Short-term Forecasting in Power Systems: A Guided Tour

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Short-term Forecasting in Power Systems: A Guided Tour

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Abstract In this paper, the three main forecasting topics that are currently getting the most attention in electric power systems are addressed: load, wind power and electricity prices. Each of these time series exhibits its own stylized features and is therefore forecasted in a very different manner. The complete set of forecasting models and techniques included in this revision constitute a guided tour in power systems forecasting.

Keywords Electricity markets · Electricity price forecasting · Short term load forecasting · Time series models · Wind power forecasting

1 Introduction

Energy has always been one of the most active areas in forecasting due to its major role for the effective and economic operation of power systems. However, since the liberalization of the electricity industry in the 1990s and the expansion of renewable sources of energy at the beginning of the twenty-first century, the interest in forecasting has spread from System Operators to Electric Utilities, energy traders, independent power producers and consumers, etc.

Electricity demand forecasters are at the core of many operational processes, including power system planning, scheduling and control. In the new competitive framework, load forecasts are additionally used by market agents as a reference variable for strategic bidding and are a fundamental driver of electricity prices. Furthermore, the liberalization of the electricity sector has stimulated the research on zonal load forecasting, where not only the aggregated load of the complete power system but also the loads of predefined transmission and distribution zones needs to be predicted to properly operate the network. In addition, energy retailers and large

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consumers need local forecasts to optimize the trading of this energy in the wholesale market. Recent advances in short-term load forecasting have been focused on modelling multiple seasonalities, the treatment of weather variables and calendar effects.

Wind power generation has become in many countries the main source of uncertainty for the operation of power systems. The impacts of increased levels of wind penetration range from power systems security assessment issues to fluctuations in electricity prices. System operators and market agents have been forced to cope with this new source of volatility in a very short time, and they have found wind power forecasting a very useful and indispensable tool for that purpose. The latest works in this area include spatial correlation, ensemble forecasting and density forecasting methods.

Since market clearing prices are obtained by crossing stepwise supply and demand curves constructed from aggregated bids, electricity prices in day-ahead markets are generally erratic and ill-behaved. In this context, electricity market agents assume a more intense risk exposure than in the traditional framework. To hedge against this risk, participants typically carry out part of their transactions through other financial markets, such as future markets or bilateral contracts. In this environment, participants need to develop efficient tools to obtain accurate energy spot price forecasts. In recent years, electricity price forecasting models are moving from univariate to multivariate, from single to multiple regime switching models and from point forecasts to interval and density forecasts.

These three forecasting topics, load, wind power and electricity prices, are covered in the next sections. The main features of actual time series are stressed, the key forecasting trends are presented and a gentle bibliography is provided for each of them.

2 Electricity Load Forecasting

Short-term load forecasting has gradually become the central piece in the electricity industry. In the traditional centralized framework, power systems were planned, designed and operated as a whole, using short-term load forecasting (STLF) mainly to ensure the reliability of supply. As electricity cannot be stored, the instantaneous generation must match the demand being taken from the system. To ensure this balance between demand and supply, as well as the security and quality of electricity supply, STLF is required. These forecasts provide the basis for generation and maintenance scheduling, and they can be used to estimate load flows to prevent the system from suffering major disturbances.

After competition has been introduced in the electricity sector, market participants need accurate load forecasts to minimize the volumetric risk associated with the energy trading process. In fact, a reduction of the forecast errors by a fraction of a percent can lead to substantial increases in trading profits. For example, according to Bunn and Farmer (1985) and Soares and Medeiros (2008), an increase of only 1%

in the forecast error (in 1984) caused an increase of 10 million pounds in operating costs per year for one electric utility in the UK.

Although STLF is synonym of hourly load data and forecasting horizons up to 24 h, there also exists literature where the sample period reduces to half-hourly data (e.g. Bunn and Farmer (1985)) or the forecasting horizon increases up to 7 days (e.g. Amaral et al. (2008)). More recently, there are a few published papers on the so-called very short-term load forecasting. For example, in Taylor (2008) methods for forecasting up to 30 min ahead are evaluated using minute-by-minute British data.

2.1 Features of Electricity Load Time Series

There exists a set of empirical findings in the electricity load series that have been systematically reported in the literature. These stylized facts of the load series are essential features of broad generalization. In fact, many of the presented characteristics are shared by most national system load in the world.

Basically, the load series displays trend with different levels of seasonality (annual, weekly, daily), short-term dynamics, calendar events dependence and non-linear effects of meteorological variables. The load trend is usually associated to economic and demographic factors, whereas the other features are related to climate variations and human behaviour.

Figure 1 provides different views of the hourly electricity load in Spain. The first panel depicts 7 years of data, illustrating the usual positive trend of an annual seasonality. Panel (b) focuses on 1 year of hourly data, where the weekly seasonal cycle is clearly visible. The calendar effects on electricity consumption become apparent, especially in summer vacations (mainly during August in Spain) and Christmas time, as well as the effect of temperature. The consumption is usually higher in winter (electric heating) and summer (air conditioning) than in autumn and spring. Finally, graphs (c) and (d) zoom in a time window of three winter and summer weeks, respectively. The systematic decrease in the load on Saturdays and Sundays, due to the different levels of activity not only in industrial and commercial sectors, but also in the behaviour of households on holidays, is also a crucial characteristic of demand series. These two plots reveal significant differences between winter and summer intra-day load patterns, especially during peak hours.

These features are further illustrated in Fig. 2, where eight daily patterns have been automatically obtained by the k-means clustering algorithm (Kaufman and Rousseeuw 1990). These mean load profiles have been classified in terms of seasons and days of the week, the main drivers of the routinary human activity. During the winter the hourly peak loads in Spain are usually in the evening, at 9PM, when lighting loads are at maximum. However, during the summer, the peak loads in working days are at 12 AM.

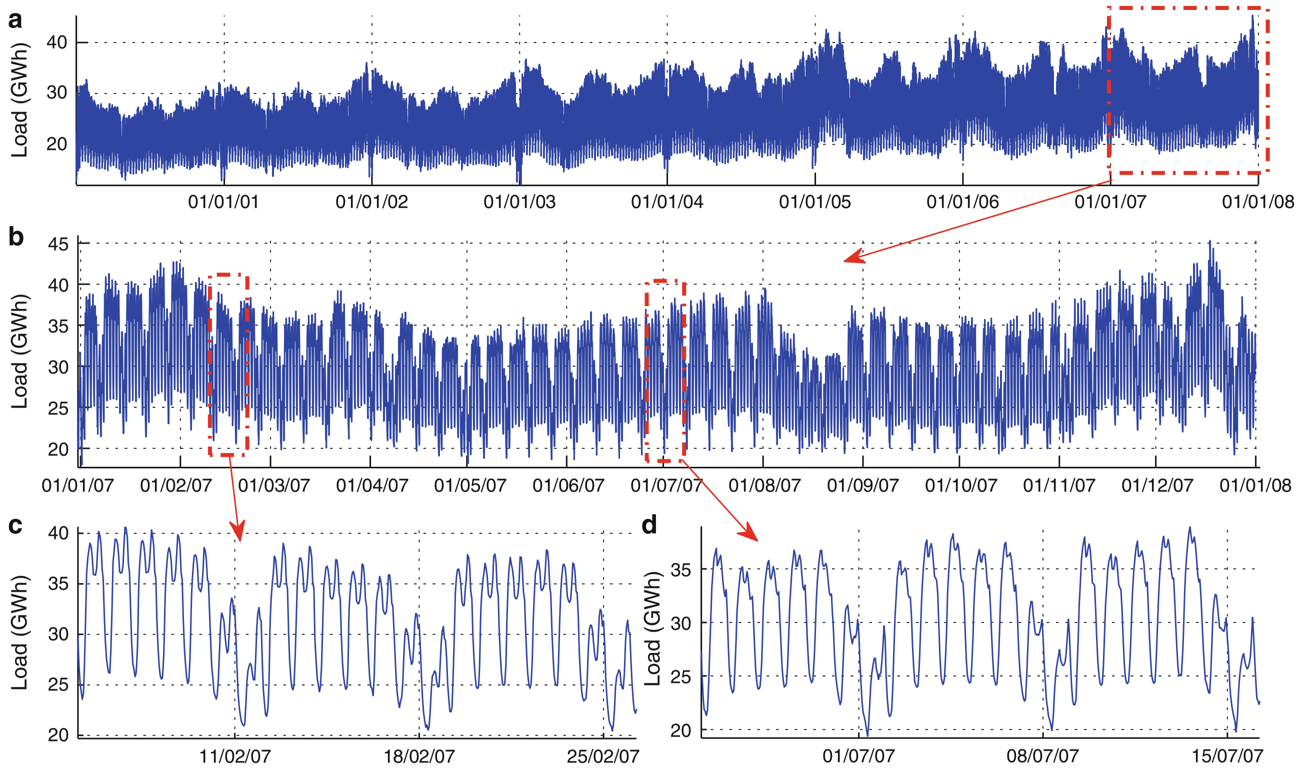

Fig. 1 Hourly electricity demand in Spain: (**a**) From 1 January 2000 to 31 December 2007; (**b**) From 1 January 2007 to 31 December 2007; (**c**) Three winter weeks (2007); (**d**) Three summer weeks (2007)

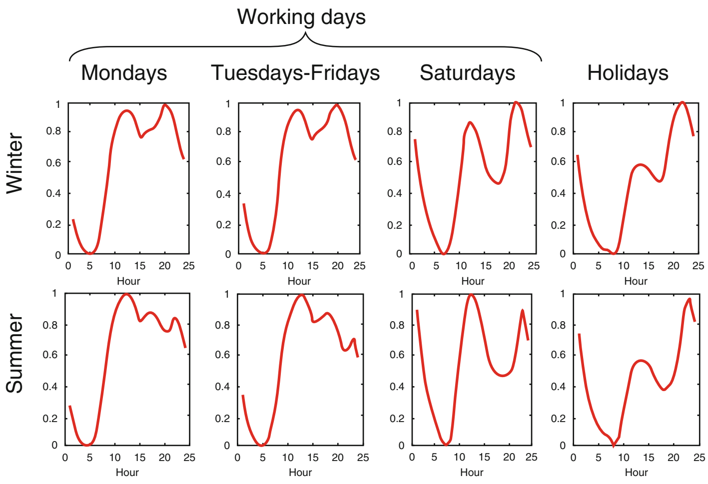

Fig. 2 Normalized intra-day load profiles for the Spanish electricity load

2.2 *Modelling Electricity Load Features*

Before reviewing the forecasting approaches proposed in the literature, we would like to mention several important issues related to the main features of electricity load series. Note that many of these characteristics are strongly linked to physical factors, motivating STLF approaches based on well-known relationships between load and exogenous variables.

2.2.1 Dealing with Trend and Annual Seasonality

Several approaches have been proposed in the literature to take the load trend into account, although most papers in the STLF literature consider taking first-order differences of the load series to handle the load trend. On the other hand, most of the annual fluctuations exhibited by the electricity load are mainly governed by climate conditions, such as the outdoor temperature or the number of daylight hours. Although these systematic fluctuations exist in the load series, in STLF the forecast lead times is substantially shorter than the length of the annual cycle; therefore, it could be surmised that methods that make no attempt to model the annual seasonality may be adequate. For that reason, most of the proposed models for STLF ignore the existing annual cycle, focusing on the intra-week and intra-day cycles (e.g. Weron (2006) and Taylor (2008)).

Alternatively, some authors have proposed recently the explicit modelling of the trend and the annual seasonality. For example, in Soares and Medeiros (2008) the trend in the load is modelled as a deterministic function of the gross domestic product, whereas in Dordonnat et al. (2008) local linear trends are estimated for each hour of the day. Concerning the annual cycle, in Dordonnat et al. (2008) and Soares and Medeiros (2008), it is modelled as a combination of sines and cosines, as in a Fourier decomposition.

2.2.2 Dealing with Intra-week and Intra-day Patterns

When modelling an hourly (or half-hourly) load series, the systematic shape of the load curve for each day together with the existing within-week seasonal cycle are two relevant characteristics that need to be modelled appropriately. Note that this intra-day shape smoothly changes between the seasons and between weekdays and weekends (Fig. 2).

In STLF there exist two main approaches for dealing with intra-day profiles: using a single-equation model for all the hours or using multiple-equation models with different equations for the different hours of the day. The first approach allows applying models that are able to model the dynamics of both intra-week and intra-day patterns, such as the double seasonal ARIMA model or the exponential smoothing method for double seasonality (see, e.g. Taylor (2003)). Another extended approach to capture the intra-day pattern consists in treating each hour as a separate time series. In its most simple version, this approach uses 24 independent models specified over a daily time scale. More sophisticated versions include vector models where the equations for the different hours are linked. This strategy has been adopted by articles, including Ramanathan et al. (1997), Cottet and Smith (2003), Dordonnat et al. (2008) or Soares and Medeiros (2008). Note that according to Cancelo et al. (2008), although there is some controversy about the best approach, most authors prefer to model each hour as a different series.

2.2.3 Dealing with Weather Variables

It is well-known that meteorological conditions have a significant influence on electricity loads. Derived factors from weather variables such as temperature, solar radiation, humidity, wind speed, cloudiness, or rainfall have been used as exogenous variables in the literature to improve load forecasting. However, according to Weron (2006), the load prediction survey (Hippert et al. 2001a) indicated that most of the considered research publications made use of temperature (19 out of 22), but only six of them made use of additional weather parameters. A review of more recent papers confirms that the majority of authors assume that temperature is the main weather variable, ignoring the additional effects on the load of the other weather variables. Note that sometimes the reason for this simplification is the unavailability of reliable recordings. For example, in Soares and Medeiros (2008), no weather data is included as exogenous variables due to the existence of deficiencies in the temperature observations (outliers and missing values).

Focusing on the relationship between electricity load and outdoor air temperature, various authors have reported similar correlation patterns (Engle et al. 1986;

Sailor and Muñoz 1997; Valor et al. 2001; Pardo et al. 2002; Moral-Carcedo and Vicéns-Otero 2005; Cancelo et al. 2008). Although this relationship depends on the climate characteristics of the geographical area to which the load data refer, principal studies indicate that it is highly complex due to several reasons. Basically, the load increases both for decreasing and increasing temperatures, the response being asymmetric and clearly non-linear due to the use of electric heating appliances in winter and air conditioners in summer. There exist also differences between working days and holidays, which change with the time of the year (Cancelo et al. 2008). Furthermore, there is a dynamic effect due to the physical inertia of buildings, as well as saturation effects because of the limited capacity of the installed heating and cooling appliances.

Figure 3 shows the relationship between the filtered electricity load[1] of a distribution area in the north of Spain and an average daily mean temperature of this

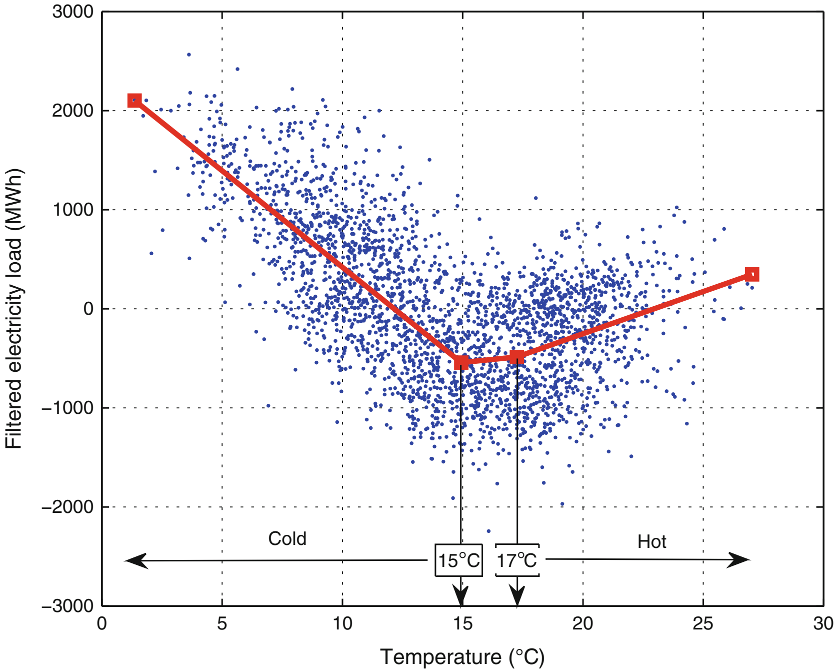

Fig. 3 Non-linear relationship between the (filtered) electricity load of a distribution area of the north of Spain and the average daily mean temperature of this region

[1] To show the response of load to temperature variations, the electricity load has been previously filtered out by removing both the trend and the calendar effects, see Moral-Carcedo and Vicéns-Otero (2005) for further details.

region.[2] To highlight this relationship, a Linear Hinges Model has been adjusted (Sánchez-Úbeda and Wehenkel 1998). This piecewise linear model summarizes the non-linear response of electricity load to temperature by automatically segmenting the temperature axis into three regions: cold (for temperatures lower than 15°C), neutral (between 15 and 17°C) and hot (for temperatures higher than 17°C).

The non-linear relationship between load and temperature is modelled in the literature by computing several degree-days transformations of the observed temperatures, usually daily high and low outdoor air temperatures.[3] The main idea of this approach is to segment the variation of temperatures into several derived variables. The heating degree-days (HDD) and the cooling degree-days (CDD) are defined as the difference between the actual temperature and a reference temperature:

$$HDD_t = \max(T_R - T_t, 0); CDD_t = \max(T_t - T_R, 0), \tag{1}$$

where T_t is the mean outdoor air temperature at time t and T_R is a reference temperature (e.g. 65°F in the USA, 15°C in Spain). If T_t is above T_R, there are no HDD, whereas if the T_t is less than T_R, there are no CDD. Thus, these degree days try to measure the intensity and duration of cold and heat in winter and summer days, respectively. Note that the reference temperature should be adequately selected to separate correctly the cold and heat branches of the load–temperature relationship.

The usual approach to STLF uses the forecasted weather scenario as an input. If multiple scenarios for the future value of a weather variable (e.g. outdoor air temperature) are available, it is possible to use the so-called ensemble approach (Taylor and Buizza 2003), where multiple load forecasts are computed from different temperature, wind speed and cloud cover scenarios, and combined to produce not only a single point load prediction, but also load prediction intervals.

2.2.4 Dealing with Calendar Events

The industrial, commercial and residential activity patterns differs from holidays to working days, leading to systematic variations in the electricity load.

Although in practice the unusual consumption on special days, including public holidays such as 1 January, is usually obtained by means of judgemental methods, there exist more refined approaches. The most common approach consists in building different models for normal and special days of the week (e.g. one model for Monday, Tuesday–Thursday, Friday, Sunday and Saturday) (Ramanathan et al. 1997). The main drawback of this approach is the treatment of special holidays, as long weekends or the first of January.

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[2] Usually a regional average temperature is built as a weighted average of temperatures recorded at different observatories that represent the different climatic regions covering the whole territory of interest. The weightings used should reflect the consumption volume of each region, and they are usually obtained from population figures.

[3] The mean outdoor temperature is also very frequent in the literature, and it is calculated from the maximum and minimum daily values.

Within the single model approach, the treatment of special days such as Easter, Christmas, or public holidays is usually carried out by means of dummy variables.[4] All in all, the number of dummies representing the different types of days can be large. For example, in Moral-Carcedo and Vicéns-Otero (2005) hundreds of dummy variables are used to deal with calendar effects. In this reference the calendar effect is finally collected by a unique variable (the so-called "working day effect"), which represents the effect of calendar in the load of a particular day as a percentage of the electricity load on a representative day of the week (e.g. Wednesday).

2.3 Electricity Load Forecasting Models

A large variety of methods and models have been applied to STLF during several decades. In spite of the numerous trials for finding a superior model, we have to agree with some authors (Taylor et al. 2006; Piras and Buchenel 1999) that no sophisticated method is clearly better than others. In this section we briefly review the most interesting and promising models.

The literature on STLF contains a variety of models that can be roughly classified into two main categories: (1) statistical time series approaches and (2) Artificial intelligence-based techniques. Within the statistical time series approaches, univariate and multivariate models can be distinguished. Expert systems, artificial neural networks (ANN), fuzzy logic and support vector machines (SVM) are the main artificial intelligence paradigms applied to STLF. A non-exhaustive overview of the most relevant models of these two groups is presented in the following sections.

2.3.1 Statistical Time Series Analysis-based Models

Statistical time series models, pioneered by Box–Jenkins (1976) and Holt–Winters (1960) methods, have been present since the dawn of electric load forecasting. Statistical methods can be classified into univariate and multivariate. Univariate methods, as ARIMA and exponential smoothing models, are usually applied in the literature as reference models for very short horizons (see Taylor et al. (2006) for an empirical comparison of univariate methods in STLF). Multivariate methods using explanatory variables, often expressed as ARIMAX and linear transfer function models with non-linear transformations of the input variables, are necessary to anticipate the effects of climatology and calendar on consumption habits (see Bunn (1982) and Weron (2006) for extended reviews). In the next paragraphs, the most common models in STLF are introduced.

[4] The working days after and before a holiday could require additional dummies.

Seasonal ARIMA Models (SARIMA)

The standard form of a multiplicative double seasonal ARIMA $(p, d, q) \times (P_1, D_1, Q_1)_{24} \times (P_2, D_2, Q_2)_{168}$ model for hourly time series is given by

$$\phi_p(B)\Phi_{P_1}(B^{24})\Phi_{P_2}(B^{168})\nabla^d \nabla_{24}^{D_1} \nabla_{168}^{D_2} L_t = C + \theta_q(B)\Theta_{Q_1}(B^{24})\Theta_{Q_2}(B^{168})\varepsilon_t, \tag{2}$$

with

$$\phi_p(B) = 1 - \phi_1 B - \ldots - \phi_p B^p \tag{3}$$
$$\Phi_P(B^S) = 1 - \Phi_1 B^S - \ldots - \Phi_P B^{PS} \tag{4}$$
$$\theta_q(B) = 1 - \theta_1 B - \ldots - \theta_q B^q \tag{5}$$
$$\Theta_Q(B^S) = 1 - \Theta_1 B^S - \ldots - \Theta_Q B^{QS}, \tag{6}$$

where L_t is the output variable, that is, the hourly electricity load, C is a constant term and ε_t is an independent and identically distributed random noise. B is a backshift operator ($BL_t = L_{t-1}$), and $\phi_p(B), \Phi_{P_1}(B^{24}), \Phi_{P_2}(B^{168})$ and $\theta_q(B), \Theta_{Q_1}(B^{24}), \Theta_{Q_2}(B^{168})$ are backshift operator polynomials, of orders p, P_1, P_2, q, Q_1, Q_2 respectively, modelling the regular, daily and weekly autoregressive and mean average effects, respectively. $\nabla^d, \nabla_{24}^{D_1}, \nabla_{168}^{D_2}$ are difference operators ($\nabla^d L_t = (1-B)^d L_t$ and $\nabla_S^D L_t = (1-B^S)^D L_t$) describing the differences applied to induce stationary in integrated processes. The Box–Jenkins methodology (Box and Jenkins 1976) offers a systematic identification procedure that has been widely tested in many areas.

In present days, univariate ARIMA models are basically being used as benchmarks for comparative purposes (see, e.g. Moghram and Rahman (1989), Taylor and McSharry (2008), Taylor (2008), Soares and Medeiros (2008)).

Exponential Smoothing for Double Seasonality

The application of exponential smoothing models to hourly data requires an extension of the standard Holt–Winters formulation to accommodate the two seasonalities (daily and weekly). This extension was proposed by James W. Taylor in Taylor (2003) and further investigated in Taylor et al. (2006) and Taylor (2008):

$$Level \quad S_t = \alpha(L_t/(D_{t-24}W_{t-168})) + (1-\alpha)(S_{t-1} + T_{t-1}) \tag{7}$$
$$Trend \quad T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1} \tag{8}$$
$$Seasonality\ 1 \quad D_t = \delta(L_t/(S_t W_{t-168})) + (1-\delta)D_{t-24} \tag{9}$$
$$Seasonality\ 2 \quad W_t = \omega(L_t/(S_t D_{t-24})) + (1-\omega)W_{t-168} \tag{10}$$
$$\widehat{L}_t(k) = (S_t + kT_t)D_{t-24+k}W_{t-168+k}, \tag{11}$$

where $\widehat{L}_t(k)$ is the k-step ahead load prediction made at time t, and α, γ, δ and ω are model parameters.

Linear Transfer Functions models (LTF)

The LTF model has the following general expression for hourly data (daily and weekly seasonalities):

$$\begin{aligned} L_t &= C + v_1(B)X_{1t} + \cdots + v_n(B)X_{nt} \\ &\quad + \frac{\theta_q(B)\Theta_{Q_1}(B^{24})\Theta_{Q_2}(B^{168})}{\phi_p(B)\Phi_{P_1}(B^{24})\Phi_{P_2}(B^{168})\nabla^d \nabla_{24}^{D_1} \nabla_{168}^{D_2}} \varepsilon_t, \end{aligned} \tag{12}$$

where the definitions made for the ARIMA model hold, and $v_1, \cdots, v_n$ represent a family of linear transfer functions able to capture a wide number of impulse responses with few parameters (see Pankratz (1991) for more details). They can be expressed as

$$v(B) = \frac{(w_0 + w_1 B + w_2 B^2 + \cdots + w_s B^s)B^b}{1 + \delta_0 + \delta_1 B + \delta_2 B^2 + \cdots + \delta_r B^r}. \tag{13}$$

Predictions are therefore obtained as linear combinations of past and present values of actual and predicted loads and, if available, of other exogenous variables as temperatures and calendar effects (see Engle et al. (1986)). The success of these models lays in a well-established identification and diagnostic checking methodology (see Box and Jenkins (1976) and Pankratz (1991)), a reduced number of parameters that can be easily interpreted, and their representation capabilities (ARIMA, ARMAX and Dynamic Regression models fit within the general formulation of LTF models). In fact, many load forecasting models reported in the literature can be expressed with transfer function models. Their main differences are related to the treatment of weather and calendar effects and the introduction of switching regimes through periodic and smooth transition models (see Pardo et al. (2002), Moral-Carcedo and Vicéns-Otero (2005), Cancelo et al. (2008), Dordonnat et al. (2008), Amaral et al. (2008), Taylor and McSharry (2008)).

2.3.2 Artificial Intelligence Based Models

The history of AI has determined the evolution of non-statistical techniques applied to STLF (Bansal and Pandey 2005). Expert systems were applied for the first time in 1988 (Rahman and Bhatmagar 1988) and improved during the 1990s by modelling calendar effects and the non-linear relationship of load and temperature (see e.g. Ho et al. (1990) and Rahman and Hazim (1993)). These knowledge-based models are rule-based techniques, where the rules are derived from human experts and not directly from data.

In the 1990s a great amount of research was devoted to the empirical application of ANN to STLF (see Hippert et al. (2001b) for a comprehensive review of ANNSTLF models published between 1991 and 1999). Most of the papers published in that period used feed-forward multilayer perceptrons (MLP) as non-linear multivariate regression models (e.g. Park et al. (1991), Chen et al. (1992), Chow and Leung (1996), Czernichow et al. (1996), Khotanzad et al. (1997)). The main characteristic of these black-box models is that their internal structure is not defined a priori, being obtained automatically from the in-sample data during the training process. They benefit from the universal approximation capability, but at the same time they suffer the risk of overfitting (this controversial issue is addressed in Hippert et al. (2005)). Recurrent networks, a class of neural network that not only operate on an input space but also on an internal state space, have been used to model the recurrent dynamics of electricity load time series (e.g. Choueiki et al. (1997), Vermaak and Botha (1998)).

The application of neural networks to STLF mixed up in the early twenty-first century with other soft computing techniques as fuzzy logic and evolutionary computation (Kodogiannis and Anagnostakis (2002); Ling et al. (2003); Senjyu et al. (2005)). These methods were introduced as an attempt to improve the learning abilities and interpretability of neural networks. SVM, derived from the statistical learning theory developed by Vapnik (1995), have also yielded promising results (Mohandes 2002; Pai and Hong 2005).

2.3.3 Error Measures for Electricity Load Forecasting

A vast array of accuracy measures can be used to evaluate the performance of forecasting methods (see e.g. DeGooijer and Hyndman (2005) for the most commonly used measures). However, in the context of STLF literature, a reduced number of measures have been used to present load forecasting errors. The most popular one is the mean absolute percentage error (MAPE), as well as the root mean squared error (RMSE). For period $[1, N]$ they are given by

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|L_t - \widehat{L_t}|}{L_t}100 \tag{14}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(L_t - \widehat{L_t})^2}, \tag{15}$$

where L_t and $\widehat{L_t}$ are the actual and predicted loads for time t.

The MAPE captures the proportionality between the forecast absolute error and the actual load, enabling a simple interpretation by those in the industry, where it has become a standard. Nevertheless, the MAPE has problems when the series has values close to (or equal to) zero, as noted by different authors (e.g. Makridakis et al. (1998), p. 45).

It is well known that without an explicit comparative test using the same data set, it is not possible to deduce general conclusions of how effective a forecasting procedure is. In spite of this, when dealing with hourly load series, the typical out-of-sample MAPE for 24 steps ahead ranges from 1 to 4%, whereas the reported results for the one step ahead range from 1 to 2%.

3 Wind Power Forecasting

In the recent years, because of the huge raise in the wind power capacity installed in an increasing number of countries all over the world, the necessity of models and tools to predict wind energy has become more and more important. The main reasons for this growth are oriented to reduce the dependence and the environmental impacts caused by the use of fossil fuels. This is the case of the principal producer of wind energy, the European Union, with a wind power capacity of 66 GW,[5] with 55% of the world total wind power capacity in 2008 and with the objective of covering around 20% of the electricity consumption in 2010 (Giebel et al. 2003; IDAE 2003). As a consequence of this growth, utilities and regulators have been forced to cope with the unpredictability and volatility of wind to integrate this “adolescent” technology in our “mature” power systems. Without wind power forecasting, wind energy would have never attained the penetration levels observed in present days.

Wind power forecasting applications can be classified into four main groups according to the prediction horizon:

1. Ultra short-term (seconds range): For wind turbine control applications
2. Very short term (from minutes to 1 h ahead): For power system security assessment applications
3. Short term (from 1 to 48 h ahead): This is the prediction horizon required for the operation of wind energy in day-ahead electricity markets, unit commitment, economic dispatch and short term maintenance planning
4. Medium and long term (up to several years): Maintenance planning, generation planning and energy policy models require wind energy scenarios as input. Simulation techniques are usually applied for that purpose

This chapter will be devoted to the third group of applications, taking into account that wind energy is being traded in many day-ahead electricity markets as any other source of energy. On the one hand, wind energy producers have to predict their hourly resources 1 day in advance to sell their predicted energies in the daily market. On the other hand, the system operator has to predict the aggregated wind generation in the whole system to estimate the effective electricity demand that has to be covered by others resources.

[5] Source GWEC

3.1 *Features of Wind Power Time Series*

Basically, wind power is highly correlated with wind speed, although a complex physical relationship exists between wind speed and generated power. This energy conversion process leads to non-linear and high-volatile wind power time series (see Fig. 4). On the one hand, the main source of non-linearity is related to the shape of wind turbine power curves (see Fig. 5). On the other hand, high volatility is inherent to the wind dynamics. These features make wind power forecasting a very difficult task, requiring very complex physical and statistical models. Short-term accuracy is significantly improved when forecasting the aggregated production of a portfolio of wind farms, in the same manner as utilities group them to send an aggregated bid to the electricity market. This fact is illustrated in Fig. 4, where the normalised hourly wind energy production of a portfolio of wind farms (integrating more than 1 GW, plot (a)) is compared to the individual time series of four wind farms of the

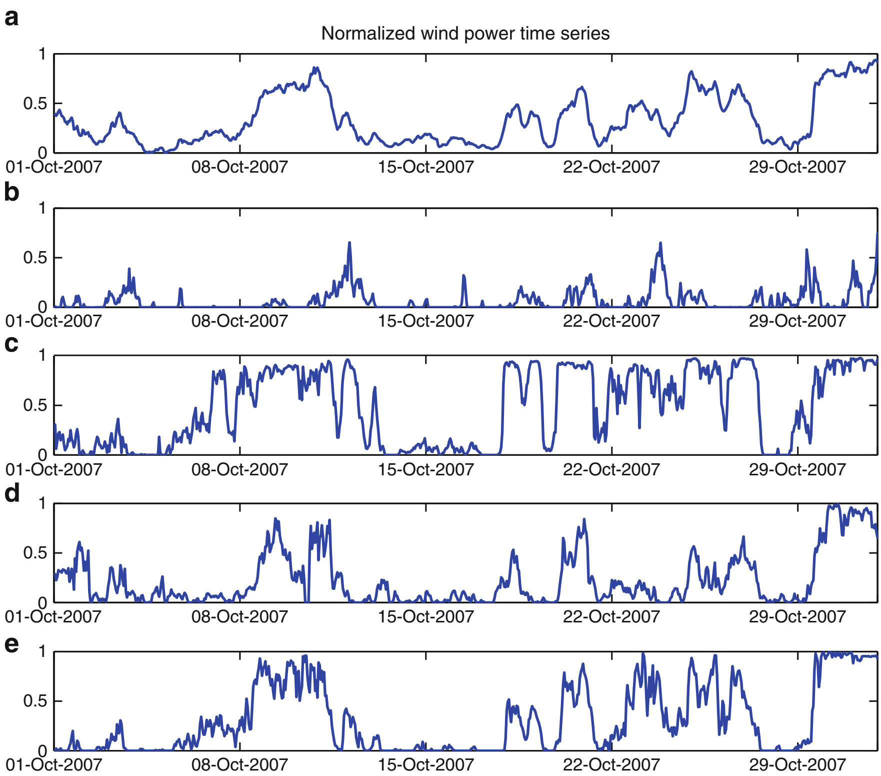

Fig. 4 Wind power time series (all hourly wind energy production time series have been normalized by the corresponding rated power: (**a**) Portfolio of wind farms (**b**) 20 MW wind farm (**c**) 25 MW wind farm (**d**) 50 MW wind farm (**e**) 20 MW wind farm)

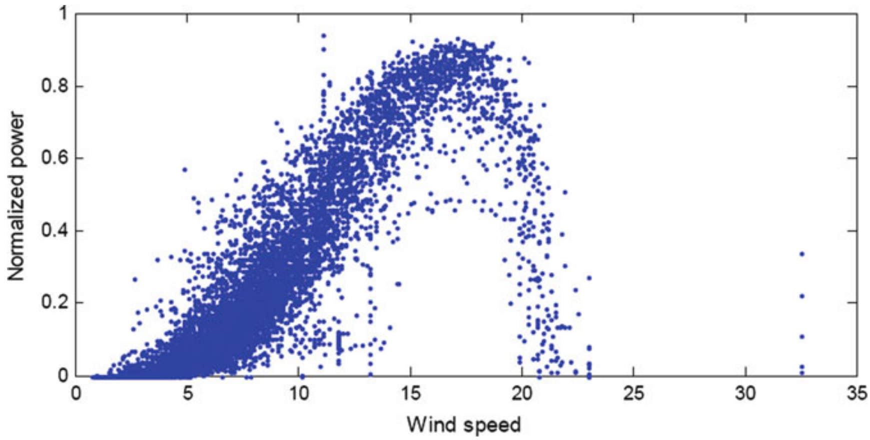

Fig. 5 Empirical power curve of a 30 MW wind farm

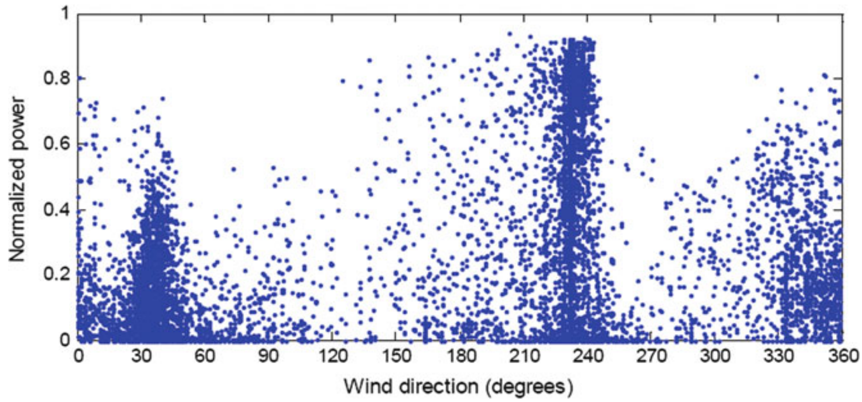

Fig. 6 Wind-speed direction vs. energy production in a wind farm

same portfolio (less than 50 MW each, plots (b–e)). The portfolio time series is significantly smoother than the individual plots.

Figure 5 shows the measured power curve of a 30 MW wind farm. It can be observed that it significantly differs from the sum of theoretic power curves supplied by wind turbine manufacturers. The non-linearity of this curve, combined with the high volatility of the wind dynamics, determines the main characteristics of wind power time series.

An empirical 30 MW wind farm output power vs. wind direction plot is shown in Fig. 6. A few predominant wind directions can easily be identified on this plot, as well as the fact that wind direction does not explain wind power by its own. When used as input variable, wind direction is always combined with wind speed.

3.2 Wind Power Forecasting Models

Most approaches to short-term wind power forecasting (see Giebel et al. (2003) and Landberg et al. (2003) for a detailed review) can be roughly classified into two groups according to the type of model used in the process: physical or statistical. In both cases a second distinction may be done according to the predicted output variable: wind speed (m/s) or power output (MW).

In this context, physical or numerical weather prediction (NWP) models use physical considerations that govern meteorological phenomena to reach to the best possible estimate of the local wind speed before using model output statistics (MOS) to reduce the remaining error. The statistical approach tries to learn (from data) functional relationships between a set of explanatory variables, including NWP estimates and online power measurements, and the desired output. The statistical approach has the advantage of being computationally much less expensive than the continuous re-evaluation of NWP models. In practice, models combining NWP estimates and online power measurements have shown to be the most accurate solution for the short term.

With respect to physical models, Landberg (1999) has shown that a simple NWP and physical downscaling approach is effectively linear, thereby being very easily amenable to improvements through MOS. Whether it is generally better to follow the complete model chain (first predicting wind at ground level, then production with the wind park specific power curve) depends – given the availability of data – on the forecast horizon: using auto-regressive models, Jensen (1994) showed that the use of wind speed predictions as explanatory variable is important for up to 8–12 h ahead. For longer prediction horizons, use of separate wind speed forecasts offered no advantage over direct wind power prediction.

Within the statistical time series approach, ARIMA models have been applied to wind power forecasting by Guoyang et al. (2005) and Sfetsos (2000). Torres et al. reported in Torres et al. (2005) that an ARMA model improved the persistence model by 12–20% for a forecasting horizon of 10 h, but produced worse forecasts for the next hour. Schwartz (Milligan et al. 2003), who applied a class of ARMA models to both wind speed and wind power output from wind farms in the US, found that the improvements he achieved over persistence were strongly dependent on the considered month. Costa et al. (2007) proposed the use of the Kalman filters for 5-min sampled wind power time series.

Many researchers have applied ANN for short-term wind power forecasting with promising results. Regarding the network structure, simple networks seem to be most suitable for precise forecasts (only six neurons in the hidden layer were used in Beyer et al. (1994)). Besides production data of the predicted wind farm, data from upwind parks can be used in an ANN approach to further improve the predictions, as was shown in Alexiadis et al. (1999). This strategy, which is known as spatial correlation, was also applied in Yang et al. (2005) and Damousis et al. (2004). In Kariniotakis et al. (1996), the authors apply an algorithm to automatically optimize the architecture of the network. Li (2001) uses an ANN for diagnostic purposes, as lower-than-expected wind power can be an early indicator for maintenance.

Barbounis (2006) compares the performance of feed-forward and recurrent neural networks, finding a significant advantage of the second ones in their case study. Sfetsos (2001) argues that hourly averaged wind measures are not able to represent the structure of the wind time series. He uses an ANN for 10-min prediction, obtaining better results than the ones obtained with hourly data.

Apart from ANN, fuzzy logic and SVM have also been applied in wind power forecasting. In Damousis et al. (2004), fuzzy variables are used to model membership to different wind scenarios. In Gou-Rui (2007), SVM are proposed to solve some of the problems of neural networks, such as over-fitting and local minimums.

A quite different approach is proposed by Ismael Sánchez in Sanchez (2006), which describes the procedure that is currently implemented in SIPREÓLICO, a wind energy prediction tool that is part of the online management of the Spanish Peninsular system. In this paper, two different sets of models are used: dynamic linear models and non-parametric models. The estimations of these models are then combined using an adaptive combination of forecasts with time varying weights.

Most efforts are now being devoted to the design of hybrid models, the combination of forecasts and ensemble forecasting. In Sideratos and Hatziargyriou (2007), neural networks and fuzzy models are integrated in a new hybrid model. Several NWP models are used in Giebel et al. (2005) to estimate the uncertainty of wind forecasts. The basic assumption is that if the different model members are differing widely, then the forecast is very uncertain, while close model tracks mean that this particular weather situation can be forecasted with good accuracy. Furthermore, it has been empirically confirmed since a long time (Newbold and Granger 1974) that a simple combination of forecasts works better in many cases than any of the models themselves.

3.2.1 Error Measures for Wind Power Forecasting

Comparing the different models is quite difficult as the performance strongly depends on the geographic situation of the wind farm (constant or volatile winds, onshore or offshore) as well as the quality and quantity of available input data. Furthermore, different reference models (like persistence[6] (Nielsen et al. 1998) or meteorological mean[7]) and error measures (mean absolute error (MAE) or mean square error (MSE), relative to wind farm installed capacity or relative to average production) are used in practice.

The most difficult case, where the highest errors are achieved independently of the method, corresponds to stand-alone onshore wind farms. In that case, the reported MAE, for prediction horizons from 3 to 10 h, ranges from 30 to 50% of the

[6] The persistence model acts on the assumption that the produced energy remains constant during the prediction horizon and is hard to beat for short prediction horizons of up to 3 h.

[7] The estimated value of the meteorological mean model is the historic average production.

energy production, depending on the complexity of the terrain. By grouping wind farms in portfolios, errors can be reduced to the range of 15–20% of energy production. The best results are obtained by integrating the results of NWP with online measures through black-box or grey-box models such as ANN (some knowledge of the wind power properties is used to tune the grey-box models to the specific domain).

4 Forecasting Electricity Prices

The new competitive framework, imposed by the worldwide liberalization of the electricity industry, has forced agents operating in wholesale electricity markets to follow the long-term, medium-term and short-term spot price movements in order to trade this new commodity on regulated markets or through bilateral contracts. In many countries, the key component of the wholesale market is a day-ahead auction (Green 2008), where sellers and buyers submit their bids in terms of prices and quantities for the 24 h (or 48 half-hour in some markets) of the next day. The hourly (or half-hourly) marginal prices are then obtained at the intersection of aggregated supply and demand curves. Many short-term decision-making processes in this framework, as the design of bidding strategies, require accurate predictions of the spot prices.

4.1 Factors Affecting Electricity Prices

As stated in Karakatsani and Bunn (2004),

> due to the idiosyncrasies of wholesale electricity markets, spot price dynamics are only partially understood.

These idiosyncrasies include the instantaneous nature of the commodity, the steeply nature of the supply function due to the presence of different generation technologies, the oligopolistic nature of these markets, complex market designs, frequent regulatory interventions and market structure changes.

However, electricity load is usually the most important factor affecting the behaviour of electricity prices time series around the world. This is an obvious fact, as market clearing prices are obtained by crossing supply and "quasi-inelastic" demand curves constructed from aggregated bids. Therefore, with stable remainder factors, an increase of demand will entail an increase of the spot price, and factors affecting the price, as economic activity, daily and hourly cycles or temperature fluctuations, are captured in a certain degree through this variable. System operators usually provide demand predictions to market agents as an input to their bidding planning processes. Notice how PJM prices are mimicking the demand in the particular case shown in Fig. 7. Nevertheless, as stated in Bunn and Karakatsani (2003), spot electricity prices display in general a rich structure much more

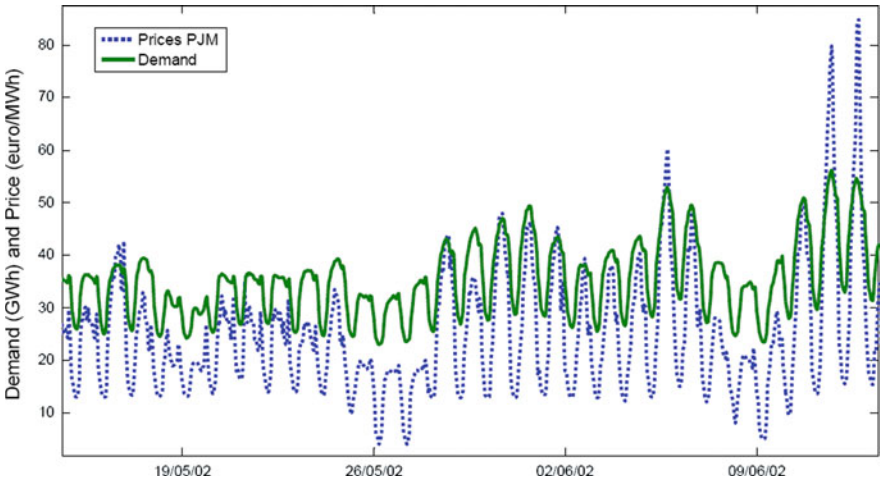

Fig. 7 Price (euro/MWh) and demand (GWh) in PJM

complicated than a simple functional rescaling of demand to reflect the marginal costs of generation.

On the supply side, the generation mix of each specific market is a determinant factor to explain the spot price. In Spain, for example, wind generation has become a very meaningful variable, due to its high volatility, high penetration level[8] and a special regulatory treatment which leads wind generators to act as price takers. In the Nord Pool, a very outstanding variable is the amount of water resources available for power generation. In general, the way in which suppliers construct their bids is strongly determined by the production costs of the generation technologies covering the demand. Therefore fuel costs, emissions costs, reserves, power exports and imports and maintenance outages, among others, determine the resulting electricity price. However, it is important to note that when hourly (or half-hourly) short-term predictions are involved, some of these variables are not useful to explain the high frequency fluctuations of the prices. Others variables, for example hydropower generation, are difficult to predict or are not available in the short time for every market participant.

A more detailed and exhaustive description of the explanatory variables affecting spot market prices can be found in Karakatsani and Bunn (2008), Bunn (2004) and Li et al. (2005).

[8] Eleven percent of the Spanish demand in 2008 was satisfied by wind generators. The maximum hourly demand in 2008 was attained on December 15th (42,961MW) and 18% of this demand was fulfilled with wind energy.

4.2 Features of Electricity Price Time Series

Electricity price time series in deregulated electricity markets are generally considered to be erratic and ill-behaved (see Knittel and Roberts (2005), Weron (2006) and Escribano et al. (2002)). The main features that characterize this behaviour are mean reversion, seasonal effects (daily, weekly and annual), different intra-day and intra-week patterns, calendar effects, time-varying volatility, fat-tailed and skew distributions, and extreme values. Note some of these features, as the daily and weekly patterns, the time-varying volatility, or the extreme values, in Fig. 2.

The most distinctive of these features is the presence of extreme values or spikes. These spikes are unanticipated extreme changes in the time series within a very short period of time. During this period, the price dramatically increases and then drops back to the previous level. They are normally observed when demand is high (peak hours) and are present in most of the electricity markets, though not with the same intensity. The lower picture in Fig. 8 illustrates some spikes that occurred in the Victoria market. The price value reached the value of 8,000 cE/MWh, two orders of magnitude above its normal level.

These spikes are usually due to a combination of different factors. On the one hand, the non-storability of electricity causes most expensive technologies to establish the price during periods of high demand. Moreover, generation outages or transmission failures can make these situations worse. In this context, the participant strategies play a very important role. On the other hand, as the electricity is an essential commodity for many buyers, they are willing to pay almost any price to secure the supply of power.

In the modelling context, it is an advisable practice to previously eliminate the spikes from the in-sample data. Otherwise, these extreme values could dramatically affect the value of the final parameters and make the model capture properly neither the usual behaviour nor the spikes. Some parametric methods have been developed to automatically detect and correct outliers (see Maravall (2005) and Chang et al. (1988)). Other ways to prevent the negative effects of spikes in the fitting process are pre-filtering using the wavelet transform (Conejo et al. 2005) or damping the prices above a certain threshold (Weron 2006). However, spikes are not incorrect values of the price time series, and well specified models should be able to model their occurrence. Jump diffusion and regime-switching models (Hamilton 2005) including at least one spike generation process have been developed for that purpose. These models will be described in more detail in Sect. 4.3.2.

Another important feature, related with spikes, is the special underlying distribution of the electricity price stochastic process. The empirical distributions obtained through the traditional Gaussian fitting framework rarely accomplish with the normality (or log-normality) assumption. There is a lot of literature pointing out the fact that electricity price distributions are heavy-tailed and skewed (see, e.g. Knittel and Roberts (2005) and Weron (2006)). Furthermore, the time-varying volatility of day-ahead market prices prevents the fulfilment of the assumption of homokedasticity. GARCH models (Generalized Auto Regressive Conditional Heterokedastic) are an attempt to capture this dynamic volatility as a function of variances of previous time

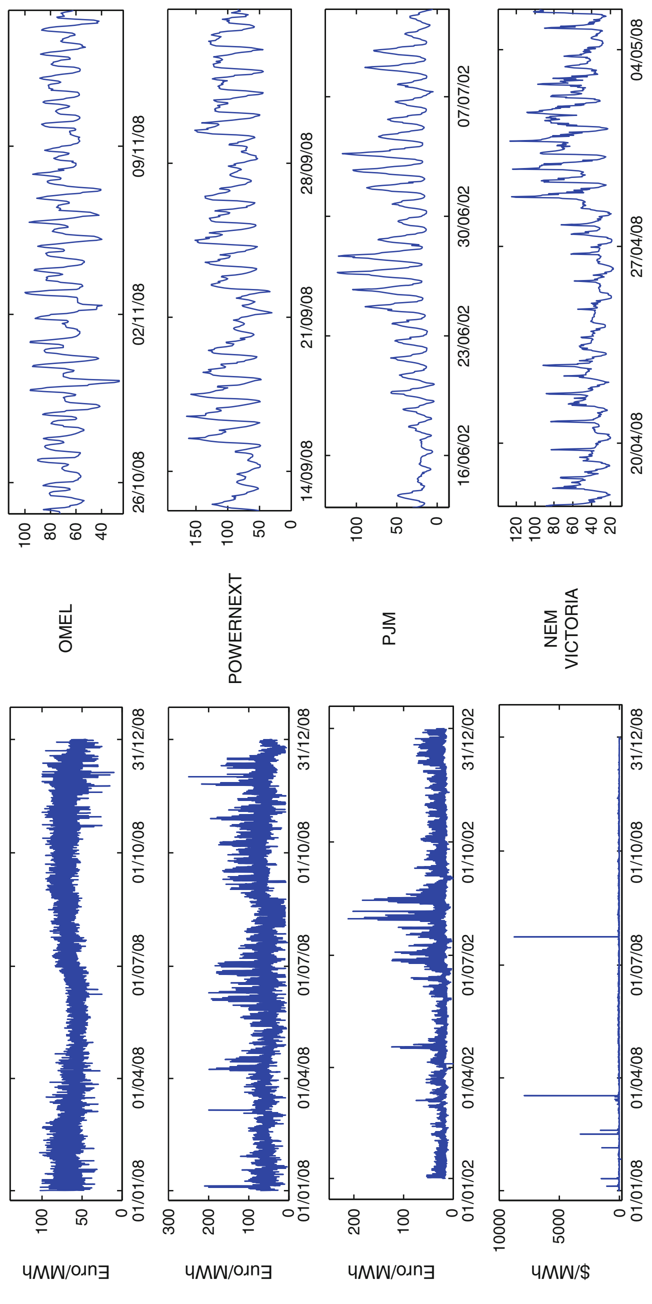

Fig. 8 Prices in OMEL (Spain), POWERNEXT (France), PJM (Pennsylvania, New Jersey, Maryland) and NEM (Victoria)

periods. However, models with GARCH noise have not shown evidences of better forecasting ability in price prediction than their homokedastic equivalent (Misiorek et al. 2006; Knittel and Roberts 2005). Recent advances trying to find a satisfactory distribution include the work of Weron (2008), where a set of non-Gaussian distributions are tested on the price time series of different electricity markets. In Weron and Misiorek (2008), a set of semi-parametric models whose density functions are estimated through kernel estimators is compared with their Gaussian parametric counterparts, concluding that semiparametric models lead to better point and interval forecasts. In Panagiotelis and Smith (2008), a VARX (Vector autoregressive) model specified through a sparse coefficients matrix and skew t distributions is proposed.

4.3 Electricity Price Forecasting Models

Many different modelling approaches have been proposed in the literature to deal with short-term electricity price forecasting. Most of these techniques may be roughly divided into three categories: (1) quantitative models, (2) models coming from the statistical time series analysis domain and (3) artificial intelligence approaches. In the following sections, an overview of the most relevant models of these three groups is presented. The overview does not pretend to be exhaustive, and so readers interested in a detailed taxonomy in short-term price prediction are referred to the published works in Weron (2006), Bunn and Karakatsani (2003), Li et al. (2005) and Mateo et al. (2005).

4.3.1 Quantitative Models

Quantitative models are generally used with the primary aim of derivatives valuation and risk management (see Pilipovic (1998)). It is important to note that they are not pretended to be accurate forecasting tools, but to capture the main characteristics of electricity prices. They include mean reversion and jump-diffusion models (see Knittel and Roberts (2005), Deng et al. (2001), Lucia and Schwartz (2002), de Jong and Huisman (2003), and Geman and Roncoroni (2006)), conditional heteroskedastic models (Escribano et al. 2002; Wilkinson and Winsen 2002) and hybrid models, which introduce fundamental explanatory variables, as demand, fuel costs or generation capacity, in the above models (Barlow 2002; Burger et al. 2004; Anderson and Davison 2008).

The mathematical formulation of these models can be illustrated with the general expression of jump diffusion models, which are described by stochastic differential equations of the form (Weron 2006)

$$\mathrm{d}P_t = \mu(P_t, t)\mathrm{d}t + \sigma(P_t, t)\mathrm{d}W_t + \mathrm{d}q(P_t, t), \tag{16}$$

where P_t stands for the price at time t, $\mu(P_t, t)$ is a drift term that induces mean reversion to a stochastic or deterministic long term mean, $\sigma(P_t, t)$ is a volatility term, W_t is a Brownian motion process and $q(P_t, t)$ is a Poisson pure jump process that produces infrequent but large jumps.

4.3.2 Statistical Time Series Analysis-based Models

Within the statistical time series analysis framework, a lot of research activity has been developed for modelling and forecasting the day-ahead spot prices of world-wide liberalized electricity markets. The models more frequently used are detailed below.

Linear Transfer Functions Models (LTF)

Some initial contributions are the papers by Nogales et al. (2002) and Carnero et al. (2003), which pointed out that dynamic regression and transfer function models are very accurate methods for the Spanish and Californian market. These conclusions are corroborated in Conejo et al. (2005b) and extended to others electricity markets in Zareipour et al. (2006a), Bunn and Karakatsani (2003), Misiorek et al. (2006).

The general expression of LTF models was introduced in (12). ARFIMA (Autoregressive fractionally integrated moving average) models are also obtained from LTF by permitting fractional integration orders (parameters $d, D_1 and D_2$). They are used in Koopman et al. (2007) to model the long memory dynamics of different European electricity market prices.

The LTF formulation can be easily extended to the multiple-input multiple-output (MIMO) case. These models provide an alternative way to forecast the 24 hourly prices of the next day. Each hourly component of the daily price vector can be differently explained through daily vectors of delayed prices and explanatory variables. Moreover, the daily price vector is predicted one-step ahead, that is, in the same manner the day-ahead market clearing process occurs. It is important to note the difference when considering the hourly approach, in which the 24 h of the next day are predicted in a sequential manner from hour 1 to hour 24, and therefore the prediction uncertainty of each hour affects the following ones. In Panagiotelis and Smith (2008), a VARX model is used to forecast the Australian electricity spot prices.

Regime-Switching Models

ARIMA and LTF models have been extended to incorporate non-linearities. This is the case of threshold auto-regressive (TAR) models, in which a different set of parameters is applied at each time according to the value of an observable variable.

These models are tested for short term electricity price forecasting in Misiorek et al. (2006), Weron and Misiorek (2008) and Bunn and Karakatsani (2003), where competitive results are reported for both point and interval forecasting. Periodic time series models are similar to threshold models, but in this case a different set of parameters is determined for each pre-defined season. Koopman et al. (2007) provides a comparison of alternative univariate time series models that are advocated for the analysis of seasonal data. Electricity prices of several European markets are investigated and modelled, taking into account the day of the week through periodic models. In Guthrie and Videbeck (2002), periodic models are used to capture the intra-day dynamics of New Zealand electricity prices.

The general expression of a LTF regime-switching process with m seasonalities is given by

$$\begin{aligned} P_t = {} & C_{R_t} + v_{1,R_t}(B)X_{1t}, +\ldots + v_{n,R_t}(B)X_{nt} + \\ & \frac{\theta_{q,R_t}(B)\Theta_{Q_1,R_t}(B^{S_1})\cdots\Theta_{Q_m,R_t}(B^{S_m})}{\phi_{p,R_t}(B)\Phi_{P_1,R_t}(B^{S_1})\cdots\Phi_{P_m,R_t}(B^{S_m})\nabla^d\nabla_{S_1}^{D_1}\cdots\nabla_{S_m}^{D_m}}\varepsilon_t, \end{aligned} \tag{17}$$

where $R_t = \{1, \cdots, K\}$ stands for the season index (case of periodic models) or the regime determined by an observable variable (case of threshold models) at time t, K being the number of seasons or regimes and having been the remainder parameters previously defined.

Markov regime-switching models are an alternative to threshold and periodic models, where the different underlying processes are not directly determined by an observable variable, but by a set of hidden exclusive states and a probability law that governs the transition from one regime to another. In the context of short-term price prediction, they have been used for modelling spikes and other anomalous behaviors. Related works can be found in Weron (2008), Bunn and Karakatsani (2003) and Huisman (2008).

4.3.3 Artificial Intelligence-based Models

The techniques coming from this field of knowledge differ from the previous ones, in that the model structure is not specified a priori, but is instead determined from data. Because of this fact, they are also known as non-parametric techniques. A large number of heterogeneous techniques lay within this category but ANN have received most attention in short-term electricity price forecasting. Other important techniques within this group which will not be covered in more detail are fuzzy Logic (Niimura and Nakashima 2001), weighted nearest neighbours (Lora et al. 2007), similar-day based methods (Mandal et al. 2007), multi-variable adaptative regression splines (Zareipour et al. 2006b), SVM (Gao et al. 2007) and dimensionality reduction (Chen et al. 2007).

ANNs are used in this context as multivariate non-linear regression models with universal function approximation capabilities (Cybenko 1989). Their main drawbacks are the risk of overfitting and their lack of interpretability.

One of the first attempts to tackle the problem of price prediction through feed-forward neural networks is presented in Szkuta and Sanabria (1999). In this work, actual and delayed system loads and reserves, and delayed prices are selected as network input variables to predict the spot prices in the Victoria electricity market. The multilayer perceptron is also used in Gao et al. (2000) to predict the prices and quantities of the Californian day-ahead energy market. In this case, historical prices, system loads, fuel costs, power imports and exports, temperatures, and hour and weekday seasonal indexes are considered as input variables. Feed-forward networks are also applied in Pino et al. (2008) after a previous selection of the training samples through an adaptative resonance theory (ART) neural network to predict Spanish electricity prices. In Pindoriya et al. (2008) and Andalib et al. (2008), feed-forward wavelet neural networks, in which wavelet functions are used as activation functions of the hidden-layer neurons (usually referred as “wavelons”), are considered for the Spanish, PJM and Ontario markets. In Rodríguez and Anders (2004) and Amjady (2006), fuzzy logic techniques and neural networks are combined in fuzzy neural networks to predict the prices in Ontario and Spain, respectively. In Mandal et al. (2007), a feed-forward neural network is used to correct the price curve obtained from a similar day approach.

More complex architectures have also been tested to cope with this task. For instance, Elman recurrent neural networks are used in Andalib et al. (2008) and Hong and Hsiao (2002). In both cases the ability to model fast non-linear variations and good generalization performance of this architecture are pointed out. Switching-regime models based on neural networks are applied in Mateo et al. (2005). In this work, an input–output hidden Markov model is proposed to model the discrete changes in competitors’ strategies. The model provides not only the point prediction but also the probability density function, which is conditioned to input variables and the previous state of the system.

4.3.4 Error Measures for Electricity Price Forecasting

Because of the erratic and changing behaviour of electricity prices, error measures are often considered for each week of the validation period. The weekly mean absolute percentage error (WMAPE) is commonly used in the literature to test the accuracy of price prediction models (see, e.g. Amjady (2006), Pindoriya et al. (2008), Nogales et al. (2002)). However, to avoid the adverse effects of prices close to zero, weekly-weighted mean absolute error (WMAE) and weekly root mean square error (WRMSE) are also frequently considered (see, e.g. Conejo et al. (2005), Weron and Misiorek (2008), Mandal et al. (2007)). These error measures are given by (P_h and $\widehat{P_h}$ are the actual and predicted prices for hour h)

$$WMAPE = \frac{1}{168}\sum_{h=1}^{168}\left|\frac{P_h - \widehat{P_h}}{P_h}\right| \tag{18}$$

$$WMAE = \frac{\sum\limits_{h=1}^{168}|P_h - \widehat{P_h}|}{\sum\limits_{h=1}^{168}P_h} \tag{19}$$

$$WRMSE = \sqrt{\frac{1}{168}\sum_{h=1}^{168}(P_h - \widehat{P_h})^2}. \tag{20}$$

The results with these measures along the literature vary a lot depending on the considered market and period of time. The Spanish electricity day-ahead market is one in which less volatility and number of spikes are observed. In this market, the reported results for the WMAPE range from 6 to 25%, depending on the considered week.

5 Conclusions

This paper has presented a survey in short-term forecasting of the three random variables that are currently getting the most attention in electric power systems: electricity loads, wind power and spot prices. Short-term forecasting in this context refers to prediction horizons that range from 1 h to 1 week, as hourly or half-hourly data is considered in the three cases. The survey has covered three main topics: (1) the special features that characterize demand, wind power and electricity price time series, (2) a classification of the modelling approaches and (3) the error measures used to quantify the forecasting accuracy.

Short-term load forecasting is a well established discipline and is in the core of many operational processes, including power system planning, scheduling and control. The key aspects to be considered when forecasting electricity loads are the treatment of multiple seasonalities, the non-linear effect of temperature on electricity consumption and the complexity of calendar effects.

The increasing integration of wind power in electricity systems has forced system operators and market agents to cope with this new source of volatility by investing in wind power forecasting tools and integrating them into their operational systems. Short-term forecasts are needed for power system security assessment applications, the operation of wind energy in day-ahead electricity markets, unit commitment, economic dispatch and maintenance planning. The high volatility of wind dynamics and the non-linear physical relationship between wind speed and generated power lead to very complex wind power time series. Recent contributions in this area include spatial correlation, ensemble forecasting and density forecasting methods.

The worldwide liberalization of the electricity industry has intensified the risk exposure of electricity generators and retailers. Many decision-making processes in this framework, as the design of bidding strategies or the pricing of derivatives, require accurate spot price predictions. Electricity price time series are generally erratic and ill-behaved, contaminated by spikes and non-Gaussian distributions. Electricity price forecasting models are moving from univariate to multivariate, from single to multiple regime switching models and from point forecasts to interval and density forecasts.

The complete set of models and techniques included in this paper, accompanied by a selected bibliography, constitute a guided tour in power systems forecasting.

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