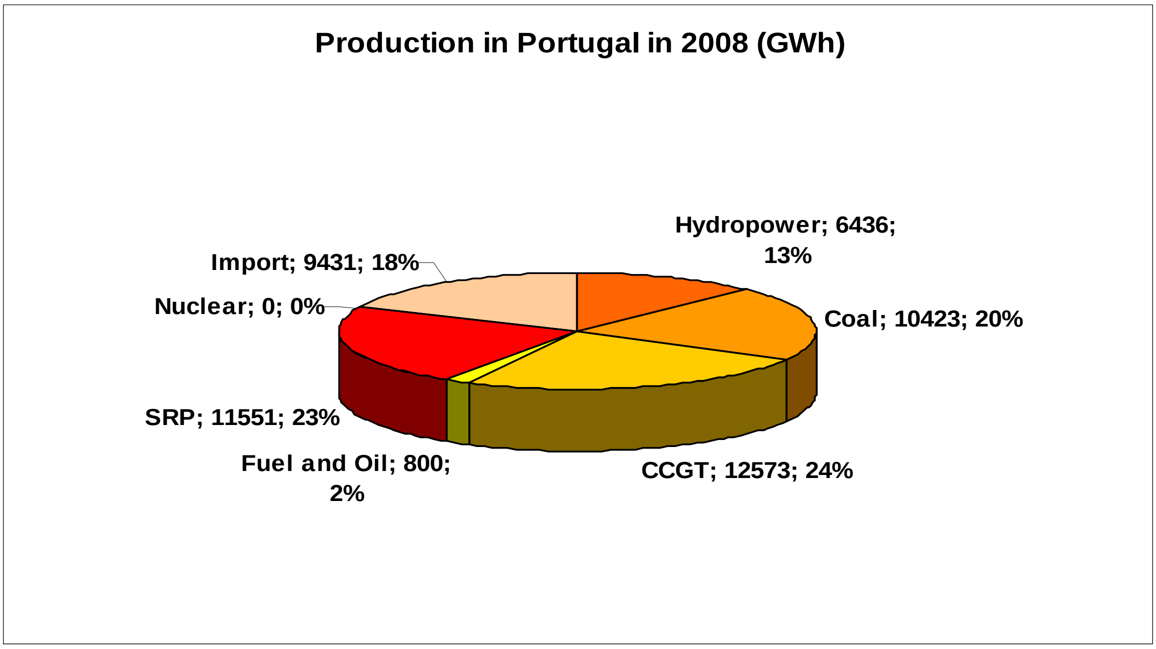
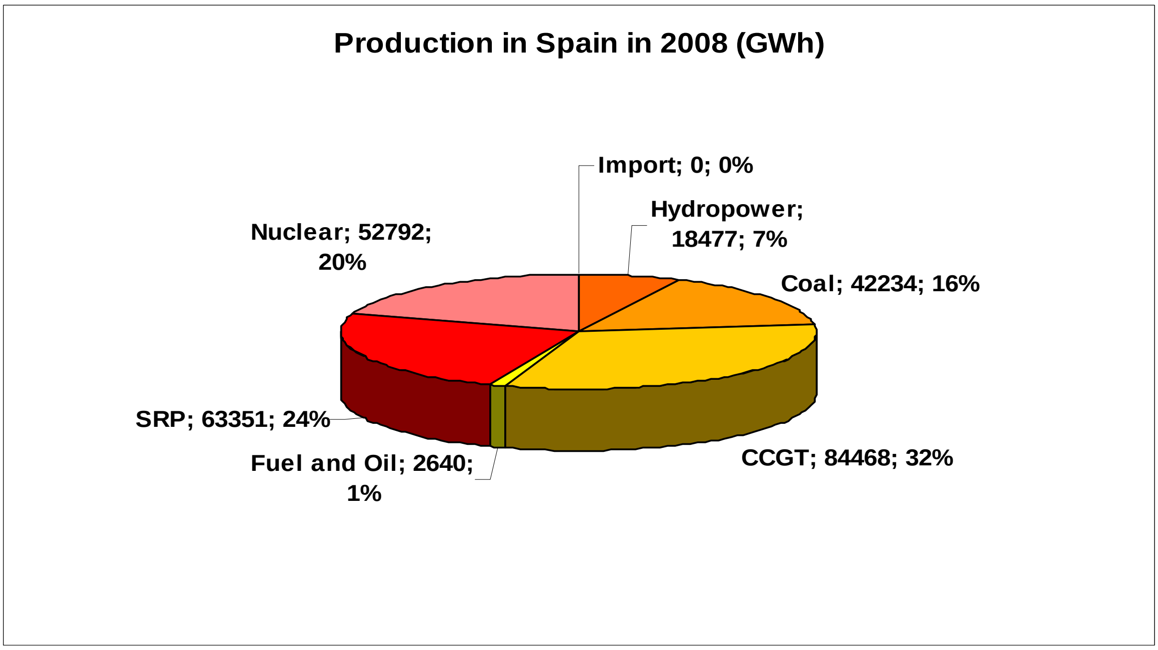
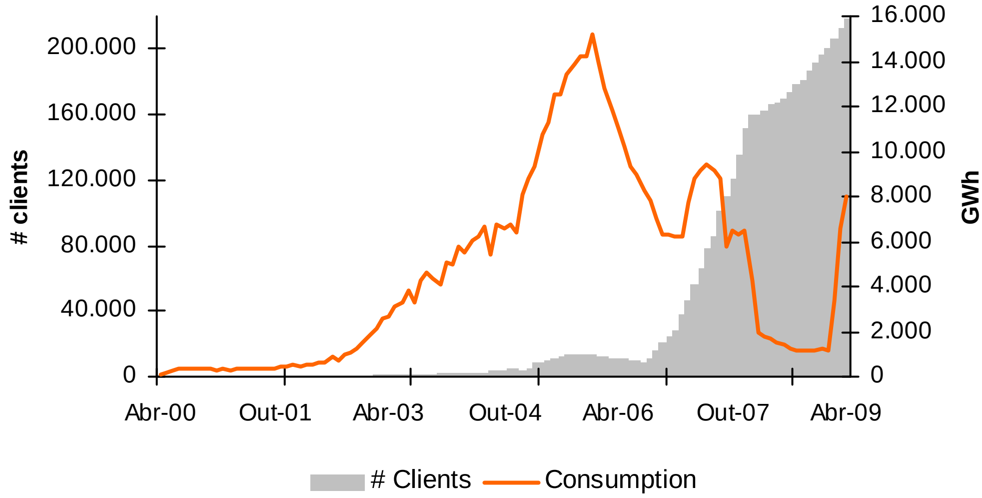


Figure 11: Production in Spain in 2008 (GWh)



4.3 The Liberalized Market in numbers:

Figure 12: Clients and consumption in the Portuguese liberalized market



The sudden growth of the consumption in the Portuguese liberalized market in the early 2009 is due to the fact that the Portuguese regulator had settled an energy price of 70 €/MWh in the regulated tariff, much higher than the daily Portuguese market's prices (until April, the 2009 Portuguese average was around 42,20 €/MWh).

The regulator's forecast was based on 2008's prices, which were extraordinarily high (average price was around 70 €/MWh), creating a deviation of more than 1.200 millions of euros, just from the difference between the market price and the price in the regulated tariff.

5. Costs and Technology

5.1 Merit Order

If we exclude SRP, the remaining technologies get into operation in each hour through the "merit order". This is no more than to sort the different technologies from the one with the lowest marginal cost until the one with the highest one. The last technology (the most expensive) to get its production sold in the market in a given hour settles the price for that hour, and all the other technologies with a lower marginal cost benefits from that price.

Usually, for each hour of the day, the merit order is this:

- SRP;
- Hydropower (run-of-river);[7]
- Nuclear;
- Combined Cycle (CCGT);
- Coal;
- Fuel;
- Hydropower (with reservoir).

Coal and Combined Cycle (Gas) have switched their positions in the merit curve due to not only the uncertainty of international markets and the price of the commodities themselves (which gets reflected in the marginal cost) but also due to the CO_2 allowances prices[8].

Besides the SRP, there are other distortions to the pure merit order, to know:

- Each plant's technical restrictions, because a power plant can not be turned off in an hourly basis, being limited to a determined number of start-ups per week/month/year. It might happen that a certain technology (a plant) is turned on at a certain hour when its marginal cost is higher than the one from another plant which, due to technical restrictions, should be off;
- The marginal cost of a hydroelectric power plant is low. The particularity of a dam with a reservoir is that it is the only known effective way to store electricity on a large scale[9], so, these plants have a precious value on the peak hours when it is necessary to inject energy to the grid in a short period of time. Once the technical restrictions are not as tight as in other power plants (thermal), the on/off flexibility is higher.

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[7] The difference between a dam with a run-of-river exploitation and a dam with a reservoir is explained later.

[8] The CO_2 allowances system will be explained on the topic *Carbon Emissions Allowances*.

[9] A battery is also a way to store energy but is has a much more limited autonomy for a national production system.

The last point applies to dams with reservoirs, where the water can be stored in a way that “arbitrage” can be practised: to turbinate in those hours in which electricity is more expensive.

A dam with no reservoir has to use the water (to generate power) as it arrives (has very low control about peaking the best hours to be turned on). This kind of hydroelectric exploitation is called run-of-river. That is why these plants get into operation before the other technologies, which, besides being more expensive, have a little more flexibility.

A hydro power plant has all of these advantages:

– Storage capacity allowing to satisfy the demand in peak hours;
– Flexibility in getting into or out of operation;
– Low marginal cost;
– The chance of articulate its functioning with eolic production in the case of a dam with a reversibility system (bombing-turbinating cycle).

The last topic demands a deeper explanation.

5.2 Eolic energy and the Bombing-Turbinating cycle

The eolic production that takes place during the night can not be wasted. Once electricity can not be stored, this production is injected in the grid, in a low consumption period. So, the value of that energy is lower.

A dam with a reversibility system (or bombing capacity) can turbinate the water but can also bomb it to the reservoir again so that it can be turbinated again. Energy is necessary to bomb the water and this is where the eolic energy appears: it is used by hydro plants to bomb the water back into the reservoir.

With this system, the importance of the hydro plants becomes higher as they consume the energy produced by the eolic turbines (avoiding some waste of energy), in a cheap period, in order they could turbinate that water on peak hours, when energy prices are higher.

This kind of dams does not work just on peak periods. They are also very useful when other technologies are unavailable (as long as there is water in the reservoirs).

5.3 Nuclear energy and the Portugal-Spain premium

As it was mentioned above, part of the energy produced in Spain comes from nuclear power plants, which have a very low marginal cost.

According to the merit order, nuclear technology is in the base. Knowing the interconnection capacity is limited, this might be one of the reasons why, sometimes, the cost of the MWh is different on Portuguese and Spanish sides of the border.

Usually, the congestion (consequence of the *market-split*) occurs in the Spain-Portugal way, leading to a higher price in the Portuguese market on these hours. The Portugal-Spain premium is formed (the difference between both prices).

A fact that strengthens the idea that Nuclear (together with the interconnection limitation) is one of the key factors concerning the existence of the Portugal-Spain premium is that this premium is higher in the off-peak hours, precisely when nuclear weight is higher (because most of the remaining technologies are off).

Figure 13: Supply and demand of energy for Portugal - hour 1 of June 16, 2009

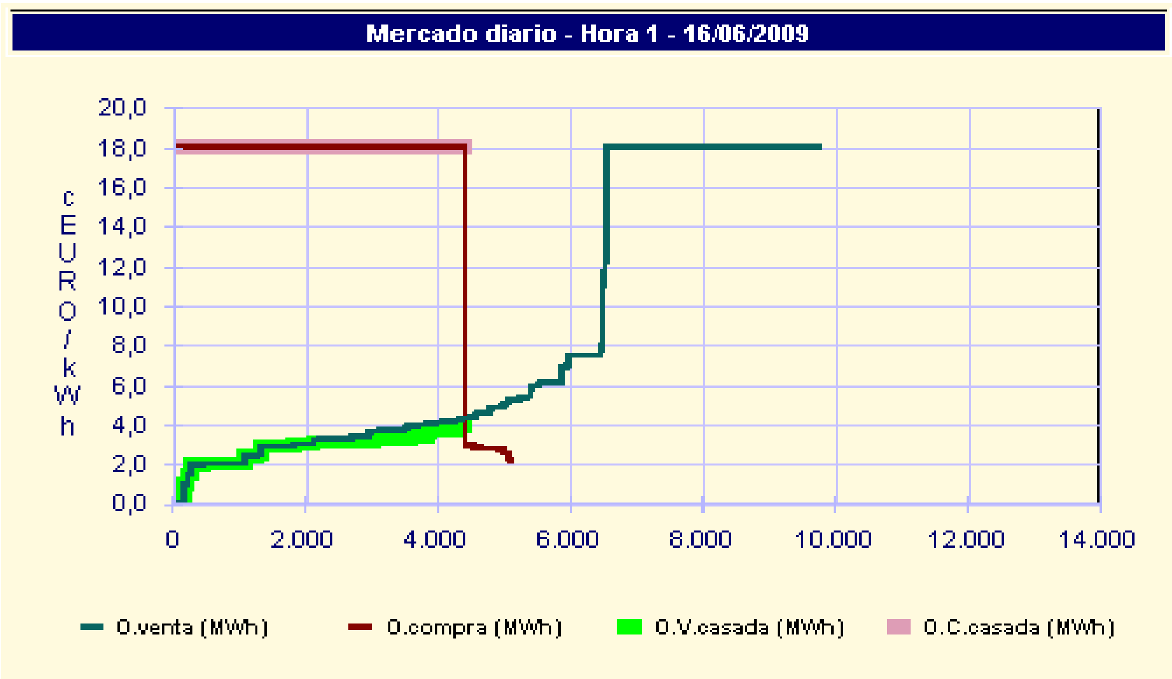
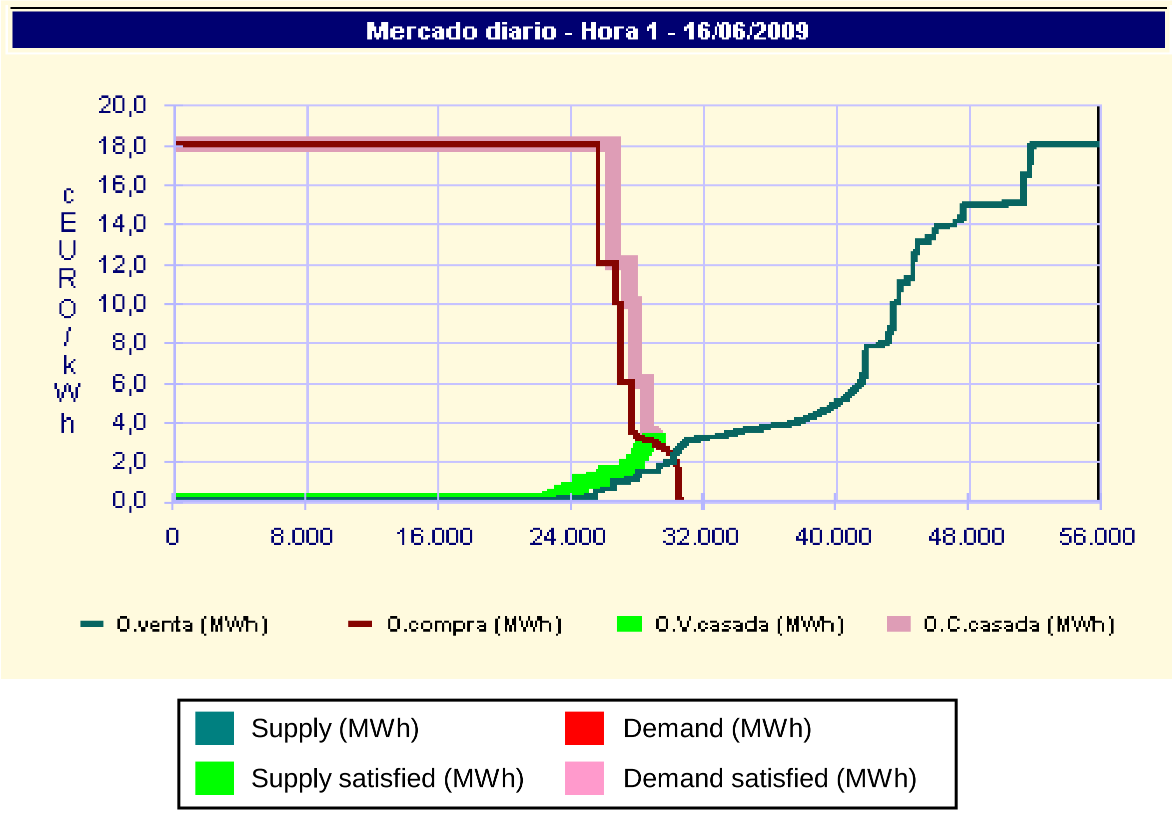


Figure 14: Supply and demand of energy for Spain - hour 1 of June 16, 2009



Figures 13 and 14 show the market's curves for hour 1 of June 16, 2009 for Portugal and Spain. We can see the difference between both prices (around 40 €/MWh for Portugal and around 32 €/MWh for Spain).

5.4 Carbon emissions allowances

With the recent environmental concerns taking a (progressive) higher importance in European governments' agendas, after the Quioto protocol, some targets where settled about the CO_2 emissions by the countries. A determined number of allowances is given to a company (based on its production and load factor (working period), and consequently, on its expected emissions). If the number of tonnes of carbon dioxide sent to the atmosphere is higher than the amount covered by the allowances, the company has to buy such a number of allowances to cover the additional amount of the released CO_2.

For the 2008-2012 period, the number of licences given by the Portuguese government (and by foreign governments also) reduced drastically: on the previous period, an experimental one, too much allowances were given (in such an excess that their value reached marginal numbers – from 20€/ton to 0,02€ or 0,03€ per tonne). It was more profitable to pollute (producing more) than to decrease production so that pollution could be reduced.

With the allowances around 20€/ton, the impact on costs is not residual anymore. It has even caused, in some periods, the exchange of positions in the merit order between Coal and Gas: usually, with no allowances, the marginal cost of a Coal Power Plant is lower than Combined Cycle Gas Turbine Plant, but with a 20€/ton allowance, both technologies switch their positions.

This is an example of how an environmental measure can impact in the industry: besides raising the costs directly, by the fact that the "darkest" technologies climb in the merit order, they get into operation later and so, they produce less energy.

5.5 Future trend

The general trend all over Europe in the last decade has been the increase of energy production by renewable sources and more efficient and less pollutant non-renewable sources (like cogeneration and CCGT).

The raise of the SRP will push the most pollutant technologies out of the system once the supply curve is translocated and thus, these (market's) technologies will satisfy a lower demand.

The costs with electricity production through the future technologies should, on one side, decrease as investigation will be developed in a way that the cost/efficiency ratio becomes lower. The spread of different power production methods, which are reaching maturity, is a sign that they are not a "green fashion" anymore. On the other side, the price such energy might achieve (because, as it will become more important, it will become more indispensable) can inflate the SRP.

So, the additional cost with the SRP should suffer opposite effects in next years because:

- The world continues to be very dependent from oil. So, a significant decrease of the renewable energy cost is not foreseen on the short term;
- SRP's installed capacity will continue to grow in a way that the targets could be reached by different countries;
- In extreme years, in which ordinary regime production has high costs, the addition SRP's cost will be lower;

- The technological development should decrease the SRP's costs as well as to improve its efficiency.

Natural gas technologies are seen nowadays as a future trend due to its high efficiency and low carbon emissions (although this is not the only pollutant gas, as there is also the sulphur dioxide, for example).

Fuel is practically out of the game (once it is very pollutant) and the hydropower will continue to exist due to it valuable contribution.

Coal will probably turn into a "frontier technology" (although the green carbon is beginning to appear as a less pollutant raw, but still needs to be verified).

"Traditional technologies" will not cease, once they are more independent from the weather conditions such as the sun or the wind, or the existence of affluences. They depend of the availability of the commodities (gas, oil, coal, ...) which should not be a problem for the next decades.

Both traditional and future technologies should continue to co-exist, with the SRP to gain more and more importance, and pushing the traditional technologies to the function of guaranteeing the energy supply.