Synergy between Residential Electric Vehicle Charging and Photovoltaic Power Generation through Smart Charging Schemes

Models for Self-Consumption and Hosting Capacity Assessments

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Abstract

The world is now in a transition towards a more sustainable future. Actions to reduce the greenhouse gases (GHG) emissions have been promoted and implemented globally, including switching to electric vehicles (EVs) and renewable energy technologies, such as solar photovoltaics (PV). This has led to a massive increase of EVs and PV adoption worldwide in the recent decade.

However, large integration of EVs and PV in buildings and electricity distribution systems pose new challenges such as increased peak loads, power mismatch, component overloading, and voltage violations, etc. Improved synergy between EVs, PV and other building electricity load can overcome these challenges. Coordinated charging of EVs, or so-called EV smart charging, is believed to a promising solution to improve the synergy.

This licentiate thesis investigates the synergy between residential EV charging and PV generation with the application of EV smart charging schemes. The investigation in this thesis was carried out on the individual building, community and distribution grid levels. Smart charging models with an objective to reduce the net-load (load - generation) variability in residential buildings were developed and simulated. Reducing the net-load variability implies both reducing the peak loads and increasing the self-consumption of local generation, which will also lead to improved power grid performance. Combined PV-EV grid hosting capacity was also assessed.

Results show that smart charging schemes could improve the PV self-consumption and reduce the peak loads in buildings with EVs and PV systems. The PV self-consumption could be increased up to 8.7% and the peak load could be reduced down to 50%. The limited improvement on self-consumption was due to low EV availability at homes during midday when the solar power peaks. Results also show that EV smart charging could improve the grid performance such as reduce the grid losses and voltage violation occurrences. The smart charging schemes improve the grid hosting capacity for EVs significantly and for PV slightly. It can also be concluded that there was a slight positive correlation between PV and EV hosting capacity in the case of residential electricity distribution grids.

Keywords: Electric vehicle, Smart charging, Photovoltaics, Residential buildings, Electricity use, Self-consumption, Distribution Grid, Hosting capacity

"Don’t compromise when you can synergize"
Stephen Covey

List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I **Fachrizal, R.**, Shepero, M., van der Meer, D., Munkhammar, J., Widén, J. (2020). "Smart charging of electric vehicles considering photovoltaic power production and electricity con-sumption: a review". *eTransportation*, Vol. 4, article id 100056.

II **Fachrizal, R.**, Munkhammar, J. (2020). "Improved Photovoltaic Self-Consumption in Residential Buildings with Distributed and Centralized Smart Charging of Electric Vehicles". *Energies*, Vol. 13, no 5, article id 1153.

III **Fachrizal, R.**, Ramadhani, U. H., Munkhammar, J., Widén, J. "Combined PV-EV hosting capacity assessment for a residential LV distribution grid with smart EV charging and PV curtailment". Submitted

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Publications not included in the thesis

IV Munkhammar, J., Shepero, M., **Fachrizal, R**. (2019). "Modeling and implementation of smart charging using Annex D standard: Initial Study". Swedish Electromobility Centre.

V **Fachrizal, R**., Munkhammar, J. (2019). "Increasing the photovoltaic self-consumption and reducing peak loads in residential buildings with electric vehicle smart charging". In proceedings of the 3rd E-mobility Power System Integration Symposium, Dublin, Ireland, 14 October 2019.

VI Shepero, M., **Fachrizal, R.**, Munkhammar, J. (2019). "Potential of battery storage systems to increase the self-consumption of photovoltaics in charging of electric vehicles in residential buildings". In proceedings of the 3rd E-mobility Power System Integration Symposium, Dublin, Ireland, 14 October 2019.

VII Shepero, M., **Fachrizal, R.**, Munkhammar, J. (2018). "Optimal De-Centralized Smart Home-Charging: Potential Study". In proceedings of the 2nd E-mobility Power System Integration Symposium, Stockholm, Sweden, 19 October 2018.

Notes on my contribution

I contributed the following to the appended papers:

Paper I, I did the literature survey and writing.

Paper II, I developed the models and algorithms, did the simulations and wrote most of the paper.

Paper III, I developed the models and algorithms, did the simulations and wrote most of the paper.

Contents

1. Introduction

A few centuries ago, humans did not have technologies as advanced as today, including those for harnessing energy. For heating purposes such as cooking, humans burned wood, straw and other dried combustible matters. For lighting, humans used fire lamps, torches and candles which were mostly fueled by animal fat. For transport, humans utilized animals such as horses and donkeys. Other heavy work was also done with the use of animal power [1].

The industrial revolution era started in the early 1700s, during which technology advanced to the level that humans were able to do things much more effectively thanks to the many inventions during this period. After this era, light bulbs replaced fire torches, cars and trains replaced donkeys and horses, and most importantly much of the work done by humans and animals was replaced by machines. Fossil fuels were discovered and used massively as energy sources, to the level that humans became strongly dependent on them. Usable and reliable electricity systems were invented, and electric power plants were massively constructed everywhere, starting in Europe and America [1]. In a nutshell, the industrial revolution significantly improved the human life quality and expectancy to the levels we have today [2].

However, not all things on earth are better after the industrial revolution. Along with the improving life quality and unprecedented population growth, human energy use drastically increased [3]. This increase was also triggered by the discovery of fossil fuels, which were the backbone of the industrial revolution and are still by far the largest energy sources today. The burning of fossil fuels produces green-house gas (GHG) emissions, which cause global warming and threaten life on earth. Now, most countries in the world have agreed to combat the global warming and set targets to limit the global temperature to well below 2°C above pre-industrial levels [4]. Since then, switching from using fossil fuels to renewable energy sources (RES) and, more recently, from fossil-fueled internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) has been massively promoted globally [5].

Replacing fossil fuels with RES as the energy sources will reduce the GHG emissions. But how about the use of EVs? While EVs do not have tailpipe emissions, which creates a healthier environment for people living close to streets, there are well-to-wheel (WTW) emissions, which in the case of EVs include the emissions produced in the power generation and delivery process to charge the EVs [6]. Research has shown that the well-to-wheel (WTW) emissions of an EV recharged from a power system that has a large share of coal-based power generation is similar to gasoline-based ICEVs [7, 8]. EVs will be more environmentally friendly if they are charged by electricity coming from RES [8]. One study estimated that charging EVs by RESs can reduce the GHG emissions by up to 400 Mtons per year [9].

The adoption of both EVs and RES, such as solar photovoltaic (PV) systems, has increased in recent years. In 2019, the International Energy Agency estimated that there were 7.2 million cars worldwide, more than double the number in 2017 [10]. This number is expected to grow significantly in the coming decade [10]. The number of installed PV systems has also grown during the last decade. The worldwide installed PV capacity was 627 GW_p in 2019, more than double the capacity in 2016, and it is expected that the increase in the coming decade will still be significant [11].

However, the massive increase in EV numbers and PV capacity pose new challenges to power systems, especially to power distribution grids where most of PV and EVs are integrated. Generally, existing distribution grids have not been designed to host large shares of new high loads such as EVs and intermittent distributed generation such as PV systems [12]. Problems such as voltage deviations and overloading of components can arise from large scale integration of PV and EVs [13]. The synergy between load and distributed generation are keys to overcoming these problems. In future cities, large amounts of PV generation and EV charging have to be accommodated and optimized. Thus, it is important to assess and improve the synergy between PV and EVs in the built environment, so that expensive reinforcements of the electricity distribution systems can be avoided. Smart charging of EVs is a potential solution to improve this synergy.

1.1 Aim of the thesis

The main aim of the thesis is to develop EV smart charging schemes and assess their impacts in improving the synergy between PV and EVs in residential buildings and power grids. Three goals are formulated in order to fulfil the main aims:

I Review the state of the art in smart charging of EVs, especially related to PV generation.

II Develop EV smart charging schemes for home-charging with the objective to improve the local PV self-consumption and reduce the peak loads in residential buildings

III Assess the impacts of the proposed residential EV smart charging scheme deployment on the local power grid and the potential of combined PV-EV grid hosting capacity enhancement with the proposed EV smart charging schemes and PV curtailment.

1.2 Overview of the thesis and the appended papers

The remainder of this licentiate thesis is structured as follows: Chapter 2 provides the background for the research conducted in this thesis. Chapter 3 introduces the data, case studies, models and methodologies that are used. In Chapter 4, the main results from the appended papers are presented. Chapter 5 provides a discussion on these results and future work. In Chapter 6, conclusions from these studies are drawn. The results in the thesis are based on the following appended papers:

I *Paper I* provides a review of the state-of-the-art in smart charging of EVs considering PV generation and electricity consumption. Besides the review of the literature, the paper also aims at providing the introduction to various control algorithms and mathematical optimization models used for smart charging schemes.

II *Paper II* presents distributed and centralized smart charging models for residential buildings based on Swedish travel survey data. The objective of the smart charging schemes is to minimize the net-load variability of the residential buildings. The impact of the smart charging schemes on both individual building and community level were quantified with self-consumption and self-sufficiency metrics.

III *Paper III* is a combined PV-EV grid integration study and hosting capacity assessment. The impact from the the proposed smart charging schemes on the local grid was assessed. In this paper, the grid impacts from and hosting capacity for PV and EV were analyzed within the same framework.

2. Background

This chapter presents the background for the research done in this thesis. Sections 2.1 to 2.3 introduce the readers to EVs, PV and residential electricity consumption respectively. Interaction between PV, EVs and other electricity consumption is presented in Section 2.4. Smart charging of EVs considering PV power generation and electricity use is presented in Section 2.5. Finally, research gaps are identified in Section 2.6.

2.1 Electric vehicles

Electric vehicles (EVs) refers to vehicles that use an electric motor for propulsion. Even though, by definition, trains, ships or aeroplanes that are powered by electric power can be categorized as electric vehicles, most often EVs refer to road transport vehicles, e.g., electric cars, buses and trucks.

There are several types of EVs. One of these is the battery electric vehicle (BEV), also called all-electric vehicle. A BEV is solely using the electric motor for propulsion and is powered by a battery [14]. The battery in a BEV is equivalent to the fuel tank in a regular ICEV. A BEV must be plugged in to the electricity grid to charge its battery [14]. Another type of EV is the hybrid electric vehicle (HEV). Being a hybrid, an HEV has both an internal combustion engine, which is powered by fuel such as gasoline, and an electric motor, which is powered by a battery. However, this type of EV cannot be plugged in to charge the battery. The battery is charged via regenerative braking or by the internal combustion engine [15]. In addition to these types, there is also the plug-in hybrid electric vehicle (PHEV), which is basically the combination of BEV and HEV. Similar to HEV, a PHEV has both an internal combustion engine including the fuel tank, and an electric motor including the battery. The difference is that unlike an HEV, a PHEV can be plugged into the electricity grid to charge its battery. A PHEV is typically powered by electricity until the battery is depleted, after which it then automatically switches to the internal combustion engine [16]. In this thesis, EV is a term that only refers to an EV that can be charged from the electricity grid, i.e., BEVs and PHEVs.

2.1.1 Electric vehicle charging

There are several available methods and technologies to charge the EV battery. In general they can be divided into inductive charging, i.e., wireless, or conductive charging, of which the latter is the most commonly used technology.

Conductive charging can be with direct current (DC) or alternating current (AC) power. DC chargers have very high power, more than 50 kW, thus they are usually used for fast charging. The most used charger worldwide is the AC charger, since it is commonly available. Thus, almost all EV chargers in homes, shopping plazas, and workplaces are AC chargers. In the Society of Automotive Engineers (SAE) standard J1772, there are two different levels of AC chargers [17]. The first one is the level 1 charger, which refers to chargers with a specification of 120V/16A, up to 1.9 kW. The second is the level 2 charger which refers to chargers with a specification of 240V/32-80A, 7.6 kW-19.2 kW. This standard is commonly used in Japan and the United States (U.S.). The European Union and China use a standard from the International Electrotechnical Commission (IEC) for slow AC chargers, which can be divided into single-phase and three-phase chargers with 220-240 V connection [18]. With single-phase connections, the charger can have a charging rate of 3.7 kW (16 A) or 7.4 kW (32 A), while for a three-phase connection, it can have a charging rate of 11 kW (16 A), 22 kW (32 A), and so on.

2.1.2 Integration of EVs in the power system

The power system is one of the most complex human-made systems ever created in the world [19]. It can be divided into four main parts: generation, transmission, distribution and loads [20]. When an EV is charged by being plugged into the grid, it becomes a part of the power systems as a load. Since most of the current power grid was not designed to host a large amount of EV charging loads, it can pose new challenges if large amounts of EVs are integrated into the power systems [12, 21]. The challenges include undervoltage problems, component overloading, and harmonic distortion [12]. These problems lead to a decrease of the lifetime of power grid components such as substation transformers. If that is the case, the power grid might need reinforcements which is most likely costly. Generally, the higher the charging power, the more significant the impact from the EV charger to the power systems. The deployment of higher power chargers will lead to high load variability since the EV charging load will ramp up and down over shorter periods [22].

In a recent study [23], it was shown that modeling the EV charging load based on mobility and travel survey data is an appropriate way to resemble the real EV charging load. Thus, it implies that EV charging profiles are commonly defined by the daily mobility patterns or activity schedules of the vehicle users [23, 24]. In [22], a Markov-chain model trained with Swedish travel survey data was developed. The model estimated the workplace charging load peaks to occur between 06.00 and 10.00, while home charging peaks occurred between 16.00 and 20.00. Similar patterns were also found in [23], where there was a validation against the real charging data. In the study, it was also shown that most of the charging occurred at home, thus the peak charging load for home charging is the highest, compared to the ones in other locations. The peaks of EV charging load coincide with the period when the electricity consumption is high. This is due to the fact that in the opportunistic charging (charging upon arrival) scheme, the charging correlates with other electricity consumption activities such as cooking, watching TV, etc., at home in the evening. The increased peak loads can lead to overloading problems, which might lead to needs for grid reinforcement [12].

2.2 Solar energy and photovoltaic systems

Most energy used on earth today originally comes from the sun. Electricity generated from hydro, wind and wave power plants is possible due to the heating of the earth and the atmosphere by the sun. Fossil fuels, such as coal, oil and natural gas, even though categorized as non-renewable sources due to the long carbon cycle process, were formed through photosynthesis, fueled by the energy from the sun. Bioenergy, such as biomass and biogas, which is also formed through the photosynthesis process, is considered renewable energy due to its short carbon cycle. The only energy sources not originating from the sun are geothermal energy, which comes from the heat derived within the sub-surface of the earth, tidal energy, which comes from the gravitational pull of the moon, and nuclear energy, which utilizes radioactive elements [25].

Energy coming from the sun can be utilized directly, either for heating or electricity production. In this thesis, only solar energy for electricity production is considered. There are mainly two techniques to generate electricity from solar irradiation, i.e., PV and concentrated solar power (CSP). In a CSP plant, mirrors are used to concentrate the solar irradiation to heat an energy carrier such as water, which is then used to drive the conventional turbine-generator to generate electricity [26]. In a PV system, electricity is generated directly from solar irradiance with solar cell technology. In this thesis, only PV electricity is studied.

2.2.1 Photovoltaic systems

PV cells convert incident photons in the sunlight into electric currents using semiconductor materials [27]. The most commonly used PV cells in the world currently are silicon-based solar cells. The efficiency of silicon-based PV cells varies between 16-24% [28], which implies PV cells with an area of 1 m^2 will generate 160-240 W electric power under standard test conditions (STC)[1].

A collection of single PV cells connected in series is called a PV module, and a collection of individual PV modules is called a PV array. Since a PV system is composed of small units, it has the advantage of scalability. This

[1] STC corresponds to an irradiance of 1000 W/m^2, cell temperature of 25 °C and air mass 1.5.

implies that a PV system can be small and fit in a rooftop of a single family house, or it can be as large as a utility scale power plant, and the net cost per watt installed will not be significantly higher for the smaller scale system.

The generated electric power from a PV array is DC power. Even though there exist DC power systems in which PV power can be used directly [29], AC power systems are by far the most common. In order to be integrated into an AC system, a PV array needs an inverter to convert DC power to AC power. PV systems can be off-grid or on-grid. In an off-grid system, the PV system is only connected to local loads and not to the main electric power grid. An off-grid PV system likely needs battery storage to handle the intermittency of solar irradiance. In an on-grid or grid-connected system, the PV system is connected to the main electric power grid and this system is the most common today in the world [11]. In this thesis, only grid-connected PV systems are studied.

2.2.2 Integration of PV in the power system

When PV systems are connected to the grid, they become part of the power system as generation units. PV systems can be integrated into the power system as centralized or distributed units. Centralized PV systems are similar to other utility-scale power plants, in the sense that they are larger in size, usually far from the location of end-users, commonly connected to transmission grids or sometimes medium-voltage (MV) distribution grids. Conversely, distributed PV systems are smaller in size, but more spread out, closer to end-users, and commonly connected to the distribution grid [30]. The end-users who produce and consume electricity, e.g., end-users who own a grid-connected PV system on their rooftops, are commonly called electricity prosumers.

Large-scale integration of PV systems into the power system can lead to several problems, such as overvoltages, component overloading and harmonic distortions, which can lead to a decrease of the lifetime of power grid components and expensive grid reinforcements [31]. However, the most challenging problem when it comes to PV systems, or generally almost all RES, is their intermittent generation profiles. Unlike the traditional power plants, in which the generation can be regulated to follow the load pattern, PV systems (without battery storage) are non-dispatchable power sources. This is a fundamental disadvantage, since power plants are essentially built to meet the power demand. PV power generation varies according to seasonal and diurnal patterns and depends on the apparent position of the sun in the sky. In the midday on a sunny summer day, the PV generation peaks and can be much higher than in other periods, whereas it is zero at night. In addition to this deterministic pattern, cloudiness intermittently decreases the power generation [32]. This variable nature of PV power can lead to several problems in the power systems, such as voltage and frequency fluctuations.

2.3 Residential electricity consumption

Generally, electricity consumption is defined by numerous factors, mainly by human and industrial activities and also by spatio-temporal and climate conditions [33, 34, 35]. For heating and cooling, people need heating, ventilation, and air conditioning (HVAC) systems. For lighting, they need lamps. For entertainment, they need TVs, computers or other electrical devices. All of these need electricity. When it comes to daily residential load shape, the pattern is strongly correlated with human activities at home [34]. On weekday mornings, people are getting ready for work, and thus the electricity consumption is usually high in the morning. However, the daily peak of electricity consumption is usually in the evening when people are back at home, cooking, watching TV, etc., and having the lights on. The electricity consumption is usually lower again after people go to sleep later in the night.

2.4 Interaction between EVs, PV and load in the power system

It is expected that the future load profile is likely to experience drastic changes due to increasing amounts of EV charging loads and RES, including distributed PV generation [35]. An example of a daily net-load (load minus generation) in a residential distribution grid with large shares of PV and EVs is shown in Figure 2.1. High PV penetration in a residential grid will lead to high load ramps in the morning and the evening. This phenomenon is often called the duck-curve [36]. The duck-curve becomes more prominent when combined with uncontrolled EV charging [37, 38]. Hence, there is a need for power system management to reduce the impact of EV charging and PV power generation.

A power grid has a specific capacity for new generation including PV, and new loads including EVs, to be integrated so that expensive grid reinforcements can be avoided. The term often used to refer to this is hosting capacity. When it comes to the hosting capacity for PV, low PV hosting capacity is often due to the mismatch between the load and the PV generation. It is shown that improved load matching, or synergies between the load and the generation, will improve the hosting capacity for new generation and new load [31, 40]. Common ways to improve the load matching is by installing battery storage or deploying demand side management (DSM) strategies, including EV smart charging. In this thesis, studies on battery storage to improve the

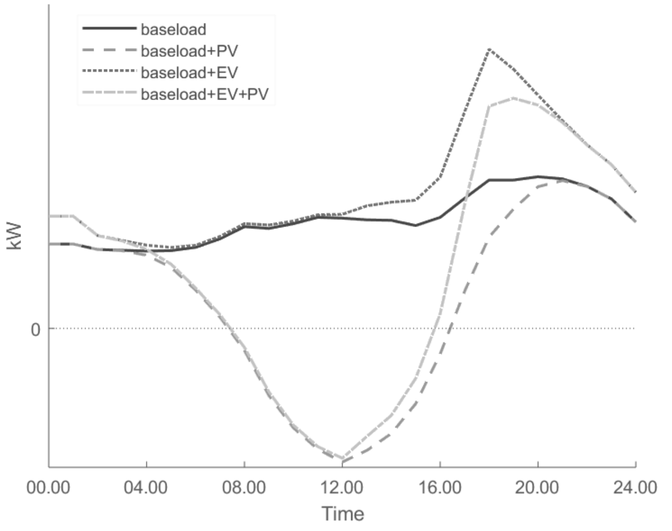

Figure 2.1. An illustration of typical net load shapes in different PV and EV scenarios in residential distribution grids, inspired by the works in [13, 39].

self-consumption are excluded, even though such a study is available in Paper VI (not included in this thesis).

A formal introduction to a load matching indicator, the PV self-consumption, is presented in Section 2.4.1. The hosting capacity concept is described further in Section 2.4.2. A general discussion on DSM is presented in Section 2.4.3.

2.4.1 Introduction to PV self-consumption

The matching between the local load and on-site PV generation is of interest to end-users as well as grid operators. It is becoming increasingly common that on-site PV system performance is assessed with load matching metrics [41]. There are several such metrics to evaluate the on-site PV system performance in buildings [41]. In this thesis, two load matching metrics, self-consumption and self-sufficiency, are used to evaluate the PV system performance.

Self-consumption is defined as the fraction of the self-consumed on-site PV electricity to the total PV electricity production, while self-sufficiency is defined as the fraction of the self-consumed on-site PV electricity to the total electricity consumption. Based on the illustration in Figure 2.2, the self-consumption SC can be defined as

$$SC = \frac{C}{B+C}. \tag{2.1}$$

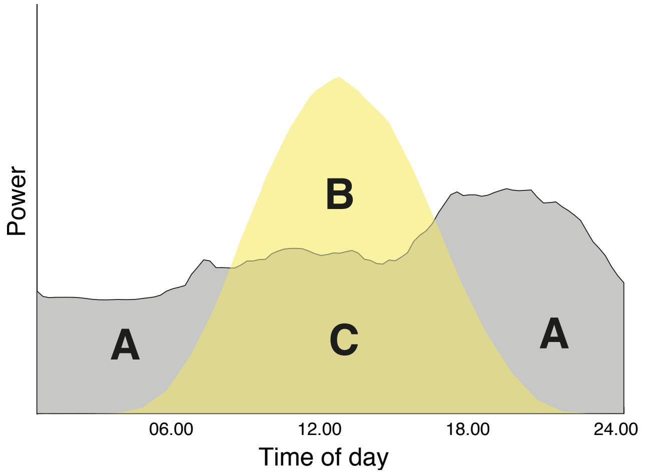

Figure 2.2. Schematic outline of daily load (A + C), PV generation (B + C), and self-consumed electricity (C).

Based on the illustration in Figure 2.2, the self-sufficiency *SS* can be defined as

$$SS = \frac{C}{A+C}. \tag{2.2}$$

In other words, the higher the self-consumption, the higher the directly self-consumed PV electricity will be compared to the generated PV electricity. The higher the self-sufficiency, the closer the PV electricity will be to covering all of the load.

2.4.2 Grid hosting capacity

The term hosting capacity is defined as the new generation and loads that can be integrated to the grid without endangering grid reliability or voltage quality for other customers [42]. There are three aspects that need to be defined for a hosting capacity study: a performance index, a corresponding limit and a calculation method for the performance index as a function of the amount of new generation or loads [40]. As the integration of new generation and loads impact more than one aspect of the power grid, there are several parameters that can be used as performance indices, to define the hosting capacity [43]. Voltage deviation levels, voltage unbalances, component loading, losses and harmonics are some examples of hosting capacity performance indices. Recent studies showed that voltage deviations and component loading have been the most common performance indices for evaluating the hosting capacity [43].

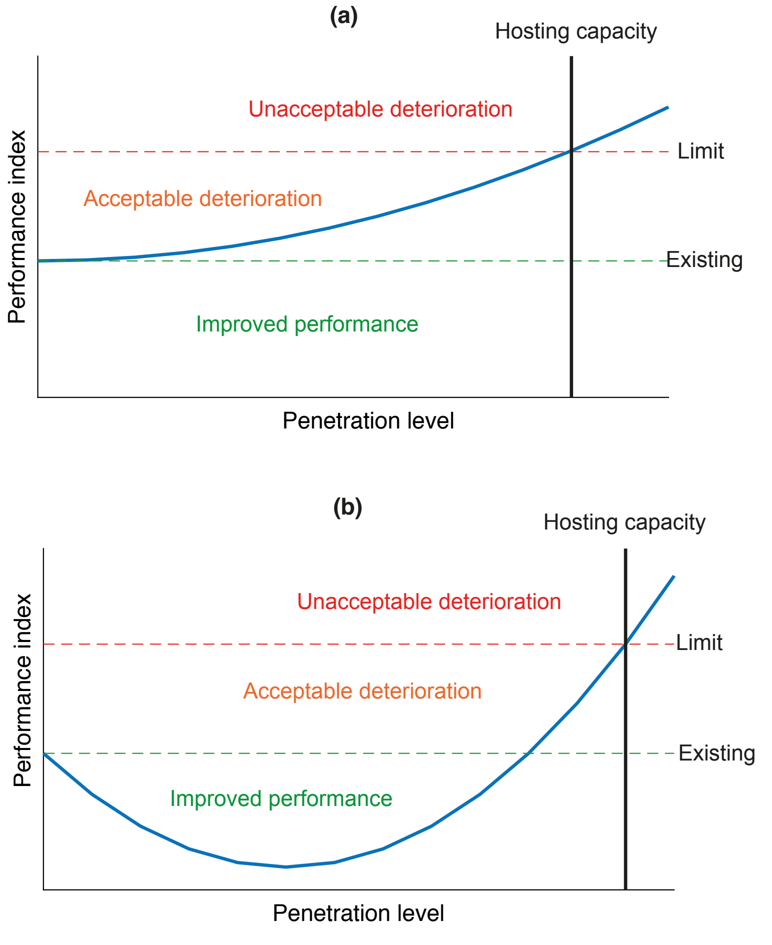

Figure 2.3. Hosting capacity as a function of the performance index, where (a) the performance deteriorates already with small amounts of local generation, and (b) the performance initially improves with small amounts of new generation, but deteriorates with larger amounts. Figure is inspired by the work in [40].

The hosting capacity as a function of new generation or load can vary depending on the performance index and the initial condition of the power grid, e.g., whether the grid already has or does not have distributed generation units from the beginning. Examples of how a hosting capacity approach for a new generator can be evaluated using performance indices, are presented in Figure 2.3. Figure 2.3 (a) represents a hosting capacity case where the performance deteriorates already with small amounts of local generation or loads, for example hosting capacity for new generation with overvoltage occurrences as the performance index. Figure 2.3 (b) represents a hosting capacity case where the performance initially improves with small amounts of new generation or loads, but deteriorates with larger amounts, for example hosting capacity for new generation with overcurrent level as the performance index.

2.4.3 Demand side management

Demand-side management (DSM) is a broad term used for any activity related to energy consumption, e.g., control and modification of energy use, device installations, policies and regulation formulation, promotion, and education [44]. On a specific case for the household level, heat pump control, turning on the dishwasher when the electricity price is low, or any other household activity that alters the use of energy on the demand side to meet some goals, can be called a DSM activity.

Peak clipping, valley filling and load shifting are common objectives in DSM activities [45]. Peak clipping or peak load reduction implies reducing electricity consumption during the peak load periods, usually evening hours. Valley filling means using more electricity when the electricity consumption is low. Load shifting is a combination of peak clipping and valley filling strategies by shifting the load in time from the peak load periods to the valley periods. Thus, flexibility of loads is of importance in DSM strategies.

At the household level, many electrical appliances are practically flexible loads, since they can be started at any desired time. Examples include electric stoves, dishwashers and washing machines. These kinds of loads need active participation from users, in the sense that any use of a DSM strategy requires behavioral change, i.e., a change in when to start and stop an appliance. Conversely, there are some flexible loads that need less active participation from the users and are more practical to be programmed with smart controls. This kind of flexible load includes heat pump or air conditioning devices that can be programmed to automatically turn on or off depending on the temperature, electricity price or even the amount of local generation. Electric vehicle charging can also be programmed with smart controls and it is possible to have such a scheme without changing the user behaviours. The next section discusses further the smart charging schemes of EVs, specifically the ones that consider PV generation and electricity consumption.

2.5 Smart charging of EVs considering PV and loads

This section covers the specific type of DSM for EVs, which is often called coordinated, controlled or smart charging of EVs [46]. The long parking duration of EVs offers the opportunity for EV smart charging control. Compared to other electric appliances, the temporal flexibility of the EV charging load is comparatively higher. Based on a travel survey in six European countries, cars are, on average, parked 22 h per day, with 16 h per day of uninterrupted or inactive parking [47]. Smart charging schemes have the potential to improve the synergy between EVs, local generation and other loads, for example by programming the EVs to charge when PV generation is high and not to charge when the load is high [38]. Several benefits of smart charging schemes related to EV-PV-load synergy include: PV self-consumption improvements, peak load reduction, grid overloading prevention, grid voltage fluctuation reduction, grid loss reduction, and economic benefits for users and charging providers. The temporal flexibility of EV parking also enables EVS to offer ancillary services, such as voltage control and frequency regulation, with vehicle-to-grid (V2G) schemes [48]. In a V2G scheme, EVs can not only charge, but also discharge and act as an energy storage for the electricity grid. There are several important aspects to EV smart charging. This section summarizes the literature review in Paper I. In general, the main aspects of smart charging schemes are objectives, charging approaches, spatio-temporal aspects, and mathematical models and algorithms.

2.5.1 Objectives

The motivations behind the deployment of smart charging can vary. The objectives can be related to technical aspects, financial aspects or a combination. The smart charging scheme with a technical objective includes increasing PV utilization, balancing electricity load, and other objectives related to the power grids. Reducing charging cost and increasing profits for charging providers are common financial objectives in smart charging schemes.

In the literature review in Paper I, it was found that smart charging with one certain objective can lead to accomplishment of other objectives. This is, for example, when a smart charging scheme with an objective of increasing PV utilization can lead to the reduction of power losses and charging cost. For the users or EV charging providers, financial objectives are more common for smart charging deployments, since they will get the benefit directly. On the other hand, for grid operators, technical aspects such as component overloading and other grid problems are more important, even though in the long run the real motivation is economic, i.e., avoiding expensive grid reinforcement.

2.5.2 Charging approach

Smart charging deployment can be centralized or distributed. In a centralized smart charging scheme, the charging schedule and power for EV fleets are coordinated by a central unit called aggregator [49]. In such schemes, the aggregator gathers the required data such as expected departure time, battery state of charge, etc., to define the charging schedule of EVs, depending the objectives. In a distributed smart charging scheme, instead of being controlled by a central unit the control is conducted on the individual EV level [49]. However, it is common that the distributed EV charging scheme is driven indirectly by a central unit, such as through a dynamic price signal from the electricity provider. A centralized charging scheme will benefit from the availability of instantaneous information regarding the systems, so that system level optimum is more likely to be achieved. In that case, the centralized approach will help the system to optimize the utilization of power grid capacity and renewable power on system level. However, centralized charging schemes need more advanced communication infrastructures which can be expensive. On the other hand, distributed charging schemes need less advanced communication infrastructures, however they will be less optimal in terms of utilizing power system capacity.

2.5.3 Spatio-temporal aspects

Spatio-temporal aspects of EV charging are of importance to the smart charging schemes, since they reflect what benefits the schemes can provide at certain locations in a given specific time frame. The number of EVs available at each location vary over time. Thus, smart charging schemes at certain location are constrained by the parking periods of EVs at that particular location.

As mentioned earlier, most of the residential or home parking is inactive or uninterrupted parking. It was shown in [22, 23] that EV home-charging on weekdays commonly peaks in the evening when people just come back from work, which most likely will coincide with and increase the power system peak loads. If high temporal flexibility is utilized, the increase in overall peak loads could be avoided by shifting the EV load to the valley load periods at midnight. It is also possible to design a delayed smart charging scheme at home, with which the users will still have the convenience of having the EV fully charged before the first trip of the day [50]. In case of matching EV charging with on-site PV generation, there is a lower potential compared to valley filling and peak load reduction potentials at home [51]. This is due to lower EV availability at home during the day when solar power peaks, and very high EV availability at home during night.

Since most of the cars are away from home during daytime on weekdays, they are either being driven or parked in non-residential buildings [23, 51]. In contrast to home-charging, smart charging schemes at non-residential buildings might benefit more from local PV production since PV peaks in the midday. There are also spatial configurations which can be different to residential and non-residential buildings, i.e., charging stations. A charging station as a single unit has a load curve that only depends on EV presence. EV fleet management is more practical to be conducted in the charging station. Thus, it is more practical for a charging station as a single unit, compared to individual users, to provide ancillary services to the Transmission System Operator (TSO) and the Distribution System Operator (DSO) or to provide energy storage services for renewable power producers. Recently, integrating PV systems with EV charging stations has become more common since it can improve technical, economic, and environmental performance of EVs [52]. Furthermore, they can be improved even more with EV smart charging schemes [53].

On a regional or territorial level, such as cities, counties and islands where multiple residential buildings, non-residential buildings and charging stations are aggregated, it can be seen that the EVs are always available to charge, assuming the charging infrastructure is available within the region, except when being driven on the roads or the battery is full. Assessing the higher system level is also important since the aggregation of EV charging load, PV generation and electricity consumption will lead to different load profiles compared to the local scale. In this case, the impact of EV smart charging on problems at higher system levels, such as system peak load management or regional emissions, can be analyzed.

2.5.4 Mathematical models and algorithms

EV smart charging schemes can be programmed with various mathematical models and control algorithms. These can be classified into two categories based on problem formulations and solution methods: optimization methods and rule based algorithms.

Optimization is a method of finding the best available solution for a certain mathematical problem [54]. In an optimization problem, one typically wants to minimize or maximize certain parameters given some constrained conditions. A general optimization problem can be written as [54]

$$\text{minimize } f(x), \quad \text{subject to } g(x) \leq b \tag{2.3}$$

with $f(x)$ as the objective function, and $g(x)$ as the constraints. Linear programming (LP), mixed-integer linear programming (MILP), and quadratic programming (QP) are some examples of various optimization methods that are commonly used in energy management systems (EMS), including in EV smart charging schemes [49, 55]. If uncertainty of variables is taken into account, then an optimization framework called stochastic programming (SP) can be used to solve such problems [56, 57].

With a rule based method, a smart charging scheme typically uses a simple problem solving approach, e.g., using if-then conditions, instead of mathematical formulation that can take a long time to compute. In many conditions, rule based methods with simple logical rules, for example, charge when there is PV power and stop charging when the electricity price and surrounding electrical load is high, can be useful and more practical [38]. Compared to the optimization method, the rule-based method might not reach an optimum condition, but it can achieve the immediate goal following simpler rules.

2.6 Research gaps

The focus of this thesis is specifically the impact of EV smart charging schemes for residential buildings equipped with PV systems. The following research gaps have been identified and addressed in the appended papers:

- The impact of smart charging schemes on PV self-consumption in residential buildings are scarce in the literature. Paper II addresses this gap by proposing smart charging models to improve PV-EV synergies at residential buildings and evaluate the potential of PV self-consumption enhancements.
- Smart charging impacts on both PV and EV grid integration in residential distribution grids are scarce. Paper III attempts to fill some of this research gap.
- Combined PV-EV hosting capacity assessment, in the sense that both PV and EV hosting capacity is assessed together, has not been conducted before and is a research gap. Paper III also attempts to fill part of this gap by introducing a combined PV-EV hosting capacity assessment approach, with a case study in a residential distribution grid.

3. Methodology

This chapter introduces the data, case studies and methods used in Papers II and III.

3.1 Data and case studies

This section presents the data and case studies used in Papers II and III. It covers the data regarding EV charging demand, solar irradiation, building electricity consumption and the power grid. Data and models for EV charging demand, solar irradiation, building electricity consumption were based on Swedish conditions, whereas the power grid model represents a standard European distribution grid.

3.1.1 EV charging demand and mobility patterns

The EV charging demand model used in Papers II and III is described in this section. Many existing papers used travel surveys of ICEV mobility as the basis of their EV charging demand modeling [21]. The assumption is mainly motivated by the fact that future EV users will not need to change their driving behaviour, given that future EVs will have sufficient driving range for daily use [58]. A recent study in [23] validated EV modeling methods based on household travel survey (HTS) data against real EV charging data and the results show that this kind of modeling is an appropriate instrument to reproduce real EV charging behaviour.

In this thesis, EV charging demand modeling was based on user mobility data from a Swedish travel survey from 2006 [59]. The survey data included the time of arrival and departure for trips made by cars, the traveled distance, and also the origin and destination locations of these trips. The daily charging requirement $E_{EV,day}$ (kWh) is estimated by:

$$E_{EV,day} = \eta_{EV} \times D, \tag{3.1}$$

where η_{EV} is the specific consumption of EVs (kWh/km) and D is the daily driving distance. In Paper II, the specific consumption of EVs η_{EV} was set to 0.15 kWh/km, while in Paper III it was set to 0.16 kWh/km. These energy consumption rates conform to the rates of many available EV models, as can be seen in [60]. The daily driving distance D was calculated by doubling the trip distance, which was randomly sampled with a Monte Carlo method from data on traveled distance for the recorded trips arriving at home in the travel survey [59]. This was assuming that each EV had two equally long trips a day, such as a trip from home to work and back to home again. The maximum usable energy in the battery was set to 30 kWh, which was based on the assumption that that the battery could provide sufficient energy for moderate trips within a city, rarely exceeding 200 km per day. It was assumed that the EVs were only charged at home and not in other places such as workplaces or supermarkets.

Besides the daily mileages, the time of home-arrival and home-departure were also randomly sampled with a Monte Carlo method from the travel survey data [59]. Papers II and III were based on home-charging, and the modeling utilized trips which had home as origin and destination. Home-workplace-home mobility patterns were used to model the EV charging demand in weekdays, while home-other-home mobility patterns were used to model the EV charging demand in weekends. For more information on the trips starting and ending at other locations, see [22]. In the studies in this thesis, the arrival and departure time of EVs were randomly sampled with a Monte Carlo method using survey data with an assumption that each EV made one round trip per day. In the uncontrolled charging scheme, the charging starts at the arrival time without considering the time of departure. The smart charging schemes utilize the temporal flexibility between time of arrival and departure. The charging schemes are presented in detail in Section 3.2. Figure 3.1 (a) shows the statistic arrival and departure times at homes. Figure 3.1 (b) shows the mean daily availability of vehicles parked at homes. In Papers II and III, the maximum charging power was set to 3.7 kW, which was based on the power of a typical home charger [61]. The charging efficiency was set to 90% which was based on the average Level 2 EV charging efficiency [62]. The charging efficiency was assumed constant regardless of the charging power. It was also assumed that the EV charger had a constant unity power factor.

3.1.2 PV generation

The PV generation model used in Papers II and III is described in this section. The PV generation used in these studies was modeled based on solar irradiance data for 2018 from Stockholm, Sweden, with latitude 59.3° N and longitude 18.0° E, recorded by the Swedish Meteorological and Hydrological Institute (SMHI) [63]. The PV generation was modeled as

$$s_t = \eta_{PV} \times I_t, \tag{3.2}$$

where s_t is PV power generation at time t, η_{PV} is the PV system efficiency times the array area (m^2), and I_t is the incident solar irradiance at time t. In Papers II and III, for simplicity reasons, the incident solar irradiance I_t was

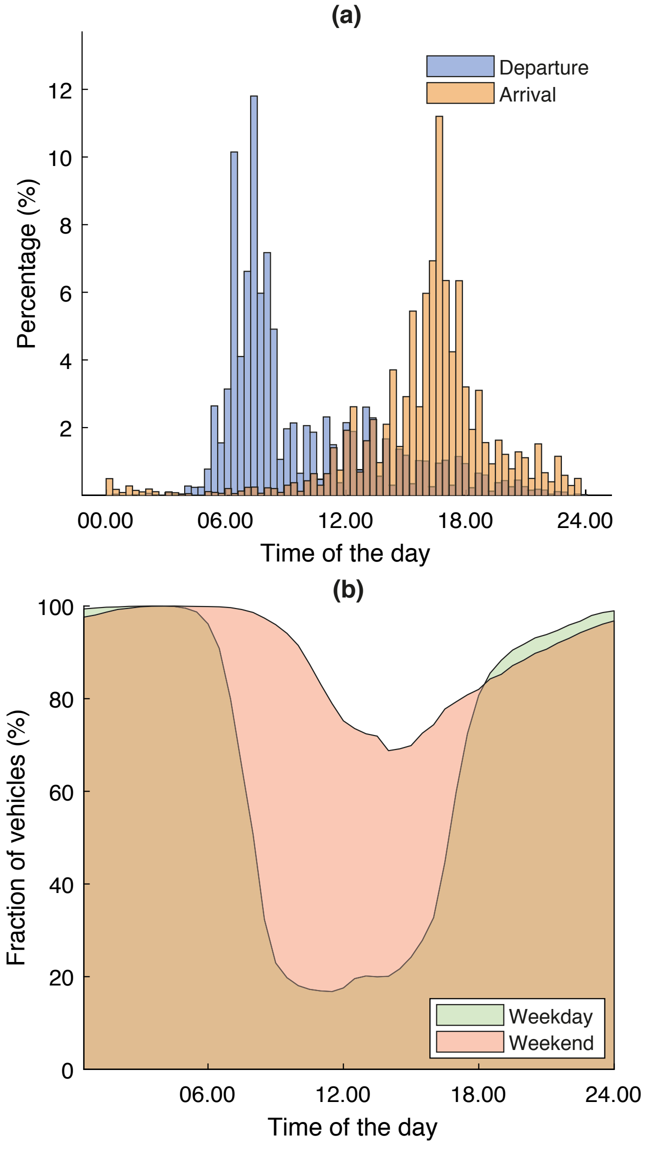

Figure 3.1. User mobility statistics: (a) time of home-arrival and home-departure and (b) mean daily fraction of vehicles parked at home. In (b), the light green area represents the weekday fraction, the light red area the weekend fraction, and the brown area just the intersection area between the two fractions.

equal to the Global Horizontal Irradiance (GHI), which means, that roof tilt was not taken into consideration.

In these studies, the PV system was scaled according to the ratio of annual PV power production to electricity consumption R_{PV}, instead of sized directly in kW_p. In that case, the PV system efficiency times footprint area η_{PV}, was calculated so that the annual PV power production satisfied the given studied R_{PV} value. The ratio of the total annual PV generation to the annual building electricity demand R_{PV} is defined as

$$R_{PV} = \frac{P_{PV}}{L_H}, \tag{3.3}$$

where P_{PV} is the annual PV electricity production and L_H is annual building electricity consumption. Then the PV system efficiency times array area η_{PV} can be defined as

$$\eta_{PV} = \frac{L_H \times R_{PV}}{(\sum_{t=1}^{t_{end}} I_t \Delta t)}. \tag{3.4}$$

The use of this kind of ratio is common, especially in the assessment of PV self-consumption and self-sufficiency as conducted in [31, 64]. In this thesis, several R_{PV} values were simulated. In Papers II and III, R_{PV} had both annual building electricity consumption and EV charging demand in the denominator part. In Paper III, R_{PV} only considered annual building electricity consumption in the denominator part, since the similar ratio for EV, R_{EV}, was introduced separately in order to assess the EV hosting capacity. The PV power was assumed to have a constant unity power factor.

3.1.3 Residential building load

The building load data used in Papers II and III is described in this section. Synthetic power consumption data was generated from the Widén Markov-chain stochastic model in [65]. The model was trained on Swedish occupant activity patterns and validated with Swedish electricity use data. In this thesis, the model was used to generate electricity use patterns without electric heating for single-family buildings with two inhabitants. The building load was assumed to have a constant power factor of 0.95.

3.1.4 Distribution grid

The power grid information used in Paper III is described in this section. The power flow computations and hosting capacity assessments were performed using the IEEE European LV Test Feeder [66]. The grid structure is shown in Figure 3.2. The grid has 55 building loads and is operated in a radial structure. Even though the grid has a three-phase system, each customer has only a single-phase connection. The transformer substation has a rating of 800 kVA 11 kV/0.416 kV. The voltage in the substation is by default set to 1.04 pu all the time.

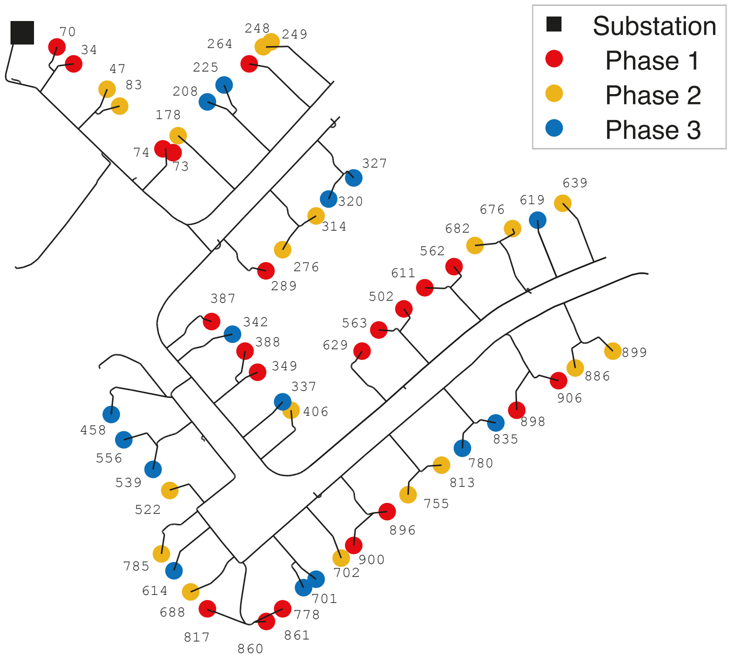

Figure 3.2. The IEEE European LV Test Feeder that was used in Paper III.

3.2 Electric vehicle charging schemes

This section presents the EV charging schemes used in Papers II and III. There are three different charging schemes used in this thesis: uncontrolled charging, distributed smart charging and centralized smart charging. The uncontrolled and the distributed smart charging schemes were simulated and studied in Papers II and III, while the centralized smart charging scheme was only simulated and studied in Paper II.

3.2.1 Uncontrolled charging scheme

In the uncontrolled charging scheme, the EVs charge opportunistically. In this scheme, the EVs start to charge upon arrival at home, with the rated charging power, without considering other parameters such as the building load or the PV generation. The charging is stopped when the SoC of the EV battery meets the targeted SoC. If the targeted SoC has not been fulfilled when the EV is to depart, the charging is stopped at the departure time.

3.2.2 Distributed smart charging scheme

In the distributed smart charging scheme, the EV charging considers other parameters, i.e., building load, PV generation, the targeted SoC, and future departure time. Since the scheme is distributed, it only considers the local parameters, i.e., those of the single building, and not the community level parameters.

The objective of the proposed distributed charging scheme is to minimize the net-load variability over the parking period. Flatter and smoother net-load is expected when the net-load variability is minimized. In that case, the self-consumption of local power production should increase and the peak loads should decrease. The variability is often measured by the variance which is defined as the average squared difference of the population values from the mean value [67]. Here, the net-load variability is represented by a variance equation. In the optimization, only numerator part of the variance equation is taken into account, since the denominator is constant and will not change the optimization outcomes. The optimization problem of the smart charging scheme is formulated with a quadratic programming approach since the variance itself is a quadratic equation. The optimization problem is defined as

$$\min_{x} \sum_{t=t_{arr}}^{t_{dep}} (x_t + l_t - s_t - \mu_{tpark})^2, \tag{3.5}$$

$$\begin{aligned} \text{s.t.} \quad & \eta_x \sum_{t=t_{arr}}^{t_{dep}} x_t \cdot \Delta t = SoC_{target} - SoC_{arr}, \\ & 0 \le x_t \le x_{max}, \end{aligned} \tag{3.6}$$

where t_{arr} and t_{dep} are the arrival and departure times of the car, respectively, x_t is the charging power at time t, l_t is the building load at time t, s_t is the solar power production at time t and μ_{tpark} is the mean net-load during the parking period including the EV charging load. In the constraint, η_x is the charging efficiency, Δt is the time step, which in this case is set to 15 minutes, SoC_{target} is the state of charge (kWh) targeted in the battery, SoC_{arr} is the state of charge (kWh) in the battery on arrival, and x_{max} is the maximum charging power. The mean net-load during the parking period μ_{tpark} is obtained as

$$\mu_{tpark} = \frac{(\sum_{t=t_{arr}}^{t_{dep}} (l_t - s_t) \cdot \Delta t) + SoC_{target} - SoC_{arr}}{t_{dep} - t_{arr}}. \tag{3.7}$$

It should be noted that the charging scheduling for the scheduled parking period is conducted only at the time of arrival t_{arr}. The optimization output is a vector containing $x_{t_{arr}}, x_{t_{arr+1}}, \dots , x_{t_{dep-1}}, x_{t_{dep}}$, which is the time-series of the smart EV charging load.

3.2.3 Centralized smart charging scheme

The centralized smart charging scheme is the extension of the distributed smart charging scheme. The difference is that the centralized smart charging considers community level parameters and the charging for several EVs at different buildings is coordinated by a central unit simultaneously. In this case, the centralized charging scheme minimizes the net-load variability of the whole community. The community power consumption L_t, PV generation S_t at time-step t with K number of buildings, respectively, can be written as

$$L_t = \sum_{k=1}^{K} l_{t,k}, \tag{3.8}$$

$$S_t = \sum_{k=1}^{K} s_{t,k}, \tag{3.9}$$

with $l_{t,k}$ and $s_{t,k}$ being the load and PV generation respectively at building k Based on that, the objective function of the centralized smart charging scheme can be written as

$$\min \quad \sum_{t=t_{arr}}^{t_{dep}} (x_t + L_t - S_t - M_{tpark})^2, \tag{3.10}$$

where the new variable M_{tpark} is introduced as the mean community net load during the parking period, taking into account the charging demand of the EV that is being scheduled. The new variable M_{tpark} is obtained as

$$M_{tpark} = \frac{(\sum_{t=t_{arr}}^{t_{dep}} (L_t - S_t) \cdot \Delta t) + SoC_{target} - SoC_{arr}}{t_{dep} - t_{arr}}. \tag{3.11}$$

The constraint of the optimization problem is identical with the one in the distributed charging, which is shown in Equation (3.6). In the centralized charging scheme, the community net-load profiles for future smart charging events are updated every time a charging load for an EV is scheduled. In this case, after each time that EV charging is scheduled, the building load forecast L'_t between the arrival time t_{arr} and the departure time t_{dep} is updated with the inclusion of the scheduled EV charging load to L_t, which can be written as

$$L_t = L'_t + x_t. \tag{3.12}$$

In other words, the charging schemes consider not only the building load and the PV generation in the neighborhood, but also other EV charging load that has been previously scheduled within the parking period of the recently arrived EV. If more than one car arrives at time step t, the order of the charging scheduling is based on the future departure time. The charging of the car that will depart earlier will be scheduled earlier, since the cars that park longer have a higher flexibility.

3.3 PV curtailment

This section provides the description of the PV curtailment methods that were used in Paper III, which were attempts to enhance the PV hosting capacity. There are two curtailment scenarios studied in Paper III, full curtailment and partial curtailment.

In the full curtailment method, the building is prevented to transfer excess PV electricity to the grid. With this curtailment method, it is expected that the maximum voltages on the customer side do not increase with the integration of the PV systems, since no excess power is flowing to the grid. The generated PV power after full curtailment $s_{curt,t}$ can be defined as

$$s_{curt,t} = \min(s_t, l_t + x_t). \tag{3.13}$$

Simulation results from deploying the full-curtailment method were compared to other results deploying other EMS strategies, i.e., no control and EV smart charging schemes, and was further used for the grid hosting capacity assessment.

In the partial curtailment method, the building is allowed to transfer excess PV power to the grid, however it is limited. The limitation is based on the results from the no curtailment scenarios which did not violate the allowable upper voltage limit. In the case that the PV power excess does not exceed this limit, there is no curtailment. When PV power excess is higher than this limit, curtailment is enforced. With this method, the maximum voltage due to the injected PV power will increase, but it should not be higher than the allowable upper voltage limit. It can be said that this curtailment method is optimal compared to the full curtailment, since only the absolutely necessary amount of excess power is curtailed. The generated PV power after optimal curtailment $s_{opt,t}$ can be defined as

$$s_{opt,t} = l_t + x_t + \min(s_t - (l_t + x_t), s_{tr,max}), \tag{3.14}$$

where $s_{tr,max}$ is the maximum allowed PV power transfer from a building to the grid, which was set after the power flow simulation of the scenario without any curtailment was conducted.

3.4 Simulation scenarios

This section describes the simulation scenarios in Papers II and III.

3.4.1 Residential building

In Paper II, there were two different scenarios with different numbers of buildings involved, i.e., a single building load and the aggregation of 100 buildings, which represented a small-sized community. The impacts of the deployment of the smart charging schemes both for single buildings and on community levels were assessed. In Paper III, the number of buildings involved was set to 55, as the distribution grid used in the study by default has 55 customers.

3.4.2 PV share

Papers II and III shared the same quantification method of the PV shares in the simulations, which were the ratio of annual production to annual consumption R_{PV}. However, there are some differences in the implementation. In Paper II, the annual consumption in the ratio R_{PV} ratios included the annual energy demand for EV charging, while in paper III it did not. In Paper II, seven different R_{PV} were simulated: 0.1, 0.25, 0.50, 0.75, 1.00, 1.25 and 1.50. In Paper III, five R_{PV} ratios were simulated, i.e., 0.00, 0.25, 0.50, 0.75 and 1.00, for combined PV-EV grid integration and hosting capacity assessment. Evenly distributed PV systems among the customers were assumed.

3.4.3 EV share

In Paper III, the ratio of the annual EV charging demand to the existing annual building electricity consumption, R_{EV}, was introduced as a way to quantify the EV charging addition to the power system. The ratio R_{EV} is similar to the ratio R_{PV}, which was defined in Equation (3.3). The difference is that R_{PV} quantifies PV share addition while R_{EV} quantifies EV share addition. The ratio R_{EV} is defined as

$$R_{EV} = \frac{L_{EV}}{L_H}, \tag{3.15}$$

where R_{EV} is the annual EV charging demand and L_H is the annual building electricity consumption, and in this case the EV load is excluded from L_H. In Paper III, five R_{EV} were simulated: 0.00, 0.25, 0.50, 0.75 and 1.00, for combined PV-EV grid integration and hosting capacity assessment. Evenly distributed EVs among the customers were assumed in the study.

3.4.4 Energy management systems

In Paper III, there were four EMS scenarios simulated: (1) without EMS, (2) with EV smart charging only, (3) with PV curtailment only and (4) with both EV smart charging and PV curtailment. In this case, the EV smart charging scheme refers to the distributed smart charging scheme, not the centralized smart charging scheme. These scenarios were simulated in order to estimate the grid impacts when different EMS strategies were deployed, and also to assess the possible combined PV-EV hosting capacity. The smart charg-

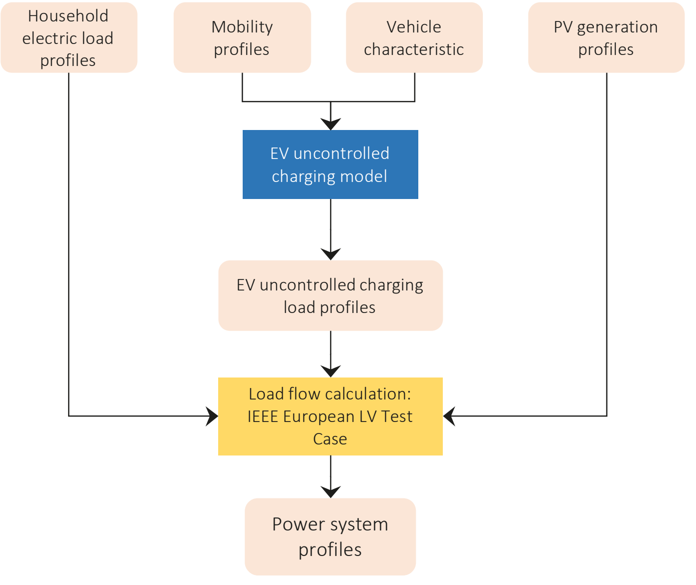

Figure 3.3. Simulation flow in the scenario without EMS.

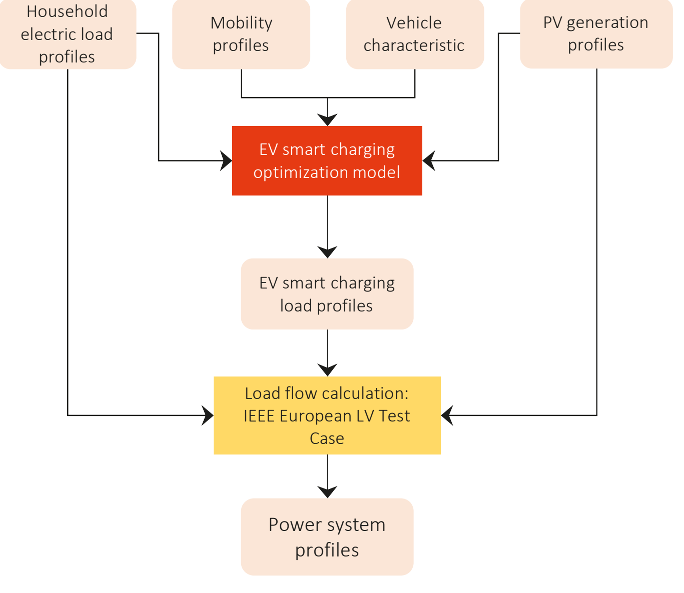

Figure 3.4. Simulation flow in the scenario with EV smart charging only.

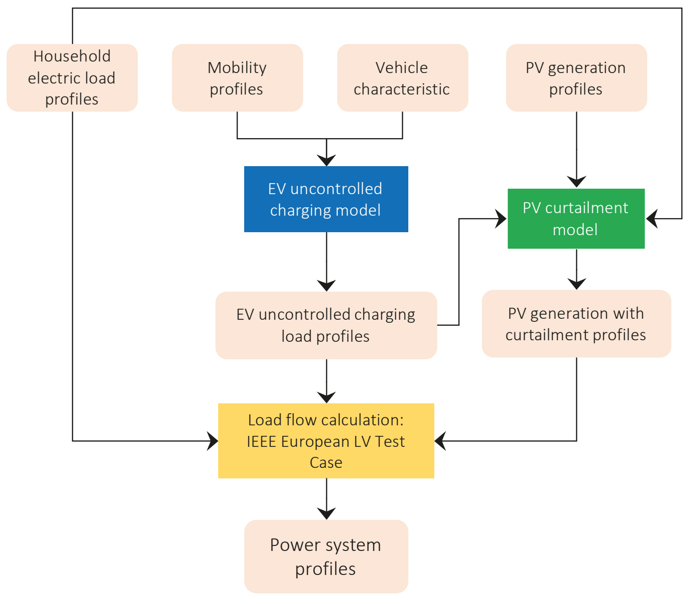

Figure 3.5. Simulation flow in the scenario with PV curtailment only.

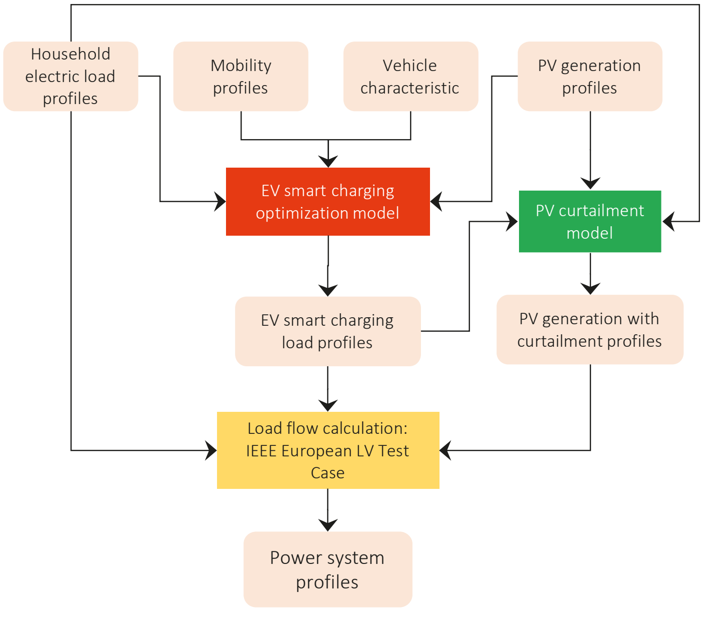

Figure 3.6. Simulation flow in the scenario with both EV smart charging and PV curtailment.

ing schemes and the PV curtailment methods were described in Sections 3.2 and 3.3 respectively.

As described earlier, the building load and the PV generation are not considered in the uncontrolled charging scheme which is illustrated in Figure 3.3. On the other hand, the EV smart charging scheme has the building load and the PV generation as two of the inputs, as shown in Figure 3.4. In Figure 3.5, the simulation flowchart for the scenario with only PV curtailment is shown. In Figure 3.6, the simulation flowchart involving both EV smart charging and PV curtailment is shown. It can be seen that the smart charging considers the PV generation profile before the curtailment, while the curtailment considers the EV smart charging load. That implies that the EV smart charging is scheduled hours ahead, and the curtailment is conducted in real-time. In all scenarios, the building load, the final PV generation and the final EV charging load are used as inputs for the load flow calculations to generate power system profiles such as voltages and system losses.

3.5 Hosting capacity quantification

In Paper III, the voltage deviation level was used as the hosting capacity performance index, since it is the most commonly used one and usually the most relevant one for defining the grid hosting capacity [43]. According to the European standard [68], rms voltages in a LV distribution system must be within the range of 0.90 - 1.10 pu during 95% of the time, on a weekly basis. Thus, the system should not allow voltage levels outside this range. In paper III, whole year power flow simulations were performed, which produced estimates of the voltage probability density. In one analysis, the whole probability density was considered for the hosting capacity assessment. In another analysis, the lowest and highest 0.01 % of voltage population were excluded; in other words, only the range between the 0.01th and 99.99th percentiles of the voltage population was included. The interpretation of this case should be that the grid tolerates very rare occurrences of overvoltage and undervoltage, but otherwise conforms to the standard [68]. To evaluate the PV and EV hosting capacity in combination, a novel graphical based analysis was proposed in Paper III. This will be presented in Section 4.3.

4. Results

In this chapter, the main results from the appended papers are summarized. The sections in this chapter are ordered according to the papers. Section 4.1 provides a summary of the results from Paper II on impacts from the smart charging schemes in residential buildings and for a community of residential houses. Section 4.2 and Section 4.3 summarize the main results from Paper III on impacts from the smart charging schemes on the distribution grid, and from the combined PV-EV hosting capacity with EV smart charging and PV curtailment, respectively.

4.1 EV smart charging at residential buildings with PV systems

This section summarizes the results presented in Paper II. Both distributed and centralized charging schemes in residential buildings were simulated.

Figure 4.1 shows the daily load and generation profiles averaged over a year for a community of 100 buildings with 0.5 production to consumption R_{PV} ratio. The amount of self-consumed PV electricity and peak load reduction in different charging schemes can be seen. As can be seen, in the scenario with the uncontrolled charging scheme, EV charging mostly occurs in the evening when people have just arrived home. In the scenario with smart charging schemes, on the other hand, the EV charging load is distributed more evenly over the night since it utilizes the flexibility of the expected long parking periods. It can be seen that the peak load is lower with the smart charging scenarios. The intersection between the PV generation profile and both the building and the EV charging load profiles indicates the amount of self-consumed PV electricity. It can be seen that compared to the intersection area with uncontrolled charging, the intersection areas with the smart charging schemes are larger, and the one with centralized charging is slightly larger than the one with distributed charging.

A summary of the numerical results on self-consumption, self-sufficiency and peak load reduction is presented in Sections 4.1.1 and 4.1.2. In Section 4.1.3, a summary of the results on net-load variability, which was the quantity minimized in of the smart charging schemes, is presented.

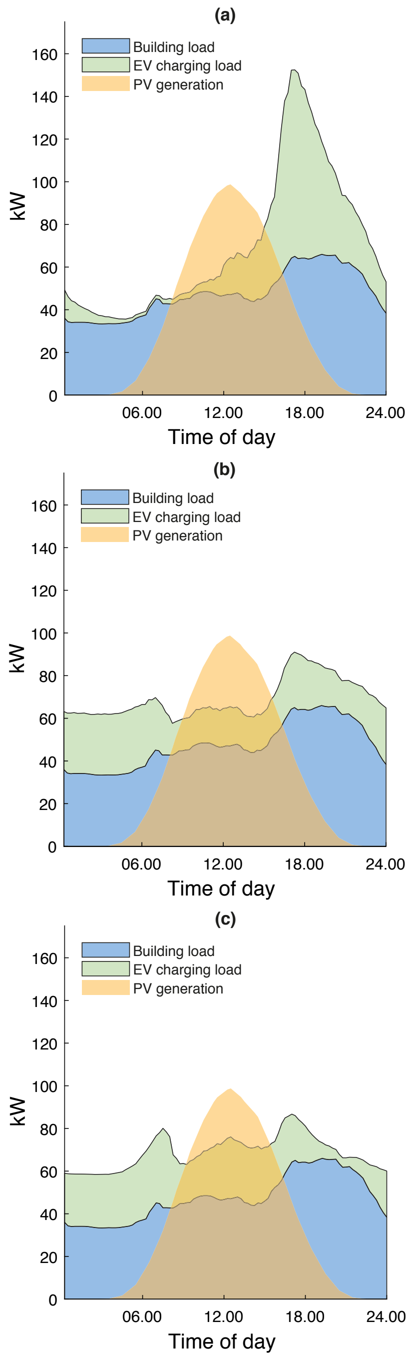

Figure 4.1. Daily load profiles averaged in a year for a community of 100 residential buildings with (a) uncontrolled charging scheme, (b) distributed smart charging scheme and (c) distributed smart charging scheme.

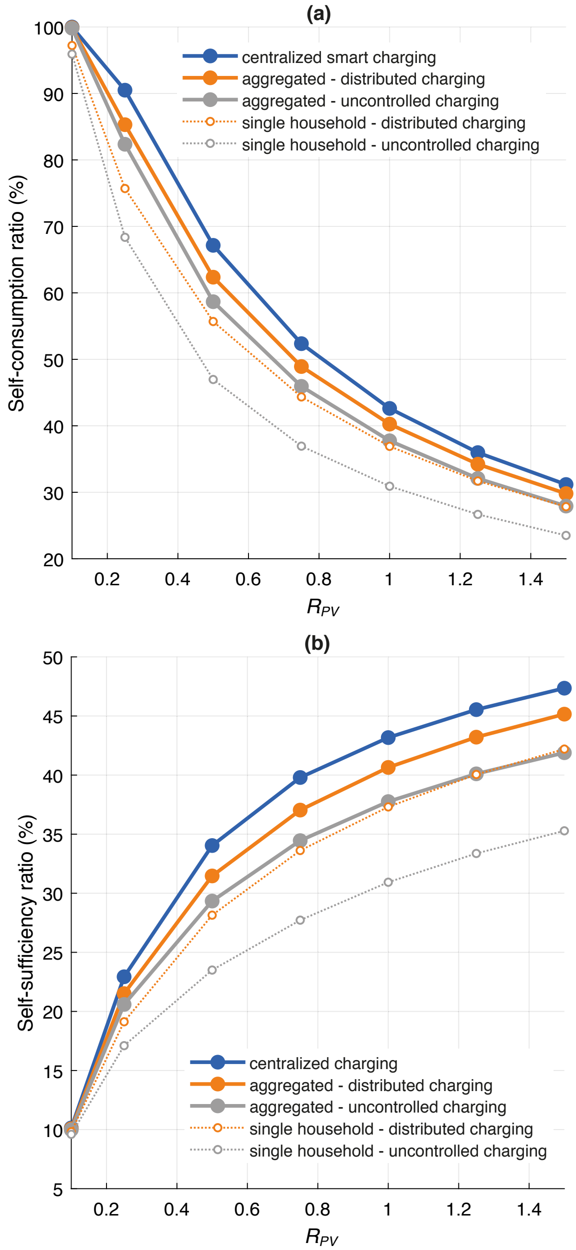

Figure 4.2. (a) Self-consumption (SC) and (b) self-sufficiency (SS) ratios versus the production-to-consumption ratio R_{PV}.

4.1.1 Self-consumption and self-sufficiency

Figure 4.2 (a) and (b) show the self-consumption (SC) and the self-sufficiency (SS) ratios versus the production-to-consumption ratio R_{PV}. In the figures, several scenarios are presented. The grey lines represent the uncontrolled charging scheme, the orange lines represent the distributed smart charging scheme and the blue line represents the centralized charging scheme. Thinner lines represent results from a single building and thicker lines represent the results from 100 buildings aggregated. As can be seen in the figures, the higher the R_{PV} is, the lower the SC, and the higher the SS. Regardless of the charging schemes, the aggregation of net-loads from multiple buildings will improve overall SC and SS. This is because when there is PV power excess in one building it can still be consumed by nearby buildings.

From Figure 4.2, it can also be seen that the SC and SS are higher in the smart charging scenarios compared to the uncontrolled charging scheme scenario. The SC and SS on the community level in the centralized smart charging scenarios are higher than in the distributed smart charging scenarios. This is because the centralized charging scheme was designed to consider the net-load in the community directly, unlike in the distributed smart charging scheme, which only considers the net-load in each single building.

The increases in SC and SS by the smart charging schemes are presented in Tables 4.1 and 4.2, respectively. The increases in SC by smart charging are highest when the ratio R_{PV} is 0.50. As for SS, the highest increase among the simulated scenarios comes from the highest simulated R_{PV}, i.e., 1.50. The impacts from the distributed smart charging at the single building are more prominent than the ones on community level. This is because the aggregation of net-loads from multiple buildings already improved the SC and SS, leaving less room for improvements with the distributed charging scheme. On community level, it can be seen that the increase in SC and SS in the centralized charging scheme are higher than with the distributed charging scheme, and close to the improvements achieved by the distributed smart charging at the single building level. It is also interesting to see that, when the centralized charging was deployed, the SC and the SS at the individual building level increased, even though not as much as the one with distributed charging. This implies that the centralized charging scheme did not penalize SC and SS at the individual building level, instead the scheme improved them to a certain extent.

Ideally, the charging is shifted in time to the hours when the solar power is high. However, it was not always possible with unchanged user driving behavior, which was an assumption in this study. Thus, the EV availability at the residential buildings was mostly low during midday when the solar power production was high. That is why the increase in both SC and SS by the smart charging schemes were limited.

Table 4.1. *Self-consumption improvements by smart charging schemes with different production-to-consumption ratios R_{PV} for a single building and on the community level with both distributed and centralized charging approaches.*

R_{PV}	Self-consumption increase			
	Distributed charging		Centralized charging	
	Single building	Community	Averaged per building	Community
0.10	1.3%	0.1%	0.4%	0.2%
0.25	7.3%	2.9%	2.8%	8.1%
0.50	8.7%	3.7%	3.8%	8.5%
0.75	7.4%	3.0%	3.5%	6.4%
1.00	6.0%	2.5%	3.4%	4.9%
1.25	5.0%	2.1%	3.0%	3.9%
1.50	4.3%	1.9%	2.7%	3.2%

Table 4.2. *Self-sufficiency improvements by smart charging schemes with different production-to-consumption ratios R_{PV} for a single building and on the community level with both distributed and centralized charging approaches.*

R_{PV}	Self-sufficiency increase			
	Distributed charging		Centralized charging	
	Single building	Community	Averaged per building	Community
0.10	0.2%	0.1%	0.2%	0.2%
0.25	2.0%	0.9%	1.0%	2.3%
0.50	4.6%	2.1%	2.3%	4.7%
0.75	5.9%	2.6%	3.3%	5.3%
1.00	6.4%	2.9%	3.8%	5.4%
1.25	6.7%	3.1%	4.7%	5.4%
1.50	6.9%	3.2%	4.7%	5.5%

4.1.2 Peak load reduction

Table 4.3 presents the peak load reduction by the smart charging scenarios, both for individual buildings and on community level. It should be noted that what is meant by peak load reduction in this case is the amount of reduced load compared to the peak load in the scenarios with uncontrolled charging. In the scenarios with uncontrolled charging, the charging of EVs often coincides with the building peak load. With smart charging schemes, a peak load reduction is achieved by shifting and distributing the EV charging load in the periods when the building load is not high.

From Table 4.3, it can be seen that the peak load reduction at the individual building level was higher than on the community level. This is because peak loads in residential buildings do not always coincide. Thus, when the net-load from multiple buildings is aggregated, the peak loads in the aggregated net-load will be lower than the sum of peak net-loads from each building. In that case, there is less room for the smart charging scheme to reduce the peak loads. On community level, the peak load reduction by the centralized charging scheme was higher than with the distributed smart charging scheme since the community net-load was directly considered in the centralized charging.

Table 4.3. *Peak load reduction with different production-to-consumption ratios R_{PV} in a single building and on the community level with both distributed and centralized charging approaches.*

R_{PV}	Peak load reduction		
	Single building	**Community: distributed**	**Community: centralized**
0.10	52.8%	36.1%	48.6%
0.25	53.6%	34.9%	47.3%
0.50	53.7%	32.7%	44.1%
0.75	52.4%	32.4%	42.6%
1.00	49.2%	32.3%	41.8%
1.25	46.6%	32.5%	41.3%
1.50	44.9%	32.7%	41.0%

4.1.3 Load variability

Figure 4.3 (a), (b) and (c) show example net-load profiles for a community of 100 buildings on spring, summer and winter days, respectively, with different EV charging schemes and with $R_{PV} = 0.50$. Among the charging schemes, it can be seen that the net-load with the smart charging schemes is less variable than the one with the uncontrolled charging scheme. It can also be seen that the net-load with the centralized smart charging is smoother than the one with the distributed smart charging.

Since the objective in the smart charging schemes in Paper II is to minimize the net-load variability, it is important to assess the performance of the smart charging scheme based on a measure related to the objective. Therefore, the variability of the net-load was by the load standard deviation. Figure 4.4 shows the net-load standard deviation per building with different R_{PV} ratios and with different charging schemes. As can be observed, the aggregation of multiple buildings decreases the net-load variability per building. It can also be seen that the higher the PV share is, the higher the variability. This is due to the fact that there is more unconsumed power when the share of PV is higher. From the figure, it can also be seen that the smart charging, as expected, reduces the net-load variability. However, the difference in net-load variability between the uncontrolled charging and smart charging scenarios is lower when the share of PV is increased. That implies that the effectiveness of the smart charging, approach-wise, is lower when the PV share is higher. This is because the

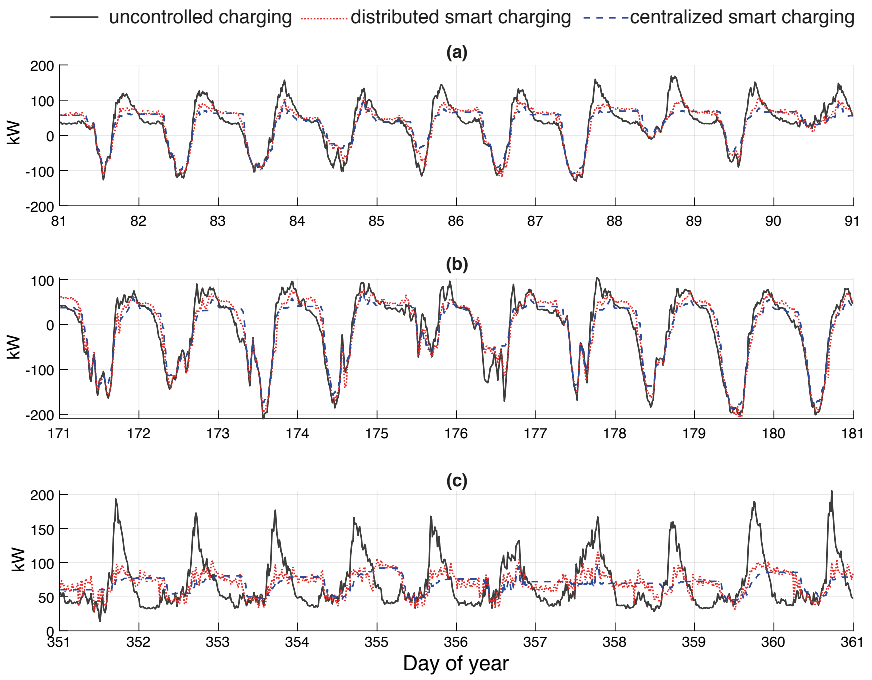

Figure 4.3. Examples of net-load profiles for a community of 100 buildings in selected (a) spring, (b) summer and (c) winter days.

EV availability is low during midday, which is when most of the PV power production is added when the PV share increases.

4.2 Grid impacts

In Paper II, the smart charging scheme with the objective to reduce the net-load variability was introduced and the energy performance of single buildings and on community level was assessed. In Paper III, a combined PV-EV grid integration study was performed and the impact of smart charging schemes on the distribution grid was assessed. Even though the objective of the smart charging scheme is to minimize the net-load variability, and is not explicitly related to grid operation, the results show that the grid performance was also improved as a result of the reduced net-load variability. The study in Paper III also involved PV curtailment. Sections 4.2.1 and 4.2.2 summarize the main results on losses and voltage profiles of this combined PV-EV grid integration study.

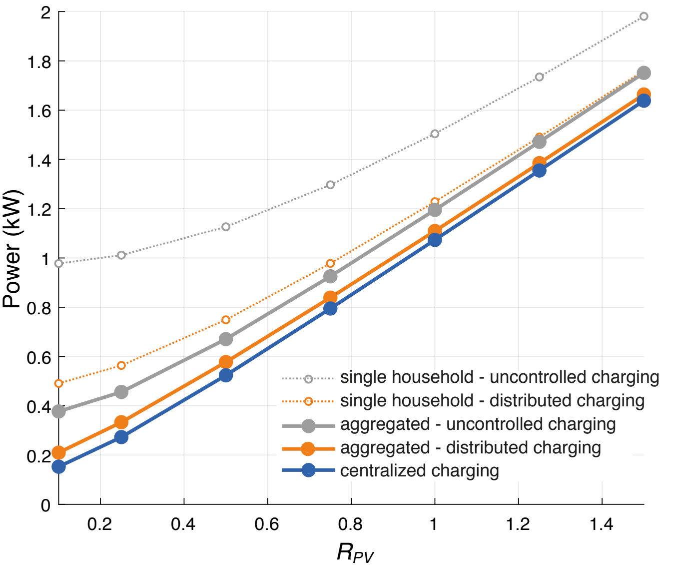

Figure 4.4. Net-load standard deviation per building versus production-to-consumption ratio R_{PV}.

4.2.1 System losses

Figure 4.5 shows the annual grid losses with different PV and EV shares and with different EMS strategies. By comparing Figure 4.5 (a) and (b), it can be seen that smart charging with an objective to minimize the net-load variability also decreases the grid losses. This is due to the electrical losses being proportional to the square of the current flowing in the line [69]. Thus, both higher excess peak load and excess generation lead to higher electrical losses. When the net-load variability is lower, it is expected that peak loads and generation excesses will be lower, which in turn leads to lower losses. In Figure 4.5, it can also be seen that the higher the EV share, the higher the grid losses. For PV, losses first decrease to a minimum, then start increasing again. This is shown in Figure 4.5 (a) and (b), where the plots of losses versus the PV share are convex-shaped. That means that the PV power injected to the grid reduces the losses provided that the size of the installed PV system is optimal. If the PV production is too high, the losses start to increase again. In the scenario with PV curtailment shown in Figure 4.5 (c) and (d), it can be seen that the electrical losses continued to decrease when the installed PV share was higher. However, it should be noted that it did not take the curtailed electricity into account, which should also be considered as system losses and could be much higher if the installed PV is excessively high.

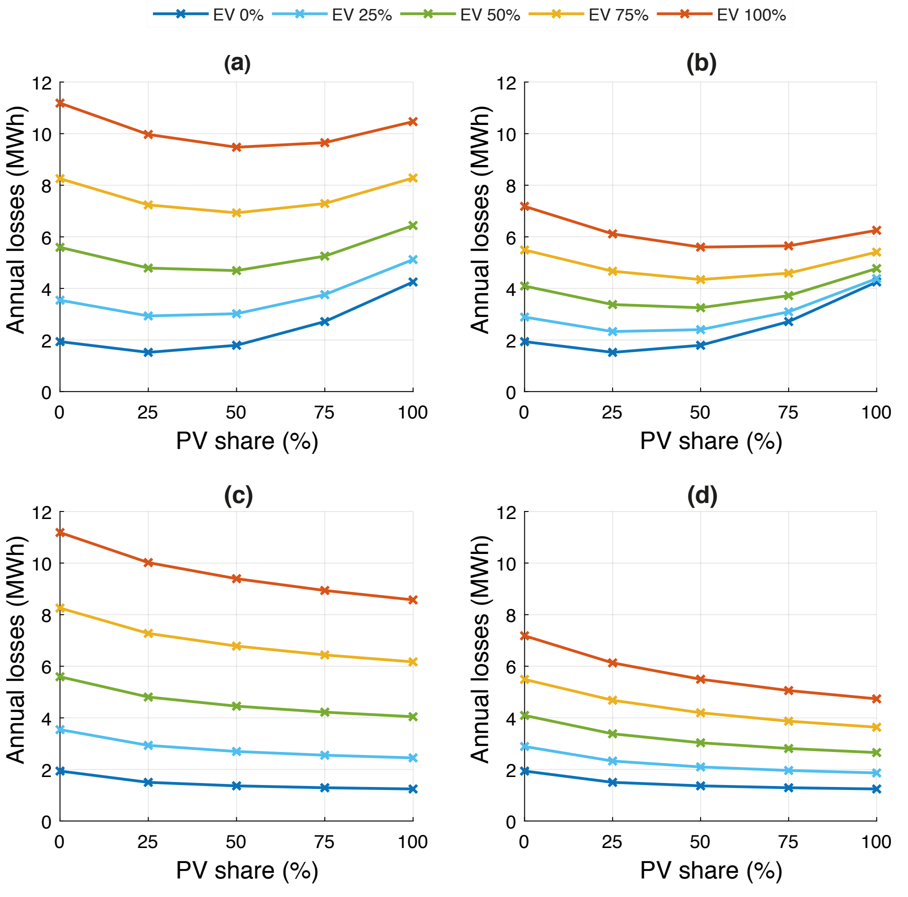

Figure 4.5. Annual electrical system losses in different PV and EV integration scenarios: (a) without EMS, (b) EV smart charging only, (c) PV curtailment only and (d) EV smart charging + PV curtailment.

4.2.2 Voltage profiles

Figure 4.6 shows the voltage probability distribution for a variety of EMS and combined PV-EV scenarios. The x-axis corresponds to different EV shares, and the y-axis corresponds to different PV shares. It can be seen that in the scenarios without EMS, there were no voltage violations if both the share of PV and EVs were under 75%. When the PV share was 100%, overvoltage occurred, and when the EV share was 100%, undervoltage occurred. In the scenario with the smart charging scheme only, the undervoltage problem in the scenarios with 100% EV share was avoided. The smart charging scheme could also reduce the maximum voltage, if the PV share was low. This can be seen in the plots for the scenarios without EMS and smart charging only, with a 25% PV share. In the scenario with PV curtailment only, the overvoltage problem in the scenarios with a 100% PV share was avoided. In the scenario with both

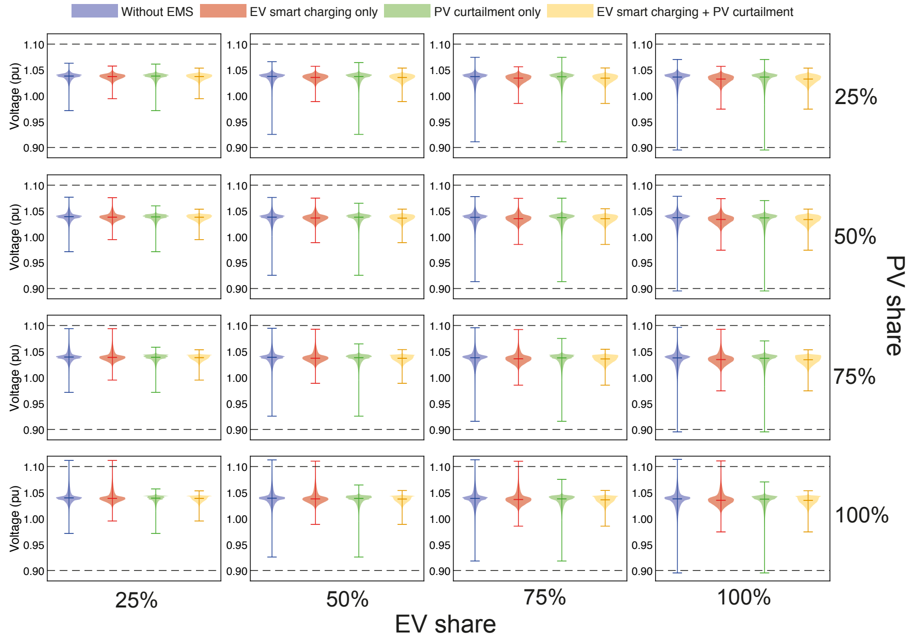

Figure 4.6. Violin plots of voltage probability distributions in different EMS scenarios and with combined PV-EV shares.

EV smart charging and PV curtailment, both overvoltage and undervoltage problems were avoided. From the voltage profiles, the grid hosting capacity for both PV and EVs can be determined, see Section 4.3.

4.2.3 Optimal curtailment and grid sufficiency

Following the results on the maximum voltages from the full curtailment scenarios, which are still far from the upper limit, the simulation with the partial curtailment was conducted to attempt to ascertain the trade-off between the PV utilization and the voltage level. As can be seen in Figure 4.6, in the scenario without curtailment, there were no overvoltage occurrences when the PV share was 75%. Thus, the maximum excess power from each building in this scenario was set as the maximum power transfer from the building to the grid in the partial curtailment scenario.

Figure 4.7 shows the voltage probability distributions for a PV share of 100% in three different curtailment scenarios. With partial curtailment, the maximum voltage reached the upper limit of the permissible voltage span. Figure 4.8 shows the various PV electricity utilization levels relative to the existing load. As can be seen in Figure 4.8 (a), the full curtailment reduced the grid self-sufficiency slightly, while the partial curtailment kept the level of self-sufficiency as it was without the curtailment scenarios. There was no

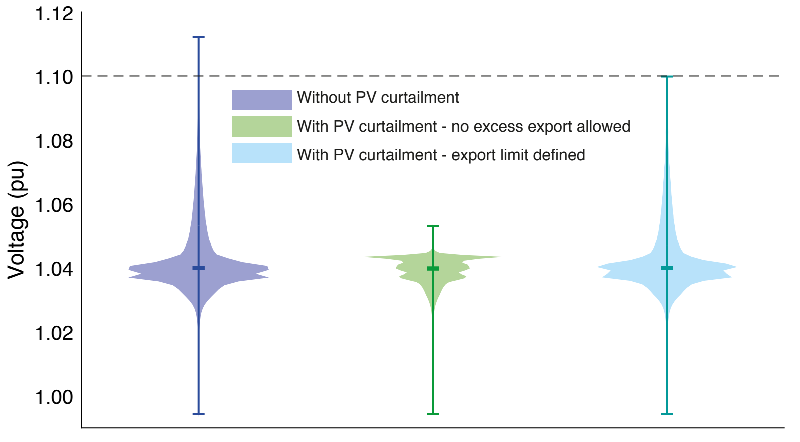

Figure 4.7. Voltage distributions in different curtailment scenarios.

transferred electricity from the building to the grid in the scenario with the full curtailment, as shown in Figure 4.8 (b), while with the partial curtailment, the amount of transferred excess electricity was identical with the scenario without curtailment, up to the 75% PV share scenario. After that, the amount of transferred excess electricity from the buildings was lower since the curtailment was enforced. Unlike the curtailed electricity which is considered to be pure losses, the transferred electricity from the buildings can still be considered utilized electricity since it can be used elsewhere, including beyond the local grid. As for the curtailed electricity, more than half of the PV electricity was curtailed when the PV share was higher than 25% in the full curtailment scenario, as shown in Figure 4.8 (c). It should be noted that only a small amount of excess electricity was curtailed in the partial curtailment scenario, even in the 100% PV share scenario.

4.3 Combined PV-EV grid hosting capacity

Figure 4.9 shows the combined PV-EV hosting capacity estimation with different EMS scenarios. Blue areas represent the scenario (1) without EMS, red areas represent the scenario (2) with EV smart charging only, green areas represent the scenario (3) with PV curtailment only, and yellow areas represent the scenario (4) with both EV smart charging and PV curtailment. In the figure, there are some intersections between areas with different colors, thus a venn diagram guide is also presented along with the figures. It should be noted that the x-axis and y-axis are limited in the figures so that the essential results can be analyzed.

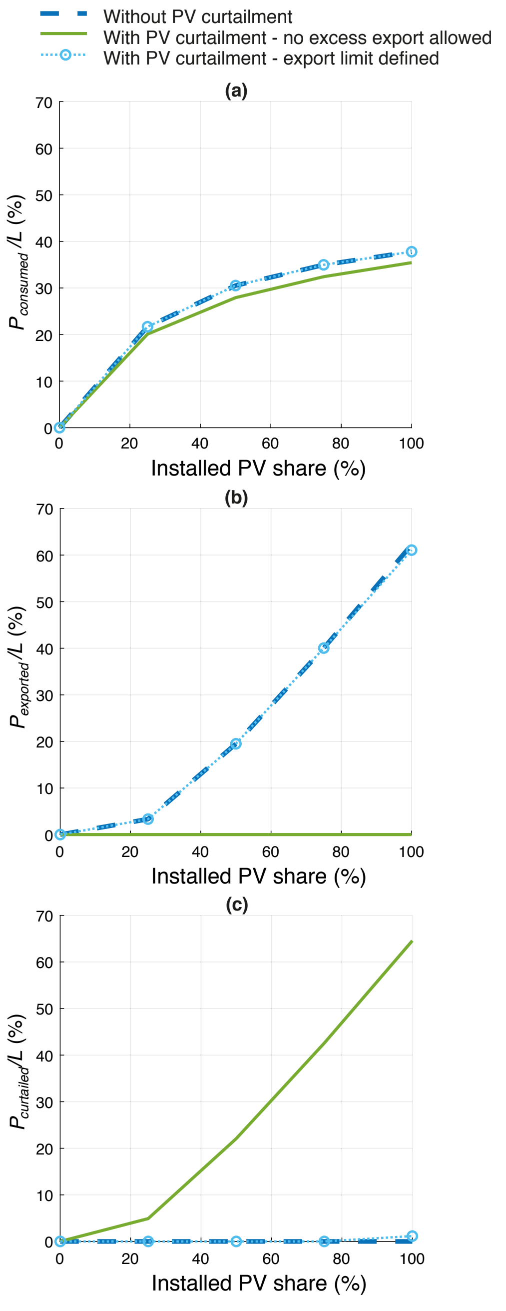

Figure 4.8. Various PV electricity utilization levels relative to the existing load for: (a) annual consumed PV electricity per total load, i.e., self-sufficiency, (b) annual exported PV electricity per total load, (c) annual curtailed PV electricity per total load. Results from different curtailment strategies are shown in each subfigure.

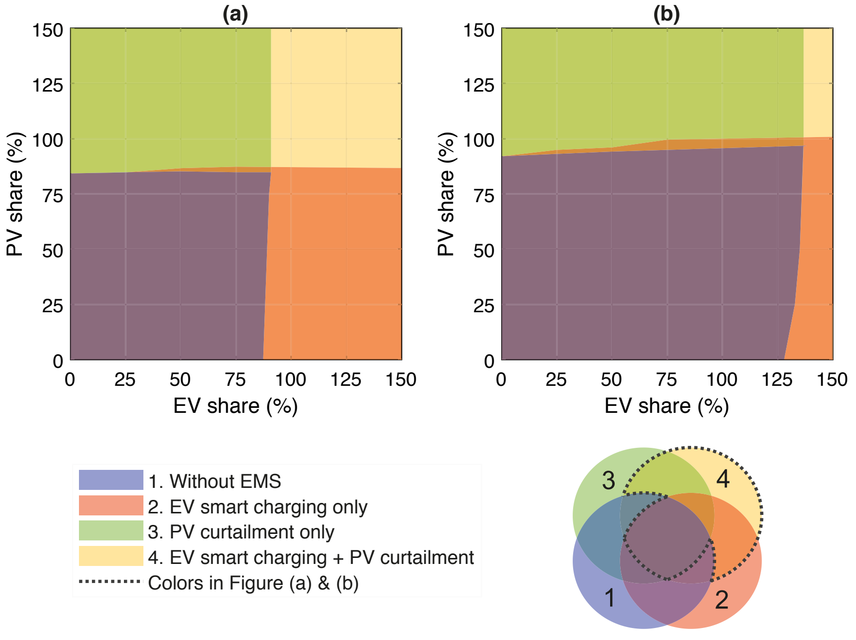

Figure 4.9. Graphical analysis of combined PV-EV grid hosting capacity with 10% allowed voltage deviation (a) within the whole voltage populations and (b) within the 0.01th and 99.99th percentiles.

It can be seen that the blue areas that represent scenario (1) are also covered by all other colors that represent scenario (2)-(4). This means that among the simulated scenarios, scenario 1 had the lowest combined PV-EV hosting capacity. It can also be seen that the red (scenario (2)) and green (scenario (3)) areas are also covered by the yellow areas (scenario (4)), while there are parts of yellow areas (scenario (4)) that are not covered by other colors. This implies that among the simulated scenarios, scenario 4 had the highest combined PV-EV hosting capacity. From the figures, it can be seen that the smart charging scheme increased the EV hosting capacity significantly and the PV hosting slightly, and that the PV curtailment increased the PV hosting capacity significantly but did not increase the EV hosting capacity at all. However, it should be noted that in this study perfect forecasts for load, PV production and time of departure were used for the smart charging schemes, as a best case assumption for EV smart charging. Thus the results on minimum voltages in the scenarios with smart charging reflect the identified upper limit of minimum voltages. Less reliable forecasts are expected to give less significant improvements. It should also be noted that for these results, full curtailment was simulated. In that case, the results on maximum voltages in the scenarios with PV curtailment reflected the identified lower limit of maximum voltages.

If the whole voltage population is included, a correlation between PV and EV hosting capacity cannot be observed. However, if the voltage within 0.01th - 99.99th percentiles are analyzed, there is a slight correlation between PV and EV hosting capacity. In that case, the increased PV share improved the EV hosting capacity, and the increased EV share improved the PV hosting capacity. It can also be seen that the EV hosting capacity was significantly higher, but that the PV hosting capacity was almost the same. This implies that the simulated minimum voltages shown in Figure 4.6 for 100% EV share were uncommon, being entirely part of the excluded values, while the simulated maximum voltages for the 100% PV share represented the expected conditions.

5. Discussion and future work

This chapter discusses the important results described in the previous chapter and provides a summary of prospective future research topics.

5.1 Discussion

The coordination of EV charging, often called EV smart charging, has a potential to improve the synergy between local generation and load as reviewed in Paper I. In the case of residential buildings, results from Paper II show that both PV self-consumption improvement and peak load reduction could be achieved by deploying a smart charging scheme with an objective of minimizing the net-load variability. The PV self-consumption improvements were limited by low vehicle availability in the residential buildings during midday when the PV power production was high, given that there was no change in mobility behavior.

Results also show that the self-consumption improvement and peak load reduction at the individual building level are higher with distributed smart charging compared to with centralized smart charging. On the contrary, on community level, the self-consumption improvement and peak load reduction was higher with centralized smart charging. In the case studies for Swedish conditions, for the individual building level with distributed smart charging, the PV self-consumption could be increased by up to 8.7% and the peak load could be reduced by up to 53.7%. For community level with centralized smart charging, the PV self-consumption could be increased by up to 8.5% and the peak load could be reduced by up to 48.6%. With the distributed smart charging scheme, the PV self-consumption improvement on community level could be increased by up to 3.7%, while with the centralized smart charging scheme, the PV self-consumption improvement at the individual building level could be increased by up to 3.7% on average.

Based on the results, it can be concluded that the DSO will get more benefits when the centralized smart charging scheme is deployed since communal PV self-consumption and system peak load reduction are higher. On the other hand, individual users will get more benefits from the distributed smart charging deployment. Even though the DSO will benefit more from the deployment of centralized smart charging, it should be noted that it will be more challenging to deploy the centralized smart charging given the EVs are parked at each user's home and the deployment requires users' agreement. At the individual building level, while self-consumption is a direct benefit for the users, the peak load reduction is not as direct. The peak load reduction could be more beneficial if a dynamic electricity price is deployed, in which the electricity price is commonly high in the peak demand periods. Therefore, it is recommended that the DSO design dynamic electricity price schemes which trigger each user to minimize the net-load variability. In this case, the DSO only gives a price signal and the users execute the charging scheme individually based on the signal and their own PV generation profile.

Even though the smart charging objective did not directly consider grid parameters, such as grid losses and voltage deviations, the deployment of the smart charging scheme improved the grid performance as a result of reduced net-load variability. Results from Paper III showed that when one deploys a smart charging scheme that minimizes the net-load variability, the grid losses and voltage deviation levels will also decrease.

The combined PV-EV hosting capacity in a residential grid with EV smart charging and PV curtailment, was also assessed in Paper III. The improved synergy between PV and EVs was expected to improve the grid hosting capacity for both. Indeed it was shown that smart charging of EVs did not only improve the EV hosting capacity, but also the PV hosting capacity. However, the improvements in EV hosting capacity were much more significant compared to the slight improvements in PV hosting capacity. The limited improvements in PV hosting capacity were also mainly due to low vehicle availability in the residential distribution grid during midday when the PV power production were high. Results also showed that there was a positive correlation between the PV share to the EV hosting capacity, and between the EV share to the PV hosting capacity. In this case, it is shown that the increased PV share improved EV hosting capacity slightly, and the increased EV share improved the PV hosting capacity slightly.

5.2 Future work

Currently, research on the integration of PV and EVs in buildings and the energy systems is gaining interest from the scientific community and stakeholders in the power and transport sectors. Therefore, there are many interesting opportunities in this research field to explored in future work.

Generally, all the studies in this thesis can be extended to the city-scale level, where it would involve non-residential energy use patterns, heterogeneous user mobility behavior and a larger distribution grid area. The inclusion of other building and energy systems and technologies, such as electric heating systems, battery energy storage systems, heat storage, and other flexible load controls, should also be considered in future studies.

The research in Paper II can be extended by including realistic forecasts of PV and loads in the smart charging scheme and assessing the forecast reliability impacts on energy system performance. Following the research gap identified in the review article (Paper I), the trade-offs between forecast simplicity and energy performance should also be assessed in the future studies. Smart charging with different objectives that are closer to a realistic scenario for the users, e.g., smart charging based on dynamic electricity prices, can also be developed and included in future work.

In the case of combined hosting capacity, which was introduced in Paper III, it would also be interesting to implement a probabilistic approach in terms of PV and EV allocations. In that case, the impact of phase unbalance in the distribution grid will be more clearly visible. Combined hosting capacity assessments for different technologies, such as PV-wind, PV-wind-EV, PV-EV-battery, PV-heat pump-battery, etc., are also interesting to explore in future studies.

6. Conclusions

Increasing penetration of PV and EVs alters the electricity consumption of buildings and communities and poses new challenges for the electricity distribution grid. An improved synergy between PV generation and EV charging in buildings is believed to be a prospective solution. Improved synergy can be achieved by several strategies, one of which is coordination of EV charging, often called EV smart charging. In this thesis, an EV smart charging scheme for residential buildings equipped with PV systems, with an objective to minimize the net-load variability, was developed. The improvements by the smart charging scheme on energy system performance, from the building level to the distribution grid level, were assessed. Results show that EV smart charging at home with the objective to reduce the net-load variability improved the synergy between the local load and PV generation, in the form of improved PV self-consumption and reduced peak loads. Better performance was achieved with a distributed charging scheme for individual buildings, and with a centralized charging scheme for a community. For the individual building level, the PV self-consumption could be increased by up to 8.7% and the peak load could be reduced by up to 54% when the distributed smart charging scheme was deployed. For community level, the PV self-consumption could be increased by up to 8.5% and the peak load could be reduced by up to 49% when the centralized smart charging was deployed. The improved synergy also led to improved grid performance, such as lower grid losses and voltage deviation levels, and an improved combined PV-EV hosting capacity.

Acknowledgments

All praises and thanks to Allah, the Lord of the Creation, the Compassionate, and the Merciful.

First of all, I want to thank my supervisor, Joakim Munkhammar, and my co-supervisor, Joakim Widén, for giving me the opportunity to pursue the PhD degree, and for all the helps, guidance and excellent supervision during this process. I also want to thank all my co-authors —besides Joakim Munkhammar and Joakim Widén— Mahmoud Shepero, Dennis Van der Meer and Umar Hanif Ramadhani, for all interesting and fruitful discussions and collaborations. Thanks to all of my colleagues at the Division of Civil Engineering and Built Environment, which has made the Division an enjoyable working environment.

I would like to thank Swedish Electromobility Centre (SEC) and Swedish Energy Agency for funding this PhD project. I would like to also thank our industrial collaborators in this PhD project, Vattenfall Research and Development AB and China Euro Vehicle Technology AB.

Special thanks to my parents in Indonesia for all the prayers, overwhelming support and everlasting love since I was born. Thanks also goes to my Indonesian friends in Uppsala, who has made life in Uppsala fun and enjoyable for my little family, playing football with you guys and having fika and food feast are my favorite activities here!

And lastly, to the most important people in my life for now. I am so happy that this thesis (the cover) got some touches from you three. Let this be a symbol of your importance and contributions in my PhD journey. To my beloved daughters, Aisyah Hanin and Maryam Hanum, thank you for making me laugh and smile everyday, I am blessed to have you and watch you grow during this journey. Thanks also for coloring the cover of this thesis, like you are coloring my life. And to my wife, Annisa, I can't ask for a better person to accompany me in my life. Many life lessons learned, and many years to come, I am really glad that you are my learning partner in this life. I love you.

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