ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA (ICAI)

INGENIERO ELÉCTRICO

AGENT-BASED EX-POST SIMULATION OF THE GERMAN MARKETS FOR CONTROL RESERVE AND THE SPOT MARKET BASED ON HISTORICAL DATA

Autor: Adrián Santos Mesa

Director: Andreas Maaz

Madrid

Agosto 2016

AUTORIZACIÓN PARA LA DIGITALIZACIÓN, DEPÓSITO Y DIVULGACIÓN EN RED DE PROYECTOS FIN DE GRADO, FIN DE MÁSTER, TESINAS O MEMORIAS DE BACHILLERATO

1º. Declaración de la autoría y acreditación de la misma.

El autor D. Adrián Santos Mesa

DECLARA ser el titular de los derechos de propiedad intelectual de la obra: Agent-based Ex-post Simulation of the German Markets for Control Reserve and the Spot Market based on Historical Data, que ésta es una obra original, y que ostenta la condición de autor en el sentido que otorga la Ley de Propiedad Intelectual.

2º. Objeto y fines de la cesión.

Con el fin de dar la máxima difusión a la obra citada a través del Repositorio institucional de la Universidad, el autor **CEDE** a la Universidad Pontificia Comillas, de forma gratuita y no exclusiva, por el máximo plazo legal y con ámbito universal, los derechos de digitalización, de archivo, de reproducción, de distribución y de comunicación pública, incluido el derecho de puesta a disposición electrónica, tal y como se describen en la Ley de Propiedad Intelectual. El derecho de transformación se cede a los únicos efectos de lo dispuesto en la letra a) del apartado siguiente.

3º. Condiciones de la cesión y acceso

Sin perjuicio de la titularidad de la obra, que sigue correspondiendo a su autor, la cesión de derechos contemplada en esta licencia habilita para:

a) Transformarla con el fin de adaptarla a cualquier tecnología que permita incorporarla a internet y hacerla accesible; incorporar metadatos para realizar el registro de la obra e incorporar "marcas de agua" o cualquier otro sistema de seguridad o de protección.
b) Reproducirla en un soporte digital para su incorporación a una base de datos electrónica, incluyendo el derecho de reproducir y almacenar la obra en servidores, a los efectos de garantizar su seguridad, conservación y preservar el formato.
c) Comunicarla, por defecto, a través de un archivo institucional abierto, accesible de modo libre y gratuito a través de internet.
d) Cualquier otra forma de acceso (restringido, embargado, cerrado) deberá solicitarse expresamente y obedecer a causas justificadas.
e) Asignar por defecto a estos trabajos una licencia Creative Commons.
f) Asignar por defecto a estos trabajos un HANDLE (URL *persistente)*.

4º. Derechos del autor.

El autor, en tanto que titular de una obra tiene derecho a:

a) Que la Universidad identifique claramente su nombre como autor de la misma
b) Comunicar y dar publicidad a la obra en la versión que ceda y en otras posteriores a través de cualquier medio.
c) Solicitar la retirada de la obra del repositorio por causa justificada.
d) Recibir notificación fehaciente de cualquier reclamación que puedan formular terceras personas en relación con la obra y, en particular, de reclamaciones relativas a los derechos de propiedad intelectual sobre ella.

5º. Deberes del autor.

El autor se compromete a:

a) Garantizar que el compromiso que adquiere mediante el presente escrito no infringe ningún derecho de terceros, ya sean de propiedad industrial, intelectual o cualquier otro.
b) Garantizar que el contenido de las obras no atenta contra los derechos al honor, a la intimidad y a la imagen de terceros.
c) Asumir toda reclamación o responsabilidad, incluyendo las indemnizaciones por daños, que pudieran ejercitarse contra la Universidad por terceros que vieran infringidos sus derechos e

intereses a causa de la cesión.

d) Asumir la responsabilidad en el caso de que las instituciones fueran condenadas por infracción de derechos derivada de las obras objeto de la cesión.

6º. Fines y funcionamiento del Repositorio Institucional.

La obra se pondrá a disposición de los usuarios para que hagan de ella un uso justo y respetuoso con los derechos del autor, según lo permitido por la legislación aplicable, y con fines de estudio, investigación, o cualquier otro fin lícito. Con dicha finalidad, la Universidad asume los siguientes deberes y se reserva las siguientes facultades:

- La Universidad informará a los usuarios del archivo sobre los usos permitidos, y no garantiza ni asume responsabilidad alguna por otras formas en que los usuarios hagan un uso posterior de las obras no conforme con la legislación vigente. El uso posterior, más allá de la copia privada, requerirá que se cite la fuente y se reconozca la autoría, que no se obtenga beneficio comercial, y que no se realicen obras derivadas.
- La Universidad no revisará el contenido de las obras, que en todo caso permanecerá bajo la responsabilidad exclusive del autor y no estará obligada a ejercitar acciones legales en nombre del autor en el supuesto de infracciones a derechos de propiedad intelectual derivados del depósito y archivo de las obras. El autor renuncia a cualquier reclamación frente a la Universidad por las formas no ajustadas a la legislación vigente en que los usuarios hagan uso de las obras.
- La Universidad adoptará las medidas necesarias para la preservación de la obra en un futuro.
- La Universidad se reserva la facultad de retirar la obra, previa notificación al autor, en supuestos suficientemente justificados, o en caso de reclamaciones de terceros.

Madrid, a 25 de Agosto de 2016

ACEPTA

Fdo...

Motivos para solicitar el acceso restringido, cerrado o embargado del trabajo en el Repositorio Institucional:

Proyecto realizado por el alumno/a:

Adrián Santos Mesa

Fdo.: …………………… Fecha: 08 / 08 / 2016

Autorizada la entrega del proyecto cuya información no es de carácter confidencial

EL DIRECTOR DEL PROYECTO

Andreas Maaz

Fdo.: …………………… Fecha: 08 / 08 / 2016

Vº Bº del Coordinador de Proyectos

Fernando de Cuadra García

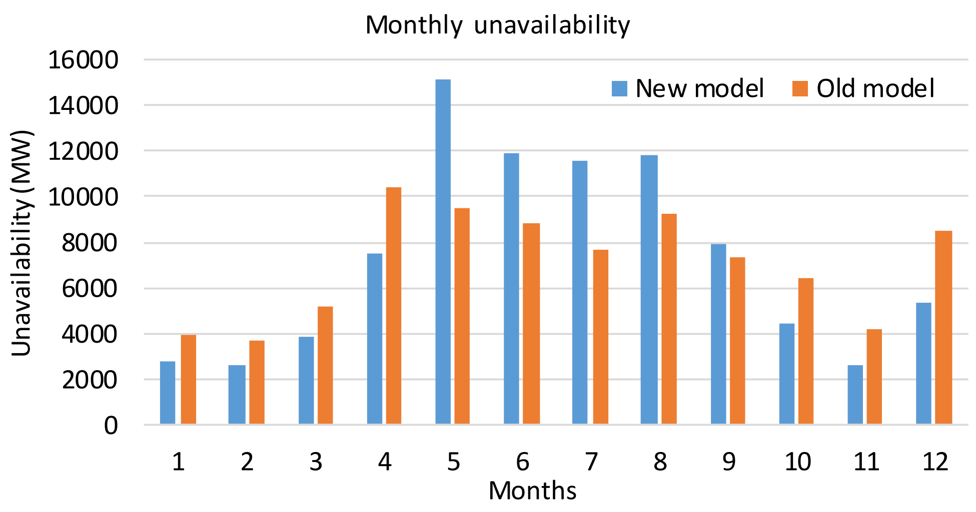
Fdo.: …………………… Fecha: ……/ ……/ ……

Resumen

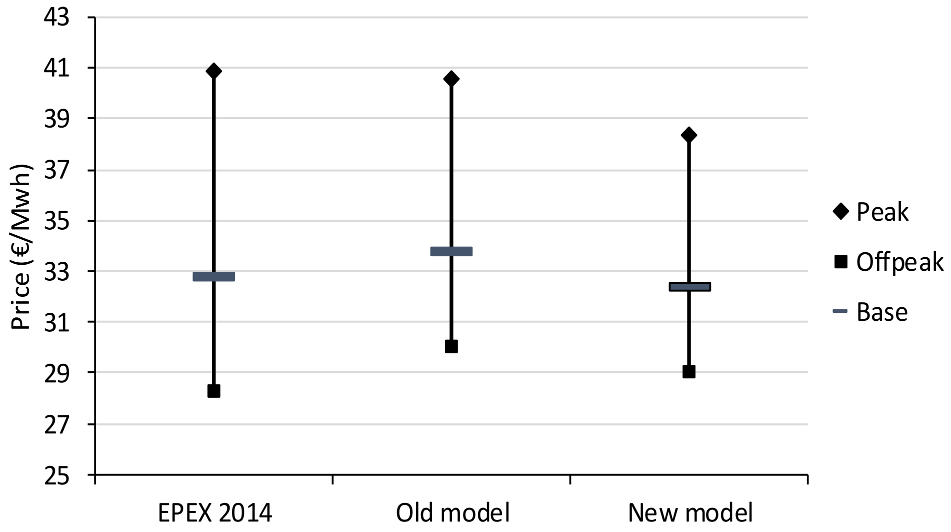
El mercado spot es una parte fundamental del suministro eléctrico. Un modelo del mercado spot alemán fue desarrollado para poder simular su comportamiento y pronosticar el comportamiento de los precios. Los datos utilizados por el modelo son las centrales térmicas e hidroeléctricas, la generación de energías renovables y la demanda. La generación de las centrales térmicas e hidroeléctricas se modela con agentes mientras que la demanda y la generación de las renovables se modela con una serie temporal fija. Los resultados de las simulaciones se comparan con los precios históricos de 2014 para evaluar la precisión del modelo.

El objetivo de este trabajo es mejorar el modelo para conseguir precios más similares a los históricos. Para ello, se modificó el modelo de la no disponibilidad de las centrales térmicas. La no disponibilidad era generada anteriormente con un método estocástico asumiendo valores medios mensuales para cada tecnología. Este modelo se sustituyó por la no disponibilidad histórica de cada central. Solo se utilizó la disponibilidad prevista porque el análisis se centra en el mercado diario.

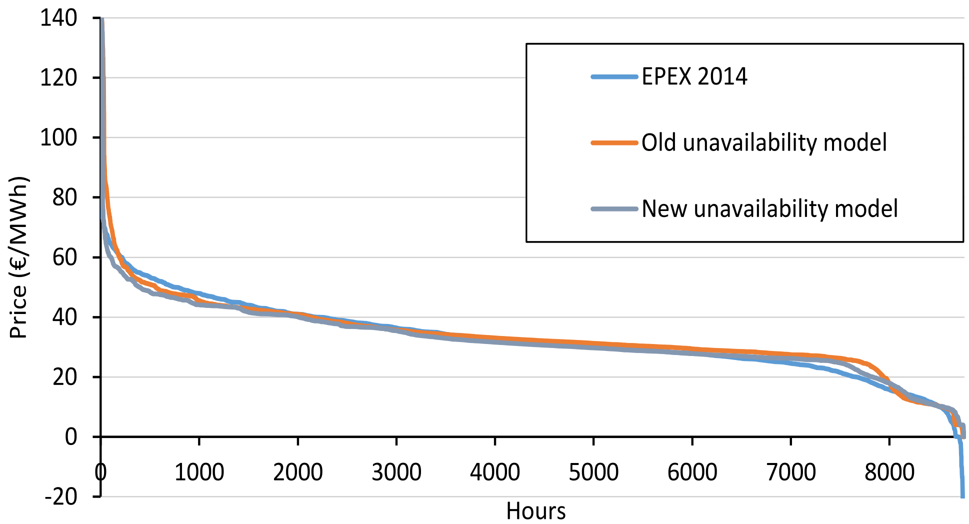
Las diferencias entre ambos modelos tienen efecto en los resultados de las simulaciones. El nuevo modelo tiene una variación mensual mayor que el modelo estocástico. Los parones son más frecuentes en los meses con menor demanda y precios. El nuevo modelo también tiene un valor medio anual ligeramente superior.



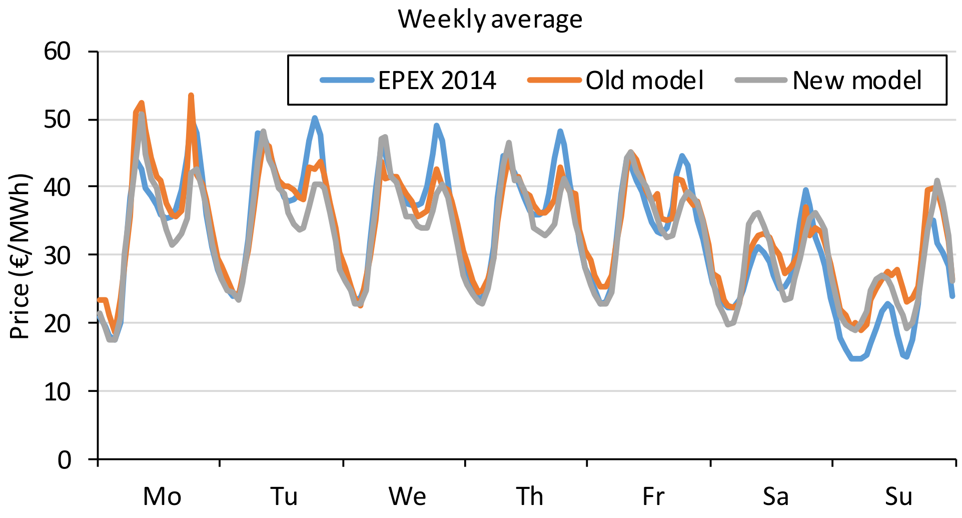
Aunque la no disponibilidad es más alta en el nuevo modelo, la media de los precios simulados es menor. Esto es provocado por la diferente distribución mensual de la no disponibilidad, el efecto en los meses con mayores precios es mayor que en los meses con menores precios por la variación de la pendiente de la curva de ofertas. La pendiente es menor en la zona con menores precios y mayor en la zona con mayores precios. El nuevo modelo aproxima mejor los precios medios y los de valle mientras que el modelo antiguo simula mejor los precios pico.



El nuevo modelo replica mejor la curva de duración que el antiguo. Reduce el número de precios muy altos y se aproxima mejor en los precios bajos (de la hora 6000 a la 8760). Los precios negativos no pueden ser simulados aún, es necesario incluir más limitaciones en el modelo de las centrales térmicas.



En el ámbito semanal, el nuevo modelo no mejora significativamente. La mayor mejora se observa en los domingos.



Una regresión multivariante se llevó a cabo para estimar hasta qué punto depende el precio de la no disponibilidad y de los otros factores del modelo. El efecto de la no disponibilidad es significativo, aunque sea menor que el de la demanda y la generación de renovables, y podría ser útil para prever precios en el futuro.

Abstract

The spot market is a part of great importance in the electricity supply chain. In order to simulate its behavior and to be able to forecast future prices a model of the German spot market was developed. The data used are the thermal and hydraulic power plants, renewable energies generation and the load. The generation of thermal and hydraulic power plants is modeled with agents while the load and the renewable energies are modeled with a fixed time series. The results of the simulations are compared with the historic prices of 2014 to evaluate the accuracy of the model.

The objective of this work is to improve the model to get prices more similar to the historic. The model for the unavailability of thermal power plants was changed in order to achieve this. The unavailability was generated previously with a stochastic method with assumed average values, and it was substituted with the historic per unit unavailability. Only the planned unavailability was used because the analysis will focus on the day ahead market.

There are some differences between the data of both models which had an effect on the market prices. The new model has a higher monthly variation than the stochastic model, with the highest values concentrated in the months with lowest load and prices. The new model also has a slightly higher average unavailability during the year.

Even though the unavailability was higher in the new model, the prices were lower on average. This could be explained by the monthly distribution of unavailability, its effect in the months with higher prices more than offsetting the effect in the months with lower prices because of the characteristics of the merit order curve. The new model approximates better both the base and off peak prices while the peak prices were better previously. The new model fits better the duration curve than the old model. It reduced the number of price spikes, and is closer to the historic prices in the lower part of the curve (from the hour 6000 to the 8760). Negative prices still cannot be simulated, further changes in the thermal power plant model will be needed. On a weekly basis, the new model performs better on Sundays while during the rest of the week it is similar to the stochastic model.

A multivariate regression was done to estimate the impact of the unavailability and the other factors of our model on the prices. The effect of the unavailability, while lower than that of the load and the renewable energies is significant and could be useful to predict future prices.

Index

1 Introduction

1.1 Background und Motivation

The electricity markets were liberalized in Germany in 1998. The previously vertically integrated monopolistic sector was unbundled and competition was introduced. Transparent competitive markets were created, where the generation companies could sell freely their production and the distribution companies bought the electricity they needed to supply the end consumers. Competition was introduced in every step of the electricity supply chain except in the operation of the network[1].

While most of the electricity is supplied in bilateral derivative contracts, the power exchanges are gaining importance. Two markets were created to enable the electricity supply, the spot market and the reserve market[2].

The spot market is handled in two exchanges, European Energy Exchange (EEX) in Leipzig and European Power Exchange (EPEX) in Paris. The spot market is divided in two parts, the Day Ahead Market and the Intraday Market. In both sections energy can be bought or sold, the difference being the time until the delivery and the differences in the price formation. The day ahead market uses the market clearing price, where all the orders are fulfilled at the same price after an auction is done. In the intraday market the pay as you bid method is used. The seller receives the price it offered as long as the bid is accepted[2].

The reserve market is organized by the system operators in order to ensure the stability of the system when there are accidents in the power plants or for balancing forecast deviations in demand or intermittent supply. The reserve capacity is sold by the generation companies and bought by the system operators. Three types of reserve exist, called primary, secondary and tertiary reserve. They are determined by their time to activate and the time they can be required to operate. The reserve markets are not completely open, the participating firms need to fulfill several requirements like minimum power offered and minimum activation times. This encourages the bidders to do strategic bidding, trying to get the price of the bid as close as possible to the highest accepted bid[3].

The European electricity markets are becoming increasingly interconnected. Interconnection will help reduce the need for reserves and the electricity price in the coming years. It is also a good way of integrating the renewable energies that different countries generate. Germany had in 2012 21.3 GW of interconnection capacity and it is increasing every year, but on average only half of the transmission capacity is used. Germany is a net energy exporter, the biggest buyers of German electricity are Austria and the Netherlands while the biggest sellers to Germany are the Czech Republic and France. In 2014 Germany's net sales were 35 TWh[4].

1.2 Objective of the research

The objective of this thesis is to model the behavior of the electricity markets in Germany. A model of the electricity market can be used as a tool to forecast the impact of possible developments in the future on the energy markets. Analyzing the impact of an increase of generation by renewable energy sources is an example of the possible uses the model could have.

The data used by the model is mainly the thermal and hydraulic power plants, the renewable energies generation and the load. The generation by thermal and hydraulic power plants is modeled with agents while the load and the renewable energies are introduced using historical data. The results of the model will be compared with the historical data of 2014 in order to evaluate the accuracy of the model. The objective of this work is to find areas where the model could be improved in order to better approximate the historic prices.

In Chapter 2 the main data that is used by the model is analyzed as well as different possibilities on how the model could be improved. Chapter 3 explains the changes in the model performed in this work and compares their differences. In Chapter 4 the results of the simulations using the new model are compared to the previous model and the historic prices.

2 Analysis

2.1 Renewable energies

The renewable energy share of Germany's electricity production has grown from 6.3% in the year 2000 to 32.5% of the gross consumption in 2015 supplying 194 TWh. The targets specified by the Renewable Energies Law (EEG) is to have 40-45% by 2025 and 55-60% by 2035[4]. The importance of renewable energies in the German electricity market has grown sharply since the turn of the century. Renewable energies power plants, solar and wind in particular, are quite different compared to conventional power plants. Because of this, we will analyze their particularities in order to determine how we can represent them in our model.

The three most important renewable energy sources are wind, biomass and solar. Wind and solar have similarities while biomass is more similar to thermal power plants in its operation. The main peculiarities of wind and solar are their intermittence, their availability and their zero marginal costs. Another issue that will be analyzed separately is the pricing mechanisms designed to incentivize the development of the renewable energies and how it influences their market behavior.

Intermittence means that the generation from wind and solar depends on the presence of wind or sun and that the generation can have very fast changes. When the wind stops blowing, or the sun is clouded, the generation by a wind turbine or a solar panel can decrease very quickly. This has big implications for the electricity supply, mainly for the reserves necessary to cover the periods of low wind and solar power generation. This results in higher costs for the system because while the installed capacity of wind and solar increases steadily, conventional power plants are not decommissioned so fast because of the need of reserves to guarantee the electricity supply[4][5].

Apart from the periods with low generation, other problem is the fast fluctuation in generation. The variation is higher for wind power than for solar power. Usually the variability in the short term due to weather conditions decreases when a large number of wind turbines and solar panels are built over a big area, and the prediction capability is also better. But still, over several hours the variation can be very big. This also increases the need of reserves, and they need to be fast in order to accommodate the quick changes in generation. When the renewable energies penetration is low, the variability can be easily accommodated in the network. The output of a big wind or solar power plant can in the worst case go from null generation to full power in a few hours or vice versa but most of the time the variations in one minute to the next or one hour to the next are small. They are usually non-dispatchable, which means that the network operator usually has very little control of their generation. The effect on reserves depends too on the diversification of the renewable energy sources, having only one big renewable energy source has higher reserve requirements than several smaller sources [5] [6].

The availability factor for solar and wind power plants are close to 100%. Their capacity factors are lower though, 25-40% for wind energy and 9-24% for solar power [7]. This means that, in contrast with thermal plants, we do not need to model solar panels and wind turbines unavailability.

Another important characteristic is their marginal cost of zero. Most of the costs of the renewable energies are incurred at the time of construction. Even if the variable costs are zero, the builder of the plant needs to amortize the investment, and usually pays interest from debt which was used to build the plant, so the market prices have to be high enough to make the investment worthwhile.

All these characteristics result in a great volatility for the electricity price depending on the amount of sun and wind generation. It can lead to prices close to zero or even negative because of the effect of feed in tariffs or the market premium. This can cause losses to the operators of base load power plants which need many hours of operation with high enough prices to amortize their plants.

One of the solutions that is being used to solve these problems is further integration of the European grids. This can help to dampen the variability and the prices, reducing the need for reserves and increasing the supply reliability[5]. The interconnections can help make better use of renewable energy generation in times of low demand in the country they are produced and also complement the different renewable energies that are more prevalent in different countries. The development of High Voltage Direct Current (HVDC) has allowed to transport energy cheaply over longer distances than before such as across the English Channel. The main problem with interconnections are the high costs of the investments to build the transmission capacity.

Storage is another option but for the moment the only economic storage solution is hydraulic pump storage power plants, and the possibilities to build these plants in Europe are quite limited[3].

Weather forecasting can be used to adapt more easily to the quick fluctuations in production. With wind generation of below 5% of the demand forecasting is not considered to be necessary[5]. The better the forecasting tools the lesser reserve power will be needed to provide for network stability. However, the benefits provided by short term forecasts will only be meaningful if the network where they are used has short term flexibility.

2.1.1 Pricing mechanisms

A brief explanation of the pricing mechanisms that were introduced to encourage the development of renewable energies is essential to understand why the wind and solar generation is price insensitive and how we will take it into account in our model.

The last version of the renewable energies law in Germany (EEG, Erneuerbaren Energie Gesetz) introduced the Direct Marketing method. Previously, the renewable energies generators had the right to sell their production to the market at a fixed price, which was determined by the law. This is called Feed in Tariff[4].

When using Feed in Tariffs, the network operator is in charge of buying the renewable energy production and paying a fixed price for it. This takes from the renewable energies investors the price risk and the forecasting risk, and these risks are socialized. The price per kilowatt hour paid is being reduced slowly to compensate for the learning curve effects in the cost of renewable energies generation. Flexible caps were introduced, so that every year if the renewables generation target was met the tariffs are reduced depending on how much the target was exceeded, or increased if the target was not met.

The network operator has to forecast the renewable energy production the day before and sell it in the day ahead market in a market price offer. The day of the delivery, the network operator does another forecast and compensates for the difference in the intraday market. The profit or the loss that the network operators make in the marketing of renewable energy production is included in the electricity bill paid by the end consumers. Some energy intensive firms are partly excluded from paying the renewable energies surcharge.

With the introduction of the Direct Marketing, the operators of existing power plants have the option of selling their generation directly to the market. It is mandatory for all new installations bigger than 500 KW and starting in 2016 for those bigger than 100 KW. This was introduced to further integrate renewable energies in the market. Direct Marketing encourages the operators to control their production to make the highest possible profits.

The sellers are compensated with the market premium model. When the operators sell a kilowatt hour to the market they get a market premium dependent on the market price at the moment and the technology used. The size of the market premium has been determined by the feed-in-tariffs given to that technology, the technologies with higher investment costs like solar get higher premiums to encourage their development. The market premium is also financed by the end consumer. The renewable energies subsidies are included in the bills of the consumers, although many industrial consumers have exemptions or reductions. In the year 2014 the renewable energy surcharge stood at 6.24 cents per KWh. It makes up for 22% of the electricity bill.

The feed in tariffs insulate the producers from the fluctuations in the electricity price. The main problem with this is that the renewable energies producers are usually price inelastic, meaning that because they always get the same price they do not care about the market price. This has led to very low prices or even negative in moments of very high renewables generation. While the market premium starts to address this problem, it still offers some protection to the producers against the volatility of the electricity price. That is why the solar and wind generation is price inelastic and that is how we will treat it in the model.

2.1.2 Wind power

Wind power had an installed capacity of 45GW at the end of 2015 in Germany, although its share of electricity production is lower because of the lower number of full load hours compared to conventional power plants (around 18% in Germany for wind compared to 70-80% for Nuclear and Coal). It is the most important renewable energy source in Germany and the one which is growing faster at the moment[8][9].

The wind speed is lowest in southern Germany, higher in northern Germany, especially in the coast, and even higher in the sea. Because of this, most of the generation is concentrated in northern Germany. Some wind farms in the sea are also being developed, called offshore wind farms[10].

Wind energy generation is usually higher during the day than in the night and higher in winter than in summer. Meteorological forecasts can help to predict the wind generation very accurately. The accuracy is 90% within 48 to 72 hours and 95% within six hours[5]. With the increase of the share of electricity produced by wind power, the need of reserves or electricity storage increases. The need of reserves depends on the accuracy of the weather forecasts.

Although offshore wind farms are more expensive than their on shore equivalents they also have some advantages. Wind speed is 70 to 100% higher than in the land. They have higher full load hours, the production is more constant because the wind speed is more constant and the lifespan of the turbines is longer.

The concentration of wind power in northern Germany, while most of the big industrial consumers are in southern Germany is a problem and it requires to further build the transmission network. Very high wind speeds can also be a problem because wind turbines get disconnected when the wind speed is higher than 25 m/s to prevent damage. This sudden disconnection can pose problems for the network stability.

In our model we will use the wind energy production as a fixed time series using the historical generation in 2014. It is the best way to reflect the behavior of the wind energy producers. All the characteristics above mentioned, mainly the non dispatchability and the pricing mechanisms, encourage the operators of the wind turbines to always sell the production to the market when there is wind available, regardless of the price. That is the reason why a fixed time series will be used and no changes will be done to it during this work.

2.1.3 Photovoltaic

Photovoltaic is the second renewable energy source with most installed capacity, 38 GW in 2014, although its energy production is lower than biomass because of the low full load operating hours[9]. The years when more capacity was built were from 2009 to 2012, when the power increased from 10 to 33 GW. Since then, because of the reduction in the subsidies, less new capacity is being added[11].

The production of photovoltaic energy has seasonal variations with a peak in summer, unless it is used in the equator. The generation also fluctuates daily, from dawn to dusk, and lastly depending on weather conditions. Clouds and rain reduce the photovoltaic production. Geographical distribution can help reduce the production volatility.

In contrast with wind power, solar power is more prevalent in south Germany, where the sun radiation is higher. In 2014, Bavaria, with 11 GW, followed by Baden-Würtenberg with almost 5 GW, were the states with more solar power capacity[12].

Solar power generation occurs during peak demand time, so it helps to avoid building more peak power plants.

The main problem with solar power is its high costs. Even if the learning curve effects and economies of scale have reduced the cost of building solar panels much more than it was expected, it still needs higher subsidies than other renewable energies. The low number of full load operation hours is the other main problem[4].

In our model we will use a fixed time series to represent the photovoltaic production, similarly to wind power. The incentives of photovoltaic producers are similar to the ones that wind power producers have and their behavior is similar, producing regardless of the price. The main cause are the pricing mechanisms, both the feed-in-tariffs and the market premium. We will also do no changes to the model for solar power.

2.1.4 Biomass

Biomass is the second most important renewable energy by generation (48.9 TWh in 2014) and the third by installed capacity (6.38 GW in 2014). Its high number of utilization hours explains that it generates more than solar even if its installed capacity is lower[4].

Biomass is biological material derived from living or recently living organisms. In the context of biomass for energy this is often used to mean plant based material, but biomass can equally apply to both animal and vegetable derived material[13].

Biomass has more similarities with thermal power plants than with other renewable energies in its operation. Its generation is restricted mainly by the availability of fuel to operate the plant. As long as there is fuel available, biomass plants operate similarly to base load power plants, the main reason is that the pricing mechanisms introduced to encourage renewable energies protects it from price fluctuations and results on a constant generation during the whole year. That is the main reason why we model biomass in our simulations as a fixed time series.

2.2 Load

Because of the difficult storage of electricity, a big challenge of the electrical system is balancing demand and supply. This is the reason why the reserve market was created, to accommodate sudden changes in demand or supply. This means the generation must be matched to the load, because the load depends on the customer’s actions and cannot be influenced significantly by the network operator. Because of this, the fluctuations of the load greatly influence the electricity market and we will mention its most important characteristics and how we will consider them in our model.

German electricity consumption in 2014 was 576.3 TWh, 3.8% less than in 2013 and a 6.5% decrease since 2008. By 2020, the goal is to reduce the consumption by 10% compared to 2008. This shows that Germany is improving its energy efficiency and that electricity consumption increases less than the size of the economy[4].

The electricity demand in Germany has a strong variation during the day. The demand peaks are reached before midday and in the early afternoon. The peak period is considered from 8h to 20h from Monday to Friday and the rest is the valley period. The difference between peak and through has diminished over the last decades as shown in Figure 1[3].

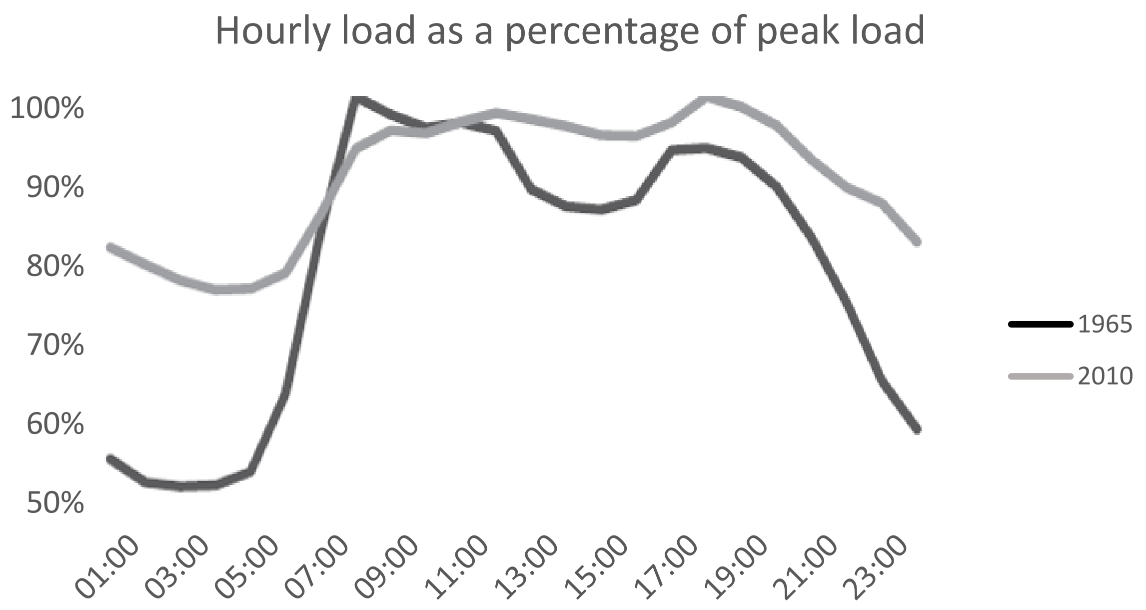


Figure 1 Changes in the load shape [3].

The peak demand in Germany is usually reached in winter, mainly because of lighting demand and power and space heating. 6.1% of Germany's heating is electrical. The peak in 2014 was 84 GW on the 7th of December at 17:00. The lowest demand in 2013 was 32.47 GW in the 2nd of June. This can seem too few compared to the 183 GW of installed power plant capacity, but excluding renewables whose production is unreliable there are around 90 GW left, so the peak demand can be covered even if the peak happens at a time with low renewable energy production[4].

Half of the electricity consumption in Germany comes from big industrial consumers. The other half is divided roughly equally between residential consumers on one hand and small industrial consumers and businesses on the other hand. Residential consumers make up the biggest group by number. The German retail energy sector has a low level of market concentration, with the four biggest suppliers having a 45.5% percent of the market, the rest are supplied by publicly owned *Stadtwerke* or smaller suppliers[4].

Consumer electricity prices of electricity have risen steadily in Germany in the past years both for retail customers and industrial customers because of the increase in taxes, levies and the renewable energies surcharge. Retail customers paid an average of 29.13 ct/KWh in 2014 out of which 13.87

cents were related to the electricity supply, 6.24 cents belonged to the renewable energies surcharge and the rest were taxes and levies. Industrial customers have exemptions in some taxes and the renewable surcharge so their prices can vary between 10 and 17 ct/KWh[4].

The electricity demand reacts in a very limited way to price changes; we can say it is almost price inelastic. The reason is that consumers have no incentive to react to price changes, because their real time electricity consumption cannot be measured and the bills they pay do not depend on the hour when the electricity was consumed. The daily fluctuation of demand, combined with the difficulty of storage, prevents the power plants from being used continuously. The minimum demand that has to be supplied all day long is called base load. The rest of the demand is called peak load. This influences the optimal composition of the power plant park. The base load is usually supplied by power plants with low variable costs and high fixed costs like nuclear plants and lignite plants while the peak load is supplied with plants that have lower fixed costs and higher variable costs. All of this influences the supply curve, called merit order, where each power plant bids at its marginal costs and depending on the demand, which we assumed almost inelastic, the price is determined[3].

A further factor to take into account is the technical requirements of the power plants. Demand can sometimes endure steep gradients which the power plants will struggle to supply and that can lead to a high price volatility. Power plants have limited power gradients, minimal power production and minimal start up and stopping time. All these limitations influence the behavior of prices in the short term. When under fast price changes, some power plant operators may decide to offer their electricity at a price below their marginal costs, if they think that because of the technical limitations of the power plant it suits them to have losses for a short time instead of shutting down the plant for a longer time. In extreme cases this has led to negative prices.

The problem of forecasting demand combined with its low elasticity requires a flexible and diversified power plant park in order to reduce the price volatility. Renewable energies make more difficult matching demand and supply. Before, the load was not controllable but the supply was. But now, the renewable energies make the supply more volatile, hardens balancing demand and supply and increases the need of reserves.

One of the solutions for this is demand side management. It is a way for the utilities to match the demand and supply curves and change the shape of the demand curve to reduce costs. This reduces the need for power plant capacity and can help reduce the costs of the electric system. The main way utilities can achieve this is by using smart meters, which can measure at what time the consumer used electricity so they can be billed according to the market prices. The objective is to use market prices as a signal for consumers to switch their consumption to lower price times. Studies show that smart meters also reduce electricity consumption by 5% approximately[14].

In our model we will also treat the demand as a fixed time series. Even if some ways to encourage demand response to price are being considered and researched, they are still at an infant stage. Smart meters in particular will only be adopted by particular groups of customers following a cost benefit analysis that concluded they were not worth the cost for most of them [15].

2.3 Thermal power plants

Thermal power plants make up the backbone of the German electricity generation. Most of the not renewable energy generation is carried out by thermal power plants. Their share of the total capacity is higher than 50% [4].

The main types of fuel used in thermal plants are lignite, hard coal, nuclear elements, natural gas and oil. Depending on the type of the turbine they are divided in steam turbines and gas turbines. Gas turbines use only oil and natural gas while steam turbines also use coal and nuclear elements, usually uranium. Combined cycle power plants combine the characteristics of the two types. Each power plant type has a different role in the electricity supply. Lignite and nuclear plants fulfill the base load function, hard coal middle load and gas turbines peak load. Base load power plants have lower variable costs and higher fixed costs; the opposite is the true for peak load power plants. Base load power plants have very slow starts while peak load power plants are much faster [2].

The main characteristic of the thermal plants is that they are dispatchable, meaning their generation can be controlled and its operators can react to changes in electricity prices, although with some technical limitations in their operation.

Thermal power plants are divided in independently operated blocks. Each block has technical limitations that we need to take into account in our model. Each block can be in two states, operating or stopped. If it is operating, the power attained is limited by the maximum power and the minimum power. The minimum power is usually 20-50% of the maximum power and it needs to be respected to operate the block safely. While stopped, the power is zero[2].

The operation of the blocks is also limited by the minimum operating time and the minimum stopping time, the change between two states cannot be done very often. Typical amounts for big steam power plant blocks are five hours when in operation and eight hours when stopped.

The power gradient is a further limitation for power plants blocks. It depends on the type of the turbine, the steam generator and the steam circuit. Gas turbines can sustain the highest power gradients, and can reach full power in a few minutes starting from null. Big power gradients should be avoided in order to increase the life expectancy of the equipment.

The unavailability of thermal power plants has a great influence in their operation. The availability ratio is the amount of time that a power plant is able to produce electricity divided by the amount of time in the period. This ratio oscillates between 70% and 90% for thermal power plants. It takes into account the time when the power plant can produce electricity, not how many time it is actually operating. The reliability of the power plant depends of the type of fuel, the size and how it is operated. Usually newer power plants have higher availability ratios because of the improved technology. Bigger plants also have a slightly higher availability[16].

Peak power plants usually show very high availability ratios, close to 100%, because their low usage reduces the need for maintenance.

Power plants accidents require the network operator to activate the reserves. The effect of the accidents on the market price can be very different depending on the time of the accident. If it happens in winter when there is strong demand, the price will increase more than in summer.

Unavailability is divided in two types, planned and unplanned unavailability. Planned unavailability has to be communicated more than 4 weeks before it will happen. Unplanned unavailability cannot be postponed or only up to 4 weeks. It is subdivided in postponable and not postponable. Postponable unavailability can be postponed from 12 hours to 4 weeks while not postponable can be postponed less than 12 hours[17]. External causes that prevent the power plant from supplying energy, like a fuel shortage, do not count towards unavailability.

Because of the importance of thermal plants in the overall electricity market in our model they are represented by agents who decide individually about the amount of their production and whether to sell it in the spot market or to participate in the reserve markets. The above mentioned limitations in their operation are incorporated in the model.

The main part of the thermal power plants model will not be changed, it will still be an agent based simulation. However, the unavailability of these power plants will be changed. Previously, our model used stochastic data to model this. This data was produced assuming an average unavailability value for each technology type and then a statistical distribution was generated. This data will be substituted with the historical data obtained from EEX webpage https://www.eex-transparency.com/. This data is presented in a per unit basis, meaning that every accident or maintenance of each power plant will be used. We will study the effect on prices when using the new data.

2.4 Hydroelectric power plants

Hydraulic power is only a small part of the German electricity market, due to the small technical potential that Germany has. It had a capacity of almost 4 GW and generated 20.8 TWh in 2014. Still, it has a great importance in particular for their storage capabilities. The main types are running water, dams and pumped storage power plants [4]. The main characteristics of the hydraulic power plants that affect the market price are:

High availability, caused by the purely mechanical nature of the power plants which reduce the possibilities of accidents and the need of maintenance. Because of this we will not model the hydroelectric power plants unavailability.

High flexibility, the limitations that hydraulic power plants have are lower than in the thermal plants because of the lack of thermal gradients. They can be started very quickly and reach maximum power in two minutes approximately. The minimum operating time and stopping time are lower than in thermal plants and they do not restrict their operation significantly. Storage power plants, which make up most of the hydraulic power plants, are used usually for peak load and for the reserve market because of their flexibility, and the installed power is big compared to the produced electricity.

Hydroelectric power plants have close to zero marginal costs, except for pumps which can have grid connection costs. Still, the opportunity cost of using water is more important than the marginal costs. This is a limiting factor inexistent for thermal plants. While running water power plants cannot control their output, dams allows the power plant to reduce its dependence on water supply. The generation can be made independent of the supply up to a certain point, dependent on the size of the storage and the water flow. Hydraulic plants have to try to use their water when the prices are high and pump water back up when the prices are low. Managing the water reserves is more important than the marginal costs in the operation of hydraulic power plants [2].

The stored water has an upper limit, namely the size of the dam and a lower limit that should not be surpassed to avoid damage to the turbines by sand. The water flow through the turbines is also limited by the technical specifications of the turbine. The water supply of hydroelectric power plants is often interconnected. This is an issue that has to be taken into account because the availability of water in one plant may be dependent on the generation of other power plants.

Some hydraulic power plants are used as pumped storage plants. They are the only economical energy storage available at a grid level and they make up for 99% of the world wide bulk storage. These power plants sell their production at peak load and then pump the water up to the storage lake when the prices are low. An overall efficiency of both cycles of about 70-80% can be obtained. Their economical use is limited by high costs and can only be built in certain locations [2][18].

In a similar way to the thermal power plants, hydraulic power plants are represented with agents in the model. The limiting factors described above are taken into account. Their bidding behavior under water restrictions is a very important factor in their modeling and is also included. No changes will be made to the hydraulic system model.

3 Model comparison

The main change we are going to do in our model is related to the downtime of thermal power plants. The previous model that was used for the simulations was based on historical values for each technology type and it was generated stochastically. The new data we are going to use is the real historical data of unavailability for each power plant in 2014.

We will only model the unavailability of thermal power plants. Hydraulic power plants have a much lower need for maintenance and its availability ratios are close to 100%. For renewable energies the unavailability is modelled implicitly in the generation time series.

First of all, we will analyze the stochastic model, and then we will see which differences the historical model presents.

3.1 Stochastic model

The data used in this model was generated stochastically, meaning randomly. For each technology type, an unavailability factor was assumed on a monthly basis. Then, the revisions would be generated randomly for each power plant based on the unavailability factor for its technology.

This model only uses the planned unavailability, because we will simulate the day ahead market and the reserve markets. Were we to simulate the intraday market, we would also use the unplanned unavailability. We will first look at the data on a monthly basis in Figure 2 and Table 1.

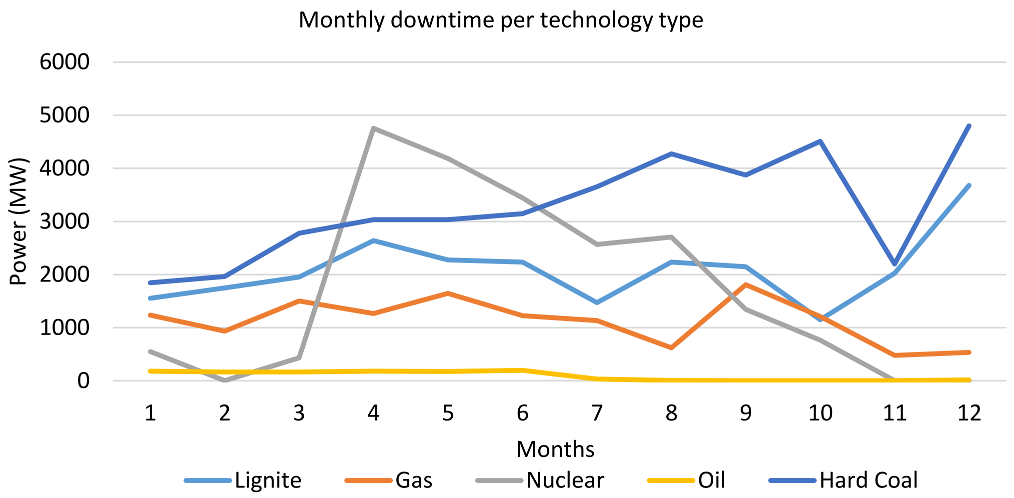


Figure 2 Monthly average unavailability (planned)

Average unavailable power (GW)

	Months											
Fuel type	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Lignite	1.6	1.8	2.0	2.6	2.3	2.2	1.5	2.2	2.1	1.1	2.0	3.7
Gas	1.2	0.9	1.5	1.3	1.6	1.2	1.1	0.6	1.8	1.2	0.5	0.5
Nuclear	0.6	0.0	0.4	4.8	4.2	3.4	2.6	2.7	1.3	0.8	0.0	0.0
Oil	0.2	0.2	0.2	0.2	0.2	0.2	0.0	0.0	0.0	0.0	0.0	0.0
Hard Coal	1.8	2.0	2.8	3.0	3.0	3.1	3.7	4.3	3.9	4.5	2.2	4.8
Total	**5.4**	**4.8**	**6.8**	**11.9**	**11.3**	**10.2**	**8.9**	**9.8**	**9.2**	**7.6**	**4.7**	**9.0**

Table 1 Monthly average unavailability (planned)

In this model, higher unavailability occurs in the months from April to September, with December as an outlier. These results are based on an assumption consistent with the usual operation of power plants. The lower demand for electricity in summer encourages the power plants operators to schedule the maintenance of the power plants in summer. In the model, the biggest value, 11.87 GW is 2.5 times bigger than the lowest, 4.7 GW in November. The higher unavailability in December is explained by the higher maintenance during the holidays.

While all of the plant types follow this pattern, the nuclear power plants have the strongest variations, with a downtime of 4756 MW in April and 0 in February, November and December. In Table 2 we show the yearly averages of each technology type.

Fuel type	**Yearly average (MW)**	**Total power (MW)**	**% of total power**
Lignite	2094	21250	9.85%
Gas	1134	28930	3.92%
Nuclear	1736	12070	14.38%
Oil	93	5480	1.69%
Hard Coal	3272	26190	12.49%
Total	**8328**	88440	9.42%

Table 2 Unavailability as a percentage of the German power plant in 2014

The highest value is hard coal, with a yearly average of 3272 MW. Oil power plants stand out because of their low downtime, caused by the low number of oil power plants in operation and their low usage reduces the need for maintenance. Even if hard coal had the highest average downtime in megawatts, nuclear had a higher percentage compared to the total of nuclear power plants. Oil downtime is very low, while lignite and hard coal had intermediate values.

The data for gas turbines is lower than what it would be expected. The real unavailability is usually higher than the values we used in this model, only 3.92%. This difference is explained because of the different modeling of Combined Heat and Power (CHP) in our program. Anyway, the influence of the unavailability of gas turbines is lower because of their lower usage, as they are peak load power plants. The unavailability of big base load power plants has a bigger influence in the prices than the values for peak power plants.

The unavailability also has weekly oscillations as seen in Figure 3.

Figure 3 Weekly average of the unavailability

The unavailability is higher during the weekends and slightly higher on Fridays. This is explained by the lower load and prices that encourage the power plant operators to schedule the unavailability in those periods. Figure 4 shows the weekly variation of the load that explains this variation of unavailability.

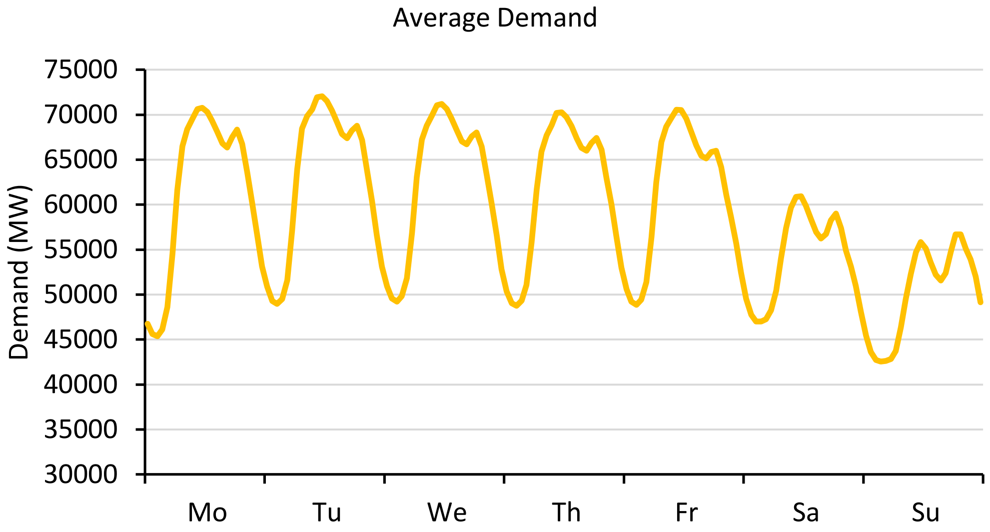


Figure 4 Average weekly demand (2014)

The load is markedly lower on weekends, with Sunday morning having the lowest load of the week. The average in the weekend is 52195 MW compared to 61920 MW during the week.

If we look at the per unit data for each technology type:

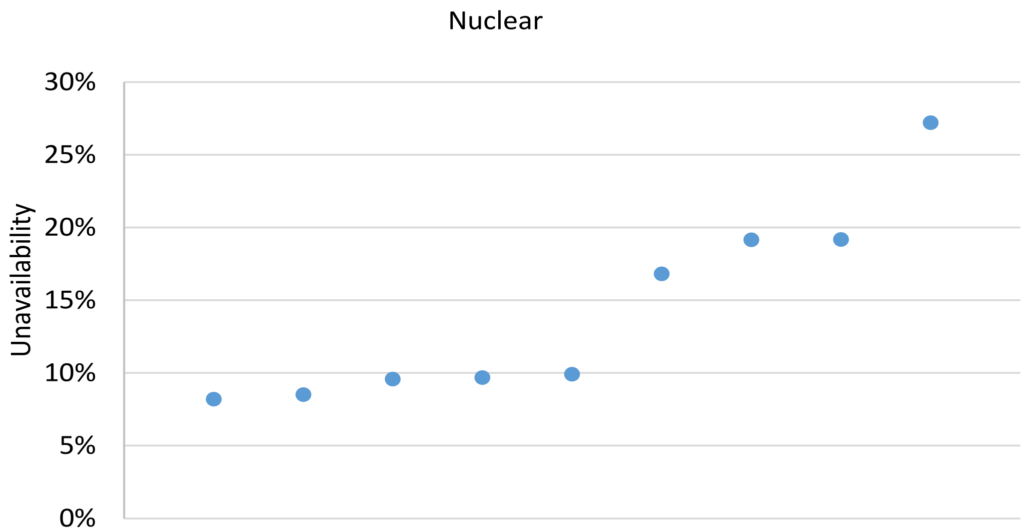


Figure 5 Nuclear plants unavailability per unit

As shown in Figure 5, there is not a big variation in nuclear power plants, all of them are in the 7%-30% interval.

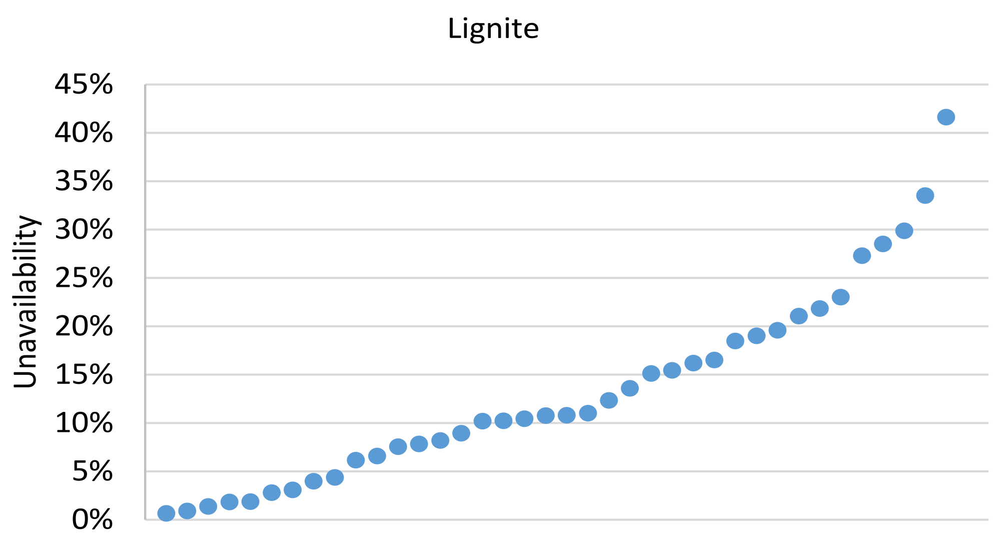


Figure 6 Lignite power plants unavailability

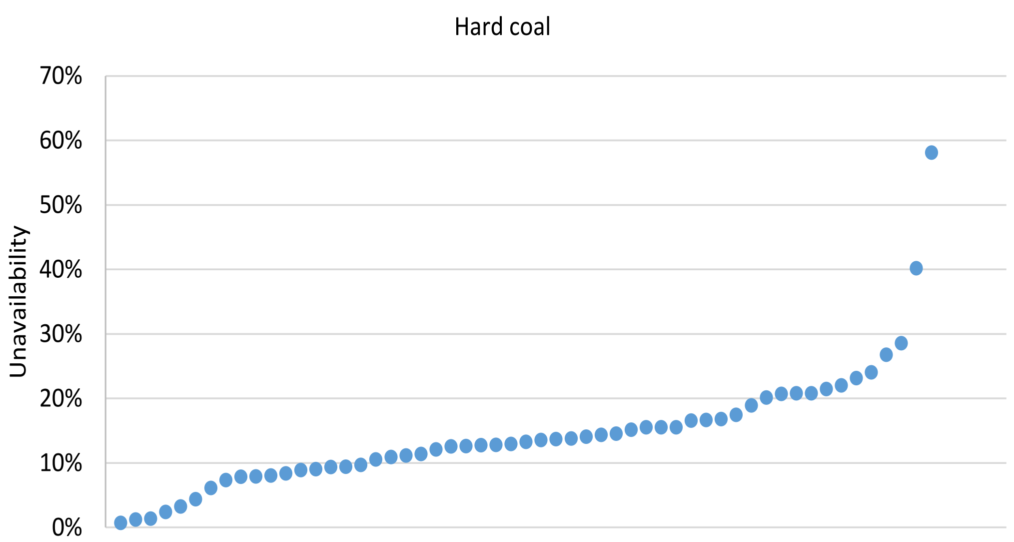


Figure 7 Hard coal power plants unavailability

Figure 6 and Figure 7 show the unavailability of hard coal and lignite. The stochastic method generates random values near the average for the technology type. If we include more values, we will have more that are further away from the average. That is why the nuclear plants have a lower variation of unavailability than lignite power plants and they, in turn, have a lower variation than hard coal plants.

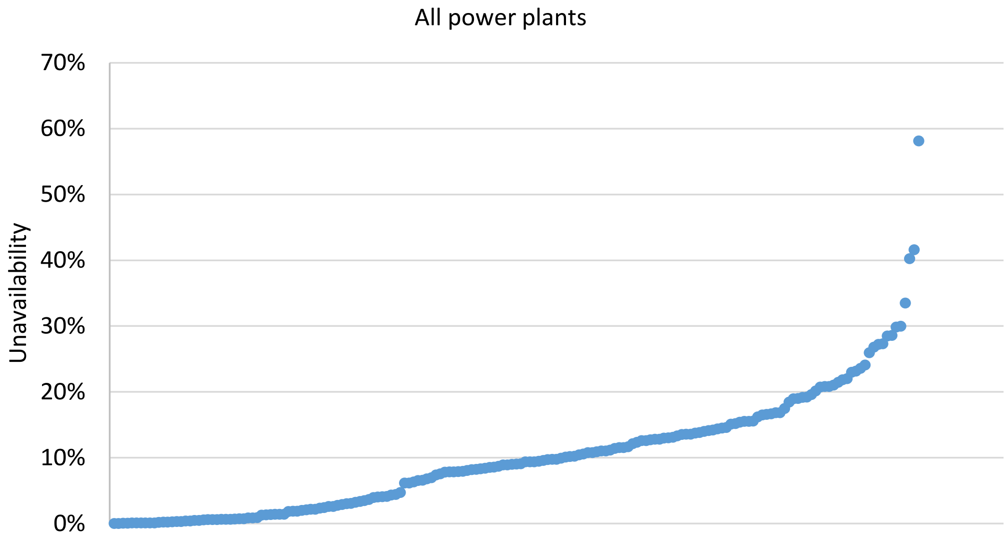


Figure 8 Unavailability by power plant

We can see that most of the data is in the range from 0% to 30% in Figure 8, except from a few outliers that don't surpass 60%. We will compare this data later with the historical per unit numbers.

3.2 Historical model

This data was obtained from the EEX website. As stated there: "The information includes both planned and unplanned unavailability for plants of any size. Every unavailability of at least 100 MW that lasts one hour has to be reported. Every unavailability of more than 10 MW that lasts more than 15 minutes can be reported"[19].

Even though we obtained the data for both planned and unplanned unavailability, we will only use the planned unavailability because we are simulating the day ahead market. Still, looking at the unplanned unavailability helps us understand planned unavailability better. Like we did with the stochastic data we will first look at the monthly averages in Figure 9.

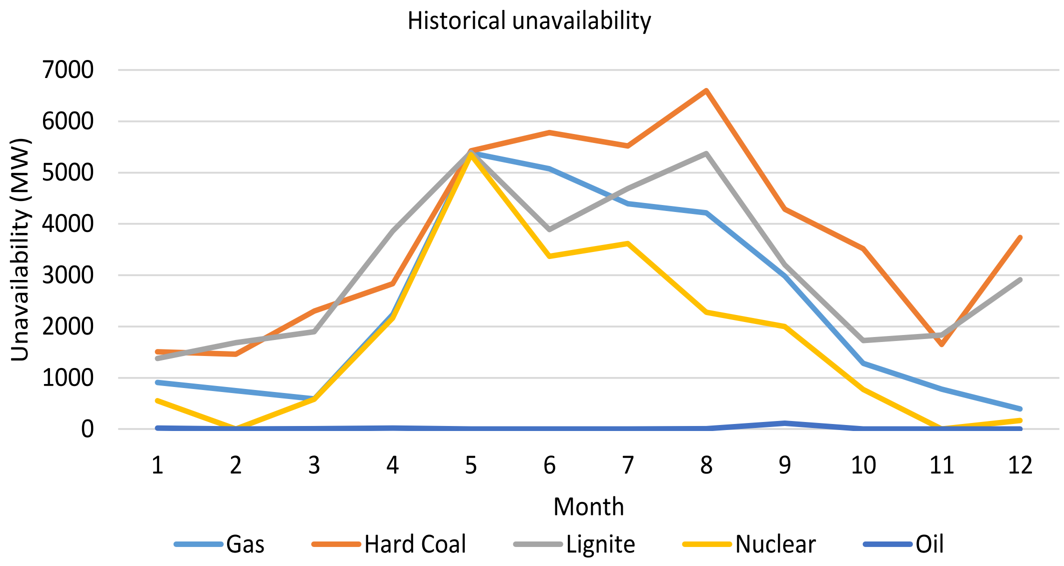


Figure 9 Historical unavailability (total)

We include the total unavailability; the unplanned unavailability does not influence significantly the monthly variation.

As we look at the historical data, our previous assumption that maintenance is higher in summer is proved. The variation is even bigger than what we assumed in the previous model as it can be easily seen in the graphic. The month with the greater number of plants in downtime was May with 21.6 GW followed by August with 18.5 GW. The months with lower unavailability were February with 4.7 GW and January with 5 GW. The difference between the biggest and the lowest amount is 4.6 times, compared with 2.5 times for the stochastic model.

Similarly to the stochastic model, the months from October to March have the lowest unavailability, with an average of 5.52 GW compared to the average of 16.7 GW from April to September. December is also a bit higher than the other winter months in both models. December is an outlier, explained by the winter holiday which is a period with low prices when some power plant operators schedule their maintenance.

Even if all the technology types have a big monthly variation, the highest value being about four times the lowest value, nuclear power stands out as the technology with the starkest differences. Nuclear power plants were very reliable in the months with higher load, most of their downtime was planned for the summer months. In February, October, November and December the unavailability was negligible. As we can see in Table 3, this can be explained by the low proportion of unplanned unavailability to planned unavailability of nuclear power plants.

Fuel type	Planned	Unplanned	Total	Unplanned/total
Gas	7.60%	1.12%	8.72%	12.9%
Hard Coal	11.21%	3.06%	14.27%	21.4%
Lignite	12.85%	2.04%	14.89%	13.7%
Nuclear	13.81%	0.70%	14.51%	4.8%
Oil	0.07%	0.49%	0.56%	87.5%
Total	10.85%	1.90%	12.75%	14.91%

Table 3 Planned compared to unplanned unavailability

Nuclear power plants are the most reliable, their ratio of unplanned to total unavailability is the lowest of all the technologies at 4.8%. This increases the system stability because planned unavailability has to be communicated at least four weeks before it happens. It also allows the market participants to anticipate the reduction of generation of nuclear power plants, which are quite large, and adjust their generation accordingly. It also encourages the operators of the nuclear power plants to schedule most of the maintenance in summer when the load is lower. Hard coal power plants have the highest ratio at 21.4%.

We will now analyze the differences between each technology type in each model. In order to compare both models we use the planned unavailability, which is the only data used in the stochastic model.

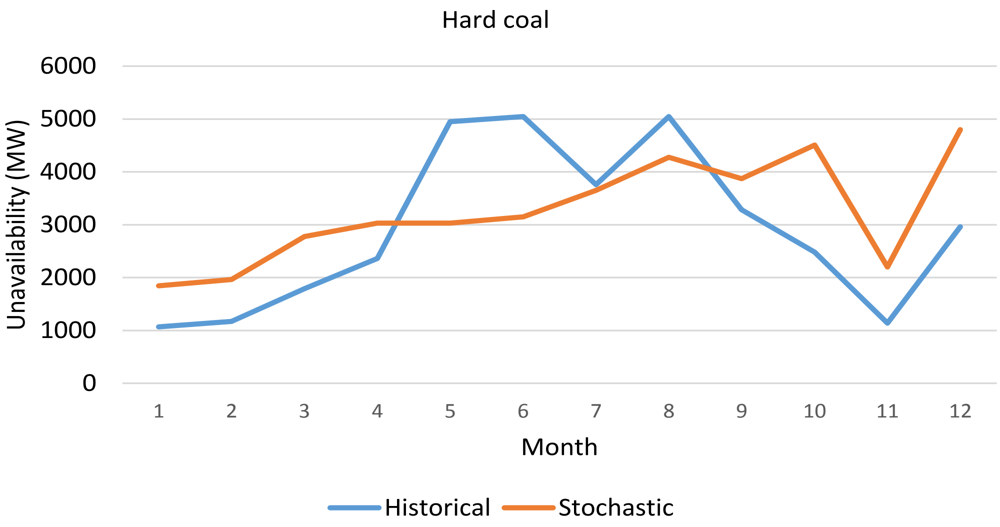


Figure 10 Hard Coal unavailability

In hard coal (Figure 10), we can appreciate the bigger monthly variation in the historical model compared to the stochastic model. The yearly averages are not very different.

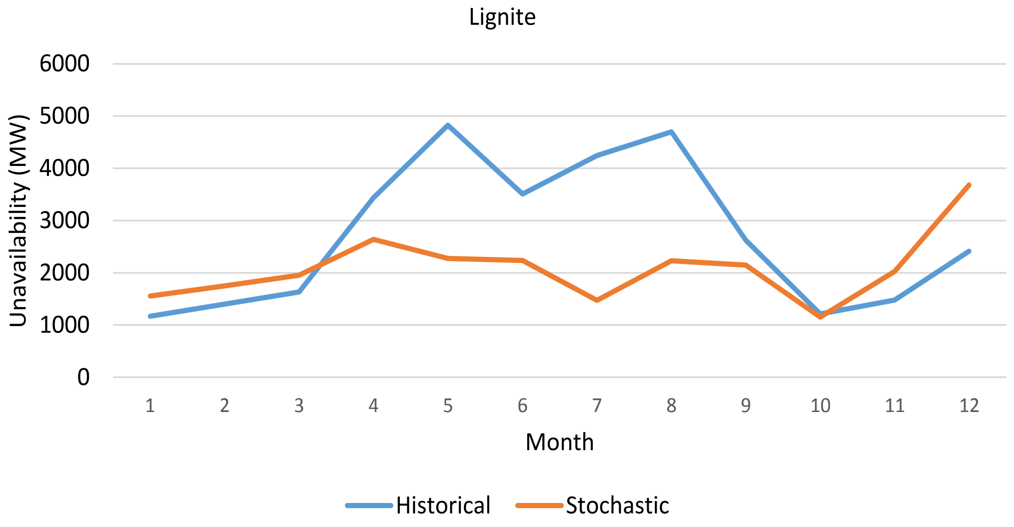


Figure 11 Lignite unavailability

For lignite the historical model also presents a higher variability, and the overall values are higher than in the historical model (Figure 11).

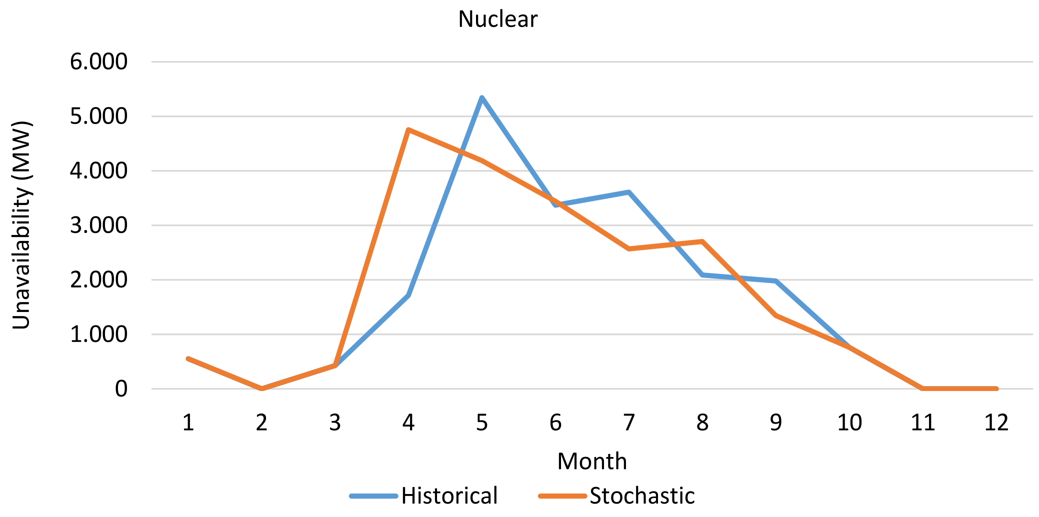


Figure 12 Nuclear power plants unavailability

Figure 12 shows that the data from both models is very similar. There were 8 nuclear power plants in Germany in 2014, all of them with a power ranging from 1200 to 1400 MW. These plants usually have maintenance once every year of about one month where the generation is stopped completely.

When this maintenance is done has a big influence in the market because of their size, and it is usually done in the months from April to September, when the load is lower. Both models have one month with a very large value, April in the stochastic and May in the historic model. The rest of the values are very similar, with unavailability decreasing steadily from the peak month until it reaches a null value in November. The low value of unplanned unavailability keeps the total unavailability extremely low in winter, when the load is higher.

We will now compare the yearly averages per technology type in Table 4.

Type		**Yearly average (MW)**	**% of total power**
Gas	New	2198	7.60%
	Old	1134	3.92%
Hard Coal	New	2935	11.21%
	Old	3272	12.49%
Lignite	New	2731	12.85%
	Old	2094	9.85%
Nuclear	New	1666	13.81%
	Old	1736	14.38%
Oil	New	4	0.07%
	Old	93	1.69%
Total	New	9599	10.9%
	Old	8328	9.4%

Table 4 Yearly averages comparison (planned)

The yearly average is higher in the historical model than in the stochastic model. The stochastic model yearly average is 8.3 GW compared to 9.6 GW for the historical model. Most of that increase, 1.1 GW, comes from the gas turbines due to the changes in the CHP. Hard Coal is 300 MW lower in the new model, nuclear power is very similar with only a difference of 70 MW and Lignite is 600 MW higher in the new model. Still, both models have values that can be expected from the historical behavior of the technologies. The average values of the models are very similar, the biggest variation comes with the gas turbines because of other changes in the model. The differences in nuclear and lignite largely balance each other. It is worth mentioning the sharp yearly variation, which is even bigger than what was assumed in the stochastic model.

In Figure 13 we look at the weekly average of the unavailability.

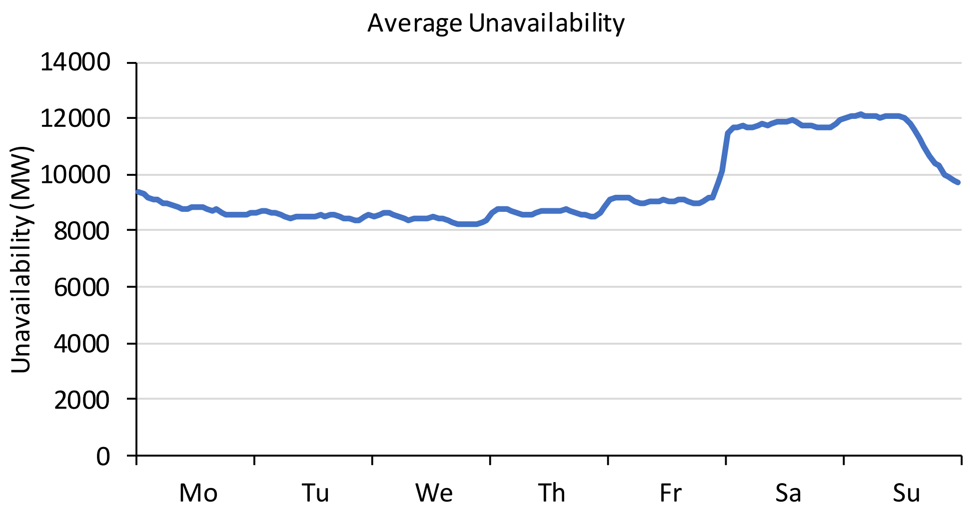


Figure 13 Average unavailability on a weekly basis

The unavailability is usually higher on weekends, 11570 MW on average compared to 8715 MW during the week. The variation of the unavailability in the historic model is relatively lower than in the stochastic as we see in Table 5.

	Week (MW)	Weekend (MW)	Weekend/Week
Historic	8715	11570	1.33
Stochastic	6643	10446	1.57

Table 5 Comparison of the weekly variation

Now analyzing the per unit values in Figure 14:

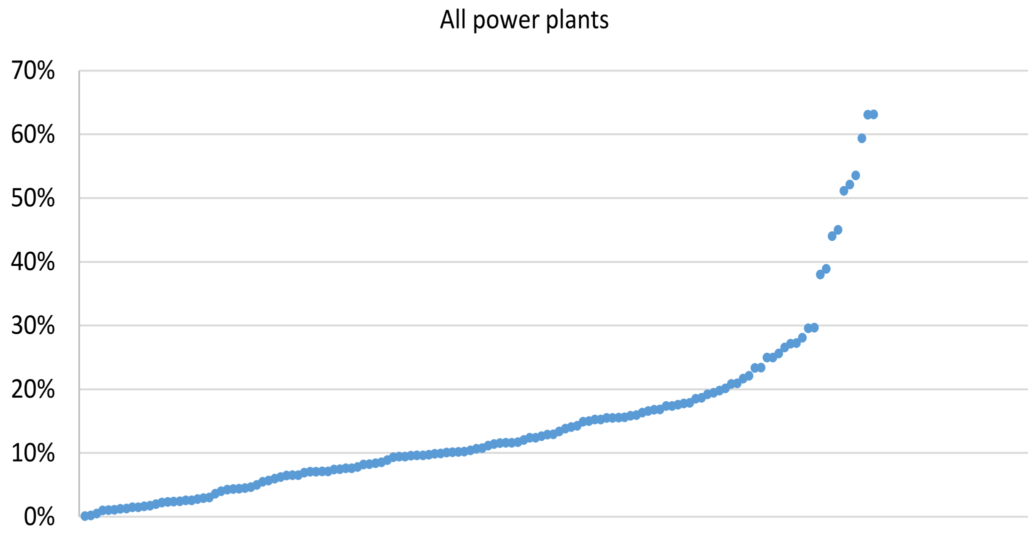


Figure 14 Unavailability in each unit

Most of the values are in the same range as the values in the stochastic model, in the 0-30% range. But the number of outliers over 30% is bigger, 10 in the historical compared to 4 in the stochastic model.

	Nuclear	Lignite	Hard coal	Gas	Total
Standard deviation (stochastic)	0.067	0.098	0.093	0.059	0.092
Standard deviation (historic)	0.060	0.085	0.119	0.181	0.128

Table 6 Standard deviation of the unavailability

The standard deviation, shown in Table 6, is higher overall in the historical model. We can say that the statistical distribution generated for the old model was more concentrated next to the average than it really happened in reality. Still, the historical model has a slightly lower standard deviation for nuclear and lignite. Hard coal has a higher standard deviation in the historical model, as well as gas turbines.

An interesting analysis is looking if there is a relation between power plant size and unavailability holds true like we mentioned in 2.3. We look at the relationship between these two variables in Figure 15 distinguishing by technology type.

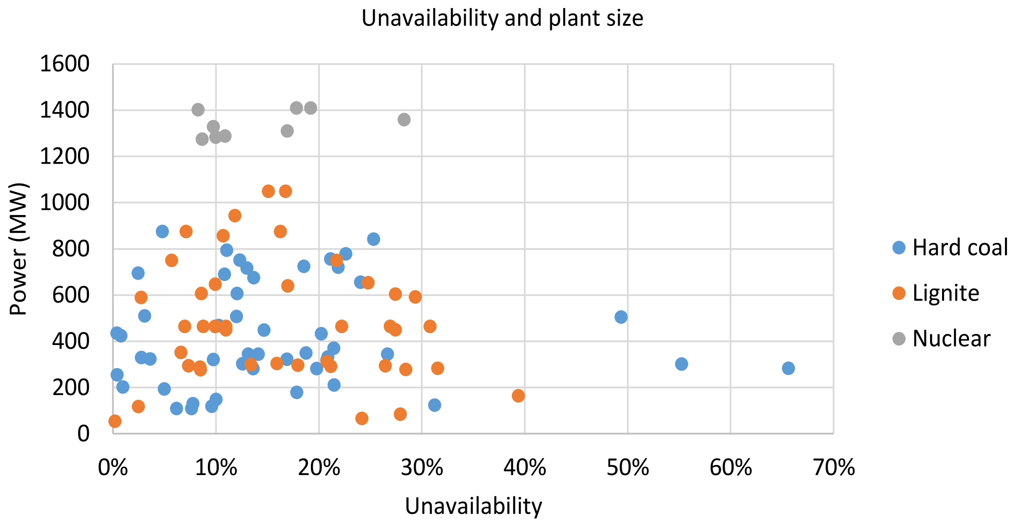


Figure 15 Unavailability compared to power plant size (nuclear, lignite and hard coal)

We only take lignite, nuclear and hard coal because they are the technology types with comparable values. Most of the power plants are in the region from 0 to 30% unavailability irrespective of size. The few outliers with higher unavailability have relatively low power but not extremely low. Even if the data does not prove this correlation, the data of one year is not enough to prove it, taking into account the low amount of data, mainly with the bigger power plants. An analysis over several years would be necessary.

4 Investigation results

4.1 Price analysis

The data that we will analyze under several viewpoints is the day ahead spot market price. These are hourly prices, meaning we have 8760 data for the whole year. We will also study how strong is the influence of the data of the new model in the price.

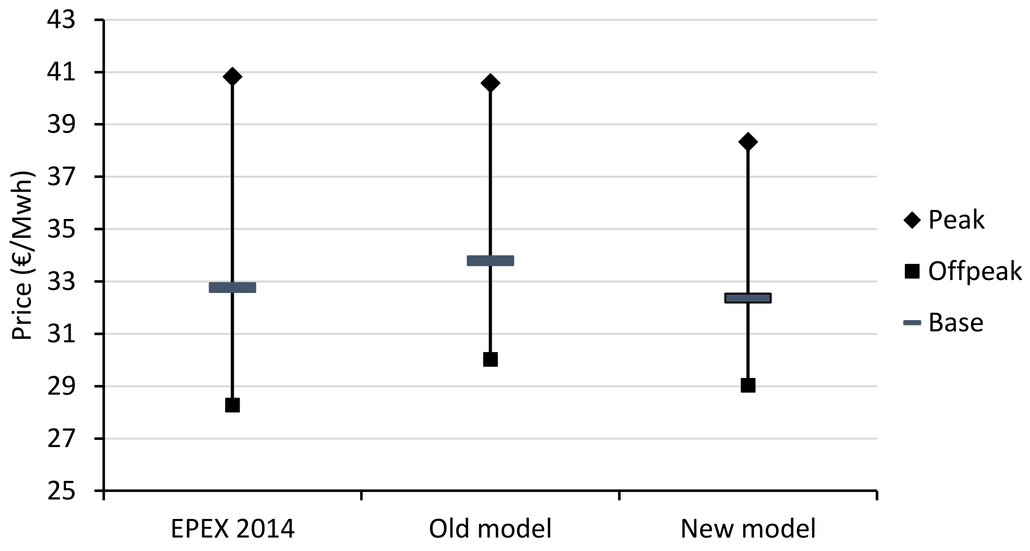


Figure 16 Base, Peak and Off peak prices

Figure 16 shows the average peak, off peak and base prices for the two models and the historic prices. The new model has an average price closer to the historic price than the old model. The historic average was 32.76 €/MWh compared with 33.8 in the old and 32.36 in the new model. On average, the prices are lower in the new model than in both the historic prices and the old model. Off peak values have an improvement too, the new model gives 29.04 €/MWh compared to 28.27 in the real data. The peak values are much lower though, this was better represented by the old model.

Figure 17 shows the weekly averages of the price. Analyzing the weekly averages is interesting in order to see how well the model performs in each day of the week. As we saw in Chapter 3.2, the demand is very similar from Monday to Friday, while it is lower on Saturday and even lower on Sunday.

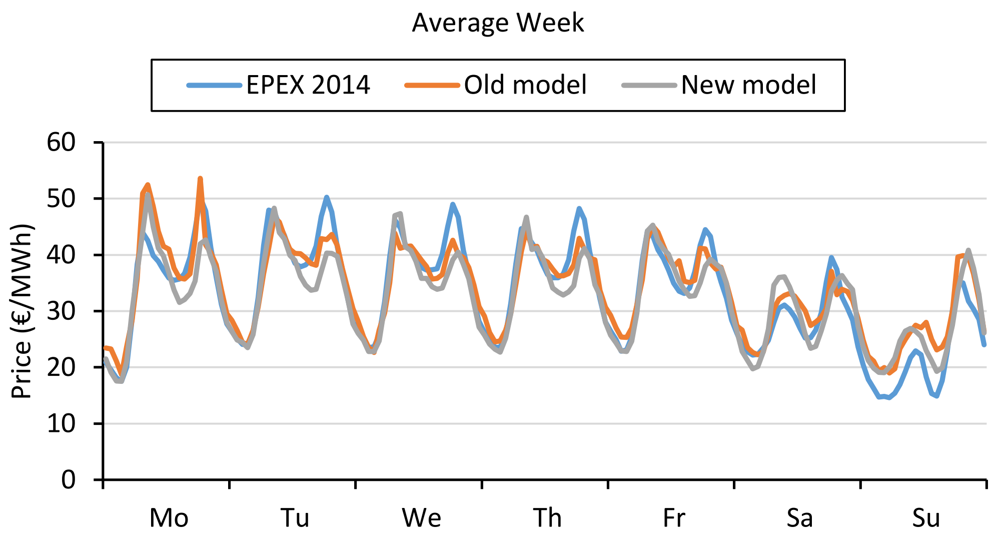


Figure 17 Average weekly price

The data from the new model is better than the old in some days and worse in others. The best improvement happens in Sundays, where both models are still above the historic data.

We will now look at the duration curve (Figure 18). This is a graph that orders the prices from highest to lowest. It is a good way to check if the distribution of the prices is similar in the models. While it does not take into account when those prices occurred, it is unreasonable to expect the model to produce the exact same values in the same time periods, especially the price spikes. But it is useful to check if the model produces a similar amount of prices in each price range.

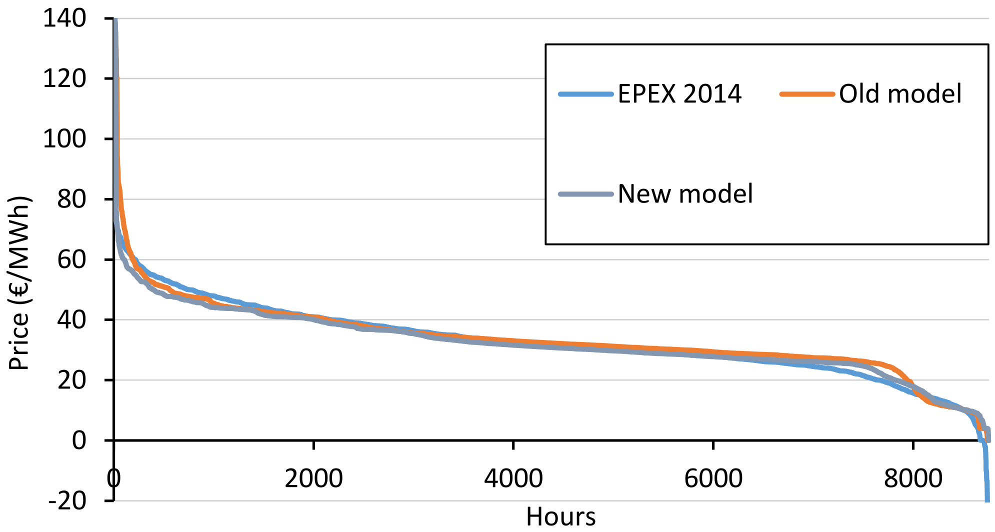


Figure 18 Duration curve

Most of the curve is fitted very well by both models but some parts fit better than others. We show some parts of the curve with greater detail. The middle range of the curve is the part that is approximated better:

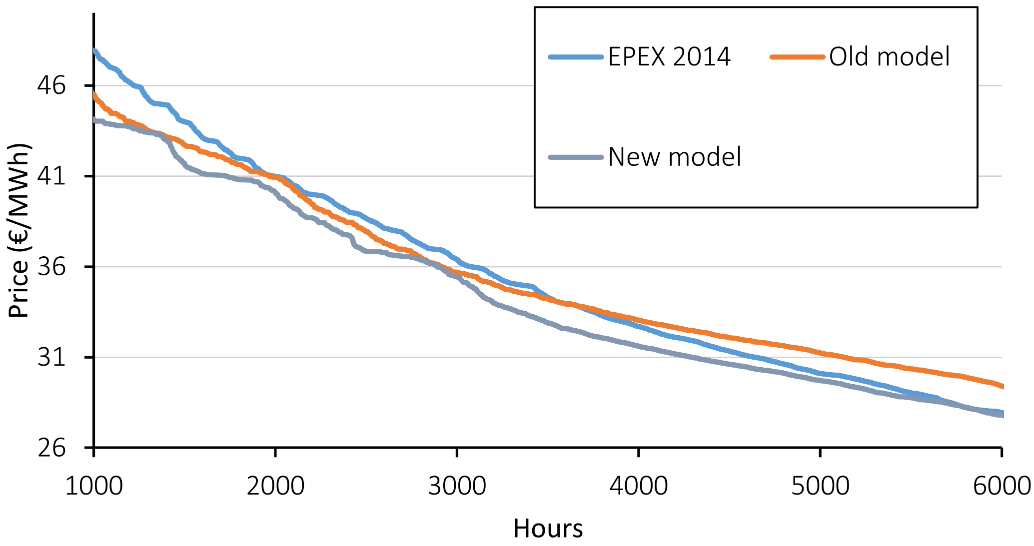


Figure 19 Duration curve from the 1000 to the 6000 hour

Both models perform similarly, with the historical better in the lower prices and the stochastic better with higher prices. This part makes up most of the year, 5000 hours out of 8760, 57% of the year. The new model is most of the time below the historical prices, like we observed in the average values.

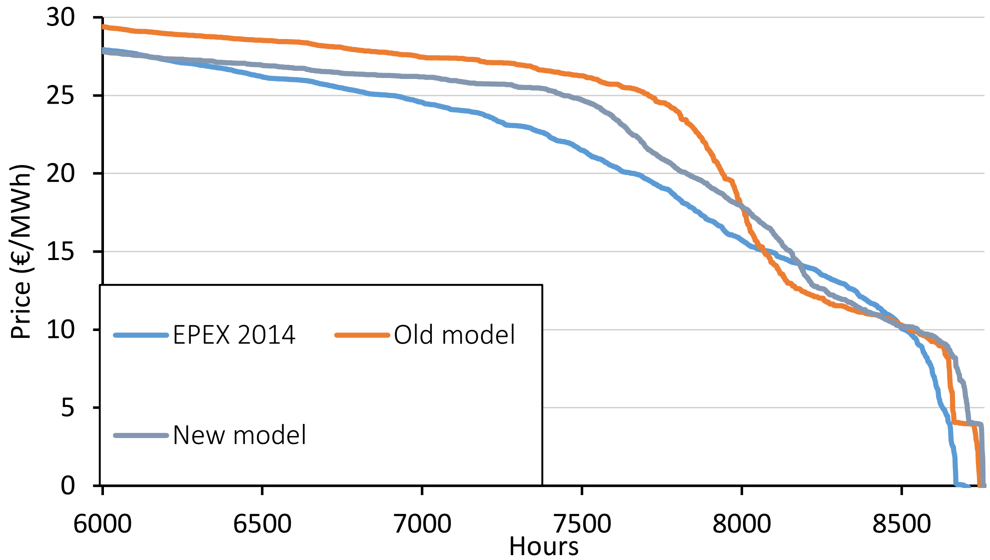


Figure 20 Prices from the hour 6000 until the 8760

The prices from the hour 6000 until the end were approximated worse with the old model, the new model gets closer to the historic values but it is still does not decrease fast enough. These lower prices are related to the lowest weekly prices which usually occur on Sundays and the new model approximates these values better than the old.

It is in the extremes of the curve where there are more differences between the model and the historical values as we see in Figure 21 and Figure 22.

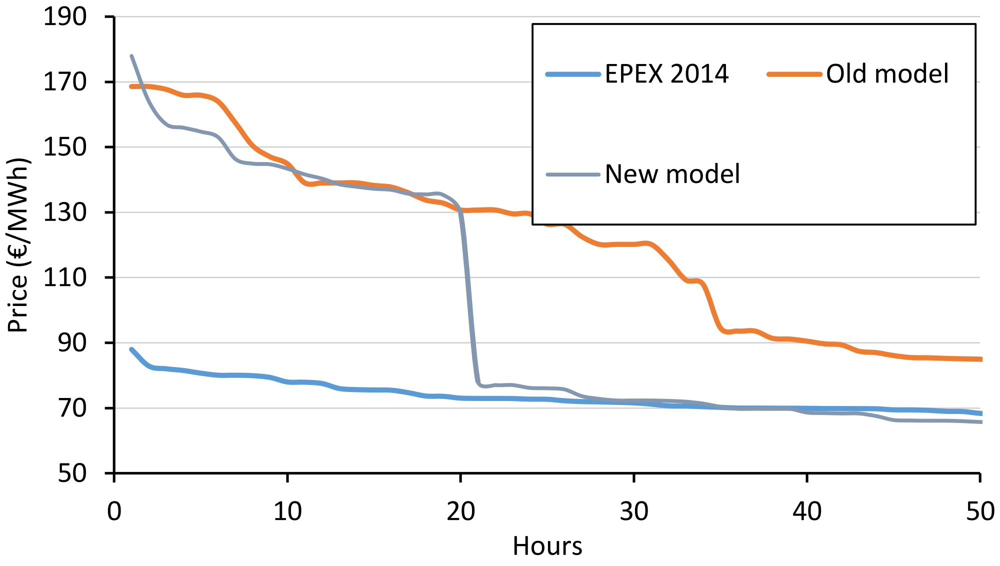


Figure 21 Highest prices of the year

Both models produce more price spikes than in reality. In fact, in 2014 there were not any prices above 90€/MWh while the old model generated 31 and the new, 20. While extremely high prices (higher than 100€/MWh) have been observed a few times, like 389.44 €/MWh on 25/07/2006, they are not that common to appear 20 times every year. We will look in Table 7 at what causes these high prices in the new model.

	Demand (MW)	Unavailability (MW)	PV (MW)	Wind (MW)
Peak	68485	8663	7453	5911
Base	59150	9528	3818	6062
Off peak	53955	10009	1795	6146
Average for prices higher than 90	68943	12636	4086	2247

Table 7 Factors that generate the highest prices

For the average of the 20 highest prices we have a load with a value usual for a peak load, while the unavailability is very high, higher than the values that would be expected for off peak. Solar power generation was average while wind was very low. While the unavailability usually occurs in the valley period, when there was a coincidence of high demand and high unavailability the price had a higher chance of shooting up. The price spikes do not necessarily occur at the same time that it did in the old model, the average prices in those same hours were 55.7 €/MWh for the old model and 47.04 for the EPEX prices. These differences between the models are probably caused by differences in the operations of the power plants and because of their limitations. Still, these prices do not have a great effect, as they are a small proportion of all the prices in a year.

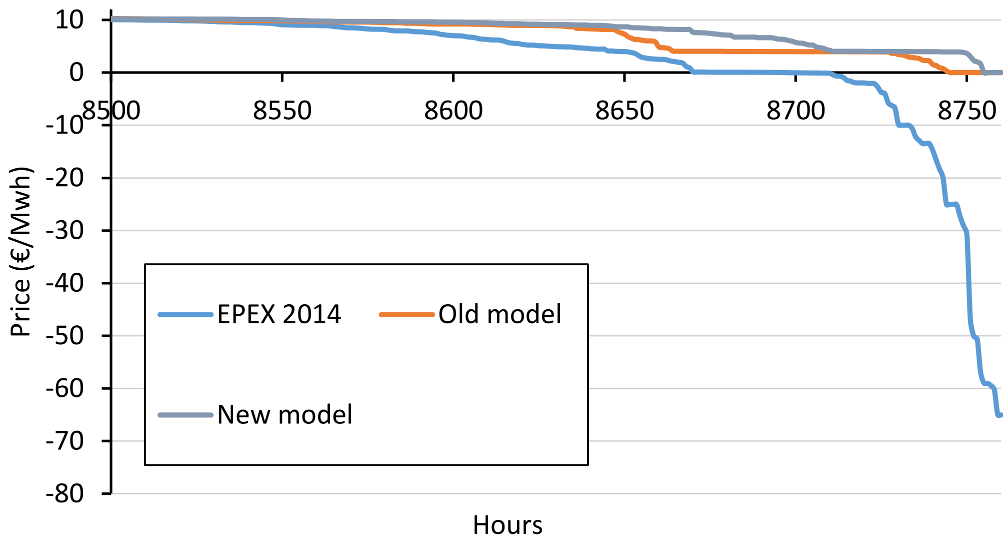


Figure 22 Lowest prices of the year

None of the two models can generate negative prices. Some of the costs power plants operators incur when shutting down their plants are not included in the models, and this prevents negative prices from appearing because the agents of the model can stop production while not incurring these costs while in reality they maybe would have continued selling electricity even at negative prices because it was the most economical choice. Like we did with the high prices, in Table 8 we will look at what values the parameters of the model had in these hours. There were 64 negative prices in 2014 which makes them bigger in number than the very high prices produced by the models.

	Demand (MW)	Unavailability (MW)	PV (MW)	Wind (MW)
Peak	68485	8663	7453	5911
Base	59150	9528	3818	6062
Off-peak	53955	10009	1795	6146
Negative prices average	49011	9650	3520	21471

Table 8 Factors that generated low prices

The negative prices were generated in periods with low demand and extremely high wind generation. The yearly average wind generation is 6 GW. While the maximum wind generation in 2014 was 28.28 GW, the wind generation only surpassed 20 GW in 290 hours of the year. The averages of the prices for the old model and the new model were 6.62 €/MWh and 9.7 €/MWh, respectively. While they were not negative like the historical prices, they were low too. The values of the unavailability and solar generation at those times were average.

Negative prices usually happen several hours in a row as we see in Table 9, usually getting more negative before they return to positive. This can also be explained by the technical limitations of the thermal power plants, the big ones in particular.

Date		EPEX 2014	Demand	PV	Wind
16/03/2014	00:00	-0.02	47819	0	20570
16/03/2014	01:00	-25.08	46129	0	21316
16/03/2014	02:00	-25.06	44584	0	21549
16/03/2014	03:00	-60.26	43819	0	21584
16/03/2014	04:00	-50.65	43969	0	21696
16/03/2014	05:00	-50.12	43832	0	21674
16/03/2014	06:00	-25.08	43668	26	21608
16/03/2014	07:00	-25.00	45676	236	21498
16/03/2014	08:00	0.05	48876	623	21619
16/03/2014	09:00	10.77	51989	1234	22168

Table 9 Eight hours of negative prices

These eight hours of negative prices were caused by a low demand (that day was a Sunday), combined with a very high wind generation. The situation got worse when the load decreased at 3:00 and the prices only increased above zero in the morning when the load started increasing again. The wind generation stayed almost constant during this interval, unaffected by the negative prices. The unavailability did not have a big influence.

4.2 Regression analysis

Now we will analyze the correlation between the load and the prices for the historic values and the new model in Figure 23 Historic prices compared to the load and Figure 24.

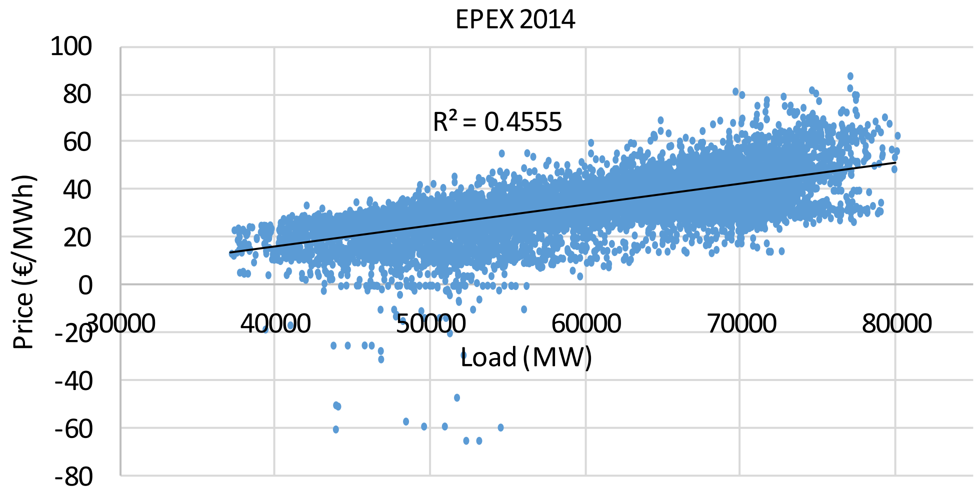


Figure 23 Historic prices compared to the load

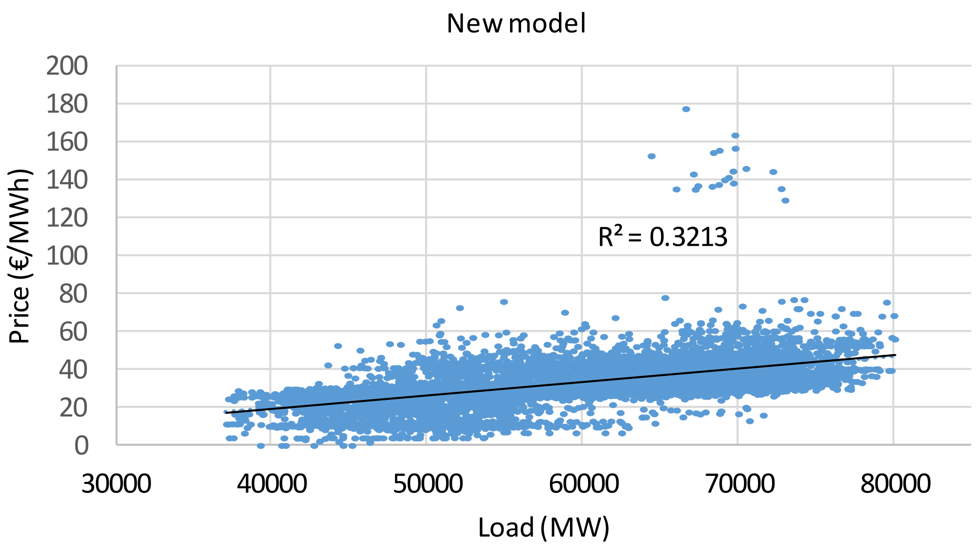


Figure 24 New model prices compared to the load

The correlation between the load and the price is significant, and it is higher in the historic prices than in the results of the simulations. The very high prices in the new model and the very low historical prices fall well outside the linear relationship. This reminds us of the low elasticity of the load, which reacts in a very limited way to extreme prices. The load is the parameter that has a biggest effect in the price when looking at them separately. The unavailability, we see in Figure 25, does not have such a strong correlation and neither do the wind and solar power generation.

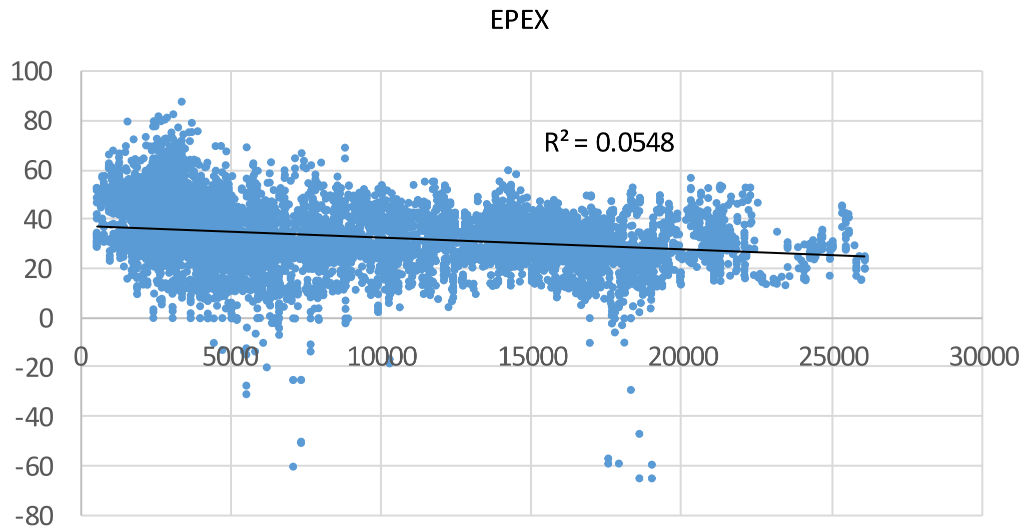


Figure 25 Unavailability compared to historic prices

The correlation between the unavailability and the price is not significant in any of the models nor in the historic prices. In fact, the historic prices were higher in periods of higher unavailability than in periods of lower unavailability. This was probably caused by the power plants operators scheduling their maintenance in periods of expected lower prices and them not causing a very big influence in the market. We will now run a regression shown in Table 10 and Table 11 to see how big their effect is if we consider all the factors at the same time. The variables we will include are solar generation, wind generation, planned unavailability and load.

EPEX 2014

Statistics of regression	
Coefficient of multiple correlation	0.8950
Coefficient of determination R^2	0.8011
Adjusted R^2	0.8010
Standard error	5.6992
Observations	8760

	Coefficients	*Std. error*	*t statistic*	*p-value*
Intersection	-28.99927	0.518571292	-55.9215	0
Solar generation (MW)	-0.00104	1.27594E-05	-81.4074	0
Wind generation (MW)	-0.00121	1.20237E-05	-100.7574	0
Planned unavailability (MW)	0.00023	1.22599E-05	18.8534	9.4275E-78
Load (MW)	0.00120	7.82138E-06	153.1860	0

Table 10 Results of the regression from historical prices

These four factors influenced the historic price greatly, having an adjusted R^2 of 0.8. Higher unavailability and load provoked higher prices while solar and wind generation reduced prices. The relationship with the load is much stronger than with the unavailability, with coefficients of 1.2E-03 and 2.3E-04 respectively. The coefficients of wind and solar generation are similar in absolute value to the coefficient of the load but with opposite sign. The p values of the four variables are almost zero, meaning we can assume that a correlation exists.

In chapter 2 we explained why we decided to represent both the load and the renewable energies generation as a fixed time series. When we look at their coefficients we can see that their effect is very similar (although with the opposite sign for the renewable energies) and justifies our decision. Their small price elasticity makes them extremely important to determine the price. On the contrary, the unavailability, the planned in particular, is scheduled to try to avoid big effects on the prices.

The independent term is negative, as it has to compensate the values of the load which are always positive and has an average of around 59 GW during the year. Now we will look at the new model, shown in Table 11.

Statistics of regression	
Coefficient of multiple correlation	0.7367
Coefficient of determination R^2	0.5427
Adjusted R^2	0.5425
Standard error	7.9776
Observations	8760

	Coefficients	*Standard error*	*t statistic*	*p-value*
Intersection	-25.34071	0.72588283	-34.91019	4.127E-250
Solar generation (MW)	-0.00075	1.786E-05	-42.03793	0
Wind generation (MW)	-0.00076	1.683E-05	-45.06066	0
Planned unavailability (MW)	0.00058	1.7161E-05	33.83363	6.122E-236
Load (MW)	0.00101	1.0948E-05	92.08819	0

Table 11 Regression of the new model

The new model has a lower correlation between these factors than the historic prices. The coefficient of the unavailability is much higher, 5.8E-04 compared to 2.3E-04 while the other coefficients are lower. The intersection is higher, probably influenced by the lack of negative prices of our model although those prices are far from the regression line.

5 Conclusions

The electric sector is undergoing intense changes in order to increase the share of the generation by renewable energies. The spot market is at the center of this transformation. Its role is extremely important to balance demand and supply; the prices are a signal to market participants to increase or reduce their production. The effects of the steadily increasing renewable energy generation are already getting reflected in the behavior of the market price, even though renewable energies still do not account for the majority of the generation. Negative prices, for instance, cannot be understood without knowing the important role that renewable energies play. The prices also give the necessary incentives to market participants so they can adapt to the changes in the future electricity markets.

The importance of the spot market led us to develop a model to simulate its behavior. This would be useful to forecast the effect on electricity prices produced by different changes in the electrical sector, like an increase of the renewable energies generation. The objective of this work was to improve the model to simulate the prices of 2014. The main parameters we used were the thermal and hydraulic power plants, the load and the renewable energies generation. Both the thermal and hydraulic power plants were modeled with agents while the load and the renewable energies generation were modeled with a fixed time series of the values of 2014.

In this work, we modified the model for the unavailability of thermal power plants. The model that was used for unavailability previously was generated stochastically assuming average values for each technology type. This was substituted by a model including the historical unavailability from 2014. There are several differences between both models that had an impact on the simulated prices. The unavailability used in the stochastic model is lower on average than the historical unavailability. The monthly distribution is also different, the historic model has a much bigger monthly variation, with the highest values concentrated in the months with lower load and prices. The last thing to note is that the historical model has a higher variation of unavailability in a per unit basis than the distribution generated in the stochastic model.

These differences in the models had effects on the prices. The higher average unavailability would be expected to produce higher average prices. However, the prices produced with the new model were lower rather than higher. This could be explained by the different monthly distribution, with the higher prices decreasing more than the increase of the lower prices. This is caused by the shape of the merit order curve; whose slope is higher in the part with higher prices. Both the base and the off peak prices are, on average, closer to the historical with the new model. The peak values were approximated better with the stochastic model though; they are too low with the new model.

The central part of the duration curve is already simulated fairly well by both models. The lower prices generated by the new model help to fit better the part from 6000 to 8760 hours. The new model also had an effect on the range of higher values. The different distribution of the unavailability could explain the reduction in the number of price spikes, decreasing the number of hours when both the load and the unavailability are high and the renewable energy generation is low. At the other side of the price range, negative prices still cannot be properly simulated, further limitations and economic costs in the operation of the thermal power plants that are not considered in the model would need to be added.

A multivariate regression was run to estimate the influence of the parameters on the price, mainly the unavailability, load and renewable generation. The correlation of these parameters with the historic price was very high, with an adjusted R^2 of 0.8. The new model had a lower but still significant correlation of 0.54.

Unavailability had the lowest effect of the factors considered. This can be explained because the unavailability, unlike other factors, is planned by the plant operator to occur at a convenient time and must be communicated four weeks before it will happen. This means it is more price elastic than the other factors. It is much more controllable and predictable, and as we observed the unavailability tends to be planned to occur in periods with lower prices. This is why the effect of unavailability on prices is lower than the other much more unpredictable and uncontrollable factors. Because of its low price inelasticity, the load and the renewable energies generation are modeled accurately with a fixed time series and the correlation with the price is high. In fact, the value of the coefficient of the regression is very similar in absolute value for the load and the renewable energies. This could change in the future if the price volatility and the negative prices encourage the load and the renewable energies generation to become more price elastic. For instance, the market premium model for remuneration of renewable energies which was recently introduced could increase their price elasticity. Smart meters could also increase the flexibility of the load.

References

[1] T. BRANDT, Liberalisation, privatisation and regulation in the German electricity sector, Wirtschafts- und Sozialwissenschaftliches Institut (WSI), 2006.

[2] A. MOSER, Stromerzeugung und -handel, IAEW der RWTH Aachen, 2015.

[3] B. LIEBAU, Der deutsche Strommarkt: Marktdesign und Anbieterverhalten, Westfälischen Wilhelms-Universität Münster, 2012.

[4] Agora Energiewende, "Report on the German power system," 2015.

[5] International Energy Agency, Variability of wind power and other renewables.

[6] D. A. HALAMAY and A. SIMMONS, Reserve Requirement Impacts of Large-Scale Wind, Solar and Ocean Wave Power Generation, 2011.

[7] International Energy Agency, "Projected Costs of Generating Electricity".

[8] EWEA, Wind in Power, 2015 European Statistics, 2015.

[9] FRAUNHOFER INSTITUTE, "Electricity production from solar and wind in Germany in 2014," 2014.

[10] J.P.Molly, "Status der Windenergienutzung in Deutschland," DEWI GmbH, 2011.

[11] Bundesministerium für Wirtschaft und Energie, "Zeitreihen zur Entwicklung der Erneuerbaren Energien in Deutschland," 2016.

[12] Bundesnetzagentur, "EEG in Zahlen 2014," 2014.

[13] Biomass Energy Centre, "http://www.biomassenergycentre.org.uk," [Online].

[14] C. a. T. J. McKerracher, " Energy consumption feedback in perspective: integrating Australian data to meta-analyses on in-home displays.," *Energy Efficiency,* vol. 6, no. 2, pp. 387-405, 2013.

[15] European Parliamentary Research Service, "Smart electricity grids and meters in the EU member states," 2015.

[16] UNIPEDE Network of Experts for Statistics, "Thermal Generating Plant (100 MW+) Availability and unavailability factors," 1998.

[17] VGB PowerTech, Terms of utility industry, 2008.

[18] "Packing some power," *The Economist,* 3 5 2012.

[19] "EEX Transparency," [Online]. Available: https://www.eex-transparency.com/.

[20] Eurelectric, Hydro in Europe: Powering Renewables.

List of figures

List of tables