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Electric load forecasting methods: Tools for decision making

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ABSTRACT

For decision makers in the electricity sector, the decision process is complex with several different levels that have to be taken into consideration. These comprise for instance the planning of facilities and an optimal day-to-day operation of the power plant. These decisions address widely different time-horizons and aspects of the system. For accomplishing these tasks load forecasts are very important. Therefore, finding an appropriate approach and model is at core of the decision process. Due to the deregulation of energy markets, load forecasting has gained even more importance. In this article, we give an overview over the various models and methods used to predict future load demands.

1. Load forecasts in deregulated markets

Decision making in the energy sector has to be based on accurate forecasts of the load demand. Therefore, load forecasts are important tools in the energy sector. Forecasts of different time-horizons and different accuracy are needed for the operation of plants and of the complex power system itself: The "system response follows closely the load requirement" (Kyriakides and Polycarpou, 2007, p. 392). The decision maker is faced with a multitude of decision problems on different time-scales as well as on different hierarchies of the power system: These problems comprise for instance the determination of an optimal secure scheduling of unit commitment and energy allocation. But decisions do not have made only with respect to the day-to-day operation of the power system but also with respect to investment decisions on new facilities based on the anticipation of future energy demands. For both ends, reliable forecasts are needed. The deregulation of energy markets has increased the need for accurate forecasts even more (see e.g. Feinberg and Genethliou, 2005; Kyriakides and Polycarpou, 2007). To participate in the market, a player needs an accurate estimate how much energy is needed at a certain time. On the one hand, an underestimation of the energy demand by a supplier may lead to high operational costs because the additional demand has to be met by procuring energy in the market. An overestimation on the other hand wastes scarce resources (see e.g. Tzafestas and Tzafestas, 2001; Feinberg and Genethliou, 2005; Kyriakides and Polycarpou, 2007). Furthermore, demand is one of the main factors for pricing. Load forecasting is therefore at the core of nearly all decisions made in energy markets. Due to the high importance of accurate load forecasting, the history of this field is quite long: A 1987 survey paper (Gross and Galiana, 1987) lists an impressive number of publications devoted to load analysis and forecasting – reaching back as far as 1966 (Heinemann et al., 1966). Up to now, various approaches have been introduced. They can be grouped into two main classes: Models and methods which follow a more classical approach, i.e., which apply concepts stemming from time series and regression analysis and methods which belong to the fields of Artificial and Computational Intelligence.

This paper gives a short survey over models and methods for load forecasting. Further survey and review papers are for example Kyriakides and Polycarpou (2007), Feinberg and Genethliou (2005), Tzafestas and Tzafestas (2001) and Hippert et al. (2001).

2. Short-term, medium-term and long-term forecasts

As we have seen, forecasts are made for various purposes: the day-to-day operation of the power system (e.g. Kyriakides and Polycarpou, 2007) requires the prediction of the load for a day ahead whereas the decision whether to undertake major structural investments requires a far longer prediction horizon. Forecasts can be distinguished therefore firstly by the time-horizon or the lead time: short-term load forecasts (STLF) usually aim to predict the load up to one-week ahead (Kyriakides and Polycarpou, 2007). Frequently, the term very short-term load forecasts is used for forecasts with a time-horizon of less than 24 hours (see Yang, 2006, p. 7). Up to now, the main focus in load forecasting has been on STLF since it is an important tool in the day-to-day operation of utility systems (see e.g. Gonzalez-Romera et al., 2006). More recently with the deregulation of energy markets, more and more attention is also paid to load forecasts with a greater time-horizon,

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i.e., medium-term load forecasts. As stated in (Gonzalez-Romera et al., 2006), medium-term load forecasts enables companies to estimate the load demand for a longer time interval which helps them for example in the negotiation of contracts with other companies. Medium-term load forecasts (MTLF) are from one week to one year. Forecasts aiming at load prediction for more than a year ahead are usually termed long-term load forecasts (LTLF) (see e.g. Feinberg and Genethliou, 2005). As stated in Kyriakides and Polycarpou (2007) the time-horizon in LTLF is usually 20 years although longer lead times of 25–30 years can be found. The differences in lead times have consequences for the models and methods applied and for the input data available and selected. The load demand is influenced by numerous factors – ranging from weather conditions over seasonal effects to socio-economic factors. Which input data has to be selected usually depends on the task and data at hand. The decision maker, therefore, is not only faced with the task of selecting an appropriate model type but also with determining important external factors. Both tasks usually depend on each other. Some general observations can be made, however.

As stated in Fidalgo et al. (2007), it depends on the region and the climatic conditions whether weather-dependent factors have a significant influence on the prediction. There is a common agreement that the air temperature is the most important weather influence (see e.g. Hippert et al., 2001; Feinberg and Genethliou, 2005). This was already recognized in the 1930s (Hippert et al., 2001). Generally, the demand is high on cold days which can be attributed to electric heating. Similarly on hot days, the increased usage of air-conditioning generates a higher demand of energy. In many countries, this results in a U-shaped and clearly non-linear response function of the load towards the temperature (Hippert et al., 2001). However, the exact shape of the curve depends on the region, the climatic conditions and of course on the consumers' behavior.

Additionally, the designated time-horizon and the availability of the data determines the input variables. As mentioned in (Taylor et al., 2006) univariate models are standard for very short-term load forecasts for up to 6 hours ahead. Furthermore, it should be noted that sometimes obtaining accurate weather forecasts may be difficult. Therefore, univariate models are also applied for longer lead times (Taylor et al., 2006; Soares and Souza, 2006).

In Kyriakides and Polycarpou (2007) three main groups of input data for short-term load forecasts are identified: seasonal input variables, weather forecast variables, and historical load data (Kyriakides and Polycarpou, 2007). Short-term load forecasts usually aim at providing the daily, hourly, or half-hourly load and the peak load (day, week) (see e.g. Tzafestas and Tzafestas, 2001) although even smaller time intervals occur. Forecasting the load profile, i.e., the load of the next 24 hours, is also a main target (Tzafestas and Tzafestas, 2001; Hippert et al., 2001).

Medium-term load forecasts usually incorporate several additional influences – especially demographic and economic factors. These forecasts often provide the daily peak and average load, although hourly loads are also sometimes given, e.g. Bruhns et al. (2005). In the case of long-term load forecasts, even more indicators for the demographic and economic development have to be taken into account (Kyriakides and Polycarpou, 2007). These are for instance the population growth and the gross domestic product. Long-term load forecasting usually aims at predicting the annual load and the peak load (Kyriakides and Polycarpou, 2007).

The time series of the loads itself has generally three seasonal cycles: an intra-daily cycle (the daily load curve or the load profile), a weekly cycle, and a yearly seasonal cycle. The weekly cycle usually shows two main groups: week-days and weekends. Due to industrial demand, the load tends to be higher during week-days. The weekend tends to influence the neighboring days so that Mondays and Fridays are often treated separately. Saturday is also often found to show a different load profile than Sunday. However, the exact weekly pattern depends on the particular region under consideration and furthermore on the season (Hippert et al., 2001). Additionally "regular" exceptional cases can be identified – for instance holidays, start and end of daylight saving time, etc. These exceptional days depend on the calendar date which is also commonly considered as a very important information. Several approaches, however, neglect these exceptional cases (e.g. Hippert et al., 2005; Taylor and McSharry, in press). One of the reasons for this is that there are typically only few data available which could be used to estimate the model parameters for these day-types.

Concerning the seasonal data patterns, different approaches are followed. Generally, local and global approaches can be distinguished. Local approaches apply distinct models for each identified feature: for instance a model for each distinct day-type or a hour. However, this may lead towards problems if the data basis is not sufficiently large (Hippert et al., 2001). Therefore, in several approaches a single monolithic model is build and the information is encoded in the input data.

3. Models and methods

This section gives an overview over various approaches for load forecasting. Many of them are developed for STLF although MTLF has gained importance which is especially due to the deregulation of electricity markets. The dominance of STLF-methods is also reflected in the survey papers (Hippert et al., 2001; Tzafestas and Tzafestas, 2001; Feinberg and Genethliou, 2005; Kyriakides and Polycarpou, 2007). Only Feinberg and Genethliou (2005) included an overview over MTLF and LTLF-methods whereas the remainders focused on short-term load forecasts. Our own non-exhaustive survey of over 100 papers shows a similar composition.

There are various approaches applied to load forecasting (Kyriakides and Polycarpou, 2007; Feinberg and Genethliou, 2005; Taylor and McSharry, in press; Hippert et al., 2001; Tzafestas and Tzafestas, 2001). These range from regression-based approaches over time-series approaches towards artificial neural networks and expert systems. In the following, a short overview over some of the models and methods is given. The error measure most frequently used to assess the performance of a model – at least in the literature found – is the mean absolute percentage error (MAPE) defined by $\mathrm{MAPE} = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right|$ with y_t the real value at point t and $\hat{y}_t$ the forecast.

3.1. Classical time series and regression methods

Statistical approaches require an explicit mathematical model which gives the relationship between load and several input factors. Several classical models are applied for load forecasting, for example regression-based methods, time series methods, state space models and Kalman-filtering. In the following, we focus on regression-based and time series models.

3.1.1. Regression-based models

Regression models are quite common in load forecasting (Kyriakides and Polycarpou, 2007) and used to model the relationship between the load and external factors, for instance weather and calendar information or customer types (Feinberg and Genethliou, 2005). Mainly, linear regression is used – the influence of the temperature is usually modeled non-linearly, however. Regression methods are relatively easy to implement. A further advantage is that the relationship between input and output variables is easy to comprehend. Regression models also allow relatively easy performance assessments (see e.g. Bruhns et al., 2005). As reported in Kyriakides and Polycarpou (2007), there may be inherent problems in identifying the correct model, though, which are due to the complex non-linear relationship between the load and the influencing factors. Further drawbacks are reported in Kyriakides and Polycarpou (2007). In the following, two examples are presented. Many more approaches appear in the literature – for example regression models based on local polynomial regression for STLF (Zivanovic, 2001), non-parametric regression (Charytoniuk et al., 1998), or robust regression methods (Jin et al., 2004). A description of further regression-based approaches can be found in Kyriakides and Polycarpou (2007) and Feinberg and Genethliou (2005).

Hor et al. developed a multiple regression model and analyzed the impact of weather variables on the load demand for England and Wales (Hor et al., 2005). They used data from 1989 to 1995 for model training and from 1996 to 2003 for testing the accuracy. Their aim was to provide an accurate model for a long-term prediction of the monthly demand. The regression model was based on two types of input variables: weather-dependent factors, i.e., temperature, wind speed V_w, rainfall M_r, relative humidity H_r, and hours of sunshine M_s and socio-economic factors, i.e., the Gross Domestic Product. Further socio-economic factors, for instance the population growth, were eliminated. First of all, they analyzed the relationship between load and temperature and found a non-linear dependence. In order to cope with this non-linearity several derived variables: heating degree days (HDD), cooling degree days (CDD), and enthalpy latent days (ELD) were introduced. The last variable takes the influence of humidity on air-conditioning into account. Three linear regression models were finally proposed: model 1 includes the CDD, HDD, and the ELD

$$\widehat{E}_A = \alpha_0 + \alpha_1 \mathrm{CDD} + \alpha_2 \mathrm{HDD} + \alpha_3 \mathrm{ELD} + \alpha_4 V_w + \alpha_5 M_s + \alpha_6 M_r. \quad (1)$$

Model 2 substitutes these values with the raw temperature and relative humidity while model 3 differs by model 1 only by a substitution of the ELD with the relative humidity. All models were then adjusted to take socio-economic factors into account. Model 1 and 3 were found to perform best with mean absolute percentage errors (MAPE) of 1.98% and 2.1% – although model 2 is also relatively good with a MAPE of 2.69%.

Bruhns et al. (2005) presented a non-linear regression model for MTLF. Their model is devoted to an hourly prediction of the load. The load was decomposed into a weather-dependent Phc_i and weather-independent part Pc_i, $P_i = Phc_i + Pc_i + \epsilon_i$ with i the ith observation and ϵ_i the error assumed to be Gaussian (Bruhns et al., 2005). The weather-independent part coveres trends, seasonal behavior, and calendar effects. The weather-dependent part is assumed to be mainly influenced by the temperature and the cloud cover. The relationship between temperature and load is fitted by a non-linear model differentiating between a heating part (temperature above a certain threshold) and a cooling part (temperature below a certain threshold) of the weather sensitive part of the load. The temperature does not enter the equations directly. First of all, it is exponentially smoothed to reflect the inertia to variations in buildings (Bruhns et al., 2005). Afterwards, it is averaged again with the observed temperature and – in the case of the heating part – with the cloud cover. This reflects the assumption that there is a mixed response to the temperature observed and to the temperature felt inside buildings (Bruhns et al., 2005). This aggregated temperature then enters the threshold function. For the weather-independent part of the load a product of two Fourier series was used. The first depended on the hour, the second on the day-type. The authors do not report the MAPE but the scale-dependent root mean squared error (RMSE). However, they note that the predecessor of their model which applied one Fourier series depending on the hour already achieved a MAPE of 2% for year ahead forecasts (known weather) and 1.5% for day ahead forecasts (Bruhns et al., 2005).

3.1.2. Time-series approaches

Time-series approaches (Box and Jenkins, 1970) are among the oldest methods applied in load forecasting. They can be distinguished on several levels. First of all, there are univariate (Taylor et al., 2006; Taylor and McSharry, in press) and multivariate methods. The former are usually used for very short-term load forecasts whereas the latter are applied for all time-horizons. The time series is usually assumed to be linear. It should be noted, though, that the assumption of linearity usually does not comprise the influence of the temperature. In this case, there appears to be an unanimous agreement that the non-linearity of this relationship has to be preserved in the model (Moral-Carcedo and Vicens-Otero, 2005). Several authors apply non-linear models (Hor et al., 2006).

A very simple class are the so-called autoregressive moving average or ARMA models (Brockwell and Davis, 1991). In short, a stationary process $(X_t)_{t\geqslant 0}$ is called an ARMA(p,q)-process if

$$X_t - \sum_{k=1}^{p} \phi_k X_{t-k} = Z_t + \sum_{m=1}^{q} \theta_m Z_{t-q} \quad (2)$$

holds. The process (Z_t) must be white noise with zero mean and constant standard deviation σ. The main steps consist of determining the order p of the autoregressive (AR)-part and q of the moving average (MA)-part and of estimating the coefficients (Brockwell and Davis, 1991). Common approaches for the estimation of the coefficients use Maximum-Likelihood or variants of least squares. It should be noted that these procedures generally require Gaussian noise. However, in Huang and Shih (2003) an ARMA-modeling procedure for STLF was presented which also allows for non-Gaussian noise. In the following, let B denote the lag or backshift operator, i.e., $BX_t = X_{t-1}$. Setting $\Phi(B) = 1 - \sum_{k=1}^{p}\phi_k B^k$ and $\Theta(B) = 1 + \sum_{m=1}^{q}\theta_m B^m$, (2) can be written shortly as $\Phi(B)X_t = \Theta(B)Z_t$.

In Huang et al. (2005) an ARMAX-model $\Phi(B)L(t) = \Theta(B)Z_t + \Psi(B)U_t$ with $\Psi(B) = \sum_{m=1}^{k}\psi_m B^m$ and exogenous variable U_t for one-day and one-week ahead hourly load forecasts for four example seasons in 1998 was presented. The exogenous variable in the case denoted the temperature. Instead of the classical algorithms to determine the model and to estimate the coefficients, particle swarm optimization (PSO) (Eberhart and Kennedy, 1995) was applied to determine both the order of the model and the coefficients. Particle swarm optimization is a so-called swarm-based optimization method and belongs to the class of Computational Intelligence (CI) methods.

The ARMA-model can be extended to so-called autoregressive integrated moving average (ARIMA) models. This model types uses differencing in order to cope with non-stationarity. An ARIMA(p,d,q)-model is thus $\Phi(B)(1-B)^d X_t = \Theta(B)Z_t$. The parameter d is required to be an integer. The models above are univariate linear models most often used for short-term load forecasts. As mentioned in Taylor et al. (2006), univariate ARIMA-models are often used as sophisticated benchmark models in STLF.

Amjady used a modified ARIMA-model to predict the hourly load demand and the daily peak loads in STFL (Amjady, 2001). His modified ARIMA-models takes not only past loads but also estimates of past loads into account. The estimates were provided by experienced human experts. Thus, in a sense the model incorporates human knowledge. First of all, Amjady identified four different day-types in the load data of the Iranian national grid: Saturday, Sunday to Wednesday, Thursday and Friday and public holidays. These models were separated again into models for hot days (average temperature above 23 degrees) and cold days. In total, 16 models were used. The parameters were estimated using data from 1996 to 1997 from the Iranian national grid and tested on data for 1998. The MAPE of the models ranged from 1.48% (Sunday to Wednesday, hot) to 1.99% (public holidays, cold).

The ARIMA/ARMA-models can be extended to take seasonality into account. Several models have been developed for this task. For example, in Espinoza et al. (2005) a periodic autoregressive model (PAR) was used of order p

$$y_t = C_S + \phi_{S,1} y_{t-1} + \cdots + \phi_{S,p} y_{t-p} + \epsilon_{S,t} \tag{3}$$

(see Espinoza et al., 2005) to represent the periodic dynamics of the series. The parameters are allowed to vary across the N_S seasons. In Espinoza et al. (2005) a PAR(48)-model was applied to model the intra-daily periodic behavior of the load curves whereas the monthly and weekly seasonality was covered by introducing dummy variables.

Taylor et al. (2006) and Taylor and McSharry (in press) presented a comparison of several univariate methods for short-term load forecasting. They analyzed four main models and two benchmark functions. The models chosen were double seasonal ARIMA (with-in day and with-in week cycle), exponential smoothing for double seasonality, artificial neural network, and a regression method with principal component analysis (PCA) (Taylor et al., 2006). The exponential smoothing method adapted by the authors is an extension of the classical seasonal Holt-Winter smoothing method to incorporate two seasonal cycles

$$S_t = \alpha \frac{y_t}{D_{t-s_1} W_{t-s_2}} + (1-\alpha)(S_{t-1} + T_{t-1}), \tag{4}$$

$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}, \tag{5}$$

$$D_t = \delta \frac{y_t}{S_t W_{t-s_2}} + (1-\delta) D_{t-s_1}, \tag{6}$$

$$W_t = \omega \frac{y_t}{S_t D_{t-s_1}} + (1-\omega) W_{t-s_2}, \tag{7}$$

$$\hat{y}_t(k) = (S_t + kT_t) D_{t-s_1+k} W_{t-s_2+s} + \phi^k (y_t - ((S_{t-1} + T_{t-1}) D_{t-s_1} W_{t-s_2})) \tag{8}$$

(see Taylor et al., 2006). The variables S_t and T_t denote the smoothed level and trend; D_t and W_t are seasonal indices (intra-day and intra-week) and $\hat{y}_t(k)$ is the forecast at $t+k$ from the starting point t (Taylor et al., 2006). The greek parameters (except ϕ) are the smoothing parameters to be determined. The parameter ϕ is an adjustment for first-order autocorrelation.

The comparison was based on two time series: the hourly demand for Rio de Janeiro in 1996 (30 weeks, 5th May 1996–30th November 1996) and the half-hourly demand for England and Wales in 2000 (30 weeks, 27th March–22nd October). Several error measures were considered, however, only the MAPE was reported since the other error measures lead to similar results. The exponential smoothing method emerged as the best approach.

In Taylor and McSharry (in press) the study was extended to an evaluation of six univariate methods based on the electricity demand of ten European countries. Again, the double seasonal exponential smoothing method was found to lead to the best results – with a MAPE below 2% even for the longest lead time of 24 hours. As it can be seen, time series based approaches are very common. However, several drawbacks are reported. As regression-based approaches time-series approaches may suffer from numerical instabilities (Huang and Shih, 2003; Kyriakides and Polycarpou, 2007).

3.2. Artificial intelligence and computational intelligence methods

Computational intelligence is a relatively new research field. The expression computational intelligence is commonly used to refer to the fields of fuzzy systems, artificial neural networks (ANN), evolutionary computation, and swarm intelligence. Of these fields, neural networks are the subtype which is most often applied in load forecasting.

3.2.1. Neural networks

Neural networks are modeled after the basic working principle of human brains. They consist of several neurons. A neuron receives information over its input nodes and aggregates the information. Afterwards, it determines its activation and propagates its response over the output node to other neurons. Neural networks are very frequently applied for load forecasting (see e.g. Hippert et al. (2001) for a survey). As stated in Hippert et al. (2005), in 1998 a software based on neural networks technology was used by over 30 US electric utilities. Several subtypes of neural networks exist (see e.g. Bishop, 1995). In load forecasting, for example, radial basis function networks (Ranaweera et al., 1995; Gonzalez-Romera et al., 2006), self-organizing maps (Becalli et al., 2004) for clustering and recurrent neural networks (Senjyu et al., 2004; Tran et al., 2006) are used. However, feed-forward neural networks (or multilayer perceptron) are the subtype which is most often applied (Hippert et al., 2001, 2005; Gonzalez-Romera et al., 2006; Becalli et al., 2004; Ringwood et al., 2001). A feed-forward network consists of several successive layers of neurons with one input layer, several hidden layers, and an output layer. The neurons are connected using weight vectors and neither feedback nor intralayer connections exist. A neuron i thus takes the output of its k input neurons, computes the weighted sum, subtracts a so-called bias θ_i and applies the activation function $a()$, i.e., $y_i = a(\sum_{k=1}^{n} w_{ik} x_k - \theta_i)$. The basic learning or weight-adjusting procedure is back-propagation (a form of steepest descent) which propagates the error backwards and adjusts the weights accordingly (Bishop, 1995). Frequently, only one hidden layer is used (see for instance Becalli et al. (2004), Fidalgo et al. (2007) and Hippert et al. (2005)). Hippert et al. (2005) provided a comparison of large neural networks (neural networks with a large number of neurons and weights) with several classical approaches. The classical approaches ranged from naive forecasting methods over smoothing filters and combination of smoothing filters with linear regression. Furthermore, hybrids of smoothing filters and neural networks were considered. The task was to forecast the 24 hours load profile based on data from a local utility in Rio de Janeiro. Used for building, testing, and validating the forecast model were the hourly loads and the temperature from April 1996 to December 1997. Hippert et al. (2005) found large neural networks to perform best – not only with the smallest MAPE (2.35–2.65%) but also with a lesser spreading of the errors. As they conclude, large artificial neural networks can be seen as competitive with other models as far as the forecasting of load profiles is concerned.

3.2.2. Support vector machines

Support vector machines (SVM) (see e.g. Vapnik, 1995) or more accurately support vector regression (SVR) were introduced relatively recently to the field of load forecasting, e.g. Chen et al. (2004), Niu et al. (2007b,c), Hsu et al. (2006), Wang et al. (2007), Afshin and Sadeghian (2007) and Li et al. (2007). Support vector machines are generally used for data classification and regression. They are non-linear kernel-based approaches. Instead of performing the regression in the original (x, y)-space the x-data are mapped into a higher-dimensional space using a mapping function ϕ. Support vector regression solves therefore

$$\min_{w,b,\zeta,\zeta^*} \quad \frac{1}{2}w^{\mathrm{T}}w + C\sum_{i=1}^{l}(\zeta_i + \zeta_i^*) \tag{9}$$

$$\text{subject to} \quad y_i - (w^{\mathrm{T}}\phi(x_i) + b) \leqslant \epsilon + \zeta_i^*, \tag{10}$$

$$(w^{\mathrm{T}}\phi(x_i) + b) - y_i \leqslant \epsilon + \zeta_i, \tag{11}$$

$$\zeta_i, \zeta_i^* \geqslant 0, \tag{12}$$

with ζ_i the lower training error (ζ_i^* the higher) subject to $| y - (w^{\mathrm{T}}\phi(x) + b) | \leqslant \epsilon$ (Chen et al., 2004). Instead of solving the problem in primal space, it is possible to switch to a dual representation

$$\min_{\alpha,\alpha^*} \quad \frac{1}{2}(\alpha - \alpha^*)^{\mathrm{T}}Q(\alpha - \alpha^*) + \epsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l}y_i(\alpha_i - \alpha_i^*) \tag{13}$$

$$\text{subject to} \quad \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0, \tag{14}$$

$$0 \leqslant \alpha_i, \quad \alpha_i^* \leqslant C, \tag{15}$$

with $Q_{ij} = \phi(x_i)^{\mathrm{T}}\phi(x_j)$ (Chen et al., 2004). The mapping function ϕ or, more exactly, the inner product remains to be determined. Instead of an explicit computation, special kernels are applied. Common examples include linear kernels $\phi(x_i)^{\mathrm{T}}\phi(x_j) = x_i^{\mathrm{T}}x_j$, polynomial kernels $\phi(x_i)^{\mathrm{T}}\phi(x_j) = (\gamma x_i^{\mathrm{T}}x_j + b)^d$, and radial basis function (RBF) kernels $\phi(x_i)^{\mathrm{T}}\phi(x_j) = \exp(-\gamma \mid x_i - x_k|^2)$. In the context of load forecasting, the RBF kernel is used in most cases. Chen et al. (2004) applied support vector regression for MTLF. The context of the application was a competition organized by EUNITE (EUropean Network on Intelligent TEchnologies for Smart Adaptive Systems). The aim of the competition was to predict the load demand (daily peak loads) in January 1999. The data made available comprised half-hourly loads from 1997 to 1998, average daily temperature from 1995 to 1998 and the dates of holidays from 1997 to 1999. The SVR-method developed by Chen et al. (2004) won the EUNITE competition followed by an Adaptive Logic Network approach (Esp, 2002), a machine-learning approach similar to standard feed-forward neural networks. In Chen et al. (2004), an extension of the original EUNITE study was presented. The best approach reached a MAPE of 1.95%. It consisted of a SVR using the load information of the past seven days and calendar information as input variables. For training, only "winter" data, i.e., load information from January to March and from October to December was taken into account, since the authors identified two clearly separate patterns for summer and winter load times series (Chen et al., 2004).

3.2.3. Hybrid and other approaches

Hybrid approaches are also very common. Generally, these approaches combine two or more different approaches in order to overcome some drawbacks of the original methods. Frequently, combinations of CI-methods and classical methods or of several CI-methods can be observed. We already mentioned that particle swarm optimization (PSO) was used to determine the order and the coefficients of an ARMAX-model (Huang et al., 2005). Particle swarm optimization (Eberhart and Kennedy, 1995) is used also in combination with fuzzy neural networks (Liao, 2007), neural networks (Bashir and El-Hawary, 2007; Niu et al., 2007a), and support vector machines (Wang et al., 2007). A particle swarm models the swarming behavior of a flock of birds or a school of fish. It consists of a population of several individuals, each representing a possible solution. The individuals update their position and velocity based on the memory of their best position and the best position in a neighborhood (or the whole swarm) (Engelbrecht, 2006). Frequently, genetic algorithms or other evolutionary algorithms are applied in combination with artificial neural networks (de Aquino et al., 2007; El Desouky et al., 2001; Liao and Tsao, 2006). In Huo et al. (2007) genetic programming (see e.g. Eiben and Smith, 2003) was used directly for load forecasting. In short, evolutionary algorithms mimic the natural evolution: they are population-based search or optimization heuristics that apply the principles of recombination, mutation, and selection to find good solutions. Since they are on the one hand population-based and on the other randomized algorithms, they are expected to be more robust against a convergence in local optima and towards noise (Kyriakides and Polycarpou, 2007). Furthermore, they do not require the same restrict assumptions as some classical approaches. Genetic programming is a specific evolutionary algorithm which evolves "programs" or functions directly. Apart from genetic programming, evolutionary algorithms and PSO appear to be applied mainly for determining an optimal setting of control parameters of the principal method.

4. Conclusions

Load forecasting is very important for decision processes in the electricity sector. In this paper, we have given an overview over commonly used input variables and forecast targets. Afterwards, we presented several classes of models and methods. Several recent trends can be identified: Support vector regression has emerged as a relatively new and competitive method for load forecasting. Furthermore, more and more attention is focused on hybrid approaches.

Load forecasting is not only important to provide accurate estimates for the operating of the power system but also as a basis for energy transactions and decision making in energy markets. The accuracy of forecasts is a very crucial factor: A decision maker in the energy sector has the need of accurate forecasts since most of the decisions are necessarily based on forecasts of future demands. One of the first decisions to be made is therefore the selection of an appropriate model. This depends on the problem and the situation currently under consideration. Therefore, no general recommendations can be given.

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