Technische Universität München

TUM School of Management

Master's Thesis submitted in partial fulfillment of the requirements for the degree
Master of Science

Optimal Flexibility Allocation in Electrical Distribution Grids

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Submitted on: 17. April 2019

I assure the single handed composition of this master's thesis only supported by declared resources.

München, der 17. April 2019

Zusammenfassung

Durch die wachsende Nutzung von Systemen zur Produktion von erneuerbaren Energien und der zunehmenden Verbreitung von Elektrofahrzeugen stehen elektrische Verteilungssysteme vor neuen Herausforderungen im Bezug auf das Engpassmanagement. Die vorliegende Arbeit diskutiert die Flexibilisierung des Verbrauchs von Elektrofahrzeugen durch kontrollierte Ladevorgänge als Lösungsmöglichkeit bei kritischen Netzengpässen. Trotz erwiesener, positiver Auswirkungen durch die Nutzung steuerbarer Flexibilitäten, sind bisher wenig Anstrengungen in Richtung eines holistischen und leicht implementierbaren Systems getätigt worden. Diese Thesis stellt einen neuartiger Ansatz zur Allokation lokaler Flexibilität von Marktteilnehmern durch Micro-Auktionen vor.
Ein funktionierender Software Prototyp simuliert eine virtuelle Markt- und Netzumgebung. Jedes Fahrzeug handelt als unabhängiger Agent durch die Abgabe eines Gebotspreis am lokalen Markt für Flexibilität auf eine 15-minütige Ladeunterbrechungen. Die Gebotspreise der einzelnen Elektrofahrzeuge variieren basierend auf individuellen Risikofaktoren und dem aktuellen Ladezustand. Der Verteilnetzbetreiber bewertet die aktuelle Auslastung und kontrahiert im Falle eines kritischen Netzzustandes positive Kapazitäten durch Annahme von Geboten.
Die Auswertung zeigt, dass unabhängig von der Anzahl an Elektrofahrzeugen, die untersuchte Netztopologie unterhalb der maximalen Auslastung geregelt werden kann. Unter den gesetzten Annahmen kann somit die neunfache Menge an Ladeanfragen und Elektrofahrzeugen gesteuert werden. Mit steigender Anzahl an Elektrofahrzeugen, konvergiert jedoch die durchschnittliche Ladungszunahme gegen null.
Durch die implementierten Intervalle von jeweils 15 Minuten werden die Elektrofahrzeuge sowohl in Gruppen zusammengefasst als auch deren Reaktionszeiten verzögert. Sobald ein Elektrofahrzeug kontrahiert wird, befindet es sich für 15 Minuten in einem fixiertem Zustand. Die Zuordnung zu einer Gruppe ändert sich während der gesamte Simulations-zeit nicht. Mit dem entwickelten Mechanismus lässt sich innerhalb der Simulation eine Reduktion der kritischen Netzzustände um 49% erreichen. Quantitative Aussagen beschränken sich auf die getroffenen Annahmen der Simulation, wohingegen qualitative Effekte in begrenztem Maße generalisierbar sind.

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1 Executive Summary

With the rising adoption of Electric Vehicle (EV) technology and Renewable Energy Sources (RES), electric distribution grids are facing new challenges regarding congestion management. The present work steps into the topic of controlled charging mechanisms to reduce physical grid extension by utilizing flexible loads from EV. Although, existing research concludes a positive impact on congestion relief, less attention is given to a holistic and light system that is implementable under current circumstances. This thesis develops a novel system towards micro-auctions for local flexibility allocation amongst EVs to reduce grid congestion.

A functional software prototype simulates a virtual market and grid environment. Each EV acts as an autonomous agent submitting bids to the local flexibility market, offering 15-minute charging breaks. Based on individual risk preference and state-of-charge, bid-prices vary amongst EVs. The Distribution Grid Operator (DSO) constantly asses grid status and contracts positive capacity during critical phases by accepting current bids.

It can be shown, that regardless of the penetration rate of EVs, the proposed model balances the tested grid topology below the maximum workload and within a predefined range. According to simulation assumptions, a ninefold increase of EVs can be accommodated with the proposed model. Although, with monotonically increasing penetration rate, average charge-increase converges to zero.

Due to the proposed intervals, EVs are grouped to continues batches with demand-response latency. Once contracted, EVs remain charging or not-charging for 15 minutes. The assignment to certain batches does not change over simulation time. Based on the proposed request control mechanism, critical grid conditions can be reduced by 49%. Whereas quantitative results are limited to the proposed simulation assumptions, qualitative effects are generalizable to a certain extend.

2 Introduction

The power industry is undergoing a major paradigm shift. With the ongoing integration of RES and the forecasted mass-adoption of EV technology, traditional approaches to reinforce electrical power girds are limited to physical extension. As an integral part and point of access, the distribution grid in particular, is at the forefront of research and development [1][2][3]. Whereas approaches towards the challenge of integration vary, the overarching objective is clear: Applying smart mechanisms and technologies to avoid physical grid extension while ensuring grid stability and availability [4]. As these goals are causing each other, managing grid congestion and balancing consumption are the key activities that need to be transformed according to the new paradigm.
The Federal Network Agency in Germany (Bundesnetzagentur (BNetzA)) considers intelligent control mechanisms as an integral part of the investment strategy by DSO. In its annual report of 2018, the BNetzA additionally mentions the increasing planning complexity on a 10-year horizon. With a faster evolution of technological advancements, DSOs can no longer anticipate extension and maintenance strategies and need to utilize new approaches to comply with changing demand. [5]
Past research has acknowledged challenges arising form RES and EV integration, but pointed out that these technologies might inherent a solution right away. More than 20 years ago, Kempton et al. (1997) identified bi-directional charging of EVs, so called Vehicle-to-Grid (V2G) technology as a possible tool for grid operators to perform decentralized congestion management [6]. Also the balancing of exceeding RES energy on residential level, can be accomplished with the use of EVs [7]. In the following decades, extensive research exposed various theoretical approaches towards the utilization of EV for this purpose [8] [9] [10]. With the Traffic Light Concept (*Ampelkonzept*) drafted by the BDEW an interaction framework was issued to make grid information more transparent and incentivize EV owners to actively participate in local congestion management. This framework allows the DSO to communicate current grid workload in the form of a yellow traffic light to EVs (and other market participants) that are, in turn payed for the responsive action [11] [4]. Although this concept paves the way for interaction between DSO and EVs, no specific market design to match supply and demand is prescribed.

2.1 Motivation and Problem Identification

However, V2G technology is barely applied and its implementation faces a set of problems ranging from physical limitations, legislative restrictions to potential customer satisfaction (see section 4.4.2). Considering the opening paragraph, the present work tries to bypass these problems by introducing a light system-design that complies with current limitations in regard to physical hardware as well as applicable law. This approach follows the idea of the Minimal Viable Product (MVP). Reducing complexity and rapidly push ideas to prototype are the core principles of lean startup [12]. In cooperation with Paatz Scholz van der Laan GmbH, a German energy consultancy focusing on digitalization and liberalization of the energy industry, the author tries to implement expert knowlegede and customer perspective from the early start. Thanks to the vital exchange of industry knowledge and fruitful discussion with experts and researchers, many hypotheses were validated before framing the research and development question.

2.2 Research Question and Objectives

The present work introduces an auction-based marked design for the Traffic Light Concept to explore possibilities of local congestion management applying controlled charging of EVs. To validate the general applicability of such a mechanism, qualitative effects are subject of investigation rather than quantitative results due to the unpredictability of future EV penetration, evolving charging technology or extensive grid topologies. Nevertheless, quantitative results are presented with regard to stated assumptions for comprehension. In the course of this work, the below stated research questions and their respective outcome are a metric for evaluating potential advantages of the proposed model. Nevertheless, the objective of the present work is not limited to these questions, as the conceptual and architectural layout as well as exceeding findings allow for a broader understanding on the issue of congestion management.

1. Does the contraction of local flexibility from EVs via the proposed auction-based marked design lead to congestion release on distribution grid level?

2. What generalizable effects arise from the proposed auction-based marked design?

3. What is the maximum EV penetration for the assumed grid topology and proposed auction-based marked design, with a minimum average charge-increase of 15%?

2.3 Structure of the Thesis

Following a brief historical outline, chapter 3 introduces the foundation of electric power transmission and trade with a focus on Germany. The concept of energy and capacity markets is explained as well as procedures to settle contracts for energy delivery. Before elaborating on the basics of electric grid congestion and issues on balancing energy, auctioning as a tool to match supply and demand at energy markets is described. Subsequent, chapter 4 introduces the concept of local flexibility as a possible solution for challenges arising from EV and RES integration. The low demand flexibility from residential consumers describes the current shortcomings for an appropriate market design. With V2G and controlled charging, two viable approaches towards the integration of EVs are discussed before elaborating on local flexibility markets and the Traffic Light Concept. Section 4.7 completes the current chapter and sets the specific focus of the present work. Chapter 5 describes the proposed model and is split in two major sections. Chapter 5.2 introduces the underlaying assumptions, the context and dependencies whereas chapter 5.3 focuses on the practical implementation of the software and its mode of execution. Chapter 6 evaluates the simulation results based on various analytical methods. Effects of interest are highlighted in section 6.4 before limitations and problems to the proposed model are juxtaposed. Chapter 7 closes with the author's conclusion and an outlook on possible further research.

3 Theoretical Foundations

Electrical energy is an omnipresent commodity. Consumers expected electricity to be affordable and available without interruption. In the background, tremendous effort is spent every day, to fulfill this expectation [13]. To ensure a ubiquitous and reliable energy supply, the German electric grid and its affiliated markets were developed, and evolved into a complex and abstract structure [14]. In times of RES and decentralization, this commodity moves further into the focus of the public debate. To give the reader a glimpse of certain mechanisms, and to understand why the topic of this work is relevant, the following chapter tries to shed more light on this essential commodity.

3.1 Brief History of the German Energy Grid

With the electrification of Europe and Germany during the 19th and 20th century, an extensive electric power grid was established to supply consumers with the highly demanded electricity. During this time, the former German Empire issued concession to a hand full of energy producers and providers. These companies were exclusively allowed to build the grid infrastructure and sell energy what made them de facto monopolist in their respective area of service. In 1997, nearly 100 years later, the European Union decided to liberalise the market for electrical energy by forcing the existing companies to allow additional providers to use their grid infrastructure. More than 10 years later, in 2009, a last step towards a fully liberalized market was taken, by unbundling grid operations and power supply. The transmission grid was therefore transferred to four independent companies, the so called Transmission Grid Operator (TSO). In 2011, local utility providers followed and split off distribution grid operations into independent entities, the DSOs. [13]

Since then, market mechanisms for wholesale energy apply independent from geographical location of supply and demand. The location of a generating unit and the point of consumption, is not reflected in the prices paid. A wind farm operator can produce energy at the North Sea and sell it at the energy exchange in Leipzig to an energy retailer located in Munich who in turn is supplying a consumer in Cologne. [15]

On the other hand, the physical grid has requirements and limitations on every distribution level. As a result, grid operators have to monitor and balance the grid continuously, using different methods to achieve an equilibrium between production and consumption. With the integration of renewable energies, the anti-nuclear commitment and a likely adoption of electric vehicles, this task is becoming more complex. [16]

3.2 Distribution and Transmission

The distribution of energy in Germany is divided according to voltage levels. The nationwide spanning transmission grid is operated at up to 380kV and supplies local distribution grids with energy from power stations located across the country. It has a total length of 35.000 km and connects the German electric grid to those of its neighbouring countries, thus enabling cross-border energy exchanges throughout Europe. Responsible for operating the transmission grid are the four TSOs. They divide the country in four *Regelzonen* or zones. [5]
To connect households and residential consumers, the voltage is reduced and further distributed. The DSO maintains a medium voltage grid at 1-30kV for regional distribution as well as a low voltage grid at 230V or 400V for residential demand. There is a total of 4.000 medium voltage grids and about 500.000 low voltage grids operated by 888 DSOs in Germany. [15]

3.3 Energy Markets

The liberalization and unbundling of energy markets and grid operators lead to a disconnection of the physical grid and virtual markets. These markets function as economic marketplaces to match supply and demand. The TSOs are responsible for administrating markets and guaranteeing access. Currently the most important markets are national and international markets hosted by the four German TSOs. The BNetzA monitors the markets mechanisms and utilizes incentive schemes to preserve grid stability, extension and maintains investments as well as a fair competition. [14]

3.3.1 Energy-Only-Markets

At Energy-Only-Markets (EOM) [17], participants can purchase and sell energy either on long term agreements, over-the-counter (OTC), day-a-head contracts or intraday trades. The most substantial amount of energy is traded in this manner. Energy suppliers can hedge their portfolio against expected demands and gain revenues from precise predictions. All different sorts of energy sources are available, from brown coal, nuclear to RES like wind, solar and hydropower. To determine the current clearing price, the so called Merit-Order-Model is applied. In simplification, all primary energy sources are sorted ascending according to their marginal costs of generation. Starting from the very cheapest offer, the current total market demand will be satisfied by adding up until the market price is set at the last offer taken. All suppliers within this range are remunerated according this equilibrium price. [14]

3.3.2 Capacity Markets

The limited storing ability of electrical energy and demand forecasting deviations make it necessary to retain a certain amount of capacity in case of exceeding demand. Demand can deviate positively or negatively from predictions and result in severe frequency changes (see 3.4.1). Thus, in contrast to EOM, capacity markets offer the possibility to trade and purchase the ability to produce or consume energy on demand. Power generators that can increase or decrease their production can offer this flexibility (see 4) at a capacity market to TSOs. So called Capacity Remuneration Mechanism (CRM) determine the price for retained capacity. The suppliers actually executing the offered capacity are remunerated additionally. Similar to the Merit-Order-Model implemented at EOMs, in case of grid imbalances, the suppliers are contracted ascending to the offered execution price. [17]

3.3.3 Contractual Balancing

Due to the nature of electric energy, bilateral transactions are limited and TSOs operate so called Balancing Group (BG) to monitor contract fulfillment amongst market participants within their area of control. The administrator of a group is called Balance Responsible Party (BRP). This role is mostly executed by an energy provider. Within its BG, the BRP aggregates all contracted clients in the respective area of control. The BRP purchases energy at the EOM to supply its consumers according to their demand. As the name suggests, each BG has the same amount of positive feed-in energy and negative consumption to establish a constant equilibrium. In reality, this equilibrium is hardly achieved and balancing mechanism must be applied by the TSO. [14] [16]

3.3.4 Auctions in Competitive Electricity Pools

> ”As electricity is a completely homogeneous good and produced by a small number of firms, [..] power markets have become a major field of applied auction analysis.” [18]

As Schwenen (2015) states, auctions are the preferred price- and matchmaking mechanisms in EOMs and capacity markets. Previously all auctions had been first-price auctions, therefore all bidders receive the same price for a homogeneous good like electricity. In simplification, sealed-bids are submitted before the auctioneer starts serving the highest bid first, giving them the number of units requested before serving the next until the good is finished [19]. This mechanism describes the Merit-Order-Model introduced in section 3.3.1.

Nevertheless, several dysfunctions and cases of manipulation supported the implementation of a second auction design. The so called discriminatory or pay-as-bid auction rewards each bidder with the individual bid price. By today, it is not empirically proofen which design works more efficient for the case of energy markets and both frameworks are in use, with advantages for certain use-cases respectively. [20]

3.4 The Problem of Balancing and Congestion

To understand the current challenges the German electric grid is facing and the necessity for innovative, decentralized technologies, it is crucial to define the problem-space carefully. The first subsection will clarify the two major physical grid threats before elaborating more on current mechanism and market designs.

3.4.1 Grid Congestions and Frequency Balance

Electrical grids differ from other distribution systems by the fact that power flows can not be steered and tracked throughout the system in the same way as a system of water pipes. Amongst others, two laws of physics describe the behaviour of electric power flows [21]. First, Kirchhoff's laws states that the algebraic sum of currents in a network of conductors meeting at a point is zero. The sum of currents flowing into a node is therefore equal to the sum of currents flowing out of the node.

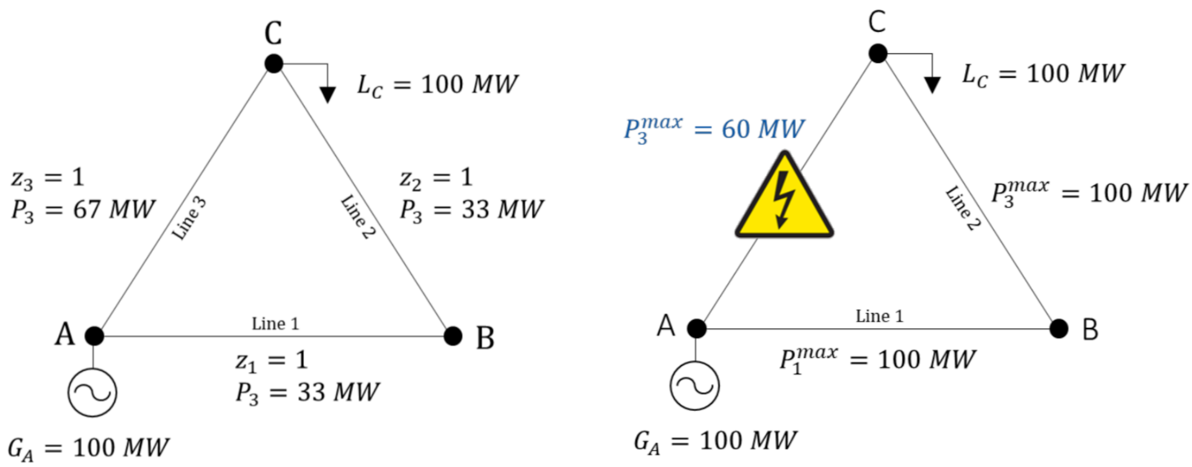
$$\sum_{k=1}^{\infty} I_k = 0$$

Secondly, Ohm's law states that the current through a conductor between two points is directly proportional to the voltage across the two points. By applying changing voltage U on a node with constant impedance Z, the current I will proportionally change.

$$I = \frac{U}{Z}$$

To put these two fundamentals of physics into action, a simplified example is given from Hirth et al. (2018). A triangle represents an electric grid. Edge A is connected to a power generator G_A with power feed-in of 100 MW and a load of 100 MW is connected to edge C. All three sides (lines) of the triangle have equal impedance Z and electricity flows equally distributed according to Kirchhoff's law. The distribution factors are proportional to the inverse of the total impedance of a pathway 1a. Considering the same example with a capacity limit to line 3 of 60 MW and 100 MW of lines 1 and 2 respectively. With the same generation and demand structure, the grid is congested due to technical limits. This can lead to severe incidents and might cause protection devices to disconnect grid elements that again causes disturbance of frequency if generated power and load demand

is imbalanced. [22][23][24]
In Germany, the transmission grid is balanced at a target value of 50Hz at all times [14]. According to Hirth et al. (2018), feasible measures are complex to identify due to the interdependence of congestions, location and magnitude. [25][21]



(a) No Congestion (b) Congested Grid

Figure 1: Three-node network with constrained capacity (Hirth et al. (2018)).

3.4.2 Congestion Mechanism

In order to overcome congestion issues, the grid operator applies mechanisms according to three principles. (1) So called *Network Options* describe interventions on physical grid level according to §13 Abs. 1 Nr.1 Energiewirtschaftsgesetz (EnWG). Due to the principle of redundancy (n-1 criterion), the congested line of power flow, in simplification, can always be supported by a second line which connects the same generator and consumer but might have higher costs of transmission. In addition, the grid operator can cancel or delay consumption to release congestion. As an ultimate solution, physical grid expansion in frequently congested areas can be feasible. [21]
The second principle (2), describes so called *Market Options*. This shifting of power generation is also referred to as *Redispatch*. According to §13 Abs. 1 Nr.2 EnWG, the grid operator is obliged to intervene in the current distribution of power generation across the country in case of a severe congestion. In simplification, if the transmission from the generation-intensive north to the high demanding south of Germany is congested, Redispatch measures switch off generation facilities in the north and ramp up capacity providers in the south. In this example, generation is shifted "behind" the congested grid segment. Costs for Redispatch increased in 2017 and amount for € 901 million according to the Federal Network Agency. [5] [21]

(3) The third principle is handled by §13 Abs. 2 EnWG and §14 Erneuerbare-Energien-Gesetzt (EEG). As a last suitable option, the *Feed-In Management* allows grid operators to switch off RES in case of severe congestion. In Germany, this can be observed while wind turbines are switched off during windy but sunny days. Nevertheless, energy from RES is prioritized according to §14 EEG and only subject to curtailment if other principles fail. In this case, the facility operator is to be compensated. In 2017, power of 5,5 GWh was lost due to Feed-In Management on DSO and TSO level. Costs of € 609 million arose from this. [26] [27]

3.4.3 Balancing Mechanism

Due to forecasting errors of production and consumption patterns, imbalances between generation and demand have to be equalized. Balancing mechanisms are cascading from BG-level, to zonal-level, to the national level and ultimately to European level where supply and demand for capacity can be matched at capacity markets. First, the TSO tries to balance inequalities amongst BGs in its area of control. This virtual balance is called balancing energy (*Ausgleichsenergie*) and will be payed by the BRP that caused in-parities. The cost for this balancing energy is by definition always higher than energy from EOM to not incentivize BRPs to shift sourcing preferences [16]. If there is no equilibrium state reached within the TSO's zone, resources at the German control reserve market (*Regelenergiemarkt*) are contracted [14]. Depending on the contracting period and activation delay, this energy is categorised in primary (PLR), secondary (SLR) and tertiary control reserve (MLR) [28]. In the meantime, the BRP will try to compensate losses and establish an equilibrium state within its BG by trading at intra-day EOMs or regulating feed-in and consumption that yields a lower cost.

4 Local Flexibility: A Novel Approach

The previous chapter explains the theoretical foundations of distribution and challenges arising from the adoption of RES and EVs. This section first introduces the current shift of responsibilities from TSO to DSO that now fuels research on new ways to guarantee stability, availability and affordability in times of volatile RES and power intensive EVs. Subsequently, the concept of local flexibility by EVs is discussed before an appropriate market design is illustrated.

4.1 The new importance of Distribution System Operators

Two major trends are currently sparking the discussion about the future of congestion and balancing mechanisms. Not that recent, the wide adoption of RES, even on residential level, made grid congestions happen to appear more frequently and severe [8] [15] [5]. The medium and low voltage grid was originally designed based on the consuming loads connected. These were mostly constant and unidirectional and could be forecasted with low variance due to the repeating use by customers. This dramatically changed with the introduction of RES. Kinetic wind and solar energy depends on the presence of wind and sunlight respectively and, relative to conventional power plants, are complex to forecast. In 1990, the share of renewable energy sources was close to zero and congestions mainly occurred on transmission grids. By 2017, the installed capacity reached more than 110 GWh which translates into 52% of the total capacity in Germany [5]. More than 90% of the RES facilities and 58% of all generation facilities in Germany are connected to the distribution grid. By 2035, this share will increase to 78%, making conventional production forecasts increasingly complex. [27]
More recent, technological advancements gave rise to a wider adoption of EVs and joined the political debate on climate change. According to the BDEW, the federal government of Germany plans to have more than one million EVs on the road by 2020 and six million by 2030. This will impose tremendous stress on DSOs since a majority of these vehicles will be charged from the distribution grid with a substantial, accumulated charging power. [29]
These figures illustrate the importance of electric distribution grids in the near future. The shift of responsibilities from TSO to DSO level, demand for increasing efforts in modernising the distribution grid and introducing new market mechanisms.

4.2 Definition of Flexibility

> ”Flexibility is defined as the modification of generation injection and/or consumption patterns, on an individual or aggregated level, often in reaction to an external signal, in order to provide a service within the energy system or maintain stable grid operation.” [30]

Following this definition from the Union of the Energy Industry in Europe (EULECTRICS), flexibility in the energy sector is the consequence to the paradigmatic shift within the European Energy Markets from the principal of ”generation follows demand” towards a more decentralized and dynamic setup. To streamline the increasing amount of small, volatile and decentralized generation units with generally rising demands, the concept of flexibility offers a viable framework to shift supply and demand peaks to prevent grid congestions and imparity. [30]
This concept is part of even bigger ambitions towards a smart grid infrastructure that sets its foundations on the ubiquity of advanced data structures and information exchange between a variety of entities. EVs represent a substantial part of the future market design. [15]

4.3 The Problem of Low Demand Flexibility

The problem of grid congestion as well as balancing supply and demand that was described in section 3.4 as a rather technical disfunction, roots back to the unpredictable and inflexible consumption patterns on consumer side. Considering all consumers and connection nodes in an energy grid, current mechanisms are executed by a centralized authority to satisfy demand even during peak times. None involves the end consumer and his flexibility to adapt consumption according to current grid and market conditions. This goes back to the design of fixed, yearly supply-contracts for standard-load-profiles (SLP) and results in a high price-inelasticity in volatile demand periods. [31]
Cramton et al. (2013) introduce the problem of low demand flexibility with the following statement:

> ”Suppose electricity markets did not suffer from demand-side flaws. In particular, suppose demand is sufficiently responsive to prices, such that the wholesale electricity market always clears. Then, the market would be perfectly reliable: If supply is scarce, the price would rise until there is enough voluntary load reduction to absorb the scarcity. Consumers would never suffer involuntary rationing.”

There is no price signal mechanism that would incentive consumers to reduce or increase demand accordingly [31]. With the adoption of EVs, the daily demand during peak hours will increase and much likely lead to more congestion with no incentives to adapt behaviour [32] .

4.4 Flexibility from Electric Vehicles

Despite the current low demand flexibility and the risk of congestion due to increasing demand from EVs, the same technology implies great opportunity to release the distribution grid [11]. In the past decade, research identified EV technology as a source of flexibility. Its ability to store power over a long period of time, controlled charging mechanisms and power release back to the grid, gave rise to an extensive amount of experiments. On the first sight, numbers are convincing. EVs are only utilized 4% of the time for transportation while being stationary parked for the rest. The battery is designed for frequent power fluctuations by its nature of roadway driving and cheap by the cost of capital per unit of power compared to large generators. [23]
With a power grid unable to store energy and therefore constantly applying congestion and balancing mechanisms [14], this technology might tremendously change the state of energy transmission.

4.4.1 V2G

> "The basic concept of V2G power is that EVs provide power to the grid while parked. The EV can be a batteryelectric vehicle, fuel cell vehicle, or a plug-in hybrid. Battery EVs can charge during low demand times and discharge when power is needed." [23]

According to Lund et al.(2015) there are various metrics defining flexibility ranging from the physical parameters of ramp magnitude, ramp frequency and response time to distinguishing flexibility power composition. V2G satisfies most of these criteria for providing grid ancillary services [33]. In contrast to centralized capacity suppliers (see 3.4.3), local flexibility providers can release congestion in the distribution grid and even transmission grid with relatively small but aggregated interventions. During windy daytimes, when RES produce over-capacities, this energy can be stored in EV batteries to be consumed in peak hours. EVs must have three required elements [23]: (1) a connection to the grid, (2) communication and control charging facility and (3) a bi-directional metering mechanism. An aggregator, an entity that virtually bundles more EVs together, which arbitrates between the needs of EVs and the grid, manages the process [34]. The aggregator again has to fulfill three major tasks. (1) Data needs to be gathered about the state of charge of each EV as well as its capacity limits. (2) A charging and discharging schedule is derived from this data, to determine when to treat which vehicle and (3), the execution of this schedule must be forced and monitored [34]. To market this capacity and turn it into revenues for the EV owner, the aggregator has several options and available capacity markets. Extensive research from the perspective of economics concludes with a wide range of different results for different markets. Kempton et al. (2005) project rather high net returns of 1700$ for participating in the regulation capacity market whereas Dalling et al. (2011) from the German Fraunhofer Institute only estimate positive returns of 180€ per year from providing negative secondary regulation capacity [23] [35]. Naturally, providing bulk energy at EOMs does not represent a viable business case for V2G since no payments for withholding capacities are paid.

4.4.2 Current Limitations of V2G

Nevertheless, it can be questioned why V2G technology has not yet found its way to commercialisations apart from several small pilot projects (see for example: Nissan Leaf at Enervie). Literature suggests six major challanges to the integration of V2G [36] [34] : (1) Battery degeneration is still not fully understood and a higher frequency of charging cycles due to V2G can possible lead to costs that have to be offset by the reveunes. (2) Bidirectional charging is an advanced technical feature only two EV support by 2017 with little efforts from the industry to change this. (3) If capacity is contracted, the EV owner is left with less kilometer range which still has to satisfy the need for mobility. (4) There is no standard for charging facilities resulting in a fragmented market for viable business cases as well as (5) no standardized communication protocol for the highly complex procedure. (6) In addition, the regulatory framework needed is by far not in place and will take more time to be passed by legislative. Condensing the above, there are technical, regulatory and behavioural challenges to be tackled before V2G might be adopted in the future.

4.4.3 Controlled Charging

In contrast to a rather holistic V2G concept, controlled charging can be seen as a subset focusing on the issue of flexible demand side management. Several studies suggest that uncontrolled charging (*dumb charging*) of an increasing amount of EVs will ultimately result in insufficient grid capacities and black outs during peak times [32]. A controlled EV can therefore be considered as a flexible load that can have multiple positive effects for a smart controlled grid [37] [38]. (1) Load curve flattening, (2) frequency regulation and (3) voltage regulation. Wang et al. (2016) provide an extensive introduction to these aspects of controlled charging [39]. The adoption of such a mechanism could ultimately accommodate a bigger amount of EVs in a particular grid segment that would have been forced to be extended [32]. Additionally, when set against the current limitations to V2G, controlled charging is facing less challenges that would slow down an implementation. (1) Battery degeneration is a minor issue and only regarding the length of a single charging cycle. (2) There is no need for bidirectional charging capabilities, (3) the battery capacity can not fall below the initial state of charge and therefore not result in an unexpected condition for the EV owner. However problem (4) and (5) still represent a substantial barrier that has to be discussed in the following chapters. Regarding regulatory leeway (6), §14 EnWG describes the EV as a controllable consumer and is therefore subject to a set of rights and duties including reduced grid fees and external controllability. Nevertheless, this paragraph does not elaborate on particular remuneration mechanisms nor on possible market environments for these flexible loads.

4.4.4 Current Research to Controlled Charging

This sections points out current research to the concept of controlled charging on a more granular level.
First, the issue of (1) scheduling complexity arises. Literature proposes a range of different approaches to the problem. Alonso et al. (2014) try to solve allocation of charging capacity amongst an exceeding amount of demand via a heuristic algorithm to reduce complexity already during architectural design [40]. Others propose a stochastic distributed algorithm and prove that an optimal equilibrium can be found [41]. Substantial research has been conducted on multi-agent systems to simulate individual preferences of EV owners in a controlled environment [32] [42]. All have in common that according to their specific assumptions, an optimal solution can be found for the problem. In chapter 4.6.2, the present work will introduce a unique approach to this problem.
(2) Controllability of EV batteries implies a very delicate control of the supplied charging power [43]. Nevertheless, with the currently available technology, discrete and constant charge control can be performed.
(3) As suggested by [39], the question on how to aggregate EVs before scheduling their capacity, a hierarchical approach seems to be more promising than centralizing or decentralizing coordination:

> "Hierarchical coordination is regarded as a hybrid paradigms of both centralized and decentralized coordination. It commonly assumes the existence of an aggregator in a price-based mechanism, which operates as the intermediate between the smart grid and EV customers."

Different concepts on how to compose an aggregator can be found in literature. A rather social community approach is given by [9]. It illustrates a neighbourhood to be its own, independent aggregator that manages its capacity. The DENA (Deutsche Energie Agentur) positions more institutional entities as potential aggregators. Also energy suppliers are interested to function as intermediates [44]. A very specific proposal is provided by the BNetzA, elaborating on possible aggregators that do not function as BRP within a BG and can act independent of these. This is particular of interest for the German market [45].

4.5 Local Flexibility Markets

Considering the shift of control responsibility from TSO to DSO level (4.1), the price inelasticity on residential level (4.3) and the inherent flexibility of EVs (4.4), local flexibility markets represent a possible market design to solve the respective challenges based on economic principles. At such a capacity market, local flexibility is offered to the affiliated DSO to prevent a critical grid condition for a market-based price. Naturally, these offers are small in terms of capacity and need to be aggregated. The Verband der Elektrotechnik, Elektronik und Informationstechnik (VDE) proposes the positioning of a local flexibility market ahead of national capacity and balancing offers. Therefore, in case of a local congestion, offers at the local flexibility market are evaluated and contracted punctually, before exceeding demand can be balanced at national markets. [3]
Figure 2 illustrates the proposed procedure and the flexibility market ahead of centralized markets like the EEX energy exchange [46]. According to the VDE, several aspects have to be considered before implementing such a market design: (1) Equal level of information, (2) a communication and monitoring framework and (3) secure authentication of market participants and activities. (1) and (2) will be discussed in the following section, as they are crucial for the proposed model, whereas possible approaches to (3) are hinted out in section 5.2.5.

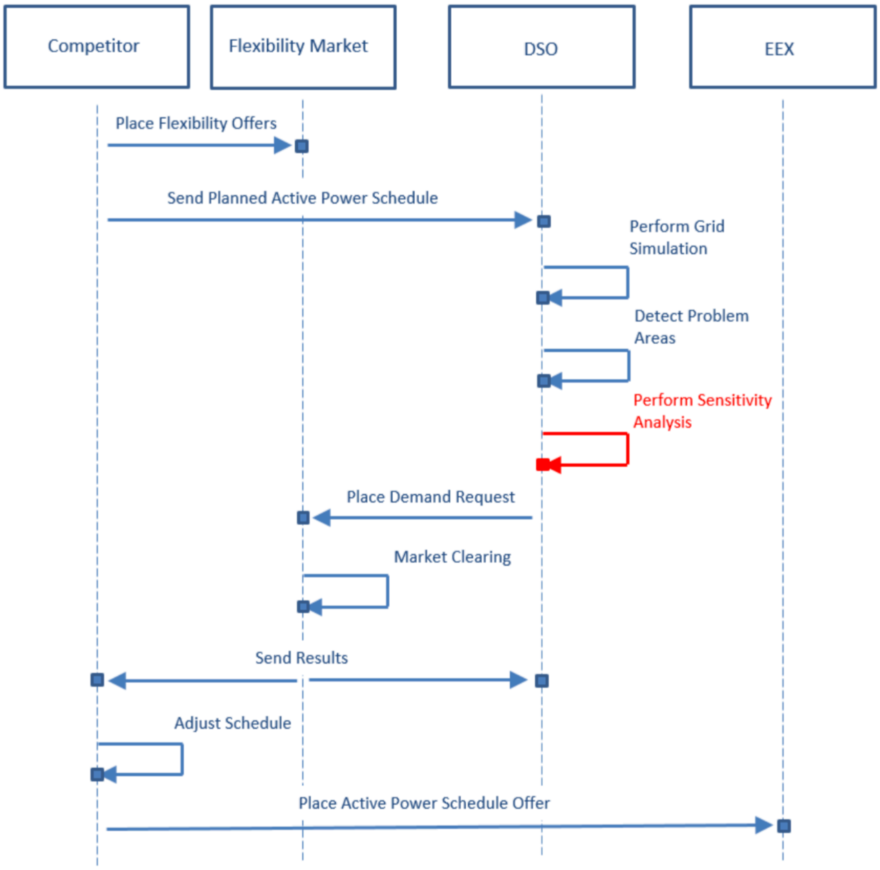


Figure 2: Principally flow chart of local flexibility market (Wagler and Witzmann (2016)).

4.6 The Traffic Light Concept

With the introduction of (1) flexibility as a framework for local congestion and balancing control, (2) EVs as a source for flexibility, (3) a controlled charging mechanism to implement this on technical level and (4) flexibility markets to match supply and demand during congestion, a last piece to a holistic local congestion management concept is missing. How is information on congestion communicated? With the Traffic Light Concept, the BDEW concludes previous research on the communication in smart grids to a tangible approach to solve information challenges between DSO and local flexibility providers. In the following, the concept and the attempt of the present work to translate certain aspects into action is explained.

4.6.1 Historical Background

In 2011, the Federal Ministry for Economic Affairs and Energy in Germany founded a research and working group to tackle future challenges for the operation of the German electrical grid [47]. The so called *Plattform Energienetze*, a think thank, consists of representatives from the industry, researchers and politicians working on concepts for a sustainable grid extension and modernization. The group is divided into several task forces of which the *AG Intelligente Netze und Zähler* is dedicated to work on issues regarding smart metering and smart grid design. The idea of a regional flexibility marketplace had been drafted by this task force before it was handed over to various agencies like the BDEW, BNE (*Bundesverband Neue Energiewirtschaft e.V.*) and the EURELECTRIC for further elaboration [48]. In 2017, the BDEW published a 12-pages discussion paper explaining a general communication concept for regional flexibility markets, namely the Traffic Light Concept in more detail [4]. Following the colours of a traffic light, it explains all three market and grid conditions, challenges as well as concepts on how to integrate the traffic light into the current setup. One year later, another paper was published by the BDEW, introducing EVs as a possible source of flexibility [11].

4.6.2 Concept

The Traffic Light Concept is derived from the three different phases of a regular traffic light and describes the current condition of a certain segment in the distribution grid. The defined goal is to reduce the demand for physical grid extension by utilizing regionally available flexibility (in particular EV) to relive grid congestions and balance frequency on DSO level during the yellow Traffic Light Phase (TLP). This is called grid-relevant (*netzdienliche*) flexibility whereas capacity that is marketed and contracted nationwide is called system-relevant (*systemrelevante*) flexibility. During the green TLP, a balanced and not congested system, all participants can trade their flexibility according to an individual utility. This is called market-relevant (*market-relevant*) flexibility. The obvious advantage of the Traffic Light Concept resides in the ability to combine these three sorts of flexibility on a continues base. Each participant can dynamically decide according to the TLP were to market its capacities. If the congestion or imbalance can not be released by contracting flexibility, the red TLP empowers the DSO to take control over certain consumer loads and market mechanism. This is due to the fact that the electrical grid is considered as critical infrastructure to the public. [4]
Section 5.2.2 clarifies the thresholds between the three TLPs.

4.7 Focus of this work

With fundamental knowledge gained until this point, the present work sets a very particular focus for the proposed concept and the executed simulation. For each previously described aspect, an assumption is taken in the following. The observed grid typology is represented by a standard distribution grid within the medium- and low-voltage level, since the challenges from RES and EV integration are most urgent there [11]. Only electric battery EVs will be considered as flexibility providers to the DSO. This excludes stationary storage systems, residential PV systems and others that are controllable according to §14a EnWG. Nevertheless, EVs are considered as standard loads with high concurrency and therefore need to be controlled more closely than RES that have to be prioritized according to §8 EEG. Charging facilities are located on residential level and represent a private charging infrastructure since this layout is more likely to profit from the proposed model. As described more closely in section 5.3.4, all market participants are modeled as coordinated, non-cooperative agents that interact with one centralized market entity. Each EV applies an independent, risk-based pricing function that is inelastic to demand (see section 6.3.1). Therefore, a sealed-bid discriminatory auction mechanism appears suitable and is applied for the local capacity market design [20]. Naturally, the flexibility offered by EVs can not be traded as bulk power and is therefore not suitable for EOMs. For simplicity, flexibility is only considered as positive capacity in case of either (1) a drop in frequency due to demand and supply imbalance or (2) congestion arising from thermal- and voltage-grid-limits. EVs only perform discrete actions of charging or not charging while offering unidirectional flexibility. Recent publications suggest *bivalent charging* [11], which implies a continues controllable charging power. Complexity of a continues simulation exceeds the scope of this work by far and is therefore neglected. As it is shown in the following chapters and literature, discrete charging patterns result in a comparable stress-test for the grid typology and lead to meaningful result [39]. Each EV acts individually at the local flexibility market with no aggregator or intermediate. In contrast to [9] [10] [32] and others, who utilize an aggregator to pool demand and flexibility of multiple EVs to market the capacity at suitable markets, the proposed concept keeps a strong focus on the DSO's intention during the yellow TLP to perform local demand side management. Therefore aggregation therefore naturally occurred due to the geographical proximity and connection to the same distribution grid. The flexibility offered by an individual EV can be considered as *Micro-Flexibility* to the local DSO. Additionally, only the yellow TLP is subject of investigation. The green TLP and the ability of all participants to trade freely across various markets and locations is already treated by literature [49].

5 Simulation Software: Concept and Design

In this chapter, the problem is overviewed before the proposed model is drafted via mathematical description. Succeeding, the architectural software layout for simulation is illustrated. Due to the inherent uncertainty of the future evolution of EV technology and the focus of the present work on an adaptable simulation software, the concept strives to produce qualitative robust methods rather than quantitative results. Thus, the architectural layout, in particular section 5.3.3, will introduce a set of input variables that are exchangeable depending on future achievements.

5.1 Problem Definition and Goal

The overarching topic of congestion management and balancing mechanisms in the German electric power grid is discussed in chapter 3.2. This work particularly focuses on the allocation of limited charging capacity amongst exceeding requests from EVs, coinciding with maximum demand of other loads on distribution grid level [32]. The following research aims to match flexibility offers from EVs with temporary congestion during the yellow TLP. A local auction-market for short term flexibility is proposed. The objected outcome is defined as a continuously balanced grid typology during peak hours.

5.2 Conceptual Design

The concept is based on a multi-agent simulation of two parties. (1) EVs connect to the distribution grid via a stationary charging facility. Hereafter, the term EV includes the charging facility and describes a closed system acting as consumers or providers of flexibility. Each EV follows the same objective to gain profits and increasing state-of-charge (SoC) in the course of the simulation via auction-bids submitted to the DSO. (2) The DSO computes the required capacities and contracts successful bidders, aiming to temporarily release grid congestion. Both parties interact on a local market environment administrated by the DSO. The price- and matchmaking follows an auction, initiated with the start of the simulation.

5.2.1 Applied Grid Environment

To test the proposed model under realistic circumstances, a dataset of loads and a specific grid topology is applied. The *IEEE Power and Energy Society* is a leading supplier of scientific and engineering information on electric power and energy. The test feeder, a dataset to simulate a fictitious low-voltage distribution grid, was specifically developed as a European test scenario. The feeder is connected to the medium voltage (MV) system through a transformer at substation. The transformer steps the voltage down from 11 kV to 416 V. The main feeder and laterals are at the voltage level of 416 V. The grid capacity is not explicitly stated, but will be set at 3800 kW. The one-line diagram of the test feeder is shown in 3. The test scenario represents 1000 connection points for consumption with a one-minute time resolution over a one-day period resulting in 1440 data points. In order to retrieve active power consumption, time-series simulations were performed using the electric power distribution system simulators OpenDSS and GridLAB-D, respectively. The resulting total workload per minute for this test grid can then be used as a baseline for further simulations. All values are available as *.csv* text file and are easily integrated into scientific simulation environments. [50]

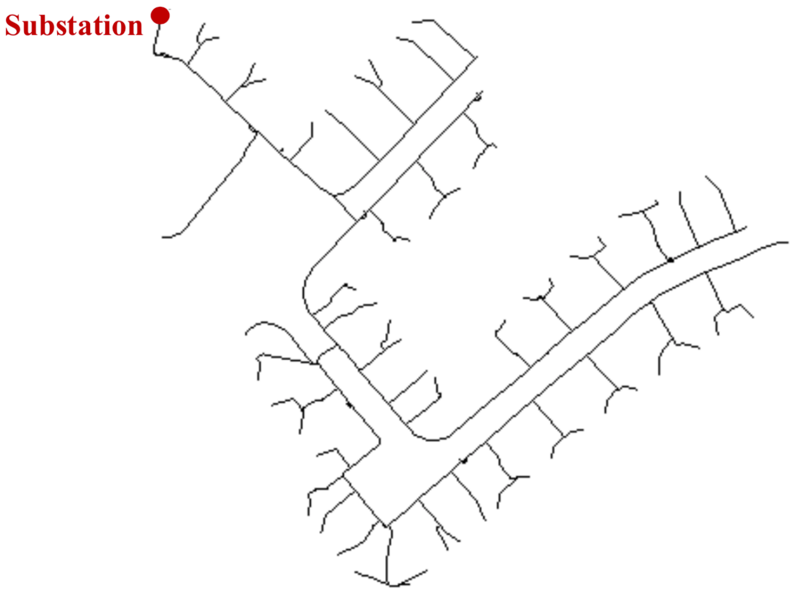


Figure 3: One-line diagram of the European low voltage test feeder.

5.2.2 Traffic Light Thresholds

Although typologies of distribution grids vary in a wide range, the Traffic Light Concept attempts to define the transitions between the three TLPs with percentage limits on power I_{max} and voltage U_{max} [4]. Table 1 indicates the proposed limits.

	Green	Yellow	Red
Power (I_{max})	0% - 80%	80% - 100%	> 100%
Voltage (U_{max}) *negative*	>-8%	-10% to -8%	< -10%
Voltage (U_{max}) *positive*	<+8%	+8% to +10%	> +10%

Table 1: TLP limits and thresholds.

With $P = I * U$, the current grid workload is proportionally determined by the current and voltage. An EV has a charging capacity of 11 kW at 420 V voltage with 26 A current. For simplification, the simulation considers a total capacity by the test feeder of 3800 kW with a threshold from green to yellow TLP at 80% and 3000 kW respectively. Thus, each charging EV diminishes the available grid capacity by 11 kW. This does not represent reality to the full extend, since electrical power systems consist of a complex interaction of factors [24] and charging power is not constant over time [39]. To reduce complexity of the simulation, these aspects are neglected. A virtual power pool with fixed capacity is sufficient to illustrate a congested scenario and test the allocation and auctioning mechanism.

5.2.3 DSO and Flexmarket Concept

The DSO operates a distribution grid with total capacity K_{total}. Capacity is allocated amongst demand from non-EV consumers D_{nonEV} and actively charging EVs D_{EV}. At each point in time, the current available capacity K_t can not be 0 due to the necessity for grid stability. Congestion appears if the threshold Φ of 80% of total available capacity K_{total} is reached. This boundary remarks the yellow TLP. Additionally, the test data suggest that demand of non-EV consumers never causes congestion. These assumptions are stated as following: $\forall t \in T$ with $t = 1, 2, 3....n$:

$$\begin{aligned} D_{t,total} &= D_{t,EV} + D_{t,nonEV} \\ K_t &= K_{total} - D_{t,total} \\ \Phi &= K_{total} * 0.80 \\ \text{if } K_t &\leq K_{total} - \Phi \;\longrightarrow\; \text{yellow TLP} \\ D_{t,nonE} &< \Phi \end{aligned} \tag{1}$$

In the proposed market environment, congestion is only caused by increasing charging requests from the set of EVs denoted as I with $i = 1, 2, 3...n$. If these requests exceed available grid capacity K_t, the grid is congested. A charging request is represented by an auction bid. The bid-price represents the price for which an EV is willing to stop charging and resign from its charging request for a period of 15 min. The DSO derives the amount of required flexibility to balance the grid in the next time period and accepts bids accordingly.

$$\forall t \in T, i \in I: \qquad b_t^i = \begin{cases} 1 & \text{if bid accepted} \rightarrow \text{Flexibility is offered} \\ 0 & \text{if bid not accepted} \rightarrow \text{EV starts charging} \end{cases} \tag{2}$$

The sum of all bids at t is denoted as B_t whereas B_t^1 and B_t^0 represent the amount of accepted and not accepted bids respectively:

$$B^1 = \sum_{i=0}^{I}\sum_{t=0}^{T} b_t^i \;\text{ with }\; b_t^i = 1 \;\text{ and }\; B^0 = \sum_{i=0}^{I}\sum_{t=0}^{T} b_t^i \;\text{ with }\; b_t^i = 0 \tag{3}$$

All EVs have the same charging capacity of 11 kW. Thus, congestion appears, if the following is true:

$$B_t * 11\text{kW} > \Phi - D_{t,total} \tag{4}$$

To DSO has to accept enough bids to balance the grid in the upcoming period below Φ. The following condition needs to be satisfied:

$$K_{t+1} - \sum_{i=0}^{I} 11\text{kW} * (1 - b_t^i) \geq K_{total} - \Phi \tag{5}$$

Every EV gets payed-as-bid p_t^i. There is a marginal bid price p_t^{max} that is paid to contract the last EV to offset requests and available capacity. All EVs with $p_t^i > p_t^{max}$ are not contracted and will charge for 15 min. Total costs for the DSO consist of the sum of individual bid-prices p_t^i for all accepted bids selected from the set of connected EVs I and over total simulation time T.

$$C_{total} = \sum_{i=0}^{I} \sum_{t=0}^{T} b_t^i \; p_t^i \tag{6}$$

5.2.4 EV Concept

After connecting to a charging facility, an EV can either charge until state-of-charge SoC is full or not charge to offer flexibility to the DSO. Arrival ($arr \in T$) and departure time ($dep \in T$) varies for each EV and is explained in more detail in section 5.3.3. All EVs have charging capacity of 11 kW, which translates in an increased charge of 11 kW per hour or to a capacity release for the DSO. D_i represents the total increased capacity over simulation time of EV i.

$$D_i = \sum_{t=arr_i}^{dep_i} (1 - b_t^i) \; \frac{11 \text{ kW} * 15 \text{ min}}{60 \text{ min}} \tag{7}$$

Thus, the SoC for an EV only increases if the bid was not accepted. Additionally, EVs can only offer bids in a fixed interval of 15 min (see 5.3.3). This results in a fixed charging or flexibility period of 15 min during which no bids are submitted. The total profit P_i made by offering flexibility to the DSO can be quantified as the sum of all selected bids over simulation time.

$$P_i = \sum_{t=arr_i}^{dep_i} b_t^i \; p_t^i \quad \text{with} \quad b_t^i = \begin{cases} 1 & \text{if bid accepted} \\ 0 & \text{if bid not accepted} \end{cases} \tag{8}$$

Each bid is priced according to the individual price function of each EV.

$$p_t^i = \frac{r_1^i}{SoC_t^i} + \frac{r_2^i}{pSoC_t^i} \tag{9}$$

SoC_t^i represents the current state-of-charge, whereas $pSoC_t^i$ denotes the potential state-of-charge at t. The two random numerators r_1^i and r_2^i represent the individual risk preference and can be set with in a range from 5 to 9. If set low, the price to not charge for one period is rather low, whereas a high value results in a high price. By choosing different values for r_1 and r_2, the focus can be set accordingly. Either on the current SoC (if SoC is low, a high bid will be submitted since utility is higher for SoC than $pSoC$) or a future expectation. This is represented by $pSoC$, to charge later and rather offer flexibility now. This potential state of charge is calculated as following.

$$pSoC_{t_i} = \frac{dep_i - t}{60} \; d \; + \; SoC_t^i \tag{10}$$

It represents a fictional value to the potential charge the EV can acquire if there is no capacity limit to its battery (>100 kWh) and the EV starts charging for every time-step starting from t. Figure 4 illustrates the function.

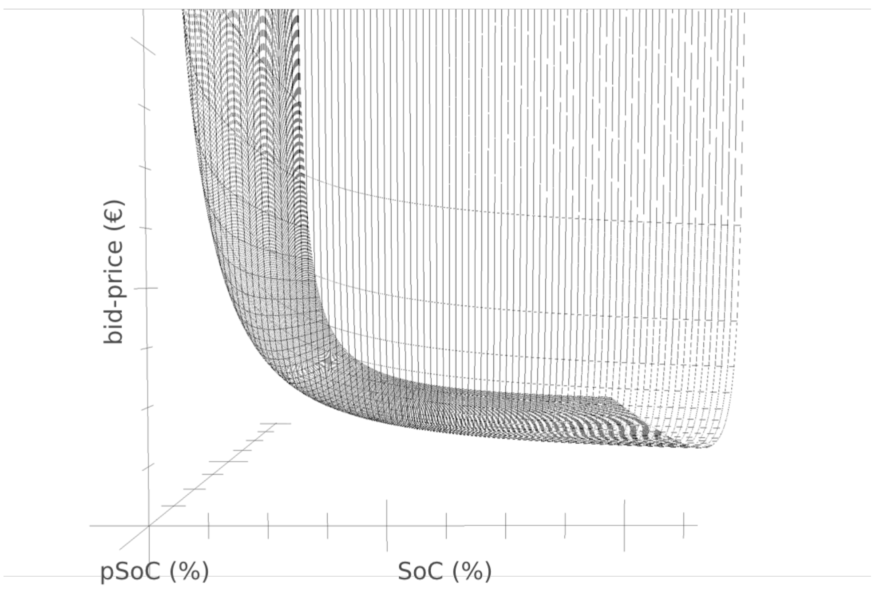


Figure 4: Schematic price function.

Condensing the previous explanations, an EV can only control its charging and trading behaviour based on the individual bid-price. This price is totally independent from external factors and is therefore inelastic to demand (see 6.3.1). Additionally, the costs for charging power are not represented in the above concept as these costs are proportional to D_i and occur in any case. Any demand-controlling power tariffs are neglected as this only leads to a peak-demand shift and no absolute grid release [32].

5.2.5 Communication and Information Concept

According to [34], in 2018, there is no communication method implemented that allows EVs to share information about SoC or overall capacity. However, there are attempts to standardize communication with the draft of ISO/IEC 15118 [51]. Nevertheless, the proposed model does not require EVs to disclose specific data since computation of bid prices is done entirely internal and on EV level. The DSO only contracts flexibility via bids on the market, regardless of other information about the provider. This lean communication model reduces response rates and required bandwidth compared to more interactive designs [34] [52] or aggregated agents [32] [9]. Furthermore, EVs receive no market information nor do they cooperate with each other. The level of information is therefore equal and no advantage can be taken. For the clearing of accepted bids, the correct execution and reimbursement, the blockchain technology can potentially be utilized [53]. Current research is reviewing this technology intensively, but is not part of the present work.

5.3 Architectural Design

The architectural design describes the developed simulation environment and the multi-agent approach on implementation level. In the following, the behaviour of entities, the algorithm of procedure as well as input variables are subject of discussion. Combined with the previous conceptual design, this represents a complete program of execution.

5.3.1 Simulation Framework

The simulation is designed and implemented in Python 3.7.1 and SimPy 3.0.9. The choice for Python as a programming language is based on its simple syntax, a wide range of available add-on modules, and its extensive use in the field of scientific data analysis. SimPy is a process-based, discrete-event simulation framework that is implemented in Python. It is possible to model processes interacting with each other while time passes in defined intervals or in real time. [54]

These aspects are critical to the proposed model since EV batteries increase charge based on power over time and auctions are time-sensitive, too.

5.3.2 System Design

The system design consists of three different classes. Cars, flexmarket and bids stand in direct relation to each other as shown in Figure 5. There is one instance of flexmarket and multiple instances of car and bid during simulation. In the course of the whole simulation, flexmarket requests bids from all cars available. Therefore, each car creates an individual bid by instantiating a bid class. Flexmarket then evaluates all bids and the current grid condition before contracting the necessary amount of bids by flagging each bid accepted or not accepted. All cars check their respective bids and start charging or pause charging for a 15 min time-interval respective to their bid.

SimPy provides a functionality to share resources amongst processes. A so called Container is a continuous, homogeneous matter that represents the amount of total available grid capacity during simulation. Each car willing to charge requests capacity from this resource and releases capacity in case of not charging respectively. If capacity reaches a critical level, the yellow TLP is activated and flexmarket starts to accept bids.

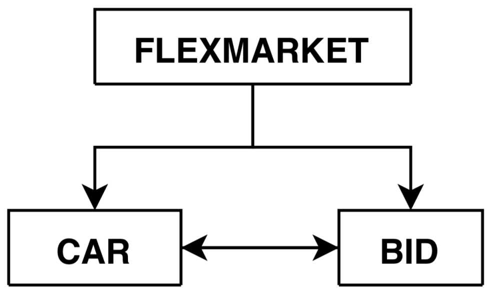


Figure 5: UML diagram of system layout.

5.3.3 Input values

The simulation is fed with predefined as well as random values. Python provides a random value function which is based on the Mersenne Twister generator to produce uniform, normal, exponential or other types of distributions. It passed numerous tests for statistical randomness and is sufficient for the proposed simulation [55]. Table 2 depicts all randomly generated variables and their respective ranges.

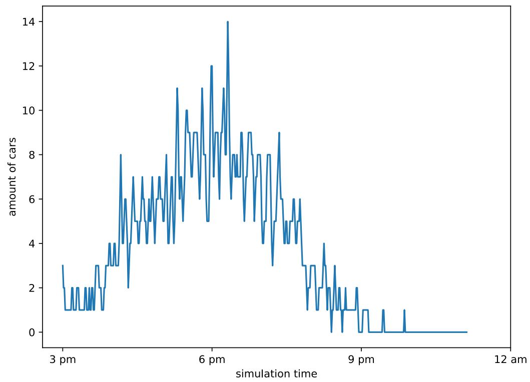
	random variable		value	unit
1	ARRIVING_HOME	(arr)	range(0,360)	min
2	END_OF_CHARGING	(dep)	range(720,1440)	min
3	RISK_FACTORS	(r_1 / r_2)	range(5,9)	-
4	SOC_START	(SoC_{arr})	range(20,90)	kWh

Table 2: Random variables.

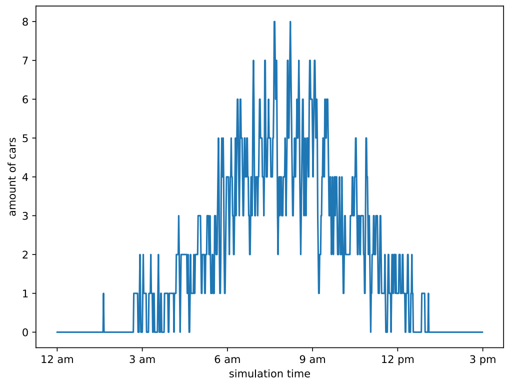
ARRIVING_HOME defines the point in time when the EV is connected to the charging facility for the first time during the simulation. It is assumed that all EVs connect randomly with a normal distribution between 3-9pm with mean $\mu = $ 6pm and standard deviation $\sigma = $ 2h. The same distribution holds true for END_OF_CHARGING, the point in time when the EV gets disconnected and stops charging. Here $\mu = $ 8am and $\sigma = $ 2.5h. Negative values and outliers are neglected. Figure 6 depicts both distributions for comprehension. [56]

The two risk preference factors are uniformly distributed between the stated range. These parameters are unique to the proposed model. The robustness against these values is subject of a sensitivity analysis in section 6.5.

SOC_START represents a normal continuous random distribution. Following calculations from [56], the initial SoC for private EVs has a mean of $\mu = 65\%$ with daily charging



(a) ARRIVING_HOME



(b) END_OF_CHARGE

Figure 6: Normal distribution of starting values.

cycles and $\sigma = 20\%$. Figure 3 indicates all variables set static during the simulation.

	static variable	value	unit
1	FLEX_TIMEOUT	15	min
2	SIMULATION_TIME	1440	min
3	CHARGING_POWER	11	kW
4	BATTERY_CAPACITY	100	kWh
5	CHARGING_INTERVAL	15	min

Table 3: Static variables.

Additionally, non-EV loads from local consumers according to section 5.2.1 are considered as static across multiple executions. Starting time is 3pm and end time is 2:59pm. These times are not significant, since simulation time is set to 1440 min which is equal to 24h. FLEX_TIMEOUT and CHARGING_INTERVAL are set to 15 min intervals in which the EV is offering flexibility or is charging. According to [41], frequently interrupted EV charging can lead to battery degeneration. Additionally, 15 min is a common time-period for energy trades at exiting EOM or capacity markets [14]. For reasons of simplicity, each charging facility has a constant charging power of 11 kW over the individual charging period. This deviates from the fact that charging loads decrease with increasing state of charge over time [56]. Nevertheless, a constant, high charging load represents a stronger assumption while reducing complexity during simulation considerably. According to [57], most three-phase charging facilities have a charging power of 11 kW. The battery capacity was set to 100 kWh which is equals to the Tesla Model S P100D (2017) [58], and represents a strong assumption again.

5.3.4 Agent Behaviour Modeling

Both classes car and flexmarket act as independent agents within the simulation. Agents are defined as autonomous, reactive, interactive and proactive entities in a defined environment. They take individual decisions based on interaction with other agents and the environment to reach the respective objective. Each agents consists of a set of dynamic and static variables describing its current state and a range of methods representing the actions it is able to perform. There is no interaction amongst individual cars but between every car and the flexmarket. The proposed concept can therefore be described as coordinative model since there is no cooperation between cars. [59]

Agent: Flexmarket
The agent class of flexmarket is depicted in listing 1. *Charger* represents the container created for the simulation and is affiliated to flexmarket. As in reality, the DSO monitors the current loads and possible grid congestions on a continuous base. With *list_of_cars*, all connected cars are known to flexmarket at any point in time. The two dynamic lists, *current_bids* and *selected_bids* represent all bids respectively all selected bids at the current point in time.

Listing 1: Flexmarket class.

```
class Flexmarket(object):
    def __init__(self, env: simpy.Environment, charger: simpy.Container, cars):
        self.env = env
        self.charger = charger
        self.list_of_cars = cars
        for car in cars:
            car.set_market(self)
        self.current_bids = []
        self.selected_bids = []

    def current_bids_submitted(self): -> int

    def cars_currently_charging(self): -> int

    def available_charging_slots(self): -> int

    def operate(self):

    def create_selected_flex_cars_list(self, flex_cars_needed, sorted_bid_list):
```

Agent: Car

Listing 2 provides an overview of the car class and its variables and methods. Cars connect and disconnect to the charging facility according to the distribution function mentioned in the previous chapter. The two boolean variables, *charging* and *flex_timeout* are set TRUE if the car is currently charging or being contracted for flexibility. After charging for one interval, *increase_soc()* increases SoC. Each Car executing *car_wants_to_bid()* evaluates weather $SoC \geq 100\%$ and charging or offering flexibility is active. If all conditions are FALSE, car submits a bid in the current period for the upcoming interval. The variables *potential_state_of_charge*, *state_of_charge* and *risk_factor* are introduced in section 5.2.4 and function as input values for *create_bid()*.

Listing 2: Car class.

```
class Car(object):
    def __init__(self, env: simpy.Environment, charger: simpy.Container, name):
        self.env = env
        self.name = name
        self.market = None
        self.charger = charger
        self.state_of_charge = random.randint(*settings.SOC)
        self.potential_state_of_charge = self.state_of_charge + 192
        self.charge_required = settings.BATTERY_CAPACITY - self.state_of_charge
        self.start_of_charging = random.choice(settings.ARRIVING_HOME)
        self.end_of_charging = random.choice(settings.END_OF_CHARGING)
        self.charging_timeout = False
        self.flex_timeout = False
        self.risk_factor = random.uniform(5, 9)

    def increase_soc(self):

    def create_bid(self): -> float

    def return_flex_price(self): -> float

    def car_wants_to_bid(self) -> bool:

    def operate(self):

    def charge(self):
```

Algorithm of Procedure
The proposed concept is implemented as a single thread application to avoid concurrency. That means processes are handled sequential and in order of appearance. The utilized SimPy framework provides a discrete time-stepping to allow processes to wait for others or a specified period of time. The simulation follows a defined procedure for every time-step. Figure 7 depicts the proposed algorithm. With the start of simulation at time-step 0, flexmarket checks B_t with *cars_willing_to_charge()*. This request happens independent from possible grid congestions to align possible concurrency between flexmarket and car. Additionally, this yields the advantage to dynamically contract flexibility regardless of the current TLP. All submitting cars are on hold until time-step 1. Flexmarket evaluates the current load on the grid and derives the available charging slots with *available_charging_slots()*. The required amount of cars stop charging B^1, is calculated as followed:

$$B_t^1 = B_t - \frac{D_{t+1,total} - \Phi}{11\text{kW}} \tag{11}$$

If B_t^1 is equal or below 0, the grid can accommodate all requesting cars and no bid is selected. If B_t^1 is greater than 0, there are more cars requesting to charge than the grid can accommodate and the yellow TLP will be activated. Flexmarket sorts *current_bids* ascending by price and continues to select bids until an amount equal to B_t^1 is reached. These bids are stored in the list *selected_bids* and each bid is set to 1. At time-step 1, each car reads out its latest bid. If it was accepted (1), car sets *flex_timeout* on TRUE and pauses for one interval before submitting a new bid. If the bid was not accepted (2), car sets *charging* on TRUE, requests 11 kW from the DSO and starts charging for one interval before releasing the capacity again and submitting a new bid. Flexmarket evaluates the updated grid status and checks bids of the next time-step 1. This loop repeats until simulation time is over.

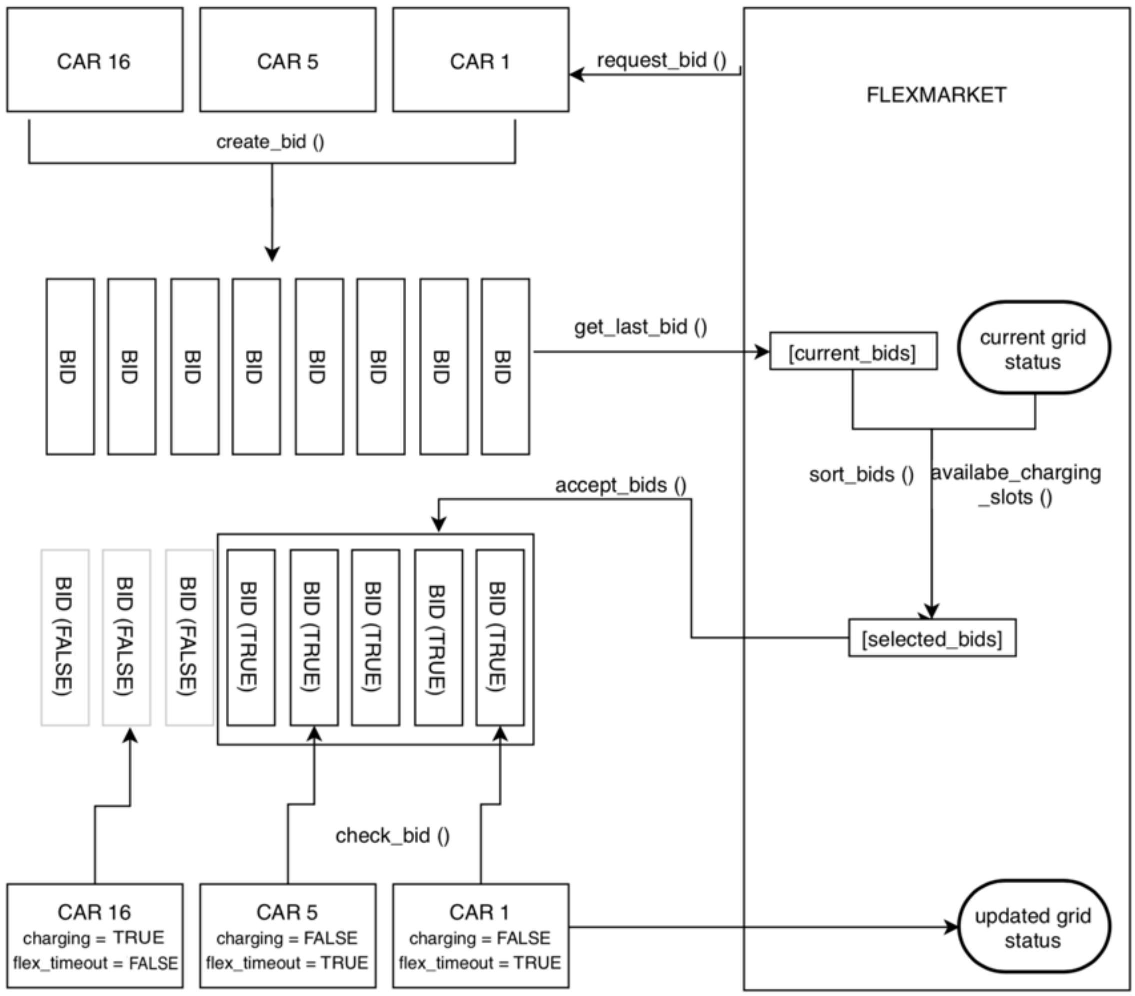


Figure 7: UML simulation procedure.

6 Evaluation

To be able to evaluate the proposed model and compare it to other approaches, a comprehensive evaluation study is designed. This involves the selection of datasets that accurately represent the problem focus with comparable data, a pre-processing technique and suitable metrics to measure the model performances. The following sections explain the proposed procedure and gives attention to the simulation results.

6.1 Evaluation process and tools

For the process of executing the simulation, exporting, pre-processing the dataset and evaluation, a set of tools and formats is used. To ensure an efficiently repeatable simulation procedure, the following pipeline is constructed.

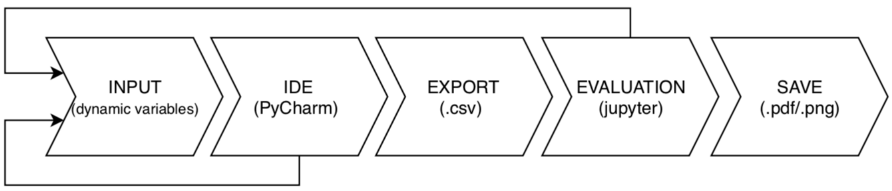


Figure 8: Process pipeline.

First, all dynamic variables are set and insert into the program that is executed in the Integrated Development Environment (IDS). Each simulation has to be initiated there. A set of processes integrated into the simulation extracts conditions from all entities at each time-step to a temporary dataframe. At the end of the simulation, the program runs an export to several .csv files to store the results for evaluation. These .csv files are imported to Jupyter notebook. Jupyter is a web-based, interactive computational environment and widely used for data analysis with Python. Time-series and sensitivity analysis is applied to investigate correlations, entity states and simulation results. The outcome is translated into visual graphs and other means of illustration. In the subsequent sections results thus obtained are presented.

6.2 Time-Series Simulation

At first, a time-series analysis is conducted to examine the simulation results over discrete time steps. The simulation time SIM_TIME is constant at 24h to visualise temporal behaviour. The penetration and the amount of EVs respectively evaluated, is set constant to 1000 units. This figure exaggerates forecasts on penetration purposely and aims on testing the robustness of the proposed system under extreme conditions. Section 6.3

elaborates further on effects related to a variable EV penetration on a per unit base and therefore allows for more qualitative conclusions.

6.2.1 Grid Workload

Figure 9 shows the workload (kW) from dumb-charging over simulation time. Dumb-charging describes an uncontrolled access to power from the distribution grid. The orange line represents D_{nonEV} and the blue line depicts D_{total} including D_{EV}. The demand peaks of D_{nonEV} are clearly located in the afternoon and morning hours when most people are at home. The yellow line at $\Phi = 3000$ kW marks the threshold for the yellow TLP whereas the red line at 3800 kW represents the red TLP. This is the maximum workload for the examined grid topology. To visualise the impact of uncontrolled charging over simulation time, an inevitable grid break down is neglected. Initially, D_{total} increases constantly until 12am with more EVs arriving at the residential charging facility. At this point, all EVs are connected and D_{total} is decreasing until all EVs are fully charged at roughly 7am. Figure 9 illustrates the necessity for a controlled-charging strategy at the assumed EV penetration to prevent the red TLP and a potential grid break down. During simulation time, the red TLP is active for 613 min and the yellow TLP for 37 min. That equals 42,56% or 2,56% of the total simulation time respectively. The maximum amount of dumb-charging EVs for the test grid to not exceed the yellow TLP under these assumptions equals 185 units. This is tested via a stepwise and repeated decrease of EV penetration.

In contrast, figure 10 illustrates the simulation with the proposed model implemented. After two hours, at 5pm, the extensive amount of EVs arriving home leads to an increase in demand until $D_{total} = \Phi$. At this point, the yellow TLP is activated and the auctioning mechanism contracts bids to balance D_{total} at this level until the EVs are leaving again. During 406 min charge requests exceed available capacity and the yellow TLP threshold Φ which equals 28,91% of total simulation time. Two demand peaks at 11:10pm and 9:40am reach the red TLP boundary. In this case, the DSO is able to actively control charging behaviour and return to the yellow TLP. Due to its complexity, the limited scope of this thesis and the negligible occurrence of the red TLP, a direct control mechanism to stop charging of certain EVs is not implemented.

Compared to a penetration of 1000 EVs, figure 11 depicts a similar result for a EV penetration of 500 and 5000. Although section 6.3 describes increasing penetration in more detail, it can be mentioned that the balancing mechanism along Φ during the yellow TLP is robust against an increasing penetration.

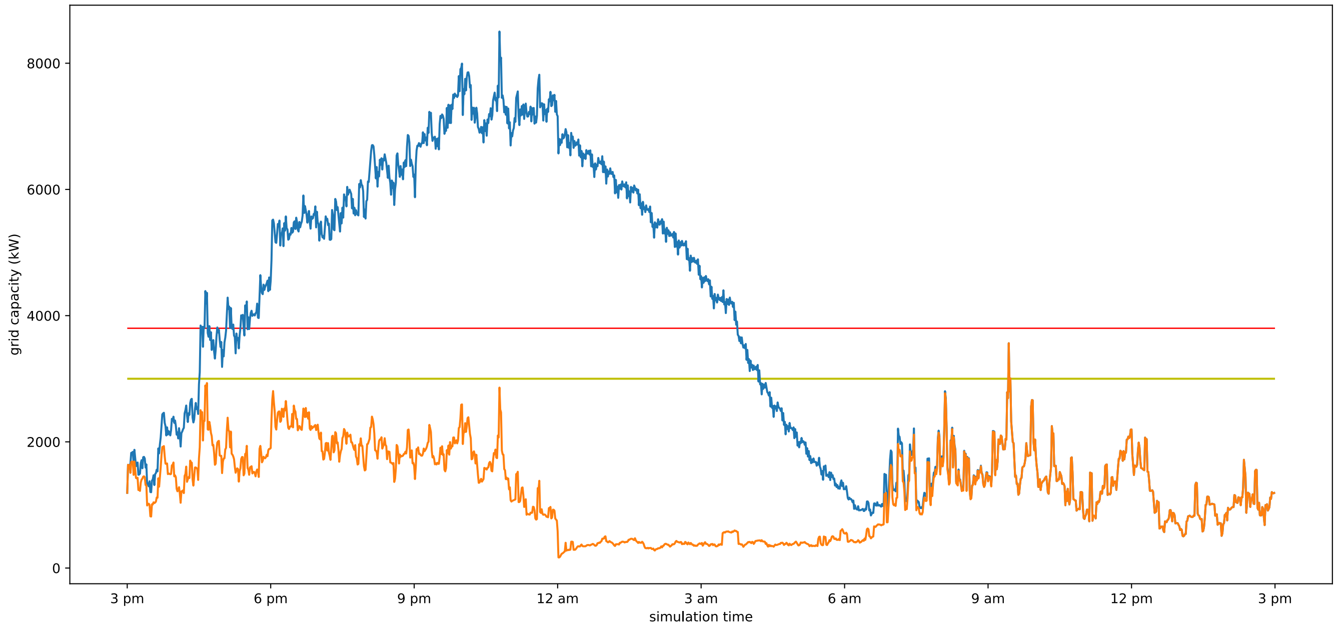


Figure 9: Consumption structure with dumb-charging.

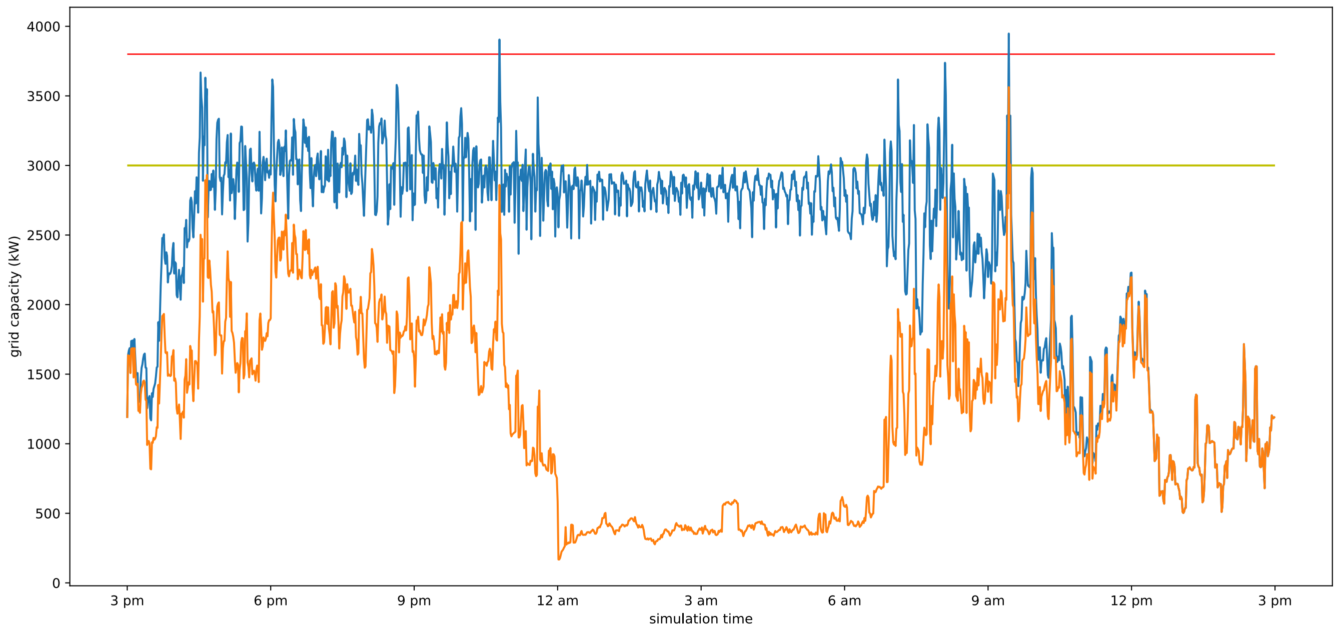
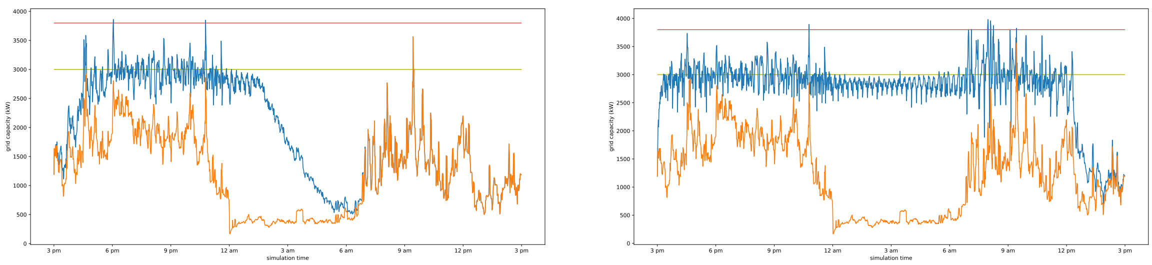


Figure 10: Consumption structure with controlled-charging.



(a) 500 EVs (b) 5000 EVs

Figure 11: Compared consumption structure.

6.2.2 Completed Charging Requests

During the controlled-charging simulation, 74,24% of all EVs were fully charged. Figure 12 depicts the percentage of fully charged EVs ($SoC = 100\%$) over simulation time. The initial, combined SoC_0^{total} of all EVs equals 62.495 kWh. At the end of the simulation, SoC_{1440}^{total} equals 93.416 kWh. Between 12am and 6am the constant, steep gradient indicates maximum workload before flattening out during morning hours. This is due to the normal distributed arrival and departure times introduced in 5.3.3 and reduced D_{nonEV} during night times.

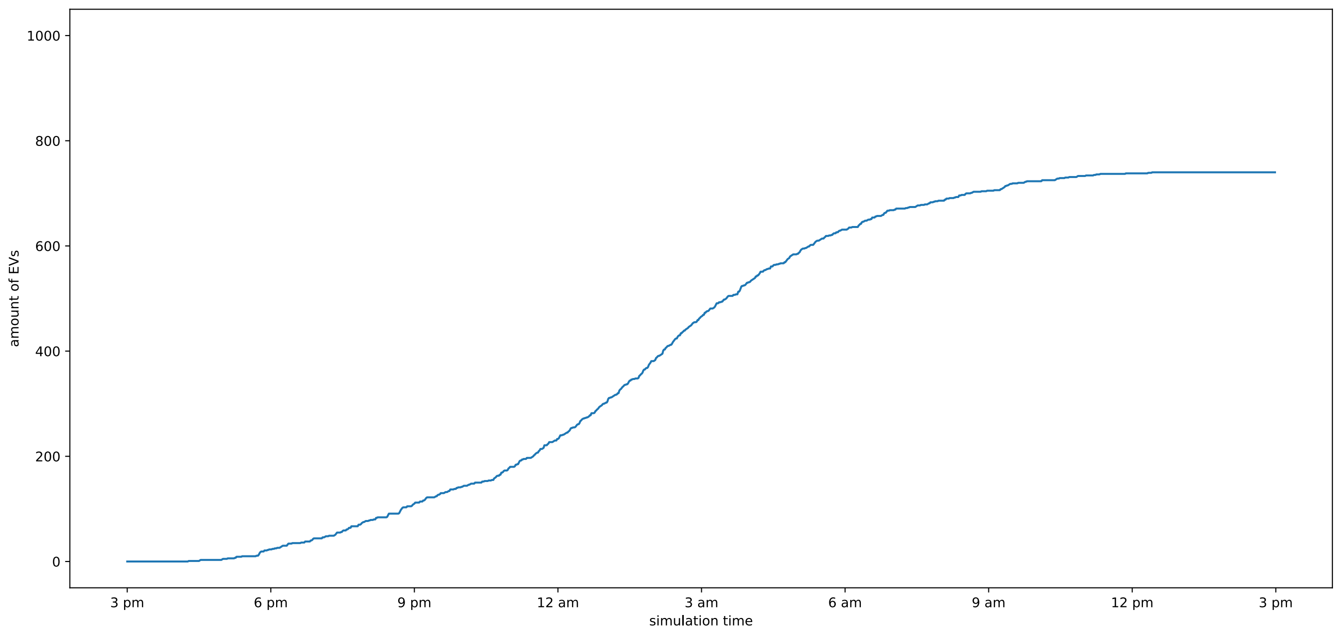


Figure 12: Completed charging requests.

6.2.3 Bid Acceptanc Ratio

The amount of bids B_t at each time step is depicted green in figure 14. Until 9pm, the amount of total bids per time step increases up to 60 before decreasing towards the end of the simulation. At 6pm, the derivative of the green line is at its maximum. This corresponds with the normal distribution of arriving EVs introduced in section 5.3.3. B_t is decreasing, as soon as all EVs are connected and an increasing amount of EVs with $SoC = 100\%$ is not submitting bids anymore. The blue line represents the amount of accepted bids B_t^1. Proportional to B_t, the DSO has to accept more bids to balance the grid at Φ starting with the yellow TLP at approximately 4:30pm. The orange line depicts the amount of not-accepted bids B_t^0, and therefore the amount of EVs starting to charge at t. Initially, the total amount of bids and not-accepted bid is identical until the yellow TLP is active. The overall bid-acceptance-rate is equal to 68,57%.

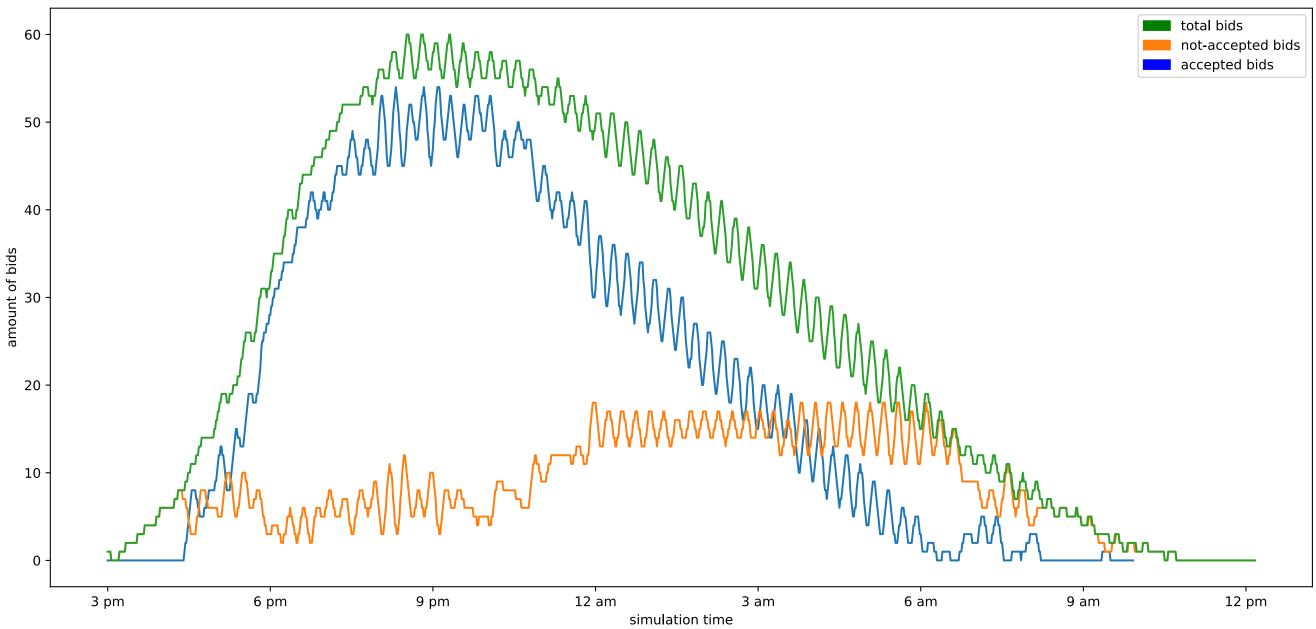


Figure 13: Bid acceptance rate.

6.2.4 Price of Bids

The maximal bid-price p_t^{max} represents the price of the most expensive and accepted bid at time step t similar to the Merit-Order-Model. Figure 14 depicts the absolute volatility of p_t^{max} over the simulation. The high variance of 0.06 results from auctions without bids and therefore $p_t^{max} = 0$ as well as spikes in D_{nonEV} (see section 6.4.2). An upward trend starting from 11pm corresponds with a decreasing total amount of bids B_t and decreasing $pSoC$ as part of the individual price function for all EVs. In contrast, figure 15 illustrates the total auction cost per time step C_t for the DSO. With increasing EVs requesting charging power and high D_{nonEV}, auction costs increase until 9pm. At this point, no new EVs arrive at the charging facility and more EVs finish charging. With decreasing D_{nonEV}, more charging slots are available and less bids need to be accepted by the DSO. Total auction cost for the simulation is equal to $C_{total} = 4.176,70€$.

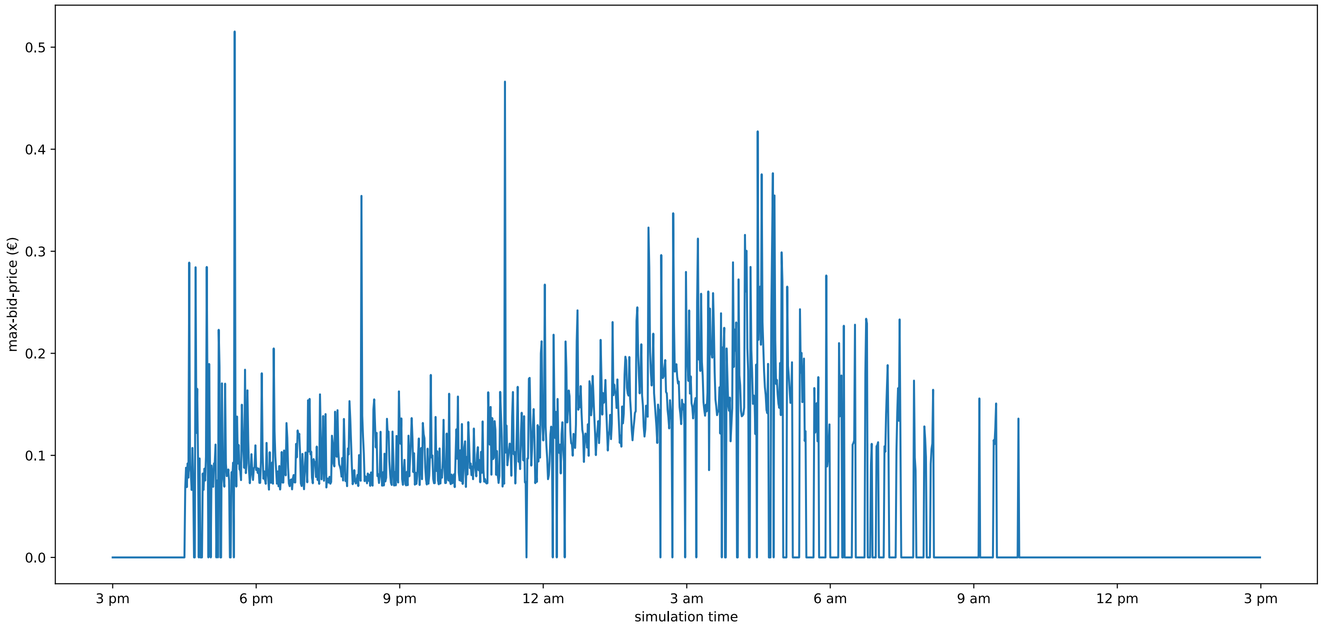


Figure 14: Maximal bid-price.

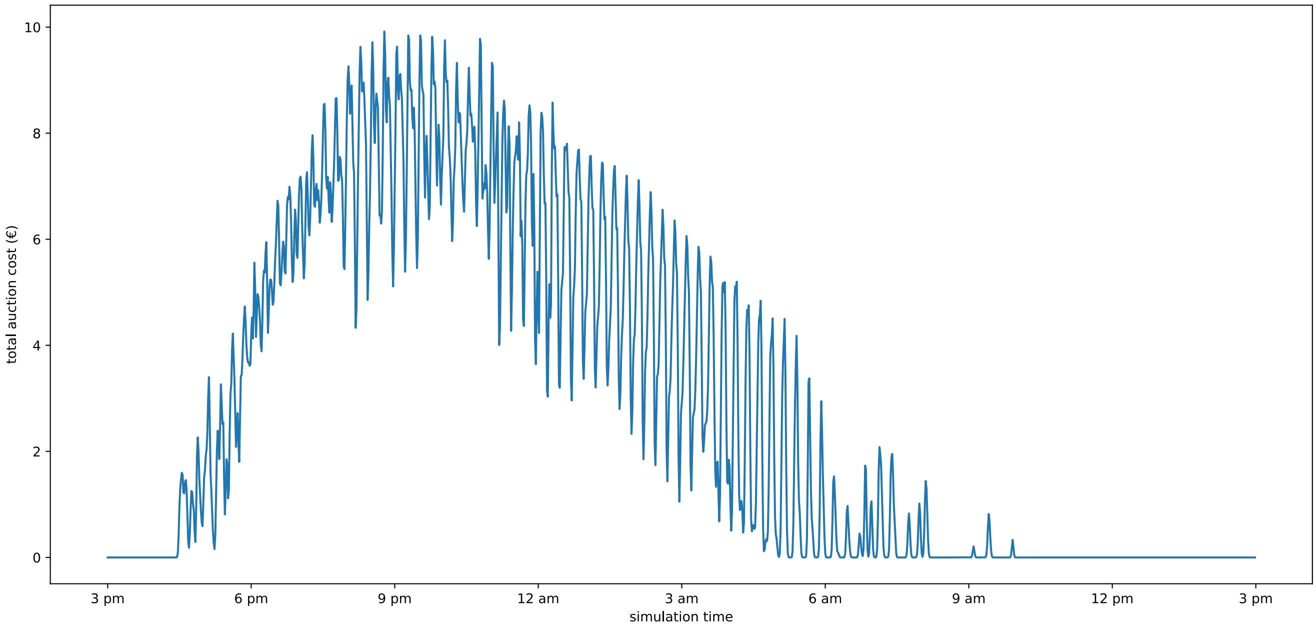


Figure 15: Total auction cost for DSO.

6.2.5 Charging pattern of Example EV

A random sample EV is examined over simulation time to visualize the intended charging behaviour. Figure 16 depicts the the SoC of example EV $i = 22$. The observed EV arrives at the charging facility at 7pm and submits its first bid. The red dot indicates a successful auction with $b_t = 1$ whereas a black dot equals $b_t = 0$ and a 15 min charging interval. With an active yellow TLP, the DSO contracts the example car in the first 30 auctions sequentially. Thus, the SoC remains at starting level until 3am, when the first auction is lost and the EV charges. In the end, the observed EV increased its SoC with 8 charging intervals and a total additional charge of 22 kWh. In addition, the EV was contracted 43 times to offer flexibility to the DSO. In this example, a total return of 12,10€ with an average bid price of 0.28€ is paid to the EV.

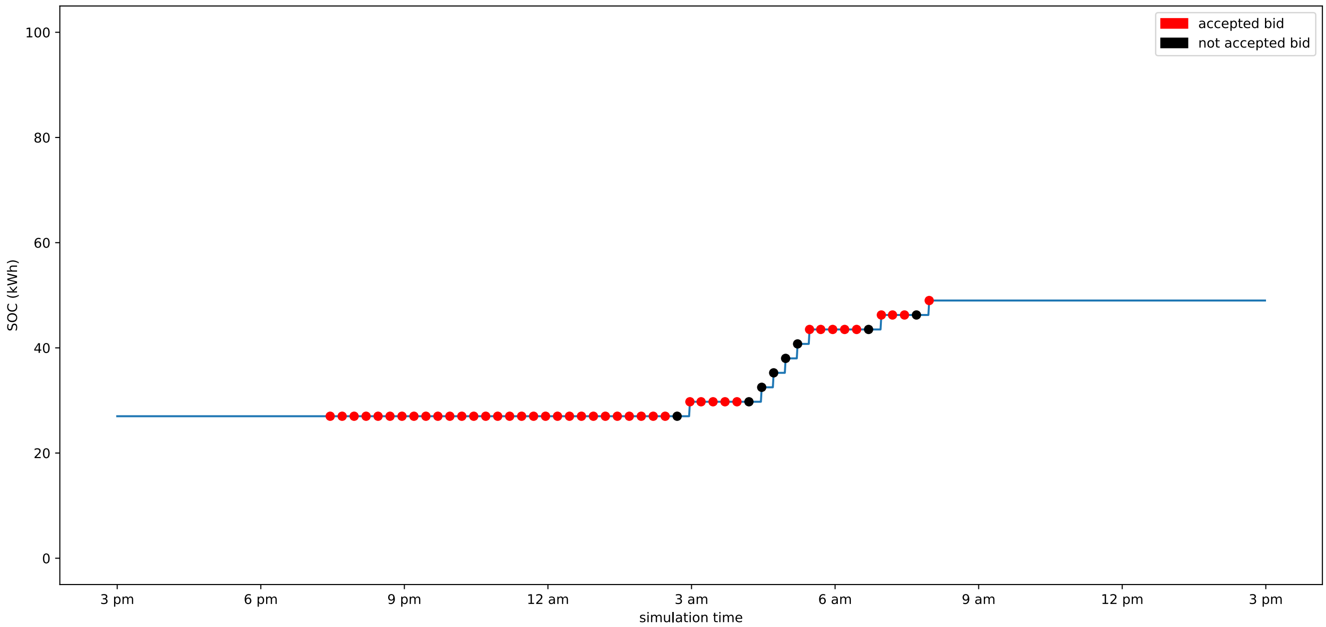


Figure 16: Charging pattern EV.

Section 5.2.4 introduces the price function implemented for all EVs. Depending on two individual risk preference (r_1, r_2), each EV evaluates its current SoC and the virtual $pSoC$ to submit a bid for the upcoming interval. Table 4 represents the charging protocol of EV number 22. Bid prices for the first 7,5h constantly increase since SoC remains constant but $pSoC$ monotonically decreases. For each interval, it is more expensive for the DSO to contract the corresponding bid. On the other hand, opportunity cost for the EV owner is increasing, since less simulation time is available to reach a certain SoC.

price (p)	(i)	(t)	$pSoC$	SoC	b
0.295991	22	267	242.050000	27.00	1
0.296333	22	282	239.300000	27.00	1
0.296682	22	297	236.550000	27.00	1
0.297039	22	312	233.800000	27.00	1
0.297405	22	327	231.050000	27.00	1
0.297780	22	342	228.300000	27.00	1
0.298164	22	357	225.550000	27.00	1
0.298558	22	372	222.800000	27.00	1
0.298961	22	387	220.050000	27.00	1
0.299374	22	402	217.300000	27.00	1
0.299798	22	417	214.550000	27.00	1
0.300234	22	432	211.800000	27.00	1
0.300680	22	447	209.050000	27.00	1
0.301139	22	462	206.300000	27.00	1
0.301609	22	477	203.550000	27.00	1
0.302093	22	492	200.800000	27.00	1
0.302590	22	507	198.050000	27.00	1
0.303101	22	522	195.300000	27.00	1
0.303627	22	537	192.550000	27.00	1
0.304168	22	552	189.800000	27.00	1
0.304725	22	567	187.050000	27.00	1
0.305299	22	582	184.300000	27.00	1
0.305890	22	597	181.550000	27.00	1
0.306499	22	612	178.800000	27.00	1
0.307127	22	627	176.050000	27.00	1
0.307775	22	642	173.300000	27.00	1
0.308444	22	657	170.550000	27.00	1
0.309135	22	672	167.800000	27.00	1
0.309849	22	687	165.050000	27.00	1
0.310587	22	702	162.300000	27.00	2
0.286022	22	717	162.116667	29.75	1
0.286735	22	732	159.550000	29.75	1
0.287526	22	747	156.800000	29.75	1
0.288344	22	762	154.050000	29.75	1
0.289193	22	777	151.300000	29.75	1
0.290072	22	792	148.550000	29.75	2
0.269683	22	807	148.366667	32.50	2
0.252424	22	822	148.366667	35.25	2
0.237664	22	837	148.366667	38.00	2
0.224895	22	852	148.366667	40.75	2
0.213741	22	867	148.366667	43.50	1
0.214594	22	882	145.800000	43.50	1
0.215542	22	897	143.050000	43.50	1
0.216528	22	912	140.300000	43.50	1
0.217552	22	927	137.550000	43.50	1
0.218618	22	942	134.800000	43.50	2
0.208864	22	957	134.616667	46.25	1
0.209902	22	972	132.050000	46.25	1
0.211060	22	987	129.300000	46.25	1
0.212268	22	1002	126.550000	46.25	2
0.203626	22	1017	126.366667	49.00	1

Table 4: Auction log of example EV.

Figure 17 shows a gaussian distribution of accepted bids B^1 over SoC. The majority of bids are accepted from EVs with SoC between 40-80%. This corresponds with the normal distributed, initial SoC with $\mu = 65\%$ and the average arrival time. All EVs request charge during peak demand hours and therefore the first set of bids gets contracted before the SoC increases as seen at the previous example car $i = 22$.

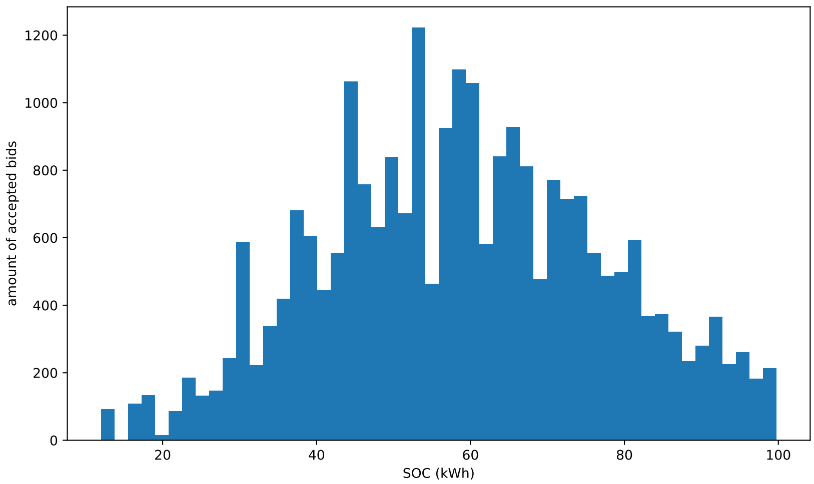


Figure 17: Distribution of accepted bids over SoC.

6.2.6 Summary Time-Series Simulation

The following table summarizes numerical results from this time-series simulation.

	parameter	result	unit	notation
1	Average Bid-Price	17,02	cent	p^{avg}
2	Average Bid-Price Spread	14,34	cent	$\frac{p^{max}-p^{min}}{B^1}$
3	Total Auction Cost DSO	4.176,70	€	C_{total}
4	Bid Acceptance Ratio	68,57	%	$\frac{B^1}{B}$
5	Yellow TLP active	406	min	
6	Completed Charging Requests	74,24	%	$\frac{\#\text{i with SoC} = 100\%}{I}$
7	Total SoC Increase	30.921	kWh	$B^0 * 11kW$
8	Average SoC Increase	30,92	kWh	$\frac{SoC_{1440}-SoC_0}{I}$
9	Average Charging Time	168,69	min	$\frac{B^0 * 15\text{min}}{I}$
10	Average Flex-Offering-Time	368,08	min	$\frac{B^1 * 15\text{min}}{I}$
11	Average SoC of Accepted Bids	68,34	kWh	$\frac{\sum_{i=1}^{I}\sum_{t=1}^{T} b_t^i * SoC_t^i}{B^1}$ with $b_t^i = 1$

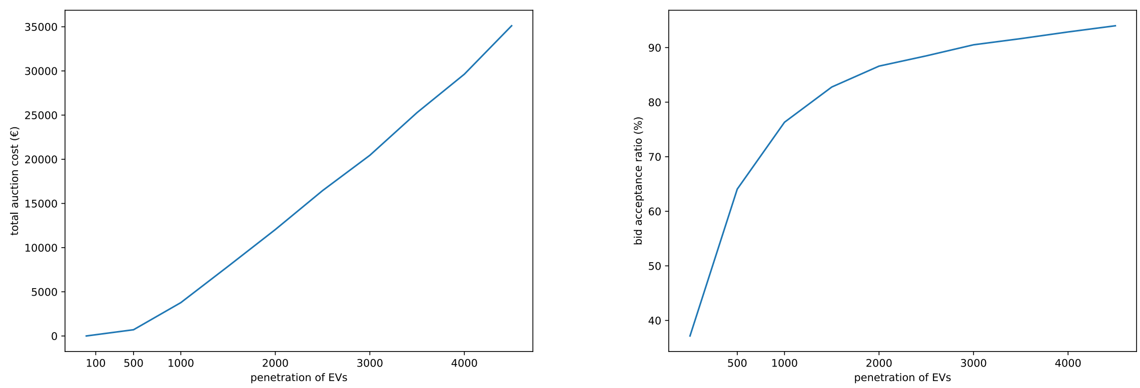
Table 5: Summary time-series simulation.

6.3 Sensitivity Simulation

This section evaluates the proposed model in regard to a changing penetration of EVs. Whereas the previous section allows to draw quantitative insights according to postulated assumptions, this sensitivity analysis includes a range of future EV penetration rates from 100 to 5000 units. A fiftyfold increase might not represent a probable evolution of EV technology in the low voltage grid topology, but the model is tested on possible effects this penetration might have. The stepping varies between test cases due to different requirements for granularity and is stated at the beginning of each section.

6.3.1 Auction Cost, EV Profit and SoC Increase

With a stepwise increasing penetration of 500 EVs, the total auction cost C_{total} rises proportionally. Due to equation (5) and the fixed total capacity K_{total}, an increase in D_{total} leads to more accepted bids B^1 and higher costs for the DSO to balance the grid. Accordingly, the accepted-bids ratio increases and converges to 100%.



(a) Total auction cost. (b) Bid acceptance rate.

Figure 18: Normal distribution of starting values.

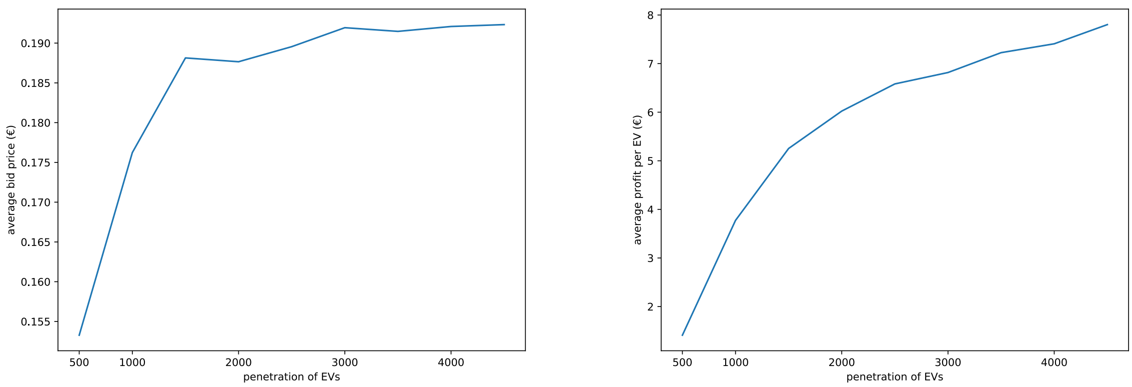
The average bid price p^{avg} increases rapidly until it converges to 0,21€. The same applies for the average profit per EV as it flattens towards 8€. This is due to the fact, that the average increase of state-of-charge (SoC^{avg}) converges to 0 kWh/EV with increasing amount I of EVs. In the folllowing, this assumption is explained.

With Φ and D_{nonEV} being constant, the available capacity for charging is limited. Therefore, the total amount of rejected bids respectively permitted charging requests is constant at $B^0 = \sum_{t=0}^{1440} \frac{\Phi - D_t^{nonEV}}{60\text{min} * 11\text{kW}} = 3883$ bids over simulation time. With increasing I, the following applies:

$$\lim_{I\to\infty} SoC^{avg} = \lim_{I\to\infty} \frac{B^0 * 11kW}{I} \to 0 \tag{12}$$

During simulation, SoC^{avg} decreased by 75,26% from 30,92 kWh/EV (1000 EV) to 7,65 kWh/EV (5000 EV).

All EVs compute their individual bid-price according to (9). Considering (12), the first summand converges over simulation time to $\frac{\mu_{r1}=7}{\mu_{Soc}=65} = 10,76€$. The second summand depends on the $pSoC$ and therefore on the ongoing simulation time t. Considering (10) and (12), its value is directly proportional to t with a maximum of 0,11€ (assuming $\mu_{Soc} = 65$ and $\mu_{r2} = 7$). Therefore, with an increasing penetration of EV, p^{max} and p^{avg} converge to 0,21€. Furthermore, since the maximum amount of bids per EV is limited to $\frac{840\text{min}}{15\text{min}} = 56$, the average profit per EV converges to 11,76€ (assuming $\mu_{arr} = 6$pm and $\mu_{dep} = 8$am. Since this profit is a direct cost to the DSO, the marginal costs for an additional EV equals 11,76€.



(a) Average bid price. (b) Average Profit per EV

Figure 19: Bid price and profit.

Figure 20 indicates this observation more granular. The orange line depicts the percentage change of yellow TLP over a stepwise increase of 10 EVs. The blue line represents the percentage change of C_{total} over the same penetration rate. First, a correlation between an increase in yellow TLP and cost is observed. Second, absolute volatility is high until flattening. This insight suggests a high variance of concurrency of charge requests and therefore accepted bids below a penetration of 300 EVs. With more than 300 EV, percentage change converges to zero since TLP is active during the whole simulation time and C_{total} only increases minorly.

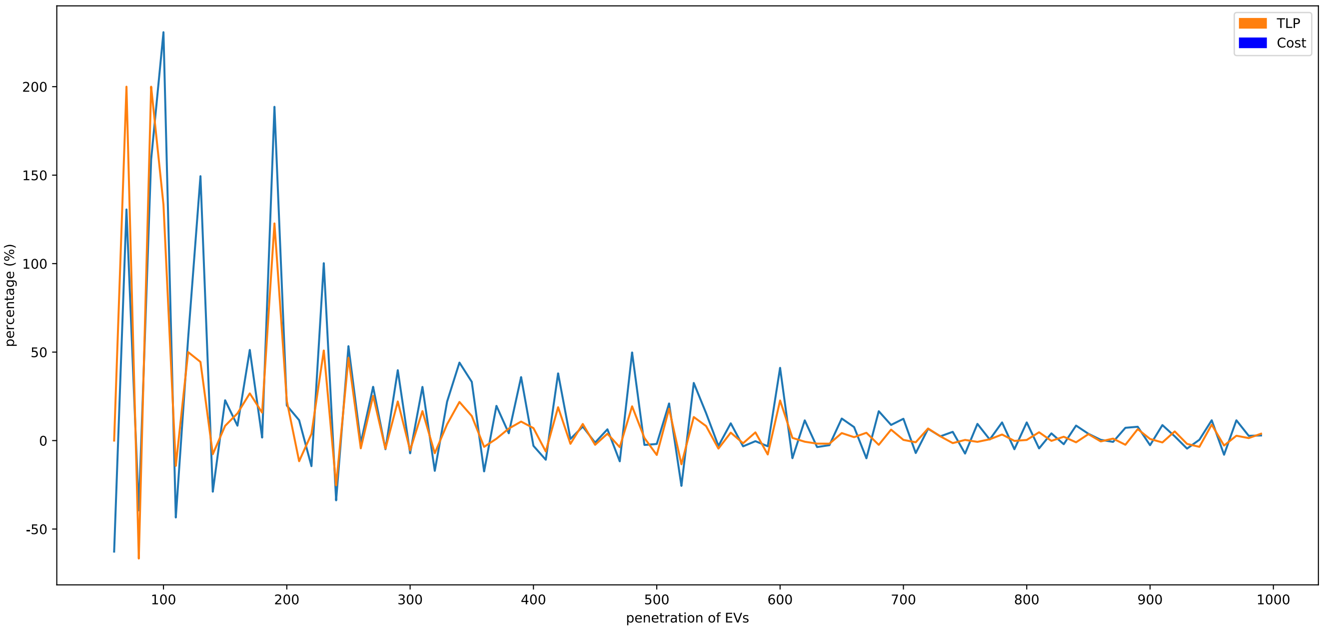


Figure 20: Completed charging requests rate.

6.3.2 Completed Charging Requests

At a penetration of 100 EVs, the model serves 100% of all charging requests until $SoC = 100\%$. With an increase of 100 EVs per simulation iteration, this rate monotonically decreases by 72,25% for 5000 EVs. Thus, completed charging requests equal 27,75%. A continued trend suggests correct processing of all auctions and allocation of charging slots. The curve falls initially and flattens at 3000 EVs until the end.

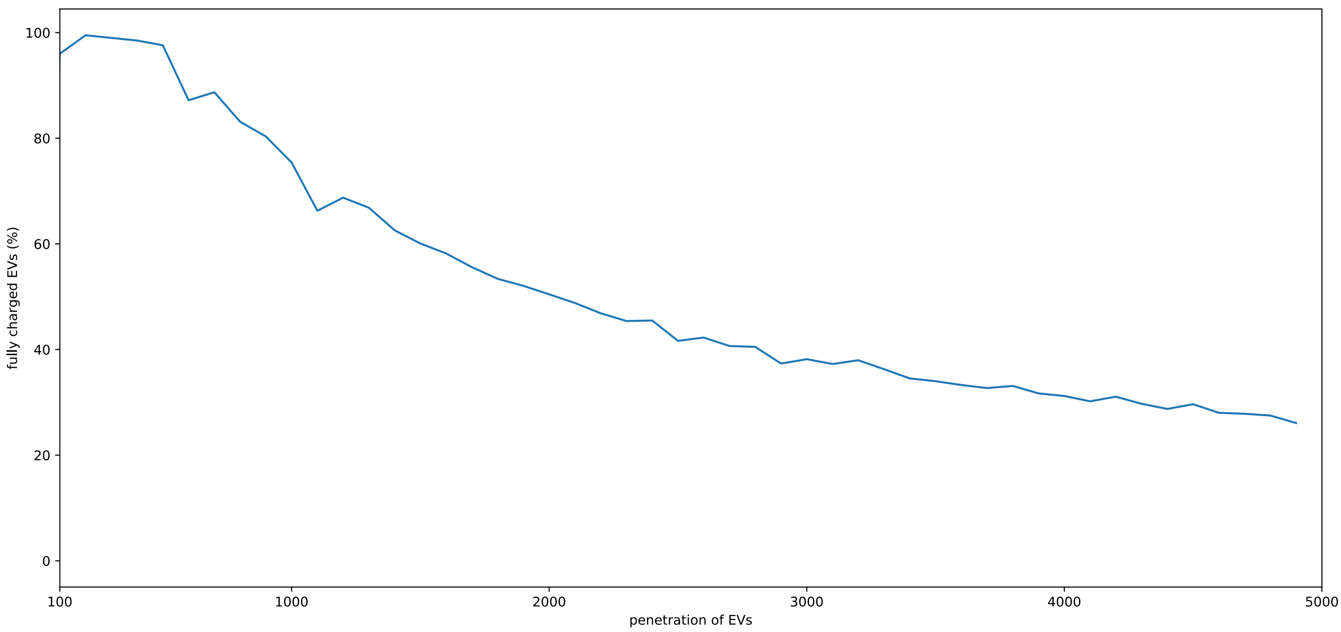


Figure 21: Completed charging requests rate.

6.3.3 State of Charge and Optimal EV penetration

Figure 22 depicts the final average and minimum SoC_{dep} over an increasing penetration of EVs. Both curves decrease with different gradient. Average SoC_{dep} converges against $\mu_{SoC_{arr}}$ as explained in 6.3.1. Minimum SoC_{dep} converges against $\mu_{SoC_{arr}} - \sigma_{SoC_{arr}} = 25\%$ (see 5.3.3). Assuming a target average $SoC_{dep} \geq 80\%$, the simulation suggests a maximum of 1745 EVs. To validate this result, the following calculation approximates a similar value based on the mean input-values. Assuming (1) $\mu_{arr} = 6\text{pm}$ and $\mu_{dep} = 8\text{am}$, (2) a total available grid capacity $\Phi - D_{nonEV} = 26857$ kWh within this particular timeframe and (3) $\mu_{SoC_{arr}} = 65\%$, the theoretical, possible amount of EV equals 1790 EV with $\mu_{SoC^{avg}} = 15\%$. Compared to 185 EVs (see 6.2.1), this is a ninefold increase.

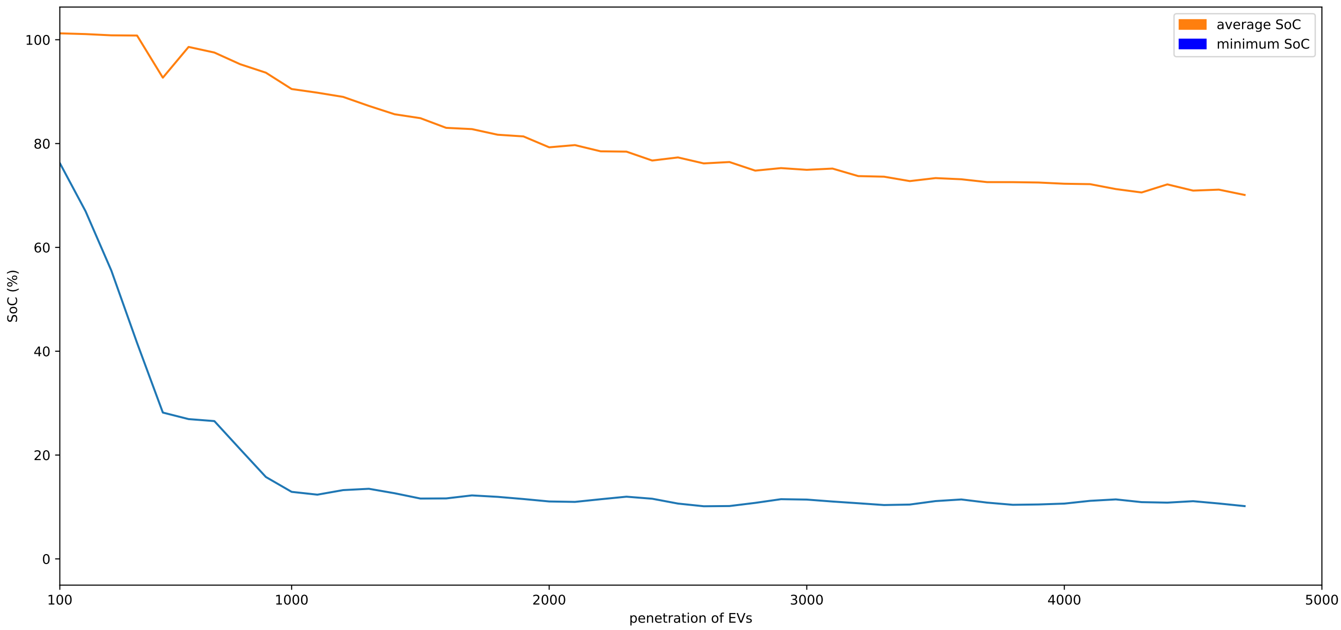


Figure 22: Final SoC (avergage vs. minimal).

6.3.4 Summary Sensitivity Simulation

The following tables overviews the qualitative and quantitative results from the sensitivity simulation.

	parameter	dependency	unit	notation
1	Average Bid-Price	convergent	€	$\lim_{I\to\infty} p^{avg} \to 0.21$
2	Total Auction Cost DSO	proportional (I)	€	C_{total}
3	Average Profit EV	convergent	€	$\lim_{I\to\infty} \sum_{t=0}^{1440} p_t b_t \to 11{,}76$
4	Bid Acceptance Ratio	convergent	%	$\lim_{I\to\infty} \frac{B^1}{B} \to 100$
6	Completed Charging Requests	convergent	%	$\lim_{I\to\infty} \frac{\#i \text{ with } SoC=100}{I} \to 0$
7	Total SoC Increase	convergent	kWh	$\lim_{I\to\infty} B^0 * 11kW \to 42713$
8	Average SoC Increase	convergent	kWh	$\frac{SoC_{1440}-SoC_0}{I}$
9	Average Charging Time	convergent	min	$\lim_{I\to\infty} \frac{B^0 * 15\text{min}}{I} \to 0$
10	Average Flex-Offering-Time	convergent	min	$\lim_{I\to\infty} \frac{B^1 * 15\text{min}}{I} \to 840$
11	Average SoC of Accepted Bids	convergent	kWh	$\lim_{I\to\infty} SoC^{avg} \to 65$
12	Average maximum EV penetration	constant	units	$\frac{\Phi - D_{nonEV}}{\mu_{SoC_{arr}} - \mu_{SoC_{dep}}} = 1790$

Table 6: Overview robustness.

6.4 Identified Effects

The evaluation of the proposed model leads to a set of observed effects. Whereas some are specific to the model, others are generally applicable. In the following, these effects and the reasons for their existence are described before a possible solution is drafted.

6.4.1 Request Control

Contrary to the Traffic Light Concept, the proposed model implies a request control mechanism that has a direct effect on the amount of yellow TLPs. At time step t, the amount of not accepted bids B_t^0 and subsequent the amount of EVs permitted to charge, is computed against the current total demand (actively charging EVs plus demand from nonEV loads) $D_{t,total}$ to not exceed Φ (see equation (5)). For the next period $t+1$, the following applies:

$$D_{t+1,total} = D_{t+1,nonEV} \; + \; \sum_{j=1}^{15} (B_{t+1-j}^0 * d) \tag{13}$$

If $D_{t+1,total} \leq D_{t,total}$, the yellow TLP will not be active in $t+1$ and additional EVs are permitted to charge although the amount of EVs requesting charge exceeds Φ. The grid stays in a stable condition within the green TLP limits (see 5.2.2). Whereas, if $D_{t+1,total} \geq D_{t,total}$ with $B_{t+1}^0 = 0$ because no new charging slots are available, Φ is exceeded and the yellow TLP is active. Considering this effect, the proposed model has the advantage of less activations of the yellow TLP. In a simulation with EV penetration of 1000, there are 786 time steps with $B_t^1 > 0$, whereas only 406 time steps with active yellow TLP are observed. Thus, compared to a market mechanism that would only intervene and contract flexibility resources with an active yellow TLP, Φ is exceeded 49,35% more. If absolute volatility of D_{nonEV} is equal to 0, the yellow TLP would never be activated, since the proposed model balances charging request below Φ.

6.4.2 Latency

In this context, latency describes the delayed reaction time of flexmarket to a drastic change in D_{nonEV}. If absolute volatility of D_{nonEV} is high, the auction mechanism can not reduce absolute volatility of D_{total}. Figure 23 shows a high resolution graph with a one hour interval. At roughly $t =$ 10:50pm, $D_{t,nonEV}$ increases and is close to Φ. Flexmarket assesses the current grid condition without forecasting expected demands. Therefore, the amount of not-accepted bids does not accommodate for future flexibility demands and equals the current available charging slots $\frac{\Phi - D_{t,total}}{11\text{kW}}$. EVs with $b_t^i = 0$ start charging for a period of 15min and increase $D_{t+1,total} = \Phi$. At $t + 1 =$ 10:51pm, $D_{t+1,nonEV}$ increases rapidly and not enough EVs finish charging to submit new flexibility bids to balance $D_{t+1,total} = \Phi$. During the next auctions this scenario repeats until D_{nonEV} reaches a peak and starts falling. This latency effect emerges due to (1) the lack of a demand forecasting mechanism and (2) the fixed, uninterruptible charging intervals. Section 6.6 explains (1) whereas (2) is due to possible battery degeneration from unequal and frequent charge interruption [41].

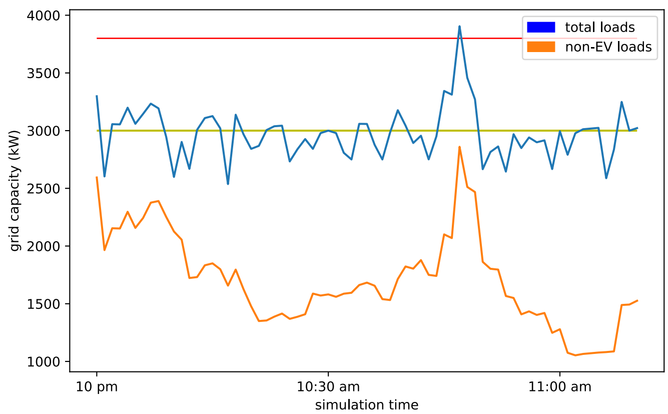


Figure 23: High resolution graph: Latency.

6.4.3 Batching

Due to the fixed intervals of 15 min for charging and flexibility, EVs are grouped to batches. A batch corresponds to the total amount of bids B_t at time step t. The affiliation of a particular EV to a certain batch does not change over simulation time. Initial allocation to a batch is equal to the arrival time. All EVs arriving at t submit their first bid at t and start charging or offering flexibility for 15 min before again participating in an auction. Batches only get bigger by new EVs arriving at $(t * 15)$ or smaller with EV complete charging at $(t * 15)$. If the batch is relatively small and demand for flexibility is high, even risk-averse EV with low SoC, low $pSoC$ and high bid-prices might be accepted. This can result in insufficient SoC after simulation and high returns respectively. Bigger Batches are more competitive and balanced amongst the EVs. The high variance of B_t also leads to high volatility in total-auction-cost simulation time. The following section 6.5.2 illustrates an equal arrival time for all EVs. During night times, the batching effect can be observed as within a 15 min interval, D_{total} oscillates due to the executed auctions and low volatility of D_{nonEV}. This effect characterizes the applied method of fixed intervals and is not unique to the proposed model. A viable solution to this effect is an asynchrony contracting mechanism. By contracting flexibility for 16 min and permitting charging for 15 min, would split big batches and reduce volatility.

6.5 Robustness against Dynamic Inputs

Following the definition of [60], robustness in statistics describes how sensitive a statistical model is towards outliers within the dataset. If sensitivity is low, type 1 and type 2 errors deviate negligible and the model is robust. The present work introduces an applied software solution rather than a statistical model, nevertheless robustness towards changing input variables is critical for implementation. Therefore, the following dynamic variables, introduced in section 5.3.3, are investigated on possible disfunction of the balancing mechanism. Static variables are discussed in the respective section.

6.5.1 Initial Sate of Charge

The amount of charge for EV i when arriving at the charging facility, is denoted as SoC^i_{arr}. This value is normally distributed as described in section 5.3.3. Shifting mean and standard deviation of this assumption results in (1) more or less required total charge over simulation time and therefore an increasing amount of bids B. (2) According to (5), the DSO needs to balance the grid at Φ by accepting more bids B^1. (3) As value $pSoC^i_t$ depends on SoC^i_t, the price function p^i_t reflects any change in the initial distribution. Therefore, also C_{total} for the DSO changes. From a DSO perspective, a lower average SoC_{arr} is comparable to effects of more EVs over simulation, as each EV submits more bids until it is fully charged. Since the previous section already concluded on robustness against increasing EV penetration, a change in SoC_{arr} distribution does not cause disfunction of the proposed model.

6.5.2 Arrival and Departure Time

A change in driving behaviour or particular characteristics of certain residential areas, can lead to a deviating distribution of arrival and departure times. Subsequently, peak demand can shift or intensify on certain time periods. Following $B_t = B_t^1 + B_t^0$ and (13), with an increasing or decreasing amount of bids, accepted bids varies, whereas the permitted charging requests remain constant and balanced below Φ. Figure 24 illustrates a simultaneous arrival at 4pm of 1000 EVs. The proposed balancing model is robust against arrival and departure time. Nevertheless, higher concurrency leads to a higher effect of batching.

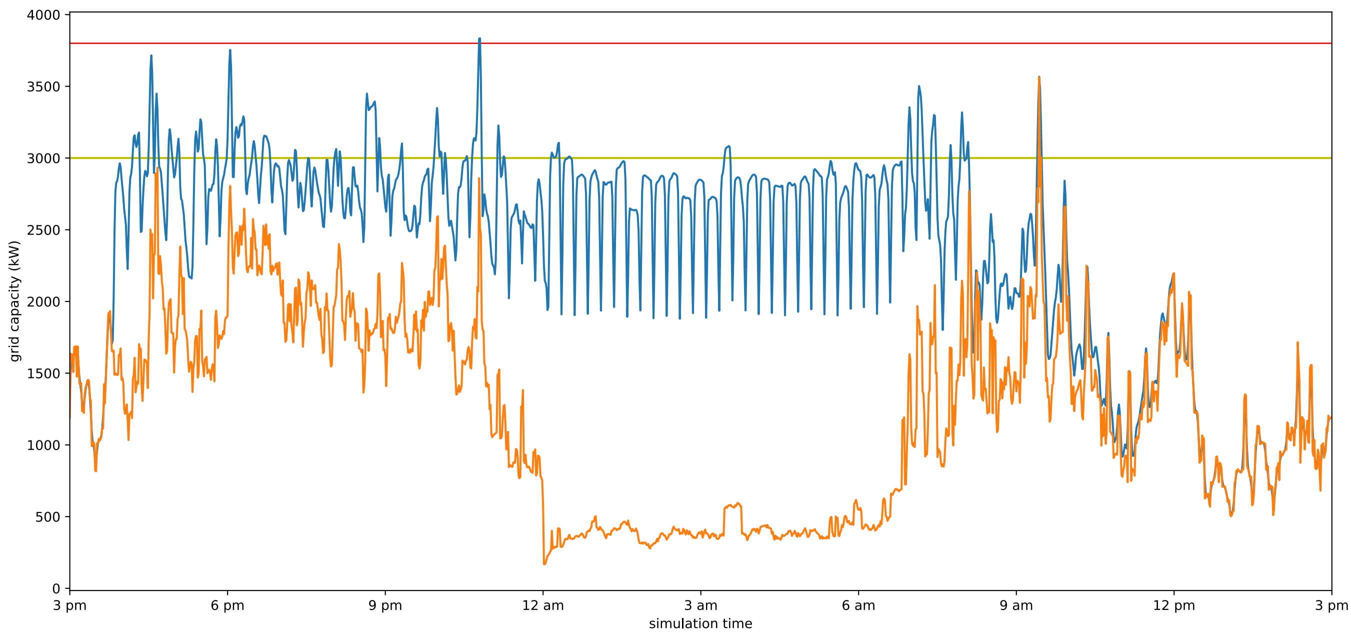


Figure 24: Simultaneous arrival time.

6.5.3 Risk Preferences

In section 5.2.4, the two risk preference factors r_1^i and r_2^i are introduced, uniformly distributed within a defined range. As numerators in the price function, both factors determine the the risk preference and therefore the bid-price of an individual EV. Nevertheless, during an auction procedure, flexmarket only sorts bids according to prices but accepts enough bids to balance the grid regardless the cost (see (5)). The DSO's demand for flexibility is inelastic to bid-prices. Therefore the proposed balancing model is robust against C_{total} and subsequent r_1^i and r_2^i.

6.5.4 Random Seed

The program's random number generator receives an initial seed to initialize internal states [61]. For comparability, this seed is set static over the course of several simulations. To test robustness against changing initial random numbers, 40 simulations with seed set to operating time are executed. Therefore, each seed value deviates. The blue line of figure 25 illustrates the mean whereas the red area marks the difference between the maximum and minimum value obtained during all simulations for the respective time step. Standard deviation for the observed simulation trails equals $\sigma = 138$ kW and can be considered as negligible. It can be concluded that seeding the random generator does not affect the robustness of the proposed model.

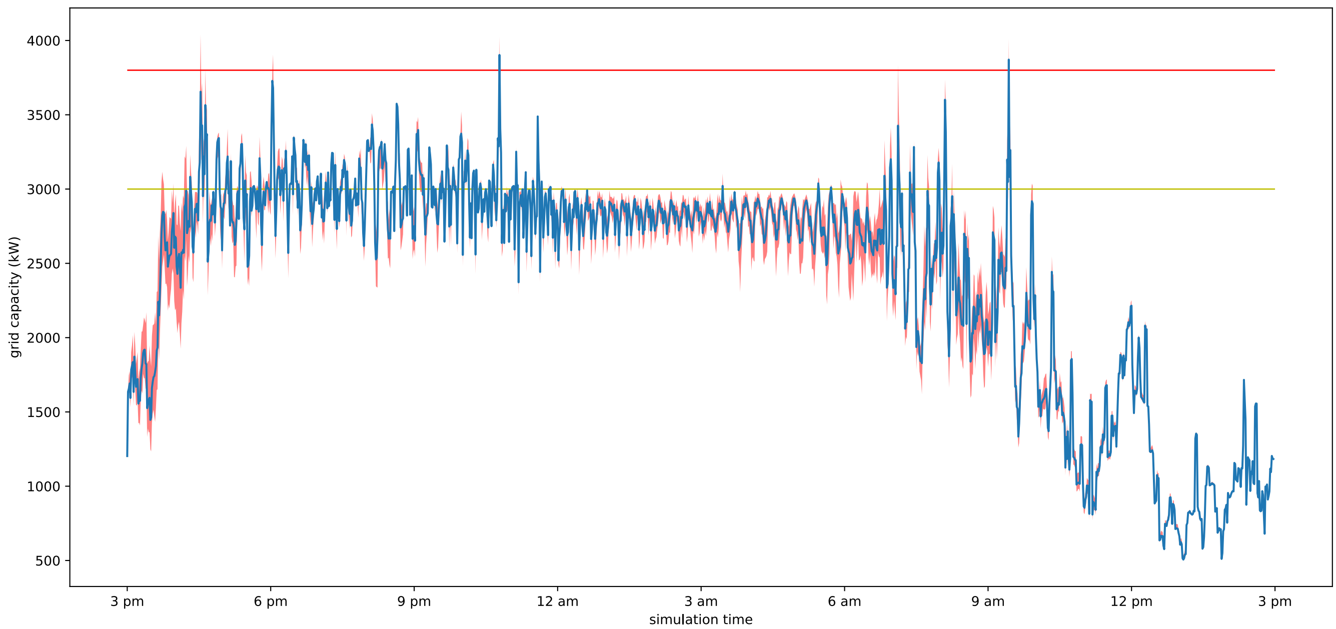


Figure 25: Maximum deviation over 20 trails.

6.6 Limitations

As an integral part of the evaluation process, this section elaborates on limitations and problems the proposed model implies in regard to implementation and feasibility. Nevertheless, some of the following shortcomings can be accommodated for with additional efforts and extensions.

6.6.1 Forecasting Demand Structure

During the last decades, a variety of forecasting techniques were adopted to the energy industry and particularly to the forecasting of demand and production structures. Traditionally, stochastic methods and new approaches in soft computing techniques are extensively applied to reduce forecasting errors. [62]
The present work is applying forecasting methods neither for capacity demand nor in the proposed market environment and price making. This is due to the limited scope and resources of this thesis, but unquestionably the model could greatly benefit from an extension towards forecasting and empirical learning.

6.6.2 Dynamic Charge Power

Another important limitation of the proposed model, is the simplified and linear charging behaviour. In reality, completing the last percentage points of SoC takes longer than the initial charge increase. Typically during the last 1/3 of the charging cycle, the effective current keeps dropping and the open circuit voltage increases. Thus, SoC is non-linear to charging time whereas discharging is linear to discharging time. [39]
In regard to this aspect, the proposed model requires a price function that incorporates this deviating time accordingly.

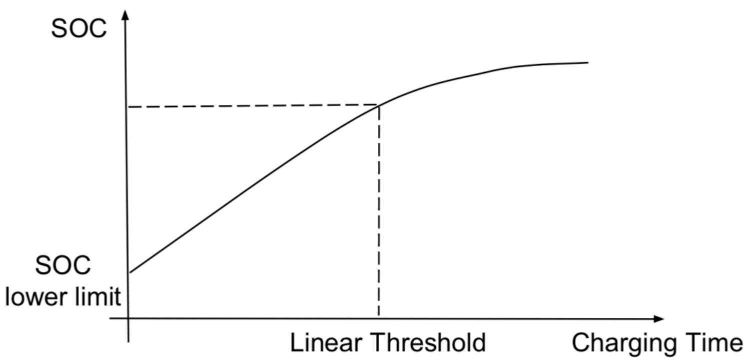


Figure 26: SoC obtained versus charging time spent (Wang et al. (2016)).

6.6.3 Optimal Segmentation

> "For the implementation of regional flexible distribution grids, the questions of how large is the area of an average flexibility market as well as the question of how many participants are able to take part in an flexibility market on the low voltage level are of upmost interest." [46]

The present work assumes a standard test feeder introduced in section 5.2.1. Although results present in the course of this investigation are significant for the proposed research questions, the simplification on the interplay of active power, reactive power and line-distance limits validity. Each node of consumption has a unique geographical position within the grid topology. This position, in regard to local congestion, results in relative impact of the respective node. [46] introduces sensitivity as a measure of potential or insufficient impact on congestion. In the framework of the proposed model, the DSO has to evaluate each bid according to its location and therefore impact instead of assuming equal sensitivity at each node. Furthermore, Wagler and Witzmann (2016) state an individual, maximum size for a single flexibility market since distance shrinks with an increasing number of sensitivity limits. The VDE introduces grid aggregation areas (*Netzaggregationsbereich*) to apply more differentiated TLPs on large distribution grid topologies [3]. Procedures need to be established to quantify the trade-off between large segments with sufficient competition but low node-sensivity and small segments with high node-sensivity but low flexibility supply.

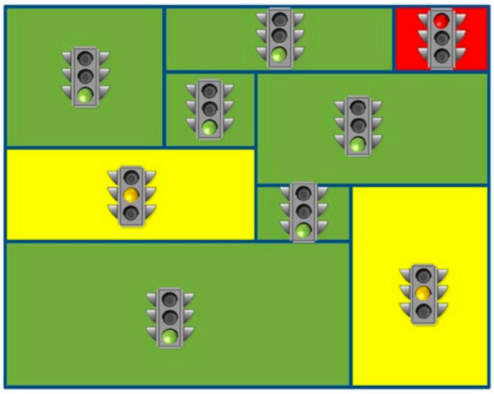


Figure 27: Schematic grid aggregation areas (VDE (2014)).

6.6.4 Balancing Group Problem

The proposed autonomous flexibility trading for residential EV owners interferes with balancing and billing mechanisms introduced in section 3.3.3. BRPs aggregate residential consumers, create consumption schedules based in standard load profiles and constantly try to balance demand and supply within a BG. [14]. If an EV dynamically reacts to local market signals outside of the BG, the BRP's forecasts might deviate and needs to be balanced which results in economical cost for the BRP [3]. With the introduction of §§26a, 27 Abs. 1 Nr. 23 StromNZV in late 2017, the so called "corrected model" is applied [63]. During contracting residential flexibility, the consumption billed by the BRP is calculated according to a baseline and not based on metered data. The EV owner is remunerated according to the bid price by the flexmarket and has to pay its BRP as if charging was never interrupted. Figure 28 depicts the schematic procedure for a 15 min interval. Currently, there are no research projects were this concept is applied to individual EVs rather than the aggregator and is therefore subject of further investigation.

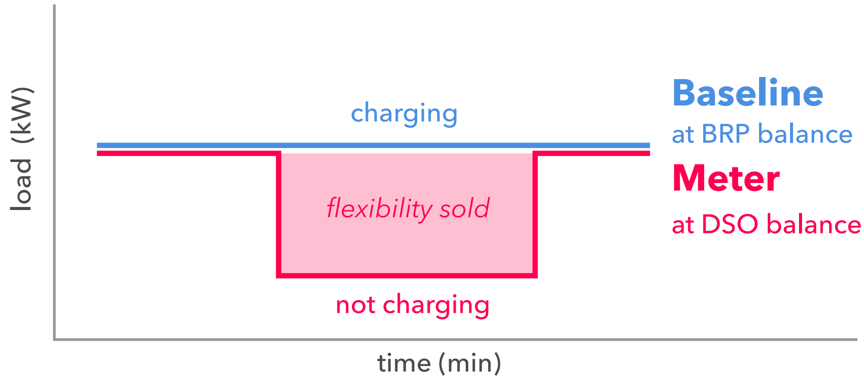


Figure 28: Schematic representation of the ”corrected model”.

6.6.5 Price Cap and Price Function

One advantage of the proposed model simultaneously represents a major drawback. As described in section 6.3.1, the DSO always accepts enough bids to balance the limited grid capacity with increasing penetration of EVs. Furthermore, the individual price function of an EV does not account for increasing supply of flexibility respectively competition. As a result, total auction cost increases unlimited whereas true competition amongst EVs might decrease bid-prices and increase the maximum threshold of EVs.

7 Conclusion, Discussion and Outlook

The proposed model stabilizes the tested grid topology during times of peak demand. Even an unrealistic penetration of 5 EVs per connection-node and high concurrency of charging requests can be balanced. The applied micro-auction-mechanism allocates charging slots and flexibility contracts amongst all connected EVs based on bids at discriminatory auctions during each time step. This lightweight consensus mechanism keeps communication and implementation efforts at a minimum. Evaluation has shown that, according to the stated assumptions and a required, average final-charge of 80%, a ninefold increase of EVs and charging requests respectively can be accommodated. The total auction cost for the DSO increases proportionally with increasing penetration of EVs. Based on this qualitative finding, DSOs are able to offset flexibility cost against traditional capital expenditures and approximate the reduced physical grid extension to provide reliable and secure energy supply.
During evaluation, techniques of time-series and sensitive analysis are applied to identify characteristic effects. Due to the battery requirements and market design, individual bidding is set to 15 min intervals. This assumption generates continuous batches with size and affiliation depending on an EV's respective arrival time. These batches cause demand-response latency, price volatility and risk-contrary bid acceptance. Asynchron contracting can resolve this effect but might result in increasing complexity and is not part of present investigations. The Traffic Light Concept describes a rather ex-post approach on grid congestion by permitting all load requests until the yellow TLP is activated before contracting flexibility. The proposed model applies an ex-ante request control of EV-loads, leading to less yellow TLPs which only result from the latency effect.
Apart from static input variables, a set of dynamic parameters tries to simulate reality. The proposed model is tested against fluctuations in concurrency, initial state of charge, risk preference and simulation randomness with positive results. Nevertheless, several aspects limit a general implementation at the moment, partly due to the confined scope of the present work or inherent to the proposed design. Whereas demand-forcasting methods can be additionally implemented, dynamic charge requests are inconsistent with the homogenous capacity approach of 11 kW per 15 min and require a conceptual redesign. Setting out the optimal grid segment is a trade off between congestion sensitive of individual nodes and decreasing subsegment-competition or availability. This issue needs to be addressed by the respective DSO based on the present grid topology and demand structure as a highly individual fitting process.

The present thesis proposes an approach towards the concept of local flexibility by combining existing technology with novel ideas about market design and implementation. The proposed model is obviously highly stylized, and while it does lead to a number of qualitative results, it does not allow to draw conclusions about their quantitative importance. Nevertheless, numerical results enhance comprehensibility and illustrate qualitative effects. Moreover, a set of parameters is distilled to benchmark the proposed model from different perspectives. Several open questions were discussed and can guide future work:

Fixed- vs. Dynamic Aggregation: The present work considers EVs as individual agents only batched on 15 min interval without a static, aggregating entity. To comply with current regulations regarding minimum capacity, this mode needs to be subject of further investigation.

Segmentation: The investigated test grid does not reflect for individual distribution grid topologies and node-sensitivity. Further research needs to introduce methods and parameters to reduce complexity in segmenting physical flexibility groups.

Cooperative vs. Non-cooperative: The present work considers EVs as non-cooperative agents in a competitive market design to reduce complexity. Cooperative agents can be more effective in price making but exponentially increase complexity with higher penetration of EVs [53]. An equilibrium state might be advantageous.

Latency: A more granular bidding strategy due to (1) dynamic flexibility intervals, (2) dynamic charging periods and (3) charging power reduces the latency effect and might enhance balancing. To not accelerate battery degeneration, an individual and optimal algorithm for each EV needs to be implemented.

Blockchain: As shortly stated in 5.2.5, Blockchain technology enables identification and communication across decentralised agents [53]. To implement the proposed model, further efforts need to be undertaken on the adoption of this technology.

Forecasting: An extended information baseline and forecasting methods might result in more efficient balancing.

Bidirectional Charging: By applying the proposed model to bidirectional charging, an increasing amount of critical grid conditions can be addressed, whereas the proposed algorithm of procedure gains complexity.

The introduced local flexibility market is a possible way to re-organize congestion management by adding locational granularity to energy prices in form of opportunity cost to the very particular load profile of EVs. This concept joins a range of ideas and proposals to complement zonal EOMs with local capacity markets to outperform expensive redispatch interventions (see 3.4.2) [64]. Whereas many of these concepts suffer from inconsistency, the unique composition of the proposed model may allow for a symbiotic arrangement of both, zonal and locational markets during and within defined ranges.
Due to the foreseeable nature of a majority of congestion in Germany, most local flexibility markets are suspect to the so called *Inc-Dec Game*. Institutional or aggregated suppliers anticipate congestion based on weather forecasts or empirical data to withhold capacity from low-price EOMs and offer to their respective high-price local flexibility market. [64] The yellow TLP as well as non-aggregation of flexible EV-loads, restrict trading activities locally to genuinely reduce structural congestion. Nevertheless, during the green TLP, aggregators might leverage on arbitrage profits. This effect and the concept of flexibility markets is amongst the most contentious aspects of the current European Commissions Clean Energy for All Europeans package [64] and requires additional attention.

Concluding the previous pages, distribution grids and DSOs face a variety of challenges. The integration of EV technology and appropriate market designs discussed in the present work are a major priority at this moment. Nevertheless, focus might shift towards the underlaying business model. New technologies automatically increase autonomy of residential consumers and therefore reduce transmission efforts on grid topologies. This has negative effects on revenue streams, as income from network charges decreases. Yet, increasing residential autonomy up to 100% might not be an economical viable approach, the role of DSOs might change from the pure supply of electric energy towards a service for supply-security for the last percentage points of grid dependency. This possible scenario in mind, the adoption of decentralised market mechanisms, will pave the way into new business cases and revenue streams while reducing costly grid-extension investments.

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The proposed software prototype can be downloaded and tested under the following link:

https://github.com/pizzipetzi/ev_charging_simulation