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On the parametric and nonparametric prediction methods for electricity load forecasting

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On the parametric and nonparametric prediction methods for electricity load forecasting

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Abstract

Accurately forecasting of electricity load is of great importance in deregulated electricity markets. Market participants can reap significant financial benefits by improving their electricity load forecasts. Electricity load exhibits a complex time series structure with nonlinear relationships between the variables. Hence, new models with higher capabilities to capture such nonlinear relationships need to be developed and tested. In this thesis, we present a parametric and a nonparametric method for short-term load forecasting, and we compare the performance of these models for different lead times ranging from one hour to one week. These methods include a modified version of Holt Winters Double Seasonal Exponential Smoothing (m-HWT) model and a Nonlinear Autoregressive with Exogenous Inputs (NARX) neural network model. Using hourly load data between 1/1/2008 to 1/1/2013 from the Dutch electricity grid, an extensive empirical study is carried out for five different provinces. Due to the promising results, in the second part of the study, NARX is applied to long-term load forecasting in one Dutch province.

Our results indicate that NARX clearly outperforms m-HWT in one-hour ahead forecasting. Additionally, our modification to HWT leads to significant improvement in model accuracy. Despite its simplicity, m-HWT outperformed NARX for 6, 12, 24, and 48-hour ahead forecasts. However NARX performs better in 1 week ahead forecasting. In addition, NARX performs clearly superior to m-HWT in terms of maximum error and on special days.

The results also indicate that with a well-trained closed loop NARX neural network model, electricity load can be forecasted successfully one and a half years ahead for hourly intervals. NARX can successfully capture nonlinear effects of special days and temperature. NARX has brought a performance improvement of 30% in terms of mean absolute percent error (MAPE) compared to the existing methodology.

Summary

Introduction

After the deregulation in Dutch electricity market, competition has increased extremely, so need for higher service levels has increased. In order to achieve high service levels, market parties need to forecast electricity load accurately.

This study was carried out in collaboration with one of the largest electricity grid operator (DNO) in the Netherlands; Enexis B.V. During transmission of electricity DNOs face with losses in the grid, named "net loss". The company needs to forecast the load accurately in order to cover the net losses. If the company fail to forecast the net loss accurately, there occurs a gap between demand and supply, which results in very high costs to the company. This has been the main motivation behind the study.

In addition to the distributors, many other parties for different purposes use load forecasts. Electricity demand forecast horizon is divided into mainly three categories: short term, mid-term and long term forecasts. In this study we focus on short and long-term load forecasting. Short-term forecasts are generally used in daily operations such as clearing electricity transactions, scheduling generation capacity, load flow analysis, etc. On the other hand, long-term forecasts are used in capital planning, in new generation and transmission capacity decisions.

Our contribution to the literature can be summarized as follows:

- Modification of HWT that enables modeling special days
- Proposition of NARX for short-term load forecasting
- Proposition of NARX for long-term load forecasting
- A comparison of parametric and nonparametric methods

Forecasting Methods

As mentioned, in this study, a comparison of parametric and non-parametric methods' performances in electricity load forecasting is studied. We have derived forecasts on short and long-term, comparing performance of Nonlinear Autoregressive with eXogenous Inputs (NARX) Neural Networks with so called substitutable parametric methods. Artificial Neural Networks modeling is a promising methodology for load forecasting due to its capability of capturing complex, nonlinear relationships between electricity infeed and other variables. In comparison to the non-parametric method, NARX, we present a modification to Holt Winters Exponential Smoothing (HWT) method. HWT is a commonly used methodology in short-term load forecasting, particularly due to its simplicity. We have modified a variation of HWT, enabling it to include effects of special days in electricity infeed forecasting.

Long-term load forecasting performance of NARX is compared to the results of a previously developed regression model's performance in a similar study. Additionally, the performance is

compared to the time shifting method performance, which has been currently used in the company.

Computational Study

Throughout the computational study, datasets of five Dutch provinces' electricity infeed are used. The data covers 256 weeks period from 1 January 2008 to 30 November 2012, referring to 43104 data points. During the data analyses it was seen that, load data contains daily and weekly cycles, with very similar patterns on weekdays, lower values during the weekends.

We believe the comprehensive data analyses we present, is another contribution of our study to the literature. In Section 5.1.1, we present that economical variables do not have any significant effect on the load data, whereas meteorological variables (temperature and sunset and sun rise times) can have significant effects. Additionally, effects of special days are studied in terms of hourly effects and year-to-year effects and the similar ones are clustered.

In the implementation part of modified Holt Winters Exponential Smoothing (m-HWT), initialization process of the model parameters and the final model parameters are presented. Next, implementation details for NARX are presented. For short–term load forecasting an open-loop network is used. Seven lag values are defined as elements of feedback loop and the network is trained as a trail and error process, limited to one hidden layer. Results of short-term load forecasting showed that m-HWT has improved the forecasting performance over a previous adaptation of HWT significantly. The improvement exceeds 30% in terms of mean absolute error (MAPE) in most of the instances. However, NARX performs better than m-HWT method for one hour and one week ahead forecasts. For forecast horizons up to 48 hours, m-HWT outperforms NARX. Another performance measure adopted in this study is maximum percent error (MaxAPE). In terms of MaxAPE, NARX outperforms m-HWT in almost all instances.

In the long-term forecasting part of the study, a closed-loop network is trained for one pilot province Brabant, which is the largest grid that Enexis owns. In this phase, temperature and sunlight are added to the input set. Architecture search is presented in detail, which was limited to two hidden layers for long-term load forecasting. Results indicate an improvement of approximately 28% compared to current methodology in terms of MAPE. MaxAPE levels almost halved with NARX forecasting compared to time shifting and regression models.

Additionally for both lead times we observed that NARX performs very well in load forecasting on special days. Special days are known as most difficult periods of the year to forecast due to divergence from regular pattern on those days. As expected NARX performed good at capturing complex relationships on these days and outperformed the conventional models.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Energy security issues have been discussed all over the world during the last decade as the natural resources have been diminishing rapidly. In order to secure effective processing of energy markets, there have been efforts to convert energy markets into more free structures. The deregulation in Dutch electricity market is an example of conversions to free markets. Electricity load forecasting is very important in electricity utilities' processes because forecasts are used in fundamental decisions in operations such as generation, infrastructure development, energy purchasing, maintenance, etc. Deregulation in electricity markets made load forecasting even more important because due to the increased competition, generators, distributors, all means of suppliers need to provide higher level of service in order to endure. Unlikely to other commodities, electricity cannot be stored and has to be available on demand. There is no available stock, no customer inventory, no backordering, etc. to meet customer demand on time. Therefore, generators, grid operators and regulators need to project electricity demand with a very high accuracy and always keep the system in balance.

The prerequisite of efficient management of power systems is the generation of accurate load forecasts for both long and short-term planning [1] [2]. Electricity demand forecast horizon is divided mainly into three: short-term, mid-term and long-term forecasts. Short-term forecasts refer forecasts between one minute to several weeks, where mid-term forecasts are one day to one year forecasts and long-term forecasts refer the forecasts for longer than one year lead times. Short-term forecasts are generally used in daily operations such as clearing electricity transactions, scheduling generation capacity, load flow analysis, etc. [4]. On the other hand, long-term forecasts are used in capital planning, in new generation and transmission capacity decisions [5]. In this study we mainly focus on short-term and long-term load forecasting.

Short-term demand forecasting helps the market participants to schedule transactions in real time [6]. After the deregulation in the market, the participants have developed the ability to adjust capacity and demand through short-term power transactions. In addition to the deregulation, technological improvements have also increased the ability to adjust capacity flexibly and meet the demand [7]. In this highly competitive setting, electricity load forecasting has become extremely important to provide uninterrupted, reliable, secure and economic supply of electricity [8]. For example from suppliers' point of view, they need to make sure they have the necessary reserve to supply their consumers; in order to avoid facing very high costs. On the other hand, in the case of over prediction; i.e. keeping excess reserves, can end up with fines, or under valuation of the available electricity. Hence both cases cost money to the market parties. Kyriakides & Polycarpou [4] summarizes functions of short-term load forecasting in:

(i) Actions such as negotiations of bilateral contracts between utilities and regional transmission operators
(ii) Studies such as economic dispatch, unit commitment, hydro-thermal coordination, load flow analysis and security studies
(iii) Operations such as scheduling of committing or decommiting generating units and increasing or decreasing the power generation.

On the other hand, long-term electricity load forecasting assists suppliers and grid operators in capital planning, in new generation and transmission capacity decisions [5]. Due to high investment costs, market parties try to avoid overestimation, which will lead to excess power facilities [9]. However underestimation means problems in supplying electricity; causes customer dissatisfaction and falling behind in the competition.

Efficient scheduling of electricity transactions is necessary to provide an economic and reliable supply of electricity, and is a key business competency of the firms in electricity markets [8]. Electricity load data includes both daily and weekly cycles. In addition, multiple factors, such as the season and time of the day, have complex and nonlinear effects on the electricity load [10]. These multiple seasonality and complex nonlinear relationships make it difficult to model electricity load with traditional regression models. In addition, during the data analysis, we observed that consumers' behavior significantly diverge from the regular pattern on special days, such as holidays, national days and the days close to them.

During the literature research, we have observed that despite many studies carried out on load forecasting there is no agreement on which method to apply for different lead times. In this study, a comparison of parametric and non-parametric methods' performances is studied on electricity load data. We have derived forecasts on short and long-term, comparing performance of Nonlinear Autoregressive with eXogenous Inputs (NARX) Neural Networks with so called substitutable parametric methods.

In addition to the computational study, we believe another important contribution of the study is our modification to Holt Winters Exponential Smoothing (HWT) method. HWT is a commonly used methodology in short-term load forecasting, particularly due to its simplicity. We have modified a variation of HWT, enabling it to include effects of special days in electricity infeed forecasting. We believe contribution of our study to the literature is fourfold:

- **Modification of HWT that enables modeling special days.** We develop a modified version of Taylor's [6] exponential smoothing adaptation to consider for the impact of special days in electricity load forecasting. The proposed model resulted in a dramatic improvement in forecasting accuracy. In particular, our modified HWT (m-HWT) model improves the average forecasting performance of Taylor's original model by around 30%. This improvement is even larger for special days and in terms of maximum error performance.

- **Proposition of NARX for short-term load forecasting.** In the literature review we observed that, mostly conventional and classical approaches are adopted for short-term load forecasting, whereas computational intelligence based and fuzzy logic methods are mainly used for longer-term forecasts. There are only a few papers, which examine the effectiveness of NARX models for short-term load forecasting. However, none of these studies apply NARX to more than a few datasets and/or for few different lead times. In this sense, our study provides a very comprehensive analysis of NARX method for short-term electricity load forecasting applying to five different data sets and generating forecasts for six different lead times.

- **Proposition of NARX for long-term load forecasting.** There are only few studies applying NARX to electricity load data in literature. Especially in long-term forecasting, there are no other papers investigating NARX networks' effectiveness. Therefore for the first time – to our best knowledge- we applied recurrent NARX networks for hourly long-term electricity load forecasting.
- **A comparison of parametric and nonparametric methods.** In this study, a widespread empirical study is carried out in order to compare artificial methods to more conventional methods**.**

This study has mainly six sections. In CHAPTER 2, literature research on electricity load forecasting is presented. Next, motivation behind this study and the case study are explained. CHAPTER 4 details forecasting methods used in this study. Computational experiments are presented in CHAPTER 5 and we conclude the study with a conclusion section.

CHAPTER 2

LITERATURE SURVEY

In 1998, Dutch electricity market was deregulated in order to build a competitive, free market that is expelled from any monopolistic power and external interventions. The aim of the deregulation was ensuring the highest customer benefit by increasing competition in the market. Former electricity market consisted of a few market players for every region, giving these players monopolistic power, as the customers had to receive electricity from market parties in that region. On the other hand, deregulated market structure allows customers to make deliberate decisions about their supplier and aims providing perfect market information to the customers to be used in their decisions. Efficient scheduling of electricity transactions is necessary to provide an economic and reliable supply of electricity, and is a key business competency of the firms in electricity markets. Efficient scheduling of electricity transactions can be achieved by accurate forecasting of electricity load. Due to the mentioned importance, which increased especially after the market deregulation in 1998, many studies have been carried out on electricity demand forecasting. In electricity market demand forecasting, two decisions should be taken very carefully, first, the lead times of the forecast, second, time interval of the forecast. These two decisions may affect both the methodology selection and the variables included in the model. Lead times of forecasts heavily depend on parties responsible from different operations on the electricity supply chain. For example, short-term models are mostly used in daily operations such as, decisions on electricity transactions, scheduling generator operation times, load flow analysis, etc. [4]. On the other hand, mid-term forecasts are mainly used to plan maintenance schedules, infrastructure adjustments, fuel purchases, etc. [11]. Lastly, long-term electricity demand forecasts are useful in capital planning, in new generation and transmission capacity decisions [5].

As mentioned, time interval of the forecasts is also very important. Unavoidably, there is a strong relationship between lead time and time interval of the forecast. In short-term forecasting, appropriate time intervals vary between quarter hour, half hour and one hour. On the contrary to considerably small intervals in short-term, in longer-term forecasts time intervals can vary from several days to one year. For example, among many studies on short-term forecasting in literature, Huang & Shih focused on daily forecasting, where Taylor's [1] focus is half hourly forecasts and Soares & Medeiros [13] generated hourly forecasts. On the other hand Mirasgedis et al. [11] derived monthly predictions up to 12 months ahead and Von Hirschhausen & Andres [14] derived yearly forecasts for next decade in China.

Most of the papers in literature are on short-term electricity load forecasting whereas number of papers on midterm and long-term forecasting also increases. Methods used in these papers vary from the simplest conventional models to complicated and very recent fuzzy logic models, to a large extent. Hahn et al. [15] divide forecasting methods mainly into two categories: classical time series and regression methods and artificial intelligence and computational intelligence methods. However hybrid models can also be stated as a separate class of forecasting methods.

2.1. Classical time series and regression methods

Regression models are commonly used in electricity demand forecasting especially due to their ability to relate external variables to electricity load [15] There are many external variables that are believed to be effective on electricity load such as calendar variables, meteorological variables and economic variables. Relating them to load carries great importance particularly in midterm and long-term load forecasting. Although, mostly linear regression models are redundant, effects of these variables are mostly nonlinear or complex to capture with linear models. However, easiness of application, understanding of relationship between input and output variables help these models keep their favorable position in the literature.

Al-Hamadi & Soliman [16] decomposed electricity load of one of the largest utility company in Canada into many simple linear models and used these models in order to forecast weekly average load profiles for 24 hours of day up to several weeks to few years. They measured accuracy over weekly average daily load and obtained mean absolute percent error (MAPE) values lower than 3.8% throughout one year. Papalexopoulos & Hesterberg [17] presented a linear regression model building process which includes parameter estimation under heteroskedasticity by using weighted least squares and diminishing the effects of potential errors on forecasts by 'reverse errors-in-variables'. Different than many other studies, they studied not load shape forecasting, but peak load forecasting, by utilizing Pacific Gas and Electric Company. Ramanathan et al. [7] derived multiple linear regression models for short-term (up to 88 hours) hourly load forecasting. They derived one model for every hour of the day. In order to capture different patterns at the weekends, weekend load is modeled separately. By incorporating exponential smoothing of the forecast errors an adaptive version of the model is derived. The adjustment enabled them to compensate for systematic errors.

Bianco et al. [18] and Mohamed & Bodger [19] also used multiple linear regression modeling, however for long-term load forecasting; yearly forecasts for several years. They both utilized economic and demographic variables and derived countrywide forecasts for Italy and New Zealand respectively. Mirasgedis et al. [11] aimed capturing nonlinear effects of external variables by building logarithmic regression models with an autoregressive component to generate daily and monthly forecasts for 12 months. They applied the models to the historical data of Greek interconnected power system from 1993 to 2002.

Time series models can be mainly divided into univariate and multivariate models. Univariate models are mostly preferred for short-term load forecasting. A very simple class of time series prediction, autoregressive moving average (ARMA) models are used by Cancelo et al. [3] by dividing data into its components for generating daily and hourly forecasts several days ahead. The models were built for Spanish system operator using 2006 data. It is stated that daily forecasts are used for weekly network outage plan and lead times vary between 4 days to 10 days. The results showed that large errors are mostly sourced from weather prediction and special days' effects on load. In the meantime, hourly forecasts are used for determining the final dispatch schedule for the next day. Highest errors were observed at the weekends, however, their model performed better than two other hybrid benchmark models. Hagan & Behr [20] stated that a simple polynomial regression analysis combined with a Box and Jenkins transfer function model can result in more accurate forecasts. Additionally, they applied nonlinear transformation to the temperature variable. The models are built by using data of moderately sized southwestern utility with 450,000 customers. The results showed that nonlinear extension model has outperformed the other three methods in hourly forecasting. Goh & Choi [21] showed that introducing a stochastic component to time series models can be used in justifying variations that cannot be attributed to a time element. They derived day ahead forecasting for half hour intervals by using four-year electricity demand data. Taylor [1] modified Holt Winters exponential smoothing formulation to accommodate two seasonalities at the same time for up to day ahead forecasting with half hour intervals. He stated that results of the empirical study carried out on England and Wales load data outperformed not only traditional Holt Winters method, but also multiplicative double seasonal ARIMA model. Taylor favored time series methods in his many other works studies ([2] [23] [22]). In these studies different alterations of exponential smoothing methods are compared to generate short-term electricity load forecasts.

Soares & Medeiros [13] also included seasonality of electricity load series in their model through a two level seasonal autoregressive (AR) model for short-term load forecasting. They used eight-year data, which was obtained from a utility company from Rio de Janeiro, Brazil. There exists also some other modifications of time series models in literature, such as Huang & Shih's [12] non Gaussian ARMA model and Huang et al.'s [24] particle swarm optimization to identify the autoregressive moving average with exogenous variable (ARMAX) model for short-term load forecasting.

2.2. Computational Intelligence Based Models

Recently, computational intelligence based models have been prevalent in the literature for electricity load forecasting. Al-Saba and El-Amin [25] developed an Artificial Neural Network (ANN) model for peak-load forecasting and compared the results to AR models. For the comparison, data of a Saudi Arabian utility, that provides services to large industrial, commercial and residential loads, was used. Results showed that ANNs provide accurate results in long-term electricity load forecasting. One of the first studies considering nonlinear autoregressive (NAR) neural network models for electricity load forecasting was introduced by Connor, et al. [26]. They compared a nonlinear autoregressive model to a recurrent nonlinear autoregressive moving average and a feed-forward nonlinear autoregressive models utilizing synthetic data on the Puget Power Electric Demand time series. They emphasize the importance of input configuration while presenting the superior performance of the recurrent networks. Efforts followed by investigation of NARX and nonlinear autoregressive moving average with exogenous variables (NARMAX) performances in short-term load forecasting [27]. The paper is mostly concerned with constructing scheme for MA part. Espinoza, et al. [28] carried out a Kernel based NARX model identification study for lead times of one hour and 24 hours. Using electricity load data from student apartments Varghese & Ashok [29] compared performances of a feed-forward back propagation neural network, a NARX network and a radial basis function model. The only paper practicing NARX models in long-term forecasting – to our best knowledge, belongs to Awan, et al. [30]. They used thirty-year data of National Transmission and Dispatch Company of Pakistan. In their paper, NARX based feed-forward neural, support vector regression and neural network methods are compared.

Studies comparing the methods have been performed to illustrate whether it is worth dealing with more complex methods like ANNs or more conventional methods perform well enough. Abraham &

Nath [31] is one of them. They compared three methods: Box Jenkins ARIMA model, a feed-forward ANN model and evolving fuzzy neural network (EFuNN) in terms of their performances in forecasting 2 days ahead half hourly forecasting. They carried out comparison on energy demand data for 10 months period in the State of Victoria. In order to make the results independent of data sample, they replicated training sample three times. Results indicate that EFuNN is superior to two other variations of ANNs and ARIMA model. Taylor et al. [32] also carried out a study on comparison of time series and computational intelligence based models. They studied 5 different models: ARIMA, exponential smoothing, ANN, components regression with PCA and seasonal version of random walk for up to one day ahead forecasting. The most unexpected result of the empirical studies, which was carried out on thirty-weeks load data, was the poor performance of ANNs. Tzafestas & Tzafestas [33] have presented a detailed study on computational intelligence based methods in their paper, which includes comparison of neural networks, fuzzy logic methods, genetic algorithms and chaos models. They also derived models that are combination of some of these methods for hourly load forecasting up to 7 days ahead.

2.3. Hybrid Models

Hybrid methods form a rising class of forecasting methods in load forecasting. [33] applied ANN and Fourier series methods for mid to long-term forecasting. For the Spanish monthly electric demand data they decreased forecast errors to values lower than 2%. Similarly, Amjady & Keynia [35] developed a hybrid model of neural networks and evolutionary algorithm for monthly load forecasting and tested their model on European Network on Intelligent Technologies (EUNITE) test data and Iran's load data. They derived forecasts for daily peak load for next month. Promising results put them on the track for developing an optimization method for adjustable parameters and preforecast structures. Desouky & Elkateb [36] developed another hybrid model that includes ANNs. They investigated possible ways of performance improvement for mid-term peak load forecasting. They had a huge dataset consisting of seven years data for training and the model performances are compared using two years load data of Jeddah city. Azadeh et al. [37] applied another hybrid approach which includes preprocessing data with time series using moving average method and fed into a multilayer perceptron (MLP) network.

In this project NARX networks will be adopted as a forecasting method, relying on neural networks ability of capturing nonlinear and complex relationships between variables and NARX networks ability of capturing time series structure in the data. Another motivation in adopting this methodology is that despite promising results in the existing few literature studies, there does not exist deeper studies on effectiveness of NARX models in electricity load forecasting. We believe NARX will perform well in electricity load forecasting and be an important contribution to the literature.

CHAPTER 3

MOTIVATION

In this chapter, the motivation behind this study, our case study and project background will be introduced. In addition to the gap observed on NARX modeling in load forecasting during literature research, the company project has been another motivation in this study. The data is provided by a semi public company in the Netherlands.

Rest of the chapter is organized as follows. Section 3.1 covers brief information about company profile. Next, project background is presented. In Section 3.3 a brief introduction about Dutch Electricity Market is presented in order to provide an understanding to the reader about how our models can help functioning of the market.

3.1. Company Profile

The company is one of the largest Distribution Network Operators (DNO), operating in six provinces, Noord-Brabant, Overijssel, Limburg, Groningen, Drenthe and Flevoland in the Netherlands. As a DNO, the company is responsible for construction, maintenance, management and development of the transportation and distribution network. The company is not only an electricity distributor but also a gas distributor, which operates with over 130.000 kilometers of electricity cables and 40.000 kilometers of gas pipes in order to distribute energy to 2.6 million customers.

The objective of the company is to facilitate the market with an affordable, reliable and sustainable energy network. It is a semipublic company that esteems customer benefit. The company is permitted to make profit but spends the profits in order to improve the service quality offered to the customers. As DNOs take a monopolistic role in the market, the tariffs are determined by market regulators considering that the company does not achieve higher returns than usual in economy. Profits are motivated to optimize network quality and earnings to run its operations. Despite no high profit targets, the company wants to become one of the most reliable players in the market. Therefore they value accurate forecasting of load in order to provide higher service levels.

3.2. Case Study Background

As mentioned before, load forecasting is very important for operations of electricity utilities, however load planning is not a simple task. There is need for uninterrupted balance in the system at all times.

There exists the common misinterpretation that distribution network operators are only responsible from transferring electricity from supplier to demand points, therefore system balance is not their concern. However, this does not reflect the reality. In addition to their responsibility for transferring electricity, DNOs are also responsible from connecting the demand points to the respective suppliers (as a well developed free market, Dutch consumers are free to choose whichever supplier they want), disconnecting the customers from the grid when they terminate their connection, detecting fraud in the grid, etc. Every failure that occurs in these operations returns to the DNO as loss in the system and forms one of the most important cost terms: distribution net loss. Distribution net loss consists of administrative losses and technical losses. Administrative losses are mostly fraud, measurement errors, faults in connecting to right suppliers, failures in disconnecting demand points in the case of termination of contract or in the cases of customers' failures to pay their bills, etc. Technical losses consist of network's own consumption during transferring the electricity, losses in the cables, losses occurring during conversion from high voltage to low voltage, etc.

Due to high uncertainty in terms of net loss, there is no statistically reinforced, accurate method for forecasting net losses. Therefore in the company, net loss is estimated as a percentage of total electricity infeed. Electricity infeed refers to the amount grid operator needs to distribute in order to operate the system appropriately. Accordingly, it is equal to the sum of the amount supplied from national grid, difference between amount supplied from other grids and demanded by other grids and difference between amount produced by generators of customers and consumed by them. Consequently, forecasting of electricity infeed carry great importance for companies generating, delivering and reselling electricity because even the slightest improvement in matching demand and supply can increase their profits significantly.

$$\begin{aligned}\begin{matrix} Electricity \\ Infeed \end{matrix} &= \begin{pmatrix} Supply\ from \\ national\ grid \end{pmatrix} + \begin{pmatrix} Supply\ from \\ other\ grids \end{pmatrix} - \begin{matrix} Demand\ of \\ other\ grids \end{matrix}\Bigg) \\ &+ \begin{pmatrix} Generation\ of \\ customers \end{pmatrix} - \begin{matrix} Consumption\ of \\ customers \end{matrix}\Bigg)\end{aligned} \tag{3.1}$$

In order to balance the net loss, Customer Services, Reporting, Analysis and Quality Market Players Department provide net loss forecasts to the finance department and finance department make the necessary transactions are held in the electricity market. Our study consists of two phases; first is short-term forecasting and the second is long-term forecasting. During the preliminary meeting that were carried out with company representatives, they asked for a short-term load forecasting model in order to assist traders and finance department for their transactions in the spot market. Company is using a time shifting method based on similar years search and by using that they derive hourly forecasts for a full year in June of the previous year. Finance department, together with traders, make the transactions one and a half year ahead in the futures market, in order to carry them out at the least cost. Throughout the year, deviations from the forecast are updated by utilizing spot market. Therefore in the first phase, short-term load forecasts are derived at different lead times in order to enhance short-term transactions. Two different methods are used in modeling of the first phase: an adaptation of exponential smoothing method, due to its simplicity and a time series neural network method - NARX, relying on its ability to capture complex and nonlinear relationships existing in the dataset.

In the second phase of the study, due to the promising results of NARX in the first phase for longer lead times, we investigated if the initial forecasting performance of the company can be improved by using NARX in long-term forecasting.

3.3. Dutch Electricity Market

In 1998, Dutch electricity market was deregulated in order to build a competitive free market that is purged from any monopolistic power and external interventions. The aim of the deregulation was ensuring the highest customer benefit by enabling competition in the market. Former electricity market consisted of a few market players for every region, giving these players monopolistic power, as the customers had to receive electricity from market parties in that region. On the other hand deregulated market structure allows customers make deliberate decisions about their supplier and aims providing perfect market information to the customers to be used in their decisions.

Current Dutch electricity market consists of mainly five parties, suppliers, program responsible parties (PRPs, traders), national grid operator (NGO), regional distribution network operators (DNO), metering companies (MC). In Netherlands national grid operator is the semi-public company: TenneT that is the owner of high voltage grid network. Traders make forecasts for electricity load of next day for every 15 minutes and deliver it to TenneT. TenneT explores if there is an imbalance in the supply demand equilibrium and announces the price respectively. TenneT is not only responsible for administrating transmission grid and maintaining the reliability and continuity of the electricity supply, but also for providing services and performing duties in order to improve functioning of electricity market. Suppliers' role is generating electricity on their own generators or making contracts with independent suppliers and providing electricity to the market. Fossil fuels, uranium, wind are some of the commonly used electricity generation resources in the Dutch market. Another responsibility of suppliers is reaching to the consumers and making contracts with them. Moreover, they are in charge of reading meters of their customers and submitting these readings to the DNOs. DNOs' main role in the market is delivering electricity to the customers through their regional low voltage and mid voltage networks. Our company is, as the operator of 130.000 kilometers of electricity cables, one of the largest DNOs in Netherlands. In Figure 1, other DNOs and their dispersion in the country can be seen. In addition to distribution function, DNOs need to allocate the total electricity load to every single small customers considering the metering information of large customers provided by MCs and transmit this information to respective suppliers to be used in billing of customers and to PRPs. PRPs might be charged by TenneT if there are huge differences between their predictions and the actual load values.

Figure 1. Distribution of DNOs in Netherlands.

CHAPTER 4

FORECASTING METHODS

In this section forecasting methods that are used in this study are presented. First method is an adaptation of Holt Winters Exponential Smoothing method. We have applied a modification to this method, in order to include effects of special days. Secondly, Nonlinear Autoregressive with eXogenous variables (NARX) neural networks is introduced.

4.1. Holt Winters Exponential Smoothing Method (HWT)

Exponential smoothing is a fairly simple forecasting method suitable for univariate time series data [38]. Despite its simplicity, it is known as one of the most successful methods in automatic forecasting. Its name origins from the fact that the method comprises weighted averages of all past observations, where the past observation's weight decreases exponentially as the observation gets older. It applies recursive updating schemes while smoothing and forecasting data [38]. The formulation of exponential smoothing for one-step ahead forecasting is provided in (4. 1).

$$\hat{y}_t(1) = \alpha y_t + (1-\alpha)\hat{y}_{t-1}(1) \tag{4. 1}$$

or equivalently in error correction form:

$$\hat{y}_t(1) = \hat{y}_{t-1}(1) + \alpha e_t \tag{4. 2}$$

$$e_t = y_t - \hat{y}_{t-1}(1) \tag{4. 3}$$

where y_t is the observed time series, $\hat{y}_t(k)$ is k-step ahead forecast made at time t, α is the smoothing factor and e_t is one step ahead forecast error.

Holt Winters method is an extension of exponential smoothing, which is designed for series with trend and seasonality; therefore it is also referred as double exponential smoothing. Holt Winters method is a robust and easy way of forecasting that works especially well for short-term sales and demand time-series data, despite its simple structure [40]. Holt Winters method models the data by means of a local mean, a local trend and a local seasonal factor. There are two different formulations for multiplicative and additive seasonality. In this study we consider Holt Winters method with additive seasonality and without a trend term. Taylor stated that including a trend term do not bring any improvements to forecast accuracy, as changes in demand level is not significant for short-term load forecasting. In addition to this, Taylor [1] developed an extension of regular Holt Winters method in order to accommodate for the presence of two seasonal cycles, which is typical in electricity load data. Taylor's extension is presented in equations **(4. 4) - (4. 8)**.

$$\hat{y}_t(k) = l_t + d_{t-m_1+k_1} + w_{t-m_2+k_2} + \phi^k e_t \tag{4. 4}$$

$$e_t = y_t - \hat{y}_{t-k}(k) \tag{4. 5}$$

$$l_t = l_{t-1} + \alpha e_t \tag{4. 6}$$

$$d_t = d_{t-m_1} + \delta e_t \tag{4. 7}$$

$$w_t = w_{t-m_2} + \omega e_t \tag{4. 8}$$

where m_1 and m_2 are the number of periods in the first and second seasonal cycles, which are in our case daily and weekly cycles. l_t is the smoothed level and d_t and w_t stand for seasonal indices for daily and weekly cycles, respectively. The smoothing parameters are denoted by α, δ and ω. $k_1 = [(k-1) \bmod m_1] + 1$ where similarly, $k_2 = [(k-1) \bmod m_2] + 1$. By addition of autoregressive component, ϕ, Taylor [1] aimed correcting first order residual autocorrelation, which leaded significant improvement in forecast accuracies.

4.1.1. Modified Holt Winters Exponential Smoothing Method with Special Days

As it is presented above, Taylor's models do not consider for special days. In Taylor's studies, periods that do not include any special days are used [1] [41]. In practice, electricity load data consists of many special days such as celebrations, national and religious holidays, bridge days, etc. and these days create the biggest challenge for generating accurate forecasts. In this study HWT is used in comparison with a nonparametric method, NARX. In order to assure a fair comparison and due to the large deviation observed on special days in load data during data analysis, we modified Taylor's HWT. Taylor's Holt Winters extension is modified to allow the model to learn from its previous errors on special days, which brought significant improvement to the model performance. The updated model formulation is provided in **(4. 9) - (4. 14)**.

$$\hat{y}_t(k) = l_t + d_{t-m_1+k_1} + w_{t-m_2+k_2} + \phi^k e_t + s_{i,t+k} * \left(\sum_{h=-L}^{L} s_{i,j} * \frac{e_j^T}{y_j} * \hat{y}_t^T(k)\right) \tag{4. 9}$$

where $j = t + k - (365 + h) * 24$

$$e_t = y_t - \hat{y}_{t-k}(k) \tag{4. 10}$$

$$e_j^T = y_t - (\hat{y}_{t-k}^T(k)) \tag{4. 11}$$

$$l_t = l_{t-1} + \alpha e_t \tag{4. 12}$$

$$d_t = d_{t-m_1} + \delta e_t \tag{4. 13}$$

$$w_t = w_{t-m_2} + \omega e_t \tag{4. 14}$$

where $s_{i,t}$ is a binary variable that is equal to 1 if t is interval on a special day of type i, where i refers to different day types and e_j^T stands for the error when demand in time j is forecasted with Taylor's adaption of HWT [41]. In our modification, the model checks if time $t + k$ is a special day. If it is a special day, first the model goes to last year's data and checks a range of days ($\pm L$) around $t + k$ to find a similar type of special day, and then updates the forecast by multiplying its forecast ($\hat{y}_t^T(k)$) by the percentage error of the last year's forecasting error on that special day (e_j^T/y_j).

For one step ahead forecasting, i.e., for $k = 1$, formulations in (4. 9) - (4. 14) are used, but for multi-step ahead forecasts (4. 9) slightly differs. Taylor [41] formulized multi-step ahead forecasts for $1 < k \leq m_1$ as follows:

$$\hat{y}_t(k) = l_t + \frac{\alpha\phi(1-\phi^{k-1})}{(1-\phi)}e_t + d_{t-m_1+k_1} + w_{t-m_2+k_2} + \phi^k e_t \tag{4. 15}$$

where the first two terms sum up to the expected value of lagged level. We derived the formula for $k > m_1$, by computing the limit of the expected value of lagged value for very large values, as presented in (4.16):

$$\hat{y}_t(k) = l_t + \frac{\alpha}{(1-\phi)}e_t + d_{t-m_1+k_1} + w_{t-m_2+k_2} + \phi^k e_t \tag{4. 16}$$

4.2. Artificial Neural Networks

Artificial Neural Networks (ANNs) are highly interconnected simple processing units that are inspired by the biological neural nets transmitting signals via neurons and synapses. The method comprises capturing complex relationships between input and output information with the network structure. The biggest advantage of ANNs compared to other computational methods is their capability of providing information about nonlinear and hidden patterns in the data. Despite the network implementation is usually called a black box, ANNs' power simply sources from their execution; they implement linear discriminants, but in a space where inputs have been mapped nonlinearly. The key power of neural networks depends on implementation of fairly simple algorithms where nonlinearity can be trained from training data [42]

In order to comprehend processing of ANNs, fundamental components of ANNs, structure of nodes (a.k.a. neurons) is illustrated. As shown in Figure 2, a node receives inputs, multiplies each input by a weight value w, adds a bias value b_0 and uses a transformation function f to generate an output y.

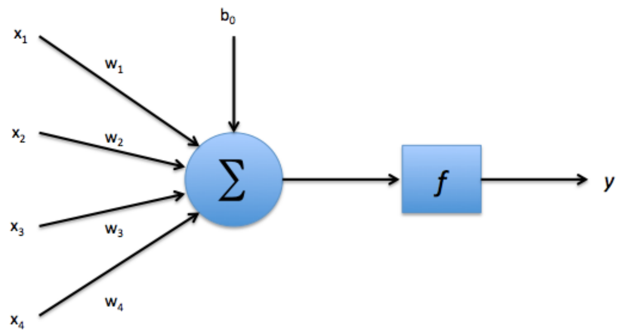

Figure 2. Structure of a single node

Some of the commonly used transformation functions are log-sigmoid, hyperbolic tangent sigmoid, linear, etc. For example a sigmoid transfer function is as follows:

$$f(net) = \frac{1}{1 + e^{-net}} \quad (4.17)$$

where *net* is the weighted input of the hidden layer and *f(net)* is the output of the hidden layer.

There are different types of neural networks present in literature and two major types with respect to connections between neurons and direction of data propagation are: feed-forward and recurrent networks [30]. In Figure 3 an example of three-layered feed-forward neural network is presented, the data is received through input layer and passed to hidden layer and transferred to output layer. The term feed-forward refers to the networks with interconnections that do not form any loops. Furthermore, recurrent or non-feed-forward networks in which there are one or more loops of interconnections also exist, so that input state is also combined with the previous state activation through an additional weight layer, an instance of recurrent networks is provided in Figure 4 [43] [44].

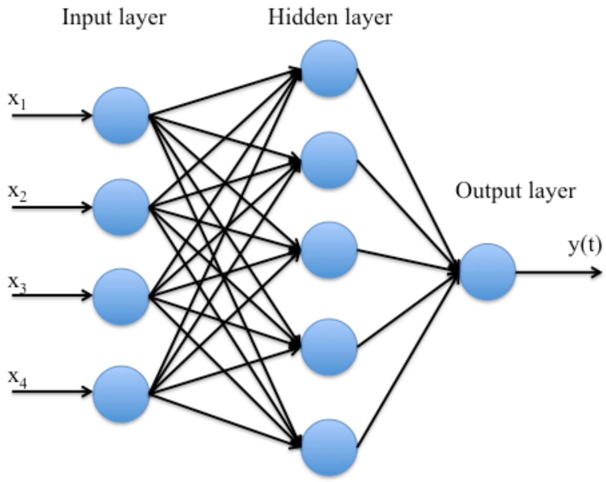

Figure 3. Example of three-layered feed-forward neural network structure.

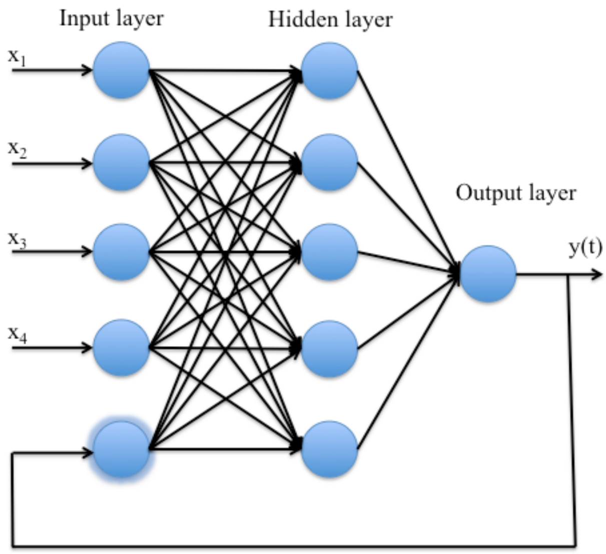

Figure 4. Example of three-layered recurrent neural network structure.

4.2.1. Nonlinear Autoregressive with eXogenous Inputs

Nonlinear Autoregressive with eXogenous Inputs (NARX) Networks is type of recurrent dynamic neural networks with feedback connections between output and input layer. NARX networks are specifically used for time series forecasting. Another important property of NARX is represented under the name of ‘eXogenous’, meaning that it allows exogenous inputs to become network inputs. It is derived from Autoregressive exogenous (ARX) model. It can be mathematically represented as:

$$\hat{y}_t = f[u_{t-D_u}, \dots, u_{t-1}, u_t \,;\, y_{t-D_y}, \dots, y_{t-1}) \tag{4. 18}$$

where u_t and y_t are inputs and outputs of the model at time t and D_u and D_y are input and outputs delays. f stands for the nonlinear transformation function [45]. In Figure 5 an example for NARX network with input delay of two and output delay of three is shown.

As mentioned NARX networks are all recursive, but there are two different types with respect to the information embed into the feedback loop: open-loop and closed-loop networks.

The network in the example is an open-loop type, which means actual output values are fed back to the network. Another name for open-loop networks is series-parallel (SP) mode networks. In the other type of architecture, closed-loop, network’s outputs, estimated values, are fed back to the network as inputs. These type of networks are also referred as parallel (P) mode. Therefore, the NARX model representation in (4.18) is for SP architecture, whereas a P architecture is mathematically represented as:

$$\hat{y}_t = f[u_{t-D_u}, \dots, u_{t-1}, u_t \,;\, \hat{y}_{t-D_y}, \dots, \hat{y}_{t-1}) \tag{4. 19}$$

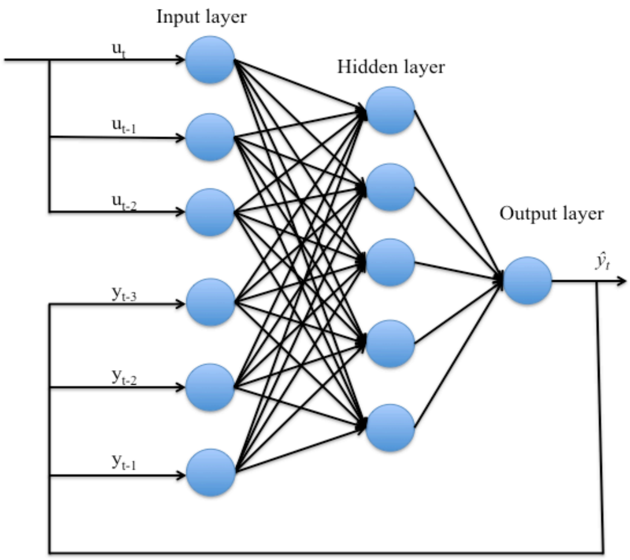

Figure 5. Example of a NARX neural network

4.2.2. Input Processing in Neural Networks

In a neural network, neurons in each layer are interconnected to each other by modifiable weights. In input layer no transformation takes place, it serves only for transferring the input. Transformation takes place only in hidden and output layers. For a network that consists of p inputs, each hidden node computes the weighted sum of its inputs, denoted by net in Equation (4.20).

$$net_j = \sum_{i=1}^{p} x_i w_{ji} + b_{j0} \tag{4. 20}$$

where i stands for the nodes in input layer, j for the ones in hidden layer; x_i stands for any type of input (multivariate inputs or input from feedback loop), w_{ji} represents the input to hidden layer weights in hidden node j, and b_{j0} 's are the bias values.

After computing net value, a transfer function is used to generate the hidden node's output, *f(net),*

$$y_j = f(net_j) \tag{4. 21}$$

Behaviour of neural networks depends heavily on transfer functions specified for the units. Transfer functions are typically categorized into three:

- **Linear (or ramp)** functions generate an output that is proportional to the total weighted sum of inputs of that unit.
- **Threshold** functions examine level of total input value, if it is greater than a threshold value output is set equal to a number, if not, it is set equal to some other predetermined value.
- **Sigmoid** functions provide more similarity to real neurons than the other functions. In those units, the output varies continuously as the input changes.

Similarly for all hidden layers and output layer units, net values are calculated as weighted sum of the values received from the previous layer nodes plus the bias value and then transformation function of the node is applied. The general representation of the practice for a three-layered network with *k, j* and *m* neurons in the hidden layers is,

$$\hat{y}_t = f\left(\sum_{j=1}^{n_H} w_{kj}\, f\left(\sum_{i=1}^{p} w_{ji} x_i + b_{j0}\right) + b_{t0}\right) \tag{4. 22}$$

where n_H is number of nodes in layer, w_{kj}'s are interconnection weights from hidden layer to output layer, p is number of nodes in input layer and b_{j0} and b_{t0}'s are bias values and each node applies a transformation function to the sum and transfers its product [42]. It should be noted that for a single layer neural network with linear transfer functions in the output layer, the system can be interpreted as a linear regression model. Similarly, same network with logistic transfer functions is equivalent to logistic regression.

4.2.3. Training of Neural Networks

As a data driven model, training is fundamental in neural network modeling. During the training phase, network adjusts weight and bias values in order to produce closest outputs to the actual values. One of the most popular methods for network training is back-propagation algorithm (generalized delta rule, a natural extension of the least mean squares – LMS algorithm), which is founded on gradient descent in error [42]. The learning process can be summarized as, starting with an untrained network, a training dataset is fed to the input layer, passes through the network and an output value is obtained. Then the obtained value is compared to the target value, which is the actual output in the dataset. The difference corresponds to the error. With respect to the learning rule, the weights are adjusted.

The training error is considered similar to LMS algorithm:

$$J(\boldsymbol{w}) = \frac{1}{2}\sum_{t=1}^{r}(y_t - \hat{y}_t)^2 \tag{4. 23}$$

where $\boldsymbol{w}$ stands for vector of all weights, y_t is the target value and $\hat{y}_t$ is the estimated value.

As back-propagation algorithm is based on gradient descent, the weights are updated in the direction of error reduction, starting from random values. For simplicity, in this text, formulations are presented only for single-layered networks.

$$\Delta\boldsymbol{w} = -\mu\frac{\partial \boldsymbol{J}}{\partial \boldsymbol{w}} \tag{4. 24}$$

where μ is the learning rate which is the proportion of error gradient by which the weights should be adjusted. Larger values can give a faster convergence to the minimum but also may produce oscillation around the minimum [43].

At each iteration the weight values are updated as follows:

$$\boldsymbol{w}(m+1) = \boldsymbol{w}(m) + \Delta\boldsymbol{w}(m) \tag{4. 25}$$

where m indexes particular pattern presentation. The weights are readjusted for every input-output pair of the training dataset until an acceptable criterion for convergence is reached.

NARX neural networks salient for being powerful, faster convergence and better generalization capability compared to other networks [46]. In this study, NARX neural networks with zero input delays and various outputs delays are considered. Outputs delays are selected with respect to autocorrelation values and seasonalities present in the data, whereas input delay is set equal to zero due to the fact that input variables include binary special day variables, so only effective on the forecasting period.

CHAPTER 5

COMPUTATIONAL STUDY

In this section, first the dataset for computational study is explained in Section 5.1. Then in Section 5.2 we present the numerical results for short-term load forecasting. In Section 5.3 we continue with the numerical results for long-term load forecasting.

5.1. Data Description

In empirical studies, we used the data set of hourly electricity load levels of five Dutch provinces for 256 weeks period from 1 January 2008 to 30 November 2012. For every province we had a dataset of 43104 data points. Load data contains daily and weekly cycles, which can be clearly seen in Figure 6. It is seen that during weekdays electricity load patterns are very similar to each other, but at the weekends load decreases significantly.

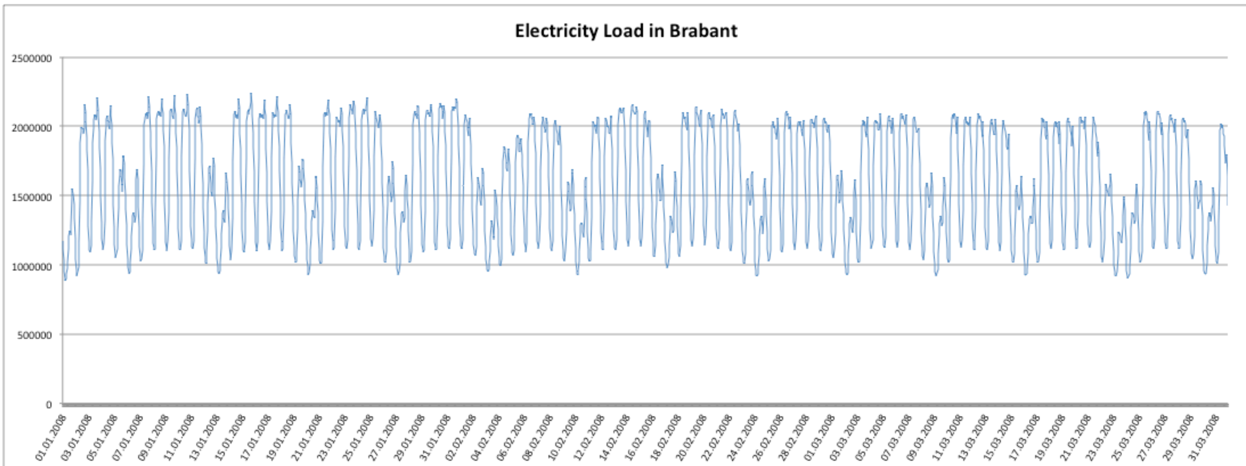

Figure 6. Hourly electricity load in Brabant between January 2008 and March 2008.

General data structures resemble each other very much from region to region. Therefore data analyses are mostly presented on Brabant region, as being the biggest grid in company portfolio.

5.1.1. Data Analysis

5.1.1.1. General Analysis

In this section general analysis on dataset will be explained, in order to give the reader a deeper insight about the difficulties and complexities of load forecasting.

Firstly, general data structure throughout one year is presented in Figure 7. In this figure hourly intervals are aggregated into four-hour intervals for easiness of the analyses.

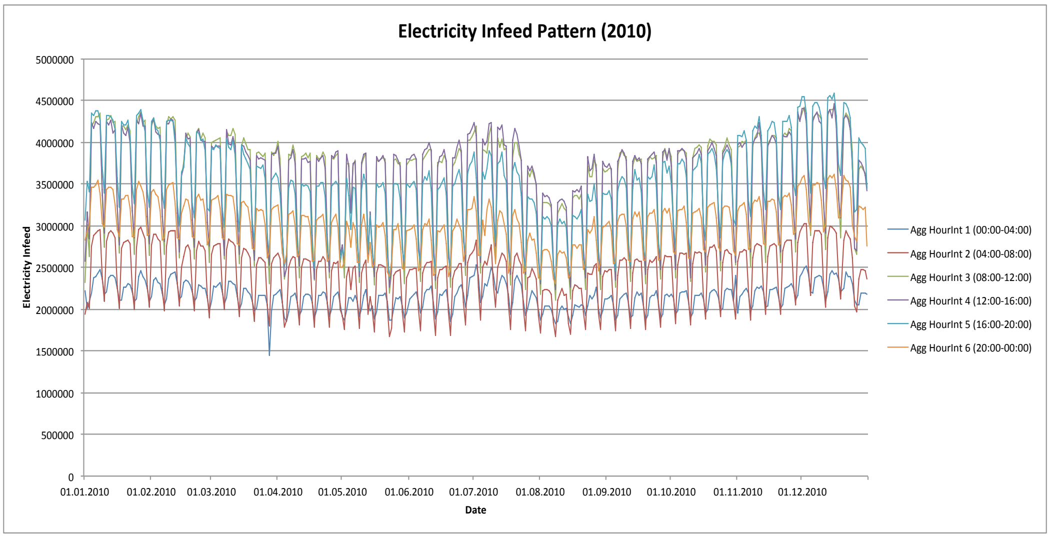

Figure 7. Aggregated hourly electricity load (GWh) in Brabant in 2010.

In Figure 7 it is seen that during late at night and early in the morning hours of the day, electricity load is at its lowest level. Then during the morning and afternoon hours, it reaches to the highest level and decreases gradually during evening hours.

If we take a closer look to one month, we can see the decrease in load levels at the weekends, shown in Figure 8. In this figure, the similarities between weekdays' load levels can be observed easily. Moreover, it is seen that despite during the week the interval between 00:00 and 04:00 has the lowest level, during the weekends, 04:00-08:00 interval is even lower and similarly load of the hour interval of 08:00-12:00 decreases significantly.

After aggregating load values four-hourly, we have plotted weekly aggregated load in Figure 9. We have observed every year load values decrease during summer weeks, resulting in a convex curve. In order to investigate if the fluctuations exist due to special days effect, in Figure 10 weekly aggregated values are plotted, but excluding the weeks that contain any kind of special days in year 2010.

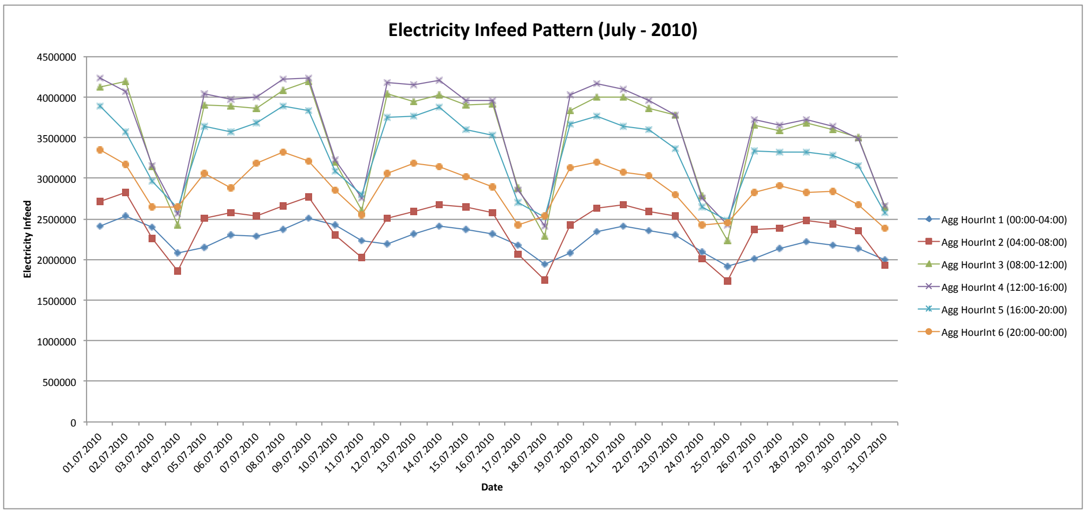

Figure 8. Aggregated hourly electricity load (GWh) in Brabant in July 2010.

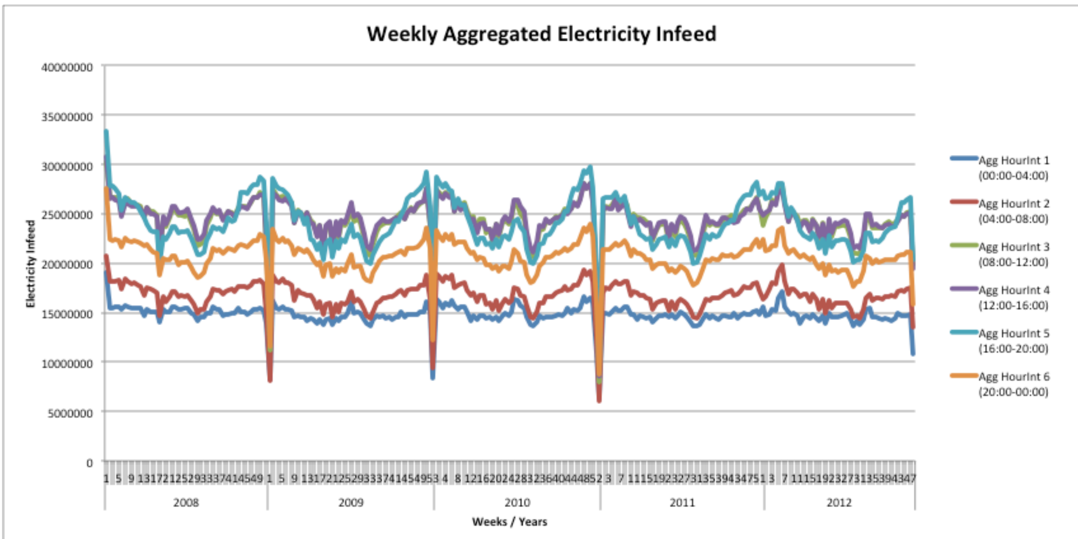

Figure 9. Weekly aggregated electricity load (GWh) in Brabant between 2008-2012.

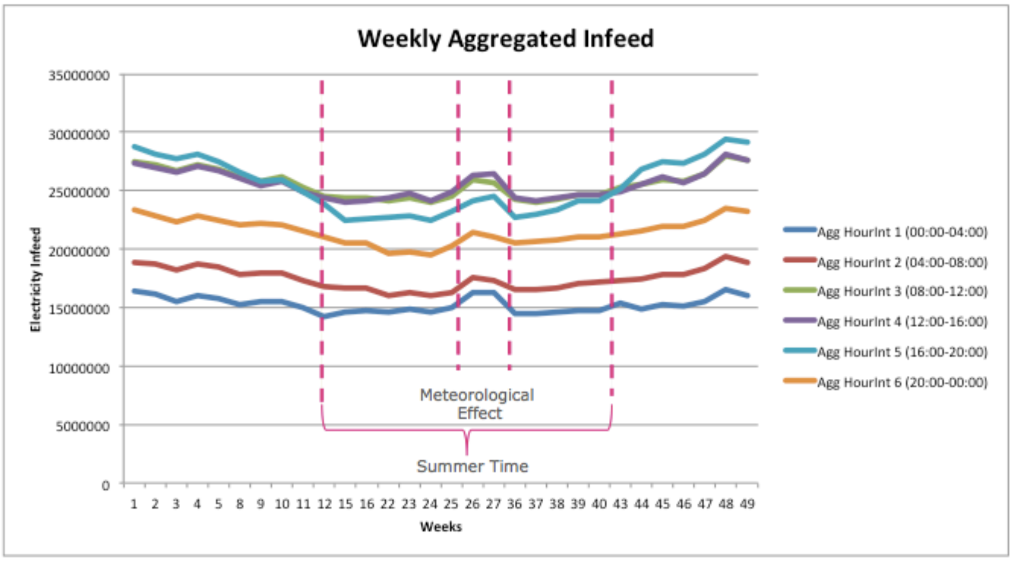

Figure 10. Weekly aggregated electricity load (GWh) in Brabant between in 2010; weeks including special days are excluded.

In Figure 10, compared to Figure 9 smoother curves are obtained after exclusion of special days. The convex shape of load throughout the year can be seen more clearly. In addition to that for the hour interval 16:00 – 20:00 the effect of switching to summer-time is pointed out on this graph. During winter-time electricity load values are at the highest level, however, after switching to summer-time, electricity load values decrease. We have pointed out an unexpected increase in load values for a period during summer under the name of meteorological effect. This is due to the fact that in 2010 for that period of the year temperature values were higher than the average, so resulted as an increase in electricity load. General distribution of hourly loads with respect to months is presented in Figure 11 with a box plot. Figure 11 shows that variation in hourly load values is higher in winter months compared to summer moths and the distributions are not skewed to either right or left.

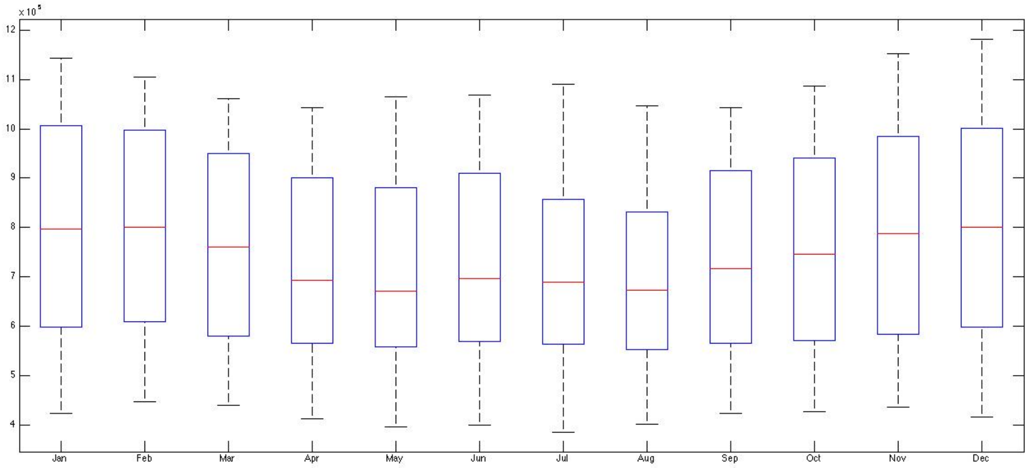

Figure 11. Box plot of hourly load values with respect to months in Brabant in 2010.

5.1.1.2. Economical Variables Analysis

Possible effects of various variables are analyzed in order to investigate relationship between economical variables and total electricity load but no clear relationship is detected. Here only two of the variables are presented. Firstly in Figure 12, scatterplot of consumer prices, as an indicator of inflation, versus respective change of load compared to same month of last year is presented. No relationship is observed between the two.

Secondly, quarterly gross domestic product (GDP) values are extrapolated monthly and plotted versus percent change in electricity load, shown in Figure 13. There seems to be a weak relationship, therefore a second graph is plotted, shown in Figure 14 in order to gain a better understanding. Figure 14 does not demonstrate any clear relationship between load and GDP. During the interviews with the analysts at the company and after comparisons with company analyses on the data, it is concluded that, GDP is effective on large customers' (plants, large facilities, etc.) load, however summed with small customers (households, public lighting, etc.) the effect disappears.

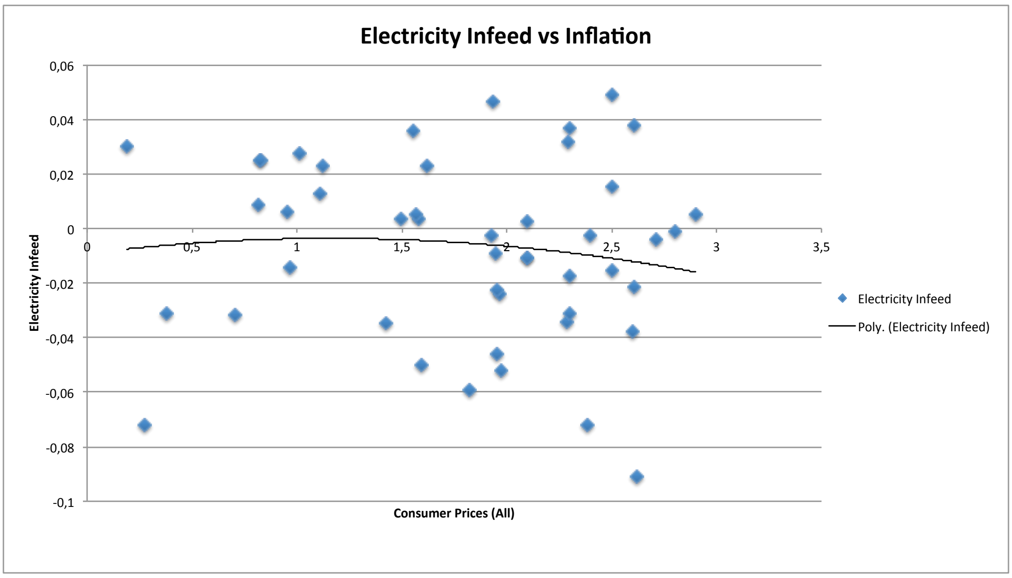

Figure 12. Scatterplot of change in total electricity load compared to one year ago vs. consumer prices index for all in Brabant.

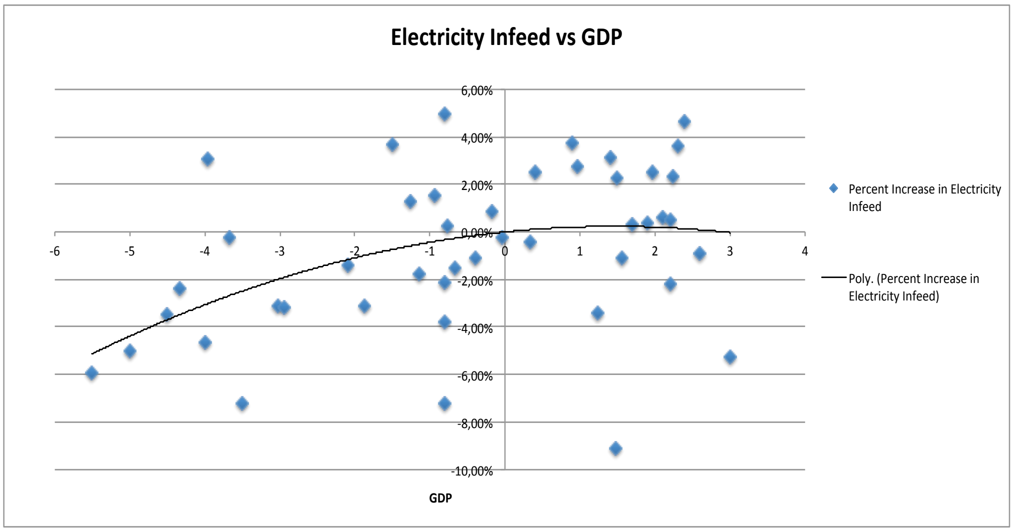

Figure 13. Scatterplot of monthly percent change in total electricity load vs. GDP in Brabant.

5.1.1.3. Meteorological Variables Analysis

As expected, meteorological analysis starts with analysis on temperature's effect on load. In Figure 15, we plotted temperature versus electricity load, but grouped the data into two; weekdays and weekends. It is observed that as the temperature values get lower or higher than 17 ºC, electricity load increases.

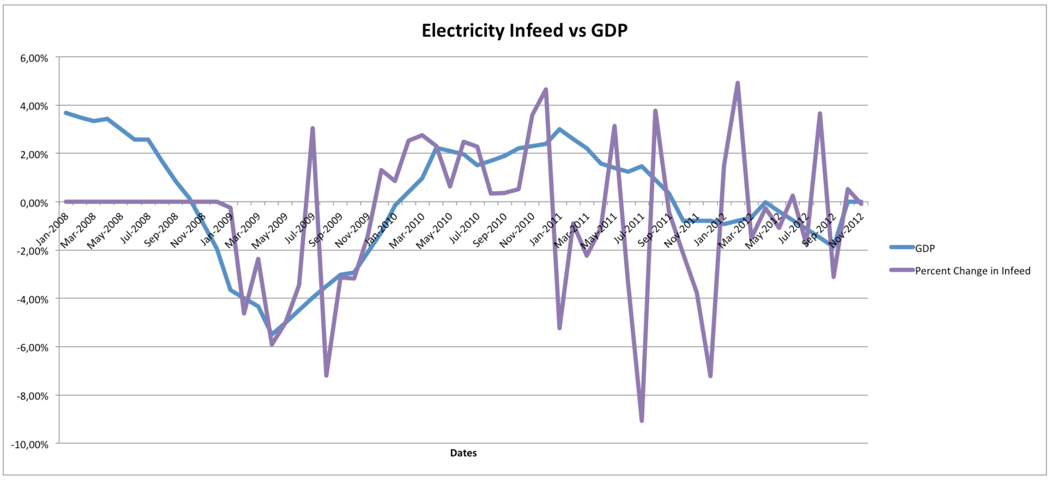

Figure 14. Graph of monthly percent change in total electricity load vs GDP in Brabant.

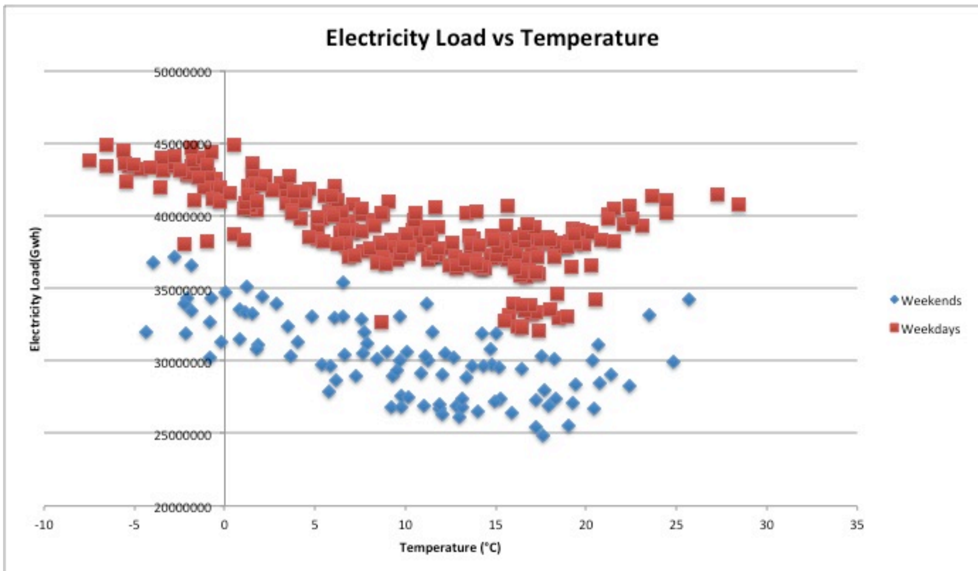

Figure 15. Scatterplot of electricity load vs temperature in Brabant.

Second meteorological variable that is discovered to be effective on electricity load is sunlight. We have represented sunlight in terms of percentage; for every hour of the day it is set equal to the percent of the hour that the sun is up. Figure 16 shows plot of a three-hours interval that is the period affected from the sunlight period the most. It is clearly seen that sunset leads people to more electricity consumption.

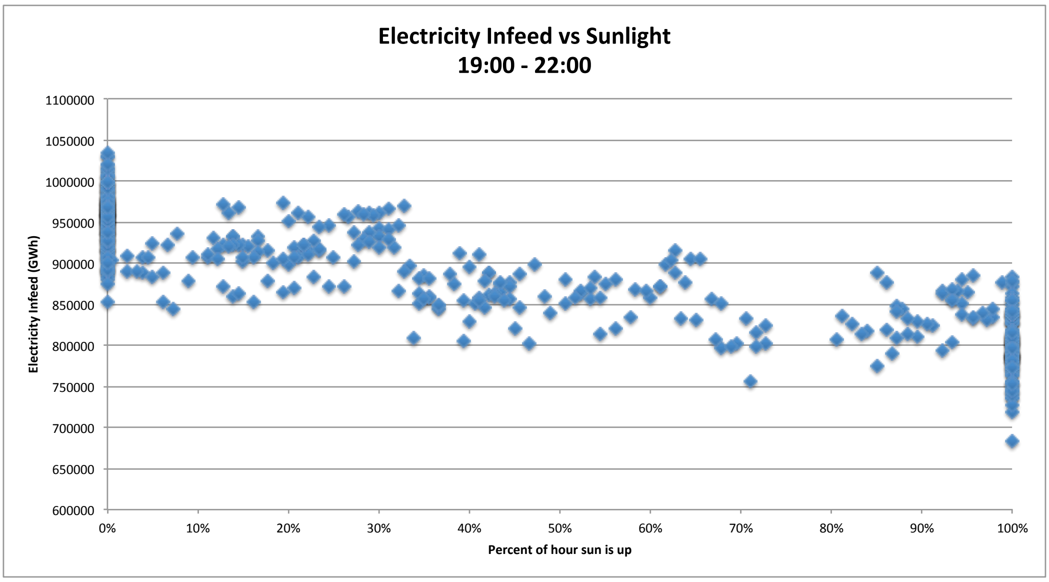

Figure 16. Scatterplot of electricity load vs sunlight in Brabant.

5.1.1.4. Special Days Effect Analysis

Another important element of the data set is calendar variables, which covers special days, such as public holidays, national days, school holidays, etc. Before deciding on which variables to include, effects of all special days are analyzed. Below, you can find a list of special days:

- **School Holidays:** The period when the schools are closed. In Netherlands, schools are on vacation during public holidays as well as for Christmas, Spring break, May holiday, Summer break and Autumn break.
- **Bouwvak:** The period when companies in construction industry are not operating during the summer.
- **Liberalization day (Independence):** Public holiday, which is celebrated once in every four years.
- **Carnival:** Three days of celebrations taking place in southern part of the Netherlands. This variable is excluded from the data set of northern regions.
- **Christmas:** In the data set not only 25th of December but also one day before and after are also defined as separate variables; because deviations from regular pattern are observed on these days as well.
- **New Year's Eve:** 31st of December of every year.
- **New Year Holiday:** 1st of January of every year.
- **Queens Day:** A public holiday for celebration of Queen of Netherlands' birthday for one day.
- **Easter, Ascension Day, Whit Sunday and Monday, Good Friday:** Christian holidays in Netherlands.

Different special days have different effects on electricity load throughout the day, depending on the region, the day of week, etc. Therefore, we have carried out numerous analyses with respect to their effects on different hours of the day and with respect to the variation in their effects from year to year. We have calculated incremental effects of each special day as follows:

Step 1 Expected values are calculated by averaging same day electricity infeed values of the weeks before and after for every hour of the day.
Step 2 Difference between actual infeed and expected value is calculated.
Step 3 Difference is divided by expected value calculated for every hour of a special day.

What we did with the series of calculations mentioned above is calculating a deviation from expected value and assigning the deviation from this value to the effects of special days.

In Figure 17, yearly average incremental effects of the special days on different hours of the day are presented. It can be seen that some special days have very similar curve shapes and the values are very close to each other. Similarly, hourly effects are averaged and plotted with respect to years in Figure 18.

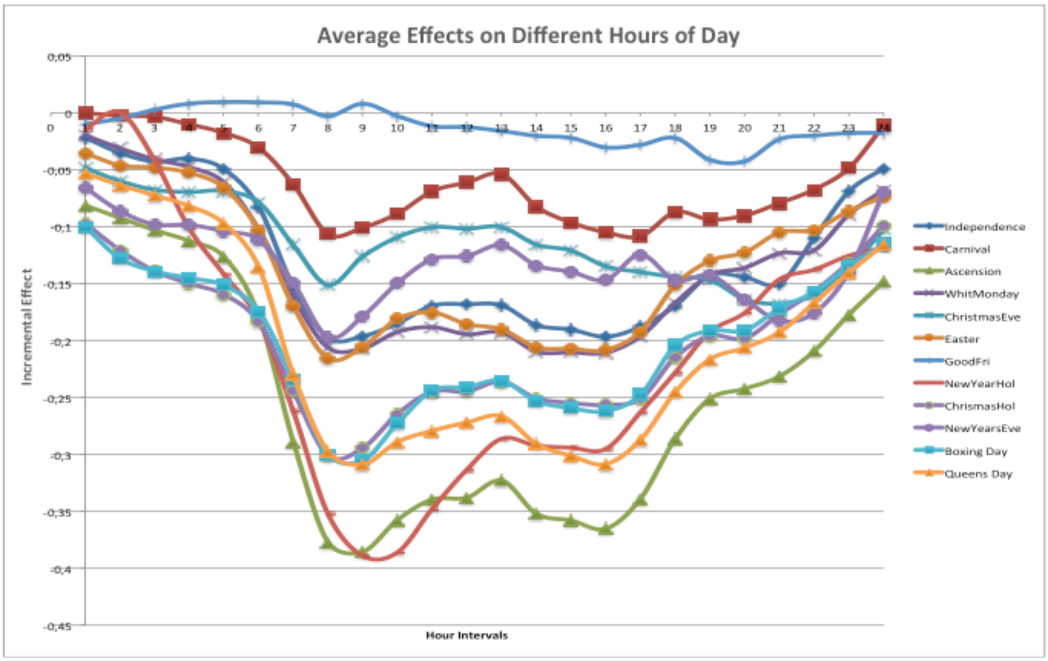

Figure 17. Effects of special days averaged for five years with respect to hours of day in Brabant.

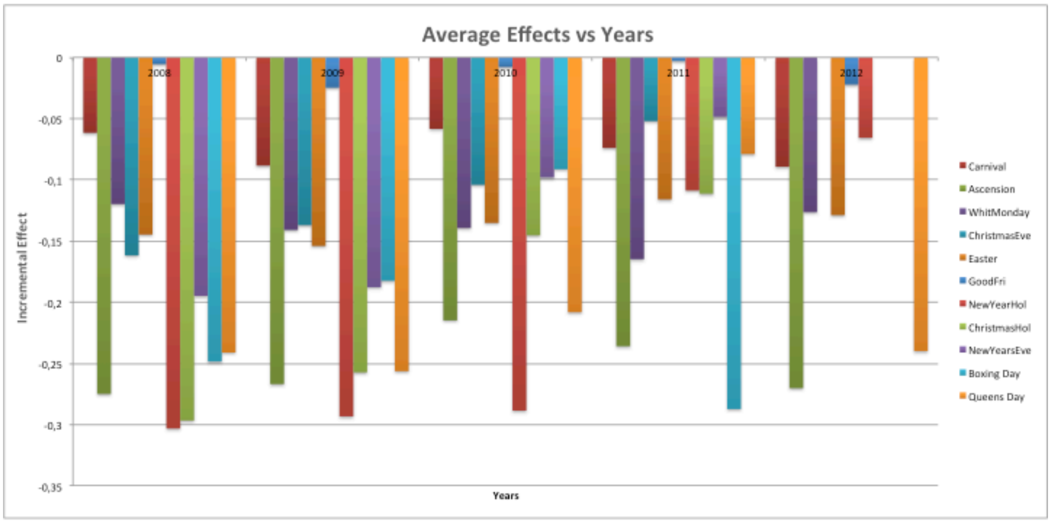

Figure 18. Average effects of special days in different years in Brabant.

Utilizing two graphs and least squared distance method between the curves; similar special dates are grouped. In Figure 19, how similarly Whit Sunday and Monday, Easter and Liberalization day affect electricity load is presented. Squared distance between these three curves are smaller than 0.01. Similarly, average effects in one day are plotted with respect to years in Figure 20. General shapes of curves are similar, however there is a significant deviation in 2011, for which higher temperature degrees during Easter and during the week before and after Whit Sunday & Monday in 2011 are accounted.

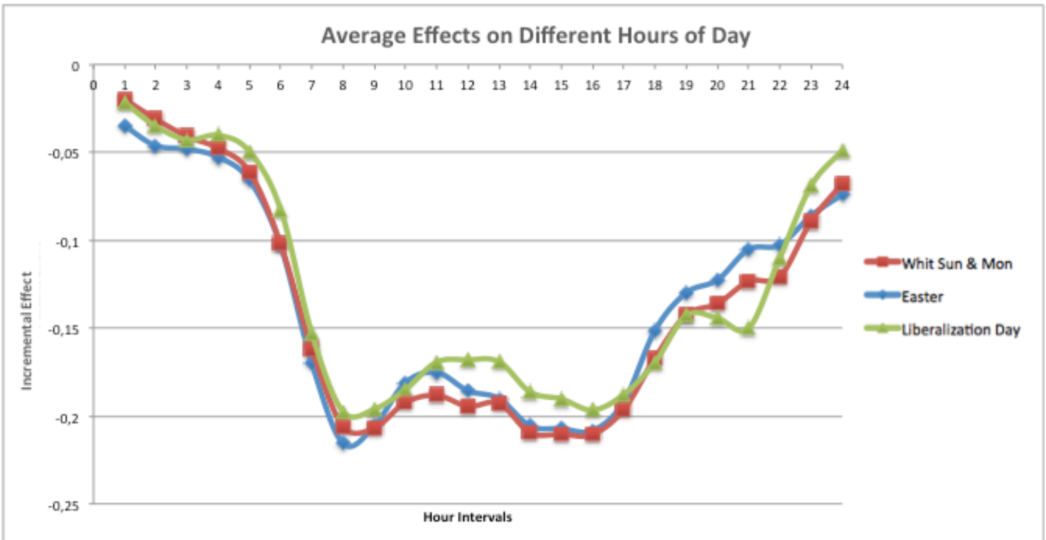

Figure 19. Effects of special days averaged for five years with respect to hours of day in Brabant (Whit Sunday & Monday, Easter and Liberalization Day).

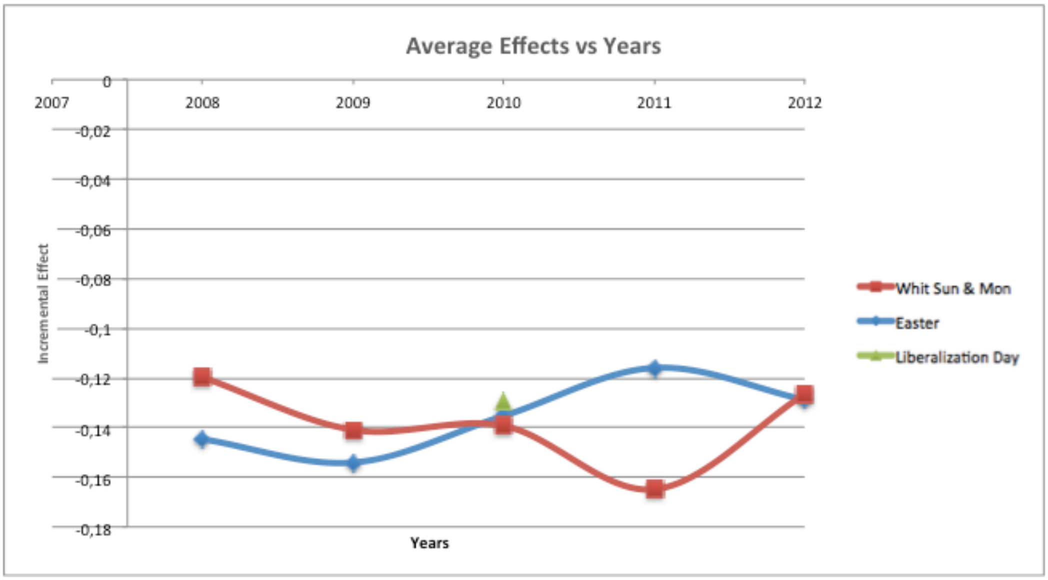

Figure 20. Average effects of special days in different years in Brabant (Whit Sunday & Monday, Easter and Liberalization Day).

Parallel to Whit Sunday and Monday, Liberalization day and Easter, Boxing day and Christmas day curves also have very small squared distance that is lower than 0.01. In Figure 21, their effects with respect to hours of day and in Figure 22 their effects with respect to years are presented. Figure 22 presents also weekdays in order to emphasize special days' different effects on electricity load with respect to days. It is seen that Boxing Day and Christmas effect decreases at the weekends.

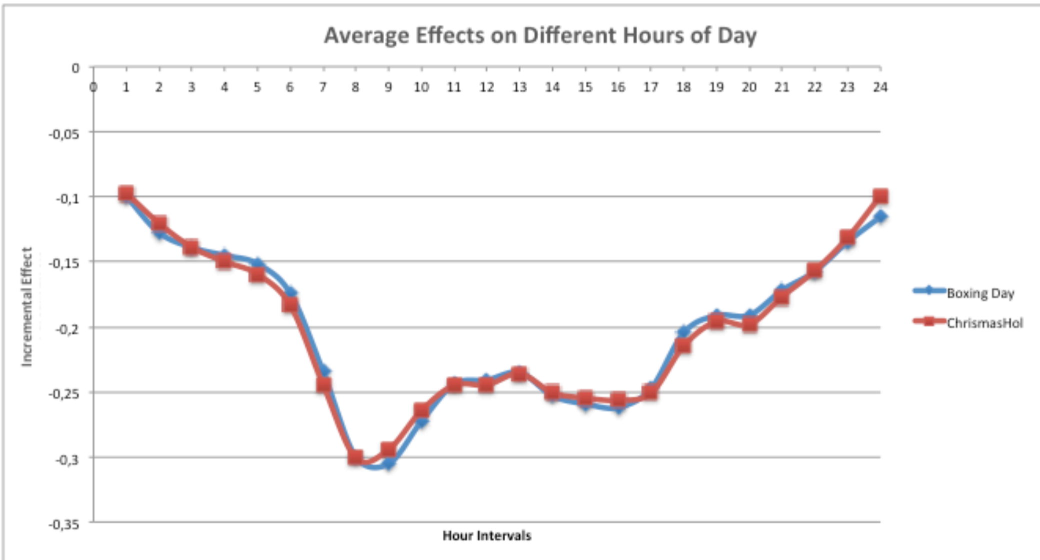

Figure 21. Effects of special days averaged for five years with respect to hours of day in Brabant (Boxing Day and Christmas Day).

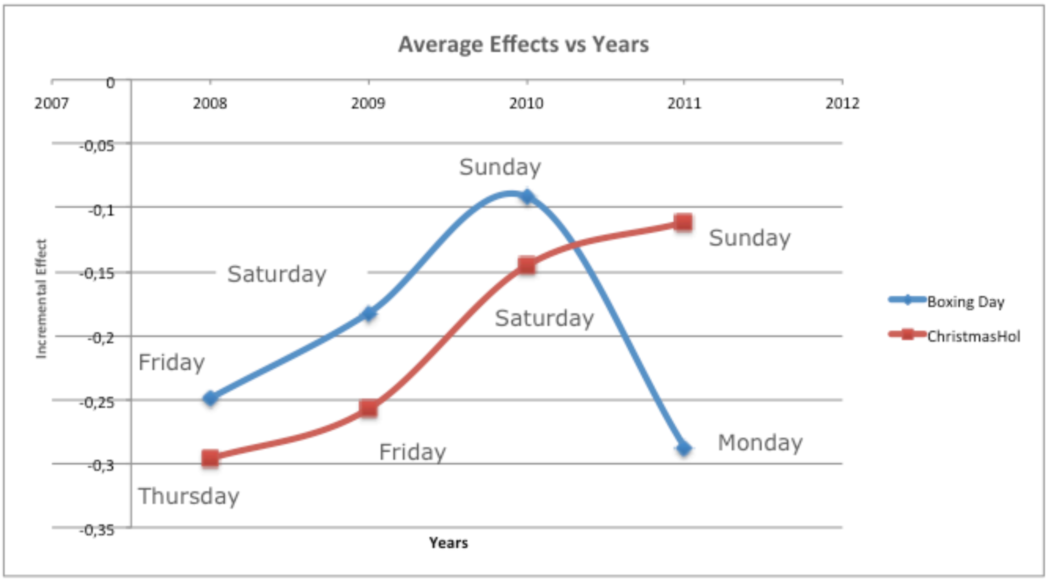

Figure 22. Average effects of special days in different years in Brabant (Boxing Day and Christmas Day).

As expected New Years Eve and Christmas Eve also have very similar effects on load, presented in Figure 22 and Figure 23. Similar to Boxing Day and Christmas Day, decrease in effect of New Years Eve and Christmas Eve clearly seen in Figure 23 at the weekends.

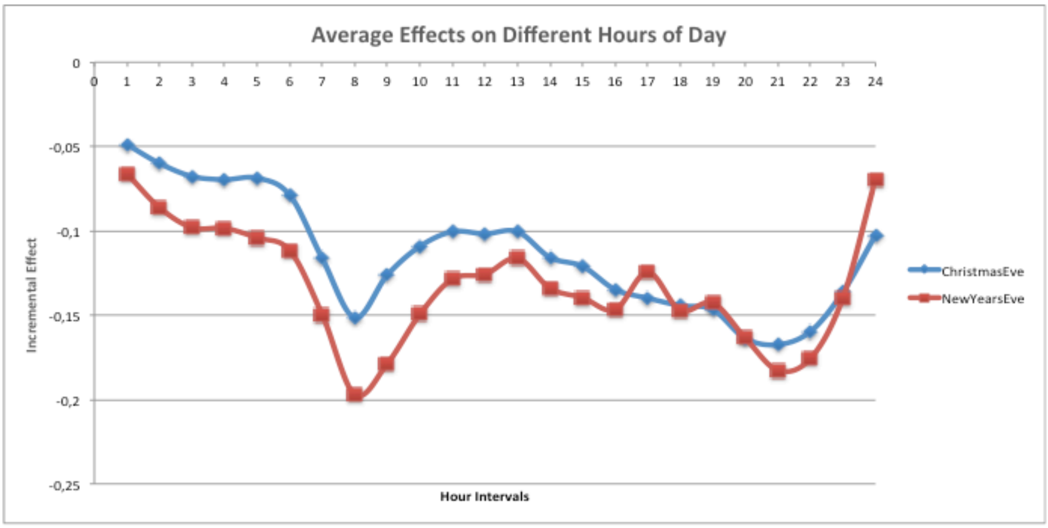

Figure 23. Effects of special days averaged for five years with respect to hours of day in Brabant (New Years Eve and Christmas Eve).

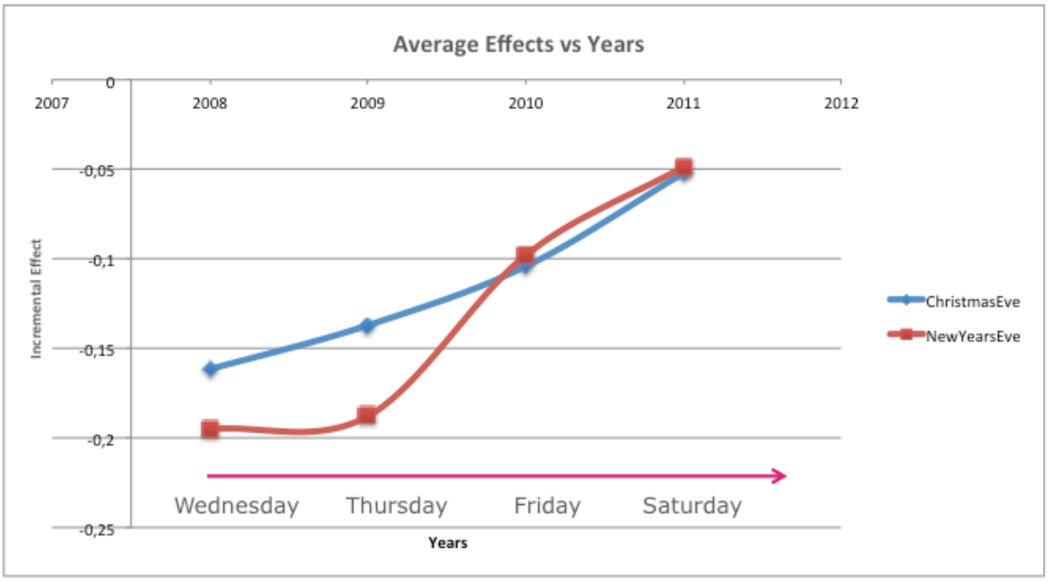

Figure 24. Average effects of special days in different years in Brabant (New Years Eve and Christmas Eve).

Among the special days mentioned above in the list, Good Friday is eliminated from the set of effective special days because of having very small effect on electricity load. Respective graphs showing the inadequate effect of Good Friday are presented in Figure 25 and Figure 26.

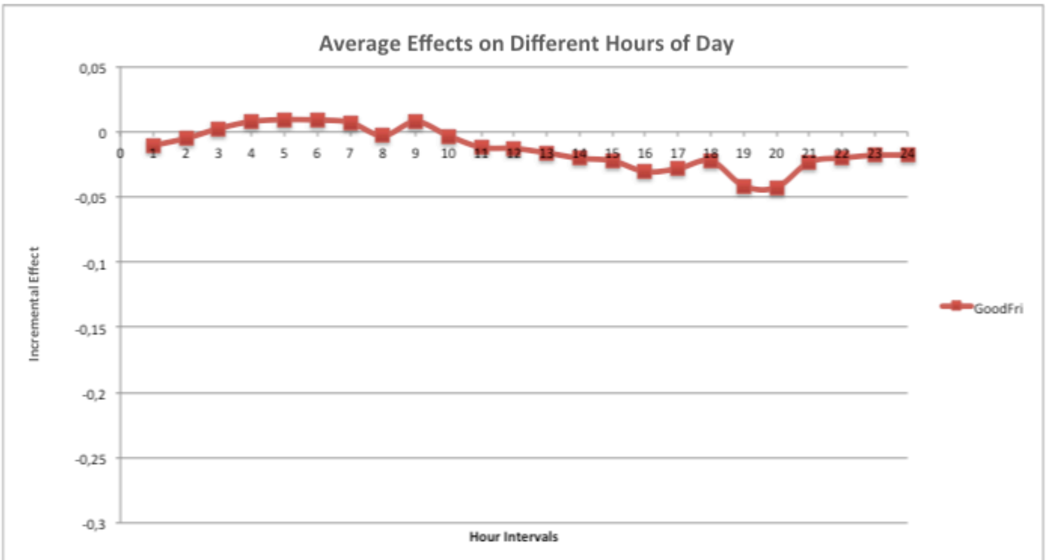

Figure 25. Effects of Good Friday averaged for five years with respect to hours of day in Brabant.

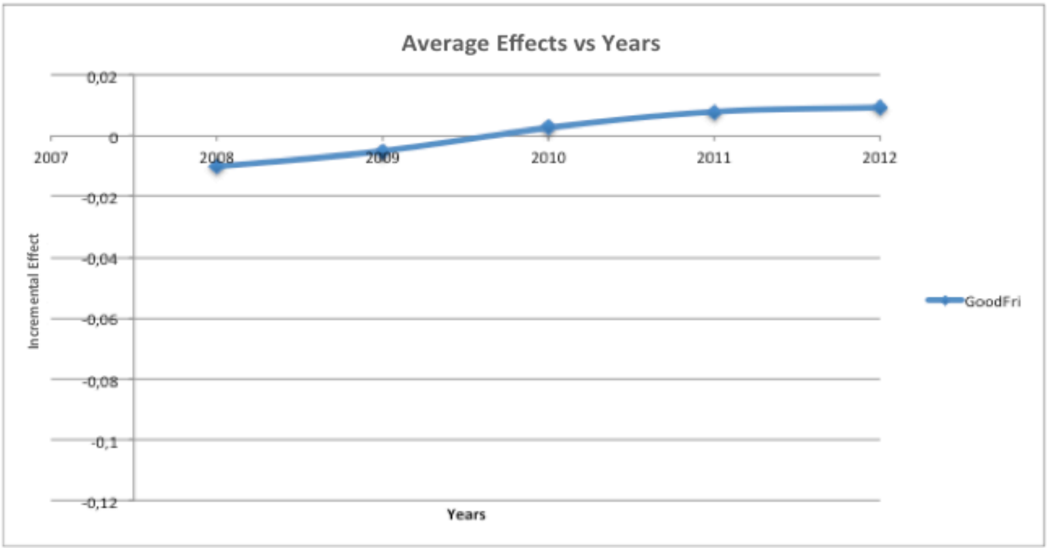

Figure 26. Average effects of Good Friday in different years in Brabant.

School holidays and Bouwvak holidays are not included in similar days analyses, because these holidays last for at least one week, so have different characteristics than the others. In Figure 27 their effects in Brabant in 2010 are presented with respect to days. Bouwvak's effect can be clearly observed in the figure, however school holiday seems to have only a slight effect on load. However, it is not always the case for school holidays, for example in Figure 28, school holidays' significance can be easily observed. Difference between two graphs is a good example to different effects of same special day in different periods of year. In Figure 28, school holiday is the 18th week; compared to summer a clearer decrease in load level is observed. Additionally, there is a significant decrease in level on Monday of 17th week, which is Easter Monday.

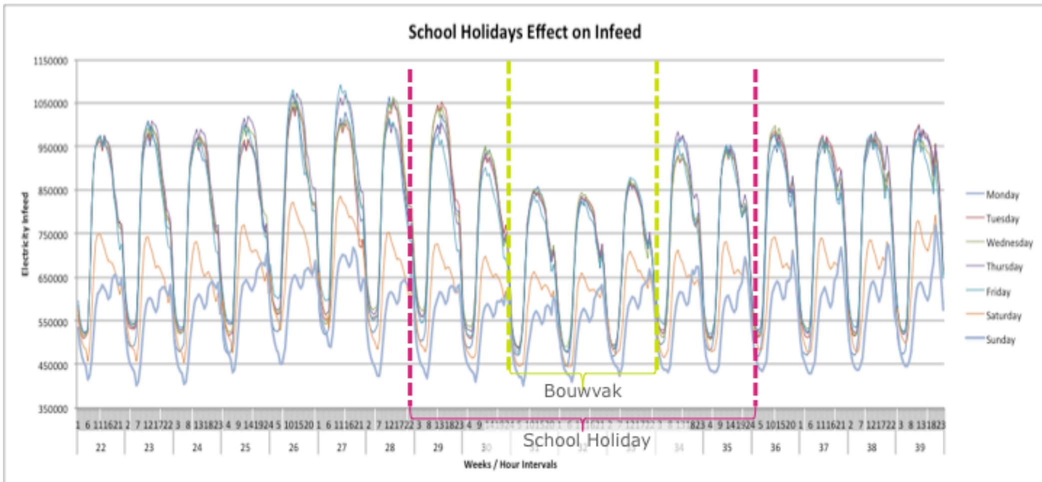

Figure 27. Electricity infeed (GWh) between weeks 22 and 29 in Brabant in 2010.

In addition to the exact dates, special days also affect the electricity load on the days close to them. Electricity load before and after holidays tends to decrease for most of the special days as shown in Figure 29. The figure shows load levels on Wednesdays of nine consequent weeks, where two Wednesdays, shown in dashed circles, are days before Christmas and New Year's Eve respectively. Significant decrease in electricity load on these days can be easily seen. Similar tendency is observed before and after other special days as well. Therefore, variables named *'Day before holiday'* and *'Day after holiday'* are defined and added to the data set.

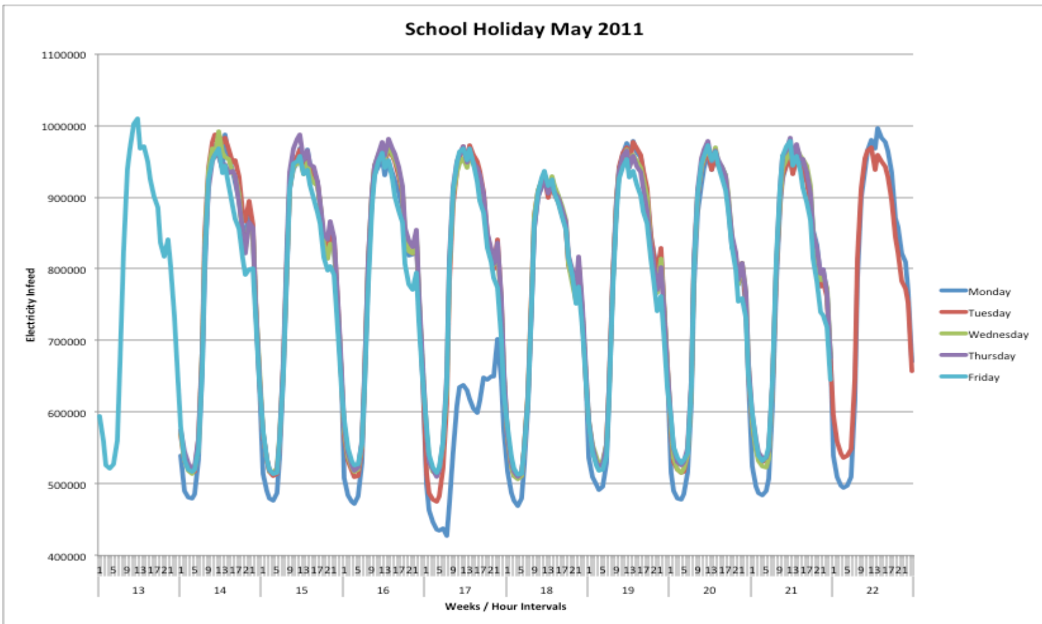

Figure 28. Electricity infeed (GWh) between weeks 13 and 22 in Brabant in 2011.

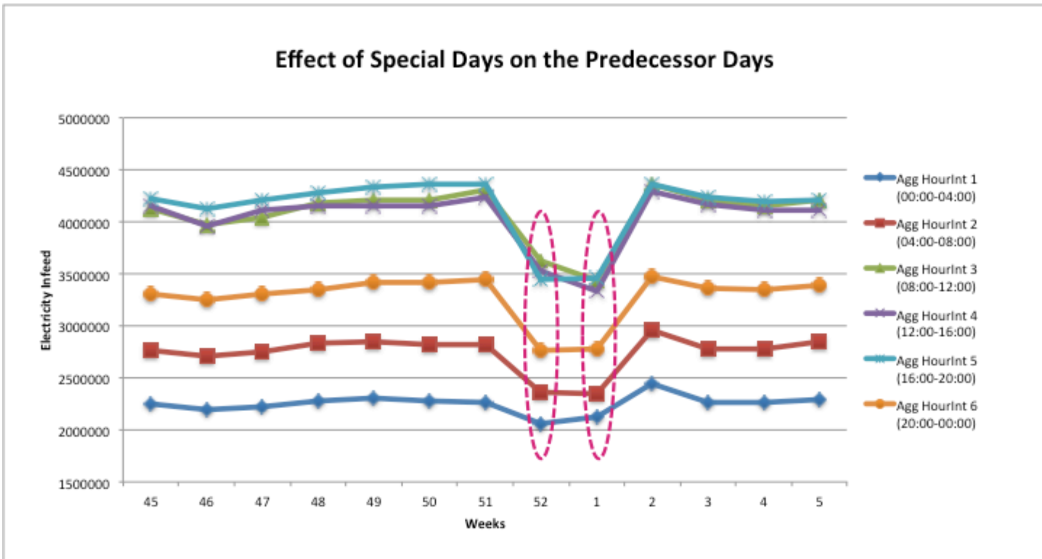

Figure 29. Electricity infeed (GWh) between weeks 45 in 2008 and 5 in 2009 on Wednesdays in Brabant.

More importantly, we observe that the effect is even more significant when the day before or after holiday falls on a Monday or Friday, due to the fact that on such days people are more willing to take one day off and have longer holidays. As an example, in Figure 30, Fridays are plotted for eight consequent weeks in order to point our decrease in electricity load day after Ascension Day. Hence, another variable named, '*Bridge day*' is added to the data set to denote these special days.

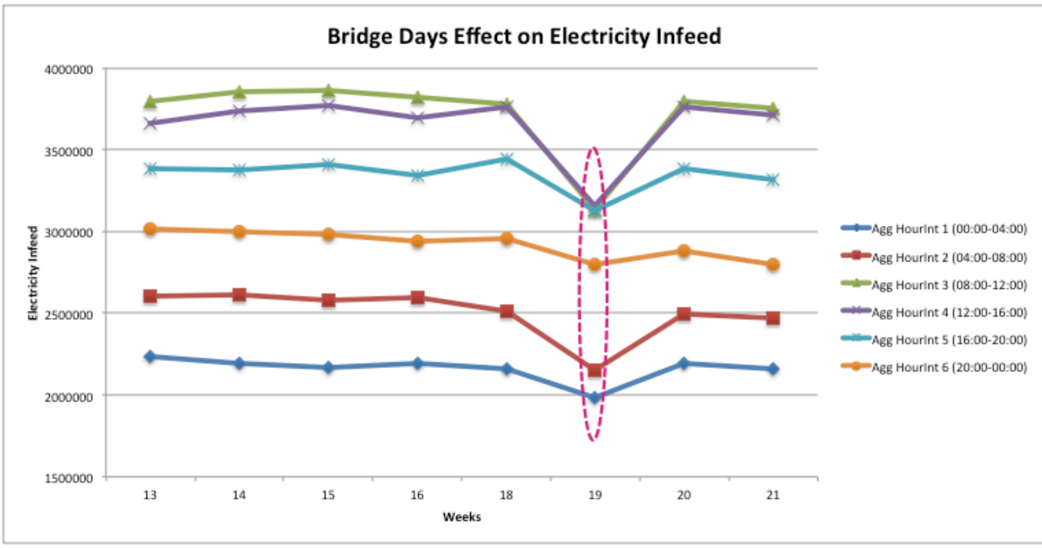

Figure 30. Electricity infeed (GWh) between weeks 13 and 21 on Fridays in Brabant in 2010.

In this section we have provided a summary of important special days analyses. Figures and graphs on the other special days are provided in Appendix A.

5.2. Short-term Load Forecasting

In this part of the study only historic data and calendar variables are used to forecast short-term electricity load. Taylor also pointed out, meteorological variables have distinct effect on electricity demand in the long-term. However, for short-term forecasts, these variables can be excluded, as consumers' adaptation to changes in these variables takes some time; it is difficult to observe their effects and there are no immediately available forecasts for these variables.

5.2.1. Adaptation of Holt Winters Exponential Smoothing

Considering the model specifications presented in **(4. 9) - (4. 14)**, in order to model time series data with HWT method, initial values for level and seasonal components and smoothing parameters need to be estimated. For initialization of the state variables in the model, i.e., for l_t, d_t, w_t, we use a similar approach to the ones followed in [1] and [47]. We used two-week intervals that do not include any special days in order to prevent any unusual observations causing misleading fluctuations in initialization.

Initialization:	given two weeks electricity load data, $c_1 = 24$, $c_2 = 168$, referring to daily cycle and weekly cycle
Iteration:	
Step 1	initialize the level, l_t, by averaging load data over the two week period.
Step 2	initialize daily seasonal state variable, d_t :
Step 2.1	compute c_1 point centered moving averages
Step 2.2	calculate differences between actual data and moving average values, that roughly gives seasonality effect
Step 2.3	average differences for c_1 hours of the day over two weeks
Step 3	initialize of the weekly seasonal index, w_t :
Step 3.1	compute c_2 point centered moving averages
Step 3.2	calculate differences between actual data and moving average values, that roughly gives seasonality effect
Step 3.3	average differences for c_2 hours of the week over two weeks

In our model, lag value $(\pm L)$ is equal to 15, meaning that we searched for an interval of one month in the last year, in order to find the effect of the respective special day. Lastly, model parameters are derived by using a similar method to Taylor's [48].

Iteration:	
Step 1	derive 10^5 vectors of four parameters which are uniformly distributed between 0 and 1
Step 2	for every vector, compute sum of squared errors (SSE) of the training dataset
Step 3	define 10 vectors with the lowest SSEs as the set of possible model parameters
Step 4	generate all possible combinations of selected 10 vectors
Step 5	for every combination vector, compute sum of squared errors (SSE) of the training dataset
Step 6	elements of the vector with lowest SSE are assigned as model parameters

Different than Taylor's approach, in our models, we derive best parameters for different forecasting horizons each time. In Table 1 model parameters for Brabant region are presented, for the parameter values of the other regions, Appendix B should be referred.

Table 1
Parameters for models of province Brabant.

Lead Times (hrs)	α_{best}	δ_{best}	ω_{best}	ϕ_{best}
1	0.5487	0.1832	0.2658	0.3399
6	0.0377	0.2354	0.1590	0.7750
12	0.0145	0.1820	0.1769	0.8330
24	0.0005	0.2649	0.1066	0.9034
48	0.0007	0.0715	0.0768	0.7265
168	0.0001	0.0225	0.1713	0.8379

5.2.2. Nonlinear Autoregressive with Exogenous Input Neural Networks

Numerical study for NARX modeling consists of two stages: (1) training the model and (2) testing the model performance. Accordingly, each dataset is divided into training (in-sample data), validation and test (out of sample data) datasets corresponding to 75%, 15% and 15% of the data, respectively. In addition to the historic electricity load data, special days are defined as binary variables and added to the data set.

Data analyses revealed that effects of some special days on load are very similar to each other. Therefore these special days are grouped together in order to decrease dimensionality of the problem and to enable the model to capture the difference in effects of special days on different weekdays. Consequently, calendar variables are grouped in seven categories as the following:

- Easter, Whit Monday and Liberalization day
- Carnival
- Christmas Eve and New Year's Eve
- Queens Day
- Boxing Day and Christmas Day
- First day of year (New Year Holiday)
- Ascension Day

As mentioned before, in addition to exact dates of special days, one-day prior and after these days and bridge days are also defined as variables and included in the model. Furthermore, *day of the week, hour of the day* and binary *summer time* variables are defined as inputs.

As mentioned in Section 4.2, a neural network model consists of three types of layers: input, hidden and output. Corresponding to the input variables, thirteen input nodes exist in our model's input layer. Additionally, input layer contains nodes of the feedback loop. Feedback delays are determined with respect to the autocorrelation values between different lags of infeed data. In this study autocorrelation values between 1 and 0,8 are identified as highly correlated. Hence, among these lag values, considering the seasonalities, the rational ones are selected as feedback delays, which are in our case: *1, 2, 23, 24, 25, 168 (1 week)* and *169 hours.* Therefore in total input layer consists of twenty input nodes. Obviously, output layer contains only one node which gives the electricity infeed forecast.

In [49] it is stated that one hidden layer architectures are sufficient for solving most of the forecasting problems but with a disadvantage of higher training times. Therefore, in the interest of keeping model architecture search to a reasonable limit, in this study single hidden layer recurrent networks are considered as candidate model architecture. For various model lags at every region, best performing architecture is searched. Due to the computational limitations, number of hidden nodes is kept between 5 and 80, tested with 5 node intervals, because it is believed that the networks with hidden nodes less than 5, would not be capable of modeling and learning the data and the networks with hidden nodes more than 80 are expected to fail at generalization and result in overfitting. Therefore, for every region, and every lead time 16 different architectures are run with 5 different initializations. The best architectures that are assigned to the models of every forecast horizon in Brabant are presented in Table 2. For each lead time best architectures are run 10 times to find the best weight and bias values and complete the network architecture. NARX neural network architectures for other regions can be found in Appendix C.

Table 2
Brabant model architectures for different forecasting horizons.

Lead Times (hrs)	Hidden Layer	Number of Hidden Nodes
1	1	30
6	1	35
12	1	75
24	1	35
48	1	30
168	1	35

Other components of neural networks, that are effective on network performance, are the training algorithm and transfer function. In this study, 'Levenberg-Marquardt' training algorithm, which is a modification of popular back-propagation algorithm, is used. Levenberg-Marquardt algorithm includes an approximation to Newton's method, which is considered to be more efficient up to a few hundred nodes [50]. In hidden layers, 'tansig' and in output layer 'purelin' transfer functions are used. Considering all the effective components and different initializations of the network, a neural network is trained for various lags for each region.

5.2.3. Results for Short-term Load Forecasting

In this section we present performances of all methods for short-term load forecasting. We first compared the performances of Taylor's HWT and our modification of his model, m-HWT. Following the mentioned comparison, performance of NARX is compared to these two methods. Post-sample accuracies are measured in terms of mean absolute percentage error (MAPE) and maximum percent error (MaxAPE) for lead times up to one week ahead in five provinces. Post-sample data accounts for 15% of the total dataset and corresponds to the period between 28.05.2012 and 30.11.2012. The results are presented in Table 3.

Table 3
Performances of NARX, HWT and m-HWT in terms of MAPE for each province.

Lead Times (hrs)	Brabant			Noord		
	NARX	HWT	m-HWT	NARX	HWT	m-HWT
1	0.61%	1.28%	0.99%	0.69%	1.25%	1.12%
6	2.43%	1.53%	1.18%	2.90%	1.67%	1.41%
12	2.11%	2.03%	1.54%	2.75%	2.39%	1.99%
24	1.91%	2.40%	1.80%	2.23%	2.15%	2.02%
48	2.49%	3.50%	2.29%	2.68%	2.84%	2.43%
168	2.59%	3.72%	2.74%	2.59%	4.27%	3.65%

Lead Times (hrs)	Limburg			Maastricht			Friesland		
	NARX	HWT	m-HWT	NARX	HWT	m-HWT	NARX	HWT	m-HWT
1	0.80%	1.69%	1.06%	1.12%	1.67%	1.35%	1.13%	1.64%	1.40%
6	2.58%	1.57%	1.29%	3.05%	1.97%	1.61%	3.57%	2.32%	2.06%
12	2.08%	2.15%	1.69%	2.80%	2.16%	2.68%	3.27%	2.62%	2.22%
24	2.20%	2.27%	1.76%	2.99%	2.88%	2.32%	2.89%	2.60%	2.23%
48	2.80%	2.87%	2.26%	3.13%	3.49%	2.72%	3.19%	2.86%	2.54%
168	2.73%	3.51%	2.55%	3.29%	5.31%	3.36%	2.83%	3.36%	3.13%

In Table 3, it is clear that our m-HWT has dramatically improved the forecasting performance over Taylor's HWT. The improvement exceeds 30% in most of the instances, and the average improvement across 5 regions and 6 lead times is 19%. The performance of our m-HWT even exceeds the performance of NARX for most of the lead times. For illustrative purposes we plot the performance of three methods for the region Brabant in Figure 31. From the figure it is clear that the correction factor for special days has clearly improved model performance of HWT. However, NARX performs better than m-HWT method for one hour and one week ahead forecasts. We observe that especially for one-hour ahead forecasting NARX is quite effective and performs with a MAPE of as low as 0,61%. Similarly, in other regions NARX is superior for one-hour ahead forecasts. However, for forecast horizons up to 48 hours, m-HWT outperforms NARX. NARX forecasts clearly deteriorate for lead times that are not multiples of 24 hours (one day). Results for other regions coincide with m-HWT's success for forecast lead times of 6, 12, 24 and 48 hours, and NARX's superior performance in one-hour and one week-ahead forecasting. Only exception is in Limburg province; for one-week ahead forecasting, NARX does not outperform m-HWT but it is still competitive.

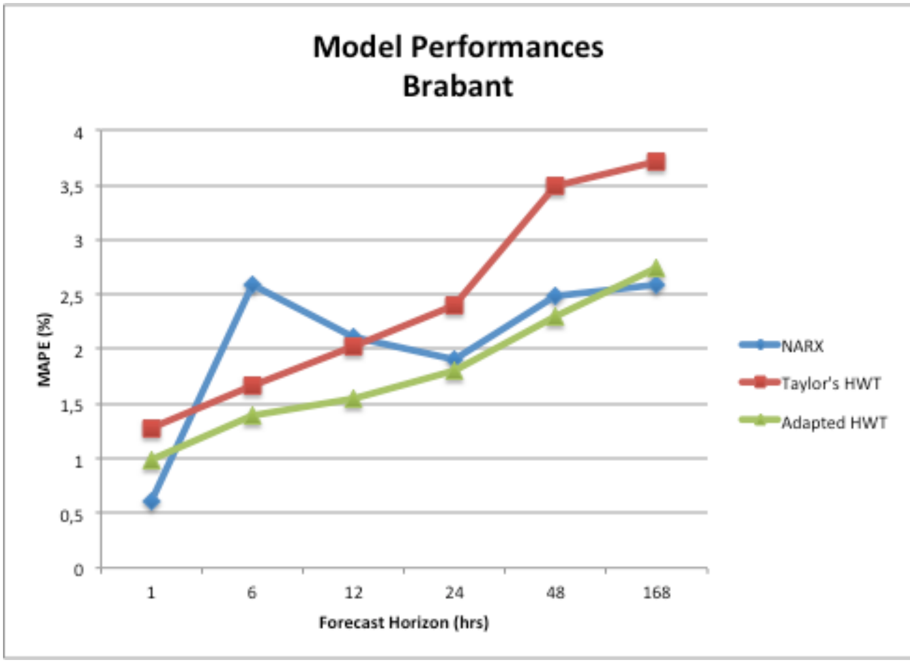

Figure 31. Performances of three models for different forecast horizons in Brabant.

Another performance measure considered in this study is MaxAPE. This measure is of significant managerial importance due to risk management and hedging reasons in practice. The maximum errors of the models for each region are presented in Table 4.

Table 4
Performances of three different models in terms of MaxAPE in five provinces.

Lead Times (hrs)	Brabant			Noord		
	NARX	HWT	m-HWT	NARX	HWT	m-HWT
1	8,63%	23,92%	15,79%	7,21%	21,44%	15,78%
6	16,03%	28,05%	15,93%	17,33%	28,64%	16,11%
12	15,95%	56,04%	31,40%	22,52%	50,32%	25,33%
24	13,82%	50,89%	25,90%	11,10%	28,16%	22,55%
48	17,23%	50,14%	25,14%	20,95%	53,45%	28,57%
168	19,63%	48,37%	23,39%	14,10%	51,10%	26,11%

Lead Times (hrs)	Limburg			Maastricht			Friesland		
	NARX	HWT	m-HWT	NARX	HWT	m-HWT	NARX	HWT	m-HWT
1	11,99%	33,40%	27,02%	10,68%	24,07%	20,66%	10,81%	28,89%	17,96%
6	14,88%	18,75%	18,75%	17,95%	20,47%	28,83%	25,97%	35,04%	16,27%
12	12,81%	42,07%	19,33%	15,92%	47,22%	26,78%	16,11%	59,88%	35,86%
24	13,46%	42,12%	17,74%	18,71%	51,40%	26,42%	16,81%	62,83%	39,48%
48	13,85%	43,55%	18,97%	18,51%	50,36%	25,36%	21,04%	64,10%	41,08%
168	14,59%	37,27%	18,47%	20,58%	49,63%	24,64%	19,44%	57,58%	33,15%

In terms of MaxAPE, NARX significantly outperforms both HWT methods for every forecast horizon and region. The only exceptions are the 6-hours ahead forecasts for Brabant and Friesland, pointing out to the aforementioned loss of NARX accuracy for 6- and 12-hour ahead forecasting. With maximum error percentages rarely exceeding 20%; NARX would be a good fit for the market parties who would like to avoid large risks. Furthermore, m-HWT has also decreased MaxAPE values up to 65% compared to Taylor's errors. In addition to the low MAPE values for one-hour ahead forecasts, NARX also gives very competitive MaxAPE values (below 12%) for one-hour ahead forecasts.

In Figure 32 and Figure 33, we further examine the performance of the forecasting methods for normal and special days. These analyses enable us to better understand the source of improvement in our forecasting models. Figure 32 presents the one-hour head forecasting performance of the methods for the Brabant province for normal and special days. Figure 33 shows the same information for 12-hour ahead forecasts. Results are materially similar for other forecasting horizons and regions. For one-hour ahead forecasts, performance of NARX on special days is slightly better than m-HWT while NARX performs significantly superior on normal days. For 12-hour ahead forecasts, however, NARX drastically improves over m-HWT on special days while its performance is lower on normal days. This is not a totally surprising result since by better adopting for the special days, NARX compromising on its ability to tract for the normal days. In particular, NARX faces an apparent trade-off between forecasting normal and special days. Overall, NARX is better at capturing complex effects of special days as we expected.

Another important result of our analysis is the tremendous improvement of forecasting performance on special days after the modification of HWT. Our modification has brought an improvement of 87.79% to special days' load forecasting for one-hour ahead forecasts for Brabant province. For all lead times, we observed that our modification has significantly decreased the forecasting errors for special days.

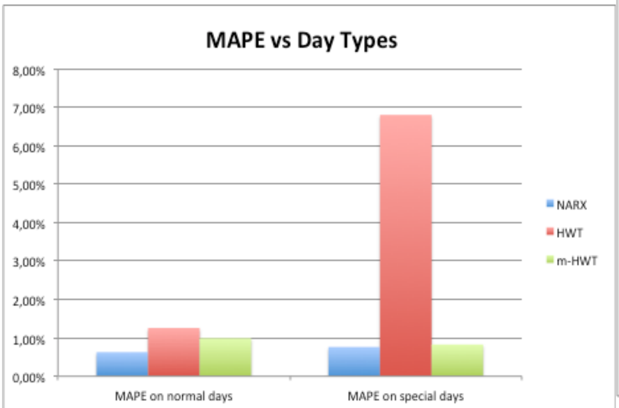

Figure 32. MAPE values for special and normal days for one-hour ahead forecasts for Brabant.

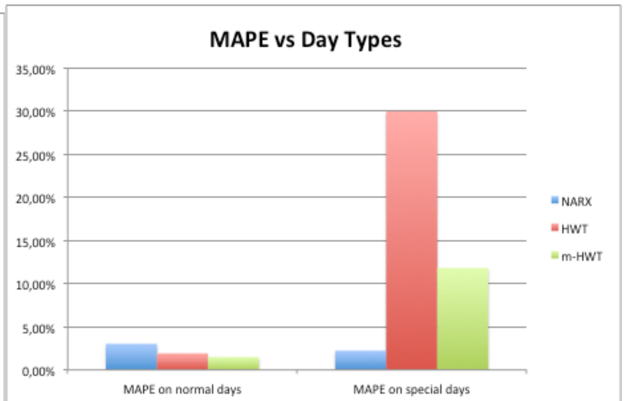

Figure 33. MAPE values for special and normal days for 12-hour ahead forecasts for Brabant.

5.3. Long-term Load Forecasting

5.3.1. Implementation Details for NARX

Promising results obtained in the first part of the study for longer lead times led us to testify NARX for long-term load forecasting. During the interviews with the company we were informed that long-term forecasts are derived in June for next year on hourly basis. Therefore we have developed a pilot model for Brabant region to see whether NARX is effective in long-term forecasting.

In terms of implementation there are some differences in the NARX model compared to the one used in short-term load forecasting. The most important difference is in terms of recurrence. In short-term forecasting we used open loop networks, meaning that in the feedback loop actual load values were fed back to the network. For the lead times longer than one hour, we derived multi step forecasts. However in long-term forecasting lead times are too long, multi-step modeling would not work. Therefore we used closed loop networks, in which with the feedback loop not the actual values but past forecasts are fed back to the network.

In addition to the difference in terms of network structure, input variables are different than the ones used in short-term load forecasting. As mentioned in Section 5.2, in short-term forecasting effects of economical and meteorological variables can be negligible, however in long-term forecasting these variables can have significant effects, hence *'Temperature'* and *'Sun light'* variables are added to the dataset.

Similar to short-term load forecasting, calendar variables are grouped. However, in training phase, despite the model generally captures special days successfully, the period between Christmas holiday and New Year's Eve performance was much lower compared to other special days. This is due to the fact that the Christmas period is the most difficult period of the year to forecast. During this period many companies and plants shut down, people take long holidays. Therefore, in order to clarify this unusual pattern during this period, another binary variable is defined, named *Christmas Period,* taking value one between 25^{th} of December and 1^{st} of January.

Analogous to short-term forecasting, in addition to the exact dates of special days, one-day prior and after these days and bridge days are defined as variables and included in the model. Furthermore, *day of the week, hour of the day* and *summer time* variables are defined as binary inputs, taking value one on respective days. Duration of sunlight is also included as binary input in the model, named as *Sun Down Percentage*; converts the information on percent of the respective hour the sun is down. For example, if sun rises at 6:30, then for 7^{th} hour interval variable takes 0,5, meaning that half of the 7^{th} hour will be with sunlight.

Lastly, as mentioned before, temperature is defined as another input. However, meteorological forecasts are not available for such a long period and hard to predict. Therefore, temperature data of last 5 years are fed into the network separately for last five years. The model is run five times with every dataset. And the results are averaged to obtain final forecast. By following the mentioned methodology, extreme effects of too low or too high temperature values' effects are included into the model. However if we simply averaged the temperature values for five years and used as an input, such nonlinear effects of temperature on the infeed would be lost. Another advantage of the mentioned method is providing not only point forecasts but also intervals, which enable market parties to better adjust their risk.

Our second NARX model contains 18 exogenous inputs and uses the same feedback delays as short-term load forecasting NARX: *1, 2, 23, 24, 25, 168 (1 week)* and *169 hours*. In total input layer consists of 25 inputs and output layer contains one output node. Unlikely to short-term forecasting, the search for best architecture is this time limited to two hidden layers, as this time we are modeling for only one region. Total number of hidden nodes is limited to thirty nodes and possible architectures are run for five times. As the network size grows larger it takes longer to train the network. Therefore what we adopted in architecture search is; first increasing number of nodes in every layer gradually by five. After determining five architectures that perform better than the others, we continued the search for the architectures closer to the chosen ones. For example, during training of two hidden layer networks, we first ran the architectures: 5 / 5, 5 / 10, 5 /15, … , 5 / 25, 10 / 5, 10 / 10, … ,10 / 20, …, 25 / 5. If 5 / 15 is one of the best performing five architectures and 5 / 10 performs better compared to 5 / 20 then we continued our search for the architectures: 5 / 11, 5 / 12, 5 / 13 and 5 / 14. As it is widely known in the literature, architecture search is a trial and error process; we did not strictly follow the process, but used as a guideline for us. While agreeing on the best performing architecture the average performances of five initializations are calculated, in order to investigate dependency of network performance on network initialization. It is not a preferable to use networks whose performance deviates to a large amount depending on the network initialization. Hence around 2500 models were run in architecture search. The final architecture is shown in Figure 35 where sun_t is the sunlight variable, $temp_t$ is the temperature variable, HI_t stands for hour interval, WD_t is the weekday, br_{it} stands for bridge day, day after special day and day before special day binary variables, s_{kt} are special days binary variables and $\hat{y}_{t-1}$ to $\hat{y}_{t-169}$ are the selected feedback loop variables.

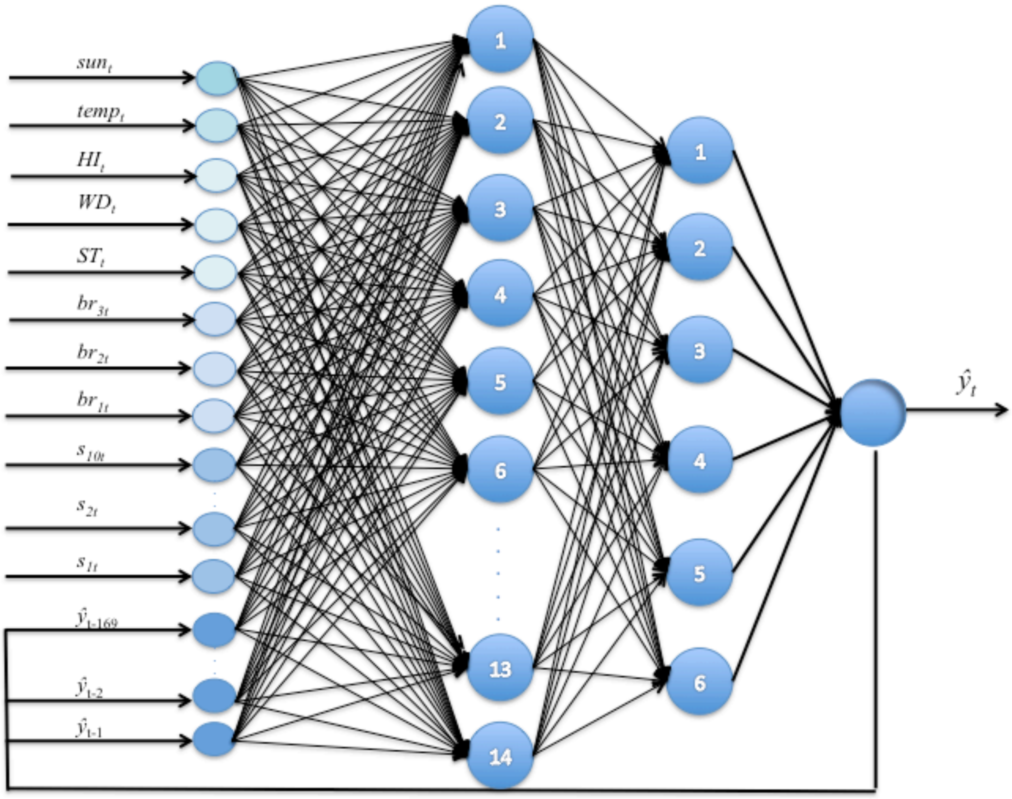

Figure 34. Final network architecture for long-term load forecasting in Brabant.

Parallel to our first NARX network training, we have used Levenberg-Marquardt' training algorithm.

5.3.2. Results of Long-term Load Forecasting

In this section performance of closed loop NARX network in long-term load forecasting is presented. Post-sample accuracies are measured in terms of MAPE and MaxAPE. Results are compared to another study implemented on the same dataset by using regression based forecasting methods [5] and the existing methodology followed in the company, which is a time shifting method based on similar years.

In this model, we did not derive multi step forecasts; instead we derived forecasts starting from June till end of the next year. Therefore first, we will present model performance for the next one year and 5 months. Then we will carry out the comparison for one-year period. Because our dataset contains data till the end of November 2012, we have included December 2011, to obtain a full year.

First of all, our model performance from June 2011 till November 2012 is provided in Table 5. In the table performances are listed for two different cases, actual temperature and unknown temperature. Actual temperature is the performance when actual temperature values are input for the respective forecasting period. Unknown temperature is the case when, as we mentioned above, past five years' temperature values are fed into the network and averaged. Despite the main indicator of the model performance is the second case, we provided the performance with the actual temperature values in order to give the reader an insight about temperature's effect on the performance. We observed that with the actual values model forecasts infeed 11% better in terms of MAPE. In Figure 35, actual and forecasted infeed values can be seen for the last three months on the same graph.

Table 5
Performance of closed loop NARX neural network in forecasting next 17 months' load in Brabant.

	MAPE	MaxAPE
Actual Temperature	2,48%	15,12%
Unknown Temperature	2,75%	18,61%

For an electricity distributor, accuracy in terms of monthly forecasting is also significant for the operations. Therefore, we have aggregated our forecasts monthly and checked the accuracy. In Table 6 aggregated forecasting performance is provided and a graph of 23 months actual infeed versus forecasted values are plotted in Figure 36. The figure proves very high accuracy values, forecasted infeed being very close to actual infeed.

Table 6
Performance of closed loop NARX neural network in forecasting 17 months' load in Brabant.

	MAPE	MaxAPE
Monthly forecasting perf.	1,69%	4,69%

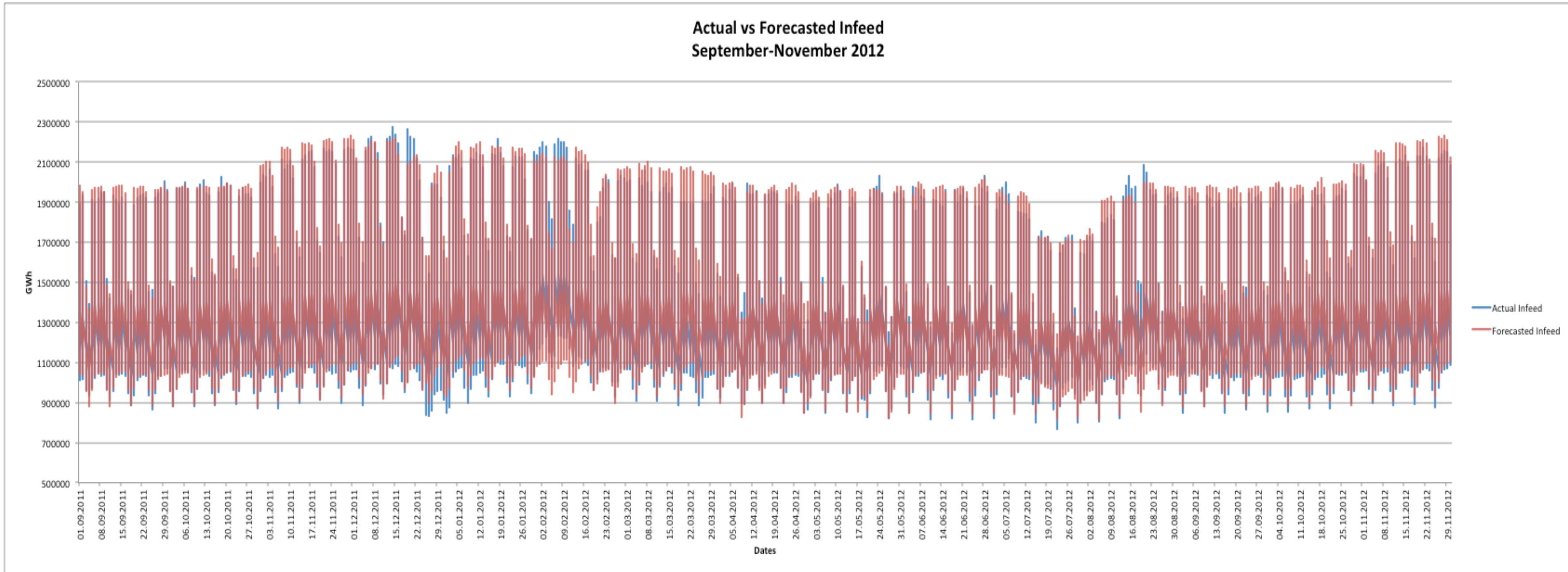

Figure 35. Actual Infeed vs Forecasted Infeed from September 2012 to November 2012 in Brabant.

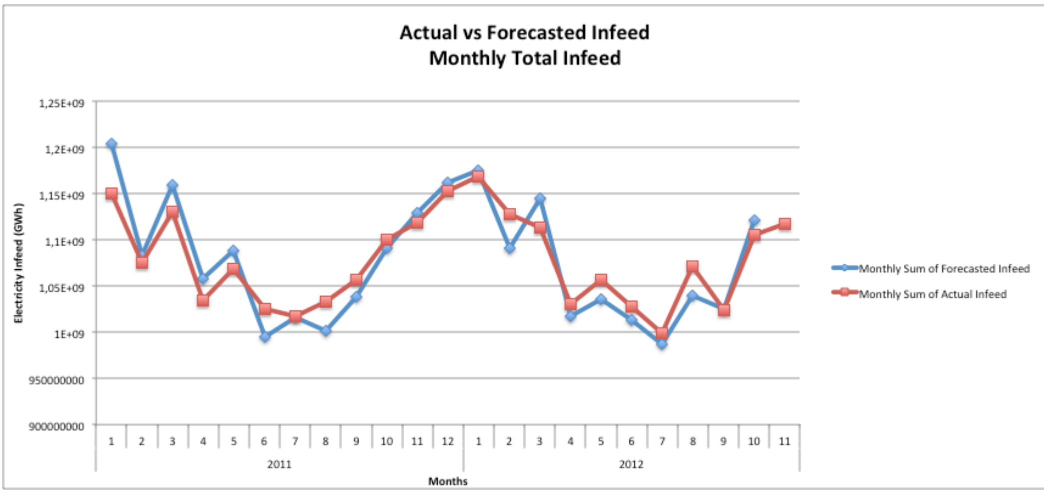

Figure 36. Monthly Actual Infeed vs Forecasted Infeed from January 2011 to November 2012 in Brabant.

In order to show how well the model performs at forecasting special days, we have provided some examples in Figure 37, presenting forecasting performance during School Holiday and Bouwvak period, highlighted with dashed circles. Figure 37 proves NARX meets the expectations of capturing special days. Clearly our model adjusts the forecasts during special days and converges very close to actual infeed. Average forecasting performance of our model throughout one year on Bouwvak and School Holidays is 3,23% in terms of MAPE. Figure 38 provides another example to special days forecasting. It includes Christmas and New Year period, which is particularly difficult for the electricity market parties to forecast. Figure 38 shows compared to its performance on other special days; our model also has some minor problems in forecasting the mentioned period. However in comparison with other methods we have received very positive feedbacks from the company about the performance during this period. Despite slight deviations from actual values, average percent error (APE) in December is 1,41%. Throughout one year, our models' MAPE on special days is 3,54%.

Thirdly, in order to also show the model's ability to capture bridge days we have provided an example from May. May 2012 was particularly difficult for the company to forecast, as it included two different types special days; Ascension and Whit Sunday & Monday. As Ascension Day is always on Thursdays, bridge day effect is expected to occur. Figure 39 shows the bridge day effect in May 2012 and our models ability to capture the effect.

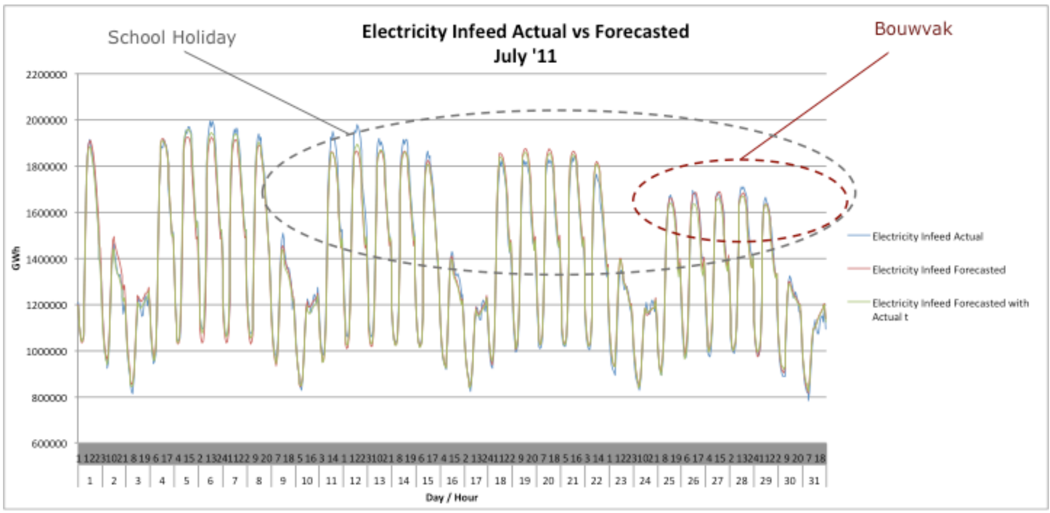

Figure 37. Actual and forecasted infeed values during school holiday and Bouwvak periods.

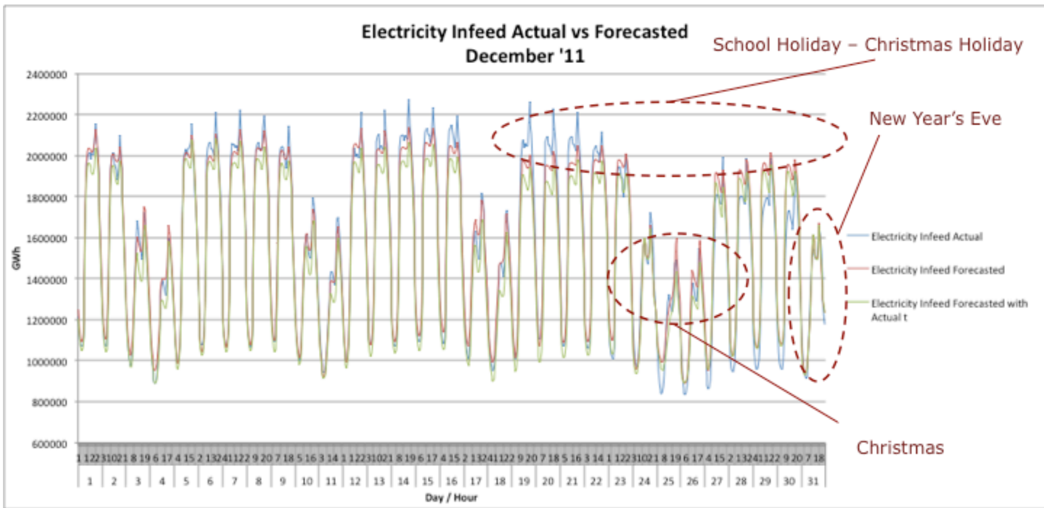

Figure 38. Actual and forecasted infeed values during Christmas and New Year periods.

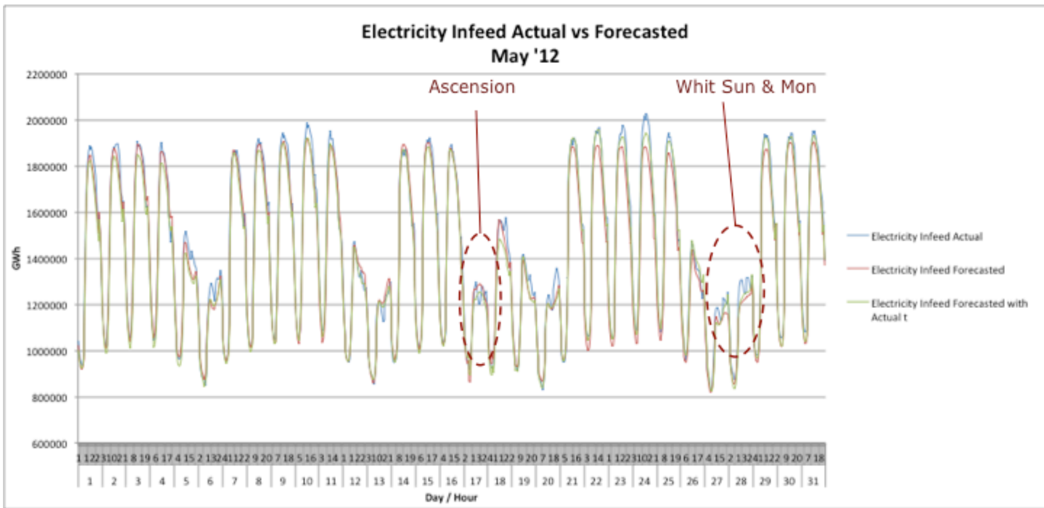

Figure 39. Actual and forecasted infeed values in May 2012.

7
Comparison of performances of Regression, NARX and Time Shifting models in one year hourly forecasting

	Time Shifting	Regression	NARX
MAPE_hourly	3,93%	4,10%	2,85%
MAPE_monthly	2,70%	2,98%	1,66%
MaxAPE_hourly	35.11%	33,40%	18,61%

Lastly, we have provided a comparison of model performances for hourly forecasting of one year in

Table 7. Tanrısever et al.'s [5] model is used as a reference regression model because they have used the same data set, but an older time period in training. Time shifting is the existing methodology being used in the company currently, which relies on using a past year as base year and assigning the load on the similar days on that year to the upcoming year.

Table 7 shows that our model has improved the model accuracy approximately 28% compared to current methodology. In addition, the maximum error is almost halved by our NARX model. Maximum error is important as it can be considered as a representation of risk the company takes. Therefore we can say that our model brings less risk to the company compared to other methods.

CHAPTER 6

CONCLUSION

After the deregulation in electricity markets, electricity load forecasting has become one of the main issues for market parties. Accurate electricity load forecasting is not an easy task, due to multiple seasonalities exiting in the datasets, complex and nonlinear relationships between the variables. In addition, different market parties need different types of load forecasting. Some need hourly forecasts, some need daily forecasts, some need peak load forecasts and for various lead times. Every need refers to different datasets; therefore there is no one correct methodology in load forecasting.

There are many studies on electricity load forecasting, dealing with aforementioned challenging issues on different datasets. However, a model performing well in dealing with one issue on one dataset, usually fails in dealing with another issue or performing as good on a different dataset. Additionally, despite the increase in number of studies, there is still dominancy of conventional and simpler methodologies in load forecasting literature. There is still the gap for applications on more recent methodologies on load data.

Our scope in this study refers to mainly two issues. First, one of the main challenges in load forecasting, incorporating special days into the models. Second, modeling of electricity load with a more recent methodology, NARX neural networks. Additionally, we provided a comprehensive computational study on the methods we proposed and compared the performances parametric and nonparametric models.

Special days are known as one of the most effective variables on the load. As reported in Section 5.1.1, special days create significant deviations from regular load patterns. Additionally, the load levels on day before and after the special day are also affected. We provided a modification to HWT in order to enable inclusion of special days to the model. HWT is a commonly used method in the literature due to its simplicity and easiness of use in the real life. However, existing studies on HWT cover the datasets that do not include any special days or switched with smoothed values. Working with datasets without special days does not reflect the real life. Our modification has improved forecasting performance of HWT on special days up to 87%. In addition, we have proposed NARX as a promising way of capturing complex effects of special days. Our computational study on short-term load forecasting in five different regions for six different lead times, proved our proposition. We reported that NARX captures special days effect in also long-term very well.

As a second contribution, we have reported that NARX performs very well in electricity load forecasting. After our modification, HWT became very competitive with NARX for short-term load forecasting. But as the lead times get larger and in long-term forecasting NARX outperforms the parametric models. We suggest that NARX stands as a very promising method in short and long-term forecasting and more studies should be carried out on different datasets in the future.

In addition to NARX applications, we suggest the emphasis on hybrid models to be increased. Hybrid models include dividing load data into two: base data and nonlinear data. The first part is modeled by using more conventional methods, such as regression and/or time series models. And the nonlinear relationships existing in the data that simple methods cannot capture accounted for the errors. Therefore the errors are modeled by using promising methods in capturing complex and nonlinear relationships such as, fuzzy logic models. During the literature research we have seen that these models have very promising performances on load forecasting, therefore deeper analyses should be carried out on their effectiveness.

We believe another methodology whose effectiveness should be investigated is Multivariate Adaptive Regression Splines (MARS). There are no studies investigating effectiveness of MARS in electricity load forecasting - to our best knowledge. MARS is a non-parametric methodology that includes an extension of recursive partitioning. Only in [51] MARS is applied to electricity price forecasting as a non-parametric regression method. In [51] results are compared to a NARX and a wavelet network performances and NARX is stated as the best performing methodology. However, MARS also produced promising results. Considering similarities between electricity load and price data and MARS' power in fitting nonlinear models in high dimensional cases, MARS stand as a promising method for electricity load forecasting.

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APPENDICES

APPENDIX A: EFFECTS OF SPECIAL DAYS

Ascension Day

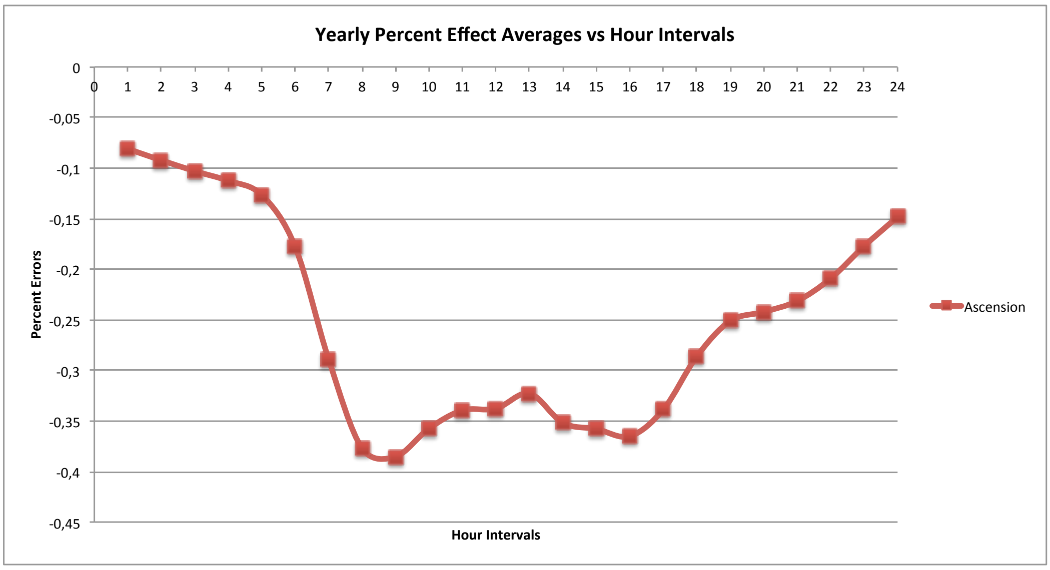

Figure 40. Effects of special days averaged for five years with respect to hours of day in Brabant (Ascension Day).

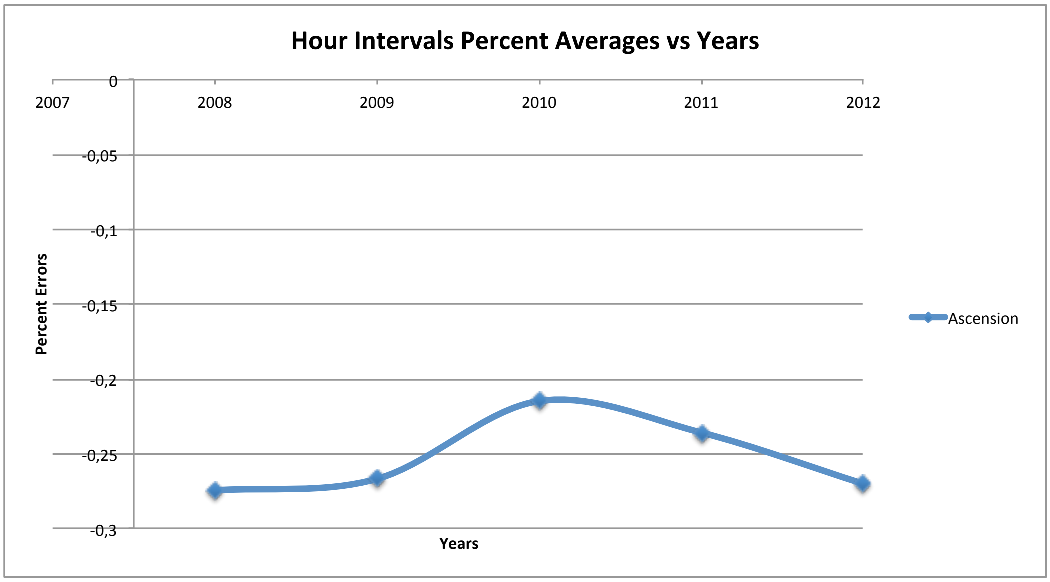

Figure 41. Average effects of special days in different years in Brabant (Ascension Day).

Queen's Day

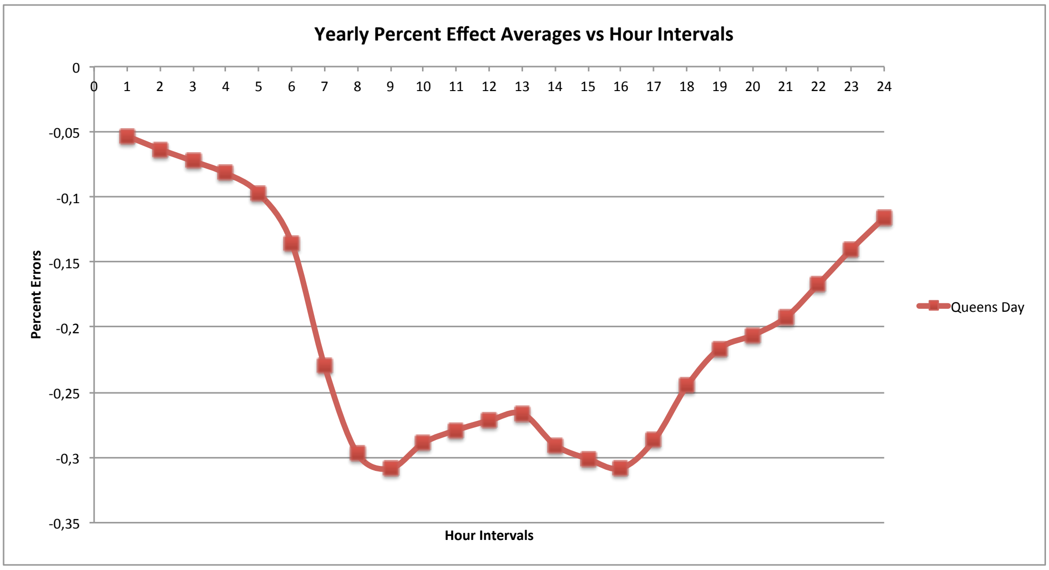

Figure 42. Effects of special days averaged for five years with respect to hours of day in Brabant (Queen's Day).

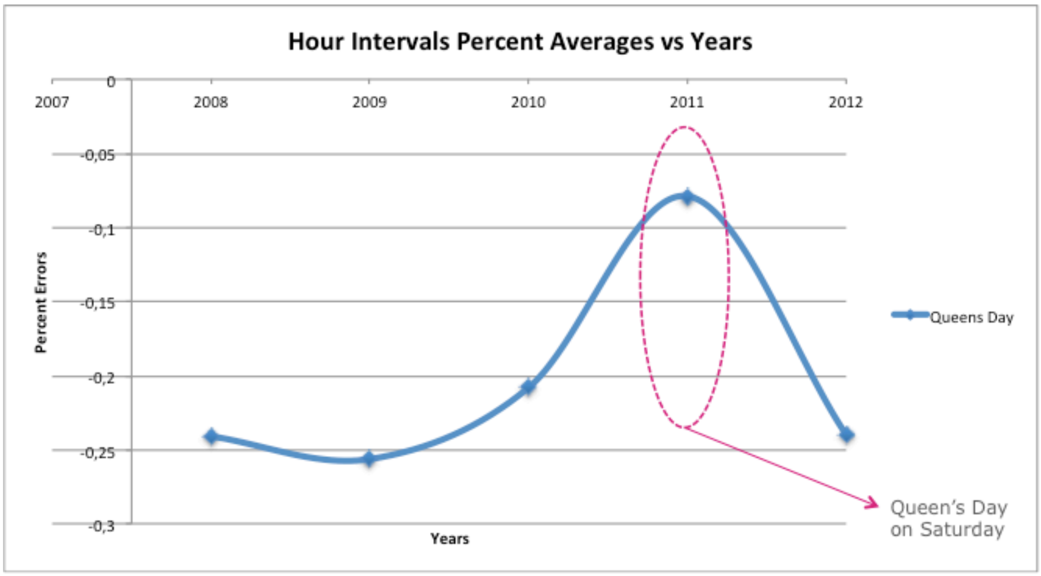

Figure 43. Average effects of special days in different years in Brabant (Queen's Day).

New Year Holiday

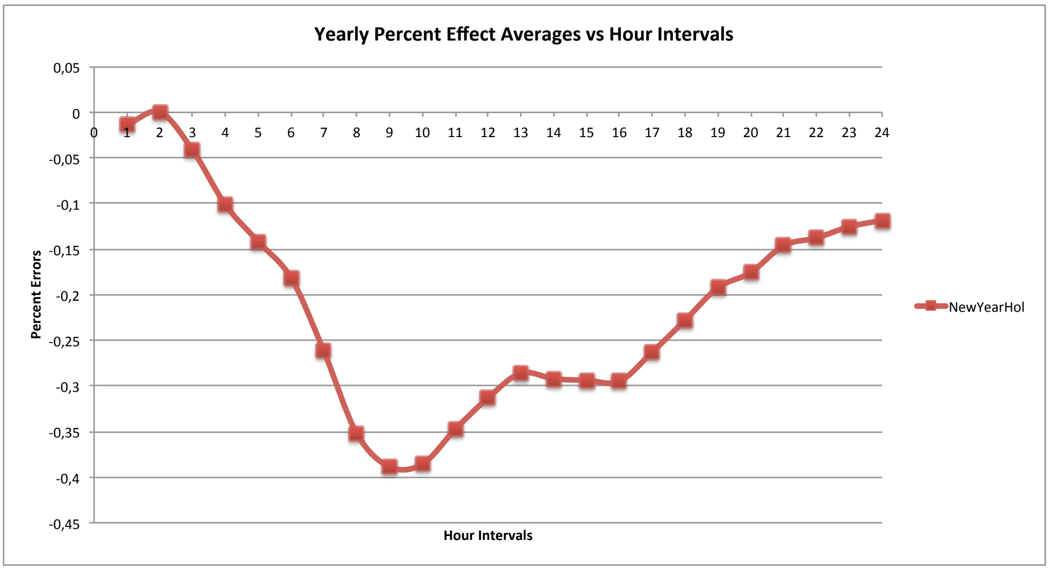

Figure 44. Effects of special days averaged for five years with respect to hours of day in Brabant (New Year Holiday).

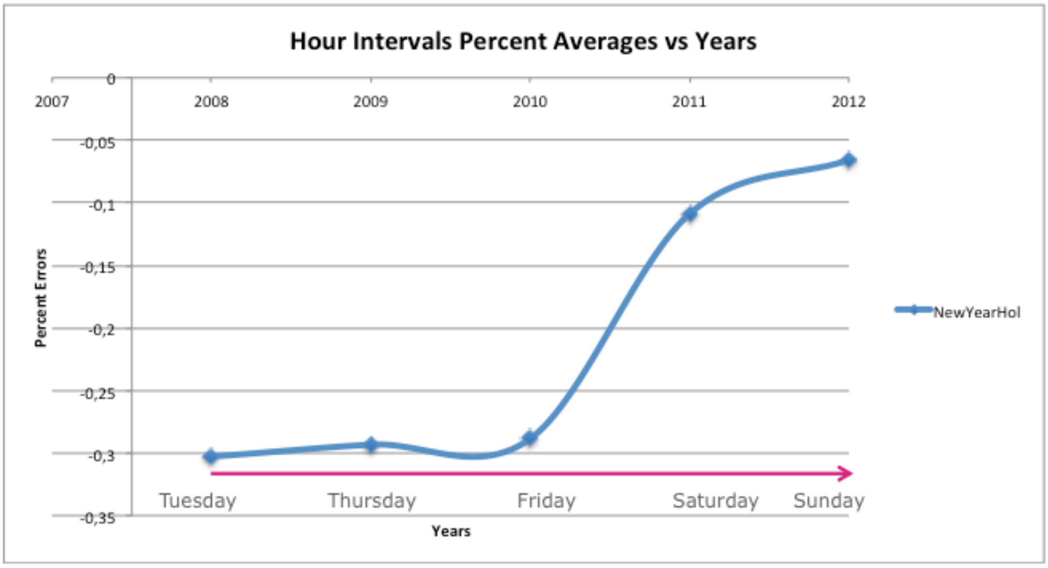

Figure 45. Average effects of special days in different years in Brabant (New Year Holiday).

Carnival

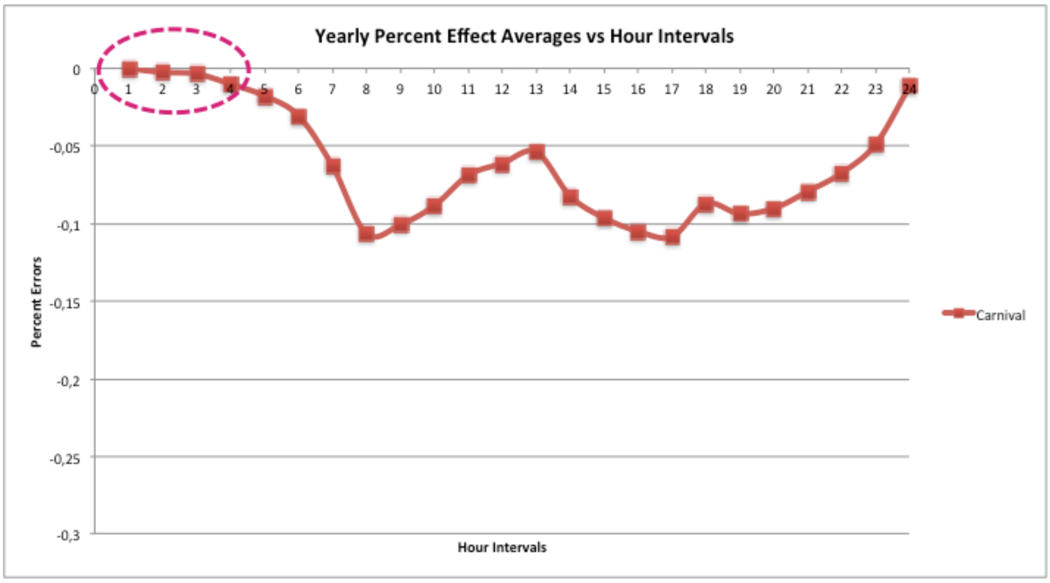

Figure 46. Effects of special days averaged for five years with respect to hours of day in Brabant (Carnival).

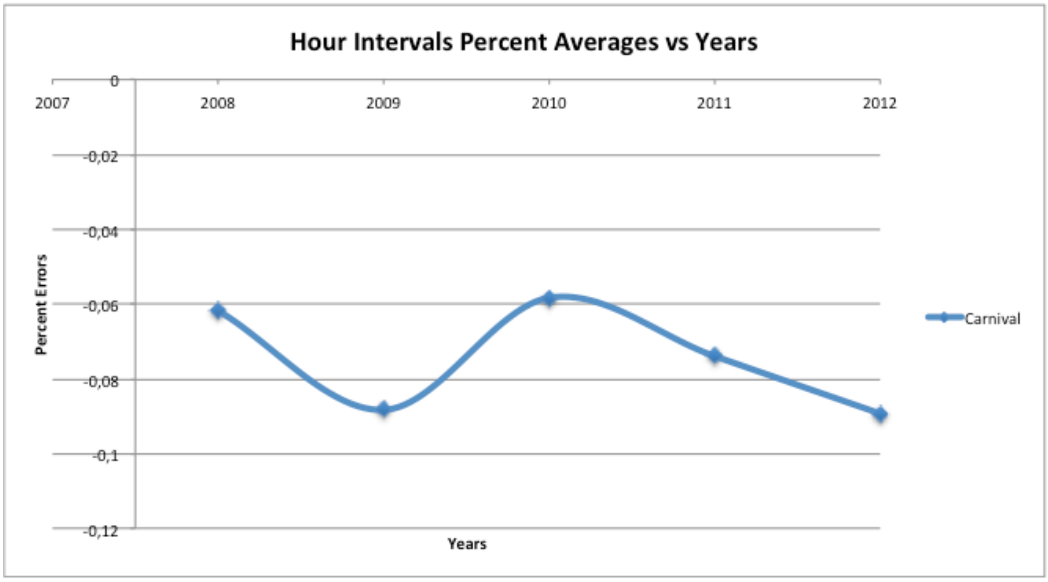

Figure 47. Average effects of special days in different years in Brabant (Carnival).

APPENDIX B: m-HWT MODEL PARAMETERS

Table 8
Parameters for m-HWT models of province Maastricht.

Lead Times (hrs)	$\boldsymbol{\alpha_{best}}$	$\boldsymbol{\delta_{best}}$	$\boldsymbol{\omega_{best}}$	$\boldsymbol{\phi_{best}}$
1	0.6099	0.1877	0.2070	0.2839
6	0.0528	0.1888	0.1300	0.7814
12	0.0262	0.1800	0.0894	0.8017
24	0.0043	0.2087	0.0729	0.7990
48	0.0004	0.0905	0.0442	0.9183
168	0.0001	0.0068	0.2103	0.9753

Table 9
Parameters for m-HWT models of province Limburg.

Lead Times (hrs)	$\boldsymbol{\alpha_{best}}$	$\boldsymbol{\delta_{best}}$	$\boldsymbol{\omega_{best}}$	$\boldsymbol{\phi_{best}}$
1	0.5623	0.1912	0.2168	0.3157
6	0.0433	0.1927	0.1305	0.7990
12	0.0203	0.2036	0.0735	0.8581
24	0.0023	0.2744	0.0943	0.9309
48	0.0035	0.0635	0.0719	0.9214
168	0.0009	0.0499	0.1648	0.8870

Table 10
Parameters for m-HWT models of province Friesland.

Lead Times (hrs)	$\boldsymbol{\alpha_{best}}$	$\boldsymbol{\delta_{best}}$	$\boldsymbol{\omega_{best}}$	$\boldsymbol{\phi_{best}}$
1	0.6107	0.1966	0.2430	0.2738
6	0.0262	0.1614	0.1662	0.8236
12	0.0115	0.2000	0.1213	0.7941
24	0.0006	0.2378	0.1423	0.8906
48	0.0035	0.0635	0.0719	0.9214
168	0.0001	0.0947	0.2340	0.9477

Table 11
Parameters for m-HWT models of province Noord.

Lead Times (hrs)	$\boldsymbol{\alpha_{best}}$	$\boldsymbol{\delta_{best}}$	$\boldsymbol{\omega_{best}}$	$\boldsymbol{\phi_{best}}$
1	0.5358	0.2287	0.2070	0.3493
6	0.0357	0.1884	0.1572	0.7887
12	0.0124	0.2078	0.1110	0.8236
24	0.0043	0.2087	0.0729	0.7990
48	0.0001	0.1435	0.0571	0.9396
168	0.0004	0.0068	0.2103	0.9753

APPENDIX C: NARX ARCHITECTURES

Table 12
Maastricht model architectures for different forecasting horizons.

Lead Times (hrs)	Hidden Layer	Number of Hidden Nodes
1	1	25
6	1	60
12	1	60
24	1	50
48	1	20
168	1	20

Table 13
Limburg model architectures for different forecasting horizons.

Lead Times (hrs)	Hidden Layer	Number of Hidden Nodes
1	1	20
6	1	30
12	1	70
24	1	55
48	1	20
168	1	30

Table 14
Friesland model architectures for different forecasting horizons.

Lead Times (hrs)	Hidden Layer	Number of Hidden Nodes
1	1	5
6	1	30
12	1	20
24	1	30
48	1	30
168	1	25

Table 15
Noord model architectures for different forecasting horizons.

Lead Times (hrs)	Hidden Layer	Number of Hidden Nodes
1	1	35
6	1	50
12	1	30
24	1	35
48	1	25
168	1	30