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# The Impacts of Forecast Quality on an Energy Company

Master´s thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Technology in the Degree Programme in Engineering Physics and Mathematics.

Helsinki, 16.9.2014

Supervisor: Professor Ahti Salo

Instructor: M.Sc. Mirka Mäkelä

| Aalto University<br>School of Science | | ABSTRACT OF THE MASTER'S THESIS |
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Abstract:

The de-regulation of the Nordic electricity markets has increased the volatility of the price of electricity and due to the increased uncertainty, forecasting has become more important for the companies that operate on the market. These companies need forecasts of the prices of electricity and fuel among other things for their operational planning, risk management and budgeting.

Forecast quality describes how well do the forecasted values correspond with the realized values. It can be used to assess whether the used forecast is good enough. If there are multiple alternatives which forecast model to use, forecast quality can also be utilized in the selection between the models. The impacts of the quality of various forecasts differ. It is useful to know the magnitude of the impacts, because it makes concentrating on the most important forecasts possible. The assessment of forecast value, which describes the influence of the used forecast on the decision making, can be utilized in this.

This Master's Thesis was made for Helsingin Energia. Its results show what methods Helsingin Energia should use to monitor the quality of the forecasts it uses and the impacts of forecast quality of different forecasts on its business.

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Tiivistelmä:

Sähkömarkkinoiden vapauttamisen johdosta sähkön hinnan volatiliteetti pohjoismaisilla sähkömarkkinoilla on kasvanut, ja tämän epävarmuuden kasvamisen johdosta näillä markkinoilla toimivien yrityksien tarve ennusteille on entistäkin suurempi. Nämä yritykset tarvitsevat ennusteita muun muassa sähkön ja polttoaineiden hinnan kehityksestä operationaalisen suunnittelun, riskien hallinnan ja budjetoinnin tueksi.

Ennusteen laadulla kuvataan sitä, kuinka hyvin ennustetut arvot vastaavat toteutuneita arvoja. Ennusteen laadun avulla voidaan päättää, onko käytetty ennuste riittävän hyvä. Ennusteen laadun määrittäminen auttaa myös ennustemallin valinnassa, jos tarjolla on useampi vaihtoehto. Käytettäessä useampia ennusteita eri ennusteiden laatujen merkitykset poikkeavat toisistaan. Tämän vuoksi on tärkeää tietää, minkä ennusteen laadulla on suurin merkitys, jotta tiedetään, mihin kannattaa keskittyä. Ennusteen arvon, joka kuvaa käytetyn ennusteen vaikutusta tehtyihin päätöksiin, määrittämistä voidaan hyödyntää tähän.

Tämä diplomityö tehtiin Helsingin Energialle. Diplomityön tuloksena saatiin selville, mitä menetelmiä yrityksen kannattaa käyttää ennusteidensa laadunvalvonnassa ja kuinka suuri merkitys eri ennusteiden laadulla on yrityksen liiketoiminnan kannalta.




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Tomi Jussila

# Contents

# 1. Introduction

Uncertainties complicate the decision making process of most companies. For example, it is impossible for a company to have precise knowledge of the future demand, costs and profits of its products. The most obvious strategy to cope with uncertainty is to reduce it (Lipshitz and Strauss, 1997). The use of forecasts is one possible way to achieve this. Therefore forecasting is an important part of the decision making. Forecasting can be exploited in many areas of a company such as operational planning and risk management. Uncertainties also make it difficult to predict expected cash flows. This information is relevant for the shareholders because it is needed for the valuation of the company (DePamphilis, 2012). Forecasting makes it possible to budgeting expenses and profits and as a result, to establish a sufficiently accurate prediction of expected cash flows.

Major changes in the electricity market during the last 20 years have raised the importance of forecasts for Finnish electricity producers. The electricity market was de-regulated in 1994 and nowadays Finland forms a single electricity market together with Sweden, Norway, Denmark, Estonia, Lithuania and Latvia (Nord Pool Spot, 2011). This has caused a significant change in the formation of electricity price. The previously regulated tariffs have been replaced with a market-based price formation. The hourly supply and demand in the wholesale market Nord Pool Spot where the majority of the electricity trading is made, determines the price of electricity. This has resulted in an increase in the volatility of the price of electricity and thus the energy producers in deregulated electricity markets are exposed to a higher price risk than on regulated markets (Möst and Keles, 2010).

Electricity producers aim to maximize their profits in the electricity market. The excessive volatility of electricity price raises the importance of the timing of electricity trading. Also because electricity is non-storable commodity, which means that it must be consumed immediately after it has been produced, the timing of generation is essential. In order to maximize the profits in the electricity market an electricity producer must optimize its production plan. Depending on the form of electricity production, other aspects than the electricity price may also have an effect on how the electricity should be produced. For example fuel prices and district heat demand have an impact on combined heat and power (CHP) generation whereas the status of hydro reservoirs affects hydropower generation. Because each of these aspects contains uncertainty, forecasts are needed to provide an optimal production plan.

Former studies have shown that companies can benefit from hedging against the market risks. Bessembinder and Lemmon (2002) argue that electricity producers are as likely to benefit from hedging the price risk that is caused by the volatility of electricity price. Hedging is done by trading different derivative instruments such as future contracts, forward contracts and options. Knowledge of the electricity price improves the quality of hedging. In order to hedge as well as possible, it is also essential to know accurately how much electricity is going to be produced on a given moment. The better the forecasts for constructing the production plan are, the more accurate the plan will be. Therefore good forecasts are vital for optimal hedging strategy.

In forecasting the five basic steps are problem definition, information gathering, preliminary analysis, choice and fitting of the model and the use and evaluation of the forecasting model (Hyndman and Anthanasopoulos 2013). Choice of the model is normally the most complicated phase of forecasting. Different circumstances require different forecasting methods. The variable that is being forecast and the forecast horizon determine which forecasting method is suitable. In some cases, multiple different methods may seem suited for the given task and the choice between these methods can be difficult. For example artificial intelligence-based models (Szkuta et al, 1999) and autoregressive models (Garcia et al, 2005) have both been applied into forecasting electricity price on short-term with good results. Due to the complexity of forecasting, many electricity producers have started to outsource forecasting to companies that have specialized in that field.

The fifth step in forecasting consists of evaluation of the used forecasting model, because it is important to know how accurate the used model is. This knowledge obtained from forecast evaluation could be used for example in defining whether the chosen model is good enough or whether it is worth its price if it is a commercial forecast. Murphy (1993) defines the goodness of forecasts with three different aspects: consistency, quality and value. Consistency shows how well the forecast corresponds with previous assumptions. Forecast quality describes how accurately forecasts correspond with realizations. The value of forecast describes simply how much value does the forecast bring to its user. The latter two of these aspects are the ones that this thesis concentrates on.

This Master’s Thesis was made for department of Helen Portfolio Management in Helsingin Energia. The main objective of this thesis is to define how Helsingin Energia should monitor the quality of the forecasts it uses. The scope of this thesis is limited into forecasts influencing CHP production due to its high share in Helsingin Energia’s electricity production portfolio. Because the importance of forecast quality may vary between different forecasts and circumstances, it is essential to identify the most significant forecasts. This can be done by determining the forecast value of different forecasts. This thesis will result in definitions of acceptable level of forecast quality for different forecasts and recommendations of the methods to measure the quality of these forecasts.

The remainder of this thesis is organized in the following way. Chapter 2 presents the basics of the Nordic Electricity markets. Chapter 3 presents how electricity production can be planned. Chapter 4 introduces various methods for both forecasting and forecast evaluation. Chapter 5 presents the method that is used to identify how the quality of different forecasts should be measured. Chapter 5 presents the results of this analysis and conclusions of this research are presented in chapter 6.

# 2. Nordic Electricity Markets

Ever since the Finnish electricity market was deregulated in 1994 and Finland joined the Nordic electricity market, Finnish electricity producers have operated in a market in which electricity is traded like other commodities. Nordic electricity market, Nord Pool Spot, consists nowadays of Finland, Sweden, Norway and Denmark, and also of Estonia, Lithuania and Latvia, who have joined the market only recently (Nord Pool Spot, 2014). This chapter presents the characteristics of Nord Pool Spot to give information on how electricity is traded in Nordic countries. It also takes a look into the fuel markets that affect electricity trading in Nordic countries.

## 2.1. Consumption

The electricity consumption in the Nord Pool Spot area is annually in the region of 400 TWh. Sweden and Norway are the biggest consumers. In 2013 the total amount of electricity consumption was 390 TWh (ENTSO-E, 2013) and its distribution between different countries is presented in figure 1. Almost equal amount of electricity is consumed both in industrial and residential sector. The major electricity consumers are paper and pulp industries in Finland and Sweden and metal, petrochemical industries in Norway and the direct electricity heating in every country.

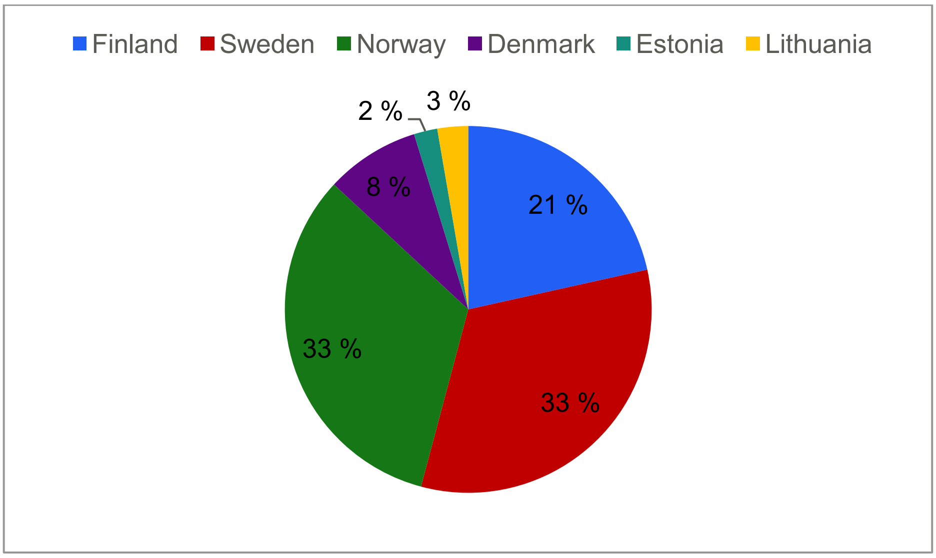


*Figure 1. Electricity consumption distribution in each countries in Nord Pool Spot in 2013 (ENTSO-E, 2013)*

Electricity consumption contains multiple seasonal variations that are caused by its nature. Direct electricity heating in households causes the consumption to be highly dependent on weather conditions which leads into seasonal variation on an annual level. Figure 2 presents the weekly electricity consumption in Nord Pool Spot area in 2012 and 2013 (Nord Pool Spot, 2014). It shows that the electricity consumption is clearly higher during the winter than during the summer. Industrial consumption on the other hand causes variation on a weekly level. Electricity consumption is significantly higher on work days than on weekends and public holidays. There is also daily variation on electricity consumption. The consumption is much lower during night hours than during daytime. There are also usually two peaks in the daily consumption, one on morning and one on afternoon. Figure 3 presents the hourly consumption on week 10 of 2014 (Nord Pool Spot, 2014). This figure shows the typical weekly consumption pattern.


*Figure 2. Weekly electricity consumption in Nord Pool Spot area in 2012 and 2013 (Nord Pool Spot, 2014)*

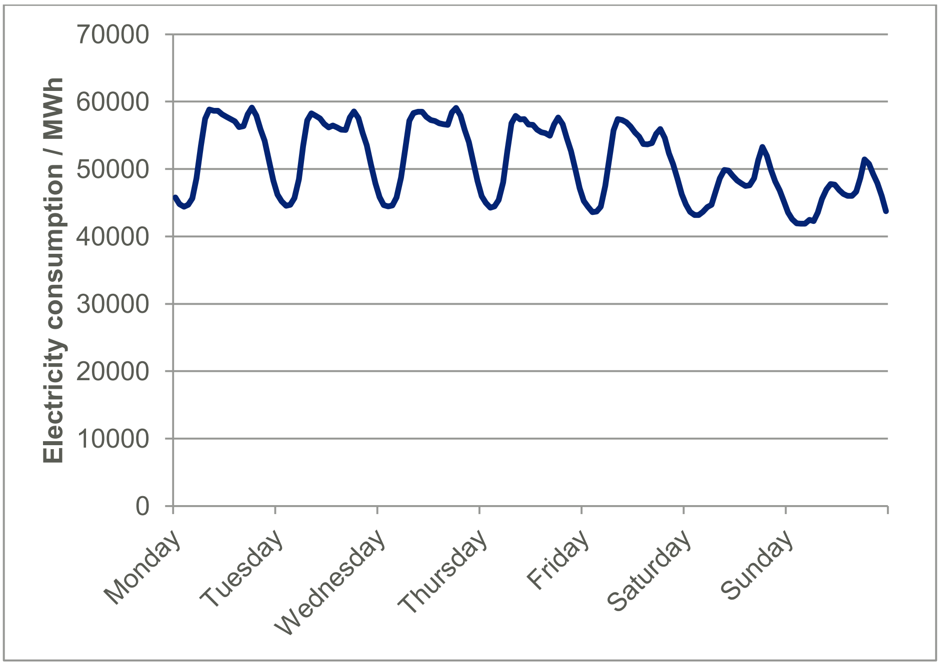


*Figure 3. Hourly electricity consumption in Nord Pool Spot area on week 10/2014 (Nord Pool Spot, 2014)*

## 2.2. Generation

Electricity in Nordic countries comes mainly from four different generation method: hydropower, nuclear power, wind power and thermal generation. The basics of these generation methods are presented in this chapter. The distribution between different generation methods in each country varies significantly. For example in Norway almost all electricity is generated by hydropower whereas in Denmark the majority of generation is thermal generation. Produced amounts also vary between different countries. Figure 4 presents the production distribution of each country in 2013 (ENTSO-E, 2013).

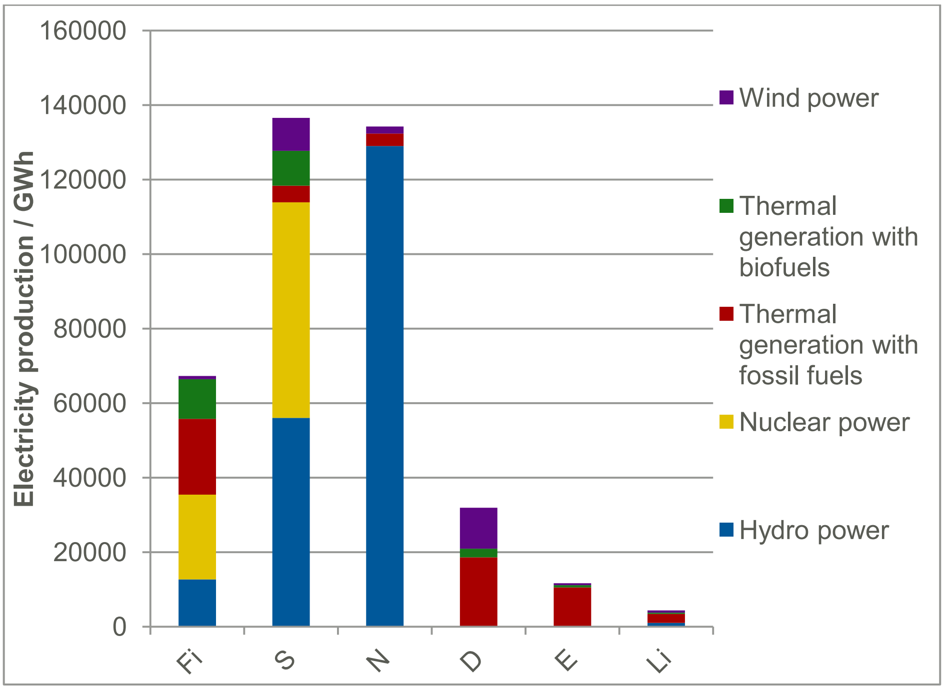


*Figure 4. Electricity production in Nord Pool Spot area in 2013 (ENTSO-E, 2013)*

### 2.2.1. Hydropower

Hydropower is an electricity generation method that transforms the potential energy of water into electricity by driving the water through turbines that are connected to electric generators. Due to this, the marginal cost of hydropower generation is low. It is also a flexible source of energy because the water flow going through the turbines can be fairly easily controlled in most situations. Hydropower is therefore suitable for both base-load and balance-power generation needs.

The location by the North Sea and especially near the Gulf Stream and the mountains in between Norway and Sweden cause plenty of rainfall and thus a possibility to utilize hydropower plants. The favorable conditions result in hydropower to be the dominant electricity source in Nord Pool Spot area (Javanainen, 2005). The amount of hydropower generated varies according to the weather conditions. When there is not much rainfall there is less water available which reduces the hydropower generation. This means that hydro balance, a variable that measures the state of the current water resources at the time, is a good indicator of how much hydropower can be produced.

Hydropower plants can be roughly divided into two categories: run-of-river plants and reservoir plants. The difference between the two is the ability to regulate the generation. Run-of-river plants contain at best only a limited ability to store water, which means that their production depend closely on the natural flow of water in its location. Reservoir plants include a reservoir where the water can be stored, such as natural or artificial lakes. This allows the planning of the production.

### 2.2.2. Nuclear Power

Nuclear power is a method of electricity generation where the excess energy of nuclear fission reaction is used to produce steam that is driven through a steam turbine connected to an electric generator. In Nord Pool Spot area the nuclear power plants are located merely in Finland and Sweden (ENTSO-E, 2013). Yet, its share of the electricity production in the whole area is significant, being 20.5 % in 2013. Because the operating costs of nuclear power plants are low, nuclear power is considered as a base-load generation. This means that basically they operate throughout the whole year on their maximum power, apart from the yearly maintenance period.

### 2.2.3. Wind Power

Wind power is an electricity generation method where the kinetic energy of wind is transformed into electricity by wind turbines. The output of wind power plants depends solely on the actual wind speed, which is unpredictable. Because of this a power system cannot rely solely on wind power. In Nord Pool Spot area wind power has a significant share in Denmark, where its share of total production was 34.5% in 2013 (ENTSO-E, 2013). In other countries it is not that significant, with the share of production in the whole Nord Pool Spot area being 6 % in 2013.

### 2.2.4. Thermal Generation

Thermal generation is an electricity generation method where the chemical energy of a fuel is transformed to thermal energy that is then used to produce steam that is driven through a turbine connected with an electric generator. Traditionally these power plants have used fossil fuels with coal, natural gas and peat being the most common fuels in Nord Pool Spot area. Nowadays the amount of biomass-fueled thermal power plants is rising, though the majority of thermal generation is still done with fossil fuels.

Thermal generation can be characterized by how it utilizes the heated steam produced during the process (Westner and Madlener, 2012). Condensing power plants produce only electricity and in the Nord Pool Spot area, they are used normally during consumption peaks. Their operation is typically determined according to their short-run marginal cost and electricity price, so that these plants are operated only when it is profitable. Combined heat and power (CHP) plants utilize the excess heat former either in the industrial process or as district heating in urban areas. CHP plants have a lower efficiency rate on electricity production than condensing power plants due to their increased production of heat. The overall efficiency of these plants can reach rates of over 90 % though, so their energy efficiency is great.

## 2.3. Transmission

The transmission of electricity from generators to consumers is an integral part of electricity markets that can affect the actions of an electricity producer. The power grid consists of high-voltage grids operated by national transmission system operators (TSOs) and local low-voltage grids operated by local grid operators. TSOs are public utilities, which are also responsible for maintaining the electrical stability in its area (Nord Pool Spot, 2014). The transmission capacity of high-voltage grids is essential for free-flow of electricity because electricity generation and consumption tend to be located on different regions.

## 2.4. Electricity Trading

The electricity trading in the Nord Pool Spot area can be divided into two categories, which are physical trading and financial trading (Nord Pool Spot, 2014). The difference between these categories can be explained by the characteristics of the trading. Physical trading involves in the actual trading of the electricity commodity and results in transactions of electricity. Financial market involves in trading of financial contracts that can be used for risk management. These contracts result only in cash settlements.

### 2.4.1. Physical Market

The majority of the electricity trading in Nordic countries takes place in Nord Pool Spot's day-ahead market, Elspot (Nord Pool Spot, 2014). In this market, every participant submits a bid for power to be delivered the following day by 12:00 CET. The buyers assess how much electricity they will need each hour and how much they are willing to pay for it. The sellers need to determine how much electricity they can deliver each hour and how much they want to be paid for it. These bids determine the supply and demand of electricity on each hour. This information is used to calculate the electricity price where the supply and demand meets. This price is called the system price (Nord Pool Spot, 2014). In a fully competed market system price would be equal to the production cost of the most expensive electricity production mean needed to fulfill the demand, i.e. the short-term marginal cost. A simplification of the price formation is shown in figure 5. The following day, the electricity must be physically delivered according to these bids.

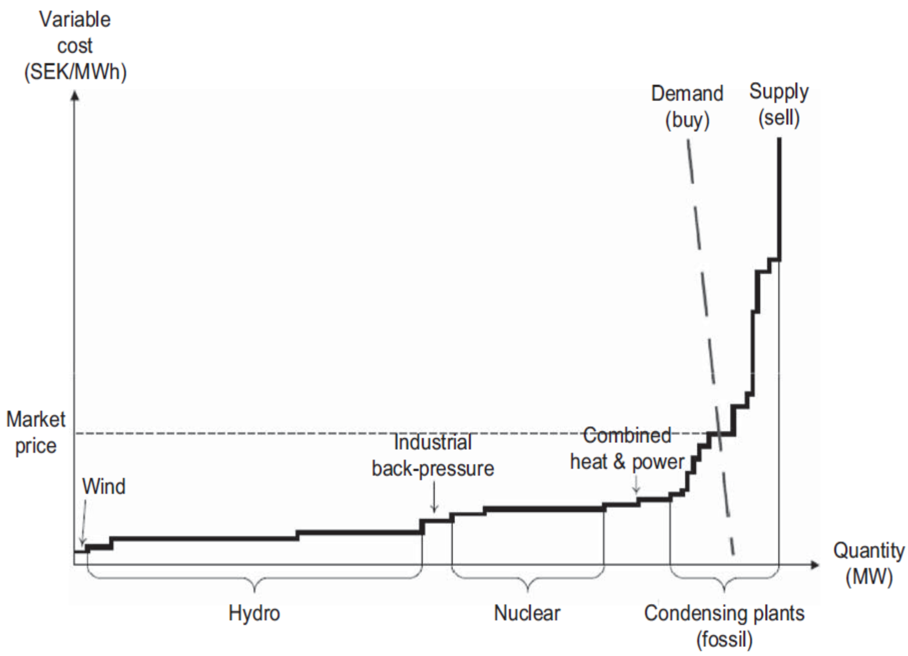


*Figure 5. Price formation on Nord Pool (Swedish Energy Market Inspectorate 2014)*

The transmission capacity in Nord Pool Spot area is limited. It is possible that in the market equilibrium electricity generation would be formed so that transmission capacity would restrict the transmission of electricity from generators to consumers. For example sometimes the system price may be calculated so that majority of the electricity is produced as cheap Norwegian hydropower and it may be impossible to transmit this to other countries due to the limited transmission capacity. Nord Pool Spot has solved this problem by forming different bidding areas (Nord Pool Spot, 2014). By definition, each country in Nord Pool Spot area is its own bidding area. National TSOs can then decide further, whether the country is then divided into several bidding areas. At the moment there are 14 different bidding areas in Nord Pool Spot area. Norway is divided into 5 areas, Sweden into 4 areas and Denmark into 2 areas. Finland, Estonia, Latvia and Lithuania each consist of one single bidding area (Nord Pool Spot, 2014).

In the case where transmission capacity restricts the optimal way to generate enough electricity to fulfill the demand, an area price is calculated for each bidding areas (Nord Pool Spot, 2014). Transmission capacity restrictions lower the demand of electricity on areas, which are exporting electricity and thus lower the price as well, whereas they lower the supply of electricity on areas that are importing electricity and thus raise the price. Area price is relevant for market participants because it is the price at which all the transactions on Elspot markets are executed on.

Due to the fact that Elspot bids are made 12 – 36 hours prior the delivery, it is possible that the market participants may wish to change the amount of electricity they are going to trade, because they probably have more accurate knowledge of their desired market outputs closer to the delivery hour. Nord Pool Spot operates an intraday market called Elbas, where market participants can trade electricity to bring the market closer to the balance. Elbas is a continuous market where the trading is possible until one hour before the delivery (Nord Pool Spot, 2014). Trading takes place when the highest buy price and lowest sell price for a given hour match.

The power balance is impossible to maintain with just Elspot and Elbas markets. National TSOs that are responsible for the stability of power grid run a regulation power market in each country (Nord Pool Spot, 2014). It is possible for participants to make offers to change their consumption or generation capacity within an hour. Increase of generation or decrease of consumption are known as up-regulation and decrease of generation or increase of consumption are known as down-regulation. TSOs can accept up-regulation offers when consumption exceeds the generation and down-regulation offers when generation exceeds the consumption.

### 2.4.2. Financial Market

The non-storable nature of electricity, uncertain demand in Nord Pool Spot area and differences between electricity generation methods cause volatility in spot prices of electricity. Therefore the market participants are exposed to the price risk of electricity. Different products of the financial market can be used to reduce this price risk. They can be used to secure a certain cash flow in the future for market participants even if the spot price level changes drastically.

Main products that are used to mitigate the price risk are futures, forwards, options and contracts for electricity price area differences (EPADs). Standardized contracts of these products are traded in a commodity exchange operated by NASDAQ OMX Commodities (Nasdaq OMX, 2014). Because these are financial contracts, no physical delivery of power will be made according to them. They result in cash payments that are determined by the difference between the contract price and the system price or the difference between an area price and the system price at the time of delivery in case of EPADs.

## 2.5. Fuel Markets

Fuel markets have an impact on electricity generation in the Nordic countries due to the notable amount of thermal generation in the region. Due to this, the characteristics of the main fuels affecting the market are presented in this chapter.

### 2.5.1. Oil

Oil is a fossil fuel that can be refined in many ways for various uses. Most oil products are consumed in the transportation sector. Oil products can be used also in thermal generation, but due to their high price, they are rarely used as a main fuel of a power plant in Nordic countries. Oil is still a fairly important commodity for an electricity producer in Nordic countries because the prices of some other fuels follow the price of oil and oil is also used for heating in residential sector. The prices for oil products are set by the supply and demand. The prices in Europe follow closely Brent Crude price (Ascha et al, 2003). The financial trading of oil in Europe also concentrates on trading derivatives based on Brent Crude. The price of oil contains usually plenty of uncertainty, and forecasting it is a difficult issue.

### 2.5.2. Coal

Coal is a fossil fuel that is used widely worldwide in electricity production, and it is also one of the main fuels used in thermal generation in Nordic countries. Coal is a good fuel for energy producers because it is relatively cheap at the moment. It is also not a scarce resource because its reserves will still last a long time (Patzek and Croft, 2010). Coal is located also in multiple parts of world which reduces the geopolitical risk associated to coal. Coal has problems as well. Burning coal is not considered environmental-friendly, which has caused political pressure to cut down on coal consumption and may lead into an increase in the costs of coal via taxation. The prices of coal in Nordic countries follow closely API2 index (ICE, 2014) though usually an additional cargo fee must be paid. The financial trading of coal products is based on derivatives based on API2 index.

### 2.5.3. Natural Gas

Natural gas is one of the main fuels used in thermal generation in Nordic countries. All of the natural gas that is used in Finland is distributed from Russia via one pipeline. The only importer in Finland is Gasum Oy, which also owns the pipelines in Finland. Because Gasum Oy has a natural monopoly, the natural gas is sold with public tariffs, which are supervised by Energy Market Authority. The price of natural gas is composed of the transmission cost and energy cost (Gasum, 2013). The energy cost is bound to an index which is composed of heavy fuel oil price with a weight of 55 %, price of coal with a weight of 20 % and a basic index for domestic markets of energy sector with a weight of 25 %, and each of these indexes are formed as 6 month averages. Natural gas consumer decides then the amount of natural gas it wishes to buy each hour whole year (yearly product) and a possible additional amount for each month (monthly product). If the consumption is lower than the sum of these products, Gasum Oy buys the extra gas (return gas) back (Gasum, 2013). The price of each of these products is tied to the index presented in this chapter and none of them changes during a month. In addition, if the consumption is higher it is possible to buy extra gas from Gasum Oy. There are also after sales markets, where it is possible to trade natural gas.

A natural gas consumer must decide each year a transmission capacity it reserves. The transmission cost is based on this capacity level of the consumer (Gasum, 2013). Transmission costs are a concave function of the capacity level. As the capacity level rises, the total transmission costs rises as well, but the unit cost lowers. Also the time of the year affects the transmission costs. During winter time the transmission costs are higher. It is still possible to buy more natural gas even when the reserved capacity is exceeded, but then an additional fee must be paid as well. At the moment, there are no financial products of natural gas for trading in Finland.

# 3. Planning Process of a Combined Heat and Power Producer

Planning process of companies consists of three different levels, which are strategic, tactical and operational planning (Bender et al, 2002). Strategic planning sets the goals and guides the decisions of the company in the long-term, with the scope of this planning level being 3 – 15 years. For CHP producer the decisions at this planning level consider mainly investment decisions. Tactical planning considers how the goals set on strategic planning can be achieved on medium-term. The scope of this planning level is normally up to 3 years and it involves risk management and budgeting. Operational planning considers the short-term planning of the company. For a CHP producer this planning level involves mainly with the production plan of the power plants. This thesis focuses mainly on tactical and operational planning.

## 3.1. Short Term Planning

Short term planning of a CHP producer considers mainly how it will produce its main products, electricity and district heat, and how it will profit from the generation of these products. District heating is a natural monopoly in larger cities of Finland. This means that the customers of a district heat generator are not able to get the heating energy they need from anyone else except their local district heat generator. Due to this, a district heat generator must produce enough district heat to meet its customers' demand and the price of district heat is regulated by the national energy authority. The electricity that is generated in this process is sold to Elspot or Elbas market on Nord Pool Spot. In addition, the actions in balancing power market are included in the operational planning of a CHP producer.

The formation of production plan is an integral part of operational planning. The problem of constructing an optimal production plan for CHP producer has been widely studied. Usually the objective in optimization of the production plan is to minimize the cost of generation so that the demand of district heat is met. Various optimization techniques have been applied into optimization of CHP production. In general this problem can be formulated as followed

$$\begin{aligned} & min \sum_{t \in T} \sum_{u \in U} c_{u,t}(p_{u,t}, q_{u,t}) \\ & s.t. \sum_{u \in U} q_{u,t} = Q_t, \qquad \forall t \in T \\ & (p_{u,t}, q_{u,t}) \in X_{u,t}, \qquad \forall t \in T, u \in U \end{aligned} \qquad (1)$$

where $p_{u,t}$ is the amount of electricity generated and $q_{u,t}$ is the amount of district heat generated in power plant *u* on time *t*, $c_{u,t}(p_{u,t}, q_{u,t})$ is the production costs of this output after the profits of sold electricity are taken into account. *U* is the set of all power plants in the system, *T* is the set of time steps, $Q_t$ is the district heat demand on time *t* and $X_{u,t}$ is the operation region of a power plant *u* on time *t*. Makkonen and Lahdelma (2005) formulate a mixed integer linear programming (MILP) model that can be used to optimize the production of CHP plants even when the behavior of these plants is non-convex. Due to the scale of this optimization problem, it is recommended that a specific algorithm, Power Simplex (Lahdelma and Makkonen, 2003), is used to solve it. Cho et al (2009) present an alternative linear programming method, which is based on network flow formulation and is also suitable for the case. There are also a few tailor-made commercial optimization softwares designed for CHP optimization.

The output of production plan is the hourly production amount of electricity and district heat in each of the power plant in the energy system. The optimization requires knowledge of production costs, electricity price and district heat load during the planning period. Production costs vary according to the development of fuel prices and the price of electricity varies also and depends on the market where it is sold. District heat load contains uncertainty as well. Therefore production optimization requires forecasts of all these factors that contain uncertainty. Usually it is assumed that the produced electricity will be sold on the day-ahead market, Elspot. Because the forecasts are rarely perfect while the Elspot offers have been made, the production plan may be inaccurate. As a result, CHP producers will usually participate in intra-day market Elbas and regulating power market, even if Elspot market would normally generate a more secure cash flow. Therefore the more accurate the production plans are, the more certain it is that all of the produced electricity can be sold with the best price possible.

## 3.2. Medium Term Planning

CHP producers usually construct a production plan for a longer time period as well. The same production optimization procedure can be used for this purpose as well, but it may be that some simplifications are needed to the model to keep the calculation times reasonable. The production plan for a longer time period is not needed for operational planning, but it is needed for example for budgeting purposes. The medium-term production plan states how much electricity is going to be produced in future and how much fuels are needed for it which then allows budgeting. Budgeting is an important part of business because it predicts how big the cash flows are going to be in the future. This will allow the assessment of the value of the company (DePamphilis, 2012), which is valuable information for the stakeholders.

The production plan for a longer time period is needed also for the risk management purposes. Due to the high volatility of electricity price, most electricity producers wish to hedge against the electricity's price risk. This can be done on the financial market by trading various derivatives such as forward contracts and options. In order to develop an optimal hedging strategy, the expected volume and price development are needed. Most producers also hedge against the price risk of fuels.

The optimal hedging strategy has also been widely studied in the past. One of the best-known hedging strategies is the minimum-variance hedging introduced by Johnson (1960). It is suitable for a totally risk-averse player because the idea of it is to take a hedging position that minimizes the variance of the cash flow on time *t*. If there are forward contracts traded in the market for the commodity which is hedged, the minimum-variance hedge position is

$$h = -W * \frac{Cov(S_t, F_t)}{Var(F_t)}, \qquad (2)$$

where $W$ is the volume of the commodity, $S_t$ is the spot price of the commodity on time $t$ and $F_t$ is the future price for that commodity on time $t$. In case the future price and spot price are equal on time $t$, the optimal hedge position is just $-W$. Taking opposite position on the forward market leaves no variance in the future cash flow and thus eliminates the price risk completely. Minimum variance hedging requires no knowledge of the price development of the commodity if the volume of the commodity is certain.

At most times though, there is uncertainty also in the volume of the commodity. For example electricity producers do not always know how much electricity they will produce in the future due to the weather-dependency of certain generation methods. McKinnon (1967) examines hedging against volumetric risk and presented that when the volume of commodity contains uncertainty, the hedge position that minimizes the variance of the future cash flow is

$$h = -\left(E[W] + E[S_T] * \frac{Cov(S_t, F_t)}{Var(F_t)}\right), \tag{3}$$

where $E[W]$ is the expected value for the volume of the commodity and $E[S_t]$ is the expected value of the spot price of the commodity on time *t*. It should be noted that the arrival of volumetric risk adds the requirement of knowledge of the development of the spot price of the commodity in order to form a minimum variance hedge.

Minimum variance hedging assumes that the hedger is infinitely risk-averse, which is not the case in most situations. Hedgers' attitude towards risk can be taken into account in hedging by forming an utility function that represents the hedger's risk attitude and then using it to determine the optimal hedge ratio. The quadratic utility function is one of the most applied forms of utility function and it is defined as

$$U(W) = W - aW^2, \tag{4}$$

where $W$ represents the wealth and $a$ is a scalar parameter that measures the risk attitude. Cotter and Hanly (2012) show that the optimal hedge ratio $\beta$ for an agent that has a quadratic utility function is

$$\beta = \frac{-E(r_{ft})}{2\lambda Var(F_t)} + \frac{Cov(S_t, F_t)}{Var(F_t)}, \tag{5}$$

where $E(r_{ft})$ is the expected return on futures and $\lambda$ is the risk aversion parameter. Also other forms of utility functions such as logarithmic utility function and exponential utility function have been applied in defining the risk attitude of an agent (Cotter and Hanly, 2012). By changing the utility function the optimal hedge ratio obviously changes as well. Still, in any case, the optimal hedge ratio will require knowledge of the development of the price of commodity. The expected amount of the commodity to be sold is essential to know also because optimal hedging position can be defined by multiplying that amount with the optimal hedge ratio.

# 4. Forecasting

It is vital for companies to prepare for the uncertain future by planning its processes carefully. The more accurate the knowledge over the future is, the better the results of the planning are. It is impossible to obtain perfect knowledge over the future, but predictions of some quality about the future can be made. The process of making as accurate predictions as possible for the future given all the information available is called forecasting (Hyndman and Anthanasopoulos, 2013). Let $y_t$ be the value of the variable on time $t$ that is desired to predict. The objective in forecasting is to conduct a prediction for that value that is written as $f_t$. Because no forecast is perfect, a forecast contains forecast error, which is written as $e_t$. The value of the variable $y_t$ is the sum of the forecast and forecast error and it can be defined as

$$y_t = f_t + e_t. \tag{6}$$

Hyndman and Anthanasopoulos (2013) argues that forecasting consists of five basic steps, which are the problem definition, information gathering, preliminary analysis, choice and fit of the models and the use and evaluation of the forecast. The problem definition involves in decisions over what needs to be forecasted. Information gathering involves in the collection of the data that is used to conduct the forecast and this data is analyzed in preliminary analysis. The choice and fit of the models is the step, where the actual forecast is conducted. Chapter 4.1. concentrates on this step. Forecast evaluation is conducted to assess whether the performance of the forecast is on an acceptable level. Chapter 4.2. concentrates on this step.

## 4.1. Forecasting Methods

There are many ways to form a forecast ranging from the use of expert opinions to complex mathematical models. The choice of which forecasting method to use can be intricate. It will depend on the characteristics and available data of the forecasted variable. This chapter presents various methods that can be used by energy companies to conduct forecasts.

### 4.1.1. The Naïve Method

Probably the simplest forecasting method is called the naïve method. The forecast this method results in is either the historical average of the forecasted variable or the previous realized value depending on the form of stationarity of the time series of the forecasted variable. If the time series is stationary, which means that its mean and variance are constant, the forecast is

$$y_t = \frac{\sum_{i=1}^{t-1} y_i}{t-1} + e_t, \tag{7}$$

where $e_t$ is the error term of the forecast. In case the time series is stationary in terms of first differences, the forecast is

$$y_t = y_{t-1} + e_t. \tag{8}$$

Sometimes the forecasted variable contains seasonal variation. In these cases, the naïve method is not suitable. Due to this, Makridakis, Wheelwright and Hyndman (1998) presents the Naïve 2 method, which adjusts the forecasts of the naïve method with the seasonality.

Although this forecasting method may seem simple, it has its uses. It has been shown that it works relatively well for forecasting oil price and the values of currencies. The forecasts conducted by naïve method can also be used in forecast evaluation, because they provide a benchmark with which other more sophisticated forecasting models can be compared to.

### 4.1.2. Regression Models

Regression analysis is an approach to model the relationship between a dependent variable and a set of explanatory variables. The goal of regression analysis is to construct a statistical model, called a regression model, to present this dependency, and this model can be used to forecast values of the dependent variable. Regression model is defined as

$$y = f(X, \beta) + e, \tag{9}$$

where $y$ is the dependent variable, $X$ is the set of explanatory variables, $f(X, \beta)$ is the systematic part of the model that defines the dependency and $e$ is the random part of the model. The assumptions made with $e$ define the method that is used in regression analysis. An integral part of regression analysis is the choice of the function $f$, estimation of parameters $\beta$ and evaluation of the goodness of the model.

Linear regression models are widely used regression models, in which the relationship between dependent variable and explanatory variables is assumed to be linear. The linear regression model is written

$$y_i = x_i^T \beta + e_i, \tag{10}$$

where $x_i^T$ is the transpose of the vector of explanatory vectors, $\beta$ is the parameter vector that contains the linear coefficients for each explanatory variables and $e_i$ is the error term. The standard assumptions for error terms are that they are zero mean with a constant variance $\sigma^2$ and they do not correlate with each other and that they are normally distributed. If these assumptions hold, the dependent variable has the following characteristics. Its expected value is $x_i^T \beta$, variance is $\sigma^2$ and that they do not correlate with each other. If the normal distribution assumption holds, they are also normally distributed with the mean $x_i^T \beta$ and variance $\sigma^2$.

Estimation of the parameters is relatively simple if all of these assumptions made to error term hold. A technique called ordinary least squares (OLS) can be applied then, with which the estimate for parameter vector would be

$$\hat{\beta} = (X^T X)^{-1} X^T y, \tag{11}$$

where $X$ is a matrix, which contains information about every observation of each independent variables and $y$ is a vector that contains every observation of the dependent variable that are used in the estimation of the parameters of the model. Sometimes the error terms of linear regression models do not fulfill all of the standard assumptions made for them. For instance the variance of the error terms is not always constant and there is also sometimes correlation between them. In this case, OLS will cause biased estimates for parameters and should not be used. Other techniques such as general least squares (GLS) can be applied in these cases.

Linear regression is a central forecasting technique for participants in Nord Pool Spot, because it is suitable for various forecasting purposes. Moghram and Rahman (1989) applies forecasting models based on linear regression on forecasting electricity heat load, where explanatory variables are various weather-related variables and Dotzauer (2002) has shown that linear regression with weather-related variables works really well for forecasting district heat load, even though both of them clearly contain seasonal variation and thus should lead into biased forecasts. This problem was corrected by adding time-specific index variables into the set of explanatory variables. Linear regression is also a suitable technique to use in forecast evaluation.

### 4.1.3. Autoregressive Models

Autoregressive models are used to model a variable by using its own historic values. This technique has been widely used in several different areas and it has also been applied widely to meet the forecasting needs in energy business. Forecasts based on autoregressive models have been used to modeling prices of commodities and consumption.

The most common methods to which these autoregressive models are based on are autoregressive moving average models. These models assume that the forecasted variable is linearly dependent on its own previous values and random noise at each point of time. They consist of two parts that are an autoregressive part and a moving average part. The autoregressive part of order $p$ is defined as

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + e_t, \qquad (12)$$

where $\varphi_i$ are the parameters, $y_{t-i}$ are the past values for the variable, $c$ is a possible constant in the model and $e_t$ is a noise term with a mean of zero and constant variance. The moving average part of order $q$ is defined as

$$y_t = \sum_{i=1}^{q} \theta_i e_{t-i}, \tag{13}$$

where $\theta_i$ are the parameters and $e_{t-i}$ are the values of the noise terms. A full autoregressive moving average model of orders $p$ and $q$, which is referred to as $ARMA(p,q)$, can be formed by summing up these two terms.

$ARMA(p,q)$ models assume that the time series of the forecasted variable is stationary. However this assumption is usually violated. It may be possible to apply a differencing step on a non-stationary time series to transform it into a stationary one. These models are referred to as autoregressive integrated moving average models, $ARIMA(p,d,q)$, where $d$ is the order of the integrated part.

The time series of the forecasted variable may contain seasonal variation. In these cases it may be reasonable to use seasonal autoregressive integrated moving average models. These models are usually referred to as $SARIMA(p,d,q),(P,D,Q)_S$, where $S$ is the length of the season and $P$,$D$ and $Q$ are the orders of the autoregressive, integrated and moving average parts of the seasonal side of the model respectively. In addition, it is possible to add an exogenous variable to these models, whereafter these models would be referred to as seasonal autoregressive integrated moving average models with an exogenous variable ($SARIMAX$). $ARMA$ model is a general term for each of these models presented in this chapter so far.

Box and Jenkins (1970) presented a systemate method to construct $ARMA$ models for forecasting purposes. This method consists of three different steps that are the identification of the model, the estimation of the model and the checking of the diagnostics. The identification step results in the choice of the orders of each part of the model and the objective in the estimation step is to estimate the parameters of the model using maximum-likelihood method. Checking of the diagnostics phase results in information whether the estimated model is good enough or not.

Sometimes forecasted variables present dynamics that violate the assumptions made in constructing $ARMA$ model and it may be required to use an advanced tool. One of the more advanced autoregressive forecasting methods, which have been applied in the needs of energy companies, is Generalized AutoRegressive Conditional Heteroskedastic (GARCH) model (Bollerslev, 1986). This method has been shown to be suitable for variables which variance varies over time.

Forecasts based on autoregressive models have been applied widely with both price forecasts and consumption forecasts. ARMA models have been applied for forecasting commodity prices such as oil (Morana, 2001), natural gas (Buchanan et al, 2001) and electricity (Contreras et al, 2003). They also provide good results while forecasting electricity load (Gross and Galiana, 1987). Garcia et al (2005) applied GARCH models on forecasting spot prices of electricity and found that GARCH models outperform ARMA models when the data is volatile. Garćia-Martos et al (2013) studied modeling jointly prices of fossil fuels, $CO_2$-emission rights and electricity using techniques presented in this chapter.

### 4.1.4. Models Based on Artificial Intelligence

Artificial intelligence-based models in forecasting are models that take no a priori assumptions about the input data it uses to generate forecasts. These models adapt their internal structure during a training process to a certain data sample. Biological neural networks serve as an inspiration on the most common artificial intelligence-based model type, artificial neural networks, which are referred to as ANN. An ANN consists of multiple artificial neurons that process the input data, and each of them can be connected to other neurons or produce output data. The connections and weights of different neurons are adjusted during the training phase so that the given input provides the desired output. ANNs has been applied so far for forecasting the prices of commodities and electricity load. Szkuta et al (1999) studies forecasting short-term electricity price with ANNs on Victorian power system in Australia. Bunn (2000) applies ANNs on forecasting both the electricity load and price in Australia and according to the study, the model works well on load forecasting but not that well on price forecasting. Sahay and Tripathi (2013) studies forecasting both load and price in New England market area using ANN, and according to them, the model gives good results.

### 4.1.5. Forecasts Based on Futures Prices

For most commodities an extensive financial market exists, where it is possible to trade various derivatives such as futures contracts of those commodities. The market prices of futures have been used to forecast the spot prices of the same commodity. Fama and French (1987) claim that the sum of a risk premium and an expected changed in the spot price can be used to express the difference between the futures price and the current spot price. Therefore the future spot price of a commodity can be forecasted by identifying the risk premium of the commodity and using the futures price for it.

## 4.2. Forecast Evaluation

Forecast evaluation is an integral part of forecasting process. It is important to know, whether the chosen forecast model performs satisfactorily. Forecast evaluation also helps in the decision-making between multiple different forecast models. The goal in forecast evaluation is to assess the goodness of the given forecast. Murphy (1993) defines the goodness of forecast with three different aspects that are its consistency, quality and value. Consistency describes how reasonable the results from the model are. Forecast quality describes how well forecasted values match the realized values. Forecast value describes the value the forecasts add for their user. Forecast quality is the aspect of these that reflects the goodness of the forecast best and it also is the aspect that most studies on forecast evaluation have concentrated on. This chapter presents means that can be used to evaluate the quality of the forecasts and to assess the impacts of this quality.

### 4.2.1 Forecast Quality

Forecast quality can be measured by analyzing the forecast errors. These are the subtraction between the forecasted value and realized value on a given moment. Let $y_t$ be the realized value of a forecasted variable on a given moment and $f_t$ be the forecasted value for it. The forecast error for this forecast would be defined as

$$e_t = f_t - y_t. \tag{14}$$

Forecast quality can be characterized with multiple different aspects. Forecast accuracy describes how small the forecast errors are in general. Bias informs whether the errors the forecast model produces that are systematic or not. Efficiency is another aspect of forecast quality. An efficient forecast is able to utilize all information available at the moment the forecast was made. In general, forecast quality can be deemed good when the forecast errors are small and random.

#### 4.2.1.1. Forecast Accuracy

Forecast accuracy can be defined with multiple different measures that are based on forecast errors. These measures can be divided into two categories, which are absolute and relative measures. Absolute measures have the same dimension as the forecasted variable. The most simple forecast error measure is the Mean Error (ME), defined as

$$ME = \frac{1}{N}\sum_{t=1}^{N} e_t, \tag{15}$$

where $N$ is the amount of data used in forecast evaluation. Mean Error simply states how much the forecast error is on average. Because positive and negative forecast errors undo themselves in this formula, this error measure does not describe forecast accuracy well. It is still useful: if Mean Error deviates from zero, the forecast model is biased. It shows if the forecast model predicts constantly either over or under.

Forecast accuracy measures deal with the problem of negative and positive errors by canceling each other out into account by transforming them into same sign. One of the most popular forecast error measures, Mean Absolute Error (MAE), does this by taking absolute values of each forecast error. It is defined as

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|e_t|. \qquad (16)$$

Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which is just a square root of MSE, are also widely used forecast error measures. RMSE is more suitable of these measures because it is in the same dimension as the forecasted variable. RMSE is defined as

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}{e_t}^2}. \qquad (17)$$

RMSE punishes much more for large errors than MAE. Due to this, RMSE is more sensitive forecast accuracy measure towards outliers than MAE. In case the forecasted variable contains spikes, RMSE may not be a suitable forecast accuracy measure. For example, the system price in Nord Pool Spot may contain spikes especially during cold winters. Failure to predict one of these may make an otherwise well performing forecast model seem not that good. One other advantage MAE has over RMSE is that its meaning is easier to understand. MAE simply states how much the forecasted values deviate from the realized values on average.

Relative forecast accuracy measures are defined in dimensionless terms, which allows comparison of forecast quality of forecasting different variables. It may also be useful to use relative forecast accuracy measures when the scale of values of forecasted variables change. One widely used relative forecast accuracy measure is Mean Absolute Percentage Error (MAPE) that is defined

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{e_t}{y_t}\right|. \tag{18}$$

Like MAE, the meaning of MAPE is easy to interpret. It states how many percentage points do the forecasted value deviate from the realized value on average. MAPE contains few problems though. It is sensitive when the realized value is close to zero. If the realized value is exactly zero on any moment, MAPE cannot be defined. MAPE should only be used if the forecasted variable is measured on a ratio scale, which means it contains an absolute zero point. For example because temperature on Celsius or Fahrenheit scale does not contain an absolute zero point, MAPE cannot be used to evaluate the forecast accuracy of forecasts in these scales. In addition, MAPE is not a symmetric measure. It penalizes more for predicting over than under. Symmetric Mean Absolute Percentage Error (SMAPE) was derived from MAPE to encounter the asymmetry (Makridakis, 1993). It is defined as

$$sMAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{2 * |e_t|}{(y_t + f_t)}. \tag{19}$$

The difference between MAPE and SMAPE is that when MAPE compares the absolute errors to realized values, SMAPE compares them to the average of realized and forecasted value. Goodwin and Lawton (1999) argue though that SMAPE is also an asymmetric error measure because it treats large positive and negative errors very differently and due to this, should not be used.

Forecast accuracy can also be measured relatively compared to another forecasting method. A common practice is to compare forecast errors of the given model to ones generated by some benchmark method. Usually the benchmark method is the Naïve method, where forecasted value is equal to the last realized value. With a seasonal data the Naïve method cannot be used as a benchmark method. The Naïve 2 method, which generates the forecast based on the last realized value after adjustment of seasonality, can be used in these situations instead (Makridakis, Wheelwright and Hyndman, 1998). Let $f_t^*$ be the forecasted value that is obtained with the benchmark model. The forecast error, $e_t^*$, is defined as in formula (14). The relative forecast error of the examined forecast model is then

$$r_t = \frac{e_t}{e_t^*}. \qquad (20)$$

The most common forecasts accuracy measures based on relative errors are Mean Relative Absolute Error (MRAE), which is defined as

$$MRAE = \frac{1}{N}\sum_{t=1}^{N}|r_t|, \qquad (21)$$

and Geometric Mean Relative Absolute Error (GMRAE), which is preferred by Fildes (1992). GMRAE is defined as

$$GMRAE = \left(\prod_{t=1}^{N}|r_t|\right)^{\frac{1}{N}}. \qquad (22)$$

Using relative errors may raise difficulties if benchmark method provides really good forecasts at some moments, which causes $e_t^*$ to be close to zero and simultaneously $r_t$ to be really high. Theoretically when the benchmark method forecasts perfectly, relative error cannot be defined. Armstrong and Collopy (1992) suggests manipulation of the data so that the moments when $e_t^*$ is close to zero are eliminated from the data.

Forecast accuracy measures can utilize forecasts generated by benchmarks even without using relative errors. Relative Mean Absolute Error (RelMAE), which is defined as

$$RelMAE = \frac{MAE}{MAE^*}, \tag{23}$$

where $MAE^*$ is the Mean Average Error of the benchmark method defined after formula (16), compares the performance of examined forecasting method to the benchmark method without the use of relative errors. Relative Root Mean Squared Error (RelRMSE) and Relative Mean Absolute Percentage Error (RelMAPE) are defined with same logic. The interpretation of these measures is simple. When RelMAE is smaller than 1, the examined forecasting method has performed better than the benchmark method, and when it is larger than 1, the benchmark method performed better.

Hyndman and Koehler (2006) argue that these forecast accuracy measures have problems as well because they cannot be used in out-of-sample forecast accuracy evaluation. They present a forecast accuracy measure based on scaled errors. The idea in that is to scale each forecast error based on the in-sample MAE from the benchmark method. When the benchmark method is the Naïve method, the scaled error is defined as

$$q_t = \frac{e_t}{\frac{1}{N-1}\sum_{i=2}^{N}|y_i - y_{i-1}|}. \tag{24}$$

The forecast accuracy measure based on these scaled errors, which Hyndman and Koehler (2006) recommend, is Mean Absolute Scaled Error (MASE), which is defined

$$MASE = \frac{1}{N}\sum_{t=1}^{N}|q_t|. \tag{25}$$

Related measures such as Root Mean Squared Scaled Error (RMSSE) can be defined with same logic as MASE. Forecast error $e_t$ just needs to be replaced with scaled error $q_t$ in these formulas. MASE can be interpreted same way as RelMAE. When MASE is lower than 1, the examined forecasting method has performed better than the benchmark method.

### 4.2.1.2. Forecast Bias

An ideal forecast generates unpredictable forecast errors, because if the forecast errors are somehow predictable, the forecast could be improved. A forecast is said to be biased, when there are consistent differences between realized values and forecasts. In general this means that the forecasted values are either too high or low by average. Forecast errors can be used to check, whether the forecast is biased or not. Mean error, which is presented in formula (15), can be used for this. If ME deviates from zero, the forecast is biased. Another simple forecast error statistic, mean percentage error (MPE), defined as

$$MPE = \frac{1}{N}\sum_{t=1}^{N}\frac{e_t}{y_t}, \tag{26}$$

can also be used. The problem with ME and MPE is that even if the values these measures give do not deviate from zero, the forecast can still be biased. It is possible that the forecast consistently over predicts low realized values and under predicts high realized values for example. This could be tested by performing a linear regression analysis for the realized values when the explanatory variable is forecast (Swidler and Ketcher 1990). This regression model is defined as

$$y_t = \alpha + \beta f_t + u_t \qquad (27)$$

where $u_t$ is the error term of the regression model that should fulfill the standard assumptions for error terms presented in chapter 4.2.1. The forecast $f_t$ is an unbiased estimate of $y_t$ if a null hypothesis that $\alpha = 0$ and $\beta = 1$ is satisfied. If this joint hypothesis is rejected, the forecast is biased. This test is also known as forecast rationality test.

### 4.2.2. Forecast Value

One of the main objectives in this thesis was to determine the impacts of the forecast quality of various forecasts an energy company requires for its operations. The third aspect of the goodness of forecasts defined by Murphy (1993), forecast value, determines, how much value does the forecast add to its user. Fox et al (1999) presents two general approaches to characterize the value of information, which are the ex ante approach and ex post. Ex ante approach measures how much better the decision maker would have been if his choices could have been based on better information. Ex post approach measures how much better off the decision maker would have been if he had known the outcome of the uncertain event beforehand. It is assumed that the decision maker makes optimal decisions given the information he has available.

# 5. The Impacts of Forecast Quality

The objective of this Master’s Thesis was to determine how Helsingin Energia should monitor the goodness of the forecasts it uses. Helsingin Energia is an electricity producer and a majority of its production portfolio consists of electricity generated with thermal generation in Helsinki on CHP plants that are operated both with coal and natural gas. This thesis concentrates on forecasts needed to plan the operations of those plants. Four different forecasted variables have been identified to have the biggest impact on the actions of this company. They are the prices of electricity, coal and natural gas and demand for district heat.

The impacts of forecast quality of different forecasts are assessed in this thesis by defining the forecast value using the ex ante approach. The forecast value is assessed with three different objectives that are defined after the needs of budgeting, risk management and electricity trading purposes. The goal of budgeting purpose is defined by how much does the planned budget with a given forecast deviate from the optimal budget made with a precise knowledge.  The goal of risk management purpose is defined by how much do the planned amounts of fuels used and electricity sold deviate from optimal amounts. Both of them are assessed on a monthly level. The goal of electricity trading purpose is to assess how much do the amount of electricity sold deviate from the optimal amount and what is the value of this. This is assessed on an hourly level.

The values of different forecasts are defined by using an optimization software that is designed to optimize the production plan of the CHP-plants. Formula (1) presents the optimization model it uses. The ex ante approach to define the forecast value is conducted by optimizing the production plan with exact knowledge of the values of forecasted variables and then with the given forecast. Three different types of forecasts were used in the calculations. The forecast values were defined of unbiased forecasts with different levels of forecast accuracy measured with MAE, MAPE and MASE and biased forecasts with two types forecast bias: consistent over or under forecasting measured with MPE and consistent over forecasting of higher values and under forecasting with lower values or vice versa measured with the forecast rationality test. Because the price of natural gas is constant throughout a whole month, only biased forecasts in the sense of MPE of it are included in the thesis. The results of the calculations of each of the three objectives are presented in appendixes A, B and C respectively.

## 5.1. The Budgeting Objective

One of the objectives of forecasting is to allow accurate predictions of future cash flows. Therefore the impacts of the forecasts that are used can be evaluated by how accurately the future cash flows are forecasted with these forecasts. In this thesis, various different forecasts were evaluated by how much the planned cash flows deviate from the optimal cash flows. Table 1 presents these results.

*Table 1. The impacts of forecast quality on the company measured with the budgeting objective*

| | District heat demand | Electricity price | Coal price | Natural gas price |
|---|---|---|---|---|
| Inaccuracy | high | low | really low | - |
| Bias (MPE) | high | really high | high | high |
| Bias (rationality) | low | really low | really low | - |

If the forecasts are unbiased, the quality of the district heat demand forecast is the most important. Inaccurate district heat demand may cause the budgeted cash flows to diverge notably from the realized cash flows. As the MAPE of district heat demand forecast becomes higher than 5 % the deviation in budget starts to grow rapidly causing higher expenses usually due to the increased demand for more expensive fuels. Inaccuracy of unbiased forecasts for both electricity price and coal price do not cause the budgeted cash flows to diverge from the realized cash flows significantly.

The impacts of the forecast quality of unbiased forecasts on budgeting objective seem to depend much on the month when the forecast quality is assessed with MAE. For example, a similar MAE in the forecast of district heat demand during summer time has a higher impact than during winter time due. MAPE seems to be a more suitable forecast accuracy measure because the impacts of forecast quality on budgeting objective do not depend on the month. MASE is the least useful forecast accuracy measure to explain the forecast value. It depends even more on the month because it measures the accuracy of the forecast method compared to the benchmark method, which performance may vary drastically during different months.

Forecast bias measured with MPE in each of the forecasts has a significant impact on the company, when forecast value is assessed using the budgeting objective. The highest deviation in the budget is caused by consistent over or under forecasting of electricity price, though the impact is relevant, when the same type of forecast bias exists in other forecasts as well. The month affects though. For example during some months the power plants that use natural gas are not in use and because of this, the quality of natural gas price forecast does not matter. Consistent over forecasting of higher values and under forecasting of lower values or vice versa, which can be identified with the forecast rationality test, has a small impact on the budgeting objective. During September, October and May this sort of forecast bias in district heat demand forecast causes a significant deviation in budget. During other months and with other forecasts, this sort of forecast bias does not seem to have an impact.

These results show that when considering the budgeting objective, forecast accuracy and forecast bias measured with MPE are the aspects of forecast quality that have the highest impact on the forecast value. Especially the inaccuracy of district heat demand forecast and the MPEs of electricity price forecast, coal price forecast and district heat demand have the biggest influence. The inaccuracy of the coal price forecast affects the least and checking the bias of the forecasts with forecast rationality test does not seem integral.

## 5.2. The Risk Management Objective

Risk management is vital for energy companies operating in deregulated electricity markets due to the high volatility of electricity price. Due to this hedging against the price risk using various financial instruments is widely popular in this field. Knowledge over the trading volume of the commodity is integral for hedging strategies. Therefore the impacts of forecast quality on the risk management objective were assessed by how accurately these volumes are predicted. It is presented as a deviation between the actual volumes and the planned volumes of the traded commodities, which are electricity, coal and natural gas. The impacts of these different types of forecast quality on this objective are presented in table 2.

*Table 2. The impacts of forecast quality on the company measured with the risk management objective*

| | District heat demand | Electricity price | Coal price | Natural gas price |
|---|---|---|---|---|
| Inaccuracy | high | low | really low | - |
| Bias (MPE) | really high | high | really low | high |
| Bias (rationality) | low | really low | really low | - |

If the forecasts are unbiased, the inaccuracy in the forecast of district heat demand has the highest impact on the forecast value when it is measured using the risk management objective as well. Inaccurate forecasts of district heat demand lead into higher differences between planned and actual volumes of the traded commodities. The inaccuracy of unbiased forecast of electricity price causes much lower differences between the planned and actual volumes of the traded commodities. Especially the planned and actual volumes of coal contain minimal difference even if the forecast of electricity price is inaccurate. The inaccuracy in the forecast of the coal price seems to have no impact on this objective. Just like with the budgeting objective, MAPE is the forecast accuracy measure that captures the forecast value the best and thus is the most suitable.

Consistent over or under forecasting may cause high differences between the planned and the actual volumes of the traded commodities. The more the district heat demand is predicted over, the more the electricity production volume is predicted over as well. There are some exceptions though. For example during January predicting district heat demand systematically too low has an effect on this objective but predicting it systematically too high has no effect. The explanation for this is the nature of the heat production during that month. For example during that January, the excess district heat would be produced as a separate heat production whereas the drop in district heat demand would cause a production plan where the amount of CHP-production lowers. Thus electricity production amount is most vulnerable to the bias in district heat demand forecast during months, where it affects the operation of CHP-plants. Similar bias in the forecasts of electricity price causes a lower impact on this objective than one in the forecast of district heat demand, but it is still relevant. Especially during March and April as the MPE is higher than 4 % or during March and December as the MPE is less than – 3 %, the impact of this type of forecast bias on predicting the electricity production volume is significant. The forecast bias in the forecast of electricity price has a small impact on the natural gas volume but no impact on the coal volume.

Consistent over or under forecasting of coal price has no impact on the risk management objective. A forecast bias of this type on natural gas forecast has an impact on this objective, though it varies heavily between different months and commodities. During January and March the impact on electricity volume is the highest and during May, June and July, when the natural gas usage is the lowest, the impact is non-existent. The forecast bias has a minimal impact on coal volume. On natural gas volume, the impact is the highest during January and March.

The forecast bias that can be assessed with forecast rationality test has almost no impact on the risk management objective. Only during January, February and March forecasting higher district heat demands too high and lower ones too low or vice versa causes the planned volumes of commodities to differ from the actual volumes. Therefore during other months and with other forecasted variables, checking of the forecast bias with forecast rationality test should not be of any importance.

The most important aspect of forecast quality on risk management objective is the forecast bias measured with MPE. It is integral to forecast the monthly average values of the different variables for this objective. The MPE of district heat demand forecast seems to hold the highest importance though the MPE of both natural gas price and electricity gas price affects much as well. Inaccuracy of district heat demand forecast has quite a large influence as well, which makes monitoring it with MAPE relevant as well.

## 5.3. The Short Term Electricity Trading Objective

The last goal was determined by the short-term needs of the company. Electricity trading on the wholesale market creates a significant cash flow and the production plan made according to forecasts show how much electricity is going to be sold each hour. If the amount gotten with certain forecast deviates from the optimal amount, the electricity trading may not be conducted in an optimal way. The forecast value according to this objective was assessed how much does the hourly trading amount deviate from optimal amount, and what is the value of these deviations each month. Because electricity trading is done on a short-term basis with a full knowledge over price of natural gas, the natural gas price forecasts are excluded from this chapter. Table 3 presents the impacts of forecast quality of the forecasts of district heat demand, electricity price and coal price on this objective.

*Table 3. The impacts of forecast quality on the company measured with the short term electricity trading objective*

| | District heat demand | Electricity price | Coal price |
|---|---|---|---|
| Inaccuracy | really high | high | really low |
| Bias (MPE) | really high | high | really low |
| Bias (rationality) | high | low | really low |

The forecast of district heat demand is the most important forecast considering short term electricity trading objective. Inaccuracy and consistent over or under forecasting has a really high impact on this objective so monitoring the MAPE and MPE of the forecast of district heat demand is essential. Also the forecast bias that can be assessed with the forecast rationality test on district heat demand forecast has an impact on this objective, though it is much smaller. The month affects though. During June, July and August this sort of forecast bias has no effect. Still, monitoring the forecast of district heat demand with the forecast rationality test may be relevant.

The inaccuracy of the forecast of electricity price has a significant impact on the short term electricity trading objective, though it is still much smaller than the one caused by the inaccuracy of the forecast of district heat demand. Similarly forecast bias measured with MPE also has a significant impact on this objective, which is still smaller than the one caused by the forecast bias in the forecast bias in the forecast of district heat demand. The forecast bias assessed with the forecast rationality test has no impact on this objective and thus monitoring the forecast of electricity price with it is irrelevant.

The quality of the forecast of coal price has no impact on the short term electricity trading objective. Both the inaccurate unbiased forecasts and the biased forecasts of the coal price do not affect the quality of short term electricity trading. Because of this, monitoring the forecast of coal price is irrelevant.

Considering the short term electricity trading objective, the aspects of forecast quality that seems to matter the most are the accuracy of district heat demand forecast and the bias in it. Therefore monitoring the MAPE and MPE of district heat demand should be important. Also, the accuracy of electricity price and the bias in it is somewhat important which raises the importance of monitoring those two. Finally forecasting higher district heat demand values too high and lower values too low or vice versa seems to have some impact as well and therefore conducting forecast rationality test on district heat demand forecast is sensible. The importance of this is though not as high as the other earlier mentioned means to monitor forecast quality.

# 6. Conclusions

The objective of this thesis was to find out how Helsingin Energia should monitor the quality of the forecasts it uses. For this purpose, a review was made into factors that affect its business. The basics of Nordic electricity markets were presented in chapter 2. Chapter 3 presented how a combined heat and power producer should plan its operations in order to act as well as possible on its market. Four variables were identified as the most integral for the forecasting needs of Helsingin Energia. They were district heat demand, spot price of electricity and the prices of coal and natural gas which are the main fuels of power plants. Chapter 4 took a look into forecasting to introduce some methods that can be used to forecast these variables. It also presented methods to assess the quality of the forecasts. Two easily measured aspects of forecast quality were identified, which were the accuracy and the bias of the forecast. The accuracy states how large the forecast errors are in general and there are plenty of measures to assess that. Mean absolute error (MAE), mean absolute percentage error (MAPE) and mean absolute scaled error (MASE) were identified as the most suitable forecast accuracy measures for the needs of the company. Forecast bias reflects if the forecasts that are used generate forecast errors that are systematic. The forecasting method may systematically forecast either too high or too low. Mean percentage error (MPE) was identified suitable to measure forecast bias of this sort. It is also possible that the forecasting method systematically forecasts higher values too high and lower values too low or vice versa. A forecast bias of this sort can be identified using a forecast rationality test, where a linear regression model is estimated to explain the realized values with the forecasted variables.

The concept of forecast value was introduced in chapter 4 to present a method that can be used to assess the impacts of forecast quality on the user of the forecasts. Forecast value simply states how much value, does the forecast add to its user. An ex ante approach – which states how much better would the decision maker have been, if he had had more precise knowledge over the uncertain event – was used to assess the impacts of the forecast quality. The impacts of the forecasts of the earlier mentioned four different variables were assessed on three different objectives, which were identified according to the needs of the planning processes introduced in chapter 3. The first of these objectives was the impacts of the forecasts on predicting expected cash flows accurately which was the budgeting objective. The second objective, which was the risk management objective, was defined through the impacts of the forecasts on the hedging policy. The third objective was defined through the impacts of the forecasts on the electricity trading on wholesale market.

## 6.1. Results

For the budgeting objective, district heat demand is the variable that needs to be emphasized most from the inaccuracy point of view, because a similar MAPE in district heat demand forecast causes higher deviations from the optimum than one in either the electricity price or coal price forecast. The forecast bias in the sense of MPE though affects this objective more. A bias in electricity price forecast causes the largest deviations, but also with district heat demand and natural gas price forecast, the deviations are significant. The forecast rationality test based on linear regression does not express forecast value well. Only with district heat demand, the deviations caused by a biased forecast in this sense are notable.

For the hedging objective, the forecast bias in the sense of MPE seems to have the highest effect on the forecast value. Especially with district heat demand, a biased forecast in this sense leads into high deviations, although the effects of forecast bias in both electricity price and natural gas price are notable as well. A bias in the coal price forecast seems to have no effect on forecast value. Of the forecast rationality tests, only district heat demand seems to be worth checking. With other variables, a forecast bias of this sort seems to be meaningless. Inaccuracy of both district heat demand forecast and electricity price forecast has an effect on forecast value. The quality of coal price forecast has no effect on forecast value.

From the electricity trading objective, the variable that seems to have the highest impact on forecast value is district heat demand. Inaccuracy in its forecast causes a significant drop in forecast value. The forecast bias in the sense of MPE also affects notably. Depending on the month, the quality of electricity price forecast affects this objective quite much as well. Both inaccuracy and forecast bias may lead into electricity trading policy that is far from optimal. The coal price forecast has a minor effect on this objective so monitoring this forecast is not important.

The results from the thesis show that MAPE is the forecast accuracy measure that reflects the forecast value quite well. Even though MAPE is a troublesome forecast accuracy measure due to its instability when realized values of the forecasted variable are close to zero, it should not cause problems for the planning context addressed in this thesis, because none of the forecasted variables have normally values small enough. MAE is not a suitable accuracy measure, because the range of forecasted variable may vary during different times of year and thus affect differently on the forecast value. For example, the district heat demand is so much lower during the summer than during the winter that a forecast with similar MAE may have a highly different value. MASE is a useful forecast accuracy measure for comparing multiple different forecasts on a same time span. It can also be used to show if the used forecast method performs better than the benchmark method, which should be the minimum requirement for the forecast model. MASE does not represent the forecast value well though over different time spans, because the performance of the benchmark method varies. For example, in a month when the benchmark method has performed well, a forecast with a high MASE may have a much higher forecast value than a forecast with a lower MASE on a month when the benchmark method did not work well at all. Therefore MAPE seems to be the forecast accuracy measure that presents the forecast value the best.

Checking forecast bias is also a noteworthy issue for an energy company. MPE is a good measure to check for the bias and the results also showed that forecast bias in the sense of MPE has an effect on forecast value. Still it is not enough to check for the forecast bias. A forecast may be biased even if its MPE is zero. A forecast rationality test based on a linear regression model can be used to show if the forecast forecasts high values systematically either too high or too low. The results of this thesis showed that for a forecast with MPE of zero, checking of forecast bias in this sense is vital, because it can also explain fluctuations in forecast value. Forecasting systematically either too high or too low has thus a far higher impact on the company than forecasting higher values too high and lower values too low or vice versa.

All in all, the quality of district heat demand forecast seems to have the highest impact on the energy company for which this Master's Thesis was made. Both inaccuracy and forecast bias affect the forecast value highly on each of the three objectives that were used to assess the impacts of forecast quality. The quality of electricity price forecast has a varying impact on the company. Some objectives are strongly affected by the forecast quality, whereas others are not. For example the bias in electricity price forecast affects the budgeting objective more than the bias in the district heat but on the risk management objective the impact of electricity price forecast quality is minimal compared to district heat demand forecast. The quality of coal price forecast has only a minor effect on the budgeting objective so monitoring this forecast should not be a priority. The quality of natural gas price forecast does not have any effect on the electricity trading objective because it is done on short-term basis with a complete knowledge over the price. A bias in its forecast has a relevant impact on both budgeting and risk management objectives.

## 6.2. Future Actions

Due to the results of this thesis, the importance of the quality of district heat forecast has been identified and monitoring it with MAPE and MPE should be the priority of the company. The qualities of electricity price forecast and natural gas price forecast also have some impact on the company as well so monitoring them with MPE and MAPE respectively should be of some importance. The quality of the coal price forecast has the lowest impact on the company and thus a minimal amount of resources should be allocated into it. The forecast bias that can be identified with the forecast rationality test does not have much impact on the objectives that were used to assess the forecast value. Still this test is relevant because it gives information on the performance of the forecasting method that was used that can be used to either improve the forecasting method or in case of a commercial forecast, complaining. Also, even if MASE is a forecast accuracy measure that does not represent the forecast value well, monitoring forecasts with it is useful because it states if the forecasting method performs better than the benchmark method. This should be the minimum requirement for any forecast model. Further studies in this area could be made assessing the effects on few of the objectives used for forecast value closely. For the risk management objective, we could analyze what impacts deviations in production amounts have on different hedging strategies. For short term electricity trading objective it could be analyzed what effects on the actual cash flows deviations in the electricity trading amounts have. Trading on intraday markets may have an effect on this subject that was not taken into account in the scope of this thesis. Also, because this thesis excluded the needs of forecasting for the long term planning purposes, it could be studied how forecast quality affects the investment decisions.

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# Appendix A

## The results of the budgeting objective

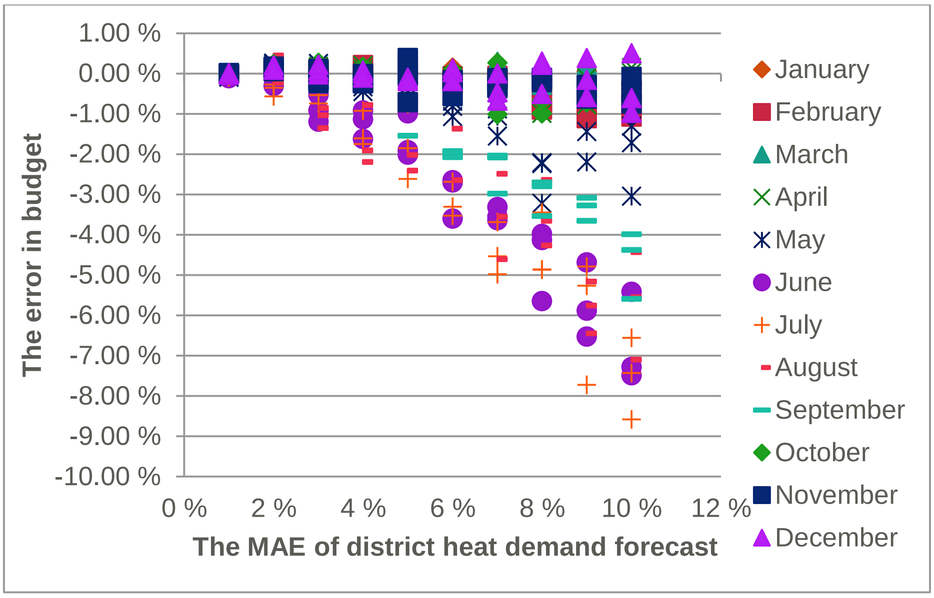


*Figure 6. The effects of MAE in district heat demand forecast on budgeting objective*

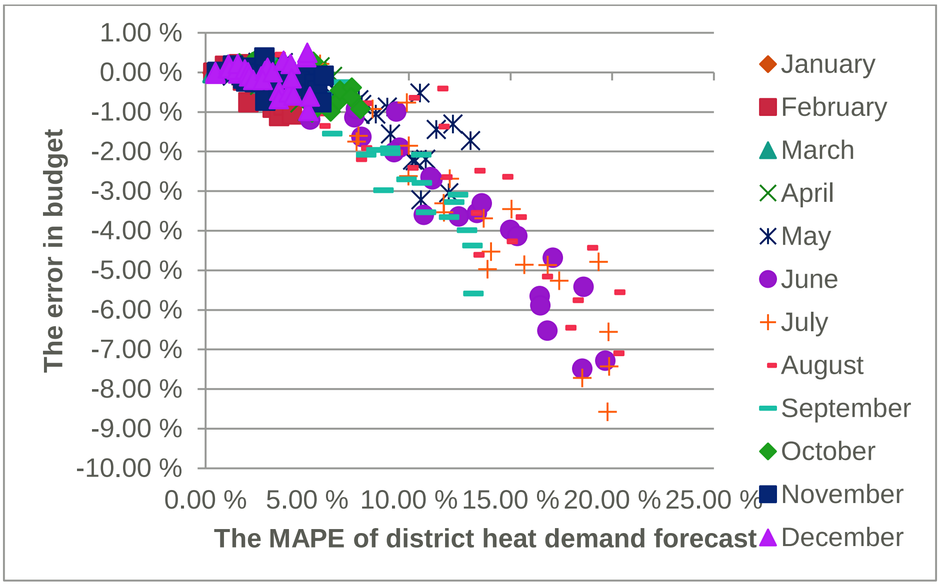


*Figure 7. The effects of MAPE in district heat demand forecast on budgeting objective*

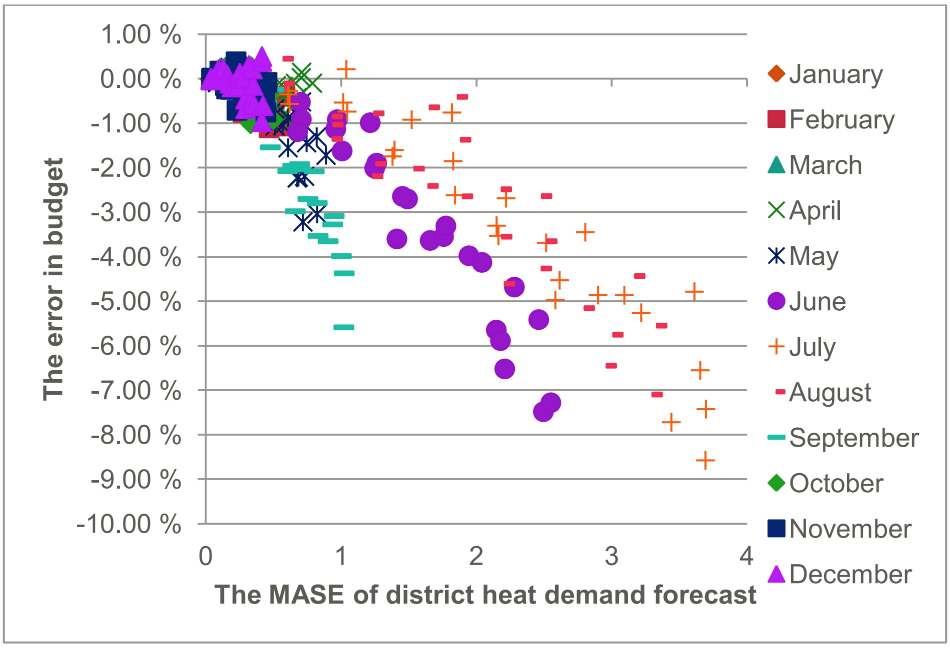


*Figure 8. The effects of MASE in district heat demand forecast on budgeting objective*

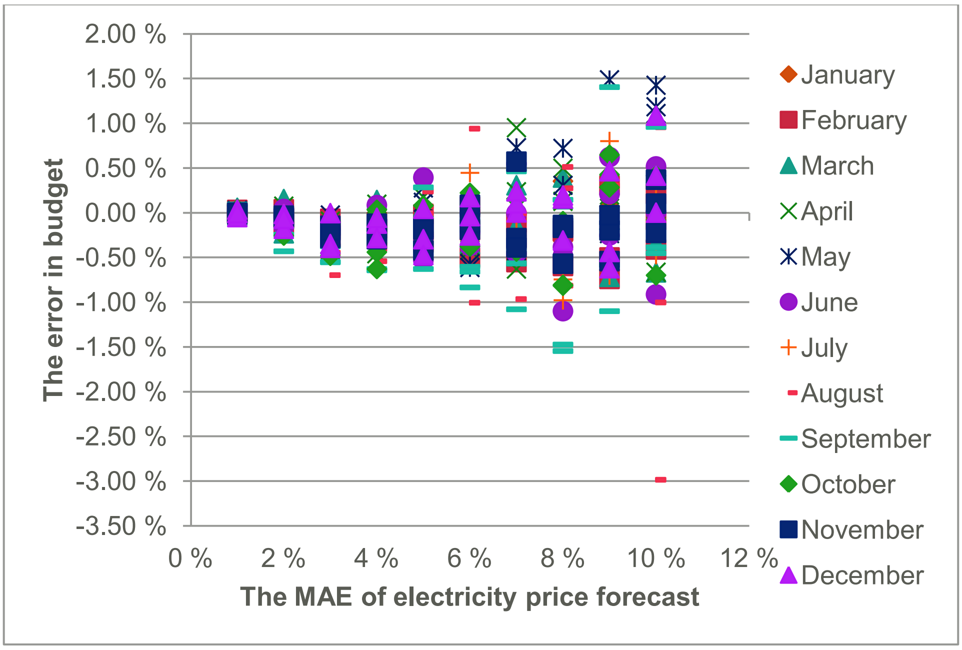


*Figure 9. The effects of MAE in electricity price forecast on budgeting objective*

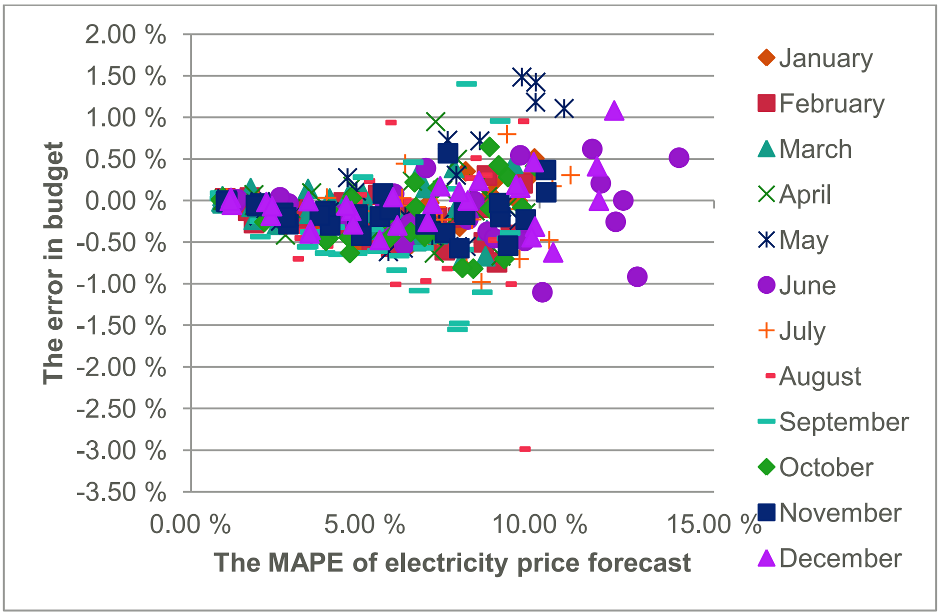


*Figure 10. The effects of MAPE in electricity price forecast on budgeting objective*

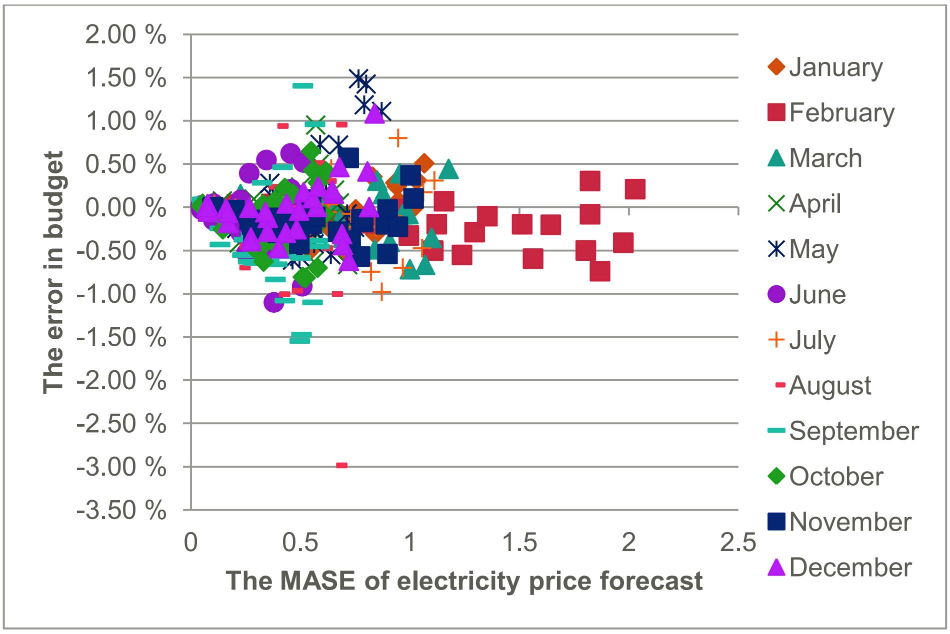


*Figure 11. The effects of MASE in electricity price forecast on budgeting objective*

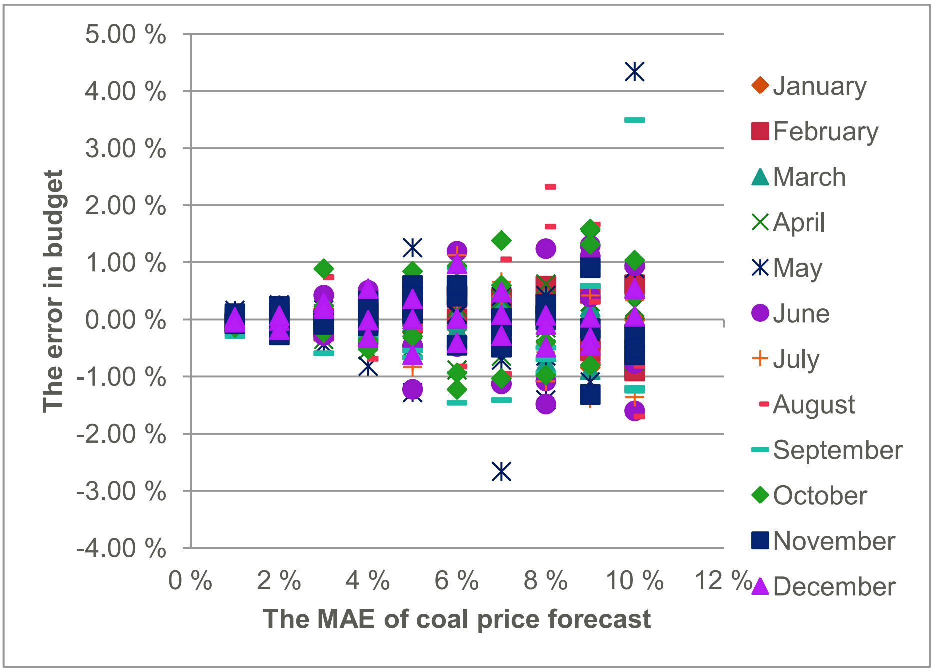


*Figure 12. The effects of MAE in coal price forecast on budgeting objective*

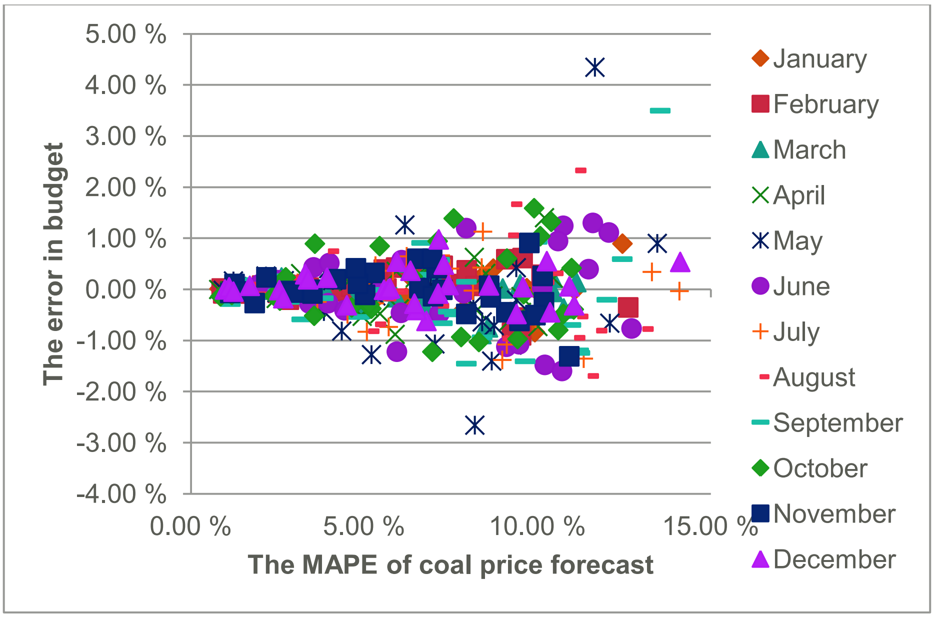


*Figure 13. The effects of MAPE in coal price forecast on budgeting objective*

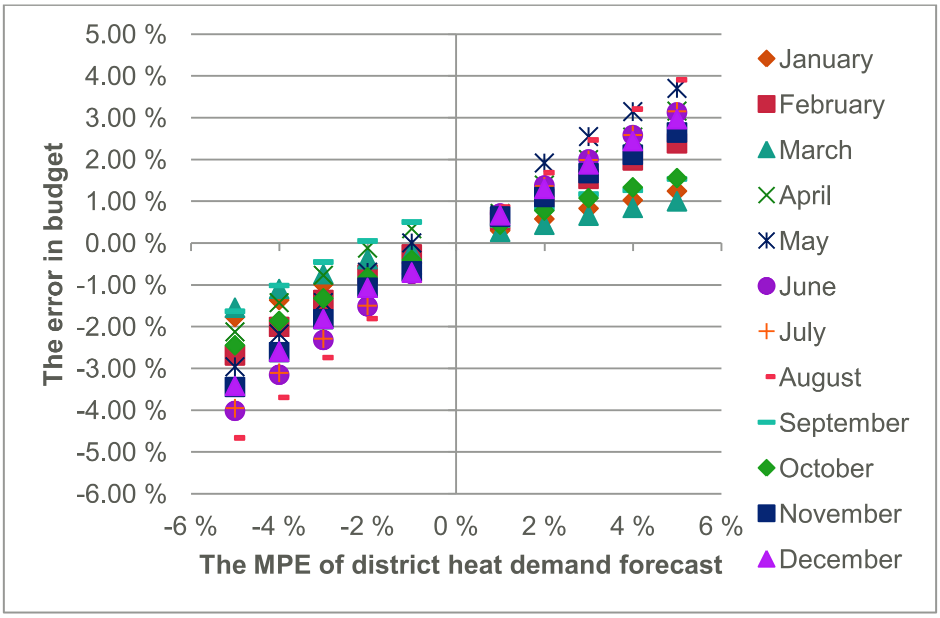


*Figure 14. The effects of MPE in district heat demand forecast on budgeting objective*

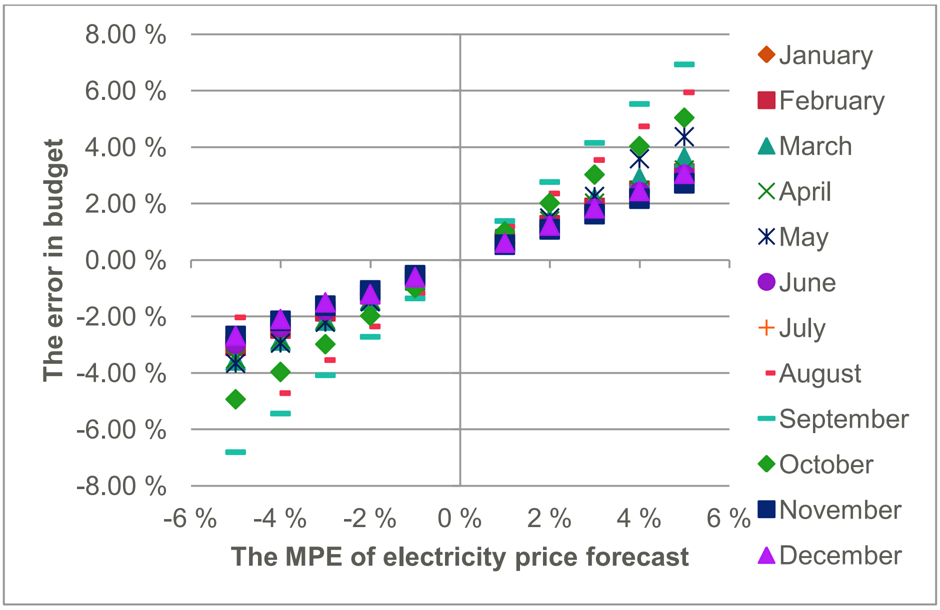


*Figure 15. The effects of MPE in electricity price forecast on budgeting objective*

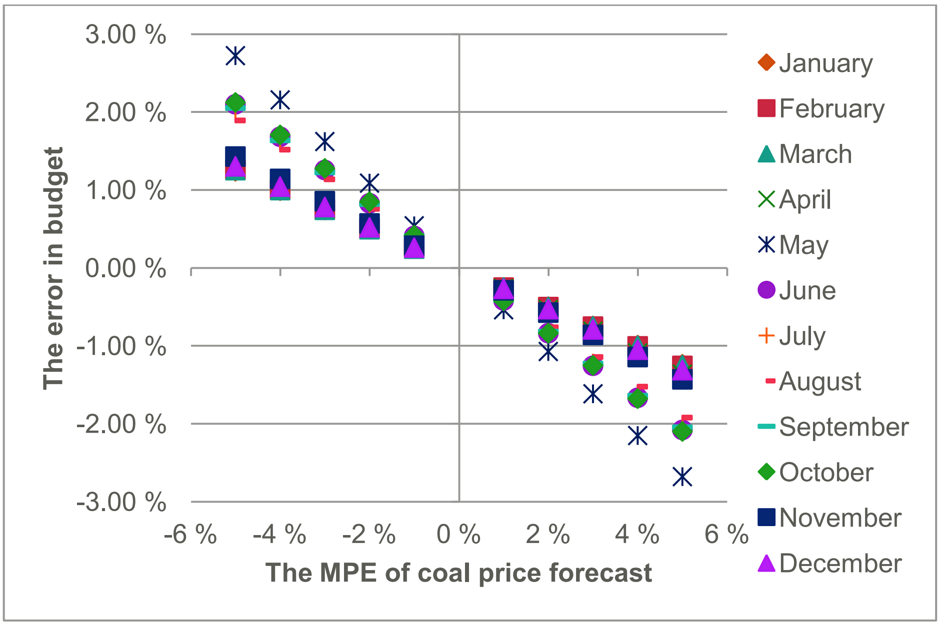


*Figure 16. The effects of MPE in coal price forecast on budgeting objective*

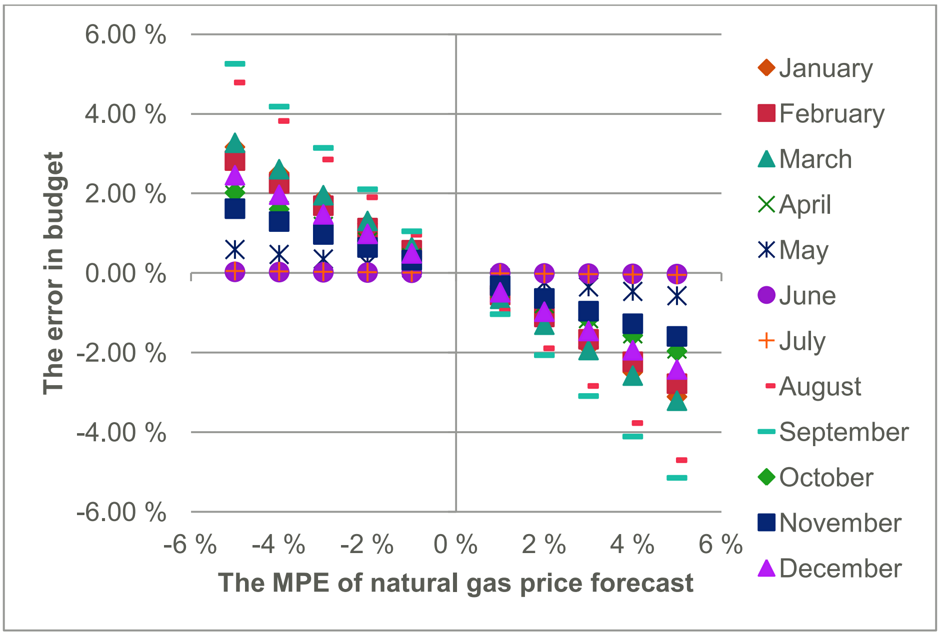


*Figure 17. The effects of MPE in natural gas price forecast on budgeting objective*

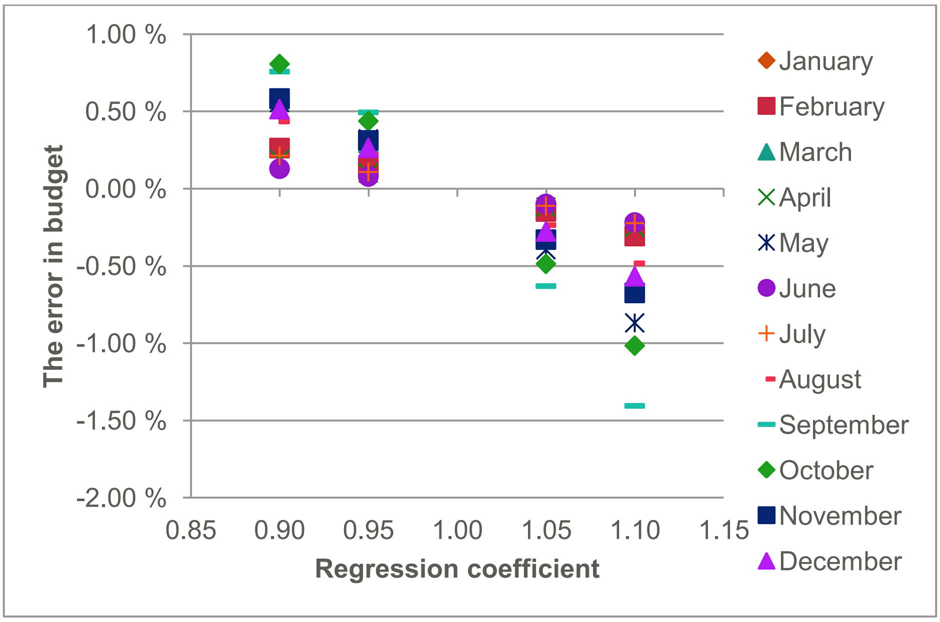


*Figure 18. The effects of forecast bias measured with the rationality test in district heat demand forecast on budgeting objective*

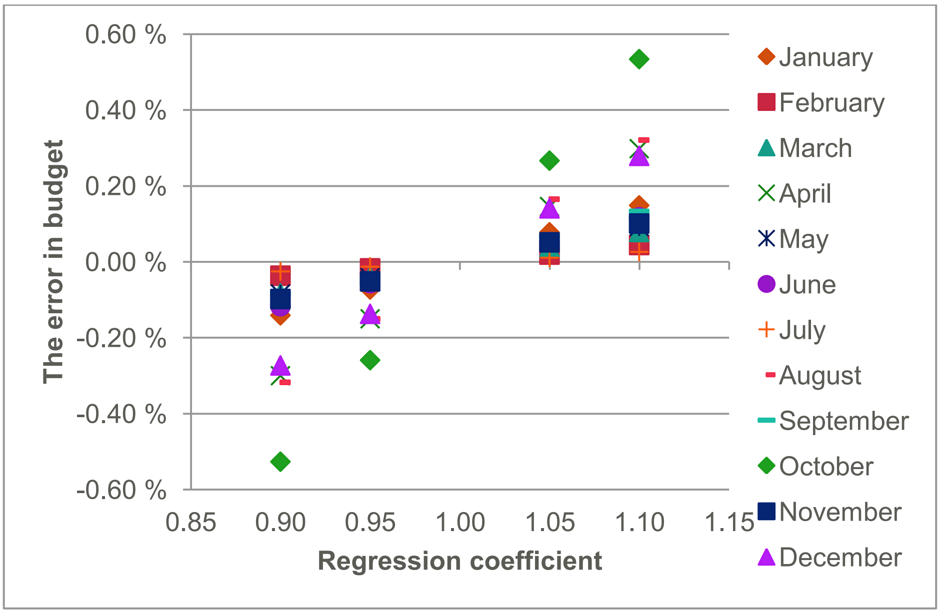


*Figure 19. The effects of forecast bias measured with the rationality test in electricity price forecast on budgeting objective*

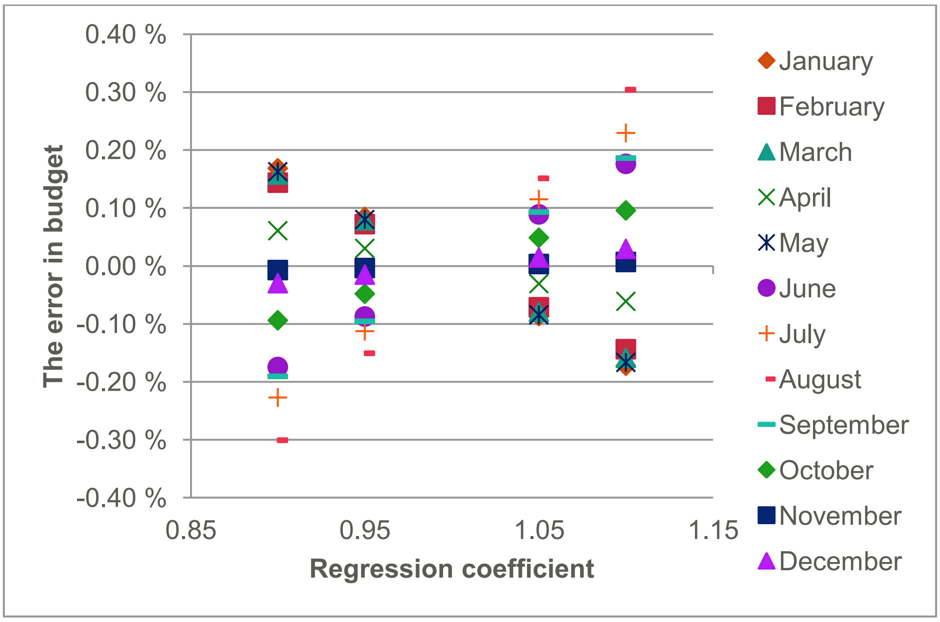


*Figure 20. The effects of forecast bias measured with the rationality test in district coal price forecast on budgeting objective*

# Appendix B

The results of the risk management objective

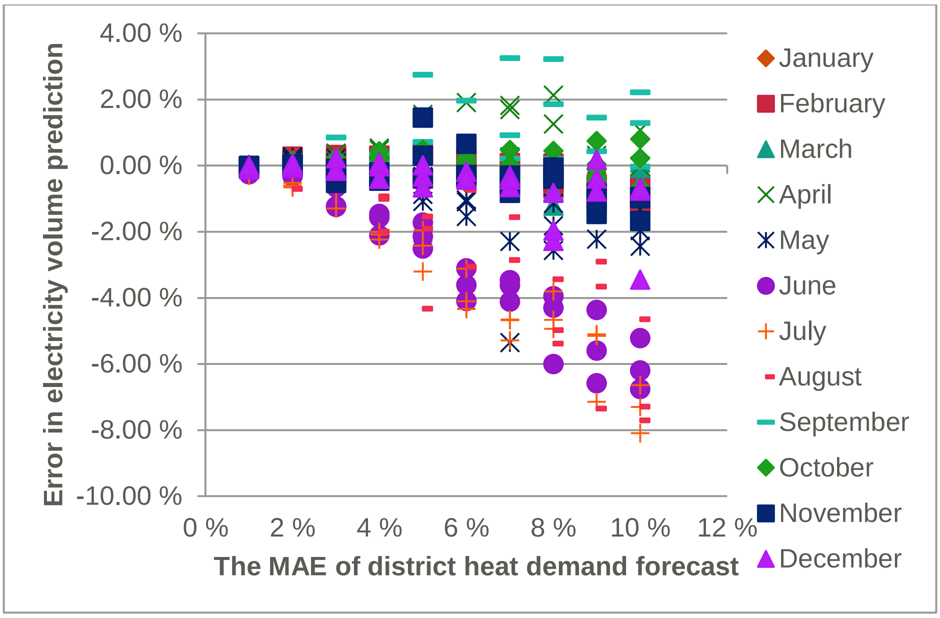


*Figure 21. The effects of MAE in district heat demand forecast on predictions of electricity production volume*

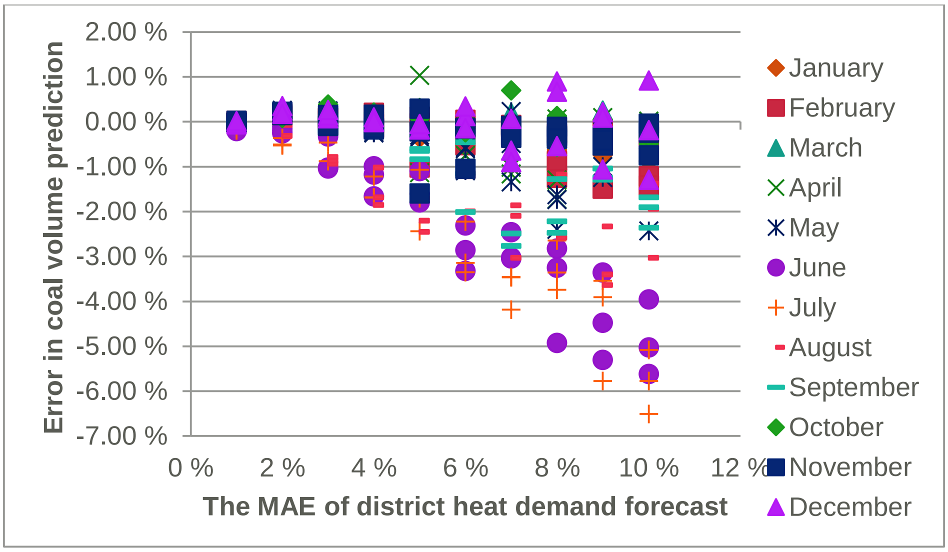


*Figure 22. The effects of MAE in district heat demand forecast on prediction of the volume of coal*

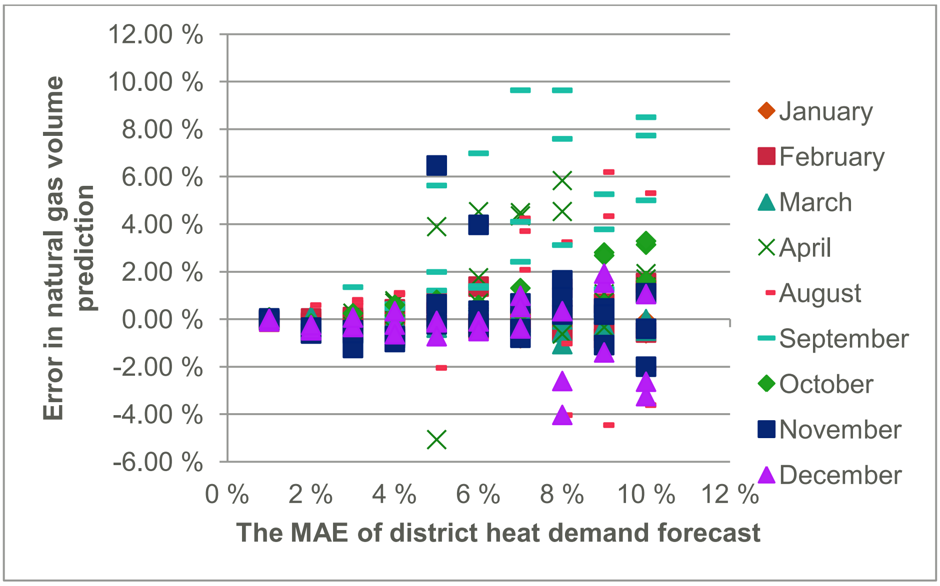


*Figure 23. The effects of MAE in district heat demand forecast on prediction of the volume of natural gas*

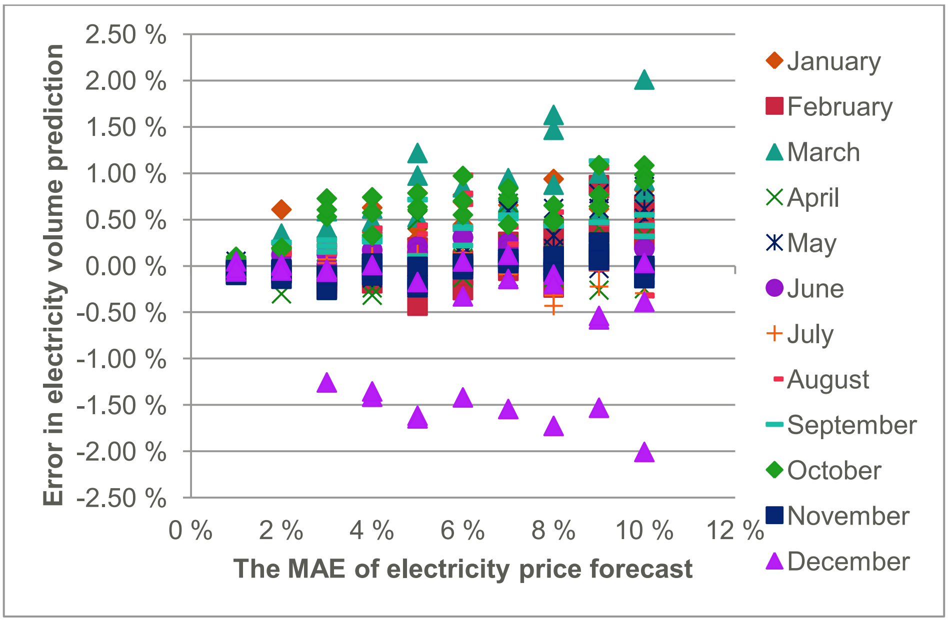


*Figure 24. The effects of MAE in electricity price forecast on predictions of electricity production volume*

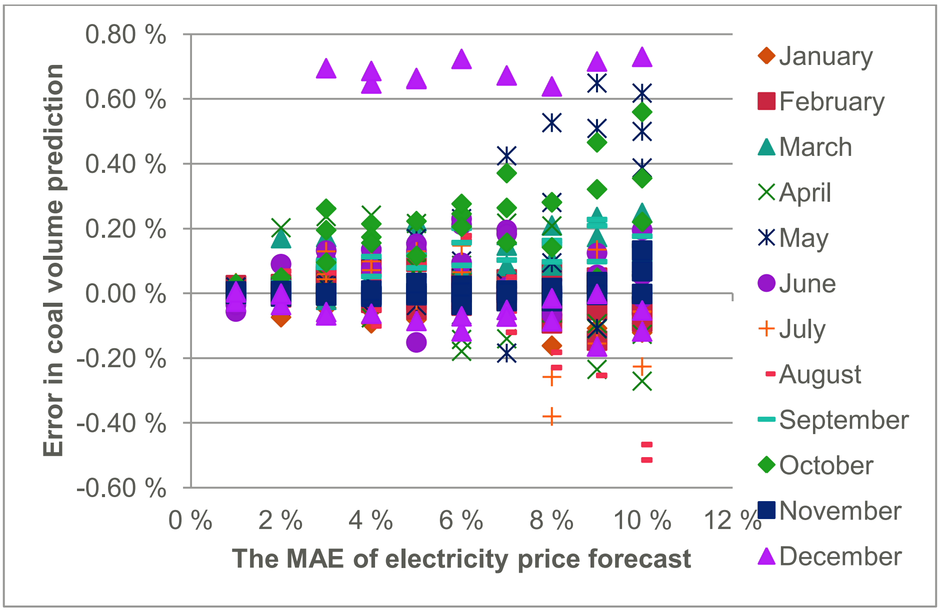


*Figure 25. The effects of MAE in electricity price forecast on prediction of the volume of coal*

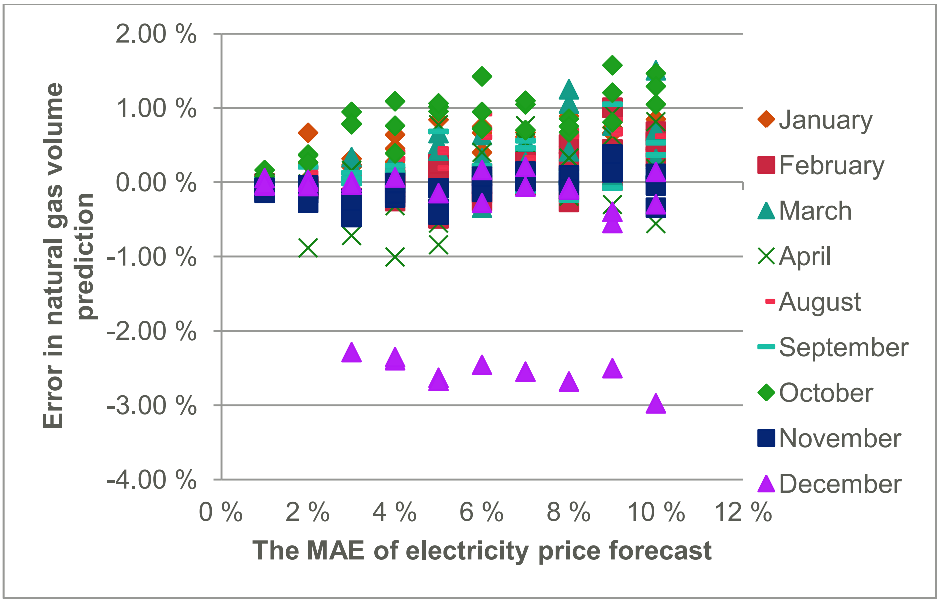


*Figure 26. The effects of MAE in electricity price forecast on prediction of the volume of natural gas*

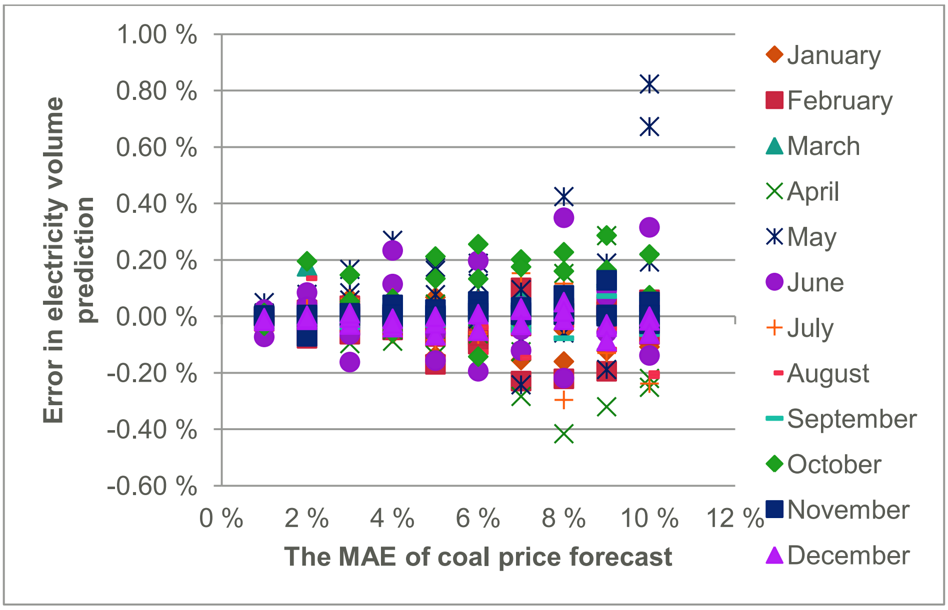


*Figure 27. The effects of MAE in coal price forecast on predictions of electricity production volume*

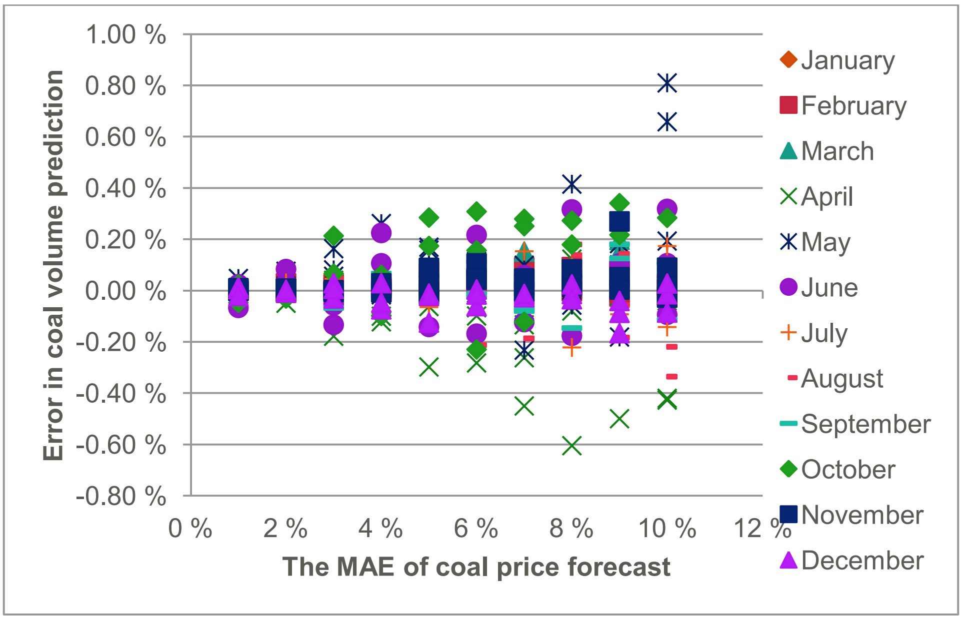


*Figure 28. The effects of MAE in coal price forecast on prediction of the volume of coal*

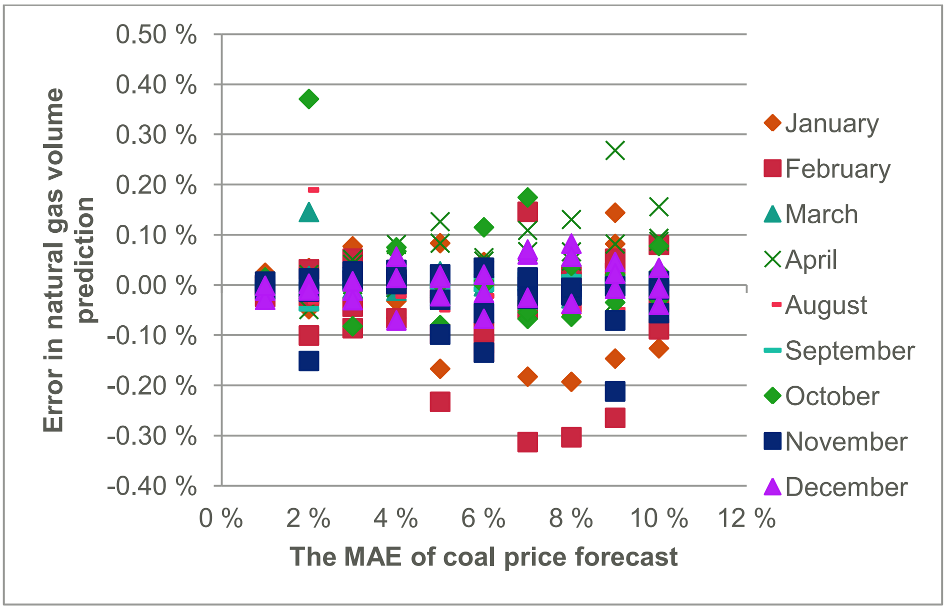


*Figure 29. The effects of MAE in coal price forecast on prediction of the volume of natural gas*

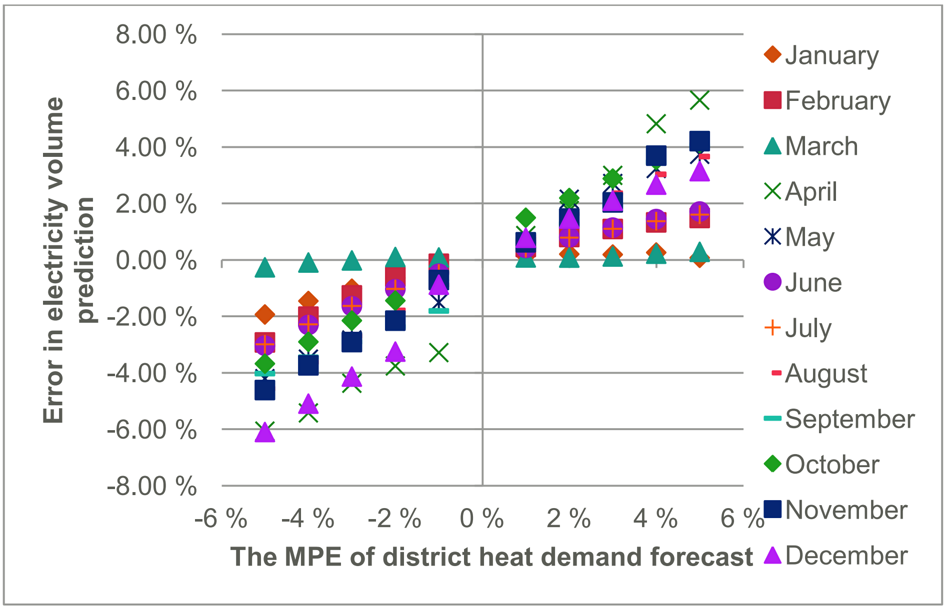


*Figure 30. The effect of MPE in district heat demand forecast on accuracy of electricity production volume prediction*

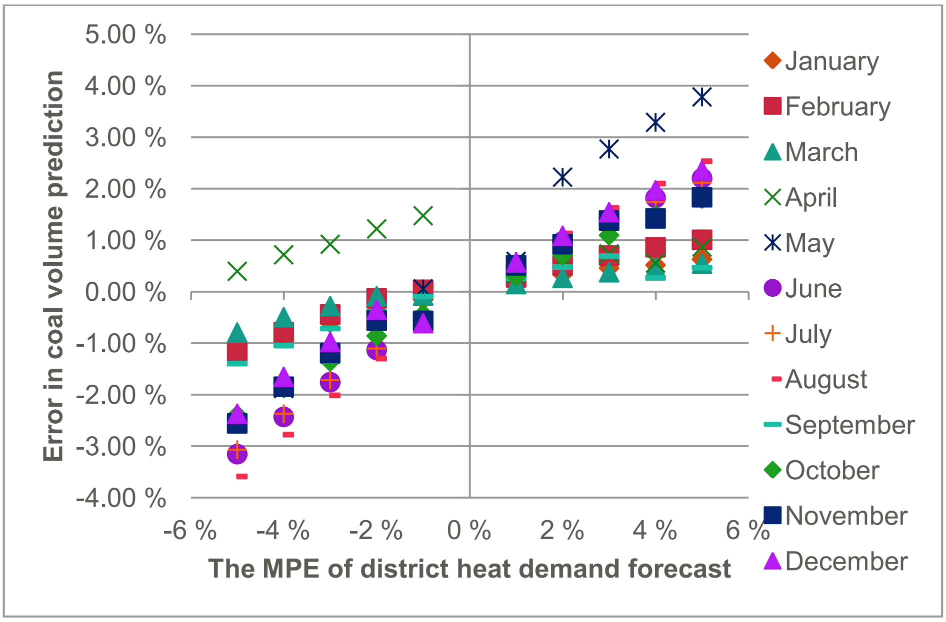


*Figure 31. The effect of MPE in district heat demand forecast on accuracy of coal volume prediction*

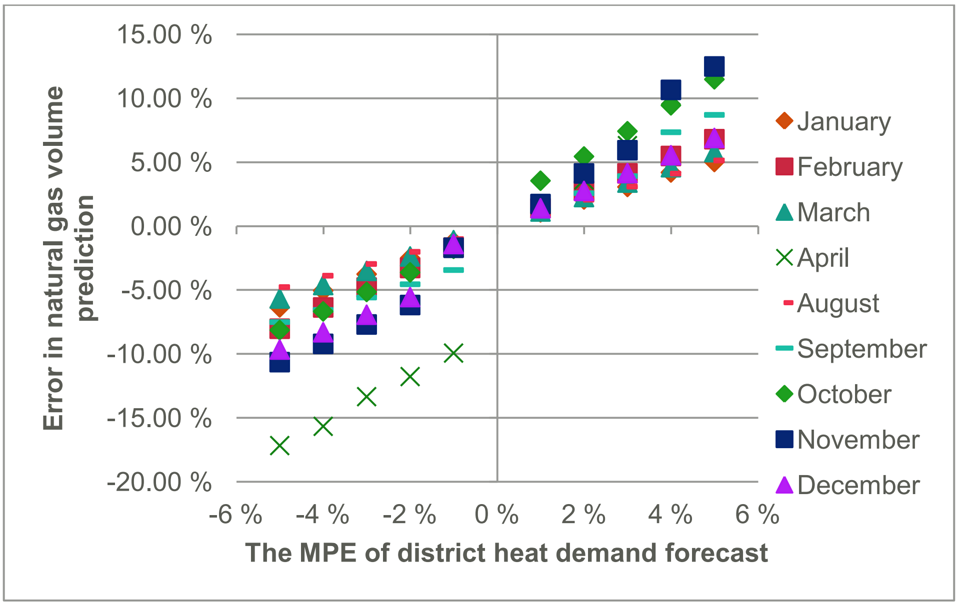


*Figure 32. The effect of MPE in district heat demand forecast on accuracy of natural gas volume prediction*

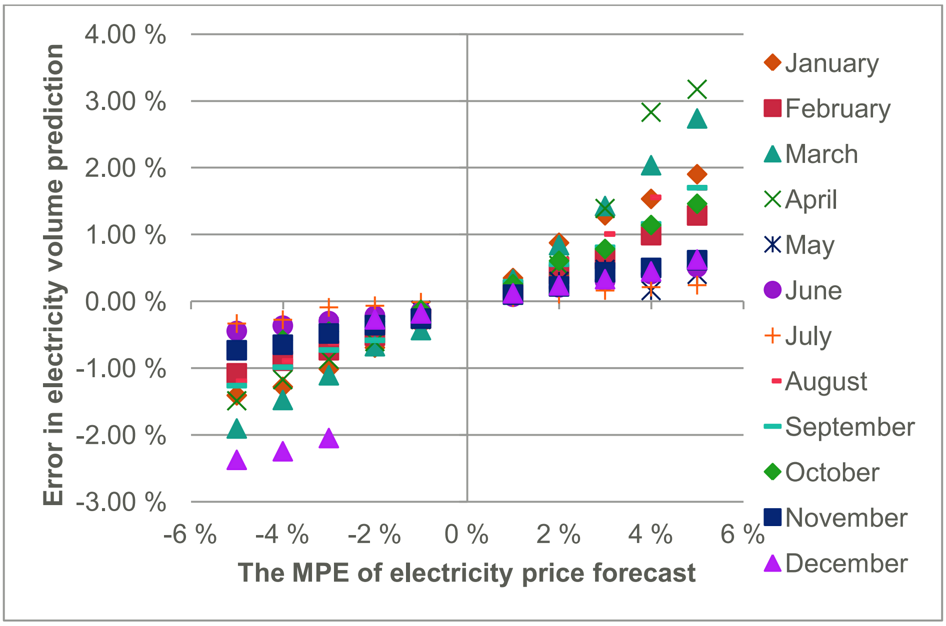


*Figure 33. The effect of MPE in electricity price forecast on accuracy of electricity production volume prediction*

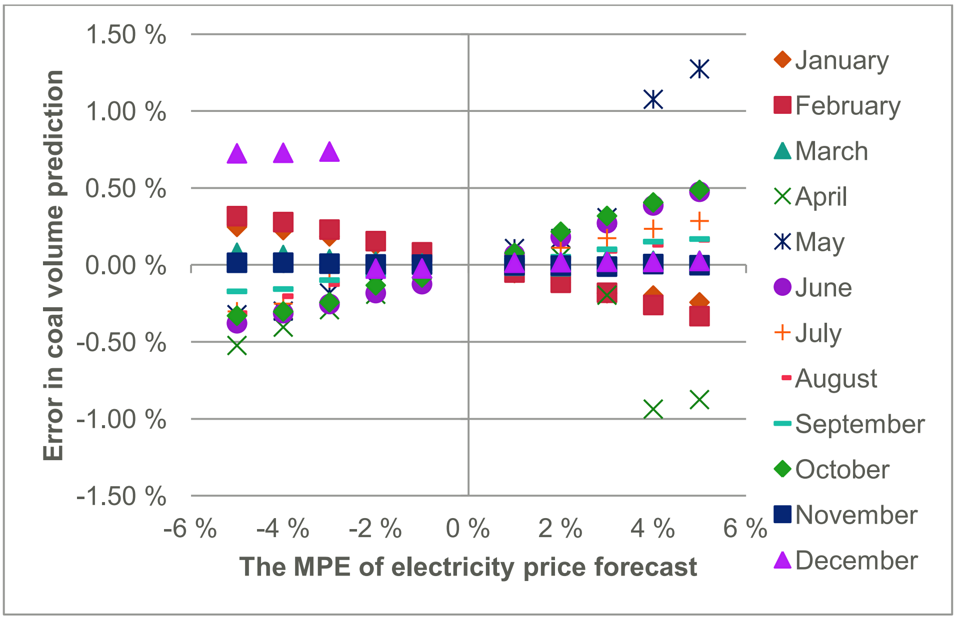


*Figure 34. The effect of MPE in electricity price forecast on accuracy of coal volume prediction*

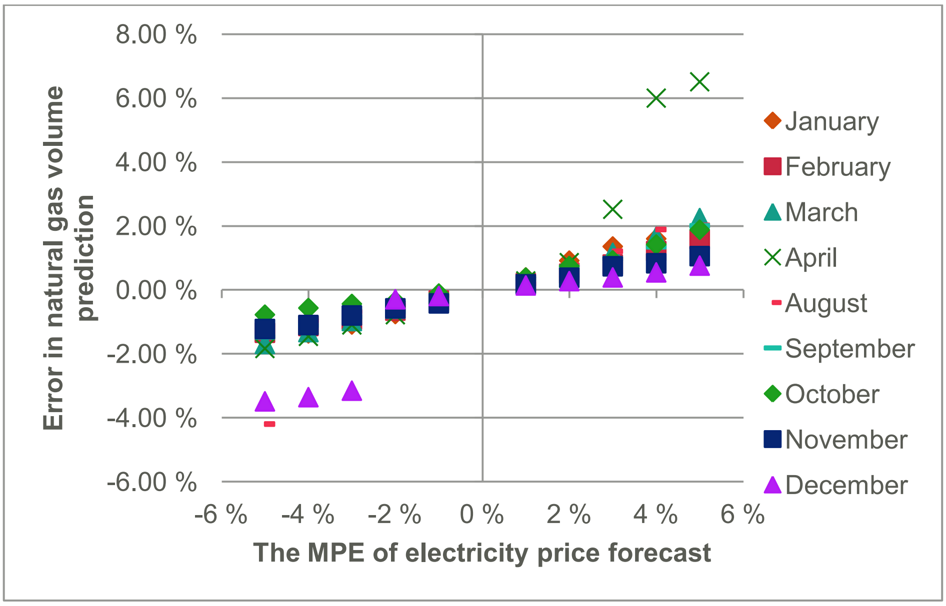


*Figure 35. The effect of MPE in electricity price forecast on accuracy of natural gas volume prediction*

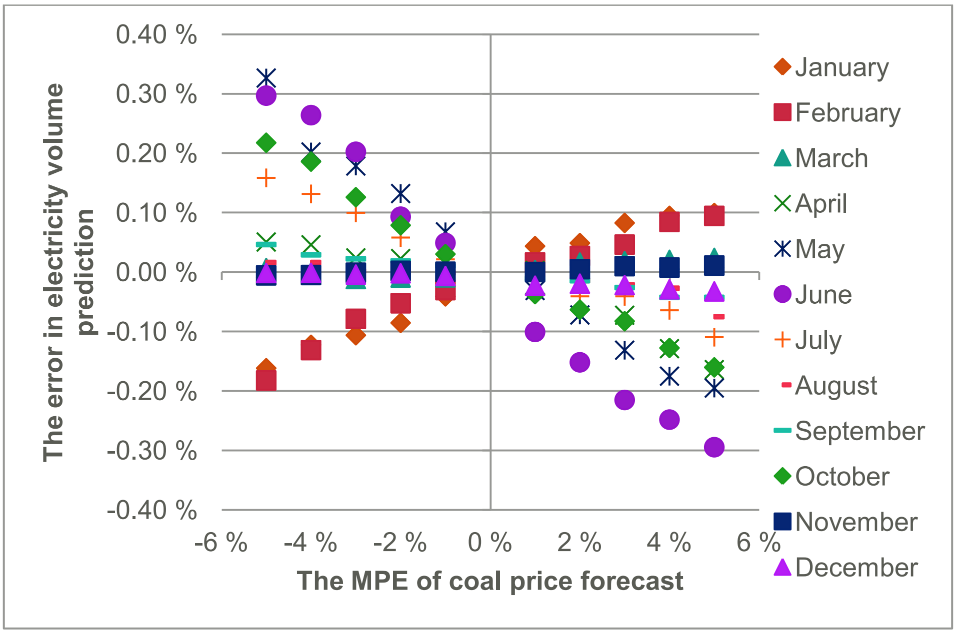


*Figure 36. The effect of MPE in coal price forecast on accuracy of electricity production volume prediction*

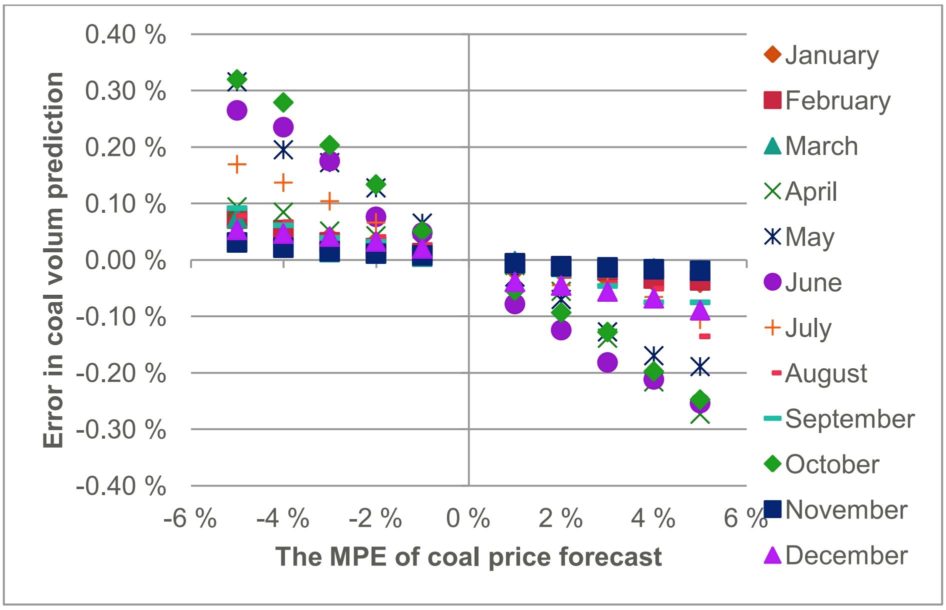


*Figure 37. The effect of MPE in coal price forecast on accuracy of coal volume prediction*

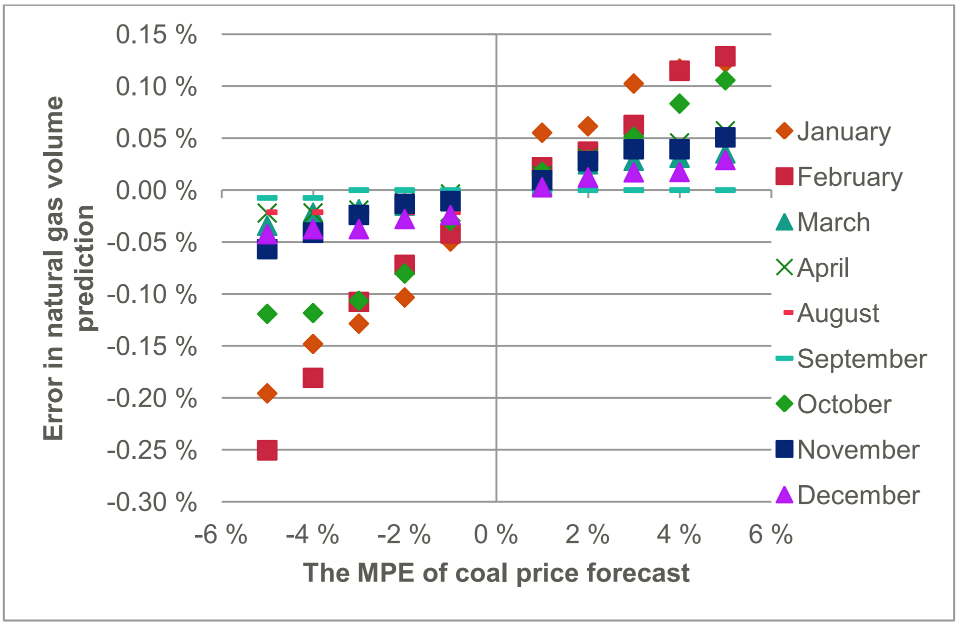


*Figure 38. The effect of MPE in coal price forecast on accuracy of natural gas volume prediction*

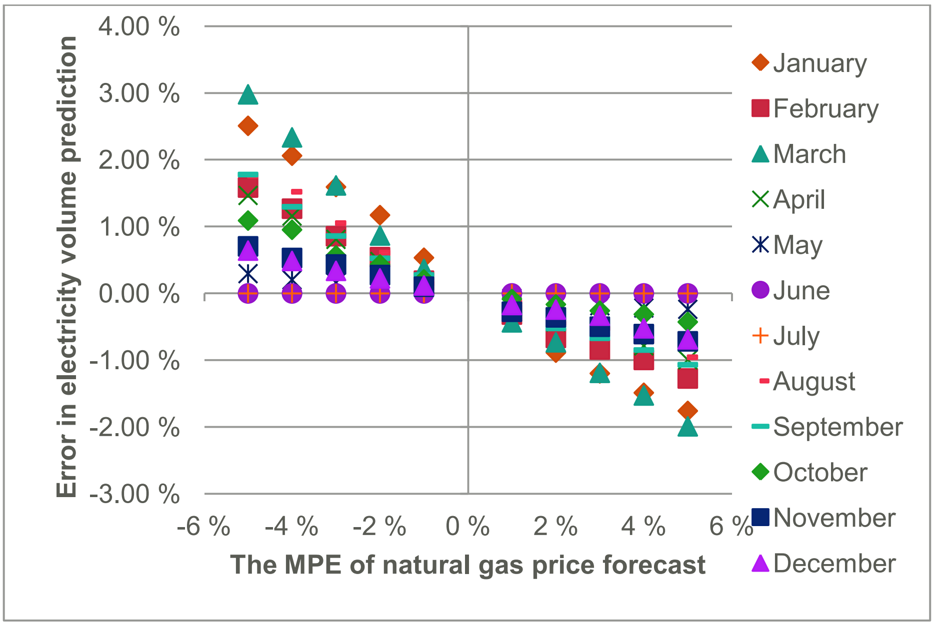


*Figure 39. The effect of MPE in natural gas price forecast on accuracy of electricity production volume prediction*

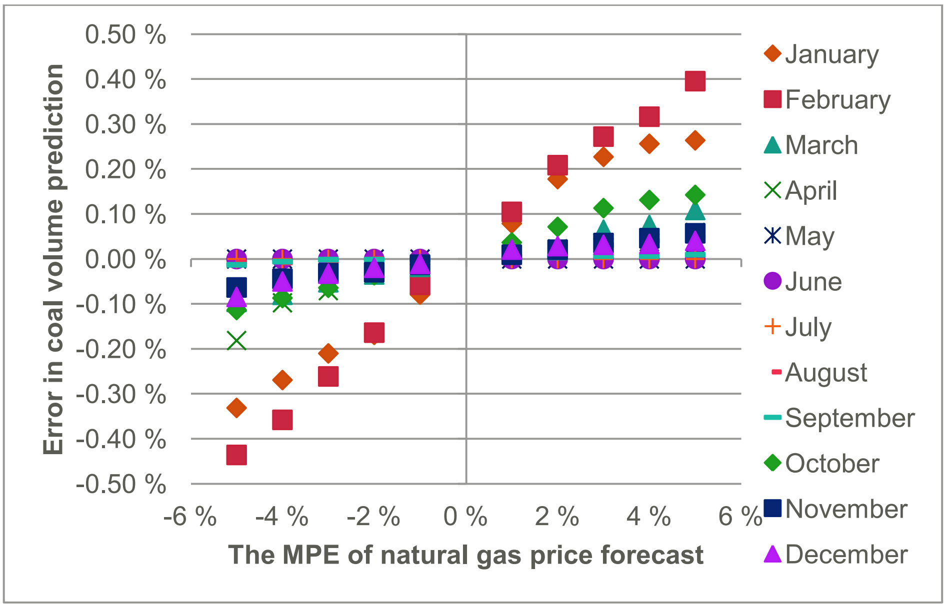


*Figure 40. The effect of MPE in natural gas price forecast on accuracy of coal volume prediction*

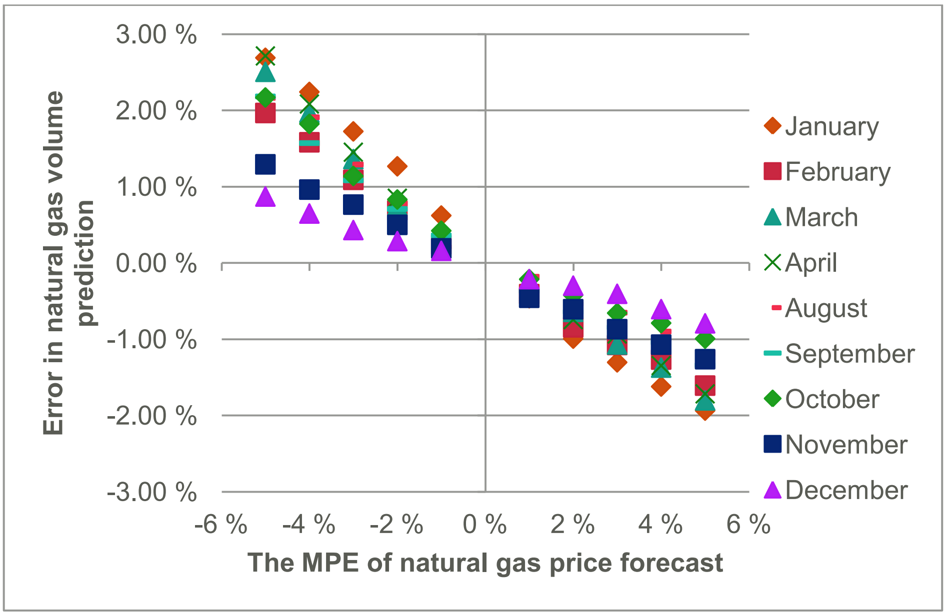


*Figure 41. The effect of MPE in natural gas price forecast on accuracy of natural gas volume prediction*

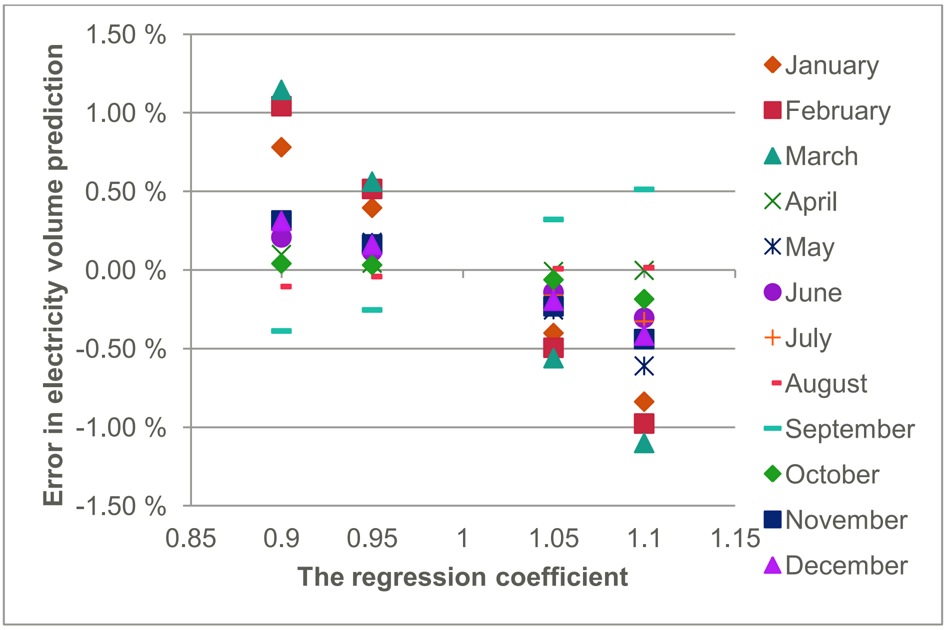


*Figure 42. The effect of bias in district heat demand forecast defined with the forecast rationality test on accuracy of electricity production volume prediction*

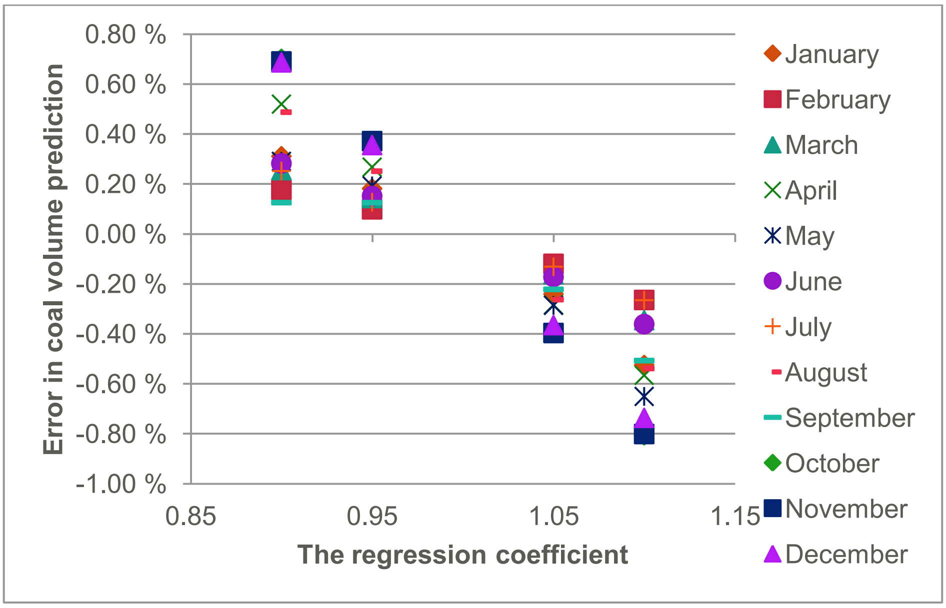


*Figure 43. The effect of bias in district heat demand forecast defined with the forecast rationality test on accuracy of coal volume prediction*

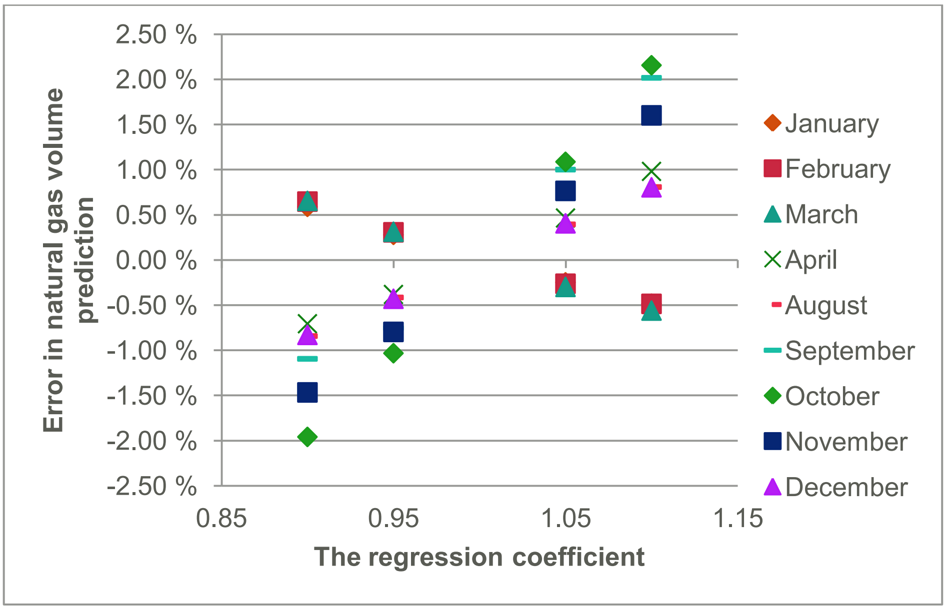


*Figure 44. The effect of bias in district heat demand forecast defined with the forecast rationality test on accuracy of natural gas volume prediction*

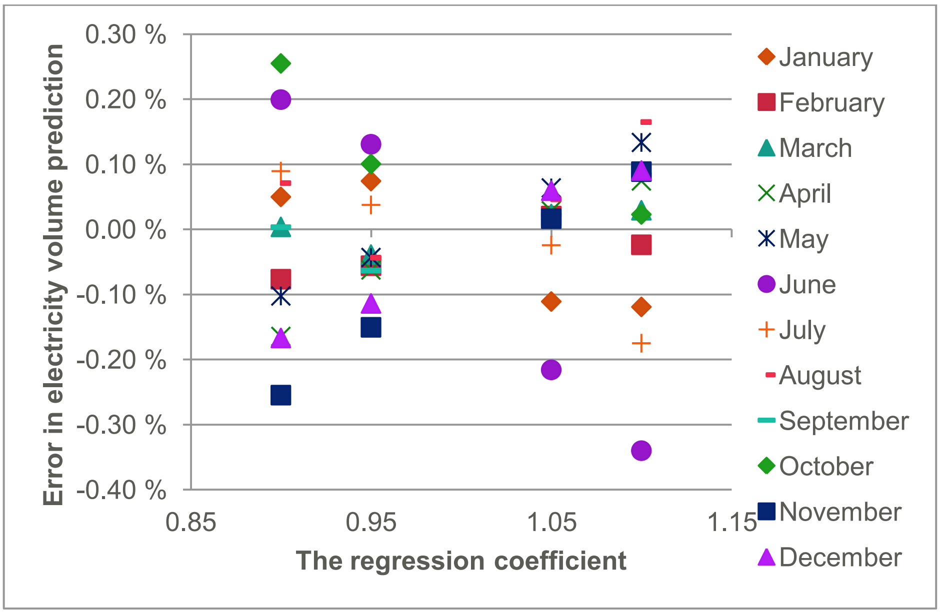


*Figure 45. The effect of bias in electricity price forecast defined with the forecast rationality test on accuracy of electricity production volume prediction*

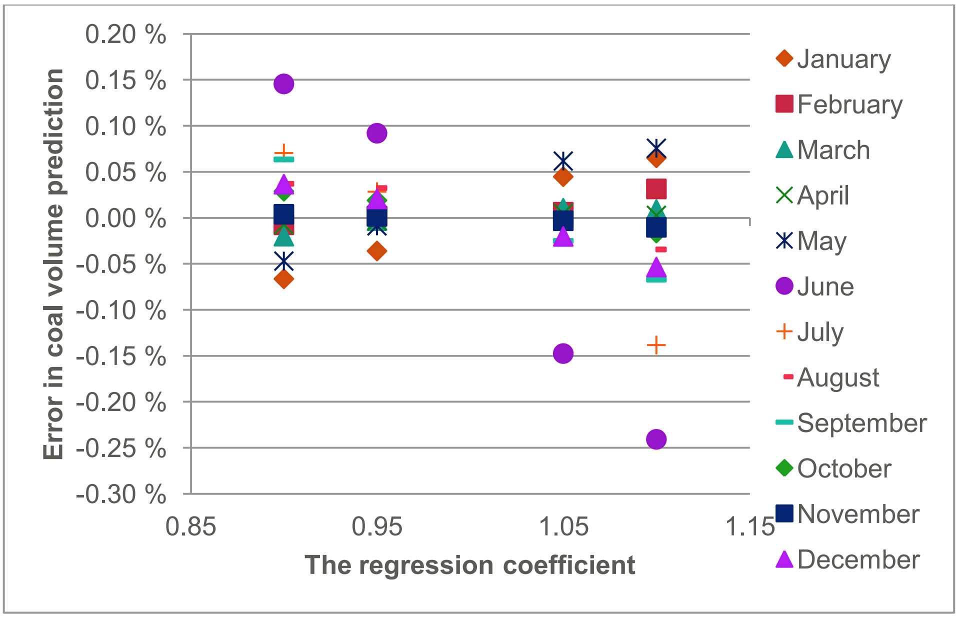


*Figure 46. The effect of bias in electricity price forecast defined with the forecast rationality test on accuracy of coal volume prediction*

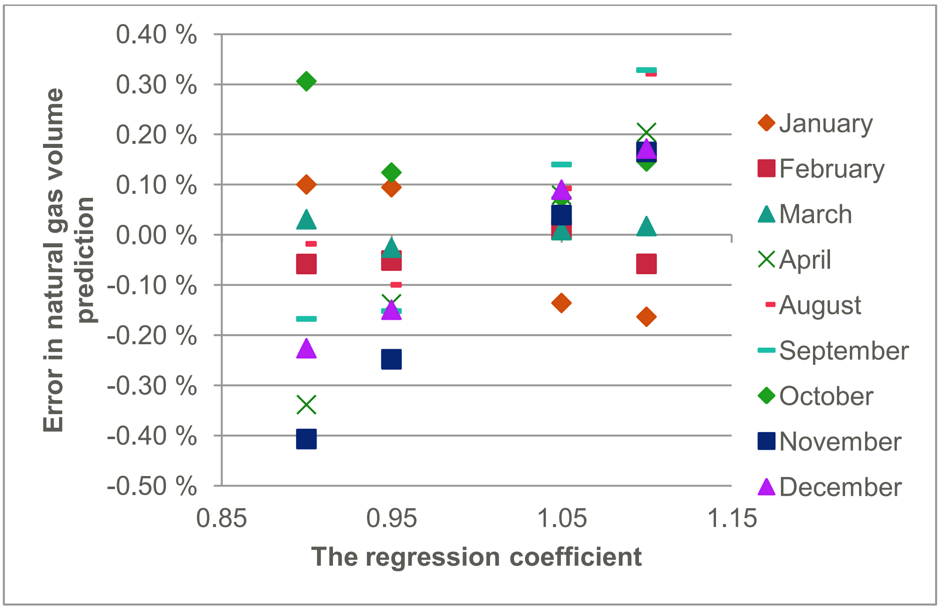


*Figure 47. The effect of bias in electricity price forecast defined with the forecast rationality test on accuracy of natural gas volume prediction*

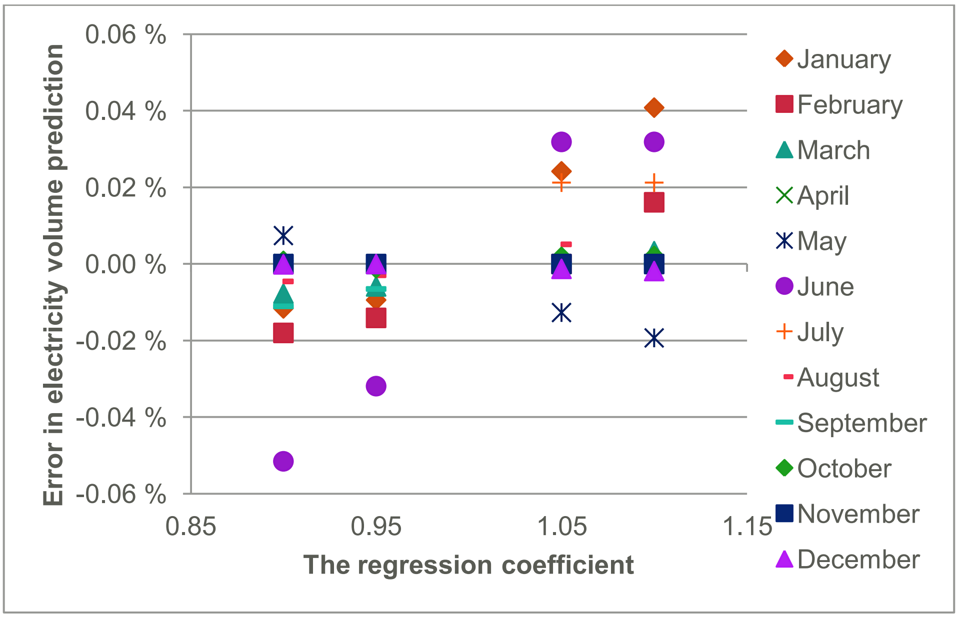


*Figure 48. The effect of bias in coal price forecast defined with the forecast rationality test on accuracy of electricity production volume prediction*

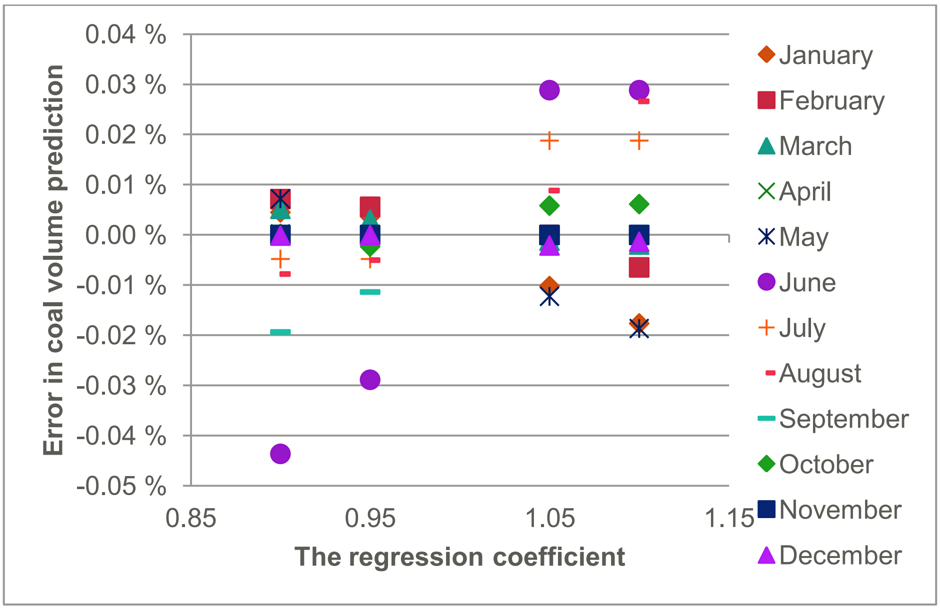


*Figure 49. The effect of bias in coal price forecast defined with the forecast rationality test on accuracy of coal volume prediction*

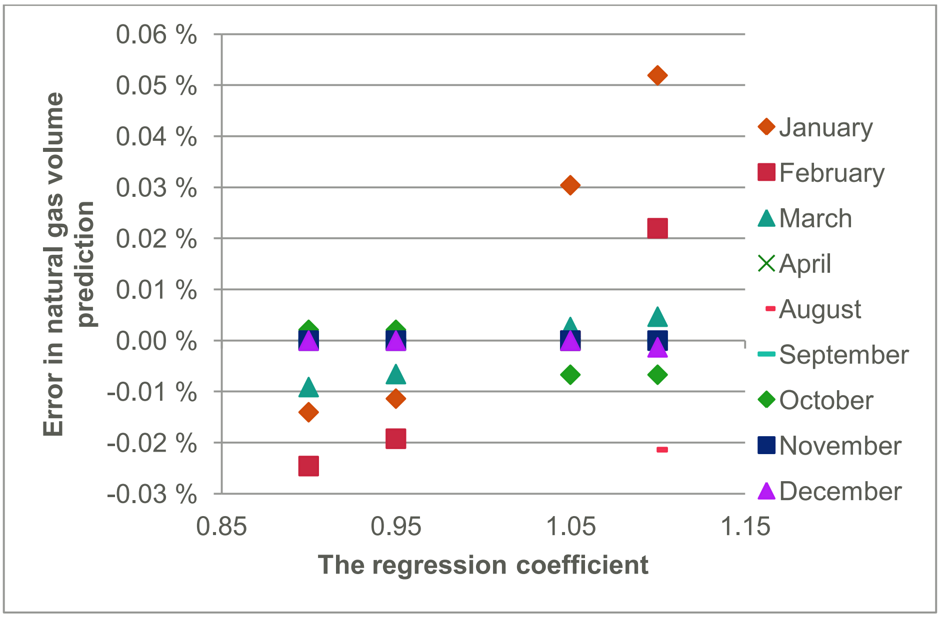


*Figure 50. The effect of bias in coal price forecast defined with the forecast rationality test on accuracy of natural gas volume prediction*

# Appendix C

The results of short term electricity trading objective

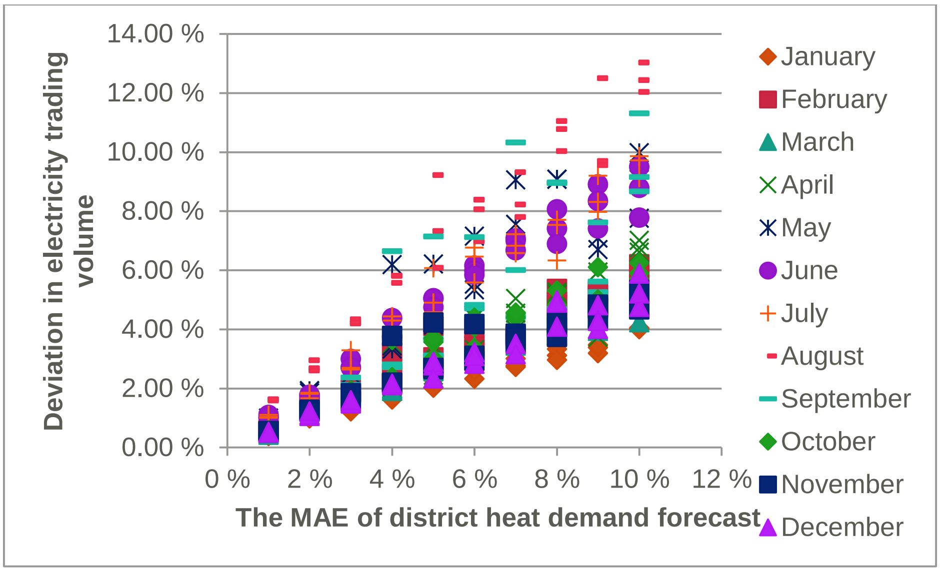


*Figure 51. The effects of MAE in district heat demand forecast on electricity trading objective*

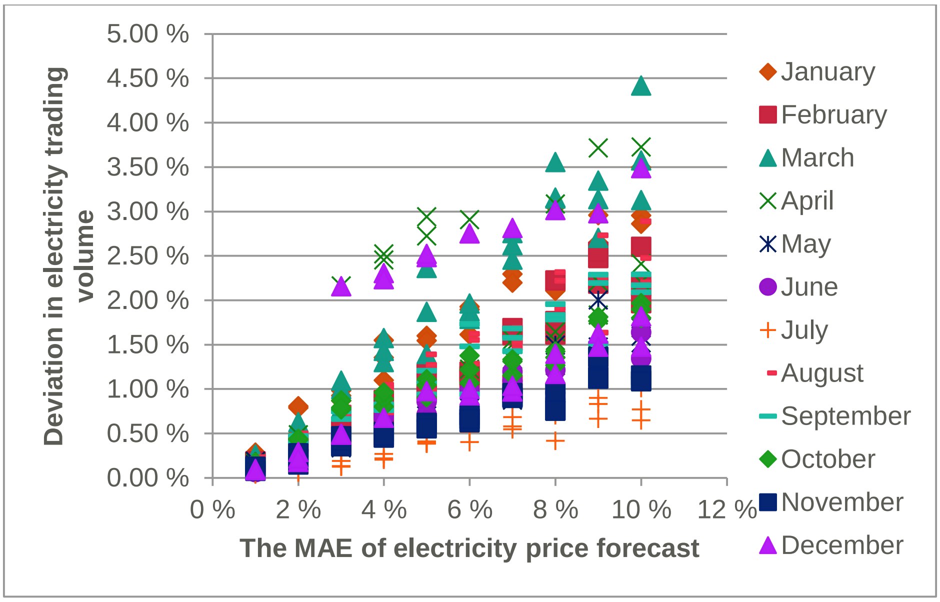


*Figure 52. The effects of MAE in electricity price forecast on electricity trading objective*

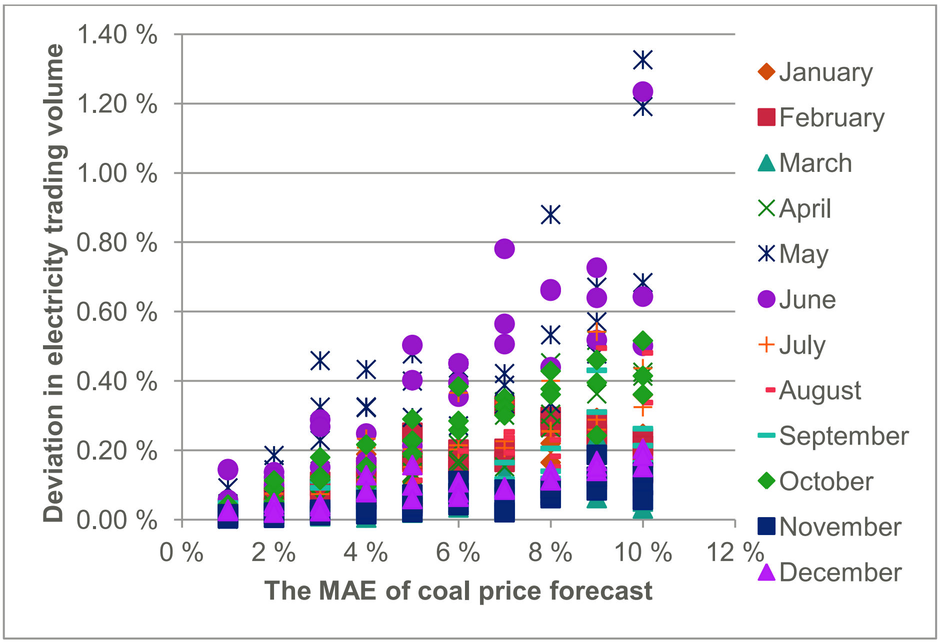


*Figure 53. The effects of MAE in coal price forecast on electricity trading objective*

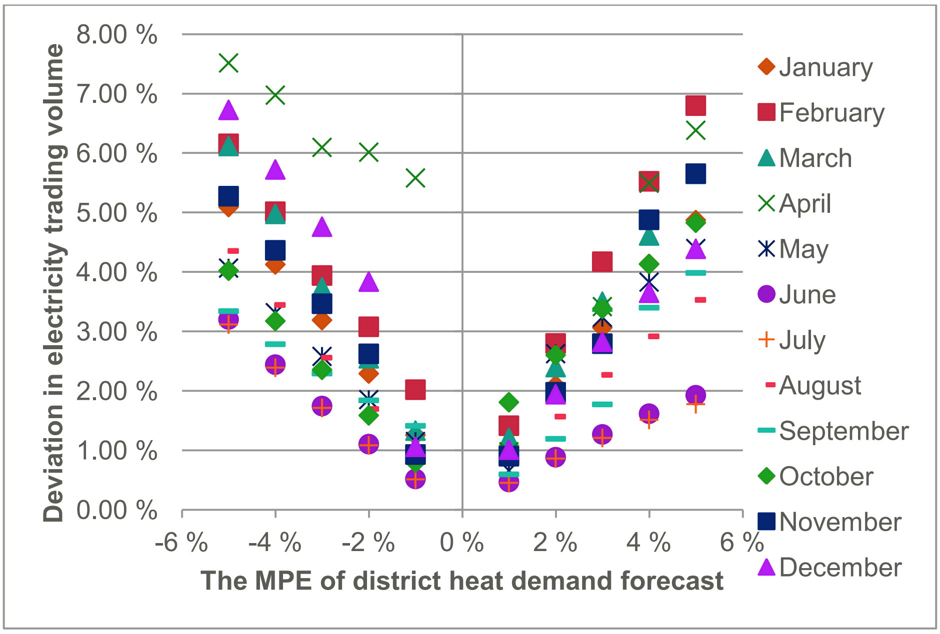


*Figure 54. The effects of MPE in district heat demand forecast on electricity trading objective*

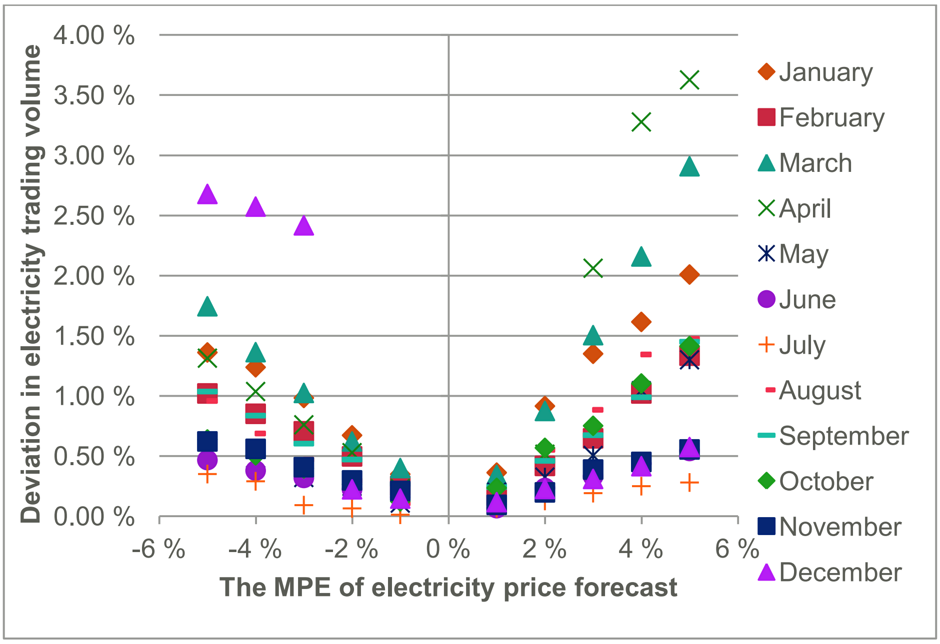


*Figure 55. The effects of MPE in electricity price forecast on electricity trading objective*

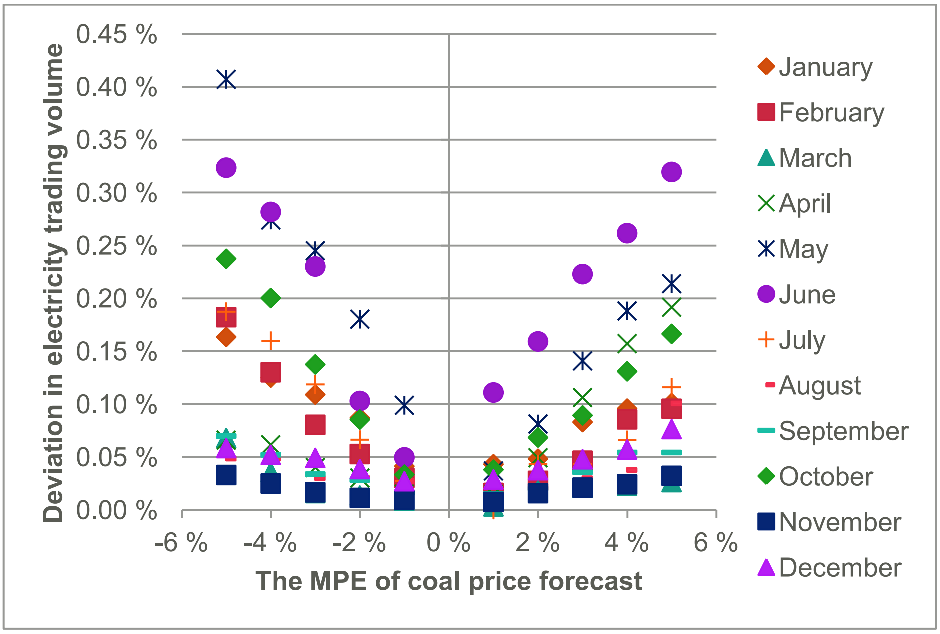


*Figure 56. The effects of MPE in coal price forecast on electricity trading objective*

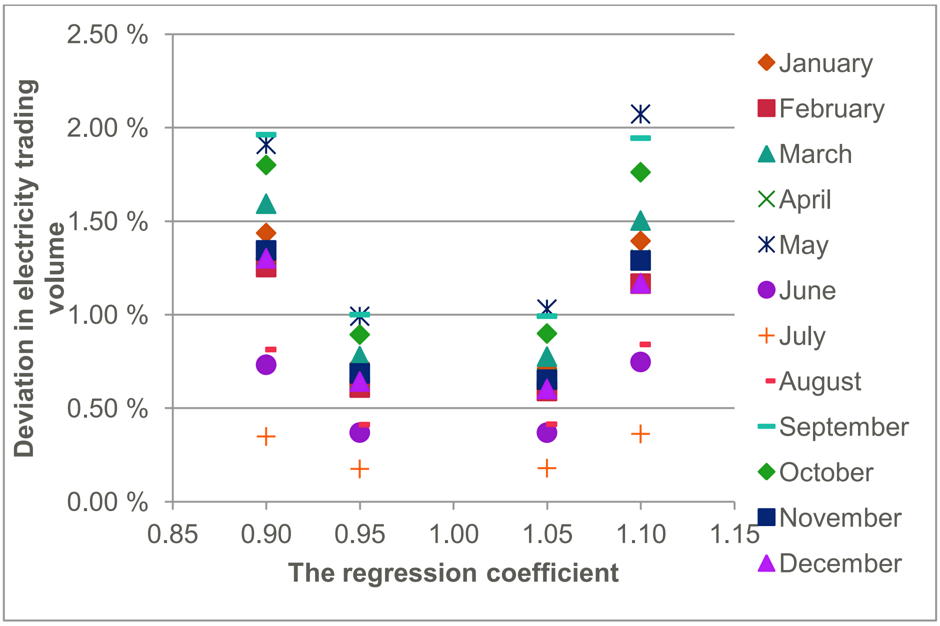


*Figure 57. The effect of bias in district heat demand forecast defined with the forecast rationality test on electricity trading objective*

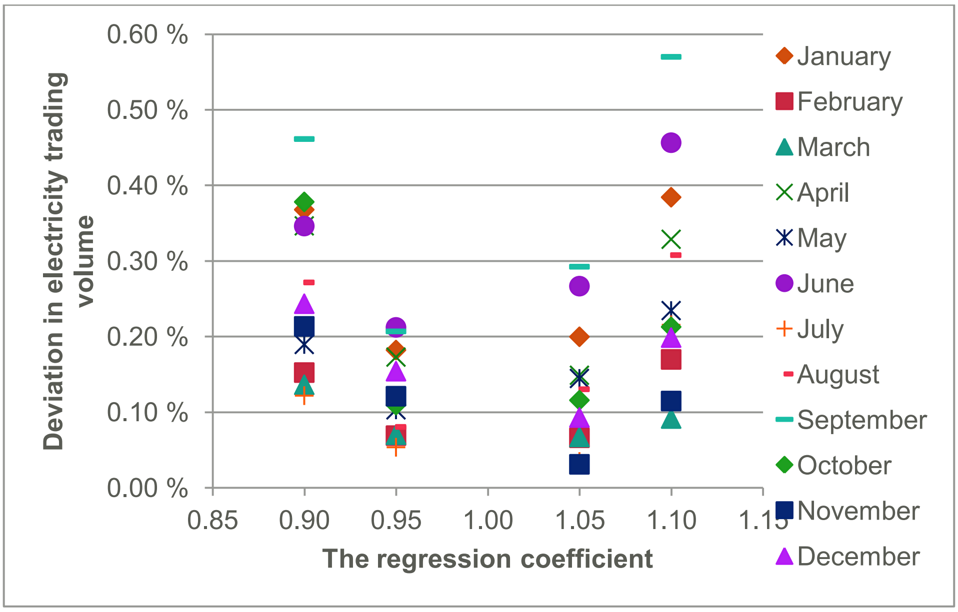


*Figure 58. The effect of bias in electricity price forecast defined with the forecast rationality test on electricity trading objective*

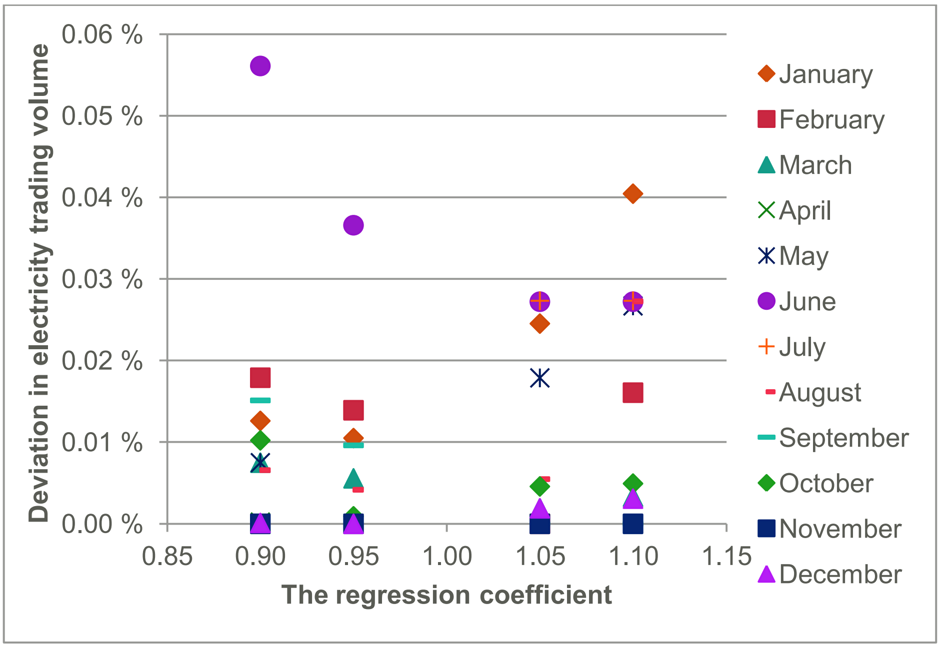


*Figure 59. The effect of bias in coal price forecast defined with the forecast rationality test on electricity trading objective*