A simulation-driven approach to optimize electric vehicle charging clusters - A more sustainable parking facility

Master Thesis

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Daniel von Koenen

Köln, den xx.xx.20xx

Abstract

[Abstract goes here (max. 1 page)]

Nach Absprache schreiben

Contents

List of Figures

List of Tables

1 Introduction

1.1 Motivation And Challenges

With the current climate change and the increasing shift to sustainable products, it is no wonder that the automotive industry has to change as well. More and more car manufacturers are focusing on the production of electric vehicles (EV), with Tesla for example being one of the pioneers. EVs are supposed to take a big part in the future for a greener and cleaner environment. They are expected to solve many of the current problems that the internal combustion engine cars (ICV) have, such as high CO2 emissions. However, the EV is not the miracle cure for all of the car's current sustainability problems. It also brings new challenges, such as increased energy consumption. To overcome these challenges, the EVs receive a special focus not only from the automotive industry, but also from the scientific community.

As EVs become more widespread, sustainable resources and sustainable and reliable power grids will become an increasingly important component of EVs success. Due to the increased electricity consumption of EVs, we also need to produce more electricity in the world, and unless it comes from clean sources, EVs do not change the current situation at all. For this reason, power grids are becoming more flexible and are adding more sustainable energy to their grids. However a large part of the produced sustainable energy comes from solar power, which means that the amount of electricity produced varies. For example, when the sun goes down no electricity is produced, or at noon when the sun is at its highest and thus produces the most electricity. Due to this increased variation in the electricity availability, there is now a more frequent mismatch of demand and supply. In addition, it can also happen that too much energy is produced and in order not to damage the power grid, certain generators are taken off the grid. This phenomenon was first discovered in California in 2013. (Denholm et al., 2015) There, the California Independent System Operator published a chart in the shape of a duck. The 'duck' is a representation of the surplus energy over midday and the increasing demand for electricity in the evening, when solar energy is already not efficient.

EVs further exacerbate this problem, since they are in operation most of the day and owners do not charge them until they get home in the evening. Therefore, an infrastructure must be created so that the charging of EVs can be distributed throughout the day. Clustering EV charging stations at key points such as Park and Ride stations, at the workplace, or in parking facilities could be a feasible solution for this challenge.

The use of new information systems technologies and approaches makes it possible to gain a better understanding of these phenomena and generate new potential solutions. Therefore the focus of this master thesis lays on parking facilities cluster and the new created EV energy consumption. With the help of proven data science approaches, it is considered what impact the installation of EV charging stations as well as photo-voltaic systems (PV) has on the energy consumption (Duck Curve).

1.2 Objectives And Scope Of This Thesis

In this thesis, the smart home charging solutions that reduce or share the energy consumption are not considered. Since the interaction of the smart solutions and the parking facilities would go beyond the scope of the research. However, it would be interesting for future work to consider all EV solutions to energy consumption as a whole, to determine the true impact of EVs on the power grid. In addition, the focus respect to parking facilities is not on the profitability of parking operations, but on reducing EV grid integration challenges associated with the Duck Curve. While the introduction of charging stations also makes a parking lot more attractive to customers and therefore more profitable. Other studies have already looked at the accepted charging prices a customer is willing to pay. In addition, ordinary parking lots are considered here in contrast to park and ride lots, which tend to have a different parking behavior, since customers usually park their car there in the morning and pick it up again in the evening. Another aspect of this work compared to similar considerations is the addition of the PVs. Producing self-sufficient and sustainable electricity can take more pressure off the power grid. However, a distinction must also be made here between the seasons. For this reason, weather data is also included in the simulation and thus reflects the variation of the energy that can be produced. In order to deal with the problem presented above, two specific research question were created.

(1)"Can the introduction of charging stations in parking facilities meaningfully reduce grid integration challenges associated with the Duck Curve phenomenon?"

(2)"Can on-site behind-the-meter PV generation and storage further improve the benefits of clustered EV charging from a grid integration perspective?"

1.3 Structure Of This Thesis

This section presents the various methodological approaches used to answer the research question, which also provides the structure for the master's thesis. Generally, the sequence of methodological approaches is such that first the data is acquired and prepared, then the simulation environments are set up and then several simulations are performed on those environments. After the simulations are completed, an evaluation is then performed based on a sensitivity analysis.

The thesis is based on the design science approach form Hevner et al. (2004). Hevner counts seven guidelines for a design science research, which are (1) Design as an artifact, (2) Problem relevance, (3) Design evaluation, (4) Research contributions, (5) Research rigor, (6) Design as a search process and (7) Communication of research. In the following table, these guidelines are mapped to this thesis.

Table 1: Design Science

Guideline	**Master Thesis**
Design as an artifact	With the help of the simulations, a viable artifact in the form of a construct is created.
Problem relevance	Since the Ev adoption is irrevocably coming, both the power grid operators and the EV owners need to find a solution.
Design evaluation	The results are evaluated in detail by using a sensitivity analysis.
Research contributions	The results provides a foundation for further research in the field of EV and smart grid sustainability.
Research rigor	The thesis is based on the application of rigorous methods for data processing, simulation and evaluation.
Design as a search process	The use of the provided data, as well as the creation of the simulations maps a search, for a desire goal.
Communication of research	By providing the code artifacts as well as the visual representation of the results, they can be processed on a technological and management level.

Since the perspective of the problem has already been dealt with in the above sections, the focus here is rather on the remaining guidelines. Furthermore, the methodological principles as well as the implementation of the evaluation are presented in the next segment. These also include the guidelines of research rigor and design evaluation.

In this section, the practical part of this thesis will be addressed in more detail. The first step of the practical part is to prepare the data. For this purpose, all relevant data are first acquired. Afterwards the business understanding as well as the data understanding are carried out. This part will be used to fully understand and prepare the parking-, weather-, EV adoption-, energy consumption- and energy generation-data. Python methodologies are used to prepare the data for the upcoming simulations. This includes for example the mapping of weather data, PV generation and park data. More about the data used in this master thesis can be found in section 3.

The next step is then to set up the model. This is based on a number of parameters, assumptions and restrictions. These describe on the one hand the represented environment (parking facilities, chargers, PV and homes) and on the other hand the behavior of the objects (EV, non EV and EV owners). Specifically, these describe and limit the following: total parking capacity, current parking capacity, number of charging stations, number of PV, EV battery capacity, EV battery status, charging process and inclusion of PV power. Based on these, a Monte-Carlo-Simulation can then be carried out with the aim of minimizing electricity consumption at peak times.

EVs are given certain properties, such as charging capacity, charging speed, current battery status and required battery status. Only with these variables, the EV would probably always be charged on the park facilities. Therefore, another component is added. The EV owners, these can react to other variables and can thus decide whether they want to charge the EV or not. Each EV is assigned an EV owner who has a unique preference. The preference of the EV owner is represented by a probability of 0 - 1 whether he would load the EV or not. To represent a simplified user behavior, this preference is initially chosen randomly. If the environment does not allow it or the EV owner is not satisfied with the service, the EV will not be charged in the parking lot. In detail the satisfaction, the amount of EV charging stations, the parking duration, the battery level and the available PV energy is responsible if the EV is charged or not. If the EV owner does not charge the EV at the parking facility, this means he will charge it at home, which then does not reduce the peak time energy consumption. Therefore, it is necessary to find an optimum, which will satisfy the customer, as well as a appropriate environment.

A process-based simulation framework called Simpy (*Simpy*, 2021) is used for the simulation. Simpy is based on Python and is an open source software that enables discrete-event simulations. With the help of these, several simulations are then carried out. The results of the simulations are constantly evaluated, which means that adjustments to the data, the environment and the assumption are very likely to occur. Once the simulation is running smoothly, a final major evaluation is performed.

A sensitivity analysis is used to examine the impact of certain factors on the results. This means that the environment of the simulation changes for a different scenarios. Simulations are performed depending on (1) EV Adoption Rate, (2) EV Charger Coverage, (3) EV Charger Level, (4) PV Systems Coverage (5) Seasons and (6) Workplace Charging. By looking at the different seasons, weather data can be used to determine how efficient the use of PVs are over the year. For example, do the PVs produce enough energy in winter to meet the demand of the EV chargers? Or do they produce enough in summer so that the grid is not affected by the chargers during the day? The consideration of the number of EV stations is also important here to find the perfect number of stations to sustainably supply the demand for electricity but also to achieve a profitable utilization of the charger. Next, the availability of charging at the workplace. This can provide interesting insights into the extent to which this approach can reduce charging at home. For example, if everyone has the option to charge at work and also in parking lots throughout the day, do they need to charge at home at all. This could result in a large drop in electricity demand in the evening and would therefore reduce the Duck Curve. The EV adoption rate determines the required energy of the EV and thus the total energy demand. Therefore, it is important to determine the optimal number of chargers at each adoption rate, as well as the number of PVs. Finally, the photo-voltaic availability. Here it is considered depending on whether the availability of PVs, i.e. whether a PV is present or not. Also whether the quantity has an influence on the result is considered. Overall, the best possible interaction between energy consumption during the day and the inclusion of charging stations and PVs in parking lots can be achieved with the help of a heuristic search.

2 State Of The Art

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2.1 Related Work

In this section the theoretical background of the master thesis is presented. For this purpose, different related works are discussed. These can be grouped into two main topic domains, which are: (1) Infrastructure and (2) EV charging clusters. The infrastructure includes electric vehicles, smart grid and smart charger. The relevant EV charging cluster which are presented here are: Home-charging, Workplace-charging, Park and Ride-charging and finally Parking Facilities-charging. All of these topics either influence the overall power consumption of EVs or are influenced by it and are thus also relevant in this context.

2.2 Infrastructure

Text

2.2.1 Electric Vehicles

In the previous sections, we have already talked a lot about the EV and what impact this introduction will have on us humans and on the power grid. This chapter addresses the capabilities and characteristics of EVs to give a better understanding of the relevance of the EV adoption and its consequences.

Faiz et al. (1996) defines an electric vehicle (EV) as a vehicle which utilizes one or more electric motors or traction motors for propulsion. This electric motor can be powered from various sources, firstly from internal sources such as battery, solar cells, fuel cells or a power generator, this method is most commonly used for the normal EVs. Secondly from external sources such as a collector system, which is also known to be used by modern trains. This is the main characteristic that distinguishes EVs from current ICVs. These, unlike EVs, consume limited natural resources for propulsion, which are bad for the environment. Therefore, the EVs also have a low carbon footprint. (Faiz et al., 1996)

When discussing EVs in this paper, the term refers to pure-electric vehicles that can be charged with plug-in technologies. There are different types of EVs, e.g. hybrid e-vehicles that are not powered purely by electricity. Furthermore, this master thesis only deals with ordinary passenger cars and thus excludes other EVs, such as electric trucks, electric buses, and so on.

The next segment addresses the question of why EVs have not established themselves earlier and why they are now becoming more accepted in recent years? This question is not easy to answer directly, as many different factors influenced the EV adaptations. The first EV was already developed and produced by Gustave Trouvé in the 1800s. (Wakefield, 1993) However, ICVs prevailed because at that time ICV technologies were more advanced and the socio-economic factors related to ICV consumption were less important than they are today. (Wakefield, 1993) At that time, the consumption of natural resources was not such a big problem and the spread of sustainable power sources was also very low. Which is why, if EVs had been widely adopted, the environment would not really have benefited as it would today, because it would have been the same polluting electricity.(Sperling, 2018) It was also easier and cheaper to get fuel at that time, so filling up the tank was a significant cost factor for customers in the long run. (Tyner, 2021) Moreover, the infrastructure for EVs was not yet in place, as businessmens had to decide which type of filling station they would offer. With the introduction of mass production by Ford, ICVs became cheaper and more cars could be produced in a shorter time period. (Banham, 2002) Therefore, the decision was made in favour of the usual petrol stations as we know them today.

The ICVs were not technologically perfect at that time, but they outperformed the EVs in terms of energy consumption, distance travelled, maximum speed and materials used in production, which is why they were cheaper to produced and more attractive for customers. (Wakefield, 1993) In addition, the batteries were not yet so advanced, which is why it took a long time to charge them. (Wakefield, 1993) Together with the short possible distance and the length of charging, the EV was very unattractive for customers who had to drive longer distances. This was also more important in the past than it is today, as you did not have almost all essential and social resources around the corner.

However, with the shift in recent years towards a greener environment, for example, also driven by Greta Thunberg. (Thunberg, 2019) The ICV with its large consumption of fuel and its air pollution is increasingly criticised by the media. (Andersen, 2021) This played very much into the hands of the EV, which is why there was constant research in this area and more and more experiments were carried out in the direction of sustainable mobility. This is also reflected in the latest events in battery technology, where the lithium battery is being pushed further and further, enabling what was then unimaginable. (Terada et al., 2001) This technological advance means that EVs can now be charged significantly faster and travel long distances on a fully charged battery. (*Electric car batteries with five-minute charging times produced*, 2021) This trend is also confirmed by the new record set by the Tesla Model S, which can drive up to 628 km on one charge. (*Tesla Model S*, 2021) Furthermore, not only is the technology of the EV constantly improving, but more and more supporting technologies are being added that make the EV more efficient. This mainly includes information system solutions, such as smart charging or battery management for a more efficient battery consumption. (Burns, 2013) With the help of these changes and the introduction of new supporting technologies, the EV has not only become cheaper to produce, but also more affordable for the end consumer. (*Electric cars 'will be cheaper to produce than fossil fuel vehicles by 2027*, 2021) For example, the batteries and other technologies in the EV are more reliable and therefore require less maintenance than the ICV.

The positive development of the EV in recent years is also very well reflected in the sales figures. These show that in recent years EV sales have increased by 44 percent and in year 2019, 2.3 million EVs were sold around the world. (*McKinsey Electric Vehicle Index: Europe cushions a global plunge in EV sales*, 2021) However, the positive development of the EV is not only due to intrinsic improvements but also to extrinsic incentives. Many countries and states support the shift from ICV to EV with different incentives. On the one hand, a lot of money is being invested in infrastructure to make EVs available and more attractive in all regions. (Whitmarsh & Köhler, 2010) Because it is not worthwhile for the end customer to get an EV if he can not really charge it anywhere. On the other hand, customers are not only financially supported when buying an EV, but also when using it. Charging a Tesla at the proper charging station, for example, was free of charge for early adopters. (*Tesla-Supercharger*, 2021) In addition to these two, there are many different campaigns and small to large incentives from the government to increase EV attractiveness. With the help of these incentives and rapid technological progress, it is expected that half of all vehicles in Australia, for example, will be electric by 2030. (Higgins et al., 2012) This would give us an adoption rate for EVs of almost 50 percent over the next ten years.

The next segment looks at the advantages and disadvantages of EVs in order to better understand the relevance of a proper and sustainable introduction of high EV penetration. The most important and best-known advantage of the EV is its environmental friendliness. (Helmers & Marx, 2012) On the one hand, it can use renewable energy, and on the other, it does not burn any resources, so no environmentally harmful gases such as greenhouse gases are released into the air. (Gelmanova et al., 2018) In addition to the improved air quality, the EV is also significantly quieter than the ICVs, which is why noise, vibrations and harshness are more pleasant for nearby people. (Verheijen & Jabben, 2010) However, this can also lead to a disadvantage, as people have become accustomed to the sounds of a car and thus older people who have poorer hearing as well as small children cannot perceive the car that well and thus do not recognise dangerous situations in time. For this reason, different manufacturers have already decided to use artificial car sounds, which are still more pleasant than those of the regular cars. (Misdariis et al., 2012) Furthermore, the EV can use energy more efficiently. This is because it can transfer 69 - 72 percent of the energy produced directly to the tyres, whereas the ICV can only apply 15 percent of the fuel energy to the tyres. (Sandalow, 2009) Another important aspect in favour but also against EVs is the geographical position. Depending on which country we are talking about and what natural or renewable resources are available, petrol or electricity is cheaper. (Kåberger, 2018)

A disadvantage of EVs is the long charging time of the batteries to be able to drive again. Although this has been steadily reduced in recent years, it is still not comparable to filling up a tank. The same applies to the distance EVs can travel. Although longer distances can be covered, the ICV is still much better suited for longer journeys. (Van Haaren, 2011) Especially if you travel such long distances that you have to refuel or charge more often. Perhaps the biggest challenge is the overall increased power demand for all EVs. If this is not sustainably covered, the EV is still as harmful to the environment as the regular car. (Van Vliet et al., 2011) Therefore, this thesis also focuses on this challenge.

2.2.2 Smart Grid

The electricity network plays a fundamental role in the overall context, as it provides power not only for the EVs, but also for everyone else. Therefore, this is given a very high priority in order to deal with the new circumstances of the EVs. (Pieltain Fernández et al., 2011)

Obi and Bass (2016) have addressed the latest trends and challenges of a future sustainable electricity networks. In this paper, they examined the impact of sustainable electricity producers, such as the PV system, on the electricity grid. As the overall demand for electricity continues to increase, as well as the demand for sustainable resources, the network must also adapt. However, this change alone will not be enough, other topics need to be included as well. Therefore Ketter et al. (2013) has developed the "Power Trading Agent Competition" (Power TAC) to simulate what impact the future retail power market will have on the power grid. They focused on the dynamics of customer and retailer decision-making to make the network more stable in the future. Another interesting electrical demand phenomenon was observed in California. (Roberts, 2018) (Denholm et al., 2015) They published a study comparing the daily variance in electricity consumption to the energy that can be produced at the same time in California. It was found that the power network is very heavily loaded in the evening by people coming home from work. This would not be a big problem at first, but at this time the influence of sustainable power sources is very low and it was necessary to fall back on old non-sustainable resources. Furthermore, the sustainable source sometimes produced too much power at midday, which was why there was a risk of the power grid overloading. As a result, certain power sources had to be taken off the grid. (Denholm et al., 2015)

In order not to simply expand the capacities of the power grid, which would cost a lot of money, the network has to become smarter. This can be made possible, for example, by predicting the demand for electricity for a certain period of time. This problem has been addressed by Johannesen et al. (2019). They compared different regression methods to find the best way to predict electricity demand in urban cities. They found that the random forest regression was very successful for short-term predictions and k-Nearest neighbor for long-term predictions. Thus, electricity providers can better adjust and plan for the upcoming capacity needed. The last research considered to the smart grid is by Kahlen et al. (2018). Here, the interaction between EVs and the smart grid was investigated. In more detail, the possibility of using EVs in such a way that they can not only draw power from the grid but also return power to the grid. They showed that car rental companies that own a large fleet can adapt their business model so that their fleet can be used as a virtual power plant. This has the advantage that the power grid can access this power source flexibly, so that it can react faster to unexpected peak demand. This procedure is also profitable for the car rental companies. (Kahlen et al., 2018)

2.2.3 Smart Charger

In addition to the smart grid, smart charging is also an approach to solving the new energy challenges. Smart charging is the use of information systems technologies to influence and optimize the charging process of EVs. (Qian et al., 2010) The devices are equipped to monitor, manage and restrict the loading of EVs via data connections. For example, they can be connected to other chargers in the neighborhood to charge EVs one after the other. Or they can access the current data of the power network to determine the current load and charge the car at a later suitable point. These and other small improvements in charging have a very strong overall impact on the power grid so that peak hours are not further overloaded.(Qian et al., 2010) However, these techniques are more likely to be used in locations where the EV is parked for longer periods, such as home charging. There, they can develop their full potential, as this is the best way to influence charging, such as charging late at night when there is enough power available and it is cheaper.

To determine the impact of smart chargers at households, Gottwalt et al.

(2011) dealt with simulations of household behavior under variable prices. To do this, they compared household load profiles at fixed prices and variable prices with the use of smart devices. It turned out that the use of smart devices is economically more beneficial, but only by a small amount. However, this deployment leads to further new energy spikes if, for example, all smart chargers react in the same way and do not coordinate with each other. In this context, Valogianni et al. (2015) dealt with a multi-agent approach to coordinate charging of EV with variable tariffs. They found that the control agent's price signals can influence the smart charger to prevent herding during EV charging and mitigate spikes in power consumption. Another energy spike may occur when there is a low price in the market and all smart chargers decide to charge at the same time. Those influences of pricing schemes on the smart grid / smart charger were addressed by Valogianni et al. (2020). They analyzed existing price schemes and developed a new scheme called adaptive pricing. Adaptive pricing learned EV owners' responses to the announced prices and adjusted them accordingly in the future. This has enabled a better balance between the load demand and energy supply, thus also reducing energy spikes.

Of course, smart charging can also be used in ordinary parking lots, but this has a limited impact, because if a car is parked for only 10 minutes while the owner just quickly picks up something in a store, the smart charger can at most decide not to charge, but it cannot charge later. Furthermore, the monitoring function of the charger can be a very important point for the normal parking lot, because so the operator can monitor the utilization and determine measures, such as building another charger or not.

It is also important to know that there are different levels of charging stations. The charging stations are generally divided into three categories. The level 1 charging station is the weakest and the level 3 is the strongest. (see table 2) They also differ in the electronic current. On the one hand, the weaker levels use alternating current (AC), on the other hand, the level 3 charging station uses direct current (DC). Since DC is a one-way current flow, it can conduct more power faster and therefore can also charge an EV battery in less time. (Falvo et al., 2014) (*What's the Difference Between EV Charging Levels?*, 2021)

Table 2: Differentiation of Charger Level

Charger Level	**Voltage**	**AC / DC**	**Charging Speed**
Level 1 Charging	120V	AC	ca. 1,8 kW/h
Level 2 Charging	<200V	AC	ca. 19,2 kW/h
Level 3 Charging / DC Fast Charging	<800V	DC	ca. 89 kW/h

Now the question arises, why distinguish between levels and not just use Level 3 chargers? If these are so much superior. This is due on the one hand to the greatly increased costs for the level 3 chargers. With an average of 50,000 euros for the purchase and installation, they are significantly more expensive than the level 1-2 chargers. Furthermore, the home charging cluster is very popular, which usually does not offer the infrastructure and capacity for a level 3 charger. In addition, the speed of charging is not that important, since EVs are usually parked at home for a long period of time and can therefore be charged overnight for several hours. (Munkhammar et al., 2015)

2.3 EV Charging Clusters

The placement of EV charger is another significant aspect that influences EV energy consumption. In city neighborhoods, with many single family homes, it is very likely that many homes will have their own EV charger in the future. These are powered largely by their own producible energy, however they also depend on the power grid on weaker days. Nevertheless, this is not so easy to implement in urban cities with large apartment complexes. Therefore, the placement of EV charger must be well thought out. (Momtazpour et al., 2012) Jia et al. (2019) use collected data from China Unicom in Tianjin, which includes the charging behavior of medium range EV to find optimum EV charging clusters. They worked with reconstructed trajectory of EV from cellular signal data (CSD), which revealed that around 50 percent of the charging stations should be located within the central city area. Another approach to the optimal placement of EV chargers comes from Pevec et al. (2018). They used a wide variety of real world data, such as historical data from charging transactions. Based on this data and various influencing factors, they were able to forecast the utilization of the charging stations in order to find the optimal placement of EV charger. With the help of this method, they support people in making decisions regarding the placement of individual EV chargers and EV charger clusters.

In addition to these procedures, however, it is also important to consider the current resources and infrastructures. If you look at the zones in which a car is parked nowadays, you can quickly deduce important clusters. The two most important clusters for charging are at home and at work, as this is where the EV is parked the longest during the day. In addition to these two, public parking facilities such as parking spaces in front of malls or park and ride facilities also form an interesting cluster.

2.3.1 Home-Charging

The first cluster presented here is home charging. This cluster is very special because no organisation or state has control over the charging stations here, but the owner himself. The EV owner himself can decide whether he wants to install a charging station at his home or not, as well as operate it individually within the framework of the regulations. A charging station at home is very convenient, as you do not always have to drive to a petrol station, as is currently the case. In combination with smart charging technologies for the home, as well as the integration of a PV system and other sustainable electricity producers, this charging cluster is very attractive for EV owners. (Traut et al., 2013)

A study by Traut et al. (2013) showed that about 47 percent of all US households have a parking space right at their house. But only 22 percent have an parking space in reach of a outlet sufficient to recharge a small plug-in vehicle battery at home. This means that homeowners must first invest either in infrastructure in the form of extensions to their electricity grid or in the construction of parking spaces or garages. (Traut et al., 2013) Installation costs can range from 500 to 2000 euros, depending on location and provider. A reliable small charging station starts at 500 euros, but the price can rise very quickly for better and faster charging stations. (*Kauf einer Ladestation für mein Elektroauto*, 2021)

As already shown in the smart charging section, many optimisations can be applied while charging the EV at home. On the one hand, this saves money and on the other hand, it reduces the load on the electricity network. However, the power does not always have to be drawn from the network. In many homes, there are already natural power generators in place such as PV systems. Although this installation is associated with a higher one-time investment, it ensures a sustainable and cheaper electricity supply in the long term. (Qian et al., 2010) However, this is also very dependent on the time of year, as a lot of energy is overproduced in the summer and too little in the winter. Therefore, in times when there is little sunshine, the power grid has to be used again. (Obi & Bass, 2016)

Although these optimisations help to relieve the energy load and distribute it better throughout the day, home charging still leads to a major challenge. The Duck Curve already presented is influenced even more by home charging.

(Denholm et al., 2015) This is because every person who comes home from work in the evening plugs in their car. (Schey et al., 2012) While smart chargers can delay charging, when each smart charger delays charging, new peaks are created at different times. Therefore, the smart chargers from different providers must also communicate with each other and be compatible, which is also a major technological challenge. (Valogianni et al., 2015) In addition, the owner can still decide when he wants to charge the car. Wan et al. (2018) has looked into this and included the random aspect of human behaviour in its EV charging strategy optimisation. Moreover, the acceptance of charging at other times and locations decreases if you have your own home charger. Because if you can always charge for free and easily at home, why should you spend money on charging in a public parking lot or at your workplace during the day. Furthermore, the EV has already been charged at home most of the time, which means that it always has a high battery status throughout the day.

If we assume that every citizen of Germany owns an EV and would like to have their own charging station, we are already talking about 83 million charging stations that would have to be built. (*Bevölkerung Deutschlands im Jahr 2020 erstmals seit 2011 nicht gewachsen*, 2021) With an average construction cost of 1.250 euro, this would be a market capacity of 104 billion euro just for building charging stations, without maintenance and upgrades. Of course, not everyone will own an EV in the future, but there are currently 66.9 million cars in circulation in Germany. (*Bestandsüberblick am 1. Januar 2021*, 2021) These figures are shown to give a sense of the impact we are talking about. In addition to the adoption rate, the geographical and demographic perspective is also an obstacle for the home charging cluster. First of all, you need space for the charging stations, as well as an adequate power line. (Traut et al., 2013) This can already be problematic for many people because, for example, the road layout does not allow an installation. Furthermore people who do not live in a single-family house, but in apartment buildings / skyscrapers usually do not have individual parking spaces to build on. As mentioned above, the average cost of installing a charging station is 1.250 euros, which, in addition to geographical restrictions, is also a barrier for many people. (*Kauf einer Ladestation für mein Elektroauto*, 2021) Therefore, it is also very important to offer publicly accessible charging clusters to give everyone the opportunity to charge an EV and thus strengthen the EV attractiveness and adoption rate.

2.3.2 Workplace-Charging

The Workplace charging cluster is probably the second most important cluster for a sustainable future of EVs after the home charging cluster. (Huang & Zhou,

2015) Because many people drive to work by car, which is then usually parked there for up to 8 hours. This time presents a good chance to reduce the impact on the Duck Curve and spread the load of the EVs over the day.

Many companies already have parking spaces for the exclusive use of employees. These provide an excellent opportunity for companies to equip them with the latest charging stations and technologies and, if geographically possible, PV systems. However, this is again related to large investments in new infrastructure and must therefore be considered individually for each company whether this investment is worthwhile or not. (Williams & DeShazo, 2014) Therefore, the implementation rate and impact of the workplace charging cluster is mainly up to the employer. The EV owners also play an important part, but they have a more positive attitude towards the cluster and would also like to use these services. (Fetene et al., 2016)

For the implementation and success of a workplace cluster, the operation and the price are important aspects. (Williams & DeShazo, 2014) On the one hand, the price for charging should not be higher than EV owners would be willing to pay, on the other hand, it has to be high enough to make it worthwhile for the company to invest in these technologies. Huang and Zhou (2015) has set up an optimisation framework for better installation and operation of workplace charging cluster. This helps to keep the costs as low as possible in order to offer the best value for the employees and company. (Huang & Zhou, 2015) (Williams & DeShazo, 2014)

However, simply placing charging stations at the workplace is not enough. This would only lead to everyone plugging in their EV in the morning before work. Which would lead the power grid only to be overloaded at a different time than usual. Therefore, Powell et al. (2020) looked at the use of smart charging technologies and a concept for better load balancing. Through controlled charging, peaks could be reduced and electricity costs could be lowered. This has also had the effect of extending the life of the company's transformer, as they now have to deal with less over and under generation throughout the day. (Powell et al., 2020)

To illustrate the impact of this cluster, Wu (2018) examined the relevance of charging at the workplace using GPS longitudinal travel data. It was investigated what influence the workplace chargers had on battery electric vehicle (BEV) and plug-in electric vehicle (PHEV). This revealed that the impact of energy cost savings from workplace charges for PHEV users are very small. However, this helps spread the load throughout the day. (Wu, 2018)

2.3.3 Parking Facilities-Charging

The last cluster considered in this master thesis is the Parking Facilities-Charging cluster. Since this cluster is at the heart of the research question posed in this master's thesis, it will also be mentioned throughout the course of the work and dealt with in greater depth.

This cluster includes all public parking lots as well as parking lots of companies, but not for employees, as is the case with the workplace charging cluster, but for customers, such as a shopping center. These types of parking lots are very homogeneous in their characteristics. Cars come and go and park on these in exchange for a fee for a certain period of time. Since it is often necessary to buy a parking ticket that is required at both the entrance and exit, it is also relatively easy to collect and process the transaction data of the cars. The biggest distinction point is the average parking time of the cars. Many different factors influence this value, which means that each parking lot has a unique pattern. But overall, these are relatively similar and usually do not differ much from each other.

Babic et al. (2018) have looked at the different new possible parking policies, so for example whether it is allowed to stand as a non EV in an Ev parking space, or if a EV is allowed to block an EV parking space without using the charging station. They simulated how the respective EV owners react to the different policies and with the help of a computed return rate of EV, which certainly also reflects customer satisfaction, and the utilization of the EV chargers, they were able to determine the most profitable policy. Nevertheless, the best performing policy has always been dependent on the current EV adoption rate, which is why in this thesis the influence of EV adoption is covered by an evaluation using a sensitivity analysis regarding this topic.

Babic et al. (2017) also discussed the use of electricity trading agent for EV-enabled parking lots. They simulated the environment of a parking facilities with the deployment of charging stations. Thereby they examined in detail how the parking lot, as a kind of energy broker, would affect this ecosystem in terms of various metrics such as parking utilization. These results also help in the decision-making process, e.g. for investments in charging stations.

Another method to optimize the efficiency of the parking lot cluster and thus protect the power grid from overloads is from Hussain et al. (2019). Here, a fuzzy logic inference based algorithm (FLIA) is proposed to analyze the various difficult input parameters to find the best charging decision. It was shown that this type of management not only distributes the available energy very well, but also satisfies the EV owners.

Jovanovic and Bayram (2019) on the other hand consider the impact of EV chargers at park and ride facilities. A scheduling approach was tested to optimally charge the parked cars throughout the day. The use and influence of PVs was also considered in this paper. A scheduling approach works relatively well for this type of parking lot, since cars park here longer on average and if they are used by workers, they can stand there for up to 8 hours. They showed that this can also reduce energy consumption at peak times and relieve the Duck Curve. (Jovanovic & Bayram, 2019)

Brenna et al. (2016) also worked on the park-and-ride cluster and a charging optimization approach. A linear programming optimization algorithm was used to find an enhanced charging scheme, the utilization of which can reduce the maximum required power of the park and ride. All of this highlighted work shows how interesting parking facilities charging clusters are and the potential they can have when used properly.

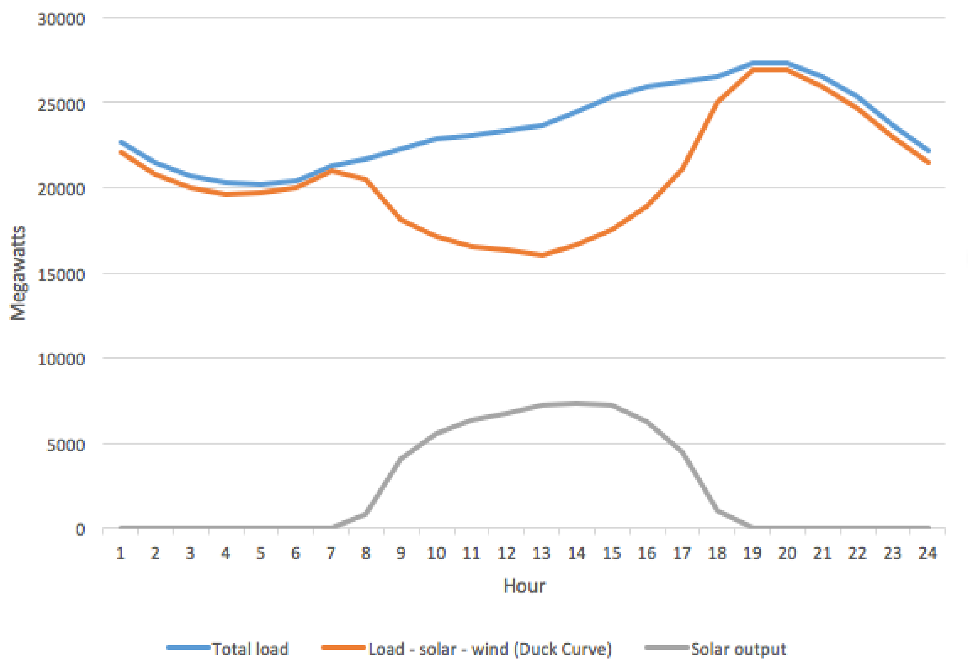
2.4 Other Challenges

The behavior of EV owners is also an important aspect regarding the adaptation of EV charging clusters, as well as the acceptance of charging prices. This topic is also very complex, as we have to consider the interplay between technical components, such as the required battery capacity of an EV, and human behavior, such as the willingness to charge a EV. Vermeulen et al. (2019) addressed the technical component of this problem by looking at the transition between fully electric vehicles (FEVs) and plug-in hybrid electric vehicles (PHEVs) in terms of charging behavior. It was found that the change in charging behavior also has an impact on the current charging stations. The human side of this problem was addressed by Lee et al. (2019). They processed and analyzed an EV load dataset of over 30,000 sessions and found some interesting user behavior in it. By learning and incorporating this user behavior, they were able to more accurately predict the energy requirements of the EVs. Another important human issue in this context is the willingness to pay for the charging services. Because you can have the best infrastructure and the fastest charging stations in the world, yet as long as the customer is not willing to pay for these services, it is all irrelevant. Therefore, Babic et al. (2016) investigated this issue and used Bayesian network approach, real-world data and a characterization of EV owners' behavior by different variables, such as EV battery capacity. In this way, they were able to create a model that reflects the willingness to pay for charging services under certain conditions. All of those results show the importance of the human perspective on the EV problem, which is why psychology science can also make a great contribution to this issue.

All of the above mentioned principles build on either information technologies (IT) or information systems (IS). These generally also lead to increased energy consumption and do not really look sustainable at first glance. However, many of these approaches provide solutions for designing and implementing sustainable processes, services and products. (Melville, 2010) As a result, less energy is required overall in the long term through the use of IS. This type of utilization is known as "Green IS" and is also embedded in this master thesis. Business intelligence systems also fall under this category, as they support sustainable decision-making. (Seidel et al., 2013) Ketter et al. (2015) also showed with his work that even wicked problems can be addressed with big data and analytic. To do this, they use competitive benchmarking, where many different data sources are combined and analyzed to address those problems. With the help of simulations in this thesis, new insights into the sustainability of EVs are provided which can help in various decision making.

The Duck Curve was already introduced in chapter 1, as well as the relevance to minimize it. The Duck Curve is shown once in Figure 1, where the shape of a duck can be seen very clearly. This graph reflects the difference between solar output and the peaks of energy demand over the day. (Denholm et al., 2015)

Figure 1: California hourly electric load vs. load less solar and wind (Duck Curve) for October 22, 2016



3 The Data

In this section, the data sets utilized in the master thesis are presented. For an optimal simulation and a meaningful result, a data set from real world parking facility is used. This data set contains the parking behavior of cars, such as arrival times, length of stay and departure times. With the help of this data and the EV adoption rate, the required charging capacity per day can be derived. To represent the general consumption and surplus of energy for a region, the Duck Curve is used as well as a general energy consumption of a modern city. Furthermore, weather data are used to predict the producible energy of the PV systems. An overview over the data sources can be found below.

Table 3: Data Sources

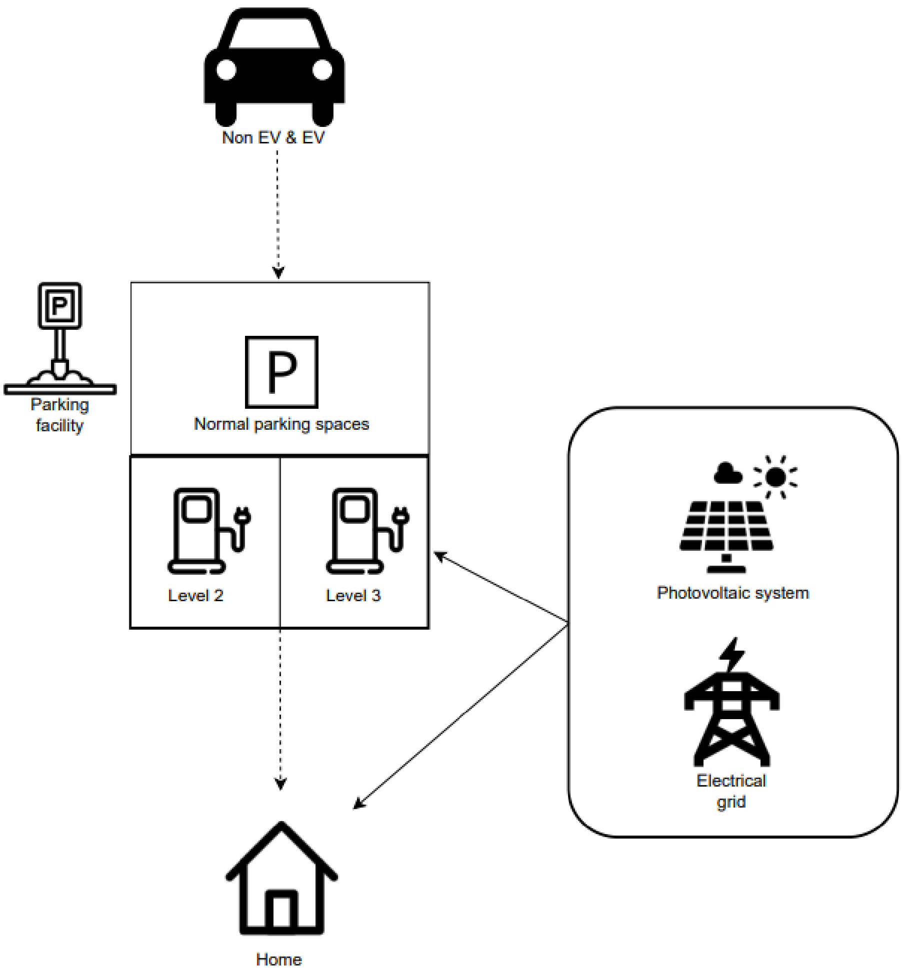
Variable	**Source**
Net energy consumption	Open data from Dutch energy providers for 2020
Daily profiles of overall energy consumption	Open data from the Dutch energy platform NEDU
Daily energy variation	The Duck Curve from California Independent System Operator
EV adoption rate	Industry reports and expert forecasts
EV energy consumption	EV adoption rate and Industry reports
Parking behavior	Transaction level data from Melbourne
Weather behavior	Open data from the Melbourne weather service
PV energy generation	Industry reports and weather behavior

3.1 Business Understanding

This section provides an understanding of the foundation and procedure of the approach. This helps to gather and select the right data sources and use them in the right context in the following step.

Figure 2 illustrates the simulation environment and a rough outline of the business process. A detailed description of the simulation process can be found in section 4.2 Simulations. As already illustrated, a non EV or an EV arrives at the parking facility and can then either park in a normal parking space or charge its EV at a level 2 or level 3 charging station. In the best case, the EV is fully charged in the parking facility, minimizing power consumption at home in the evening. The charging station has the option of either drawing electricity directly from the power grid or using green electricity if the PV systems have produced sufficient energy. The charging station prefers green electricity, as this preserves and protect the power grid.

Figure 2: Business Understanding



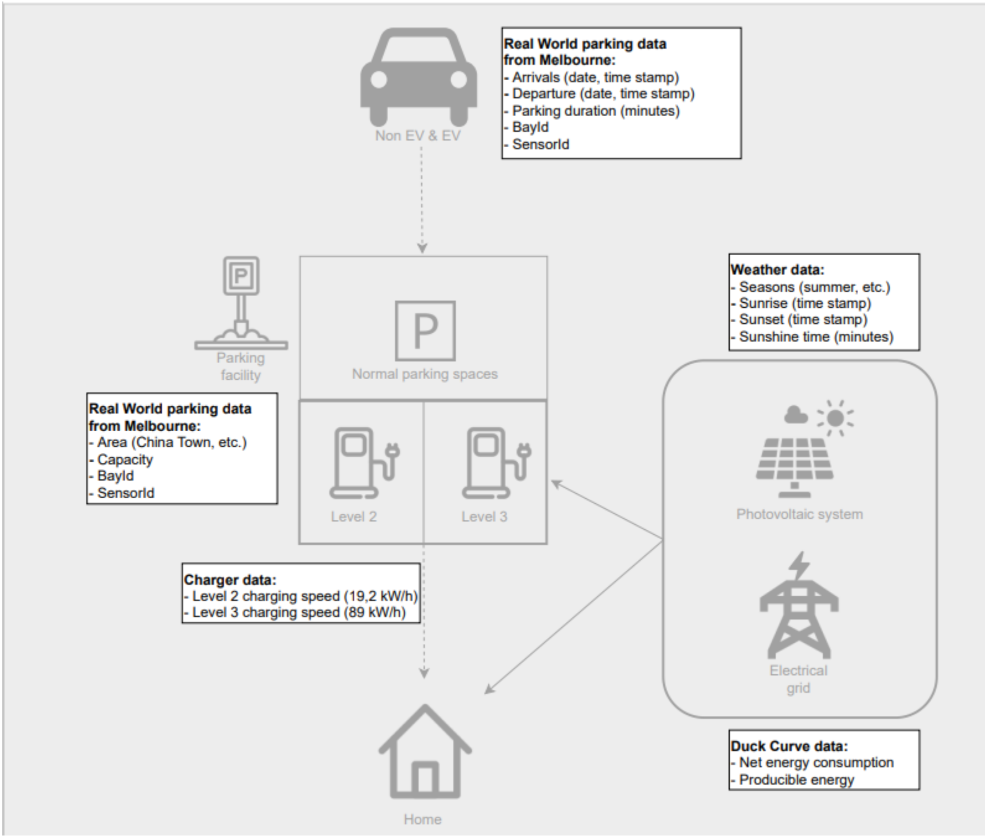
The aim is to analyze to what extent the introduction of charging stations in parking lots minimizes electricity consumption at home in order to reduce the Duck Curve. For this, it must also be considered how many charging stations and PV systems are sufficient to have a real impact on this problem. As well as the increasing penetration of EV, which will grow steadily over time. All these properties and special features must be taken into account to ensure a smooth data understanding and preparation. With the help of the simulations this problem should be examined and be a reliable estimation for the future of the parking lots.

To model this, transaction data from a parking facility is needed to track the movement of cars. Data is also required on the characteristics of the parking facility, such as the capacity of the parking facility. In addition to these two, weather data is also important to determine the energy that can be generated by PV systems. A fitted duck curve is required to evaluate the respective impact of the new parking facility. More on this is discussed in the next section.

3.2 Data Understanding

Based on the previous business understanding, this section describes the data sources used for the simulation and explain their purpose. The main data sources are the parking facility data and the associated vehicle movement data. After all, it is on this basis that the simulation will be carried out later, so they are selected and prepared very carefully. In this case, real world data of parking facilities of Melbourne are used. (*On-street Car Parking Sensor Data - 2020 (Jan - May)*, 2021) The city of Melbourne has equipped its parking lots with sensors to track the arrival and departure of each car. With the help of this publicly available data, it is possible to determine the parking duration, the parking capacity and the area of the associated parking lot. All these data help to perform a meaningful simulation later on. For the selection of charging stations, charging stations of level 2 and 3 were considered. Level 1 charging stations were excluded as they have a relatively slow charging speed in comparison. In addition, parking facilities are inherently faster-moving than, for example, a workplace parking facility. This means that a car is usually parked in a parking lot for only a short time period, while at the workplace it is parked continuously for about 8 hours. Therefore, Level 1 charging stations are simply not suitable for this scenario to charge the EV battery in a feasible way and minimize charging at home.

Figure 3: Data Understanding



The loading speed of Level 2 and Level 3 again varies in their levels depending on the provider and size. (Falvo et al., 2014) (*What's the Difference Between EV Charging Levels?*, 2021) For simplicity, we use an average defined loading speed. Since a parking lot owner is more likely to buy charging stations from one provider. Thus, we get a charging speed of 19.2 kW/h for level 2 and 80 kW/h for level 3. Using these values and the previous parking data, especially the parking duration, the possible charging energy for the respective EV arrivals can be calculated.

In addition to the energy needed for parking, the energy required at home in the evening is also taken into account. For one thing, it cannot always be guaranteed that an EV will park long enough to charge its battery to 100 percent. But even if every EV could be charged to 100 percent , those EV will also have to drive home again, causing the battery level to drop again. This variable can be reflected in small changes in the battery or result in large ones, assuming the owner of the EV continues to travel longer distances throughout the day. More about the exact implementation of this approach can be found in chapter 4.3. In order to represent the effects of this new energy demand, the Duck Curve is used, which has already been introduced in the previous chapter.

Finally, the weather data will be discussed. These help determine the average solar exposure per day based on sunrise and sunset data. Additionally, weather conditions such as rain and cloud cover have an important role to contribute to the energy production of the PV systems. Since the effects of the different seasons are also analyzed later in the sensitivity analysis, the average solar radiation is divided into spring, summer, fall, and winter. This allows for a more accurate assessment of the impact of low-sun or high-sun days on PV systems.

3.3 Data Preparation

This section deals with the data preparation in order to be able to use them for the simulations and to derive important insights from them. The rough flow of this phase is as follows. After the identified data from the "Data Understanding" phase has been obtained, it must be transformed in order to work with it further. After that, different filters have to be applied to get only the relevant data. Then, various analyses and formulas are applied to the extracted dataset to gain further insight into the dataset.

The first step is to convert the exported file into a readable CSV file. With the help of a Python file and the use of pandas *pandas* (2021), this file is then filtered to the relevant columns. (See appendix A.1) After only the columns "DeviceId", "BayId" for the identification of the parking lot and "ArrivalTime", "DepartureTime" and "DurationTime" for the transaction data, as well as "AreaName" for the assignment of the parking lot are available, the actual filters can now be applied.

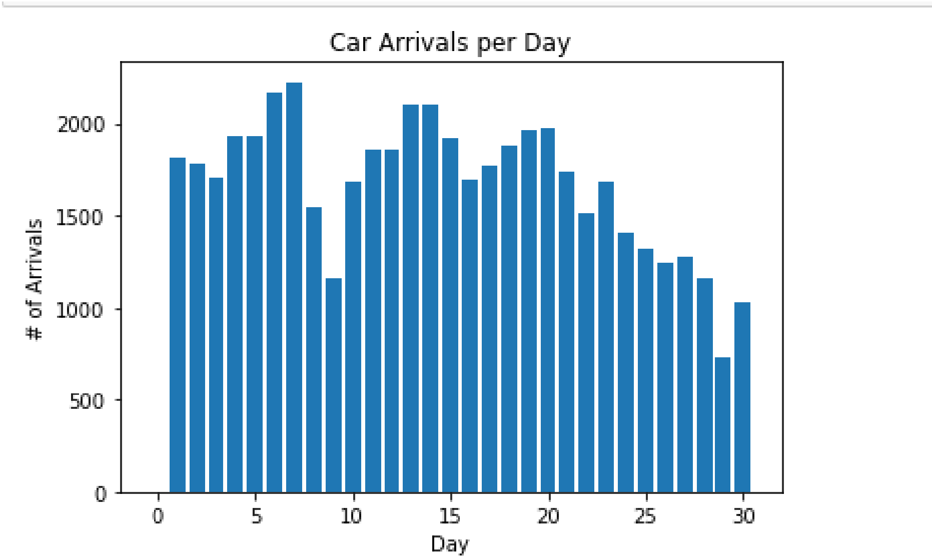
The first important filter used refers to the "AreaName" column. This allows it to identify the parking spaces and to gain further insight into their characteristics. With the help of this filter and the nunique counting of pandas, the size of each parking lot could be calculated. This new information is responsible that the area China Town is used in the simulations, since it has a reasonable size with 35 parking spaces (see appendix A.2).

For further analysis, the data set had to be adjusted once again. The columns "ArrivalTime" and "DepartuereTime" were stored as strings. Therefore, the types of both columns were converted to datetime64 types in order to work with the data more easily but also to visualize them more effectively. This conversion also allowed to filter the dataset to a specific month. For the first simulations, the month of March was chosen because it is well suited for the simulation of PV systems and contains promising data sets.

With the newly converted dataset, arrivals and departures are also available for analysis. Figure 4 shows the total arrivals of each day in March. It can be seen that on 7 March the most arrivals were recorded with approx. 2.225

arrivals. March 29, on the other hand, contains the fewest arrivals with approx. 728 arrivals. On average, however, about 1,700 cars arrive daily at the parking lot. And stay there for 30 minutes on average before they leave the parking lot again. In total, about 50,000 cars arrive and use the parking lot in the whole month of March.

Figure 4: China Town Car Arrivals in March



If we now break down the arrivals to the respective weekdays, we do not see any major fluctuations. (see Figure 5) This shows that the parking lot has a very stable arrival rate and is still heavily used even on Sundays. And thus the approximately 50,000 arrivals in March are almost equally distributed with about 7,000 arrivals on the individual weekdays. If we would only look at these two figures, we would simply simulate the simulations for one day with about 1,700 cars. This would mean that about 71 cars would enter the parking lot every hour. Unfortunately, this is not so easy to transfer, because the simulation would be then too static.

Therefore, the dynamics of the daily arrivals will be discussed in more detail in this paragraph. Figure 6 shows the average hourly arrivals per day. It can be observe that arrivals are lowest at night and in the early morning hours, with an average of 30 - 40 arrivals per hour. At 5 o'clock the lowest point is reached with about 33 arrivals. In the morning, the number of arrivals increases due to the simultaneous start of work shifts. Throughout the day, the number of arrivals increases and decreases, until it reaches its peak at 6 p.m. with about 105 arrivals. This can also be traced back to work, as many car owners either drive home and thus release new parking spaces for further arrivals, and others return home from work. After this peak, the number of arrivals flattens out and remains relatively stable in the evening hours with about 50 arrivals per hour. With this information it is now possible to make the simulation more dynamic and closer to the real world.

The corresponding code for data analysis and data preparation can be found in Appendix A.3.

Figure 5: China Town Car Arrivals per Week Day

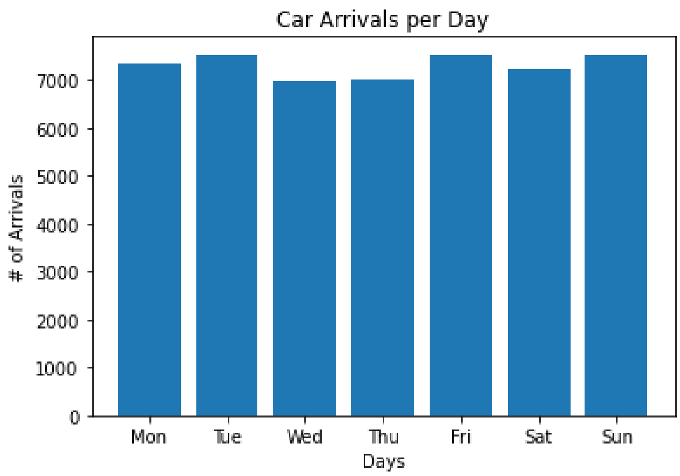
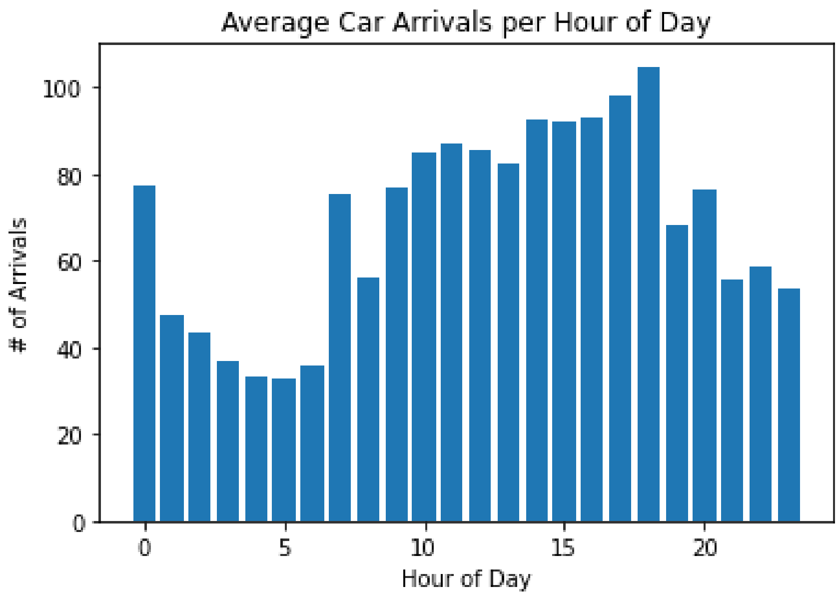


Figure 6: China Town Average Car Arrivals per Day



4 Implementation Of The Methods

This chapter describes the final preparations for the simulation. The previous data preparations will be taken into account. Furthermore, the process and the implementation of the simulation will be explained. Afterwards, the results of the simulation are presented and discussed.

4.1 Preparation Of The Experiment

4.1.1 Assumptions And Constraints

For a successful simulation and a transfer to the real world, some assumptions are required. The assumptions made and considered here are presented in this section.
Constraints: The data only tracks whether a parking space is free or not. Thus it is not possible to identify the car that is parked there.

Assumption 1: Therefore, the simulation assumes that it is always a new car that enters the parking facility. For this reason, no vehicles are taken into account that have already used the parking facility during the day. Each vehicle is generated completely new with properties and requirements.

Assumption 2: This scenario also assumes that each car using the parking facility charges a certain amount of energy at home. For example, cars that use the parking facility in the morning may drive around all day discharging the battery. Therefore, a small threshold is considered in the simulation, which is always recharged in the evening, even if the car was previously able to charge 100 percent in the parking lot.

Assumption 3: There are many different chargers with different technologies and characteristics. Level 2 and Level 3 charging stations with a charging speed of 19.2 kW/h and 80 kW/h were selected for the simulations.

Assumption 4: When creating a new EV, it is assumed that different models may be involved. Therefore, EVs with small batteries and EVs with large batteries are considered equally. Thus, it is assumed that EVs can have battery sizes ranging from a minimum of 30 kW/h to a maximum of 100 kW/h.

Assumption 5: Since it is almost impossible for a parking operator to know the battery level of an EV before its arrival, the battery level is determined randomly. It is assumed that the battery level upon arrival can range from 5 to 99 percent. The reason for this is that the owner of the EV may have just left his or her home and thus traveled only a short distance. Moreover, it is assumed that a battery level below 5 percent is too risky for EV owners and is therefore not taken into account.

Assumption 6: It is assumed that normal cars are only allowed to park in normal parking spaces.

Assumption 7: It is assumed that every EV uses the charging function unless one of the three assumptions are true. The first is that an EV parks for less than 6 minutes. The second is that the battery state of the EV is above 95 percent. And the last assumption is that the owner of the vehicle personally chooses not to use the charging function.

4.1.2 Parameters

In this section the parameters used in the simulation are presented. These can be derived from the data preparation on the one hand and from the assumptions and constraints on the other hand.

$$SimulationTime = 86.400 seconds = 1 day \tag{1}$$
$$ParkingSpots = 35 \tag{2}$$
$$NomalParkingSpots = 25 \tag{3}$$
$$ChargingStationL2 = 5 \tag{4}$$
$$CharingStationL3 = 5 \tag{5}$$
$$PhotovoltaicSystems = 3 \tag{6}$$
$$PVGeneration = 0,4\ kWh \tag{7}$$
$$EVAdoptionRate = 25\% \tag{8}$$
$$BatteryCapacity = 30\ to\ 100\ kWh \tag{9}$$
$$BatteryLevel = 5\ to\ 99\%\ of\ BatteryCapacity \tag{10}$$
$$RequierdPower = BatteryCapacity - BatteryLevel \tag{11}$$
$$PowerPossible = ChargingSpeed * TimeofStay \tag{12}$$

4.1.3 Provision Of The Environment

The simulations are performed using Python and Simpy. These features and previously defined parameters can now be used to create a simulation environment. In addition to the parameters that specify the properties for certain objects in the environment, other technical requirements must be met. These include the mapping of the charging stations, the parking lot, the PV systems, the power grid and the measurement of the charging power at home. All these components of the environment, on the one hand pick up the parameters defined above and on the other hand can be triggered by processes. The different processes will be discussed in more detail in chapter 4.2 Simulation.

The entire simulation environment in which the individual simulation objects interact is provided by Simpy. For this purpose, only one environment is declared using "simpy.Environment()". All processes are then executed in this environment and can be captured via internal timestamping.

The parking facility is mapped as a "simpy.Resource". In order to implement this, on the one hand the previously set up environment is required and on the other hand a limit is required for the capacity. The parking facility as well as the resource is therefore bound to the environment. The capacity can be derived from the previous data analysis and is 35 parking spaces. These 35 resource slots can then be requested by other processes, e.g. when a new car arrives. Since in this case not all resource slots can be treated the same way, as the parking facility consists of different parking spaces (EV charging station 2, EV charging station 3 and normal parking spaces), the resource must be extended. For this purpose, additional variables are created to declare the parking spaces and define their individual capacity. This also makes it possible to find out whether one of the three parking space types is free or occupied throughout the simulation. Furthermore, an exception ensures that even in the case that all resource slots are busy at the same time and thus no parking space is available the simulation does not crash. Instead it allows the EV to exit the parking lot without any problems.

To map the resource with all its properties, a collector is used. The collector consists of a collection of namedtuples that represent the above-mentioned resource and its properties. As a result, a new subclass of tuples is created that can act as a full-fledged parking facility, which is the first cornerstone in the environment.

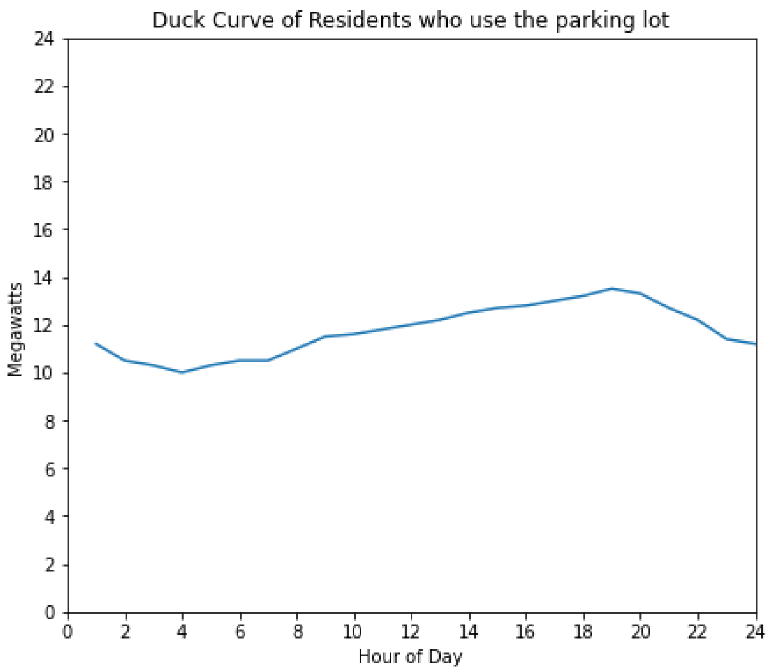
The PV system, the power grid and the home charging are created as simple "simpy.Container". Like the parking resources, they are bound to the overall environment. Similarly to the resource, a certain capacity must be set at the beginning. However, this capacity does not represent the available free resource slots that a process can access, but only the maximum amount that fits into the container. This is comparable to a glass that can hold 1 liter or 10 liters of water, depending on its size. Just like an ordinary glass, the container can only be filled or emptied and cannot take on any other properties or functionalities.

The capacity of the PV system container is determined with the help of the number of PV systems and their storage. In order for a container to always know its current state, a specific initial state must also be defined during initialization. For the simulation, the generated electricity of the PV system is set to 0. For the grid and home charging, the initial value is also set to 0 to be able to quickly understand how much electricity has already been drawn from the grid or home consumption. Since the capacity of the grid can never be overloaded due to the small number of charging stations alone, the value of the capacity is chosen so that it can never be reached.

4.1.4 Data Calibration

Now that all assumptions, constraints and parameters have been outlined and the environment has been provided, small adjustments need to be made to the data. In order to visualize the results of the simulation, the Duck Curve must be adjusted. For this purpose, the net energy consumption from the open data of the Dutch energy providers for the year 2020 and the daily profiles of the sum from the open data from the Dutch energy platform NEDU are analyzed. With the help of this and the parking facility data, the original Duck Curve is scaled down to the consumption of the number of daily arrivals. Without this step, the small changes in consumption would not be visible in the original graph. The new Duck Curve, which is compared to the results of the simulation, is shown in Figure 7.

Figure 7: Total Load of Parking Space Visitors



4.2 Simulations

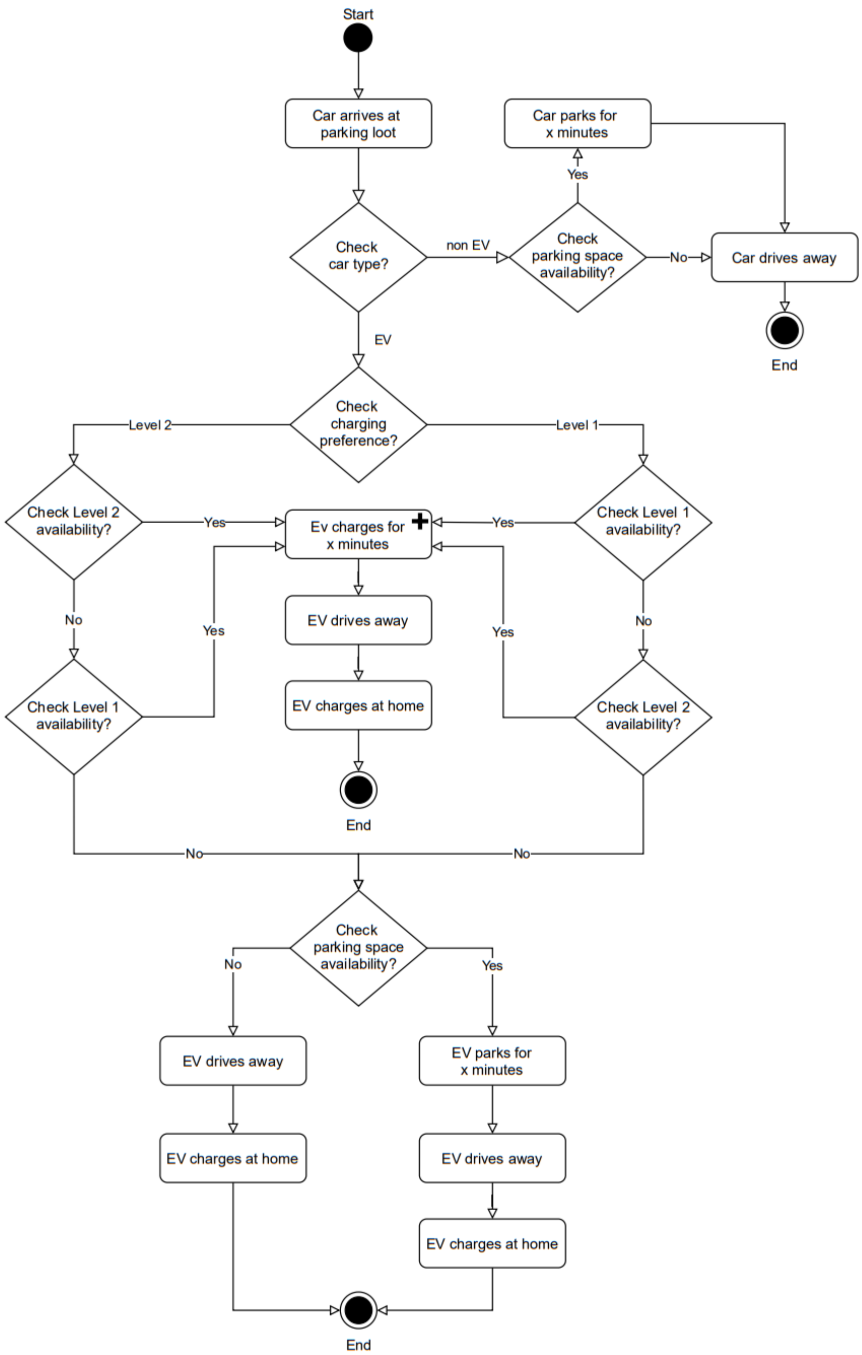
Due to the detailed and careful preparations, the simulation is now described in this chapter.

The simulation can be divided into two main processes. One is the generation of the individual cars and the other is the interaction of the cars in the parking facility. The interaction includes further small processes, which will be discussed in more detail here. An overview of the simulation can be found in the appendix B.1.

First of all, the description and explanation of the car generations. Here, cars are generated continuously over a day based on the previously defined parameters and data sets. On the one hand, the predefined EV adoption rate plays an essential role. This determines the probability that a newly generated car is an EV. Then, once an EV is defined, it is given the opportunity to use the charging stations and thus can take advantage of the charging process. In addition to this property, it also receives a random charging preference. This is determined at the beginning of the simulation and describes, which of the two charging options the EV owner prefers. Accordingly, the EV owner initially tries to find the preferred charging station, but if it is not available, it can also switch to the other charging station. However, if no EV is selected, a car is generated that is given the usual characteristics of a car. This means that it too can enter the parking lot and occupy a parking space for a certain period of time. With the assignment of these properties, interactions in the parking lot can now be simulated based on the previously created environment. The assignments outlined above can all be found in the "def car_generator" function. (see appendix B.2)

This section is dedicated to the simulation process. For a better understanding and transparency, the entire simulation process is modeled in Figure 8. It is important to note that the visualization of the process starts when a car enters the parking facility and ends when the car leaves the parking facility. The first step is to check what type of car enters the simulation. Based on this, either the normal parking process or the charging process is triggered. If a normal car is identified during this query, it is checked whether a normal parking space is still available or not. If a parking space is free, the car parks there for a certain amount of time and then leaves the parking space again. However, if there is no free parking space, the car must leave the parking facility directly. This is because in this scenario, a normal car is not allowed to occupy a charging station, thus limiting the full potential of reducing the Duck Curve. This ends the simulation and the associated process of a normal car, which means the next car can arrive. The handling of cars described here is found in the "def_arrival()" function, and the associated parking process is found in the "def_parking-process()" function. (see appendix B.2)

Figure 8: Simulation Process

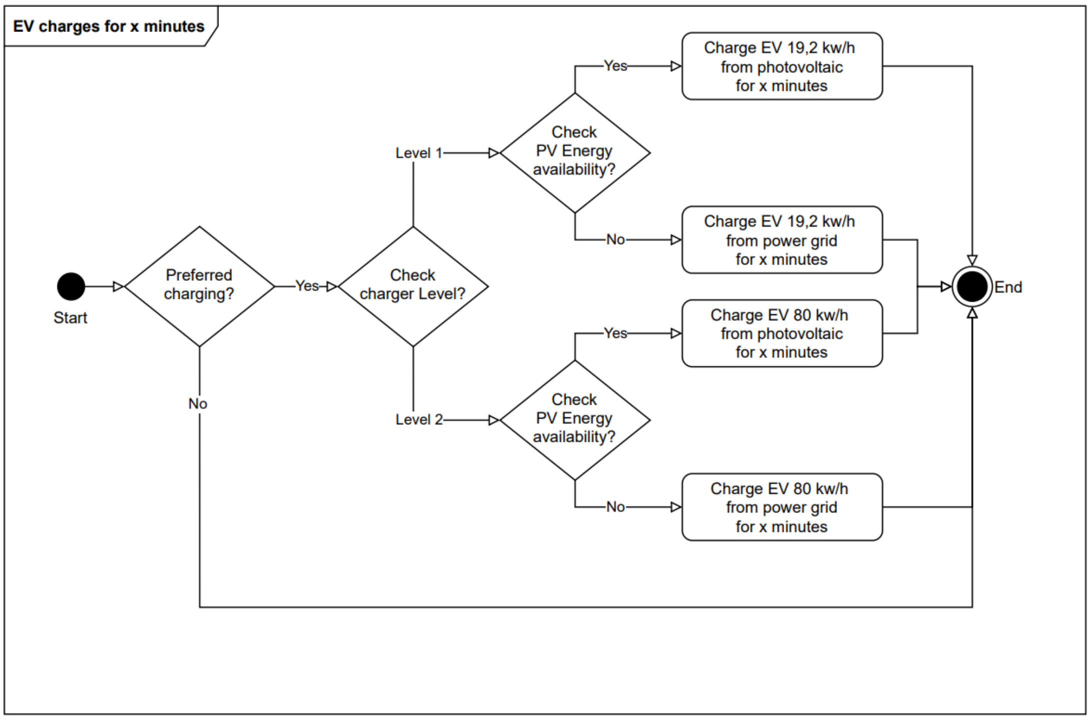


If the query determines that the incoming vehicle is an EV, the simulation initially validates its preference. The simulation then checks whether one of the preferred charging stations is available or not. If the preferred charging station is not available, the simulation first checks whether another charging station is available. Should this also not be the case, a final check is made to see whether a normal parking space is available. In the event that the entire parking facility is occupied, the EV leaves the parking facility again and must recharge all of its missing battery as well as the consumption for the trip home at its location. This process is also implemented in the function "def_arrival()". (see appendix B.2)

Once the preferred charging station or the second option is available, the charging process starts. Figure 9 shows the process described below. At this stage, it is checked in advance whether the owner of the vehicle wants to charge or not. The owner of the EV will not use the charging process if his battery level is at 95 percent, he does not park for more than 6 minutes, and he generally does not feel like charging in the parking lot. However, if none of these cases occur, the simulation checks what type of charging station is being used. Based on this information, as well as the request for available generated energy from the PV systems, the required energy can be obtained either from the grid or from the PV systems with the correct charging rate. After the EV has received the maximum possible energy during its parking period, it leaves the parking facility. In the best case, the vehicle is 100 percent charged, so that at home only the energy consumed on the way home needs to be recharged. The technically sophisticated implementation for this can be found in the functions "def charge_processL1()" and "def charge_processL2()". (see appendix B.2)

In addition to the main process, energy generation by the PV systems runs in parallel during the simulation. The energy is generated based on the previously defined parameters of the environment. This means that on a normal spring day the sun shines for about 7 hours and the PV systems can generate most of the energy at midday and a little less in the morning and afternoon. Therefore, a single PV system can generate about 0.3 - 0.5 kW per hour. In this scenario, this means that 3 PV systems with a total area of about 24 to 30 square meters can generate up to 1.5 kW per hour. This energy is freely available to the charging stations, with the energy from the PV systems always having priority over the power grid. This also has the effect of flattening the Duck Curve throughout the day. The implementation of the PV systems and their energy curve is shown in the "def pv_producer()" function. (see appendix B.2)

Figure 9: Charging Process



4.3 Results

In this section, the results of the simulation are presented and discussed.

Before discussing the results in detail, a brief explanation of how they were obtained from the simulation is given. After the simulation is complete, the data was tracked and stored at specific points. Meaning that at any point where the state of one of the containers (PV system, power grid, house charging) changes, an event is triggered that captures that data. This data is then initially generated during the simulation as an item consisting of a tuple of the current timestamp of the environment and the respective value of the change of a container. As a result, this item is stored in a simple Python list.(See Appendix B.2)

After the simulation run, the states of the individual containers are evaluated to determine the total consumption. These values can be easily read using the Simpy methods provided. In addition, Pandas is used to convert the individual tracking list with the timestamps and the value of the change into a pandas.DataFrame. This allows for a simple export of the data to a CSV file. This CSV file can then be used to visualize the data so that the results can be displayed and analyzed. (See Appendix B.2)

After the 100 simulations are run, the 100 CSV files are loaded into a Jupyter notebook and combined into a single complete list. For this purpose, the CSV files will be converted to a pandas.DataFrame to better process the data. (See Appendix C) In order to pilot test the simulation and evaluate the impact of the charging stations and PV systems, the first simulation was run without charging stations and PV systems. This means that every EV that uses the parking facility will also be charged at home in the evening. Figure 10 shows the energy consumption of these EVs in such a scenario. Here you can see very well that a lot of energy is needed for the EVs in the evening. This would also put a lot of strain on the power grid, as the solar energy would no longer produce any power at this time. This simulation also shows how important it is to find new approaches and technologies to contain the high energy demand of the EVs.

Figure 10: EV Load without any Charger

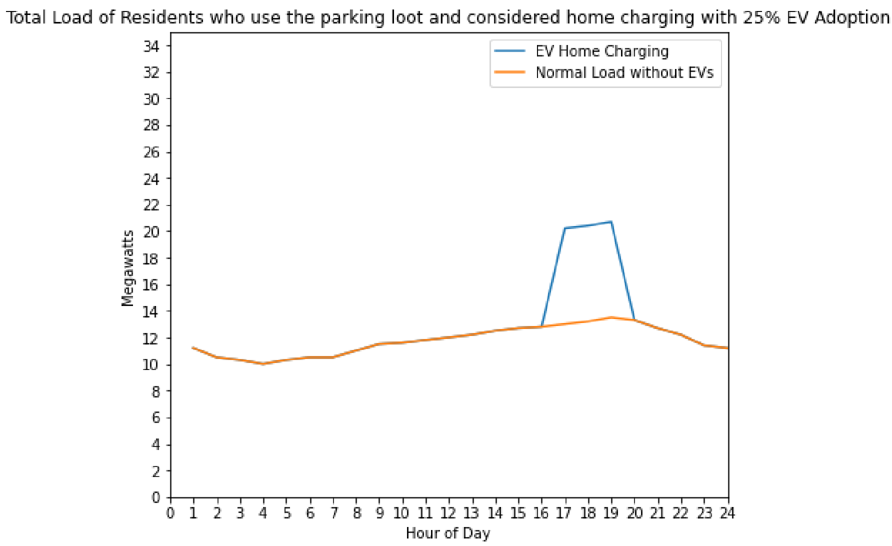
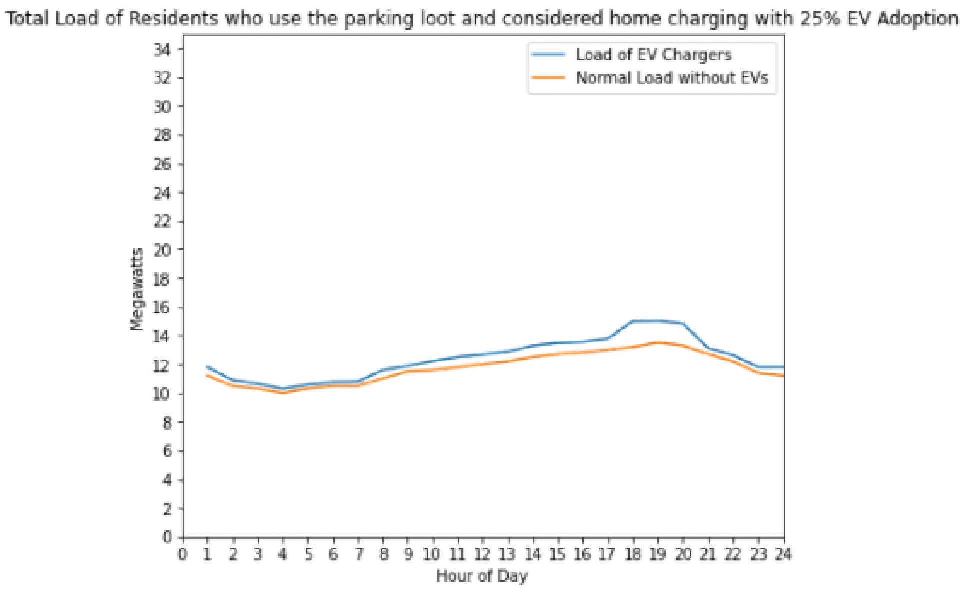


Figure 11 shows the next results of the simulation with EV charging stations. As in the previous analysis, the 100 CSV files are again analyzed for home charging consumption. This result was then combined with the consumption over the day. Using this file, the average amount of electricity in the evening could be calculated. Compared to Figure 10, it can be seen that the evening peak has become much smaller. Since not every EV leaves the parking lot with 100 percent battery power, the peak is not completely flattened. However, this result shows the significant impact charging stations can have on the power grid. (See Appendix C)

The recorded data on charging station usage and consumption was stored in another 100 CSV files. These also had to be converted into a pandas.DataFrame. In addition, the tracked time of the environment also had to be converted into a pandas.datetime type. This allowed the average energy consumption of the EVs at the charging stations to be determined for each hour of the day. As seen in Figure 11, the total energy consumption increases, but is very well distributed throughout the day. Thus, there are no additional peaks that strain the power grid. Moreover, the continuous increase in energy consumption can be better predicted, allowing the power grid to better handle it. In this case, the use of solar energy in the power grid can be even more beneficial, since there is also some energy demand distributed throughout the day, and not only in the evening hours. (See Appendix C)

Figure 11: EV Load with Charger



The next section deals with the result when three PV systems are included in the simulation. As already presented, these produce energy throughout the day, which can be used by the charging stations. Now looking at Figure 12, at first glance the results do not look much different from the results without the PV systems. The peak value in the evening remains very similar as the PV systems only change the type of electricity consumed in the parking facility, but not the amount needed to charge an EV at home. Since there is always enough electricity available from the power grid, the integration of the 3 PVs does not affect the evening trend. However, the curve flattens out very slightly over the midday period, since at this time the electricity production of the PV systems is running at maximum speed. Therefore, less electricity is required from the power grid at these hours. Figure 13 shows the average energy that can be generated by the 3 PV systems. However, this energy is very low compared to the energy required by the EVs. (See Appendix C)

Figure 12: EV Load with Charger and PVs

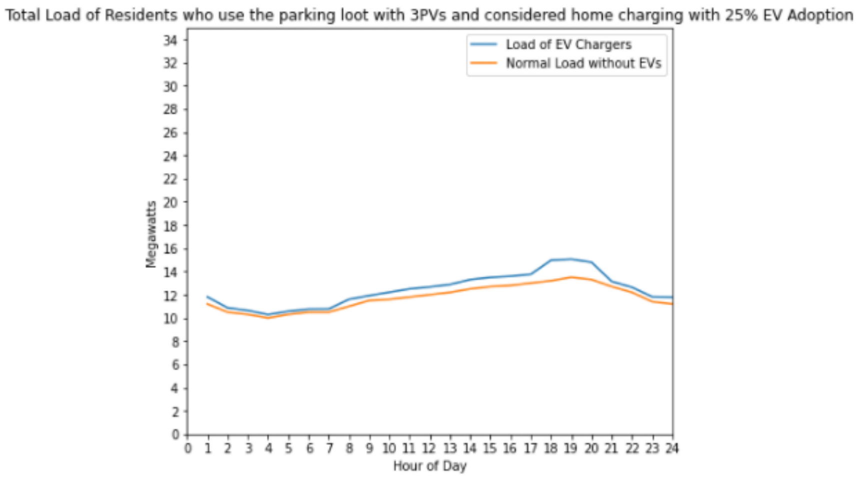
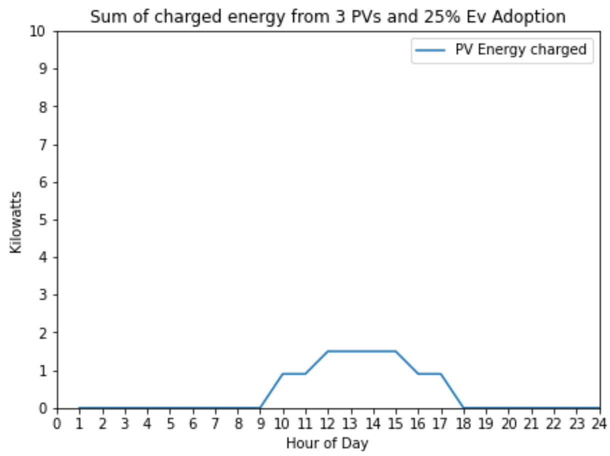
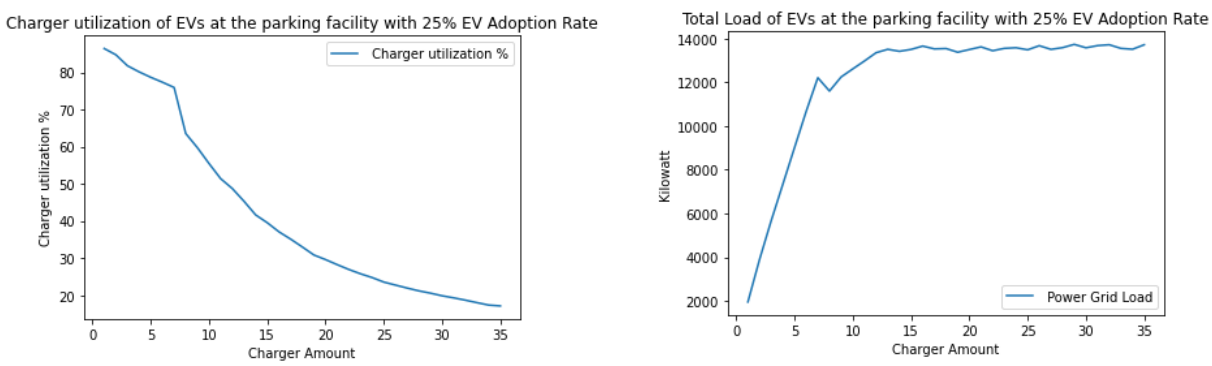


Figure 13: PV Energy Consumption of 3 PVs



After the main consideration of the simulations, we now go one step further and determine the optimal number of charging stations and the optimal number of PV systems for an EV adoption rate of 25 %. To calculate the number of EV chargers, an objective function is used to determine the optimal amount of EV charger chargeable energy. This is determined with the help of 3,500 individual simulations for the respective number of chargers. This is represented in (i) as follows. This function is then maximized, adding a further constraint. Without this restriction, the largest number of Chargers would always be selected. The restriction states that the service level of the EV charger cannot be less than 50 %. The corresponding function and constrain are shown in (ii) and (iv). This results in the following objective function as seen in (iii). A visual representation of the respective functions is shown in figure 14.

Figure 14: Charger utilization and total load of EVs at the parking facility with 25 % EV Adoption Rate



$$Given : x = \{1, 2, ..., 35\} \tag{13}$$

$$f(x) = ChargeableEnergy(x) \tag{14}$$

$$g(x) = ChargerUtilization(x) \tag{15}$$

$$Maximize : \max_{x \in N} f(x) \tag{16}$$

$$Subject\ to : g(x) > 50 \tag{17}$$

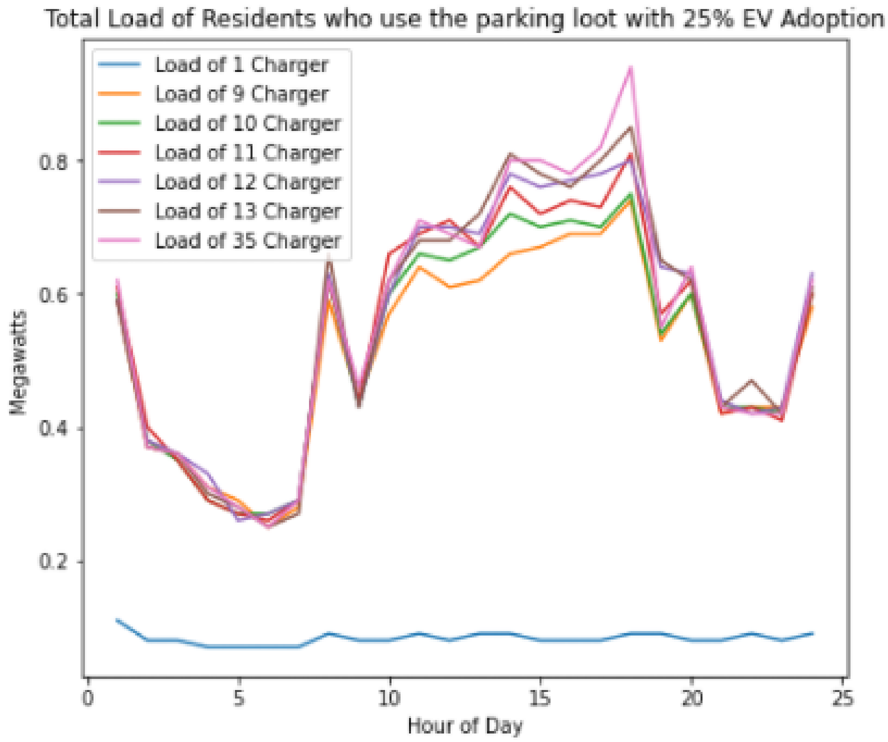
With the help of these, the optimum number of 11 EV Chargers could be determined. These can handle approx. 13,000 kilowatts at a service level of 51.37 %. If we now consider similar results with the optimum charge curve, we obtain the following losses shown in table 4. These were determined using the Mean Square Error loss function (18). For illustration purposes, the respective graphs are compared below in figure 15.

$$\frac{1}{35} * \sum_{i=1}^{35} (f(11) - f(x_i))^2 \tag{18}$$

Table 4: Mean Square Error Loss Function from 11 Chargers

EV Charger	1	...	9	10	11	12	13	...	35
Loss	0.2414	...	0.0021	0.0007	0.0	0.0008	0.0012	...	0.0016

Figure 15: Total Load of Residents who use the parking loot with 25 % EV Adoption



Based on this result of 11 chargers, the optimal number of PV systems can now also be calculated. For this purpose, the energy that can be produced during the midday hours is compared with the charged energy at the parking facilities. The possible energy that can be produced is defined in (20). Based on this, the loss function between the optimal energy demand of the 11 chargers and the respective producible energy of the PV is minimized (21).

$$Given : \forall x \in N, EnergyProduction = y = 0.8, t = time \tag{19}$$

$$h(x) = \sum_{t=9}^{16} \begin{cases} (y + 0.1) * x & \text{if } 11 \leq t \leq 15 \\ (y - 0.1) * x & \text{if } 9 \leq t < 11, 15 < t \leq 16 \end{cases} \tag{20}$$

$$Minimize : \min_{x \in N} \frac{1}{N} * \sum_{i=1}^{N} (f(11) - h(x_i))^2 \tag{21}$$

This showed that 836 PV systems are most capable of generating the required energy for the 11 EV chargers. These have a loss of 0.003492 and thus offer the best overlap of the two.

4.4 Discussion

In this section, the initial results are discussed. The final discussion of the results, taking into account the sensitivity analysis, takes place in section 5.2.

First, the results are discussed in Figure 10, where only home charging is possible. These clearly show that the introduction of EVs brings with it major problems. The new high energy consumption of EVs leads to extreme peaks and poses new challenges for electricity providers. In this case, we consider only the EVs that occupy the parking space. These already have an electricity consumption of 1.7 megawatts. If we now consider all EVs, the new energy consumption is not conceivable for today's power grid. The strong peak in the evening would mean that the power grid would only be available to a limited extent or would even fail completely. In addition, the power suppliers would have to invest enormous amounts of money in expanding the power grid. This would not only be economically hardly feasible, but also ecologically unsustainable for our future. These results assume that the EV adoption rate is 25 percent. This adoption rate alone leads to a very large demand for additional electricity and a strong peak in demand in the evening. If we now imagine that every car is an EV, the magnitude is even larger. Therefore, this result already shows how important it is to find new solutions and technologies for the upcoming introduction of further EVs. Naturally, the results do not match reality 100 percent, as the cars can arrive home and charge their battery at other times as well. However, these results show a good overview of what the EVs cause. Moreover, this result confirms that the implemented simulation works and the further simulations can be compared to it.

The results with the charging stations in the parking facility are very interesting. As already shown in Figure 11, these have caused a strong change in energy demand. These introductions spread the load evenly throughout the day, which also leads to an overall increase in electricity demand. This cannot be avoided, as EVs require a large amount of electricity. Therefore, expansion of the power grid is inevitable, as well as a greater integration of green energy. However, this means that the power grid does not need to be expanded as much as it would without this approach. Since energy demand is thus very stable with only minor fluctuations and a smaller peak in the evening, the power grid does not have to cover the strong peaks. As a result, the power grid in general can avoid the dramatic expansion of the grid. In addition, due to the more stable energy demand, forecasts and other technologies can be integrated more efficiently. These results also show that the Duck Curve phenomenon is mitigated by this approach. While there is still some increase in the evening hours, it is not as strong as before. Additionally, by distributing the energy throughout the day, more generated solar energy can be consumed in the midday hours. Moreover, the increase in the evening hours is so small that it is likely to be flattened further with the help of other approaches and technologies, such as smart charging. In general, it can be said that the introduction of charging stations in parking facilities is very beneficial. Not only can they increase the attractiveness for EV owners, but they can also significantly shift energy consumption throughout the day. The result is a significant reduction in grid integration challenges associated with the Duck Curve phenomenon, while creating a promising EV ecosystem where everyone benefits from charging stations.

Finally, let's take a look at the results of the simulation with PV systems. Unfortunately, the integration of PV systems in this scenario did not produce the desired change. The reason for this is that the energy demand of the power grid is in fact far too high compared to the energy generated from the PVs. Therefore, it will be interesting to see how well the impacts of the PV systems perform in the sensitivity analysis. Therefore, the question of whether on-site behind-the-meter PV generation and storage further improve the benefits of clustered EV charging from a grid integration perspective cannot be answered at this point. However, it can already be said here that with a small area of PV systems, the effects are not exactly large. Of course, every bit of electricity from the PV systems is an improvement because not only is the load on the power grid reduced, but more green electricity is consumed. This will protect the environment a little more, which is also the main idea behind the introduction of EV. However, this low impact of PV systems can also lead to parking lot operators or investors who have a strong economic perspective not considering the installation of PV systems. From an environmental perspective, each individual PV system is meaningful because even if it does not create much of a difference on its own, as one small component of all PV systems, collectively they can make a huge impact and change the world for the better.

5 Evaluation

In this section, the simulation and the results are evaluated. For this purpose, a detailed sensitivity analysis is carried out on the one hand and a discussion on the other hand.

5.1 Sensitivity Analysis

The sensitivity analysis focuses on 6 influencing factors. These influencing factors are: (1) EV Adoption Rate, (2) EV Charger Coverage, (3) EV Charger Level, (4) PV Systems Coverage, (5) Seasons and (6) Workplace Charging. These are discussed in more detail in the following subsections.

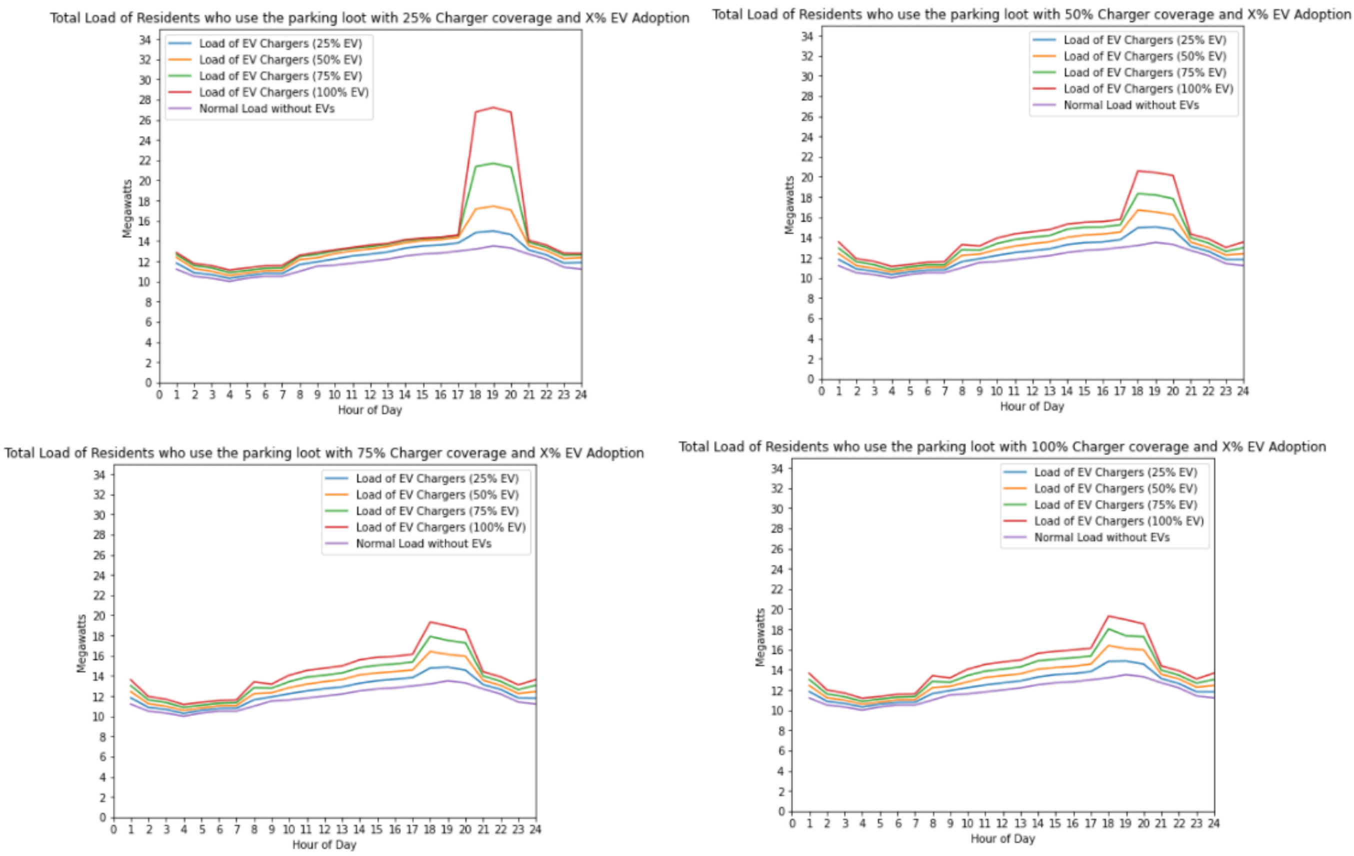
5.1.1 EV Adoption Rate And Charger Coverage

In this section, EV adoption rate and charger coverage are considered together. In order to analyze and evaluate them, simulations were performed based on the original simulation for 4 different percentages of charger coverage. This included 4 simulation scenarios (25%, 50%, 75%, and 100%) for EV adaptation for 25%, 50%, 75%, and 100% charger coverage, respectively. The results of these simulations are shown in Figure 14.

The first thing you notice when you look at all 4 graphs is that they all look relatively similar. In the evening and morning hours, consumption is rather low. During the day, it increases and peaks in the evening, where charging at home has the biggest impact. All graphs also show the increased load spread throughout the day. It gets interesting when looking at the simulations where the EV adoption rate are greater than the charge coverage. The greater the distance between these two values, the greater the peak in the evening. This effect can be seen best at a charger coverage of 25% and an EV adoption rate of 100%. This effect can also be detected in all other simulations.

Optimal distribution of energy throughout the day and a low peak in the evening is achieved at the same EV adoption rate than charger coverage. Naturally, also as soon as more charging stations are available. However, a larger number of charging stations has no other positive effect, so more charging stations than EVs have no impact on the result. Furthermore, a larger deviation of the two values results in another smaller peak in the morning. However, apart from these second peak, the distance between the different evening peaks decreases from simulation to simulation.

Figure 16: Total Load of Arrivals with X% Charger Coverage and X% EV Adoption

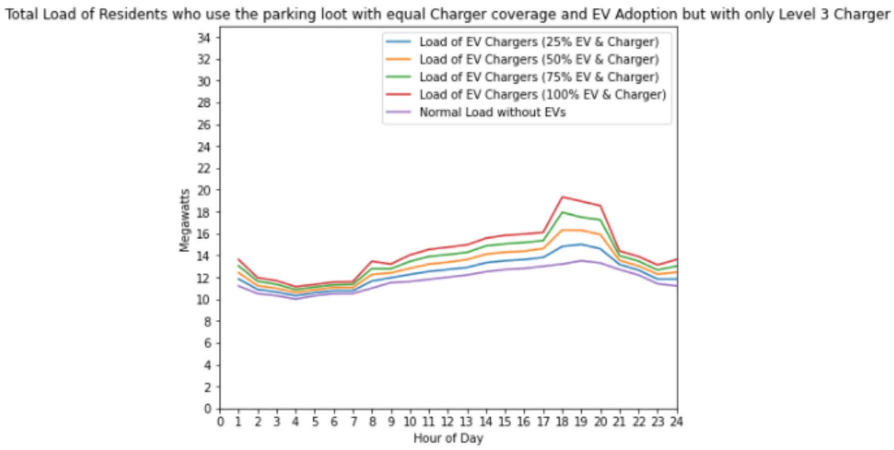


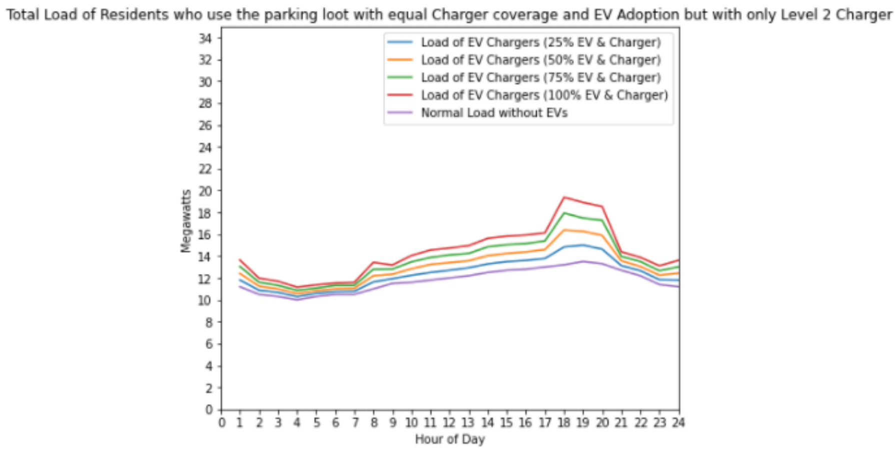
5.1.2 EV Charger Level

The next sensitivity analysis examines how much the difference between Level 2-only and Level 3-only chargers affects energy demand. In this regard, four simulation scenarios were created, ranging from 25% to 100% charging coverage and EV adoption rate. Figure 15 shows the results of the level 2 charging stations at the top and the results of the level 3 charging stations at the bottom.

Both diagrams look almost completely identical. However, the energy consumed is only slightly lower at the level 3 charging stations. This is due to the fact that there are always enough charging stations available for EVs. In addition, this means that cheaper and slower charging stations can be used with the same coverage and adaptation rate without any disadvantage.

Figure 17: Total Load of Arrivals with equal Charger Coverage and EV Adoption but with only Level 2 or Level 3 Charger





5.1.3 Photo-voltaic Coverage And Seasons

For the PV systems, two key factors were considered in the sensitivity analysis. The first one is the PV coverage and the other one is the different seasons.

During the simulations of the different seasons, it was very quickly determined that it was not practical to include winter and heavy rain days. Because at these times the PV systems produce no or only a very small amount of electricity. This small amount of electricity can in no way keep up with the electricity demand of the EVs, which is why no further diagrams can be found for them. Therefore, for the following simulations and the corresponding diagrams, only time periods including sunny days or mixed days were selected in each case. In addition to the division into sunny and mixed days, the EV adoption rate and the coverage by the charger are also taken into account.

With the help of these, the simulation could then be carried out in which the respective PV coverage was selected to match the charger coverage. For clarity, this approach is applied once for the simulation of 25% charger coverage. In each case, about 1.700 cars arrive at the parking facility. With an EV adoption rate and charger coverage of 25%, this means that about 425 EVs visit the parking facility per day. Therefore, in this case, a number of 425 PV systems corresponds to 100% coverage. This results in approx. 850 PV plants for 200%. The other diagrams are also structured according to this procedure.

Simulations below 100% were also carried out in advance, but these had only a minor influence on the results. Therefore, and in order to be able to better identify the other results or lines, these were not presented in the diagrams. Furthermore, the results in this section are simulated using only the features described above. Of course, the increasing penetration of EVs brings many more changes. In the future, more and more technologies and approaches will be added that will influence the simulation. These include, for example, the ability to charge in more places or new technology that ensures the battery discharges more slowly. Therefore, in the next section, the PV systems will be simulated again based on a higher average battery level at the entrance of the parking lot.

Now to the results. It can be seen in all diagrams that in the summer days, when the sun shines the longest and strongest, the required energy over the midday hours is also reduced. This effect also exists in the mixed days, but it is not as strong as in the summer. In general, it can be said that 100% PV coverage ensures that about 50% less of the energy demand is taken from the grid during midday hours on sunny days. This value is around 25% for mixed days. This effect is best seen in the last diagram with 100% charger coverage, since the distances are furthest apart there. Furthermore, 200% PV coverage on sunny days can carry the entire load of EVs until noon. On inconsistent days, up to 50% can also be covered in this way.

Figure 18: Total Load of Arrivals with 25% Charger Coverage and EV Adoption with X PV Coverage on sunny and mix days

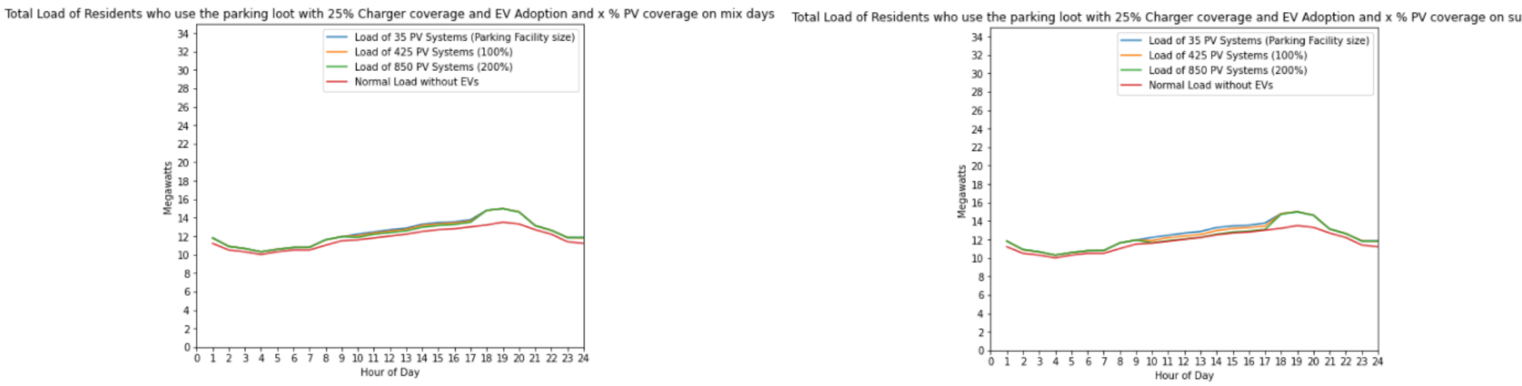


Figure 19: Total Load of Arrivals with 50% Charger Coverage and EV Adoption with X PV Coverage on sunny and mix days

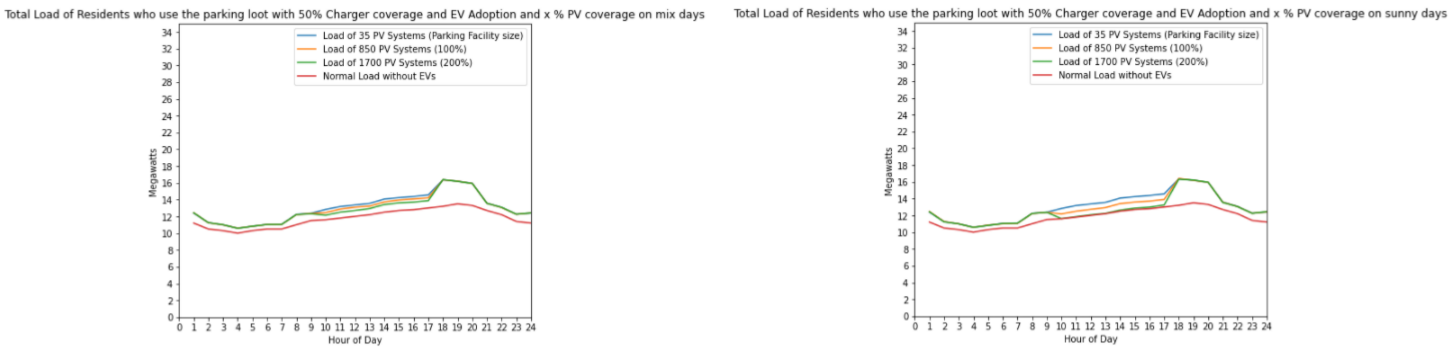
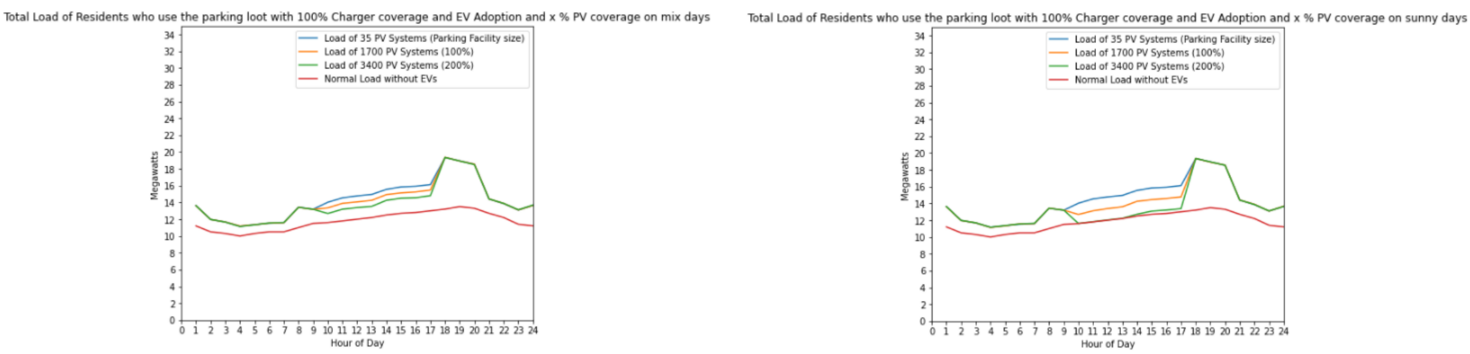


Figure 20: Total Load of Arrivals with 100% Charger Coverage and EV Adoption with X PV Coverage on sunny and mix days



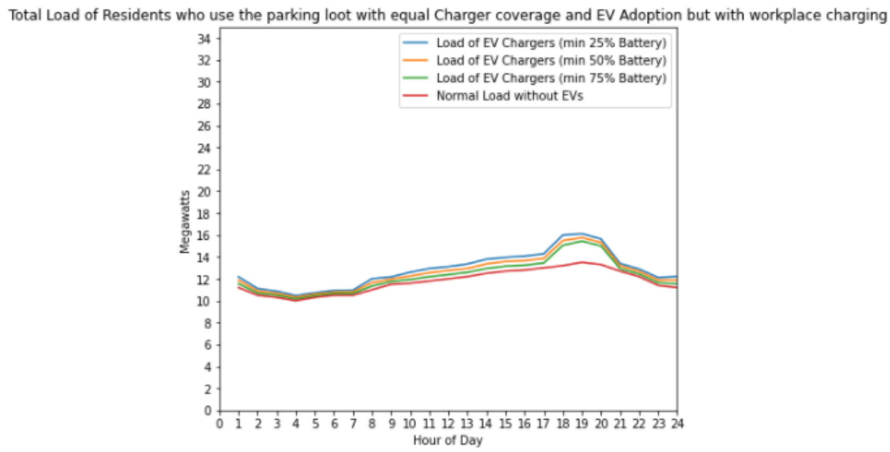
5.1.4 Workplace Charging

This section presents the results of the sensitivity analysis for the workplace charging. Here, the impact of workplace charging on the power grid alone is examined first, and then the impact of adding other approaches and optimizations for this scenario.

In general, it can be said that with time and an increased adoption rate, other influencing factors must also be taken into account. This would include new technology or approaches. An example of such technology would be better batteries that can store more energy and consume it more slowly. For further approaches, one example would be the introduction of additional EV charger clusters. On the one hand, these can lead to fewer EVs using the charging functions and, on the other hand, EVs with a higher average battery level entering the parking lot. Therefore, the influence of an additional EV charger cluster was integrated into the existing simulation. The Workplace charging cluster is a very attractive option, as the EVs are usually parked there for up to 8 hours at a time. To represent this cluster in the simulation, as well as other technologies and approaches, new ranges were defined for the battery status of the incoming EVs. Figure 19 shows the results of this sensitivity analysis. Shown are the normal consumption as well as the minimum battery level at 25 %, 50 % and 75 %. A minimum height of 100 % is excluded in this case, as the EVs each have to travel a different length to reach the parking facility. Although this case can occur occasionally, the charging function would not be used in this case anyway.

In general, the higher the minimum battery level, the lower the load on the power grid. The peak in the evening can not be completely reduced in this scenario. However, the peak is mitigated more and more with each step. In addition, it can be observed that when the arrival rate is rather low, the new load has practically no influence on the total load already present. This can be seen very well in the morning hours where the load is almost the same. Moreover, the load is distributed throughout the day and is reduced. Therefore, more EV charging clusters have a positive impact on individual parking facility power consumption and its impact on the power grid. The complete impact of this interaction will be discussed in the next chapter.

Figure 21: Total Load of Arrivals with equal Charger Coverage and EV Adoption but with workplace charging



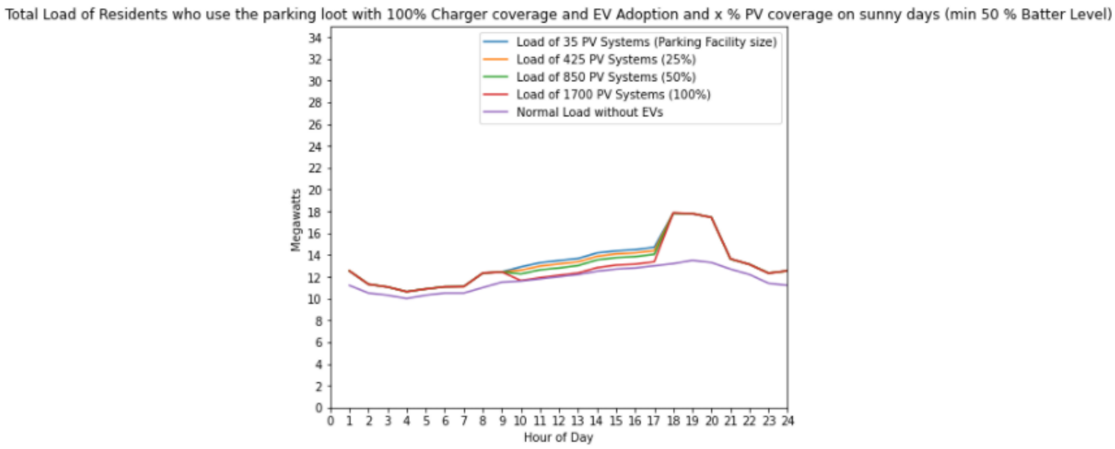
The next section deals with the sensitivity analysis of workplace charging in combination with PV system coverage. For this purpose, simulations with 100 % charger coverage and 100 % adoption rate are performed on sunny days with the respective PV system coverage. These were then implemented for a minimum battery level of 50 % and 75 %. The results of these two sensitivity analysis are shown in Figure 20.

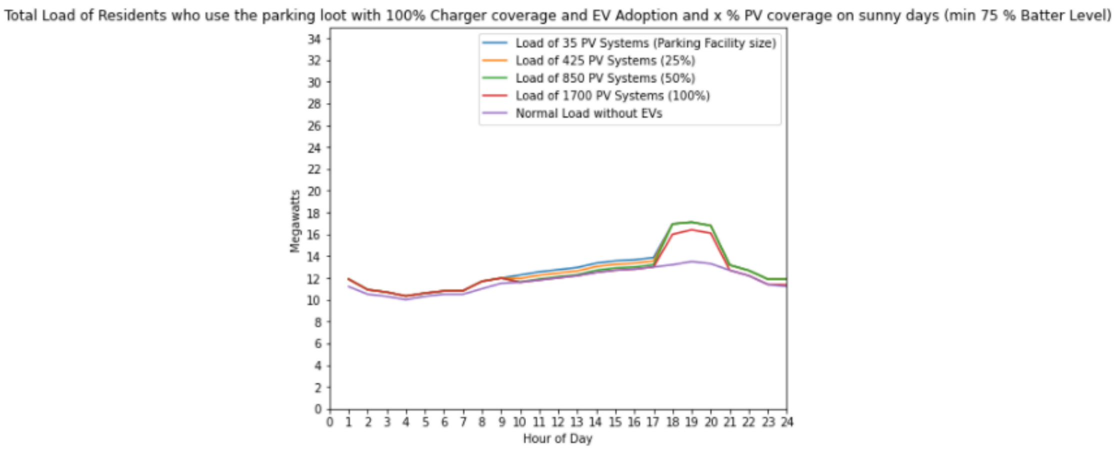
The pure impact of PV systems has already been presented in chapter 5.1.3, but these sensitivity analysis are intended to explore the full potential of PV systems. In the previous section, it was observed that the PV systems have a positive effect on the power grid only when the number of PVs are extremely high compared to the size of the parking facilities. In combination with other approaches and technologies, the influences and feasibility of installing PV systems appear quite different.

In general, this combination has a very positive impact on the power grid. In the sensitivity analysis with at least 50 % battery level, in contrast to the previous results of the sensitivity analysis of PV systems, the same results can be obtained with only half of the total PV systems. Thus, a 100% PV coverage on a sunny day can already absorb the entire load of the EV over the midday and completely relieve the power grid from the EV. However, this is still about 1700 PV systems that would need to be installed for a 35 large parking facility. Furthermore, the results for 25 - 50 percent PV coverage also look more promising. These can have a positive impact with as few as about 425 to 850 PV systems, not as much as 100%, but compared to the area and number of PV systems needed, this seems like a feasible option. Thus, this combination can relieve the power grid considerably, especially during the midday hours.

For the sensitivity analysis with a minimum battery level of 75 %, the effect described above is even stronger. Here, with a PV coverage of 100 %, the peak in the evening can be reduced since the PV systems produce enough electricity that is available in the evening even when the PV systems are no longer producing electricity and can therefore be utilized by the EVs in the parking facility. Moreover, thanks to the high battery level, 50% PV coverage is already quite sufficient to carry the entire load of the EVs over the midday period. Even 25% PV coverage already achieves a very strong difference in reducing the required energy from the power grid. Thus, workplace charging with EV charging stations and PV systems at a parking facility has the largest positive impact on the power grid and can even carry the entire load of EVs with a feasible approach.

Figure 22: Total Load of Arrivals with 100% Charger Coverage and EV Adoption with X PV coverage on sunny and mix days with workplace charging





5.2 Discussion

In this section, the results of the simulation as well as the associated sensitivity analysis are critically discussed. To structure this more transparently, the topic of EV chargers will be discussed first, followed by the PV systems, and finally the entire interaction of including other technologies. In the previously presented results of the sensitivity analysis, in addition to the description of the results, some slight hints on their interpretation have already been given. Among others, these will be discussed in more detail here as well.

In order to discuss the results of introducing EV charging stations to a parking facility in more detail, the original research question of the master's thesis on EV charging stations is revisited. It states, "can the introduction of charging stations in parking facilities meaningfully reduce grid integration challenges associated with the Duck Curve phenomenon?". EV chargers can, on the one hand, generally distribute the load of newly required energy very well throughout the day and, on the other hand, reduce the peak load in the evening. However, the EV charger alone can never completely solve the evening peak load. Since these only offer the possibility to fully charge the EV in the parking lot, but can not influence what the EV does after leaving the parking lot. The EV could for example reduce its battery level to 0 after leaving the parking lot and would have to recharge it at home. Based on the sensitivity analysis, it was determined that a high coverage with EV charging stations also leads to a better load distribution throughout the day and a reduction of peak load. However, this is not always the case, since above a certain threshold the number of charging stations is no longer relevant and thus has no further influence on the load distribution of the energy. This is the case when the EV adoption rate is below the EV charger coverage of the parking facility. This leads to the most effective energy distribution possible with approximately equal adoption rate and coverage with EV charging stations. So it can be said in advance that the EV charger has a positive impact on the issues associated with the Duck Curve.

These simulation results also show how difficult it is for parking lot owners and investors to make the right decision regarding EV charger. The general investment in charging stations is definitely worthwhile, at least from the point of view of the power grid operators. Whether this is also worthwhile for the owners would have to be considered separately. In contrast, it becomes more difficult to find the right number of charging stations. As mentioned earlier, an equal percentage for the adoption rate is optimal and larger values are not meaningful. One option would therefore be to install more and more charging stations over time in line with the adoption rate. However, it is difficult for a parking facility to determine the exact percentage of EVs arriving. This can vary strongly depending on the type of parking lot and can also fluctuate from day to day. Therefore, it would need a certain buffer of charging stations to absorb the fluctuations of the EVs. However, this also means that on certain days, the charging stations are not optimally utilized and are not profitable for the operators.

Another critical aspect for the transfer of the results into the real world, is the available space. This aspect is mainly discussed in the field of PV systems, as these require a very large area, but charging stations for EVs also need a certain amount of open space. Therefore, it is necessary to look from parking facility to parking facility to see if 100 % coverage of parking spaces is possible. Either only a lower coverage is possible or a reduction of parking spaces is necessary to get to 100 %.

The results of this work show the importance of new approaches, such as the introduction of charging stations at parking facilities, for the sustainable development of EVs and a sustainable power grid. EV charging stations can solve the problems associated with EVs and the Duck Curve to some extent, although that will become increasingly difficult as more EVs are introduced. In this case, the load is still distributed throughout the day, and the peak is reduced in the evening. However, the total energy demand is already so high, that both the distribution and the reduction no longer have much influence compared to the total energy.

The sensitivity analysis shows how valuable the EV charger can be in combination with other technologies and approaches, such as PV systems and workplace charging. Thus, EV chargers are not only a valid solution for the Duck Curve problem, moreover, they form an essential basis for further optimizations and new approaches. So, overall, it can be said that the introduction of charging stations in parking facilities can meaningfully reduce the grid integration challenges associated with the Duck Curve phenomenon.

This section discusses the results of the simulation and sensitivity analysis of the PV systems. Like the previous section, this section begins with the second research question in order to answer it with the results. The question is, "can on-site behind-the-meter PV generation and storage further improve the benefits of clustered EV charging from a grid integration perspective?". This question is not so easy to answer, which is why a breakdown into three different perspectives is performed here. This enables, a more detailed discussion of the results and a deeper evaluation. The three perspectives consist of three different parking facilities to which the results are applied and evaluated. The first type of parking facilities are parking facilities with only a small amount of open space and a small parking capacity. The second type are parking facilities with some open spaces, as well as the possibility to roof the parking facility and install PV systems there. The third and final type are large parking facilities or planned parking facilities that have a large or unlimited amount of open space.

The first type of parking includes, for example, small underground garages or small urban parking lots for restaurants. For this type, only PV systems have an impact on the Duck Curve when very few EVs use this parking lot and the parking duration is relatively long, resulting in a low fluctuation of EVs. If there is a high activity of new EVs, then it is not worth it, because in this scenario only a small number of about 3 PV systems can be installed and they cannot keep up with the high energy demand. Moreover, such a small parking lot also has no impact on the total energy demand of EVs, but if all parking lots of this type are equipped with charging stations as well as PV systems, they will take at least part of the change. In addition, the weather does not play a major factor with this small amount of PV. Thus, from this perspective, PV systems have a positive impact on the Duck Curve only in a very limited scenario.

In the second perspective, it is possible to build at least as many PV systems as there are parking spaces, or even a few more if there is enough space. This is because a parking space is about the same size as a PV system, which is about 11 m^2. Since in this scenario the parking lot can be covered, the same number of PV systems can be installed. This is not only beneficial for the PV systems, but also brings other advantages. The roofing makes it more convenient and attractive for EV owners to use these parking spaces, as now not only is more green energy available, but the vehicles are also protected from sun, bad weather, dirt, leaves, and so on.

However, like the first type, it also exhibits very low performance with high EV fluctuations in the parking lot. Therefore the 35 PV systems did not have a large effect on the Duck Curve in any of the simulation results. At higher EV adoption rates, this effect is even smaller. However, in this scenario, other approaches and technologies in combination with the PV systems, can make this type of parking facility a valid solution.

The analysis for the third type of parking facility is likely to be the most interesting for the future because it has the greatest impact on the electric grid, as it has a very high energy demand for EVs and is critical to the design and construction of future parking facilities. These not only provide sufficient space for the PV systems, but can also be optimally designed.

In this scenario, a high number of PV systems can, in the best case, carry the entire load of EVs over the midday period. Since the PV systems only produce electricity over the midday period and this electricity is also consumed very quickly by the EVs, the amount of electricity for home charging does not change. Although a very high number of PV systems can produce enough energy, which can then be stored allowing the EVs to utilize this energy at the parking facility in the evening. This results in a reduction of the evening electricity peak, but not in a reduction of the amount of energy required at home in the evening. Looking at the numbers, it actually sounds pretty good that you can sustain the entire load at a 100 % adoption rate with approximately 3400 PV systems. Considering now the results of the best-case scenario with additional technologies and charging clusters, even 850 PVs can mitigate the entire EV energy demand. However, when the numbers are compared to the number of parking spaces, it quickly becomes clear that a much larger number of PV systems are required. For 35 parking spaces, you would need about 850 to 3.400 PV systems, depending on the scenario.

However, comparing this to the required size of the PV systems and the size of the parking lot, it becomes clear how big the difference is. Taking into account the pure parking area of the parking facilities, the size is about 385 m^2. Considering the PV systems, which have a size of approx. 10 m^2 in our simulation assumption, the area required is approx. 8.500 m^2 to 34.000 m^2. For comparison, a soccer field is about 7.140 m^2. This means that the parking lot has a pure parking area of 0,05 soccer fields. The PV systems, on the other hand, require 1,19 to 4,76 soccer fields. By integrating other technologies and approaches, this area can certainly be reduced even further. And if, for example, the intention is not to cover the entire load, but only a large part, 425 PV systems with a 100 % adoption rate will suffice in this case.

Here, too, the adoption rate is an important influencing factor. The smaller the adoption rate, the fewer PV systems are needed to cover the new load. In the long term, however, the adoption rate will increase steadily, so that the space issue must always be kept in mind when building a new modern parking facility. This is especially important, because there is always a higher cost and effort afterwards, if you want to adjust them again. If at all then it is still possible to expand the parking facility or the amount of PV systems.

The lesson from this PV system discussion is that PV systems can always cover the entire load of EVs, provided there is enough space. However, realistically this is very rarely the case in these large dimensions. However, PV systems perform very well at lower adoption rates, since in this case the number PV systems or area required is still very small to relieve the power grid of the new EV energy load.

In summary, on-site behind-the-meter PV generation and storage can further enhance the benefits of clustering EV charging from a grid integration perspective only in certain environments, such as small parking facilities with low EV traffic, low EV adoption rates, in combination with other technologies and approaches, or when there is sufficient free space to install a large number of PV systems.

The last big item in this discussion is the inclusion of workplace charging and other technologies. Thanks to the sensitivity analysis, it is observed that workplace charging, as well as other technologies, contributes a very important part to the success of PV systems. This is because these can drastically reduce, as well as increase, the number of PV systems needed to reduce the energy demand of the EVs. Moreover, they have only a minor impact on the effects of EV charging stations. This is because they depend more on the duration of parking than on the battery level. A high battery level therefore only has a positive effect on parked EVs that are only parked for a short period of time. For example, they can be charged to 100 % instead of 75 % during this short time.

Therefore, additional clusters such as workplace charging can have a very positive impact on the energy demand of the individual parking facility. However, in this way, the total power demand is merely divided among several clusters and not reduced. This means that each individual cluster or parking space requires less power, but the power grid as a whole is still loaded the same. In special cases, this can also be helpful for the power grid, e.g. if a region as a whole already has a high energy demand and the load can then be distributed outside this region thanks to another charging cluster. Thus, charging at the workplace can distribute the load spatially over the power grid and to a small degree also distribute the load in general slightly over the day. Looking only at the EVs entering a fully optimized parking facilities, the new cluster has hardly any impact on the load distribution, since the parking facilities already do this optimally. However, if we now consider additional EVs, then each additional cluster leads to an improved load distribution over the day, so that the phenomena of the Duck Curve are reduced.

In general, therefore, it can be said that the combination of all the approaches presented results in a very large potential for the EV charging cluster in parking garages. Moreover, this cluster is essential as a basis for further technologies and approaches.

6 Future Work

This chapter proposes further research topics that could build on or be of interest alongside this thesis. To better structure this section, the topics were sorted into four superior clusters. These four are: (1) consideration of parking facilities, (2) addition of further criteria, (3) different approaches and technologies and (4) other.

In general, parking facilities are very similar. Therefore, the results can be well applied to other types of parking facilities. However, the sensitivity analysis demonstrated that EV traffic is an important influencing factor. Therefore, the first proposal for future work is the transfer and analysis of different parking facilities. Parking facilities are essentially the same, i.e., a car parks in the lot for a certain amount of time and then leaves, but parking duration and traffic can vary greatly. This applies not only to different types of parking facilities, but also to individual parking facilities of the same type. Therefore, it seems interesting to run this simulation for park-and-ride facilities, grocery parking facilities, shopping mall parking facilities, urban parking facilities, etc., and compare the results.

On this basis, it also seems very interesting to test and analyze a real world prototype. Analyzing data from real parking facilities with EV chargers and PV systems can provide even deeper and new insights. Although the real world can be simulated very accurately with today's technology, the real world still looks a little different. In addition to the classic parking facilities listed above, it may also be interesting to consider new modern parking garages. Those include new and extraordinary parking garages, which, for example, are located below the surface to save space and independently transport cars to a parking space with the help of cranes. To what extent can these be equipped with charger technologies and PV systems.

Besides parking facilities, the addition of other influencing factors or simulation objects can be interesting for further research. As mentioned above, the choice of parking facilities is very important. Therefore, it can be interesting to run this simulation for a specific parking facilities. In this case, other factors can be taken into account, such as the performance of a geo-analysis. Thus, other EV charging clusters in the area, traffic, types of residents, and specific weather data can then be added. In addition, a future analysis can also be conducted for this location, for example, to predict the EV adoption rate for this area or the attractiveness for additional businesses in the area. This could lead to an increase or decrease in population and therefore lead to high traffic volumes.

In addition to these other aspects, the inclusion of other electric vehicles could also be interesting. It is not impossible that in the future there will be electric buses, electric trucks, electric motorcycles or other small electric vehicles such as electric bicycles, in addition to the usual electric vehicles. While an electric bus would probably not use regular parking facilities, it would use, for example, a parking lot at a highway rest stop. Each of these EV types has different characteristics, such as larger or smaller batteries, different parking times and parking duration. Therefore, it is very interesting to see how the simulation of a parking facility reacts to these new circumstances and how the Duck Curve responds to them.

Other new influencing factors that could be considered would be the integration of detailed EV owner behavior. For that, willingness to pay for the charging feature or other demographic factors could be added to analyze the influence and power of users behaviour.

In the presented simulation, it is possible that the parking facilities can be used twenty-four hours every day of the week. Therefore, it might be interesting to see how the simulation reacts to different opening hours.

Next, possible future work will be presented with a focus on additional approaches and technologies. One could extend the simulation so that the energy from the EVs can also be fed back into the power grid. This approach could further address the Duck Curve issues and provide strong support to the power grid at critical moments. However, the owner of the EV would always have to agree to this, as it is not pleasant for him if, for example, he comes back from shopping and his EV is suddenly empty. These and other interactions could be studied based on the presented simulation to analyze their effects.

Another complex but also important aspect is smart charging. This may be difficult to implement in crowded parking garages with short parking duration, but the longer the parking duration, the more likely it is that smart charging can also solve some issues regarding the Duck Curve. For example, the smart chargers could decide to temporarily disable the charging function of the parking facilities when the power grid is overloaded by other unforeseen problems. This way, the power grid can be protected from collapses and other problems. Therefore, it also seems very interesting to integrate and analyze this approach in a simulation.

The last approaches and technologies presented here for further work are related to PV systems. For example, you could compare different manufacturers of PV systems with each other and see how the individual PV systems performs in the simulation. This can help parking facility owners make the right choice for themselves and check which type is best for the power grid. In addition, it is of interest to analyze the impact of distributing the energy generated in the parking facilities in a smart way instead of immediately. For example, more green electricity could be used in the mornings or evenings, when the parking facility's and other PV systems can no longer produce electricity. This could possibly have a stronger effect on the peak in the morning and evening.

Furthermore, the impact of additional external energy sources could be considered. Optimally, these would be other green energy sources such as wind energy, but other external suppliers could also have an impact on the power grid. This could also help to cover the new energy requirements of EVs.

In the present simulation, only the electricity from the PV systems on the parking facilities was stored and used by the EVs to relieve the load on the power grid. However, one could also simulate and analyze the possibility when storing electricity from the grid. For example, electricity could be drawn from the grid at night, when demand is very low, and then made available again at parking facilities at different peak times without affecting the power grid. However, this principle could also be analyzed in the other direction. If a parking facility has a high and highly fluctuating volume of EVs, it could also feed surplus PV energy into the power grid on weak days. In this way, not only the power grid operators benefit, but also the parking operators. Which also makes it more attractive for them to invest in a few more PV systems than in a couple less.

Other interesting topics for future work in this context could be risk and crisis scenarios. Questions such as "What happens to the charging stations if the power grid fails?", "What impact would this have on EV owners and charging station operators?", "What happens if the charging stations are faulty?", "What environmental factors could affect my charging stations?", "Are they protected from heavy rain and flooding?". These and other questions could be considered in such a risk analysis or simulation.

So far, the simulation has assumed that the acceptance of EVs will increase continuously. However, another interesting scenario for analysis would be if EVs did not prevail over ICVs or other technologies. For example, hydrogen cars could become popular or new technologies could be discovered that have not been considered before. Therefore, the development of new modern parking facilities should always consider what will change if this case occurs. An analysis of the flexibility of parking facilities and their ability to adapt to changes could be interesting. So could be a template for sustainable implantation of PV systems and charging stations for EVs. After all, we are talking about huge amounts of technology and other materials that should not be left to decompose in a secluded landfill in the future.

Based on the results of the presented simulation and the addition of further information and data, an investment plan for the smart grid could also be created. This can then help the power grid operator make valuable decisions and sustainably expand the power grid. The same applies to the perspective of the parking facilities operator. For this purpose, an analysis and simulation could also be carried out not on the basis of ecology, as is the case here, but on the basis of economics. For example, it could be considered how many PV systems bring the greatest profit.

7 Conclusion

Nach Absprache schreiben

A Appendix: Data Analysis Code

A.1 First Data Filter

Data Prep > Filter.py

```python
"First filter of the whole Data Set"

path = r'C:\Users\Danie\Simpy Master\Data Prep'            # Set the path of the folder where the data is located


import pandas as pd                                         # Pandas offers tools for the management of data and their analysis.

# Only read the relevant columns from the data set
data = pd.read_csv('Car.csv', usecols= ['DeviceId','ArrivalTime', 'DepartureTime', 'DurationMinutes', 'AreaName', 'BayId'])


data = data[data['AreaName'] == 'China Twon']               # Filter the new Data Set for the area China Town

data.to_csv('outputCT.csv')                                 # Create a new CSV File


print ("finished")

```

A.2 First Data Analysis

Data Prep > DataAnalyse.py > ...

```python
"Data Analyse: first impression and some key facts"

path = r'C:\Users\Danie\Simpy Master\Data Prep'         # Set the path of the folder where the data is located


import pandas as pd                                     # Pandas offers tools for the management of data and their analysis.

data = pd.read_csv('outputCTMar.csv')                   # Import all arrivals of China Town in march



print('China Town parking spaces = %d' %(data['DeviceId'].nunique()))    # Count all sensors by just filtering through unique sensors

index = data.index                                      # Determination of the index
number_of_arrivals = len(index)                         # Count the number of arrivals in March


print('China Town arrivals in Mar = %d'  % (number_of_arrivals))

print ('China Town mean parking duration = %d' % (data['DurationMinutes'].mean()))  # Determination of the mean parking duration


print ("finished")
```

A.3 Data Analysis And Data Preparation

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import datetime as dt
import numpy as np
import math
```

In [204]:
```
# Read the filtered Data from car arrivals of China Town
sample_data = pd.read_csv('outputCT.csv')
```

In [205]:
```
# First impression of the consisting data
sample_data
```

Out[205]:

	Unnamed: 0	DeviceId	ArrivalTime	DepartureTime	DurationMinutes	AreaName	BayId
0	3281	18167	02/21/2020 05:27:31 AM	02/21/2020 10:30:18 PM	1023	Chinatown	1007
1	5361	18167	03/22/2020 07:30:00 AM	03/23/2020 12:00:00 AM	990	Chinatown	1007
2	17774	18167	04/10/2020 10:30:18 PM	04/11/2020 12:00:00 AM	90	Chinatown	1007
3	34953	18167	04/10/2020 07:30:00 AM	04/11/2020 12:00:00 AM	990	Chinatown	1007
4	35096	18196	04/22/2020 04:55:50 AM	04/22/2020 09:58:37 PM	1023	Chinatown	878
...	...	...	...	...	...	...	...
204118	13747834	28758	04/01/2020 01:23:29 PM	04/01/2020 01:41:16 PM	18	Chinatown	869
204119	13747852	28758	03/02/2020 09:31:09 PM	03/02/2020 09:32:15 PM	1	Chinatown	869
204120	13747855	28758	02/22/2020 01:57:13 PM	02/22/2020 02:02:27 PM	5	Chinatown	869
204121	13747858	28758	02/23/2020 05:47:41 PM	02/23/2020 06:20:21 PM	33	Chinatown	869
204122	13747867	28758	02/23/2020 05:49:04 AM	02/23/2020 07:30:00 AM	101	Chinatown	869

204123 rows × 7 columns

In [206]:
```
# Check the Type of the collums
type(sample_data.ArrivalTime.iloc[1])
```

Out[206]: str

In [207]:
```
# Use the fact that it is a string and the month is at the beginning
# Filter the data to get all the records from march
data = sample_data.ArrivalTime.str.startswith('03')
```

In [208]:
```
# New data set of true and false if it start with an 03 or not
data
```

Out[208]:
```
0         False
1          True
2         False
3         False
4         False
          ...
204118    False
204119     True
204120    False
204121    False
204122    False
Name: ArrivalTime, Length: 204123, dtype: bool
```

In [209]:
```
# Combine the two data to get the final data set which then only contains 03
sample_data = sample_data[data]
sample_data
```

Out[209]:

	Unnamed: 0	DeviceId	ArrivalTime	DepartureTime	DurationMinutes	AreaName	BayId
1	5361	18167	03/22/2020 07:30:00 AM	03/23/2020 12:00:00 AM	990	Chinatown	1007
6	42790	18196	03/03/2020 07:30:00 AM	03/04/2020 12:00:00 AM	990	Chinatown	878
27	1099330	26526	03/20/2020 02:01:23 PM	03/20/2020 02:02:15 PM	1	Chinatown	932
29	1214087	25984	03/20/2020 01:39:38 PM	03/20/2020 01:39:57 PM	0	Chinatown	877
33	2583956	28758	03/18/2020 01:24:53 PM	03/18/2020 01:25:00 PM	1	Chinatown	869
...	...	...	...	...	...	...	...
204106	13747623	28758	03/08/2020 11:11:42 AM	03/08/2020 11:13:33 AM	2	Chinatown	869
204109	13747692	28758	03/04/2020 03:46:47 PM	03/04/2020 03:48:26 PM	2	Chinatown	869
204112	13747726	28758	03/17/2020 09:09:01 PM	03/17/2020 09:18:46 PM	9	Chinatown	869
204114	13747774	28758	03/09/2020 07:18:40 PM	03/09/2020 07:20:35 PM	2	Chinatown	869
204119	13747852	28758	03/02/2020 09:31:09 PM	03/02/2020 09:32:15 PM	1	Chinatown	869

51118 rows × 7 columns

In [210]:
```
# Change the type to work with the time in future steps
update_data= sample_data.astype({'ArrivalTime':'datetime64[ns]'})
```

In [211]:
```
# Change the type to work with the time in future steps
update_data2= update_data.astype({'DepartureTime':'datetime64[ns]'})
```

In [212]:
```
# Show new data set
update_data2
```

Out[212]:

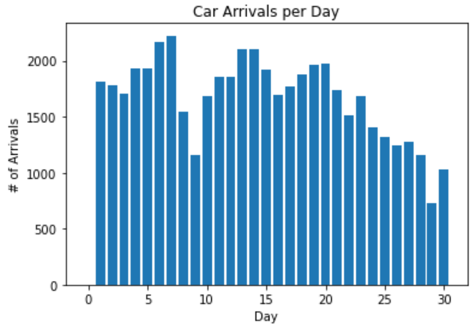
	Unnamed: 0	DeviceId	ArrivalTime	DepartureTime	DurationMinutes	AreaName	BayId
1	5361	18167	2020-03-22 07:30:00	2020-03-23 00:00:00	990	Chinatown	1007
6	42790	18196	2020-03-03 07:30:00	2020-03-04 00:00:00	990	Chinatown	878
27	1099330	26526	2020-03-20 14:01:23	2020-03-20 14:02:15	1	Chinatown	932
29	1214087	25984	2020-03-20 13:39:38	2020-03-20 13:39:57	0	Chinatown	877
33	2583956	28758	2020-03-18 13:24:53	2020-03-18 13:25:00	1	Chinatown	869
...	...	...	...	...	...	...	...
204106	13747623	28758	2020-03-08 11:11:42	2020-03-08 11:13:33	2	Chinatown	869
204109	13747692	28758	2020-03-04 15:46:47	2020-03-04 15:48:26	2	Chinatown	869
204112	13747726	28758	2020-03-17 21:09:01	2020-03-17 21:18:46	9	Chinatown	869
204114	13747774	28758	2020-03-09 19:18:40	2020-03-09 19:20:35	2	Chinatown	869
204119	13747852	28758	2020-03-02 21:31:09	2020-03-02 21:32:15	1	Chinatown	869

51118 rows × 7 columns

In [213]:
```
# Check if the type change worked
type(update_data2.ArrivalTime.iloc[1])
```

Out[213]:
```
pandas._libs.tslibs.timestamps.Timestamp
```

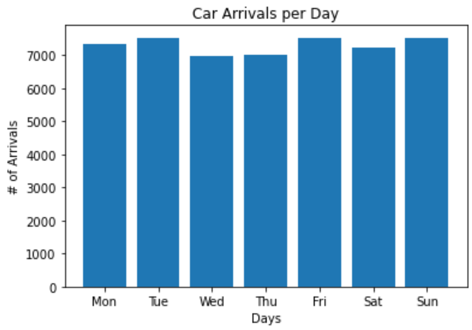
In [214]:
```
day_data_ev = []

# Append the count of car arrivals for every hour of the day
for i in range(0,31):
    day_data_ev.append([i,update_data2['ArrivalTime'].loc[(update_data2['ArrivalTime'].dt.day) == i].count()])

# Change array to DataFrame for visualization

day_data_ev = pd.DataFrame(day_data_ev)

# Bar chart the hour of day data and give labels
plt.bar(day_data_ev[0],day_data_ev[1])
plt.xlabel('Day')
plt.ylabel('# of Arrivals')
plt.title('Car Arrivals per Day')
plt.show()
```



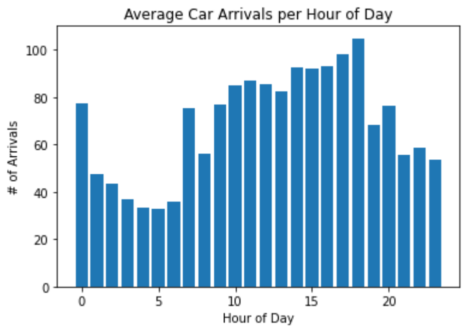
In [215]:
```
# Define the days of the week
daysofweek = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
```

In [216]:
```
dayofweek_data_ev = []

# Append the count of every day of the week to the array
for i in range(0,7):
    dayofweek_data_ev.append([i,update_data2['ArrivalTime'].loc[(update_data2['ArrivalTime'].dt.dayofweek) == i].count()])

# Change array to DataFrame for visualization
dayofweek_data_ev = pd.DataFrame(dayofweek_data_ev)
```

In [217]:
```
# Bar chart day of week data
plt.bar(daysofweek,dayofweek_data_ev[1])


# Give titles
plt.xlabel('Days')
plt.ylabel('# of Arrivals')
plt.title('Car Arrivals per Day')
plt.show()
```

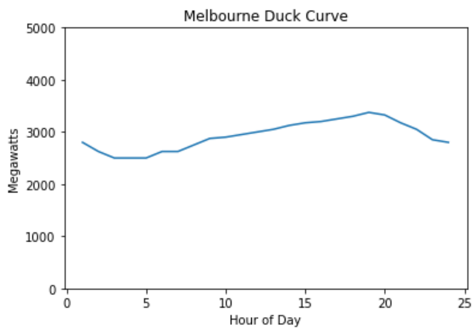


In [218]:
```
hourofday_data_ev = []

# Append the count of car arrivals for every hour of the day
for i in range(0,24):
    hourofday_data_ev.append([i,update_data2['ArrivalTime'].loc[(update_data2['ArrivalTime'].dt.hour) == i].count()])

# Change array to DataFrame for visualization
hourofday_data_ev = pd.DataFrame(hourofday_data_ev)
hourofday_data_ev[1] = hourofday_data_ev[1].div(31).round(2)

# Bar chart the hour of day data and give labels
plt.bar(hourofday_data_ev[0],hourofday_data_ev[1])
plt.xlabel('Hour of Day')
plt.ylabel('# of Arrivals')
plt.title('Average Car Arrivals per Hour of Day')
plt.show()
```

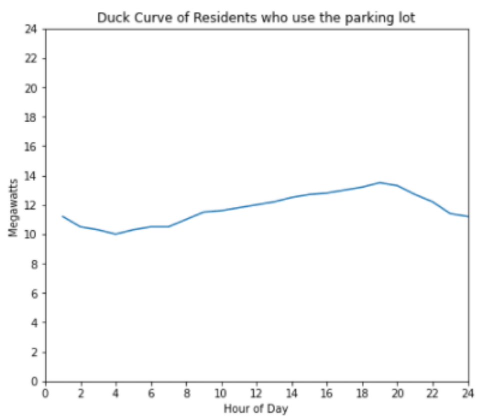


```
In [ ]: #The Duck Curve of California transformed to the "Duck Curve" of Mellbourne
        # California has 40 million and Melbourne has 5 mil inhabitants
```

```
In [12]: # plot the data
         # x = hours
         # y = Energy consumption

         x = [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24]
         y = [2800, 2625, 2500, 2500, 2500, 2625, 2625, 2750, 2875, 2900, 2950, 3000, 3050, 3125, 3175, 3200, 3250, 3300, 3375, 3325, 31

         plt.ylim(ymin=0, ymax=5000)

         plt.plot(x,y)
         plt.xlabel('Hour of Day')
         plt.ylabel('Megawatts')
         plt.title('Melbourne Duck Curve')
         plt.show()
```




```
In [11]: #Duck Curve for our Parking Space arrivals (204.199)
         #This illustrate the impact better, since the Megawatts are reduce
         # 5.000.000 / 200.000 = 250  --> 2.800 / 250 = 11,2
         # x = hours
         # y = Duck Curve

         x = [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24]
         y = [11.2, 10.5, 10.3, 10, 10.3, 10.5, 10.5, 11, 11.5, 11.6, 11.8, 12, 12.2, 12.5, 12.7, 12.8, 13, 13.2, 13.5, 13.3, 12.7, 12.2,


         f = plt.figure()
         f.set_figwidth(7)
         f.set_figheight(6)

         plt.ylim(ymin=0, ymax=20)
         plt.xlim(xmin=0, xmax=24)
         plt.xticks(np.arange(0, len(x)+1,2))
         plt.yticks(np.arange(0, len(y)+1,2))


         plt.plot(x,y)
         plt.xlabel('Hour of Day')
         plt.ylabel('Megawatts')
         plt.title('Duck Curve of Residents who use the parking lot')
         plt.show()
```



B Appendix: Simulation Code

B.1 Simulation Overview

```python
"import relevant library"
import itertools                # Functional tools for creating and using iterators.
import random                   # Random variable generators.
import collections              # This module implements specialized container datatypes providing alternatives to Python's general purpose built-in containers, dict, list, set,
import pandas as pd             # Pandas offers tools for the management of data and their analysis.

import simpy                    # Simulation Environment

"Scenario / Environment Properties"
SIM_TIME = 86400                # Simulation time in seconds

#Parking Spaces Properties
NORMAL_SPACES = 25              # Amount of normal parking Spaces

#PV Properties
PV_COUNT = 3                    # Amount of PVs with 1 killowatt-peak equals 4 to 6 moduls, which together occupy a area of 8 to 10 square meters.
PV_GENERATION = 0.4             # PV Generation per 1 hour  - approx. 7 hours sunlight 1 killowatt-peak approx. 1,000 kw per year / 365 /7 = 0.4; Later weather dependent
PV_STORE = 3                    # Max Energy a PV Generator can store kwh

#Charging Stations Properties
CS_COUNT_1 = 5                  # Amount of Charging Stations Level 1
CS_COUNT_2 = 5                  # Amount of Charging Stations Level 2
CS_SPEED_1 = 19.2               # Charging Speed - Level 2
CS_SPEED_2 = 80                 # Charging Speed - Level 3 DC

#Car Properties
BATTERY_SIZE = [30, 100]        # Min von 30 kw/h - Max 100 kw/h
BATTERY_LEVEL = [5, 99]         # Min/max levels of battery level (in volt)
TIME_OF_STAY = [300,2000]       # Min/max duration of a car parking
CHARGING_PROBABILITY = [1,100]  # Percentage of an EV owner probabilty of charging his EV
EV_ADOPTION = 25                # Percentage of EV Adoption


"A car arrives at the parking loot."
def arrival(name, env, parking_loot, car_type, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2):···

"A EV charges at a Level 1 Charging Station"
def charge_processL1(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2):···

"A EV charges at a Level 2 Charging Station"
def charge_processL2(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2):···

"A Vehicle parks at a regular parking spot"
def parking_process(name, env, p_space, num_tickets, ChargingStation, car_type, export_data):···

"The Production of Energy from the PV systems"
def pv_producer(env, pv_generator):···

"A Vehicle / EV is generated for the Simulation"
def car_generator(env, parking_loot, charge_station, export_data, export_data1, export_data2):···


"Set Up of the Simulation Environment"
i = 1
while i < 101:      #101···
```

B.2 Entire Simulation Code

```python
"""
Simulation of a Parking lot with charging stations and PV systems



Scenario:
  A parking lot has a limited number of charging stations and PV systems.
  The charging stations always use the generated PV energy first before accessing the power grid.

"""


"import relevant library"
import itertools                # Functional tools for creating and using iterators.
import random                   # Random variable generators.
import collections              # This module implements specialized container datatypes providing alternatives to Python's general purpose built-in containers, dict, list, set, and tuple.
import pandas as pd             # Pandas offers tools for the management of data and their analysis.

import simpy                    # Simulation Environment

"Scenario / Environment Properties"
SIM_TIME = 86400                # Simulation time in seconds

#Parking Spaces Properties
NORMAL_SPACES = 25              # Amount of normal parking Spaces

#PV Properties
PV_COUNT = 3                    # Amount of PVs with 1 killowatt-peak equals 4 to 6 moduls, which together occupy a area of 8 to 10 square meters.
PV_GENERATION = 0.4             # PV Generation per 1 hour  - approx. 7 hours sunlight 1 killowatt-peak approx. 1,000 kw per year / 365 /7 = 0.4; Later weather dependent
PV_STORE = 3                    # Max Energy a PV Generator can store kwh

#Charging Stations Properties
CS_COUNT_1 = 5                  # Amount of Charging Stations Level 1
CS_COUNT_2 = 5                  # Amount of Charging Stations Level 2
CS_SPEED_1 = 19.2               # Charging Speed - Level 2
CS_SPEED_2 = 80                 # Charging Speed - Level 3 DC

#Car Properties
BATTERY_SIZE = [30, 100]        # Min von 30 kw/h - Max 100 kw/h
BATTERY_LEVEL = [5, 99]         # Min/max levels of battery level (in volt)
TIME_OF_STAY = [300,2000]       # Min/max duration of a car parking
CHARGING_PROBABILITY = [1,100]  # Percentage of an EV owner probabilty of charging his EV
EV_ADOPTION = 25                # Percentage of EV Adoption

```

```python
"A car arrives at the parking loot."
def arrival(name, env, parking_loot, car_type, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2):
    """
    If the car is an EV it tries to request the charging process.
    If the car is a normal vehicle it tries to request the parking process.

    """


    print('%s arriving at parking loot at %.1f' % (name, env.now))        # A vehicle enters the parking loot
    with parking_loot.request() as req:
        start = env.now                                                   # Timestamp of the arrival

        yield req                                                         # Ressource solt is requested


        "normal vehicle process"

        if car_type == 1:                                                 # Identify a normal vehicle
          if(not ChargingStation.available[p_space]):                     # Check if a normal praking space is free
            print('There is no free parking spot for %s and it can not park at a charging station.' % p_space)
            return                                                        # No parking spot is available / The EV leaves the parking loot
          else:
            yield env.process(parking_process(name, env, p_space, num_tickets, ChargingStation, car_type, export_data))
            return                                                        # The parking process was triggerd




        "EV process Level 1 Preference"

        if p_space == 'Level 1':                                          # Check charger Level preference
          if not ChargingStation.availableL1[p_space]:                    # Check charger availability
           print('There is no free parking spot for %s' % p_space)
          else:
            yield req                                                     # Ressource solt is requested
            yield env.process(charge_processL1(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2))
            return                                                        # The charging process was triggerd

          if not ChargingStation.availableL2[p_space]:                    # Check availability of the second charger Level preference
            print('There is no free parking spot for Level 2')
          else:
            yield env.process(charge_processL2(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2))
            return                                                        # The charging process was triggerd

          if not ChargingStation.available[p_space]:                      # Check if at least a normal parking space is free
            print('There is no free parking spot for %s ' % name)

            # Set Up the properties of the EV for the Home Charging consumption
            battery_capacity = random.randint(*BATTERY_SIZE)
            battery_level = random.randint(5,battery_capacity-1)
            power_required = battery_capacity - battery_level
```

```python

                # Track the requiered energy for the EV at home
                home_charg.put(power_required + random.randint(5,battery_level))
                item = (env.now, power_required + random.randint(5,battery_level))
                export_data.append(item)
                return
            else:                                                           # Nomal parking spot is available
                yield env.process(parking_process(name, env, p_space, num_tickets, ChargingStation, car_type, export_data))
                return                                                      # Parking process was triggered



        "EV process Level 2 Preference"

        if p_space == 'Level 2':                                            # Check charger Level preference
            if not ChargingStation.availableL2[p_space]:                    # Check charger availability
                print('There is no free parking spot for %s' % p_space)
            else:
                yield env.process(charge_processL2(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2))
                return                                                      # The charging process was triggerd

            if not ChargingStation.availableL1[p_space]:                    # Check availability of the second charger Level preference
                print('There is no free parking spot for Level 1')
            else:
                yield env.process(charge_processL1(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2))
                return                                                      # The charging process was triggerd

            if not ChargingStation.available[p_space]:                      # Check if at least a normal parking space is free
                print('There is no free parking spot for %s ' % name)

                # Set Up the properties of the EV for the Home Charging consumption
                battery_capacity = random.randint(*BATTERY_SIZE)
                battery_level = random.randint(5,battery_capacity-1)
                power_required = battery_capacity - battery_level

                # Track the requiered energy for the EV at home
                home_charg.put(power_required + random.randint(5,battery_level))
                item = (env.now, power_required + random.randint(5,battery_level))
                export_data.append(item)
                return
            else:                                                           # Nomal parking spot is available
                yield env.process(parking_process(name, env, p_space, num_tickets, ChargingStation, car_type, export_data))
                return                                                      # Parking process was triggered


        return
"A EV charges at a Level 1 Charging Station"
def charge_processL1(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2):

    # Set Up of the EV and the Charger
    start = env.now
    battery_capacity = random.randint(*BATTERY_SIZE)
    battery_level = random.randint(5,battery_capacity-1)
    parking_time = random.randint(*TIME_OF_STAY)
    charge_preference = random.randint(*CHARGING_PROBABILITY)
    power_required = battery_capacity - battery_level
    power_possible = CS_SPEED_1 * parking_time
    if power_possible >= power_required:                            # Compare power possible & power required, so that not to much energy is wrongly consumed
        power_possible = power_required




    ChargingStation.availableL1[p_space] -= num_tickets             # Occupy the parking lot

    "Check charging willingness"
    if parking_time < 350 | charge_preference < 20 | power_required < 5:                           # Check park duration of the EV
        yield env.timeout(parking_time)                             # EV parks for x minutes
        print('%s parked in Level 1 for %.1f seconds, but did not charged due too low parking time' % (name, env.now - start))
        ChargingStation.availableL1[p_space] += num_tickets         # Parking lot becomes available again

        # Track the requiered energy for the EV at home
        home_charg.put(power_required + random.randint(5,battery_level))
        item = (env.now, power_required + random.randint(5,battery_level))
        export_data.append(item)
        return





    "The actual charging process"

    if pv_generator.level < power_possible:                         # Check PV energy availability for the upcoming charging process

        yield power_grid.put(power_possible - pv_generator.level)   # Track power grid energy consumption
        item = (env.now, power_possible-pv_generator.level)
        export_data1.append(item)
```

```
            if not pv_generator.level == 0:                                     # Check PV energy level
                item1 = (env.now, pv_generator.level)
                export_data2.append(item1)
                yield pv_generator.get(pv_generator.level)                      # Track PV energy consumption / empty the pv system
        else:
            item1 = (env.now, power_possible)
            export_data2.append(item1)
            yield pv_generator.get(power_possible)                              # Track PV energy consumption / get the energy requiered


        yield env.timeout(parking_time)                                         # EV parks for x minutes



        print('%s finished charging Level 1 in %.1f seconds.' % (name, env.now - start))
        ChargingStation.availableL1[p_space] += num_tickets                     # Parking lot becomes available again

        # Track the requiered energy for the EV at home
        if not power_required == power_possible:
            home_charg.put(random.randint(power_required - power_possible + 5))
            item = (env.now, random.randint(power_required - power_possible + 5))
            export_data.append(item)
        else:
            home_charg.put(5)
            item = (env.now, 5)
            export_data.append(item)

        return
```

```
"A EV charges at a Level 2 Charging Station"
def charge_processL2(name, env, p_space, num_tickets, ChargingStation, export_data, export_data1, export_data2):

        # Set Up of the EV and the Charger
        start = env.now
        battery_capacity = random.randint(*BATTERY_SIZE)
        battery_level = random.randint(5,battery_capacity-1)
        parking_time = random.randint(*TIME_OF_STAY)
        charge_preference = random.randint(*CHARGING_PROBABILITY)
        power_required = battery_capacity - battery_level
        power_possible = CS_SPEED_2 * parking_time
        if power_possible > power_required:                                     # Compare power possible & power required, so that not to
            power_possible = power_required

        ChargingStation.availableL2[p_space] -= num_tickets                     # Occupy the parking lot


        "Check charging willingness"
        if parking_time < 350 | charge_preference < 20 | power_required < 5:                                            # Check park
            yield env.timeout(parking_time)                                     # EV parks for x minutes
            print('%s parked in Level 2 for %.1f seconds, but did not charged due too low parking time' % (name, env.now - start))
            ChargingStation.availableL2[p_space] += num_tickets                 # Parking lot becomes available again

            # Track the requiered energy for the EV at home
            home_charg.put(power_required + random.randint(5,battery_level))
            item = (env.now, power_required + random.randint(5,battery_level))
            export_data.append(item)
            return





        "The actual charging process"

        if pv_generator.level < power_possible:                                 # Check PV energy availability for the upcoming charging

            yield power_grid.put(power_possible - pv_generator.level)           # Track power grid energy consumption
            item = (env.now, power_possible-pv_generator.level)
            export_data1.append(item)
            if not pv_generator.level == 0:                                     # Check PV energy level
                item1 = (env.now, pv_generator.level)
                export_data2.append(item1)
                yield pv_generator.get(pv_generator.level)                      # Track PV energy consumption / empty the pv system
```

```python
            else:
                item1 = (env.now, power_possible)
                export_data2.append(item1)
                yield pv_generator.get(power_possible)                        # Track PV energy consumption / get the energy requiered


            yield env.timeout(parking_time)                                   # EV parks for x minutes


            print('%s finished charging Level 2 in %.1f seconds.' % (name, env.now - start))
            ChargingStation.availableL2[p_space] += num_tickets               # Parking lot becomes available again

            # Track the requiered energy for the EV at home
            if not power_required == power_possible:
                home_charg.put(random.randint(power_required - power_possible + 5))
                item = (env.now, random.randint(power_required - power_possible + 5))
                export_data.append(item)
            else:
                home_charg.put(5)
                item = (env.now, 5)
                export_data.append(item)

            return

"A Vehicle parks at a regular parking spot"
def parking_process(name, env, p_space, num_tickets, ChargingStation, car_type, export_data):


    if car_type ==  2:                                                        # Check if an EV parks at the regular parking spot
        # Set Up the properties of the EV for the Home Charging consumption
        battery_capacity = random.randint(*BATTERY_SIZE)
        battery_level = random.randint(5,battery_capacity-1)
        power_required = battery_capacity - battery_level

        # Track the requiered energy for the EV at home
        home_charg.put(power_required + random.randint(5,battery_level))
        item = (env.now, power_required + random.randint(5,battery_level))
        export_data.append(item)

    parking_time = random.randint(*TIME_OF_STAY)                              # Set the parking duration
    ChargingStation.available[p_space] -= num_tickets                         # Occupy the parking lot
    yield env.timeout(parking_time)                                           # Vehicle / EV parks for x minutes
    print(name + ' Parks for %.1f' % (env.now))
    ChargingStation.available[p_space] += num_tickets                         # Parking lot becomes available again
    return

"The Production of Energy from the PV systems"
def pv_producer(env, pv_generator):


        while True:                                                           # PV produce every hour a certain amount of energy


            if env.now >= 32400 and env.now <= 57600:                         # from 9 am - 4 pm
                if env.now >= 39600 and env.now <= 52200:                     # from 11 am - 2:30 pm
                    pv_generator.put((PV_GENERATION + 0.1) * PV_COUNT)        # Produce more energy and store it

                else:
                    pv_generator.put((PV_GENERATION - 0.1) * PV_COUNT)        # Produce less energy and store it


            print(pv_generator.level)
            yield env.timeout(3600)                                           # Update every hour
```

```python
"A Vehicle / EV is generated for the Simulation"
def car_generator(env, parking_loot, charge_station, export_data, export_data1, export_data2):
    "Generate new cars that arrive at the parking loot."

    for i in itertools.count():                                  # Generate cars depending on the time of Day

        if env.now <= 3600:                                      # 3 600 Seconds = 1 Hour
            yield env.timeout(random.randint(40,50))
        elif env.now <= 7200:
            yield env.timeout(random.randint(70,80))
        elif env.now <= 10800:
            yield env.timeout(random.randint(75,85))
        elif env.now <= 14400:
            yield env.timeout(random.randint(90,100))
        elif env.now <= 18000:
            yield env.timeout(random.randint(100,110))
        elif env.now <= 21600:
            yield env.timeout(random.randint(100,110))
        elif env.now <= 25200:
            yield env.timeout(random.randint(95,105))
        elif env.now <= 28800:
            yield env.timeout(random.randint(40,50))
        elif env.now <= 32400:
            yield env.timeout(random.randint(60,70))
        elif env.now <= 36000:
            yield env.timeout(random.randint(40,50))
        elif env.now <= 39600:
            yield env.timeout(random.randint(35,45))
        elif env.now <= 43200:
            yield env.timeout(random.randint(35,45))
        elif env.now <= 46800:
            yield env.timeout(random.randint(35,45))
        elif env.now <= 50400:
            yield env.timeout(random.randint(30,40))
        elif env.now <= 54000:
            yield env.timeout(random.randint(30,40))
        elif env.now <= 57600:
            yield env.timeout(random.randint(30,40))
        elif env.now <= 61200:
            yield env.timeout(random.randint(30,40))
        elif env.now <= 64800:
            yield env.timeout(random.randint(25,35))
        elif env.now <= 68400:
            yield env.timeout(random.randint(45,55))
        elif env.now <= 72000:
            yield env.timeout(random.randint(40,50))
        elif env.now <= 75600:
            yield env.timeout(random.randint(60,70))
        elif env.now <= 79200:
            yield env.timeout(random.randint(60,70))
        elif env.now <= 82800:
            yield env.timeout(random.randint(60,70))
        elif env.now <= 86400:
            yield env.timeout(random.randint(40,50))


        #create a EV or a regualr vehicle
        car_type = random.randint(0,100)
        if car_type <=  EV_ADOPTION:                             # Craete EV depending on the EV Adoption
          car_type = 2                                           # EV
        else:
          car_type =1                                            # regular vehicle



        if car_type ==  2:                                      # Set Up charging station Level prefference
          p_space = random.choice(['Level 1', 'Level 2'])

        else:
          p_space = 'normal'


        num_tickets = 1                                         # Set Up car size 1 = 1 parking space / For future Work with Trailer or truck
        print(p_space, car_type)

        env.process(arrival('Car %d' % i, env, parking_loot, car_type, p_space, num_tickets, charge_station, export_data, export_data1, export_data2)) # Arrival process is triggered
```

```python
"Set Up of the Simulation Environment"
i = 1
while i < 101:      #101

 #Create ParkingFacility as a collecter
 ParkingFacility = collections.namedtuple('ChargingStation', 'parking_loot, parking_space, available, availableL1, availableL2 ''sold_out')


 # Setup and start the simulation
 print('Parking Loot with Chargingstations')
 env = simpy.Environment()

 # Create ParkingFacility
 parking_loot = simpy.Resource(env, NORMAL_SPACES + CS_COUNT_1 + CS_COUNT_2)
 parking_space = ['normal','Level 1', 'Level 2']
 available = {p_space: NORMAL_SPACES for p_space in parking_space}
 availableL1 = {p_space: CS_COUNT_1 for p_space in parking_space}
 availableL2= {p_space: CS_COUNT_2 for p_space in parking_space}
 sold_out = {p_space: env.event() for p_space in parking_space}

 ParkingFacility = ParkingFacility(parking_loot, parking_space, available, availableL1, availableL2, sold_out)

 pv_generator = simpy.Container(env, PV_STORE, init=0)
 power_grid = simpy.Container(env, 100000, init=0)
 home_charg = simpy.Container(env, 100000, init=0)

 export_data = []            #Home Charge Energy
 export_data1 = []           #Energy Consumption over the Day
 export_data2 = []           #PV Energy Used

 # Create environment and start processes
 env.process(pv_producer(env, pv_generator))
 env.process(car_generator(env, parking_loot, ParkingFacility, export_data, export_data1, export_data2))

 # Execute!
 env.run(until=SIM_TIME)


 #Analyze
 print (' %d was gatherd from the power grid' % (power_grid.level))
 print (' %d was gatherd from the power grid at home' % (home_charg.level))


 # Convert track data
 my_df = pd.DataFrame(export_data)
 my_df1 = pd.DataFrame(export_data1)
 my_df2 = pd.DataFrame(export_data2)


 #Export data
 my_df.to_csv('homechargewithevandPV +%i.csv' % (i), index=False, header=True)
 my_df1.to_csv('chargeenergywithPV +%i.csv' % (i), index=False, header=True)
 my_df2.to_csv('PVEnergyConsumption +%i.csv' % (i), index=False, header=True)
 i  += 1
```

C Appendix: Results Code

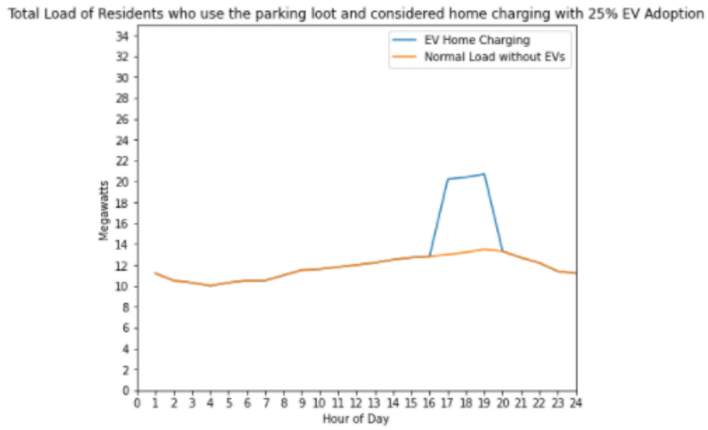
In [ ]:
```
# Results 1
# On this basis the results can be visualized
# The first results are focus only on the impact of home charging
# This means in this simulations the amount of charging stations at the parking facility is zero
```

In [27]:
```
home_charge_energy = []

# read all the 100 exported csv files from the simulation
# add all records together to calculate the total consumption of one day
for i in range(1,101):
    homedata = pd.read_csv('homecharge +%i.csv'%(i))
    netenergy = homedata['1'].sum()
    home_charge_energy.append([i,netenergy])


# get the mean of 100 days / simulations
home_charge_energy = pd.DataFrame(home_charge_energy)
mean_home_energy = home_charge_energy[1].mean()
```

In [29]:
```
#Mean home energy charging capacity over 100 Simulations
mean_home_energy
```

Out[29]: 22332.29

In [223]:
```
# Plot the data
# x = hours
# y = Duck Curve
# y2 = Duck Curve + Home charging

x = [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24]
y = [11.2, 10.5, 10.3, 10, 10.3, 10.5, 10.5, 11, 11.5, 11.6, 11.8, 12, 12.2, 12.5, 12.7, 12.8, 13, 13.2, 13.5, 13.3, 12.7, 12.2,

# Energy requiered 22 MW distributed 1/3 for 17,18,19pm when people are coming home from work
y2 = [11.2, 10.5, 10.3, 10, 10.3, 10.5, 10.5, 11, 11.5, 11.6, 11.8, 12, 12.2, 12.5, 12.7, 12.8, 20.2, 20.4, 20.7, 13.3, 12.7, 12

f = plt.figure()
f.set_figwidth(7)
f.set_figheight(6)

plt.ylim(ymin=0, ymax=35)
plt.xlim(xmin=0, xmax=24)
plt.xticks(np.arange(0, len(x)+1,1))
plt.yticks(np.arange(0, 35+1,2))

plt.xlabel('Hour of Day')
plt.ylabel('Megawatts')
plt.title('Total Load of Residents who use the parking loot and considered home charging with 25% EV Adoption')


plt.plot(x,y2, label="EV Home Charging")
plt.plot(x,y, label="Normal Load without EVs")
plt.legend()
plt.show()
```



In [ ]:

```
# Results 2:
# The next results represent the simulations with charging stations
```

In [224]:

```
home_charge_energy_with_EV_Spaces = []

# read all the 100 exported csv files from the simulation
# add all records together to calculate the total consumption of one day
for i in range(1,101):
    homedata = pd.read_csv('homechargewithev +%i.csv'%(i))
    netenergy = homedata['1'].sum()
    home_charge_energy_with_EV_Spaces.append([i,netenergy])

# get the mean of 100 days / simulations
home_charge_energy_with_EV_Spaces = pd.DataFrame(home_charge_energy_with_EV_Spaces)
mean_home_energy = home_charge_energy_with_EV_Spaces[1].mean()
```

In [261]:

```
# Show data
home_charge_energy_with_EV_Spaces
```

In [267]:

```
#Mean home energy kw charging capacity over 100 Simulations with 10 EV Charger
mean_home_energy
```

Out[267]:

```
1753.17
```

In [244]:

```
charge_energy_over_the_day = []


# read all the 100 exported csv files from the simulation about the chargers
# get the data for each hour
for i in range(1,101):
    chargedata = pd.read_csv('chargeenergy +%i.csv'%(i))
    chargedata['0'] = pd.to_datetime(chargedata['0'], unit='s')
    for i in range(0,24):
        charge_energy_over_the_day.append([i,sum(chargedata['1'].loc[(chargedata['0'].dt.hour) == i])])
```

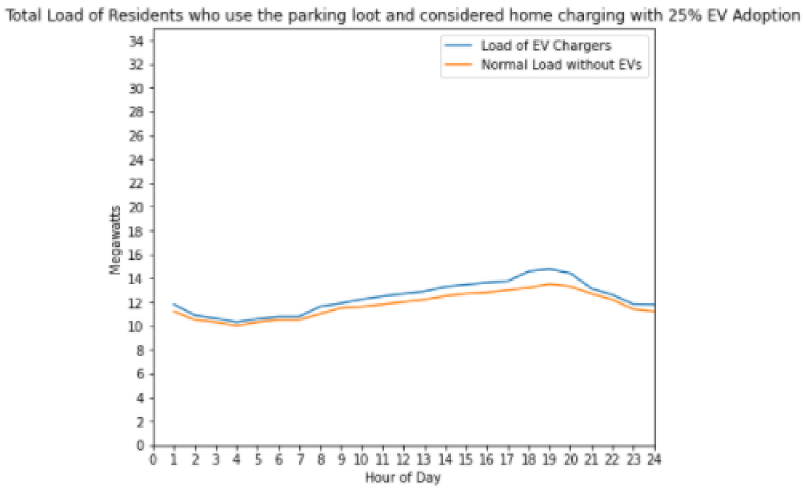
In [246]:

```
charge_energy_over_the_day = pd.DataFrame(charge_energy_over_the_day)
tmp = []

# summarize the data for each hour

for i in range(0,24):
        tmp.append([i,sum(charge_energy_over_the_day[1].loc[(charge_energy_over_the_day[0]) == i])])

tmp = pd.DataFrame(tmp)
```

In [248]:

```
# Calculate average per hour
tmp[1] = tmp[1].div(100).round(2)

# Convert KW to megawatts
tmp[1] = tmp[1].div(1000).round(2)
```

In [278]:
```
# plot the results
# x = hours
# y = duck curve

x = [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24]
y = [11.2, 10.5, 10.3, 10, 10.3, 10.5, 10.5, 11, 11.5, 11.6, 11.8, 12, 12.2, 12.5, 12.7, 12.8, 13, 13.2, 13.5, 13.3, 12

# Add new Energy requiered from EV Charger over the Day
sumCharge = tmp[1] + y
# Add new Energy requied from Home Charging in the evening 1.7 MW
sumCharge[17] = sumCharge[17] + 0.5
sumCharge[18] = sumCharge[18] + 0.7
sumCharge[19] = sumCharge[19] + 0.5

f = plt.figure()
f.set_figwidth(7)
f.set_figheight(6)

plt.ylim(ymin=0, ymax=35)
plt.xlim(xmin=0, xmax=24)
plt.xticks(np.arange(0, len(x)+1,1))
plt.yticks(np.arange(0, 35+1,2))

plt.xlabel('Hour of Day')
plt.ylabel('Megawatts')
plt.title('Total Load of Residents who use the parking loot and considered home charging with 25% EV Adoption')



plt.plot(x,sumCharge, label="Load of EV Chargers")
plt.plot(x,y, label="Normal Load without EVs")
plt.legend()
plt.show()
```



In [ ]:
```
# Results 3
#PV will be integrated; we start with 3 PVs
```

In [21]:
```

home_charge_energy_with_EV_Spaces_PV = []

# read all the 100 exported csv files from the simulation
# add all records together to calculate the total consumption of one day
for i in range(1,101):
    homedata = pd.read_csv('homechargewithevandPV +%i.csv'%(i))
    netenergy = homedata['1'].sum()
    home_charge_energy_with_EV_Spaces_PV.append([i,netenergy])

# get the mean of 100 days / simulations
home_charge_energy_with_EV_Spaces_PV = pd.DataFrame(home_charge_energy_with_EV_Spaces_PV)
mean_home_energy = home_charge_energy_with_EV_Spaces_PV[1].mean()
```

In [272]:
```
# Show the mean
mean_home_energy
```

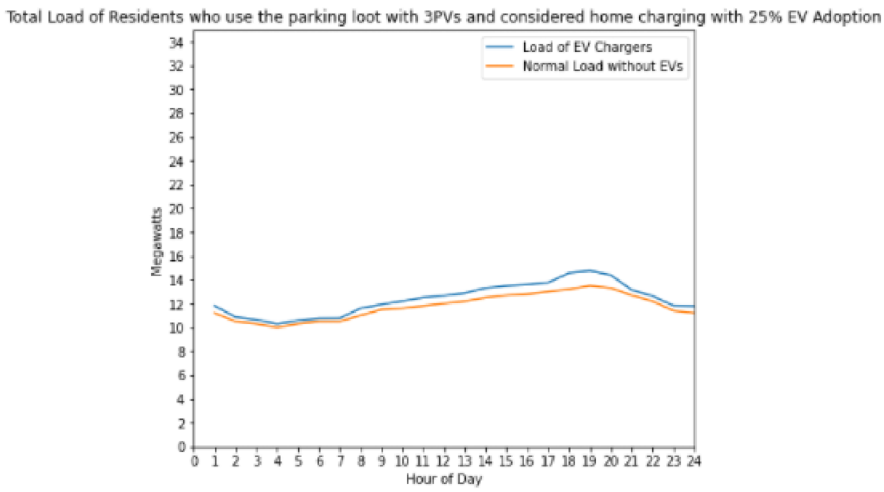
Out[272]: 1756.16

In [22]:
```
# Day Energy Consumption with PVs

charge_energy_over_the_day_withPV = []

# read all the 100 exported csv files from the simulation about the chargers
# get the data for each hour
for i in range(1,101):
    chargedata = pd.read_csv('chargeenergywithPV +%i.csv'%(i))
    chargedata['0'] = pd.to_datetime(chargedata['0'], unit='s')
    for i in range(0,24):
        charge_energy_over_the_day_withPV.append([i,sum(chargedata['1'].loc[(chargedata['0'].dt.hour) == i])])
```

In [23]:
```
charge_energy_over_the_day_withPV = pd.DataFrame(charge_energy_over_the_day_withPV)
tmp1 = []


# summarize the data for each hour
for i in range(0,24):
        tmp1.append([i,sum(charge_energy_over_the_day_withPV[1].loc[(charge_energy_over_the_day_withPV[0]) == i])])

tmp1 = pd.DataFrame(tmp1)
```

In [24]:
```
# Calculate average per hour
tmp1[1] = tmp1[1].div(100).round(2)

# Convert KW to Megawatt
tmp1[1] = tmp1[1].div(1000).round(2)
```

In [25]:
```
# plot the results
# x = hours
# y = duck curve

x = [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24]
y = [11.2, 10.5, 10.3, 10, 10.3, 10.5, 10.5, 11, 11.5, 11.6, 11.8, 12, 12.2, 12.5, 12.7, 12.8, 13, 13.2, 13.5, 13.3, 12.7, 12.2,

# Add new Energy requiered from EV Charger over the Day
sumCharge1 = tmp1[1] + y
# Add new Energy requied from Home Charging in the evening 1.7 MW
sumCharge1[17] = sumCharge1[17] + 0.5
sumCharge1[18] = sumCharge1[18] + 0.7
sumCharge1[19] = sumCharge1[19] + 0.5

f = plt.figure()
f.set_figwidth(7)
f.set_figheight(6)

plt.ylim(ymin=0, ymax=35)
plt.xlim(xmin=0, xmax=24)
plt.xticks(np.arange(0, len(x)+1,1))
plt.yticks(np.arange(0, 35+1,2))

plt.xlabel('Hour of Day')
plt.ylabel('Megawatts')
plt.title('Total Load of Residents who use the parking loot with 3PVs and considered home charging with 25% EV Adoption')



plt.plot(x,sumCharge1, label="Load of EV Chargers")
plt.plot(x,y, label="Normal Load without EVs")
plt.legend()
plt.show()
```



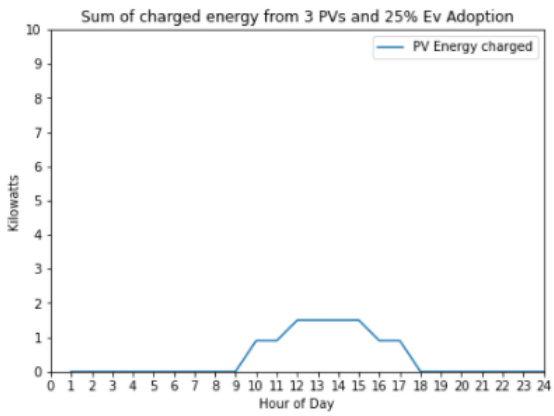
In [ ]:
```
#Data Analysis of the PV Energy production
```

In [3]:
```
charge_energy_over_the_day_ofPV = []


# read all the 100 exported csv files from the simulation about the consumption of the PV Energy
# get the data for each hour
for i in range(1,101):
    chargedata = pd.read_csv('PVEnergyConsumption +%i.csv'%(i))
    chargedata['0'] = pd.to_datetime(chargedata['0'], unit='s')
    for i in range(0,24):
        charge_energy_over_the_day_ofPV.append([i,sum(chargedata['1'].loc[(chargedata['0'].dt.hour) == i])])
```

In [5]:
```
charge_energy_over_the_day_ofPV = pd.DataFrame(charge_energy_over_the_day_ofPV)
tmp2 = []

# summarize the data for each hour
for i in range(0,24):
        tmp2.append([i,sum(charge_energy_over_the_day_ofPV[1].loc[(charge_energy_over_the_day_ofPV[0]) == i])

tmp2 = pd.DataFrame(tmp2)
```

In [7]:
```
# Calculate average per hour
tmp2[1] = tmp2[1].div(100).round(3)
```

In [19]:
```
# plot the data
# x = hours
# tmp2 = energy consumption from the PV

x = [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24]

tmp2


f = plt.figure()
f.set_figwidth(7)
f.set_figheight(5)

plt.ylim(ymin=0, ymax=10)
plt.xlim(xmin=0, xmax=24)
plt.xticks(np.arange(0, len(x)+1,1))
plt.yticks(np.arange(0, 10+1,1))

plt.xlabel('Hour of Day')
plt.ylabel('Kilowatts')
plt.title('Sum of charged energy from 3 PVs and 25% Ev Adoption')


plt.plot(x,tmp2[1], label="PV Energy charged")

plt.legend()
plt.show()
```



References

Andersen, T. (2021). *Car pollution killed hundreds in mass. and thousands across 12 states, researchers say.* https://www.bostonglobe.com/2021/06/08/metro/car-pollution-killed-hundreds-mass-thousands-across-12-states-researchers-say/. The Boston Globe. (Accessed: 2021-06-19)

Babic, J., Carvalho, A., Ketter, W., & Podobnik, V. (2016, 05). Modelling electric vehicle owners' willingness to pay for a charging service..

Babic, J., Carvalho, A., Ketter, W., & Podobnik, V. (2017). Electricity trading agent for ev-enabled parking lots. In S. Ceppi, E. David, C. Hajaj, V. Robu, & I. A. Vetsikas (Eds.), *Agent-mediated electronic commerce. designing trading strategies and mechanisms for electronic markets* (pp. 35–49). Cham: Springer International Publishing.

Babic, J., Carvalho, A., Ketter, W., & Podobnik, V. (2018). Evaluating policies for parking lots handling electric vehicles. *IEEE Access*, *6*, 944-961. doi: 10.1109/ACCESS.2017.2777098

Banham. (2002). *Das ford jahrhundert.* Tehabi books.

Bestandsüberblick am 1. januar 2021. (2021). https://www.kba.de/DE/Statistik/Fahrzeuge/Bestand/Jahresbilanz/bestand_jahresbilanz_node.html. Kraftfahrt-Bundesamt, Flensburg. (Accessed: 2021-07-03)

Bevölkerung deutschlands im jahr 2020 erstmals seit 2011 nicht gewachsen. (2021). https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/_inhalt.html;jsessionid=31517E402EF0FBEFE1D126B7C4E70B7D.live732. (Accessed: 2021-07-03)

Brenna, M., Foiadelli, F., Longo, M., & Grillo, S. (2016). Charging optimization for electric vehicles in large park amp; ride areas. In *2016 ieee power and energy society general meeting (pesgm)* (p. 1-5). doi: 10.1109/PESGM.2016.7741336

Burns, L. D. (2013, 05). A vision of our transport future. *Nature*, *497*, 181-182. doi: 10.1038/497181a

Denholm, P., O'Connell, M., Brinkman, G., & Jorgenson, J. (2015, 11). Over-generation from solar energy in california. a field guide to the duck chart. Retrieved from https://www.osti.gov/biblio/1226167 doi: 10.2172/1226167

Electric car batteries with five-minute charging times produced. (2021). https://www.theguardian.com/environment/2021/jan/19/electric-car-batteries-race-ahead-with-five-minute-charging-times. the Guardian. (Accessed: 2021-06-19)

Electric cars 'will be cheaper to produce than fossil fuel vehicles by 2027. (2021). https://www.theguardian.com/business/2021/may/09/electric-cars-will-be-cheaper-to-produce-than-fossil-fuel-vehicles-by-2027. the Guardian. (Accessed: 2021-06-19)

Faiz, A., Weaver, C., & Walsh, M. (1996). *Air pollution from motor vehicles: Standards and technologies for controlling emissions.* World Bank. Retrieved from https://books.google.de/books?id=Hqsyv_KD0lgC

Falvo, M. C., Sbordone, D., Bayram, I. S., & Devetsikiotis, M. (2014). Ev charging stations and modes: International standards. In *2014 international symposium on power electronics, electrical drives, automation and motion* (pp. 1134–1139).

Fetene, G. M., Hirte, G., Kaplan, S., Prato, C. G., & Tscharaktschiew, S. (2016). The economics of workplace charging. *Transportation Research Part B: Methodological*, *88*, 93-118. Retrieved from https://www.sciencedirect.com/science/article/pii/S0191261515302009 doi: https://doi.org/10.1016/j.trb.2016.03.004

Gelmanova, Z., Zhabalova, G., Sivyakova, G., Lelikova, O., Onishchenko, O., Smailova, A., & Kamarova, S. (2018). Electric cars. advantages and disadvantages. In *Journal of physics: Conference series* (Vol. 1015, p. 052029).

Gottwalt, S., Ketter, W., Block, C., Collins, J., & Weinhardt, C. (2011). Demand side management—a simulation of household behavior under variable prices. *Energy Policy*, *39*(12), 8163-8174. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421511008007 (Clean Cooking Fuels and Technologies in Developing Economies) doi: https://doi.org/10.1016/j.enpol.2011.10.016

Helmers, E., & Marx, P. (2012). Electric cars: technical characteristics and environmental impacts. *Environmental Sciences Europe*, *24*(1), 1–15.

Hevner, March, Park, & Ram. (2004). *Design science in information system research.* Retrieved from https://www.researchgate.net/publication/201168946_Design_Science_in_Information_Systems_Research

Higgins, A., Paevere, P., Gardner, J., & Quezada, G. (2012, 05). Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles. *Technological Forecasting and Social Change*, *79*, 1399-1412. doi: 10.1016/j.techfore.2012.04.008

Huang, Y., & Zhou, Y. (2015). An optimization framework for workplace charging strategies. *Transportation Research Part C: Emerging Technologies*, *52*, 144-155. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0968090X15000303` doi: https://doi.org/10.1016/j.trc.2015.01.022

Hussain, S., Ahmed, M. A., & Kim, Y.-C. (2019). Efficient power management algorithm based on fuzzy logic inference for electric vehicles parking lot. *IEEE Access*, *7*, 65467-65485. doi: 10.1109/ACCESS.2019.2917297

Jia, J., Liu, C., & Wan, T. (2019). Planning of the charging station for electric vehicles utilizing cellular signaling data. *Sustainability*, *11*(3). Retrieved from `https://www.mdpi.com/2071-1050/11/3/643` doi: 10.3390/su11030643

Johannesen, N. J., Kolhe, M., & Goodwin, M. (2019). Relative evaluation of regression tools for urban area electrical energy demand forecasting. *Journal of Cleaner Production*, *218*, 555-564. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0959652619301192` doi: https://doi.org/10.1016/j.jclepro.2019.01.108

Jovanovic, R., & Bayram, I. S. (2019, 10). Scheduling electric vehicle charging at park-and-ride facilities to flatten duck curves. In (p. 1-5). doi: 10.1109/VPPC46532.2019.8952394

Kåberger, T. (2018). Progress of renewable electricity replacing fossil fuels. *Global Energy Interconnection*, *1*(1), 48–52.

Kahlen, M. T., Ketter, W., & van Dalen, J. (2018). Electric vehicle virtual power plant dilemma: Grid balancing versus customer mobility. *Production and Operations Management*, *27*(11), 2054-2070. Retrieved from `https://onlinelibrary.wiley.com/doi/abs/10.1111/poms.12876` doi: https://doi.org/10.1111/poms.12876

Kauf einer ladestation für mein elektroauto. (2021). `https://www.mobilityhouse.com/de_de/ratgeber/was-muss-ich-beim-kauf-einer-ladestation-fuer-mein-elektroauto-beachten`. greenspeed. (Accessed: 2021-07-03)

Ketter, W., Collins, J., & Reddy, P. (2013). Power tac: A competitive economic simulation of the smart grid. *Energy Economics*, *39*, 262-270. Retrieved from https://www.sciencedirect.com/science/article/pii/S0140988313000959 doi: https://doi.org/10.1016/j.eneco.2013.04.015

Ketter, W., Peters, M., Collins, J., & Gupta, A. (2015). Competitive benchmarking: An is research approach to address wicked problems with big data and analytics. *MIS Quarterly, ERIM Report Series Reference*, *No. ERS-2015-015-LIS*. Retrieved from https://ssrn.com/abstract=2700333 doi: http://dx.doi.org/10.2139/ssrn.2700333

Lee, Z. J., Li, T., & Low, S. H. (2019). Acn-data: Analysis and applications of an open ev charging dataset. In *Proceedings of the tenth acm international conference on future energy systems* (p. 139–149). New York, NY, USA: Association for Computing Machinery. Retrieved from https://doi.org/10.1145/3307772.3328313 doi: 10.1145/3307772.3328313

Mckinsey electric vehicle index: Europe cushions a global plunge in ev sales. (2021). https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/mckinsey-electric-vehicle-index-europe-cushions-a-global-plunge-in-ev-sales. McKinsey. (Accessed: 2021-06-19)

Melville, N. P. (2010). Information systems innovation for environmental sustainability. *MIS quarterly*, 1–21.

Misdariis, N., Cera, A., Levallois, E., & Locqueteau, C. (2012). Do electric cars have to make noise? an emblematic opportunity for designing sounds and soundscapes. In *Acoustics 2012.*

Momtazpour, M., Butler, P., Hossain, M., C. Bozchalui, M., Ramakrishnan, N., & Sharma, R. (2012, 08). Coordinated clustering algorithms to support charging infrastructure design for electric vehicles.
doi: 10.1145/2346496.2346517

Munkhammar, J., Widén, J., & Rydén, J. (2015). On a probability distribution model combining household power consumption, electric vehicle home-charging and photovoltaic power production. *Applied Energy*, *142*, 135–143.

Obi, M., & Bass, R. (2016). Trends and challenges of grid-connected photovoltaic systems – A review. *Renewable and Sustainable Energy Reviews*, *58*(C), 1082-1094. Retrieved from https://ideas.repec.org/a/eee/rensus/v58y2016icp1082-1094.html doi: 10.1016/j.rser.2015.12.28

On-street car parking sensor data - 2020 (jan - may). (2021). https://data.melbourne.vic.gov.au/Transport/On-street-Car-Parking-Sensor-Data-2020-Jan-May-/4n3a-s6rn. City of Melbourne Open Data Team. (Accessed: 2021-11-03)

pandas. (2021). https://pandas.pydata.org/. NumFOCUS. (Accessed: 2021-11-03)

Pevec, D., Babic, J., Kayser, M. A., Carvalho, A., Ghiassi-Farrokhfal, Y., & Podobnik, V. (2018). A data-driven statistical approach for extending electric vehicle charging infrastructure. *International Journal of Energy Research*, *42*(9), 3102-3120. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1002/er.3978 doi: https://doi.org/10.1002/er.3978

Pieltain Fernández, L., Gomez San Roman, T., Cossent, R., Mateo Domingo, C., & Frías, P. (2011). Assessment of the impact of plug-in electric vehicles on distribution networks. *IEEE Transactions on Power Systems*, *26*(1), 206-213. doi: 10.1109/TPWRS.2010.2049133

Powell, S., Kara, E. C., Sevlian, R., Cezar, G. V., Kiliccote, S., & Rajagopal, R. (2020). Controlled workplace charging of electric vehicles: The impact of rate schedules on transformer aging. *Applied Energy*, *276*, 115352. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261920308643 doi: https://doi.org/10.1016/j.apenergy.2020.115352

Qian, K., Zhou, C., Allan, M., & Yuan, Y. (2010). Load model for prediction of electric vehicle charging demand. In *2010 international conference on power system technology* (p. 1-6). doi: 10.1109/POWERCON.2010.5666587

Roberts, D. (2018, 3). Solar power's greatest challenge was discovered 10 years ago. it looks like a duck. *Vox*. Retrieved from https://www.vox.com/energy-and-environment/2018/3/20/17128478/solar-duck-curve-nrel-researcher

Sandalow, D. B. (2009). *Plug-in electric vehicles: what role for washington?* Brookings Institution Press.

Schey, S., Scoffield, D., & Smart, J. (2012). A first look at the impact of electric vehicle charging on the electric grid in the ev project. *World Electric Vehicle Journal*, *5*(3), 667–678. Retrieved from https://www.mdpi.com/2032-6653/5/3/667 doi: 10.3390/wevj5030667

Seidel, S., Recker, J., & Brocke, J. v. (2013, 12). Sensemaking and sustainable practicing: Functional affordances of information systems in green transformations. *MIS Quarterly*, *37*, 1275-1299. doi: 10.25300/MISQ/2013/37.4.13

Simpy. (2021). https://simpy.readthedocs.io/en/latest/. (Accessed: 2021-04-24)

Sperling, D. (2018). *Three revolutions steering automated, shared, and electric vehicles to a better future.* Washington, DC: Island Press. doi: 10.5822/978-1-61091-906-7

Terada, N., Yanagi, T., Arai, S., Yoshikawa, M., Ohta, K., Nakajima, N., ... Arai, N. (2001). Development of lithium batteries for energy storage and ev applications. *Journal of Power Sources*, *100*(1-2), 80–92.

Tesla model s. (2021). https://www.tesla.com/de_de/models. (Accessed: 2021-06-19)

Tesla-supercharger. (2021). https://greenspeed.de/mobilitaet/tesla-supercharger-kostenlos-kostenpflichtig-laden/. greenspeed. (Accessed: 2021-06-19)

Thunberg, G. (2019). *No one is too small to make a difference: Illustrated edition.* Penguin UK.

Traut, E. J., Cherng, T. C., Hendrickson, C., & Michalek, J. J. (2013). Us residential charging potential for electric vehicles. *Transportation Research Part D: Transport and Environment*, *25*, 139-145. Retrieved from https://www.sciencedirect.com/science/article/pii/S1361920913001260 doi: https://doi.org/10.1016/j.trd.2013.10.001

Tyner, W. (2021). *Electricity pricing policies may make or break plug-in hybrid buys.* https://www.purdue.edu/newsroom/research/2011/110113TynerHybrids.html. Purdue University. (Accessed: 2021-06-19)

Valogianni, K., Ketter, W., & Collins, J. (2015). A multiagent approach to variable-rate electric vehicle charging coordination. In *Aamas.*

Valogianni, K., Ketter, W., Collins, J., & Zhdanov, D. (2020). Sustainable electric vehicle charging using adaptive pricing. *Production and Operations Management*, *29*(6), 1550-1572. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/poms.13179 doi: https://doi.org/10.1111/poms.13179

Van Haaren, R. (2011). Assessment of electric cars' range requirements and usage patterns based on driving behavior recorded in the national household travel survey of 2009. *Earth and Environmental Engineering Department, Columbia University, Fu Foundation School of Engineering and Applied Science, New York*, *51*, 53.

Van Vliet, O., Brouwer, A. S., Kuramochi, T., van Den Broek, M., & Faaij, A. (2011). Energy use, cost and co2 emissions of electric cars. *Journal of power sources*, *196*(4), 2298–2310.

Verheijen, E., & Jabben, J. (2010). Effect of electric cars on traffic noise and safety.

Vermeulen, I., Helmus, J. R., Lees, M., & van den Hoed, R. (2019). Simulation of future electric vehicle charging behavior—effects of transition from phev to fev. *World Electric Vehicle Journal*, *10*(2). Retrieved from https://www.mdpi.com/2032-6653/10/2/42 doi: 10.3390/wevj10020042

Wakefield, E. H. (1993). *History of the electric automobile. society of automotive engineers.* SAE International.

Wan, Z., Li, H., He, H., & Prokhorov, D. (2018). A data-driven approach for real-time residential ev charging management. In *2018 ieee power energy society general meeting (pesgm)* (p. 1-5). doi: 10.1109/PESGM.2018.8585945

What's the difference between ev charging levels? (2021). https://freewiretech.com/difference-between-ev-charging-levels/. FREEWIRE. (Accessed: 2021-11-03)

Whitmarsh, L., & Köhler, J. (2010). Climate change and cars in the eu: the roles of auto firms, consumers, and policy in responding to global environmental change. *Cambridge Journal of Regions, Economy and Society*, *3*(3), 427–441.

Williams, B., & DeShazo, J. R. (2014). Pricing workplace charging: Financial viability and fueling costs. *Transportation Research Record*, *2454*(1), 68-75. Retrieved from https://doi.org/10.3141/2454-09 doi: 10.3141/2454-09

Wu, X. (2018). Role of workplace charging opportunities on adoption of plug-in electric vehicles – Analysis based on GPS-based longitudinal travel data. *Energy Policy*, *114*(C), 367-379. Retrieved from https://ideas.repec.org/a/eee/enepol/v114y2018icp367-379.html doi: 10.1016/j.enpol.2017.12.0