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Master Thesis

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Self-Consumption of Residential PV Systems in Hamburg

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Abstract:

The analysis of self-consumption and self-sufficiency of household PV systems in Hamburg for the year 2021 is conducted in this thesis. The data for the analysis was obtained from a publicly accessible open-source database. This study aimed to determine the effects of implementing battery storage and integrating electric vehicles as energy storage systems on the patterns of self-consumption and self-sufficiency of residential PV systems. In this research, a total of 4490 Hamburg households with PV systems are accessed. The results clearly demonstrate how seasonal fluctuation affects self-consumption and self-sufficiency profiles. Furthermore, findings indicate that the adoption of battery storage and the penetration of electric vehicles significantly enhances self-consumption and self-sufficiency when compared to the absence of energy storage.

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List of Abbreviation

AC	Alternating Current
BDEW	Bundesverband der Energie- und Wasserwirtschaft
BEV	Battery Electric Vehicle
CHP	Combined Heat and Power
DC	Direct Current
DHI	Diffuse Horizontal Irradiance
DSM	Demand Side Management
EEG	Erneuerbare-Energien-Gesetz
EU	European Union
EV	Electric Vehicle
FIT	Feed-In Tariff
GHI	Global Horizontal Irradiance
LA	lead-acid
Li-ion	lithium-ion
LV	Low Voltage
MaStR	Marktstammdatenregister
NiCad	nickel-cadmium
NiMH	nickel metal hydride
NREL	National Renewable Energy Laboratory
nZEBs	nearly Zero Energy Buildings
PV	Photovoltaic
SC	Self-Consumption
SLP	Standard Load Profiles
SOC	State Of Charge
SS	Self-Sufficiency
TMY	Typical Meteorological Year
TSO	Transmission System Operator
V2G	Vehicle to Grid

List of Symbols

ΔE_{Bat}	Delta energy battery
ΔE_{EV}	Delta energy EV
$E_{bat,c}$	PV energy use to charge the battery
$E_{bat,d}$	Battery energy discharge to meet load demand
$C_{EV,Charg}$	Charging capacity of household EV charging station
E_{load}	Total load demand
$E_{pv,load}$	PV energy fed directly to load
E_{pv}	PV energy
η_{EV}	Self-discharge of EV
η_{bat}	Self-discharge of battery
η_{conv}	Conversion efficiency
kW, MW, GW	Kilowatt, Megawatt, Gigawatt
kWh, MWh, GWh	Kilowatt hour, Megawatt hour, Gigawatt hour
kWp, MWp, GWp	Kilowatt peak, Megawatt peak, Gigawatt peak
t	Timestep

1. Introduction

One of the greatest challenges of this century is climate change. To avoid irreversible climate change effects, it is critical to use and develop low-emission energy sources in the wake of this issue. Based on current energy sector developments, the most crucial pillars of a sustainable energy policy and the energy transition are worldwide renewable energy sources and higher energy efficiency. Photovoltaic (PV) systems, which have grown from approximately 7 GW in 2006 to about 775 GW at the end of 2020, are expected to play a prominent role in the global energy transition [1]. Germany adopted a climate protection plan to enhance renewable energy use and reduce greenhouse gas emissions as part of this endeavour. For this purpose, the important intermediate targets are defined in 'Erneuerbare-Energien-Gesetz (EEG)'(Renewable Energy Act) [2]. In the course of this action, Germany is trying to achieve target of 200 GW_p installed PV solar by 2030 from today's 54 GW_p, with aim to increase renewable energy share in power generation to 80% [3].

As per EUPD research on PV market[4], the reforms in EEG21 have been driving force to increase the PV installation in pandemic time. Figure 1 shows the survey forecasting the installation of around 6 GWp in 2021, which is 23% more than PV installation in 2020. In particular, a considerable number of small and medium-scale systems of under 30 kilowatts-peak (kWp) have emerged during the past few years. Figure 1 shows the increase in PV installation of capacity less than 10 kWp in Germany from 1.1 GWp in 2020 to estimated 1.5 GWp in 2021. The strong growth in solar rooftop segment is derived from the German feed-in tariff, decreasing prices for PV systems, and increasing interest in sustainable energy. As a consequence, around 30-40% of the installed PV capacity is connected to the low-voltage (LV) grid, which was not designed for purpose of handling generation [5].

Due to the rapid growth in demand for solar rooftop systems, the stability and frequency regulation of the power grid are challenged. A considerable amount of power is fed into the grid at noon (when PV power generation is at its peak). This leads to overvoltage, and as PV is non-inertial source, the frequency regulation capacity is being constrained[6]. The PV system output should be regulated to avoid such power grid fluctuations and to maintain its normal

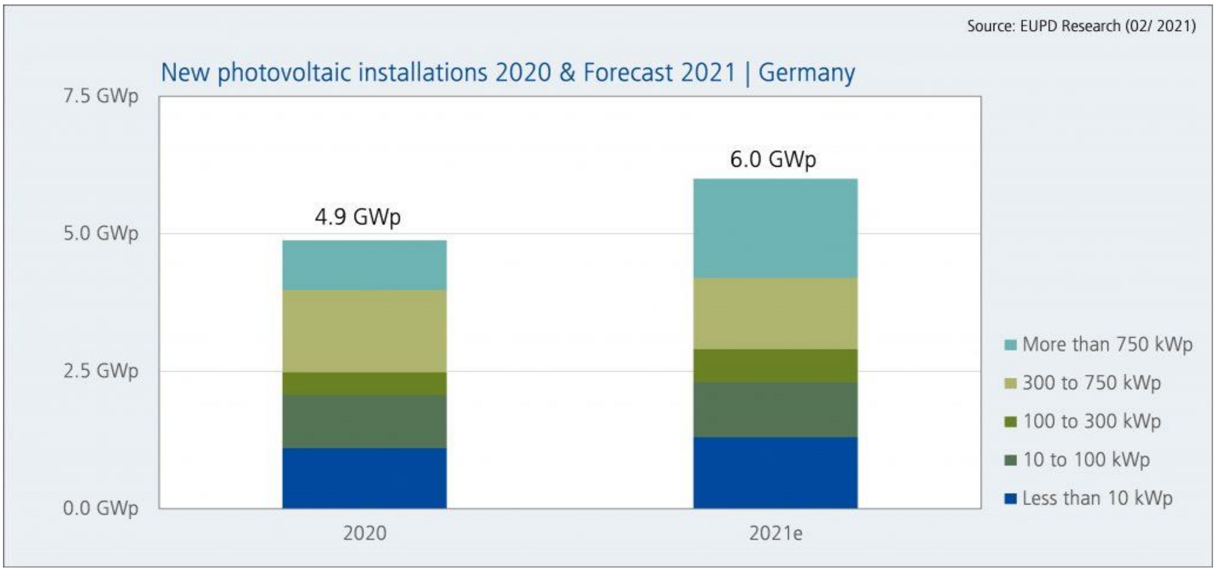

Figure 1 New PV installation 2020 and forecast 2021 for Germany[4]

operation. In order to overcome this problem, new developments are taking place in the field of energy efficiency. The grid regulations in Germany have incorporated criterion [2], requiring newly installed PV systems to be able to limit 70 percent of their maximum feed-in power. Germany has also increased its electricity prices and reduced its feed-in tariff to increase self-consumption by rooftop mounted solar systems. It encourages users to utilise generated energy at the same site where it is produced by implementing energy storage systems or by shifting the load, ultimately reducing high penetration of generated solar energy to grid.

In order to understand the effect of PV generator on local energy balance, it is important to focus on self-consumption analysis and its improvement methods from local perspective. To strengthen the integration of PV self-consumption with the electrical grid, energy storage and demand side management (DSM) techniques are used [7]. Energy storage can be used to store the generated energy during peak generation time and utilise it during non-production hours, mainly to reduce the evening consumption peaks. DSM focused into shifting the load to match the generation time, displacing the consumption peaks. Despite the fact that the load shifting approach uses more direct PV generated energy without the expense associated with energy storage systems, it has limits in terms of meeting the load demand. Improving self-consumption reduces energy exchange with the electrical grid, however grids must handle generation and consumption peaks due to the stochastic nature of solar energy. As PV penetration increases, this issue is projected to become more prevalent [8].

1.1 Motivation

As more PV power is connected to the distribution network and its output is effectively invisible to the system operator, the task of balancing supply and demand of electricity on the low-voltage grid in real time has grown more complex. The amount of power generated by PV systems is determined by the amount of insolation or sunshine available at any given location and time. Because of the stochastic behaviour of solar energy, there is a possibility of excessive generation, as well as a sudden drop in generation due to the broad cloud cover. Both under-generation and over-generation have the potential to cause grid instability. Today's distribution networks are challenged with the unprecedented dilemma of connected solar energy generation surpassing demand, and they may resort to power curtailment by limiting PV generator fed-in capacity, resulting in energy inefficiency. Considering the continuous PV development, it is vital to understand the impact it has on local distribution grid. PV generation predictions can assist in addressing this issue. However, in addition to forecasting PV generation, a greater understanding of self-consumption from local PV systems may be more helpful for grid operators in managing the grid and introducing other sources of power. Self-consumption is particularly useful analysing how high penetration of intermittent electricity production impacts electrical systems [9]. Self-consumption has the advantage of competing with retail pricing rather than wholesale prices from an economical perspective. As a result, even in the absence of legislative incentives, self-consumption is already profitable in many countries [9]. Considering the economic benefits, many residential PV system users are opting for self-consumption. In this context, self-consumption plays important role because the extent to which the energy consumption behaviour of household changes to use PV generation has a direct impact on the net load demand profile. Grid management is challenged by a lack of reliable data on the quantity of solar energy generated and consumed for new PV installations and growing demands. The analysis of household PV system’s self-consumption patterns will assist grid operators in more effective power system operation. In addition, from an economic perspective, since predictions of saving by households on electricity bills are often used to determine the optimal feed-in tariff rate for achieving PV deployment targets. Thus, estimating self-consumption and calculating the electricity bill savings are particularly important for policymakers [9]. The self-consumption(SC) pattern of local grid will help Transmission System Operators (TSOs) to manage grid smoothly with increasing number of PV installations.

1.2 Objective and Scope

Germany's objective of 200 GWp installed PV solar by 2030, rising interest in sustainable energy, and favourable new legislation have all contributed to a rise in residential PV installations. Considering the growing PV market, this thesis aims to present a realistic analysis of self-consumption of residential PV systems with and without energy storage systems. Given the large research area and the numerous factors influencing on-site consumption of PV energy across Germany, the scope of this study is narrowed to the Hamburg region for better analysis. Hamburg is one of the growing players in solar energy market with PV installed capacity more than 55 MW_p with around 30 MW_p of residential PV systems [10]. The objective of this study is to analyse self-consumption of residential PV systems in Hamburg and impact of energy storage systems on it. This study can be expanded to take advantage of the analysed self-consumption pattern to cope with the growing nature of grid-connected PV installations in Hamburg.

The self-consumption pattern can be altered by adopting demand side management (DSM) and by adding energy storage systems. Since both have distinct applications, they can be used separately or in combination. Given the time constraints to complete this thesis, the focus of this study is solely on residential energy storage systems and their impact on the self-consumption pattern. As for the energy storage systems, the study analyses different scenarios for stationary battery storage systems, electric vehicles as energy storage systems, and combinations of these technologies.

The scope of this study is determined by the information available on the public domain. The data on PV systems, energy storage systems and standard load profiles is gathered from an open-source database [10]–[12]. For this thesis, the dataset with sufficient accuracy regarding the location and the specification of installed PV systems in the study area (here Hamburg) for year of 2021 is obtained [10].

This thesis work attempts to analyze how the introduction of energy storage technologies would affect self-consumption and self-sufficiency patterns. Furthermore, this work will try to place some focus on the challenges faced by grid operators with expanding PV installation capacity, as well as the approaches they use to handle it, and then how analysis of self-consumption patterns will assist them. This work will also attempt to shed light on various self-consumption and self-sufficiency influencing elements as it advances its thesis.

1.3 Definition of terms

The terminologies that are used frequently in this thesis are defined as follows:

Self-consumption: The consumption of on-site generated PV energy to fulfill local load demand, either instantaneously or over a period of time [7]. It is measured in this thesis as a percentage of the total PV production over the given time period. Self-consumption is calculated for the duration when sunlight was available during the specified timeframe.

Self-sufficiency: Total PV energy self-consumed compared to the total load over a period of time. It is measured in this thesis as a proportion of the overall load demand over the given time period [7].

Excess solar energy: After meeting the immediate load requirement, any remaining solar energy is referred to as excess solar energy. In some instances, the word "surplus solar energy" is used instead of "excess solar energy", which implies the same meaning.

Residual load demand: The additional load demand that remains after solar energy is used up is referred to in this thesis as the residual load demand.

Sunshine hours: The duration of sunshine during a specific time period is measured in sunshine hours. It is also sometimes referred to as "sunshine duration", and is generally expressed in hours per year [13].

Feed-in: After self-consumption, the extra solar energy is transferred from the house to the grid. This is referred as feed-in.

Oversizing and Undersizing: Oversizing refers to installing a system with a bigger capacity than what is necessary for it to function optimally. Undersizing, on the other hand, is the installation of a system with a capacity that is less than adequate.

1.4 Structure of the thesis

The thesis is basically divided into four sections:

The Chapter 2 gives a literature review of relevant publications on self-consumption of household PV systems. This chapter states the methods addressed by various scholarly sources that follow the proposed objectives of the thesis, the work done around an analysis methods of self-consumption referred during the thesis process, and the integration of energy storage systems with PV.

The introductory chapter 3 forms the fundamentals section for this thesis. First, the chapter begins with short introduction of self-consumption (SC) and self-sufficiency (SS) along with its definition and mathematical equation. After that the impact of expanding PV installations on grid, effective solution, and role of self-consumption in it is discussed. This is followed by influencing factors of SC and SS, and residential energy storage systems. The chapter closes with an insight on the software packages and tools used in process of modelling.

The core section begins with the chapter 4, which presents the methodology for analysing the self-consumption of residential PV systems in Hamburg. At start, the approach used for data gathering of household PV systems in Hamburg is explained. Based on this, the developed simulation models for load demand, PV power generation, self-consumption and self-sufficiency, and models for residential energy storage systems along with different scenarios is presented. This is followed by a validation of the model’s assumptions based on low voltage(LV) grid calculation and simulation. The subsequent chapter 5 then presents and discusses the results of all scenarios graphically, along with a comparison.

The final section (chapter 6) summarizes all findings of the thesis and gives an outlook on the improvement, optimization, and extension possibilities of the presented method.

2. Literature Review

In recent years, with the increasing proportion of PV installations, the analysis of self-consumption and self-sufficiency of residential PV systems has become a popular topic in renewable energy and solar energy research. Although the topic of PV self-consumption is not relatively unknown, various aspects of it are still extensively studied. As a result, the literature on self-consumption is diverse, covering a wide range of technologies and systems. There are numerous studies that examine residential PV self-consumption from technical, economic, and environmental perspectives [14], [15]. Luthander et al. [7] did a review and comparison of different research papers around self-consumption of photovoltaic of buildings. The analysis demonstrates that, in comparison to the initial rate of self-consumption, it is possible to enhance the relative self-consumption by, on average, 13–24 % points with a battery storage capacity of 0.5–1 kWh per installed kWp of PV power and between 2–15 % points with DSM. They concluded that implementing battery storage capacity normalised with installed PV capacity would be more efficient as compared to DSM methods in improvement of self-consumption [7].

Growing interest on PV installations, its impact on grid, and solution

Before moving further into self-consumption, the various factors influencing energy consumers for adaptation of solar energy and its impact on power system have to take into account. PV is becoming economically competitive with other renewable resources throughout the world, especially because of the considerable reductions in PV production costs due to widespread deployment [15]–[18]. The Luthander et al. [7], Bertsch et al. [14], Wirth [19] explain how the decreasing cost of solar systems and batteries along with Germany's government policies, subsidies towards PV installations, and feed in tariff (FIT) being the main influencing factor for massive installation of PV in Germany. The study of consumer behavioural patterns with respect to PV self-consumption [20] or public attitude towards developments in PV [21] indicates that economic efficiency is key driver behind the adoption of solar energy by residential user. Even though the growing market of solar energy is environmentally friendly and must, the natural uncontrollability of PV could lead to power system issues with high intensity PV penetration. Patil et al. [22] mentioned the favourable and unfavourable effects of high PV penetration on grid. The analysis by Gupta et al. [23] explains the low voltage distribution grid impacts such as reverse power flow, voltage surcharge, overloading of distribution lines. Von Appen et al. investigates and presents concerns with the low voltage German distribution grid caused by significant PV penetration during peak solar radiation [5]. The impact of rooftop PV penetration on voltage profile of Thailand city was simulated by Punyachai et al. [24]. This study explains problems of voltage rise, current and frequency instability associated with LV grid. A good review of different literature about impact of photovoltaics on grid and its mitigation methods has been provided by Shivashankar et al. [25]. Several other authors researched about different challenges with current PV penetration and studied or simulated for future scenarios, explaining different solutions for the same [26], [27]. All such studies concluded that the technical issues with PV integrated networks are still in their early stages, and that they will become more significant as penetration rises and demand falls. The most efficient remedy for such challenges is to implement centralised or decentralised energy storage, implying that local consumption should be increased to lessen high penetration [5], [22], [26], [27]. Another effective solution to reduce adverse impact on grid due to PV penetration adopted by many countries is PV power curtailment [25], [28]. Even Germany has placed restrictions on small-scale PV facilities, allowing maximum 70 % of installed capacity to be fed in [19]. Restricting the maximum feed-in of PV-generated electricity by increasing household self-consumption can reduce grid congestion to some extent [29], [30]. However, the curtailment losses are significant and much of the generated energy during peak production time is being wasted. In thesis of residential PV self-consumption [31], Luthander highlights a flaw with the curtailment method and concluded improving self-consumption by energy storage or DSM could decrease the negative impact on grid due to the PV penetration. As a result, especially given the economic benefits, interest in self-consumption, its implementation, and various approaches to improve it is a very intriguing topic for most studies and researchers. Given that, a brief overview of the studies on self-consumption improvement is presented in the section that follows.

Improvement of residential PV system's self-consumption

In recent years, there has been lot of studies about how to improve self-consumption, with a particular emphasis on residential PV systems. Many of this research mostly focuses on economic viability of the self-consumption. The methods used to analyse the self-consumption from [9], [32] are with the smart metering system, where [32] have used net metering method for analysing. Improvement of self-consumption can be carried out either by storing solar energy or by managing the load, known as demand side management(DSM) or by implementing combination of both [7], [33]. There has been a significant amount of work about improving PV self-consumption using above mentioned methods. The research of 200 Swedish households to improve self-consumption using the load shifting and scheduling method revealed a minor percentage gain in self-consumption [34]. This study concluded that there is limited potential in SC improvement by load scheduling. Another study utilising active demand side management revealed that combining a small capacity battery with DSM may yield greater results in improving self-consumption [35]. The scheme of these works is based on shifting and matching household loads to the high solar production times. Apart from that, many more research are concentrating on energy storage systems, primarily on battery storage systems [36]–[39], hydrogen storage [40], [41], heat storage [42]–[46] and also recently focusing on storing excess solar energy into electric vehicles [47]–[49]. The result of one study conducted on Swedish nearly Zero Energy Buildings (nZEBs) by comparing self-consumption and self-sufficiency to PV-Load matching shows that energy storage has higher potential for load matching as compared to load shifting or DSM [28]. As a result, and considering the time and effort required to evaluate DSM methods, as well as the time constraints to complete this study, this thesis primarily focuses on the analysis of self-consumption of residential PV systems with and without energy storage devices, rather than the DSM technique. The studies on enhancing self-consumption and self-sufficiency with the help of residential energy storage systems are reviewed in the following section of this chapter.

Residential energy storage systems

Most previous works regarding self-consumption enhancement using energy storage are focused on battery storage along with EV, hydrogen storage, and power to heat storage technologies. One study done by simulating single UK house with 4.5 kWp PV and 10 kW battery, and 1kW fuel cell concluded that battery system is best for daily demand cycle and daily storage, while hydrogen can be used with another applications like heating with combined heat and power (CHP) to increase efficiency [41]. Another study presented a simulation model for determining the optimal size of PV and storage systems for self-consumption and self-sufficiency profitability [14]. This research also demonstrates the various factors that influence self-consumption in Germany and Ireland. Another work analysed the financial and technical aspects of several electric and thermal storage with power to heat technology for the PV integrated systems in residential sector of Germany [45] and discussed how PV energy storage is cost-effective and improves self-consumption. Another study compared future potential of heat integrated hydrogen storage with battery storage as residential energy storage systems by means of its economic viability for energy self-sufficient buildings [40]. This study concluded that by 2030, the annualised cost of hydrogen storage can be reduced by 80% compared to li-ion battery storage, making it an appealing element of residential energy storage alongside photovoltaic systems. In this thesis, primarily the battery storage system and electric vehicle as storage are analysed as residential storage to assess self-consumption of residential PV system in Hamburg.

Battery storage systems

Several scholars have investigated into the use of batteries to improve self-consumption, limit peak penetration, and reduce household peak power demand [37], [50]–[52]. Due to rapid technological advancements, new incentive schemes, and a growing trend, the effective cost of a battery energy storage system has decreased in recent years, resulting in a large growth in the usage of battery storage to store renewable energy by residential users [53]–[56]. According to a study that investigated on approximately 2000 Swedish households, implementing a battery storage system at the domestic level can increase self-consumption by 20-50 percent and eventually improve self-sufficiency by 12.5–30 percent compared to no storage [37]. Another study simulated self-consumption for different EU nations with variable load consumption to conduct a techno-economic analysis of domestic solar-battery systems. The difference in self-consumption with and without battery storage is seen in this study [38]. Another work analyses the effect of combining a lead-acid battery as residential storage with a photovoltaic system on self-sufficiency. The results show that with an energy storage system, self-sufficiency can be increased beyond 40% [57]. Another research concluded that adding a lithium-ion battery to a household can increase self-consumption by more than 50% [33].While all reviewed studies above have a single focus, particularly maximizing self-consumption or minimizing household electricity costs by implementing battery storage, some authors presented a study that focuses on grid relief rather than only improving self-consumption [30], [36]. These authors looked into various energy storage and management approaches that could assist reduce high PV penetration and aid in future PV installations.

There are certain research concentrating on the size of battery storage and its impact on self-consumption in addition to all the works linked to battery storage systems. According to a study that examine the impact of PV system size and battery storage on 144 households in Ulm, Germany, increasing the size of PV systems to meet annual energy consumption reduces self-consumption by 20 to 40% [58]. This study examined PV systems with varying capacities and battery capacities. This study found that combining a PV system that produces half of the annual energy consumption with an energy storage system can boost self-consumption by 75-80%. Another research that looked at the mismatch between household demand and PV generation discussed a solution that includes optimal battery sizing along with peak load shaving at the district level. This research emphasises the rise in self-consumption and self-sufficiency, as well as peak shaving, by choosing the appropriate battery system size [59]. According to the findings of Bertsch et al. a PV system combined with an appropriate storage capacity is highly profitable; however, optimal battery capacity is achieved at a specific battery load, beyond which battery size has less impact on self-consumption and thus only increases initial investment [14]. According to one more study that conducted techno-economic analyses on the sizing of residential PV battery systems, the degree of self-consumption and self-sufficiency is highly dependent on the size of the PV system and battery storage [60]. This study concluded that the combination of PV systems and batteries is critical not only for storing excess PV energy, but also for maximising PV potential. The review of all works related to self-consumption of residential PV systems concluded that it is possible to increase the relative self-consumption by 13–24% points with a battery storage capacity of 0.5–1 kWh per installed kWp PV capacity, compared to the original rate of self-consumption [7]. It is apparent from all of this research that energy storage system sizing is crucial for self-consumption and self-sufficiency assessments. As a result, the battery storage capacity in this study is defined at 0.5–1 kWh/kWp of PV capacity. Furthermore, the impact of increasing battery capacity on SC and SS is also evaluated.

The current literature on the integration of PV systems with batteries has some limitations. In terms of considering energy consumption or PV energy generation, several research focus on single households [30], [57], [61] or small sample size households [51], [62]. These approaches have the disadvantage of not having the statistical capacity to determine the differences that occur between households. As a result, this research aims to analyse the impact of battery storage systems on SC and SS for all households with PV systems in Hamburg, totalling 4490 households. This study, however, did not examine how each household's level of self-consumption and self-sufficiency varies as a result of the deployment of a battery storage system.

EV energy storage system

Recently, other authors have focused on the use of Electric vehicles (EVs) as energy storage or integration of EVs to grid, with some affirming that the use of EV can favour the increase of self-consumption and self-sufficiency. One study conducted a techno-economic analysis of various solar energy storage systems in German households. This paper presents how the demand profile changes following the introduction of EVs and how controlled EV charging improves load flexibility and self-generation [63]. Another research that assess the effect of 400 different real time EV charging profiles on self-consumption and self-sufficiency level of household with a PV system demonstrates the technological feasibility of using an EV battery as an energy storage unit [64]. Based on a stochastic model, author of this work demonstrated that when an EV is introduced into a residential household, the total annual electricity demand increases by around 40% on average. Besides that, the author observed a decrease in self-sufficiency with the introduction of EV charging, despite increasing PV capacity in proportion to demand. In one study on Sweden's EV sector, smart charging schemes for EVs were suggested as a way to improve self-consumption of residential PV systems and reduce peak load demand [48]. This study examined centralised and distributed smart charging methods, concluding that centralised charging stimulates self-consumption at a community level, whereas distributed charging increases it at the household level. Another study conducted empirical research on 78 BEVs in Switzerland using four different smart charging schemes. According to their findings, an optimised controlled charging approach could cover up to 90%

of EV demand and help users increase their own PV consumption [49]. Another case study conducted on a microgrid in Lombok, Netherlands, revealed that a smart charging approach increased self-consumption from 49% to between 62% and 87% [65]. However, this study does not use smart charging approaches in EV modeling to determine the influence on SC and SS. Some research focuses on bi-directional energy transfer from an EV battery to house or anything and vice versa, referred to as vehicle-to-anything (V2X), in order to emphasise self-sufficiency by storing energy for usage during non-sunny hours [66]–[68].

All of the studies agree that EV charging in residential buildings could enhance self-sufficiency and self-consumption, but that this improvement is limited by the low number of vehicles available for charging during peak PV output periods [48], [64]. Because of the growing number of EVs, it is critical to assess the distribution grid congestion issues caused by high penetration. One study modelled and simulated congestion management concepts for various EV penetration scenarios on Hamburg's low voltage distribution grid [69].

Most of the studies that have been reviewed have a specific interest in and focus on maximizing self-consumption and self-sufficiency with the use of energy storage technologies including batteries or EVs for financial benefit. This study, on the other hand, focuses on the technical analysis of the SC and SS patterns, as well as how seasonality and energy storage systems influence their profile. For this analysis, the PV power model has been developed in this study to produce solar energy generation profiles for PV systems. In the section that follows, a quick summary of studies surrounding the PV generation model is presented.

PV generation model

There are various tools available that assist in calculating and creating solar energy production using the specifications of PV systems. The PVsyst [70], SAM [71], and Pvlib [72] are some of the commonly available PV system modelling tools. According to comparison by [73], these applications were developed to achieve unique objectives; therefore, they have specific features for different tasks, and their selection should be dependent on the specific demand from modeling. Taking into consideration the specifications and requirements of this study, the open-source tool Pvlib is used to develop a PV generation model for the analysis of all residential PV systems in Hamburg. For PV generation profiles, sometimes solar irradiation is used as the only input [74], occasionally combined with temperature [38]. In practice, PV-generated electricity depends on many more factors, such as tilt and orientation of the PV system [75]. The majority of research takes into account the optimum tilts and azimuths. However, in the residential sector, those depend mostly on the location, orientation, and inclination of rooftops. As a result, assumed values of this may result in a different profile of solar production for PV systems than those usually addressed in the research [76]. Given that, this thesis will take into account a dataset with more precise values for each PV system, including information on the location of the system and the panel orientation to generate timeseries of solar generation with greater accuracy.

As self-consumption becomes more economically viable due to fast-changing technology and prices, customers are willing to transition away from grid power and toward self-energy reliance. A faster transition would, however, have a more significant impact on the grid and energy system. Few publications discuss the impact of a rapid transition to self-consumption and its impact on the grid [39], [77], [78]. To comprehend this effect, it is necessary to first analyse SC and SS, as this thesis attempts to do. As such, the purpose of this study is to fill in some of these gaps while estimating and analysing the self-consumption and self-sufficiency of residential PV systems in Hamburg. In addition, this study offers frameworks for determining the impact of energy storage systems on SC and SS profiles. Furthermore, the factors affecting SC and SS profiles are observed, and the findings are compared with those of other empirical studies of households with PV systems.

3. Fundamentals

In this chapter, the basics on which this master thesis is based are presented. Self-consumption and self-sufficiency are defined at the outset of this chapter, along with their mathematical expressions. Following that, this chapter covered the effects of growing PV installations on the grid and how self-consumption analysis helps operators manage the grid by addressing the issue. The chapter then goes on to describe the elements that influence the SC and SS, as well as the impact of residential energy storage systems on them. The final section of this chapter will provide a quick overview of the software tools and modules utilized in the building of models.

3.1 Self-Consumption and Self-Sufficiency

As indicated in the introduction, it is critical to investigate the influence of distributed energy generators on the local grid by analysing the consumption of generated energy close to the production site. In this context, self-consumption and self-sufficiency are two energy metrics used to evaluate the utilisation of local energy generation. In this section , the concepts of self-consumption and self-sufficiency are more formally defined, and the mathematical expressions used throughout the context of the present study are addressed.

The self-consumption (SC) is defined as an amount of generated PV energy utilised by household or owner of PV system either immediately or over the period of time, expressed as a percentage of total solar energy generation. Whereas, the self-sufficiency (SS) is defined as an quantity of total local load demand supplied by on-site generated PV energy over period of time, measured in percentage of total load demand [7].

Figure 2 illustrates the schematic outline of on-site PV generation profile and load demand profile for understanding self-consumption. PV energy output(blue) usually has a bell-shaped curve, with a peak at midday hours. The daily consumption curve(green), on the other hand, has peaks during morning and late evening, differing from the solar energy production. The overlapping portion in orange represents the PV energy directly used to meet load demand, commonly referred to as the self-consumption. However, when an energy storage system is included, self-consumption is measured in terms of overall PV power usage rather than just the immediate use of PV energy. Similarly, when the total on-site PV power consumption is calculated in relation to the total load demand, then it is called as self-sufficiency.

The mathematical expressions to calculate self-consumption and self-sufficiency are given as follows [60]:

The self-consumption of PV system without energy storage, SC is calculated by taking ratio between the generated PV energy fed directly to household load $E_{pv,load}$, and the total generated energy from PV system E_{pv}.

$$SC(t) = \frac{E_{pv,load}(t)}{E_{pv}(t)} \tag{1}$$

Where, t is the time resolution in which ratio is calculated for timesteps (hourly, daily, monthly, and yearly).

The SC of PV system with energy storage, SC_{bat} is defined with the directly used PV energy $E_{pv,load}$, the generated PV energy used to charge the battery $E_{bat,c}$, and the total generated energy from PV system E_{pv}. The energy lost as heat during charging/discharging is not considered as self-consumed, and therefore, is not included in the calculation.

$$SC_{bat}(t) = \frac{E_{pv,load}(t) + E_{bat,c}(t)}{E_{pv}(t)} \tag{2}$$

The self-sufficiency of PV system without energy storage, SS is described as the ratio of the load demand directly fulfilled by generated PV energy $E_{pv,load}$ to the total load demand of the household E_{load}.

$$SS(t) = \frac{E_{pv,load}(t)}{E_{load}(t)} \tag{3}$$

And the SS of PV system with energy storage, SS_{bat} is calculated with the load directly fulfilled by PV energy $E_{pv,load}$, the load demand fulfilled by discharging the battery $E_{bat,d}$, and total load demand of the household E_{load}.

$$SS_{bat}(t) = \frac{E_{pv,load}(t) + E_{bat,d}(t)}{E_{load}(t)} \tag{4}$$

Generally, the amount of SC and SS are dynamic and changing depending on PV production and consumption profile. When PV generation exceeds consumption, the surplus solar energy is either injected into the grid or wasted, resulting in low SC. On the contrary, when consumption exceeds PV generation, the remaining load is supplied by consuming grid electricity, boosting SC but resulting in a low SS value.

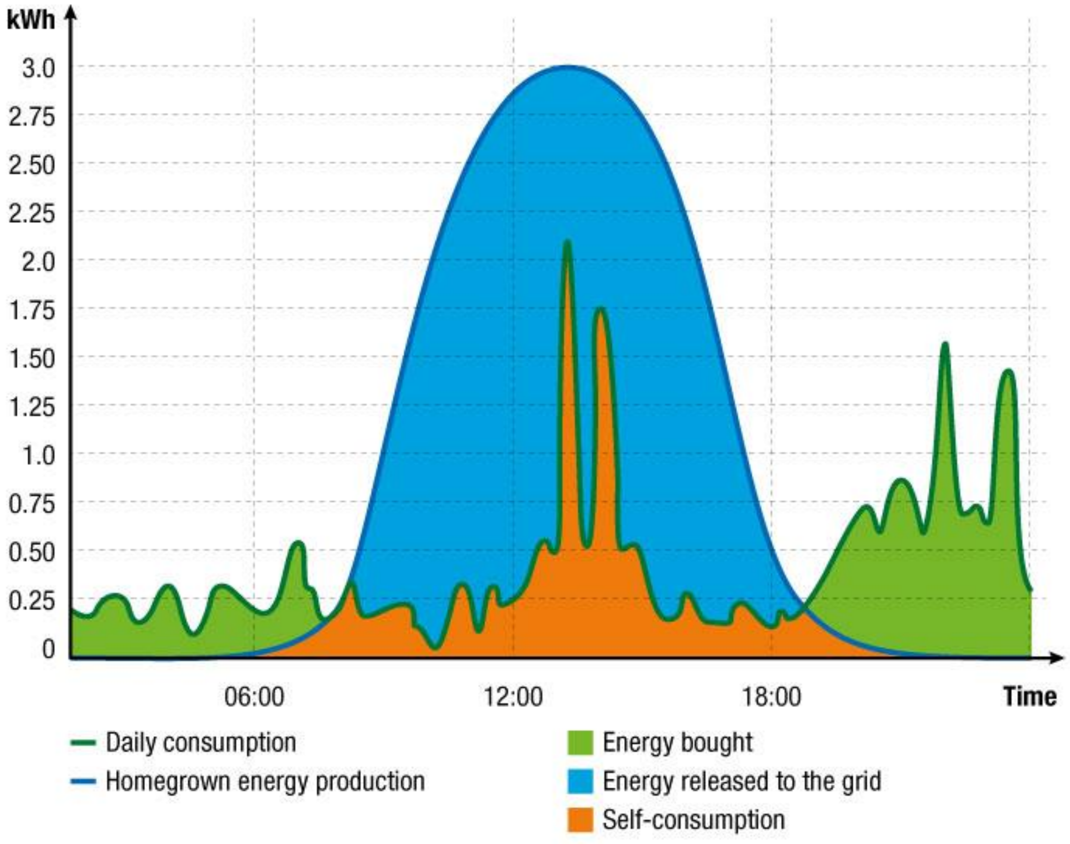

Figure 2 Schematic of self-consumption of PV system [79]

3.2 Impact of expanding PV installation capacity on grid

To comprehend the role of self-consumption in addressing grid operator difficulties caused by high PV penetration, the expanding PV energy market and its influence on the grid must be examined.

Subsidies and pro-policies have always been a boost for PV installation as PV system costs have historically been high. Schemes such as net metering and feed-in tariffs have been helpful in promoting PV installation and PV power. The total solar photovoltaic installed capacity of the world in 2020 estimated to be 773.2 GW [1] with residential PV system share of around 15%. Figure 3 shows the graph representing growth of the PV installations from 2000 to 2020. The PV market's expansion has resulted in significant price reductions for new installations, with an average PV system price decline of 10-12 % for last year [80]. Many of these PV systems have been integrated with the low-voltage distribution grid due to the necessity for decentralized (distributed) power generation. Installation of PV systems has expanded tremendously due to their reliability and ease of implementation, government policy backing, low cost, and ability to be placed at numerous points in the distributed grid, including actual load points.

While PV installations on distribution grids reduce electricity power demand and ease grid congestion, increasing PV penetration has several other grid-related effects, both favourable and unfavourable [22]. Power flows unidirectionally from the high-voltage national transmission grid to the medium-low voltage distribution grid and then to end users (consumers) through the low-voltage distribution grid. As more rooftop PV systems are installed, these consumers become prosumers, who produce and consume electricity, posing stability, reliability, and monitoring concerns to the distribution grid [31]. The intermittent nature of PV output, its lack of inertia compared to synchronous generators, and the distribution network's unidirectional power flow nature provide a significant obstacle for increasing levels of PV penetration [27]. The two key challenges with high penetration of PV are increase in voltage level and imbalance in current and voltage leading to power factor instability. Reverse power flow from rooftop PV systems can cause over-voltage in low voltage (LV) distribution systems in residential areas where load demand is low with high solar radiation (high PV generation). A significant mismatch between PV generation and electricity demand could cause frequency stability issues. Voltage stability, frequency stability, and overall power quality are some of the significant concerns connected with Solar-Grid integration. Voltage and frequency are just two examples of power quality difficulties, but there are others as well, such as current harmonics, phase imbalance, and direct current(DC) injection [24], [26], [27]. The solution to such challenges can be achieved by rapidly starting and ramping electricity generation, managing the consumption with immediate solar generation, and reducing the penetration of generated PV energy from residential solar systems.

The traditional solution for voltage instability is to reinforce components in grid, which could be more expensive than curtailment of PV power. Some countries have implemented renewable energy curtailment legislation, like as Germany, which has set restrictions on small-scale PV plants, allowing up to 70% of installed capacity to be fed in [81]. However, power curtailment is not the best approach because it wastes energy and reduces the profitability of PV systems by selling less electricity [31]. Distributed generators' self-consumption can mitigate this problem in part. Direct penetration to the grid will be reduced if the producer, or owner of the system, consumes more PV energy directly. This can be accomplished by implementing demand side management or adding a battery storage system [7]. Many countries are promoting self-consumption to tackle the issue with distribution grid management. Reduction in feed-in tariff(FIT) and increasing electricity retail prices has made self-consumption more attractive for prosumers.

The growing interest in SC and SS has altered household energy consumption behaviours, encouraging PV energy being used. Other factors, apart from financial advantages, influence the SC and SS patterns throughout the year. This has a direct and indirect impact on the household's net load demand profile. As a result, it is critical to investigate the elements that improve or alter the SC and SS.

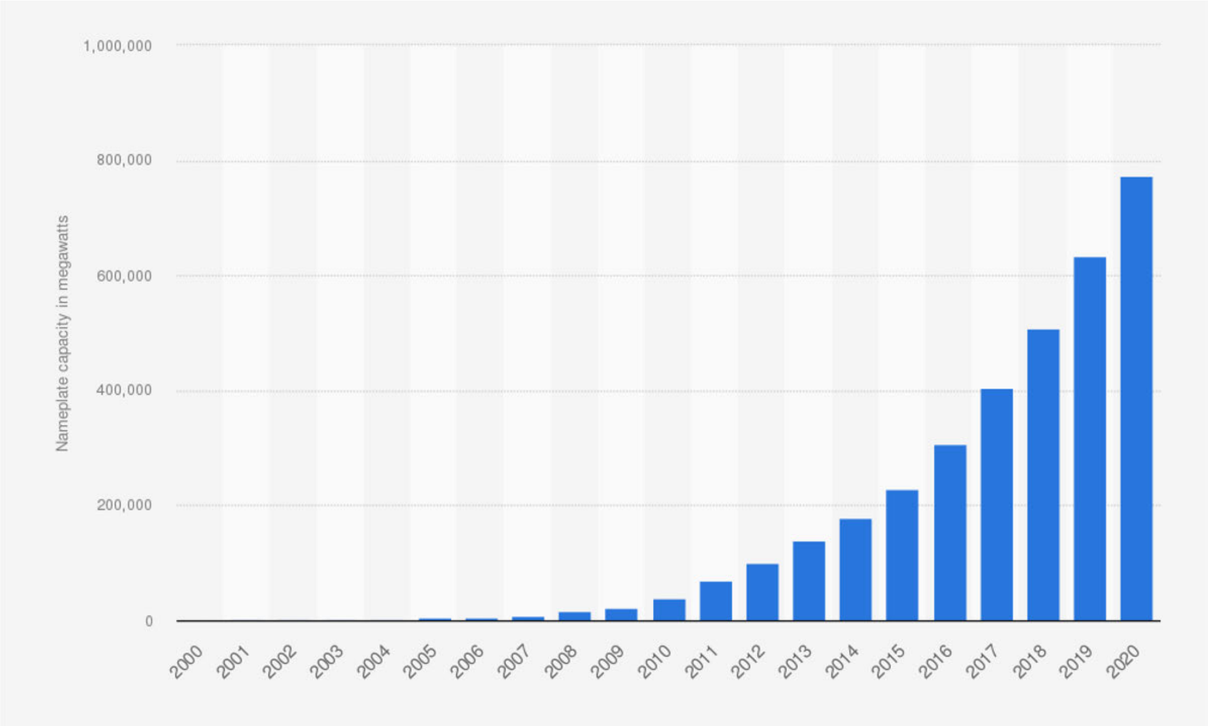

Figure 3 Total Installed Solar PV Capacity Worldwide from 2000-2020 in MW [1]

3.3 Influencing factors of Self-consumption and Self-sufficiency

In Germany, there are numerous influential drivers for self-consumption, which can be further divides as financial oriented and technical oriented factors. The adoption of self-consumption is influenced by attractive policies, schemes such as retail and feed-in tariffs, as well as the decreasing cost of PV systems and storage systems; simultaneously, variation in solar generation and energy consumption driven by the geographical and meteorological characteristics change the SC pattern [14]. The analysis and evaluation of relevant driving factors for self-consumption in Germany could help in the alteration of this factor for improved energy efficiency.

By introducing 'Erneuerbare-Energien-Gesetz (EEG)' in 2000, Germany made lucrative policies and investment to increase renewable energy share in energy market. The alluring feed-in tariff on PV installation significantly increases its installed capacity up to 54 GWp by 2020. With increasing development and investment in solar sector the installation price per kWp decreased and at same time the feed-in tariff also reduced from 43cents/kWh to 12.7cents/kWh by 2019 [82]. On the other hand, the residential electricity retail price increases to 32.05 cents/kWh by 2020 [83], which makes self-consumption more attractive for household PV systems. Since feed-in prices are lower than energy prices, prosumers are more likely to increase on-site consumption rather than feed power to the grid. Profitability in self-consumption has encouraged prosumers to use energy storage systems or load-shifting techniques to increase local consumption, resulting in a change in the SC and SS pattern. The development and mass production of energy storage systems in recent years decreases prices of batteries and other storage technologies. The economics and effectiveness of deploying battery storage with rooftop PV systems has influenced self-consumption compatibility in the German market.

From technical point of view, the significant metrics of SC and SS pattern are solar generation and energy consumption profile. The generation of solar energy is altered by many factors, with season being the most influential one. The variation in solar energy generation between summer and winter, as well as load demand at the same time, has a significant impact on it. In compared to shorter and foggier days in the winter, the longer days of summer result in more sunlight, which generates more solar energy. This means that more on-site generated energy is dedicated to meet the load demand, which increases the overall SS of the system, but it may also result in solar energy surplus, which lowers the SC. Cloudy days are more common in Hamburg in the winter and autumn, when the intensity of solar radiation is already lower than in the spring and summer. During this time of year, when solar production is reduced, the cold winter and shorter daylight hours demands increased energy usage, which may require drawing electricity from the grid. As a result, the SS of the domestic PV system would gradually decrease. The effect of seasonal variation on self-consumption and self-sufficiency is represented and discussed in result section.

The geographical placement of PV system is also another crucial factor in SC and SS estimation. Compared to northern regions, countries in southern Europe or close to the equator experience higher solar radiation and longer sunshine duration in a year. For instance, the duration of sunshine in 2021 in Germany was 1631 hours, compared to 2800 hours in Spain [84]. Due to the longer sunshine hours in southern European countries, PV and energy storage system combination could result in higher SC and SS due to longer utilization times [37]. In terms of sunshine duration within Germany, northern state Hamburg had 1468 hours in 2021, while southern states such as Baden-Württemberg had 1800 hours [84]. As one moves further north, the short sunshine hours change the electricity generation and residential load demand profile, resulting in variation in SC and SS values.

Apart from these factors, the relative size of overall PV system and power demand modify the SC and SS pattern. Self-consumption as defined above, is measured in relation to total PV energy generation and self-sufficiency is normalised by total power demand. As a result, increasing size of PV system relative to local demand would always decrease the SC while SS increases or remains unchanged. On the other hand, when power consumption or the number of loads increases, resulting in under-sizing of the PV system, the SS always decreases while the SC remains constant or increases [7].

Different factors that influence self-consumption and self-sufficiency are categorised based on their financial and technological aspects in Table 1.

Table 1 Influencing factors of self-consumption and self-sufficiency

Finance oriented drivers	**Technology oriented drivers**
Legislation around self-consumption	Supply: Solar energy generation
Retail electricity prices	Demand: Energy consumption profile
Feed-in-tariff (FIT)	Geographical location
PV system cost	Meteorological characteristics
Storage system cost	Relative size of PV system and power demand

The factors mentioned above influence the self-consumption and self-sufficiency on more general terms. On the other hand, the SC and SS can be altered manually on local level by two techniques,

1. By adopting Demand Side Management (DSM) Methods
2. By adding Energy Storage System

Because these methods have distinct applications, they can be employed separately or in combination [7], [35].

Demand side management optimises load energy consumption in order to achieve savings and higher efficiency in energy usage [35]. DSM does not have proper definition but article [85] has described it as; ”The organisation, execution and monitoring of group of actions aimed to influence customer behaviour of electricity usage, resulting changes in load demand profile, time pattern and its magnitude.” The main three methods of DSM are Valley Filling, Peak Clipping and Load Shifting. The proper implementation of these DSM techniques can alter self-consumption considerably. The load shifting technique can be used to shift movable load to peak PV generation time, hence increasing SC and SS. For most of traditional houses, this technique will have to be handled manually, but applying these methods in planning phase of smart homes by scheduling of programmable loads (for example, Washing-machine, Dryer, Dishwashers etc.) can help in self-consumption improvement [34].

As stated in the introduction and in accordance with the findings of literature [28], [34], the DSM approach has less potential to increase SC and SS than an energy storage system, despite being less expensive approach. This is because there is limitation in flexible load that can be shifted to match solar generation. As a result of the foregoing facts and the time constraints to complete the thesis, the scope of this study is confined to an investigation of residential energy storage systems.

3.4 Residential energy storage system

Adopting an energy storage system is another method for increasing self-consumption and self-sufficiency. With energy storage, excess solar energy can be stored for later use in the evening, night, and morning, when solar production is low or none. The energy storage systems available differs according to its storage type, capacity, efficiency, usage, and self-discharge(Batteries, Electric Vehicles, Hydrogen storage, Heat storage etc.). The more efficient and investigated system in all storage technologies is battery. Due to advancement in research, recent development, and mass production, the price of battery storage unit has drastically decreased over years [80], which is advantageous over other forms of energy storage [52]. Depending on the purpose and duration of storage, chemical storage in batteries or hydrogen storage utilising an electrolyser and fuel cell are the more appropriate solutions for residential PV storage systems [7], [31]. Battery storage has high conversion efficiency but has high self-discharge, making it more ideal for dealing with daily fluctuations. In contrast, even with a near-zero self-discharge rate, the round-trip efficiency of hydrogen storage technology is quite low, making it more suitable for monthly or seasonal long-term storage [40], [41]. Another approach might be thermal storage, which involves converting excess energy into heat energy and storing it in a hot water tank or the equivalent alternative. Thermal storage for residential use is intended for building heating applications because converting heat energy back into electricity is not the optimal solution. [33], [43]. All these storage technologies are referred as stationary energy storage system, on same side, increasing interest on electric vehicle has changed means of storing energy in stationary system. The application of electric vehicles in smart grids has grown in recent years, and they are now a critical element of storage systems and, eventually, self-consumption [64].

Taking into account all the aspects of storage technologies would take a great deal of time and effort, therefore, in the context of this thesis, only the battery storage system and electric vehicle as storage system are evaluated as residential energy storage systems.

Battery storage system

Residential battery energy storage is also referred to as stationary battery storage systems because weight and volume are less significant factors when it comes to household batteries. The most widely used and highly invested technology is battery storage since it can assist in regulating voltage, reducing peak power, reducing peak demand, and minimising the need to reinforce grid infrastructure [37]. Battery storage systems are now more affordable because of recent advancements and mass manufacture, making them a more acceptable and preferred method for storing electricity.

The four most popular battery types currently on the market for household usage are lead-acid (LA), lithium-ion (Li-ion), nickel-cadmium (NiCad), and nickel metal hydride (NiMH). Every technology has its own distinct properties. The LA battery is an older, less expensive technology but has a quick deterioration cycle. On the other hand, Lithium-ion batteries have a better potential for future growth and residential energy storage due to its high efficiency, long life, and greater energy density [7], [59]. Additionally, the Li-ion batteries' self-discharge occurs at a rate of 1% per month which is relatively lower compared to other technologies. Given these details, the Li-ion battery is used as a reference technology in this study.

As mentioned in influencing factors of self-consumption, the size of the battery storage system is important. The potential of batteries to boost PV electricity SC and SS decreases with increasing battery capacity, hence oversizing the battery without comparably adequate solar generation will only increase costs rather than increasing self-consumption beyond a certain level. Similar to this, undersizing the battery capacity could restrict the SC of the system and potential of storage system to reduce peak demand. Therefore, choosing the optimal battery size is crucial for achieving high SC and SS as well as maximising PV potential [58], [59]. In the context of this thesis, the size of the battery capacity is calculated in relation to the installed PV capacity.

Electric vehicle as storage system

The adoption of electric vehicles (EV) has lately accelerated in order to achieve the decarbonization of the transportation sector. This is entirely dependent on the extensive integration of renewable energy sources into the energy grid. Growth in the rooftop PV sector offers a greater potential for decarbonization with the introduction of EV at home charging stations. Similar to a battery storage system, the battery in an electric or hybrid vehicle can be utilised to store excess solar energy, boosting the overall self-consumption of the residential PV system. The major drawback of employing an electric vehicle (EV) as a storage system is the discontinuity between solar energy generation and EV charging times, which are often concentrated in the morning, evening, or night hours [49]. With regard to this, the stability of the distribution grid has been threatened by large-scale generation and consumption, which have caused fluctuating peaks in both production and demand. Since solar energy production is stochastic, it is not possible to change the time at which it is produced. However, the EV charging profile can be changed to increase energy consumption when solar energy is being produced. The optimal controlled charging strategy combined with a straightforward EV profile adjustment may assist in increasing owners' PV consumption. The introduction of EVs into household environments has altered the profile of residential energy consumption. Due to the vehicle to grid (V2G) technology's bidirectional energy flow, it may be possible to store surplus solar energy for use at a later time during off-peak hours, which would increase SC and SS [68]. This thesis analyses the impact of EV and its profile on SC and SS of residential PV systems.

Although, energy storage system is promising technology, the losses during charging, storing, and discharging energy cannot be neglected as compared to using PV generated energy immediately to satisfy the load [7]. As storage systems are not generating entity, the optimal size needs to be calculated while planning by considering its capacity, price, and load demand of house during non-production hours of PV system.

3.5 Software tools

The development of all models is based on Python language because of its simple structure and functionality. Guido van Rossum created the high-level general-purpose Python language in the late 1980s. Due to its simplicity and readability, Python has grown to be one of the most widely used programming languages [86]. The Python programming language was chosen mostly because of the following features: open source and rapid development, structured in a simple and understandable manner, large number of useful libraries are available, large, and growing community.

In course of this work, following Python modules has been used:

Pvlib

Pvlib python is a community-supported application that provides a functionalities and models for simulating the performance of photovoltaic energy systems. Many of the models and procedures developed by Sandia National Laboratories are implemented in pvlib python, which was originally adapted from the PVLIB MATLAB toolbox. For users that prefer object-oriented programming, pvlib-python additionally includes a set of classes, which provide some smart methods with more flexible inputs [72]. This library give access to TMY3(Typical meteorological year) weather data, which can be called for simulation purposes.

The following functionality is provided by this module [87] :

- Large number of classes and simple functionality

- Can develop own model chain subclass

- Use NREL defined function for poorly specified PV-system data

- Can provide weather data manually

- Access to all PV modules in the latest databases of Sandia and the CEC

The weather data and PV system parameters are provided to the Pvlib module for modelling of PV system, which provides solar energy generation timeseries.

Demandlib

Demandlib is standalone application developed by oemof group, which create power and heat profiles for various sectors [88], [89]. It generates power and heat demand timeseries for required year by scaling BDEW profiles to desired demand. BDEW profiles are standard load demand and heat demand profiles for every sector. The standard load demand profile (SLP) for residential sector is scaled up to desired Hamburg level with the help of Demandlib module.

Pandapower

The Pandapower program is a Python-based algorithm that creates an easy-to-use program that automates analysis and optimization of power systems. This software provides power system analysis such as power flows, optimal power flows, state estimations, topological graph searches, and short circuit calculations [90]. The power flow analysis of the grid is conducted to analyse the reliability of the model.

Simbench

Simbench is an application and project that creates and offers a benchmark data set that will allow for the comparison of various innovative developments in the areas of network analysis, network planning, and network operation management. It consists of benchmark grid datasets with electrical parameters for static modeling of power grids and voltage ranges from low to extra-high voltage [91], [92]. The low voltage benchmark grids representing rural and urban grids are obtained from the Simbench dataset for grid power flow simulation using Pandapower.

4. Methodology

To analyse the self-consumption of PV systems, the simultaneous data of the electricity consumption and the PV power generation of the household with high resolution is necessary. Since the consumption and generation vary seasonally, the simulation model was set to conduct over a one-year timeframe. The following chapter deals with the methodology for analysing the self-consumption of residential PV systems in Hamburg. The models for load demand profiles, PV power generation, battery storage systems, electric vehicle storage systems, and self-consumption and self-sufficiency models will be explained in this chapter.

The simulation of self-consumption and self-sufficiency for each individual household with a PV system in Hamburg is a complicated and time-consuming process. Therefore, it is decided to simulate PV power output model and energy storage system model for each grid node point. All households with PV systems in close proximity to a grid node are grouped together and treated as an individual system. As a result, while the PV systems, load demand, and energy storage systems for each household operate independently; in this thesis, it is assumed that all households shared an electricity meter and an energy storage unit with a capacity equal to the sum of all the individual storage units. A shared electricity meter would allow electricity to be transferred from one home with excess PV power output to another home with more load demand while still counting the PV power production as self-consumed.

4.1 Data for Residential Photovoltaic Systems in Hamburg

The majority of residential photovoltaic (PV) systems have installed capacities ranging from 0 to 25 kWp. The targeted systems for this thesis are residential PV systems and therefore, all PV plants in Hamburg with capacity less than 25 kWp are assumed to be residential PV systems. According to the data from MaStR, there are total 4490 active residential PV systems in Hamburg by the end of year 2021 [10]. For the purposes of this thesis, these PV systems are assumed to be households, and the load from these households is considered for assessment of self-consumption.

4.2 Model for Load Demand Profile of Hamburg

The available reference grid structure representing the area of Hamburg was chosen as the basis for the simulation model. The feed-in of the generated solar energy from household PV systems is to the low voltage (LV) nodes. There are a total of 73 grid nodes with 110/10 kV transformer stations in the Hamburg region (refer appendix A.1.1). As a result of location-based filtering the total number of grid nodes taken into consideration in this thesis is 50. Additionally, as mentioned to operate for individual grid node points, PV systems are allocated to the nodes in accordance with their location in close proximity (refer appendix A.1.2).

The publicly available standard load profile (SLP) for residential buildings is not suitable for creating load profile time series for households, as it assumes that every household has a similar energy consumption pattern. In practice, the load distribution or electricity consumption varies from house to house depending on size and type of household, the number of occupants, location, and the use of various electrical appliances, among other considerations [93]. Due to the increasing use of electronic devices, the culture of work-from-home due to the pandemic, the use of electric vehicles, and the change in individual consumption patterns, the deviation between the SLP and actual consumption is likely to be higher during the simulation period of this study. Unfortunately, the latest validated and publicly available energy consumption profile for Hamburg was not available at the time of writing this thesis, so it was decided to conduct the study using publicly available SLP for Germany. As a result, the standard household load profile (SLD) from BDEW was selected to represent these loads [11]. For more accuracy the distribution of the load used in this thesis is based on distribution of households by household members in Hamburg [94]. For this purpose, the proportion of residents in households in different regions of Hamburg associated with grid node location is estimated (refer appendix A.1.3) [94]. In order to create load profile for simulation model, the Demandlib tool is used to scale the standard load profile with the average electricity consumption of Germany based on number of residents in house. Table 2 shows the average electricity consumption in Germany based on number of occupants in the house [95].

This load demand model generates hourly resolution time series of load demand from the SLP of the BDEW, which is presented in this thesis as load demand profiles of households with PV systems connected to each grid node in Hamburg.

Table 2 Average Electricity Consumption of Households based on number of Occupants[95]

House Occupants	Average Electricity Consumption kWh
1 person	1700-3000
2 persons	2500-3600
3 persons	3000-4300
4 and more persons	3500-5000

4.3 Model for PV Power

In order to estimate and understand the behavioural patterns and attributes of self-consumption and self-sufficiency of residential PV systems under real climate conditions, it is important to analyse the power generation of the PV system for a given household. In this context, a PV power model was built using the Python environment to estimate the instantaneous solar energy generation. This model takes the installed capacity of PV systems as an input along with meteorological data for a particular location.

The weather data is obtained from the Deutscher Wetterdienst, which maintains comprehensive database of meteorological parameters measured at every station in Germany [96], [97]. The meteorological data contains temperature and wind parameters as well as irradiation parameters such as ‘global horizontal irradiance(GHI)’, ’diffuse horizontal irradiance(DHI)’, and ‘solar zenith angle’. It is presumed that all PV systems in the Hamburg region experience identical weather conditions. The weather data for Hamburg was taken from the nearest weather station located at Fuhlsbüttel, therefore it may not reflect the precise weather conditions for the PV system's targeted location, thus expect relatively minor differences in weather between the weather station and the system's location. The approach of considering each solar plant separately and providing it as input to simulation model along with weather parameters is efficient when considering small number of systems with different meteorological data; however, while considering solar systems for entire Hamburg with weather parameters from same station, this approach will take longer computational time due to the thousands of solar system entries. Therefore, as decided to combine all solar systems in vicinity of grid node location together(refer section 4), this model processed all grid node points as an individual solar system. This method has significantly reduced computing time while also being efficient.

The information about residential PV plants in Hamburg, comprising their installed and net capacity, working status, commissioning and decommissioning dates, location, panel orientation, and grid feed-in status is gathered from the MaStR (refer section 4.1). This information about PV plants associated with specific grid node varies over time due to the introduction of new plants or the decommissioning of old plants. Therefore, updating the capacity database is necessary to achieve greater accuracy over a one-year simulation. As a result, the updated capacity for each month is recognized in the PV power model, and the solar plant data is processed by sorting with the plant's commissioning date. Furthermore, one of the most essential parameters for the accuracy and reliability of a PV power model is the tilt angle and orientation of PV panels. According to Fraunhofer ISE research, the average PV modules are mounted at a tilt angle of 30° to 40° to horizontal [19]. As a result, the tilt angle in the PV power model is considered to be 35 degrees. The information about orientation of each photovoltaic systems in Hamburg has been taken from MaStR [10]. The PV modules with missing information about its orientation are assumed to be facing south.

The PV power model defines the PV system parameters by system capacity, location, tilt angle and orientation, and temperature coefficient. The processed weather data in accordance with every grid node is operated by Pvlib module with defined PV system parameters. As a result, the simulation model creates hourly resolution timeseries representing solar energy generation for given capacity of PV systems associated to each grid node in Hamburg. A flowchart of the PV power model is shown in Figure 4.

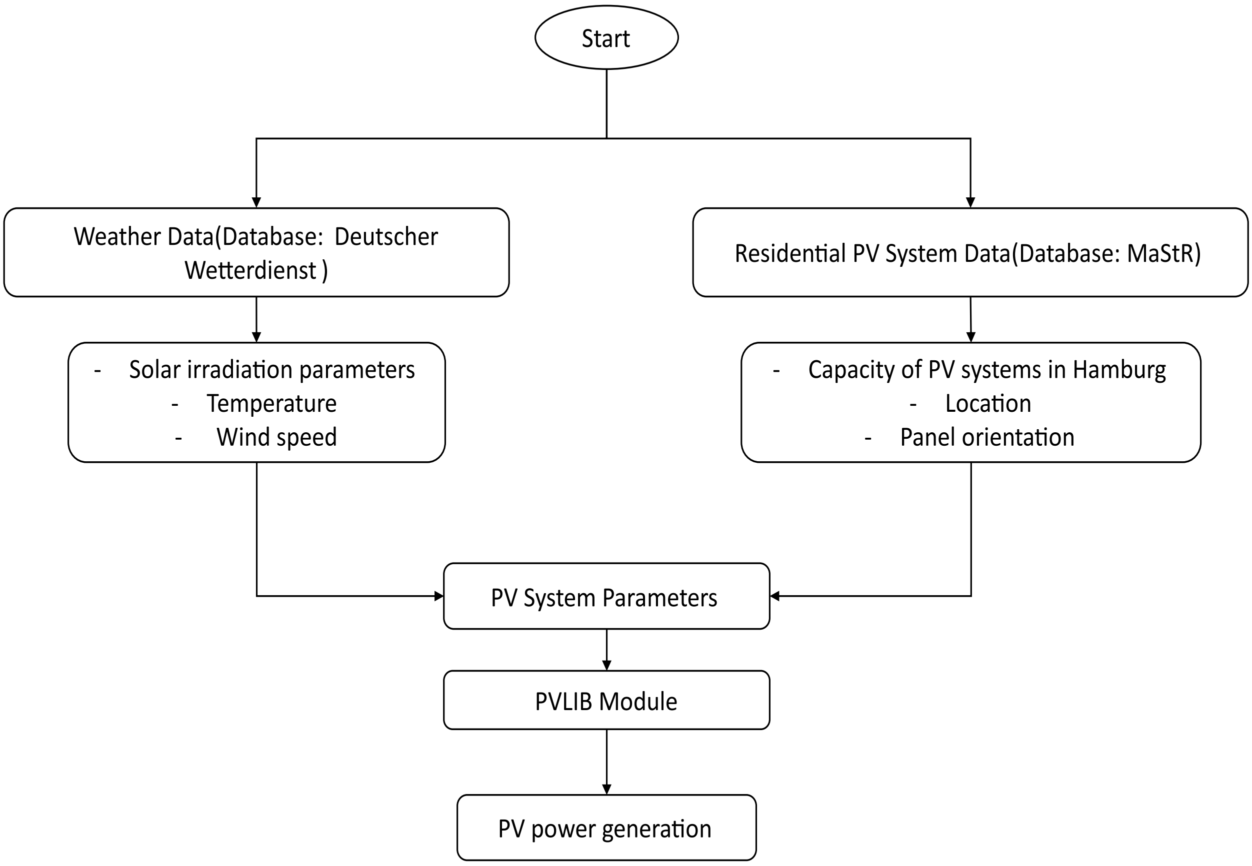

Figure 4 A flowchart of the PV power model

4.4 Model for Self-Consumption and Self-Sufficiency

Thus far, the previous section has shown the development of the load demand model and the PV power model. The output of these models gives the energy consumption profile and solar energy generation profile of residential PV systems in Hamburg. The synthesis and evaluation of the self-consumption and self-sufficiency model for PV systems with and without energy storage are now covered in this section and the ones that follow.

The mathematical expressions for self-consumption and self-sufficiency estimation, discussed in section 3.1, are used to develop and configure the SC and SS models for PV systems without energy storage. Solar generation data and load demand data with hourly resolution are used to evaluate the SC and SS models for PV systems without energy storage.

4.5 Model for Battey Storage System

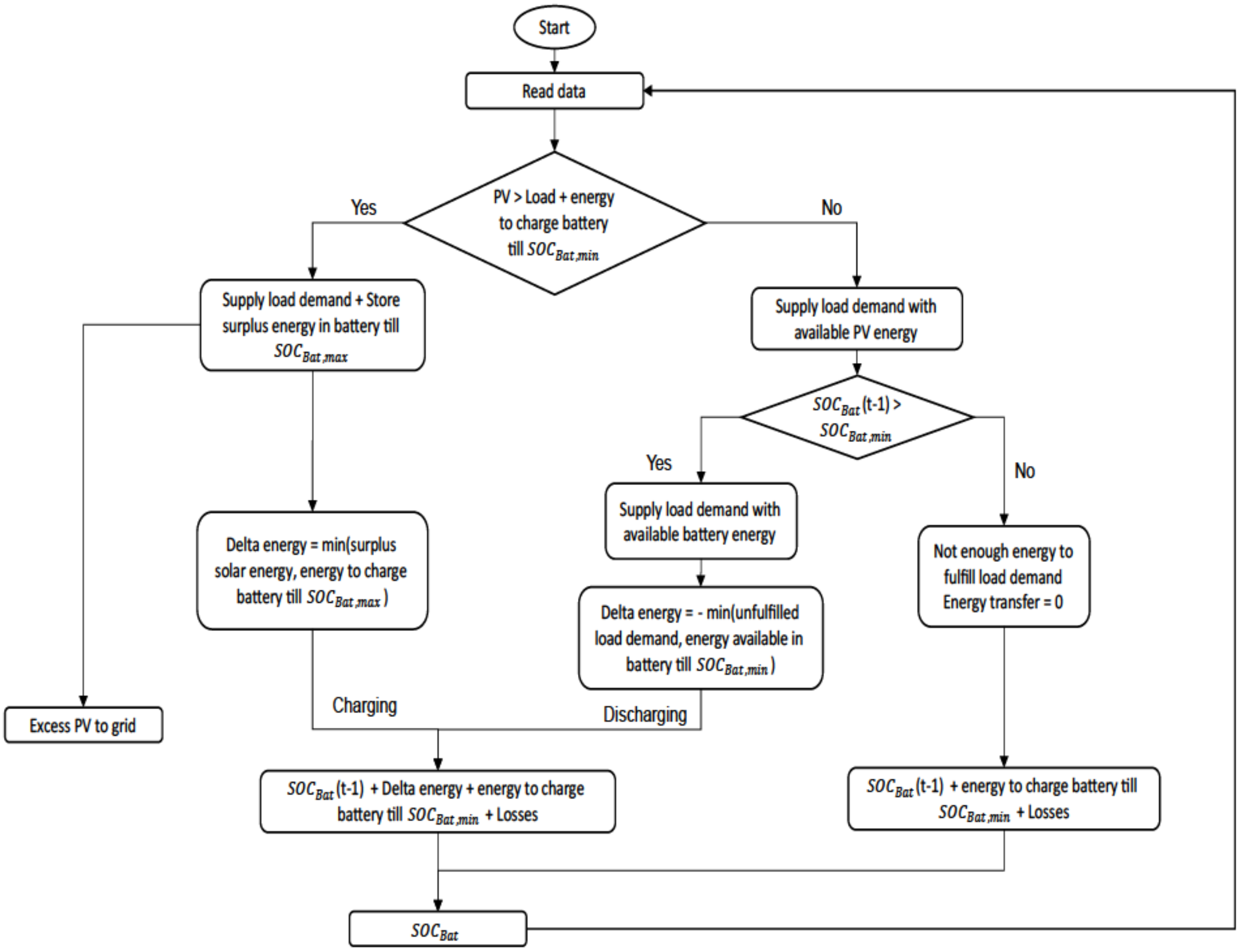

Figure 5 A flowchart of the battery energy storage system simulation

If the PV system is connected to a battery storage system, the excess generated PV energy can be stored in the battery after meeting the immediate load demand. When the PV generation is less than the actual demand, this stored energy can be used. To analyse the model of PV system with battery storage, it is necessary to estimate the charging and discharging cycle, as well as the efficiency of the battery and energy conversion. The self-consumption and self-sufficiency increase with an economically optimal battery size of 0.5-1 kWh per installed kWp of the PV system, so in this thesis, the battery capacity is assumed to be 1 kWh/kWp of PV system [7]. It should be noted that the battery's c-rate is not taken into account in this model. The quantity of surplus solar energy fed into and extracted from the battery is assumed to be a factor in how the battery charges and discharges.

The most commonly used PV systems with energy storage are AC coupled because they are flexible and offer advantages over DC coupled systems [52]. For the purpose of this work, it is considered that the residential PV systems in Hamburg are AC coupled. The calculations for the simulation over the year are performed using a battery model that considers each time step at a given resolution.

The surplus generated PV energy is excess PV energy after meeting the direct load demand at given time. It is calculated by taking difference of the generated PV energy E_{pv} and local load demand E_{load} for that timestep. The amount of energy required to fully charge the battery is estimated by subtracting state of charge of battery SOC_{Bat} at previous timestep from the maximum capacity of the battery $SOC_{bat,\max}$.

When generated solar energy is more than load demand, the delta energy of battery for given timestep, ΔE_{Bat} is estimated by considering the minimum of surplus generated PV energy and energy required to fully charge the battery.

$$\Delta E_{Bat}(t) \ = min\left(\left(E_{pv}(t) - E_{load}(t)\right),\ \left(SOC_{Bat,max} - SOC_{Bat}(t-1)\right)\right) \tag{5}$$

Once the demand exceeds the generated PV energy, the quantity of energy that can be supplied to the household is determined by the amount of energy available in the battery until $SOC_{Bat,min}$ is reached, which is considered in this model as zero(see Table 3).

$$\Delta E_{Bat}(t) \ = -\,min\left(\left(E_{load}(t) - E_{pv}(t)\right),\ max\left(0, \left(SOC_{Bat}(t-1) - \ SOC_{Bat,min}\right)\right)\right) \tag{6}$$

The battery is in charging mode when ΔE_{Bat} is greater than zero and in discharging mode when ΔE_{Bat} is lower than zero. When the demand load exceeds the generated solar energy, the amount of energy discharged, ΔE_{Bat}, is determined by the available energy in the battery at given timestep. Since the system is AC coupled, the conversion losses from AC to DC(charging mode) or DC to AC(discharging mode) must be taken into account, which can be achieved by multiplying ΔE_{Bat} with conversion efficiency η_{conv}. In this thesis the conversion efficiency, η_{conv}, is defined as 93 percent for the simulation model [52]. The state of charge of battery SOC_{Bat} for given timestep depends on whether battery is being charged or discharged. Furthermore, the change in state of charge of battery from previous timestep considers the self-discharge of the battery η_{Bat}, which is set to 2% per month [52], [98].

$$SOC_{Bat}(t) = SOC_{Bat}(t-1) * \eta_{Bat} + \Delta E_{Bat}(t) * \eta_{conv} \tag{7}$$

The main essential consideration in this model is that the charging of the battery above $SOC_{Bat,min}$ will occur only with surplus generated PV energy after meeting the local load demand, but as $SOC_{Bat,min}$ is set to zero for this simulation, the complete charge cycle of the battery will occur with the PV energy. As the simulation commences at midnight, the battery is assumed to be completely discharged at the start of the simulation. The model examines the load demand and determines whether it can be supplied with the generated PV energy, battery energy or a combination of both. The surplus energy being stored in the battery or extracted from it is evaluated using the delta energy of the battery equations, ΔE_{Bat}. When PV energy is not available and state of charge of the battery reaches $SOC_{Bat,min}$ (see Table 3), the energy will be extracted from the grid to meet the load demand. While, when there is excess PV energy that cannot be stored in battery, it is fed into the grid.

Lastly, the mathematical equations for estimating self-consumption and self-sufficiency using a battery storage system, mentioned in section 3.1, are employed in the model to estimate the SC and SS. Table 3 lists the model parameters of the battery energy storage simulation model and Figure 5 shows a flowchart of the battery model.

As described in section 3.4, the sizing of energy storage is one of the crucial parameters for evaluation of the SC and SS. The undersizing and oversizing of battery capacity has influence on self-consumption and self-sufficiency of the system. As a result, the scenario with four different battery sizes—0.5 kWh/kWp, 1 kWh/kWp, 1.5 kWh/kWp, and with 2 kWh/kWp—is simulated in the context of the battery model in order to evaluate the effects of varying battery capacity on SC and SS.

Table 3 Model parameters for the battery storage system simulation

Parameter	**Value**
Optimal battery capacity [7]	1 kWh/kWp
Conversion Efficiency, η_{conv} [52]	93%
The self-discharge rate of the battery, η_{Bat} [98]	2% per month
SOC at initial timestep and $SOC_{Bat,min}$	0% of the total SOC
$SOC_{Bat,\max}$	100% of the total SOC

In this section, the development of the battery simulation model is explained, and now the chapter that follows moves on to describe the configuration of the EV simulation model.

4.6 Model for Electric Vehicle Energy Storage System

The growing interest in and development of electric vehicles has altered the methods of storing energy in stationary battery storage system. Similar to the battery storage, the surplus PV energy after fulfilling local demand can be stored in EV and utilised it during low solar energy production. To assess the model of a PV system with EV energy storage, it is essential to quantify the EV's availability at different times of the day, the average daily commute by vehicle and power consumption, the minimum energy buffer available at all times, along with the battery and energy conversion efficiency.

The diverse distribution of mobility patterns of EVs plays a crucial role while modeling EV charging behaviour [49]. This study does not investigate every aspect of charging behaviour, because the analysis of SC and SS and the impact that the introduction of EVs has on them is the main emphasis of the thesis. Although the availability of EVs at homes and their charging for both fixed and variable departure and arrival times are studied to determine their overall impact on SC profiles.

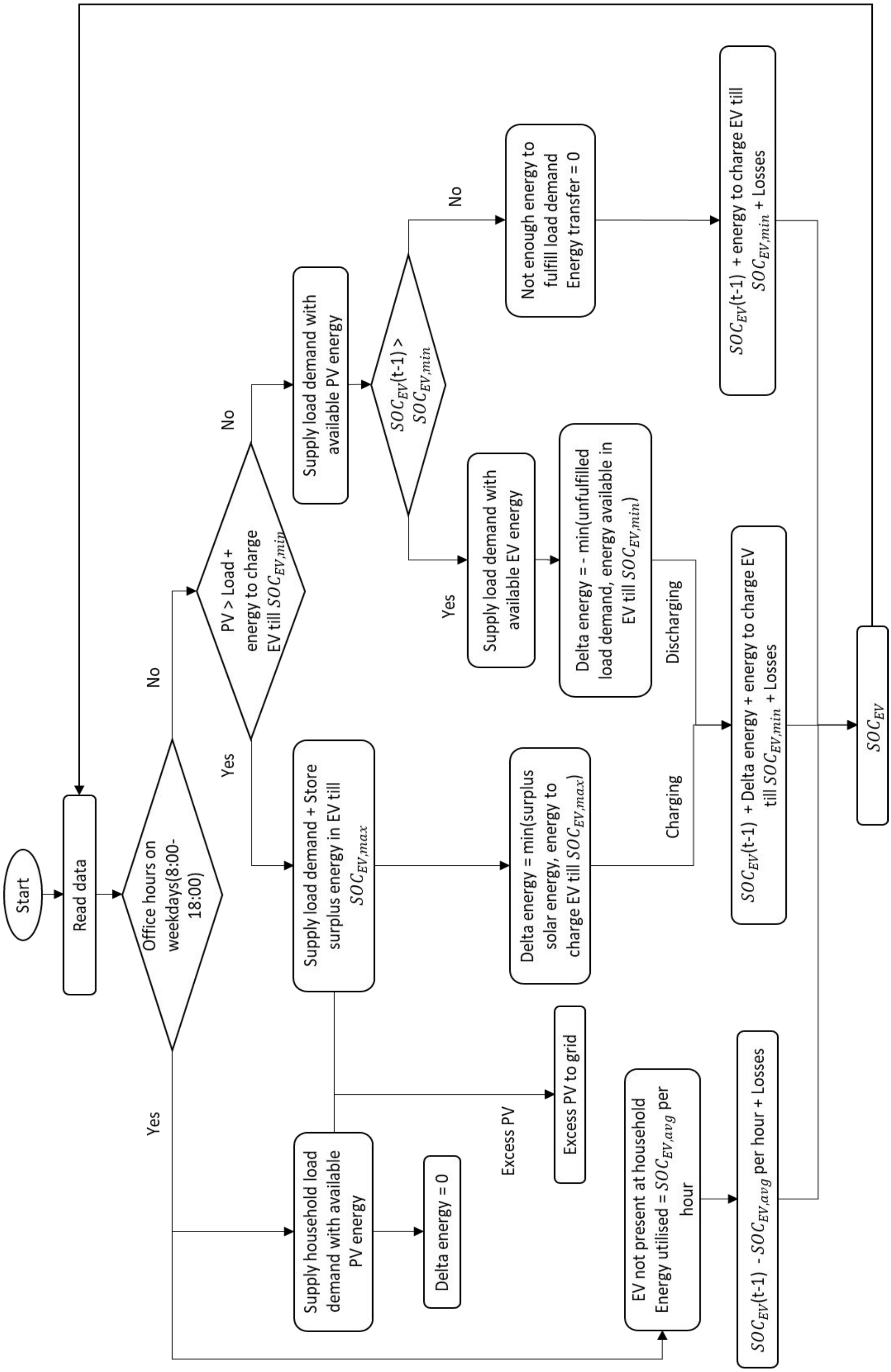

Figure 6 A flowchart of the EV energy storage system simulation model

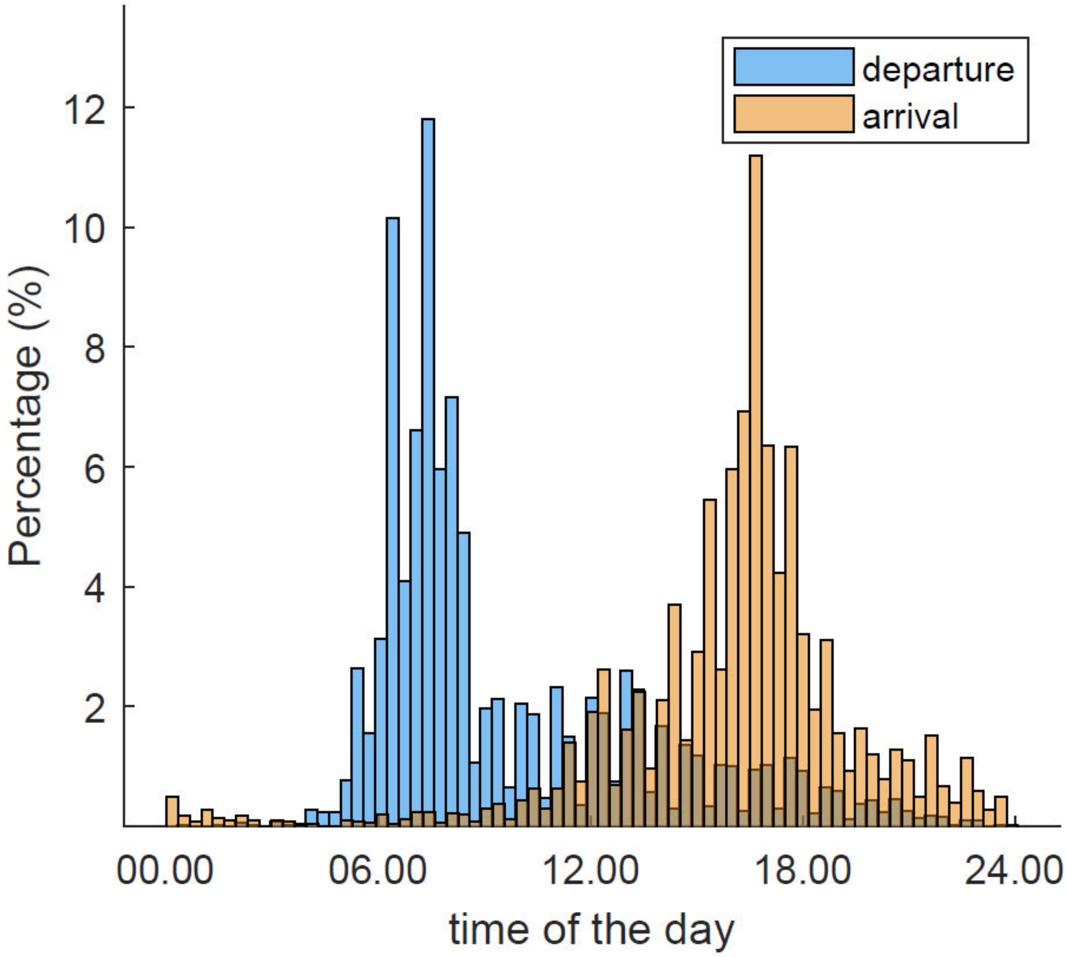

Figure 7 Distribution of departure and arrival time of the EVs at home[48]

Figure 7 shows the probability distribution of the departure and arrival time of the EVs at home during weekdays [48]. According to the distribution, the peak departure time is around 08:00, while the common arrival time is around 18:00 of the day. Furthermore, the typical office hours are from 9:00 to 17:00, and considering a one-hour buffer time required to commute to the office, the time when e-vehicles are not available at home is defined for the simulation model as 8 o'clock to 18 o'clock on the weekdays. During weekend, it is assumed that the EVs will be parked at home connected to the grid. There has been one fundamental condition in this simulation model, that is apart from office hours on weekdays, the EVs are connected to the house power grid all the time so that they can either supply to the load or utilised energy from the grid.

While using EV as an energy storage system, the minimum amount of energy required in the EV battery to meet the daily average transportation demand must also be considered. Taking into account the daily average distance travelled per vehicle in Germany and average energy consumption per unit distance travelled(see Table 4), the minimum amount of energy must be available in the battery, $SOC_{EV,min}$, is defined as 30% of the total SOC [47], [99].

The one assumption for the EV model is that the EV is charged only at the home charging point and charging of the EV above $SOC_{EV,min}$ is done solely with the generated PV energy.

Therefore, when EV is connected to the house power, the total demand, $E_{total\ load}$, is composed of the load demand, E_{load}, and amount of energy require to charge the EV battery until $SOC_{EV,min}$ is reached. To give the model more relation to real-world scenarios, the limitation of the maximum charging capacity of the home charging station, $C_{EV,Charg}$ is considered. The standard household charging station has a capacity ranging from 7 to 22 kW [100]. For the EV simulation model, the charging capacity, $C_{EV,Charg}$, is assumed as 11 kW. The point to be consider is that the uncontrolled charging methods for EVs are adopted in this model, therefore peak load demand after regular office hours will be reflected in $E_{total\ load}$.

$$E_{total\ load}(t) = E_{load}(t) + min(C_{EV,Charg}, max(0, (SOC_{EV,min} - SOC_{EV}(t-1)))) \tag{8}$$

When an Electric vehicle is not present at home, the total demand, $E_{total\ load}$, is only the load demand, E_{load}.

$$E_{total\ load}(t) = E_{load}(t) \tag{9}$$

Aside from that, if the main consideration of the EV model is that charging of an EV until it reaches $SOC_{EV,min}$ may be done at a charging station other than a home charging point, then simulations with that scenario can be done with the model for Battery storage system(section 4.5), but with the battery being unavailable during office hours.

The equation to calculate delta energy of the EV, ΔE_{EV}, at given timestep is same as that of the delta energy equation of the battery model. When solar energy generation is higher than load, ΔE_{EV} is calculated by taking the minimum of surplus PV energy and energy require to charge EV till $SOC_{EV,max}$.

$$\Delta E_{EV}(t) = min(C_{EV,Charg}, min\left(\left(E_{pv}(t) - E_{total\ load}(t)\right), \left(SOC_{EV,max} - SOC_{EV}(t-1)\right)\right)) \tag{10}$$

When load exceeds the PV generated energy, the amount of energy that can be supplied to the load depends on amount of available energy in battery till it reaches $SOC_{EV,min}$.

$$\Delta E_{EV}(t) = -min(C_{EV,Charg}, min\left(\left(E_{total\ load}(t) - E_{pv}(t)\right), max\left(0, \left(SOC_{EV}(t-1) - SOC_{EV,min}\right)\right)\right)) \tag{11}$$

While connected to the home grid, the EV battery gets charged when ΔE_{EV} is positive and supply energy to the load(discharge) when ΔE_{EV} is negative. Since energy is transferred between AC to DC throughout the charging and discharging process, the conversion efficiency must be evaluated. There has been few scientific research on roundtrip efficiency of vehicle to grid technology which shows the values between 83% to 87% [68]. Considering the speculative study, the conversion efficiency, η_{conv}, from AC grid to EV and EV to AC grid has been set at 93% each, resulting roundtrip efficiency as 86.5 %. When present at home, the state of charge of the EV, SOC_{EV}, is determined by the charging and discharging status of the EV, along with the SOC_{EV} at previous timestep. The self-discharge losses, η_{EV}, of the EV of around 2% per month have also been considered in equation of SOC_{EV} [12]. It also takes into account the energy needed to charge the EV battery until $SOC_{EV,min}$ is reached, which is included in $E_{total\ load}$.

$$SOC_{EV}(t) = SOC_{EV}(t-1) * \eta_{EV} + \Delta E_{EV}(t) * \eta_{conv} + min(C_{EV,Charg}, max(0, (SOC_{EV,min} - SOC_{EV}(t-1)))) * \eta_{conv} \quad (12)$$

When not available at home, the amount of energy used for commutation during the day, $SOC_{EV,\text{avg}}$, must be deducted from the SOC_{EV}. For simplicity of the model, the average hourly energy consumption by EV is subtracted from SOC_{EV} of the preceding timestep. Then equation of SOC_{EV} will be modified as,

$$SOC_{EV}(t) = SOC_{EV}(t-1) * \eta_{EV} - (SOC_{EV,avg} / \ No.of\ hours\ when\ EV\ is\ unavailable) \quad (13)$$

The batteries in electric vehicles can receive and supply electricity within the limits of their maximal storage capacity, $SOC_{EV,max}$, and a minimum amount of energy must be present in the vehicle at all times, $SOC_{EV,min}$ (see Table 4). The mathematical expressions for estimating self-consumption and self-sufficiency profiles with an energy storage system, which are presented in Section 3.1, are then applied to the present model.

Table 4 Model parameters for the EV storage system simulation

Parameter	**Value**
Average EV battery capacity [12]	60.3 and 80 kWh
Electric vehicle energy consumption [47]	0.224 kWh/km
Average daily distance travel per vehicle [99]	40 km
Charging capacity of home charging station, $C_{EV,Charg}$	11 kW
Time of the day when EV is not available(Weekdays)	08:00 to 18:00
Conversion Efficiency, η_{conv} [68]	93%
Self-discharge losses of EV	2% per month
Daily energy consumption per vehicle, $SOC_{EV,\text{avg}}$	20% of the total SOC
SOC at initial timestep and $SOC_{EV,min}$	30% of the total SOC
$SOC_{EV,\text{max}}$	100% of the total SOC

At the starting of the simulation, the SOC_{EV} is set to the 30% of the total SOC, which is also the $SOC_{EV,min}$. The EV model analyses the generated PV energy, total load demand and available SOC_{EV}. Whenever an electric vehicle is not present at home, the load demand is met by available PV energy, with excess energy being fed to the grid or remain unused. When EV arrives home, it is assumed that it has utilised daily average state of charge, $SOC_{EV,avg}$, while commuting, and if the EV level falls below minimum SOC limit, then that energy demand is being satisfied from the home grid until it reaches $SOC_{EV,min}$. The home grid is restricted from feeding more energy than is required to achieve $SOC_{EV,min}$. When there is surplus PV energy available and the EV is connected to the grid, charging will occur until EV reaches $SOC_{EV,max}$. If PV energy is unavailable and the battery's state of charge reaches $SOC_{Bat,min}$, the energy will be extracted from the grid to meet the load demand. Whereas, when excess PV energy is generated that cannot be stored in batteries, it is fed into the grid or wasted. The model parameters of the EV storage system simulation model are listed in Table 4, and a flowchart of the EV model is shown in Figure 6.

In this thesis, the focus of EV simulation model is on three scenarios. As it is highly improbable that every house with a PV system will own an electric vehicle in the near future, the first scenario takes into account the varied fractions of households that own an EV. The three shares of EV-owning households with PV systems, 50 percent, 75 percent, and 100 percent are chosen to simulate and assess the influence of EV penetration on self-consumption and self-sufficiency patterns of grid. The number of EV-owning houses in each grid is determined by considering the number of houses in that grid as well as the proportion of a specific scenario. However, since this thesis assumes that all houses with PV systems in the region of a specific grid are connected (refer section 4), the energy stored and supplied from EVs will be distributed among all households in the grid.

For the past several years, the average range of all-electric vehicles has been increasing as new EVs with larger battery capacities reach the road. By considering this rapidly expanding adoption of EVs, the average EV battery capacity parameter is altered in the second scenario to analyse its effect on self-consumption and self-sufficiency. The model simulates for average EV capacity of 60.3 kWh and 80 kWh (see Table 4)and also takes into account the first scenario characteristics for both.

The sun's availability during the day varies according to the season (section 3.3), with summer having long sunshine hours and winter smaller. Therefore, the availability of EV at home at various times of the day would influence the pattern of self-consumption and self-sufficiency. As a result, the third scenario investigates the effect of varying departure and arrival time of EVs on the grid's SC and SS, considering that 50 % of households with a PV system in the grid owns the EV. As shown in Figure 7, on weekdays, the departure time of the e-vehicles varies between 7 a.m. and 2 p.m., and the arrival time varies between 3 and 10 p.m. [48], [101]. Table 5 shows the average percentage of all EVs that leave and arrive during each hour of the day. The data shown indicate that the majority of the time when an EV is not available at home is concentrated around noon when solar generation is at its highest.

Table 5 Portion of total EVs depart and arrive for each hour of the day

Hours of Day	Percentage of EVs Depart	Percentage of EVs Arrive
0	0.00%	0.00%
1	0.00%	0.00%
2	0.00%	0.00%
3	0.00%	0.00%
4	0.00%	0.00%
5	0.00%	0.00%
6	4.00%	0.00%
7	17.00%	0.00%
8	25.00%	0.00%
9	13.00%	0.00%
10	6.00%	0.00%
11	5.00%	0.00%
12	4.00%	5.00%
13	4.00%	6.00%
14	4.00%	6.00%
15	4.00%	8.00%
16	4.00%	12.00%
17	4.00%	24.00%
18	4.00%	16.00%
19	2.00%	8.00%
20	0.00%	5.00%
21	0.00%	5.00%
22	0.00%	5.00%
23	0.00%	0.00%

A new simulation model, which examined the SC and SS of the system taking into account EV arrival and departure times, was created by performing a minor modification to the EV model. Figure 8 presents the working flow and logic diagram of the same.

As was previously discussed for the EV model, in this model as well, when the generated PV energy exceeds the load requirement, the surplus solar energy is stored in EVs that are accessible and connected to the households. By the end of the day, every vehicle is assumed to have returned to the house and consumed the daily average amount of energy required to travel, $SOC_{EV,avg}$, except on weekends, when each vehicle is assumed to be at home connected to the grid. The priority is assigned while charging the available EVs with excess PV production, with vehicles yet to be departed consuming surplus energy first(Delta energy depart), and then charging of the vehicles that have arrived occurs(Delta energy arrive). This is done to simplify the complexity of the simulation model because the number of EVs departed and arrived every hour varies throughout the day. Due to the fact that one of the key presumptions is that every PV-equipped household in a grid is connected to each other, allowing for the exchange of stored energy, this configuration would have little effect on SC and SS. However, in the real world, it is possible to charge all of the available vehicles simultaneously.

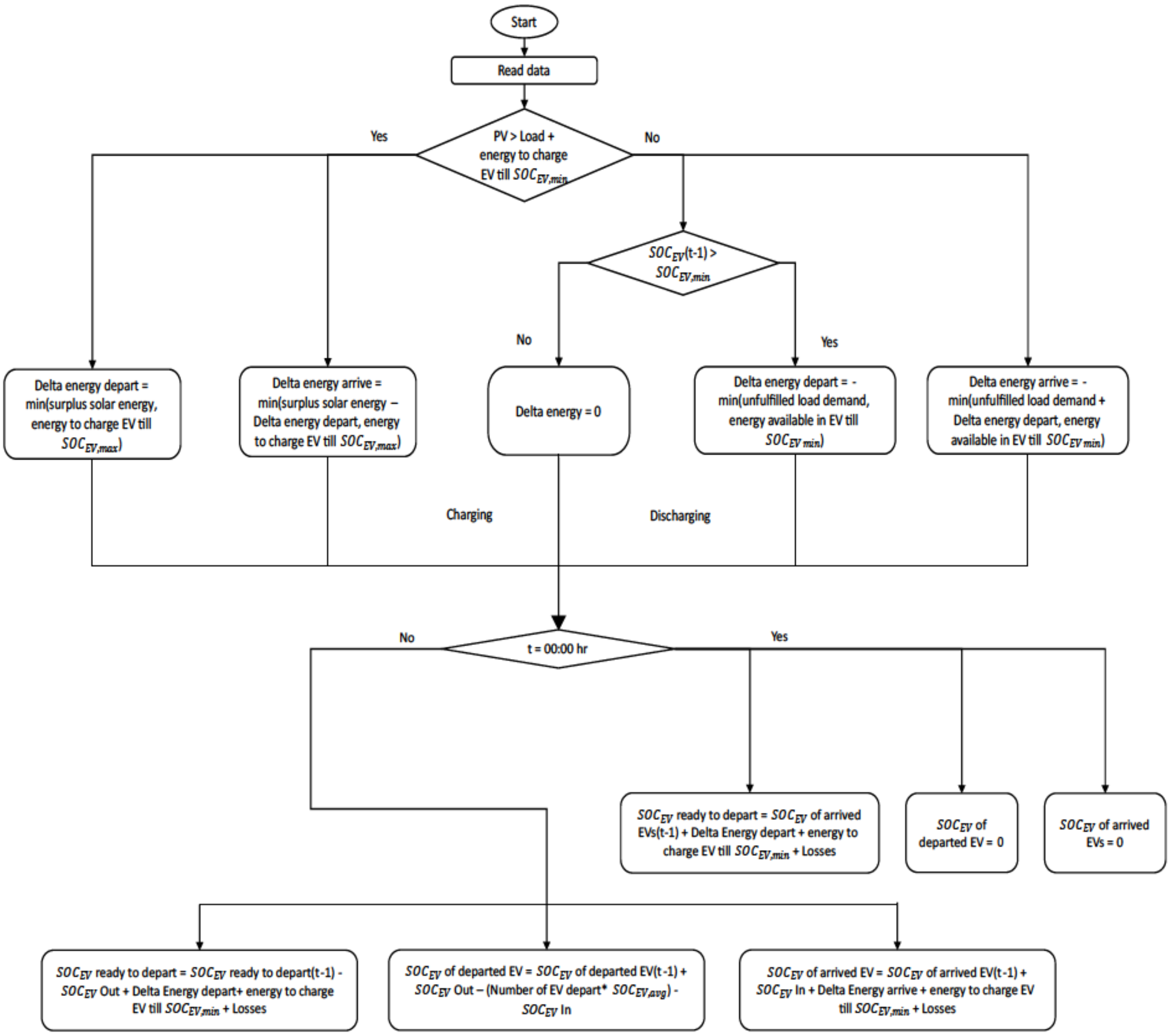

Figure 8 A flowchart of EV energy storage simulation model with arrival and departure time of EVs

In a similar way, when energy demand exceeds solar energy generation and sufficient stored energy is present above $SOC_{EV,min}$ in available EVs, the EVs that are ready to depart supply the necessary energy up until $SOC_{EV,min}$(Delta energy depart), after which any remaining load demand is satisfied by the available stored energy in the vehicles that have arrived(Delta energy arrive).

As each vehicle departed the home at a different time, the SOC of vehicles available to depart, SOC of departed vehicles, and SOC of vehicles arrived are calculated separately in order to maintain the $SOC_{EV,min}$ level of each individual EV. As shown in Figure 8, the SOC at previous timestep, the Delta energy depart, the SOC of the EVs departed at given timestep, and losses all contribute to the SOC of the EVs ready to depart for the given timestep. The SOC of vehicles that have left, SOC_{EV} Out, is calculated by dividing the SOC of individual units among all EVs that were ready to depart at a previous timestep by the total number of vehicles that have left at given timestep.

$$SOC_{EV}\ Out(t) = \frac{SOC_{EV}\ ready\ to\ depart\ (t-1)}{No.of\ EVs\ available\ to\ depart\ (t-1)} * No.of\ EV\ departed(t) \qquad (14)$$

SOC of the departed EVs for given timestep is determined by the SOC of the EVs that are not available at household. It reflects the SOC of EVs that left the household, SOC_{EV} Out, average daily consumption by each departed vehicle, $SOC_{EV,avg}$, and SOC of EVs that arrive home at that timestep, SOC_{EV} In.

Similarly, the SOC of arrived EV is determined by the SOC at previous timestep, Delta energy arrive, SOC of vehicles that arrive home, and losses. The SOC of vehicles that arrive home, SOC_{EV} In, is calculated by multiplying SOC of an individual vehicles that were not present at home at the previous timestep with the number of vehicles that arrive at the given timestep.

$$SOC_{EV}\ In(t) = \frac{SOC_{EV}\ of\ departed\ EV\ (t-1)}{No.of\ EVs\ unavailable\ at\ home\ (t-1)} * No.of\ EV\ arrived(t) \qquad (15)$$

The SOC_{EV} of vehicles ready to depart began to decline as the vehicles started to depart, eventually reaching zero. On the other hand, the SOC_{EV} of arrived vehicles then started rising until the 0 timestamp of midnight, at which point this SOC_{EV} of arrived EVs was transferred to the SOC_{EV} of vehicles ready to depart.

For all the scenarios of EV model, it is considered that the $SOC_{EV,min}$ of the model as 30 %. The presumption is determined by calculating the typical amount of energy needed to travel the typical distance in a day (see Table 4) and taking the buffer of 10 % into account. However, not every consumer would likely experience this ideal scenario. The change in $SOC_{EV,min}$ would affect the maximum amount of energy that could be stored and extracted from the EV. Because one of the assumptions also demands keeping EV capacity constantly above its $SOC_{EV,min}$ value, even by drawing energy from the grid in the absence of solar energy, there is possibility of change in the load demand, which might significantly alter the SC and SS. Consequently, the scenario with variable $SOC_{EV,min}$ is simulated in order to examine the impact of it on the SC and SS pattern as well as on load demand.

In this section, the development of the EV model to evaluate SC and SS is explained. In addition, different scenarios that may have an impact on both SC and SS patterns are also examined. The section that follows considers the combination of two different energy storage systems.

4.7 Model for Combination of Battery and Electric Vehicle Energy Storage System

The model development for self-consumption and self-sufficiency assessment with battery energy storage system and EV energy storage system is individually described in section 4.5 and 4.6, respectively. This section of the methodology continues to describe the model designed to evaluate the effect of combining both of these energy storage technologies on the SC and SS patterns in greater detail.

In order to increase overall self-consumption and self-sufficiency, the battery storage system is an economically viable solution to be implemented in conjunction with the PV system. As a result, it is the most widely used form of energy storage. In addition, EVs are being adopted at an increasing rate as the e-mobility sector develops, which provides another means for storing excess solar energy locally for later use, thus increasing the SC and SS. In the future, as electric vehicles become more prevalent, energy storage in EV's will become more common alongside battery storage. The excess energy stored in the battery and available EV would enhance self-consumption more than with an individual system. Therefore, in the context of this thesis, the effect it has on the SC and SS pattern may be an interesting subject to investigate.

The new model, which also includes the parameters of the battery model (section 4.5), is configured by modifying the EV model for varying arrival and departure times (section 4.6). The battery is considered to have a capacity of 1 kWh/kWp, while the EV is assumed to have a capacity of 60.3 kWh, with 50% of households with PV system owning them. The priority is given to storing excess PV energy in EVs first before storing it in batteries because EV availability varies throughout the day. This allows for a larger window of time to store excess energy in EVs. Consequently, the amount of excess energy left over after storing it in available EVs is taken into account when calculating the battery's delta energy for a given timestep (it should be noted that the EV that is ready to depart will charge first, followed by EV arrived). Therefore, the modified version of the ΔE_{Bat} equation (5) is as follows:

$$\Delta E_{Bat}(t) = min\,((E_{pv}(t) - E_{load}(t) - \Delta E_{EV\ available}),\ (SOC_{Bat,max} - SOC_{Bat}(t-1))) \tag{16}$$

Moreover, this arrangement automatically draws stored energy from EVs first, then from the battery, when energy consumption rises during non-production or low-production hours. Therefore, equation (6) is altered as follows:

$$\Delta E_{Bat}(t) = -\,min\,((E_{load}(t) - E_{pv}(t) + \Delta E_{EV\ available}),\ max(0, (SOC_{Bat}(t-1) - SOC_{Bat,min}))) \tag{17}$$

The model's other characteristics are identical to those of the battery and electric vehicle models.

It is essential to understand how charging the battery or the EV first affects the SC and SS patterns when using an EV and battery. Due to the priority given to the electric vehicle in this model, a new scenario is simulated in which energy is stored in and extracted from batteries first. This scenario is used to analyse the impact on SC and SS as well as the total load that needs to be extracted from the grid for charging the EV in the absence of solar energy. This is achieved by modifying equations (16) and (17) of ΔE_{Bat}. When solar energy exceeds load demand, excess solar energy is used to charge a battery, and the remaining energy is stored in an electric vehicle (EV). Similar to this, when the amount of energy requirement exceeds the amount of solar energy that is available, the stored energy in battery is used first.

4.8 Low Voltage grid calculation

The methodology for developing and configuring models for self-consumption and self-sufficiency with and without energy storage technologies has been covered up to this point in previous sections. In this research, the residential PV systems have been studied, so the primary focus is on the low voltage (LV) grid power system. When considering analysis for residential PV systems with energy storage systems and increasing demand for EV by households, the model of self-consumption and self-sufficiency assumed some parameters that could affect the power flow of the LV grid. As a result, it is essential to evaluate how these models impact the power quality parameters of the systems to confirm the legitimacy of the assumptions we made when developing the models. To accomplish this, pandapower (refer section 3.5) was used to perform grid calculations for all the simulation models set up in this thesis.

The benchmark grid data from Simbench (refer section 3.5) is used as a reference for comparing the power flow parameters in order to analyse the proposed models for various scenarios. This data includes both rural and urban LV power systems.

1. The benchmark grid for rural region is ‘1-LV-rural1--0-no_sw_test’. This simbench network includes the following parameters:
   Bus – 15 elements
   External grid – 1 element
   Load – 13 elements
   PV generator – 4 elements
   Figure 9 shows the grid's network diagram along with the position of the PV systems in grid.

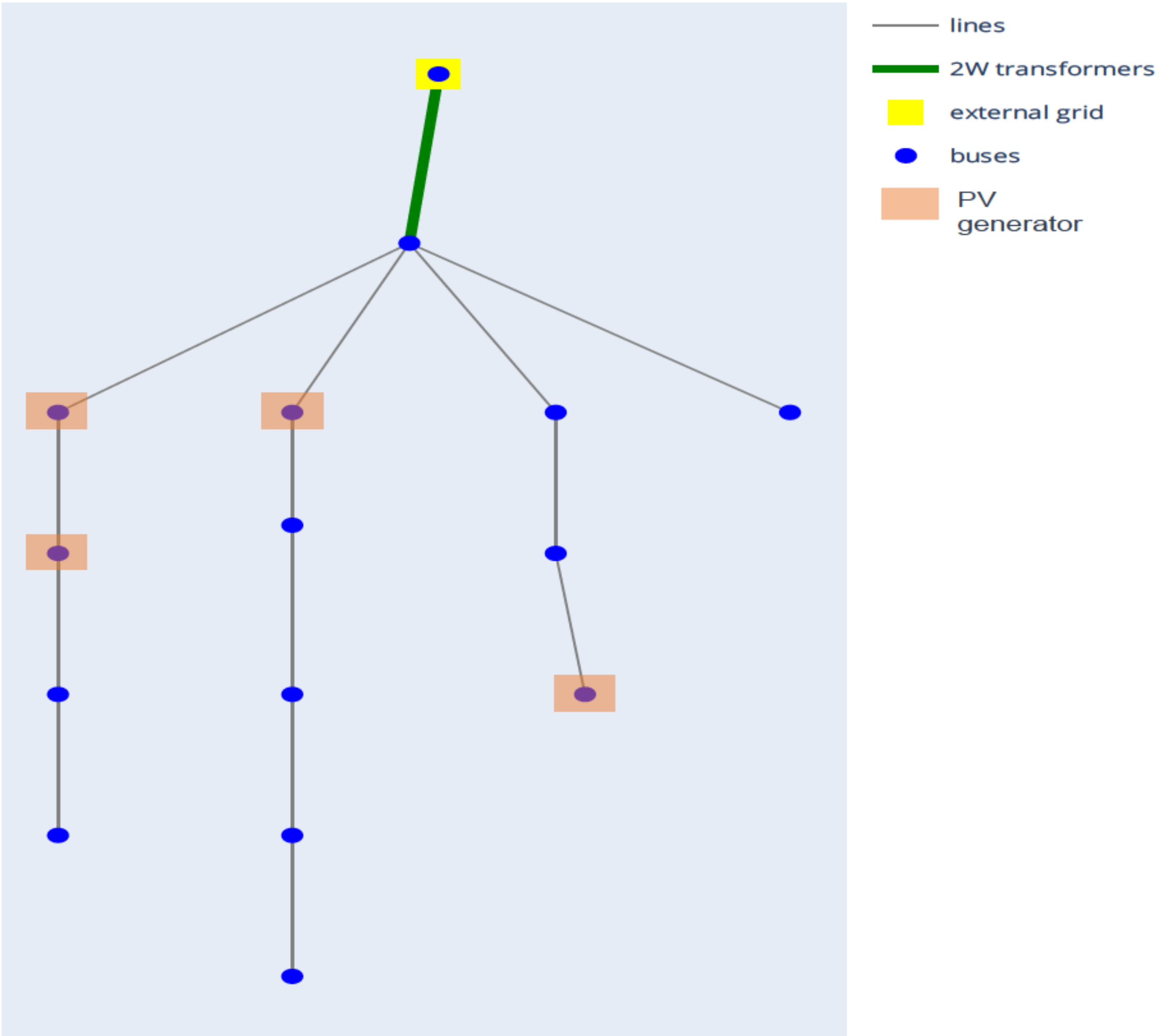

Figure 9 Grid structure of benchmark grid '1-LV-rural1--0-no_sw_test'

2. The second benchmark grid representing urban network is '1-LV-urban6--0-no_sw_test'. The following parameters are included in this simbench network:
   Bus – 59 elements
   External grid – 1 element
   Load – 111 elements
   PV generator – 5 elements
   Figure 10 displays the grid network diagram and the placement of the PV systems.

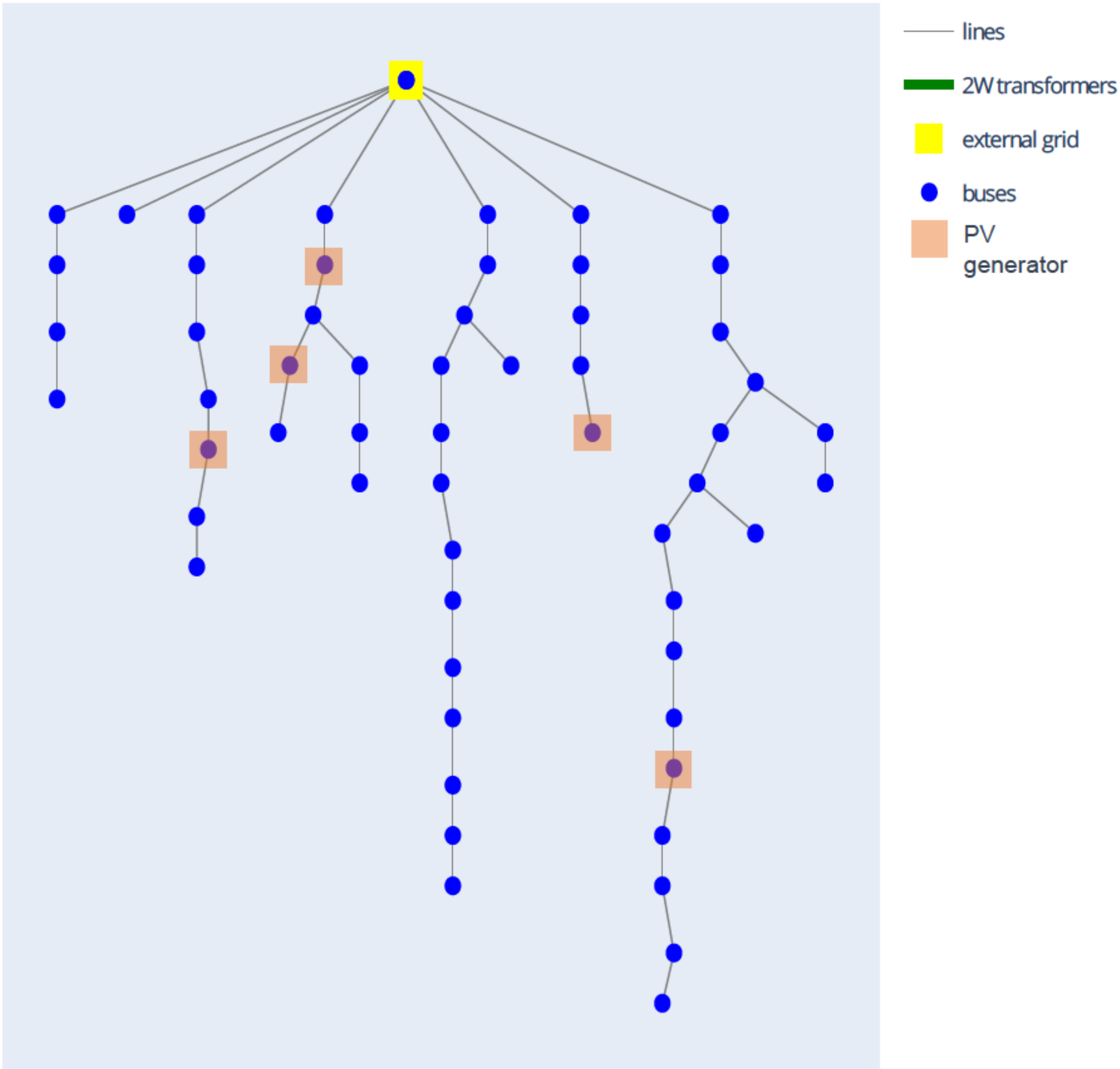

Figure 10 Grid structure of benchmark grid '1-LV-urban6--0-no_sw_test'

Each self-consumption model, with and without an energy storage system, is simulated for both grids. The annual load demand profile associated with each bus and solar generation time series for each static generator was available in resolution of 15-min. The simulation is carried out for both grids and for all models while taking into account the available input data and parameters considered while configuring the models. According to the battery model, the size of the battery is assumed to be the same as the size of a PV generator. For the EV model, each bus with a PV generator is assumed to have one EV with a 60.3 kWh battery size. With the introduction of batteries and EVs, there will be change in surplus solar energy and load demand. When an energy storage system is used in conjunction with a PV generator, any surplus energy available after meeting local load requirements is stored in the system rather than being fed into the grid. Similarly, if there is no PV energy available, the EV will be charged by obtaining energy from the grid, which will ultimately change the load profile of the associated bus node. This is going to be reflected in the results of simulation models.

Every simulation model generate outputs that include self-consumption and self-sufficiency profiles, timeseries of excess solar energy, and data on the residual load demand associated with each bus. The excess solar energy and modified load profiles for each grid have been provided to Pandapower for the purpose of timeseries grid calculation.

The outcomes of the pandapower timeseries calculations are the voltage per unit and the line loading percentage. To authenticate the functioning of the simulation model and the assumptions established in it, it is necessary to analyse these parameters. As a result, in this thesis, the power flow simulation for all scenarios will be carried out in order to validate all SC and SS models, and the results will be analysed.

4.9 Accuracy of the data and validation of the model

When analysing the findings, the accuracy of the data and methods used for the simulation is crucial. As the fundamental objective of this thesis is the analysis of the SC and SS patterns, the reliability of the input data of load demand and solar energy generation is important. There is the possibility of a small degree of error in the data, which could have influenced the results. The following is a list of possible sources of differences:

- Solar energy generation data is highly dependent on meteorological conditions such as irradiance, temperature, wind factors, cloud cover, and so on. The meteorological data for Hamburg used in this thesis was obtained from the weather station in Fuhlsbüttel, Hamburg. Given the distribution of residential PV systems throughout Hamburg, the cloud cover or shadowing effects may have influenced the solar generation data by a small margin. Therefore, it is possible for the potential inaccuracy in solar generation timeseries.
- The load demand data for households in Hamburg was not available during the preparation of this study. As a result, the open-source standard load profile for households in Germany is scaled up to the Hamburg level. For greater accuracy, the number of households with PV systems associated with each grid node, as well as the distribution of occupants in households in that region, were estimated. Due to this fact, the accuracy of measurements of the electricity consumption might have varied when compared to real households with PV systems.
  The results of the model would be more precise if the load demand profile were more exact and reliable or if it included direct consumption data from smart meters.
- The data on PV generation and household demand used in this research have a temporal resolution of one hour. As peaks in PV production and load demand play a significant part in it, there is a possibility of inaccuracy when considering a 1-hour resolution for PV production and household demand as opposed to a 1-minute resolution [102]. When matching solar energy generation with load demand, a lower resolution can minimize the error factor and provide a better assessment of self-consumption [103].
- The SC and SS pattern for Hamburg is estimated by simulating the models for one year of 2021. The simulation should be conducted for a number of years, and the average should then be taken into account for greater accuracy. However, the seasonal variation could be seen with yearly simulation, and this variation in irradiation and temperature is greater than the change between different years [31]. Additionally, the impact of these fluctuations on the SC and SS profile throughout the year is the main focus of this thesis.

Since the model's accuracy is largely dependent on the input data, only reliable input data can guarantee accurate outputs. However, for this thesis, the annual trend of SC and SS is more interesting than the exact statistics due to the growing PV installed capacity and the rising trends in energy storage and e-mobility.

Now that we have seen the data's accuracy, it is important to validate the models that were utilized for simulation. Validation is required for the PV power production model as well as other models configured for SC and SS estimation, including without and with energy storage systems. The model validation could be carried out in one of two methods. First, simulate the system model for which available observed results are accessible. The validity of the systems might then be confirmed by comparing the simulated results with the observed findings. The second way is to trace the intermediate simulation result for all possible outcomes and assess the logical operation of the model when the real world or observed system is unavailable.

Since the real-world system with observed output values is accessible for the PV power model. The PV power model is simulated, and the results are compared with those of the PV system at Energie Campus, Bergedorf. The model was provided with information regarding the orientation and angle of inclination of PV systems as well as input meteorological parameters. The results are displayed in the results section.

The system to compare all SC and SS models was not accessible, and because of the time constraint for finishing the thesis, its potential integration with the systems at Energie Campus was also not feasible. As a result, these models are verified by monitoring the simulation output for one Hamburg node throughout the course of one week. A trace of each output parameter is conducted, and the results are analysed as per the logical assumptions made when designing that model. The result section shows the outcomes for each model.

5. Result

Using the methods and models mentioned in section 4, this thesis examined the detailed self-consumption behaviour of residential PV systems in Hamburg, as well as the impact of battery storage system and electric vehicle deployment on its profile. This chapter summarizes the impact of the season, location, and implementation of energy storage systems on the self-consumption profile. Section 5.1 presents results from all SC models with and without energy storage system. The simulation results of all models on the LV benchmark grid are shown in Section 5.2.

5.1 Self-consumption and self-sufficiency models

The results and findings of all SC and SS models, including solar energy generation, load demand, and energy storage system, are presented, and discussed here. The data represented here are for the entire year of 2021, from January to December, with a resolution of one hour. The simulation is conducted for a complete year in order to understand and investigate seasonal fluctuation and its impact.

5.1.1 Load Demand Profile of Hamburg

The electricity consumption for all households in Hamburg with PV systems for the year 2021 is shown in Figure 11. As explained in section 4.2, the load demand data for the household is derived from BDEW standard load profiles and the number of inhabitants. Then, the load demand of each household was summed up to obtain the net load profile for the entire Hamburg. It should be emphasized that this data shows the entire load demand profile of households in Hamburg with installed PV systems, which comprised 4490 households.

The general annual trend for net electricity consumption demonstrates that the load demand of households is higher during the winter months and lower in the summer season. There is a higher demand for electricity on weekends, so the peak values reflect weekend electricity consumption, while the trough values represent weekday electricity consumption. As a result of more daylight, less or no need of heating appliances, and more people spending time outside, there is a lower consumption and peak demand in the summer. Even though temperature variations throughout the year affect energy consumption, it is difficult to justify this result since this study did not analyze electricity consumption within the household for different areas (such as cooling and heating, lighting, and water heating).

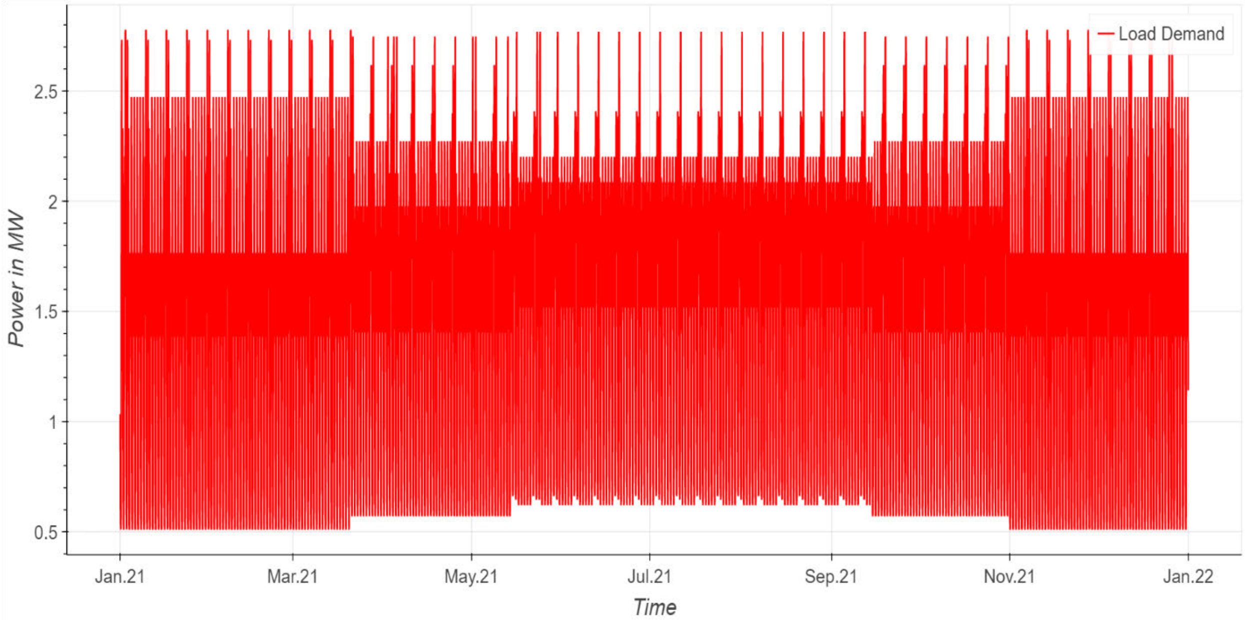

Figure 11 Load demand profile of households with PV system in Hamburg

Due to the unavailability of a reliable load demand profile for residential buildings in Hamburg and the fact that the load demand profile is derived from SLP, there is a possibility that it will deviate from the actual energy consumption pattern. In support of this thesis, even while the load consumption profile varies by individual household, with some houses consuming less and others consuming more than the reference demand, it is assumed that the actual consumption pattern will not differ significantly when analyzing Hamburg as a whole.

5.1.2 PV Energy Generation Profile of Hamburg

In addition to the load demand profile of Hamburg, which is shown in the previous section, one other crucial factor in the calculation of SC and SS is PV power profile. This section will describe the findings of the PV power model as well as the validation of the same.

Validation of PV power model

The validity of the PV power model is checked by simulating the PV system at Energy Campus, Bergedorf. The simulation result is compared with the actual production data available for the given PV system.

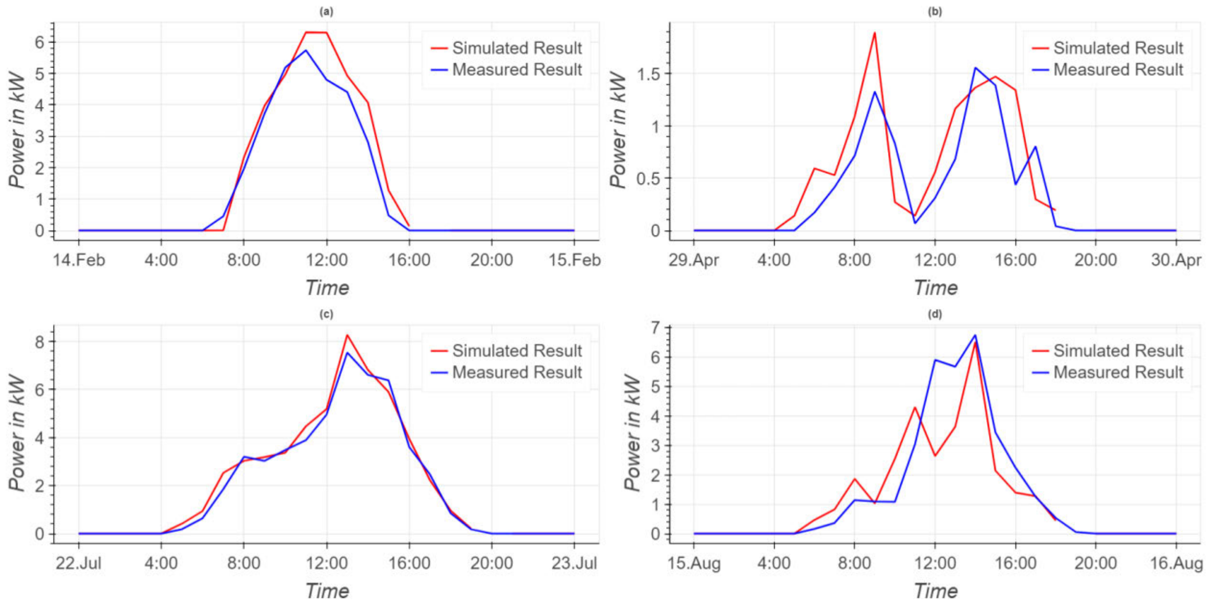

Figure 12 Solar energy generation profile of PV system in Energy Campus, Bergedorf (Red : Simulation output, Blue : Measured output) (a = 14th Feb, b = 29th Apr, c = 22nd July, d = 15th Aug)

The Figure 12 shows the solar energy generation of the PV system at Energy Campus, Bergedorf, at four different times of the year, representing every season. The red line depicts the simulated result of PV generation by the PV power model, whereas the blue line reflects the PV system's actual measured solar energy production. The outcome shown in figure demonstrates that the simulated solar output complies with the measured solar energy trajectory when comparing the output with actual PV production. This verifies the authenticity of the weather data used in the PV model. Although there is a discrepancy between simulated and actual output, this may be attributed to assumptions made in the PV power model that does not reflect reality. Ultimately, it appears that the data presented here support the accuracy of the PV power model as well as the effectiveness of the solar model.

PV energy profile of Hamburg

Figure 13 represents the PV power production for residential PV systems in Hamburg for the entire year of 2021 with hourly resolution. The PV profile is a simulation result of the PV power model, which evaluated the PV production of each residential PV system based on installation capacity, panel orientation, and weather data from Hamburg. The green line represents the hourly time series of PV energy produced by 4490 household PV systems in Hamburg over the course of the year. On the other hand, the black line depicts the average daily PV generation. The PV profile trend shows the impact of seasonal variance, with spring and summer being the most productive periods. Taking into account the hours when the sun was shining, the average solar energy generation for 2021 was 3.8 MW per hour.

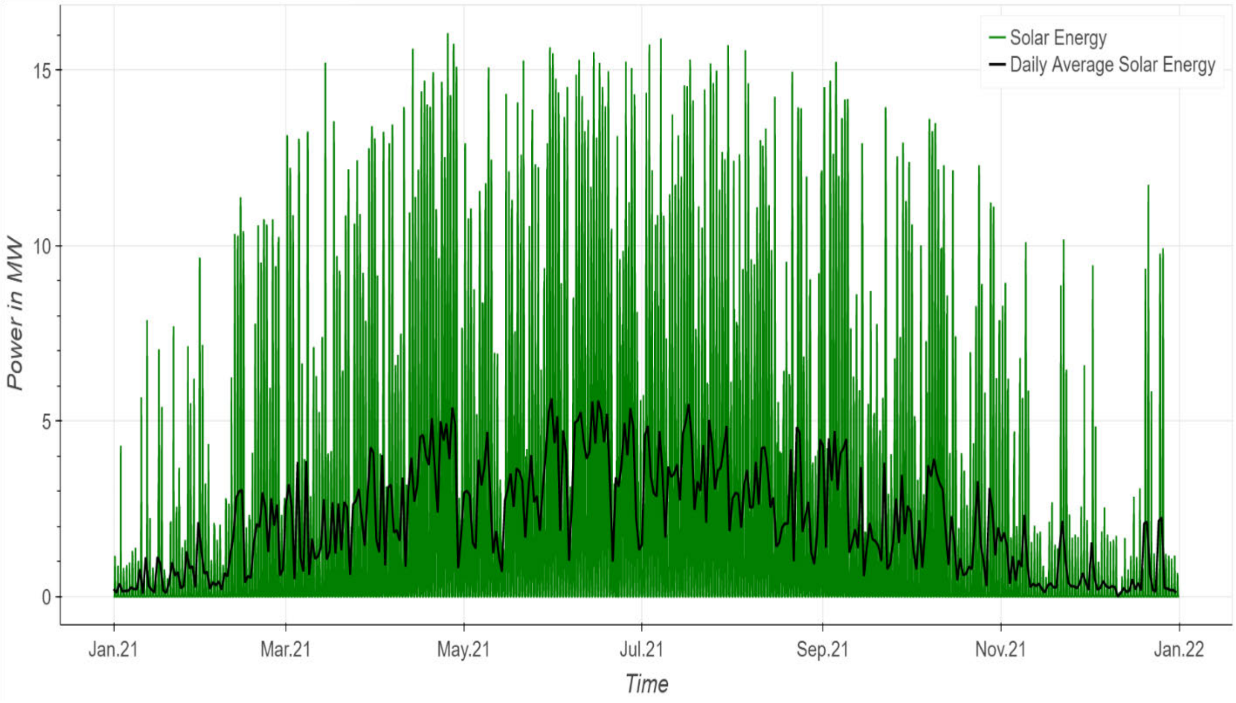

Figure 13 PV energy generation of residential PV systems in Hamburg

The average solar generation distribution per different seasons is shown in Table 6. It should be emphasized that self-consumption is calculated for the hours when sunlight was accessible during the given timeframe, also referred to as sunshine hours (refer section 1.3). The peak season for solar energy generation is spring and summer, with an hourly average generation of 4.68 MW from June to August 2022. The longer daylight hours, clear skies, and intense solar radiation are some of the driving forces behind summer's higher solar energy production. Due to the cloudy and foggy days, some summer days exhibit decreased PV power generation. However, regardless of the fact that solar energy production is comparatively lower on cold winter days, there are certain days when PV generation is higher due to clear skies and adequate sunlight exposure.

Table 6 Average solar energy generation per season

Season	**Spring**	**Summer**	**Autumn**	**Winter**
Average solar energy generation in MW per sunshine hour	4.29	4.68	3.37	1.93

5.1.3 Self-consumption and self-sufficiency of the residential PV systems in Hamburg without energy storage system

As described in section 4.5, the SC and SS is estimated by analysing the PV energy generation and the total electricity consumption of households with PV systems in Hamburg. Table 7 shows the average self-consumption and self-sufficiency of residential PV systems without any energy storage system for year 2021. The average SC rate of 61.4 percent is comparatively high and shows that the PV system is undersized compared to the load consumption. As a result, only a small portion of household energy consumption is being met by locally produced solar energy, which brings the SS rate down to 42.6%.

Table 7 Average self-consumption and self-sufficiency without energy storage system

Model	Self-Consumption in %	Self-Sufficiency in %
Without energy storage system	61.41	42.58

Figure 12 represents the graph showing the daily average value of SC for residential PV systems in Hamburg, while the daily average SS is shown in Figure 13. The SC profile demonstrates seasonal fluctuation in trend, with winter having the highest value of SC and summer having lower on-site consumption of generated solar energy. The solar energy profile and variable energy consumption demand primarily influence the SC pattern. During the winter season, when PV production is lower, and load demand is higher, the generated energy is promptly used to meet load demand, using practically all of the generated energy. On the other hand, during the summer, when load demand is lower and solar energy generation is higher, excess solar energy is left over even after directly meeting load demand, causing the majority of the energy to remain unused and lowering SC. Simultaneously, as all immediate load demand was met by locally generated solar energy, self-sufficiency increased during the summer season. Due to the same reason noted above, very little demand is met by on-site generated energy during the winter season, requiring more energy to be extracted from the grid to meet overall demand, resulting in a lower SS during the winter period. Although a reciprocal relationship seems to exist between the patterns of self-consumption and self-sufficiency, it is not always true. The deployment of an energy storage system or the oversizing or under-sizing of a PV system can have a similar effect on SC and SS rather than the opposite.

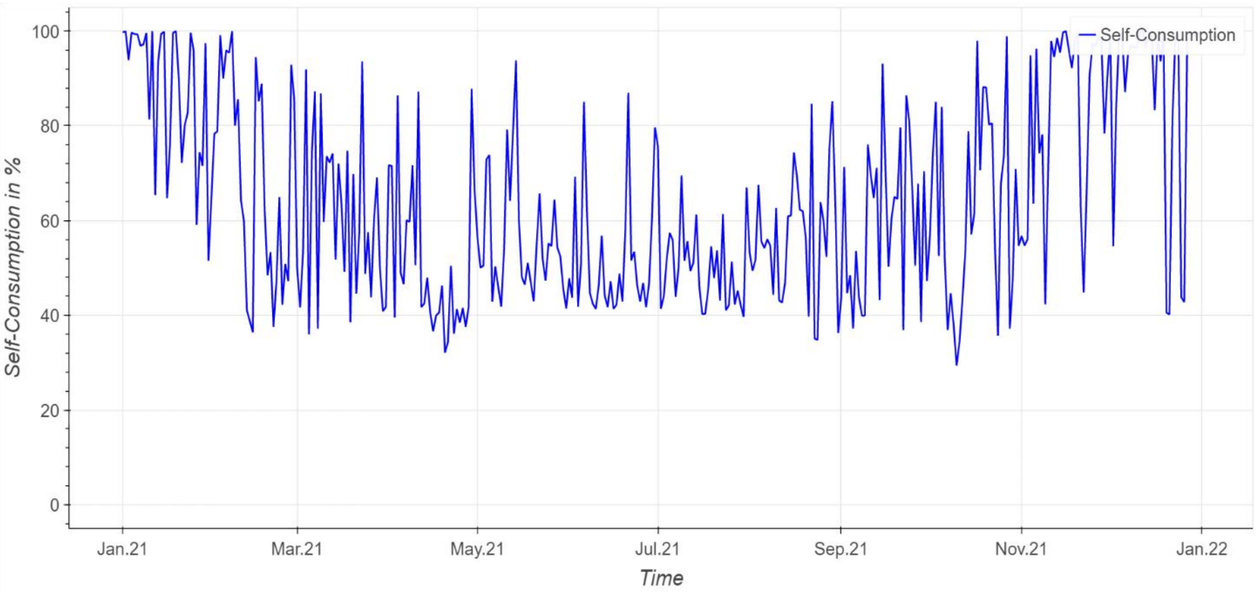

Figure 14 Daily average self-consumption of residential PV systems in Hamburg without energy storage system

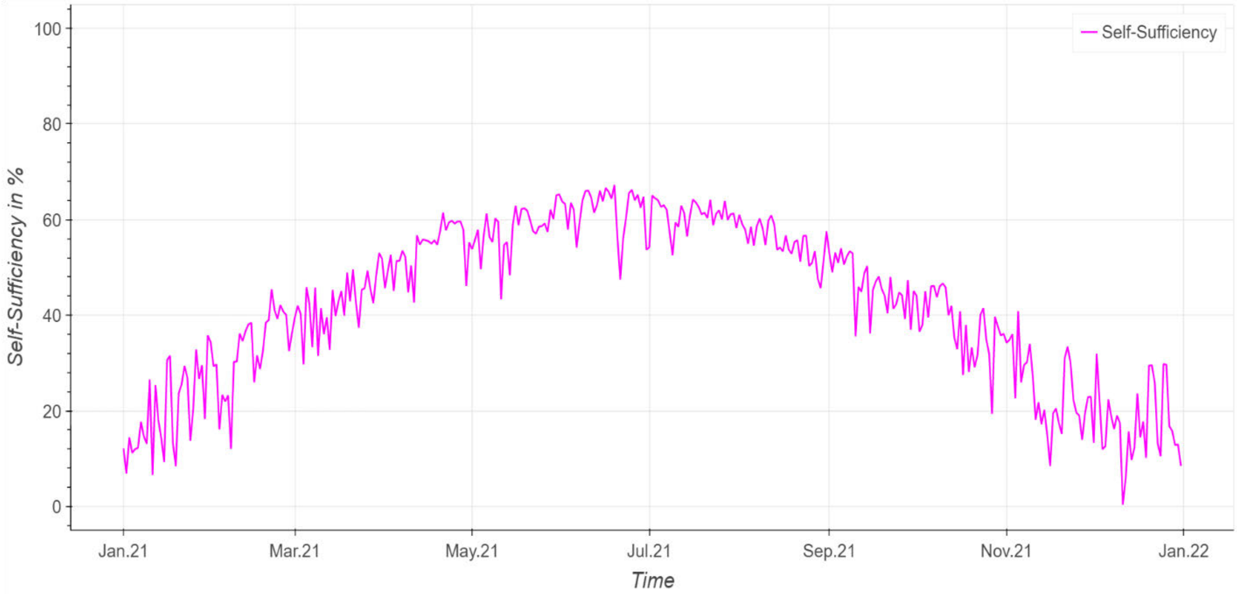

Figure 15 Daily average self-sufficiency of residential PV system without energy storage system

5.1.4 Self-consumption and self-sufficiency of the residential PV systems in Hamburg with battery storage system

Up to this point, study has concentrated on the PV system's self-consumption and self-sufficiency without any type of storage system. The findings demonstrating the influence of energy storage systems on SC and SS patterns will be discussed in further sections. This section will discuss the results of the first and most commonly used energy storage system, the battery. At the end of the section, the results of a scenario with different battery system sizes will be described.

Validation of battery energy storage model

As a real-world system for verifying the reliability of the battery storage model did not exist during the time of writing of this thesis, it was decided to analyze all the PV systems associated with a single grid node in Hamburg for a week in order to test its validity. The state of charge (SOC) of the battery, as well as SC and SS for an hourly resolution, are analyzed by examining the logical operation of charging and discharging cycles. Figure 16 displays the simulation results for residential PV systems connected to the Allermöhe grid. The reason for choosing this time frame is that it represents the best-case scenario because there are days when PV production is both higher and lower than load demand, and the SOC has also reached both its maximum and minimum capacity.

On May 10, when solar production was higher, extra energy was used to charge the battery up to its maximum capacity while maintaining the highest possible SC. However, with the battery reaching its full capacity, there was no room left for the surplus energy to be stored, decreasing self-consumption. During the evening, when solar production was zero and energy consumption was high, the battery was discharged in order to meet load demands. This resulted in 100 percent self-sufficiency. On the 13th and 14th of May, when PV power production was lower than energy consumption, the battery discharged to meet load demand, lowering the SOC. When the battery SOC reached its minimum and no energy was available to meet the local load demand, the SS dropped to 0%. The charging and discharging cycle operation demonstrated the battery model's logical operation.

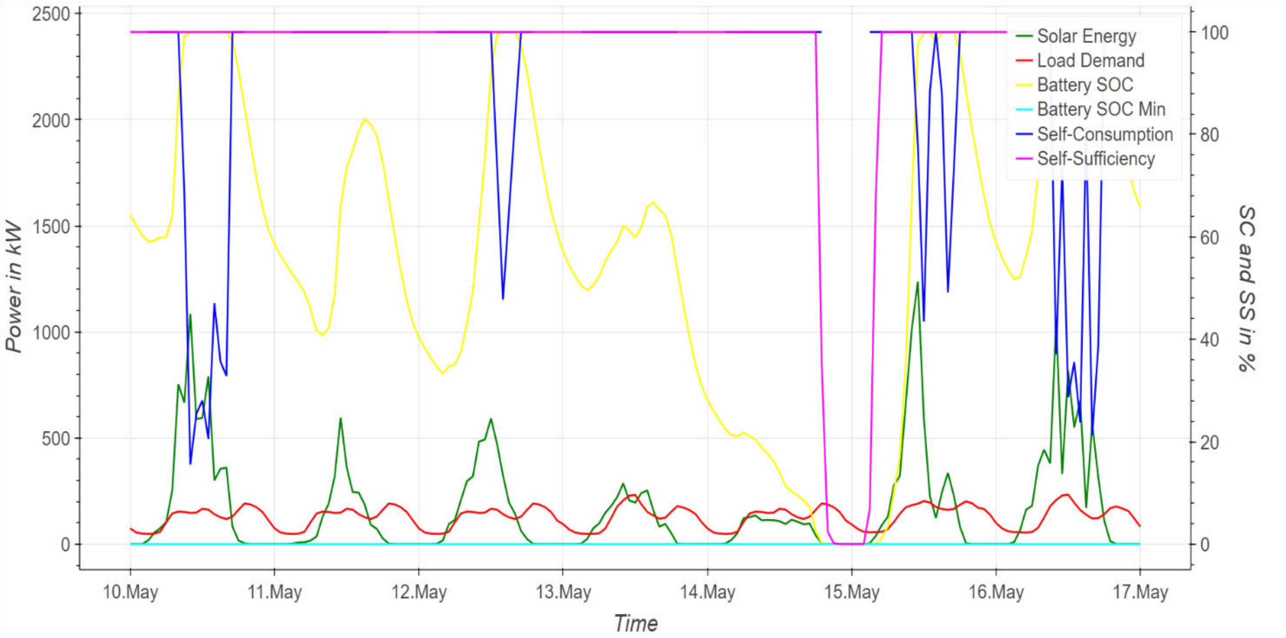

Figure 16 Analysis of SOC of the battery for validation of battery model

SC and SS profile of the PV system with battery storage

When stationary battery storage systems are installed alongside residential PV systems, the self-consumption rises by about 28 %, and the self-sufficiency increases by 87 %, bringing the SS rate to roughly 80 percent, assuming that the system size is optimal, which is in this case as 1 kWh/kWp. Table 8 displays the average self-sufficiency and self-consumption of residential PV systems in Hamburg with battery storage systems. The SC and SS rates of systems without storage are also included in the table for better value comparison.

Figure 17 portrays the daily average graph of the self-consumption of a residential PV system in Hamburg that uses a battery as an energy storage system. At the same time, Figure 18 shows the daily average graph of the system's self-sufficiency. The impact of seasonal variation can be seen in the SC and SS pattern, as was mentioned in section 3.3. Considering that surplus solar energy can be stored in batteries for later use, their incorporation has resulted in elevated self-sufficiency. The on-site generated solar energy consumption has increased because unused excess energy can be stored in batteries, particularly during the summer. As a result of this, along with the right battery size, it allows storing enough energy to meet household energy demand during off-peak and non-production hours, enabling self-sufficiency of up to 100 percent on some summer days. With slight variations in SC and SS values, a similar result can be observed during the winter.

Table 8 Average self-consumption and self-sufficiency with battery energy storage system

Model	Self-Consumption in %	Self-Sufficiency in %
Without energy storage	61.41	42.58
With battery energy storage	78.44	79.75

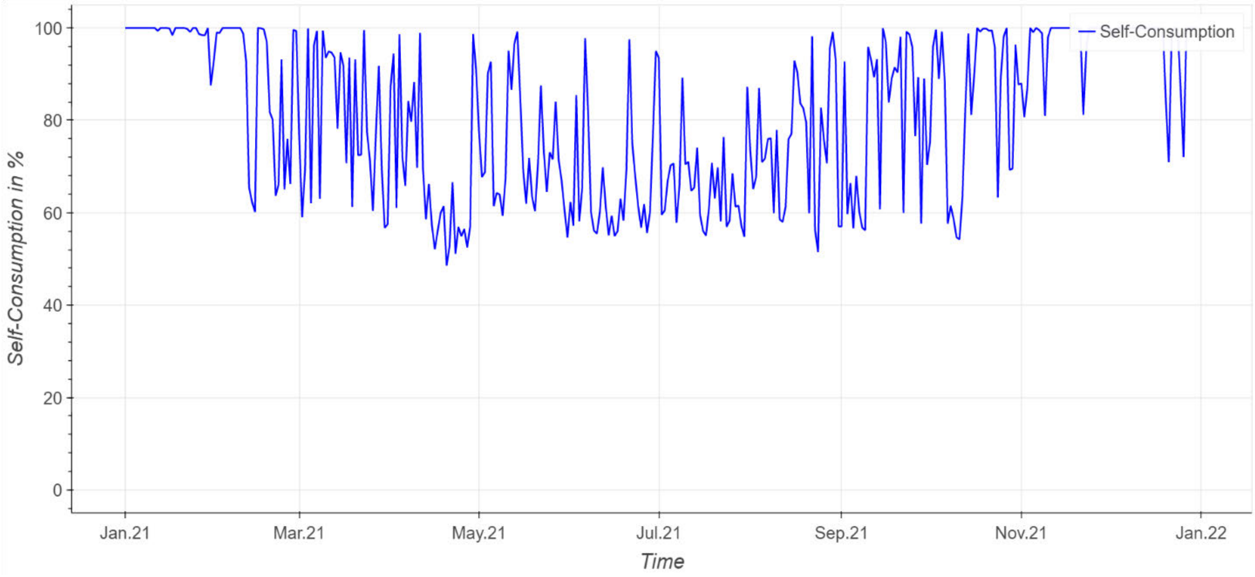

Figure 17 Daily average self-consumption of residential PV system with battery energy storage system

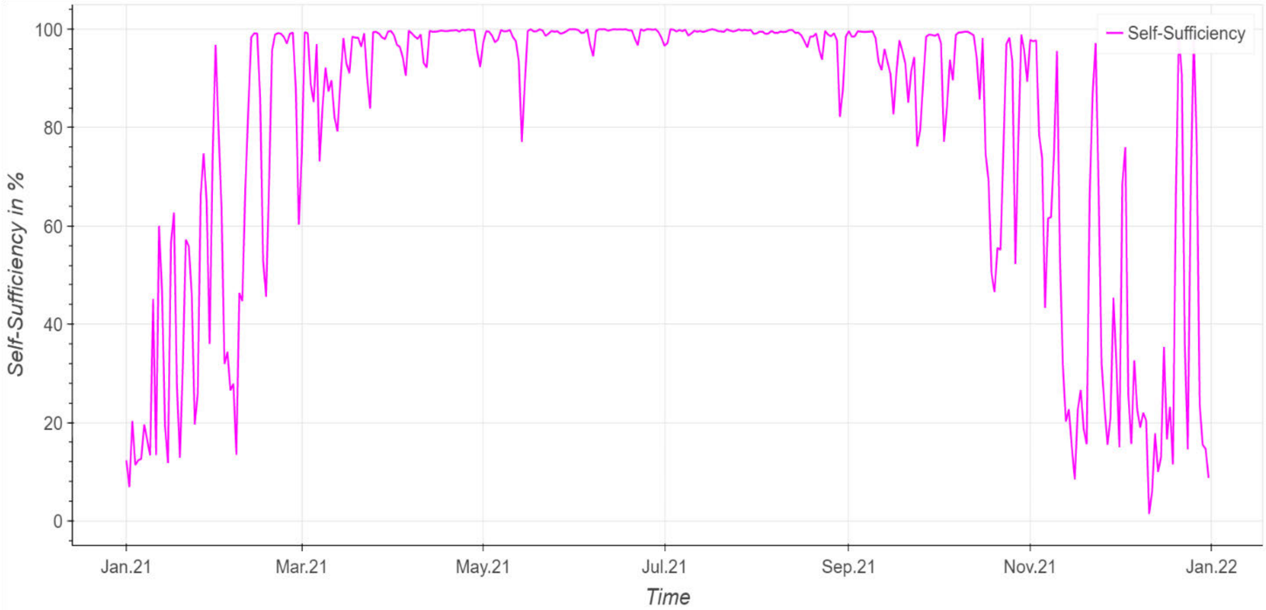

Figure 18 Daily average self-sufficiency of residential PV system with battery energy storage system

According to the findings of some pieces of literature, a PV-battery system with a storage capacity of 0.5 to 1 kWh per kWp of installed PV capacity increases self-consumption by 13% to 24% when compared to a system without any energy storage [7]. Other studies that investigated the implementation of a battery storage system at the domestic level show that the system can increase self-consumption by an average of 20 to 50 percent [37], sometimes even by 75 to 80 percent [58]. In contrast, the level of self-sufficiency, which is around 30 to 35 percent without an energy storage system, can increase by 12.5 to 30 percent or up to 55 to 60 percent [38], [60]. According to the simulation's results, the average SC value has increased, which is consistent with the results of previous studies, but the degree of SS has increased more significantly. The reason for this is that energy consumption varies greatly between households and thus the SS. The works examined in the context of this thesis performed simulations on a small number of households, whereas, in this study, all residential PV systems were taken into consideration, making it difficult to completely rule out the possibility of discrepancies. The precise value of SS can be obtained by using actual measured electricity consumption data for each and every household equipped with the PV system in Hamburg.

Scenario with changing battery size:

As described in section 3.4, the sizing of energy storage is essential while analyzing the SC and SS. Therefore, to assess the effects of varying battery capacity on SC and SS, a simulation for the scenario with four different battery sizes— 0.5 kWh/kWp, 1 kWh/kWp, 1.5 kWh/kWp, and with 2 kWh/kWp—was performed. The results of the simulation are represented in Figure 19 and Figure 20, which show the effects of different battery sizes on SC and SS profile, respectively. Table 9 shows the average SC and SS value for the same.

Based on the results and as shown in Figure 21, as energy storage size increases, the degree of SC and SS increases exponentially. As the daily average pattern of SC demonstrated, during the winter season, the on-site consumption of solar energy increases as battery size increases in comparison to summer, when the marginal difference is minimal. Due to the limited amount of solar energy that remains unutilized in winter, adding energy storage size increases the extent of the system's self-consumption by greater proportions. In contrast, with more significant PV production on sunny days, even increasing storage system size is not enough to utilize all the unused surplus amount of solar energy, resulting in smaller growth in solar self-consumption. On the other hand, the SS pattern varies in size slightly during cold winter days. In the summer, larger batteries were able to store more energy, which was sufficient to meet non-production hour load demands. This eventually increased self-sufficiency, but with less surplus solar energy available to store in the winter, the degree of SS remained relatively constant.

Table 9 Average SC and SS of residential PV system for different size of battery energy storage

Battery Energy Storage capacity	Self-Consumption in %	Self-Sufficiency in %
0.5 kWh/kWp	76.88	72.76
1 kWh/kWp	78.44	79.75
1.5 kWh/kWp	79.00	81.93
2 kWh/kWp	79.30	83.03

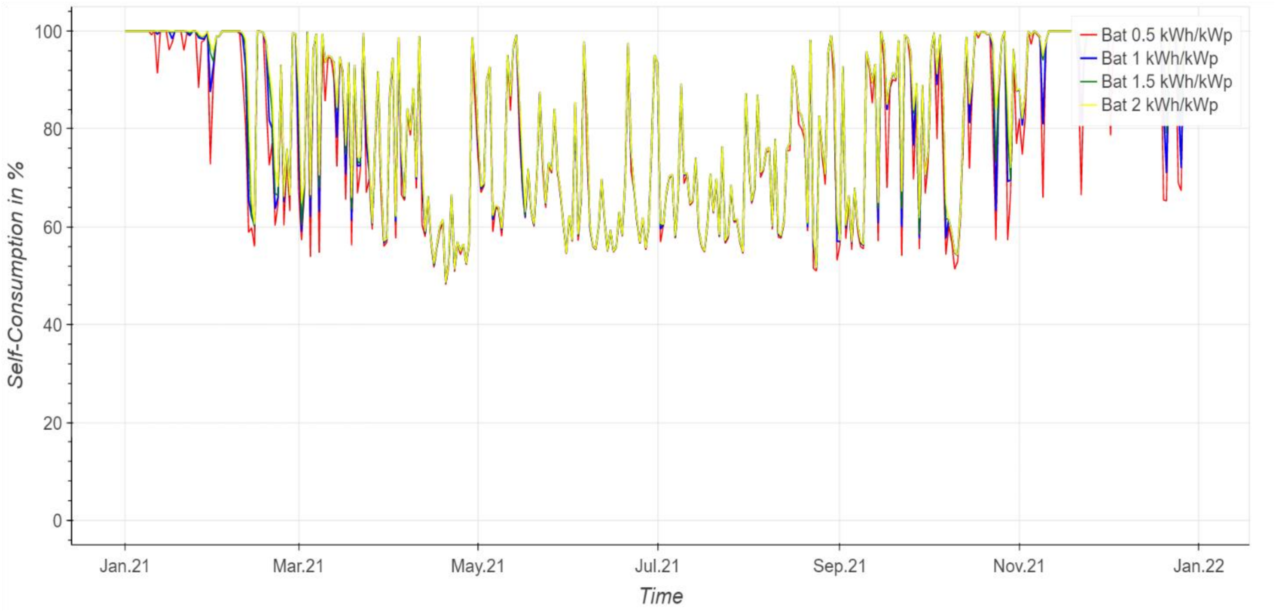

Figure 19 Comparison of daily average SC of residential PV system with different battery storage size

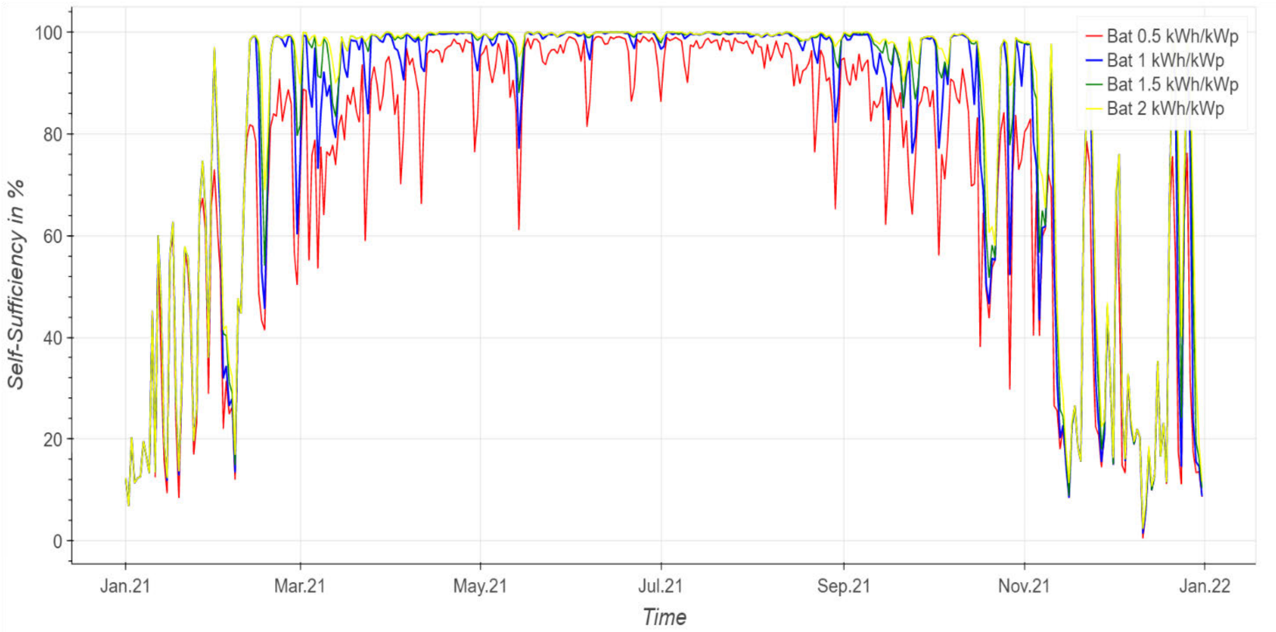

Figure 20 Comparison of daily average SS of residential PV system with different battery storage size

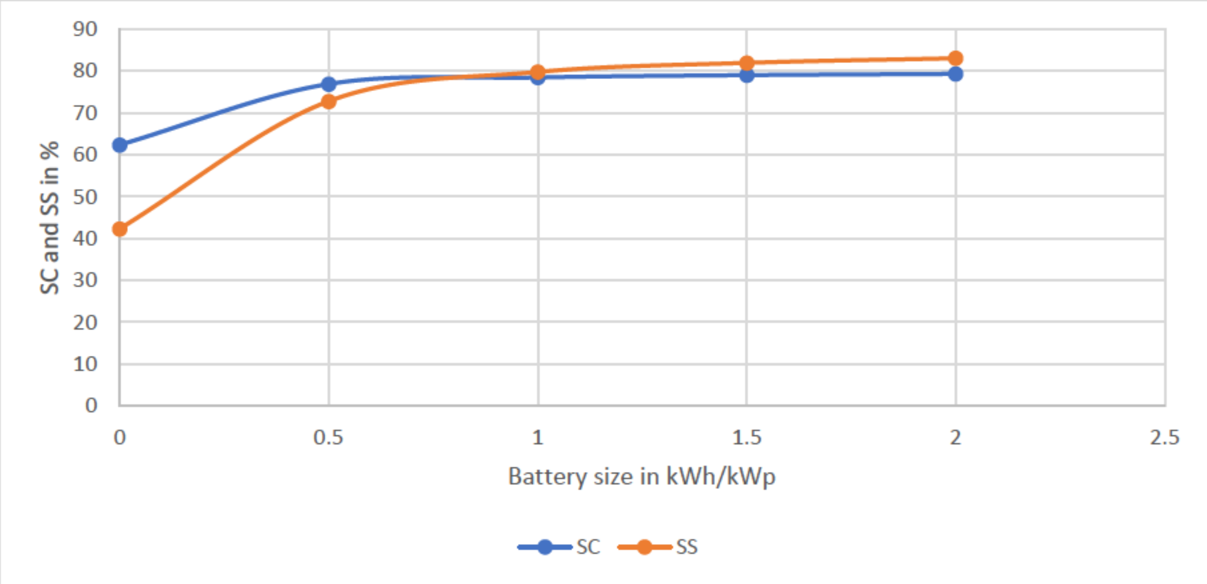

Figure 21 Analysis of degree of SC and SS for varying size of battery capacity per kWp

5.1.5 Self-consumption and self-sufficiency of the residential PV systems in Hamburg with EV as energy storage system

With the growing interest in EV mobility, a number of studies have been conducted to examine the impact of EV on self-consumption and self-sufficiency patterns. To assess the influence of the mobility sector on the SC and SS of Hamburg, the simulation model, which is described in section 4.6, is developed. This chapter includes a description of the outcomes from this EV model along with findings of various scenarios.

Validation of electric vehicle as energy storage model

Similar to the validation of the battery model, the investigation of the model's performance for one grid node in Hamburg over the course of one week is carried out because of the lack of a real-world system to verify the validity of the EV model. By tracking the EV's charging and discharging cycle, the SOC of the EV per timestep, as well as SC and SS at an hourly resolution, are analyzed. The simulation results for residential PV systems connected to the Allermöhe grid are shown in Figure 22. There are 370 households with PV systems connected to the Allermöhe grid node in total. Given that 50% of households own EVs, the total maximum capacity of all EVs would be 11.137 MWh. The $SOC_{EV,min}$, which is set to be 30 % of maximum SOC would be 3.34 MWh, which is represented by sky-blue line.

The SOC of the EVs on May 10th was initially at its maximum and began to decline starting at 8 am when EVs begin to depart and start consuming the average daily energy required for traveling. The surplus solar energy and unavailability of EV to store energy leads to decrease in self-consumption during daytime and at non-sunshine hours, the SC is considered as none (refer section 1.3). Even though solar energy was not accessible at the end of the day when EVs returned to their homes, as long as soc was above $SOC_{EV,min}$, it began supplying stored energy to meet the load requirement, increasing SS. The discharging lasts until May 12 when, as a result of energy use while traveling, the SOC_{EV} falls below the $SOC_{EV,min}$. As a result, after returning home in the evening, EVs extracted energy from the grid to charge the battery, resulting in a substantial spike in load demand. Similar to this, a sudden drop in self-sufficiency can be seen on that time period as solar energy and stored energy are unable to meet the load requirement. On May 13th, during the daylight, when EV was not available and solar energy marginally exceeded load demand, SC decreased for a short period of time. The surplus solar energy generated on May 15th and 16th, on the weekends, when EVs are assumed to be connected to grid home, is stored in electric vehicles until $SOC_{EV,min}$ is met, eventually leading to an increase in self-consumption and self-sufficiency. The charging and discharging cycle as well as tracing of SOC of EV demonstrated the EV model's logical functioning.

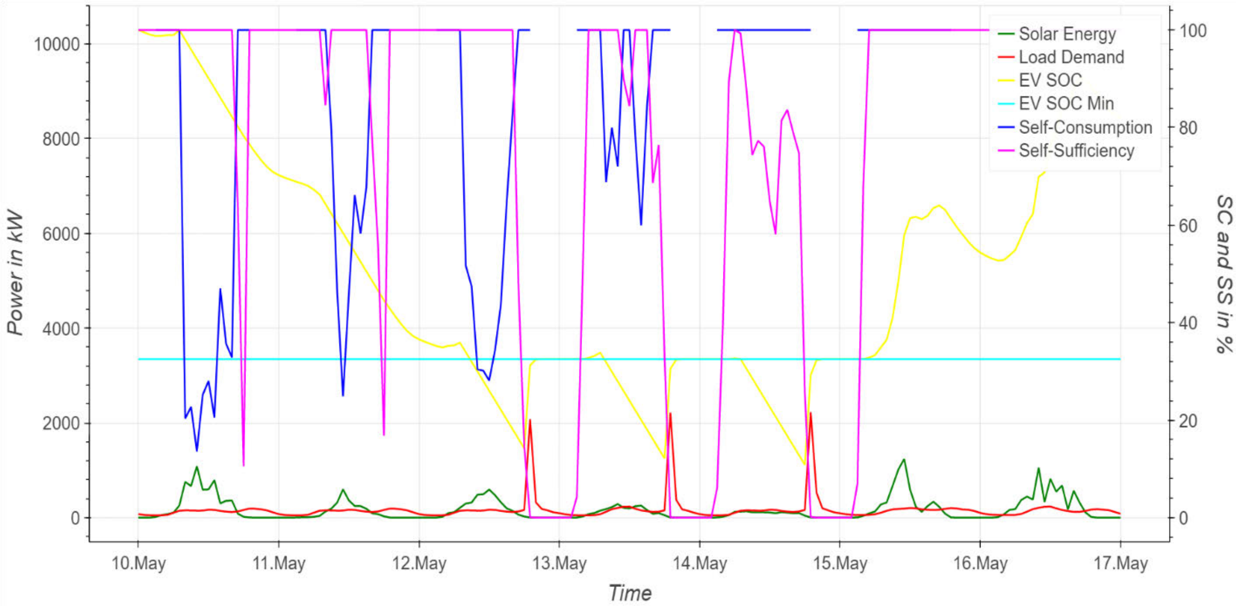

Figure 22 Analysis of SOC of the EV battery for validation of EV model

SC and SS profile of the PV system with EV as energy storage

Although the introduction of EVs increases PV self-consumption, it also significantly raises electricity demand. In the context of this thesis, it is further assumed that $SOC_{EV,min}$, the minimum amount of energy that must be present in an EV, would be maintained by drawing power from the grid in the absence of solar energy. This leads to an alteration in the load demand profile of Hamburg. Figure 23 represents the modified load demand profile for all PV-equipped households in Hamburg. The highest demand spikes occur during the weekday evening hours as all EVs return home by the predetermined arrival time of 6 p.m. and plug their vehicles into the grid to recharge their batteries. One possible explanation is that controlled charging methods are not adopted in the course of this EV simulation model. Furthermore, it is assumed that out of 4490 households in Hamburg, 50% of all households own EVs. With an individual EV having an average battery capacity of 60.3 kWh, the amount of energy usually required to charge an EV up to $SOC_{EV,min}$ advocates the peak in demand graph. Consequently, we might expect, based on this graph, that the charging of EVs will take place with surplus solar energy rather than grid energy during summertime.

Recent research has suggested that introduction of EV into residential household increases the annual electricity demand by on average 40 % [64]. Furthermore, according to findings from the EV simulation model, Hamburg's total annual load demand has grown by an average of 42 %, from 13.2 GWh to 18.7 GWh. However, because charging of the EV by drawing energy from grid is only considered until $SOC_{EV,min}$ is achieved and as the load demand is derived from SLP, caution should be exercised, as the findings may differ when considering the practical load profile for Hamburg households.

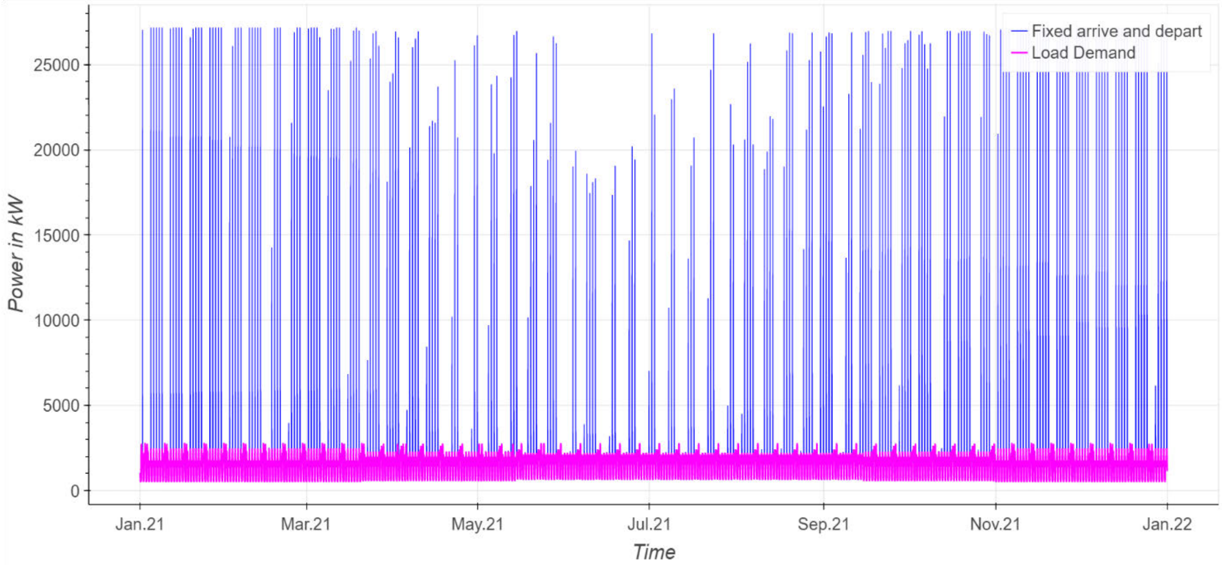

Figure 23 Load demand profile of Hamburg with introduction of EVs

Having defined the changes in energy consumption with introduction of EVs, this section will now move on to discuss the impact of it on SC and SS of the PV system.

When 50 % of households in a grid adopt EV as energy storage system alongside residential PV systems, the average self-consumption level increases to around 76 %, while the self-sufficiency increases by 34 %. Table 10 displays the average value of SS and SC of residential PV systems in Hamburg by considering the EV as energy storage system. The SC and SS level of systems without storage and with battery energy storage are also included in the table for better value comparison.

The self-consumption of a residential Hamburg PV system with an EV as an energy storage system is visualized in Figure 24 as a daily average graph. Figure 25 depicts the system's daily average self-sufficiency graph in a similar manner. Along with the impact of seasonal variation, which is also visible in the pattern of battery storage systems, the impact of EV unavailability during weekday peak production time can also be seen. On weekends, EVs are connected to the grid throughout the day and have batteries as large as 60.3 kWh, which allows excess solar energy to be stored in the EV and used during non-production hours. This could account for the weekly peaks in the SC and SS patterns. Taken together, these results suggest that even with the addition of an EV with a 60.3 kWh battery size, the average SC and SS have dropped as compared to the battery storage model. The reason is that, despite having a larger battery, EV availability on weekdays is limited to the early morning and late evening, providing only a small window of interaction to store excess solar energy. Additionally, as was previously observed, the increased local load demand caused by EVs had a significant impact on the system's SS.

Table 10 Average self-consumption and self-sufficiency with EV energy storage system

Model	Self-Consumption in %	Self-Sufficiency in %
Without energy storage	61.41	42.58
With battery energy storage	78.44	79.75
With EV energy storage	75.63	57.14

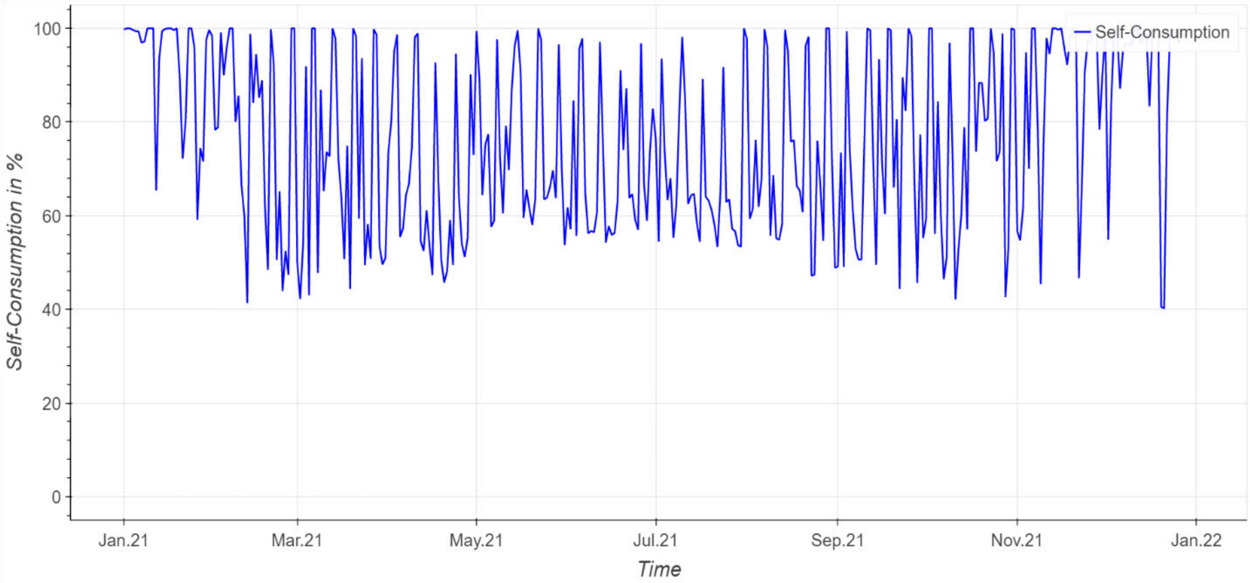

Figure 24 Daily average self-consumption of residential PV system with EV as energy storage system

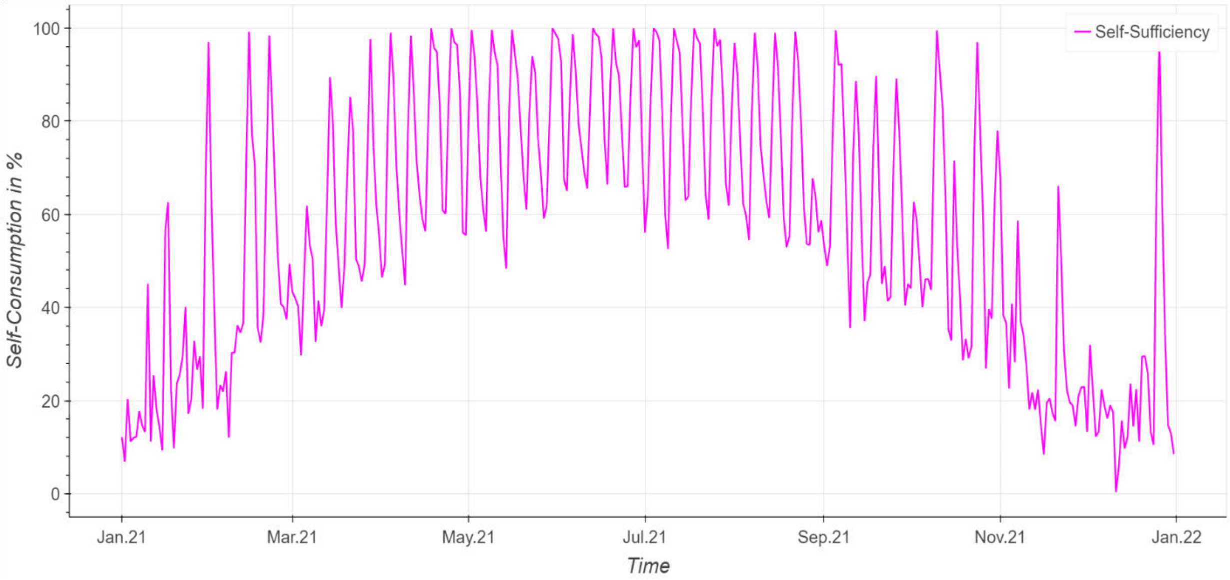

Figure 25 Daily average self-sufficiency of residential PV system with EV as energy storage system

Scenario with different shares of households in a grid owning EV:

Another significant aspect of increasing interest in electric mobility is that in the future more EVs would get introduced to the grid. It is crucial to comprehend how this affects the SC and SS pattern in light of this fact. To investigate these effects, the EV model is used to simulate a scenario with a different proportion of houses owning EVs. The findings indicate that as more households own EVs, the average value of self-consumption has slightly increased. However, as the percentage of homes owned by EVs rises, the value of self-sufficiency appears to be slightly declining. The graphs of the daily averages for SC and SS are shown in Figure 26 and Figure 27, respectively. The capacity to store excess solar energy when EVs are available increases as the number of EVs and battery size both increases. Due to the availability of EVs only in the morning or evening, the majority of the on-site consumption of surplus energy took place on weekends or during the summer. Because of this, the margin of difference is more noticeable in the summer or at the weekly peak. Similar to this, as battery size increased, the combined size of the minimum state of charge $SOC_{EV,min}$, as well as and average states of charge for electric vehicles, $SOC_{EV,avg}$, also increased. This elevated energy demand for the household suggests a decrease in the level of self-consumption.

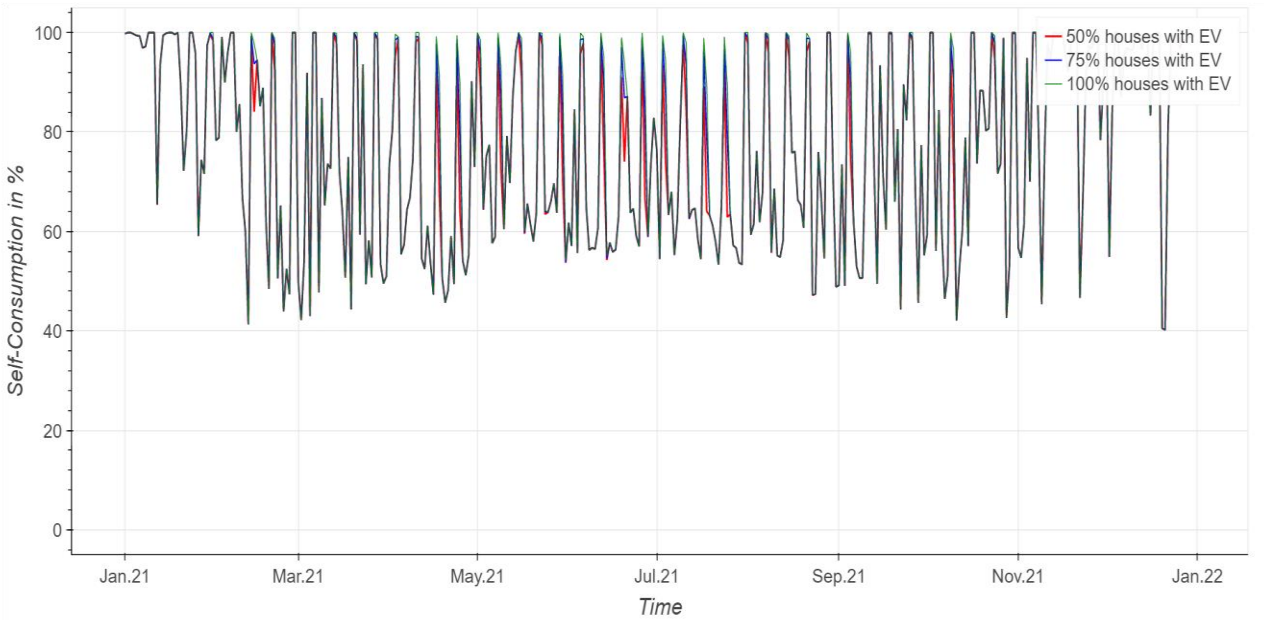

Figure 26 Self-consumption of EV as energy storage with different share of households owning EV

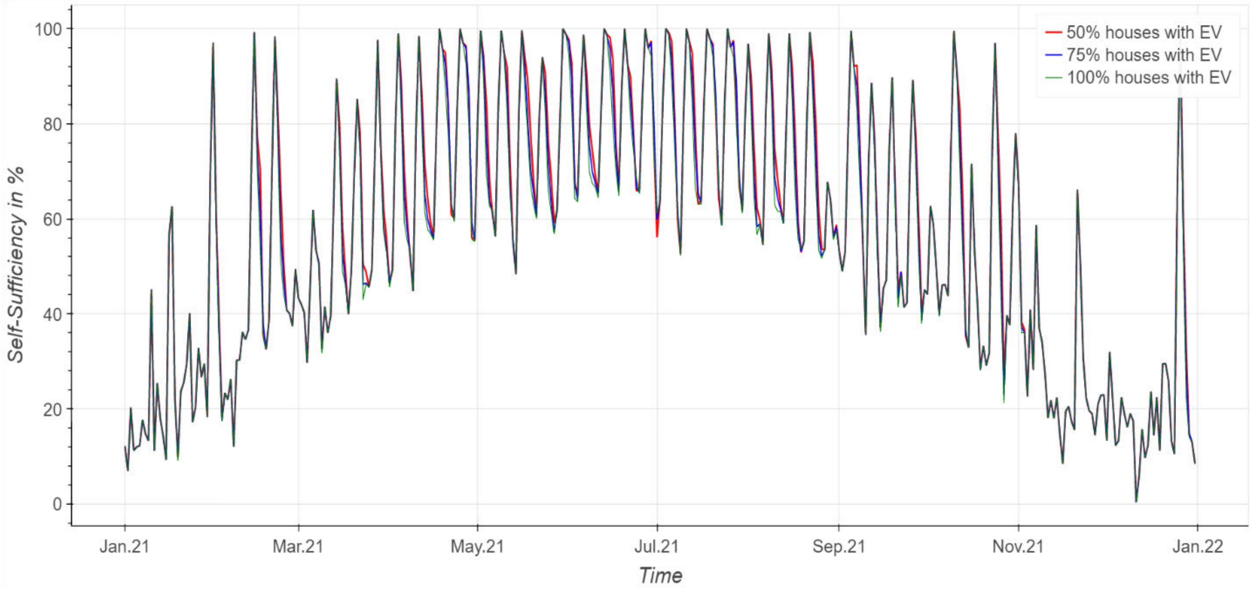

Figure 27 Self-sufficiency of PV system with EV as energy storage with different share of households owning EV

Scenario with changing EV battery size:

In addition to the preceding scenario, recent advancements in EV driving range and battery capacity have opened the door for future increases in average EV battery capacity. As a result, the effect of it on SC and SS is evaluated by simulating an EV model for two different average battery sizes, with a capacity of 60.3 kWh and 80 kWh, which also incorporates the first scenario. In Table 11, the average SC and SS values for both EV capacities are shown. Figure 29 shows the SC and SS pattern of PV systems with 50 % of households utilizing EV as energy storage with different average EV battery capacities. According to the results and analysis graph in Figure 28, as average EV battery capacity increased, SC increased slightly whereas the SS slightly decreased. With very little exposure to surplus solar energy, the potential of EV to store unused solar energy is limited, resulting in a very small increase in SC despite a significant increase in average EV capacity. On the other hand, as the size of the EV battery increased, so did the $SOC_{EV,min}$ and $SOC_{EV,avg}$, which raised the household's load demand. This leads to a decrease in SS.

Table 11 Average self-consumption and self-sufficiency of PV system with EV energy storage for different average EV battery capacity

Average EV battery capacity	**60.3 kWh**		**80 kWh**	
Share of households owning EV	Self-consumption in %	Self-sufficiency in %	Self-consumption in %	Self-sufficiency in %
50 %	75.63	57.14	76.35	56.64
75 %	76.60	56.33	77.01	55.44
100 %	77.02	55.44	77.24	54.51

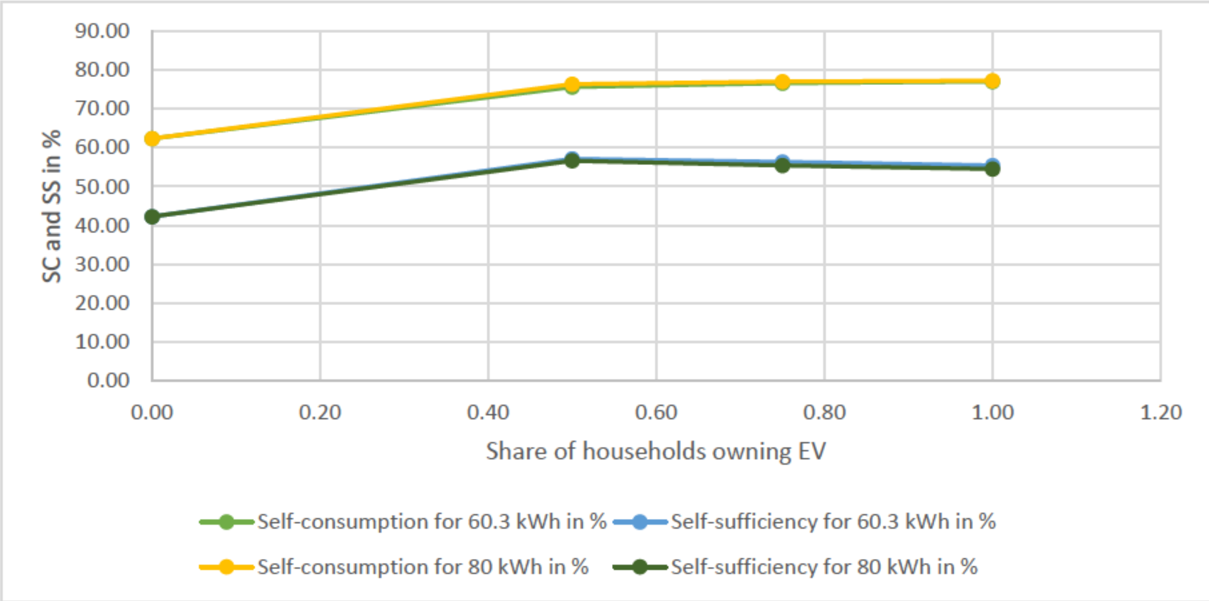

Figure 28 Analysis of SC and SS of the PV system with EV energy storage for different number of households owning EVs and different average EV battery capacity

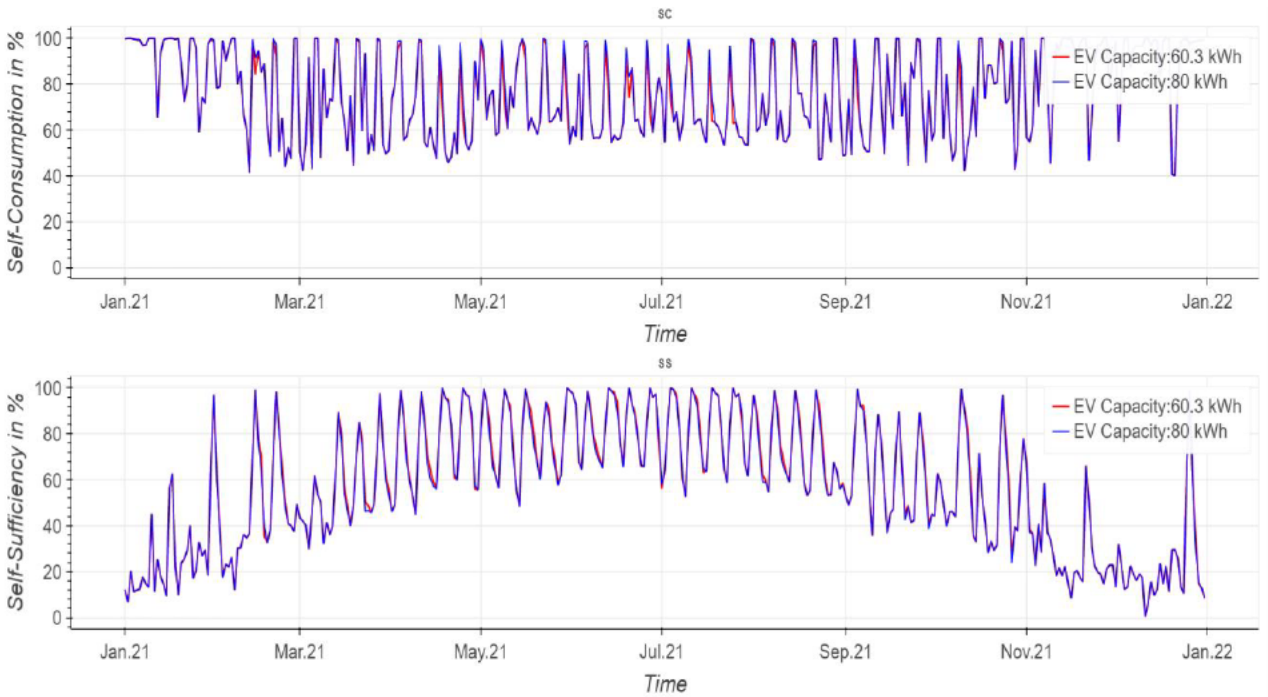

Figure 29 Daily average SC and SS of the system with two different average EV battery capacities with 50 % of household owning EVs

Scenario with variable EV arrival and departure times:

This EV model has so far concentrated on the fixed hours, from 8 am to 6 pm on weekdays, during which EVs are not available at home. But in reality, it's essential to recognize how EV commuters behave while taking into account all the vehicles in the community. As a result, the following scenario is created by analysing the typical EV arrival and departure times for each hour of the day on workdays. The EV model is altered as described in section 4.6, and a simulation model based on various numbers of EVs leaving and entering the houses is carried out.

Similar to what was previously mentioned regarding the change in load demand caused by EV models, it is possible to observe the difference in energy consumption profile for this scenario of varying arrival and departure times of EVs. The charging of EVs used to be done in the evening with fixed arrival and departure times, which caused a significant increase in load demand. However, because the arrival and departure times of EVs vary throughout the day, the time when they are connected to the grid and extracting energy from it for charging varies as well, which changes the load demand profile. Figure 30 shows and compares the load demand profile for fixed and variable departure and arrival times. The demand profile has experienced a significant decline, and load peaks have reduced considerably. Even if the controlled charging techniques are not taken into account in this model, charging EVs in a community would result in a decrease in load peaks. There is a noticeable decrease in load demand throughout the summer due to increased solar energy generation and longer sunshine hours.

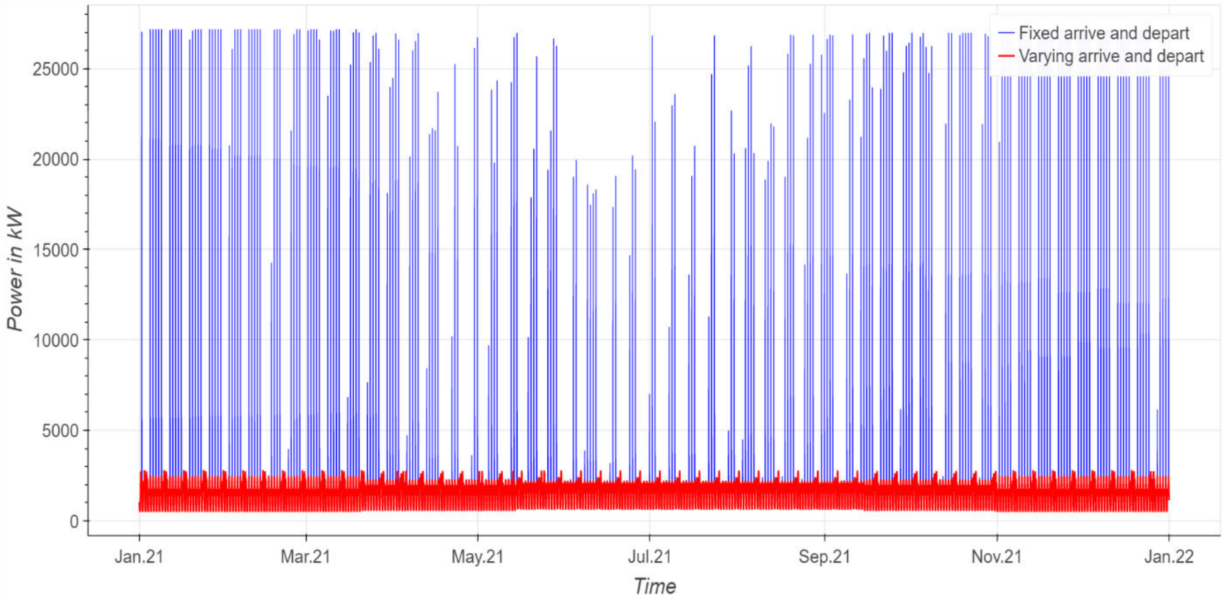

Figure 30 Total load demand of residential PV systems in Hamburg with EV

Figure 31 and Figure 32 compare the self-consumption and self-sufficiency profiles of the system with an electric vehicle as energy storage and variable departure and arrival times (red) with SC & SS profiles of the system with fixed departure and arrival times of an electric vehicle (blue). The SC and SS have increased significantly due to the varying commute behaviours of EVs. The availability of EV during periods of excess PV production has become much more likely as a result of the EVS's variable departure and arrival times. This results in increased on-site consumption of generated energy. Additionally, all vehicles arrive at different times of the day, which causes different charging patterns, since not all cars are connected to the grid at the same time for battery recharging. This significantly reduced reliance on grid energy to recharge EV batteries. Furthermore, the arrival of the EV begins at 2:00 PM, when solar energy is still being produced, providing a larger window for storing excess PV energy or charging the EV above $SOC_{EV,min}$. This is most noticeable in the summer when longer daylight hours and variable EV charging schedules increase self-sufficiency to almost 100%.

In accordance with some recent reports, adding an EV to a residential PV system and controlling charging behaviour increases self-consumption to between 62% and 87% [65]. In accordance with that, the annual average SC degree of this simulation EV model is approximately 89 %. Although the simulation model does not use controlled charging, the spread-out charging of EVs throughout the day due to their different arrival and departure times helped to reduce the unwanted load demand peaks. There are likely to be differences in the conclusions of this simulation model, as the work is based on different assumptions that may not correspond with real-life situations. More accurate results may be possible with the given algorithm, which can be used to perform the simulation with the actual load demand profile and EV commute behaviour of Hamburg.

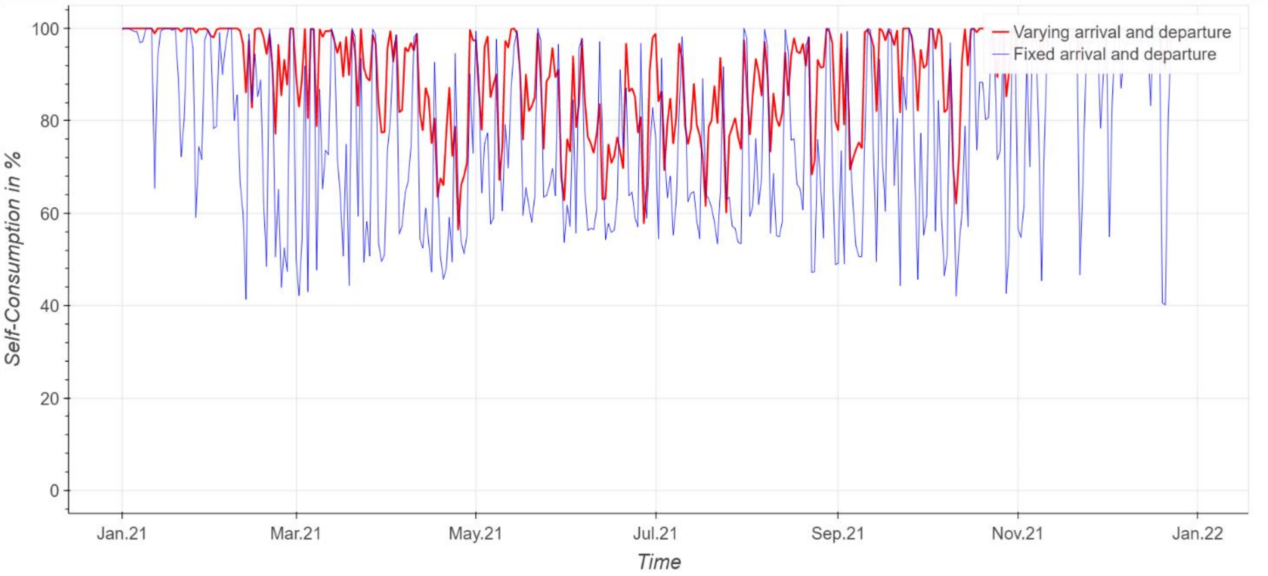

Figure 31 Self-consumption profile of the PV system using EV with varying departure and arrival behaviour

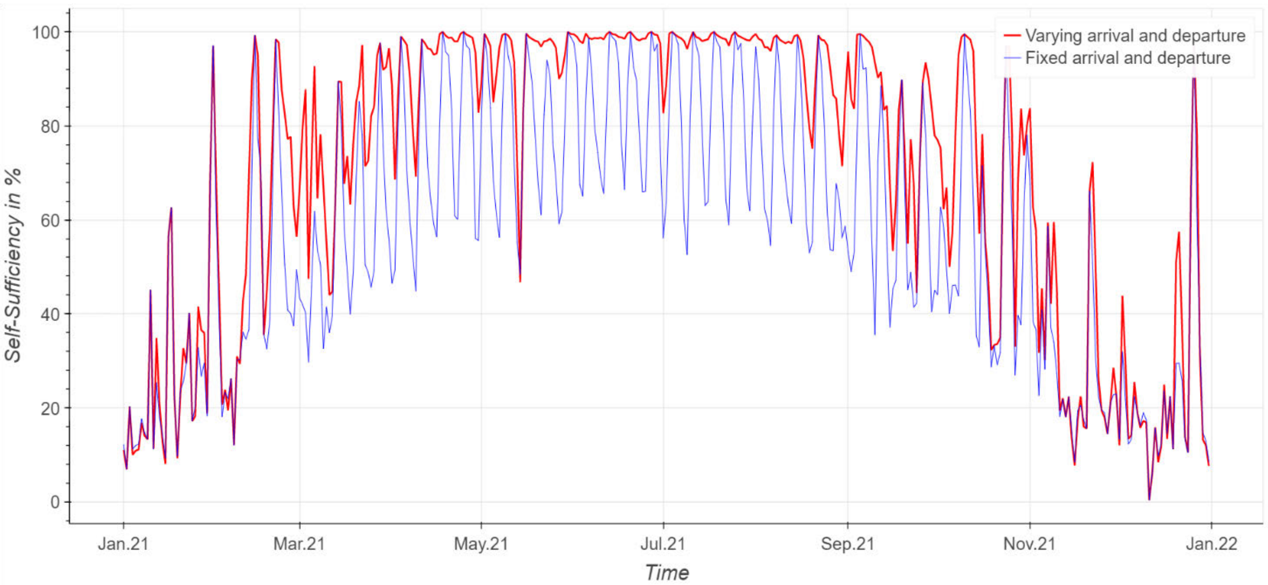

Figure 32 Self-sufficiency profile of the PV system using EV with varying departure and arrival behaviour

Scenario with changing $SOC_{EV,min}$ of EV with variable arrival and departure times:

However, it's also critical to comprehend how $SOC_{EV,min}$ affects the system's SC and SS pattern. Previously, it was assumed that the average daily amount of energy consumed by an EV while traveling was 20%, and thus, with a buffer of 10%, the minimum amount of energy that must be present in an EV is defined as 30% of total capacity. As a result, by running simulations with different values of $SOC_{EV,min}$, the impact of it on SC and SS is examined.

Table 12 displays the outcomes of SC, SS, and sum of total load demand in year. The results of this scenario show that the SC and SS slightly decline with rising $SOC_{EV,min}$ at first, but then SS starts decreasing drastically. This is due to the fact that as the value of $SOC_{EV,min}$ is raised, even though the space available to store solar energy is constant, there is a reduction in the amount of stored solar energy that is eventually used later during non-production hours. Additionally, as $SOC_{EV,min}$ increases, the energy required to charge the EV increases as well, which can be seen with increasing value of total load demand. Furthermore, the amount of energy pulled from the grid to meet load demand is increasing exponentially. Eventually, this rise in load demand causes SS to decline. With $SOC_{EV,min}$ value at 80 %, the decrease in self-sufficiency is around 20 % as compared to 30 % of $SOC_{EV,min}$. Until 50 percent $SOC_{EV,min}$ for each step of a 10 percent increase, this change in SS was relatively very small. The evidence from this discovery therefore implies that the ideal SC and SS level for EV can be seen until the $SOC_{EV,min}$ level is at or below 50 %.

Table 12 Average SC and SS of system with varying minimum SOC of EV

$SOC_{EV,min}$ in % of total capacity	Self-consumption in %	Self-sufficiency in %	Total annual load demand in GWh	Excess energy extracted from the grid in GWh
30 %	88.99	71.18	16.05	6.02
40 %	88.51	69.84	16.15	6.23
50 %	87.84	67.93	16.26	6.51
60 %	86.87	65.36	16.43	6.93
70 %	85.43	61.86	16.68	7.57
80 %	82.98	56.84	17.13	8.70

Figure 33 Daily average SC and SS of the system with varying value of minimum SOC of EV

The self-consumption and self-sufficiency profile for a year with varied values of $SOC_{EV,min}$ is shown in Figure 33. The decrease in self-sufficiency during the summer, with an increase in $SOC_{EV,min}$, can be seen as a result of increased solar energy production and decreased usable stored energy. The lack of significant change in self-consumption may be due to the fact that, regardless of changes in $SOC_{EV,min}$, the amount of energy that can be stored in EV remains constant. However, as $SOC_{EV,min}$ increased, the load demand increased as well, as seen in Figure 34. Which also implies that, the quantity of excess solar energy that is being stored in EVs during production hours is reduced as a result of the fact that EVs eventually get charged when they are below the minimum SOC value by extracting grid energy. This leads to decreasing in overall SC. Figure 34 demonstrates that while $SOC_{EV,min}$ grew, the load demand likewise increased, mostly during the summer. The load peaks caused by the charging of EVs using grid energy are often reduced with sufficient solar energy output and a longer time period of sun availability during summer.

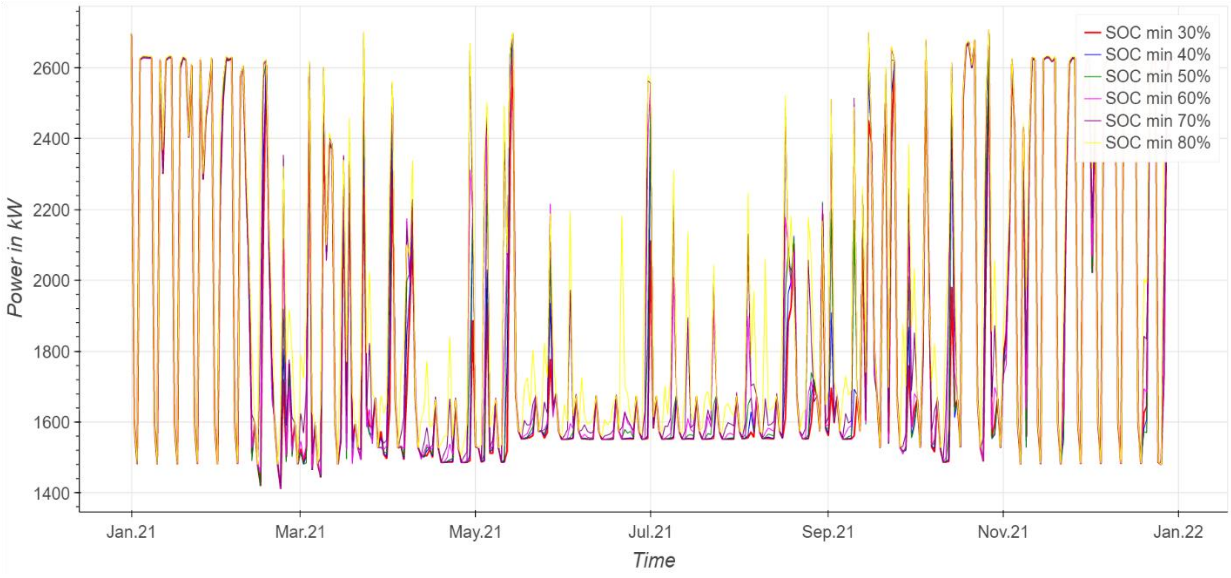

Figure 34 Load demand profile of the system with varying value of minimum SOC of EV

5.1.6 Self-consumption and self-sufficiency of the residential PV systems in Hamburg with combination of battery storage and EV energy storage system

In earlier sections, the findings of the battery model and the EV model were illustrated. When compared to a system without energy storage, an increase in self-consumption and self-sufficiency is seen with each energy storage model. The effect of combining EV energy storage with batteries will now be discussed in this section, along with how it affects the SC and SS patterns.

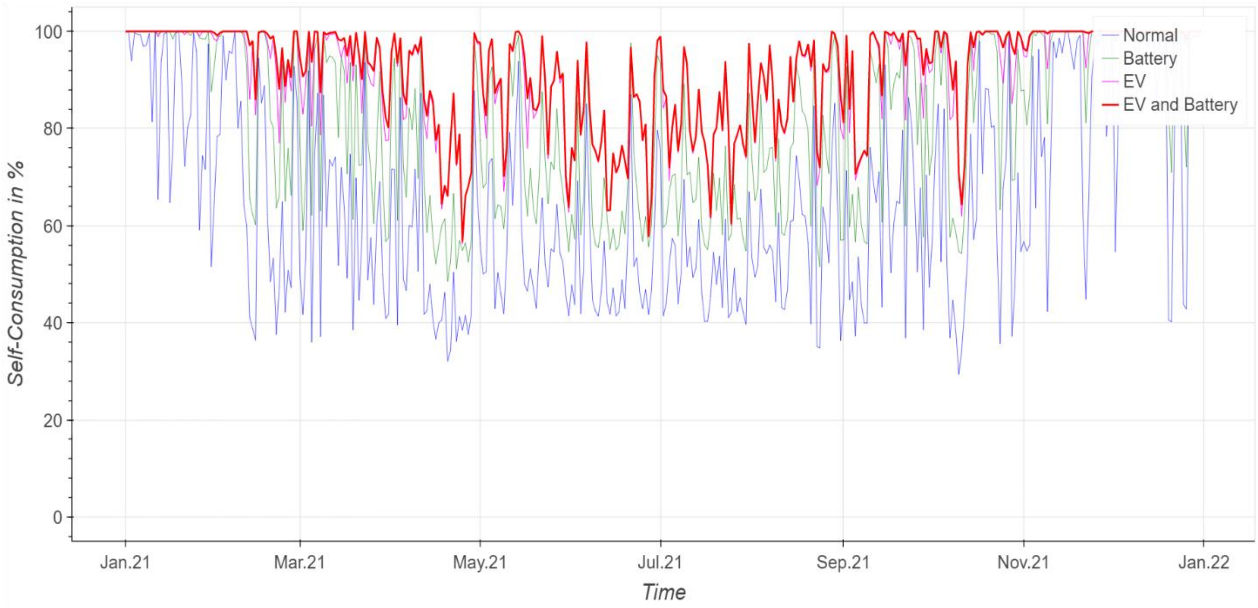

Figure 35 Self-consumption of residential PV systems in Hamburg with combination of EV and Battery as energy storage system

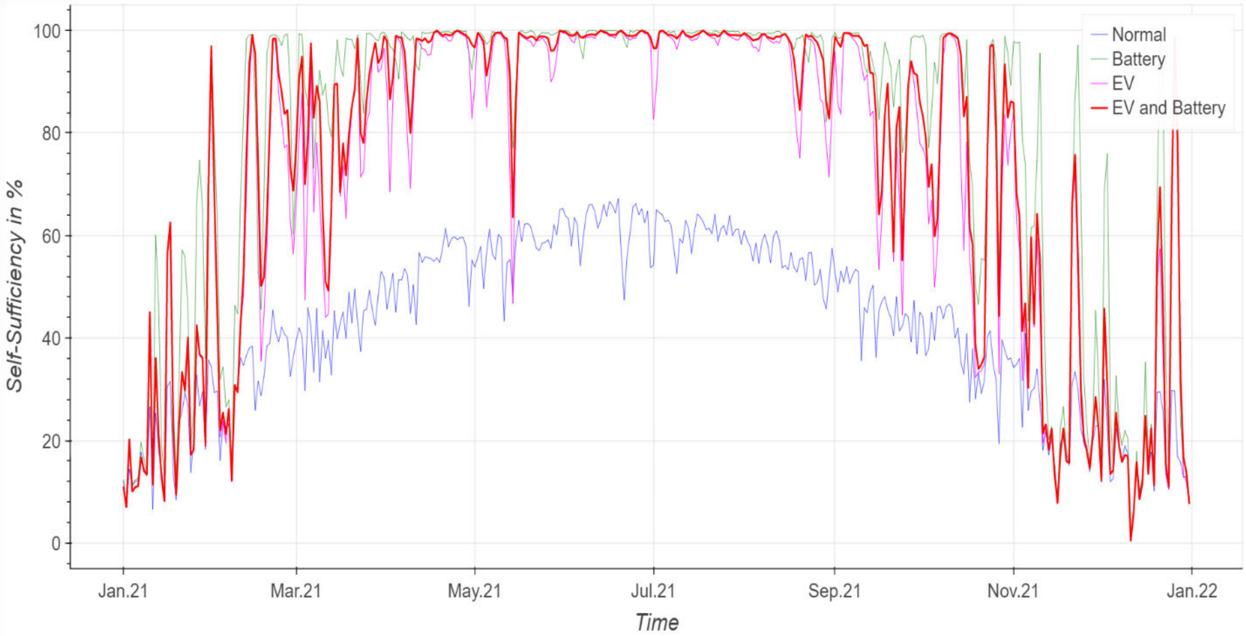

Figure 36 Self-sufficiency of residential PV systems in Hamburg with combination of EV and Battery as energy storage system

Figure 35 illustrates the self-consumption of residential PV systems in Hamburg using an energy storage system that combines an electric vehicle and batteries. Additionally, for meaningful comparisons, the graph displays the SC pattern evaluated using all configurations. The SC profile, though with a greater degree of SC, stretches along the same path as the EV model's SC pattern. The outcome in Table 13 and the graph demonstrates that the combination of both energy storage systems significantly increases the SC in all aspects, with a 20 percent increase in SC compared to an EV model. Similarly, the graph of self-sufficiency of the system with integration of EV and battery, shown in Figure 36, indicates a higher level of SS than with the EV model. According to the graph, battery energy storage has a higher level of SS than either electric vehicles (EVs) alone or when combined with batteries. The cause of this is that the household's energy consumption rises significantly with the introduction of EVs, which reduces the system's capacity for self-sufficiency. Nonetheless, the combination of EV and battery results in a significant increase in SS level. In Table 13, the average SC and SS values for all models are shown.

Table 13 Average self-consumption and self-sufficiency for all simulation models

Model	**Self-Consumption in %**	**Self-Sufficiency in %**
Without energy storage	61.41	42.58
Battery energy storage	78.44	79.75
EV energy storage (Fixed arrival and departure)	75.63	57.14
EV energy storage (varying arrival and departure)	88.99	71.18
Combination of Battery and EV (varying arrival and departure)	90.00	74.03

Scenario with different charging priorities:

So far, as described in section 4.7, this model has prioritized the charging and extraction of energy from the EV, which will be followed by the battery. However, a new scenario is simulated in which the excess solar energy will be stored and drawn from the battery first to take into account the impact of changing this priority on the outcomes. For the purpose of analyzing the effects, changes in SC, SS, total unused solar energy, and total energy demand are observed.

Table 14 indicates that, the model that prioritizes battery storage over EV has a slightly higher level of SC and SS. In contrast, a model where the excess energy is first stored in an EV result in a slightly higher overall amount of solar energy that is fed to the grid or wasted. This justifies the lower on-site consumption of generated solar energy. The reason for this could be a mismatch between the availability of electric vehicles and excess solar energy. The total load demand of all residential PV systems in Hamburg, another important parameter, shows that charging the EVs first reduced the total amount of energy required yearly to fulfill load demand and charge the EV until $SOC_{EV,min}$ is reached. Although the amount of extra energy drawn from the grid to meet load demand is nearly similar in both situations. This suggests that there are no substantial changes in the various parameters in either scenario, and the slightly increased SC and SS when storing excess energy in batteries first is caused by the increased overall load demand that is being satisfied by solar energy generation.

Table 14 The various results of the first scenario for the model using an EV and battery energy storage

Model priority	EV followed by battery	Battery followed by EV
Average self-consumption	90.00 %	90.07 %
Average self-sufficiency	74.03 %	74.46 %
Total unused solar energy in year	3.916 GWh	3.915 GWh
Total load demand in year	16.057 GWh	16.71 GWh
Excess energy extracted from grid	5.62 GWh	5.62 GWh

5.2 Grid calculation of LV benchmark grids

This chapter has thus far examined and discussed the results of all simulation models and various scenarios. As we move into the second section of the chapter, in this section, the power system parameters will be studied in order to analyse the reliability of these simulation models and the assumptions made during configurations. As a result, after modeling their load demand and solar energy with all SC and SS models, as was described in section 4.8, grid calculations are performed for two benchmark power networks, one representing a rural grid and the other an urban grid.

1. Rural benchmark grid:
   For each of the four scenarios, both without and with energy storage technologies, the rural grid with 13 load elements and 4 static generators was simulated. The load demand and solar timeseries of the grid network were derived using the simulation results, the excess solar energy profile, and the residual load demand profile. The output from each simulation model was used to configure the four grid network scenarios.

For the purpose of power flow calculation, grids with all potential scenarios were then simulated using pandapower. To evaluate the effectiveness and credibility of the simulation model, the results of voltage per unit and line loading in percentage for each scenario were compared.

Figure 37 and Figure 38, respectively, display the voltage distribution and the distribution of line loading for each scenario. Figure 37 demonstrates how the overall voltage distribution is pushed toward the right of the reference voltage for rural grid networks with moderate load demand profiles and adequate solar energy generation, indicating overvoltage by about 2%, whereas with EV scenario, the voltage has dropped. Additionally, Figure 38 demonstrates that the line loading never increased above the 20 percent level. The on-site increased use of excess solar energy caused by the battery storage technology causes a slight leftward shift in the voltage distribution. Additionally, there is a considerable change in voltage distribution and a minor increase in line loading when EVs and EV-battery combinations were introduced. The most plausible explanation is that EVs used more surplus solar energy and extracted energy from the grid during non-production hours, which ultimately had an impact on voltage distribution and line loading. In summary, this suggests that more solar energy is being produced and fed into the grid causing overvoltage and that the introduction of EVs reduced the overvoltage by consuming the majority of the generation.

A peak at voltage magnitude of 1.025 can be seen on the graph as an indication of the external grid.

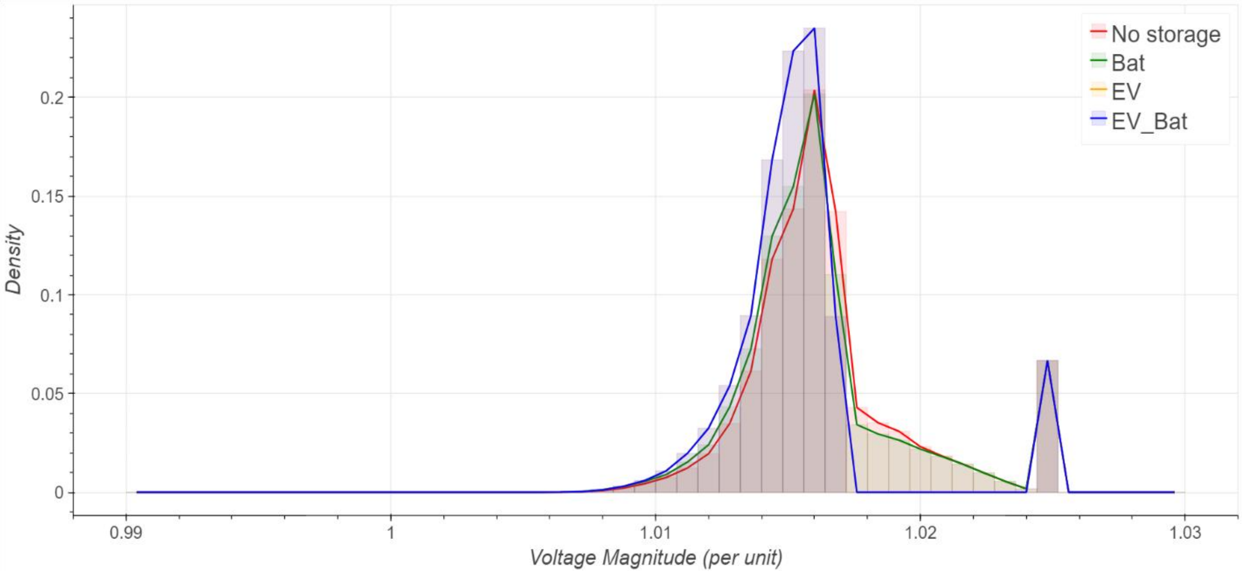

Figure 37 Voltage(per unit) distribution for all simulation models representing rural grid

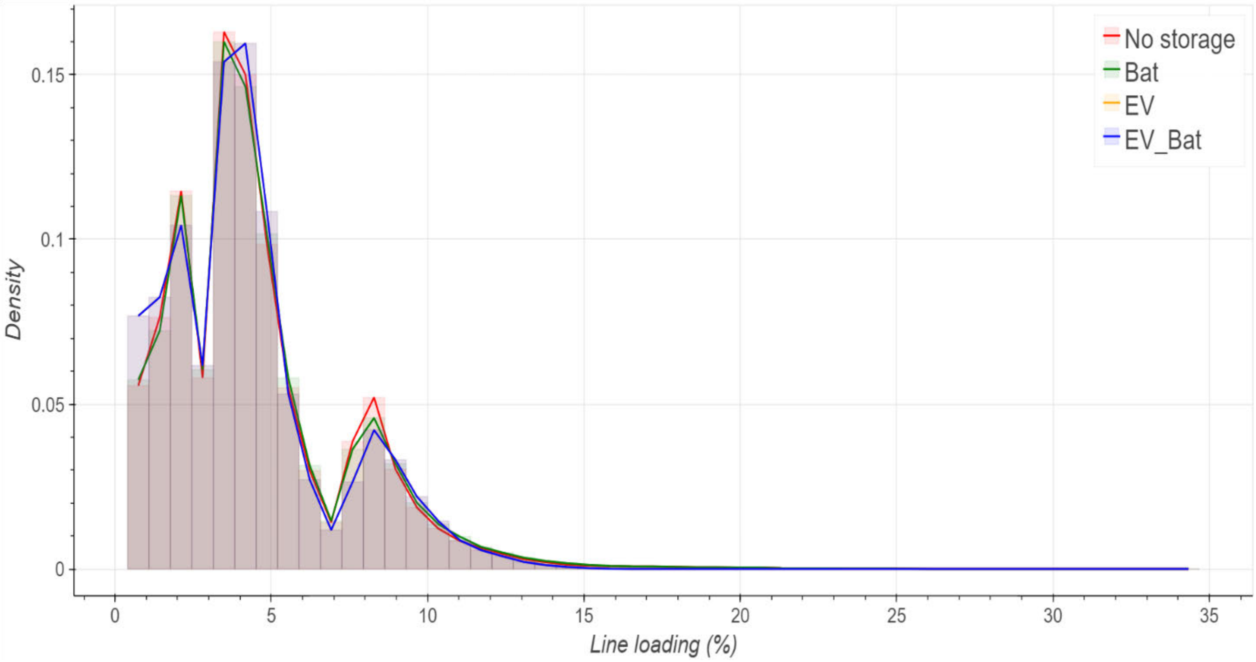

Figure 38 Line loading(%) distribution for all simulation models representing rural grid

2. Urban benchmark grid:
   The urban grid was simulated in the same manner as the rural grid for all four simulation models. The four scenarios were configured using simulation output data, and the grid calculation was performed using pandapower.
   In comparison to rural networks, there are 5 PV generators and 111 load elements, which significantly alters the voltage distribution and line loading. The distributions of voltage and line loading for each scenario are shown in Figure 39 and Figure 40, respectively. Figure 39 demonstrates that voltage varies by 1% of its reference mark. The presence of undervoltage indicates that more energy is being consumed than is being produced and supplied to the system. The voltage has slightly shifted to the left after the introduction of EV. A peak at a voltage magnitude of 1.025, similar to that in the Figure 37, can be noticed on the graph which is associated to the external grid. Since there has been little to no change in line loading (see Figure 40), it is likely that load demand exceeds the solar energy feed-in for urban grid.

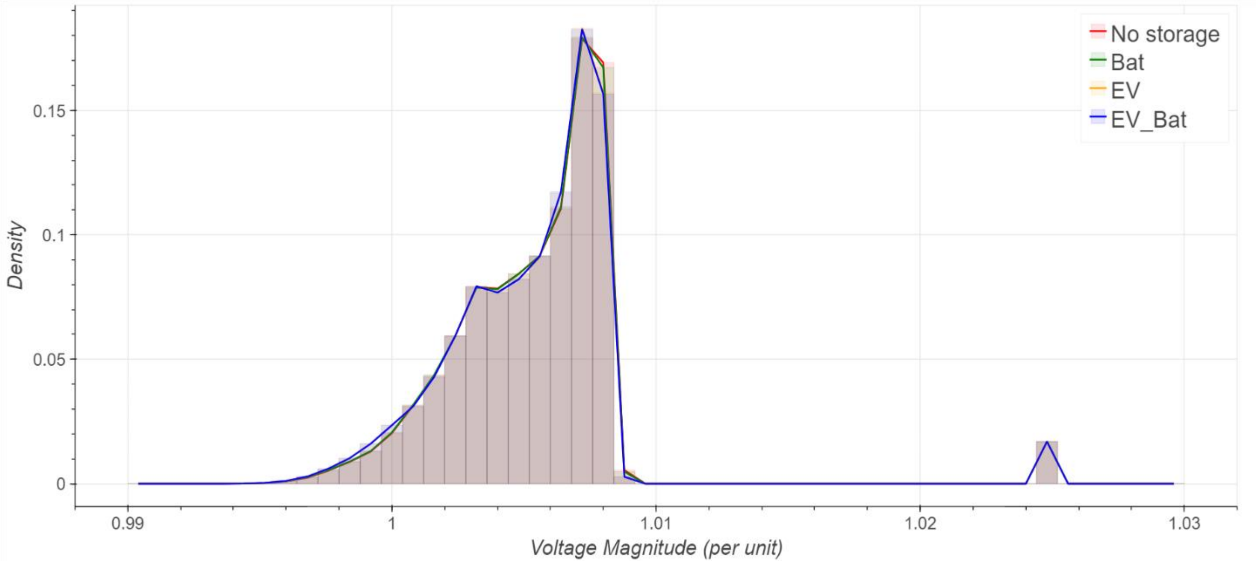

Figure 39 Voltage(per unit) distribution for all simulation models representing urban grid

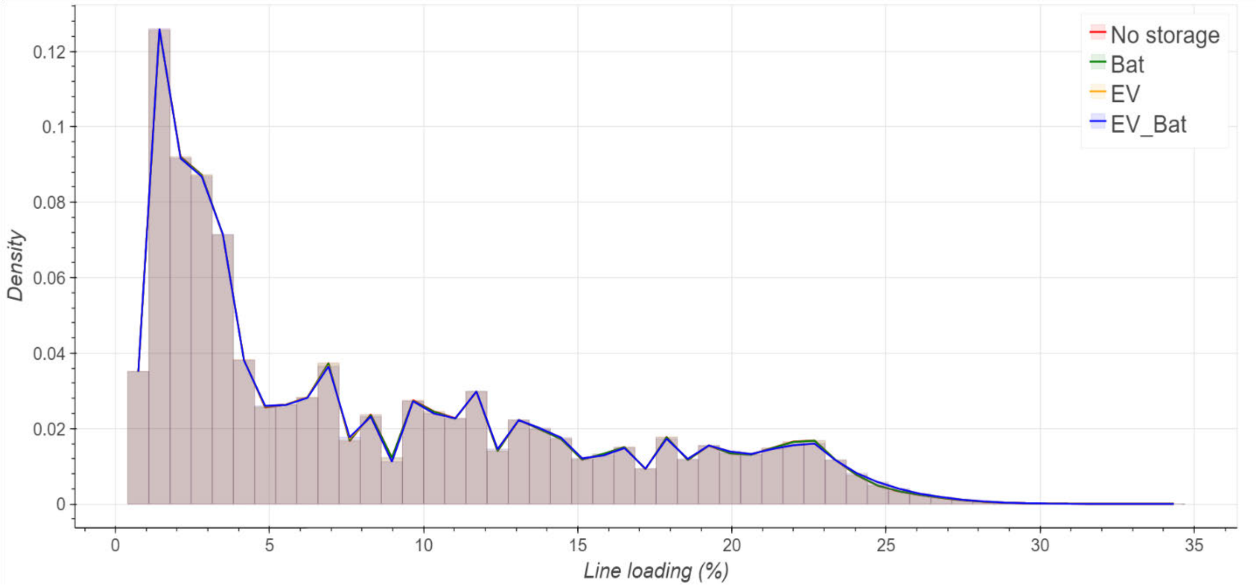

Figure 40 Line loading(%) distribution for all simulation models representing urban grid

As was mentioned above, compared to an urban grid, a rural grid with lower load demand and higher solar energy production experiences overvoltage in the network (see Figure 41). Figure 41 shows the voltage distribution for both grids when EVs and batteries are used as energy storage technologies. According to Figure 42, the line loading is more evenly distributed for urban grids, where it ranges from 0 to 30 %, whereas it is more concentrated for rural grids between 0 and 15 %.

Taken together, the power flow parameters from both grids appear to support the credibility of assumptions made for the simulation models.

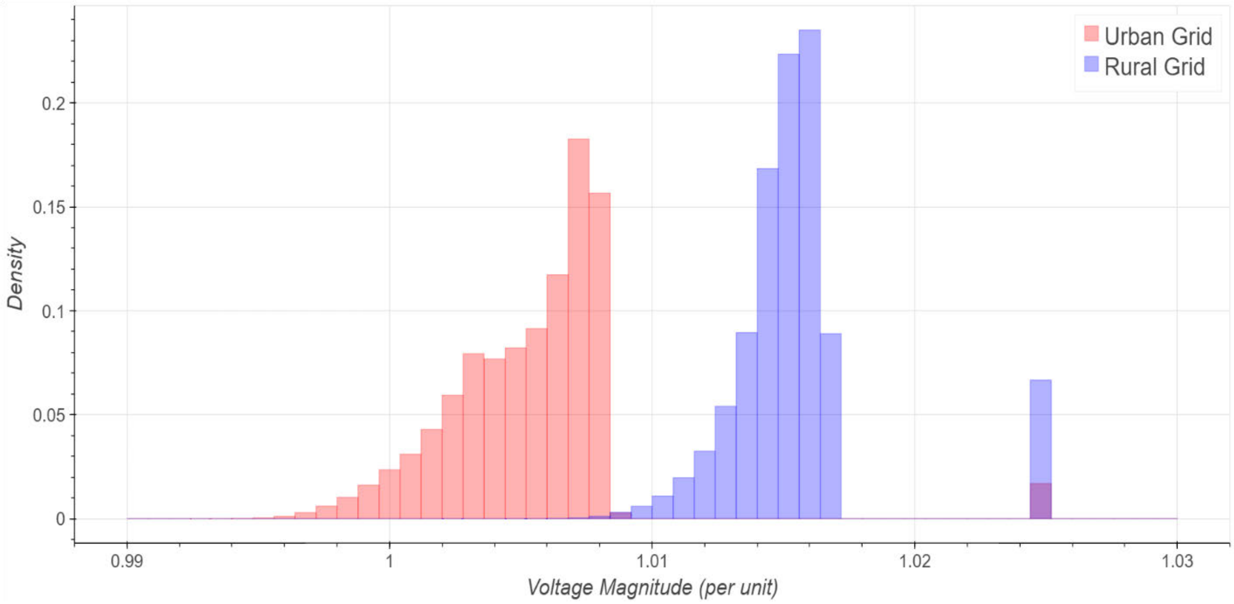

Figure 41 Comparison of voltage(per unit) distribution for urban(red) and rural(blue) grid considering EV and Bat model

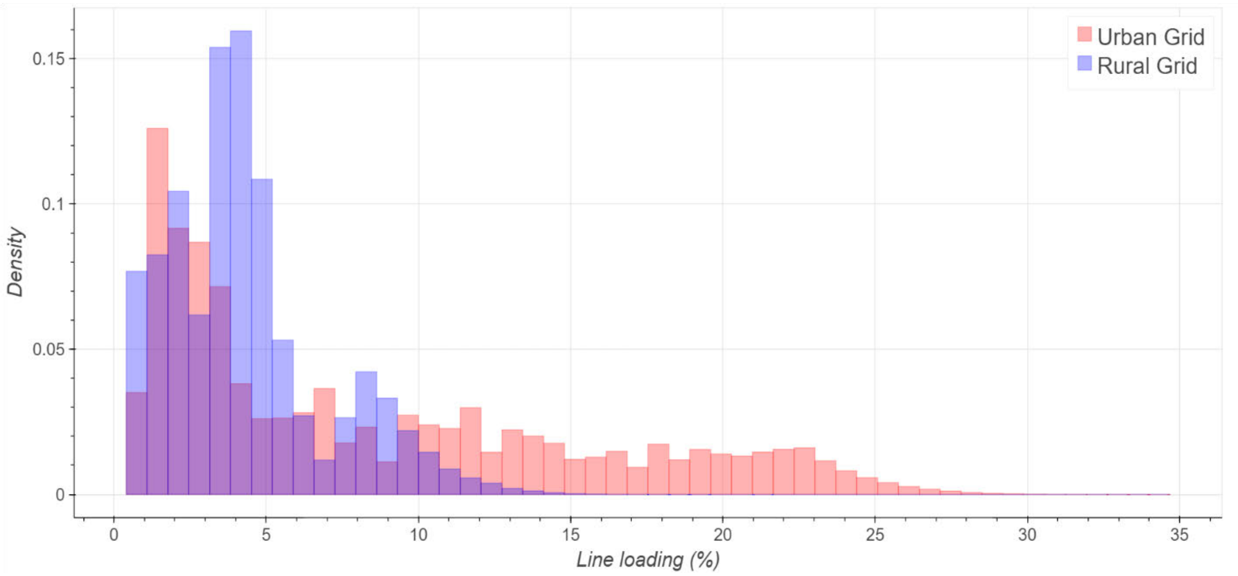

Figure 42 Comparison of line loading(%) distribution for urban(red) and rural(blue) grid considering EV and Bat model

In summary, this section has reviewed the two main aspects of self-consumption and self-sufficiency profile.

1. Seasonal variation : The findings from all models imply that the season has a significant impact on SC and SS profile of Hamburg. The seasonality effect on on-site solar generation and load demand has a greater impact on self-consumption. Summer, with longer sunshine hours and slightly lower energy consumption, drives SS significantly, whereas winter, with more cloudy days, eventually utilizing almost all generated solar energy, improves SC.

2. Energy storage system : The study demonstrates that implementing an energy storage system of the appropriate size improves and modifies the SC and SS profiles. The stationary battery storage system increases the on-site use of excess solar energy without putting additional strain on the grid. However, even though EVs use generated surplus PV energy, they could result in an increase in the household's overall load demand. The SC and SS pattern for the residential sector of Hamburg with PV systems, taking into account both EV and battery energy storage, shows that even with SS reaching almost 100% during summer and with 90% of average self-consumption, more energy has to be drawn from the grid to meet the load demand for the majority of the year. The increased energy demand is primarily due to the introduction of EVs to the grid.

These findings should be interpreted with caution because they do not rule out the influence of other real-world circumstances.

6. Conclusion, Summary and Outlook

This chapter will give a summary of all findings of the thesis and discuss the extent to which the objectives of the study are fulfilled, followed by the outlook on the possible extension of this study.

6.1 Summary

Self-consumption of residential PV systems has emerged as a very fascinating research topic, given the numerous new and interesting findings, the world's growing PV market, and the possibility of it becoming a significant market driver in the future [31]. From the start of the research of this thesis, the reason to do the analysis of SC and SS profiles of households with PV systems in Hamburg, which is the main objective of the thesis, was clear. The energy consumption behaviour of households is changing with increasing PV installations and growing interest in self-consumption. A comprehensive summary of the effects of growing PV installations on the grid is provided in Section 3.2. The analysis of self-consumption and self-sufficiency is highly significant for grid management due to the impact of growing new grid connections, shifting load demand patterns, and a lack of reliable data. More importantly, it is crucial to concentrate on aspects that improve or change the SC and SS patterns. In section 3.3, the factors that affect self-consumption and self-sufficiency from a technological and financial perspective were briefly covered.

Within the scope of this thesis the models were developed, to perform a realistic analysis of the impact the seasonal variation as well as energy storage systems having on self-consumption and self-sufficiency profiles of residential PV systems in Hamburg. For the first step, in order to estimate the SC and SS, the timeseries of solar energy generation were matched with the load demand of all Hamburg households with PV systems. Given that the information on the systems associated with the residential sector was unknown, all PV systems with installed capacities lower than 25 kWp were classified as residential PV systems. Instead of analysing each individual household independently, it was decided to aggregate the load demand and solar generation profiles of all the households connected to each grid point while evaluating the SC. Eventually, the average SC and SS of all grid nodes in Hamburg were taken into account. When provided with PV system parameters and weather data (refer section 4.3), the PV power model created PV production timeseries with a given temporal resolution. While a load demand profile was generated by scaling up BDEW's SLP to the Hamburg level (refer section 4.2). The model's output demonstrates the impact of seasonality on SC and SS profiles of Hamburg. The impact of higher solar radiation and longer sunshine hours in summer, as well as reduced irradiation in winter, on solar production is reflected in the SC and SS profiles.

After that, two models were created to assess the SC and SS of systems with energy storage, including both battery storage and EV energy storage. In view of increasing PV installations, this thesis investigates how battery energy storage impacts SC and SS. In comparison to without using any energy storage, the model considering optimal battery size with 1 kWh per kWp of installed PV capacity showed a 28 % increase in SC and an approximate 87 % increase in SS. Seasonality also played an important part when using battery storage systems. As compared to winter, more energy was consumed on-site and stored for later use during the summer, enhancing both SC and SS. This study also conducted simulations to examine the impact of increasing battery storage size on SC and SS. The findings demonstrate that SS and SC levels rise exponentially, eventually reaching a saturation point beyond which only the expense of the battery system rises without significantly altering SC.

The second model explored the influence of EVs as energy storage on SC and SS. The model examines SC and SS for both constant and variable EV arrival and departure times. The impact of a future scenario where 50%, 75%, and 100% of households with PV systems own EVs was simulated and examined in light of the growing interest in e-mobility. According to the statistics, implementing EV and considering fixed departure and arrival times of 8 am and 6 pm improves SC to 76 percent but does not significantly raise SS. The cause of such, as well as another significant effect of EV, is the rise in residential energy consumption with evening load peaks. On the other hand, the results of varying departure and arrival times demonstrate that the load demand peaks have greatly decreased and therefore SC and SS have significantly improved.

With the use of a battery and an electric vehicle, the most remarkable value of self-consumption—almost 90%—can be observed while taking into account the varying arrival and departure times of EVs. But when compared to other technologies, the PV system with battery energy storage exhibits a higher degree of self-sufficiency. Even with greater storing capacity, the increased load demand caused by EV adoption reduces total self-sufficiency value when considering EV as energy storage, even when combined with battery storage.

When considered collectively, it indicates that, the implementation of battery storage or adaptation of EV have larger influence on SC and SS profiles, improving the self-consumption of residential PV systems significantly. Although, given the impact of seasonal variation, neither the degree of self-consumption nor the degree of self-sufficiency will attend continuous and stable 100 percent value in a real-world scenario. After a certain point, oversizing the PV system or energy storage system would just drive-up system costs and not SC and SS. Additionally, the demand profile of households will change in the near future as the e-mobility market expands, which will impact the SC and SS profiles. Overall, self-consumption modifies the high PV energy penetration, ultimately affecting the energy feed-in from residential PV systems. Therefore, the SC and SS profiles derived from the algorithms presented in this thesis would assist the grid operator in controlling the grid.

6.2 Outlook

This thesis covers a wide range of topics, from battery and electric vehicle storage modeling to PV generation models. Consequently, a variety of assumptions and simplifications are made while developing these models. The identified limitations that can be addressed in future investigations are highlighted in this section. In addition, possible approaches to deal with these limitations are discussed.

In general, the solar energy generation timeseries and load demand profile for residential PV systems in Hamburg are well suited to the purpose of the thesis. However, as stated in section

4.9, more precise information could be gathered to estimate self-consumption and self-sufficiency with greater accuracy. There are different approaches for gathering more exact data. The solar energy data was produced using a PV power model and meteorological information from a weather station close to Hamburg. By estimating cloud cover and obstacle shadowing at a given location for PV systems, or by enriching the model with more information about PV systems, the accuracy of the data can be improved. Another approach could be the gathering of observed solar energy generation data from households. This is something that smart meter installation may make achievable in the near future. Another constraint is the load demand profile, which was generated by scaling the BDEW residential SLP to the Hamburg level. Given the growing awareness of sustainable energy and energy efficiency, as well as a result of the pandemic, changes in energy consumption behaviour could be possible. As a result, more accurate and latest load demand profile of Hamburg households might be obtained from 'Stromnetz-Hamburg’ [104].

In terms of PV systems with EVs as energy storage, basic assumptions such as a) EV average daily energy consumption, b) charging capacity of home charging station, and c) EV departure and arrival behaviour must be investigated further. By monitoring the characteristics of EVs, the first and second assumptions can be confirmed and revised. The third assumption could have changed as a result of the rise in home offices during the COVID pandemic over the past two years, which may have impacted the general mobility pattern. Another limitation is the assumption that all vehicles will be parked at home and linked to the grid for the whole weekend. As a result, precise information on EV behaviour during the weekend could help in more accuracy of SC and SS profiles. Thus, monitoring the behaviour of EV users in Hamburg and modifying the model accordingly could be a further expansion of this topic.

Another limitation is that for the sake of simplicity, the assumption has been made that charging of all vehicles occurs solely at the house charging point. The distribution of charging of EVs can be analysed by monitoring e-mobility behaviour, and further modifications to the model can be made. So far, the model has taken into account known assumptions, whereas the parameters and constraints that will be introduced in the future are entirely unknown. Taken together, this subject could be further extended to focus on the self-consumption of residential PV systems in Hamburg with e-mobility.

Given the effort and time constraints, only battery storage and EV storage systems and their effect on SC and SS were analysed in this thesis. The study of other energy storage technologies such as, heat energy storage(heat pump) and hydrogen energy storage in relation to self-consumption of Hamburg residential PV systems is another promising topic for a future project. Also, this topic can be further extended to work on demand side management (DSM) techniques and its impact on SC and SS.

The SC and SS analysis for Hamburg, as well as the methodology used to conduct the analysis, are crucial. Residential PV system installations are expected to increase significantly as a result of the government's new goal of achieving 215 GWp of installed capacity by 2030 and its new commitments in the "Easter package" [3], [105], [106]. Additionally, beginning in 2023, all new buildings in Hamburg must be equipped with PV systems [107]. As a result, this will increase PV installations and, eventually, PV penetration. Consequently, the SC and SS patterns may alter with residential development and PV systems. The method outlined in this thesis would assist grid operators in assessing SC and SS patterns. The outcomes of the SC and SS profiles also demonstrate the influence of seasonal variation as well as the impact of energy storage on the profiles. As a result, grid operators would be able to approximate the behaviour of new household connections.

The presented models for self-consumption and self-sufficiency have the potential to increase their accuracy by considering different parameters and enriching new data sources. The research in this thesis can be expanded upon for the entirety of Germany or any other region. This model can also be used in conjunction with forecasted data on load demand and solar energy production to help predict short-term SC and SS patterns.

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A. Appendix

A.1 Data preparation for load demand profile of Hamburg

A.1.1 Hamburg Grid Nodes Data

The data for the Hamburg grid node was obtained from CC4E. There are 73 grid nodes with 110/10 kV transformer stations in total. The grid nodes, their voltage level, and their location over the Hamburg region are shown in the Table 15.

Table 15 Hamburg's grid nodes with 110 kV voltage level

Number	Node Name	Voltage level in kV	Latitude	Longitude	Postcode
1	Arcelor Mittal (110kV)	110	53.52461	9.90067	21129
2	h_Allermöhe	110	53.488371	10.1131077	21035
3	h_Billwerder	110	53.531947	10.0776056	22113
4	h_Eidelstedt	110	53.598326	9.9129758	22525
5	h_Langenhorn	110	53.674475	10.0564263	22399
6	h_Rissen	110	53.581669	9.7710449	22559
7	h_Tilsiter_Straße	110	53.593979	10.0993241	22047
8	h_Tonndorf	110	53.583119	10.1251547	22045
9	Hamburg/Nord (50Hz) (110kV)	110	53.7399	9.98666	22844
10	Hamburg/Ost (110kV)	110	53.55442	10.15528	22117
11	Hamburg/Süd (110kV)	110	53.48871	9.90767	21079
12	Moorburg (110kV)	110	53.48825	9.94894	21079
13	TRIMET Aluminum (110kV)	110	53.51032	9.89835	21129
14	Umformerwerk Harburg (Bahnstrom)	110	53.44909	10.00121	21079
15	UW Allermöhe (110kV)	110	53.48862	10.11278	21035
16	UW Alsterdorf (110kV)	110	53.60644	10.00816	22297
17	UW Altenwerder (110kV)	110	53.51636	9.91435	21129
18	UW Altona (110kV)	110	53.55045	9.9443	22767
19	UW Bahrenfeld (110kV)	110	53.56112	9.91957	22761
20	UW Barmbek (110kV)	110	53.58205	10.02413	22083
21	UW Bergedorf (110kV)	110	53.48183	10.2102	21029
22	UW Berne (110kV)	110	53.61386	10.12613	22147
23	UW Bille (110kV)	110	53.54355	10.03706	20537
24	UW Billstedt (110kV)	110	53.53831	10.12927	22117
25	UW Billwerder (110kV)	110	53.53113	10.07871	22113
26	UW Bramfeld (110kV)	110	53.61406	10.076	22177
27	UW Drehbrücke (110kV)	110	53.51147	9.96694	21107
28	UW Eidelstedt (110kV)	110	53.59731	9.90569	22525
29	UW Eilbek (110kV)	110	53.566146	10.0410649	22089
30	UW Eimsbüttel (110kV)	110	53.57773	9.95652	20255

31	UW Eppendorf (110kV)	110	53.59113	9.98884	20249
32	UW Finkenwerder (110kV)	110	53.53694	9.84369	21129
33	UW Fuhlsbüttel (110kV)	110	53.63633	10.01619	22335
34	UW Großneumarkt (110kV)	110	53.55045	9.98023	20459
35	UW Hafencity (110kV)	110	53.54384	10.00711	20457
36	UW Hamburg Mitte (110kV)	110	53.55217	10.00059	20095
37	UW Hamburg West (110kV)	110	53.58184	9.87058	22549
38	UW Harburg (110kV)	110	53.46474	9.98074	21079
39	UW Hausbruch (110kV)	110	53.48148	9.90595	21147
40	UW Hellbrook (110kV)	110	53.59557	10.05064	22307
41	UW Hinschenfelde (110kV)	110	53.5913	10.08843	22047
42	UW Hoheluft (110kV)	110	53.58146	9.97829	20251
43	UW Holsten (110kV)	110	53.56078	9.95131	22765
44	UW Horn (110kV)	110	53.55677	10.07929	22111
45	UW Jenfeld (110kV)	110	53.57416	10.10179	22043
46	UW Karoline (110kV)	110	53.56077	9.97491	20357
47	UW Kuhwerder (110kV)	110	53.53639	9.96913	20457
48	UW Langenhorn (110kV)	110	53.658895	10.0099312	22419
49	UW Lehmsahl (110kV)	110	53.69062	10.10746	22397
50	UW Lohbrügge (110kV)	110	53.50294	10.19819	21031
51	UW Lokstedt (110kV)	110	53.60756	9.95076	22453
52	UW Neuengamme (110kV)	110	53.42711	10.23299	21039
53	UW Neugraben (110kV)	110	53.47303	9.85864	21149
54	UW Neuhof (110kV)	110	53.51575	9.96208	21107
55	UW Neuland (110kV)	110	53.45211	10.00279	21079
56	UW Neustadt (110kV)	110	53.55235	9.98715	20354
57	UW Niendorf (110kV)	110	53.62716	9.93661	22459
58	UW Poppenbüttel (110kV)	110	53.64773	10.09041	22391
59	UW Rahlstedt (110kV)	110	53.60718	10.15852	22143
60	UW Rathaus (110kV)	110	53.54962	9.99429	20095
61	UW Rissen (110kV)	110	53.58123	9.76862	22559
62	UW Siemersplatz (110kV)	110	53.59888	9.961	22529
63	UW St. Georg (110kV)	110	53.55456	10.01837	20099
64	UW Sülldorf (110kV)	110	53.57768	9.80944	22589
65	UW Tiefstack (110kV)	110	53.52705	10.06833	22113
66	UW Tonndorf (110kV)	110	53.58336	10.12512	22045
67	UW Veddel (110kV)	110	53.52413	10.02609	20539
68	UW Volksdorf (110kV)	110	53.65262	10.16479	22359
69	UW Wandsbek (110kV)	110	53.5746	10.07871	22041
70	UW Wedel (110kV)	110	53.57098	9.72776	22880
71	UW Wilhelmsburg (110kV)	110	53.5068	9.982	21107
72	UW Wilstorf (110kV)	110	53.44128	9.9942	21079
73	UW Winterhude (110kV)	110	53.59027	10.0036	22299

A.1.2 Hamburg grid nodes and associated PV systems Data

MaStR was used to access the location of residential PV systems throughout Hamburg [10], however, information on their connection to the grid node was unavailable. Consequently, the grid nodes in this thesis are assigned to PV systems that are located in closer proximity. As noted in section 4, all PV systems connected to each grid node are taken into account collectively and function as a single PV system. In this process, to keep the model simple, only one node is taken into account when more than one node is present at a single location. Therefore, according to this thesis, all households with PV systems will feed to and extract the energy from the nearest grid node, even if in reality they may have actually connected to another grid node.

Because of this filtration, in the end, 50 of the 74 grid nodes were taken into consideration for this thesis. Hamburg grid nodes, and number of houses and PV capacity associated with each grid node are shown in the Table 16.

Table 16 Hamburg's grid nodes with associated number of households and PV capacity

Number	Node Name	Postcode	Installed PV Capacity in kWp	Net PV Capacity in kW	Number of Households with PV system
1	Arcelor Mittal (110kV)	21129	967.70	865.00	109
2	Hamburg/Ost (110kV)	22117	156.23	133.00	28
3	Hamburg/Süd (110kV)	21079	1825.14	1576.00	269
4	UW Alsterdorf (110kV)	22297	334.03	283.00	50
5	UW Altona (110kV)	22767	78.87	62.00	10
6	UW Bahrenfeld (110kV)	22761	1066.15	906.00	171
7	UW Barmbek (110kV)	22083	222.20	191.00	28
8	UW Bergedorf (110kV)	21029	337.51	305.00	41
9	UW Berne (110kV)	22147	517.92	440.00	89
10	UW Bille (110kV)	20537	190.08	174.00	22
11	UW Bramfeld (110kV)	22177	1149.00	977.00	198
12	UW DrehbrÃ¼cke (110kV)	21107	175.60	160.00	14
13	UW Eilbek (110kV)	22089	32.27	26.00	5
14	UW Eimsbüttel (110kV)	20255	262.06	214.00	55
15	UW Eppendorf (110kV)	20249	107.63	92.00	15
16	UW Fuhlsbüttel (110kV)	22335	68.72	59.00	10
17	UW Großneumarkt (110kV)	20459	7.33	6.00	3
18	UW Hafencity (110kV)	20457	85.26	63.00	7
19	UW Hamburg West (110kV)	22549	542.96	456.00	101
20	UW Hausbruch (110kV)	21147	784.62	656.00	124
21	UW Hellbrook (110kV)	22307	222.15	196.00	21

22	UW Hoheluft (110kV)	20251	44.46	35.00	10
23	UW Holsten (110kV)	22765	121.97	112.00	18
24	UW Horn (110kV)	22111	55.22	39.00	6
25	UW Jenfeld (110kV)	22043	548.61	475.00	84
26	UW Karoline (110kV)	20357	100.72	68.00	13
27	UW Langenhorn (110kV)	22419	773.16	645.00	146
28	UW Lehmsahl (110kV)	22397	2199.41	1885.00	393
29	UW Lohbrügge (110kV)	21031	269.01	237.00	37
30	UW Lokstedt (110kV)	22453	371.40	309.00	59
31	UW Neuengamme (110kV)	21039	910.10	714.00	111
32	UW Neugraben (110kV)	21149	792.36	698.00	125
33	UW Neustadt (110kV)	20354	86.96	80.00	11
34	UW Niendorf (110kV)	22459	828.51	698.00	130
35	UW PoppenbÃ¼ttel (110kV)	22391	2192.93	1872.00	367
36	UW Rahlstedt (110kV)	22143	1085.82	938.00	156
37	UW Siemersplatz (110kV)	22529	292.91	257.00	44
38	UW St. Georg (110kV)	20099	88.41	80.00	12
39	UW Sülldorf (110kV)	22589	695.70	595.00	124
40	UW Veddel (110kV)	20539	623.55	550.00	91
41	UW Volksdorf (110kV)	22359	910.57	790.00	158
42	UW Wandsbek (110kV)	22041	311.98	269.00	43
43	UW Winterhude (110kV)	22299	36.92	32.00	8
44	h_Allermöhe	21035	2473.02	2093.00	378
45	h_Billwerder	22113	166.42	132.00	21
46	h_Eidelstedt	22525	1257.65	1071.00	201
47	h_Langenhorn	22399	1223.76	1048.00	205
48	h_Rissen	22559	344.83	293.00	56
49	h_Tilsiter_Straße	22047	133.56	122.00	18
50	h_Tonndorf	22045	498.92	423.00	92

A.1.3 Distribution of Number of Residents in Household per Grid Node

The number of households with PV systems connected to each grid node is displayed in Table 16. In order to represent Hamburg's residential load, the SLP for German households was chosen because information on the load demand profile for households in Hamburg was not accessible during the writing of this thesis. The SLP from BDEW needs to be scaled up in accordance with the annual energy usage of households to create load demand profile [11]. For greater accuracy, the annual energy consumption as per the distribution of the number of occupants per household is taken into consideration rather than using the same average annual load demand estimate for all households.

From "Statistikamt Nord" [94], the distribution of residents by households in each region of Hamburg was compiled, and as a result, the distribution per grid node was approximated. Table 17 displays the proportion of households based on occupants associated with each grid node.

Table 17 Distribution of number of residents per grid node

Number	**Node Name**	**Number of Households with PV systems**	**Distribution as per number of occupants in %**			
			1 person	2 people	3 people	4 and more persons
1	Arcelor Mittal (110kV)	109	51.2	26.1	11.4	11.4
2	Hamburg/Ost (110kV)	28	47	26.5	12.2	14.3
3	Hamburg/Süd (110kV)	269	53.4	24.7	9.1	12.8
4	UW Alsterdorf (110kV)	50	53.9	25.6	10.5	10
5	UW Altona (110kV)	10	62.8	20.6	8.7	7.9
6	UW Bahrenfeld (110kV)	171	59.8	21.8	9.2	9.3
7	UW Barmbek (110kV)	28	68.6	20.1	6.6	4.6
8	UW Bergedorf (110kV)	41	49.3	28	11.3	11.4
9	UW Berne (110kV)	89	47.5	28.2	12.5	11.8
10	UW Bille (110kV)	22	53	31.6	8	7.4
11	UW Bramfeld (110kV)	198	54	27.1	10.2	8.6
12	UW Drehbrücke (110kV)	14	57.8	22.8	9.4	10
13	UW Eilbek (110kV)	5	65.6	21.8	7.2	5.5
14	UW Eimsbüttel (110kV)	55	67.3	19.6	7.4	5.7
15	UW Eppendorf (110kV)	15	62	22.4	8.3	7.4
16	UW Fuhlsbüttel (110kV)	10	56	25.4	9.8	8.9
17	UW Großneumarkt (110kV)	3	69.2	18.7	7.2	4.9
18	UW Hafencity (110kV)	7	33.1	36.9	15.7	14.2
19	UW Hamburg West (110kV)	101	45.5	26.5	13	14.9
20	UW Hausbruch (110kV)	124	39	29.9	14.9	16.3
21	UW Hellbrook (110kV)	21	70	19.5	6.3	4.3
22	UW Hoheluft (110kV)	10	65.6	21	7.9	5.5
23	UW Holsten (110kV)	18	62.8	20.6	8.7	7.9
24	UW Horn (110kV)	6	59.7	22.5	8.8	9

25	UW Jenfeld (110kV)	84	48.4	25.8	12.2	13.6
26	UW Karoline (110kV)	13	68.1	17.9	7.1	6.8
27	UW Langenhorn (110kV)	146	48.4	27.8	11.8	11.9
28	UW Lehmsahl (110kV)	393	29.2	35	16.9	18.9
29	UW Lohbrügge (110kV)	37	49	29.1	11	11
30	UW Lokstedt (110kV)	59	53.6	24.6	10.6	11.2
31	UW Neuengamme (110kV)	111	36.1	32.4	16.6	14.9
32	UW Neugraben (110kV)	125	39.8	30.3	13.3	16.6
33	UW Neustadt (110kV)	11	69.2	18.7	7.2	4.9
34	UW Niendorf (110kV)	130	48.9	29.2	11.3	10.6
35	UW PoppenbÃ¼ttel (110kV)	367	41.6	32.4	12.2	13.9
36	UW Rahlstedt (110kV)	156	46.5	29.3	12.2	11.9
37	UW Siemersplatz (110kV)	44	53.6	24.6	10.6	11.2
38	UW St. Georg (110kV)	12	67	20.6	6.8	5.5
39	UW Sülldorf (110kV)	124	47	26.7	12.2	14.1
40	UW Veddel (110kV)	91	56	19.9	10	14.1
41	UW Volksdorf (110kV)	158	38.7	31.5	13	16.7
42	UW Wandsbek (110kV)	43	60.9	23.5	8.7	6.8
43	UW Winterhude (110kV)	8	64.2	21.5	7.8	6.5
44	h_Allermöhe	378	40.7	33.5	11.8	14
45	h_Billwerder	21	69	19.1	7.2	4.6
46	h_Eidelstedt	201	48.8	27.4	11.9	11.9
47	h Langenhorn	205	48.4	27.8	11.8	11.9
48	h Rissen	56	45.3	29	11.3	14.3
49	h Tilsiter Straße	18	53.3	25.1	10.3	11.2
50	h_Tonndorf	92	53.3	25.1	10.3	11.2

A.2 Data Access

The data basis and models used for this work and results derived from it are stored in internal drive of CC4E with consultation of supervisors. For the data access please contact Prof. Dr. Hans Schäfers and Mr. Sebastian Farrenkopf, from CC4E.

Declaration of independent work on a thesis

I hereby confirm that I am the author of the Master Thesis with topic:

Self-Consumption of Residential PV Systems in Hamburg

I have written this master thesis independently without any external help, using only the sources and references stated in the text.

Hamburg	14.07.2022	[redacted]
Place	Date	Signature: Ruturaj Rajendra Chavan