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Abstract

The increasing share of renewable energy systems and decentral electricity generation provides challenges for the energy sector mainly due to their intermittent and unpredictable generation. This results in high costs to guarantee security of energy supply. Also the current electricity market environment is problematic for the direct marketing of decentral energy resources (DERs). By combining different DERs and operating them together, a more stable and controllable electricity output can be achieved. The increased controllability helps to support their market integration. The aggregation of different decentral energy resources is often referred to as "virtual power plants".

To quantify the added value of combining DERs into a virtual power plant, a short term optimization model for the spot market Day-Ahead was designed. It is based on two-stage stochastic programming and provides optimal decisions under uncertainty considering different scenarios of stochastic processes. A risk measure is implemented that provides the possibility to set different risk preferences. The spot market price Day-Ahead, imbalance price and the output of the wind power plants are stochastic parameters in the optimization model and approximated with a finite number of scenarios. The stochastic solution is around 8 % higher compared to the deterministic solution, where stochastic processes are expressed by their respective expected values.

Scenarios are generated via multivariate autoregressive time series analysis regarding the influences between time series on each other. It turns out that spot market prices and the difference between realized and predicted wind generation (wind error) have impacts on the imbalance price. The forecast tool provides acceptable root mean squared errors (RMSE). The imbalance price has a rather high RMSE due to its unforeseeable nature. Therefore a conservative offer strategy penalizing deviations between contracted and delivered energy is chosen. Via the optimization model the performance of the participating energy units is evaluated in separate and joint operation. Thereby the added value of forming a VPP is assessed. The virtual power plant consists of wind power plants, combined heat and power plants and temporarily controllable loads. The joint operation of DERs provides a better performance by creating a more stable generation output in comparison to separate operation. Thereby imbalance costs of intermittent generation can be reduced. The added value is in the range of 4-41 %.

Kurzfassung

Der steigende Anteil erneuerbarer Energien und dezentraler Erzeugungsanlagen (DEA) stellt hohe Herausforderungen an den Energiesektor. Durch volatile und schwer zu prognostizierende Erzeugung fallen beträchtliche Kosten an, um Versorgungssicherheit zu gewährleisten. Darüberhinaus ist das Marktumfeld relativ unattraktiv für die Direktvermarktung von DEA. Durch Kombination mehrerer DEA in einen Analgenverbund kann ein ausgewogener Betrieb erreicht werden, was die Netz- und Marktintegration von DEA erleichtert. Dieser Anlagenverbund wird oft als "virtuelles Kraftwerk" bezeichnet.

Um den Mehrwert des gemeinsamen Bertiebs zu evaluieren, wurde ein Optimierungs-Modell für den Day-Ahead Spot Markt erstellt. Es basiert auf stochastischer Programmierung und stellt ein Werkzeug für Entscheidungen unter Unsicherheit dar. Unsicherheit wird über verschiedene Szenarien stochastischer Eingangsdaten abgebildet. Diese stochastischen Prozesse sind Day-Ahead Spot Preis, Erzeugung aus Windkraftwerken und der Ausgleichsenergiepreis. Die stochastische Lösung ist um 8 % höher als die deterministische Lösung, bei der die stochastischen Prozesse durch ihren Erwartungswert angenähert werden. Die Szenarien werden mittels multivariater autoregressiver Zeitreihenanalyse erzeugt. Damit werden die Dynamiken und Abhängigkeiten in den Zeitreihen mitberücksichtigt. Es zeigt sich, dass sowohl der Day-Ahead Preis, als auch der Windvorhersagefehler den Ausgleichspreis beeinflusst. Das Vorhersagemodell ist akzeptabel und erstellt plausible Szenarien der stochastischen Eingangsdaten mit einem akzeptablen mittleren quadratischen Fehler (RMSE). Es fällt auf, dass der RMSE des Ausgleichsenergiepreises relativ hoch ist. Darum wurde eine eher konservative Bieter-Strategie gewählt, die Abweichungen zwischen plazierten Marktgeboten und Erzeugung bestraft. Mit dem Optimierungs-Modell wird der separate und gemeinsame Betrieb der DEA verglichen, um den Mehrwert zu quantifizieren. Das virtuelle Kraftwerk besteht aus Windkraftanlagen, Kraft-Wärme-Kopplung und steuerbaren Verbrauchern.

Der gemeinsame Betrieb der DEA in einem virtuellen Kraftwerk führt zu Synergieeffekten und erhöhter Steuerbarkeit. Damit können Ausgleichsenergiekosten volatiler Erzeugungsanlagen vermieden werden. Es ergibt sich ein Mehrwert zwischen 4-41%.

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1 Introduction

1.1 Motivation

Over the last years the share of decentral generation (DG) units is constantly rising. DG is a general term that comprises mainly small scale and geographically distributed energy devices like volatile renewable energy systems (RES), co-generation units for a combined heat and power supply (CHP) and small run-of-river hydro power plants (HPP), just to name a few. In Germany and Austria especially the increasing share of RES like photovoltaic systems (PV) and wind power plants (WPP) has significant consequences on the energy sector due to their volatile, weather dependent electricity production. RES are supported by several countries in the European Union via special incentive programs like feed-in tariffs to comply with climate and emission targets. The support schemes for RES are time limited (around 10 - 20 years depending on the specific country) and gradually reduced in order to make RES ready for participating in conventional electricity markets. After a certain time (depending on the countries, Austria/Germany) RES facilities have no privileges anymore and they are confronted with the same market situation like other market participants, i. e. conventional power plants. One key prerequisite for electricity markets is the match of supply and demand of electricity. Usually operation schedules are created for the specific generation units which have to be complied with. Otherwise compensation payments have to be paid to make good for the costs caused by those deviations. Energy producers with a high share of RES are faced with many challenges when leaving the “secure” support schemes and entering the energy market environment:[1] [2]

- In order to participate in certain electricity markets, several criteria regarding minimal offer size and incremental offer changes have to be fulfilled, representing difficulties for small scale DG units.
- Mainly due to the stochastic output of WPP and PV (because they depend on the actual weather) there is a significant risk of not meeting bilateral contracts or trades made on electricity markets, which could result in significant compensation payments for not delivered energy.

[1] Saboori, Mohammadi, and Taghe (2011), p.2
[2] Pandžić, Kuzle, and Capuder (2013), p.134f

- Operators of DG often do not have the required know-how to enter those markets.
- Considerable fixed costs (like annual fees or pre-qualification of energy units) have to be paid to gain access to energy markets.
- Many DG units are operated as stand alone units usually by different operators, mainly providing regional energy supply, compensated by feed-in tariffs without communicating with other units to use synergy effects for market or grid integration.

Besides energy generation units also the involvement of the demand side is a heavily discussed topic in the energy sector. Concepts focusing on electricity customers are typically summarized under Demand Response (DR). DR can be defined as *"changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."*[3] Electricity consumers that feature an electricity consumption pattern that can react to market signals or can be directly controlled within technical limits, have the potential to balance supply and demand of electricity. Different DR customers are usually managed by an aggregator that brings the DR service to market. Different ways to integrate DG and DR into the energy system are discussed in literature. In this context an often discussed approach is the integration of DG and DR into a "Virtual Power Plant" (VPP). A VPP aggregates many different DG units, creates a single generation profile similar to conventional central power plants. The joint operation of many DG units in combination with DR and electrical storage systems in a VPP increases their controllability and therefore grid and market integration. From market view the VPP acts as one entity although in reality it consists of many units combined through an adequate IT infrastructure. [4] A VPP provides the possibility to harness synergy effects and reduce market barriers for DG. There are different ways of benefiting from the flexibility potential of a VPP from an economic as well as technical point of view. Concerning market issues VPPs can minimize or diversify risk and overcome market barriers. Energy producers with a well balanced portfolio can hedge themselves against variable outputs of RES by integrating them into a mix of conventional power plants and energy storage systems. Costs of not meeting contracts on energy markets can therefore be reduced. Those VPPs focusing on market integration of DG are commonly summarized under the

[3] http://www.ferc.gov/industries/electric/indus-act/demand-response/dem-res-adv-metering.asp, accessed on: 13.01.2016

[4] Pandžić, Kuzle, and Capuder (2013), p.134

term “commercial virtual power plants” (CVPP). Usually they focus solely on the economic part. Their typical aim is to maximize benefits from the specific generation and demand portfolio often neglecting electrical network restrictions. The aggregated output of a CVPP is the sum of the participating units and their cost characteristics. It can be marketed at wholesale electricity markets, reduce imbalance costs or provide ancillary services to the Transmission System Operator (TSO).

Besides economic issues, also technical aspects can be addressed by a VPP. Distribution System operators (DSO) are often confronted with grid congestion and voltage violations with an increasing amount of DG. In this context main challenges from DSO view are keeping thermal and voltage limits of the grid equipment (according to EN 50160[5]). These devices, usually located at the same geographical site, can be merged into technical virtual power plants (TVPP) to support local grid operation. The objective of a TVPP usually is to prevent local grid congestion and meet network restrictions of the distribution grid. Recently, concepts combining both the advantage of CVPPs and TVPPs, gain increasing attention. In “hybrid” concepts the VPP can schedule its units in an economically efficient way and participate on energy markets while also taking its impact on the distribution grid into account.[6] [7] A VPP offers many benefits mainly due to the resulting flexibility in contrast to normal, isolated operation. This thesis focuses solely on the market participation of CVPPs. The operation of a VPP on electricity markets is usually subject to uncertain parameters due to the variability of RES and the fact that auctions on electricity markets are usually settled in advance. So, at the time of decision making the real market prices and RES output are not known.

1.2 Research Question

The various potential benefits of the VPP concept should be tested in a real case study to better understand and estimate the economic value of combining different complementary DG and DR units. Therefore, a short term VPP offering model for the electricity spot market was developed. The model aims at finding optimal offer strategies of a VPP operator having dispatchable (controllable) as well as intermittent generation units at its disposal. In this context the value of Distributed Generation as well as Demand Response

[5]http://www.beuth.de/de/norm/din-en-50160/136886057?SearchID=407805367, accessed on 13.01.2016

[6]Peik-Herfeh, Seifi, and Sheikh-El-Eslami (2013), p.89

[7]Koopmann, Nicolai, and Schnettler (2014), p.2

and their contribution to a Virtual Power Plant is analyzed. The units are evaluated by their performance on the spot market Day-Ahead. The market offers made, are created with the help of an optimization model considering uncertain parameters.

1.3 Outline

The structure of the thesis is organized as follows: Section 2 deals with the fundamentals of VPPs, the modeling of different DG and DR units and price-based control strategies. After elaborating on the energy economic background in Section 3 the applied methodology is discussed in Section 4. A central element of the thesis is a stochastic optimization problem taking into account different scenarios to meet the requirements of uncertain input factors. The scenario generation approach is based on time series analysis and described in Section 5. Section 6 deals with the optimization model for a VPP operating under uncertainty. For every DG and DR unit participating, operational constraints are implemented. The optimization model is fed with a case study in Section 6.6 and the results are shown and discussed in Section 6.7. Final conclusions are drawn and further aspects are mentioned in Section 7.

2 Virtual Power Plant

2.1 Definition

Generators (G) and loads (L) of different grid levels (low, middle or high voltage level) are merged together to a Virtual Power Plant (VPP) to get a power plant comparable to conventional ones (Figure 1). This is mainly achieved by adequate information and communication technologies (ICT) that connect the different units to an energy management system (EMS). Thereby an operator can jointly control the VPP units depending on the chosen operation strategy like market or grid participation.

A VPP can consist of all types of energy generation, storage or flexible consumption units. Generally there are no constraints to the installed capacity of the different VPP units. The aim of aggregating different, technically complementary devices in a VPP, is to obtain a better performance compared to separate operation. Thereby a VPP is more reliable, has a higher controllability and a better ability to temporarily change the actual power generation or consumption than the single units.[8]

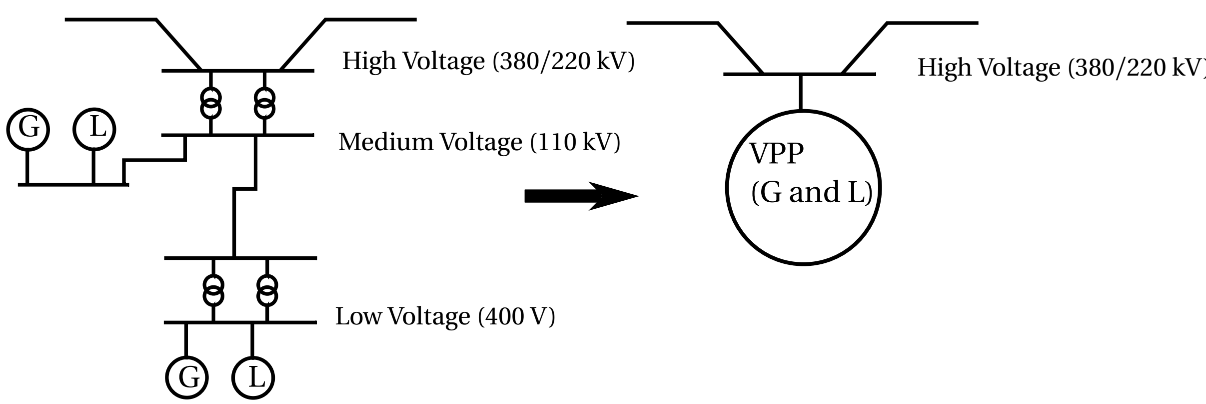


Figure 1: Combining generators (G) and loads (L) of different grid levels in a Virtual Power Plant. (Pudjianto, Ramsay, and Strbac, 2007, p.11)

[8]Steck (2013), p.16

Often the concept of a VPP aims at pooling distributed generation (DG) and Demand Response (DR) to use synergy effects. With the development of large scale wind and photovoltaic plants the term DG refers more to systems where no separate operating schedule (dispatch) can be created because of their volatile output or low installed capacity.[9] Subsequently the terms DG, energy storage systems and DR are summarized under Distributed Energy Resources (DER).[10] [11] *"A [...] VPP aggregates the capacity of many diverse DERs [and] creates a single operating profile from a composite of the parameters characterizing each DER."*[12] This enables trading at wholesale markets and providing ancillary services to the grid. A well balanced combination of different DERs offers synergy effects, by:

- combining different energy systems, like non controllable and controllable ones (e. g. WPP, PV and CHP units),
- using their compensatory effect, e. g. wind power is often more abundant in winter, while PV generates more energy in summer,
- considering geographical aspects and their possibility to even out weather effects on DER,
- including both the producer and customer side by means of generators, energy storage systems and flexible loads via DR,

The next sections mention important modeling issues regarding different VPP units which are later incorporated into a VPP simulation model.

2.2 Modeling Distributed Energy Resources

The diverse energy units of a VPP can be roughly separated in different modeling groups:

- controllable power plants where an operation schedule (dispatch) can be done,
- stochastic generation units that feature an intermittent character depending on weather effects,
- storage systems being able to charge and discharge the storage at other times,

[9] Steck (2013), p.16
[10] Saboori, Mohammadi, and Taghe (2011), p.2f
[11] Peik-Herfeh, Seifi, and Sheikh-El-Eslami (2013), p.88
[12] Pudjianto, Ramsay, and Strbac (2007), p.11

- and flexible customer loads via DR which are significantly influenced by user specific factors.[13]

Dispatchable power plants are typically driven by fossil fuels (gas,oil etc.) or biomass. The output of these generators can basically be controlled as long as technology specific technical constraints are met. Some devices like gas fired power plants are very flexible in terms of load changes, start ups and shut downs. Others like coal fired power plants are more inert, only able to react to changing operation parameters with a higher time delay. Devices that use both the resulting heat and electricity are referred to as CHP units which feature a high efficiency. With CHP plants there exists a direct dependency of heat and electricity production. One output can only be produced in relation to the other. If, for example, heat is the main aim of the co generation process, then a limit is set to the electricity produced by a CHP. The heat and electricity dependency can be reduced by means of a thermal storage tank.[14] Thereby the production of the CHP and the electrical or thermal load can be decoupled providing flexible operation times to react to market prices, to provide ancilliary services and to reduce on and off switches. This is economically more attractive, because start up costs (usually higher fuel consumption during start) and wear of the components (higher maintenance) from many on/off steps can be avoided.[15] CHP systems can be operated in different modes depending on their main objective of use. Typically, a distinction is drawn between heat-controlled and electricity-controlled operation. **Heat-controlled** operation focuses on covering the current heat demand or providing a certain level of an attached thermal storage tank. The heat demand is subject to hourly, daily, seasonal and yearly deviations. Additionally user specific actions can affect the actual heat demand of room heating applications. As a result the actual electricity output of the heat controlled CHP is hard to anticipate. In case the CHP is **electricity-controlled**, the operation is determined by the electricity price and aims at reducing electricity costs or maximizing profits while supplying the needed heat load at the same time. This can either be achieved by selling the produced electricity on electricity markets or by an increased self consumption. The electricity production is thus easier controllable, but from an energy related point of view, the overall efficiency of the system can be lower if the heat output exceeds the required demand. The use of a thermal storage system can reduce this effect by decoupling electricity and heat.[16] Over the last years,

[13] Morales, Conejo, Madsen, Pinson, and Zugno (2014), p.243ff
[14] Bollen (2011), p.53
[15] Bollen (2011), p.54
[16] Steck (2013), p.16

micro CHP systems experienced rising interest in recent scientific works. Usually "micro" refers to small scale CHP systems with rated electric power in the field of a few kW up to 50 kW, but the term lacks a clear definition in literature regarding accurate power capacity.[17] Micro-CHPs are decentral energy generation systems near consumers and often regarded as a vital component for a VPP.

Power plants directly depending on weather effects are assigned to stochastic generation units. Renewable energy resources (RES) typically refer to wind power plants (WPP), photovoltaic systems (PV) and small hydro power plants (HPP). All of them have in common that their output is weather dependent and hard to anticipate. Compared to other renewable energy technologies WPPs have the highest share of electricity produced by variable RES. WPPs feature an intermittent power output depending on the specific wind speeds. Their output is therefore rather not controllable. As electricity markets are usually cleared in advance (see Section 3) fixed operation schedules are desirable which is a real challenge due to the volatility of wind. As a result exact forecasts are vital for market and grid integration of RES. Altogether forecasting of electricity produced from RES is very complex. When it comes to forecasting usually a model is fitted with historic data and future predictions are made by applying the model on new input data. Forecasts usually assume that processes in the future can be predicted with their past realizations by keeping their dynamics. Figure 2 shows a histogram of Day-Ahead wind generation errors from the transparency platform of ENTSO-E[18] for Austria since the beginning of 2015 until June. The wind error is here defined as the difference between real and predicted wind power generation. The probability for the wind error being in the interval between -50 and +50 MW is around 22,5%. Often also higher wind errors occur, up to around 50% of the overall installed capacity. Nonetheless forecasts are very important in scheduling wind power plants. The challenge to market WPPs directly at wholesale markets, is to best use their stochastic output. In this thesis, the variability of the production of WPPs is modeled as a stochastic process (see Section 6.5.2). The forecast method here applied is based on time series analysis and described in detail in Section 5.

[17] Rezania and Haas (2012), p.217

[18] https://transparency.entsoe.eu/generation, accessed on: 13.01.2016

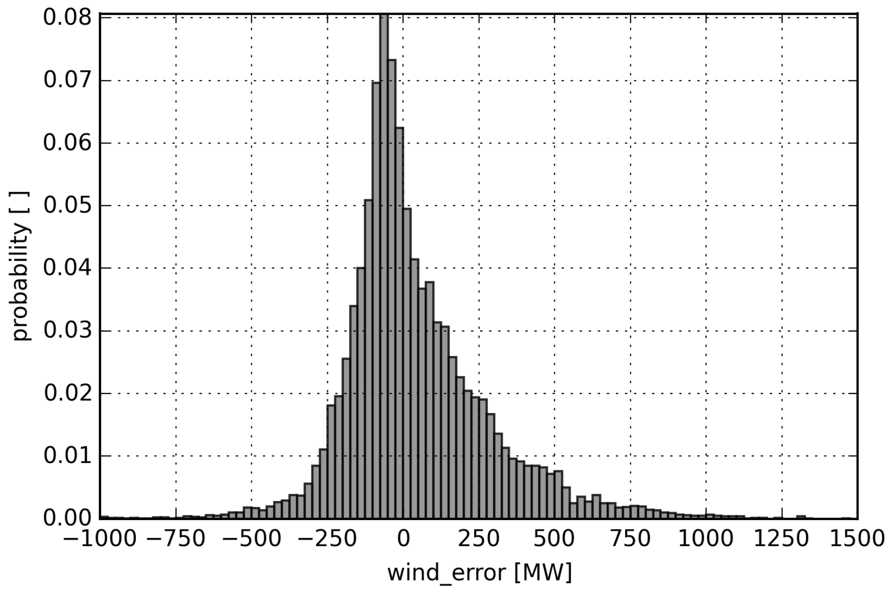


Figure 2: Histogram of wind errors for Austria from the beginning of 2015 until June. (own illustration, data obtained from https://transparency.entsoe.eu/generation, accessed on: 13.01.2016)

The last group refers to DR as an incentive for flexible consumers to change their electricity consumption pattern. DR is regarded as an important component of a VPP. DR influences the load pattern mainly in two ways. These are load shedding and load shifting (Figure 3). The first refers to the act of reducing the demand by resigning from a certain process like switching off a process that requires electrical energy. Of course the inconvenience or value of the lost process has to be compensated. Load shifting however enables a temporary shift of a process to another time step, either by advancing or delaying the process. In sum the amount of shifted load equals to zero. So load shifting poses significantly less disadvantage to the customers, the process is only shifted in time. These two measures are generally seen as the major DR measures.[19] [20]

[19]Paulus and Borggrefe (2011), p.435
[20]Feuerriegel and Neumann (2014), p.362

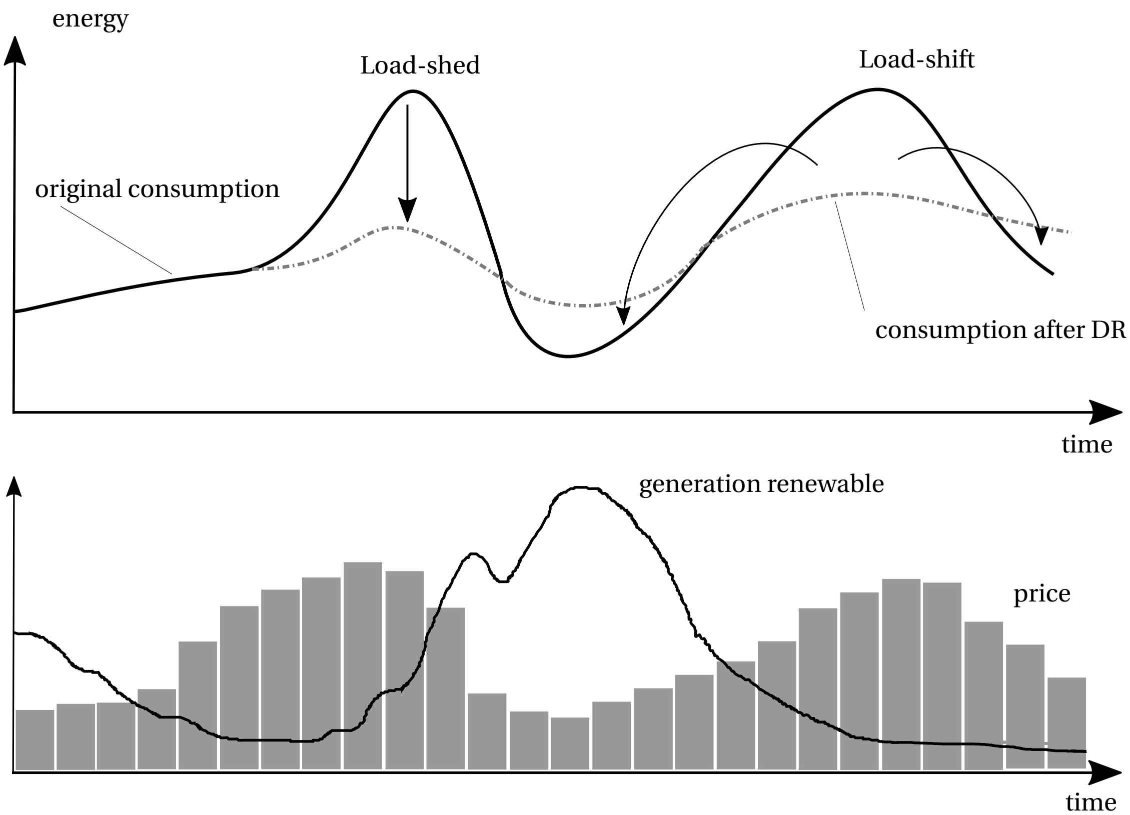


Figure 3: Schematic changes of original consumption pattern of end-use customers through Demand Response, triggered by price signal or grid issues like high feed-in of renewable energy systems. Generally a distinction is drawn between load sheds and load shifts.

In order to use flexibility potentials of consumers and compensate the involved comfort loss, monetary motivations are necessary. To some extent also other factors like avoiding black outs or contributing to the integration of RES could encourage customers to provide DR but this is negligible. Especially in the United States of America different DR programs were implemented to stimulate the change of the electricity consumption patterns. Generally these programs are divided in time based and incentive based programs.[21]

In time-based programs, the control remains with the customers who can directly adapt their current consumption to electricity price signals. The electricity pricing can either be static or dynamic depending on the specific program. In this kind of schemes time dependent prices are offered to the customers motivating them to rearrange their demand characteristics. At peak times, where electricity prices are usually high, DR

[21] Siano (2014), p.465

customers could be inclined to shift their consumption to off peak times and thus saving costs on energy bill level.[22] This is of course only possible if price signals from wholesale electricity markets are passed on to the customers. A very simple form of this program is the already existing night tariff where electricity prices at night are lower than during day time. But with a rising share of RES (especially wind) not only the time of the day but rather the current residual load[23] is a dominating factor for pricing processes on electricity markets. This supports the importance of dynamic pricing schemes. The different time based programs mainly differ in the regulation of electricity prices of the DR customers. In *time-of-use* programs static prices may be imposed for every hour of the next day. Prices can be set days, weeks or years in advance. Other schemes like *critical peak pricing* consider the state of the grid / market and adapt prices according to the current situation / prices. Normally these programs are only applied during peak times or grid congestion. With an increasing proximity to the market, in *real time pricing* schemes, Day-Ahead prices are directly forwarded to the customers.

In incentive based programs however, participants are willing to surrender the control of selected processes / electric devices to some extent to the DR operator who in return remunerates that flexibility. Devices for heating, ventilation and air conditioning are often used for this kind of DR programs. The operator of incentive based programs can send mandatory or voluntary DR requests to the customers depending on the applied program. Both technical factors like grid congestion and temperature levels of vital grid components or economic factors like price signals may trigger DR requests. *Direct load control* grants complete control of the customers devices to the DR operator. Within *interruptible/curtailable load programs* certain DR limits are contractually agreed, like maximum of DR activities in a year. On the other hand, in *emergency demand response programs* customers can voluntarily adapt their consumption pattern to emergency requests when stable grid operation is jeopardized. *Capacity market programs* offer the possibility to customers to make demand reduction offers to the market.[24] [25] [26] The above described characteristics have certain implications for aggregators. The most important factor is, if the request sent by the aggregator is compulsory or not. Under direct load control and interruptible/curtailable load programs the DR potential of the different

[22] Vardakas, Zorba, and Verikoukis (2014), p.1

[23] residual load is defined as the current electrical demand minus the feed-in of photovoltaic systems and wind power plants

[24] Shariatzadeh, Mandal, and Srivastava (2015), p.344

[25] Palensky and Dietrich (2011), p.382

[26] Arasteh, Parsa Moghaddam, Sheikh-El-Eslami, and Abdollahi (2013), p.153f

customers can be very well evaluated because the consumption of electrical devices can be directly controlled by the DR operator. In time based programs the response of the demand depends on the price elasticity of customers and also stochastic factors. In this thesis DR is incorporated via direct load control described in Section 6.5.4. Besides modeling the different VPP units, also their control is an important component of a VPP.

2.3 Price-based Control and Bidding Strategies

The pooling of many electrical generation and consumption devices in a VPP needs considerable information and communication technologies ICT. An EMS acts as a higher level control to dispatch the VPP portfolio depending on the chosen operation strategy like maximizing profits at electricity markets or supporting the grid. The units must be connected to the EMS, to guarantee the optimized use of each DER.[27] [28] The basis for that is an adequate infrastructure in order to measure and process all relevant data and sending requests to the corresponding devices.

The price-based control strategy uses market mechanisms to dispatch the different units of the VPP in an optimal way. Usually market signals have to be forecasted for the next trading period. The signals are processed by the VPP control which returns an operation schedule based on the marginal operating costs of the single VPP units. The marginal costs express the costs of increasing the output of an energy resource by one output unit. Under the assumptions of a competitive market environment the dominant strategy is to bid its marginal costs. Over the time market signals generally become more deterministic due to better forecasts of important factors like prices and RES feed-in. Between forecasted and real values there is most likely some kind of deviation. Therefore the operation schedule has to be updated over time until a defined tolerable deviation is reached or a defined number of iterations is executed. The marginal costs depend on the type of the DER and can change over time. This is illustrated in Figure 4. For some devices the marginal costs are clear to determine like fuel based electricity generators and RES. Regarding fuel based devices like diesel and gas generators the marginal costs are a function of the fuel price, whereas RES typically feature low marginal costs only depending on maintenance costs therefore producing at any positive market price. Other

[27] Palensky and Dietrich (2011), p.385
[28] Saboori, Mohammadi, and Taghe (2011), p.2

DER like electric energy storage systems charge energy at one time at a given price level and discharge it at another profiting from price spreads. In this case they are on the other end of the bidding spectrum. Their bidding strategy is fully price history based and therefore highly depend on the market context the VPP is operating in. Devices like CHP systems which also provide district heating services are positioned somewhere between the extreme cases of the bidding spectrum. A factor influencing the marginal costs of CHP are so called must run criteria, e. g. when heat has to be delivered, then the CHP is obliged to run and the costs associated to it are low. Another factor is an optional heat buffer which reduces the interdependency between heat and electricity. Depending on the storage level it can be economically more or less attractive to run the CHP. When the CHP produces excess heat that can not be used otherwise than the economic efficiency declines. Systems that directly use electric energy for heating and cooling (like heat pumps etc.) should be operated at lowest cost while satisfying a required comfort level of the user at the same time for example by shifting heating / cooling requests to low price periods. This fact assigns them to price history based bidding strategies.[29] [30]

Inside the VPP every unit is associated with specific marginal costs depending on the position within the bidding spectrum. As a rule, the VPP unit providing the requested service with the lowest costs, is selected. Therefore the costs of the DER are ranked from low to high marginal costs. A price-based control algorithm is later applied in the optimization model described in Section 6. The corresponding market framework is described in the next section.

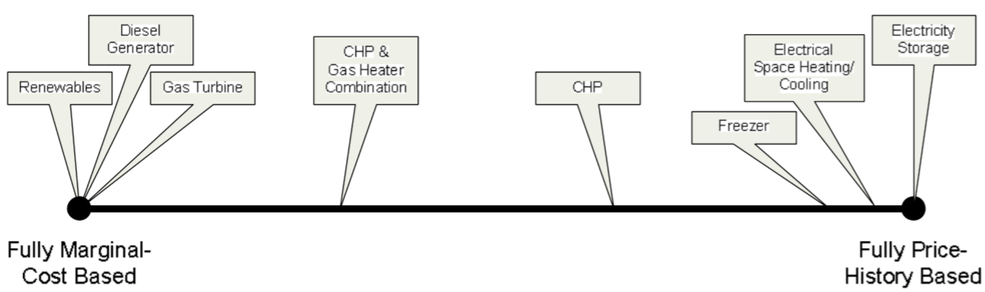


Figure 4: Bidding spectrum of different DER, marginal cost based and price history based approaches (Kok, 2009, p.1)

[29]Ruthe, Rehtanz, and Lehnhoff (2012), p.2
[30]Kok (2009), p.1

3 Market Framework

A significant amount of electricity is traded on energy-only markets like the European Energy Exchange (EEX). For generators like thermal power plants, large combined heat and power plants or nuclear facilities an operation schedule can be prepared. Electric delivery contracts for those units can be made with a long lead time. Also large consumer (industries) can often predict their demand very well in advance. Volatile units however like RES feature an improved predictability with shorter lead time to contract fulfillment. For those units markets near to real time are more favorable when their output can be forecasted more accurately. Therefore markets with different time spans between settlement and contract fulfillment exist. **“Futures**” offer long term contracts which are especially interesting for participants with a rather deterministic operation schedule by providing planning security. **“Day-Ahead**” markets on the other hand have a shorter lead time where prices are determined for every time step of the next day. Market participants can place offers until 12:00 pm about their generation or consumption for every hour of the next day (00:00 to 24:00). After market closing, the generation offers are sorted beginning with the cheapest offer and accumulated until they match the demand for electricity sorted beginning with the highest prices for every hour of the day. This is called Merit Order. Usually the offers correspond to the marginal costs of power plants. The intersection between the demand and supply curve represents the market equilibrium and results in the market clearing price (MCP). The MCP constitutes the costs of the marginal power plant necessary to fulfill the demand request. Offers lower or equal to the MCP get acceptance and have to fulfill the contracts made. All participants are rewarded with the MCP. The lower the marginal costs of a power plant compared to the MCP, the higher is the profit margin for the respective electricity producer. The pricing mechanism at the Day-Ahead market is illustrated in Figure 5.

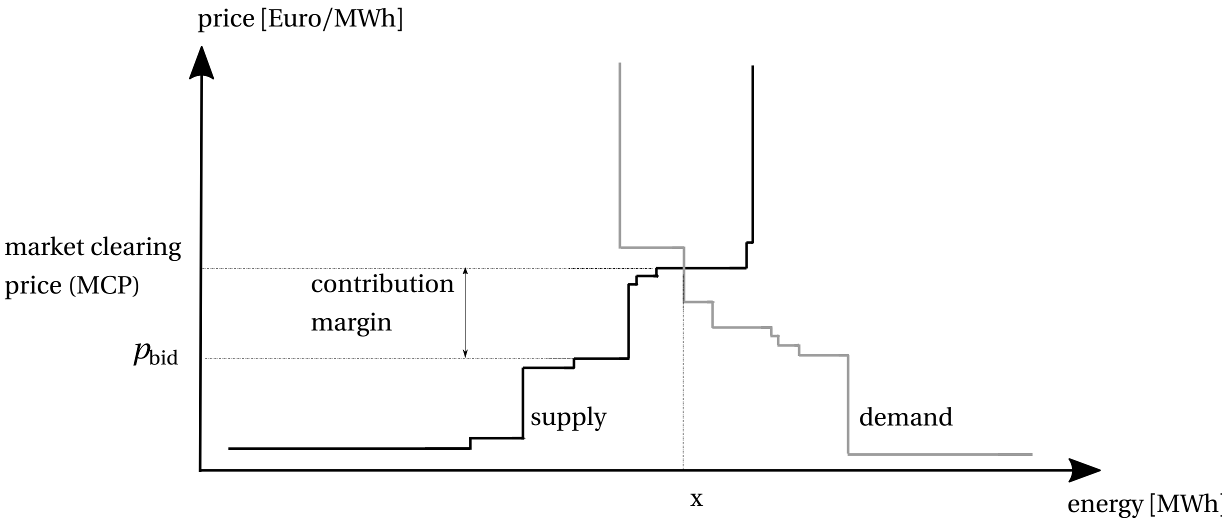


Figure 5: Pricing mechanism of Day-Ahead market

Approximately half of the market share is traded on the Day-Ahead market. Single contract orders (for every hour) as well as block orders (for different time blocks) can be submitted. Typically the flexibility of the demand side is lower than the one of the supply side. RES feed-in often does not match the predicted amount and also outages of conventional power plants are not uncommon. Deviations thereby occurred can be settled in the "**Intraday**" market. Here contracts are made up to 45 min before contract delivery and offers at hourly or 15 min basis are possible. Deviations of RES feed-in can be better compensated with shorter lead time by incorporating actual weather data about wind and solar irradiation. The Intraday market is continuous and contracts are remunerated precisely by the price made in the offer. This is called "pay as bid". Every participant can make offers into the market with a certain price and other participants can accept or decline that offer. These deals can be used to compensate short term deviation of the planned schedule either of the demand or the supply side. Apart from standardized trades on the EEX, contracts can also be settled directly between two entities. These are called "over the counter" markets and principally offer planning security with typically long lead times similar to Futures. The advantage of Future markets primarily lies in its standardized way, transparency and comfort in contract settlement. Every agent trading on energy-only markets is obliged to adhere to the offers made and is assigned to a balancing responsible party (BRP). In case a BRP can not meet its schedules, despite the possibilities on the Day-Ahead and Intraday market, imbalance costs have to be paid to the balancing group coordinator.[31] [32]

The described sequential bidding process is illustrated in Figure 6. Day-Ahead ($D-1$) offers can be made until 12 pm. Following the above described principle the MCP is evaluated and announced to the market. At 15 pm the Intraday market is open and offers are possible until 45 min before contract fulfillment. On the actual delivery day (D) the contracts have to be fulfilled or deviations from schedule are optionally settled in the imbalance settlement market.

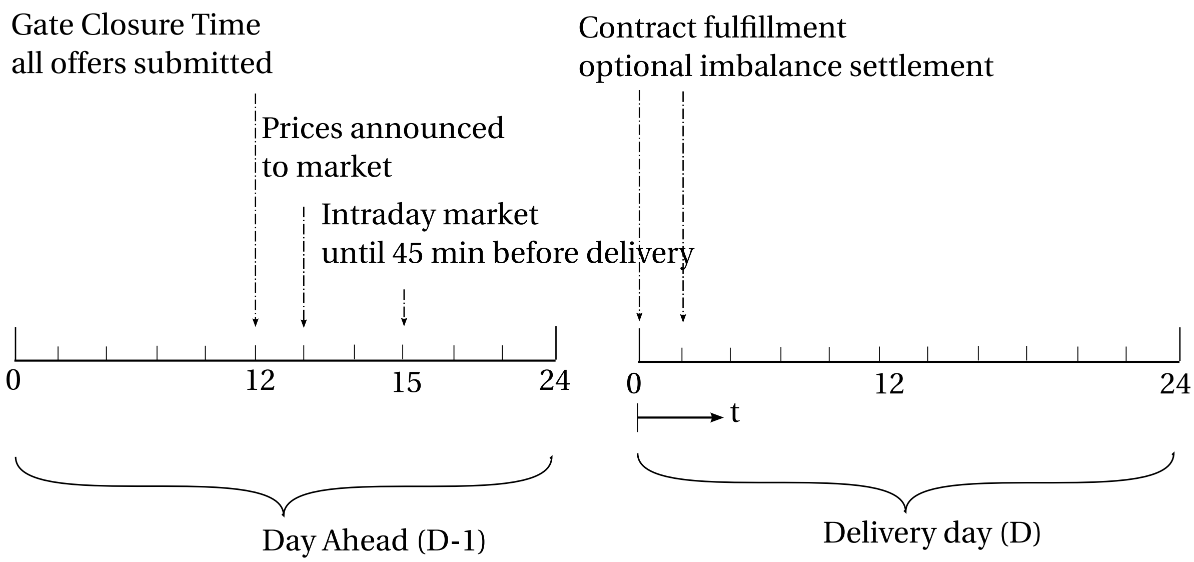


Figure 6: Bidding process on Day-Ahead markets

An electricity trader on the energy-only market usually tries to make realistic forecasts for different market prices based on the actual predictions of the power plant portfolio. Deviations in schedules and actually measured load and generation profiles have to be compensated with imbalance energy. The costs for imbalance energy are supervised by the Balancing Group Coordinators and have to be paid by the specific member of the Balancing Group causing the deviation. On the generation side, deviations are mainly caused by weather influences which especially affect the output of RES and CHP. Regarding the consumption side also weather factors or user specific behavior can result in deviations from schedules.

Apart from energy-only markets, there are also markets to incentivize ancillary services to the grid. Those markets reward the reservation of a defined power-capacity in order to

[31] E-Control (2013), p.7ff
[32] von Roon, Hinterstocker, and Eberl (2014), p.2ff

react to short-term deviations. Generation and consumption of electrical power have to be in balance at every moment. To guarantee that enough compensation energy can be provided, Transmission Service Operators (TSOs) tender auctions of positive as well as negative balancing power. If generation exceeds the demand, negative balancing power is necessary to bring the system back in balance. This can be achieved by decreasing the generation or increasing the demand. If on the other hand demand exceeds generation than positive balancing power must be provided. In this case increasing the generation or reducing the demand again results in a stable operation of the electric infrastructure. In Austria this is supervised by the Austrian Power Grid (APG). Partaking units have to be prequalified to ensure their suitability for providing this service. Three different balancing products are tendered with well defined areas of responsibility. Their main objective is to provide frequency stability around the set point of 50 Hz by evening out differences in generation and demand. The costs for reserve calls - in consequence of uneven operation schedules - have to be paid by the specific BRP. The allocation of the resulting costs to the specific BRP is handled in the imbalance clearing process and later described in the optimization model in Section 6.[33]

As the VPP portfolio consists of DG and DR, Futures markets are not considered due to the long lead time and their requirement for rather high predictability. Although the balancing market provides interesting possibilities for VPPs especially the volatility of RES is problematic. The focus of the thesis lies on the spot market Day-Ahead because the majority of electricity is traded here.

[33] von Roon, Hinterstocker, and Eberl (2014), p.5f

4 Methodology to Model Uncertainty

To answer the research question an optimization model was designed. Special attention is given to the uncertainties in electricity markets. For a VPP operating in a market framework similar to that described in Section 3, several sources of uncertainty exist, like:

- power plant or equipment outages,
- power output of non dispatchable energy resources like RES,
- uncertainties of actual market prices: for the spot market Day-Ahead, Intraday and imbalance settlement prices or balancing market prices,
- and electrical energy demand of consumers.

Of the above mentioned uncertainties, the output of RES (especially wind) and market prices are further taken into account. The applied methodology is schematically shown in Figure 7. It consists of a scenario generation model that provides possible realizations of the uncertain data and a subsequent optimization model that optimally schedules the VPP on the spot market considering different realizations of uncertain parameters.

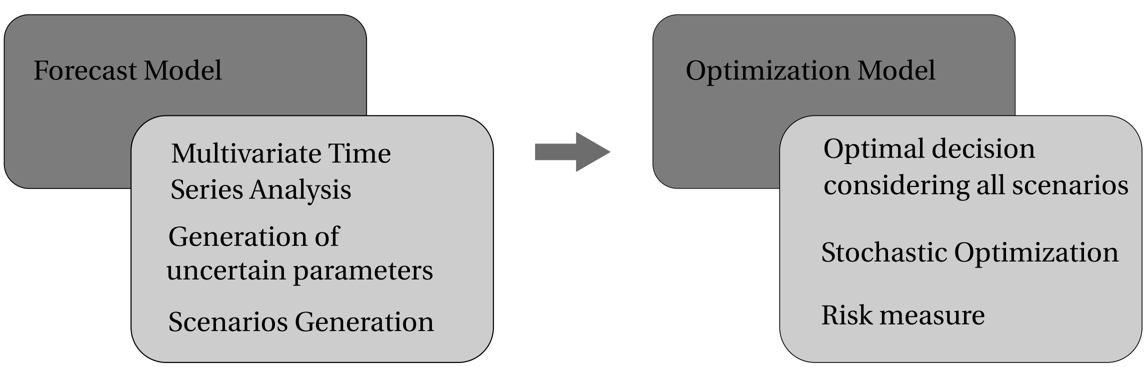


Figure 7: Principle of modeling approach for a Virtual Power Plant operating on electricity markets under uncertainty. First different scenarios of uncertain parameters are generated and then used as input for the optimization model, considering different scenarios and a risk measure.

Uncertain parameters are modeled as discrete stochastic processes $\boldsymbol{\lambda}$ spanning over a certain time horizon $\boldsymbol{\lambda} = \{\lambda_t,\ t = 1,2,...,N_T\}$, whereas λ_t is considered the state of the stochastic process at time t of the set T. A discrete stochastic process $\boldsymbol{\lambda}$ can be formulated with a sufficient amount of vectors $\boldsymbol{\lambda}_s$, in the form of $\boldsymbol{\lambda} = \{\boldsymbol{\lambda}_s,\ s = 1,2,...,N_S\}$, in which s denotes the scenario index and N_S the number of scenarios of the set S. Every realization of $\boldsymbol{\lambda}_s$ is assigned with a probability π_s so that:[34]

$$\sum_{s=1}^{N_S} \pi_s = 1 \tag{4.1}$$

The expression $\lambda_{s,t}$ refers to the state of the stochastic process in scenario s at time t. In this thesis *Day-Ahead spot price* $\boldsymbol{\lambda}_s^{\text{da}}$, *wind generation of WPPs* $\boldsymbol{P}_s^{\text{res}}$ and *imbalance price* $\boldsymbol{\lambda}_s^{\text{imb}}$ are considered as stochastic processes. A scenario spans over the time horizon of the offering day D, for which an optimized schedule is to be computed, in discrete time steps of 15 minutes. Relevant market data is also published in this resolution. Therefore every scenario s has a length of $N_T = 24x4 = 96$ time steps. Exemplary this is shown for the Day-Ahead spot price $\boldsymbol{\lambda}_s^{\text{da}}$ for a number of $N_S = 10$ scenarios:

$$\boldsymbol{\lambda}_1^{\text{da}} = (\lambda_{1,1}^{\text{da}}, \lambda_{1,2}^{\text{da}}, ..., \lambda_{1,96}^{\text{da}}), \text{ with } \pi_1$$

$$\boldsymbol{\lambda}_2^{\text{da}} = (\lambda_{2,1}^{\text{da}}, \lambda_{2,2}^{\text{da}}, ..., \lambda_{2,96}^{\text{da}}), \text{ with } \pi_2$$

$$\vdots$$

$$\boldsymbol{\lambda}_{10}^{\text{da}} = (\lambda_{10,1}^{\text{da}}, \lambda_{10,2}^{\text{da}}, ..., \lambda_{10,96}^{\text{da}}), \text{ with } \pi_{10}$$

$$\pi_1 + \pi_2 + ... + \pi_{10} = 1$$

Time series of the uncertain parameters are used as information set for scenario generation. The time series range to the specific offering day D, for which an optimized schedule is computed. This guarantees, that only relevant information up to the time of decision making, is used as input. The scenario generation model is based on vector autoregressive models taking into account possible influences of uncertain parameters on each other (Section 5). Every scenario s, consists of a specific combination of possible realizations of uncertain parameters $\{\lambda_{s,t}^{\text{da}}, P_{s,t}^{\text{res}}, \lambda_{s,t}^{\text{imb}}\}, \forall t = 1,2,...,N_T$. It is supposed, that

[34] Conejo, Carrión, and Morales (2010), p.29

the so obtained scenario tree, sufficiently describes the involved uncertain parameters. This is clarified in Figure 8.

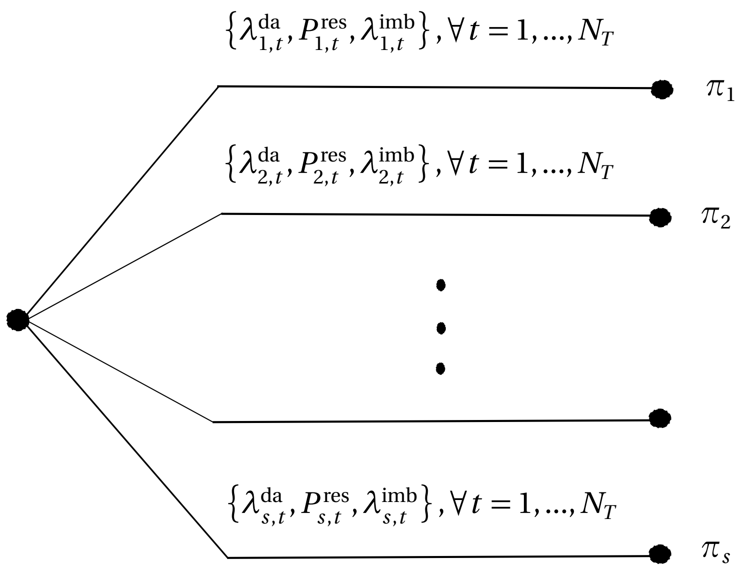


Figure 8: Scenario tree considering different outcomes of the stochastic processes with corresponding probability.

The subsequent optimization model is based on stochastic optimization and provides an optimal solution for the offering day D regarding all input scenarios s of uncertain parameters. It generates reasonable operation schedules of the considered DER for the spot market Day-Ahead. The expected profit so obtained is used to evaluate the VPP and its components (Section 6). The generation of multiple scenarios aims at better tackling the involved uncertainty in contrast to a deterministic approach with only one possible outcome. To sum up, the implemented short-term dispatch tool executes the following steps for a specific offering day D:

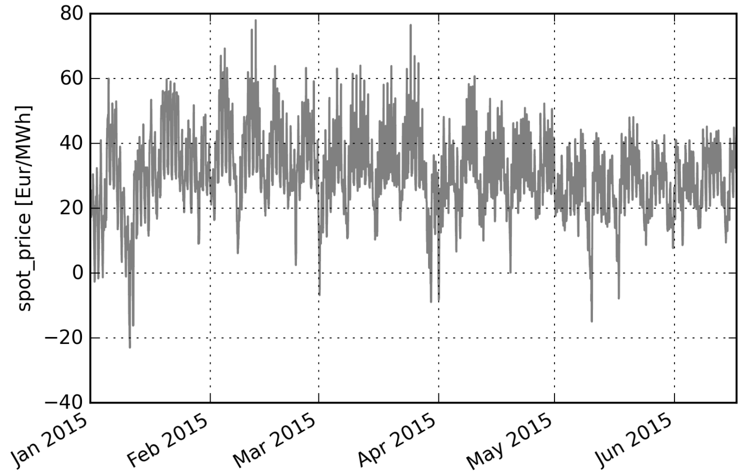
- At first uncertain parameters are approximated by an adequate number of N_S scenarios. Scenarios, spanning over the offering day D with N_T time steps, are generated using time series analysis. The time series used, do not include the offering day D to account for the fact, that only information available at $D-1$ can be used for scenario generation of the random variables on day D. Scenario generation is based on vector autoregressive models and described in detail in Section 5. The scenarios are organized correspondingly, as shown in Figure 8.

- After that, the scenarios, assumed to sufficiently describe uncertain parameters, are fed into the optimization model (Section 6). The optimization model is based on stochastic programming and computes optimal market offers for a VPP considering all N_S scenarios over all N_T time steps of the offering day D. Additionally a risk measure is implemented as a tool to manage the trade-off between expected profit and risk.

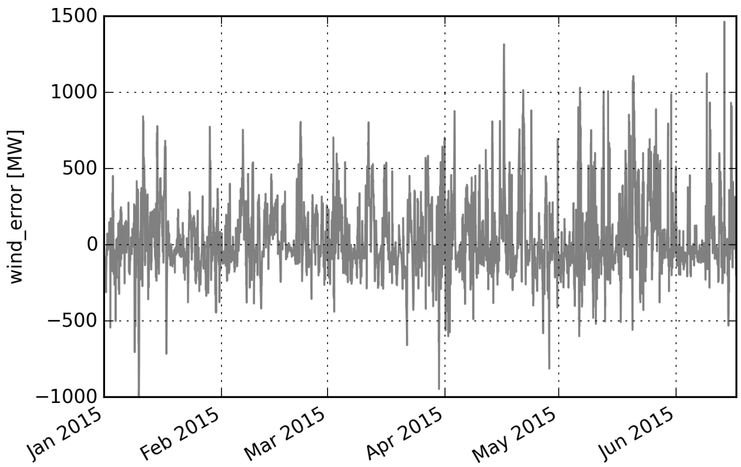
5 Scenario Generation Model

This section describes the applied method to consider the characteristics of the volatile stochastic processes involved. Figure 9 shows the history of wind generation error from WPPs, spot market price and imbalance settlement price from beginning of 2015 until mid of June in a granularity of 15 minutes respectively, which are openly available.[35] [36] [37] It can be seen that all time series are subject to volatility. Whereas the spot market price features a more regular cyclic pattern with occasional peaks over the considered time, the wind error and imbalance price are highly volatile. Both the occurrence as well as the amplitude of the peaks are noteworthy. Although wind forecasts are improving there are still considerable errors between real and predicted wind generation (see Figure 2). As the concept of reserve power and imbalance settlement is to even out unforeseen events, also the imbalance price is very volatile ranging from 500 to -500 Eur/MWh. All statistical models were implemented with the *Python* package *statsmodels*.

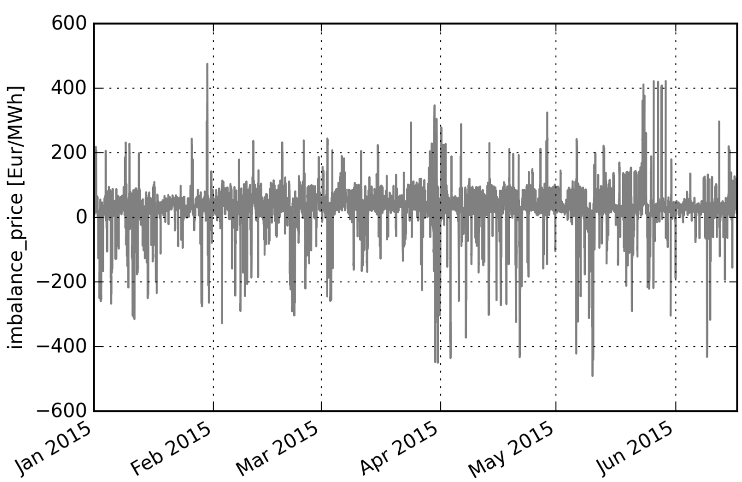
[35]http://www.exaa.at/de, accessed on: 13.01.2016
[36]https://www.transparency.entsoe.eu, accessed on: 13.01.2016
[37]http://www.apcs.at, accessed on: 13.01.2016



(a) EXAA spot market price data



(b) ENTSO-E wind error data



(c) APCS imbalance clearing price data

Figure 9: Time series of spot market price Day-Ahead, wind error for Austria and imbalance price used as input for the vector autoregressive model to simulate scenarios uncertain parameters for the next day.

5.1 Vector Autoregressive Model

The quality of the optimization results performed in Section 6 highly depends on the input data of deterministic and stochastic variables. Especially stochastic processes should be described and predicted with sufficient accuracy. This section presents the method to simulate different scenarios of the uncertain parameters in the optimization model. Historical data of the random variables exist as equidistant, discrete time series in a granularity of 15 minutes. By means of vector autoregressive (VAR) models, scenarios of the random input variables of the optimization problem are generated. VAR models assume that future realizations of stochastic processes involved can be adequately modeled by their past values and their influence on each other. The advantage of this method is that the dynamic behavior of different stochastic processes can be simultaneously analyzed. Other studies use autoregressive (integrated) moving average (AR(I)MA) methods either assuming no correlation between the involved stochastic processes or modeling the dependency with cross correlation.[38] For this thesis the VAR approach was chosen because a correlation between the random variables *wind generation, spot price* and *imbalance market price* is assumed. A stationary, finite order VAR(p) model with a set of i endogenous time series over the period $t = \{1, ..., T\}$ expressed by $\boldsymbol{y}_t = \left(y_{1,t}, y_{2,t}, ..., y_{i,t}\right)^T$, is usually formulated as

$$\boldsymbol{y}_t = \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \boldsymbol{A}_2 \boldsymbol{y}_{t-2} + ... + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \mathbf{u}_t \tag{5.1}$$

where $\boldsymbol{A}_p$ is a $i \times i$ matrix of the lagged terms describing the effect of past realizations on future realizations of $\boldsymbol{y}_t$. The vector of the error term $\mathbf{u}_t$ is regarded as *Gaussian white noise* with constant variance, expressed as $\boldsymbol{u}_t \sim N(0, \boldsymbol{\Sigma}_u)$.[39] [40]

5.2 Fitting Model

The use of (5.1) requires the stochastic process $\boldsymbol{y}_t$ to be *stationary*. The process $\boldsymbol{y}_t$ is stationary, if all *eigenvalues* z of $\boldsymbol{A}_p$ have *modulus* $|z|$ less than 1, so that:[41]

[38] Conejo, Carrión, and Morales (2010), p.68ff
[39] Schröder (2012), p.185
[40] Lütkepohl (2005), p.13
[41] Lütkepohl (2005), p.25

$$\det(\boldsymbol{I}_i - \boldsymbol{A}_1 z - \ldots - \boldsymbol{A}_p z^p) \neq 0 \qquad \text{for } |z| \leq 1, \tag{5.2}$$

where *det* stands for the *determinant* and $\boldsymbol{I}_i$ for the i x i *unity matrix*. If (5.2) holds, then the reverse characteristic polynomial of (5.1) has no roots in and on the complex unit circle.[42] To test if the involved stochastic processes are stationary, *Augmented Dickey-Fuller* test were carried out on the single time series forming the VAR(p) model. If a stochastic process has a unit root, then 1 is a root of its characteristic polynomial rendering the process non-stationary. The Null-hypothesis H_0 of the Augmented Dickey-Fuller test is that there is a unit root in a specific time series sample. If H_0 can be rejected then the process is stationary at some confidence interval.[43] The results of the Augmented Dickey-Fuller tests are shown in Appendix 8.1. For all considered time series, H_0 can be rejected with the significance level of 1%. Therefore it is assumed that the involved stochastic processes are stationary.

The order of p is obtained via *Akaike Information Criterion* to settle the tradeoff between over fitting the data and finding sufficient lagged terms representing the model characteristics.[44] Models were fitted with training data sets varying in length, to get an idea about the sensitivity of the model to the input data. Appendix 8.2 shows the results of the model fit up to the order of four. The standard error of the estimated spot price lagged terms especially in the equation for wind error and imbalance price is noteworthy. With longer training data sets however the standard error is declining.

Additionally also a structural analysis was performed with *Granger-causality* test, *Impulse Response Function* and *Forecast Error Variance Decomposition* are used, provided by the python-package *statsmodels*. Granger-causality describes the dynamic interaction of endogenous variables and their value for predicting each other. If y_1 is not Granger-causal for y_2 than there is no influence of the lagged terms of y_1 on the actual value of y_2 which is not settled by the lagged terms of y_2 itself. In case this hypothesis can be rejected y_1 has a significant effect on y_2.[45] Appendix 8.3 summarizes the results of the Granger-causality tests. It shows that the spot market price as well as the wind error is Granger-causal for the realization of the imbalance price which supports the use of a VAR model (the H_0 hypothesis was rejected in all cases) in contrast to one dimensional models. An Impulse Response Function on the other hand analyzes the reaction of one

[42] Lütkepohl (2005), p.16
[43] Hamilton (1994), p.501f
[44] Schröder (2012), p.99ff
[45] Schröder (2012), p.185ff

variable to sudden shocks in other variables. The shocks can be of magnitude one or in case of different scales of the time series, one unit of standard deviation. Impulse Response Functions provide insights of the reaction of one variable to sudden shocks in other variables potentially affecting it.[46] Section 8.4 shows the impulse response of the used time series. Sudden shocks in the wind error time series are strongly affecting imbalance prices. Regarding the spot market, the influence on the imbalance price is rather low, with the confidence intervals being not significantly different from zero. At last the aim of Forecast Error Variance Decomposition is to trace the uncertainty of one variable to the variance of all variables.[47] The input data suggests that the imbalance price is especially influenced by the wind error (Section 8.5), which is in line with the above mentioned tests.

5.3 Scenario Generation

In this thesis, scenarios are considered as plausible outcomes of uncertain parameters in the future. Aim of scenario generation is to provide plausible input data for the subsequent optimization model (Section 6). The following steps are executed to generate N_S scenarios spanning over a certain number of time steps N_T.

- *Step 1:* For a certain offering day D, time series of uncertain parameters are used to fit a VAR(p) model. Only time series data *before* the beginning of day D is used as input, to account for the fact that only data available at the moment of making an offer, can be used.
- *Step 2:* Initialize scenario counter: $s \leftarrow 0$.
- *Step 3:* Update scenario counter: $s \leftarrow s+1$, initialize time period counter $t \leftarrow 0$.
- *Step 4:* Update time period counter $t \leftarrow t+1$.
- *Step 5:* Randomly sample $\boldsymbol{u}_t \sim N(0, \boldsymbol{\Sigma}_u)$.
- *Step 6:* Evaluate (5.1) to get $\boldsymbol{y}_{s,t}$.
- *Step 7:* New VAR(p) model is fitted including the previously generated $\boldsymbol{y}_{s,t}$.

[46] Schröder (2012), p.185ff
[47] Schröder (2012), p.185ff

- *Step 8:* If $t < N_T$ jump back to *Step 4,* else continue with *Step 9* (Here $N_T = 96$ representing one offering day D in 15 minutes granularity).
- *Step 9:* If $s < N_S$ jump back to *Step 3,* else the desired amount of scenarios is generated over a certain time horizon and scenario generation is completed.

The generated scenarios are all assigned with the same probability $\pi_s = \frac{1}{N_S}$. The methodology of scenario generation is based on Conejo, Carrión, and Morales (2010), with the difference that vector autoregressive models are used and fitted again for every newly generated $\boldsymbol{y}_{s,t}$.

The above described methodology generates scenarios of wind error, spot and imbalance prices. To get different scenarios for the electrical wind output, the Austrian day-ahead wind generation forecasts P_t^{forecast} of the ENTSO-E[48] are superimposed with the obtained values of the wind generation error from the VAR model, referred to as $\varepsilon_{s,t}$. The scenarios for the wind power output $P_{s,t}^{\text{real}}$ are obtained by:

$$P_{s,t}^{\text{real}} = P_t^{\text{forecast}} + \varepsilon_{s,t} \tag{5.3}$$

These resemble the basis for the uncertain wind output. After that the wind output is scaled to the installed capacity of WPPs participating in the VPP. The resulting wind output scenarios $P_{s,t}^{\text{res}}$ are based on the assumptions, that the geographic dispersion of participating WPPs is sufficient enough to use ENTSO-E forecasting data for the wind production of the whole of Austria for the next day, scaled by the ratio of the installed capacity of the WPPs inside the VPP P^{vpp} compared to the installed capacity in Austria P^{total}:

$$P_{s,t}^{\text{res}} = P_{s,t}^{\text{real}} \cdot \frac{P^{\text{vpp}}}{P^{\text{total}}} \tag{5.4}$$

5.4 Results

The model provides ex post and out of sample forecasts. The time series were separated into training data to fit the model coefficients and test data to analyze the quality of the VAR model. One way to determine the accuracy of the VAR model is the root mean squared error (RMSE) of predicted y_t^{pred} and observed values y_t^{real} (5.5) over the forecast horizon (the next day). Forecasts of the stochastic processes y_t^{pred} are obtained by *linear*

[48]https://www.transparency.entsoe.eu, accessed on: 13.01.2016

minimum mean squared error predictor. The forecast horizon is one time step. Forecast are done for every time step of the offering day.[49] [50] [51]

$$\mathrm{RMSE} = \sqrt{\frac{1}{N_T} \cdot \sum_{t=1}^{N_T} \left(y_t^{\mathrm{real}} - y_t^{\mathrm{pred}} \right)^2} \tag{5.5}$$

The output of the VAR model and the scenario generation process is exemplarily presented for a summer day (15.06.2015). The predicted spot market price features a RMSE of 7 Euro/MWh. The RMSE of the generated imbalance price is 56 Euro/MWh which is rather high. Because of the limited predictability of imbalance prices, a conservative bidding strategy avoiding deviations is chosen in the optimization model (see Section 6). The RMSE of the wind error is quite substantial with 336 MW. As the resulting wind scenarios are obtained by superimposing the ENTSO-E forecast with the wind error of the VAR model and afterwards scaled to the size of installed power in the VPP, the high RMSE of wind error has not such a severe effect.

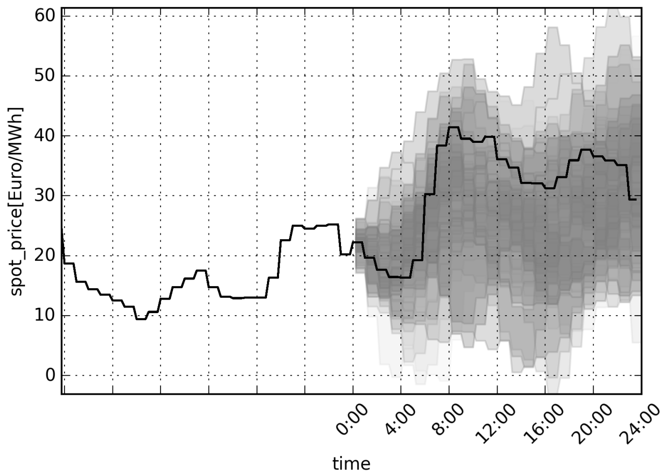
Based on the VAR model, scenarios are generated by the process described in 5.3. Figure 10 shows the scenarios generated by the VAR model in a fan chart and the real value of the respective stochastic processes (black line). Time series data before 0:00 are used for training data. The scenarios start at the time 0:00 and span over one day until 24:00. Darker areas of the fan chart suggest scenario realizations with a higher probability of occurrence.

The scenarios of the spot market price cover the values of the observed realization whereas the darker areas follow the behavior of the real values (Figure 10a). Figure 10b shows the scenarios for the wind output. The scenario generation model profits from the sophisticated ENTSO-E forecast tool, which is then superimposed by historic wind error data from the VAR model. Except for two peaks around 13:00 and 17:00 the wind scenarios approximate the real trend relatively well. Imbalance settlement prices are volatile and therefore hard to predict. This can be observed in Figure 10c where the real imbalance price level ranges between 200 and -100 Euro/MWh. The scenarios generated cover more or less the true realization of the stochastic process but a clear trend can not readily be observed.

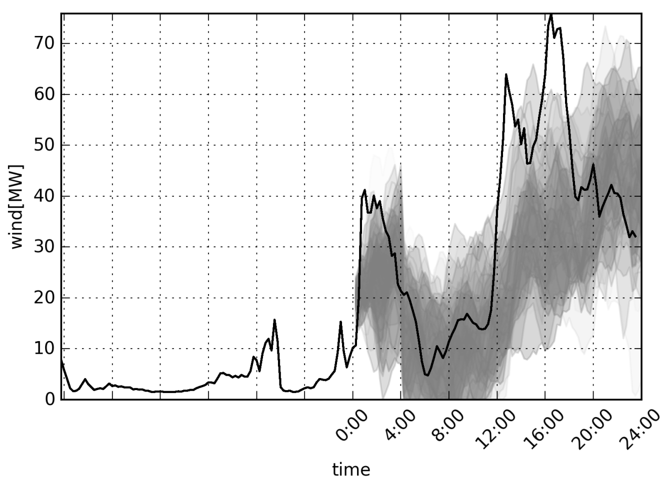
The performance of the subsequent optimization model highly depends on the input data. Therefore the scenarios fed into the optimization model should sufficiently

[49] Crespo Cuaresma, Hlouskova, Kossmeier, and Obersteiner (2004), p.98
[50] Conejo, Contreras, Espínola, and Plazas (2005), p.447
[51] Lütkepohl (2005), p.35f

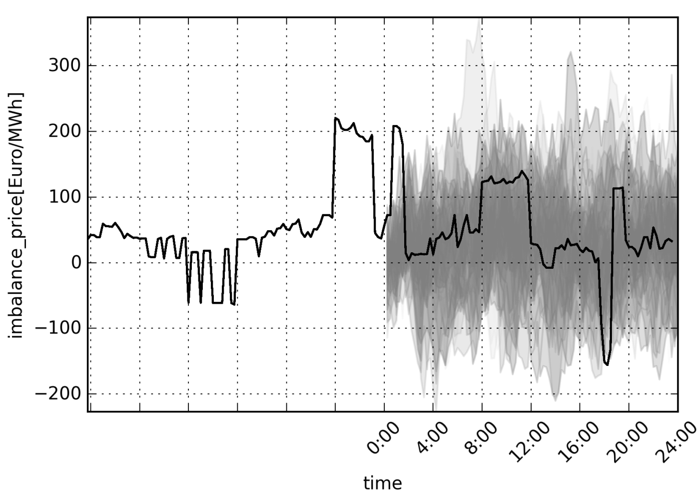
resemble observed realizations of the uncertain values. Furthermore applied scenario generation models should be continually improved and validated. Of course, additional input variables like the electrical demand may improve the RMSE obtained by the VAR model. Also other information criteria for the lag order p might be more appropriate. The scenario generation model here applied, provides reasonable scenarios to feed the optimization model.



(a) Spot market price



(b) Wind output



(c) Imbalance price

Figure 10: Fan chart of the scenarios generated with the VAR model and the real realization of the stochastic process (black). Dark areas of the fan chart suggest scenario outcomes that appear more frequently considering all scenario outcomes.

6 Optimization Model

Various optimization approaches exist to get an optimal schedule for energy resources. Generally it can be distinguished between: single optimization of all resources, game theory and agent based approaches. Single optimization strategies focus on modeling every participating unit of a single market player. Game theory and agent based models in contrast take the interactions of different players in the energy sector into account.[52] For this paper only the actions of the VPP operator are considered, therefore single optimization techniques are applied. These include methods like linear programming, mixed-integer programming, stochastic programming or non-linear programming. While linear programming features the lowest computational burden, discrete variables like integer or binary variables can not be implemented. These are often used to model on/off states and other discrete events and solved with mixed-integer and non-linear programs. Often a more realistic model also considering discrete values comes with the drawback of higher computing times. Coefficients in the model can be deterministic or stochastic. Uncertainty in decision making can be considered by applying stochastic programming.

The following paragraphs describe the implemented stochastic optimization problem. The first part deals with mathematical fundamentals, after that the model for optimal program planning of a VPP is described. The aim of the model is to generate for every time step optimal bidding offers at the spot market Day-Ahead under uncertainty while also regarding imbalance costs. Different DERs are modeled to evaluate their contribution to a VPP like RES, CHP and DR. The simulation model was developed with the programming language *Python*. The problem is formulated with the package *Pyomo* and solved with *Gurobi*.

6.1 Stochastic Programming

6.1.1 Fundamentals

Deterministic models assume that all input data can be deterministically described. In reality, processes like price developments on electricity markets, demand of customers

[52] Li, Shi, and Qu (2011), p.4689ff

or the feed-in of RES can not be deterministically predicted. To make decisions under incomplete information, stochastic optimization procedures can be applied. Usually recursive stochastic optimization programs are modeled with stages describing points in time where decisions have to be made and / or information about the states of the system unfolds. One application of stochastic optimization are two stage problems where decisions have to be made before the outcome of a stochastic process $\boldsymbol{\lambda}$ is clear. The choice $\boldsymbol{x}$ has to be made before realization of $\boldsymbol{\lambda}$, while $\boldsymbol{y}$ is computed afterward. Thus $\boldsymbol{y}_s$ depends on the chosen value for $\boldsymbol{x}$ and the realization of the stochastic parameter $\boldsymbol{\lambda}_s$ in the respective scenario s. The variable $\boldsymbol{x}$ is referred to as first stage (or here and now) variables for which decisions have to be made before the outcome of a stochastic process is known and so do not depend on the stochastic process. $\boldsymbol{y}_s$ describes a second stage (or wait and see) variable that is determined after the outcome of a stochastic process is known. In case uncertain parameters have a continuous joint distribution the problem is non-linear and in general not a trivial problem. This can result in long computing times which are unfavorable in electricity trading where decisions have often to be made on short notice because of the dynamic market framework. Assuming a joint discrete distribution of the random variables described by a finite set of scenarios, stochastic problems can be expressed by their *deterministic equivalent* and efficiently solved.[53]

Throughout this thesis stochastic programs are expressed by their deterministic equivalent. Equations (6.1) - (6.4) describe a maximization problem whereas $\boldsymbol{c}^T$, $\boldsymbol{b}$, $\boldsymbol{q}_s^T$, $\boldsymbol{h}_s$, $\boldsymbol{B}$, $\boldsymbol{T}_s$, $\boldsymbol{W}_s$ are known coefficient vectors and matrices of appropriate size, representing the input parameters for the optimization problem. The uncertainty in problem (6.1) - (6.4) is assumed to be adequately described by a set of scenarios S and its specific realization s. The future realizations of uncertain variables in the objective function are determined by the sum of their realizations over all scenarios, weighted by their respective probability of occurrence π_s.[54] [55] After a supposedly optimal first-stage choice for $\boldsymbol{x}$ is made, the optimal second-stage choice for $\boldsymbol{y}_s$ is an optimization problem where uncertain data is revealed. If a decision for $\boldsymbol{x}$ results in a violation of $\boldsymbol{T}_s \cdot \boldsymbol{x} = \boldsymbol{h}_s$ in (6.3), the term $\boldsymbol{W}_s \cdot \boldsymbol{y}_s$ guarantees that expression (6.3) is met, coupling $\boldsymbol{x}$ and $\boldsymbol{y}_s$ for every scenario s. This however results in costs $\boldsymbol{q}_s^T \cdot \boldsymbol{y}_s$ considered in the objective function (6.1).

$$\max_{\boldsymbol{x},\boldsymbol{y}_s} \; \boldsymbol{c}^T \cdot \boldsymbol{x} + \sum_{s \in S} \pi_s \cdot \boldsymbol{q}_s^T \cdot \boldsymbol{y}_s \tag{6.1}$$

[53] Kall and Mayer (2011), p.4
[54] Morales, Conejo, Madsen, Pinson, and Zugno (2014), p.369ff
[55] Conejo, Carrión, and Morales (2010), p.34ff

subject to

$$\boldsymbol{B} \cdot \boldsymbol{x} = \boldsymbol{b} \tag{6.2}$$

$$\boldsymbol{T}_s \cdot \boldsymbol{x} + \boldsymbol{W}_s \cdot \boldsymbol{y}_s = \boldsymbol{h}_s \qquad \forall s \in S \tag{6.3}$$

$$\boldsymbol{x} \in X,\ \boldsymbol{y}_s \in Y, \forall s \in S \tag{6.4}$$

Stochastic problems can be graphically described with a scenario tree (Figure 11). It consists of nodes and branches. Nodes describe states where decisions have to be made and/or uncertain parameters become known. Branches connect different nodes spanning trajectories of different scenario outcomes. A stochastic optimization problem can consist of various nodes. For every stage in a decision process another node can be introduced. The end of each scenario trajectory is referred to as leaves.

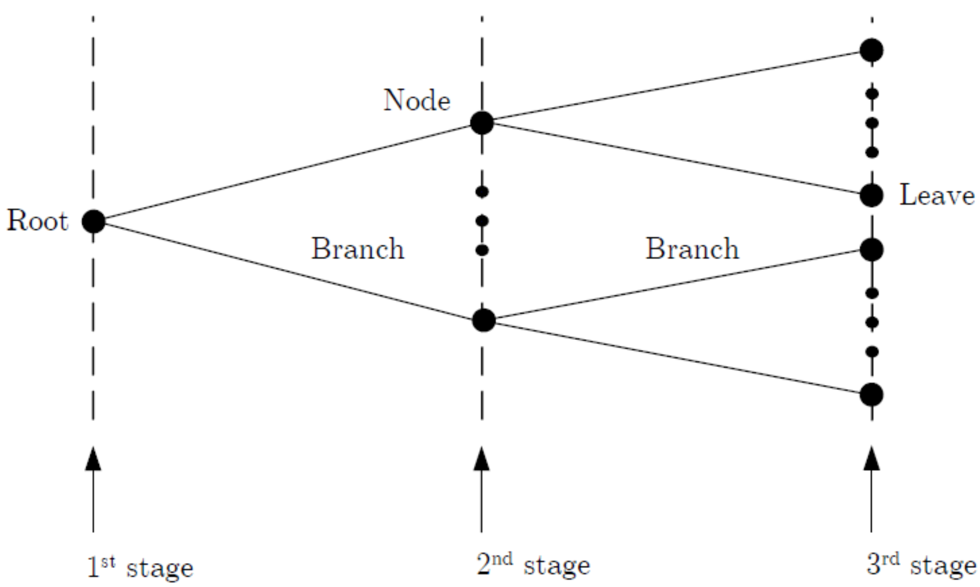


Figure 11: Scenario tree of three-stage stochastic programming problem (Conejo, Carrión, and Morales, 2010, S.35)

Stochastic programming is a common tool to model uncertainties in electricity markets and find optimal offering strategies for VPPs.[56] [57] [58] [59] [60] Consider the market framework described in Section 3. Before gate closure time offers to the Day-Ahead market have to be done. These offers can be regarded as here and now (first stage) decisions where market prices as well as intermittent generation from RES are unknown. Once a offer is made, it has consequences on the overall performance depending on the possible outcomes of the involved stochastic processes. If e. g. the output of variable RES differs from its expected value, imbalance energy is due. In the context of stochastic optimization those deviations can be regarded as wait and see (second stage) variables. The above described methodology guarantees that optimal offers at electricity spot markets are made taking into account all possible realizations of the stochastic processes with their respective probability.

6.1.2 Mean-Risk Analysis

The above described stochastic model optimizes an objective function, e. g. the expected profit, under different scenarios consisting of favorable as well as unfavorable realizations of random variables. Risk management techniques provide the possibility to evaluate the outcomes of a stochastic process to prevent high probabilities of unfavorable objective values. There are different frameworks to handle risk, like the expected utility approach, stochastic dominance or mean-risk analysis.[61] In this thesis, the mean-risk approach is chosen. The idea is, that *"a decision under uncertainties may be evaluated in terms of tradeoff between its risk and reward"*.[62] Consider a function $f(\boldsymbol{x}, s)$ that characterizes a certain profit in scenario s. The idea is to include a risk functional $r_s\left\{f(\boldsymbol{x}, s)_s\right\}$ that assigns to every profit $f(\boldsymbol{x}, s)$ a real number representing the risk attached to that profit. According to the mean-risk analysis, a weighted combination of expected profit and risk is used as objective function.[63] [64] [65]

[56] Pandžić, Kuzle, and Capuder (2013), p.141-143
[57] Pollok, Sowa, Koopmann, Raths, Elstermann, and Schnettler (2012), p.1-4
[58] Pandžić, Morales, Conejo, and Kuzle (2013), p.282-292
[59] Conejo, Carrión, and Morales (2010), p.27ff
[60] Morales, Conejo, Madsen, Pinson, and Zugno (2014), p.243ff
[61] Krokhmal, Zabarankin, and Uryasev (2011), p.52
[62] Krokhmal, Zabarankin, and Uryasev (2011), p.52
[63] Conejo, Carrión, and Morales (2010), p.127
[64] Morales, Conejo, Madsen, Pinson, and Zugno (2014), p.376
[65] Ogryczak and Ruszczynski (1999), p.37

$$\max \mathbb{E}\left\{f(\boldsymbol{x},s)\right\} - \beta \cdot r_s\left\{f(\boldsymbol{x},s)\right\} \tag{6.5}$$

where $\mathbb{E}\{.\}$ is the expectation operator and $\beta \in [0,\infty)$ a risk weighing factor, representing the tradeoff between expected profit and risk. For the risk weighing factor β usually a value between 3 and 5 is applied, depending on the specific market environment. All feasible solutions of the process under consideration, feature different combinations of expected profit and risk attached to it. *"An efficient point is a pair expected profit/risk in such a way that it is impossible to find a set of decision variables yielding simultaneously greater expected profit and lower risk"*.[66] Efficient points are elements of an efficient frontier. The efficient points dominate all other solutions to the right of the efficient frontier in the risk / expected profit image space. A risk averse decision maker would therefore never settle for solutions to the right of the efficient frontier. Points on the efficient frontier do not dominate any other points on the frontier. Which solution on the efficient frontier to choose depends on the risk preference of the specific decision maker.[67]

The expressions (6.5) and (6.6) are equivalent in the sense that they generate the same efficient points.[68] The benefit of formulation (6.6) is that the modified risk weighting factor $\hat{\beta}$ is an element of the defined interval [0,1] making parameter variations more intuitive. The modified risk weighting factor can be estimated by $\hat{\beta} = \dfrac{\beta}{\beta+1}$. This formulation is later used to include risk in the optimization problem (see Section 6.4):

$$\max\,(1-\hat{\beta})\cdot\mathbb{E}\left\{f(\boldsymbol{x},s)_s\right\} - \hat{\beta}\cdot r_s\left\{f(\boldsymbol{x},s)_s\right\} \tag{6.6}$$

As a risk measure, the conditional value at risk is applied (Section 6.4). It is considered suitable, because it is a coherent risk measure[69] that can be integrated into the optimization problem as a linear program.

6.2 Modeling Assumptions

To implement the characteristics of electricity markets and stochastic generation of RES into the optimization model, various assumptions have been made which are described in this section. It is assumed that stochastic processes involved can be sufficiently described

[66] Conejo, Carrión, and Morales (2010), p.127
[67] Rachev, Stoyanov, and Fabozzi (2008), p.155
[68] Conejo, Carrión, and Morales (2010), p.130
[69] Rachev, Stoyanov, and Fabozzi (2008), p.266

by a joint discrete distributions of finite size. The model can therefore be formulated using the deterministic equivalent of a stochastic problem. Due to the small installed capacity of the VPP compared to other market participants, the VPP operator is regarded as a pure price taker without influencing market prices with the offering decisions made.[70] [71] At energy markets, offers of the different participants are either met or refused depending on the interaction between supply and demand (see Section 3). In this thesis it is assumed that the operator always gets acceptance for the offers made. The bidding problem of a VPP operator is separated in different stages where decisions have to be made and uncertainty partially vanishes:

1. For every scenario s and time step t of the next day an offer $P^{\text{da}}_{s,t}$ has to be done to the Day-Ahead spot market. Offers for the offering day D can only be done until gate closure time (see Figure 6). At gate closure time however, the output of RES $P^{\text{res}}_{s,t}$, the spot market prices $\lambda^{\text{da}}_{s,t}$ and also the costs for compensation energy $\lambda^{\text{imb}}_{s,t}$ are uncertain. $P^{\text{da}}_{s,t}$ is modeled as a first stage variable. It can vary over the offering day D, but at every time step only one decision can be made which should be optimal for every scenario s.

2. After gate closure time the market clearing prices for every time step of the next day are announced to the market participants. Before the delivery of the Day-Ahead contract also the output of non dispatchable units like RES is known to the VPP operator. In this stage the VPP operator can either use its dispatchable units to balance out deviations from expected and real RES feed-in or settle the deviation as imbalance energy $\Delta_{s,t}$ whereas the imbalance prices are not yet known. The VPP-operator has N_N CHP units whose electrical output is expressed by $P^{\text{chp}}_{n,s,t}$ representing the output of CHP n in scenario s at the time step t, N_K load-shift DR units expressed by $DR^{\text{shift,down}}_{k,s,t}$ and $DR^{\text{shift,up}}_{k,s,t}$ respectively, and N_M load-shed DR units expressed by $DR^{\text{shed}}_{m,s,t}$ at its disposal. The schedule of dispatchable units and the deviations are considered as second stage variables which can react to the actual realization of the wind output and spot market prices.

3. In the last stage costs for compensation energy arise. Actually at this step no decision is made therefore the deviations occurred in the second stage have to be valued with the expected imbalance prices $\lambda^{\text{imb}}_{s,t}$.

[70] Pandžić, Morales, Conejo, and Kuzle (2013), p.284
[71] Raths, Pollok, Sowa, Schnettler, Brandt, and Eckstein (2013), p.4

The market framework is similar to that applied in (Pandžić, Morales, Conejo, and Kuzle, 2013, p.284). As described in Section 4 uncertainty is accounted for by considering a set of possible scenarios sufficiently describing a stochastic process. Here spot market prices, the output of the WPPs and the corresponding imbalance market price are modeled as random variables. The above described stochastic problem is summarized in Figure 12 in scenario based form.

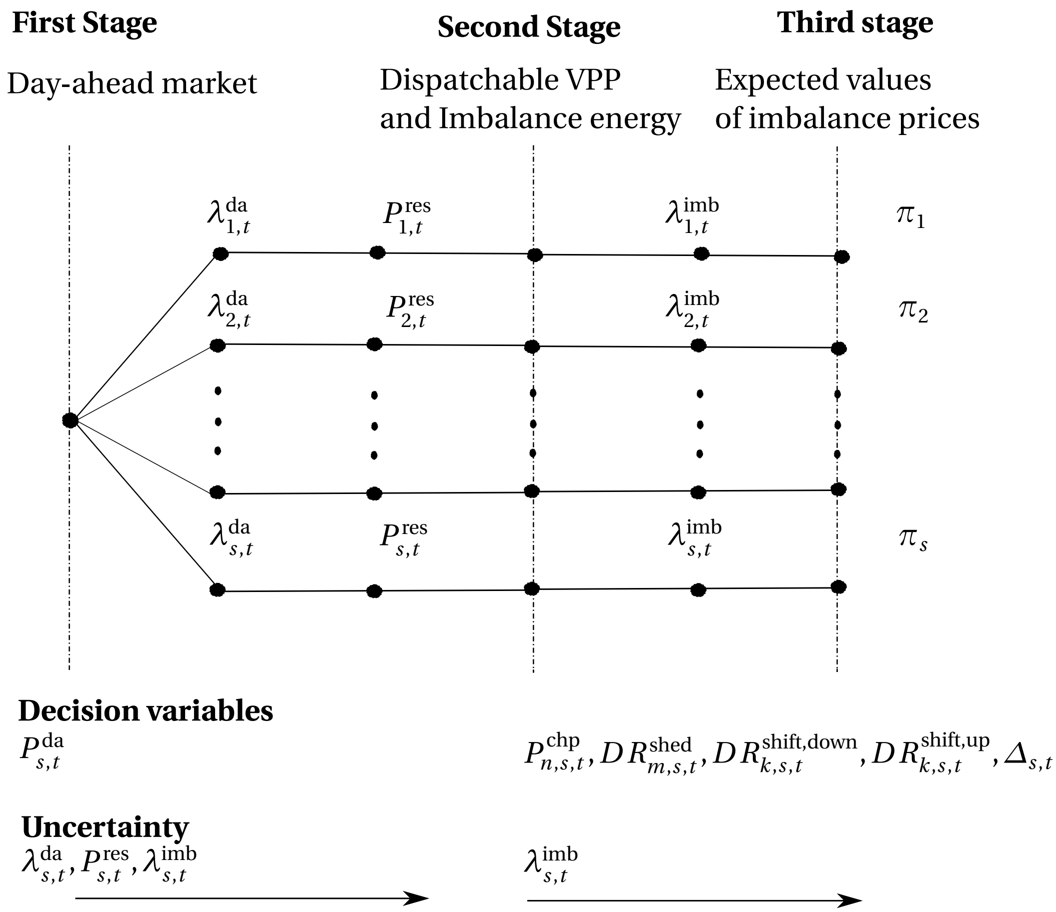


Figure 12: Scenario tree of applied bidding problem of a VPP operator

6.3 Expected Profit

The model aims at getting optimal offers at spot markets for a VPP. This is expressed by the expected profit whereas the profit consists of revenues minus costs. Uncertainty is accounted for by considering the different realizations of spot price, wind output and imbalance price over the time horizon of one day. The objective function consists of different terms for the spot market, imbalance market and costs of the corresponding power plants which are discussed in more detail in the following paragraphs.

Spot market term

The revenues gained at the spot market are described by offer quantity $P_{s,t}^{\mathrm{da}}$ times the actual simulated spot market price $\lambda_{s,t}^{\mathrm{da}}$ during the time step dt. The trades on spot market $P_{s,t}^{\mathrm{da}}$ include positive selling offers and offers to buy energy with a negative sign (6.7). Power producers usually place selling orders whereas a VPP featuring also customers, needs to buy the corresponding energy if the demand can not be coped by the generation units in the VPP. The decisions made for the spot market are treated as first stage (or here and now) variables. To meet this requirement anticipativity constraints have to be included that guarantee that only one offer is submitted Day-Ahead (6.8). The revenues respective cots gained at the spot market, are therefore expressed by:

$$\text{spot market} = \lambda_{s,t}^{\mathrm{da}} \cdot P_{s,t}^{\mathrm{da}} \cdot \mathrm{d}t \tag{6.7}$$

$$P_{1,t}^{\mathrm{da}} = P_{2,t}^{\mathrm{da}} = \ldots = P_{s,t}^{\mathrm{da}} \qquad \forall t \tag{6.8}$$

Imbalance market term

Compensation energy is needed to balance out deviations from offers made to the spot market and actual production/demand at contract fulfillment. In Austria the costs for those imbalances are calculated by the Power Clearing & Settlement Austria (APCS), in a process called clearing. The concept of compensation energy clearing aims at punishing those market participants who cause system deviations and reward those that help to restore system balance. To guarantee that, special imbalance price mechanisms are implemented. This section focuses on the clearing of the Austrian and German compensation energy. If electrical supply equals demand no reserve power is needed and the system is zero regulated. If however deviations exist, the system can either be upwards regulated (energy is added to the system) by calling positive reserve or downwards regulated (energy is withdrawn from the system) by activating negative reserve. From the costs for called positive and negative reserve energy, a reference imbalance price λ^{ref} can be calculated. The sign as well as the absolute value of the imbalance price depends on the system as a whole. To reduce speculations with compensation energy, the preliminary imbalance price λ^{ref} is coupled to the spot market price λ^{da}, so that:[72]

- If the system is upwards regulated ($\delta > 0$) the lower limit for the imbalance price is λ^{da} in order to consider the fact that for additional energy a price above λ^{da} is necessary because positive reserve energy has been activated. Supply has to be increased or demand reduced which comes at higher costs than λ^{da} (6.9).

$$\lambda^{\text{up}} = \max(\lambda^{\text{ref}}, \lambda^{\text{da}}) \tag{6.9}$$

- If the system is downwards regulated ($\delta < 0$) the imbalance price can have values up to λ^{da} due to the fact that the excess energy is not needed at the moment from system view. As a consequence the imbalance price is below or equal to λ^{da} (6.10).

$$\lambda^{\text{down}} = \min(\lambda^{\text{ref}}, \lambda^{\text{da}}) \tag{6.10}$$

The Austrian clearing system is regarded as a one-price system because positive and negative deviations of BRPs are settled with the same price. The resulting Austrian clearing price consists of a base price λ^{base} plus a reallocation term T (6.11) and depends on the direction the system is regulated (6.12).

$$\lambda^{\text{imb}} = \lambda^{\text{base}} + T \tag{6.11}$$

$$\lambda^{\text{base}} = \begin{cases} \lambda^{\text{up}} & \text{, if } \delta > 0 \\ \lambda^{\text{down}} & \text{, if } \delta < 0 \end{cases} \tag{6.12}$$

Note that for every time period there is only one imbalance price λ^{imb}. The resulting price however depends on the system deviation, the amount of called reserve with its corresponding energy price and the spot market price. The above mentioned mechanism of calculating the imbalance price λ^{imb}, is implemented in various countries (e. g. Germany, Austria) and clarified in Figure 13. The resulting revenue respective costs for imbalance energy depend on the direction the system is regulated and on the sign of the imbalance price.

[72] APCS (2015), p.7f

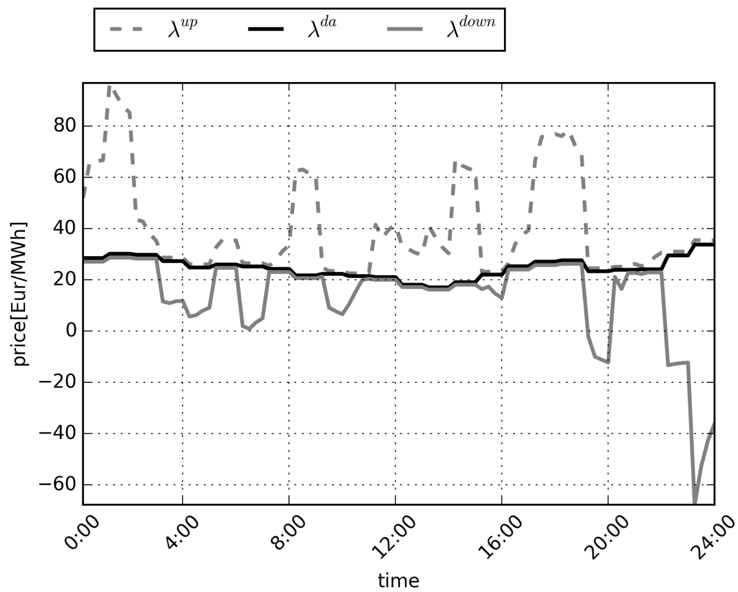


Figure 13: The interrelationship of spot market price and up and downwards regulated prices

The above described characteristic is integrated in the optimization model, so that deviations from spot market offers are avoided. Deviations from the spot market offers are referred to as $\Delta_{s,t}$. They can either be positive (delivery of more energy than expected) or negative (delivery of less energy than expected). The resulting deviations depend on the spot market offer and the energy produced and consumed by the DER inside the VPP. For modeling convenience the term $\Delta_{s,t}$ is separated in two non-negative variables $\Delta_{s,t}^{\text{pos}}$ and $\Delta_{s,t}^{\text{neg}}$ in the form of $\Delta_{s,t} = \Delta_{s,t}^{\text{pos}} - \Delta_{s,t}^{\text{neg}}$. In this formulation $\Delta_{s,t}^{\text{pos}}$ describes an excess generation, whereas $\Delta_{s,t}^{\text{neg}}$ describes a shortage of generation. As described above an excess generation can only be sold at a price $\lambda_{s,t}^{\text{down}}$ below the spot market price whereas a shortage of generation $\Delta_{s,t}^{\text{neg}}$ results in a penalty $\lambda_{s,t}^{\text{up}}$ higher than the spot market price. As a result, the costs at the imbalance market are modeled by the term:[73]

$$\text{imbalance market} = \lambda_{s,t}^{\text{down}} \cdot \Delta_{s,t}^{\text{pos}} - \lambda_{s,t}^{\text{up}} \cdot \Delta_{s,t}^{\text{neg}} \tag{6.13}$$

(6.13) reduces speculations on the imbalance settlement market. In reality the resulting imbalance settlement costs/profits depend on the real imbalance settlement price and on the deviation of the BRP. If the signs of deviations of the BRP and the imbalance market prices $\lambda_{s,t}^{\text{imb}}$ correlate the BRP gets paid for its deviations because the deviation has a positive effect on system stability. If the opposite is the truth, the BRP is confronted

[73]Conejo, Carrión, and Morales (2010), p.222

with costs. As the real imbalance prices (see Section 5) and the direction the system is regulated are very hard to anticipate, the optimization model allocates imbalances with reduced profits respective higher costs, representing a rather conservative offer strategy.

Costs of power plants

Also the costs of the different VPP units have to be considered. These include the aggregated costs $C_{s,t}^{\text{chp}}$ for all N_N CHP units, the aggregated costs $C_{s,t}^{\text{dr}}$ for all N_K and N_M DR units and the aggregated costs for RES described by $C_{s,t}^{\text{res}}$. The marginal costs of RES are assumed to be zero, no further costs are necessary to increase the output for one unit due to their weather dependency. Therefore the costs term is:

$$\text{costs} = C_{s,t}^{\text{chp}} + C_{s,t}^{\text{dr}} + C_{s,t}^{\text{res}} \tag{6.14}$$

The aggregated costs for the DR units can be separated in costs for shedding $C_{s,t}^{\text{shed}}$ and shifting load $C_{s,t}^{\text{shift}}$. The costs for load shifts are here neglected because processes are only shifted in time and not canceled. Load sheds however must be compensated with the value of the lost process. The aggregated costs $C_{s,t}^{\text{shed}}$ consist of the costs of the single units $C_{m,s,t}^{\text{shed}}$.

$$C_{s,t}^{\text{shed}} = \sum_{m=1}^{N_M} C_{m,s,t}^{\text{shed}} \tag{6.15}$$

Also the costs for CHP units have to be considered in the model. Usually fuel based power plants are modeled by considering the fuel costs of the single power plants $C_{n,s,t}^{\text{fuel}}$ and costs for starting up $C_{n,s,t}^{\text{start}}$ to incorporate the wear of components. The aggregated costs of the CHP units are:

$$C_{s,t}^{\text{chp}} = \sum_{n=1}^{N_N} \left(C_{n,s,t}^{\text{fuel}} + C_{n,s,t}^{\text{start}} \right) \tag{6.16}$$

The profit $p_{s,t}$ in scenario s at time t is obtained by:

$$p_{s,t} = \text{spot market} + \text{imbalance market} - \text{costs} \tag{6.17}$$

$$p_{s,t} = \lambda_{s,t}^{\text{da}} \cdot P_{s,t}^{\text{da}} \cdot \mathrm{d}t + \lambda_{s,t}^{\text{down}} \cdot \Delta_{s,t}^{\text{pos}} - \lambda_{s,t}^{\text{up}} \cdot \Delta_{s,t}^{\text{neg}} - C_{s,t}^{\text{fuel}} - C_{s,t}^{\text{start}} - C_{s,t}^{\text{shed}} \tag{6.18}$$

The profit p_s in a certain scenario over the modeling time t is defined as:

$$p_s = \sum_{t=1}^{N_T} p_{s,t} \tag{6.19}$$

The resulting term for the expected profit $\mathbb{E}\{p_s\}$ is obtained by considering the respective probability of occurrence π_s over the number of N_S scenarios:

$$\mathbb{E}\{p_s\} = \sum_{s=1}^{N_S} \pi_s p_s \tag{6.20}$$

6.4 Risk Measure

Often decision makers are not only interested in the expected profit but also in the variability of the profit. Risk management techniques provide the possibility to evaluate the outcomes of a stochastic process to prevent high probabilities of unfavorable objective values. As a risk measure the conditional value at risk (CVaR) approach was chosen. The CVaR can be defined as *"the expected value of the profit smaller than the $(1-\alpha)$-quantile of the profit distribution."*[74] With α being the confidence level adequately chosen to assess the desired risk properties, typically between 0,9 and 0,99.[75] The CVaR is an adaption of the value at risk (VaR) approach. The VaR is defined as the $(1-\alpha)$-quantile of the profit distribution. In contrast to the VaR as the $(1-\alpha)$-quantile, the CVaR regards the distribution of the profit smaller than the $(1-\alpha)$-quantile. Thereby flat tails of the profit distribution are considered. With the help of the CVaR unfavorable outcomes are reduced within a given confidence level.[76]

The CVaR can refer to a loss or profit function. If it refers to a function $f(x,s)$ representing loss, the CVaR of a discrete distribution can be obtained by solving the minimization problem:[77]

$$CVaR(x) = \min_\zeta \zeta + \frac{1}{1-\alpha} \cdot \mathbb{E}\left\{\left[f(x,s) - \zeta\right]^+\right\} \qquad \text{where } [F]^+ = \max\{0, F\} \tag{6.21}$$

If the CVaR is defined for a function $f(x,s)$ representing profit, it can be equivalently

[74] Conejo, Carrión, and Morales (2010), p.142
[75] Li, Wang, and Zhang (2012), p.66
[76] Conejo, Carrión, and Morales (2010), p.142
[77] Rockafellear and Uryasev (2002), p.1454

obtained by the following maximization problem:[78]

$$CVaR(x) = \max_{\zeta} \zeta - \frac{1}{1-\alpha} \cdot \mathbb{E}\left\{\left[\zeta - f(x,s)\right]^{+}\right\} (6.22) \tag{6.22}$$

Here, the CVaR is used as the expected value of the profit smaller than the $(1-\alpha)$-quantile of the profit distribution, so minimizing risk equals to maximizing the profit of the worst scenarios, which is considered using the CVaR formulation according to (6.22).[79] The CVaR is implemented in the objective function in the form of:

$$\max{}_{p_s,\zeta,\eta_s} (1-\hat{\beta}) \cdot \mathbb{E}\left\{p_s\right\} - \hat{\beta} \cdot \left(-\zeta + \frac{1}{1-\alpha} \sum_{s=1}^{N_S} \pi_s \cdot \eta_s\right) \tag{6.23}$$

subject to

$$\zeta - p_s \leq \eta_s \qquad \forall s \tag{6.24}$$

$$\eta_s \geq 0 \qquad \forall s \tag{6.25}$$

The term η_s is a non negative auxiliary variable that equals the maximum of $\zeta - p_s$ or 0 in (6.22). The expressions (6.24)-(6.25) ensure the behavior of the definition of the CVaR for discrete distributions (6.22).

(6.23) expresses the expected profit while also considering an appropriate risk measure. With the risk weighting coefficient $\hat{\beta} \in [0,1]$ a desired trade off between expected profit and profit variation can be chosen. The objective function is restricted by the following constraints.

6.5 Constraints

6.5.1 Energy Balance

For every time step t and scenario s an energy balance (6.26) has to be fulfilled. Selling offers at the spot market $P^{\text{da}}_{s,t}$ must be backed with electricity generation units while deviations $\Delta^{\text{pos}}_{s,t}$ and $\Delta^{\text{neg}}_{s,t}$ can be settled in the imbalance market. The produced energy

[78] Conejo, Carrión, and Morales (2010), p.142
[79] Morales, Conejo, Madsen, Pinson, and Zugno (2014), p.379

can be sold at the spot market or used to supply an electrical load D_t^{el}. The electrical consumption pattern can be modified by $\Delta D_{s,t}^{\mathrm{el}}$ which is later described in the Demand Response model 6.5.4.

$$P_{s,t}^{\mathrm{res}} \cdot \mathrm{d}t + \sum_{n=1}^{N_N} P_{n,s,t}^{\mathrm{chp}} \cdot \mathrm{d}t + \Delta_{s,t}^{\mathrm{neg}} = P_t^{\mathrm{da}} \cdot \mathrm{d}t + D_t^{\mathrm{el}} \cdot \mathrm{d}t + \Delta D_{s,t}^{\mathrm{el}} \cdot \mathrm{d}t + \Delta_{s,t}^{\mathrm{pos}} \qquad \forall s,t \tag{6.26}$$

6.5.2 Renewable Energy Systems Model

The RES output $P_{s,t}^{\mathrm{res}}$ is modeled as an external random parameter depending on the specific scenario. It is not a decision variable owing to the intermittent character of RES. In principle the modeling techniques here applied can be adapted to several RES facilities like wind power, photovoltaics or small run of river plants. $P_{s,t}^{\mathrm{res}}$ is a $N_S x N_T$ matrix describing the RES output in scenario s during the time step t. In other words the optimization model reacts to the external and volatile RES input $P_{s,t}^{\mathrm{res}}$ by optimally dispatching its controllable units.

6.5.3 Combined Heat and Power Model

The CHP model provides restrictions for every CHP plant n at every time step t of the modeling period. Power restrictions guarantee that the power $P_{n,t}^{\mathrm{chp}}$ of the CHP plants stays in their defined minimum and maximum power limits $P_n^{\mathrm{chp,min}}$and $P_n^{\mathrm{chp,max}}$ (6.27). The binary variable $u_{n,s,t}^{\mathrm{chp}}$ denotes the operation state of the CHP plants (6.28).

$$P_n^{\mathrm{chp,min}} \cdot u_{n,s,t}^{\mathrm{chp}} \leq P_{n,s,t}^{\mathrm{chp}} \leq P_n^{\mathrm{chp,max}} \cdot u_{n,s,t}^{\mathrm{chp}} \qquad \forall n,s,t \tag{6.27}$$

$$u_{n,s,t}^{\mathrm{chp}} = \begin{cases} 1 & \text{, if unit } n \text{is running at time step } t \\ 0 & \text{, otherwise} \end{cases} \tag{6.28}$$

Only a certain amount of the input flow $\dot{Q}_{n,s,t}^{\mathrm{fuel}}$ of the fuel can be transformed in electricity depending on the electric efficiency factor μ_n^{el} of the CHP plant (6.29). (Steck, 2013, p.34) implements a term to model part load efficiency of the CHP units but due to the rather insignificant drop of efficiency of two percent points this was neglected (Steck, 2013, p.78). The combined heat and electricity generation process is characterized by the power to heat ratio r_n^{p2h} representing the relation of electrical output $P_{n,s,t}^{\text{chp}}$ to heat output $\dot{Q}_{n,t}^{\text{chp}}$ described by (6.30).

$$\dot{Q}_{n,s,t}^{\text{fuel}} \cdot \mu_n^{\text{el}} - P_{n,s,t}^{\text{chp}} = 0 \qquad \forall n,s,t \tag{6.29}$$

$$P_{n,s,t}^{\text{chp}} - r_n^{\text{p2h}} \cdot \dot{Q}_{n,s,t}^{\text{chp}} = 0 \qquad \forall n,s,t \tag{6.30}$$

Additionally minimum run times (6.31) and minimum down times (6.32) are imposed for the CHP units to guarantee an economic operation and reduce the wear of components by an excessive amount of starts and stops. Often a certain time is necessary for the unit to reach its rated power. If a specific unit is turned on it has to stay on for $t_n^{\text{chp,run}}$. Similarly if a unit is turned off, it must be off for $t_n^{\text{chp,down}}$.

$$\left(u_{n,s,t}^{\text{chp}} - u_{n,s,t-1}^{\text{chp}}\right) \cdot t_n^{\text{chp,run}} \leq \sum_{\tau=0}^{t_n^{\text{chp,run}}-1} u_{n,s,t+\tau}^{\text{chp}} \qquad \forall n,s,t \tag{6.31}$$

$$\left(u_{n,s,t-1}^{\text{chp}} - u_{n,s,t}^{\text{chp}}\right) \cdot t_n^{\text{chp,down}} \leq t_n^{\text{chp,down}} - \sum_{\tau=0}^{t_n^{\text{chp,down}}-1} u_{n,s,t}^{\text{chp}} \qquad \forall n,s,t \tag{6.32}$$

(6.33) and (6.34) ensure that over the modeling time t only a certain number of start ups $g_n^{\text{start,max}}$ is possible.

$$u_{n,s,t}^{\text{chp}} - u_{n,s,t-1}^{\text{chp}} \leq u_{n,t}^{\text{chp,start}} \qquad \forall n,s,t \tag{6.33}$$

$$\sum_{t=1}^{N_T} u_{n,s,t}^{\text{chp,start}} \leq g_n^{\text{start,max}} \qquad \forall n,s \tag{6.34}$$

While some types of CHP plants often only allow the discrete states “on” and “off”, others are capable of power modulations, whereas changes of the current power are limited by technical restrictions like power gradients (6.35). The power of the CHP plant n between two consecutive time steps can only be altered by the power gradients $dP_n^{\text{chp,pos}}$ and $dP_n^{\text{chp,neg}}$.

$$dP_n^{\text{chp,neg}} d\text{t} \leq P_{n,s,t}^{\text{chp}} - P_{n,s,t-1}^{\text{chp}} \leq dP_n^{\text{chp,pos}} d\text{t} \qquad \forall n,s,t \tag{6.35}$$

It is assumed that the heat produced by the CHP plants $\dot{Q}_{n,s,t}^{\text{chp}}$ only provide the base heat load while a separate auxilliary burner $\dot{Q}_{n,s,t}^{\text{aux}}$ manages peaks in the thermal load. In the electricity let operation mode, the electricity price is the main control variable whereas heat supply still has to be guaranteed (6.36). The produced heat that is actually used to cover the thermal load $D^{\text{th}}_{n,t}$ is assessed with a certain value to model different marginal costs of the CHP depending on the chosen operation mode. μ^{aux}_{n} represents the efficiency factor of the auxilliary burner.

$$\dot{Q}^{\text{chp}}_{n,s,t} + \mu^{\text{aux}}_{n} \cdot \dot{Q}^{\text{aux}}_{n,s,t} = D^{\text{th}}_{n,t} \qquad \forall n, s, t \tag{6.36}$$

Every CHP start up is combined with specific start up costs c^{start}_{n}(6.37) to account for a higher fuel consumption and wear of components when starting up. Additionally operating costs for CHP and the auxilliary burner are considered which are usually expressed by a quadratic cost function. To keep the model linear, here CHP costs are regarded with (6.38).

$$C^{\text{chp,start}}_{n,s,t} = c^{\text{start}}_{n} \cdot u^{\text{chp,start}}_{n,s,t} \tag{6.37}$$

$$C^{\text{fuel}}_{n,s,t} = c^{\text{fuel}}_{n} \cdot \left(\dot{Q}^{\text{fuel}}_{n,s,t} + \dot{Q}^{\text{aux}}_{n,s,t}\right) \tag{6.38}$$

To reduce the interdependency between heat and power, storage systems can be implemented. Excess heat that might arise from CHP production can be used to fill a storage system. (6.39) shows the heat balance in the presence of heat storage systems. The heat output from the CHP units and the storage $\dot{Q}^{\text{st,out}}_{n,s,t}$ can be used to supply the thermal load $D^{\text{th}}_{n,t}$ or in case of excess heat, the heat flow $\dot{Q}^{\text{st,in}}_{n,s,t}$ can be filled into the storage system, as long as (6.41) and (6.42) are fulfilled, until the capacity maximum is reached (6.40). The energy balance condition at the storage is complied by (6.43). The state of charge (SOC) of the storage is the difference between the in and outflow in the time step $\mathrm{d}t$. Additionally (6.44) and (6.45) can be applied to define special initial or end conditions of the SOC via the parameter soc.

$$\dot{Q}^{\text{chp}}_{n,s,t} + \dot{Q}^{\text{st,out}}_{n,s,t} + \mu^{\text{aux}}_{n} \cdot \dot{Q}^{\text{aux}}_{n,s,t} = D^{\text{th}}_{n,t} + \dot{Q}^{\text{st,in}}_{n,s,t} \qquad \forall n, s, t \tag{6.39}$$

$$0 \leq E^{\text{st}}_{n,s,t} \leq E^{\text{st,max}}_{n,t} \qquad \forall n, s, t \tag{6.40}$$

$$0 \leq \dot{Q}^{\text{st,in}}_{n,s,t} \leq \dot{Q}^{\text{st,in,max}}_{n,t} \qquad \forall n, s, t \tag{6.41}$$

$$0 \leq \dot{Q}^{\text{st,out}}_{n,s,t} \leq \dot{Q}^{\text{st,out,max}}_{n,t} \qquad \forall n, s, t \tag{6.42}$$

$$E^{\text{st}}_{n,s,t} = E^{\text{st}}_{n,s,t-1} + \mathrm{d}t \cdot (\dot{Q}^{\text{st,in}}_{n,s,t} - \dot{Q}^{\text{st,out}}_{n,s,t}) \qquad \forall n,s,t \tag{6.43}$$

$$E^{\text{st}}_{n,s,t=0} = soc \cdot E^{\text{st,max}}_{n} \qquad \forall n,s,t \tag{6.44}$$

$$E^{\text{st}}_{n,s,t=T} = soc \cdot E^{\text{st,max}}_{n} \qquad \forall n,s,t \tag{6.45}$$

6.5.4 Demand Response Model

Load shedding

Similar to the CHP model, (6.46) describes a process with linear power modulation that can be operated between its lower (zero) and upper limit $DR^{\text{shed,max}}_{m}$. The binary value $u^{\text{shed}}_{m,s,t}$ is the operation variable and characterizes whether the shedding process m is on or off 6.47.

$$0 \leq DR^{\text{shed}}_{m,s,t} \leq DR^{\text{shed,max}}_{m} \cdot u^{\text{shed}}_{m,s,t} \qquad \forall m,s,t \tag{6.46}$$

$$u^{\text{shed}}_{m,s,t} = \begin{cases} 1, & \text{if unit } m \text{is operating in time step } t \\ 0, & \text{otherwise} \end{cases} \tag{6.47}$$

$DR^{\text{shed,max}}_{m}$denotes the maximal potential for demand shedding of the specific resource m. It is assumed that processes can be triggered for the maximum duration of $t^{\text{dr,on}}_{m}$. This is formulated in equation (6.48). After the duration of the process the signal has to be switched off again and has to stay off, for a defined time $t^{\text{dr,off}}_{m}$. This is guaranteed by equation (6.49). When a process is on in time step $t-1$ but not at t, then the process has been switched off at period t and therefore is not available for the duration $t^{\text{dr,off}}_{m}$. Mathematically this means the operation variables $u^{\text{shed}}_{m,t}$are set to 0 for the time they are inactive.

$$\sum_{\tau=0}^{t^{\text{dr,on}}_{m}+t^{\text{dr,off}}_{m}} u^{\text{shed}}_{m,s,t+\tau} \leq t^{\text{dr,on}}_{m} \qquad \forall m,s,t \tag{6.48}$$

$$t^{\text{dr,off}}_{m} \leq t^{\text{dr,off}}_{m} - \sum_{d=0}^{t^{\text{dr,off}}_{m}-1} u^{\text{shed}}_{m,s,t+\tau} \qquad \forall m,s,t \tag{6.49}$$

Another important aspect is that the analyzed resources vary in the allowed maximal activations in a given period. Some resources can be used only once a day while others can be activated several times. When a process is activated, the binary variable $u^{\text{shed,act}}_{m,s,t}$ has the value one (6.50). To impose an upper limit for the number of activations, equation (6.51) is applied. At last the process specific opportunity costs c^{shed}_{m} have to be paid, to compensate the value of the lost process as described in equation (6.52). During a certain period, shedding processes can only be activated for a given amount of $g^{\text{act,max}}_{m}$ (6.51).

$$u^{\text{shed}}_{m,s,t} - u^{\text{shed}}_{m,s,t-1} \leq u^{\text{shed,act}}_{m,s,t} \qquad \forall m,s,t \tag{6.50}$$

$$\sum_{t=1}^{N_T} u^{\text{shed,act}}_{m,s,t} \leq g^{\text{act,max}}_{m} \qquad \forall m,s \tag{6.51}$$

$$C^{\text{shed}}_{m,s,t} = c^{\text{shed}}_{m} \cdot DR^{\text{shed}}_{m,s,t} \tag{6.52}$$

Load shifting

The load shift formulation is similar to the load shed model with the main exception that a shifting process that was increased or decreased must be compensated over the modeling period. A process can only be shifted within a certain time period when it is available otherwise it is already scheduled for an industrial process.

Again this is guaranteed by $DR^{\text{shift,down}}_{k,s,t}$and $DR^{\text{shift,up}}_{k,s,t}$. Regarding the minimum and maximum power limits and the process characteristics, the formulation is identical to equations (6.46). Also the maximal duration for a process and the idle time is equivalent to equation (6.48) and (6.49). Equations (6.50) and (6.51) referring to the activation limit must also be valid for load shifts.

To model load shifts additional restrictions are necessary. At every time period a process can either be shifted up or down (6.53). Over the modeling time period the sum off all load shifts must sum up to zero (6.54). $u^{\text{shift,down}}_{k,s,t}$and $u^{\text{shift,up}}_{k,s,t}$ are again binary variables describing if a process is switched.

$$u^{\text{shift,down}}_{k,s,t} + u^{\text{shift,up}}_{k,s,t} \leq 1 \qquad \forall k,s,t \tag{6.53}$$

$$\sum_{t=1}^{N_T}\left(DR_{k,s,t}^{\text{shift,down}} - DR_{k,s,t}^{\text{shift,up}}\right) = 0 \qquad \forall k, s \tag{6.54}$$

In this model it is assumed that load sheds pose monetary disadvantages because processes are canceled. Load shifts however only shift the energy consumption in time. In sum all DR actions sum to up zero therefore opportunity costs are not considered. At last it has to be ensured that the current electrical load poses an upper limit for load sheds and downwards load shifts at any given moment (see equation (6.55)). In other words demand can not be further reduced than the existing demand D_t^{el}:

$$\sum_{m=1}^{N_M} DR_{m,s,t}^{\text{shed}} + \sum_{k=1}^{N_K} DR_{k,s,t}^{\text{shift,down}} \leq D_t^{\text{el}} \qquad \forall s, t \tag{6.55}$$

Regarding Direct Control measures the resulting change of electrical load $\Delta D_{s,t}^{\text{el}}$ is:

$$\Delta D_{s,t}^{\text{el}} = -\sum_{m=1}^{N_M} DR_{m,s,t}^{\text{shed}} + \sum_{k=1}^{N_K}\left(DR_{k,s,t}^{\text{shift,up}} - DR_{k,s,t}^{\text{shift,down}}\right) \tag{6.56}$$

6.6 Case Study of Virtual Power Plant

This section defines the case study that serves as input data for the VPP modeled by the above described optimization problem. The considered VPP consists of wind turbines, combined heat and power plants and controllable loads of demand side customers. The electric demand is approximated via standardized load profiles obtained from APCS.[80] According to Austrian energy law for end customers under 100.000 kWh annual electricity consumption or under 50 kW connection capacity, standardized load profiles have to be used.[81] With a rising amount of customers, the use of standard load profiles provides a pretty reasonable approximation of the electric consumption pattern. The electric demand is exemplary displayed in Figure 14 for a summer day in June.

[80]http://www.apcs.at, accessed on 13.01.2016
[81]E-Control (2011), p.9

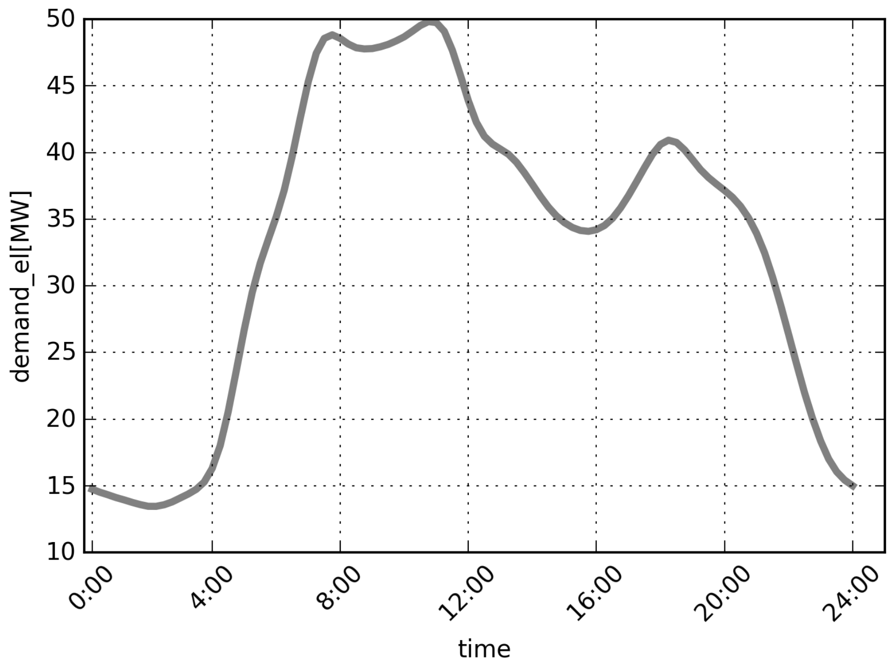


Figure 14: Example of the daily behavior of the electric demand inside the Virtual Power Plant used in the case study

The input data for direct controllable DR units, used for this case study, is shown in Table 1. $t_k^{\text{dr,on}}$refers to the maximum time a DR-process can be modified, whereas $g_k^{\text{act,max}}$ is a counter referring to the maximum number of activations over the modeling time. The input data is gathered from industrial companies at mid voltage level which results in high power shifts in the MW scale. The data available showed mainly shiftable DR processes therefore here no DR costs are considered.

Table 1: Case study input data for Direct Control Demand Response

	$DR_k^{\max}$[MW]	$t_k^{\text{dr,on}}$[15min]	$g_k^{\text{act,max}}$
process 1	3	4	1
process 2	7,3	8	1
process 3	2	4	1
process 4	0,4	8	1
process 5	2,5	8	1

CHPs provide both electricity and heat, therefore also a thermal demand has to be considered which is also approximated via standard heat load profiles. It is assumed that the CHP are not connected through a heat grid so for every CHP an own heat profile is implemented. This implies that electricity can be marketed in a CHP pool whereas individual heat loads have to be supplied by the individual CHP units. Technical and operational data of the CHPs is provided in Table 2. In this case study the restrictions concerning power gradients are neglected due to the flexibility of CHP which is in line with the assumptions made in (Steck, 2013, S.78). The fuel price c^{fuel} is set to 25 Euro/MWh. To reduce computational complexity, the single CHP units are not modeled separately. Instead it is assumed that 1000 units of each CHP-type are aggregated. The CHP-portfolio therefore sums up to 15 MW installed capacity.

Table 2: Combined heat and power plants input data used in the case study

	$P_n^{\text{chp,min}}$[kW]	$P_n^{\text{chp,max}}$[kW]	r_n^{p2h}	μ_n^{el}	μ_n^{aux}	$g_n^{\text{start,max}}$	c_n^{start}[Eur]	$E_n^{\text{st,max}}$[kWh]
CHP	1	15	0,35	0,33	0,9	10	0,1	20

The thermal demand of the buildings the CHPs are operated in, is generated by applying a sigmoid soothing function 6.57 taking building specific parameters A, B, C, D, a thermal reference temperature ϑ^0 and the outdoor temperature ϑ as input. The influence of building specific parameters is shown in Figure15. Thereby a normalized coefficient of heating and warm water is computed for a day. Considering the average daily heat demand $\bar{D}_d^{\text{th}}$ and the normalization coefficients of the specific day, results in the characteristic thermal demand profile D_t^{th}.[82] [83] Average outdoor temperatures are taken from database of the German weather service.[84] The resulting heat load is shown in Figure 16 for a summer day.

$$h_\vartheta^{\text{day}} = \frac{A}{1+\left(\frac{B}{\vartheta-\vartheta^0}\right)^C} + D \tag{6.57}$$

[82]Hellwig (2003), p.46ff

[83]Rezania and Haas (2012), p.217ff

[84]DWD (2016)

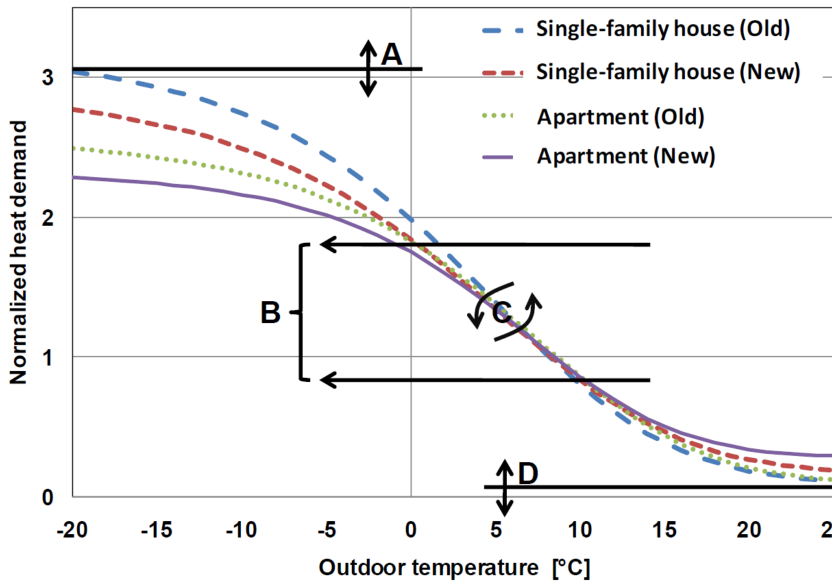


Figure 15: Influence of building parameters on the behavior of the sigmoid function representing the daily thermal demand of a building (Rezania and Haas, 2012, p.225)

Table 3: Input parameters to generate the thermal demand of buildings for each day of a year

	A	B	C	D	$\bar{D}^{th}$ [kWh/d]
Building	2,794	37,2	5,4	0,17	200

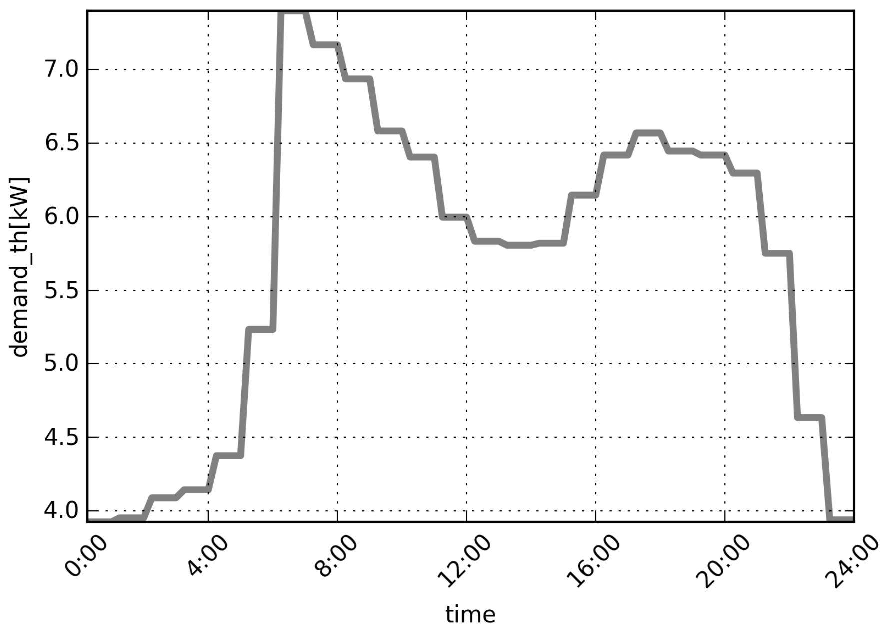


Figure 16: Example of heat load including space heating and warm water

WPPs with an installed capacity of 100 MW are also included in the VPP. Here it is assumed that the regional dispersion of the WPPs is sufficient enough to use the wind power forecasts of ENTSO-E for the next day for the whole of Austria (Section 5.3). A more precise approach would be to respect the specific regional wind speeds and the operational characteristics of each WPPs. The portfolio of the considered VPP is shown in Table 4.

Table 4: Portfolio of analyzed virtual power plant

Type of DER	**installed capacity [MW]**	**Share [%]**
WPP	100	76,8
CHP	15	11,5
DR	15,2	11,7

6.7 Results

To better understand the behavior of the implemented stochastic optimization problem, the results are divided into two parts:

- The first part deals with the behavior of the stochastic optimization model and analyzes if the applied stochastic model is appropriate for the problem. Therefore, in a first step, only the stochastic components i. e. the wind turbines are considered. To evaluate the quality of the stochastic model the expected value of perfect information and the value of the stochastic solution are assessed, using the risk neutral formulation of the objective function (see Section 6.3). After that the applied risk measure is closer examined and the mean-risk efficient frontier of the optimization problem is shown.

- In a next step each DER is analyzed separately to assess their operational characteristics. After that the DERs are combined into a VPP. By comparing the profits before and after pooling the added value of forming a VPP is measured. For this part, also the risk neutral formulation of the optimization problem is used. The performance of the VPP and its components was analyzed for the year 2015 using a summer (15th of June), transition (15th of April) and winter (15th of January) working day respectively.

6.7.1 Expected Value of Perfect Information

The expected value of perfect information $EVPI$ indicates the added value if the future realizations of all stochastic processes $\boldsymbol{\lambda}$ are known at the time of decision making. It therefore gives a benchmark what a decision maker gains for the perfect information of future realizations of the involved stochastic processes. Consider a general recursive stochastic program, where a decision of $\boldsymbol{x}$ has to be done before an observation of the random vector $\boldsymbol{\lambda}$ is possible, referred to as $z(\boldsymbol{x}, \boldsymbol{\lambda})$. Then the stochastic solution SS is obtained by:

$$SS = \max_{\boldsymbol{x}} \mathbb{E}\{z(\boldsymbol{x}, \boldsymbol{\lambda})\} \tag{6.58}$$

In this thesis SS is approximated by the deterministic equivalent (6.1). To obtain the $EVPI$ the anticipativity constraints of SS are relaxed assigning different first stage decision variables to every scenario. The decision maker is now able to react to every scenario realization in an optimal way having perfect information over the stochastic processes. The optimal value thus obtained is referred to as the “wait-and-see” solution WS:

$$WS = \mathbb{E}\{\max_{\boldsymbol{x}} z(\boldsymbol{x}, \boldsymbol{\lambda})\} \tag{6.59}$$

In case of a maximization problem, evaluating (6.60) yields the $EVPI$.[85] [86]

$$EVPI = WS - SS \tag{6.60}$$

For the here considered case, under perfect information the expected profit can be significantly improved (see Table 5). The rather high value of the $EVPI$ might be caused by the high volatility in the stochastic processes especially of the imbalance settlement prices. This results in high values of the wait and see solution. Here, improvements of the forecasts of the random variables would result in high profit gains. The availability of reasonable forecasts of the stochastic processes is therefore one central point for successfully operating a VPP at the spot market.

Table 5: Expected value of perfect information (EVPI) over all stochastic processes involved ($\hat{\beta} = 0$).

	Wait and see	**Stochastic**	**EVPI**
Profit [Eur]	62.897	23.872	39.025
Profit [%]	263%	100%	163%

6.7.2 Value of Stochastic Solution

Stochastic programming considers the distribution of stochastic processes instead of merely their expected values. In the expected value model EV, uncertain parameters are replaced by their expected values:

$$EV = \max_{\boldsymbol{x}} z(\boldsymbol{x}, \bar{\lambda}), \text{ with } \bar{\lambda} = \mathbb{E}\{\boldsymbol{\lambda}\} \tag{6.61}$$

The solution thus obtained is referred to as $\bar{x}(\bar{\lambda})$. Usually stochastic programming pro-

[85] Conejo, Carrión, and Morales (2010), p.49
[86] Morales, Conejo, Madsen, Pinson, and Zugno (2014), p.373f

vides better solutions than its associated deterministic model, where first-stage decision variables are fixed to the solution of the expected value model:

$$EEV = \mathbb{E}\left\{z(\bar{x}(\bar{\lambda}), \boldsymbol{\lambda})\right\} \tag{6.62}$$

The value of the stochastic solution VSS for maximization problems is defined as:[87] [88]

$$VSS = SS - EEV \tag{6.63}$$

In case the objective function is to be minimized the terms SS and EEV of (6.63) are exchanged. The VSS is a tool to assess the additional value of using stochastic programming compared to a deterministic approach, where uncertain parameters are replaced by their expected value. The higher the VSS the more is gained by using a stochastic optimization model.[89] The key findings are shown in Table 6. The value of the deterministic solution accounts for 22.183 Euro for the considered day. With the case study input data as of above, the stochastic model respecting the distribution of the random variables, results in a higher profit of 23.872 Euro. The VSS is 1.680 Euro or 7.6% higher than the deterministic solution. The added value argues in favor for applying a stochastic approach, as long as the scenarios generated sufficiently describe the random processes involved.

Table 6: Value of stochastic solution (VSS) compared to a deterministic approach ($\beta = 0$).

	Deterministic	**Stochastic**	**VSS**
Profit [Eur]	22.183	23.872	1.689
Profit [%]	100%	107,6%	7,6%

6.7.3 Mean-Risk Efficient Frontier

Figure 17 shows the mean-risk efficient frontier (black line) of the optimization problem in the CVaR / expected profit space with $\alpha = 0,9$. The higher the respective risk a decision maker is willing to take, the higher the expected profit. On the other hand, the additional expected profit achieved by accepting another unit of risk is declining. Figure 17 also

[87] Conejo, Carrión, and Morales (2010), p.52
[88] Morales, Conejo, Madsen, Pinson, and Zugno (2014), p.374
[89] Conejo, Carrión, and Morales (2010), p.52

shows indifference curves with different risk preferences (grey lines). In the CVaR / expected profit space the iso-utility lines of a risk averse decision maker are upwards sloped. An additional unit of risk is only tolerated if there is a gain in expected profit. The slope of the indifference curves depends on the risk weighting factor $\hat{\beta}$. Along these indifference curves the decision maker is equally satisfied. In general, indifference curves in the north-west direction of the graph are superior because they either feature a higher expected profit at a given risk level or less risk at a given level of expected profit. Therefore decision makers would like to position themselves on the highest indifference curve. The portfolio here investigated however, is not able to serve the highest indifference curve. The optimal location on the efficient frontier is the tangent point with the marginal indifference curve, just coinciding with the efficient frontier.

In case of a risk-neutral decision maker ($\hat{\beta} = 0$) the slope of the indifference curves is zero. Therefore the decision maker regards no compensation for the involved risk and would settle with the highest expected profit available. A risk averse decision maker with $\hat{\beta} = 0,3$ on the other hand, tolerates another unit of risk only at a certain increase in expected profit. In this case, the tangent point with the efficient frontier is at a different location where the expected profit but also the risk attached to it is reduced. A more risk averse decision maker $\hat{\beta} = 0,5$ and $\hat{\beta} = 0,75$ chooses a portfolio with a lower risk, but also a lower expected profit. At the minimum risk location the efficient frontier is very steep. This is the tangent point at a risk preference of $\hat{\beta} = 1$. The optimal location for a very risk averse decision maker will be near the minimum risk location.

The risk measure provides the possibility to influence the distribution of the profit. Due to the variability of wind, an offer made can result in undesirable outcomes depending on the actual scenario realization. This has to be considered when trading with WPPs on the spot market. Figure 18 shows the histograms of the profit distribution obtained by different risk preferences. In the risk neutral case ($\hat{\beta} = 0$) the profit spans from -60,000 Euro to +90,000 Euro (Figure 18a) depending on the respective scenario which can pose challenges for the direct marketing of WPPs. A negative profit corresponds to costs. By incorporating the CVaR risk measure and choosing $\hat{\beta} = 0,3$, unfavorable scenario outcomes are significantly reduced. This is achieved by maximizing the profit of the $(1-\alpha)$-quantile of the profit distribution. The profit now ranges between -40.000 to 90.000 Euro. By choosing a higher value for $\hat{\beta}$ ($\hat{\beta} = 0,5$ and $\hat{\beta} = 0,75$) this effect is more prominent. However, this comes with the drawback of a lower value of the expected profit. By applying a risk measure the decision maker has a tool to set individual risk preferences.

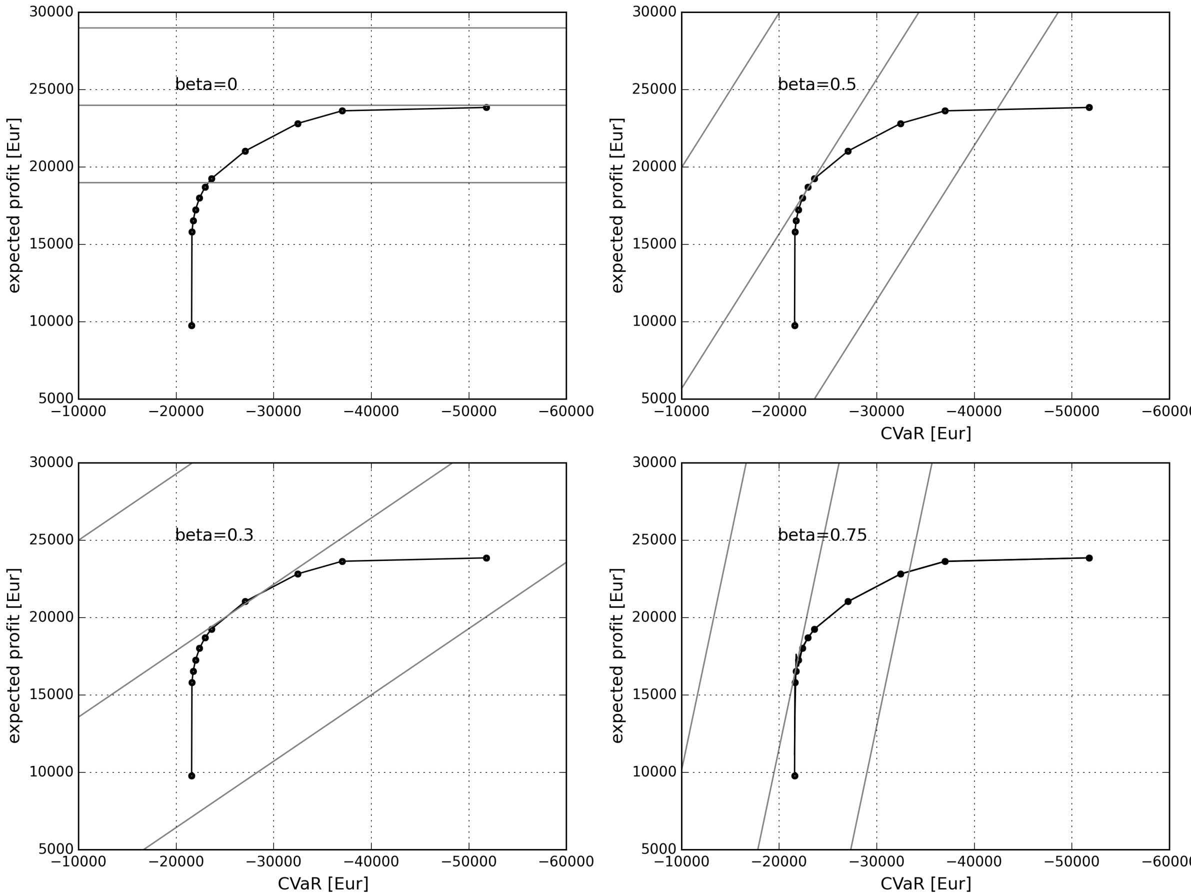
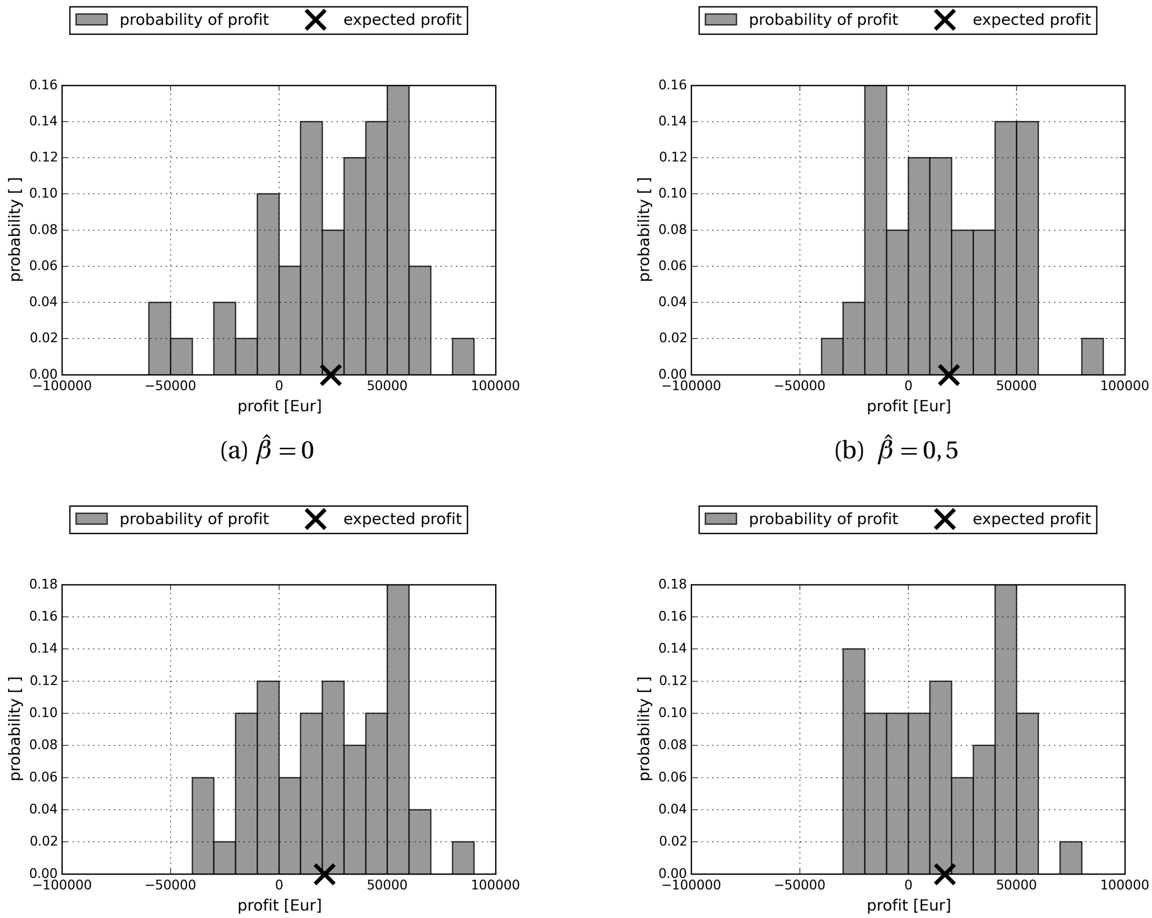


Figure 17: Mean-risk efficient frontier of the optimization problem in the CVaR / expected profit space. The points forming the frontier are efficient in the sense that they have the highest expected profit at a given level of risk represented by the CVaR. Optimal location on the frontier depends on the risk preference of the decision maker.



(a) $\hat{\beta} = 0$

(b) $\hat{\beta} = 0,5$

(c) $\hat{\beta} = 0,3$

(d) $\hat{\beta} = 0,75$

Figure 18: Histogram of the profit distribution across the different scenarios s. In the risk neutral formulation ($\hat{\beta} = 0$), the profit has a wider range of possible scenario outcomes, also featuring very unfavorable outcomes (negative profit). By choosing different values for the risk weighting parameter ($\hat{\beta} = 0,3$; $\hat{\beta} = 0,5$ and $\hat{\beta} = 0,75$ respectively), the probability of obtaining unfavorable scenario outcomes is reduced. This however comes at the expense of a lower expected profit.

6.7.4 Wind Power Plants

To better present the performance of the single units inside the VPP, the following results are now computed considering three scenarios. Figure 19 shows the WPP schedule in relation to the realization of the stochastic processes. The first three graphs show the price scenarios of spot and imbalance prices.

In the fourth graph the resulting Day-Ahead offers (black line) and the different wind power output scenarios are displayed (grey lines). There is no incentive to place Day-Ahead offers higher than the highest wind output scenario or offers lower than the lowest wind output scenario due to the conservative bidding model. So the optimal Day-Ahead offer quantities (black line) are between the highest and lowest wind output scenario (grey). Speculations on imbalance energy are eliminated owing to the imbalance settlement market model where deviations always result in penalty costs. The last graphs shows the resulting imbalances for the different scenario outcomes. Imbalances occur because Day-Ahead offers have to be submitted before the realization of the wind power output is known. High negative imbalances are accepted in times of upwards imbalance prices near the spot market price. Correspondingly this also holds for high positive imbalances at times of downwards imbalance prices near the spot market price. The applied model provides rather conservative spot market offers due to the high volatility and limited predictability of the imbalance price (see Section 5).

Figure 20 shows the corresponding offer quantities separately for every scenario. For every trading time step the selling quantities at the spot market are equal for every scenario (first-stage decision variable). Due to the different wind outputs per scenario the resulting imbalance energy (second-stage decision variable) varies significantly. Positive deviations outweigh negative deviations due to the imbalance market model which penalizes negative deviations in general with values above the spot market price. In reality this strategy might be favorable, in that WPP output can be restricted by switching off a WPP whereas additional output is hard to achieve and only possible by operating WPPs in part load. This is rather uncommon, because of the high opportunity costs involved. It is noticeable, that almost no energy is sold on the spot market Day-Ahead from 6:00 to 9:00 o'clock. Under the assumptions here made, it is better to settle the RES feed-in in scenario 1 and 2 as excess generation (delta_pos), although lower revenues than on the spot market exist and even costs might occur in case of negative imbalance settlement prices. As can be seen in scenario 3 (see $s = 3$), there is no energy traded because negative deviations are avoided.

In general, operating RES under feed-in tariffs is highly preferable under the here considered market situation. The Day-Ahead prices are in general too low to compete with the feed-in tariff of 9,45 Cent/kWh. Furthermore in the feed-in scheme no imbalance costs have to be considered. [90]

[90] https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=20007993, accessed on: 13.01.2016

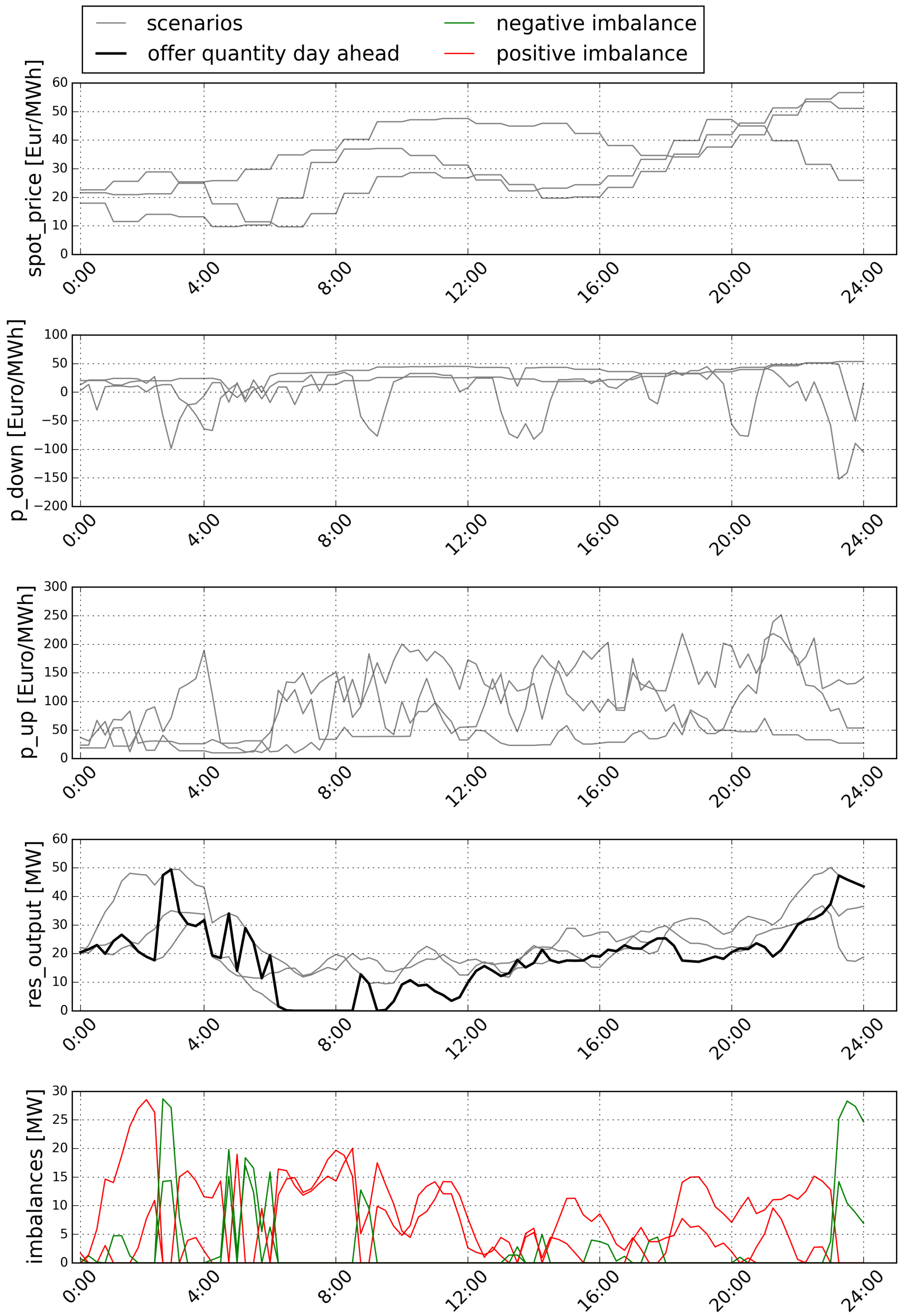


Figure 19: Offers in dependence of realization of stochastic processes. From top down: different scenario realizations of spot price, imbalance price for excess generation and imbalance price for shortage of generation. Fourth subplot shows the offer quantities Day-Ahead with corresponding wind output scenarios. Last subplot shows the resulting imbalance energy for every scenario.

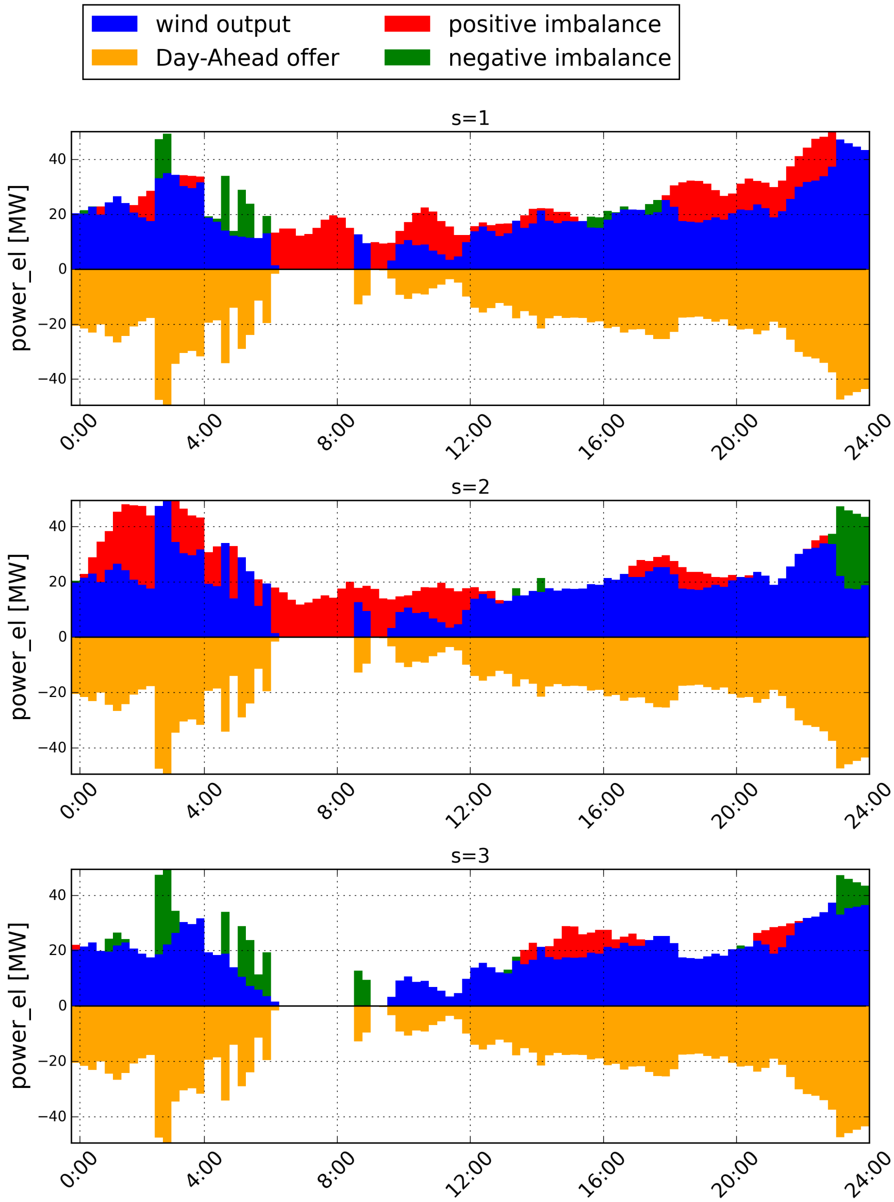


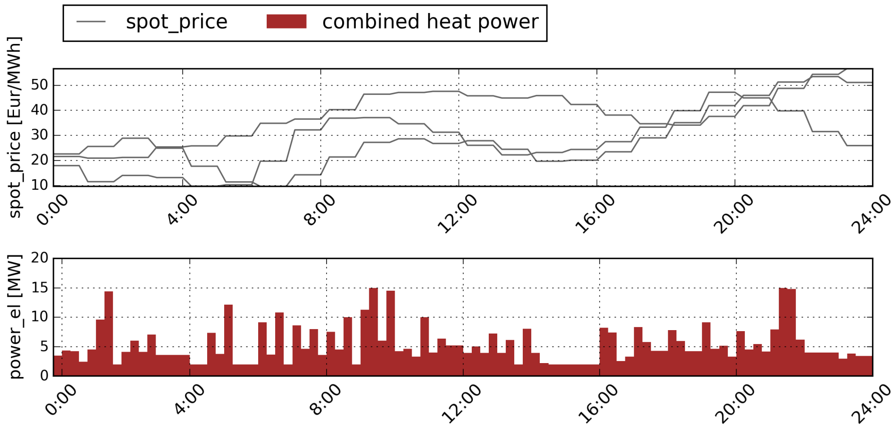
Figure 20: Offer quantities for a wind operator. Optimal offer quantity Day-Ahead (orange graph) considering all scenario realizations of wind output (blue graph) as well as the resulting positive (red graph) and negative imbalances (green graph).

6.7.5 Combined Heat and Power

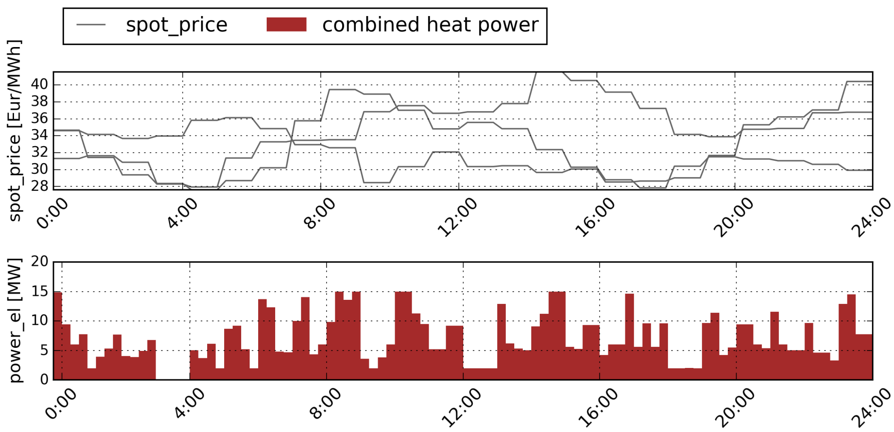
CHP plants can be operated either heat or electricity controlled. Micro CHP without pooling concept are usually heat controlled. In this case electricity is produced whenever there is a heat demand regardless of the current current electricity price. By pooling many CHPs there is the possibility to participate at electricity markets and operate them at favorable market prices. In electricity controlled mode the profits of CHPs can be increased around 4 % compared to heat controlled operation. Although the percent value is rather small over the year considerable gains can be achieved. Figure 21 depicts the schedule of the CHP pool with the corresponding Day-Ahead prices. The operation of the CHPs aims at providing the required heat load of the specific building, taking advantage of operating at times of high spot market prices. The heat storage is used to decouple demand and supply of thermal energy in a such a way, that high price periods can be exploited (Figure 22) while eventually incurring excess heat is stored and later used to cope with the heat demand. The CHPs feature different marginal costs in dependance of the heat load. With the input data here applied the CHPs would not be switched on at the existing spot market prices if the provided heat is not accounted for because of the high fuel costs in relation to spot market prices. Providing heat is a must run condition that lowers the marginal costs of CHPs.

On a summer and transition period day the auxiliary burner is not really needed, the base heat load (D_th) can be provided by the CHPs alone (Figure 22a and 22b). For a winter day on the other hand heat peaks are covered with the aid of the auxiliary burner when the installed CHP capacity is not sufficient (Figure 22c). Despite a lower thermal efficiency factor it is favorable to switch on the CHPs instead of the auxiliary burner because the produced electricity can be sold at the spot market. In winter the totally produced electricity is higher due to the higher heat demand. During the winter months the flexibility of the CHPs is restricted because of the high base heat load.

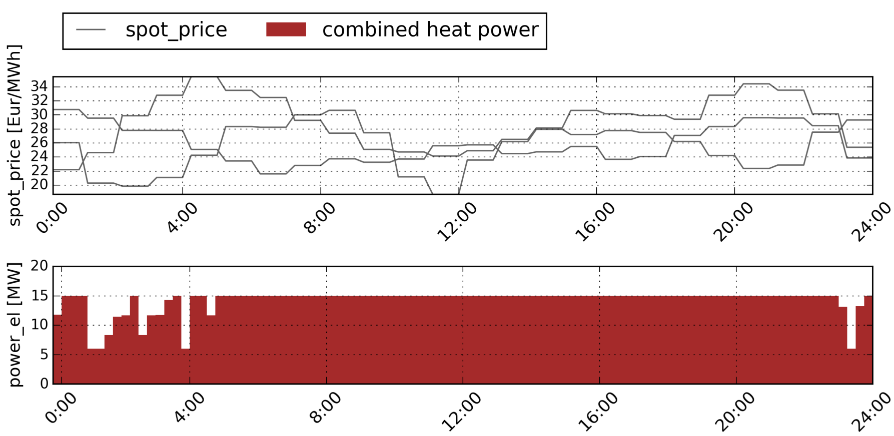
The flexibility of the CHP plants depends on the the thermal storage system. For the considered day the profit of the CHPs is 877 Euro higher when a thermal storage system (20 kWh) is available which corresponds to around 7 %. With rising capacity of the thermal storage also the profits increase due to the higher flexibility potential (Figure 23).



(a) Summer day

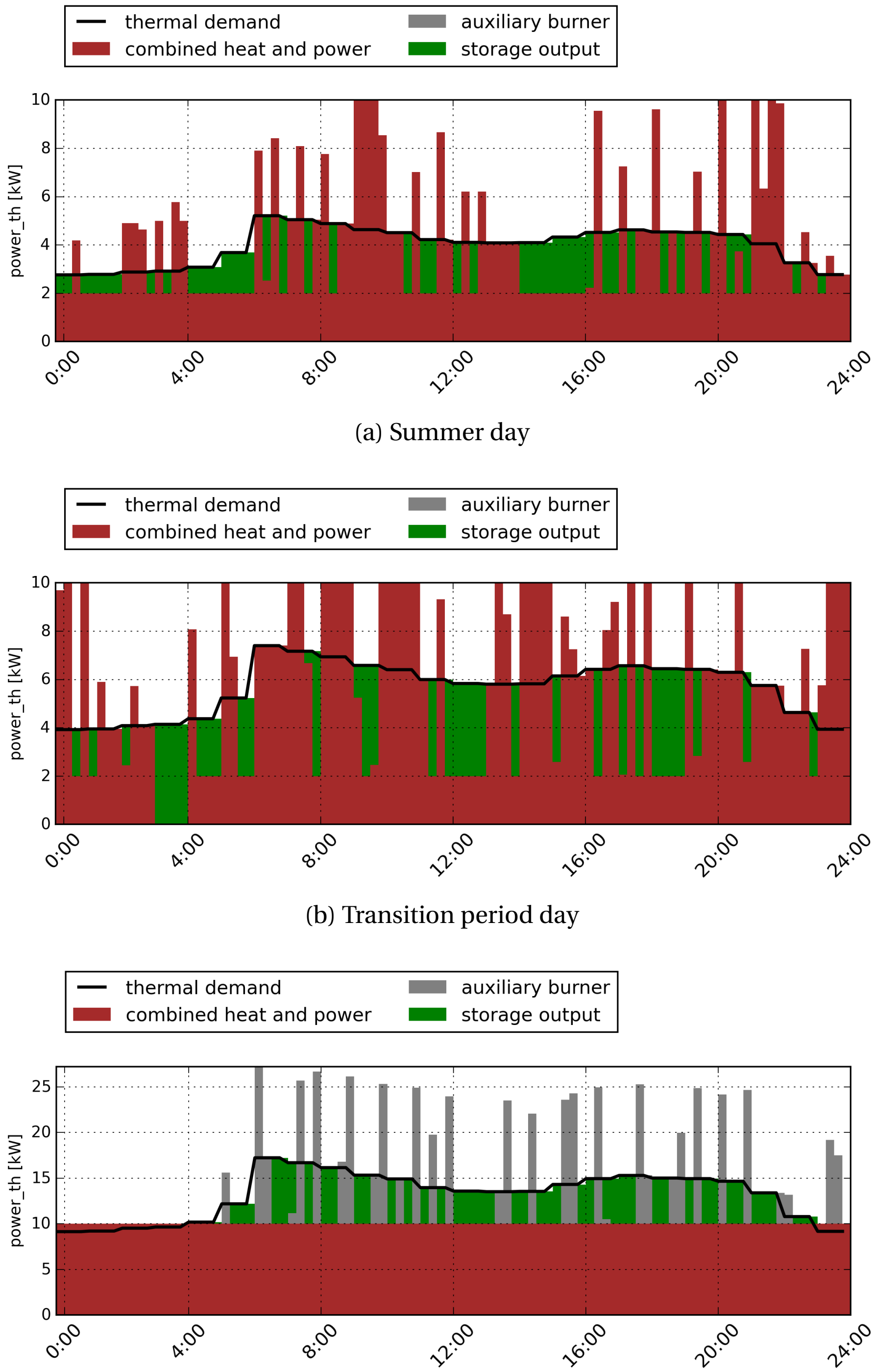


(b) Transition period day



(c) Winter day

Figure 21: Schedule of CHPs on a summer, transition period and winter day respectively. Times of high spot market prices are used to sell electricity as long there is flexibility available.



(a) Summer day

(b) Transition period day

(c) Winter day

Figure 22: Heat load coverage by the CHP unit in combination with auxiliary boiler and heat storage on a summer, transition period and winter day respectively

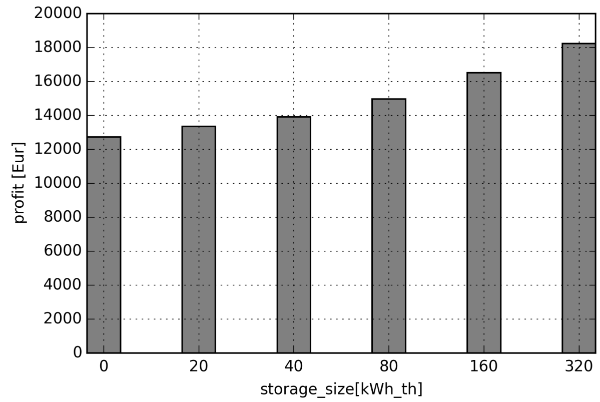


Figure 23: Influence of thermal storage size variation on daily profit

6.7.6 Demand Response

Electrical loads can adapt their electricity consumption pattern and therefore use price spreads to switch processes from high price to low price periods. To analyze the potential benefits of DR, the electrical load of the customers is at first solely covered at the spot market Day-Ahead without any flexibility. After that, the electrical load is altered by DR measures and the benefits are compared.

In a reference case it is assumed that there is no adaption of the electric load therefore energy has to be bought at any current spot market price. In reality an energy trader can hedge against spot market price risks on the Futures market. Here however the short term flexibility is used as the evaluation parameter so only the Day-Ahead market is analyzed. Without any flexibility of the demand side high price periods tend to coincide with periods of high electrical demand resulting in rather high electricity procurement costs (Figure 25a).

Now the electrical demand is allowed to be modified according to the direct control program described in Section 6.5.4. By employing the DR measures a reduction of the costs for energy procured Day-Ahead can be achieved by shifting loads to other times profiting from price differences of high and low spot market prices. As no shedding process where considered the total electricity consumption before and after the DR events is equal. The potential savings for the considered days are shown in Figure 24. In case DR processes are available the whole day, the average savings account for 2000 Euro. In case units are blocked between certain time spans the potential gains from DR tend to decline. The lower the availability the lower is the possibility to profit from price spreads which reduces extreme savings as well as average savings. Figure 25 clarifies the meaning of available and blocked units. When a unit is blocked it is not able to alter its consumption pattern because it is needed for other processes. Often this results in a reduced price spread between high and low electricity prices.

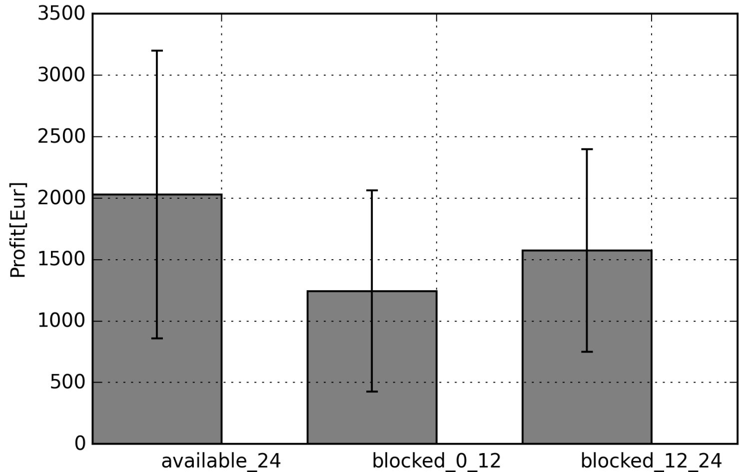
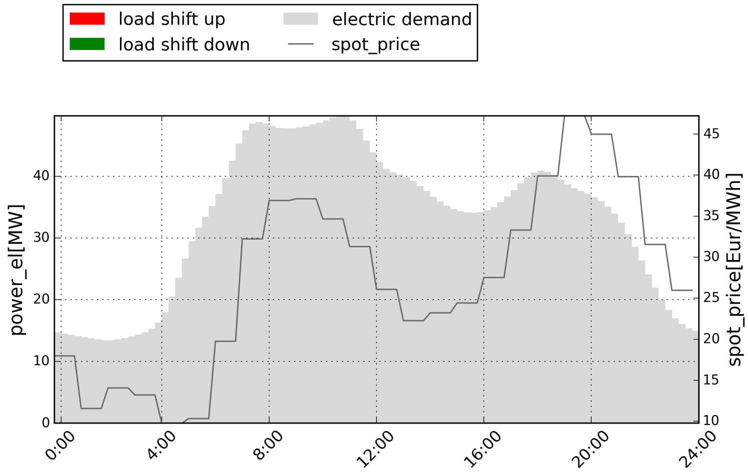
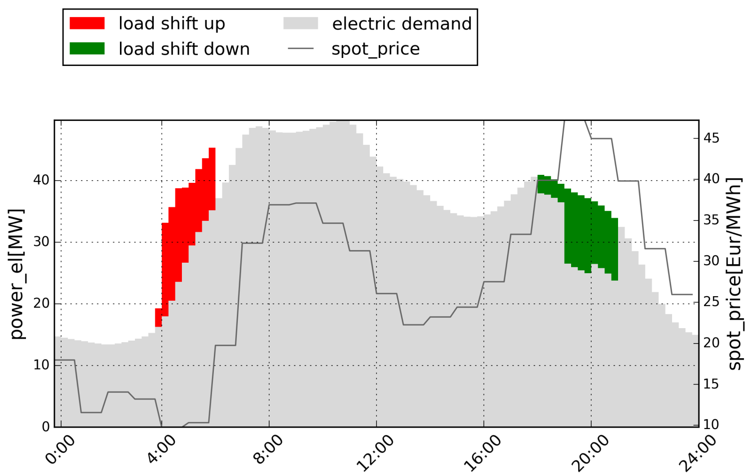


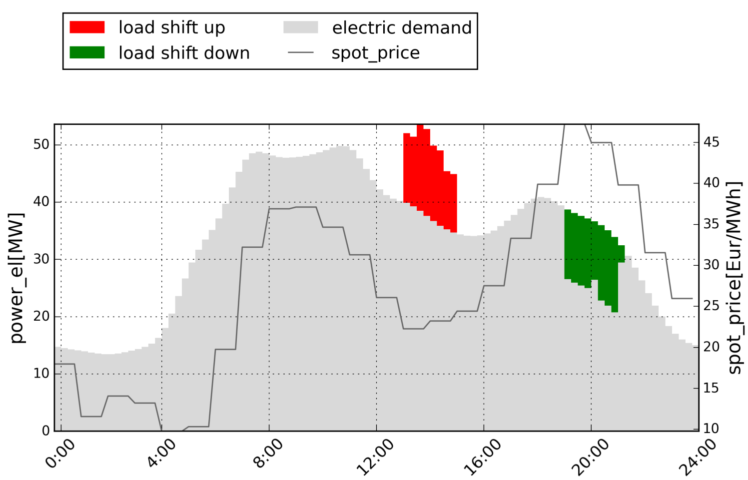
Figure 24: Daily profits of Demand Response measures on the spot market depending on the availability of the units on the time of the day



(a) No Demand Response potential



(b) Demand Response units considered, available 24h a day



(c) Demand Response units, blocked from 00:00 - 12:00

Figure 25: Adaption of the electrical load curve via Demand Response

6.7.7 Virtual Power Plant

At last the DERs are combined in a VPP and optimized together. The results are shown exemplary for a summer day in Figure 26 and 27 respectively (transition period and winter day in appendix 8.6). There is again the tendency to approve rather high positive imbalance (overproduction) compared to negative imbalance (shortage of production). As described above this is due to the imbalance settlement model. Generally reducing the absolute value of the imbalances, is different from reducing imbalance costs which result from deviations multiplied by the respective imbalance market price. As a consequence even if there is the ability to reduce deviations it is not necessarily the optimal decision to do so. When combined in a VPP, several effects can be observed.

The flexibility of CHPs can be used to reduce negative imbalances (see scenario $s = 3$, from 23:00 to 24:00). In the third scenario ($s = 3$, from 6:00 to 9:00) where WPP output is zero, the CHPs are increasingly used. In the first scenario ($s = 1$) in contrast, the operation of CHPs is shifted to other times because wind is actually present. Must-run restrictions of the CHPs, imposed by a simultaneous heat load, can also result in higher imbalances when there already is an excess of WPP production. ($s = 3$, from 14:00 to 16:00).

DR reduces electrical load mainly in times of high spot market prices compensating the load at low price periods. The integration of RES can be supported by increasing the electrical demand, in case there is overproduction from wind power, which is otherwise settled as imbalance energy ($s = 2$, from 2:00 to 4:00). But there is also the effect of reducing electrical load although there is already a positive imbalance. In times of high spot prices this can be favorable when price-spreads can be used and the corresponding imbalance price is near the spot market price. The joint operation of DERs in a VPP creates a more stable operation profile. Overall it can be observed that the assured selling quantity on the spot market Day-Ahead can be increased.

A VPP business model should consider, that it must create enough value to remunerate the companies for their flexibility and cover all necessary expenses. In order to assess the monetary advantage of a VPP, the profits obtained before and after pooling the DERs into a VPP are compared. As a reference case only the WPPs and the electric demand are considered. Because of the nature of wind power, imbalance costs occur. The gain of combining the DERs into a VPP should be higher than in separate operation. In case of separate operation, the participation of DR and CHPs at the spot market is evaluated. Regarding CHPs, separate operation refers to heat-led operation, while in the VPP electricity-led operation is assessed.

After that the whole VPP portfolio including the controllable systems are analyzed. The results are shown in Table 7 and Figure 28. The added value of the joint operation in a VPP is compared to the performance of DERs operated separately. For the here considered working days of summer, transition period and winter the daily synergy potential ranges between 4 - 41% which corresponds to 1.000 - 7.500 Euro. Assuming that the three simulated days are representative for the whole year, the yearly gains sum up to around 1.500.000 Euro. Considering the case study here applied, the flexibility from DR and CHPs is worth around 50.000 Euro/MW over the whole year for a wind power pool trader operating at the spot market Day-Ahead.

Table 7: Added value of joint operation of DERs compared to separate operation. Separate operation refers to the performance of the DR and CHPs on their own. In separate operation CHPs are in heat-led operation. Joint operation uses synergy effects between the DERs and operates CHPs electricity-led.

	Added Value
Summer day	41 %
Transition period day	4 %
Winter day	9 %

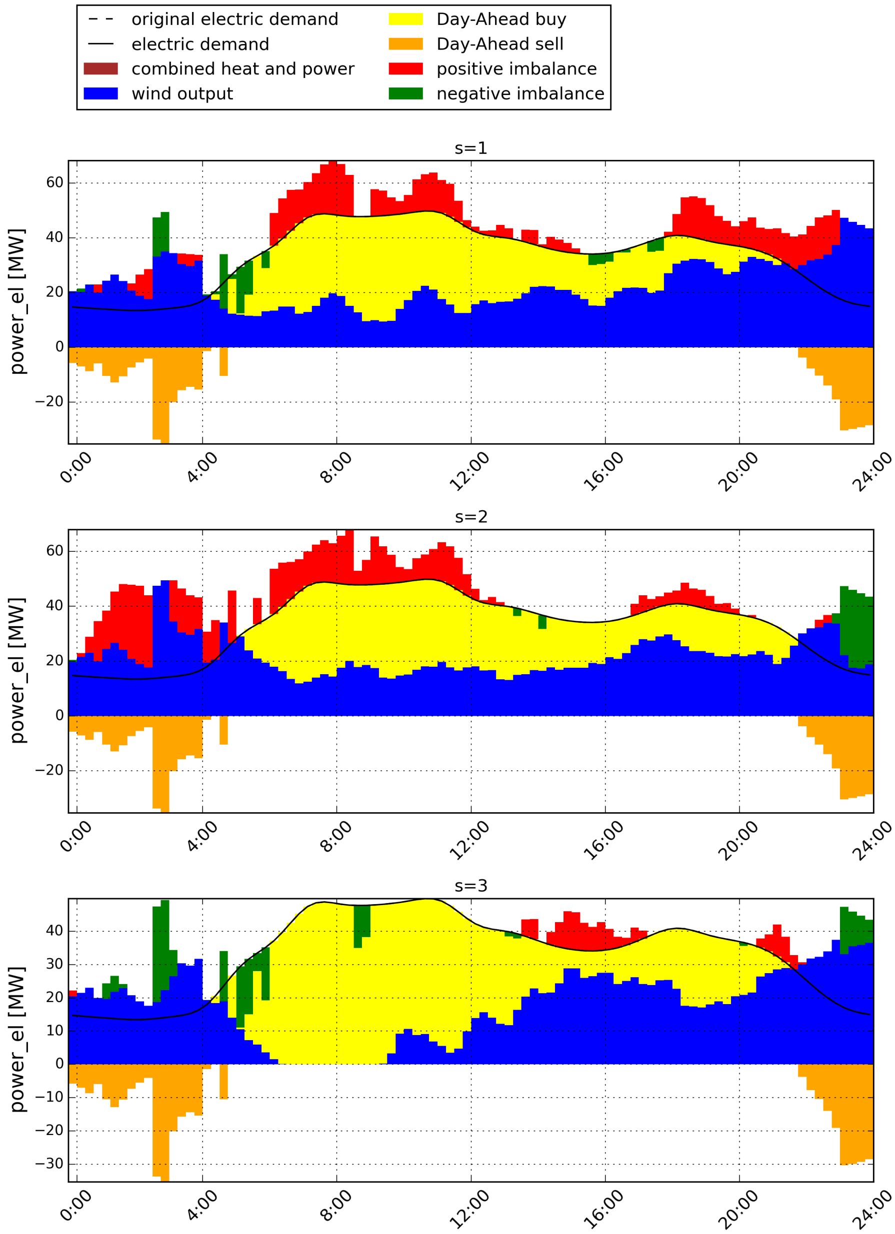


Figure 26: Covering the electrical load with WPPs (reference case) on a summer day

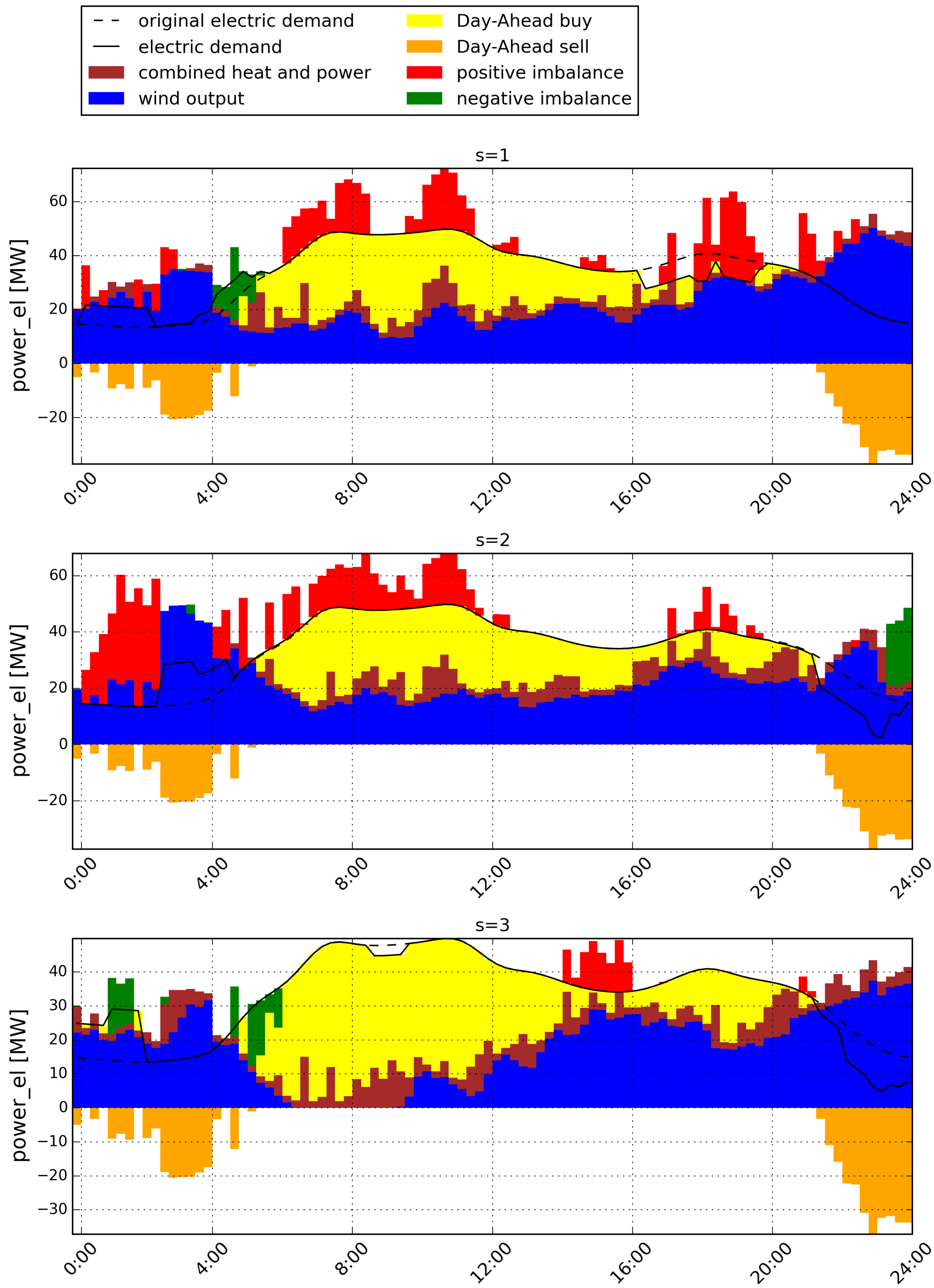
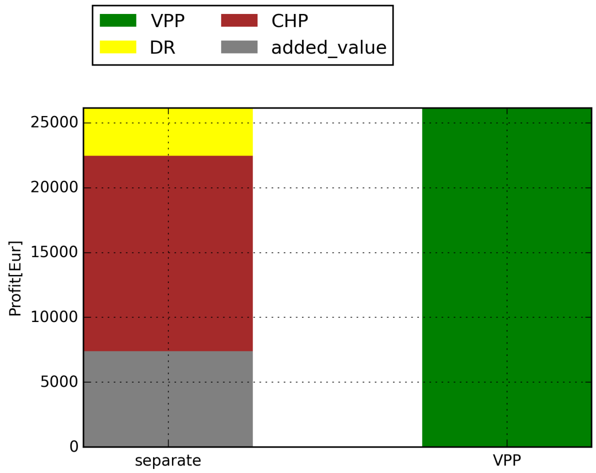
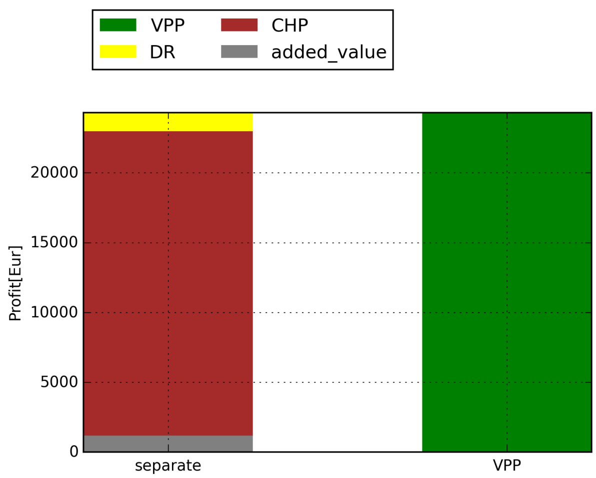


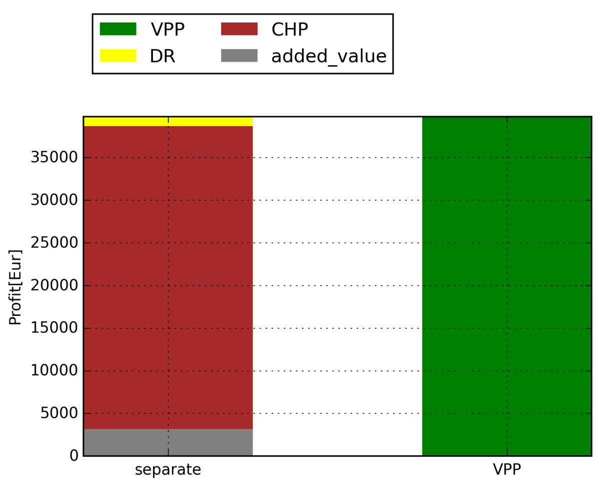
Figure 27: Including controllable units to the VPP with DR and CHPs for a summer day



(a) Summer day



(b) Transition period day



(c) Winter day

Figure 28: Comparison of separate operation of DERs to joint operation in a VPP in relation to the reference case

7 Conclusion

A forecast model was combined with an optimization model to operate a virtual power plant at the spot market Day-Ahead under uncertainty. Input data for the optimization model is generated with a vector autoregressive model. A structural analysis of the vector autoregressive model was conducted. It turned out, that the spot market price as well as the wind error Granger-cause the respective imbalance price. Also impulse response function and forecast error variance decomposition indicate that there is some kind of interrelation of wind error and imbalance prices. With longer training data sets the standard deviation of the estimated lagged terms is declining. The forecasts generated by the vector autoregressive model were compared to the real values. The root square mean error is used to access the quality of the vector autoregeressive model. Whereas the error of spot market is comparatively low, the errors of the imbalance price and wind error are substantial. The applied process and vector autoregressive model proved reasonable as a tool for scenario generation of spot market prices, imbalance prices and wind error terms.

The stochastic optimization model considers different scenarios of uncertain parameters and offers a risk weighting parameter to handle the variability of the profit. The knowledge about uncertain parameters significantly enhances the expected profit because the expected value of perfect information is about 163 %. For the problem of a virtual power plant operator the stochastic approach is superior to a mere deterministic one with the value of the stochastic solution being around 7,6 %. It is assumed that the scenarios generated are representative for the real values. Furthermore it is presumed that the market offers made always get accepted, which must not necessarily be the case.

The forecast and optimization tools were applied to a virtual power plant case study containing wind power plants, combined heat and power plants and demand response. The characteristics and profits before and after joint operation in a virtual power plant were measured to access the added value of a virtual power plant. By combining the energy devices in a virtual power plant a more stable operation profile is achieved. Economically, the added value for a wind power pool trader, operating at the Day-Ahead market, sums up to around 1.500.000 Euro for the year 2015 or around 50.000 Euro for 1 MW of controllable energy resource. The daily added value is in the range of 4 - 41 % depending on the season and the current market prices. A reason for higher added values might be the variability of the stochastic processes, especially wind feed-in. If the wind output scenarios are likely to be significantly varying from each other, then the flexibility of the virtual power plant is more valuable. In contrast, if it is likely that wind feed-in is similar to each other across the scenarios, than the flexibility potential is not really needed. Another factor for a low added value could be that, even in the reference case, there is already an optimized schedule respecting imbalances.

The potential benefits are supposed to increase when participating at more markets. Here only the spot market Day-Ahead was analyzed. A promising market especially for demand response and combined heat and power plants is the balancing market where the provision of reserve power is remunerated. It is planned to extend the optimization model by additional markets. The added value must be put in relation to the costs to build up the necessary information and communication infrastructure, operate the virtual power plant and provide incentives for its participants to use their flexibility. These topics provide interesting opportunities for further research.

8 Appendix

8.1 Augmented Dickey-Fuller Test

```
==============================================================
augmented dickey-fuller test:
'wind_error'
lags:    40L
obs:     15891L
==============================================================
   Test statistic        critical values based on MacKinnon
                         1%              5%              10%
--------------------------------------------------------------
z       -14.840851       -3.430762       -2.861722       -2.566867

==============================================================
MacKinnon approximate p-value for Z = 1.838114e-27

H_0: there is unit root in ['wind_error']
Conclusion: reject H_0 at 1.00% significance level
```

```
==============================================================
augmented dickey-fuller test:
'spot_price'
lags:    40L
obs:     15891L
==============================================================
   Test statistic        critical values based on MacKinnon
                         1%              5%              10%
--------------------------------------------------------------
z       -8.721327        -3.430762       -2.861722       -2.566867

==============================================================
MacKinnon approximate p-value for Z = 3.379264e-14

H_0: there is unit root in ['spot_price']
Conclusion: reject H_0 at 1.00% significance level
```

```
==============================================================
augmented dickey-fuller test:
'imbalance_price'
lags:    6L
obs:     15925L
==============================================================
   Test statistic        critical values based on MacKinnon
                         1%              5%              10%
--------------------------------------------------------------
z       -24.708879       -3.430761       -2.861722       -2.566867

==============================================================
MacKinnon approximate p-value for Z = 0.0

H_0: there is unit root in ['imbalance_price']
Conclusion: reject H_0 at 1.00% significance level
```

8.2 Model Fit

training set1
Summary of Regression Results

Model:	VAR
Method:	OLS
Date:	Wed, 20, Jan, 2016
Time:	15:23:41

No. of Equations:	3.00000	BIC:	15.2568
Nobs:	3347.00	HQIC:	15.1159
Log likelihood:	−39292.8	FPE:	3.39392e+06
AIC:	15.0375	Det(Omega_mle):	3.27509e+06

Results for equation wind_error

	coefficient	std. error	t−stat	prob
const	1.424069	1.367037	1.042	0.298
L1.wind_error	1.565473	0.017392	90.011	0.000
L1.spot_price	−0.456803	0.335866	−1.360	0.174
L1.imbalance_price	0.020883	0.016403	1.273	0.203
L2.wind_error	−0.662954	0.032319	−20.513	0.000
L2.spot_price	0.566567	0.472283	1.200	0.230
L2.imbalance_price	−0.076818	0.020559	−3.736	0.000
L3.wind_error	0.083667	0.034318	2.438	0.015
L3.spot_price	−0.455969	0.471943	−0.966	0.334
L3.imbalance_price	0.036945	0.020631	1.791	0.073
L4.wind_error	−0.029085	0.034345	−0.847	0.397
L4.spot_price	0.340844	0.472674	0.721	0.471
L4.imbalance_price	0.037129	0.020640	1.799	0.072

Results for equation spot_price

	coefficient	std. error	t−stat	prob
const	0.411497	0.070327	5.851	0.000
L1.wind_error	−0.001569	0.000895	−1.753	0.080
L1.spot_price	0.986751	0.017279	57.108	0.000
L1.imbalance_price	0.000343	0.000844	0.406	0.685
L2.wind_error	0.000859	0.001663	0.517	0.605
L2.spot_price	0.002694	0.024297	0.111	0.912
L2.imbalance_price	0.000520	0.001058	0.491	0.623
L3.wind_error	0.002222	0.001765	1.258	0.208
L3.spot_price	−0.002186	0.024279	−0.090	0.928
L3.imbalance_price	−0.001094	0.001061	−1.031	0.303
L4.wind_error	−0.002897	0.001767	−1.640	0.101
L4.spot_price	0.585205	0.024317	24.066	0.000
L4.imbalance_price	−0.001120	0.001062	−1.055	0.292

Results for equation imbalance_price

	coefficient	std. error	t−stat	prob
const	−1.167667	1.448703	−0.806	0.420
L1.wind_error	0.003587	0.018431	0.195	0.846
L1.spot_price	0.745609	0.355931	2.095	0.036
L1.imbalance_price	0.756462	0.017383	43.516	0.000
L2.wind_error	0.061098	0.034250	1.784	0.075
L2.spot_price	0.114405	0.500496	0.229	0.819
L2.imbalance_price	0.061610	0.021787	2.828	0.005
L3.wind_error	−0.078027	0.036368	−2.145	0.032
L3.spot_price	−0.232200	0.500136	−0.464	0.642
L3.imbalance_price	−0.004439	0.021863	−0.203	0.839
L4.wind_error	−0.210581	0.036397	−5.786	0.000
L4.spot_price	−0.358877	0.500911	−0.716	0.474

L4.imbalance_price	0.071567	0.021873	3.272	0.001

Correlation matrix of residuals

	wind_error	spot_price	imbalance_price
wind_error	1.000000	0.036319	0.034504
spot_price	0.036319	1.000000	−0.003073
imbalance_price	0.034504	−0.003073	1.000000

training set2
Summary of Regression Results

Model:	VAR
Method:	OLS
Date:	Wed, 20, Jan, 2016
Time:	15:23:43

No. of Equations:	3.00000	BIC:	15.3193
Nobs:	6015.00	HQIC:	15.1011
Log likelihood:	−70372.3	FPE:	3.22058e+06
AIC:	14.9851	Det(Omega_mle):	3.06515e+06

Results for equation wind_error

	coefficient	std. error	t−stat	prob
const	1.220691	1.168223	1.045	0.296
L1.wind_error	1.584795	0.013005	121.860	0.000
L1.spot_price	−0.208643	0.223218	−0.935	0.350
L1.imbalance_price	0.015766	0.011593	1.360	0.174
L2.wind_error	−0.694630	0.024369	−28.505	0.000
L2.spot_price	0.356621	0.314249	1.135	0.256
L2.imbalance_price	−0.041504	0.014595	−2.844	0.004
L3.wind_error	0.095929	0.025982	3.692	0.000
L3.spot_price	−0.472595	0.314332	−1.503	0.133
L3.imbalance_price	0.019239	0.014605	1.317	0.188
L4.wind_error	−0.017795	0.025999	−0.684	0.494
L4.spot_price	0.458446	0.314402	1.458	0.145
L4.imbalance_price	0.018753	0.014609	1.284	0.199

Results for equation spot_price

	coefficient	std. error	t−stat	prob
const	0.407262	0.067773	6.009	0.000
L1.wind_error	−0.000619	0.000754	−0.820	0.412
L1.spot_price	0.990861	0.012950	76.516	0.000
L1.imbalance_price	0.001268	0.000673	1.886	0.059
L2.wind_error	0.000466	0.001414	0.329	0.742
L2.spot_price	0.003024	0.018231	0.166	0.868
L2.imbalance_price	0.000726	0.000847	0.858	0.391
L3.wind_error	0.001134	0.001507	0.753	0.452
L3.spot_price	−0.001705	0.018236	−0.094	0.925
L3.imbalance_price	−0.001156	0.000847	−1.365	0.172
L4.wind_error	−0.001906	0.001508	−1.264	0.206
L4.spot_price	0.556210	0.018240	30.494	0.000
L4.imbalance_price	−0.002065	0.000848	−2.437	0.015

Results for equation imbalance_price

	coefficient	std. error	t−stat	prob
const	−0.460489	1.309763	−0.352	0.725
L1.wind_error	0.014322	0.014581	0.982	0.326
L1.spot_price	0.495622	0.250263	1.980	0.048
L1.imbalance_price	0.764942	0.012998	58.851	0.000
L2.wind_error	−0.002582	0.027322	−0.094	0.925
L2.spot_price	0.534364	0.352323	1.517	0.129
L2.imbalance_price	0.027034	0.016363	1.652	0.099
L3.wind_error	−0.001095	0.029130	−0.038	0.970
L3.spot_price	−0.371580	0.352417	−1.054	0.292

L3.imbalance_price	0.019182	0.016375	1.171	0.241
L4.wind_error	−0.223735	0.029149	−7.676	0.000
L4.spot_price	−0.484091	0.352494	−1.373	0.170
L4.imbalance_price	0.046465	0.016379	2.837	0.005

Correlation matrix of residuals

	wind_error	spot_price	imbalance_price
wind_error	1.000000	0.010406	0.019736
spot_price	0.010406	1.000000	−0.016516
imbalance_price	0.019736	−0.016516	1.000000

training set3
Summary of Regression Results

Model:	VAR
Method:	OLS
Date:	Wed, 20, Jan, 2016
Time:	15:23:49

No. of Equations:	3.00000	BIC:	15.5716
Nobs:	8983.00	HQIC:	15.3964
Log likelihood:	−106650.	FPE:	4.43907e+06
AIC:	15.3060	Det(Omega_mle):	4.27709e+06

Results for equation wind_error

	coefficient	std. error	t−stat	prob
const	0.500736	1.092140	0.458	0.647
L1.wind_error	1.591958	0.010624	149.843	0.000
L1.spot_price	−0.181470	0.184572	−0.983	0.326
L1.imbalance_price	−0.003767	0.010011	−0.376	0.707
L2.wind_error	−0.722983	0.019975	−36.194	0.000
L2.spot_price	0.374972	0.260344	1.440	0.150
L2.imbalance_price	−0.021578	0.012546	−1.720	0.085
L3.wind_error	0.139665	0.021395	6.528	0.000
L3.spot_price	−0.366081	0.260349	−1.406	0.160
L3.imbalance_price	0.007616	0.012551	0.607	0.544
L4.wind_error	−0.066221	0.021441	−3.088	0.002
L4.spot_price	0.383310	0.260419	1.472	0.141
L4.imbalance_price	0.043413	0.012552	3.459	0.001

Results for equation spot_price

	coefficient	std. error	t−stat	prob
const	0.419834	0.062786	6.687	0.000
L1.wind_error	−0.000760	0.000611	−1.244	0.214
L1.spot_price	0.993500	0.010611	93.630	0.000
L1.imbalance_price	0.001085	0.000576	1.885	0.059
L2.wind_error	0.000224	0.001148	0.195	0.845
L2.spot_price	0.001117	0.014967	0.075	0.941
L2.imbalance_price	0.000914	0.000721	1.267	0.205
L3.wind_error	0.001212	0.001230	0.985	0.325
L3.spot_price	−0.000316	0.014967	−0.021	0.983
L3.imbalance_price	−0.000755	0.000722	−1.046	0.296
L4.wind_error	−0.000919	0.001233	−0.745	0.456
L4.spot_price	0.500893	0.014971	33.457	0.000
L4.imbalance_price	−0.002435	0.000722	−3.375	0.001

Results for equation imbalance_price

	coefficient	std. error	t−stat	prob
const	0.495103	1.157758	0.428	0.669
L1.wind_error	0.005761	0.011262	0.512	0.609
L1.spot_price	0.636185	0.195661	3.251	0.001
L1.imbalance_price	0.756460	0.010613	71.278	0.000
L2.wind_error	−0.018217	0.021176	−0.860	0.390

L2.spot_price	0.046117	0.275986	0.167	0.867
L2.imbalance_price	0.026712	0.013300	2.008	0.045
L3.wind_error	0.044955	0.022681	1.982	0.047
L3.spot_price	−0.189416	0.275991	−0.686	0.493
L3.imbalance_price	0.004593	0.013305	0.345	0.730
L4.wind_error	−0.238910	0.022729	−10.511	0.000
L4.spot_price	−0.099416	0.276065	−0.360	0.719
L4.imbalance_price	0.072447	0.013306	5.445	0.000

Correlation matrix of residuals

	wind_error	spot_price	imbalance_price
wind_error	1.000000	0.021816	0.029762
spot_price	0.021816	1.000000	−0.020326
imbalance_price	0.029762	−0.020326	1.000000

training set4

Summary of Regression Results

Model:	VAR
Method:	OLS
Date:	Wed, 20, Jan, 2016
Time:	15:23:57

No. of Equations:	3.00000	BIC:	15.3466
Nobs:	11863.0	HQIC:	15.2077
Log likelihood:	−139951.	FPE:	3.75119e+06
AIC:	15.1376	Det(Omega_mle):	3.64692e+06

Results for equation wind_error

	coefficient	std. error	t−stat	prob
const	0.243958	0.989700	0.246	0.805
L1.wind_error	1.610147	0.009230	174.447	0.000
L1.spot_price	−0.245525	0.167297	−1.468	0.142
L1.imbalance_price	−0.010640	0.008679	−1.226	0.220
L2.wind_error	−0.745553	0.017496	−42.612	0.000
L2.spot_price	0.390135	0.236142	1.652	0.099
L2.imbalance_price	−0.013895	0.010910	−1.274	0.203
L3.wind_error	0.167606	0.018807	8.912	0.000
L3.spot_price	−0.266869	0.236164	−1.130	0.258
L3.imbalance_price	0.004686	0.010912	0.429	0.668
L4.wind_error	−0.091239	0.018897	−4.828	0.000
L4.spot_price	0.274167	0.236171	1.161	0.246
L4.imbalance_price	0.038514	0.010913	3.529	0.000

Results for equation spot_price

	coefficient	std. error	t−stat	prob
const	0.396947	0.054532	7.279	0.000
L1.wind_error	−0.001123	0.000509	−2.207	0.027
L1.spot_price	0.994987	0.009218	107.940	0.000
L1.imbalance_price	0.001474	0.000478	3.082	0.002
L2.wind_error	0.001154	0.000964	1.197	0.231
L2.spot_price	0.000099	0.013011	0.008	0.994
L2.imbalance_price	0.000827	0.000601	1.376	0.169
L3.wind_error	0.000467	0.001036	0.451	0.652
L3.spot_price	0.000469	0.013013	0.036	0.971
L3.imbalance_price	−0.000749	0.000601	−1.245	0.213
L4.wind_error	−0.000848	0.001041	−0.814	0.416
L4.spot_price	0.501503	0.013013	38.539	0.000
L4.imbalance_price	−0.002804	0.000601	−4.664	0.000

Results for equation imbalance_price

	coefficient	std. error	t−stat	prob
const	0.570935	1.051660	0.543	0.587
L1.wind_error	−0.002396	0.009808	−0.244	0.807

L1.spot_price	0.582631	0.177771	3.277	0.001
L1.imbalance_price	0.761293	0.009222	82.550	0.000
L2.wind_error	0.000474	0.018591	0.025	0.980
L2.spot_price	0.063119	0.250926	0.252	0.801
L2.imbalance_price	0.014895	0.011593	1.285	0.199
L3.wind_error	0.020443	0.019984	1.023	0.306
L3.spot_price	−0.135564	0.250949	−0.540	0.589
L3.imbalance_price	0.012839	0.011595	1.107	0.268
L4.wind_error	−0.226406	0.020080	−11.275	0.000
L4.spot_price	−0.130978	0.250956	−0.522	0.602
L4.imbalance_price	0.064529	0.011596	5.565	0.000

Correlation matrix of residuals

	wind_error	spot_price	imbalance_price
wind_error	1.000000	0.010663	0.030191
spot_price	0.010663	1.000000	−0.025540
imbalance_price	0.030191	−0.025540	1.000000

training set5

Summary of Regression Results

Model:	VAR
Method:	OLS
Date:	Wed, 20, Jan, 2016
Time:	15:24:06

No. of Equations:	3.00000	BIC:	15.6729
Nobs:	15991.0	HQIC:	15.5649
Log likelihood:	−191757.	FPE:	5.45218e+06
AIC:	15.5115	Det(Omega_mle):	5.33920e+06

Results for equation wind_error

	coefficient	std. error	t−stat	prob
const	0.443007	1.035429	0.428	0.669
L1.wind_error	1.561309	0.007936	196.746	0.000
L1.spot_price	−0.133046	0.189548	−0.702	0.483
L1.imbalance_price	−0.010259	0.008545	−1.201	0.230
L2.wind_error	−0.681507	0.014714	−46.317	0.000
L2.spot_price	0.362085	0.267559	1.353	0.176
L2.imbalance_price	−0.008699	0.010731	−0.811	0.418
L3.wind_error	0.152260	0.015677	9.712	0.000
L3.spot_price	−0.404400	0.267576	−1.511	0.131
L3.imbalance_price	−0.008886	0.010732	−0.828	0.408
L4.wind_error	−0.128719	0.015727	−8.185	0.000
L4.spot_price	0.230927	0.267643	0.863	0.388
L4.imbalance_price	0.035014	0.010740	3.260	0.001

Results for equation spot_price

	coefficient	std. error	t−stat	prob
const	0.351820	0.043330	8.120	0.000
L1.wind_error	−0.000782	0.000332	−2.355	0.019
L1.spot_price	0.994883	0.007932	125.424	0.000
L1.imbalance_price	0.001159	0.000358	3.242	0.001
L2.wind_error	0.000783	0.000616	1.272	0.203
L2.spot_price	0.001741	0.011197	0.156	0.876
L2.imbalance_price	0.000781	0.000449	1.740	0.082
L3.wind_error	0.000214	0.000656	0.327	0.744
L3.spot_price	−0.001225	0.011197	−0.109	0.913
L3.imbalance_price	−0.000825	0.000449	−1.838	0.066
L4.wind_error	−0.000184	0.000658	−0.280	0.780
L4.spot_price	0.502957	0.011200	44.906	0.000
L4.imbalance_price	−0.002325	0.000449	−5.173	0.000

Results for equation imbalance_price

	coefficient	std. error	t−stat	prob

const	0.104003	0.961017	0.108	0.914
L1.wind_error	0.005195	0.007365	0.705	0.481
L1.spot_price	0.835205	0.175926	4.747	0.000
L1.imbalance_price	0.759116	0.007931	95.716	0.000
L2.wind_error	−0.030149	0.013657	−2.208	0.027
L2.spot_price	−0.193140	0.248331	−0.778	0.437
L2.imbalance_price	0.009587	0.009960	0.963	0.336
L3.wind_error	0.044456	0.014551	3.055	0.002
L3.spot_price	0.003135	0.248347	0.013	0.990
L3.imbalance_price	0.043970	0.009961	4.414	0.000
L4.wind_error	−0.168931	0.014597	−11.573	0.000
L4.spot_price	−0.317559	0.248409	−1.278	0.201
L4.imbalance_price	0.021968	0.009968	2.204	0.028

Correlation matrix of residuals

	wind_error	spot_price	imbalance_price
wind_error	1.000000	−0.002741	0.004464
spot_price	−0.002741	1.000000	−0.024360
imbalance_price	0.004464	−0.024360	1.000000

8.3 Granger-causality

```
Granger causality f-test
==============================================
Test statistic   Critical Value   p-value   df
----------------------------------------------
     31.391880         1.410934     0.000  (37, 36693)
==============================================
H_0: ['wind_error'] do not Granger-cause imbalance_price
Conclusion: reject H_0 at 5.00% significance level

Granger causality f-test
==============================================
Test statistic   Critical Value   p-value   df
----------------------------------------------
      5.135126         1.410934     0.000  (37, 36693)
==============================================
H_0: ['spot_price'] do not Granger-cause imbalance_price
Conclusion: reject H_0 at 5.00% significance level

Granger causality f-test
==============================================
Test statistic   Critical Value   p-value   df
----------------------------------------------
     18.492463         1.285289     0.000  (74, 36693)
==============================================
H_0: ['wind_error', 'spot_price'] do not Granger-cause imbalance_price
Conclusion: reject H_0 at 5.00% significance level
```

8.4 Impulse Response Function

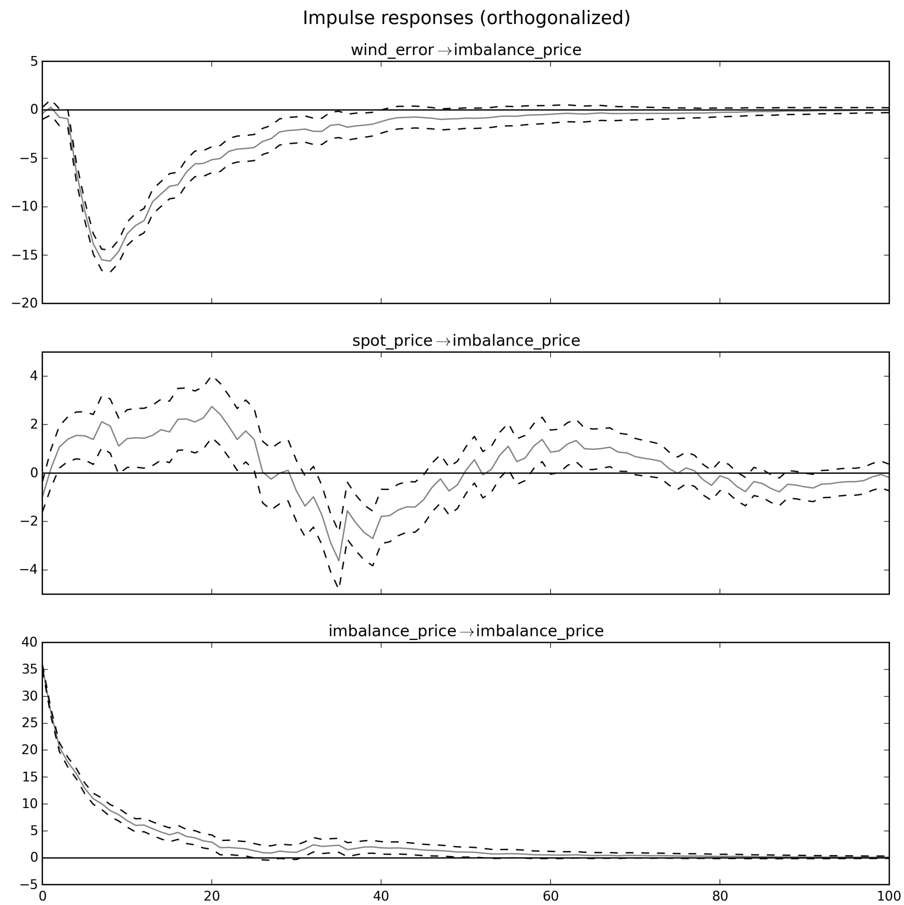


Figure 29: Impulse response function tests of the VAR(p) model consisting of wind error, spot price and imbalance price

8.5 Forecast Error Variance Decomposition

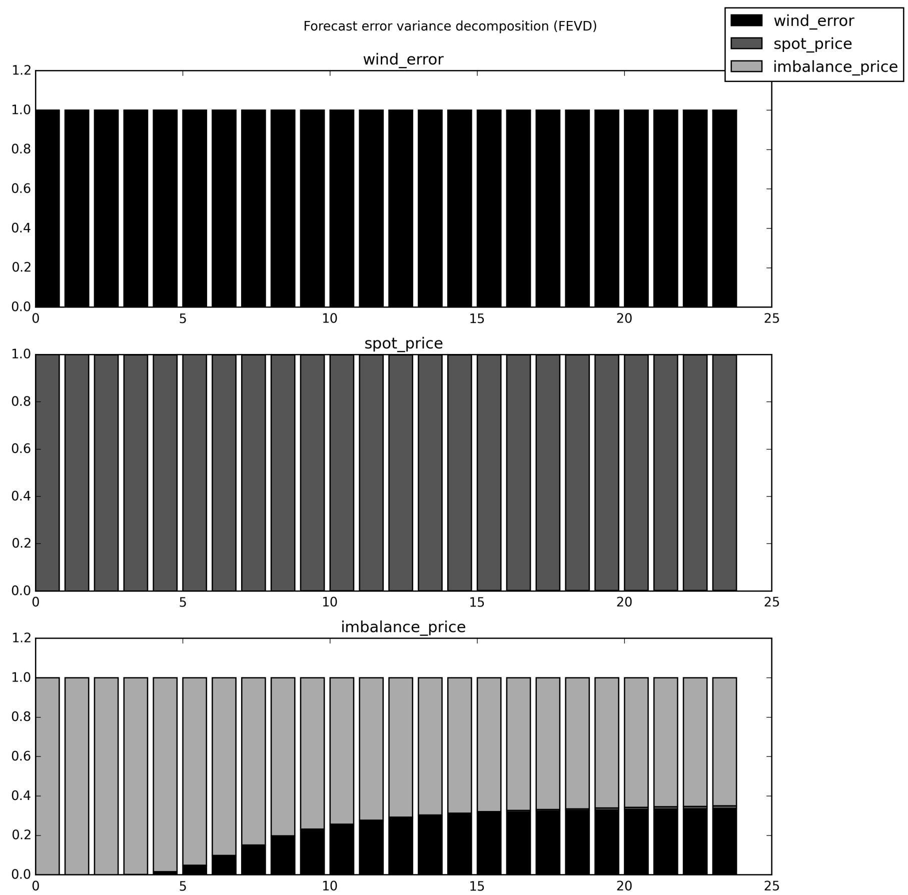


Figure 30: Forecast Error Variance Decomposition of the VAR(p) model consisting of wind error, spot price and imbalance price

8.6 Virtual Power Plant Schedule

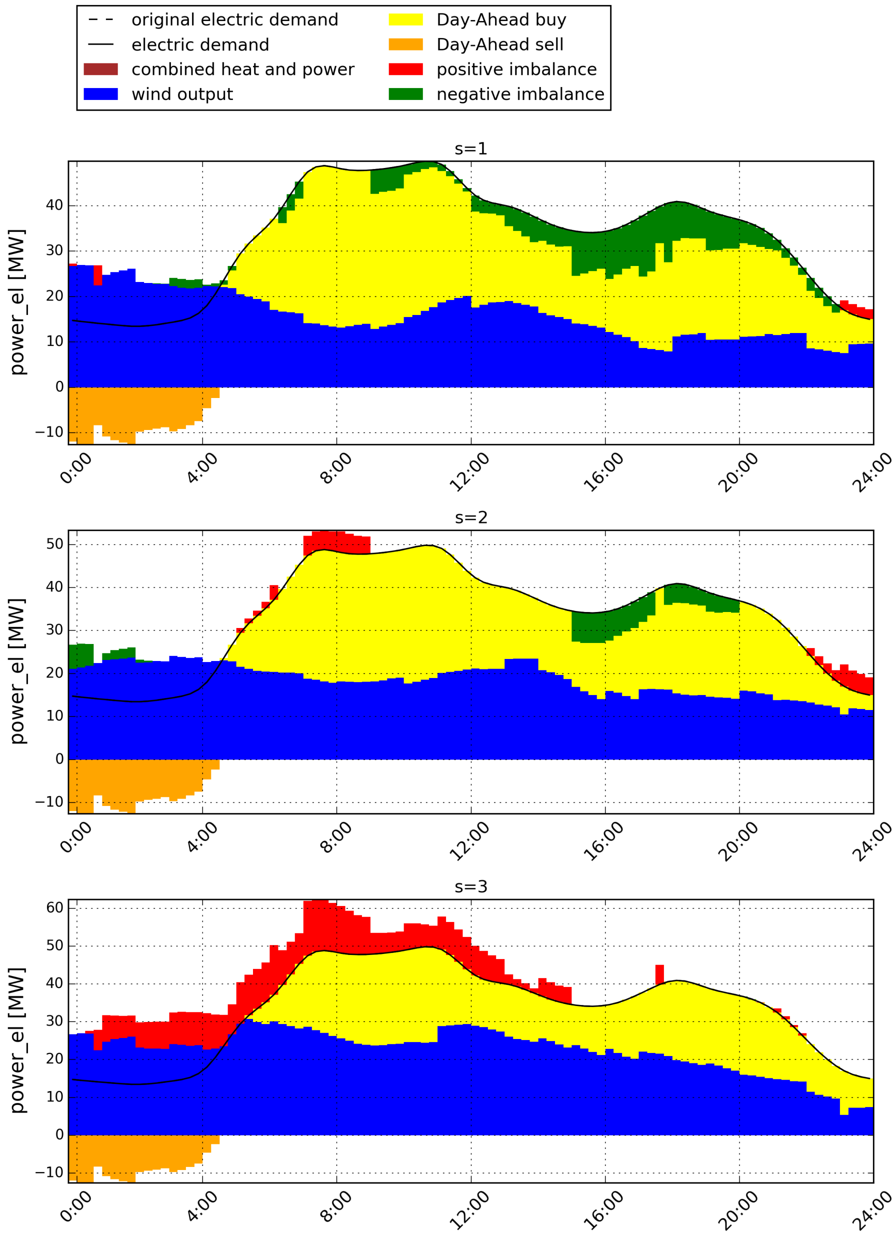


Figure 31: Covering the electrical load with WPPs (reference case) on a transition period day

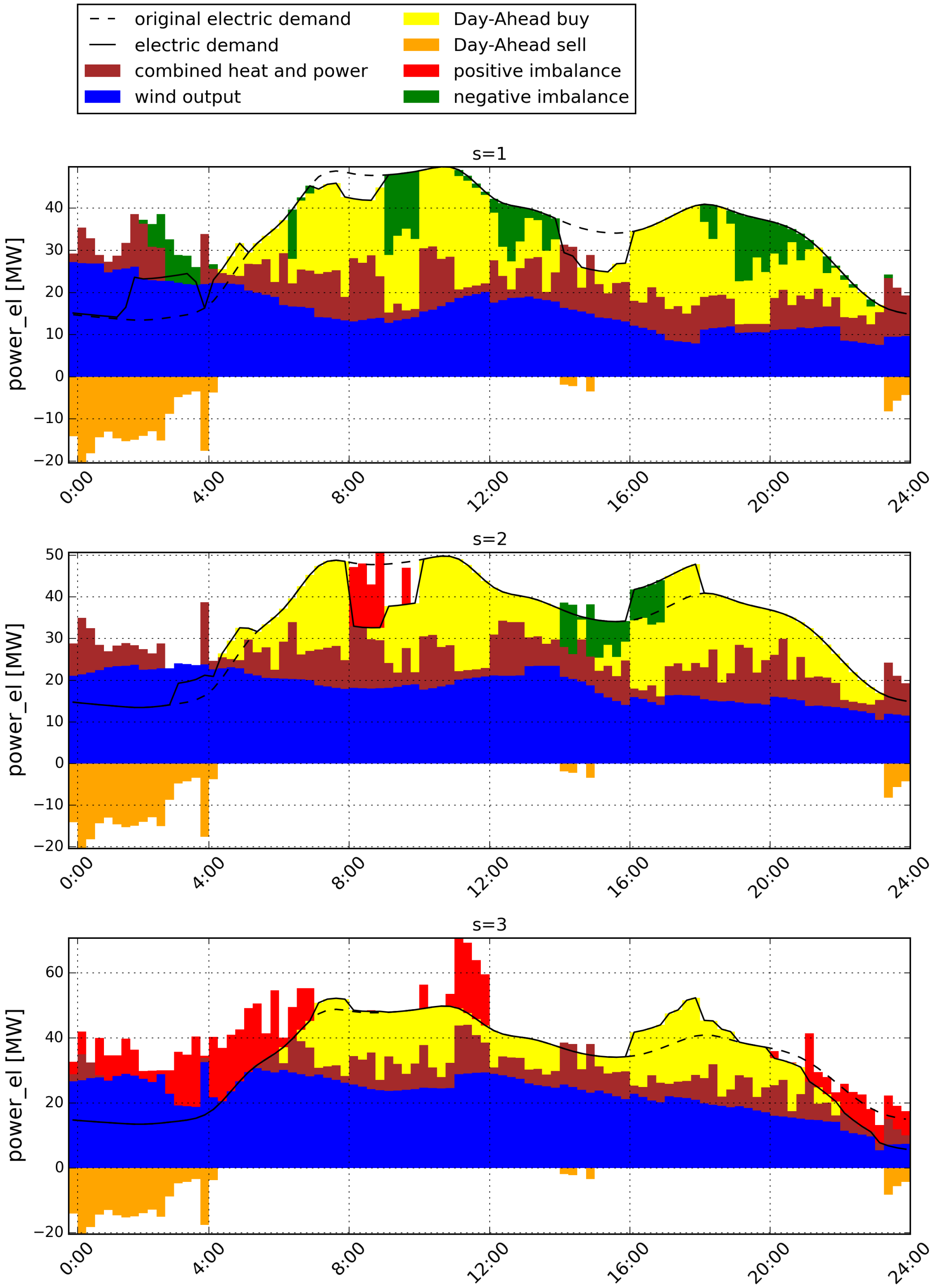


Figure 32: Including controllable units to the VPP with DR and CHPs for a transition period day

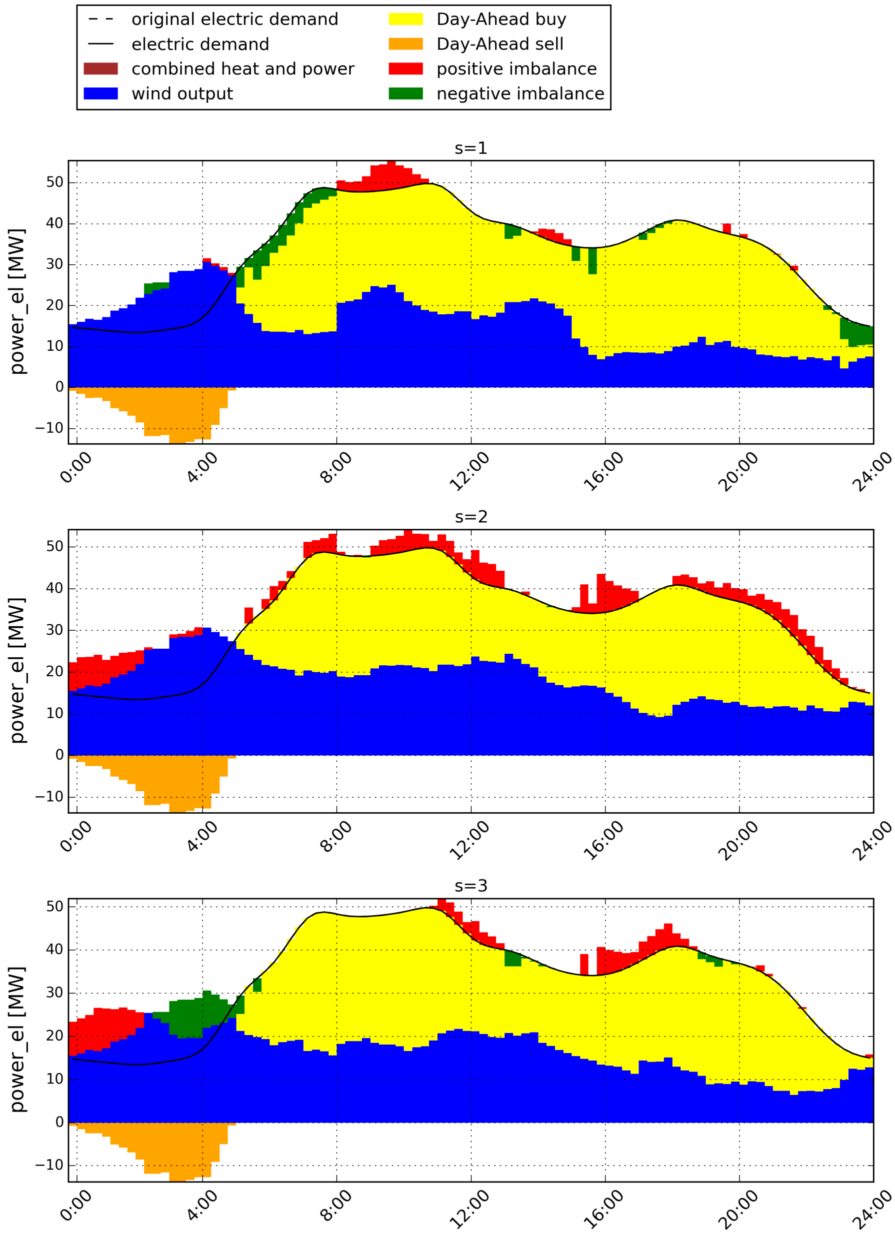


Figure 33: Covering the electrical load with WPPs (reference case) on a winter day

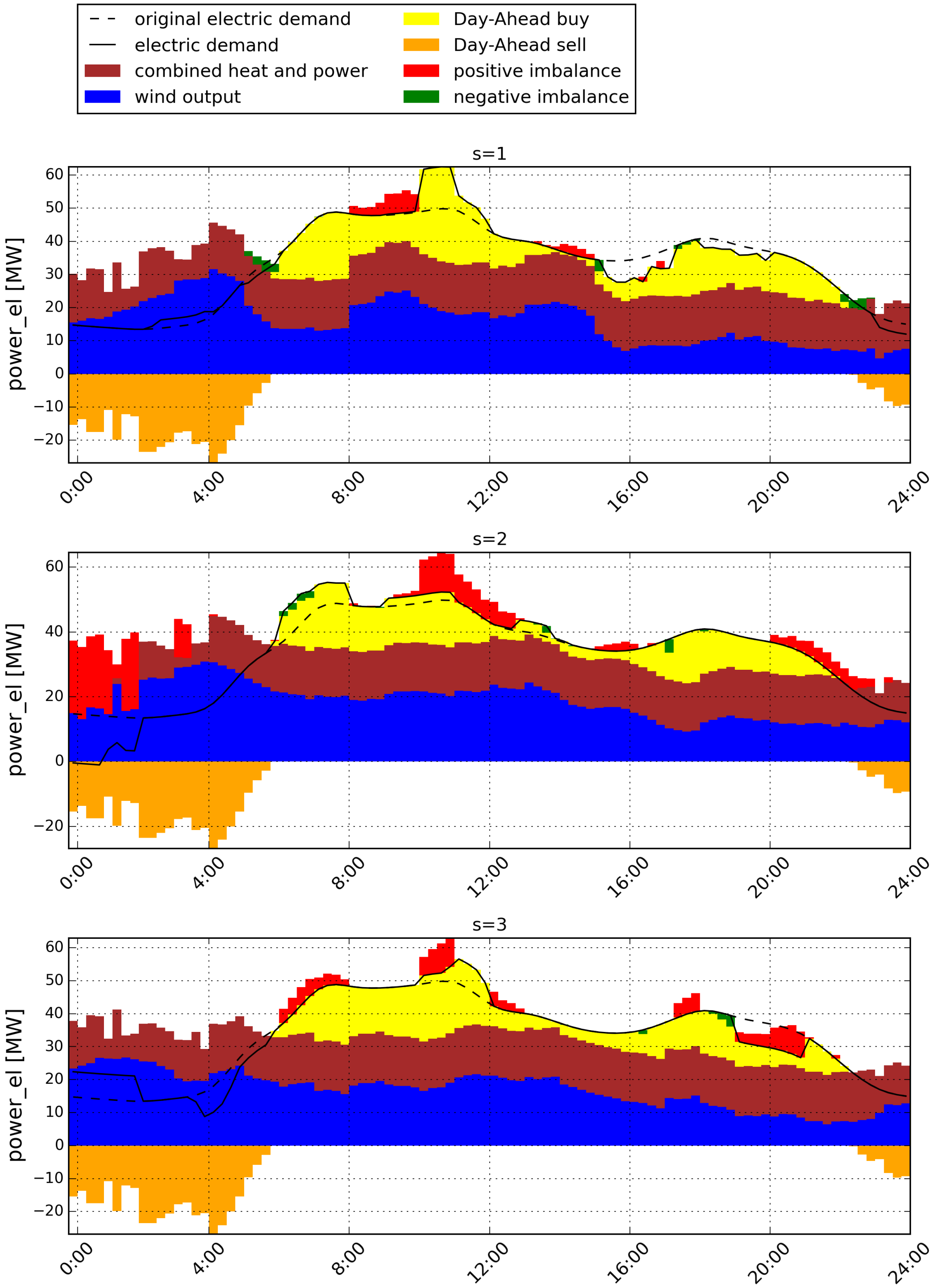


Figure 34: Including controllable units to the VPP with DR and CHPs for a winter day

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Glossary

APCS	Power Clearing and Settlement Austria
APG	Austrian Power Grid
AR(I)MA	Autoregressive (Integrated) Moving Average
BRP	Balancing Responsible Party
CHP	Combined Heat and Power Plants
CVaR	Conditional Value at Risk
CVPP	Commercial Virtual Power Plants
D	Actual delivery day
D-1	Day-Ahead
DER	Distributed Energy Resources
DG	Decentral Generation
DR	Demand Response
DSO	Distribution System Operator
EEX	European Energy Exchange
EMS	Energy Management System
ENTSO-E	European Network of Transmission System Operators for Electricity
HPP	run-of-river Hydro Power Plant
ICT	Information and communication technologies

MCP	Market Clearing Price
PV	Photovoltaic System
RES	Renewable Energy Sytems
RMSE	Root Mean Squared Error
SOC	State of Charge
TSO	Transmission System Operator
TVPP	Technical Virtual Power Plant
VAR	Vector Autoregressive Model
VaR	Value at Risk
VPP	Virtual Power Plant
WPP	Wind Power Plant

Vector Auto-regressive Model

I_i	i x i unity matrix.
$P^{\mathbf{total}}$	total installed capacity of wind power plants in Austria.
$P^{\mathbf{vpp}}$	installed capacity of wind power plants in virtual power plant.
$P^{\mathbf{res}}_{s,t}$	wind power production in scenario s at time t.
$P^{\mathbf{forecast}}_{t}$	ENTSO-E wind forecast.
$P^{\mathbf{real}}_{t}$	wind forecast for all wind power plants obtained by superimposing the ENTSO-E forecast with error terms from VAR model.
$\boldsymbol{A}_p$	matrix of lagged terms of vector auto-regressive model.
$\boldsymbol{\Sigma}_u$	covariance matrix of innovation terms.
$\boldsymbol{y}_t$	vector containing i-time series as input for vector auto-regressive model.
$\lambda^{\mathbf{da}}_{s,t}$	spot price day ahead in scenario s at time t.
$\lambda^{\mathbf{imb}}_{s,t}$	imbalance price in scenario s at time t.
$\boldsymbol{\lambda}$	stochastic process.
$\mathbf{u}_t$	innovation term regarded as Gaussian white noise.
π_s	probability of scenario s.
RMSE	root mean squared error.
ε_t	wind error term defined as the difference between real wind feed-in and wind forecast.

i	index representing the number of time series.
p	order of vector auto-regressive model.
$y_t^{\textbf{pred}}$	predicted data points.
$y_t^{\textbf{real}}$	real data points.

Stochastic Programming

X, Y	set of decision variables.
β	risk-weighting parameter.
$\boldsymbol{T}_s, \boldsymbol{W}_s, \boldsymbol{B}$	matrices of adequate size.
$\boldsymbol{c}^T, \boldsymbol{h}_s, \boldsymbol{b}, \boldsymbol{q}_s^T$	vectors of adequate size.
$\boldsymbol{x}$	first stage decision variable.
$\boldsymbol{y}_s$	second stage decision variable.
$\hat{\beta}$	modified risk-weighting parameter.
ζ, η_s	auxiliary variables to model conditional value-at-risk.
p_s	profit in scenario s.
$r_s\left\{p_s\right\}$	risk functional.

Indices

N_K	number of load shift units.
N_M	number of load shed units.
N_N	Set of combined heat and power units.
N_S	number of scenarios.
N_T	number of time steps.
S	set of scenarios.
T	set of time steps.
k	index of load shift units.
m	index of load shed units.
n	index of combined heat and power units.
s	index of scenario.
t	index of time.

Parameters

A, B, C, D	building specific coefficients for standardized heat profiles.
$DR_m^{\mathbf{shed,max}}$	maximum capacity of load shed.
$D_{n,t}^{\mathbf{th}}$	thermal demand.
$D_t^{\mathbf{el}}$	electrical demand.
$E_{n,t}^{\mathbf{st,max}}$	capacity of thermal storage.
$P_n^{\mathbf{chp,max}}$	maximum power of combined heat and power unit.
$P_n^{\mathbf{chp,min}}$	minimum power of combined heat and power unit.
$P_{s,t}^{\mathbf{res}}$	electrical power of renewable energy systems.
α	confidence interval.
β	risk weighting parameter.
$Q_{n,t}^{\mathbf{st,\dot{in},max}}$	heat charge capacity of thermal storage.
$Q_{n,t}^{\mathbf{st,\dot{out},max}}$	heat discharge capacity of thermal storage.
$\lambda^{\mathbf{imb}}$	imbalance settlement price.
$\lambda_{s,t}^{\mathbf{da}}$	price at day-ahead spot market.
$\lambda_{s,t}^{\mathbf{down}}$	imbalance settlement price in case of down regulation.
$\lambda_{s,t}^{\mathbf{up}}$	imbalance settlement price in case of up regulation.
$\mu_n^{\mathbf{aux}}$	efficiency factor of auxiliiary burner.
$\mu_n^{\mathbf{el}}$	electrical efficiency.
π_s	probability of scenario s.
$\mathbf{d}t$	time step.

ϑ	outdoor temperature.
ϑ^0	reference temperature.
$c_m^{\mathbf{shed}}$	cost coefficient for load sheds.
$c_n^{\mathbf{fuel}}$	fuel costs coefficient.
$c_n^{\mathbf{start}}$	start-up costs coefficient.
$dP_n^{\mathbf{chp,neg}}$	negative electrical power gradient of combined heat and power units.
$dP_n^{\mathbf{chp,pos}}$	positive electrical power gradient of combined heat and power units.
$g_m^{\mathbf{act,max}}$	maximum amount of activations.
$g_n^{\mathbf{start,max}}$	maximal start-ups of combined heat and power units.
$h_\vartheta^{\mathbf{day}}$	normalization coefficient of heat load f specific day.
$r_n^{\mathbf{p2h}}$	power-to-heat ratio.
soc	start and end value of state of charge of thermal storage system.
$t_m^{\mathbf{dr,off}}$	minimum down-time of demand response process.
$t_m^{\mathbf{dr,on}}$	maximum activation time of demand response process.
$t_n^{\mathbf{chp,down}}$	minimum down time of combined heat and power units.
$t_n^{\mathbf{chp,run}}$	minimum run-time of combined heat and power unit.

Decision Variables

$C_{s,t}$	total costs.
$C_{s,t}^{\mathbf{chp}}$	costs for combined heat and power units.
$C_{s,t}^{\mathbf{dr}}$	costs for demand response units.
$C_{s,t}^{\mathbf{fuel}}$	fuel costs.
$C_{s,t}^{\mathbf{res}}$	costs for renewable energy systems.
$C_{s,t}^{\mathbf{shed}}$	costs for load sheds.
$C_{s,t}^{\mathbf{shift}}$	costs for load shifts.
$C_{s,t}^{\mathbf{start}}$	start-up costs.
$DR_{k,s,t}^{\mathbf{shift,down}}$	downward load shift.
$DR_{k,s,t}^{\mathbf{shift,up}}$	upwards load shift.
$DR_{m,s,t}^{\mathbf{shed}}$	load shed.
$E_{n,s,t}^{\mathbf{st}}$	energy in thermal storage.
$P_{n,s,t}^{\mathbf{chp}}$	electrical power of combined heat and power units.
$P_{s,t}^{\mathbf{da}}$	offer quantities at day-ahead spot market.
$Q_{n,s,t}^{\dot{\mathbf{st}},\mathbf{in}}$	heat charge rate of thermal storage.
$Q_{n,s,t}^{\dot{\mathbf{st}},\mathbf{out}}$	heat discharge rate of thermal storage.
$\dot{Q}_{n,s,t}^{\mathbf{aux}}$	heat output of auxiliary burner.
$\dot{Q}_{n,s,t}^{\mathbf{chp}}$	heat output of combined heat and power plants.
$\dot{Q}_{n,s,t}^{\mathbf{fuel}}$	usable thermal power of fuel.
$\mathbb{E}\{p_s\}$	expected profit.

CVaR	conditional value-at-risk.
$\Delta D^{\mathbf{el}}_{s,t}$	change of electrical load.
$\Delta^{\mathbf{neg}}_{s,t}$	deficit generation settled as imbalance energy.
$\Delta^{\mathbf{pos}}_{s,t}$	excess generation settled as imbalance energy.
ζ, η_s	auxiliary variables to model conditional value-at-risk.
p_s	profit in scenario s.
$u^{\mathbf{shift,down}}_{k,s,t}$	binary variable representing on/off state of downwards load shift.
$u^{\mathbf{shift,up}}_{k,s,t}$	binary variable representing on/off state of upwards load shift.
$u^{\mathbf{shed,act}}_{m,s,t}$	binary variable for activation of load shed.
$u^{\mathbf{shed}}_{m,s,t}$	binary variable representing on/off state of load shed.
$u^{\mathbf{chp}}_{n,s,t}$	binary variable representing on/off state of combined heat and power unit.
$u^{\mathbf{chp,start}}_{n,t}$	binary variable for start-up of combined heat and power plants.