DTU Wind

Optimal operation of renewable-powered EV charging stations

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Abstract

This master's thesis focuses on the development and evaluation of smart charging strategies for electric vehicles (EVs) in workplace settings. The objective is to optimize the charging process and support the integration of EVs into the energy system. The thesis begins by analyzing real-world EV charging data from workplace charging stations, which provides insights into charging patterns and user behavior. These patterns are then used to design and test various smart charging strategies that utilize renewable resources and minimize costs.

The simulations and evaluations are conducted in a specific reference location, a school on the island of Bornholm, Denmark, which has an existing photovoltaic installation. The charging strategies are divided into unidirectional models that incorporate two charging sources, a photovoltaic installation and the power grid, and a bi-directional smart charging model that also enables direct charging between EVs.

The results of the simulations reveal several important findings. Workplace charging stations experience high charging activity in the early morning hours, followed by a more consistent pattern throughout the day. The most common charging power level is found to be 3.7 kW, and idle times of 4-8 hours are prevalent, indicating opportunities for the implementation of smart charging strategies.

The performance of the charging strategies is evaluated under different scenarios, considering factors such as the price profile of the day-ahead market and the availability of renewable resources. The simulations demonstrate that no single strategy is optimal for all situations. The bidirectional vehicle-to-vehicle (V2V) strategy becomes attractive in scenarios with strong cannibalization of renewable energies, allowing for energy transfer between vehicles during expensive hours. Strategy 3, which effectively utilizes abundant solar resources and prioritizes charging based on vehicle urgency irrespective of power prices, demonstrates excellent performance in scenarios with ample solar availability. Strategy 4, which takes advantage of cheap market periods while maximizing PV energy absorption, is beneficial in scenarios without significant cannibalization and limited PV production. Overall, the simulations highlight the significant advantages of smart charging strategies compared to dumb models.

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1 Introduction

This report provides an overview of the development process and characteristics of various electric vehicle (EV) charging strategies programmed in the Python environment. These strategies are designed to be tested and simulated in different scenarios, aiming to optimize the charging process for EVs.

The initial four charging strategies exemplify unidirectional models, which not only rely on grid charging but also incorporate a secondary charging source, specifically a photovoltaic installation. This secondary source serves as a reference for the final simulations, introducing the concept of utilizing renewable energy for EV charging. Additionally, the report presents the development of a bi-directional smart charging model with a specific focus on vehicle-to-vehicle (V2V) charging. This model extends beyond the previous energy sources by enabling direct charging between EVs.

To ensure the fidelity of the simulations, it was crucial to utilize real-world data. Spirii [21], both a charge point operator and platform provider, that have been leading the charge towards smarter, simpler eMobility, supplied an extensive dataset of EV charging events. The dataset was analyzed to identify the main charging patterns, which were then applied to a representative sample.This representative sample was then utilized to conduct simulations for the different charging strategies, enabling a thorough evaluation of their performance.

While the ultimate objective of this thesis is to contribute to the development and deployment of large-scale EV charging infrastructure, the simulations are conducted within a specific reference location. The reference location is an existing photovoltaic installation at a school on the island of Bornholm, Denmark. This installation, part of the H2020 European project EV4EU, plans to install 12 EV charging points. By utilizing this reference location, the simulations can demonstrate the potential benefits and effectiveness of the developed charging strategies in a practical setting.

1.1 Motivation

The urgent need to mitigate the impact of CO_2 emissions and promote sustainable energy solutions has propelled governments worldwide to actively discourage the use of fossil fuels and embrace environmentally-friendly technologies. In the pursuit of sustainable transportation, the global deployment of electric vehicles (EVs) is expected to witness exponential growth, with estimates projecting 50 million units by 2025 and 140 million units by 2030 [22]. This rapid adoption of EVs presents a significant opportunity for reducing greenhouse gas emissions. However, the widespread integration of large-scale EV fleets into the power grid introduces new challenges related to the stability and security of the distribution system [23],[24].

The primary concern associated with the integration of EVs is the increased power demand that may exceed the capacity of existing grid components, potentially causing disruptions and compromising grid stability [25]. To effectively manage this challenge, smart charging technology emerges as a viable solution. By implementing intelligent control strategies, smart charging enables the regulation of EV charging power, offering flexibility and adaptability to the charging process. This flexibility can be achieved through various control architectures that allow for modulation and shifting of the charging load.

To this scope, this master thesis seeks to compare and evaluate different smart charging strategies for various EV charging scenarios, with a specific focus on electric vehicle parking lots at workplace settings. The aim is to demonstrate the feasibility and effectiveness of these strategies in supporting network enhancement and providing assistance to the distribution grid. By showcasing the potential benefits of smart charging, this research contributes to the efficient integration of EVs into the energy system and facilitates the transition towards a sustainable and resilient transportation infrastructure.

1.2 Objective

The primary objective of this thesis, conducted as part of the H2020 European project EV4EU, is twofold.

What is the optimal way to manage EV charging in workplace charging stations?

This is the fundamental question that drives the objective of this thesis. The primary goal is to develop energy management strategies specifically tailored for electric vehicle (EV) parking lots in workplace settings. These strategies will address the challenges associated with renewable resource availability and spot market prices, aiming to optimize EV charging efficiency.

Through exhaustive evaluation and comparison, the thesis aims to assess the performance of these strategies using various metrics such as cost, self-sufficiency, and EV charging satisfaction. Different scenarios will be considered, encompassing varying levels of renewable resource quantity and spot market prices throughout the year.

The ultimate goal of this project is to demonstrate efficient EV management strategies that facilitate the widespread adoption of electric vehicles, taking into account the current and future market dynamics and the availability of renewable resources.

2 State-of-the-Art of Electric Vehicle Smart Charging

This chapter describes the state-of-the-art of smart charging technology for electric vehicles (EVs). This content covers different configurations, the concept of smart chargers, advantages of smart chargers over traditional chargers, and the control architectures employed in smart charging systems. The information provided highlights how smart charging contributes to grid flexibility, optimizes EV charging, and enables EVs to become valuable assets in the power system.

2.1 Smart charging definition

At the heart of smart charging lies the concept of a smart charger, which offers significant advantages over traditional, non-intelligent chargers, commonly referred to as dumb chargers. A smart charger is a device equipped with advanced functionalities that enable it to interact with the grid, adapt power consumption, and provide grid services. In contrast, a dumb charger operates without the ability to adjust its charging behavior based on grid conditions or user preferences [26]. A smart charger provides protection, communication, at least scheduling and at most modulation and phase curtailment (3 to 1-phase switch) for the EV charging process [27].

2.2 Dumb and smart charger comparison

Compared to dumb chargers, smart chargers offer several key advantages that contribute to grid flexibility and optimize EV charging [28]. Firstly, smart chargers provide the capability to schedule charging, allowing users to optimize charging times and take advantage of lower electricity prices during off-peak hours. This feature not only benefits individual EV owners but also supports grid stability by shifting charging demand to periods of lower overall electricity consumption [29].

Secondly, smart chargers possess modulation capabilities, allowing for control over the charging current. By adjusting the charging rate, smart chargers can respond to grid conditions and dynamically manage power flow. This ability enables load balancing and helps mitigate the negative impacts of simultaneous EV charging, reducing strain on distribution transformers and preventing grid congestion [30].

Furthermore, smart chargers can incorporate bidirectional power flow capabilities, as seen in vehicle-to-grid (V2G) technology. This means that EVs equipped with V2G-enabled chargers can not only draw power from the grid but also inject surplus energy back into the grid during periods of high demand or grid instability. This bidirectional power flow capability offers the potential for EVs to provide ancillary grid services, such as frequency regulation and demand response, enhancing grid reliablity and resilience [31],[32].

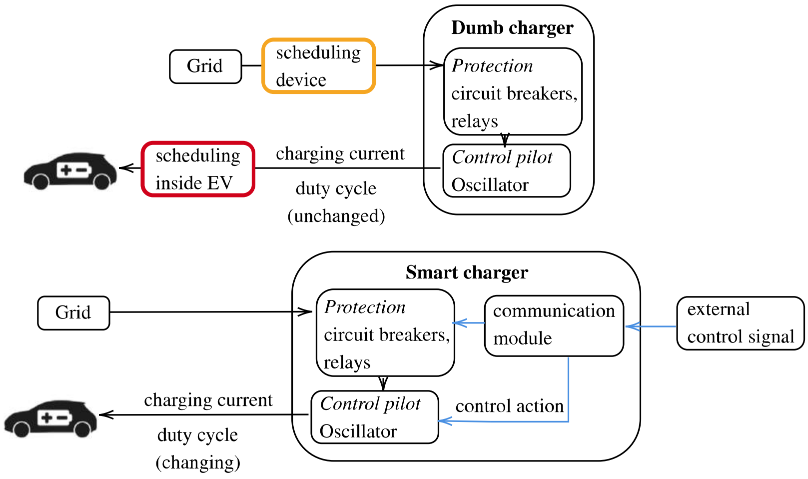

Figure 2.1. Illustration of different smart charging configurations [26]

A smart charger contains a communication module and can manage the control pilot duty cycle, thus modulating or scheduling the charging process. Scheduling refers to turning on–off the charging process. Modulating refers to controlling the charging current through the control pilot. An optional action of smart chargers is the ability to control the open-closure of the relays, which allows a three-phase capable EV to perform a switch from three-to-one phase charging, hence, curtailing two of the phases [26]. Here, it should be underlined that those chargers which can control their relays also offer the 0 A, Amp current option. This means that they can keep the EV on-board charger awake without drawing any current for the charging process.

2.3 Smart charging configurations

EV clusters can be deployed both behind the meter (BTM) and in front of the meter (FTM). BTM services are services provided to the users and they consist of load coordination among different EVs, buildings (residential, commercial or industrial) and eventual distributed energy resources (DER) at the connection point. FTM services are provided to the Distribution System Operators (DSOs). In this case the EVs can be coordinated in groups by aggregators and provide their flexibility directly to the grid [33].

In figure 2.2 the possible smart charging configurations are illustrated. The unidirectional power flow (V1G) chargers allow the car to adjust its rate of charging. Additionally, the vehicle-to-grid (V2G) technology allows to inject power back to the grid. These configurations are FTM because the charger interacts directly with the grid and can be directly controlled by the DSO or aggregator [34]. The other two are vehicle-to-home (V2H) and vehicle-to-vehicle (V2V), both BTM configurations.

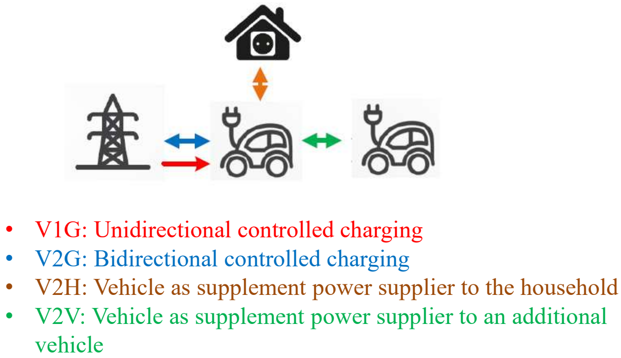

Figure 2.2. llustration of different smart charging configurations [35]

2.4 Control architecture

The coordination and control of different clusters of smart chargers need to be performed effectively by the DSO, user or aggregator. Different control architectures have been proposed and investigated in the literature [33]. They can be categorized into centralized, decentralized or distributed control architectures. The centralized architectures rely on a central intelligence called Cloud Aggregator (CA), which controls all the chargers directly.

In the decentralized approach, the intelligence is called Virtual Aggregator (VA). The VA resides in each charger and is therefore sensitive to local measurements. Since the centralized control relies on a single server, it is prone to disconnection errors and delays. On the other hand, the decentralized system is very robust, although its controlling capacity is less efficient due to the limited data it receives from the system. Finally, the distributed control approach combines the benefits from both architectures. It is able to coordinate between local control and global control because it communicates both with VA and CA [36],[37],[38].

Table 2.1. Advantages and drawbacks of EV chargers control approaches [26],[39]

Control approach	Advantages	Drawbacks
Centralized	• System wide observation • Easier implementations of optimization algorithms	• Need of a backup server system • Heavy communication and computation when scaled-up • Subject to cyber-attacks and possible data privacy violation • Vulnerable to cloud aggregator malfunction being spread on all chargers
Decentralized	• Diverts data privacy challenges • Low communications and computation capabilities when scaled-up • Low sensitivity to errors and cyber-attacks, thus high system robustness • High deployment scalability • Low communication delays	• Lack of grid observability • Immature control architecture • Risk of avalanche effects • Difficult to reach optimal solutions from optimization algorithms
Distributed	• High scalability and autonomy • System wide observation • Low sensitivity to errors, thus high system robustness • Diverts data privacy challenges • Possibility of plug and play protocols • Low communication delays	• Novel control architecture, thus not mature • Prone to cyber-attacks • High complexity on charger design

2.5 Current research on smart charging strategies

The upcoming section will provide an overview of various smart charging strategies proposed in existing literature. These strategies have been developed to address the challenges associated with the integration of electric vehicles into the power grid and optimize their charging process. Following the discussion of existing strategies, this thesis aims to contribute to the field by proposing novel smart charging approaches tailored specifically for workplace charging stations.

2.5.1 Existing strategies

Table 2.2. Comparison of different studies considering various aspects of EV charging

Reference	Aspect considered	Study contribution
Deilami et al., 2011 [40]	Coordinated EV charging	Proposes a novel load management solution for coordinating the charging of multiple plug-in electric vehicles incorporating time-varying market energy prices and owner preferred charging time zones.
Hexeberg, 2014 [41]	Smart charging	Creates different scenarios for testing its proposed profit maximization smart charging strategy in Matlab, considering V2G capability based on low price signals, allowing to improve voltage stability in lines.
Nour et al., 2019 [42]	Smart charging	Smart charging technique is proposed and tested with simulation based on a controller that regulates and controls the EV charging power depending on electricity price signal and battery state-of-charge.
Zweistra et al., 2020 [43]	Smart charging	Smart charging strategy varying charging power based on DSO signals to keep grid within certain limits and operated it in real world with a great EV fleet.
Tveit et al., 2023 [44]	Smart charging	Price based: In the first strategy, EV charges according to an electricity price signal, based on day-ahead market and time-of-use tariffs. Emission based: aims to minimize carbon footprint by charging during periods of lower carbon levels in the grid, based on the day-ahead and intraday market which predicts the generation mix and the subsequent emissions.

2.5.2 Contribution of this thesis

This thesis makes the following contributions to the research of smart charging strategies in EV parking lots at workplaces.

1. **Realistic User Behavior Analysis**: It tests all smart charging (SC) strategies considering realistic electric vehicle (EV) user behavior in terms of plug-in/out times,

varying energy demands, and charging power levels.

2. **Integration of Multiple Market Prices and Renewable Energy**: Several strategies are proposed that integrate day-ahead market prices with real solar photovoltaic generation, thereby maximizing the use of renewable energy as well as minimizing costs.
3. **Broad Charging Strategies**: Not only unidirectional strategies are proposed but also bi-directional vehicle-to-vehicle strategies to take full advantage of the low market prices.
4. **Coordinated Charging through Queue Management**: It innovatively coordinates the simultaneous charging of multiple vehicles through queue management, which distinguishes this research from other studies.
5. **Extensive Simulation Scenarios**: Simulations are conducted across different seasons of the year and for an extended period (one week), rather than being limited to a single scenario, which enhances the thoroughness and applicability of the findings.

3 EV CHARGING ANALYSIS

This chapter describes the process of analysing electric vehicle charging data from real charging events provided by the charging operator Spirii.

The objective of this analysis is to understand the typical charging patterns observed in workplace stations where slow chargers are used. By studying these patterns, it is aimed to gather important information about the charging processes, such as their duration, power, and energy consumption. This data will then serve as a representative sample, allowing testing and running simulations based on real-world scenarios.

3.1 Provided data

A total of 4214 real EV charging events from five different workplace stations across Denmark were provided, containing the following information:

- City
- chargeBox-Identity
- Arrival time
- Departure time
- Energy consumed (kWh)
- Charging time (s)
- Idle time (s)
- Park time

It is worth mentioning that idle time is defined as the period when the EV is connected but no current is flowing through the charger, i.e. when the charger is plugged in but the battery is not being charged/discharged (see Figure 3.1).

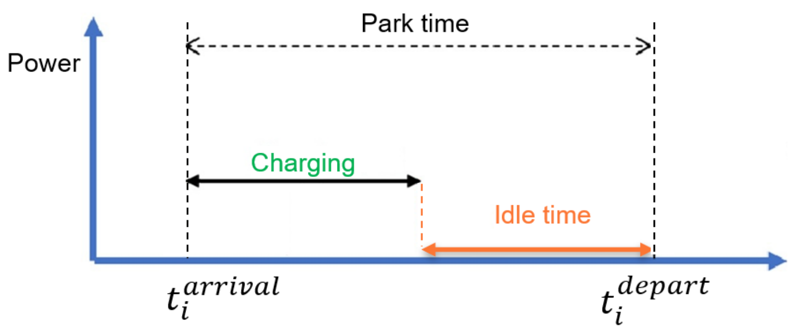

Figure 3.1. Charging process

3.2 Data clearing

With the information available for every charging event, the average charging power was calculated as follows:

$$Average\ Power\ (kW) = \frac{Energy\ consumed\ (kWh)}{Charging\ time\ (h)}$$

In compliance with the international standard (IEC 61851-1) [1] that specifies the requirements and testing methods for electric vehicle conductive charging systems, it has been dismissed any charging event that does not qualify for the AC slow charging requirements under the above-mentioned standard.
This is, either having an $Average\ Power(kW)$ under $1.4\,kW$ [4], which means operating under $6\,A$ ($230\,V$, $1-phase$) or above $22\,kW$, i.e. $32\,A$ ($230\,V$, $3-phase$). After removing all the inconsistencies, the total number of events dropped to 3522.
In the following section the different charging patterns will be discussed.

3.3 Charging patterns

In order to gain an initial understanding of the relevant variables associated with the charging events, a visualization was conducted using probability density plots. This method allows for a comprehensive analysis of the distribution and main characteristics of the variables. By plotting the probability density of the *Arrival time*, *Idle time*, *Average power*, *Energy consumed*, *Charging time*, and *Park time*, it is observed the shape and trends within the data.

This approach enables a subsequent comparative analysis between the population and the randomly drawn samples, facilitating a rigorous assessment of the sample's representativeness. By juxtaposing the population data with the randomly selected samples, it is possible to discern any disparities or similarities in their characteristics. This efficient methodology aids in evaluating the extent to which the sample accurately reflects the broader population.

It is noteworthy that the charging behaviors exhibit consistent patterns across seasons, indicating that the characteristics described below remain relatively stable throughout the year. This finding suggests that the factors influencing EV charging, such as arrival times, charging durations, and power levels, do not exhibit significant variations based on seasonal changes. This consistency in charging behaviors reinforces the potential for developing robust and reliable models and strategies for EV charging management that can be applied consistently throughout the year.

3.3.1 Arrival time

The analysis of the probability density curve in Figure 3.2 reveals a distinct peak in electric vehicle arrivals around 07.00h-09.00h, aligning with the start of many work shifts. This observation underscores the strong correlation between charging patterns and typical commuting hours. Moreover, the probability density curve extends throughout the day until 12 midnight, although with significantly lower probabilities. This signifies the possibility

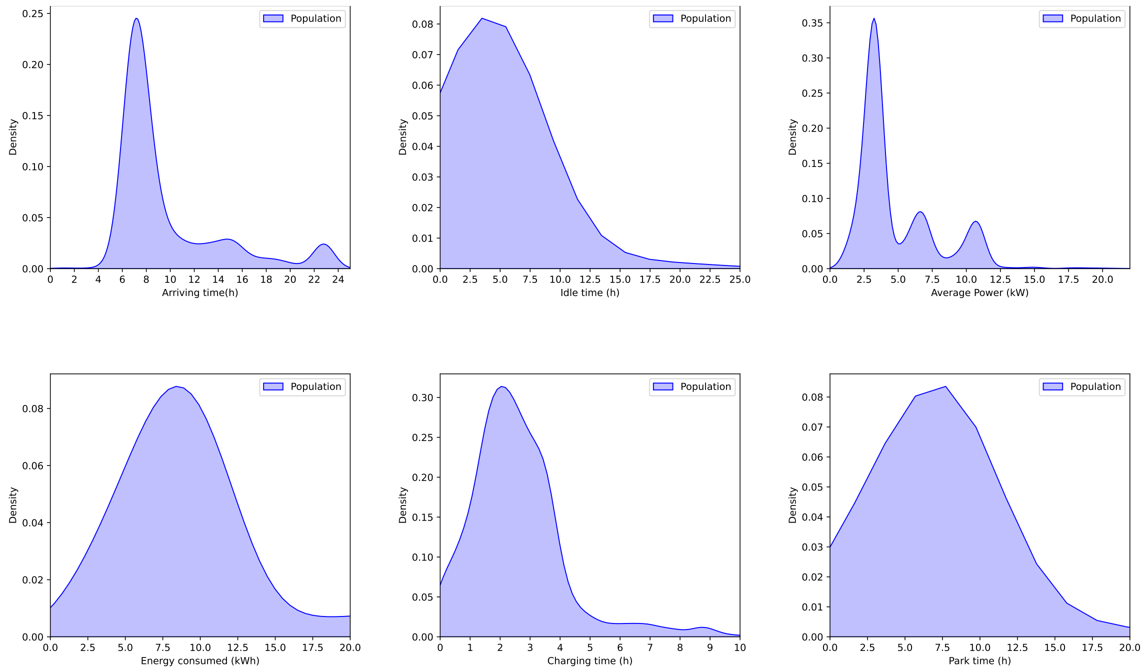

Figure 3.2. Distribution density of population variables

of EVs visiting the charging station at various times, albeit with diminished frequency beyond the early morning peak.

3.3.2 Idle time

The probability density plot of the idle time reveals that the total park time does not always match with the total charging time. Specifically, there are instances where the vehicle remains connected to the charging station without drawing any current for the charging process. This observation highlights the potential for developing advanced smart charging models in subsequent stages of research. The findings underscore the importance of studying and addressing the idle time phenomenon, which can significantly impact the optimization and efficiency of EV charging processes.

3.3.3 Average power

In this analysis, three prominent peaks are observed in the probability density plot, each associated with distinct average charging powers: 3.7 kW, 7.4 kW, and 11.04 kW. Notably, the probability of encountering a charging power of 3.7 kW is significantly higher compared to the other two power options, which exhibit lower probabilities and remain less frequent. These findings underscore the prevalence of EV charging instances characterized by a charging power of 3.7 kW, suggesting its dominant usage in the examined context. The above-mentioned charging powers, correspond to the following charging conditions:

1. $P_{3.7kW} = 16A \cdot 230V/1000 \cdot (1 - phase) = 3.68kW$
2. $P_{7.4kW} = 32A \cdot 230V/1000 \cdot (1 - phase) = 7.36kW$
3. $P_{11.04kW} = 16A \cdot 230V/1000 \cdot (3 - phase) = 11.04kW$

3.3.4 Energy consumed

The analysis reveals that the probability density function closely resembles a normal distribution, indicating that the mean energy charged per event is typically around 8-10 kWh. It is important to note that the specific energy charged can vary based on the state of charge (SOC) of the vehicle upon arrival at the charging station. However, for the purpose of developing subsequent models, the SOC consideration lies beyond the scope of this research. By focusing on the probability distribution of energy charged, valuable insights can be gained for the optimization and design of charging strategies, regardless of the initial SOC.

3.3.5 Charging time

This property is intimately linked to the power (specifically the current (A)), and the amount of energy consumed, since the charging time is defined as

$$Charging\ time(h) = \frac{Energy\ consumed(kWh)}{Average\ power(kW)}$$

Hence, a notable range of probable charging durations (1-4 hours) is observed, influenced by the specific power level at which the charging process occurs among the three distinct options identified earlier. The actual charging time within this range is contingent upon the chosen power level.

3.3.6 Park time

Lastly, the total parking time encompasses the cumulative effect of both idle time and charging time, capturing the combined duration of the vehicle's presence at the charging station. It serves as an indicator that accounts for the time spent not only during the charging process but also during periods of idleness when no current is flowing. By considering the total parking time, a broad view of the overall utilization of charging stations can be obtained.

3.3.7 Correlation between key variables

Examining the correlations between key variables is crucial due to the importance of arrival time in shaping charging strategies and managing diverse vehicle arrivals. 3D probability density plots are utilized to depict the relationships between these variables. By analyzing these correlations, insights can be gained into the complex interactions and dependencies among the variables, providing a deeper understanding of their interplay in the context of EV charging management. Figure 3.3 reveals a crucial finding regarding the correlation between arrival time and idle time, highlighting the considerable flexibility exhibited by the majority of vehicles arriving at the charging station, which is during the morning hours. This observation indicates that these vehicles are more prone to having a significant period of parking time when no power is drawn (idle time) lasting approximately 4-8 hours. This extended idle time presents an opportunity for the development and implementation of smart charging strategies and technologies, enabling efficient utilization of charging resources.

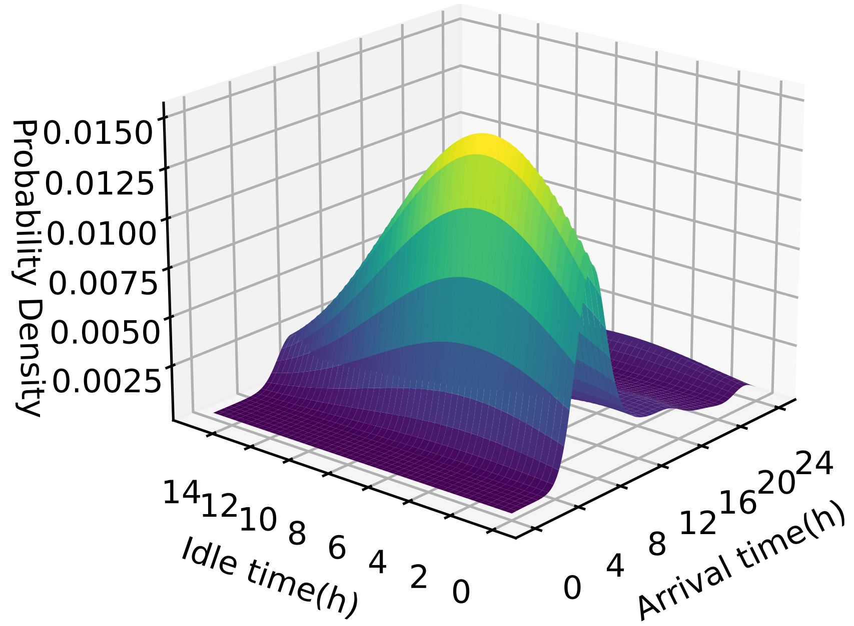

Figure 3.3. Probability density plot *arrival time-idle time*

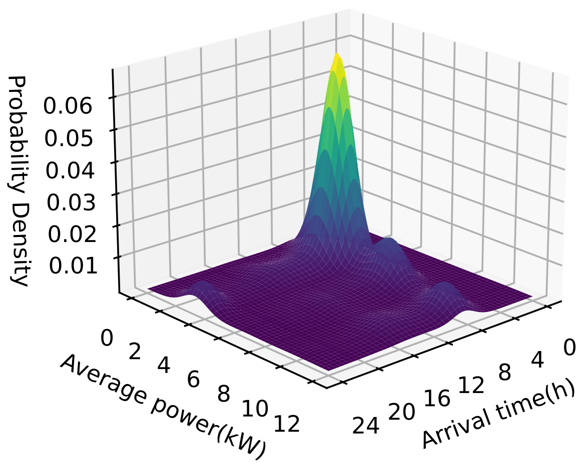

Figure 3.4. Probability density plot average power - arrival time

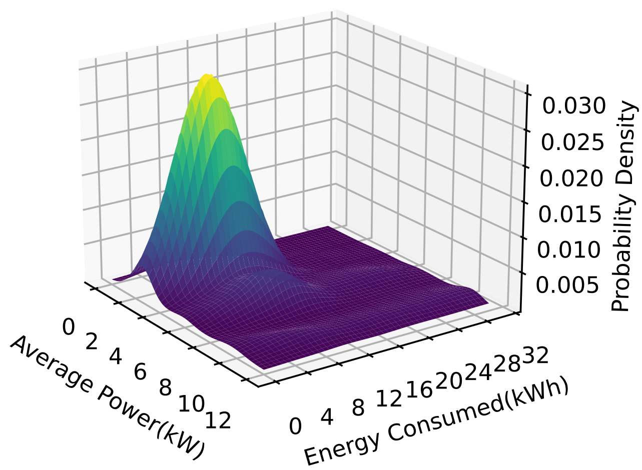

Figure 3.5. Probability density plot average power - energy consumed

In Figure 3.4, it is evident that the distribution of the three types of charging power (as analyzed in Figure 3.2) maintains a consistent proportion among vehicles arriving early in the morning (7-9 am). However, this pattern shifts as the day progresses. Towards the end of the day, the presence of EVs with a charging power of 7.4 kW becomes increasingly rare, and even among the late arrivals, vehicles predominantly exhibit a charging power of 3.7 kW. This shift in the distribution of charging power throughout the day signifies a changing preference for lower power levels among EVs arriving at later hours.

Figure 3.5 provides insights into the distribution of energy consumed, reinforcing the earlier findings of the most probable values centered around 8-10 kWh (as analyzed in Figure 3.2) for charging powers of 3.7 kW and 7.4 kW. However, for the highest observed power of

11.04 kW, the energy distribution exhibits a more dispersed pattern without a prominent peak in the vicinity of the aforementioned energy range. Additionally, small elevations can be observed at very low energy figures, likely representing short-duration charging events, as well as at higher energy levels, possibly indicating larger EVs with higher energy requirements.

3.4 Representative sample extraction

The subsequent section outlines the methodology employed to extract a representative sample from the original dataset, aiming to capture the behavioral characteristics of the larger population. This sample will be utilized to validate and execute simulations using the developed models in subsequent sections. By carefully selecting a sample that accurately reflects the population's behavior, the validity and applicability of the developed models can be effectively evaluated, enabling insightful analysis.

Step 1
In order to capture the significance of the *arrival time* variable, which serves as a key determinant of EV charging behavior, a systematic approach was employed to collect a representative sample. Specifically, "N" random arrival times were selected from the original dataset. This sampling strategy ensures that the selected arrival times effectively capture the diverse range of EVs arriving at different hours throughout the day.
Step 2
To preserve the correlation between the key variables, a meticulous process was undertaken. For each of the initial "N" *arrival time* samples, a new range was derived by adding and substracting "0.5h", as an example, $[n_1 - 0.5,\ n_1 + 0.5]$. This range was then used to filter the original dataset, resulting in a subset of data specific to each arrival time. Subsequently, random values were assigned to the associated variables, namely *energy consumed*, *average power*, and *park time*, within this filtered dataset. This rigorous methodology ensures that the selected variables maintain their intrinsic relationships and allows for a exhaustive exploration of the interdependencies among them.
Step 3
As a crucial step in the data processing, an adjustment is required for the average power values obtained in step 2. These values need to be converted into plausible power levels identified in section 3.3.3, namely 3.7 kW, 7.4 kW, and 11.04 kW. To accomplish this, the *average power* data is utilized and the new variable *average power'* is obtained by assigning the closest feasible power level.

Then, the charging time is calculated as

$$Charging\ time\ (h) = \frac{Energy\ consumed\ (kWh)}{Average\ power'(kW)}$$

which allows for the determination of the duration required for charging.

Subsequently, the idle time can be derived by subtracting the charging time from the park time as

$$Idle\ time\ (h) = Park\ time\ (h) - Charging\ time\ (h)$$

Step 4

In the final step, the obtained samples undergo a viability check to ensure their physical feasibility. Specifically, if the calculated idle time is found to be negative, the sample is deemed impractical and subsequently discarded. This criterion is applied to ensure that the vehicle has a sufficient duration of park time to accommodate the minimum required charging time at the designated power level. By excluding samples with negative idle times, the dataset is refined to include only viable charging scenarios that adhere to the minimum power and time requirements.

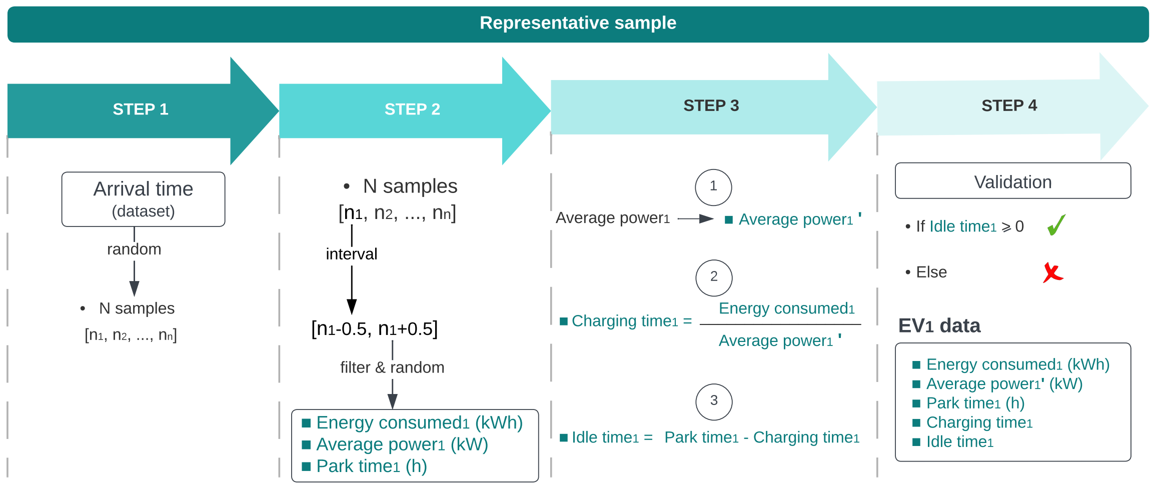

Figure 3.6. Representative sample extraction process

Sample comparison

To provide a visual representation of the sample extraction results, two different sample sizes are presented. It is important to note that the population consisted of 3522 charging events. Figure 3.7 depicts a comparison of the sample (N=20) and the original population dataset, in terms of the six key variables that define the EVs. Although variables like *charging time* or *arrival time* do not precisely match the probability profile of the population, they exhibit a similar overall shape. However, variables such as *average power* fail to accurately represent the three characteristic peaks observed in the original population.

The comparison for the sample size of N=400, Figure 3.8, demonstrates a remarkable similarity between the probability density profiles of all variables and the corresponding profiles observed in the population dataset. The sample accurately captures the existing peaks and closely follows the distribution patterns of the population. This indicates that the sample dataset is highly representative of the population characteristics.

The sample size of N=400, provides a reasonable and sufficient number of cars to be considered as input for the simulations conducted in the subsequent sections. With this sample size, the simulations can effectively capture the diversity and variability of the EV charging behavior observed in the population.

During the validation process, it is noteworthy that out of the first sample size of N=20, a total of 18 cases were deemed viable after applying the feasibility check (step 4). This indicates that the majority of the samples successfully met the necessary criteria for physical viability.

In the case of the second sample size, a significant number of 345 cases, out of 400, passed the feasibility check, highlighting the suitability and representativeness of the sample dataset.

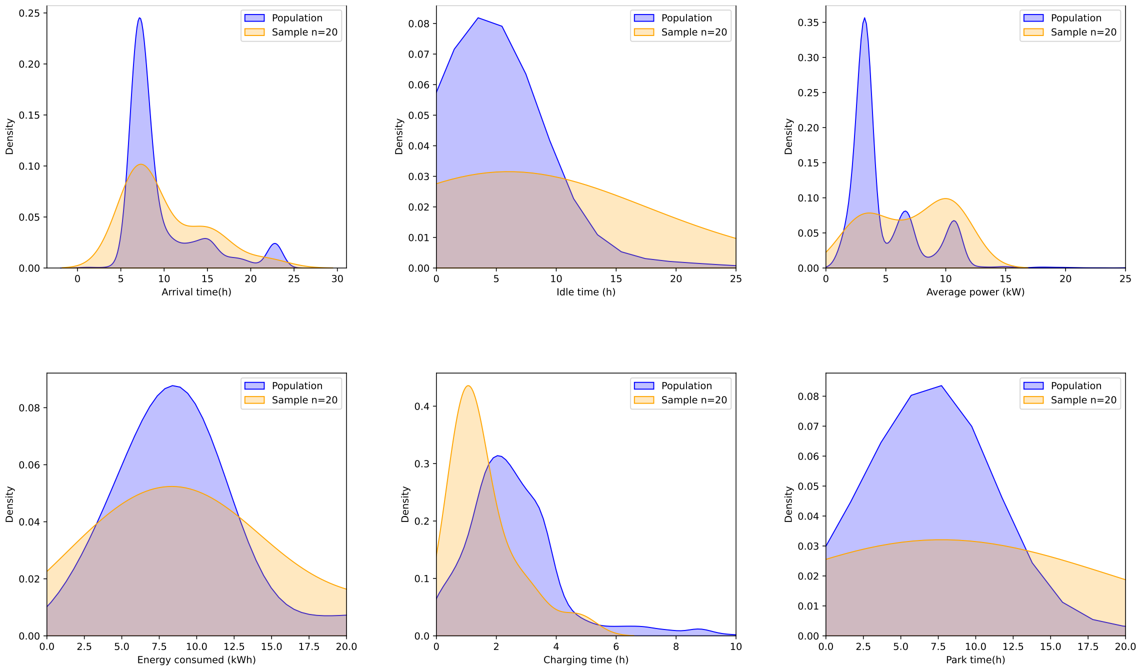

Figure 3.7. Sample extraction, N=20

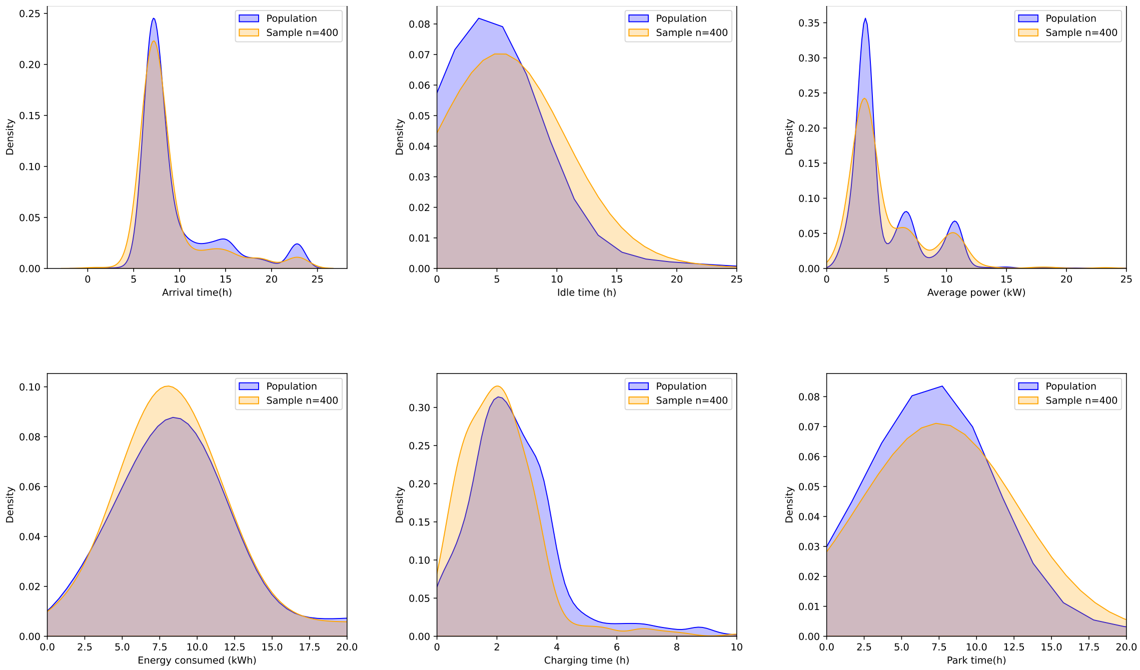

Figure 3.8. Sample extraction N=400

3.5 EV data for charging

During the simulations applying the smart charging strategies that will be below developed, the goal is to have access to the following information, which is obtained through the above-mentioned process:

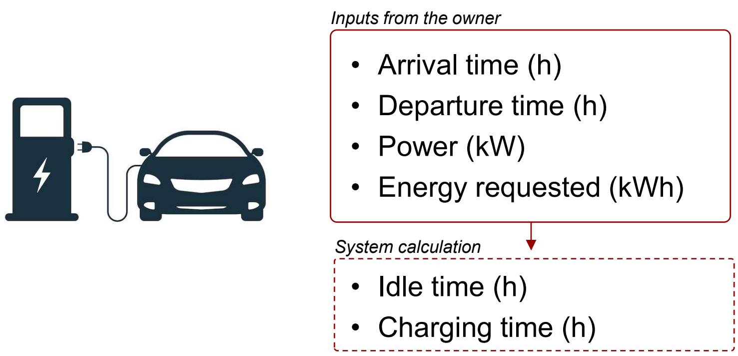

Figure 3.9. Available EV data for the charging process

4 EV CHARGING STRATEGIES

In the following section, a detailed description of the developed EV charging strategies will be provided. This exploration aims to offer a broad understanding of the distinct features and functionalities of each strategy. Through a thorough examination of these characteristics, a meaningful comparison between the strategies will be shown in the subsequent simulations.

The first strategy that has been developed is referred to as "dumb charging." This strategy replicates the conventional approach commonly observed in current EV chargers, where vehicles are charged without the application of any smart charging techniques.

The second model aims to ensure that all vehicles receive a minimum amount of renewable energy. This approach involves the equal distribution of renewable energy throughout the charging period among all connected EVs.

The third strategy focuses on prioritizing the allocation of renewable energy to vehicles with limited remaining park time. By doing so, this strategy aims to optimize the use of renewable resources.

In addition to considering urgency, the fourth strategy also incorporates spot market prices into its decision-making process. This enables vehicles to charge a portion of their energy during periods when electricity prices are lower, further optimizing the cost-effectiveness of charging.

The fifth and final strategy builds upon the principles of the previous strategies by considering market prices and encouraging charging during off-peak hours. Furthermore, this strategy introduces the concept of bi-directional charging, enabling energy exchange between vehicles.

4.1 Strategy 1: Dumb charging

4.1.1 Rationale

The main reason for developing this strategy is to be able to benchmark the most commonly adopted EV charging model [3], in order to compare it in the different scenarios with the subsequent suggested strategies.

4.1.2 Characteristics

The main characteristic of a dumb charger, as defined in [2], is that the electric vehicle begins charging at its maximum power as soon as it connects to the charging station. The charging process continues at this maximum power until the EV acquires the desired amount of energy demanded. The maximum power, $P_{ev\,max}$ which will be one of those analysed in section 3.3.3 i.e., (3.7, 7.4, 11.04 kW) can be supplied either solely from the grid, or exclusively from solar photovoltaic generation, or through a combination of both sources.

Note that *PV available* indicates the amount of photovoltaic power that could potentially charge the EV in consideration, and is updated for each vehicle as it is calculated as the total solar resource available in a time step, minus the power already allocated to the first arriving vehicles.

4.1.3 Flowchart

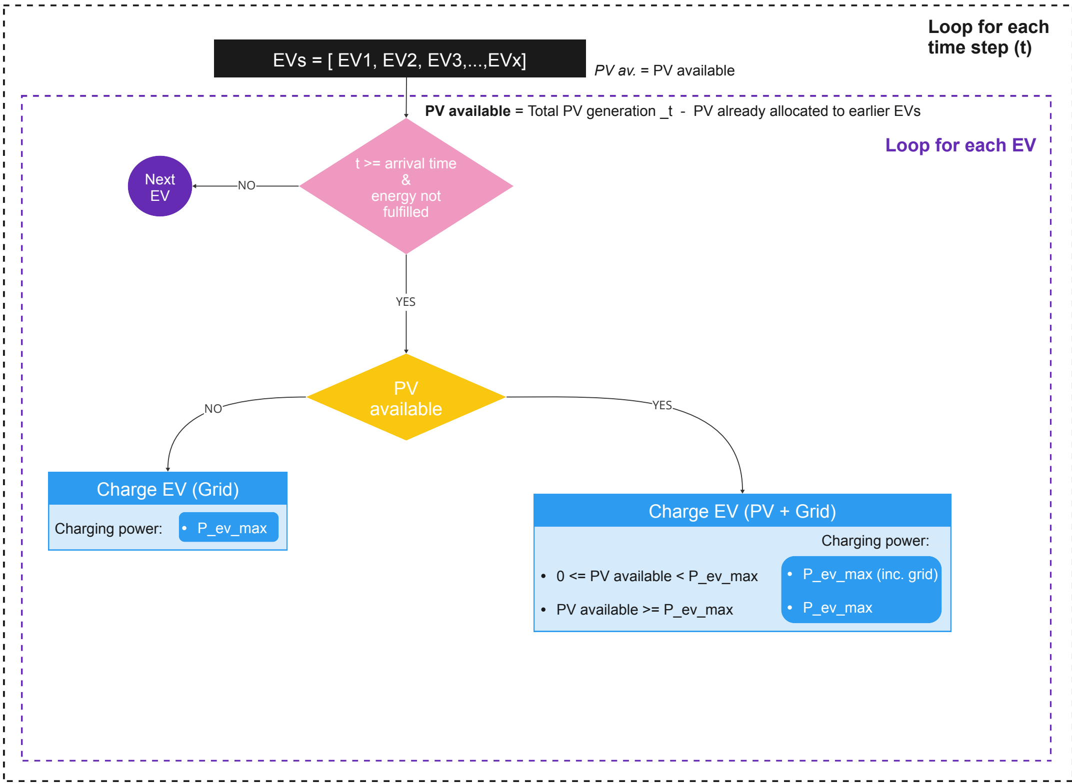

Figure 4.1. Flowchart dumb model

4.2 Strategy 2: Equal share of PV

4.2.1 Rationale

To prioritize the use of renewable energy, a strategy is implemented where any available power generated by the photovoltaic (PV) system is allocated equally among all vehicles present at the charging station. This approach ensures that each vehicle receives a fair share of renewable energy for charging purposes. By distributing the available renewable power among all vehicles, the strategy aims to maximize the utilization of clean energy sources and minimize reliance on conventional grid electricity.

4.2.2 Characteristics

In this strategy, smart charging techniques are implemented to enhance the efficiency and utilization of renewable energy. Modulation of charging power levels is employed, allowing for charging at various levels that differ from the maximum power capacity of the electric vehicle $P_{ev\,max}$.

Furthermore, the strategy utilizes idle time management, where vehicles are kept on standby until a certain amount of renewable energy generation becomes available.

Moreover, if the distribution of available PV power among vehicles results in a value less than the minimum power requirement of 1.4 kW, following (IEC 61851-1) [1] standard requirements, the remaining power up to the minimum is drawn from the grid. This approach ensures that no solar energy is wasted, regardless of how small the available amount may be.

At the point where there is no more available idle time, the vehicle needs to be charged within subsequent time steps until its departure, it is worth mentioning a new variable P_{ev} that is utilized to minimize the power drawn from the grid, and is updated every time step. As a reminder:

$$P_{ev\,max}(kW) = \frac{Energy\ demanded(kWh)}{Charging\ time(h)}$$

and,

$$P_{ev\,t}(kW) = \frac{Energy\ demanded\ (kWh) - Energy\ supplied_t\ (kWh)}{Park\ time\ left\ (h)}$$

Basically, P_{ev} represents the power at which the EV should be charged for the remaining parking time to leave the charging station with all the required energy fulfilled. See a simple example to understand how P_{ev} varies over the parktime. In this example, the time

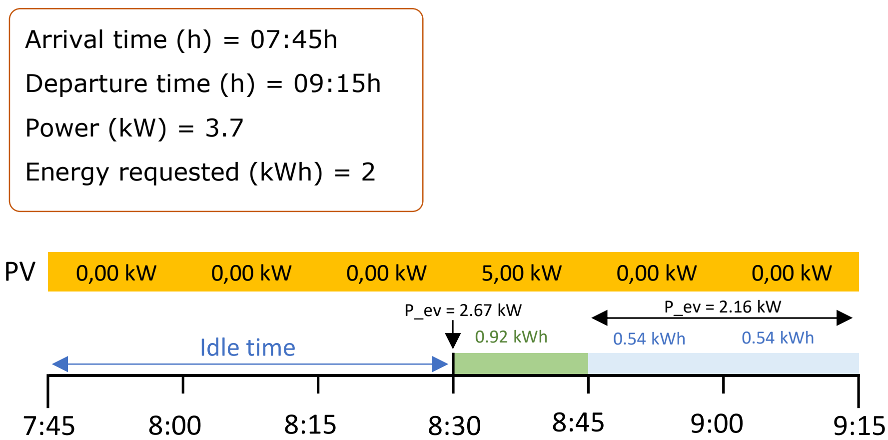

Figure 4.2. Example of how P_{ev} varies with time

resolution is 15 minutes, and there is only PV available at 8:30 for 15 minutes, with the power indicated in Figure 4.2, $P_{PV\,08:30} = 5kW$. From the moment the EV is connected, as there is still some idle time available and there is no PV, the car remains on standby, until the point is reached (08:30h) at which it must start charging from the grid to meet the energy demand in time.

- (08:30h) If there was no PV power available, the EV should have charged from the grid at:

$$P_{ev\,8:30}(kW) = \frac{2-0\,(kWh)}{\frac{45\,min}{60\,min/h}\,(h)} = 2.67\ kW$$

  However, the model prioritizes the use of renewable energy sources above grid electricity to minimize waste of available PV power. As a result, in this time step, the EV charges at the maximum power capacity, denoted as $P_{ev\,max}$, utilizing $3.7kW \cdot 15/60h = 0.92\ kWh$ of clean energy from the renewable source.

It can be seen that in absence of PV power at 08:30h, the EV would not have charged from the grid at its maximum power capacity, but rather at the minimum power necessary to meet the energy demand requirement, i.e., P_{ev}. This approach enables the opportunity to capture and utilize the maximum available renewable power during the remaining parking time.

- (08:45h) At this point there is no more PV power available, and as the remaining energy to be charged (2-0.92) kWh is too much to be fulfilled only in the last time step, it is required to start charging at this point. The power at which the energy is drawn from the grid, is:

$$P_{ev\,8:45}(kW) = \frac{2-0.92\ (kWh)}{\frac{30\,min}{60\,min/h}\,(h)} = 2.16\ kW$$

  Consequently, the energy charged at that time step is 0.54 kWh from the grid.

Same procedure occurs in the following time step starting at 09:00h.

4.2.3 Flowchart

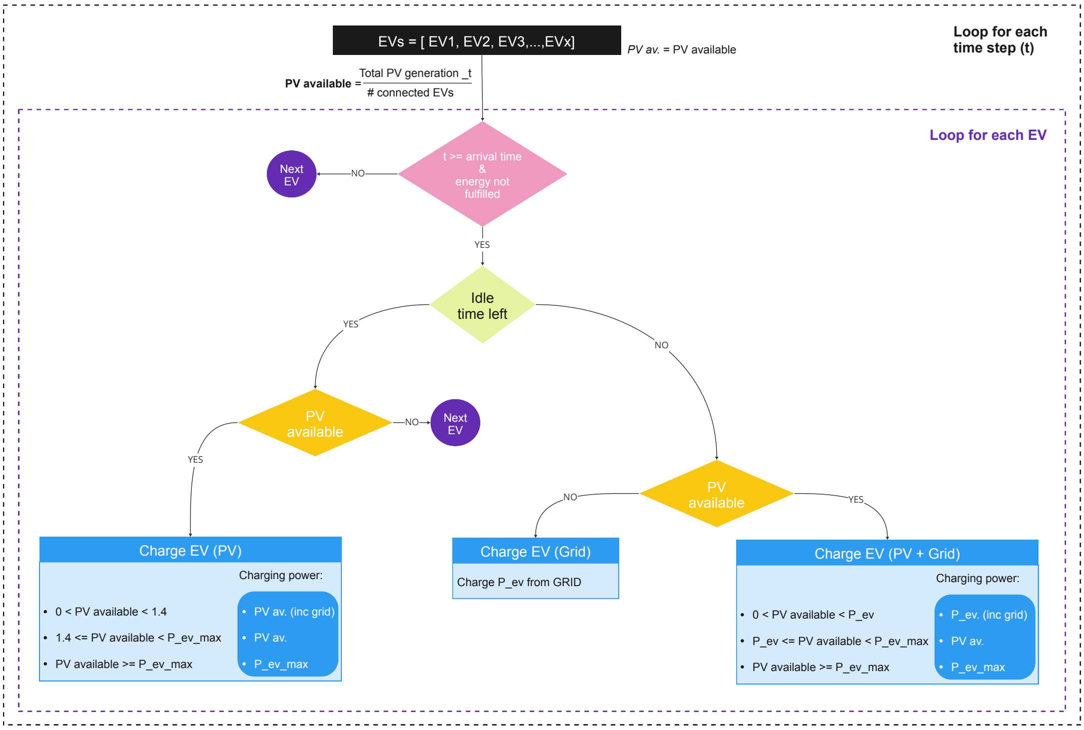

Figure 4.3. Flowchart equal PV share

4.3 Strategy 3: EV sorting by urgency

4.3.1 Rationale

Strategy two, which focuses on distributing renewable energy resources equally among vehicles, may encounter certain challenges. One potential issue is that an electric vehicle (EV) could receive more solar power than it can effectively charge due to its limiting $P_{ev\,max}$. Additionally, under this strategy, there is a possibility that a vehicle that still has several hours of idle time remaining, is assigned the same charging power as another vehicle that is about to complete its park time and might experience the necessity to complete its energy demand from the grid. In such cases, the charging power may not be optimally allocated, which might result in inefficient charging.

In order to overcome the challenges just mentioned, strategy three aims to prioritize the allocation of available solar power to the electric vehicle that is in most urgent need of charging and is expected to depart from the charging station soon.

4.3.2 Characteristics

To achieve the goal of this model, a criterion of urgency is established, utilizing the previously explained variable P_{ev}. The EVs are sorted in descending order based on the

$\frac{P_{ev}}{P_{ev\,max}}$ ratio. This ratio represents the power requirement in the remaining park time of an EV compared to its maximum charging power.

See an example of the ratio calculations for three different EVs with a possible time resolution of 10 min. In this case, the first vehicle to receive the maximum available PV

		EV1	EV2	EV3
	Arrival	8:20	8:20	8:30
	Departure	9:30	10:00	9:00
	Power (kW)	3,7	7,4	3,7
	Energy requested (kWh)	2	4	1,5
Time = 08:30h	Energy charged (kWh)	0,5	1,2	0
	P ev (kW)	1,5	1,9	3,0
	ratio prioritisation	0,4	0,3	0,8

Figure 4.4. Example of EV ratio prioritisation

power would be the EV3, followed by the EV1, and finally the EV2. Therefore, note again in the flowchart that $P\,av$ within a certain timestep, it is calculated for each EV within the timestep, and corresponds to the PV power available at that point in time minus all that has already been allocated to the vehicles with the highest prioritisation ratio. That is why in the subsequent flowchart can be seen that the calculation for the *available PV* is calculated for every EV.

Furthermore, in contrast to the previous model, the scenario where the available PV resource is less than 1.4 kW and there is still some *idle time* is treated differently. In this case, the option of charging from the grid up to the minimum power level in this specific case is not considered. Instead, it has been decided to continue utilizing the idle time while waiting for a sufficient amount of solar resources to become available. However, if there is no alternative but to charge during the short remaining *park time*, the procedure remains the same as in the previous strategy. This can be seen in the following flowchart.

4.3.3 Flowchart

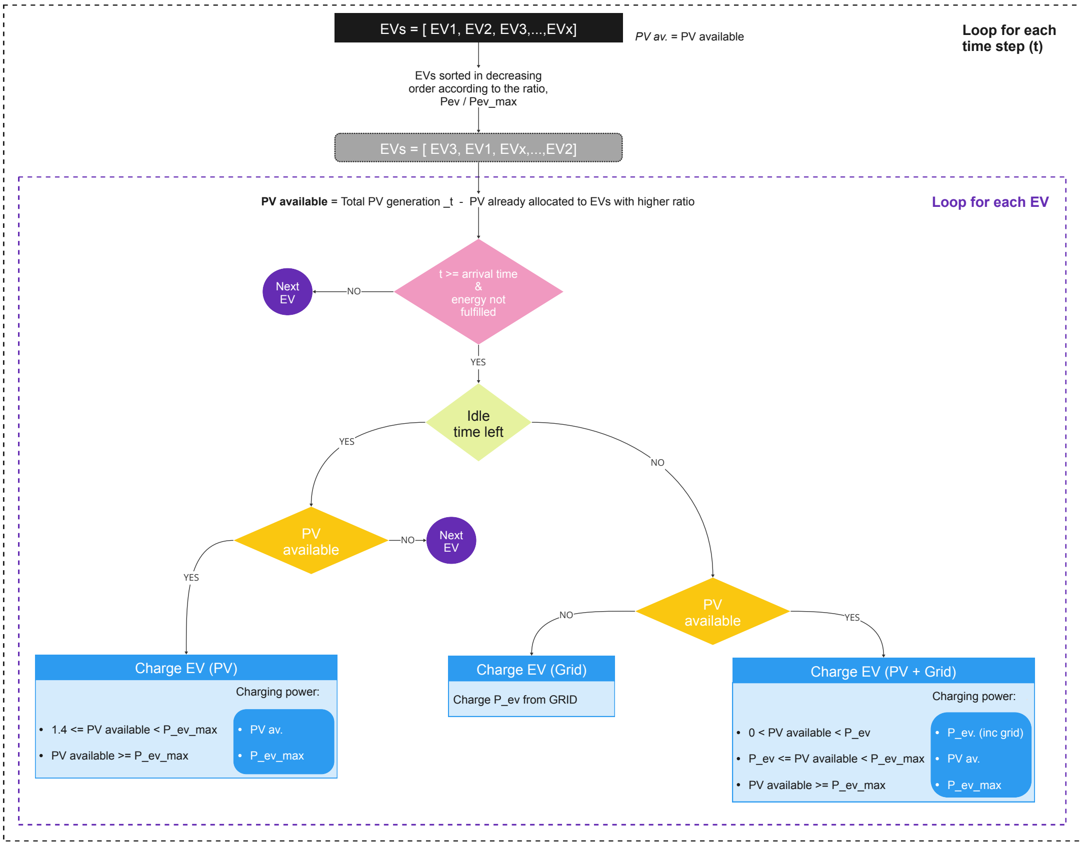

Figure 4.5. Flowchart sort EV urgency

4.4 Strategy 4: EV sorting and Day-Ahead prices

4.4.1 Rationale

Until now, the models have primarily focused on managing the PV power available during the idle time of vehicles to minimize the reliance on grid energy imports. However, the cost of grid energy varies throughout the day, making it crucial to consider day-ahead prices in the charging strategy. By incorporating this pricing information, the model aims to prioritize energy consumption from the grid during the hours when electricity prices are deemed to be the most economical. This approach ensures that the charging process is not only driven by the availability of PV power but also takes into account the cost-effectiveness of grid energy.

4.4.2 Characteristics

This strategy maintains the criteria for allocating solar resources based on the $\frac{P_{ev}}{P_{ev\ max}}$ ratio. While distinguishing between cheap and expensive hours throughout the day, the strategy continues to prioritize the consumption of PV power whenever it is available.

It is important to note that a new parameter called *max grid share* has been introduced in the model. This parameter defines the maximum allowable proportion of energy, during the idle time, that can be drawn from the grid during cheap hours, relative to the total energy demand.

Therefore, in this particular scenario, the vehicle will be charged even if the available power from the PV system is less than 1.4 kW when the vehicle's charging process occurs during a cheap hour and the required grid charging power to reach 1.4 kW does not exceed the *max grid share*.

For the simulations in this report, a *max grid share* value of 0.3 has been selected for strategy 4.

4.4.3 Flowchart

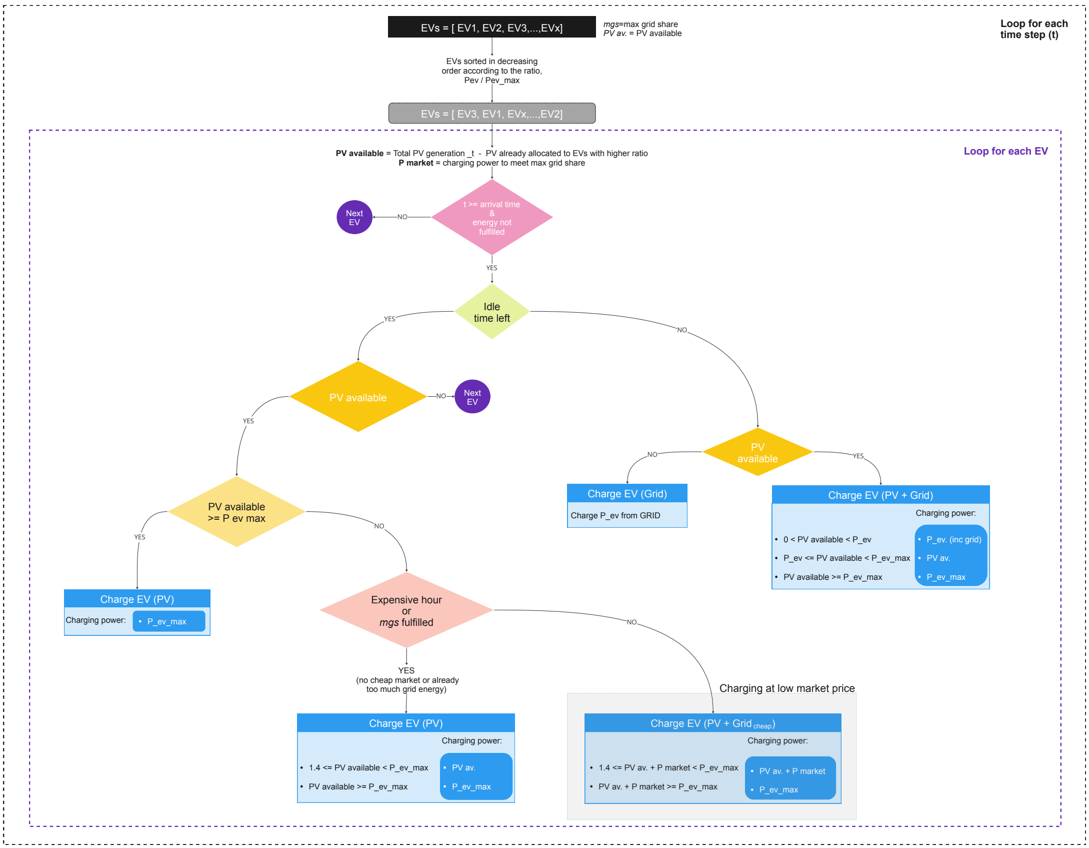

Figure 4.6. Flowchart sort EV and Day-Ahead

4.5 Strategy 5: EV sorting, DA and Vehicle-to-Vehicle

4.5.1 Rationale

So far, a model has been developed which is able to manage the allocation of PV generation through a prioritisation process and which also allows a certain amount of energy to be charged during idle time in periods of low daily market price.

In such cases where there are limited low price hours or when those hours do not align with the arrival of vehicles at the charging station, it becomes necessary to adapt the charging strategy to maximize the utilization of available low-cost energy. This can be achieved by allowing the vehicles that are able to charge during the cheap hours to obtain more energy than their initial demand. Subsequently, the excess energy can be shared with other vehicles during the expensive hours, ensuring a bidirectional charging strategy.

4.5.2 Characteristics

Upon the arrival of a vehicle at the charging station, an initial categorization is performed to determine whether the vehicle is a candidate for vehicle-to-vehicle (V2V) charging or not. This categorization is based on various known variables, Figure 3.9.

For an electric vehicle (EV) to be categorized as a candidate for providing vehicle-to-vehicle (V2V) charging, several criteria need to be met. Firstly, the EV's arrival time should fall within the designated cheap hours, while its departure time should occur during the subsequent expensive hours, allowing for a sufficient duration of at least 1 hour for energy exchange. This ensures that the EV has the potential to receive surplus energy during the cheap hours and deliver it to other vehicles upon their arrival during the expensive hours. To facilitate this energy exchange, V2V candidates are assigned a specific maximum grid share. If a V2V candidate fails to meet its energy demand during the cheap hours, it will not have surplus energy available for distribution to other vehicles.

In the case where two distinct periods of cheap hours are established, with one of them coinciding with the peak arrival period (7-9 am) as shown in Figure 3.2, a criteria will be followed to establish V2V candidates. EVs will become V2V candidates when arriving in the later period of cheap hours, aiming to streamline the flow of vehicles and avoid occupying a charger for the entire day.

For EVs that do not qualify as V2V candidates, a max grid share of 0.3 has been selected for the subsequent simulations. However, for the candidates, the grid share limit is extended to 1.3.

Kindly review the provided flowchart below, which showcases the pertinent characteristics discussed above. Notably, it is crucial to highlight that when determining the availability of vehicle-to-vehicle (V2V) power, if the electric vehicle under consideration is identified as a potential candidate to provide this type of charging, it will invariably be assigned a negative status. So, a V2V candidate provides, not receives, V2V power.

4.5.3 Flowchart

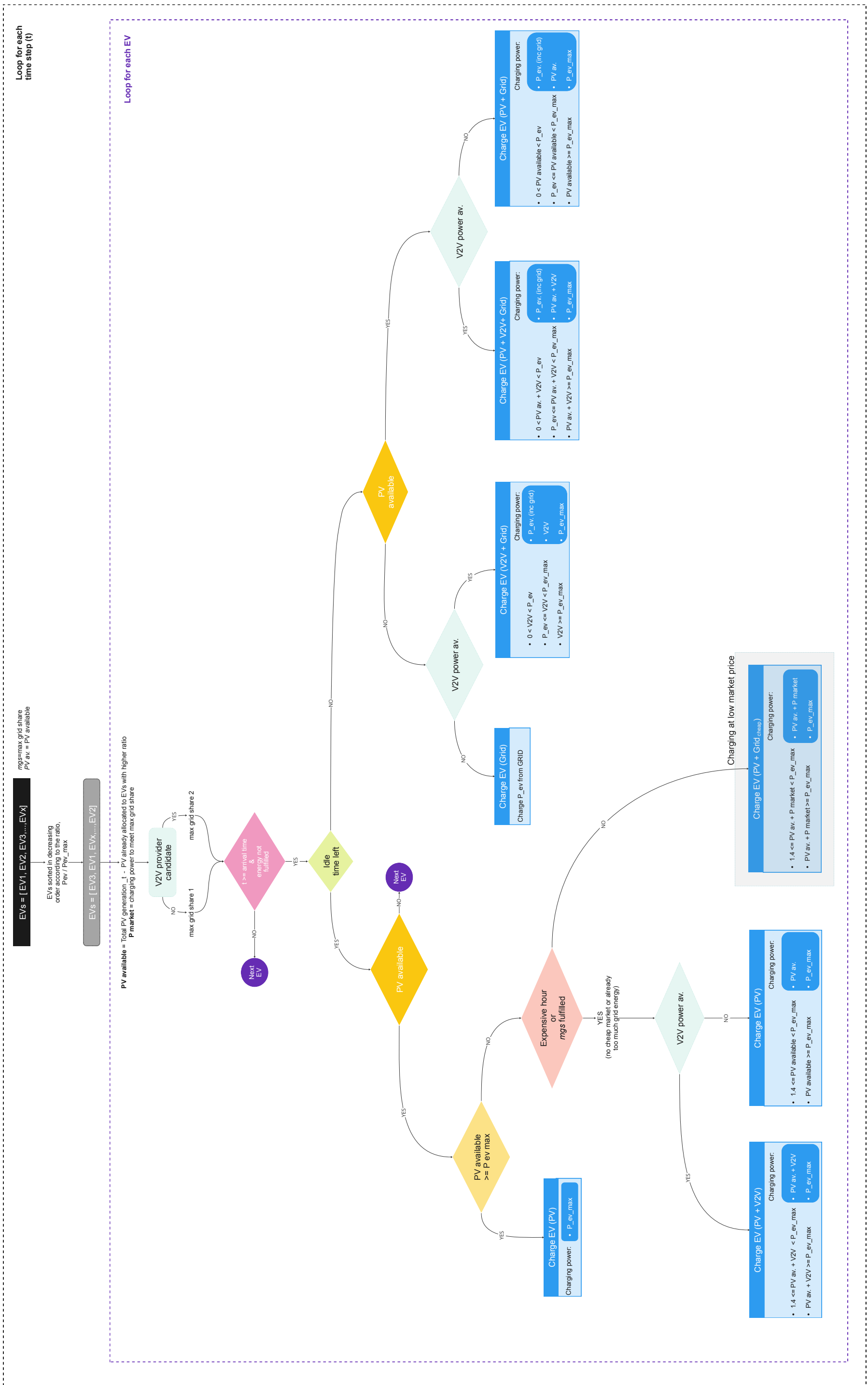

Figure 4.7. Flowchart bidirectional EV charging V2V

5 Set-up description, Bornholm

In the following chapter, a more detailed description of the selected location will be provided, emphasizing its significance in the testing of the charging strategies. The location serves as a critical factor in the development and evaluation of the strategies, as it provides essential inputs and parameters that are utilized throughout the simulation process. By examining the characteristics and attributes of this location, a deeper understanding of its influence on the strategies' performance and effectiveness can be gained.

5.1 The site

Although the primary objective of this thesis is to showcase the advantages and feasibility of various smart charging strategies, it is important to consider the specific context in which the data and use case are derived. As part of the H2020 European project EV4EU, the focus is on a pilot installation at Campus Bornholm. Therefore, it becomes necessary to delve into the specific details of this installation, including the type of infrastructure to be implemented and any relevant restrictions that may impact the application of the charging models.

5.1.1 Installation

The site under consideration for this thesis comprises a school building that features a photovoltaic (PV) installation on the roof. The PV system consists of three arrays, including two arrays with a capacity of 60.95 kWp each, and one array with a capacity of 55.46 kWp. For the purpose of EV charging analysis, only one of the 60.95 kWp arrays was considered. Furthermore, within the parking area, plans are in place to install six electric vehicle slow chargers, each equipped with two outlets, allowing for a total of 12 EVs to be charged simultaneously. It is important to note that for the purpose of this thesis, the energy consumption of the building itself is not taken into account. Instead, the main focus lies in studying the interaction between EV charging and renewable energy generation, specifically in the form of PV.

The restriction on the number of chargers will be considered during the simulations, with the understanding that this parameter can be modified, as it is an input to the model. Its implementation is as follows: if there are already 12 EVs connected to the charging station and another EV arrives, it will have to wait until one of the connected EVs has finished charging or reaches its designated departure time. The departure time is considered a crucial variable for the user and cannot be extended beyond its predetermined value.

An EV charging session is considered complete if either of the following conditions is met:

1. The departure time of the EV has been reached, indicating that the vehicle must leave the charging station as scheduled.
2. At any point during the designated park time, the EV successfully charges the requested amount of energy. In this case, it is assumed that the user would be notified that their EV is ready to be removed from the charging station. The user is then given a grace period of 1 hour to remove the EV.

See below, the current state of the site. The schematic illustrates the planned installation, showcasing the proposed arrangement and configuration of the EV charging stations and the photovoltaic system.

Figure 5.1. EV charging site

The figure presented below illustrates a simplified representation of a single-line circuit, outlining the potential configuration of the installation. This diagram serves as an example to demonstrate the conceptual layout and key components of the system. It incorporates several assumptions that will be utilized in the subsequent simulations. Figure 5.2 depicts

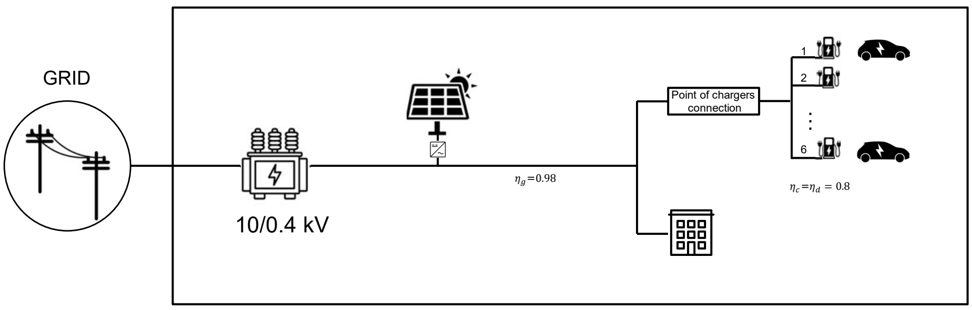

Figure 5.2. EV charging potential configuration

the assumed efficiency of the grid components involved in the low-voltage circuit, including the transformer [16] and inverter [5], as $\eta_g = 0.975$. This assumption accounts for the energy losses that occur during the conversion and distribution of power.

When considering the efficiency of chargers, it is important to differentiate between unidirectional Vehicle-to-Grid (V1G) charging strategies and bidirectional ones like Vehicle-to-Vehicle (V2V). This efficiency accounts for the main factors influencing the EV charging losses, on-board charger, charging cable, charging power, EV battery [10].

- For unidirectional V1G charging, the efficiency of the chargers it is chosen to be constant throughout the charging process, and equal to $\eta_c = 0.8$ [6].

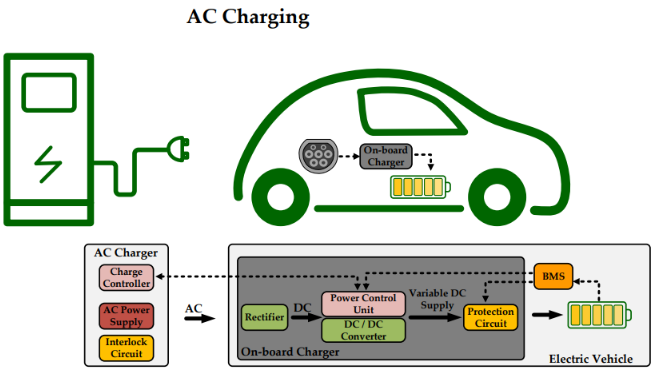

Figure 5.3. V1G AC onboard charging potential configuration [8]

- For the V2V case it has to be taken into account that the charging system must also allow the battery to be discharged and sent to other EVs, that is why all EVs have to be equipped with a bidirectional on-board charger. A bidirectional charge consists of a combined AC/DC rectifier and DC/AC inverter [11]. That is why a discharging efficiency must be considered, therefore $\eta_c = \eta_d = 0.8$ [7].

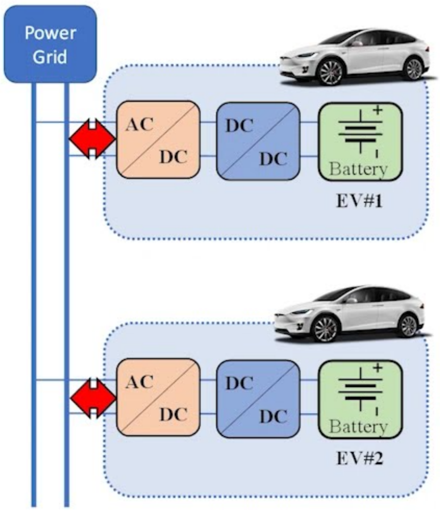

Figure 5.4. V2V operation mode [9]

Finally, in accordance with the configuration of the EV clusters described in section 2.3, it is important to note that a behind the meter (BTM) configuration is employed. This configuration enables the provision of services to users, such as load coordination between different EVs and a distributed energy source. The primary objective of this configuration is to minimize electricity costs by minimizing the amount of imported energy. In terms of the control architecture (section 2.4), a centralized control approach is utilized, where a central intelligence directly controls all the chargers.

5.2 PV production

The subsequent section presents a graph displaying the data derived from the solar photovoltaic generation of the building's installation. This data will serve as input for the simulations and will be adjusted according to the selected resolution and time frame.

To showcase the most recent data and provide a concise overview of the solar photovoltaic generation, the obtained data covers the period from June 2021 to September 2022. However, for the purpose of presenting a concise representation of the solar generation patterns throughout the year, the data has been aggregated to display the hourly averages for each month from September 2021 to September 2022.

In Figure 5.5, an anomaly can be observed in the data obtained for the month of March. Typically, when calculating the hourly average for a month, the resulting values should exhibit a pretty smooth shape. However, in this case, the data appears to be discrete rather than continuous. To further investigate this discrepancy, Figure 5.6 provides a closer look at the generation data for a week in March with a resolution of 5 minutes, as well as data for the month of February. The comparison between these two datasets clearly highlights the difference in the nature of the obtained data, therefore March data will not be used for running the simulations.

Regarding the other months, the PV generation values align well with the expected patterns for each season of the year. This observation implies that during spring and summer, a significant portion of the EVs' demand can be met by solar generation, potentially reducing the differentiation between charging strategies. On the other hand, during autumn and winter, it is anticipated that solar generation may be less abundant, leading to a greater reliance on grid energy. In these seasons, the market price of electricity may play a more significant role in determining the total cost of charging for EVs.

To generate different scenarios for the simulations, a parameter called PV factor will be introduced. This parameter allows for the modification of the original photovoltaic curve by multiplying it by a specific value. By adjusting the PV factor, the intensity of the PV generation can be scaled up or down, creating variations in the available solar resource for charging EVs.

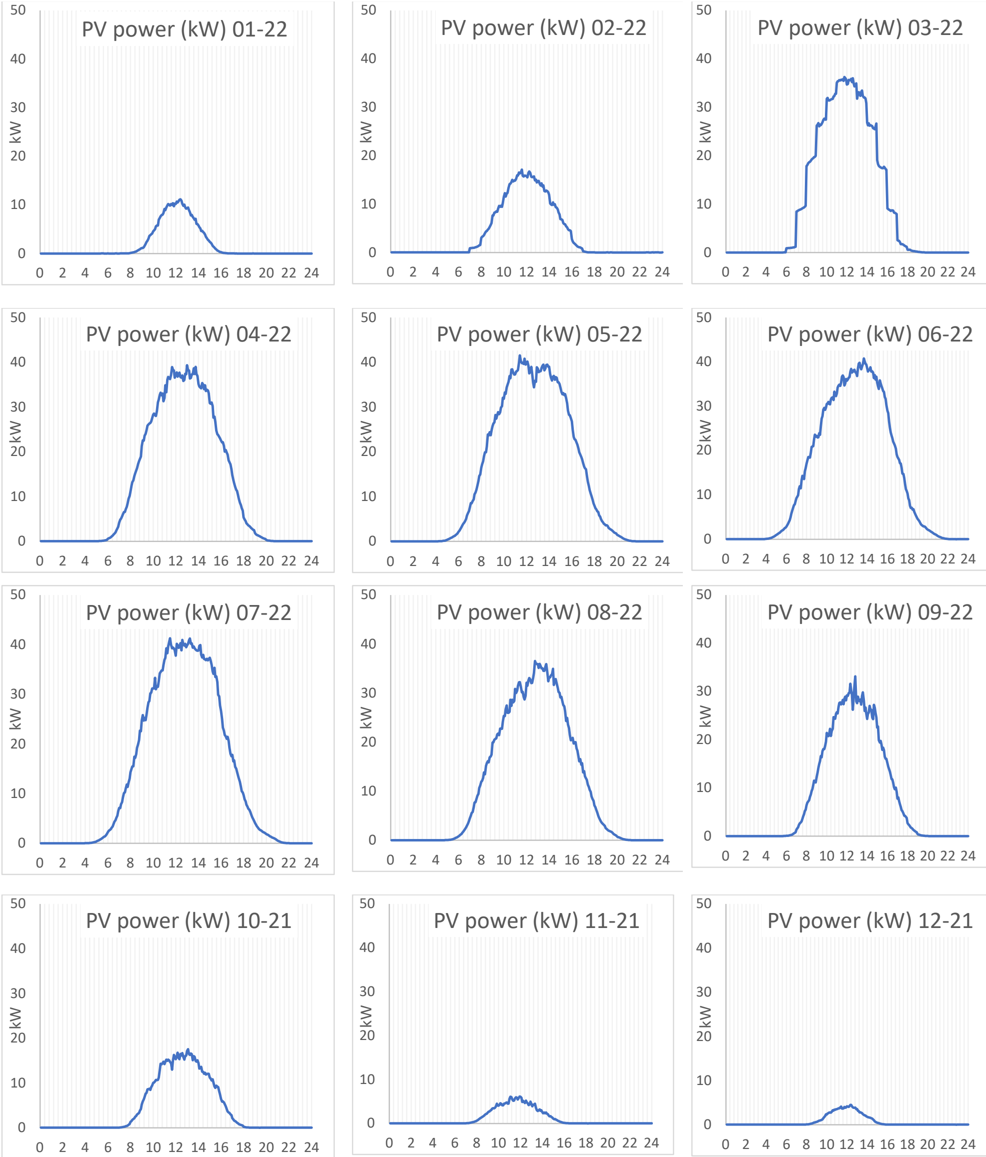

Figure 5.5. Daily average PV production Oct21-Sep22

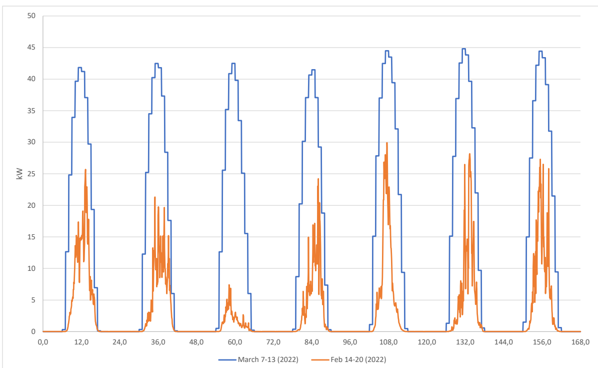

Figure 5.6. PV production (5 min resolution) for a random week March vs February

5.3 Market analysis, Day-ahead DK2

Due to the site's location on Bornholm, the day-ahead market prices considered in this analysis correspond to the DK2 bidding zone. Although it would have been preferable to have solar production data for a full calendar year, the figure below displays the market prices for the same period as Figure 5.5. The daily averages for each month are presented. It is noteworthy that for the months relying on the 2021 production, such as October, November, and December, the prices and the overall shape of the average day show minimal differences from one year to another, indicating that the data from 2021 remains representative for those months. When examining the price trends over the 24-hour period

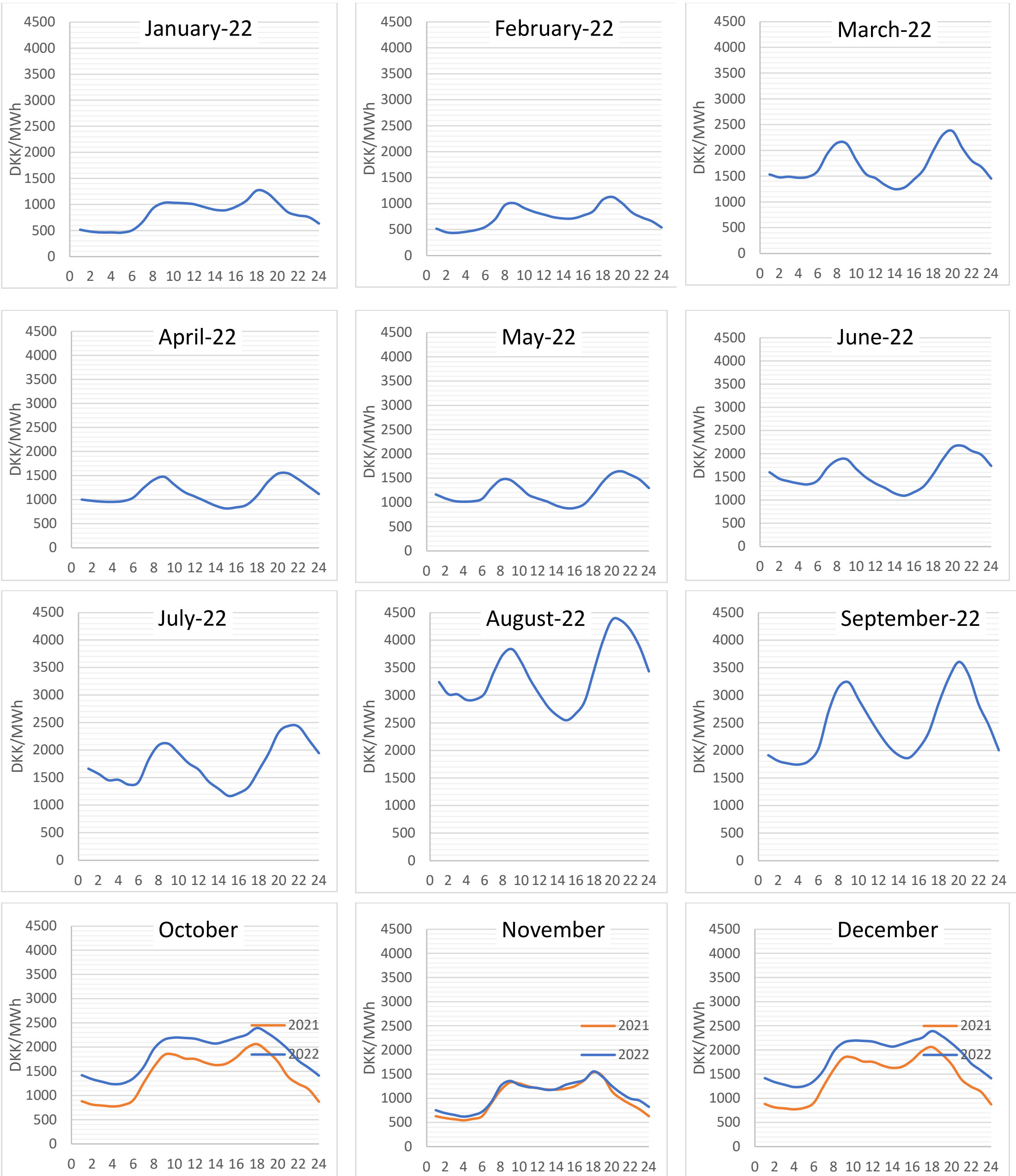

Figure 5.7. Daily average spot price (DKK/MWh) Oct21-Sep22

for each month, a clear pattern emerges. In months with high solar production, there is a noticeable price peak around 6-8 am, followed by a period of low prices characterized by a valley shape, and then another price peak occurring around 18-22 pm. This pattern can be attributed to the combination of abundant renewable generation during sunny hours and low demand during those periods. These conditions create favorable circumstances for leveraging the benefits of V2V charging, particularly for overcharging during the midday valley, followed by an energy exchange with other vehicles arriving at the charging station in the evening.

It is important to highlight that this phenomenon is less prominent during the winter months when solar production is diminished. In these months, the midday price curve tends to be flatter, without pronounced morning peaks. This shift in price dynamics reflects the reduced contribution of solar generation during the winter season and the increased reliance on other sources of energy.

Furthermore, as the site includes a solar plant, it is crucial to quantify the significance of the price drop during the sunny hours of the day. To achieve this, two key metrics will be utilized: the average market price (*baseload price*) and the average price weighted by PV production. The latter metric represents the price that a PV producer, also called *PV capture price* [12], could obtain from the wholesale market. Additionally, a useful metric known as *PV capture* (%) can be derived by calculating the ratio between the capture price and the average market price, and can assist in understanding and interpreting future results. The observed phenomenon of lower prices during the sunny hours is commonly referred to as *cannibalization*, which occurs when renewable energy sources with similar generation profiles produce simultaneously, resulting in a depression of the wholesale electricity price [13].

Moreover, a price projection for DK2 until 2030 is presented, encompassing *baseload price*, *PV capture price*, and *PV capture* (%). The projection indicates a clear trend towards a decrease in *PV capture*, signaling an increase in cannibalization. This trend is attributed to the growing deployment of renewable energy sources, leading to a larger share of renewables in the energy mix [15]. As the renewable energy buildout expands, the PV capture price is expected to decline relative to the baseload price, reflecting the intensified competition and lower market value for PV generation during periods of high renewable generation.

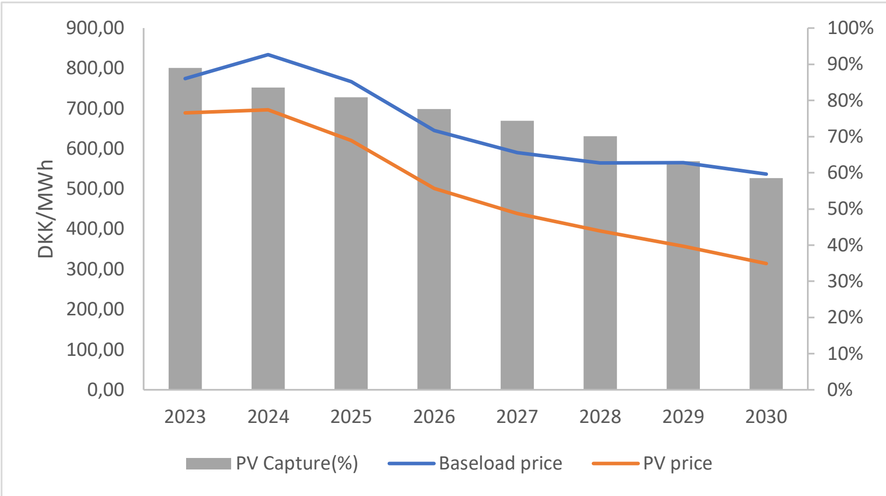

Figure 5.8. DK2 market projection [14]

Finally, spot market prices are showcased for the selected weeks that are utilized in the simulations. Specifically, one week is chosen during the winter season, spanning from 17th to 23rd January, while another week represents the summer season, ranging from 8th to 14th August. These two weeks serve as representative examples, encompassing the variations observed throughout the year. Additionally, the sensitivity analysis section will further explore the impact of different parameters, allowing for an extensive understanding of the dynamics involved in EV charging management.

During the selected week in August, the higher solar production during the day leads to increased cannibalization, resulting in lower wholesale market prices during sunny hours. However, as the day progresses and approaches sunset, there is a noticeable increase in prices, with some hours experiencing peak prices. In contrast, the week in January exhibits more diverse price trends. Some days show a gradual increase in prices throughout the day, while others exhibit the opposite pattern. However, what remains consistent is the higher PV capture during this season compared to summer, which is evidenced by a flatter curve in midday hours.

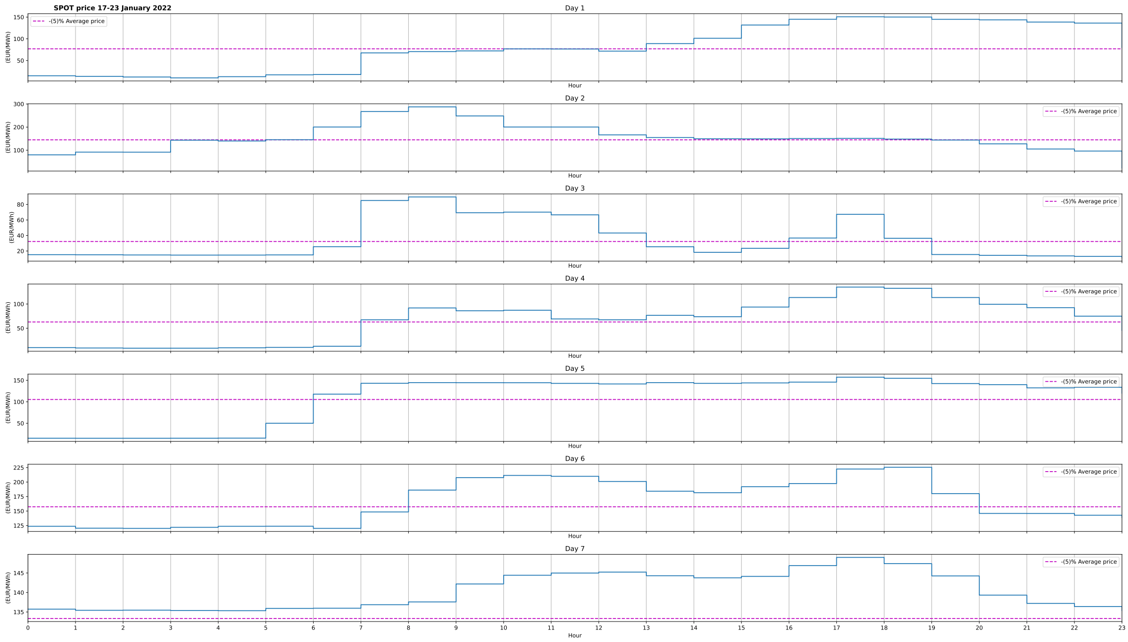

Figure 5.9. Hourly spot price (EUR/MWh) 17th to 23rd January - 2022

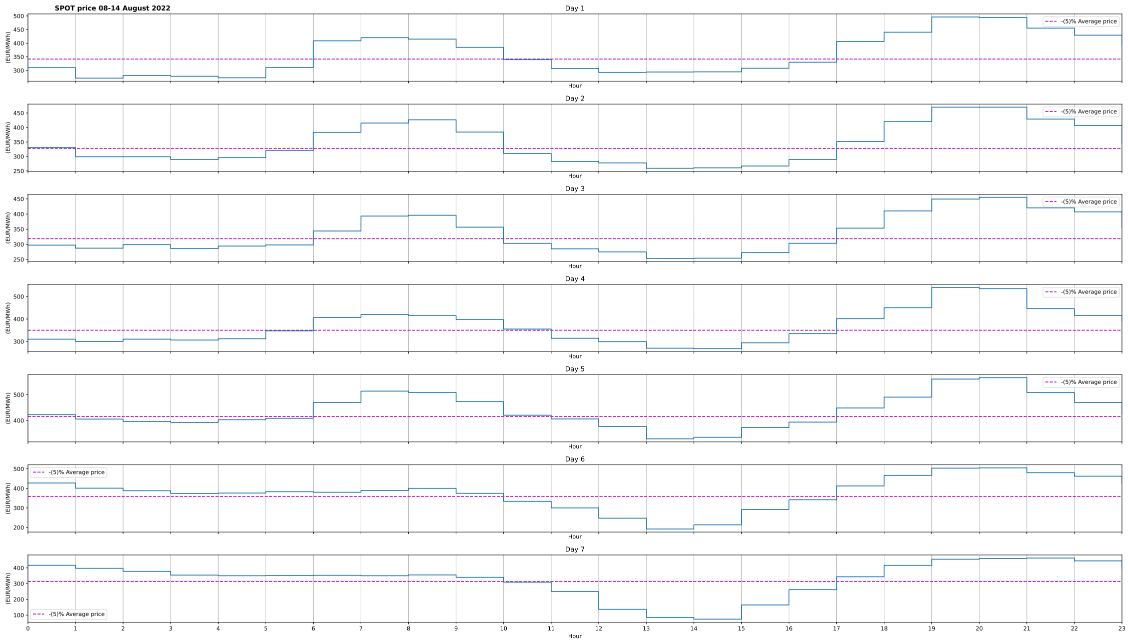

Figure 5.10. Hourly spot price (EUR/MWh) 8th to 14th August - 2022

6 Results and discussion

In the next section, the calculations used to obtain the key metrics for each simulation are presented, along with the main results.

6.1 Methodology

6.1.1 Cheap spot price

As discussed in the market section 5.3, there is a general understanding of the daily trends and patterns of day-ahead prices. However, to pinpoint and differentiate between low-cost and high-cost hours, the average price is calculated for each day's 24-hour period. A factor is then applied to reduce this average by a percentage, which helps in identifying the hours that are significantly cheaper compared to the rest. This factor, as shown in Figures 5.9, 5.10 has been established for the subsequent simulations as (-5 %).

6.1.2 Total strategy cost

Before calculating the total cost of each strategy, it is essential to differentiate between these terms: (Variables with *timestep* resolution (t))

- **Grid Consumption (kWh)**: The amount of energy drawn from the grid, including system and charging efficiency (Figure 5.2).
- **PV Consumption (kWh)**: The amount of energy consumed from the photovoltaic installation, including system and charging efficiency (Figure 5.2).
- **PV Export (kWh)**: The amount of energy generated by the photovoltaic installation that is not used for charging the electric vehicles and is thus exported to the grid

For market prices, it's important to note that there are two prices for each time step: the electricity selling price and the buying price. These prices are aligned with the regulations of the site's location. The purchase price is typically higher as it includes tariffs and VAT. More information on this can be found in references [17, 18, 19].

Therefore, the total cost is obtained as:

$$\begin{aligned}\text{Total cost (DKK)} = {} & \text{Grid consumption (kWh)} \cdot \text{buy price} \left(\frac{\text{DKK}}{\text{kWh}}\right) \\ & + \text{PV consumption (kWh)} \cdot \text{sell price} \left(\frac{\text{DKK}}{\text{kWh}}\right) \\ & - \text{export energy (kWh)} \cdot \text{sell price} \left(\frac{\text{DKK}}{\text{kWh}}\right)\end{aligned} \tag{6.1}$$

It is important to highlight that the second component of Equation 6.1, which is the PV consumption multiplied by the sell price, represents the opportunity cost of using the photovoltaic generation for charging instead of selling it to the grid. By consuming the PV energy, there is a foregone revenue that could have been obtained by selling it.

6.1.3 Self-sufficiency

Self-sufficiency has been widely used for evaluating the operating performance of energy systems at different scales. For systems without energy storage, self-sufficiency can be calculated as [20]:

$$\sigma = \frac{E^{\text{gen}}}{(E^{\text{gen}} + E^{\text{import}})}, \quad \sigma \in [0,1]$$

where E^{gen} is the local generation (PV in this case) and E the grid import.

6.1.4 Serviced cars

Finally, the analysis will also include the evaluation of the unmet energy demand for the EVs that could not be fully satisfied due to the limited number of chargers. Additionally, it will consider the vehicles that were partially met in terms of their energy demand. This information will provide insights into the effectiveness of the charging strategies.

6.1.5 Parameters

Variable	Value
max grid share	Strategy 4: 0.3 Strategy 5: 0.3/1.3 (not/ V2V candidate)
market factor	-5 %
PV factor	0.6 (Base-case)
# EVs at the charging station	15 EVs /day (Base-case)
resolution	5 min

In Appendix A.1 an example of the characteristics of the EVs that serve as input for the different models is provided for both day 1 and day 5 of the week.

6.2 Base-case simulation

Firstly, a high-level comparison between the results of the base case for the winter and summer weeks will be examined, providing an initial overview of the performance of each charging strategy. This comparison allows for a preliminary assessment of how each strategy performs under different seasonal conditions.

At first glance, it is evident that each season presents a strategy that appears to be the most favorable in terms of its performance. Specifically, in the summer season, strategy 3 stands out as the most advantageous option. This strategy demonstrates a high level of self-sufficiency, indicating its ability to effectively utilize the available solar resources for EV charging. With a self-sufficiency rate of 0.9, strategy 3 minimizes its reliance on grid energy, resulting in significantly lower grid consumption compared to other strategies.

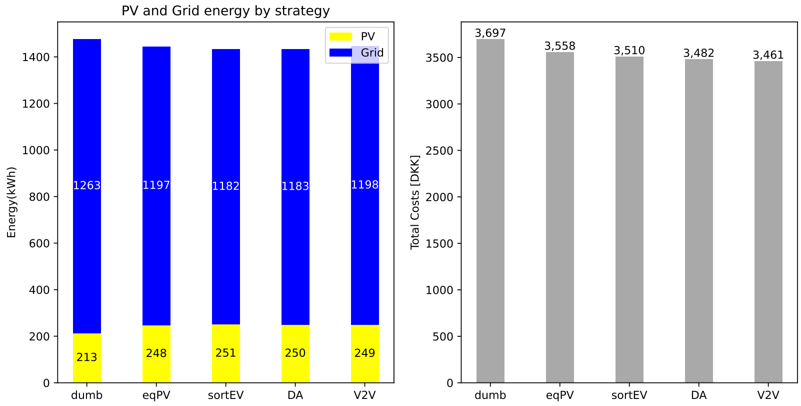

Figure 6.1. Base-case, winter (17-23) January 2022

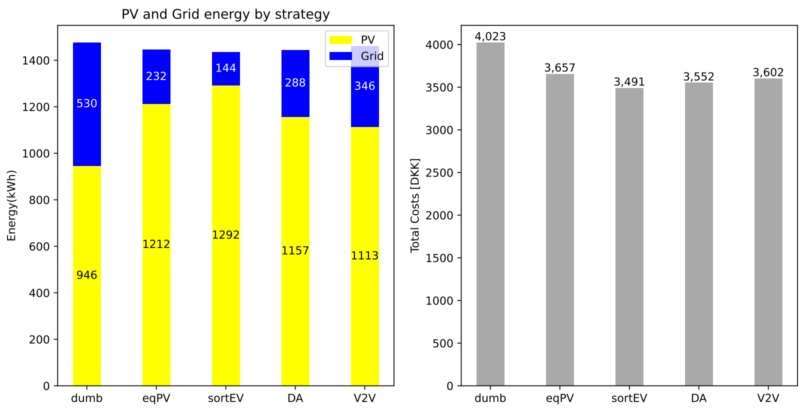

Figure 6.2. Base-case, summer 08-14 August 2022

	Self-sufficiency	
	Summer (total PV 1495 kWh)	Winter (total PV 252 kWh)
Strategy 1	0.74	0.17
Strategy 2	0.87	0.17
Strategy 3	0.91	0.18
Strategy 4	0.84	0.18
Strategy 5	0,81	0.17

	Not serviced EVs	
	Summer	Winter
Strategy 1	0	0
Strategy 2	0	0
Strategy 3	1 - 6.68 kWh	1 - 6.68 kWh
Strategy 4	0	1 - 6.68 kWh
Strategy 5	0	1 - 6.68 kWh

Table 6.1. Self-sufficiency and not serviced EVs, Base-case

In contrast to the summer week, the winter week presents a different set of challenges due to the reduced availability of the solar resource. As a result, strategies that prioritize interaction with the grid during cheap hours become more advantageous in this scenario. In particular, the properties of the last two strategies, which emphasize charging from the grid during low-cost periods, stand out. Among these strategies, strategy 5 demonstrates the lowest cost and the best overall performance in the winter week. By allowing overcharging during cheap hours and enabling energy exchange between vehicles, strategy 5 optimizes the utilization of grid energy and minimizes the associated costs.

It is worth noting that in three out of the five strategies, there is one EV left uncharged during the winter week. In the summer week, this occurs only in one strategy (number 3). This EV has a specific arrival and departure time, and its charging requirements clash with the charging status of other vehicles at the station. Specifically, this EV arrives at 12:45h, being the 13th EV at the station where there are only 12 outlets, and departs at 13:30h, making it a high-priority vehicle that requires immediate charging. However, due to the charging progress of other vehicles, it is unable to receive the necessary charge in many cases. This issue is more prevalent during the winter week compared to the summer week. In August, the abundant solar resource accelerates the charging process of vehicles, allowing them to leave the station earlier once they are fully charged. This results in a smoother flow of EVs and reduces the instances where a vehicle is left uncharged.

In contrast, the first two strategies, although relatively more expensive in terms of cost, demonstrate a better performance in terms of customer satisfaction. The first strategy prioritizes charging EVs as soon as they are connected to a charger, regardless of the availability of PV power. This ensures that vehicles are charged promptly upon arrival, mitigating the risk of uncharged vehicles. Similarly, the second strategy, when the available PV power is not sufficient to meet the minimum charging power for connected vehicles, utilizes energy from the grid to accelerate the simultaneous charging process.

In the following section, a more detailed analysis will be conducted to examine the behavior of different strategies on specific days. In addition, the performance of particular vehicles will also be analysed.

6.2.1 Summer week, 08-14 August 2022

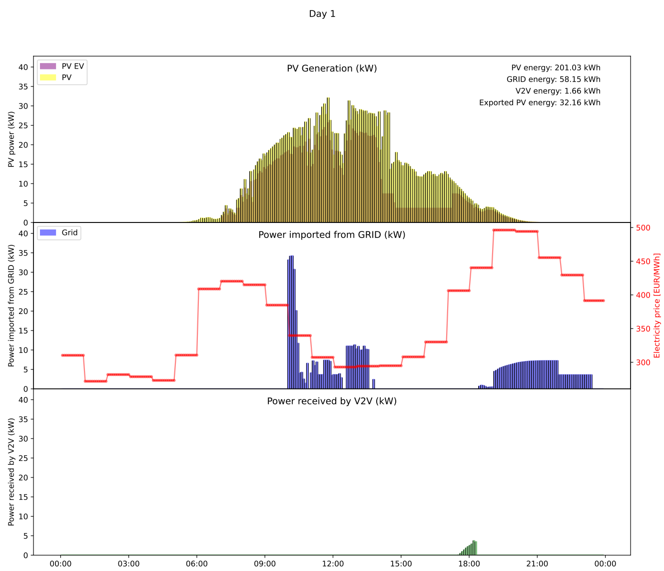

Figure 6.3. Day-1, V2V (Strategy 5)

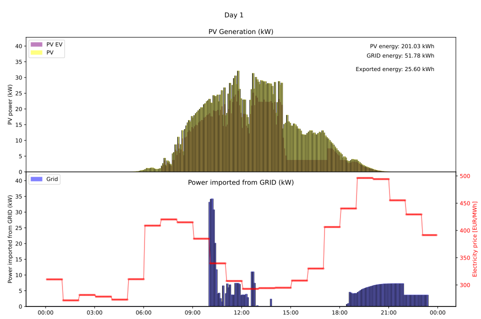

Figure 6.4. Day-1, Day-Ahead (Strategy 4)

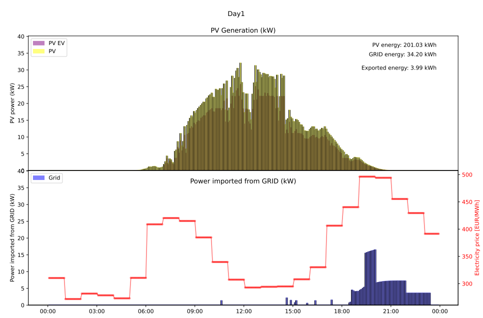

Figure 6.5. Day-1, sortEV (Strategy 3)

These plots illustrate the solar generation in yellow for the selected PV array at the site. The overlapping power allocation to the EVs at each moment in time is also depicted. The difference between the PV EV and the generated PV represents both the losses in the system and the amount of PV energy that is exported from the site. In the lower part of the plots, the power imported from the grid by all the EVs is shown, along with the corresponding spot prices for that day. Additionally, in the case of strategy 5, the energy exchanged (received) between EVs within the parking lot is represented in the lower section of the plot.

When comparing the behavior of the three strategies, it is evident that in this scenario with abundant solar resource, strategies 4 and 5, which involve charging from the grid during cheap hours, are not as advantageous. This is because when charging with cheap grid energy starting from 10:00h, the batteries get partially charged, leading to a situation where not all of the available PV energy can be utilized from 15:00h onwards (see top subplot of the figures). On the other hand, strategy 3, as shown in Figure 6.5, demonstrates minimal grid imports during the peak solar production hours.

Furthermore, what exacerbates the performance of strategy 5 compared to strategy 4 is the overloading from the grid during the cheap hours (around 13:00h) for the V2V candidate vehicles. This results in even less utilization of the abundant solar resource. Additionally, considering the losses associated with the discharge efficiency to other vehicles (slightly earlier than 18.00h), strategy 5 ends up incurring higher costs compared to strategy 4.

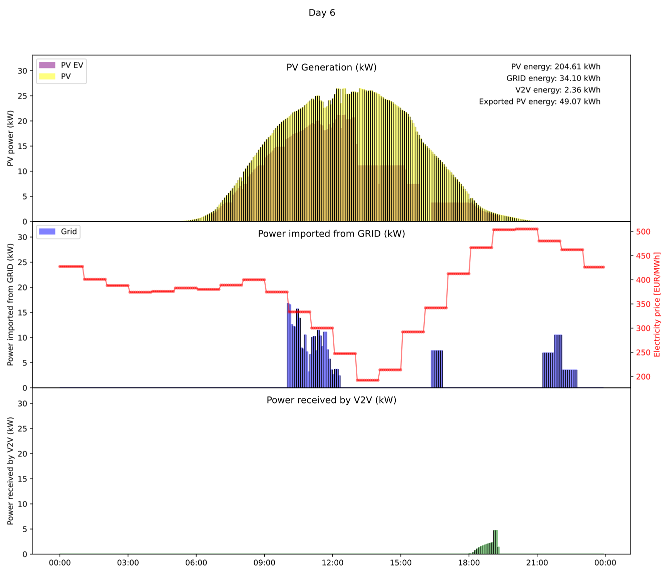

Figure 6.6. Day-6, V2V (Strategy 5)

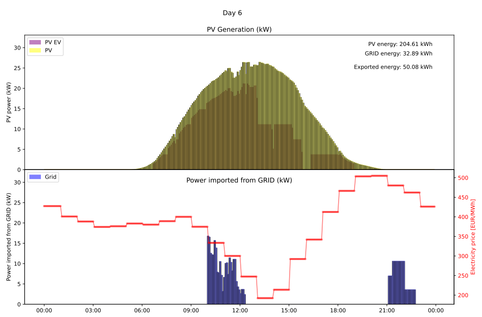

Figure 6.7. Day-6, Day-Ahead (Strategy 4)

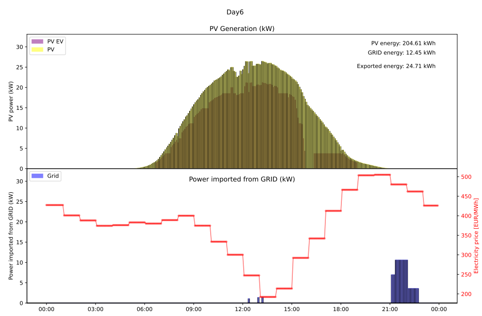

Figure 6.8. Day-6, sortEV (Strategy 3)

The load testing plots for day 6 provide further evidence of the efficient utilization of solar generation by strategy 3. It can be observed that strategy 3 exports the least amount of PV energy, followed by strategy 2, 4, 5, and 1. The plots for the performance of strategy 1 and

2 can be found in the appendix in section A.2. Despite the limited PV exports by "eqPV" strategy, it incurs a relatively high cost due to the need to complement PV generation with expensive grid energy during the early morning hours. The dumb strategy, characterized by immediate charging upon EV arrival at the charging station and the inability to modulate power, exhibits the poorest performance in terms of renewable absorption and cost.

Now, in order to gain a better understanding of the functioning of the different strategies, the charging behavior at the level of individual EVs will be depicted.

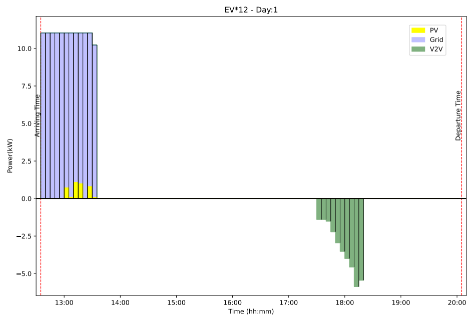

Figure 6.9. EV 12, V2V

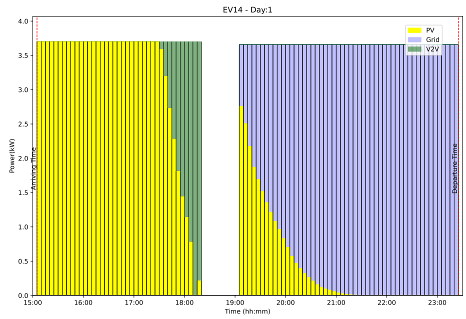

Figure 6.10. EV14, V2V

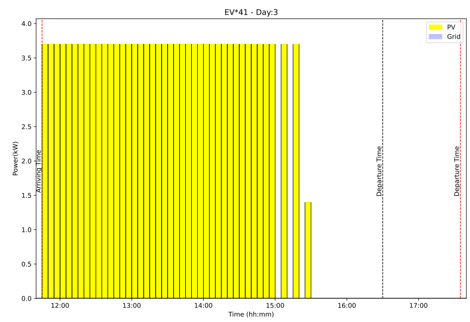

Figure 6.11. EV41, sortEV

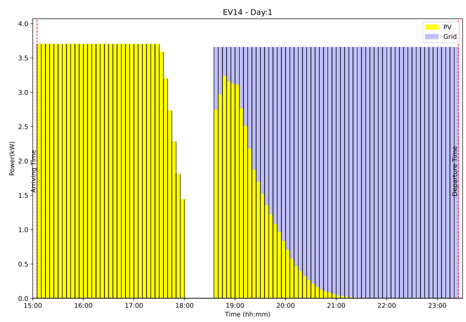

Figure 6.12. EV14, sortEV

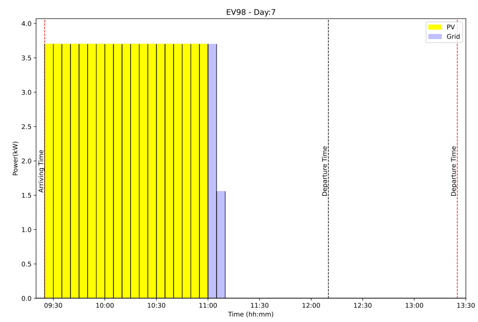

Figure 6.13. EV98, Day-Ahead

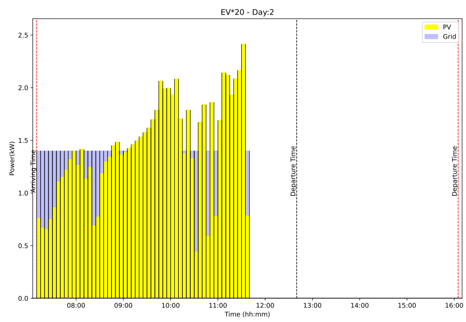

Figure 6.14. EV20, eqPV

Figure 6.9 illustrates the energy emission from EV12 to other vehicles. At around 18:00, as shown in Figure 6.10, EV14 benefits from this third power source exclusive in the bidirectional strategy 5. During this time, when the market prices are considered high, EV14 consumes this energy from another EV, resulting in a reduced consumption of energy from the grid. It is evident how EV12 adjusts its discharge to meet the requirements of EV14, prioritizing the utilization of PV power while maintaining a minimum power level of 1.4 kW.

Figure 6.12 depicts how EV14 would be charged using strategy 3, sortEV. The plot demonstrates how the idle time is utilized to enable the battery to charge from the renewable source while implementing priority ratios between vehicles. At a certain point, EV14 is no longer considered a priority in terms of urgency. However, shortly thereafter, with remaining energy needed for a full charge, it becomes necessary to supplement the PV power with additional energy to reach the required Pev power before the scheduled departure time of the EV.

Figure 6.11 provides another example of strategy 3, sortEV, where it is observable the utilization of idle time to fully charge the EV solely with photovoltaic energy. In this case, since the vehicle is able to obtain the required energy before 1 hour prior to its departure time, a notification is given to the user to retrieve the vehicle, resulting in an updated departure time displayed in black. The asterisk symbol next to the EV number indicates that it has been charged with a slightly higher amount of energy than initially demanded. This is due to the fact that in the last time step of charging, the vehicle charges at minimum power since it requires less than 1.4 kW to reach its desired charge level. This asterisk symbol is also observed for the V2V candidates in the simulation.

Figure 6.13 showcases a charging scenario with strategy 4, where the priority is given to PV charging. However, if at a specific time slot, a cheap day-ahead hour occurs and no PV power is allocated to the vehicle, it proceeds to charge from the grid up to the maximum grid share. In this particular case, the vehicle does not reach the maximum grid share limit because it quickly meets its energy demand by charging from the grid and leaves the charging station within the next hour.

Figure 6.14 presents the case of vehicle 20 charging with strategy 2. In this scenario, when the available PV power is divided among all the EVs connected to the station, it results in several instances where the allocated power is less than the minimum requirement. Therefore, the charging process is complemented with energy from the grid. While this approach effectively utilizes renewable energy, it also results in a significant consumption of grid energy during high-price hours.

An example of charging using strategy 1 (Dumb) can also be seen in appendix A.2 with EV7.

6.2.2 Winter week, 17-23 January 2022

In the following, the charging processes in more detail for the week of January will be examined to better understand why strategy 5 (V2V) has proven to be the most efficient during this period with lower solar resource.

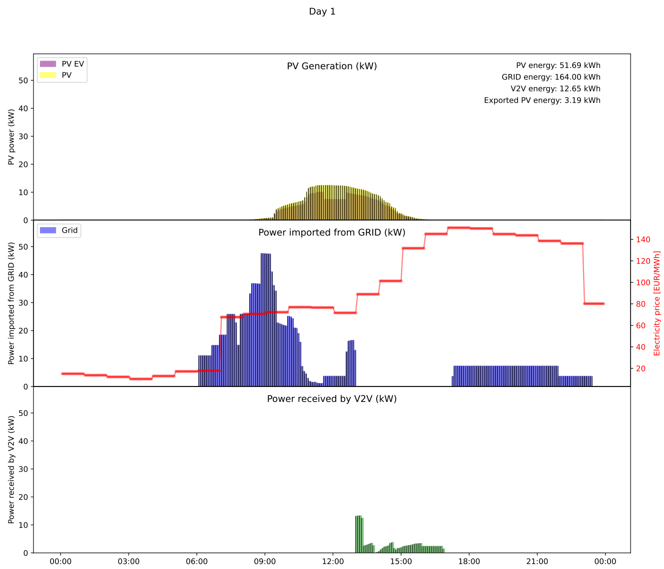

Figure 6.15. Day-1, V2V (Strategy 5)

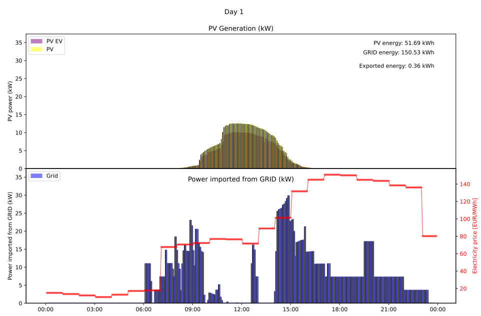

Figure 6.16. Day-1, Day-Ahead (Strategy 4)

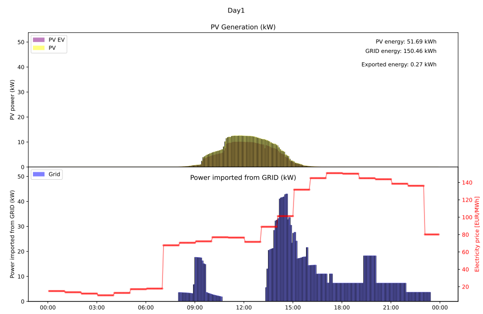

Figure 6.17. Day-1, sortEV (Strategy 3)

The first observation is focused on a day with low solar resource, characterized by a rising price curve during the sunny hours. This presents an opportunity for V2V charging, as overloading the vehicles before the prices rise allows for a reduction in grid consumption during expensive hours. In strategies 4 and 5, charging from the grid begins around 06:00h, taking advantage of the cheap hour. However, in sortEV (strategy 3), this is not possible. The cheap hour charging continues throughout the day until the maximum grid share is reached. Strategy 5, which includes V2V candidates, shows a significant power peak around 9:00h-10:00h am as these vehicles can continue to overcharge. Between 13:00h and 17:00h, thanks to the energy exchanged through V2V charging, the grid consumption is significantly reduced, leading to lower costs.

It is worth noting that despite the V2V model being the cheapest in terms of cost, it does not necessarily result in the highest capture of PV energy. In this case, strategies 3 and 4 perform equally well in capturing PV energy, as shown in Figure 6.15, where a gap in PV energy capture can be observed around 12:00h.

On other days of the week with low solar resource and price profiles that are either falling or not favorable for V2V charging, the behavior of the three strategies is similar, except for the early consumption in cheap hours feasible in strategies 4 and 5.

6.3 Sensitivity analysis

In this section, it will be explored how the costs and various parameters of the strategy behavior change when key factors, such as solar generation and the number of vehicles using the charging station, are modified. This analysis will be conducted for both the August and January weeks.

6.3.1 Summer week

In Figure 6.18, the evolution of metrics for the summer week is depicted as parameters such as available solar production (generation) and the number of vehicles per day (demand) vary. Focusing on the "15EV/day" column, it is observable a transition from the base-case scenario (0.6 PV) where strategy 3 performed the best, to a situation where the photovoltaic generation is restricted to 0.2. In this scenario, the importance of importing energy from the grid and the ability to supply energy to vehicles through other vehicles (V2V) becomes more significant. It demonstrates the high efficiency of the V2V strategy when solar resources are limited, and there is a significant level of cannibalization in the market.

Upon analyzing the column further downwards, the solar resource is increased to showcase the original values of the PV array. In this scenario, strategy 3 once again proves to be highly efficient in capturing the majority of the available PV resource, resulting in reduced reliance on the grid and lower costs. Conversely, strategies 4 and 5 are penalized for partially charging the batteries from the grid at a lower price, as this limits their ability to accommodate the abundant PV production during later hours. It is also noteworthy that strategy 2 performs well in this situation, as the ample PV power distributed equally among the EVs allows for the minimum power requirement to be exceeded, resulting in a lesser need for grid importation.

When considering the 25EVs/day scenario, a way to increase demand while conserving solar production, it becomes apparent that the dynamics shift. Initially, in the base case, strategy 3 demonstrated efficiency and cost-effectiveness. However, upon increasing the demand, it is observed that although strategy 5 consumes a higher amount of energy from the grid (682 kWh) compared to strategy 3 (536), it does so during cheap hours and effectively redistributes this energy later in V2V mode, taking advantage of the typical curve influenced by renwable energy (RE) cannibalization, showing the lowest cost. Furthermore, when maintaining the demand at 25EVs/day but utilizing the generation of the original PV array (1.0PV), it represents a scenario with an abundant renewable energy source. Once again, strategy 3 proves to be effective and the most efficient under these conditions.

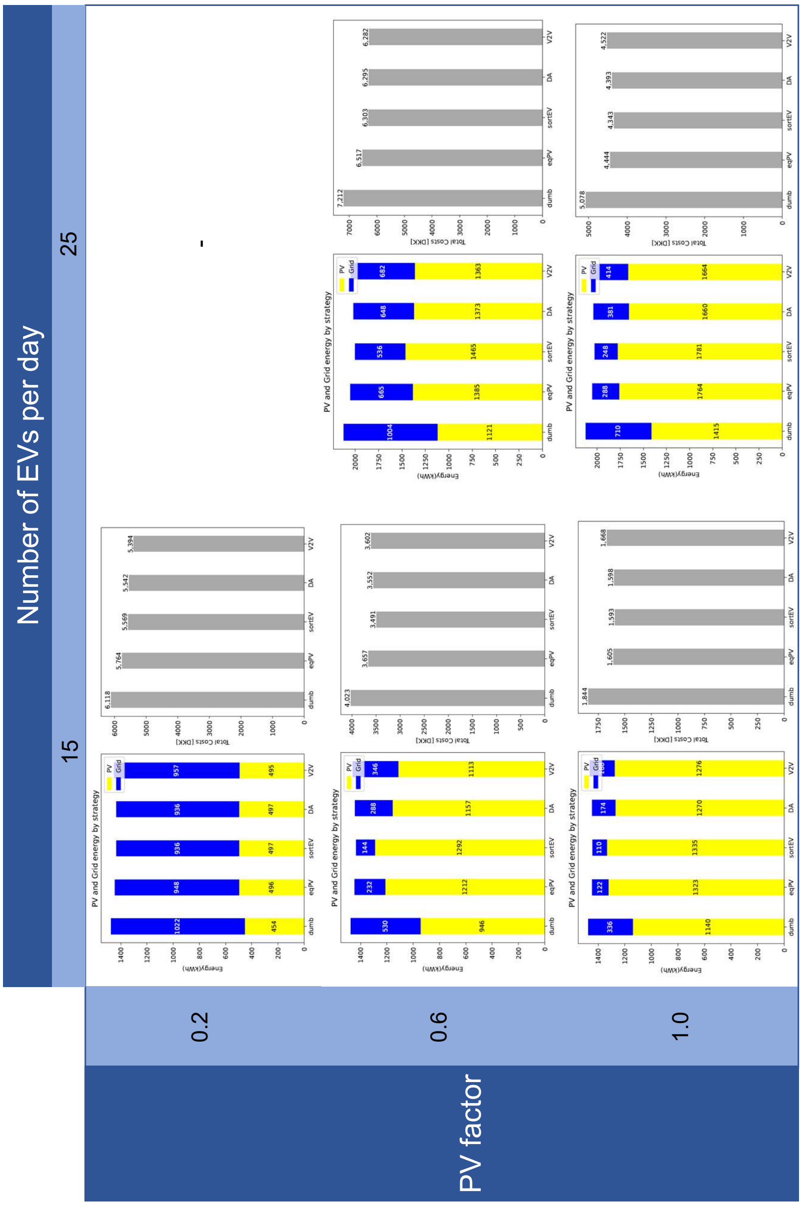

Figure 6.18. Summer week, 08-14 August, 2022

Scenario 0.2PV-15EV/d

In this case of 0.2PV-15EV/d, strategies 3 and 4 are unable to meet the charging needs of the aforementioned EV that only connects for 45 minutes. To gain a deeper understanding of what transpires in this scenario, let's examine the performance of individual EVs and delve into the details of a specific day, e.g., day 5.

In Figure 6.19, it is observable that the vehicles begin to charge around 11:00h, taking advantage of a decline in day-ahead prices. This grid energy consumption continues until around 17:00h when prices are no longer favorable. At this point, the V2V mechanisms come into play, and the green area at the bottom of the graph indicates the energy that various EVs are receiving from other EVs within the charging station. This energy exchange among vehicles mitigates the need to import electricity from the grid during expensive periods. This is exactly what happens in strategy 3, and to a lesser extent, in strategy 4 (Figures 6.21 and 6.20), where a significant peak in grid consumption is observed around 18:00h.

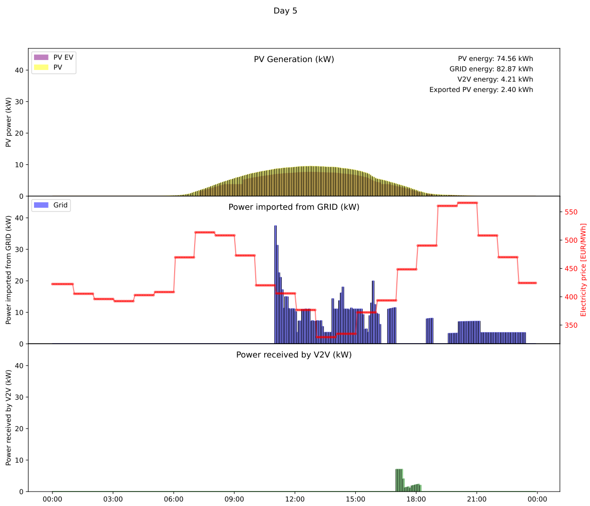

Figure 6.19. Day-5, V2V (Strategy 5) 0.2PV-15EV

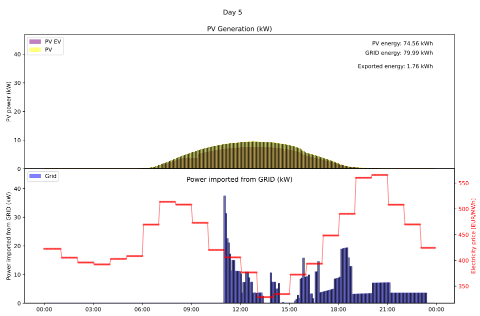

Figure 6.20. Day-5, Day-Ahead (Strategy 4) 0.2PV-15EV

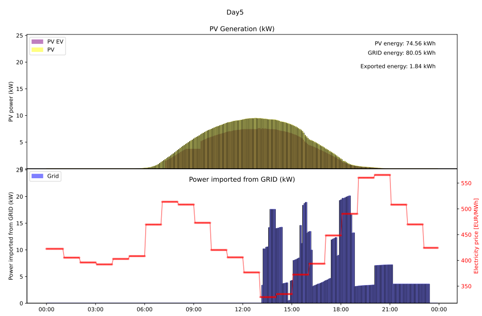

Figure 6.21. Day-5, sortEV (Strategy 3) 0.2PV-15EV

The charging behavior of vehicle 39 on day 3 is analyzed in detail. Figure 6.22 illustrates the charging process in strategy 5, starting with an initial grid charging during the off-peak period until reaching the maximum grid share after 11:00h. Subsequently, the idle time is utilized to allocate the available renewable resource, as observed when charging with PV power begins around 14:30h. As the vehicle is no longer a priority and does not receive renewable energy, it starts relying on the grid to fully meet its demand before the departure time. However, it still benefits from the energy exchanged with other EVs in V2V mode, reducing the reliance on grid imports.

In the case of strategy 3, which attempts to utilize the idle time for PV resources, the limited availability of renewable generation becomes apparent. As a result, there comes a point where it becomes necessary to charge from the grid until the departure time, leading to a significant amount of grid imports during expensive periods. This ultimately translates into higher costs compared to other strategies.

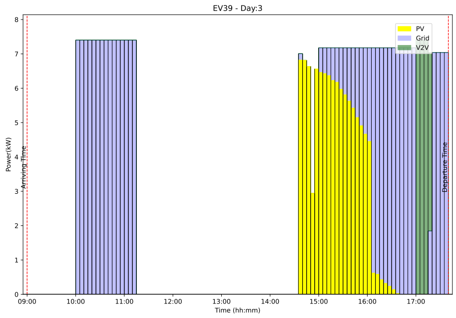

Figure 6.22. EV39, V2V 0.2PV-15EV

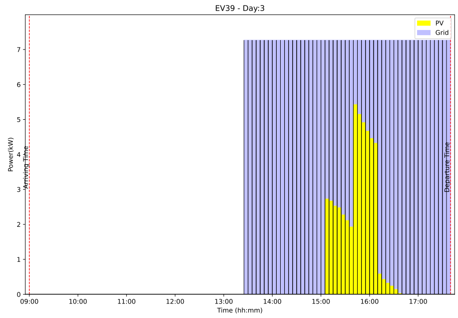

Figure 6.23. EV39 sortEV, 0.2PV-15EV

Scenario 1.0PV-15EV/d

In situations with abundant PV resource, it becomes evident once again that strategy 3 is the most effective in harnessing it. This strategy demonstrates excellent results in terms of cost and lower PV energy export. The detailed charging process during day 5 is provided below (day 3 is also available in the appendix A.3, including eqPV performance).

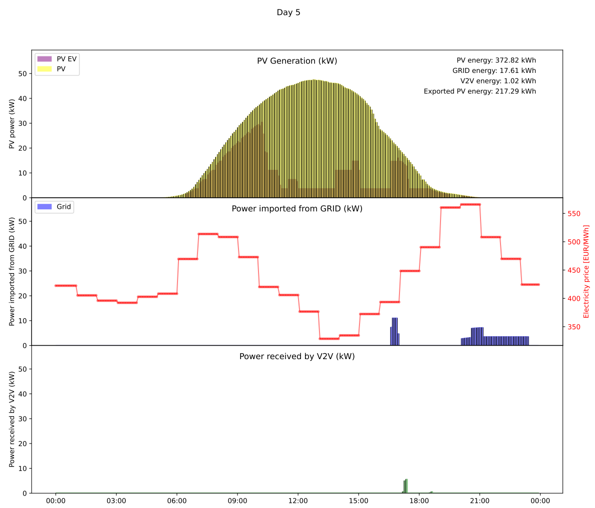

Figure 6.24. Day-5, V2V (Strategy 5) 1.0PV-15EV

In the case of day 5, when comparing figures 6.25 and 6.26, which depict the behavior of Day-ahead and sortEV strategies respectively, no significant differences can be observed. This is because in this scenario with abundant solar resources, it has been found that strategy 4 performs very closely to strategy 3 in terms of cost. However, these small differences become apparent when looking at day 3 (A.3), which shows how strategy 4 charges during cheap hours, as a result, in later hours, it is unable to allocate all the available renewable energy.

On the other hand, V2V strategy performs worse in the presence of ample solar resource. Even on day 5, it charges during cheap hours when strategy 4 does not. This is due to the second maximum grid share that characterises those vehicles that qualify for V2V. Specifically, the eleventh vehicle on day 5 highlights the inefficiency of V2V strategy in this scenario. Although it qualifies for V2V charging, it ends up getting 11.30 kWh of energy in the battery when it only demanded 8.88 kWh. This is because it was only able to provide back to other EVs 0.61 kWh in V2V mode, as other receiving vehicles prioritized absorbing PV energy.

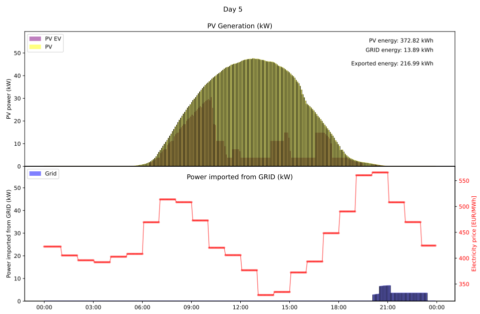

Figure 6.25. Day-5, Day-ahead (Strategy 4) 1.0PV-15EV

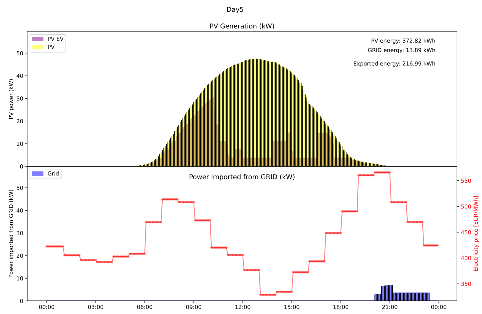

Figure 6.26. Day-5, sortEV (Strategy 3) 1.0PV-15EV

6.3.2 Winter week

In the case of January, the sensitivity matrix reveals how strategies 3 and 4 start to become more cost-effective as more PV energy is supplied, gradually diminishing the significance of strategy 5. It is worth noting that even with an increase in solar resources, the net increase per day is not that remarkable, even in the fictitious scenario of 40% higher generation than the original. In these cases, the ability to charge from the grid at low prices while also allocating the limited available solar energy makes strategy 4 the most attractive. On the other hand, in these cases, strategy 5 losses effectiveness as it tends to overcharge more than it can supply back to other vehicles, considering as well the significant losses during charging and discharging processes.

When the analysis is taken to the extreme by reducing the demand to simulate a scenario with slightly more abundant solar resource, the situation returns to the previously analyzed case where strategy 3 exhibits excellent performance. Strategy 3 makes optimal use of PV energy, minimizes grid dependency, and shows the lowest costs. However, it should be noted that even with a decrease in demand (7 EVs/day), when solar resources are very scarce (0.6 PV), strategy 5 still demonstrates good performance by utilizing the V2V mode.

In general, it becomes evident that the optimal strategy depends on the specific conditions of demand and renewable generation. When there is low demand or abundant renewable generation, the third strategy consistently shows better results. This is because strategy 3 maximizes the utilization of renewable energy and minimizes grid consumption, leading to lower costs.

However, when the contribution of photovoltaic generation is reduced and there is no clear cannibalization effect in the spot market, the effectiveness of vehicle-to-vehicle (V2V) charging may be diminished. In such cases, the fourth strategy proves to be the most favorable. Strategy 4, with its ability to take advantage of cheap electricity prices during off-peak hours, allows for cost reduction even in scenarios with limited renewable generation and no clear cannibalization.

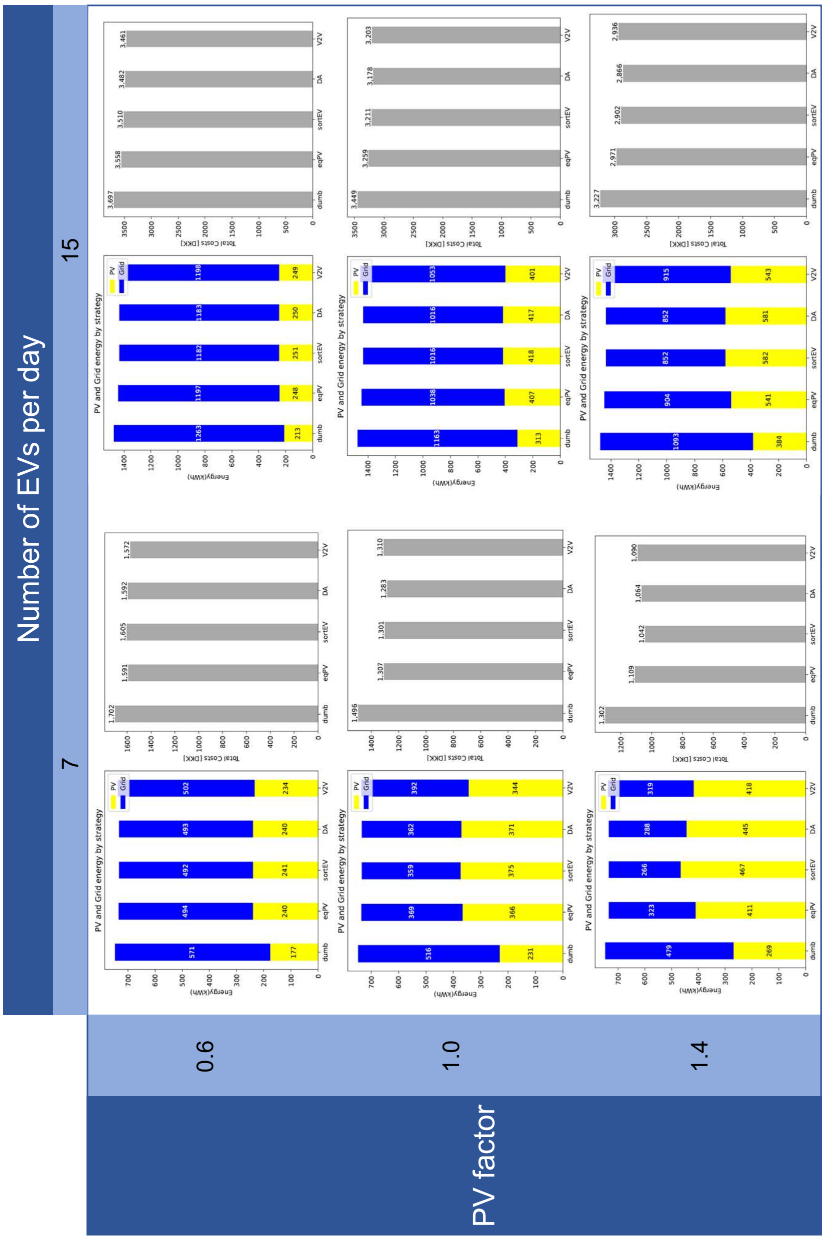

Figure 6.27. Winter week, 17-23 January, 2022

Scenario 1.0PV-15EV/d

Analyzing day 1 in more depth, it becomes apparent that strategy 5, which utilizes V2V charging, leads to a higher amount of energy imported from the grid. This is primarily because several vehicles qualify for V2V and are overcharged, meaning they receive more energy than initially demanded. However, the effectiveness of V2V charging depends on being able to discharge the excess energy during expensive hours. In the case of this winter day, expensive hours begin around 13:00h, which coincides with solar production. Consequently, the potential receiving vehicles prioritize PV energy, and by the time the V2V candidates have to leave the charging station, they have not been able to provide all the extra energy they had charged. This results in additional costs.

For example, in Appendix A.4, the charging behavior of EV3 and EV8 is examined. It can be observed that both vehicles leave the station with more energy than initially demanded (both having the asterisk; around 3 more kWh). Hence, they fail to provide all the extra energy to receiving vehicles, which do not prioritize V2V charging during peak solar production hours.

Analyzing the performance of models 3 and 4, an important difference becomes evident due to the ability to charge during cheap hours. This characteristic allows strategy 4 to avoid peak grid consumption during hours close to 15:00h. Despite the similarity in the total amount of energy imported and utilized from PV generation between the two strategies, strategy 4 achieves cost reduction by consuming energy during cheaper hours.

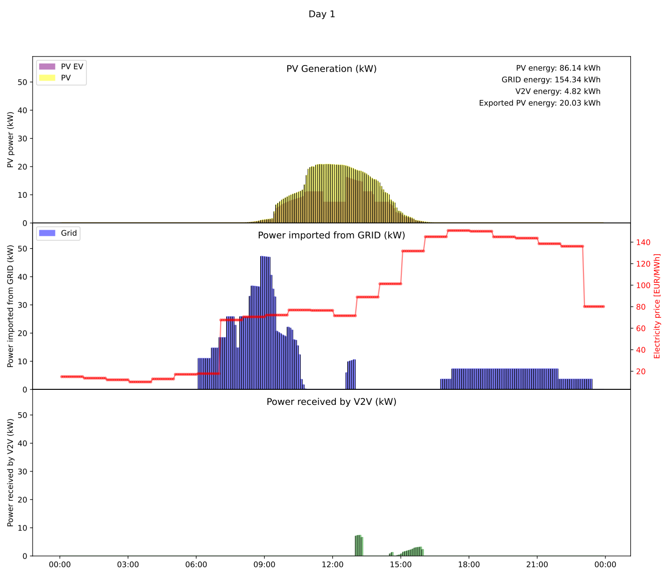

Figure 6.28. Day-1, V2V (Strategy 5) 1.0PV-15EV

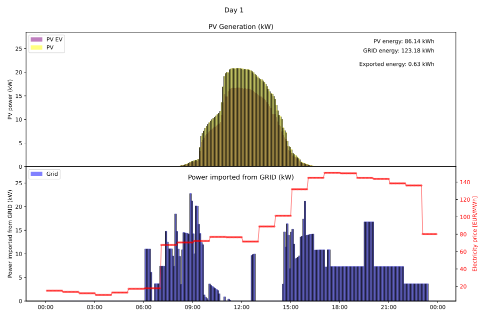

Figure 6.29. Day-1, Day-Ahead (Strategy 4) 1.0PV-15EV

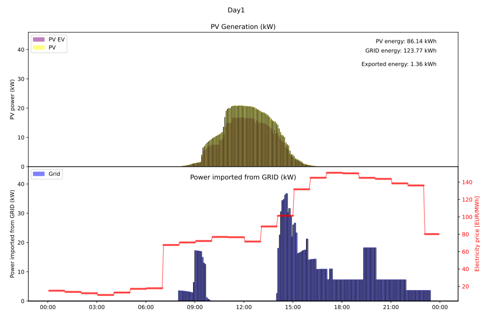

Figure 6.30. Day-1, sortEV (Strategy 3) 1.0PV-15EV

6.4 Limitations

One of the main limitations of the models developed in this work, is related to the charging behavior at the electric vehicle (EV) level. As depicted in Figure 6.11, the plot demonstrates how the charger can initiate the charging process for an EV during the idle time, but due to changes in prioritization ratios, it may subsequently abort the charging order and keep the vehicle in standby.

This limitation arises from the potential constraints imposed by certain EV manufacturers. Some EVs may not allow for intermittent or continuous charging and discharging periods, which are necessary for implementing certain charging strategies. Therefore, the effectiveness and feasibility of the proposed strategies may be limited by the charging capabilities and restrictions imposed by specific EV models.

7 Conclusion

Throughout this work, various aspects have been considered to develop and evaluate charging strategies for electric vehicle (EV) charging at workplaces. The analysis began with the examination of real EV charging data from workplace charging stations, which provided valuable insights into the charging patterns and behaviors of EV users. These patterns were then utilized to design and test smart charging strategies that can optimize the use of renewable resources and minimize costs. The next step involved analyzing the specific characteristics of the site where the charging strategies are to be implemented. Factors such as the available renewable generation capacity, grid connection constraints, and EV charging infrastructure were taken into account to ensure the feasibility and applicability of the proposed strategies.

Once the base scenario was established, simulations were conducted for multiple weeks of EV charging, considering different demand and generation scenarios. By comparing and analyzing the results of these simulations, firm conclusions were drawn regarding the optimal utilization and suitability of each charging strategy in different external conditions.

7.1 Results

One notable observation regarding the EV charging behavior at workplace stations is the high level of charging activity in the early morning hours, typically between 7:00 and 9:00. Following the initial surge in charging activity, the pace slows down, and a more consistent charging pattern is observed throughout the day. In terms of charging power values, it has been found that 3.7 kW is the most common charging power level among EV users at workplace stations. Furthermore, the analysis has shown that idle times of 4-8 hours are prevalent among EV users at workplace stations, which provide an opportunity for the implementation of smart charging strategies. Lastly, it has been observed that EV charging at workplace stations typically requires an energy contribution ranging between 6-12 kWh.

The simulations have provided valuable insights into the performance of different strategies under various scenarios. It has been established that no optimal strategy for all situations. Two key factors that significantly impact the outcomes are the price profile of the day-ahead market and the availability of renewable resources.

In scenarios where there is a strong cannibalisation of renewable energies, characterized by a drop in prices during sunny hours followed by a sharp increase around sunset, the bidirectional V2V strategy has proven to be advantageous. This strategy allows for overloading vehicles during cheap hours and then transferring the excess energy to other vehicles during expensive hours. However, it is important to note that if this occurs simultaneously with a large solar resource, it can lead to precharging from the grid at cheap prices, limiting the optimal utilization of solar generation. Additionally, the efficiency of charging and discharging should be taken into account, as it incurs losses that contribute to overall costs.

In scenarios with abundant solar resources, strategy 3 has demonstrated its attractiveness. This strategy prioritizes charging based on the urgency of vehicles, disregarding electricity market prices. As a result, it efficiently utilizes the available solar resource to a great extent. On the other hand, when there is no significant cannibalisation of market prices, which is more common during winter periods with low solar production, strategy 4 has shown to be beneficial. This strategy takes advantage of cheap market periods while maximizing the absorption of PV energy.

Indeed, the simulations have clearly demonstrated the significant advantages of smart charging techniques compared to the traditional "dumb" charging method, which falls short in terms of grid support, cost-effectiveness, and utilization of renewable resources. Smart charging strategies, on the other hand, offer numerous benefits such as better coordination and optimization of charging schedules, taking into account factors like renewable resource availability and electricity market prices. By leveraging these strategies, the charging process can be aligned with the availability of renewable energy, minimizing the reliance on grid power and reducing overall costs.

7.2 Future work

There are several avenues for further research and improvements in the charging strategies and models developed in this work.

1. Optimization algorithms: Applying cost optimization algorithms to the developed rule-based strategies can further enhance their performance. By considering various factors such as electricity prices, renewable resource availability, grid constraints, and user preferences, the charging schedules can be optimized to minimize costs while maximizing the utilization of renewable energy.
2. Bidirectional charging models: Expanding the study to include bidirectional charging models, such as Vehicle-to-Grid (V2G) strategies, can be an interesting direction. V2G allows electric vehicles to not only consume energy but also supply power back to the grid when needed. This can provide grid support, enable participation in ancillary services, and potentially generate revenue for EV owners.
3. Battery state of charge modeling: Incorporating battery state of charge (SoC) into the charging strategies can provide a more realistic representation of the charging and discharging process.

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A Simulation

A.1 EV input

Arrival	Departure	Power(kW)	Energy(kWh)	Day
6:05:00	14:40:00	11,04	13,959	1,00
6:40:00	10:40:00	3,7	9,614	1,00
7:00:00	15:15:00	3,7	9,8505	1,00
7:20:00	15:10:00	3,7	8,2698	1,00
7:20:00	15:15:00	3,7	9,35	1,00
7:55:00	14:50:00	3,7	21,8064	1,00
7:55:00	14:55:00	7,4	7,8056	1,00
8:20:00	15:55:00	7,4	12,7435	1,00
8:25:00	17:05:00	3,7	11,5566	1,00
8:50:00	9:40:00	11,04	7,293	1,00
10:00:00	16:25:00	3,7	17,2821	1,00
12:35:00	20:05:00	11,04	8,2005	1,00
12:40:00	17:25:00	3,7	8,9397	1,00
15:05:00	23:25:00	3,7	27,8729	1,00
17:15:00	21:55:00	3,7	17,05	1,00
6:20:00	13:25:00	3,7	10,2322	5,00
6:45:00	14:25:00	3,7	9,5051	5,00
7:00:00	15:35:00	3,7	14,8258	5,00
7:20:00	14:45:00	3,7	3,7103	5,00
7:40:00	16:10:00	3,7	12,716	5,00
8:05:00	16:15:00	7,4	4,0249	5,00
8:35:00	15:55:00	7,4	2,4981	5,00
9:10:00	14:25:00	7,4	9,8351	5,00
9:40:00	14:00:00	3,7	8,5635	5,00
11:30:00	18:35:00	3,7	12,6995	5,00
13:50:00	18:40:00	7,4	8,8814	5,00
14:40:00	17:45:00	3,7	10,3752	5,00
16:35:00	18:50:00	11,04	9,2752	5,00
17:15:00	21:10:00	3,7	9,0453	5,00
20:05:00	23:25:00	3,7	12,046	5,00

Table A.1. Input EVs for day 1 and day 5

A.2 Base-case, summer week

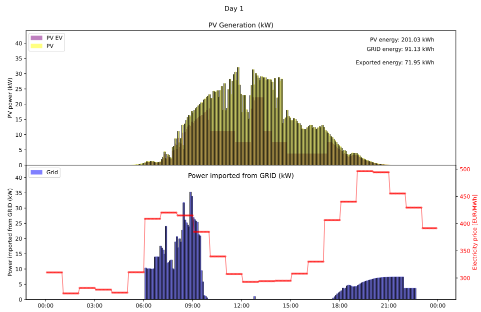

Figure A.1. Day-1, Dumb (Strategy 1)

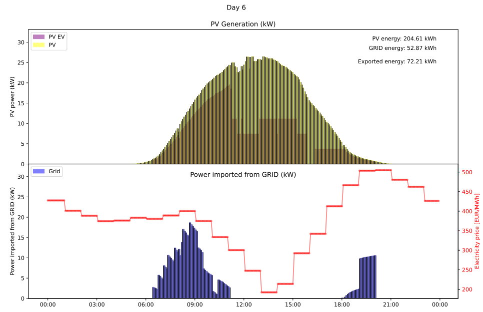

Figure A.2. Day-6, Dumb (Strategy 1)

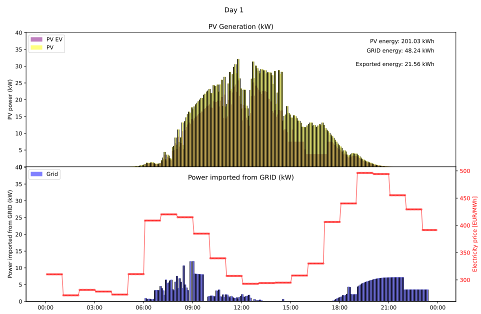

Figure A.3. Day-1, eqPV (Strategy 2)

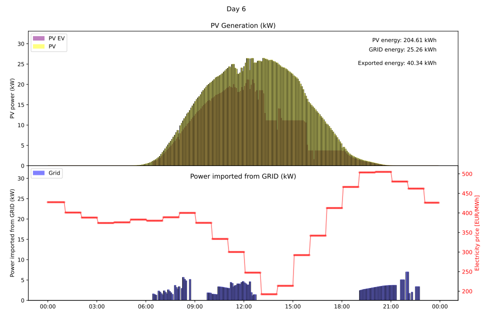

Figure A.4. Day-6, eqPV (Strategy 2)

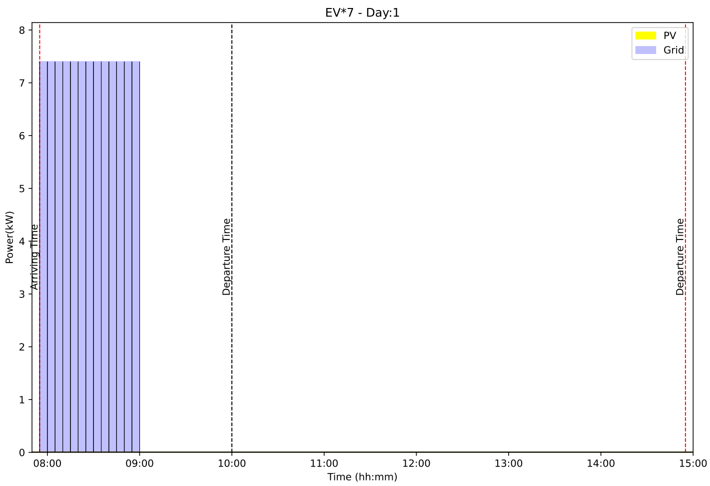

Figure A.5. EV7, Dumb (Strategy 1)

A.3 1.0PV - 15EV/day (day 3), summer week

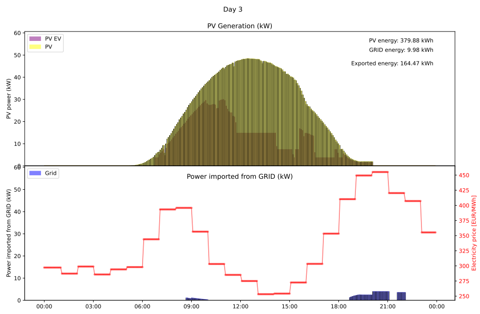

Figure A.6. Day-3, eqPV (Strategy 2) 1.0PV-15EV

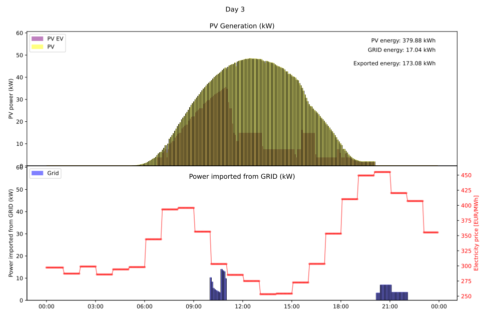

Figure A.7. Day-3, Day-ahead (Strategy 4) 1.0PV-15EV

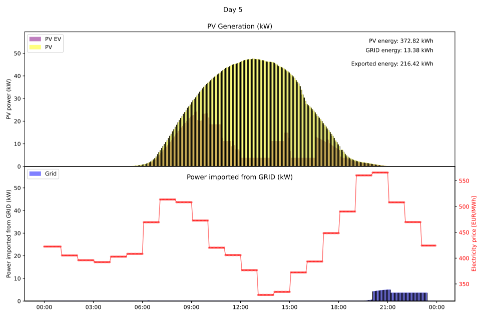

Figure A.8. Day-5, eqPV (Strategy 2) 1.0PV-15EV

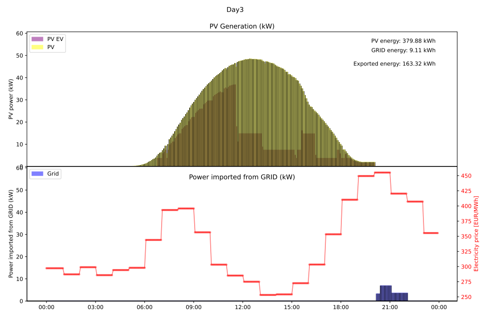

Figure A.9. Day-3, sortEV (Strategy 3) 1.0PV-15EV

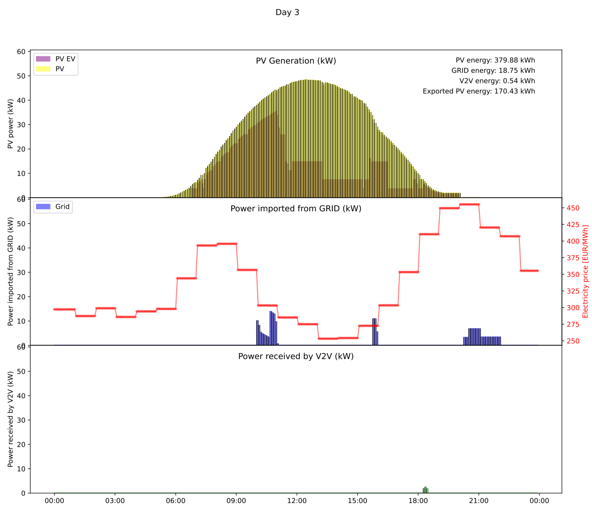

Figure A.10. Day-3, V2V (Strategy 5) 1.0PV-15EV

A.4 1.0PV - 15EV/day (day 1), winter week

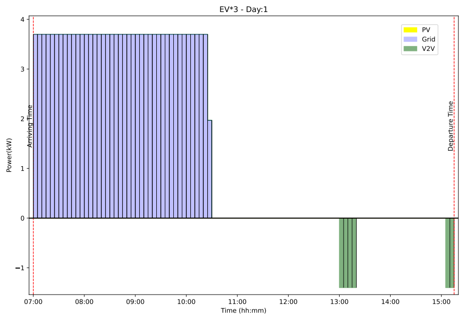

Figure A.11. EV3, V2V 1.0PV-15EV

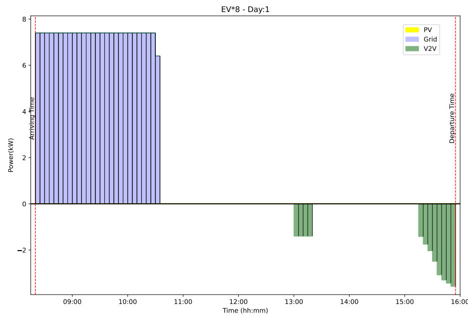

Figure A.12. EV8, V2V 1.0PV-15EV

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