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STATISTICAL APPROACHES TO SHORT-TERM ELECTRICITY FORECASTING

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THIS DISSERATION IS DEDICATED TO MY HUSBAND, CHILDREN,
AND TO ALL MY FAMILY.

ABSTRACT

The study of the short-term forecasting of electricity demand has played a key role in the economic optimization of the electric energy industry and is essential for power systems planning and operation. In electric energy markets, accurate short-term forecasting of electricity demand is necessary mainly for economic operations.

Our focus is directed to the question of electricity demand forecasting in the Czech Republic. Firstly, we describe the current structure and organization of the Czech, as well as the European, electricity market. Secondly, we provide a complex description of the most powerful external factors influencing electricity consumption. The choice of the most appropriate model is conditioned by these electricity demand determining factors. Thirdly, we build up several types of multivariate forecasting models, both linear and nonlinear. These models are, respectively, linear regression models and artificial neural networks. Finally, we compare the forecasting power of both kinds of models using several statistical accuracy measures. Our results suggest that although the electricity demand forecasting in the Czech Republic is for the considered years rather a nonlinear than a linear problem, for practical purposes simple linear models with nonlinear inputs can be adequate. This is confirmed by the values of the empirical loss function applied to the forecasting results.

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1 INTRODUCTION

During the last two decades the electric power industry all over the world significantly restructured. In the past, the electricity industry was organized as vertically integrated monopolies that were mostly state-owned. The growing ideological and political disaffection with vertically integrated monopolies and the liberalization successes in other network industries have led to liberalization initiatives in the electricity industry. Vertically integrated utilities have been vertically separated or unbundled and barriers to entry in generation and supply are being removed to create competition, seen as a vehicle to increase the competitiveness of the electricity industry (Meeus et al., 2005).

The original monopolistic situation was replaced by deregulated markets, where consumers in principle were free to choose their provider, i.e. the market place for electric power had become competitive. To facilitate trading in these new markets, exchanges for electric power have been established. Everything from spot contracts to derivatives, like forward and futures contracts, are traded. Simonsen et al. (2004) claim that even if a power exchange is not a necessity for a deregulated power market, the establishment of such exchanges has contributed to high trading activity, promoted competition and created liquidity in the market.

New market places add another dimension of complexity to the trading process. Electricity has become a commodity traded at power exchanges and off-exchange on an informal bilateral basis, i.e. on over-the-counter (OTC) markets at market prices (Strecker and Weinhardt, 2001).[1]

In order to succeed in new electricity market conditions, the electricity utilities have to deal with two complex statistical tasks: how to forecast both electricity demand and the wholesale spot price of electricity. –A failure to implement efficient solutions for these two

[1] Lesourd (2004), however, claims that electricity is a composite good that complies only partially with features that can be expected from an internationally traded commodity since electricity does not represent a storable commodity, and does not represent capital or running assets in the form of stocks.

forecasting problems can directly result in multimillion-dollar losses through uninformed trades on the wholesale market" (Smith, 2003). Particularly, accurate short-term electricity demand (ED) forecasting is essential for a power system's operation and expansion and can help to build up cost effective risk management plans for the companies participating in the electricity market. From this point of view, high forecasting accuracy and speed are required not only for reliable system operation, but also for adequate market operation. Both over- and under-forecasts of ED would result in increased operational costs and loss of revenue. Forecasting errors also have considerable implications for profit, market shares, even for the shareholder value in the deregulated market. It is relatively easy to get a forecast with about a 10% mean absolute percent error; however, an increase of 1% in the forecasting error would imply (in 1984) a £10 million increase in operating costs per year, to name an often-quoted estimate by Bunn and Farmer (1985).

The time horizon of the ED forecast depends on the way the forecast will be used. Generally, there are three types of forecast: short-term, which is usually from one hour to one week, medium-term, which is usually from a week to a year, and long-term, which is longer than a year. Since the establishment of competitive energy markets, particularly short-term forecasts have become extremely important, and during recent years they have reached a high level of performance.

Many forecasting models and methods have already been applied to ED forecasting, with varying degrees of success. Hippert et al. (2001) in their review of short-term ED forecasting classified the forecasting methods used to date into two main groups: time series (univariate) models and causal models. In time series models ED is modeled as a function of its past observed values. Models like multiplicative autoregressive models (Mbamalu and El-Hawary, 1993), dynamic linear (Douglas et al., 1998; Huang, 1997) or nonlinear models (Sadownik, and Barbosa, 1999), and methods based on Kalman filtering (Infield and Hill, 1998; Al-Hamadi and Soliman, 2006) come also under this group.

In the causal model group ED is modeled as a function of some exogenous factors, basically calendar, weather and social variables. Some models of this class are ARMAX models (Yang et al., 1996), optimization techniques (Yu, 1996), nonparametric regression (Charytoniuk et al., 1998), structural models (Leith et al., 2004), and curve-fitting procedures (Taylor and Majithia, 2000). Lotufo and Minussi (1999) categorize all these forecasting techniques as statistical or traditional methods.

Despite this large number of different kinds of models, the most popular still remain the linear regression ones and models that decompose ED into basic and weather-dependent components. They are very attractive because of their relative simplicity of interpretation. However, they are basically linear devices, and as we will show below, ED series are nonlinear functions of the exogenous variables.

The nonlinear response of ED to some of the exogenous variables was also the reason why researchers tried to develop new forecasting techniques that would be more suitable for forecasting purposes. In the early 1990s artificial intelligence techniques, above all artificial neural networks (ANNs) and fuzzy logic (Papadakis et al, 1998) have been applied to the ED forecasting problem. Lotufo and Minussi (1999) classify these two techniques as two more groups of forecasting methods. ―However, the models that have received the largest share of attention are undoubtedly the artificial neural networks‖ (Hippert et al., 2001). The principal feature of ANNs is their ability to handle the nonlinear relationships and interactions between ED and the factors affecting it, directly from historical data without specifying these relations explicitly in advance.

ANNs have been used for all forecasting periods: long-term ED forecasting (Kermanshahi and Iwamiya, 2002), short-term, and very short-term ED forecasting where the prediction period can be as short as a few minutes (Liu et al., 1996). Particularly, different types of ANNs have been applied to short-term ED forecasting: recurrent (Vermaak and Botha, 1998; Senjyu et al., 2002), functional links (Dash et al., 1997), radial basis (Ranaweera et al., 1995), and multilayer feed-forward ANN. By far the most popular remain single hidden layer feed-forward ANN models (Hobbs et al., 1998; McMenamin and Monforte, 1998; Chen et al., 2001). A more comprehensive review of the published research in the area of ANN forecasting is in Zhang et al. (1998).

In view of the explanatory factors, Sugianto and Lu (2003) in their survey claim that the most important factors for short-term ED forecasting include the day of the week, temperature, seasonal effects, and humidity. In long-term ED forecasting influential factors include economic and political aspects, and degree of industrial development.

There are also a number of papers that have contrasted the accuracy of ANNs with more traditional forecasting methods with different conclusions. McMenamin and Monforte (1998) compared the results of a linear regression model with ANN model results and concluded that –ANN models provide a modest improvement in forecast accuracy relative to well-specified regression models‖. Darbellay and Slama (2000) focused on two forecasting techniques used on Czech data covering the years 1994 and 1995: ANNs and linear models of the ARMA type. They found that the forecasting abilities of a linear model and a nonlinear model were not very different.

Hobbs et al. (1998) surveyed 19 electric utilities on their uses of ANN forecasts, and simulated how improved accuracy lowers the expected generation costs. They found that 16 electric utilities using ANN forecasting systems –significantly reduced errors in daily ED forecasts, while only three found otherwise‖. The estimated economic value of this error reduction was on average 800,000 USD per year per utility for those utilities that reported that savings occurred.

As we can see, even after many years of investigation in ED forecasting, the researchers are not consistent on the issue, whether sophisticated nonlinear models of the ANN type symbolize progress, or whether less complicated linear models are sufficient for application in day-to-day practice. –The findings as to whether and when ANNs are better than classical methods remains inconclusive‖ (Darbellay and Slama, 2000). Zhang et al., 1998 also conclude that –while ANNs have many desired features which make them quite suitable for a variety of problem areas, they will never be a panacea‖.

As a result, the central target of this dissertation is to discuss the nature of short-term ED forecasts on recent Czech data in the dynamic environment of the liberalized Czech power industry. However, this dissertation also is more comprehensive. We start with a brief description of the liberalization process in the Czech Republic, and we discuss the organization and operation of the electricity markets, as well as their flaws, and possible future advancement.

Afterwards we study ED characteristics, as well as the factors determining ED behavior. We describe the forecasting procedures and investigate which approach, linear regression or nonlinear ANN, is more appropriate for our data. Although the ANN models are already widely applied to short-term ED forecasting, many users often do not entirely understand what these models are or how they work. Therefore we present and explain ANN models from a statistical and econometrical point of view. We briefly introduce the ANNs, their main principles and architecture. Then we describe step by step the designing procedure of the ANN forecasting model. The estimation results of the ANN foresting model are analyzed in order to understand the model implications. The ANN model results are directly compared with the traditional regression approach. In order to find the most appropriate forecasting model, we apply various measures of forecast accuracy to our forecast results. Our surprising results show that applying only one error measure to the forecast values is not sufficient. The common statistical error measures, like Mean Absolute Percentage Error and Mean Absolute Deviation, suggest that the ANN approach is more suitable to model the Czech ED data. However, the results of the empirical cost function that measures the losses in Czech Crowns have shown that the overall cost of the ANN forecast errors is higher than the total cost of the linear regression model forecast errors. Therefore the empirical loss function clearly gives priority to a simple linear regression model with an autoregressive error structure. As a result, the LRM with an autoregressive error structure regardless of the poorer out-of-sample statistics, in the end outperforms the more sophisticated nonlinear ANN and is considered as sufficient for practical purposes.

The dissertation is structured in the following way. Section 2 describes the process of the liberalization and deregulation of the electricity markets, focusing on the Czech electricity market. We also clarify the structure and organization of the wholesale electricity market and explain the importance of accurate demand forecasts. In Section 3 we characterize the Czech ED data and give an overview of the factors that affect electricity consumption in the Czech Republic. The reasons for preferring the linear regression and artificial neural network models are explained in this section as well. Section 4 compares the performance and forecast accuracy of the defined models. Section 5 briefly concludes.

2 THE DEREGULATED ELECTRICITY MARKET

2.1 LIBERALIZATION OF THE EU ELECTRICITY MARKET

Until recently, the electricity industry was a monopoly sector but as a result of the liberalization process, electricity can now be traded across borders in a competitive market. In general, the liberalization process was designed to break up the regulated monopoly and introduce competition where feasible, namely in electricity power production and retail (Kočenda and Čábelka, 1999; Strecker and Weinhardt, 2001), and ―to use the economic regulation of the wholesale and retail power markets to promote competition and protect consumer interests‖ (Bacon and Besant-Jones, 2001).

The liberalization reforms began during the 1980s in Chile, England and Wales, and Norway and many developed countries started to follow them during the 1990s (Bacon and Besant-Jones, 2001). In the Czech Republic the liberalization process started in 2002. The Czech electricity market was fully liberalized on 1 January 2006, when the last remaining customer category, households, became eligible to choose their supplier. To date, about 70 developing countries and transition economies have embarked on reforming their power markets - some to a considerable extent, others more tentatively (Besant-Jones, 2006).

Generally, there is no unique concept for the electricity market design but the basic underlying idea remains the same. The core concept is to firstly separate the natural monopoly functions of transmission and generation from the functions of power production (also generation) and retail. Secondly, there must be established a wholesale electricity market for generation and a retail market for electricity retailing. Establishment of the wholesale electricity market facilitates trading between generators, retailers and other financial intermediaries. The trading article is the delivery of electricity both for short-term period and for future delivery period. The role of the retail electricity market is to provide the end costumers with the possibility to choose their supplier from rival electricity retailers. Although wholesale market reform usually precedes the retail reform, it is still possible to have a single electricity generator and functioning retail market.

The market structure of the power sector before the power sector liberalization is following: there is a single state-owned national power utility with endowed monopoly and a vertically integrated supply chain comprising electricity generation, transmission, distribution, and customer services. This structure allows the state to minimize the cost of coordination between these functions and the financial expenses of the development of the power system. (Bacon and Besant-Jones, 2001)

–A full-scale power reform program generally consists of the following main elements: (1) formation and approval of a power policy by the government, followed by the enactment of legislation necessary for implementing this policy; (2) development of a transparent regulatory framework for the electricity market; (3) unbundling of the integrated structure of power supply and establishing a market in which electricity is traded as a commodity; and (4) divestiture of the state's ownership at least in most of the electricity generation and distribution segments of the market‖ (Bacon and Besant-Jones, 2001). These four key elements create the core of the power reform program but the actual design of each program depends on each country's circumstances. Hence, final reform programs result in a variety of, above all, market structures.

Bacon and Besant-Jones (2001) categorize the variety of models of market structures according to increasing degrees of competition as follows:

Model 1 – Monopoly – has no competition at all, there is only a monopoly at all levels of the supply chain. A single monopolist produces and delivers electricity to the users.

Model 2 – Purchasing agency – allows a single buyer or purchasing agency to encourage competition between generators by choosing its sources of electricity from a number of different electricity producers. The agency on-sells electricity to distribution companies and large power users without competition from other suppliers.

Model 3 – Wholesale competition – allows distribution companies to purchase electricity directly from generators they choose, transmit this electricity under open access arrangements over the transmission system to their service area, and deliver it over their local grids to their customers, which brings competition into the wholesale supply market but not the retail power market.

Model 4 – Retail competition – allows all customers to choose their electricity supplier, which implies full retail competition, under open access for suppliers to the transmission and distribution systems.

A common consecution is to start with model 1 and progress through models 2 or 3, eventually reach model 4, the full liberalization of retail market.

In the 1990s the purchasing agency model 2 spread mainly across Asian and Central American countries. Model 3 has been widely adopted in South America, while some Eastern European countries (e.g. Georgia, Moldova) have implemented alternates of this model. Model 4 has been introduced in several U.S. states, and in already more than 60% of EU member states.

In the Czech Republic the liberalization process started with the enactment of the so-called "Energy Act" No. 458/2000 Coll. (hereinafter "Energy Act" or "Act"). The Energy Act started to come into effect on 28 November 2000 with full effect in 1 January 2001. The Act has been important especially from the electricity market point of view.

In accordance with the Energy Act, the first step of opening up the electricity market in the Czech Republic began on 1 January 2002. All end users with an annual consumption of more than 40 GWh and power producers with an installed electricity capacity greater than 10 MW were permitted to buy and sell electricity in the electricity marketplace. From 1 January 2003 the power marketplace was opened to end users with an annual consumption greater than 9 GWh, and to all electricity producers. From 1 January 2004, regulated access to the grid was offered to end users with continuous metering (except for households) and to all electricity producers, from January 2005 forward, to all end users and electricity producers but households. From January 2006 the electricity market was opened for all end users. All clients were free to buy and sell electricity from any party they chose. From the theoretical point of view, the Czech Republic had finally reached model 4, while model 3 was transitional. The particular stages of liberalization are summarized in Table 1.

Stage of Liberalization	1.	2.	3.	4.	5.
Date of market opening	1.1.2002	1.1.2003	1.1.2004	1.1.2005	1.1.2006
Entitled customers	Yearly consumption greater than		End users with continuous metering (except households)	All end users (except households)	All end users (no exceptions)
	40 GWh	9 GWh			

Table 1: Stages of Czech electricity market liberalization.
Source: Kubát and Balcar, 2003

In general, the liberalization process had been applied to electricity power generation and supply, while electricity transmission and distribution continue to be natural monopolies. Typical of the Czech Republic's open electricity market is the fact that there is no more regulation of activities in which competition is feasible.[2] Only the monopoly activities remain to be regulated. They are conceived as public services and are provided for regulated prices. Figure 1 describes the splitting of the Czech open electricity market into competitive and regulated parts.

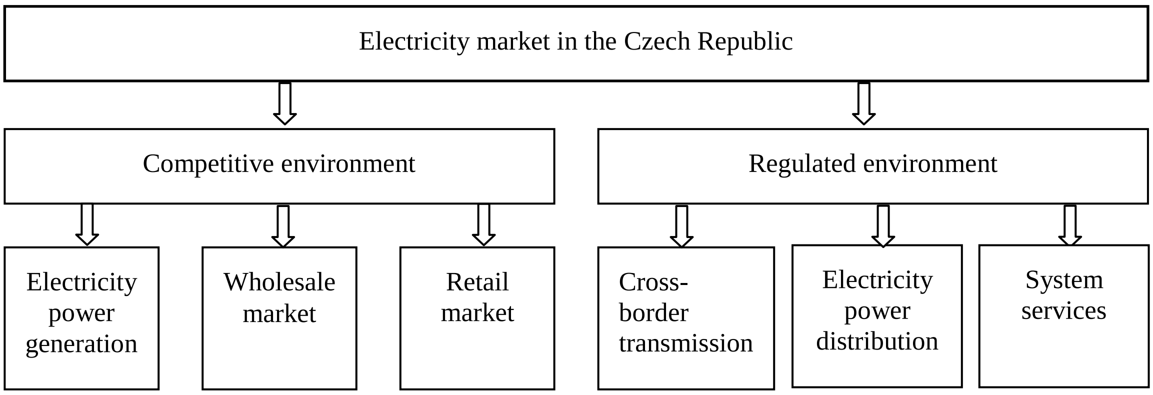


Figure 1: Competitive and regulated elements of the Czech electricity market.
Source: Wedochovič, 2003

[2] See "The Czech Republic's National Report On The Electricity And Gas Industries For 2005"

2.2 SINGLE EUROPEAN ELECTRICITY MARKET

The electricity markets of many EU countries are already fully opened, and the remaining countries are in the process of doing so. These developments are mainly due to European economic policies that aim at the creation of a single European market for goods and services, including electricity (Zachmann, 2005). The integration of European wholesale electricity markets is the ultimate goal of the liberalization process. –Mandated by Directive 2003/54/EC,[3] all EU electricity markets must have been completely opened up for competition by 1 July 2007 at the latest‖ (Cocker at al., 2005). The process of integration at the European level should be finalized by 2012.

The main purpose of these liberalization reforms is to stimulate competition and reap common gains from international competition. Clearly, competition will increase by enlarging the electricity markets geographically since with functional cross-border trade the number of active market participants increases.

In order to reach a functional single EU electricity market, the market should evolve through the successful liberalization of national markets, followed by the development of regional markets that should finally be linked together to form the internal EU electricity market. Thus the full liberalization of the wholesale markets and the growing wholesale markets liquidity represent a basic driver for market integration. Strong interlinked wholesale markets should result in as large price areas as possible and consequently, if possible, in one single European price area. (Cocker et al., 2005) However, as Cocker et al. (2005) further claim, this requires liquid day-ahead and forward markets together with open intra-day and balancing markets reflected in trustworthy day-ahead prices.

–The European wholesale markets have been developed and organized well in a relatively short time period‖ (Cocker et al., 2005). Wholesale markets have been established all over Europe with a significant volume traded above all on OTC markets and power exchanges (also organized short-term electricity markets). All the major markets already have created

[3] Directive 2003/54/EC of the European Parliament and of the Council of 26 June 2003 concerning common rules for the internal market in electricity.

their national or regional exchanges. (Cocker at al., 2005) The potential strength of integrated wholesale markets is evidenced through the convergence of day-ahead prices in a number of markets and the steadily growing volume traded on market places. However, as is pointed out in Lesourd (2004), Zachmann (2005), Cocker et al. (2005), and in several other studies, the development of strong and liquid wholesale markets is an on-going process that is not yet completed. Above all, there are still significant differences between local electricity prices.

Particularly, Zachmann (2005) investigates –the success of the European electricity sector reforms by analyzing the development of wholesale prices over time‖. He states that –similar electricity prices throughout Europe are evidence‖ of a global EU electricity market. Data on three West European countries (France, Germany, the Netherlands), two Central European EU member states (Poland, the Czech Republic) and three North European price areas (East Denmark, West Denmark, Sweden) are studied. The conclusion is that although a noteworthy –progress in the efficiency of cross-border electricity trade has been made, a single EU electricity market is still far off‖.

2.3 WHOLESALE ELECTRICITY MARKETS

As we have noted, the trading of electricity in wholesale markets is the core of power sector liberalization. Before the European electricity markets were deregulated, electricity trading took place only to a limited extent. –As a consequence of the liberalization process, trading procedures, contract designs, and market structure are undergoing radical changes‖ (Strecker and Weinhardt, 2001). The restructuring and opening of the electricity market has resulted in the replacement of the cost minimization paradigm by the profit maximization paradigm (Conejo et al., 2005). –In the profit maximization framework, generators, retailers and end customers interact through a market seeking to maximize their respective profits‖ (Conejo et al., 2005). Two market structures arise commonly in practice: a bilateral contract framework and an organized electricity market (also a pool or organized power exchange).

Most wholesale trade volume in electricity markets is traded bilaterally in forward and OTC types of markets.[4] In a bilateral transaction market any given generator agrees with suppliers to supply specified amounts of energy during a contract horizon. Suppliers buy electricity in advance using long-term and forward contracts to cover their consumption portfolio. However, as Ringel (2003) claims, electrical power is generally –a low-interest homogeneous product‖ that is by its nature difficult to store, to keep in stock, or to have customers queue for it, and it has to be available on demand. Consequently, real electricity demand is not completely predictable, thus –there is also a need for additional daily and even hourly contracts in spot markets‖ (Meeus et al., 2005). On the other hand, as we have emphasized above, both over- and under-forecasts of electricity demand, i.e. forecast errors, are very costly and often result in considerable profit loss.

As far as trading on the short-term electricity market is concerned, Conejo et al. (2005) explain that in an organized power exchange generators –submit to the electricity market operator (hereinafter –EMO‖) production bids that typically consist of a set of energy blocks and their corresponding minimum selling prices for every hour of the market horizon. Analogously, retailers and large consumers submit to the EMO consumption bids that consist of a set of energy blocks and their corresponding maximum buying prices. The EMO uses a market-clearing algorithm to clear the market, which results in a market-clearing price as well as the scheduled production and consumption for every hour of the market horizon. The market-clearing price is the price to be paid by retailers and to be charged by producers.‖ In the case of the Czech Republic, an organized short-term electricity market coexists with a bilateral contract framework.

The organized electricity market offers, besides the short-term day-ahead market, a lot of other products. Particularly, in the Czech Republic common intra-day and balancing markets have been recently introduced. Both markets are designed as a continuous trading scheme where hourly contracts are traded. The main purpose of these continuous markets is to allow for market participants to fine-tune their trading positions on an hourly basis.

[4] The market participants involved in electricity market operations are described in the section –Description of Electricity Market Participants‖.

The objective of the intra-day market is to minimize differences between market participants. The participants of the intra-day market are the balance-responsible parties. In the balancing market, the Transmission System Operator (hereinafter –TSO‖) is the counter party to all deals. The aim is for the TSO to purchase electricity in order to reduce the volume of ancillary services and thereby minimize the overall cost of imbalances for the participants. The introduction of a forward electricity marketplace is also expected. The proposed forward market should provide for hedging instruments to offset positions in a long-term horizon greater than five months. The main purpose of these markets is to allow for approved market participants to "fine-tune" their trading positions on an hourly basis. (Kubát and Balcar, 2003)

Cocker et al. (2000) divide the products in electricity markets into two broad categories: physical and financial products. –Physical products are traded for real physical delivery between parties‖ (Cocker et al., 2000). These products allow a market participant to sell or buy electricity at a present price for weeks, months or years ahead. For example, physical forwards can be traded on a power exchange or in a bilateral manner through OTC transactions. The power exchange traded forwards use standardized contracts that specify a single MW (mega watt) quantity and a single price. –The price of physical forward contract is quoted daily by the power exchange‖ (Skantze and Ilic, 2000). Their advantage is the fixing of transparent prices in relation to which bilateral deals may be defined.

–Financial products include different electricity power derivatives, such as options, contracts for differences, and futures, which are based on the underlying spot market price‖ (Cocker et al., 2000). These products are traded on power exchanges (Skantze and Ilic, 2000). They also allow market participants to buy or sell electric power at the present price for weeks or years ahead. However, these products do not usually lead to the physical delivery of electricity; rather they are settled financially between involved parties. Financial products are mostly used to hedge the risks of power price volatility. (Cocker et al, 2000) The basic structure of the wholesale market is shown in Figure 2.

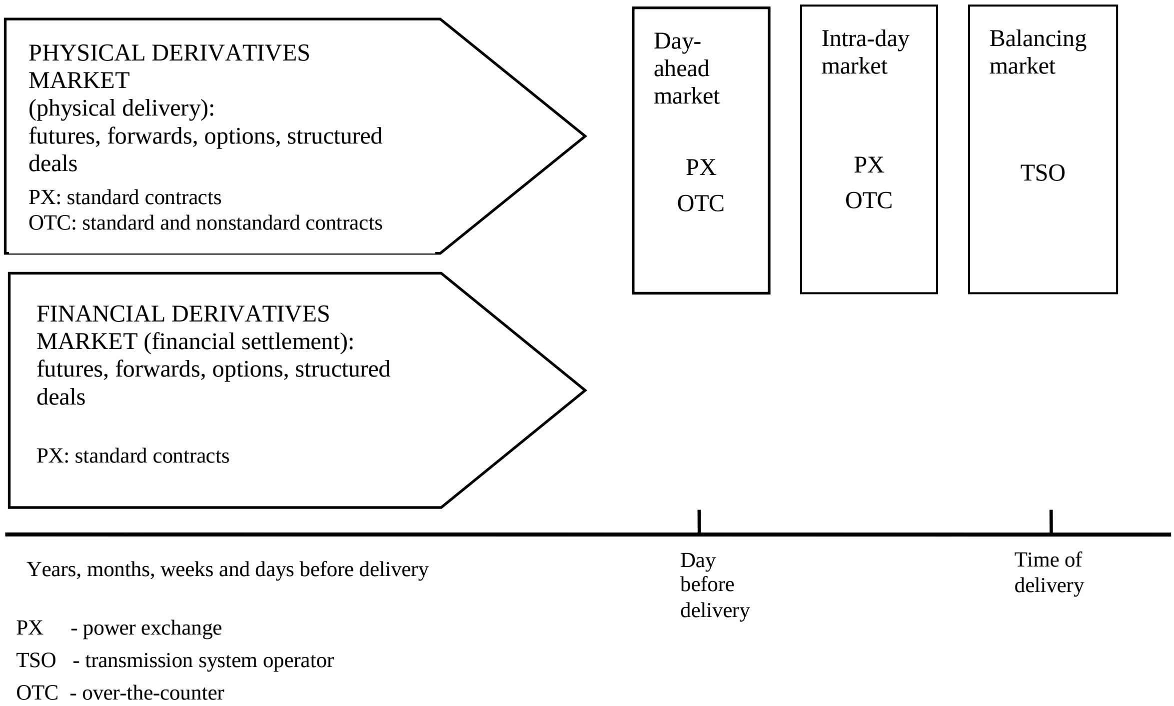


Figure 2: Wholesale market structure.
Source: EURELECTRIC, Cocker et al., 2005

Throughout Europe electricity trading markets are at very different stages of development. In many European countries there have been established power exchanges, offering day-ahead spot markets but only some of them offer also financial products based on the spot market. One of the most advanced markets is the Nordic Market, composed of Finland, Sweden, Norway, and Denmark. The characteristic feature of this market is the very strong role given to the regional power exchange, the Nord Pool that offers both physical and financial products. The turnover on the Nord Pool day-ahead market was about 40% of electricity consumption in 2004 (Cocker et al., 2005).

In many EU countries, irrespective of the level of achieved market liberalization, bilateral OTC transactions are the dominant form of trading. As shown in Figure 2, OTC products can be negotiated individually (non-standardized products) but there is also a growing trend towards the trading of standardized products. –The central clearing of bilateral OTC contracts is becoming an increasingly important activity of power exchanges. This is explained by the fact that the so-called counterparty risk that exists in the OTC markets can be largely eliminated by the power exchange acting as a central clearing point.– (Cocker et al., 2000)

In the Czech Republic as well most of the electricity trades (more than 99% of electricity consumption) are realized through bilateral contracts. The remaining volume of electricity is traded on short-term markets (day-ahead and intra-day markets), which account for less than one per cent of the total electricity traded in the Czech Republic.[5] The following Table 2 shows the electricity day-ahead market volume traded in the Czech Republic.

	2002	2003	2004	2005	2006
Electricity demand in TWh[6]	58.5	59.9	61.5	69.9	71.7*
Day-ahead market volume in TWh	0.4	0.5	0.3	0.4**	0.6**
Electricity traded (% of total electricity consumption)	0.68	0.83	0.49	0.57	0.84

Table 2: Electricity power traded at the Czech day-ahead market.
Source: EURELECTRIC, Cocker et al., 2005; *the Czech Energetický regulačný úřad; **the Czech Operátor trhu s elektřinou, a.s.

As can be seen from Table 2, after a considerable decrease of day-ahead market volume in 2004, the day-ahead market rose by more than 50 per cent in 2006. Even though the Czech power exchange attracts a relatively small fraction of the total trade so far, there is a growing trend towards trading on this short-term electricity market. This has accelerated the demand for more accurate short-term forecasts of the spot price and electricity power demand since the imbalances, i.e. the difference between the sum of the agreed electricity power supplies and real consumption in a given time period, are very expensive. Moreover, as Smith (2003) claims, electricity demand forecasting is even more important –because demand is a major determinant of the electricity spot price‖.

[5] See –The Czech Republic's National Report on the Electricity and Gas Industries for 2005‖.

[6] Tera Watt hour

3 FORECASTING FRAMEWORK

3.1 ELECTRICITY DEMAND CHARACTERISTICS

"Electric power is generally a low-interest product that is noticed only when it is missing. The main reason for this is that consumers perceive electricity as a homogenous product, i.e. the supply of kilowatt-hours by one distributor equals that of another" (Ringel, 2003). Moreover, in contrast with conventional goods, electricity is a product that has to be released upon consumer request, thus electricity is to be delivered instantaneously at the time the consumer needs it. Furthermore, electricity demand fluctuates every moment since it is affected by a broad spectrum of factors such as weather conditions, special events, trend effects, random effects like human activities or ED management, and many others. All these factors produce considerable uncertainty ex ante over demand and the consequent choice of risk of either overproduction or underserving the market (Boffa, 2004). Probably the most serious consequence of uncertainty in demand is the occurrence of blackouts– a variety of countries have recently been hit by blackouts, including the United States, Italy, and even the Czech Republic in 2006. To summarize, since the relatively high volatility of electricity demand is one of the demand's most striking features, ED forecasting is a difficult, very complex and exceedingly challenging task.

Feinberg and Genethliou (2005) claim that from the mathematical point of view there are two important categories of electricity demand models: additive models and multiplicative models. An additive model can take the form of predicting ED as the function of the following separate components (for example in Chen et al., 2001):

$$D = D_n + D_w + D_s + D_r \qquad (3.1),$$

where D stands for the total system electricity demand, D_n represents the "normal" part of the electricity demand, D_w corresponds to the weather-sensitive part of the electricity demand, D_s corresponds to the special events that may occur, and D_r corresponds to the random "unexplained" part.

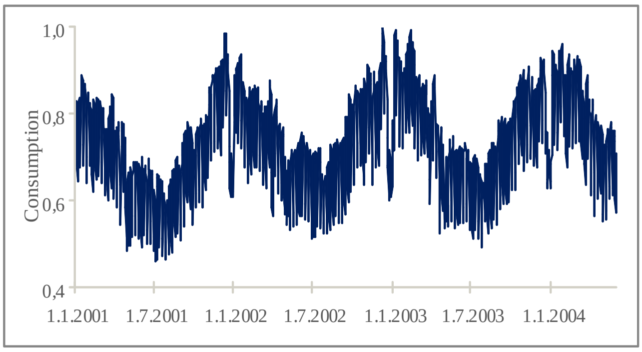
The "normal" part of ED represents a standardized ED shape for each type of day that has been found as occurring throughout the year. The weather-sensitive part of ED is tightly coupled to the season of the year. The special event part of ED represents the occurrence of an unusual or special event causing a significant deviation from typical ED behavior, e.g. state approved holidays, important sporting events, etc. The random –unexplained‖ part is supposed to behave as zero mean white noise.

A multiplicative model may be of the form:

$$D = D_n \cdot F_w \cdot F_s \cdot F_r \qquad (3.2),$$

where D_n represents the –normal‖ part of electricity demand and correction factors F_w, F_s, and F_r are positive numbers that can increase or decrease overall demand. These corrections are related to current weather (F_w), special events (F_s), and random fluctuation (F_r). (Feinberg and Genethliou, 2005) Other factors like price or trend aspects may be included, too.

In this dissertation, we build several forecasting models of both additive and multiplicative types. For developing the forecasting models, we consider the time series of electricity demand of the Czech Republic. Data covering the time span from January 2001 to May 2004 are available on an hourly basis, giving a total of 29,952 observations. The dependent variable data is the system of hourly ED of the north and northeast of the Czech Republic. All sectors (industrial, commercial, and residential) are included. Figure 3 shows the dynamic nature of the investigated ED.



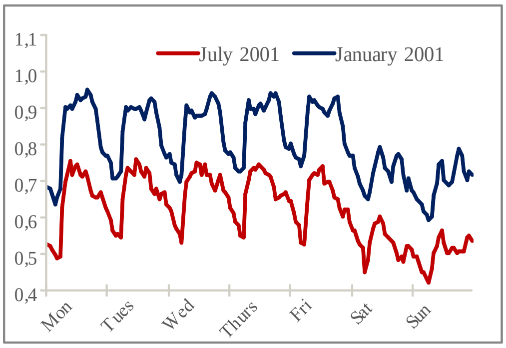
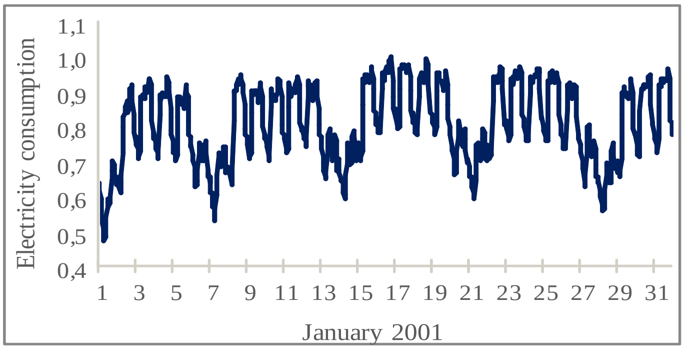


Figure 3: Dynamic nature of daily electricity demand with seasonal variations.
Figure 4: Winter and summer daily electricity consumption through a typical week.
Source: Author's own computations. Data are scaled between 0 and 1.

On Figure 3 we can observe a seasonal structure with typically higher consumption during the winter period and lower consumption during summer time. –This structure can be attributed to the weather, in particular to outdoor temperatures‖ (Simonsen et al., 2004). In detail, the differences between the winter and summer electricity consumption during a typical week are illustrated in Figure 4. Interestingly, the differences between these two data sets are not only in the amount of electricity consumed but also in the electricity consumed for each hour of a day. In other words, we can see that the daily peaks are shifted. In summer months the peak demand occurs in the morning hours, while in winter months the peak moves to the evening hours.

Furthermore, it should be mentioned that the Czech Republic is situated in a moderate climate thus there are in reality two relevant high ED consumption extremes: in relatively cold winters and in hotter summers. This is in contrast to for instance Nordic countries where winters are very cold but summers are less extreme or to California where the highest consumption is in the summer months (McMenamin and Monforte, 1998) rather than during the winter period.



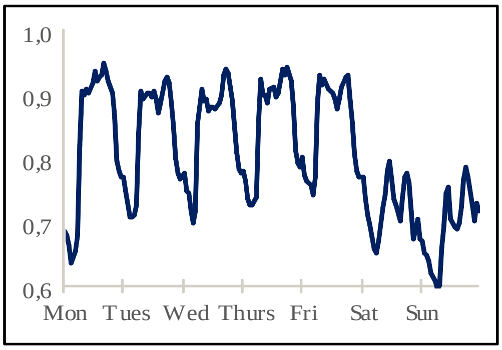


Figure 5: Weekly cycles of electricity demand.
Figure 6: Daily cycles of electricity demand.
Source: Author's own computations. Data are scaled between 0 and 1.

In fact, the electricity consumption data have at least three types of periodicities: annual (seasonal), weekly and daily. The annual effects are depicted in Figure 3. The weekly and daily cycles can be observed in Figure 5 and Figure 6. The ED is highly volatile on a day-to-day basis. The weekly pattern comprised of a daily shape (Monday through Sunday) is strongly affected by especially working activities and by weather conditions. The working activity effect can be clearly seen in Figure 6 where is depicted a typical ED curve through a standard winter week. In general, the electricity consumption pattern on common weekdays remains almost constant with small random variations caused by industrial activities or weather conditions. The daily ED values are functions above all of the short-term historical electricity consumptions and forecast values of weather parameters such as temperature, humidity, and others (Khan et al., 2001). Usually the ED on Mondays and Fridays is different from that of other workdays. The reason is the extensive ED increase on Monday mornings when businesses and industries start work and on Friday evenings when consumers are starting the weekend. The ED pattern of Tuesdays, Wednesdays and Thursdays is usually very similar. The ED variations on weekends are different when compared to other days: people's activities are distributed through a weekend day in another way.

The shape of the ED curve on Sundays is similar to that on so-called special days. Special days may include public holidays and days with major political or sport activities. Particularly, electricity consumption during public holidays is generally lower than other normal workdays (for instance see January 1st on Figure 5). Moreover, the public holiday effect spills into the surrounding days, i.e. the peak ED considerably decreases before and after a major public holiday. For this reason the public holidays have to be treated separately and very carefully. Since their inclusion is likely to be unhelpful in our forecasts modeling, public holidays are not included in the dataset.[7] An alternative to this can be to smooth the public holidays out (Taylor and Buizza, 2003).

To summarize the basic electricity demand characteristics, we can say that in most electricity markets the series of electricity consumption exhibit the following features (Conejo et al., 2005):

1. annual, weekly, and daily seasonality,
2. high volatility,
3. calendar effects of holidays and weekends, and
4. presence of outliers (mostly caused by special day effects).

Mathematical models suitable for ED forecasting can be developed after these characteristics are inspected and understood. In our models seasonalities and calendar effects are mostly taken into consideration through the careful choice of explanatory

[7] The following public holidays are excluded from the data set: January 1st, Easter Monday, May 1st, May 8th, July 5th, July 6th, September 28th, October 28th, November 17th, and December 24th, 25th and 26th.

variables. The high volatility of electricity consumption is a feature that is inherent to these data and cannot be changed. Outliers other than public holidays are not explicitly treated.

In order to build day-ahead hourly forecasts, we have to, in fact, develop 25 models: a daily energy model and 24 separate models for each hour in the day (McMenamin and Monforte, 2007). However, for the purposes of this dissertation, we focus on a daily electricity demand model. –The predicted values from this daily ED model are further used as right hand side drivers in the hourly models. The hourly models are then used to shape the forecasted daily energy‖ (McMenamin and Monforte, 2007). Moreover, all the hourly models are quite analogous to the daily ED model using similar explanatory variables adjusted to the actual hour of the day. The daily energy model is developed for example in Peirson and Henley (1994), Ranaweera et al. (1995) or in Pardo et al. (2002). The daily ED model is applied to Czech daily electricity demand for 2001–2004, giving 1247 observations (days), where the ED data of 2001–2003 are used for estimation purposes and data of January-May 2004 for test purposes.

The time framework to forecast day-ahead electricity demand is explained and illustrated in Figure 7. The ED forecasts for day d are required on day $d-1$, usually at hour h_f in the morning. However, the most recent usable data concerning the electricity consumption known in the morning of day $d-1$ are the data for day $d-2$ quantified at hour h_0 of day $d-1$. Therefore, the actual forecasting of the ED for day d can take place between hour h_0 and hour h_f of day $d-1$.

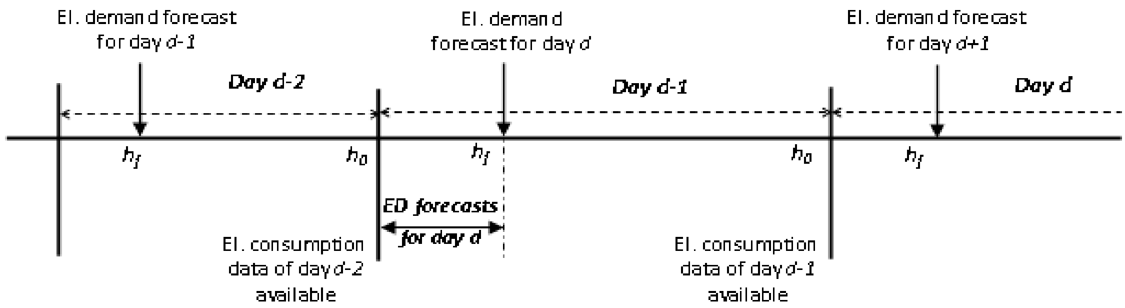


Figure 7: Time framework to forecast electricity demand for day d.

3.2 OVERVIEW OF ELECTRICITY DEMAND DETERMINING FACTORS

Electricity consumption is affected by many factors; however, only a few of them can be accounted for in a forecasting model. The majority of previous studies has shown that the most important factors to determine the shape of the ED profile are weather variables (in particular air temperature) calendar variables, and past electricity consumption itself. Based on these studies, five types of variables are used as inputs in our models: a) weather related inputs, b) calendar and sun related inputs, c) historical ED, d) electricity price inputs, and d) interactions.

3.2.1 WEATHER VARIABLES

Weather conditions are considered one of the most important parameters in ED forecasting. ―A good understanding of the effect of weather conditions, like temperature, cloud cover, rainfall or wind speed on electricity consumption can significantly improve forecast accuracy‖ (Sugianto and Lu, 2003). In our models, the electricity demand is modeled using two types of weather variables: temperature and illumination variables.

The key weather variable to be included in the daily ED model is air temperature. It has been proven by many previous studies (Papalexopoulos, Hao and Peng, 1994; Hippert et al., 2001; Pardo et al., 2002; and many others) that outdoor temperature is the most important factor affecting electricity consumption. Particularly, Sugianto and Lu (2003) claim that ―the inclusion of temperature as an input variable reduces forecast errors, since electricity consumption changes are very sensitive to temperature changes‖.

In order to model the daily electricity demand we use, in the same way as Papalexopoulos et al. (1994), four types of temperature variables: a) direct temperature variables, b) indirect temperature variables, c) temperature change variables, and d) cooling/heating degree day variables. Maximum and minimum past and forecasted temperatures are selected as direct temperature inputs.

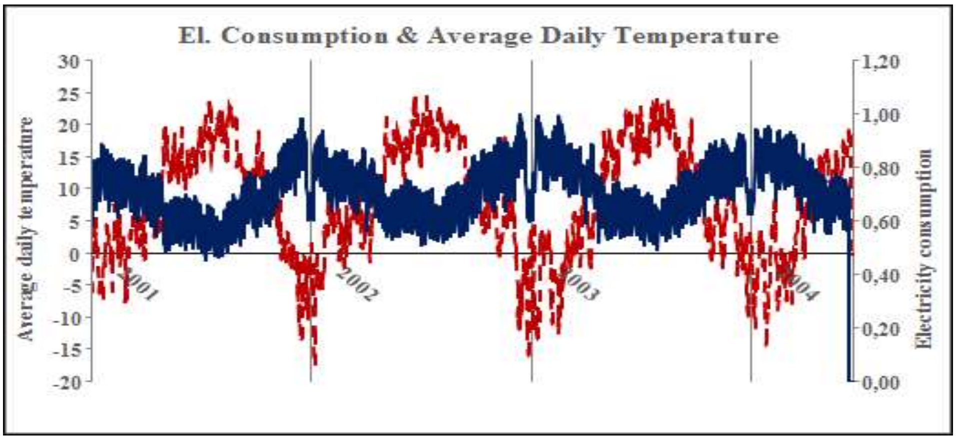
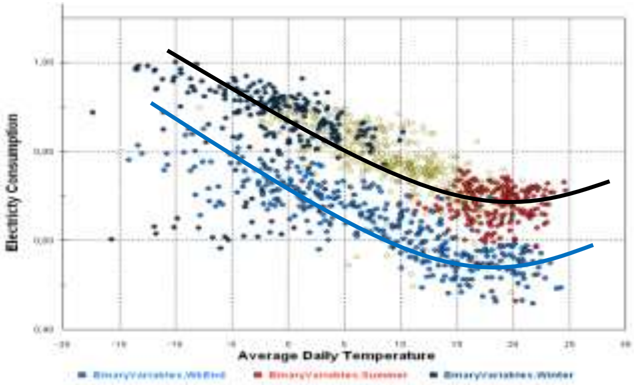


Figure 8: Evolution of electricity consumption and average daily temperature.
Source: Author's own computations. Electricity demand data are scaled between 0 and 1.

Including the average daily temperature variable that belongs to the indirect temperature variable group, can significantly improve the performance of the daily energy model. In Figure 8 is depicted the relationship between the daily ED and the average daily temperature. We can observe that the demand peaks coincide with the highest (summer) and lowest (winter) temperatures.

This strong relationship can be even better observed in the following Figure 9 that explains the double-extreme electricity consumption mentioned in the previous section. Correspondingly to Figure 3 in McMenamin and Monforte (1998), Figure 9 shows a scatter plot of daily ED against the daily average temperature. The points are coded with symbols that separate weekends from the weekdays in each season. In winter months the ED increased due to low temperatures – the lower the temperature, the higher the electricity consumption, i.e. the weather response slope is negative. This probably reflects the use of electric heating. On the contrary, ―in summer, increased temperature values appear to be positively correlated with increased ED‖ (McMenamin and Monforte, 1998). This situation is most likely caused by the extensive use of air conditioning. Finally, during the spring months the electricity consumption decreases with the increase of temperature, and vice versa in the fall months. Consequently, a combination of positive and negative weather response slopes results in a U-shape curve. In other words, the relationship between daily ED and the average daily temperature is clearly nonlinear (Figure 9).



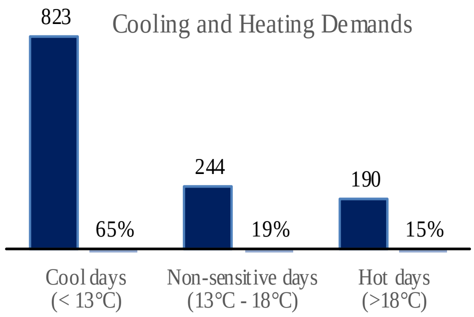


Figure 9: Electricity demand versus average daily temperature with respect to weekends and seasons.

Figure 10: Cooling and heating demands.

Source: Author's own computations. Electricity demand data are scaled between 0 and 1.

In addition, it needs to be pointed out that there is also –significant variation in daily energy for a given temperature, leaving much to be explained by other conditions and input calendar variables‖ (McMenamin and Monforte, 1998).

Moreover, since people's physical sensation of coldness or warmth usually persists for at least one day, the weighted average of yesterday's and the day before yesterday's average daily temperatures may have a strong impact on ED, too. –The influence of lagged temperatures aims to reflect the delay in the response of heating appliances within buildings to changes in external temperatures‖ (Taylor and Buizza, 2003). These variables come under indirect temperature inputs.

Generally, ED is very sensitive to temperature changes. –To capture the sensitivity of the nonlinear influence of temperature change on ED‖ (Papalexopoulos et al., 1994), the difference of two consecutive average daily temperatures will be used as a temperature change variable.

The nonlinear response of ED to temperature effects suggests using two temperature-derived functions: cooling and heating degree-day variables. These functions allow us to separate the winter and summer data and help us to get better results, above all, in the linear forecasting model. The degree-day functions are defined as:

heating degree-days (HDD)

$$HDD_t = \max(HTT - AvgTemp_t, 0) \quad (3.2.1)$$

and cooling degree-day (CDD)

$$CDD_t = \max(AvgTemp_t - CTT, 0) \quad (3.2.2),$$

where CTT is the cooling temperature threshold and HTT stands for the heating temperature threshold. The thresholds are based mostly on physical considerations. Since there is a neutral zone between 13°C and 18°C (see Figure 9) where the demand is inelastic to temperature changes, the CTT was set to 18°C, while the HTT was set to 13°C. In Figure 10 is shown the number and percentage share of three types of days in our data set separated by the average daily temperature on cold days, non-sensitive days and hot days. –The cooling degree-day function is zero until the CTT is reached and then it increases‖ (Papalexopoulos et al., 1994) linearly. In other words, below the CTT there is usually no need to cool the indoor climate; however, with increasing temperature, a lot of (mainly) offices turn on the air conditioning, trying to keep the indoor temperature at a particular threshold (Papalexopoulos et al., 1994). The heating degree function works in the same form but in the opposite way; in other words, the values of the heating degree function increases as the outdoor temperature decreases.

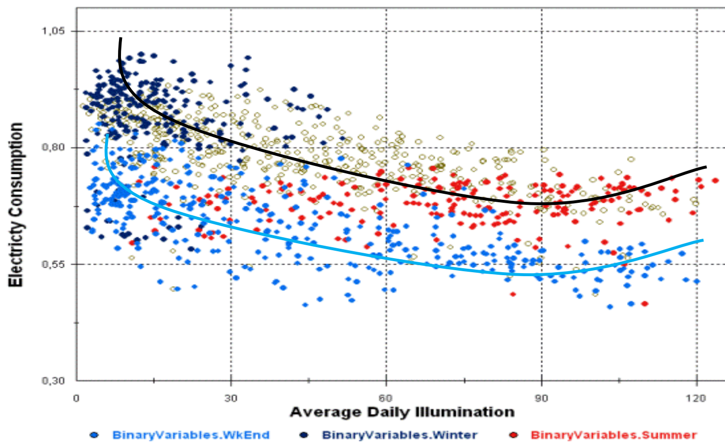


Figure 11: Electricity consumption versus average daily illumination with respect to weekends and seasons.

Source: Author's own computations.

The next weather variable used in our daily ED models is average daily illumination. This factor indicates the hypothetical amount of sunlight that reaches the earth's surface and is measured in W/m^2 (Watts per square meter). The illumination level affects human vision and light sensors, which can lead to switching electric lights on or off. In fact, illumination is a complex function of visibility, cloud cover and the amount and type of precipitation (Taylor and Buizza, 2003). When it is cloudy and rainy, the level of illumination is very small or almost zero. On the contrary, this variable reaches the maximum level during sunny days. Our simulations show that this kind of variable affects the level of ED significantly. Therefore average daily illumination is included in our explanatory variable set. Figure 11 illustrates the nonlinear relationship between daily electricity consumption and average illumination with respect to seasons. Although the illumination variable has, as our model results show, strong explanatory power, it has been introduced in only a few studies, for example in Esp (2001) or in Taylor and Buizza (2003).

In a number of ED forecast studies the authors have experimented with other weather variables, such as humidity, wind speed or cloud cover. However, not all weather factors are of great consequence. –Some are typically random during a period of time, such as wind-speed or thunderstorms‖, and some factors are interrelated. –For example, temperature is partly controlled by cloud cover, rain and snow. Among all these factors, temperature is still the most important because it has a direct influence‖ on electricity consumption (Papalexopoulos et al., 1994; Hippert et al., 2001).

Finally, it should be pointed out that ED forecasts require weather forecasts. –Murphy (1993) defined three types of weather forecast –goodness‖: consistency, quality and value. Consistency refers to the relationship between the forecasts‖ and judgments of the forecaster, –quality refers to the relationship between the forecasts and weather events, and value refers to the relationship between the forecasts and the benefits or losses accrued by users‖ (Brooks and Douglas, 1998). A standard practice in ED forecasting is to run ED forecast simulations using observed weather values instead of forecasted ones; however, in practice the forecasting errors will be larger than those obtained in simulations because of the added weather forecast uncertainty (Hippert et al., 2001). Brooks and Douglas (1998) examine the relationship between forecast quality and value for the user and claim that weather forecasts have the potential to have economic impacts on utility. They found out that considering the value of the forecasts for the entire year, the cold day forecasts have a lower impact. Thus the value of forecasts is concentrated on the cases when temperatures are high.[8] As a result, weather information may be significant –enough even on a small number of days to have large economic impact‖. Further, Brooks and Douglas (1998) assert that improvement in 3–5 day forecasts could make a huge difference in value given that annual differences between 1–2 day and 3–5 day forecasts are on the order of $5-10 million.

3.2.2 CALENDAR VARIABLES

The other important factor to determine the shape of the ED curve is the calendar day. Many previous studies have shown significant seasonal daily variations in electricity consumption (the daily variations of the Czech ED data are shown in Figure 6). In order to capture them, we introduce a qualitative variable day indicator into our models. The day indicator is specified as a dummy variable representing all the days in the week except the base day of Sunday.

Although we have decided not to include the major public holidays into our data set, we have to treat an impact on days surrounding a particular holiday. Therefore, following Pardo et al. (2002), the following dummy variables have been defined: the day before a holiday, the day after a holiday, and a bridge day corresponding to a workday between a holiday and weekend days (usually Monday or Friday).

A typical electricity demand curve also exhibits a strong monthly seasonality. Figure 12 shows the average, minimum and maximum electricity consumption for each month of the year.

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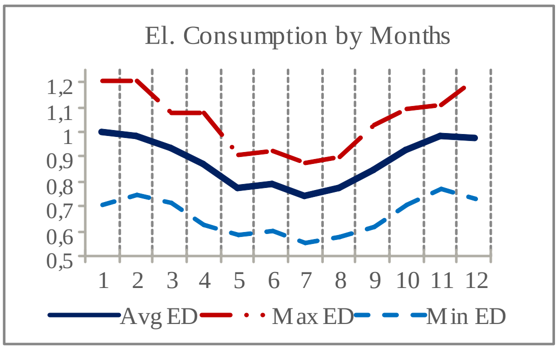
[8] The percentage shares of cold, non-sensitive and hot days in our data set (see Figure 10) are very similar to that of Brooks and Douglas (1998).



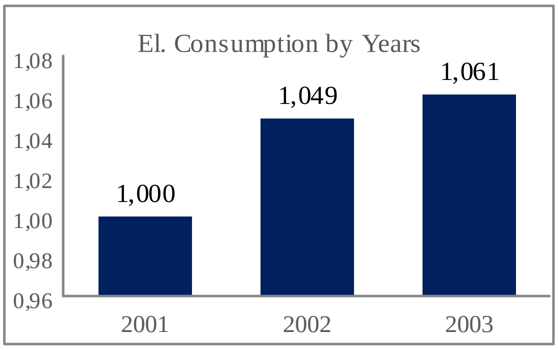


Figure 12: Average, maximum and minimum monthly electricity consumption for the years 2001–2003.

Figure 13: The growing yearly electricity consumption in our data set.

Source: Author's own computations. Electricity demand data are scaled.

The average ED curve represents the usual electricity consumption behavior during a year, while the difference between the maximum and minimum ED curves gives an indication of deviations from the mean behavior observed. Figure 12 suggests that the highest consumption is in January, consumption is lower in spring and fall (in fact, electricity demand is very similar for February, November and December, then for March and October, April and September, and finally for May, June and August with a relative maximum in June), and the lowest is typically in the hottest summer month, July. The drop in July is probably caused by summer vacation that has, however, two contrasting effects: on the one hand, the vacation causes a reduction in the industrial ED, and on the other hand there is an increase in residential and commercial sectors due to tourism (Pardo et al., 2002). Since the reviewed ED data come from an industrial part of the Czech Republic, the former effect is probably stronger than the latter one.[9] In order to catch this monthly

[9] Generally, taking into consideration the whole Czech Republic (not only the industrial parts like the north-east of the CR), the drop in July is probably because the only temperature-related effect on electricity consumption in the Czech Republic is when it's cold. All workplaces and residences are heated, and some portion of heating requires electricity, so when it gets cold in winter electricity use rises (also people are inside more, using radios, TVs, lights, etc. more). But when it gets hot in summer, a corresponding increase in use does not occur because the number of offices and residences in the Czech Republic that are air-conditioned is rather small. This would be different with data from another area such as the U.S. Midwest. Since air conditioning takes much more electricity than heating, there are problems with electricity provision sometimes when it is very hot in the summer (when everyone has their AC on), but never in the winter when it is cold.

seasonality, we introduce a dummy variable month indicator. This variable represents all months in a year taking December as a base month.

Figure 13 illustrates the escalation in the yearly electricity consumption during the considered years, 2001–2003. As we can see from the Figure, the 2002 electricity consumption increased almost 5% relative to the 2001 consumption. The difference between the electricity consumption in 2002 and 2003 is not so significant. To account in our models for the yearly growth factor, the dummy variable year indicator is introduced in the initial explanatory variable set for the years of 2001 and 2002, taking 2003 as the base year.

The next calendar variable that could provide important information is daylight savings. Daylight savings is a binary variable representing the change to daylight savings time the last weekend in March, as well as the change back in October.

3.2.3 LAGGED ELECTRICITY DEMAND

One of the most powerful factors determining electricity consumption is almost certainly the consumption itself. Since the ED series is strongly autocorrelated, lagged EDs are powerful explanatory variables for the day-ahead ED forecasting. The time framework to forecast day-ahead ED (Figure 7) suggests that the most recent data available for day d predictions are the data from two days ago, i.e. from day d-2. Additionally, in order to capture the effect of same day electricity consumption, the historical data from seven days ago can be a noteworthy factor determining the electricity demand profile. Thus, in our day-ahead forecasting models we consider two types of lagged EDs: historical data from two and seven days ago. Both of these historical EDs provide the demand shape and magnitude reference for the forecasted daily demand (Papalexopoulos et al., 1994).

3.2.4 ELECTRICITY PRICES

In the present competitive electricity markets, the price of electricity should be considered as another significant influencing factor in short-term ED forecasting (Sugianto and Lu, 2003). Naturally, price decreases or increases affect consumer preferences and usage of energy. Chen et al. (2001) claim that large cost-sensitive industrial consumers –can adjust their consumption behavior according to price information and thus achieve maximum benefit‖. However, there are still only several studies that included electricity price into their demand forecasting models and very few of them reported more accurate estimates using price as an explanatory variable, such as Chen et.al (2001) or McMenamin (1997). As far as the Czech energy market is concerned, adding electricity price as a factor affecting demand into the forecasting models is at least questionable and needs much more research.

In any case, the key condition for adding the electricity price into the forecasting models is the price elasticity of consumers. However, Borenstein (2001) states that demand insensitiveness to price fluctuation is one of the two fundamental problems with deregulated wholesale electricity markets. Unlike markets where consumers can easily substitute another product or buy the same product in another location and where demand is responsive to price changes, in electricity markets there is very little opportunity for real-time demand response. –As energy demand increases during daily operation, the clearing price goes up until it matches the production cost of the most expensive supply. If there is a supply shortage, this process could raise the price enormously, as inelastic demand will have to settle for any price bid by suppliers.‖ (Keyhani, 2003)

Figure 14 shows the development of daily electricity prices in the Czech Republic as reported by the Czech electricity market operator (EMO), OTE.[10] The daily electricity price in this figure is, in fact, a simple average of all the day-ahead spot prices for that day. By comparing the spot price series in Figure 14 with the daily consumption data in Figure 15 for the same time period, we can only hardly observe similar cycles for the price and the corresponding consumption.

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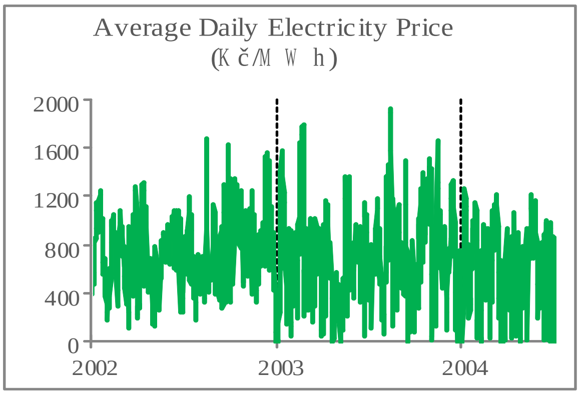
[10] The spot price data are available from www.ote-cr.cz. More information about the Czech electricity market operator, OTE, is available in the section below entitled –Descriptions of Electricity Market Participants‖.



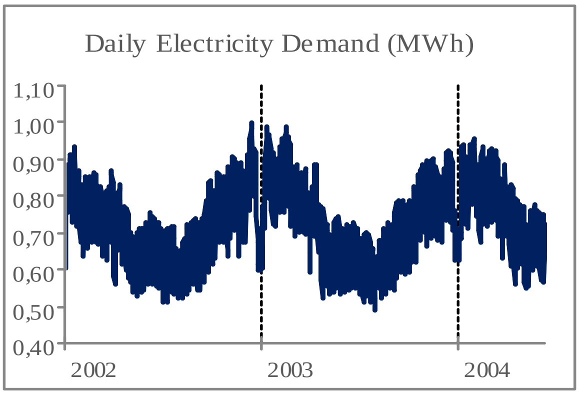


Figure 14: Daily average electricity spot price series (CZK/MWh) for 2002–2004.
Source: www.ote-cr.cz.

Figure 15: Daily electricity consumption for 2002–2004.
Source: Author's own computations. Electricity demand data are scaled.

This simple data examination might suggest that Czech consumer demand is probably quite inelastic with respect to the market price. There are most likely two main reasons for such demand-inelastic behavior of consumers. Firstly, the Czech EMO was established at the beginning of 2002, thus the electricity short-term market in the considered time period 2001–2004 had only started to work. Therefore the spot price data are available only for the years 2002–2004. Consumers, especially price-elastic consumers such as huge industrial companies, just started to take electric energy as a commodity that can be bought and sold on the market like other goods. Secondly, in our electricity demand data set are included both residential and industrial sectors. Although large industrial companies should be sensitive to electricity price changes in the interest of their revenues, the number of market participants and day-ahead market volumes were in the considered period still quite low. Residential customers, such as households, typically have very low demand elasticity with respect to electricity price changes. In the following Figure 16 is shown the development of yearly electricity consumer prices (in Czech Crowns per kilowatt hour). Having stable electricity consumption, residential customer electricity bills differ only by a few hundreds of Crowns from year to year.

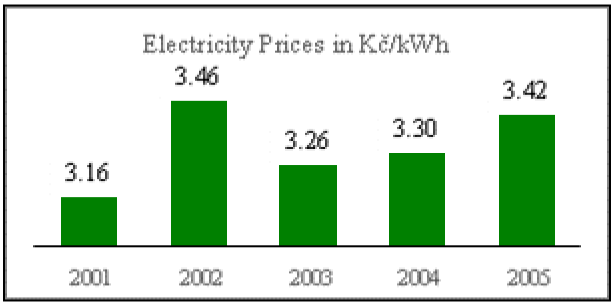


Figure 16: Relationship between daily electricity consumption and average daily electricity price.
Source: The Czech Statistical Office.

It could be worth mentioning the other significant problem that occurs in nearly all electricity markets – the relatively high volatility of short-term electricity prices as compared to other commodities. Conejo et al. (2005) note that spot price series are more volatile than electricity demand series that might be possibly caused by irrational bidding behavior by market participants. Borenstein (2001) defines and describes three main reasons for electricity prices to be volatile as follows:

1) The supply side of the electricity market is physically constrained.

   Because of the physical properties of electricity production, as well as transition and distribution, there are fairly hard constraints on the amount of electricity that can be delivered at any point in time. This means that the supply-demand matching between any customer and supplier at any point in time at any location on electricity is especially difficult.

2) Too little flexibility on the demand side of the electricity market.

   Although the technology to meter consumption on an hourly basis is widely available, no electricity market in operation today makes substantial use of real-time pricing, i.e. to charge a customer time-varying prices that reflect the time-varying cost of procuring electricity at the wholesale level.

3) Electricity generation is very capital intensive.

   Because a significant part of generation costs are fixed, the marginal cost of production will be below the average cost for a plant operating below its capacity. So long as the market price is above a plant's marginal operating costs, a competitive firm is better off generating than not. As a result, excess capacity in a competitive market will cause prices to fall to a level below the average cost of producing electricity, and generators will lose money. This capital intensity, implying a high cost of idle capacity, is also the reason that it is very costly for firms to maintain the ability to increase electricity production on very short notice.

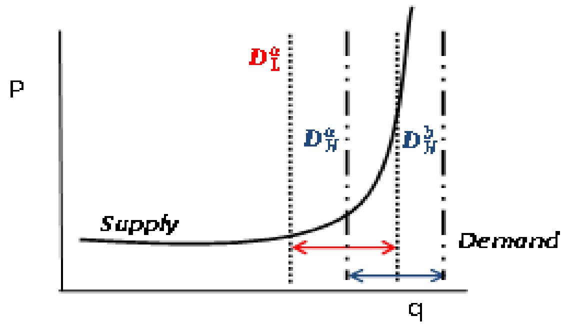


Figure 17: Rightward shift of the demand distribution.
Source: Borenstein, 2001

The effects of these characteristics of the electricity market are shown in Figure 17. Let's assume that demand is uniformly distributed between D_L^a and D_L^b. –Now consider a relatively small rightward shift of the demand distribution to between D_H^a and D_H^b. This small shift replaces hours that were at very law prices, with the hours that are at extremely high prices at the right side of the distribution‖ (Borenstein, 2001). Even this small shift can cause the average price to increase drastically.

Borenstein (2001) further explains that –the critical point here is that the electricity markets are especially vulnerable to these supply-demand mismatches due to the extreme inelasticity of supply and demand. In markets where output is storable or capacity constraints are more flexible, supply can adjust to such mismatches within extreme price movements. In markets where buyers can see time-varying prices and respond to them, demand can adjust to such mismatches and thus pull down the price.‖

Besides consumer demand inelasticity with respect to prices there is also another important aspect that should to be taken into consideration when adding electricity price as a factor affecting the demand: the deterministic relation between the price and demand itself. In functioning electricity markets the price and corresponding consumption usually have very similar cycles, i.e. when consumption is high, the price of electricity is high and vice versa. Therefore, one might suspect that the cyclic behavior in the price data is a result of the electricity consumption pattern (Simonsen et al., 2004). Indeed, Simonsen et al. (2004), using the normalized cross-correlation function, demonstrate that the seasonality that can be observed in the system price can be attributed to the consumption patterns for electricity demand. As a result, consumption drives electricity prices. Smith (2003) also claims that ED forecasting is even more important than electricity price forecasting because demand is a major determinant of the electricity spot price. Conejo et al. (2005) in their electricity price forecasting study have considered the demand as the only explicative variable since the effects of the temperature and other weather-related variables are usually embodied in the demand forecasts. McMenamin et al. (2006) have included in the price determining variables besides demand the lagged price data and supply side factors, too. On the other hand, as we noticed earlier, there are very few studies that include price as a determining factor to the electricity demand forecasting models.

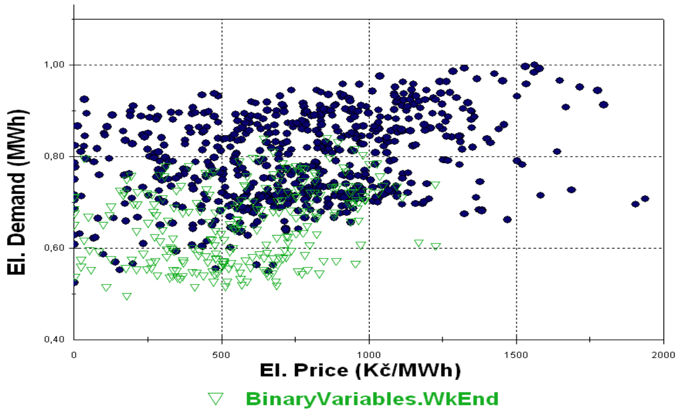


Figure 18: Relationship between daily electricity consumption and average daily price.
Source: Author's own computations. Electricity demand data are scaled.

Although the Czech electricity price and corresponding consumption data do not suggest that high prices occur in periods of high demand and vice versa (see Figure 14 and 15), the scatter plot in Figure 18 shows that there might be a non-linear relationship between price and consumption. Figure 18 provides a scatter plot of daily demand versus daily average prices, coded by type of day.

Additionally, the market-clearing prices for the day d electricity demand forecast are required on day $d-1$ at hour h_f, at the latest. However, the day-ahead market-cleared price data concerning demand forecast for day d are available on day $d-1$ at hour h_c, whereas $h_f < h_c$. Therefore, as Figure 19 shows, the most recent available price data for the day d demand forecast are the price data for day $d-1$.

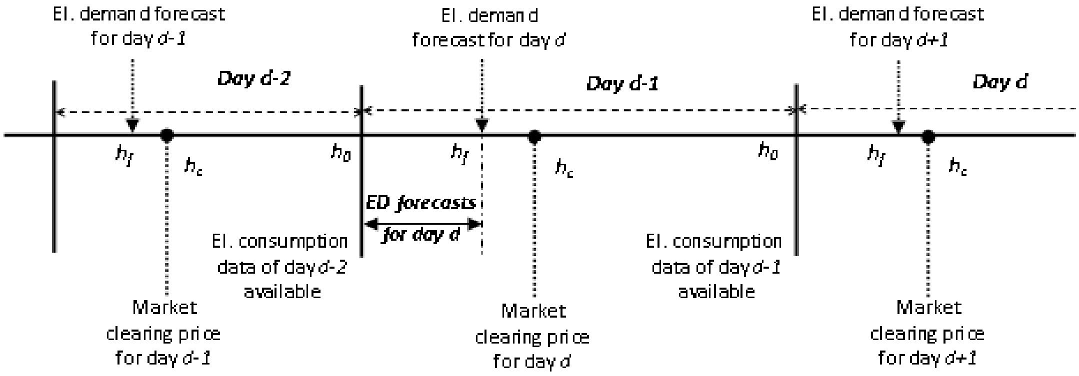


Figure 19: Time framework to forecast electricity demand for day d including the market-clearing prices.

3.2.5 INTERACTIONS

All the calendar, weather, price and historical electricity consumption data are powerful tools in the day-ahead ED forecasting process; however, sometimes these factors themselves are not enough. Therefore, similarly to McMenamin and Monforte (1998), we introduce variable interactions. The most important interactions are the interactions between calendar and weather variables and calendar and lagged ED variables (McMenamin and Monforte, 1998).

Calendar variables and weather variables:

In Figure 9 it is shown that –an extra degree of temperature has a different impact on a workday than on a weekend day‖ (McMenamin and Monforte, 2007). Similarly, the weekday slopes in spring or fall for a given temperature are different than the weekday slopes in summer or winter. This fact suggests that the interactions of the temperature variables and day-of-week or season variables may be helpful in ED forecasting.

Calendar variables and lagged ED variables:

–The relationship between yesterday's and today's electricity consumption may differ significantly across days‖ (McMenamin and Monforte, 2007). Since one of our explanatory variables is two-day lagged ED, on a Monday, the lagged ED will be for a Saturday, and therefore the slope is different than on a Wednesday, when the lagged ED is for a Monday. Thus in order to estimate the differential influence of lagged ED variables across different days, these interactions must be allowed in the model.

The following Table 3 summarizes the explanatory variables considered in our daily energy models:

WEATHER	CALENDAR	LAGGED EDs	EL. PRICE
Max Daily Temperature	Day Indicator	Lagged ED day-2	Lagged Price day-1
Min Daily Temperature	Month/Season Indicator	Lagged ED day-7	
Avg Daily Temperature	Year Indicator		
Avg Daily Temperature Squared	Days near Holidays		
Weighted Avg Daily Temperature	Day-light-savings		
Temperature Change			
Cooling/Heating Degree Day			
Average Daily Illumination			
Avg Daily Illumination Squared			
← Interactions →			

Table 3: Summary of explanatory variables.

3.3 FORECASTING PROCEDURES

In order to find the most appropriate forecasting model for our ED data, we estimate a series of multivariate models and compare their performance. However, it is difficult to find a good standard for comparison in ED forecasting. –If there is no comparison, the reports on the performance of a proposed method are difficult to interpret‖ (Hippert et al., 2001). Only very few papers made any kind of comparison. McMenamin and Monforte (1998) used as a point of reference a linear regression model. They estimated this model using various combinations of the input variables (including nonlinear inputs) and appropriate interactions. Papalexopoulos et al. (1994) presented the development and implications of an artificial neural network-based short-term system ED forecasting model for the Energy Center of the Pacific Gas and Electric Company (PG&E). Until that time PG&E for its forecasting purposes used –a powerful linear regression model that utilized nonlinear transformations‖ to effectively capture the ED variations. This linear regression model was in this paper also used as a point of reference. Azadeh et al. (2007) use analysis of variance (ANOVA) to compare the estimated ED results of the selected ANN, regression method and actual data. Hippert et al. (2001) in their review indicate that papers that made any kind of comparison usually reported these comparisons to standard linear models.

Based on these previous studies, we also build up both linear and nonlinear models and compare their performance. The former type of model is represented by multivariate linear regression models. In the class of nonlinear models we consider artificial neural networks. The modeling structure is in fact in both classes of models a stepwise scheme, starting with the basic simple model and adding new terms, so we are able to evaluate the effects of different factors that influence the daily electricity demand. This procedure is similar to that used by Pardo et al. (2002).

Regression models are one of the most widely used statistical techniques in ED forecasting. The performance of these models has an advantage of clear interpretation and is used – like in other above-mentioned papers – as a good point of reference. Linear regression models model the relationship between electricity consumption and other determining factors, such as weather, the calendar, lagged electricity demand, and electricity price. Additionally, the significance of autoregressive patterns in error terms is also checked.

On the other hand, as we have shown, there exist the complex nonlinear relationships between the electricity demand and a series of factors that influence it, particularly between the temperature and ED (Figure 9), illumination and ED (Figure 11) and electricity prices and ED (Figure 18). However, the traditional regression methods cannot properly represent these nonlinear relationships. Ranaweera et al. (1995) define the three main theoretical limitations of the most conventional statistical methods as follows:

  the nonlinear relationships of the input and output variables are difficult to capture;

  the co-linearity problem of the explanatory input variables limits the number of these inputs that can be used in the model; and

  the models are not very flexible to rapid electricity demand changes.

As Ranaweera et al. (1995), Chen et al. (2001), and other researchers state, the application of ANN technology to power systems has made it possible to overcome some of these limitations in the short-term ED forecasting problem. Artificial neural networks have become "a widely studied electric ED forecasting technique since 1990" (Feinberg and Genethliou, 2005). They have been well accepted in practice, and they are used by many utilities, especially in the areas of forecasting, security assessment, and fault diagnosis. In general, besides the application of ANN in engineering, they also began to be used in various fields including finance, medicine, military, biology or hydrology. Pulido-Calvo et al. (2007), for instance, use linear regressions and neural networks to forecast water demand in irrigation districts of southern Spain during two irrigation seasons, 2001–2002 and 2002–2003.

In recent years, ANN's success in formulating solutions lies mostly in the area of financial problems. Since the 1990s a large number of studies design and use an ANN model for financial simulation, financial forecasting and financial evaluation. Dutta et al. (2006) model Indian stock market price index data (weekly closing values) using ANN. Panda and Narasimhan (2006) compare the performance of ANN with the performance of random walk and linear autoregressive models in the forecasting of daily Indian stock market returns. The prediction of the volatility of the Korean stock price index is the subject of an ANN application in Roh (2007). Zhang et al. (1999) and Yang et al. (1999) present a general framework for understanding the role of ANN in business bankruptcy prediction. Celik et al. (2007) work on evaluating and forecasting banking crises through ANN models. Callen et al. (1996) uses an ANN model to forecast quarterly accounting earnings for a sample of 296 corporations trading on the New York Stock Exchange. The objective of Tkacz (2001) is to improve the accuracy of the forecasts of Canadian GDP growth by using leading indicator ANN models. Pao (2007) adopts multiple linear regressions and ANN models to analyze the important determinants of capital structures of high-tech and traditional industries in Taiwan. Huang et al. (2004) make a comparative study of the application of support vector machine and backpropagation NN to the problem of credit rating prediction. Vojtek and Kočenda (2006) identify ANN as one of the most common methods in the process of the credit scoring of applicants for retail loans.

As far as energy systems themselves are concerned, Kalogirou (2000) presents various applications of ANN in a wide range of fields for the modeling and prediction of energy problems. He claim that ANNs have been commonly used in the field of heating, ventilation and air-conditioning systems, solar radiation, modeling and control of power-generation systems, refrigeration, as well as in prediction of energy consumption. –Errors reported when using these models are well within acceptable limits‖ (Kalogirou, 2000) which clearly suggests that the application of ANN for energy problems is well-founded and ANN can be used for modeling also in other fields of energy-engineering systems.

Particularly, the main advantage of ANN when applied to ED forecasting lies –in their good capability of mapping nonlinear relationships between the demand and demand-affecting factors‖, their ability to learn nonlinear relationships from examples, and enabling the –easy inclusion of any relevant factors into the model‖ (Charytoniuk et al., 2000). ANNs should be especially useful when a researcher –has a large amount of data, but little a priori knowledge about the laws that govern the system that generated the data‖ (Hippert et al., 2001). Although a lot of studies conclude that ANNs –are not unambiguously superior to other methods, they are frequently the most accurate approach, especially when dealing with nonstationary or discontinuous data series‖ (Hobbs et al., 1998).

4 MODEL SPECIFICATION, ESTIMATES AND VALIDATION

In this section we look for the most appropriate forecasting model applicable to the Czech electricity demand data. We start with multivariate models where the existence of seasonal and dynamic effects in the electricity demand series is addressed. We compare the results of both linear and nonlinear models. In order to capture the questionable effect of electricity price on demand, we develop two groups of models: the first one is linear and nonlinear models without price effects, the second one is models where the price factor is included.

In the second stage, we turn our attention to models where the dynamics of electricity demand is substituted by introducing an autoregressive structure in the error term. We again judge both linear regression models and artificial neural networks, with and without price factors.

4.1 ARTIFICIAL NEURAL NETWORK SPECIFICATION

In order to better understand how artificial neural networks work, we briefly describe their basic principles. Then we develop a neural network model to predict electricity demand.

Principally, ANNs are a nonlinear optimization tool inspired by how the human brain processes information and its natural propensity for storing experimental knowledge and making it available for use. There are a number of different types of ANNs; for an overview refer to, for instance, Bishop (1995). Valuable reviews of their use in short-term electricity demand forecasting provide Zhang et al. (1998) and more recently Hippert et al. (2001).

Although various types of network architecture can be used, we are interested in the ANN design called multilayer feed-forward ANN that is still the most popular network architecture in electricity demand forecasting. The multilayer network consists of several nodes (also –neurons‖) organized in one input, one or more hidden and one or more output layers. The way the nodes are organized is called the architecture of the ANN. Feed-forward ANNs are probably the simplest type of ANNs. The information progresses from the input nodes, through the hidden nodes to the output nodes, i.e. in only forward direction in this network. The network considered is fully connected; i.e. every node belonging to each layer is connected to every node of the neighboring forward layer. In feed-forward ANNs there are no cycles or loops. The absence of feedbacks and interconnections between the nodes in the layers makes this system a feed-forward system.

Figure 20 shows an example of an multilayer feed-forward ANN with one input layer with K input nodes, one hidden layer with n_H nodes and one output layer with one output node.

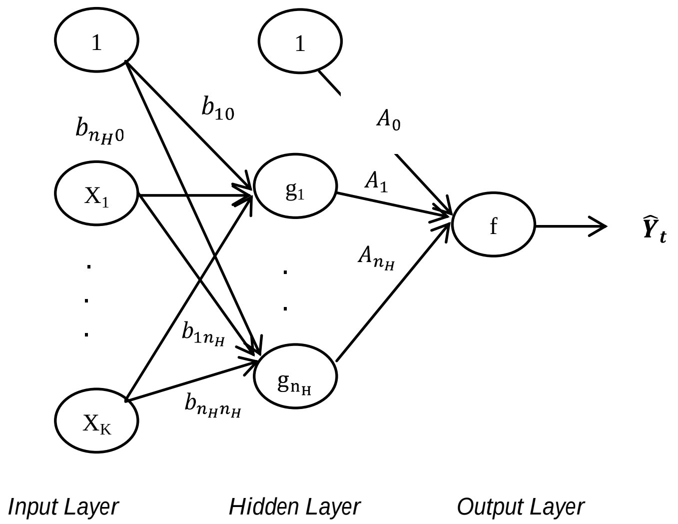


Figure 20: Example of artificial neural network architecture.

The basic unit of the ANN is the artificial neuron. The neuron receives information through a number of input nodes, processes it internally and generates output value that is transmitted to the neurons in the subsequent layer. Firstly, the input values are linearly combined. In other words, each input node is multiplied by the weight b_{nk} that corresponds to each connection and these products are added together with a constant bias term b_{n0}. The result is then passed through a nonlinear activation function $g_n(x)$. Activation functions for the hidden units are needed to introduce nonlinearity into the network. Almost any nonlinear function (except for polynomials) can be suitable. The activation function must be a non-decreasing and differentiable function. There are a number of functional forms, for example step, sign or identity functions, but the most common are the bounded sigmoid (s-shaped) functions such as the logistic, the hyperbolic tangent and the Gaussian function. The outcome of each node in the hidden layer is called the activation of the node

$$H_n^t = g_n(\textstyle\sum_k b_{nk} X_{kt} + b_{n0}) \qquad (4.1.1).$$

The activation value for each outgoing connection is then multiplied by the specific weight A_n and transferred to the final output layer

$$Y_t = f\left(\sum_n A_n H_n^t + A_0\right) = f\left(\sum_n A_n g_n(\sum_k b_{nk} X_{kt} + b_{n0}) + A_0\right) \qquad (4.1.2),$$

where f is known as transfer function. The transfer function is chosen with respect to the required range of output. If the output should take discrete values, the transfer function can be chosen to be a threshold, piece-wise linear or a sigmoid function. If the range of the output function is not restricted to a particular interval, then the preferred transfer function can be set to the simple identity function.

The estimation of the parameters is called the training or learning of the ANN. From the forecaster's point of view, the real goal is to make out-of-sample forecast errors small. In this way, the aim is to minimize the overall mean square error between the desired and the estimated output values, i.e. to minimize the error (also –cost‖ or –loss‖) function

$$\min_{\substack{A_n, b_{nk} \\ n=1,\cdots,n_H \\ k=1,\cdots,K}} \sum_{t=1}^{T} \left[Y_t - \hat{Y}_t(A_n, b_{nk})\right]^2 \qquad (4.1.3),$$

where Y_t is the true observed value of electricity consumption for day t, $\hat{Y}_t$ denotes the estimates demand for day t, T stands for the number of true demands used for training, n_H is the number of neurons in the hidden layer and K is number of input data.

There are many optimization methods used to estimate the network parameters, for example recursive algorithms, such as back-propagation, optimization algorithms, such as the Newton method, or steepest descent and least squared algorithms, such as the Levenberg-Marquardt algorithm (McMenamin, 1997). The first and still most widely used training algorithm is the error back-propagation optimization procedure. The basic back-propagation algorithm is similar to the steepest-descent technique; both are based on the computation of the gradient (the first derivatives) of the cost function with respect to the network parameters.[11]

Creedy and Martin (1997) claim that the combination of a nonlinear model and a sum of squared objective functions suggests for the parameter estimation the use of a standard gradient algorithm, or more specifically, a nonlinear least squared procedure like the Levenberg-Marquardt (LM) algorithm. The LM algorithm is another widely used estimation method. It is a second-order method that blends gradient vector and Hessian matrix. Creedy and Martin (1997), McMenamin (1997) and Darbellay and Slama (2000)

[11] That is the reason why the activation functions must be differentiable.

found this method to be superior to the back-propagation approach since the LM algorithm is relatively faster and more efficient. Although both of these estimation methods give the same results, for the type of forecasting problem focused on in this dissertation, we decided to use the LM algorithm, too.

Finally, –it can be shown that the least squared objective function for a neural network is extremely complex with a huge number of local optima, as opposed to a single global optimum‖ (McMenamin et al., 1998). To avoid local minima, the training is initialized from different initial conditions and rerun. The network that achieves the smallest error on the estimation set is then used for forecasting.

Since ANN is a complex nonlinear model, finding the appropriate design takes much more time and computational effort than building a linear model. In the design-searching procedure a number of choices must be made. Generally, before making the first forecasts, the designer has to select: the number of input nodes, the number of nodes per output layer, the type of activation function, the number of hidden layers and the number of nodes per hidden layer.

In designing an ANN forecasting model the number of input variables is the most important problem of selection. –Currently, there is no suggested systematic way to determine this number‖ (Zhang et al., 1998) selection of input variables. However, as the short-term ED forecast has been intensively studied for years, there are some studies and statistical analysis that can be helpful in determining which variables have significant influence on the ED. There are at least two main variables to be included in the explanatory data set: the ED itself and the weather variables (Doulai, Cahill, 2001; Chen et al., 2001; Papalexopoulos et al., 1994, and others).

Since we want the neural network to produce a one-step-ahead forecast, i.e. a forecast for the next day daily electricity demand, we develop an ANN with a one-node output layer. For the output layer the linear combination of the activation functions will be the most suitable. In fact, at the output level we can use instead of linear combination any other nonlinear function. However, for most problems with continuous outcomes, there is no real gain from further nonlinearity at this level (McMenamin, 1997).

Figure 9 suggests that the relationship between the total daily ED and the average daily temperature is clearly nonlinear. For that reason the desired combination of activation functions must result in a U-shaped curve. Since the combination of one positively and one negatively sloped logistic curves really results in the desired U-shaped curve, it is rational to use an S-shaped logistic curve as the activation function in the hidden layer

$$g_n(X) = \frac{1}{1+e^{-\left(\sum_{k=1}^{K} b_{nk}X_{kt}+b_{n0}\right)}} \qquad (4.1.4).$$

Moreover, the exponential we can rewrite as follows

$$e^{\left(\sum_{k=1}^{K} b_{nk}X_{kt}+b_{n0}\right)} = e^{b_{n1}X_{1t}}e^{b_{n2}X_{2t}} \dots e^{b_{n0}} \qquad (4.1.5).$$

Since this specification is automatically interactive for each node, it seems likely the most appropriate choice, especially if the underlying process has multiplicative interactions.

–The universal approximation theorem claims that every continuous functions defined on a compact set can be arbitrary well approximated with‖ a multi-layer feed-forward –neural network with one hidden layer‖ (Csáji, 2001). This result is restrained to a limited classes of activation functions, for instance for sigmoid functions. Hippert et al. (2001) also argue that it has been shown that one hidden layer is enough to approximate any continuous functions. As a result, we also keep the approved ANN guidelines, and develop an ANN with one hidden layer.

Deciding for one hidden layer, we face another important question: how many nodes should be selected for this hidden layer? Determining the number of these nodes may be more difficult since there are no hard and fast rules. The problem is that –if there are too few, the model is not flexible enough to model the data well; if there are too many, the model will overfit the data‖ (Hippert et al., 2001). This means that too many parameters aim to explain also very specific events in the sample period but these specialized results do not necessarily generalize to out-of-sample conditions. Although there are no generally established statistics for deciding on the number of nodes, the following statistics can be relevant for this issue: adjusted R-squared, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). All of these statistics provides means for evaluating the trade off between model parsimony and model fit. The common feature of these statistics is that they improve when the sum of squared errors reduces, –but impose some penalty for the increased number of parameters‖. (McMenamin, 1997)

With respect to the details described above, we develop the ANN and repeat its estimation. The procedure is similar to that of McMenamin and Monforte (1998). Variables included in the model are temperature, illumination, calendar, lagged ED and interactive variables. All these variables are included in all nodes. In all nodes the logistic activation functions are used. Table 4 shows that the optimal number of nodes appears to be between 2 and 5. This table suggests that after adding more parameters the sum of squared errors always declines, the adjusted R-squared slowly improves, and the AIC statistic and the in-sample Mean Absolute Percentage Error (MAPE) steadily declines. All these statistics indicate that –the improvement of model fit outweighs the penalty caused by an increased number of coefficients‖ (McMenamin and Monforte, 1998). On the other hand, with the increasing number of input variables, the BIC statistic also declines and the lowest is for 3- and 4-node specification. However, for the 5-node model it raises again showing that a higher number of nodes can cause a possible loss of predictive power.

	1-Node ANN	2-Node ANN	3-Node ANN	4-Node ANN	5-node ANN
Adjusted R-squared	0.463	0.975	0.984	0.987	0.988
AIC	15.912	12.506	12.488	12.316	12.26
BIC	16.1	13.263	13.044	13.042	13.199
In-sample MAPE	6.63	1.63	1.43	1.30	1.18
Out-of-sample MAPE	9.38	1.50	1.24	1.60	1.76

Table 4: Results for the ANN model performance for different numbers of nodes.

Obviously, the in-sample MAPE is lowest for the 5-node model. However, from the forecaster's point of view the most important statistic is the out-of-sample MAPE. Therefore the out-of-sample MAPE was chosen as the decisive criterion for the final ANN specification. Table 4 shows that the minimum BIC statistic as well as the lowest out-of-sample MAPE corresponds with the 3-node specification. As a result, 3-node ANN was chosen as the final specification of our ANN model.

To summarize, using the language of (McMenamin and Monforte, 1998), our ANN has the following properties:

It is a single-output feed-forward artificial neural network.
It has one hidden layer with three nodes.
It uses a logistic activation function in each node of the hidden layer.
It uses a linear activation function at the output layer.

4.2 MEASURES OF FORECAST ACCURACY

Through past two decades many forecast accuracy measures have been proposed, and several authors have made recommendations about their use. Makridakis (1993) claims that –from the theoretical point of view, there is a problem as no single accuracy measure can be designed as the best‖. In other words, the most appropriate performance measure has to be related to the purpose of the forecasting. From a practical point of view, as Makridakis (1993) states further, –it must make sense, be easily understood and convey as much information about accuracy (errors) as possible‖. Finally, it is important to distinguish between pure academic research focused mainly on evaluating forecasting competition and reporting the performance of methods and forecasters, for instance, in business (Makridakis, 1993).

Generally, there are a number of measures of accuracy in the forecasting literature and each has it advantages and limitations. Chen and Yang (2004) assert that –it is desirable to compare different accuracy measures to find out which measures perform better in what situations and which ones have very serious flaws and thus should be avoided in practice‖. The comparison of different accuracy measures is a very demanding task since there is no obvious way how to do it.

Basically, some forecast accuracy measures are useful when comparing different methods applied to the same data set (also single or individual time series), but these measures do not ought to be an appropriate choice for cross-series comparison (Hyndman and Koehler, 2006; Chen and Yang, 2004). For studies comparing multiple forecast accuracy measures applied to the empirical evaluation of forecasting methods in M-competition (M2- or M3-

competition) refer to, for instance, Makridakis (1993), Tashman (2000), or Chen and Yang (2004). Chen and Yang (2004) claim that the most preferred performance measures used in M1-competition are MSE (Mean Squared Error), MAPE (Mean Absolute Percentage Error), and Theil's U-statistics. More measures are used in M3-competition: sMAPE (Symmetric Mean Absolute Percentage Error), sMdAPE (Symmetric Median Absolute Percentage Error), MdRAE (Median Relative Absolute Error), and Percentage Better.

However, Hyndman and Koehler (2006) have found out that –many of these proposed measures of forecast accuracy are not generally applicable since they can be infinite or undefined, and can produce misleading results‖. The authors have proposed a new measure MASE (Mean Absolute Scaled Error) for comparing forecast accuracy across multiple time series. As Hyndman and Koehler argue, MASE is easy to interpret, is always definite and finite, and does not substantially affect the main conclusions about the best-performing methods.

Further, Hyndman and Koehler (2006), who discuss and compare measures of the accuracy of univariate time series forecasts in their study, divide the accuracy measures into four groups: scale-dependent measures, measures based on percentage errors, measures based on relative errors, and relative measures. Scale-dependent measures are useful when comparing different methods applied to the same set of data. The most commonly used scale-dependent measures are based on the absolute error or squared errors, for example MSE (Mean Square Error), RMSE (Root Mean Square Error), MAD (Mean Absolute Error), and MdAE (Median Absolute Error).

The percentage error measures have the advantage of being scale-independent. The most widespread error measure is without a doubt MAPE (Mean Absolute Percentage Error), which is the average of the absolute values of the percentage residuals for each day. Other frequently used measures are MdAPE (Median Absolute Percentage Error), RMSPE (Root Mean Square Percentage Error), and RMdSPE (Root Median Square Percentage Error).

The third group of performance measures comprises measures based on relative errors, i.e. measures where each error is divided by the error obtained using another standard method of forecasting. Usually the benchmark method is the random walk. Hyndman and Koehler include in this group MRAE (Mean Relative Absolute Error), MdRAE (Median Relative Absolute Error), and GMRAE (Geometric Mean Relative Absolute Error).

Finally, relative measures compare the forecasts to a baseline/naive forecasts, for instance random walk, or an average of available forecasts (Chen and Yang, 2004). RelMAE (Relative Mean Absolute Error), Percentage Better, and Theil's U-statistics come under this group.

In electricity demand forecasting the selection of appropriate error measures is always a difficult task because, as Hippert et al. (2001) point out, –no single error measure could possibly be enough to summarize‖ the forecasting performance. On the other hand, the use of multiple measures makes comparison between forecasting methods difficult and unwieldy (Goodwin and Lawton, 1999). Although many error measures have been proposed, only some of the existing measures are preferred for the demand forecasting problem. Hippert et al. (2001) in their review state that the most reported accuracy measure in the demand forecasting problem is MAPE. Few also reported measures based on the squared error as they penalize large errors: MSE, RMSE (for example in Armstrong and Collopy, 1992), NMSE (Normalized Mean Square Error in Darbellay and Slama, 2000), or MSPE (Mean Square Percentage Error). Since utilities usually prefer error measures that are easy to understand and are closely related to the needs of decision-makers, measures based on absolute errors, for example MAD, are often preferred. MAD as the key error measure was reported, for instance, in Papalexopoulos et al. (1994).

On the other hand, Zhang et al. (1998) in their review of forecasting with ANN claim that although –MSE is the most frequently used accuracy measure in the literature‖, it is not –appropriate enough for ANN building with a training sample since it ignores important information about the number of parameters‖ the model has to estimate. Similarly, Hyndman and Koehler (2006) affirm that MSE and RMSE are more sensitive to outliers than, for example, MAD.

Most papers report MAPE as an adequate measure; it has become somewhat of a standard in the electricity supply industry. However, several authors argue that the main disadvantage of the MAPE error measure is that it treats forecast errors above the actual observation differently from those below this value. This observation led Makridakis (1993) to propose the use of a so-called –symmetric‖ MAPE (sMAPE) which involves dividing the absolute error by the average of the actual observation and the forecast. However, lately Goodwin and Lawton (1999) show that this –symmetric‖ measure lacks symmetry in that it treats large positive and negative errors very differently. Moreover, Hyndman and Koehler (2006) point out that sMAPE –can take negative values although it is meant to be an absolute percentage error‖.

The performance of the models is measured in several complementary ways in this dissertation. We basically consider the error measures that are directly relevant to the users. In our case, the decision-makers are particularly interested in the MAD

$$In-sample\ MAD = \frac{1}{T}\sum_{t=1}^{T}\left|Y_t - \hat{Y}_t\right| \tag{4.2.1}$$

$$Out-of-sample\ MAD = \frac{1}{F}\sum_{f=1}^{F}\left|Y_{T+f} - \hat{Y}_{T+f}\right| \tag{4.2.2}$$

and MAPE

$$In-sample\ MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| * 100 \tag{4.2.3}$$

$$Out-of-sample\ MAPE = \frac{1}{F}\sum_{f=1}^{F}\left|\frac{Y_{T+f} - \hat{Y}_{T+f}}{Y_{T+f}}\right| * 100 \tag{4.2.4}$$

measures, where T stands for the number of true demands used for training and F corresponds to the number of forecasted daily demands. It is needed to note that some authors, for example Makridakis (1993), Goodwin and Lawton (1999), Tashman (2000), or Chen and Yang (2004) do not recommend to use MAPE as the performance measure since it is unstable when the original value is close to zero and is sensitive to outliers. However, none of these flaws is the case in our electricity demand time series.

–Forecasters generally agree that forecasting methods should be assessed for accuracy using out-of-sample tests rather than goodness of fit to past data, i.e. in-sample tests‖ (Tashman, 2000). Thus with all forecasting models, we implement Theil's Inequality

Coefficient (also Theil's U- or U1-statistics) as a statistic for the ex-post evaluation process. However, Theil's Inequality Coefficient is used only very rarely since it is less easy to understand and communicate. This statistic is applied to the forecast results, for instance, in Stevenson (2002) who in his study models and forecasts the volatile spot pricing process for electricity.

Theil's Inequality Coefficient –is related to the root mean square forecast error, scaled such that it always falls between zero and one‖ (Stevenson, 2002)

$$U = \frac{\sqrt{\frac{1}{F}\sum_{f=1}^{F}\left(Y_{T+f} - \widehat{Y_{T+f}}\right)^2}}{\sqrt{\frac{1}{F}\sum_{f=1}^{F}\left(Y_{T+f}\right)^2} + \sqrt{\frac{1}{F}\sum_{f=1}^{F}\left(\widehat{Y_{T+f}}\right)^2}} \qquad (4.2.5)$$

For a perfect fit, i.e. for $Y_{T+f} = \widehat{Y_{T+f}}$, the value of the statistic is equal to zero, i.e. $U = 0$. If $U = 1$, the forecast is as poor as could be since in this case either all Y_{T+f} are equal to zero and $\widehat{Y_{T+f}}$ are nonzero or vice versa. The value of Theil's Inequality Coefficient can be decomposed into three components, which are defined as follows:

$$U^{Bias} = \frac{\left(\overline{Y}^F - \overline{\hat{Y}}^F\right)^2}{\sqrt{\frac{1}{F}\sum_{f=1}^{F}\left(Y_{T+f} - \widehat{Y_{T+f}}\right)^2}} \qquad (4.2.6)$$

$$U^{Var} = \frac{(\hat{\sigma}^F - \sigma^F)^2}{\sqrt{\frac{1}{F}\sum_{f=1}^{F}\left(Y_{T+f} - \widehat{Y_{T+f}}\right)^2}} \qquad (4.2.7)$$

$$U^{Covar} = \frac{2(1-r)\hat{\sigma}^F\sigma^F}{\sqrt{\frac{1}{F}\sum_{f=1}^{F}\left(Y_{T+f} - \widehat{Y_{T+f}}\right)^2}} \qquad (4.2.8),$$

where $\overline{\hat{Y}}^F$ is the mean of the model predicted values over the forecast period, $\overline{Y}^F$ is the mean of the actual data values over the forecast period, σ^F is the standard deviation of the dependent variable over the forecast period, $\hat{\sigma}^F$ is the standard deviation of the predicted values during the forecast period, and r is the correlation coefficient.

The bias proportion, U^{Bias}, indicates how the average values of forecasts systematically deviates from the actual values. The variance proportion, U^{Var}, is a measure of how the forecasts reflect the variability of the actual demand data. Finally, the covariance proportion, U^{Covar}, measures unsystematic error which accounts for the remaining error after deviation from the average have been incorporated into U^{Bias}. (Stevenson, 2002)

We apply this decomposition to our forecast errors to evaluate the ability of the model to capture the mean effects and the variability of the true demand values. As Stevenson (2002) further states, for both the U^{Bias} and U^{Var} a value above 0.1 –is troubling and indicates the need for a revision of the forecasting model‖.

In addition, most authors believe that the loss function associated with the forecasting errors, if known, should be used in the evaluation of the method. However, this kind of accuracy measure is only rarely used in the electricity demand forecasting. Armstrong and Fildes (1995) argue that a well-specified loss function, while desirable, cannot be regarded as sufficient. Loss functions are typically in currencies and depend on the forecast errors in a complex way. Moreover, recent studies show that the loss function in the demand forecasting problem –is clearly nonlinear‖ and is only rarely available for researchers (see Hippert et al., 2001 for a discussion).

To conclude, Bunn and Taylor (2001) state that selecting an appropriate error measure is still a controversial area in forecasting research. Similarly, Zhang et al. (1998) also claim that –a suitable performance measure for a given problem is not universally accepted by the forecasting academicians and practitioners‖. Deciding on the measures depends upon the situation involved and needs of the decision-makers. Armstrong and Fildes (1995) claim that the appropriate error measure should have the following attributes: –the error measure should be reliable, resistant to outliers, and comprehensible to decision-makers‖. Tashman (2000) argues that for a single time series, the desirable characteristics of an out-of-sample test are adequacy, i.e. enough forecasts at each lead time, and diversity, i.e. desensitizing forecast error measures to special events. Having this in mind, in this dissertation the performance of the models is measured by four complementary accuracy measures: the in- and out-of-sample MAD and MAPE measures, Theil's Inequality Coefficient, as well as the very seldom used empirical loss function.

4.3 MODELS WITH SEASONAL AND DYNAMIC EFFECTS

The first issue that must be captured in our models is the existence of seasonal effects. To account in the models for seasonal effects not related to weather factors, we use the calendar variables, such as day, month and year indicators, days near public holidays, and dummy daylight savings variables. The seasonal effects caused by weather are caught by a number of temperature and illumination variables, such as average daily temperature and illumination, cooling/heating degree day, and other variables (see Table 3: Summary of explanatory variables).

Peirson and Henley (1994) claim that in the modeling of short-term electricity demand, it is often common to ignore the dynamic specification. Both the studies of Peirson and Henley (1994) and Pardo et al. (2002) show the importance of dynamic specification in modeling the relationship between electricity demand and temperature. In other words, there are factors that suggest the influence of past temperatures in present electricity consumption. In order to check this hypothesis on Czech data, we introduce in our models a lagged effect of temperature represented by the weighted average of yesterday's and the day before yesterday's average daily temperatures, considering that the lagged effect can be relevant only over a short period.

Incorporating a number of lags on the dependent variable is another method used to introduce dynamics into a forecasting model. In our models we consider the historical demands from two and seven days ago.

Table 5 presents a brief correlation matrix of these data. As expected, the table shows that the daily demand is most highly negatively correlated with average temperature and illumination and most highly positively correlated with the heating degree-day variable. As can be seen, the demand rises through the weekdays, as well as through the fall and winter days, while the weekends, spring and summer days remarkably reduce the electricity consumption.

	D_t	HDD	Week-day	Week-end	Spring	Sum	Fall	Winter	After Hol	Before Hol	Avg Temp	Avg Illum
D_t	1											
HDD	0.653	1										
Weekday	0.59	-0.024	1									
Weekend	-0.59	0.024	-1	1								
Spring	-0.096	-0.123	-0.004	0.004	1							
Summer	-0.496	-0.5	0.002	-0.002	-0.35	1						
Fall	0.109	-0.12	0.012	-0.012	-0.345	-0.286	1					
Winter	0.47	0.72	-0.009	0.009	-0.383	-0.318	-0.313	1				
After Hol	-0.003	-0.017	0.033	-0.033	0	-0.042	0.074	-0.03	1			
Before Hol	-0.031	-0.081	0.076	-0.076	0.029	0.016	0.027	-0.071	-0.013	1		
Avg Temp	-0.676	-0.963	0.022	-0.022	0.038	0.643	0.025	-0.677	0.008	0.069	1	
Avg Illum	-0.549	-0.623	0.002	-0.002	0.266	0.509	-0.264	-0.514	0.006	0.065	0.693	1

Table 5: Correlation matrix of fundamental input factors.

Taking into account all the described effects, a generic equation for both the linear and nonlinear models can be written as

$$ElectricityDemand = f(Calendar, LaggedDemand, Weather, InteractiveVar) \quad (4.3.1).$$

Letting D_t represent the daily electricity demand, the linear regression model (LRM) is finally given by:

$$D_t = c_1 + \sum_{i=1}^{6} \alpha_{i1} W_{it} + \sum_{i=1}^{11} \alpha_{i2} M_{it} + \sum_{i=1}^{2} \alpha_{i3} Y_{it} + \alpha_4 H_{t-1} + \alpha_5 H_{t+1} + \beta_1 D_{t-7} + \beta_2 D_{t-2}$$
$$+ \gamma_1 T_t + \gamma_2 I_t + \delta InterV_t + e_{1,t} \quad (4.3.2),$$

where W_{it} represents all of the days in the week except the base day of Sunday, M_{it} symbolizes all the months in the year except of base month of December, Y_{it} corresponds to the years of 2001 and 2002, H_{t-1} and H_{t+1} are the days near a holiday, D_{t-2} and D_{t-7} denote the two- and seven-day lags of demand, T_t and I_t stand for all the temperature and illumination variables, $InterV_t$ is a symbol for all interactive variables used in the forecasting models, $c_1, \alpha_{i1}, \alpha_{i2}, \alpha_{i3}, \alpha_4, \alpha_5, \beta_1, \beta_2, \gamma_1, \gamma_2, \delta$ are the coefficients to be estimated, and e_{1t} is the residual term.

The performance of this model is compared with the neural network model. In the following, the ANN consists of an input layer with 38 nodes, one hidden layer with three nodes that is the type of ANN chosen as the final specification, and an output layer with a single output node. Our network will be of the following feed-forward type with a logistic (sigmoid) activation function in each node of the hidden layer:

$$D_t = A_0 + \sum_{n=1}^{3}\left(A_n * \frac{1}{1+e^{-(b_{n,0}+\sum_{k=1}^{K} b_{n,k}X_k^t)}}\right) + e_{2,t} \qquad (4.3.3),$$

where K is the number of input data, $A_0, \cdots, A_3, b_{n,0}, \cdots, b_{n,k}$ are the coefficients to be estimated for the terms considering the different effects, and X_k^t represents a set of all input variables.

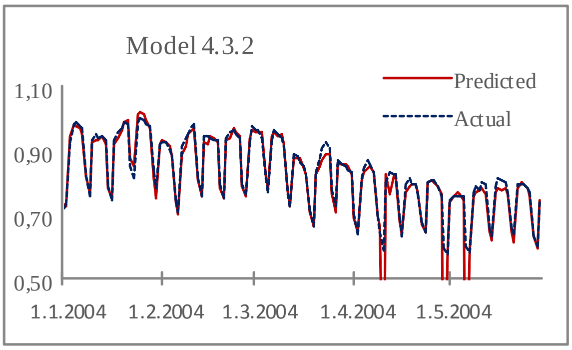
We are interested in daily demand data covering the time span from January 2001 through December 2003, for a total of 1053 sample data points. The observations for January through May 2004, i.e. 147 sample points, are reserved as a test period for the evaluation of forecasting power. The results for the estimation of (4.3.2) and (4.3.3) are summarized in Table 6.

	LRM (4.3.2)	ANN (4.3.3)
PANEL A: In-sample performance		
Number of observations	1053	1053
In-sample MAD	407.81	356.39
In-sample MAPE	1.70%	1.47%
Adjusted R-squared	0.979	0.983
AIC	12.651	12.513
BIC	12.820	12.050
PANEL B: Out-of-sample performance		
Forecast observations	147	147
Out-of-sample MAD	348.37	309.85
Out-of-sample MAPE	1.29%	1.15%
Theil's Inequality Coefficient	0.0087	0.0076
-- Bias Proportion	10.45%	10.15%
-- Variance Proportion	0.42%	0.75%
-- Covariance Proportion	89.12%	89.10%

Table 6: Estimation results for models 4.3.2 and 4.3.3.

Panel A of Table 6 summarizes the overall in-sample performance of both models. We can see that the ANN model slightly outperforms the regression model. Both models present a high predictive power, with an adjusted R-squared of 97.9% and 98.3%; however, there are relatively significant differences in the in-sample mean absolute deviations (MAD) and mean absolute percent errors (MAPE) between the models.

The results in Panel B show that the ANN specification gives better demand forecasts than the regression model. The overall out-of-sample MAPE for the LRM is 1.29%, while the ANN model takes the value of 1.15%. Theil's Inequality Coefficient provides another means of assessing the forecast errors. The inequality coefficient is an indication of systematic bias; a lower value is preferred. Its decomposition shows that 89.12% for the LRM and 89.10% for ANN of the coefficient captures the inequality caused by random factors. The remaining part is distributed between the inequalities due to the bias (10.45% and 10.15%, respectively) and that due to the different variances of the predicted and observed values (0.42% and 0.75%, respectively). Overall, these statistics show a high agreement between the true observations and forecasted values. Figure 21 and Figure 22 visualize the predicted power of the models.



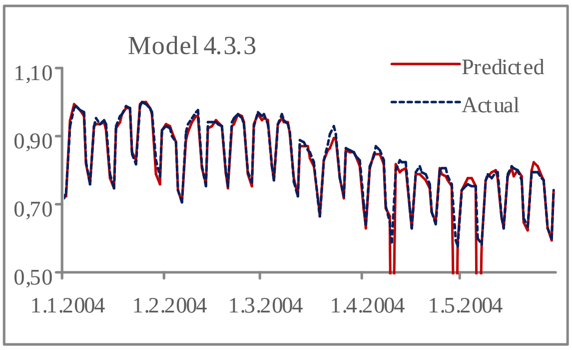


Figure 21: Out-of-sample performance of model 4.3.2.
Figure 22: Out-of-sample performance of model 4.3.3.

4.4 MODELS WITH SEASONAL, DYNAMIC AND PRICE EFFECTS

On 1 January 2002 the electricity market in the Czech Republic started to open up and ranked among the world deregulated electricity markets where consumers are supposed to be price-sensitive. So far, our econometric models used for forecasting electricity demand do not explicitly account for any price effect on demand. Khotanzad et al. (2002) claim that short-term ED forecasting models –customized to price-insensitive historical data from a regulated era would no longer be able to perform well‖. Therefore we consider the price effect to be valuable and include the ability to adjust for price changes in our current ED forecasting models. As a result we develop price-sensitive forecasting models where the price variable is factored in the relationship between system electricity demand and the influencing factors that capture the seasonal (calendar and weather variables) and dynamic (lagged variables) effects:

$$ElDemand = f(Calendar, LaggedDemand, Weather, Price, InteractiveVar) \quad (4.4.1).$$

Since the Czech Market Operator was established at the very beginning of 2002, the available electricity prices cover the period of 1 January 2002 through 31 May 2004. Accordingly, we consider daily demand data covering the same time span, for a total of 700 sample data points. The observations for January through May 2004 are kept for test purposes.

Average Daily Price: 1 January 2002 to 31 May 2004

	Mean	Std. Dev.	Minimum	Maximum
Daily Price	1420.7	1148.6	0.04	3160.0

CORRELATION COEFFICIENT

	D_t	HDD	Week-day	Week-end	Spring	Sum	Fall	Winter	After Hol	Before Hol	Avg Temp	Avg Illum
Daily Price	0.397	0.178	0.259	-0.259	-0.153	0.050	0.113	0.012	-0.019	-0.006	-0.140	-0.106

Table 7: Summary of the average daily price of electricity data.

Table 7 describes a statistical summary of the price variable. The standard deviation of the price data is high indicating very volatile data. Conejo et al. (2005) state that price series are more volatile than demand series. The electricity prices are the most positively correlated with the demand data, although the causality of these two data series is questionable. The prices rise through weekdays and fall with on-coming weekends. As can be seen, weather data also considerably influences the electricity price. Especially decreasing daily temperatures have rising effects on prices.

Including the price effects into the electricity demand specification, the final linear regression will be equivalent to the following system:

$$D_t = c_3 + \sum_{i=1}^{6} \alpha_{i1} W_{it} + \sum_{i=1}^{11} \alpha_{i2} M_{it} + \alpha_3 Y_t + \alpha_4 H_{t-1} + \alpha_5 H_{t+1} + \beta_1 D_{t-7} + \beta_2 D_{t-2} + \gamma_1 T_t$$
$$+ \gamma_2 I_t + \delta P_{t-1} + \vartheta InterV_t + e_{3,t} \quad (4.4.2),$$

where P_{t-1} corresponds to the one-day lag of average daily electricity price.

The corresponding mathematical model for neural network is expressed as

$$D_t = A_0 + \sum_{n=1}^{3} \left(A_n * \frac{1}{1+e^{-(b_{n,0}+\sum_{k=1}^{K} b_{n,k} X_k^t)}} \right) + e_{4,t} \quad (4.4.3),$$

where price variable is included in the set of input variables X_k^t.

	LRM (4.4.2)	ANN (4.4.3)
PANEL A: In-sample performance		
Number of observations	700	700
In-sample MAD	372.10	294.51
In-sample MAPE	1.51%	1.20%
Adjusted R-squared	0.982	0.987
AIC	12.528	12.267
BIC	12.755	13.047
PANEL B: Out-of-sample performance		
Forecast observations	147	147
Out-of-sample MAD	387.13	356.38
Out-of-sample MAPE	1.44%	1.34%
Theil's Inequality Coefficient	0.0096	0.0085
-- Bias Proportion	11.97%	1.64%
-- Variance Proportion	1.27%	2.48%
-- Covariance Proportion	86.77%	95.88%

Table 8: Estimation results for models 4.4.2 and 4.4.3.

Table 8 summarizes the main estimation results for (4.4.2) and (4.4.3). Comparing the results of models 4.3.2 and 4.3.3, including the price variable into the input data set improved the overall in-sample performance of both models. While the adjusted R-squared improved only slightly, the MAD and MAPE statistics decrease notably. However, comparing Panel B of Table 6 and Panel B of Table 8 we can see that the predictive power of models 4.4.2 and 4.4.3 considerably declined. The out-of-sample MAPE of the LRM model is 1.44% against 1.29% for model 4.3.2 and takes a value of 1.34% against 1.15%

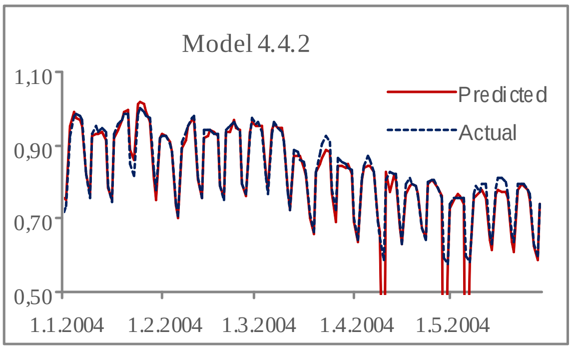
for the ANN model. The Theil's Inequality Coefficient for both models is higher than for models without price effects suggesting that consumers are not able to adjust their consumption to the price information. This behavior is mainly justified by the fact that during the considered years of 2002–2004 the Czech electricity market was opening stepwise only for large industrial consumers (see Table 1) while our data include both industrial and residential consumers.

In addition, the following Table 9 shows the significance of the price variable in the model estimation. The values of T-statistics and their P-values suggest that in none of the models is the price variable significant except node 3 in the ANN model specification.

	Coefficient	T-Stat	P-value
LRM (4.4.2)			
$DailyPrice_{t-1}$	0.100	1.234	21.75%
$DailyPrice_{t-1}$*WkEnd	-0.119	0.765	44.43%
ANN (4.4.3)			
Node1: $DailyPrice_{t-1}$	0.010	1.235	21.73%
Node1: $DailyPrice_{t-1}$*WkEnd	0.015	0.278	78.13%
Node2: $DailyPrice_{t-1}$	0.027	0.798	42.52%
Node2: $DailyPrice_{t-1}$*WkEnd	0.041	0.141	88.75%
Node3: $DailyPrice_{t-1}$	0.355	-3.293	0.11%
Node3: $DailyPrice_{t-1}$*WkEnd	2.507	0.935	0.75%

Table 9: Significance of the price variable in the LRM and ANN specifications.

Overall, comparing the results of (4.4.2) and (4.4.3), the ANN model again appears to be slightly superior to the linear regression model despite the effort to include the nonlinear inputs and interactions in the regression model. On Figures 23 and 24 are depicted the observed and forecasted values of both of the estimated models



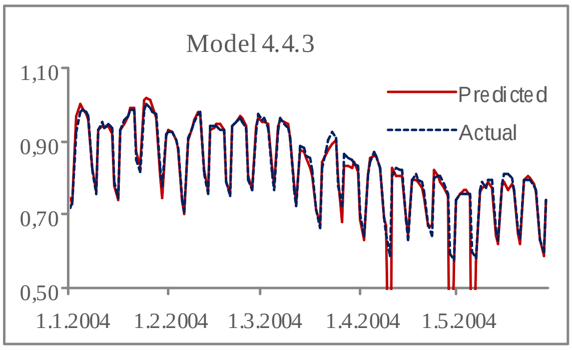


Figure 23: Out-of-sample performance of model 4.4.2.
Figure 24: Out-of-sample performance of model 4.4.3.

An econometrically tractable nonlinear extension of the linear autoregressive model is the threshold autoregressive model with exogenous variables (TARX). TAR models are especially –suited for time-series processes that are subject to periodic shifts due to regime changes‖ (Enders et al., 2007). These models are quite popular in the nonlinear time series literature since they are relatively simple to specify, estimate and interpret. Hansen (1997) developed a distribution theory for least squares estimates of the threshold in TAR models and applied this theory to the U.S. unemployment rate. He found statistically significant threshold effects. Johansson (2001) investigated the usefulness of TAR models for modeling real exchange rate dynamics. His conclusion is that –the power of the tests for TAR behavior can be very low for realistic parameter settings‖. Teräsvirta et al. (2005) examined the forecast accuracy of linear autoregressive (AR), smooth transition autoregressive (STAR),[12] and neural network (NN) time series models for 47 monthly macroeconomic variables of the G7 economies. Their point forecast results have indicated that the STAR model generally outperformed the linear AR model. Enders et al. (2007) applied the TAR process to real U.S. GDP growth, and constructed confidence intervals for the parameter estimates. However, since the confidence intervals were too wide, they concluded that it is problematic to assert that there are different degrees of persistence in positive versus negative growth regimes.

[12] If the discontinuity of the threshold is replaced by a smooth transition function, the TAR model can be generalized to the smooth transition autoregressive (STAR) model (Hansen, 1996).

There is a sizeable literature on the performance of the TAR models in the area of electricity spot price forecasting. For example, Stevenson (2002) applied the linear AR model and TAR model to electricity price series for the Australian state of New Wales. He concluded that –models from the TAR class produce forecasts that best appear to capture the mean and the variance components‖ of the price data. The short-term forecasting powers of AR and TAR models in the Nord Pool electricity spot market are compared also in the paper of Weron and Misiorek (2006). They found that nonlinear regime-switching models outperform the linear AR models especially during volatile weeks.

Next we examine whether a model from the TARX class produces better forecasts of the electricity demand than the one-regime linear equivalent given by (4.4.2). The linear AR model is often taken as the typical linear benchmark, for instance in Stevenson (2002) or Khmaladze (1998).

For our purposes we consider a two-regime threshold autoregressive model with electricity price as a critical variable. What determines whether the forecasted electricity demand belongs to one regime or another is whether the change in electricity price is positive or negative. It follows that the threshold level is equal to zero. Namely, the specification of the TARX model is given by:

$$\begin{cases} D_t = \propto_0 + \propto_1 P_{t-1} + \propto_2 D_{t-2} + \propto_3 D_{t-7} + \propto_4 T_t + \propto_5 I_t + \sum_{i=1}^{6} \propto_{6,i1} W_{it} + \sum_{i=1}^{11} \propto_{7,i2} M_{it} + \\ \quad + \propto_8 H_{t-1} + \propto_9 H_{t+1} + \propto_{10} InterV_t + e_{\propto,t} \qquad if \;\; v_t \leq 0 \\ D_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 D_{t-2} + \beta_3 D_{t-7} + \beta_4 T_t + \beta_5 I_t + \sum_{i=1}^{6} \beta_{6,i1} W_{it} + \sum_{i=1}^{11} \beta_{7,i2} M_{it} + \\ \quad + \beta_8 H_{t-1} + \beta_9 H_{t+1} + \beta_{10} InterV_t + e_{\beta,t} \qquad if \;\; v_t > 0 \end{cases} \tag{4.4.4}$$

where v_t is the threshold variable. We have decided to use two kinds of threshold variables. For the first TARX specification (TARX_1) we use a v_t equal to the difference in average daily prices for yesterday and eight days ago, i.e. $v_{1t} = P_{t-1} - P_{t-8}$. The reason for employing this one-week price difference is to compare the electricity prices according to the same day in the week. For the next TARX model (TARX_2) we have decided to set v_t equal to the difference in average daily prices for yesterday and the day before yesterday, i.e. $v_{2t} = P_{t-1} - P_{t-2}$, in order to capture the latest day-to-day change in the electricity price.

The following Table 10 contains statistics for the estimation and forecasting results for both kinds of TARX models. The performance of both the TARX models are very similar, independent on the threshold level demonstrating again the demand inelasticity of consumers with respect to market price. On the whole, the performance of both the models are comparable with the LRM models developed above, as well as the non-linear ANN models. In comparison with the LRM models, applying TARX models to our data results in an overall slight improvement of in-sample statistics while all out-of-sample statistics noticeably worsen. The forecasting results of the ANN models suggest that the ANN model is more appropriate for electricity demand data modeling than the TARX model. Overall, while it may seem tempting to analyze the electricity demand data using TARX models with the electricity price as the threshold variable, attempts are likely to founder on the very low price elasticity of consumers. Consequently, the simpler LRM and ANN models remain the more suitable candidates for modeling the electricity demand data.

	TARX_1	TARX_2
PANEL A: In-sample performance		
Number of observations	700	700
In-sample MAD	352.48	359.25
In-sample MAPE	1.43%	1.46%
Adjusted R-squared	0.982	0.981
AIC	12.492	12.558
BIC	12.934	13.020
PANEL B: Out-of-sample performance		
Forecast observations	147	147
Out-of-sample MAD	412.31	406.62
Out-of-sample MAPE	1.54%	1.53%
Theil's Inequality Coefficient	0.0100	0.0100
-- Bias Proportion	13.92%	14.27%
-- Variance Proportion	1.91%	0.25%
-- Covariance Proportion	84.17%	85.48%

Table 10: Estimation results for TARX_1 and TARX_2 models.

4.5 MODELS WITH AUTOREGRESSIVE SPECIFICATION

In order to account for dynamic effects in our models, we introduce the two- and seven-day historical values of electricity consumption into the input variable set. However, there are two possible problems with this procedure. Firstly, in the presence of other explanatory variables, the introduction of the lagged dependent variable into the model would –impose a common dynamic autoregressive structure on the remaining variables‖ including weather variables. (Pardo et al., 2002) With daily data the degree of autocorrelation may extend beyond the first order. Secondly, it may appear that the lagged dependent variables may serve to model the data rather than represent actual dynamic behavior. Therefore, Peirson and Henley (1994) developed an ED forecasting model where the dynamic behavior of the data is captured through the error process, without the inclusion of lagged dependent or lagged explanatory variables.

The introduction of the autoregressive error structure in the forecasting model specification is a quite common approach; see for instance Ramanathan et al. (1997) or McNelis (2005). Moreover, Ramanathan et al. (1997) developed a short-run hourly forecasting model system using simple multiple regression models, one for each hour of the day with a dynamic error structure. Their results show that this very straightforward forecasting strategy has performed extremely well in tightly controlled experiments against a wide range of alternative models. However, the results of Peirson and Henley (1994) and subsequently also Pardo et al. (2002) demonstrate that capturing dynamic effects only through an autoregressive specification of the error structure will result in an over-prediction of the effect of a change in temperature on demand by up to 100%. The authors conclude that the electricity demand is affected by both the autoregressive error specification and by the dynamic components of weather variables.

As a result, with respect to the findings of these studies, next we develop models where the dynamic effects are captured both through the lagged weather variables and through an autoregressive representation of the error structure, i.e. without the inclusion of a lagged dependent variable. Since the demand, weather and price data are typically of a daily frequency, the autoregressive specification AR(i) would require i to be at least seven.

The general estimating equation takes the following form

$$ElectricityDemand_t = f(Calendar_t, Weather_t, InteractiveVar_t)$$

$$e_t = \varepsilon_t + \theta(L)e_{t-1} \qquad (4.5.1),$$

$$\varepsilon_t \sim N(0,\sigma^2)$$

where e_t is the error term, ε_t is white noise and $\theta(L)$ is a polynomial function of the backshift operator L. $\theta(L)e_{t-1} = \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_k e_{t-k}$ and k is the number of polynomial coefficients.

In order to be able to compare the estimation results of particular models, we present two groups of models. Firstly we develop a multiple regression and neural network model with seasonal and dynamic effects and with an AR specification of error terms. After that we turn our attention to models that capture seasonal, dynamic and price effects and include lagged errors.

Specifically, the linear regression model of the first group of models is specified by introducing a six-order autoregressive process in the error term:

$$D_t = c_5 + \sum_{i=1}^{6} \alpha_{i1} W_{it} + \sum_{i=1}^{11} \alpha_{i2} M_{it} + \sum_{i=1}^{2} \alpha_{i3} Y_{it} + \alpha_4 H_{t-1} + \alpha_5 H_{t+1} + \gamma_1 T_t + \gamma_2 I_t + \vartheta InterV_t + e_{5,t}$$

$$\varepsilon_{5,t} = (1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3 - \cdots - \theta_6 L^6) e_{5t} \qquad (4.5.2).$$

The disturbance term $e_{5,t}$ consists of a current period white-noise shock $\varepsilon_{5,t}$ in addition to six lagged values of this shock, weighted by the vector θ.

The corresponding neural network model with a four-order autoregressive error structure is given by:

$$D_t = A_0 + \sum_{n=1}^{3} \left(A_n * \frac{1}{1 + e^{-(b_{n,0} + \sum_{k=1}^{K} b_{n,k} X_k^t)}} \right) + e_{6,t}$$

$$\varepsilon_{6,t} = (1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3 - \theta_4 L^4) e_{6t} \qquad (4.5.3),$$

where lagged demand values are not included in the input data set X_k^t.

The multiple regression model that comprises seasonal, dynamic and price effects with a seven-order autoregressive process in the error term is given as follows:

$$D_t = c_7 + \sum_{i=1}^{6} \alpha_{i1} W_{it} + \sum_{i=1}^{11} \alpha_{i2} M_{it} + \sum_{i=1}^{2} \alpha_{i3} Y_{it} + \alpha_4 H_{t-1} + \alpha_5 H_{t+1} + \gamma_1 T_t + \gamma_2 I_t$$

$$+\delta P_{t-1} + \vartheta InterV_t + e_{7t} \qquad (4.5.4).$$

$$\varepsilon_{7,t} = (1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3 - \cdots - \theta_7 L^7) e_{7t}$$

Finally, adding the price effect in ANN model where the errors are assumed to follow an autoregressive specification leads to the following system of equations:

$$D_t = A_0 + \sum_{n=1}^{3} \left(A_n * \frac{1}{1 + e^{-(b_{n,0} + \sum_{k=1}^{K} b_{n,k} X_k^t)}} \right) + e_{8,t}$$

$$\varepsilon_{8,t} = (1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_6 L^6)\, e_{8t} \qquad (4.5.5),$$

where price variable is a part of the set of input variables X_k^t.

The results of estimating all four equations (4.5.2)-(4.5.5) are reported in Table 11. As can be seen, including the price variable into the input factors improves the overall in-sample performance of both the linear and nonlinear models with the AR error structure. While the R-squared statistics are comparable for all models, the MAD and MAPE values are the best for the ANN model given by (4.5.5). On the other hand, the price variable in the models with the AR error structure heavily worsens the out-of-sample performance, suggesting that this variable brings no additional information for the forecasters. The simple regression model provides the best out-of-sample performance (4.5.2) with the lowest MAD and MAPE value of 329.8 MW and 1.24%, respectively. The decomposition of the inequality coefficient of the model (4.5.2) shows that the greatest part of the coefficient 97.3% captures the inequality caused by random factors.

Data range	Models with seasonal and dynamic effects and AR structure in the error term 1 January 2001 – 31 May 2004		Models with seasonal, dynamic and price effects and AR structure in the error term 1 January 2002 – 31 May 2004	
	LRM (4.5.2)	ANN (4.5.3)	LRM (4.5.4)	ANN (4.5.5)
PANEL A: In-sample performance				
Number of observations	1047	1049	693	694
In-sample MAD	373.27	378.05	346.86	332.75
In-sample MAPE	1.55%	1.57%	1.40%	1.35%
Adjusted R-squared	0.982	0.976	0.984	0.983
AIC	12.506	12.879	12.379	12.524
BIC	12.691	13.385	12.634	13.251
PANEL B: Out-of-sample performance				
Forecast observations	147	147	147	147
Out-of-sample MAD	329.77	354.33	391.93	422.35
Out-of-sample MAPE	1.24%	1.42%	1.46%	1.70%
Theil's Inequality Coefficient	0.0089	0.0104	0.0105	0.0137
-- Bias Proportion	1.56%	1.77%	1.22%	3.82%
-- Variance Proportion	1.14%	1.72%	0.07%	3.10%
-- Covariance Proportion	97.30%	96.51%	98.71%	93.08%

Table 11: Estimation results for models with an autoregressive specification in the error terms.

4.6 SUMMARY OF MODELS PERFORMANCE

Summarizing the performance of all eight models, we can say that the price of electricity as an explanatory factor significantly affected the in-sample performance of the models. The neural network model (4.4.3), i.e. the model incorporating the seasonal, dynamic and price effects without lagged errors, provides the best values for almost all the chosen in-sample statistics. On the contrary, the price variable overly decreases the forecasting power of both the models with and without a dynamic error structure. The neural network model (4.5.5) with a six-order error structure and price effects shows the worst out-of-sample performance. Its mean absolute deviation is more than 422 MW, MAPE statistics takes the value of 1.70% and the Theil's Inequality Coefficient has the highest value of 0.0137.

Including the dynamic error structure into the models significantly improves the in-sample performance of the linear models. The LRM (4.5.4) incorporating both the price effects and lagged errors presents the best MAPE value of 1.40%. Also the out-of-sample statistics of both the LRMs with lagged residuals are slightly better or at least comparable with the LRMs without a lagged AR error structure. The LRM (4.3.2), i.e. the simple regression model without price effects and lagged errors, gives among the all linear models the worst in-sample statistics with a MAPE value of 1.70% and MAD 407.8 MW.

Adding in the dynamic error structure into the neural network specification has the opposite effect. Both the in- and out-of-sample performance of this nonlinear type of model considerably worsens. Among the ANN types, model (4.5.3), i.e. the model with AR error structure presents the worst in-sample performance. The ANN model (4.4.3) has the best in-sample statistics, demonstrating again that the price factor helps to improve in-sample performance. The simplest ANN model (4.3.3) without price effects and dynamic error structure provides us with the overall best forecasting power with MAPE statistics of 1.15%, MAD statistics 309.9 MW and an inequality coefficient of 0.0076.

To conclude, from the forecaster's point of view, the forecasting abilities of the best linear model (4.5.2) and the best neural network model (4.3.3) are not very different. However, while the LRM needs for the improvement of its performance to incorporate a dynamic error structure, the ANN model gives the best forecasts in its simplest specification. Further, the price factor reveals to be not significant for demand forecasting. This fact demonstrates that at least during the considered time period consumers were not price-elastic enough to react promptly to the changing electricity price conditions.

DAY-TYPE	ANN (4.3.3) Abs Error (MW)	ANN (4.3.3) Out-of-sample MAPE (%)	LRM (4.5.2) Abs Error (MW)	LRM (4.5.2) Out-of-sample MAPE (%)
Monday	220.4	0.8	334.2	1.22
Tuesday	411.2	1.44	359.8	1.26
Wednesday	432	1.57	249	0.87
Thursday	336.4	1.20	273.5	0.96
Friday	308.7	1.10	336.8	1.20
Saturday	191.4	0.84	329.5	1.50
Sunday	237.8	1.06	376.2	1.65
Average	305.4	1.15	322.7	1.24

Table 12a: Forecast comparison results for each day-type for the period 1 January 2004 to 31 May 2004.

In Table 12a is compared the forecast accuracy of both models according to day-types for the period 1 January 2004 to 31 May 2004. As can be seen, with the ANN model the average absolute ED forecast error was slightly reduced from 322.7 MW to 305.4 MW. While the linear model has significantly higher foresting power especially for Tuesday, Wednesday and Thursday, it provides relatively poor forecasts for weekend days. Using the average electricity price of CZK per MWh as given by the Czech Market Operator, the reduction in forecast errors may result in financial savings of tens of thousands of CZK.

		ANN (4.3.3)		LRM (4.5.2)	
MONTH-TYPE	DAY-TYPE	Abs Error (MW)	Out-of-sample MAPE (%)	Abs Error (MW)	Out-of-sample MAPE (%)
PANEL A		(2001-2003)	(2001-2003)	(2001-2003)	(2001-2003)
WINTER MONTH (January, February, November, December)	Monday	357.6	1.34	356.1	1.37
	Tuesday	335.3	1.22	338.5	1.25
	Wednesday	338.9	1.24	302.0	1.11
	Thursday	363.7	1.28	323.4	1.16
	Friday	384.9	1.35	364.7	1.33
	Saturday	382.3	1.55	393.0	1.65
	Sunday	353.2	1.52	321.7	1.38
	AVERAGE	359.4	1.36	342.7	1.32
SUMMER MONTHS (Jun, July, August)	Monday	452.5	2.05	484.2	2.21
	Tuesday	418.3	1.85	429.4	1.90
	Wednesday	342.0	1.48	416.0	1.84
	Thursday	397.9	1.77	431.0	1.95
	Friday	392.9	1.83	378.9	1.77
	Saturday	319.9	1.81	269.8	1.54
	Sunday	287.3	1.68	331.6	1.92
	AVERAGE	373.0	1.78	391.6	1.88
PANEL B		(Jan-May 2004)	(Jan-May 2004)	(Jan-May 2004)	(Jan-May 2004)
WINTER MONTHS (January, February)	Monday	348.6	1.15	553.2	1.82
	Tuesday	446.1	1.45	291.0	0.94
	Wednesday	129.3	0.42	166.6	0.54
	Thursday	206.0	0.67	163.1	0.53
	Friday	267.1	0.86	359.6	1.16
	Saturday	271.1	1.04	578.7	2.34
	Sunday	262.6	1.05	433.4	1.72
	AVERAGE	275.8	0.94	363.6	1.29
SPRING MONTHS (March, April, May)	Monday	147.9	0.61	208.9	0.88
	Tuesday	396.3	1.47	406.9	1.49
	Wednesday	634.3	2.35	301.3	1.09
	Thursday	415.1	1.51	354.5	1.28
	Friday	328.6	1.23	316.6	1.20
	Saturday	148.7	0.66	148.3	0.66
	Sunday	215.6	1.04	336.2	1.60
	AVERAGE	326.6	1.27	296.1	1.17

Table 12b: Comparison of estimation and forecast results for the day-type with respect to winter and spring months.

Going into more in detail, Table 12b sums up the comparison of estimation (Panel A) and forecast (Panel B) results with respect to the day-type divided into winter and spring or winter and summer months, respectively. The results are mixed. During the estimation period 2001–2003 the linear model shows higher predictive power in the winter months, hile for the ANN model better results are obtained in the summer months. Conversely, throughout the forecasting period January to May 2004 the ANN model generally yields better point forecasts in the cold months and unambiguously works more accurately during the weekends. On the other hand, the linear model overall yields very small deviations from the nonlinear model for each day in the week except Sunday, thus LRM is preferred for the spring months. Generally, the results of both of the models are comparable. However, with respect to the average values, the ANN model is slightly preferable to the LRM model.

Table 13 shows the overall in-sample and out-of-sample forecasting ability of both the linear and nonlinear models with respect to month-type. Generally, the ANN as given by (4.3.3) performs better than or comparably to the LRM as defined by (4.5.2) for almost all month-types. The most significant difference in forecasting error occurs in the out-of-sample January month-type where the neural network MAPE statistics take the value of 0.88% while the LRM out-of-sample MAPE has the value 1.75%. On the whole, considering all the linear and nonlinear model statistics, the neural network specification appears to be slightly superior to the regression model.

	ANN (4.3.3)		LRM (4.5.2)	
MONTH-TYPE	In-sample MAPE (%) (2001-2003)	Out-of-sample MAPE (%) (2004)	In-sample MAPE (%) (2001-2003)	Out-of-sample MAPE (%) (2004)
1	1.10	0.88	1.18	1.75
2	1.06	1.04	1.20	0.96
3	1.14	1.03	1.31	1.00
4	1.29	1.59	1.77	1.20
5	1.29	1.20	1.38	1.31
6	1.42		1.31	
7	2.64		2.75	
8	1.32		1.60	
9	1.48		1.63	
10	1.66		1.53	
11	1.30		1.20	
12	1.90		1.72	
Average	1.47	1.15	1.55	1.24

Table 13: Estimation and forecast comparison results for each month-type.

Makridakis and Hibon (2000) state that the criterion of forecast evaluation is the degree of accuracy of the forecast. From the economic point of view, the performance of both the neural network and linear regression models could be judged through the financial losses of inaccurate demand forecasts. –The relationship between the size of a forecast error and the cost to an organization or the user of the forecast has often been referred to as a loss function‖ or an error cost function (Lawrence and O´Connor, 2005). An unbalanced loss or cost function is often denoted as an asymmetric loss or cost function. –In addition to symmetry/asymmetry, the cost function may exhibit a linear or nonlinear shape‖ (Lawrence and O´Connor, 2005). As Lawrence and O´Connor (2005) further claim, –in a perfect world the minimization of error will also minimize cost and maximize benefit‖. In the asymmetry condition, where the errors are predictable, the cost of under-forecasting may not be equivalent to the cost of over-forecasting. Particularly, in the world of electricity demand forecasting, overestimating the future demand results in unused spinning reserves that are –burnt‖ for nothing (Darbellay and Slama, 2000). Underestimating the future demand is probably even more harmful since buying at the last minute from other suppliers is obviously very expensive. Altalo and Smith (2001) also assert that the costs associated with over-forecast errors are less costly than the under-forecasted demand, since system stability, reliability and reputation are not at stake. In Figure 25 is depicted the average monthly market price of electricity together with the average price of positive and negative imbalances[13] associated with the over- and under-forecasts as reported by the Czech Market Operator. Evidently, in this asymmetrical condition, a unit of cost of an under-forecast error is much higher than a unit of cost of an over-forecasted error, although it is also high. For instance, in March 2004 the average market price was 658 CZK per MWh, the price of positive imbalance fell to almost 0 CZK per MWh while the price of an additional purchased MWh escalated to 1220 CZK per MWh.

[13] Imbalance is the difference between the actual and the agreed electricity power consumption.

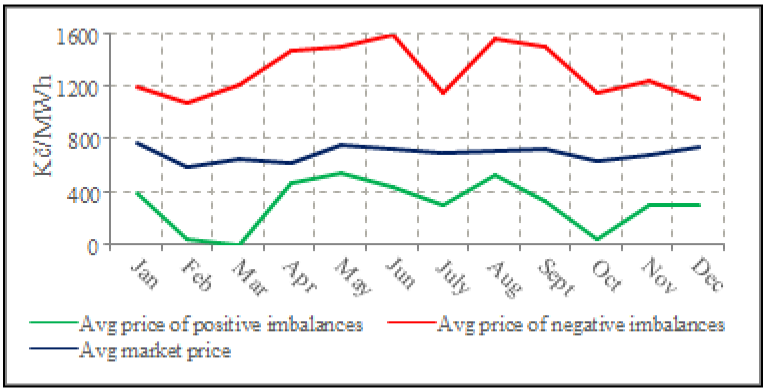


Figure 25: Average price of positive and negative imbalances and average market price of electricity through the months of 2004.

Source: www.ote-cr.cz.

Now we turn our attention again to the out-of sample performance of the neural network model (4.3.3) and linear regression model (4.5.2). Both of the models have a tendency to underestimate the future electricity demand; while the number of neural network under-forecasts was 92 out of a total 147 forecasts, the number of linear regression underestimated values was 84 of 147 forecasts. Taking the average price of positive and negative imbalances, we computed the cost curves for under- and over-forecasting for both of the models, see Figure 26.

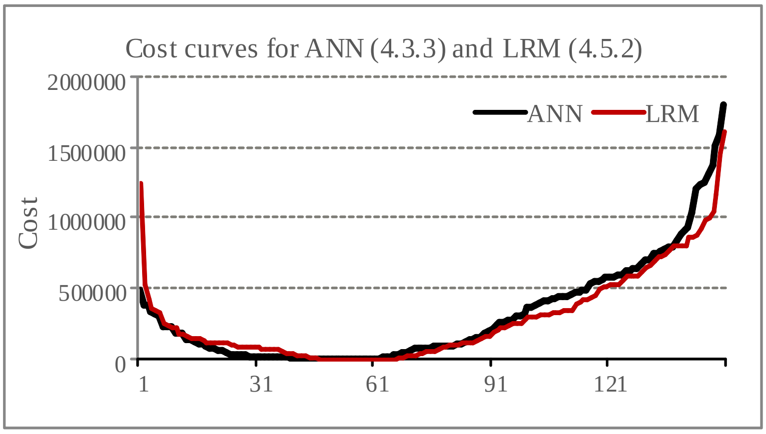


Figure 26: Cost curves for the ANN model (4.3.3) and for the LRM (4.5.2) for under- and over-forecasting, showing asymmetry.

Obviously, both of the curves are of nonlinear shape and clearly show asymmetry. As can be seen from the figure, the ANN model provides a lower number of overestimated values. The left-hand part of its cost curve lies under the cost curve of the LRM indicating that the overall cost of the over-forecasts of the ANN model is generally lower. On the other hand, the financial losses caused by the under-prediction of future demands by both models amount to billions of Czech Crowns. Surprisingly, although the overall out-of-sample performance of the ANN model suggests that the nonlinear model has higher forecast power and provides more reliable demand forecasts, the right-hand part of the ANN cost curve lies evidently over the cost curve of the linear regression model. In other words, the total loss of the ANN under-forecasts seems to be slightly higher than the LRM under-forecasts loss. Using again the average imbalance prices, the cost of under-forecasts for the whole forecasted period add up to more than 42 billion CZK for the ANN model as specified in (4.3.3) and more than 36 billion CZK for the linear regression model given by (4.5.2). Finally, the overall cost of forecast errors come to more than 46 billion CZK in the case of the ANN model and to more than 44 billion CZK for the linear model. As a result, the simple linear regression model with autoregressive error structure despite a slightly poorer out-of-sample statistics finally outperforms the ANN model and can be considered as more effective and reliable.

5 CONCLUSION

In this dissertation we have tried to take the reader over the whole problem of electricity demand forecasting in the Czech environment. We started with a brief description of the current stage and structure of the Czech, as well as the European, electricity market. We have depicted the importance of an accurate ED forecast. We show that an ED forecasting model is becoming a principal decision–support tool for effective functioning of an electric power system. This forecasting device is ―important not only for system operators, but also for market operators‖ (Chen et al., 2001). Participants in the electricity market need to have accurate forecasting tools to optimize their buying and selling decisions. The main reason why the market operators call for high accuracy and speed of ED forecasts is especially because both over- and under-forecasts of the ED are costly and result in loss of revenue. As we have shown on the case of Czech data, this loss can be measured in hundreds of thousands, even millions, of CZK.

To date there have been developed hundreds of demand forecasting models, both linear and nonlinear. The choice of the most appropriate model is conditioned by the underlying factors that determine electricity consumption. Our results show that the most influential external factors are temperature and calendar variables. However, unlike Darbellay and Slama (2000) who argue that the relationship between electricity consumption and temperature is linear in the Czech Republic, we demonstrate that the relationship is, especially in recent years, nonlinear. We illustrate that also the relationship between illumination and price variables and electricity demand is nonlinear.

We build several types of multivariate forecasting models, both linear and nonlinear. These models are, respectively, linear regression models and artificial neural network models. Although artificial neural networks are not the only nonlinear modeling tool, many studies show that they are they well suited to short-term electricity demand forecasting since they are able to capture nonlinearities and handle the co-linearity problem of the explanatory variables. In order to provide a comparison with standard regression models, we tried to find the best forecasting results for both the linear regression model with nonlinear inputs and the ANN model.

These models were evaluated and compared using a variety of standard model statistics, such as R-squared, MAD or MAPE values, as well as an empirical loss function. Our results are quite surprising. Based on the most frequently used accuracy measures– out-of-sample MAPE and MAD– we chose a linear model incorporating seasonal and dynamic effects and the six-order autoregressive error structure, and an ANN with seasonal and dynamic factors. The preferred ANN model appeared to be slightly superior to the LRM. However, the empirical loss function showed that the overall cost of the ANN forecast errors is higher than the total cost of the LRM forecast errors. As a result, the LRM with an autoregressive error structure regardless of the poorer out-of-sample statistics finally outperforms the more sophisticated nonlinear ANN.

The MAPE and MAD accuracy measures are reported in most electricity demand forecasting studies as the key error measures since they are directly relevant to the users. The empirical loss function is not used at all or is used very rarely. This is quite remarkable, as the values of the empirical loss function are typically expressed in a currency, which speaks a very clear language to the users. In any case, our results show the empirical loss function can be a powerful accuracy measure in electricity demand forecasting.

The main point of this dissertation is the following: although we found that the electricity demand forecasting in the Czech Republic is for the considered years rather a nonlinear problem than a linear problem, for practical purposes simple linear models with nonlinear inputs can be adequate. Of course, the intensity of the factors influencing the demand can vary with time (summers can become ever hotter, electricity prices are supposed to have a much stronger effect on Czech electricity consumption, etc.). In these changing conditions nonlinear models such as neural networks could be particularly valuable.

DESCRIPTIONS OF ELECTRICITY MARKET PARTICIPANTS

All the following terms are taken from Energy Act No. 458/2000 Coll:

THE GENERATOR OF ELECTRICTY POWER (hereinafter –generator‖) is any individual or legal entity generating electricity and holding an electricity generation license. He has a right to supply electricity through the transmission system or distribution network. The generator also has the right to offer electricity it produces on the short-term electricity trading marketplace.

The reliable flow and development of the whole transmission system and the distribution of electricity on contractual bases is provided by the cross-border TRANSMISSION SYSTEM OPERATOR (hereinafter –TSO‖). In the Czech Republic the main TSO provider is Česká přenosová společnost (ČEPS). The TSO manages the electricity flow in the transmission system with respect to the electricity flow among the systems of other countries and in cooperation with the electricity distribution company. The TSO cannot be a license holder for electricity trading, electricity production and distribution.

The succeeding distribution of electricity to end customers, such as industrial factories and households, as well as the flow and development of the electricity distribution network is arranged by electricity DISTRIBUTION SYSTEM OPERATORS (hereinafter –DSOs‖).

The END CUSTOMER is a natural or juridical person who takes electricity for his own use. There are two basic categories of end customers:

A PROTECTED CUSTOMER has the right to be linked to the distribution network and the right to be supplied with electricity in a given quality and for regulated prices.

AN ELIGIBLE CUSTOMER is according to Energy Act No. 458/2000 Coll. defined as a person who has the right to be linked to a distribution network as well as to the transmission system. He has also the right to buy electricity directly from the electricity production licensees and from the electricity trading licensees. Finally, he is entitled to buy electricity directly on the short-term electricity trading marketplace.

THE ELECTRICITY MARKET OPERATOR (hereinafter –EMO‖) organizes the short-term electricity market and processes electricity trading balances. In conformity with the energy law and the liberalization of the energy sector the Operátor trhu s elektřinou (OTE), a stock state-owned company, was established in the Czech Republic in 2002 to introduce an organized short-term electricity trading marketplace. One of the EMO's activities is to evaluate the deviations of individual settlement entities, i.e. differences between actual (metered) and contracted electricity volumes.[14]

The role of the ELECTRICITY TRADER (hereinafter –trader‖) is to buy electricity from the electricity production licensees and from the electricity trading licensees, and to sell it to end customers

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[14] Source of information: www.ote-cr.cz.

LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
ANN	Artificial neural network
ARMA model	Autoregressive Moving Average model
ARMAX model	Autoregressive Moving Average model with exogenous inputs
BIC	Bayesian Information Criterion
CDD	Cooling degree-day
CTT	Cooling temperature threshold
CZK	Czech Crown
ED	Electricity demand
EMO	Electricity market operator
GMRAE	Geometric Mean Relative Absolute Error
GWh	Giga Watt hour
HDD	Heating degree-day
HTT	Heating temperature threshold
LRM	Linear regression model
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MdAE	Median Absolute Error
MdAPE	Median Absolute Percentage Error
MdRAE	Median Relative Absolute Error
MRAE	Mean Relative Absolute Error
MSE	Mean Squared Error
MSPE	Mean Square Percentage Error
MW	Mega watt
NMSE	Normalized Mean Square Error
OTC	Over-the-counter
OTE	Operátor trhu s elektřinou
PX	Power exchange
RelMAE	Relative Mean Absolute Error
RMdSPE	Root Median Square Percentage Error
RMSE	Root Mean Square Error
RMSPE	Root Mean Square Percentage Error
sMAPE	Symmetric Mean Absolute Percentage Error
sMdAPE	Symmetric Median Absolute Percentage Error
TAR model	Threshold autoregressive model
TARX model	Threshold autoregressive model with exogenous inputs
TSO	Transmission system operator
TWh	Tera Watt hour
D_t	Daily electricity demand at time t
D_{t-2}	Two-day lags of electricity demand
D_{t-7}	Seven-day lags of electricity demand
H_{t+1}	Day after holiday
H_{t-1}	Day before holiday
$InterV_t$	Interactive variables
I_t	Illumination
M_i	i-th Month
P_{t-1}	One-day lag of average daily electricity price
T_t	Temperature
W_i	i-th day in the week

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