Temporal analysis of power system violations due to electric vehicles

The case of the Swedish low-voltage distribution grid

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Abstract

Vehicle fleet electrification is part of the strategy to meet the European Green Deal targets. Thus, while electric vehicles (EV) are becoming increasingly popular among Europeans, implications of an escalated charging demand for the electricity grid are yet to be explored. Since electricity demand follows temporal patterns throughout the year, the time dimension of impacts takes on great importance.

This thesis analyses the implications for the low-voltage (LV) electricity distribution grid from a high EV penetration scenario, considering Sweden and the year 2050 as base assumptions. Current regulations on thermal and voltage violations in feeder cables and transformers are used to assess the impact on the grid. Two models are employed to simulate the scenario: (i) a cost optimization model to predict the future energy system structure and electricity dispatch; (ii) a reference network model to simulate the Swedish LV distribution grid capacity and operation. Furthermore, grid vulnerability findings are leveraged to provide feedback to the energy system model. Hence, presenting a flexible future energy system that will allow the application of smart charging strategies to preserve electricity network components.

The results show that frequent power system violations would be registered, especially in winter months and the evenings when residential electricity demand in Sweden is elevated. Yet, price-optimization charging strategies mitigate this correlation and breaches of grid regulations are significantly reduced. Vehicle-to-grid (V2G) charging is also examined, presenting no advantages compared to a unidirectional flow price-optimization approach in terms of grid susceptibility. Furthermore, findings show that many violations occur when EVs charge at maximum charging power rate (CPR) at certain time intervals of the day. Hence, as a grid vulnerability alleviation solution a temporal CPR constraint is suggested, leading to a notable reduction of grid issues. In terms of electricity production mix, a system mainly composed of wind power and hydropower with a few backup technologies provides flexibility to securely accommodate EVs in the LV distribution grid.

Keywords: Electric vehicles, EV charging, Optimization, Energy systems modelling, Renewable energy sources, Power system violations, Distribution grid.

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Lastly, I would like to give special thanks to my parents for supporting my decision of coming to Sweden, constantly pushing me to pursue my dreams and bringing me up to be a great person. To my sister, Celia, for leading my way in life and always having unconditional confidence in my success. To all the friends that I have met in Gothenburg who have filled up my time here with unforgettable experiences. To the ones that come along in my stepping out of the comfort zone journey.

"Whether you think you can or you can't, you're right"

- Henry Ford

Pablo Romero del Rincón, Gothenburg, June 2022

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

BEV	Battery Electric Vehicle
CCS	Carbon Capture and Storage
CPR	Charging Power Rate
CHP	Combined Heat and Power
DG	Distributed Generation
DSO	Distribution System Operator
EV	Electric Vehicle
GIS	Geographic Information System
HV	High Voltage
LV	Low Voltage
MV	Medium Voltage
PHEV	Plug-In Hybrid Electric Vehicle
RES	Renewable-based Energy Sources
SoC	State of charge

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Introduction

1.1 Background

As part of the European Green Deal published in December 2019 [1], the European Union (EU) agreed to reduce Green House Gas (GHG) emissions to 55% by 2030 compared to 1990 and achieve zero net emissions by 2050. In order to reach this goal, all the European industries need to be transformed. However, electricity production and transport sectors have one of the greatest potential since they account for 30% and 31% of total CO_2 emissions in the EU, respectively [2]. To decarbonize the European electricity generation, strategies are focused on boosting the share of renewable energy sources (RES) such as solar or wind power. As these technologies are intrinsically intermittent, electricity production will be more variable. Thus, there is a need to develop mechanisms to balance electricity generation to be able to satisfy electricity demand instantly.

Electrification of passenger cars is usually regarded as a possible solution to achieve the desired decarbonization of the transport sector [3]. In fact, EV sales are currently experiencing a significant increase in the EU accounting for 19% of newly registered cars in 2021 compared to 11.4% in the previous year [4]. Consequently, the electricity demand is expected to increase. This electricity demand by EV together with the increased variability of electricity generation could have both negative and positive impacts on the transmission and distribution of electricity.

Regarding the negative impacts, power demand from EVs would increase the total system load, thus creating congestion in the weakest areas of the network and raising power losses [5]. As a result, grid components would degrade at a higher speed [5]. Hence, Distribution System Operators (DSOs) would need to invest in infrastructure enhancement to provide a proper service quality to customers [5]. The impacts mentioned above will vary among different grid topologies, EV penetration rate, driving behaviour and specially time. This stems from several factors. One is the irregular residential energy consumption throughout the year. In northern countries as Sweden, that would make winter months more vulnerable since they concentrate the highest load peaks. Moreover, in an intra-day time-scope the grid is more stressed at certain hours due to commuting patterns and energy demand from industries.

Nevertheless, a high EV penetration also increases load flexibility. This is due to the fact that CPR, starting time and final state-of-charge (SoC) are highly adjustable since these parameters are dependent on user behaviour. In fact, it is estimated that private cars are parked 80% of the time and the daily energy demand could be fulfilled in only 3h with a standard slow home charger [5]. Consequently, EV charging could be optimized to reduce implications on the electricity grid. New technologies such as vehicle-to-grid (V2G), which enables injecting electricity from the battery back to the grid, boost the flexibility potential. Therefore, forecasting the implications of a high EV penetration while assessing various charging strategies will allow great economic savings for DSO and avoid expensive grid reinforcement.

1.2 Literature review

Recent studies [6, 7, 8, 9] have investigated the characteristics of the future electricity demand increase due to EVs considering different charging strategies and geographic areas. Qian, Zhou [8] simulated several scenarios with four charging approaches: (i) uncontrolled domestic charging; (ii) uncontrolled off-peak domestic charging; (iii) “smart” charging to reduce costs; and (iv) uncontrolled public charging. It showed that a 20% level of EV penetration would lead to a 35,8% increase in power peak load, for the worst-case scenario in the U.K. distribution system. Moreover, it highlighted the importance of implementing “smart charging” to avoid sharp increases in the power load curve peaks. Muratori, M. [6] presents a bottom-up methodology to quantify energy use from households’ regular consumption together with EV charging requirements, showing that uncoordinated charging could substantially change the shape of the load curve.

A major conclusion of the findings above is the significant modification of the energy consumption patterns in scenarios with a higher penetration of EVs. Current electricity grids might not be designed for the new upcoming scenario and vulnerabilities in the LV distribution grid related to thermal capacity or voltage regulations are likely to occur [10]. Several articles [11, 12, 13] assessing the impacts of future EVs penetration scenarios on the power system can be found in the literature. Gemassmer, Daam [11] simulated six synthetic LV grids in the cities of Brandenburg and Berlin in a 2040 scenario and found that a pure market-oriented strategy is the most harmful for grid components since it leads to significant peaks in the power load curve. Therefore, it would cause repeated overload of transformers and feeders. Rodriguez Pajarón, P. et al [12] analyzed power quality impact (harmonics and voltage unbalance levels) of non-linear loads and EVs concluding that charging modes which involve simultaneous charging start time can lead to severe unbalance problems. Moreover, EV charging location (distributed or concentrated) has a strong effect on power system violations probability, thus being of importance to consider demographic data to study rural/urban distribution grids.

Other papers [14, 15, 16, 17] focus their research on a temporal assessment of the implications of EV charging on the power system. Some articles [14, 15] propose numerical models to predict intra-day voltage fluctuations on local grids in Japan and United Kingdom. Paevere, Higgins [16] disaggregates the analysis to hourly time-steps over a full year in the state of Victoria (Australia) under nine different charging behaviour scenarios. They found that under a 35% EV penetration level, load peak can be up to 15 % on high-demand summer days, although they do not investigate the possible implications on grid components. Heymann, Miranda [17] analyzed the impact differences between daytime and overnight EV charging on Porto's distribution grid. They found that over-night charging would lead to less transformer overloading due to less degree of clustering and pointed out that commuting patterns will heavily influence the grid impacts.

As it has been shown, it is widely documented that an increased share of EV fleet will lead to power quality implications of various degrees. However, not only the demand side is changing, but also the supply side will face strong modifications due to RES growth. Here is where large scale diffusion of EVs can also have benefits for the electricity system if adequate strategies are put in place. For instance, literature is fairly unanimous in the statement that EVs can increase the amount of RES that can be brought into the system while reducing the negative consequences for the grid [18]. Recent studies [12, 19, 20, 21, 22] analyzed EV uptake together with wind or PV energy integration in the system. Results show that PV distributed generation contributes reducing transformer loading [12], but only between the hours when sunlight is available [22]. In terms of wind energy, Wu, Li [21] concludes that power system reliability is increased when coordinating EVs and wind energy dispatch since excess energy can be added to the EVs. Moreover, wind curtailment in Europe could be reduced by up to 10% and solar curtailment up to 23% with a higher degree of EV penetration [20]. However, when peaks in wind energy production take place (low electricity prices), market-oriented charging strategies to reduce costs lead to 10-30% more loaded power network, affecting the health of the grid elements [19].

A particularly interesting technology to accommodate more variable RES in the power system is Vehicle-To-Grid (V2G) in which the flow of electricity is bidirectional, so that batteries could inject energy to the grid when electricity prices are high and consume in low-demand hours. This could mean the creation of a distributed network of energy storage in private car batteries so that providing support to the excess of renewable energy generation. Habib, Kamran [23] presents a detailed analysis of V2G impacts on distribution networks. The main benefits found are regulation of active power, support reactive power, load balancing by valley fillings, peak load shaving and reduce utility operating cost. In contrast, V2G creates some challenging issues such as battery degradation, extensive communication between EV and grid and changes in the whole infrastructure of distribution systems. Moreover, Wang, Liu [24] found that using V2G systems to smooth the fluctuations of large-scale wind power achieve noticeable performance improvements over other techniques. However, a previous study [10], carried out a geographical analysis of power system implications from residential EV charging on the Swedish LV grid, finding that V2G is expected to cause more power system violations than unidirectional charging.

Only a handful of studies [9, 10, 25] analyse complete national power grids and just one at the distribution level [10] which is a crucial point for system violations. In addition, these global-view research do not analyse the implications for the power system from a temporal point of view, which is of great importance due to the fluctuations of electricity demand over 24h periods but also throughout the year. Some studies also point out [25] the importance of spatial disaggregation and considering geographic singularities such as rural and urban grids. Moreover, further research could be done on the potential of V2G technology to accommodate more RES in the system.

1.3 Aim

The goal of this thesis is to gain knowledge on how LV distribution grid violations can be prevented in a high EV penetration scenario. Insights drawn here, together with previous findings could be used to design future charging strategies that comply with grid regulations and customer needs. Therefore, this study sets out to develop a temporal analysis of the implications of EV charging in the LV distribution grid assuming different charging strategies and by geographical grid typology. Moreover, previous studies have pointed out the potential benefits and risks of V2G and "smart" charging strategies for the power system . Hence, it will also analyse the importance for integrating variable RES in the system that EVs can apply these strategies.

1.4 Research questions

Based on the aim, the primary research questions of this thesis are broke down into:

- What are the temporal characteristics of power system violations on the overall Swedish LV distribution grid in a 100% EV penetration scenario?
- What EV charging limitations can be put in place in order to prevent power system violations and how effective are they?
- How does the optimal energy system structure change when applying EV charging limitations?

1.5 Limitations

Since this research needs to estimate a future scenario that has never existed before, models need to be developed. As every model, a balance between simplification and creating a realistic representation of the actual system needs to be found. With that aim, this study focuses solely on the Swedish LV grid because it notably simplifies calculations and reduces complexity, but can minimize accuracy in areas where the supplying grid is weak [26]. In addition, previous studies [10] in the Energy Technology division at Chalmers have found that most power system violations would be registered in highly populated areas, with rural areas being rarely vulnerable. Consequently, rural areas are excluded from this analysis, thus exclusively areas above a population density of 200 per km^2 are studied. Moreover, since the focus of this thesis is in the temporal aspect over one year and the structure of the energy system, only a 100% EV penetration scenario is analysed. This is expected to be achieved by 2050 in Sweden (see 2.2). Relevant studies on the assessment of different EV penetration scenarios can be found in the literature [8, 19]. Other limitations to this thesis are introduced by the hypothesis and technical simplifications considered in the models to make them feasible. However, they are addressed throughout the methodology and discussion chapters.

2

Theoretical Framework

2.1 Swedish Power System

The electrical power systems around the world share the same purpose, delivering electricity to population and industries so that they can use a wide range of devices that consume electric power. However, the power system implementation and design greatly differ between countries around the world. As this thesis' analysis and results are focused on the Swedish power system, it seems essential to describe its main layout and operations characteristics in order to better comprehend the potential implications of a EV high-penetration scenario.

2.1.1 System structure

Swedish power system consists of two types of networks: transmission and distribution.

1. **Transmission network** transports electricity from large power plants to distribution networks where it is consumed. This transportation is done in the form of high-voltage (HV) AC electricity (mainly 400 kV and 220 kV lines) to reduce current, hence avoiding unnecessary power loses. Svenska Kraftnät is the public utility company that owns and operates the transmission grid in Sweden, thus responsible for the well-functioning of its 17.000 km-long lines [27]. Since most Swedish energy consumption is concentrated in the southern part of the country, transmission lines are similar to highways conveying mainly hydro-power energy from the low demand areas to the more populated regions. This feature can be observed in figure 2.1.

2. The next level of the electricity grid is the **distribution network** which is further subdivided into two types:

    - **Regional** (or sub-transmission). It uses voltages between 130 - 70 kV, accounting for a total length of around 30.000 km to distribute energy within the regions. Some smaller power plants are connected directly to the regional grid and large industries can be fed directly at 130 kV level. Moreover, to ensure that power is always available from the transmission

Figure 2.1: Map of the Swedish Transmission Network [28]

network, there are normally several entry points to each regional network and are often connected as closed loops. In contrast to the transmission network which is a national monopoly, regional grids are owned by three main DSOs depending on the region: Vattenfall Eldistribution, Ellevio and E.on Elnät Sverige [29].

- **Local**. It uses voltages between 20 - 0,4 kV, accounting for 160.000 km of overhead lines and 339.000 km of underground cable [27] to distribute electricity along distances of up to 10 km from the transformer to the final customer. Local grids are owned and operated by multiple smaller companies, in total there are 170 local grid operators in Sweden. In order to increase system reliability, closed loops fed from two directions are often used, but switching has to be done manually and it can take several hours to switch in case of a fault. In urban areas, the local grid is built with underground cables which very rarely incur in a failure and therefore are not always implemented as closed loops. The last step of voltage transformation down to 400 V phase-to-phase (230 V phase-to-neutral) is done at a neighborhood level in transformers with a rated power between 50 - 1.000 kW. At that voltage, electricity is transported through normally no more than 1 km until reaching the residential consumer. In this report, this final stage from the neighbourhood transformers to the consumers is referred as *LV Distribution Network* (See 2.1.4).

2.1.2 System operation and management

The fact that electricity still cannot be economically large-scale stored determines the operational conditions of electric power systems. As it is known, electricity supply and demand must match all the time. An imbalance between generation and load would put stress in synchronous generators at power plants, preventing them from working properly which eventually would lead to a shortage of electricity supply [30] . Therefore, system operators must monitor constantly that the system is in balance. In AC systems, this task can be done by controlling that frequency is permanently in a range of $\pm1\%$ of the rated value (50 Hz). If consumption is higher than production the frequency will sink, and operators will bring the system back to normal by increasing generation at power plants (e.g. opening an additional hydro-power turbine). In contrast, if production is higher than consumption the frequency will rise and operators will activate mechanisms to lower generation [31].

Operating a power system entails more duties than dispatching active power by keeping the balance between supply and demand. It is also essential to maintain voltage levels at every grid node approximately constant, between $\pm5\%$ and $\pm10\%$ depending on the country. At power plants, electricity is injected at a nominal value, which ideally would reach the destination in a fixed voltage after several level transformations. Yet, exact voltage level at each location is dependent on the voltage drop along the cables associated with resistive losses. This is, the voltage decreases as one moves from the substation toward the end of the distribution feeder due to the effect of Ohm's law ($U = I \cdot Z$). The voltage drop is subjected to the connected load as higher demand leads to greater current while the line impedance remains the same. On the whole, the actual final voltage value continuously varies with demand, both system-wide and locally. Technically, this is referred as *Voltage Stability* and it is a major parameter to monitor in distribution systems since voltage drops are significant specially for long cables [32].

Nowadays, the significant presence of intermittent RES and distributed generation (DG) offers new possibilities for grid operators in terms of voltage and frequency regulation. DG refers to the production of electricity in small scale for use on-site instead of transporting it long distances from huge power plants to end consumers, some of the most common DG technologies are solar photo-voltaic panels and small wind turbines. In addition, energy storage technologies and controllable loads such as EVs will play a major role in maintaining a balance between supply and demand.

2.1.3 Current state of Swedish grid infrastructure

As it has been seen, operating the power system is a complex task that involves forecasting demand in various time-frames to adjust instant generation but also to plan new investments in grid infrastructure. Furthermore, transmission grid investments have an economic lifetime of approximately 40 years and apart from providing a high delivery reliability now, they must guarantee that the new-built grid will cope with the future electricity system [33]. The previous statement justifies studies as this thesis, future scenarios analysis are relevant to strategically plan grid strengthening in advance so that adapting the current infrastructure to future shape of energy demand. Specially, in an ever changing time when both supply and demand are susceptible to major alterations for multiple reasons such as: increase of RES share and DG, raise in EV market share, geopolitical conflicts, etc.

The Swedish electrical network is constantly evolving through replacement of ageing equipment but also adding new generation and power lines to meet society's delivery reliability demands. In Sweden, a major driving force for grid investment in recent years has been to weatherproof the electrical grid since it showed weather-related vulnerabilities after two big storms (Gudrun in 2005 and Per in 2007) hit the country. Private companies had a voluntary agreement with the Government to transform overhead lines to underground cables, thus reducing its weather dependency. However, grid ageing is also becoming and urgent reason to invest in grid renewal. According to the Swedish Energy Market Inspectorate, 70% of the regional and local grid components are more than 20 years old and around 37% are more than 38 years old [33]. Although, the grid went through an important expansion 40 - 50 years ago, it has not been steadily renovated. As a result, it is now in need of an investment boost. In addition, grid reinforcement will be deployed following demographic trends. For instance, urbanization in Sweden is generating a population influx from rural areas to big cities with higher population density which will put more pressure on urban power grids as population increases.

2.1.4 Low-voltage distribution network structure and regulations

As it has been explained in 2.1.1, the LV distribution grid is the last level of the electricity grid where residential customers are connected to the system. This is one important reason to operate at LV, to make it safe for unprofessional people to use electricity for domestic purposes. Since the majority of population relies on LV electricity supply to perform daily tasks, it is regulated under quality and safety standards. Some of the monitored parameters that are taken into account in this report are voltage stability and thermal capacity in feeders and transformers.

Voltage Stability

Voltage quality is standardized in a European level by the norm **EN 50160** ("Voltage characteristics of electricity supplied by public distribution systems") [34]. It specifies the main characteristics of the voltage at the supply terminals of the LV and medium voltage (MV) public distribution systems under normal conditions. In other words, it gives threshold values within which the voltage properties should remain to function well and extend the components' life expectancy. Voltage characteristics may surpass the limit levels even under normal operating conditions due to changes of load or disturbances produced by special equipment. As a result of these variations, it is contemplated that the regulations may be breached in a small number of occasions since some of the causes are unpredictable. The monitored voltage characteristics are frequency, magnitude, wave form and symmetry of the three-phase voltages, although in this report only magnitude is considered.

According to EN 50160, voltage magnitude variations should not exceed $\pm 10\%$. Continuous voltages over and under this value has been shown to be very unlikely and residential electrical appliances are normally designed to bear this voltage fluctuations. The concrete guidelines are [34]:

- During each period of one week 95% of the 10 min values of the supply voltage should be within the range of $\pm 10\%$ of the rated voltage (230 V).

- All the 10 minutes values of the supply voltage should be within the range of $+10\%/-15\%$ of the rated voltage (230 V).

In addition to the European standards, the Swedish energy regulator, the Energy Markets Inspectorate ("Energimarknadsinspektionen") sets stricter directives regarding voltage quality. The norm **EIFS 2013:1** [35] states that over a period equivalent to one week, all the the ten-minute values of the voltage magnitude shall be between 90% and 110% of the rated voltage. It is the responsibility of the network operator to ensure that voltage of quality is delivered to customers. In order to avoid complaints and investigations, operators carry out field measurements regularly [36]. Nevertheless, many countries have stricter national limits, so in order to reduce this impact, a $\pm 5\%$ voltage deviation is applied in this thesis [10].

Thermal capacity

Distribution networks are restricted by heating in their capacity to transmit power. Continuously flowing current increases temperature in the conductor, thus setting a limit for the acceptable loading, referred as *Thermal capacity*. Moreover, as the conductor heats up, its resistance increases. Although this is generally a small effect, constant overloading may create a negative feedback loop since increased resistance will in turn rise temperature again. In the worst-case scenario, if a fault is not cleared, the conductor can actually melt down [32]. The most common impact on grid components is reduced lifetime. An often overloaded transformer or sporadically overloaded but at high powers, will need a sooner replacement than a well operated one.

In order to select an acceptable conductor for a specific distribution network, expected power demand that the cable is called to carry for long periods of time need to be estimated. This is the *design current*. Then, a conductor is selected according to the *maximum permissible current* which is the maximum value of current that an insulated conductor or cable can carry indefinitely without reducing its normal life expectancy. Similarly, heating also limits transformers operation. Here, the amount of energy dissipated relies on other factors too, such as frequency. But, loading and demanded current are again the main factors to be monitored. Transformer ratings are given in terms of apparent power (kVA) [32].

2.1.5 Electricity market

The Swedish electricity market was one of the first in Europe to be reformed towards a more liberal framework. In the year 1996, production and sale of electricity was detached from transmission which remained as a natural monopoly operated by Svenska Kraftnät. On the contrary, production and trading switched to markets opened to competition.

The marketplace for exchange of electricity in the Nordic countries is Nord Pool. On its spot market, Swedish, Norwegian, Danish and Finish participants trade hourly contracts for the 24 hours of the following day. Every morning, when the market is opened, producer and consumer companies submit bids for the volume of electricity that they are willing to buy or sell in these 24 hours. The market ceases receiving bids at 12:00 and Nord Pool starts to construct the supply and demand curves. The price and amount of electricity being traded is determined by the point where both curves cross each other. This same price applies to all the contracts within each of the 24 hours in the same bidding area regardless of the generation technology or electricity volume [37].

The Nordic market is split into 15 pricing areas to reflect physical bottlenecks in electricity transmission systems and to consider regional market peculiarities. When a bottleneck is found between two regions, electricity will always flow from low-price areas to high-price areas, so that consumers pay more where the power demand is the highest [38]. Sweden is divided into four price areas: SE1, SE2, SE3 and SE4 ordered from north to south (see figure 2.2). Usually, supply exceeds demand in the northern regions in contrast to the southern regions where demand surpass generation. Thus, prices are equal or higher in the south (SE4).

Supply and demand characteristics

Electricity generation in Sweden has historically relied on nuclear and hydro power. This has been the case since the 80s when the Swedish government strengthened its commitment to reduce dependency on foreign fossil fuels. In 2019, which is the most recent year with available data at the time of writing this report, electricity generation reached 166 TWh with the following sources distribution: 39% nuclear power, 39% hydro power, 12% wind power, 0,4% solar power. The remaining 9,6% is produced with combustion-based technologies, principally combined heat and power plants (CHP) and industrial processes [39].

Installed generation capacity has been raising in the last years due to increased in-

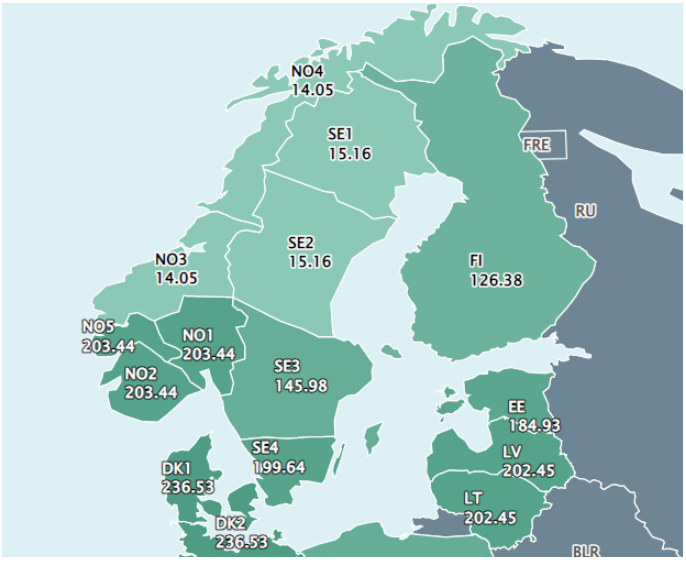


Figure 2.2: Nordic bidding areas in the NordPool spot market. Prices in Euros per MWh for March 23rd 2022 (average of all hours)

vestments in RES such as wind and solar, while traditional sources remain approximately constant (See figure 2.3). The only exception is the reduction of nuclear power capacity as a result of shutting down one reactor at Ringhals power plant in December 2019. In relative numbers, solar PV is the fastest growing generation technology which saw an increase of 50% from 2019 to 2020, reaching an overall capacity of 1.090 MW.

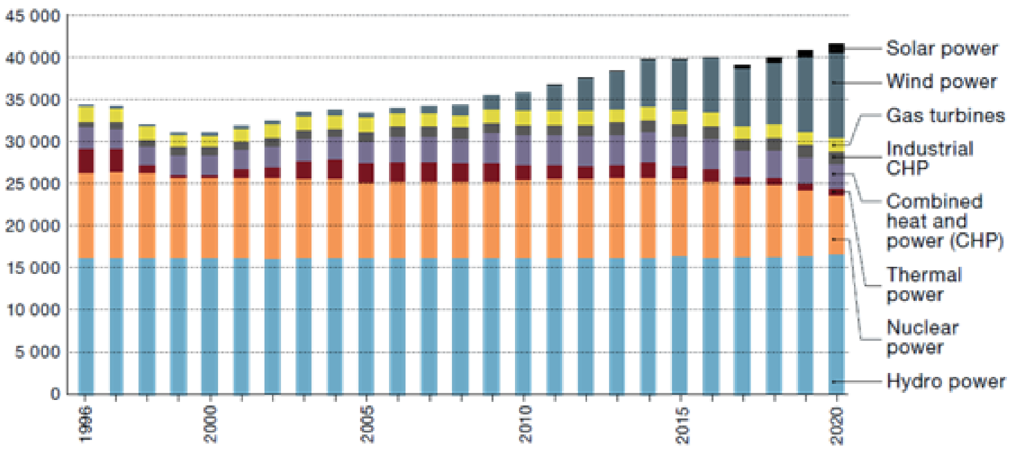


Figure 2.3: Installed electricity generation capacity by type of power in MW [39]

2.2 Electric vehicles

Environmental concerns are driving the electrification of the transport sector. It entails a high number of benefits for society such as reducing CO_2 emission if coupled with a renewable-based power system, local air pollution decrease and noise levels reduction. These perks have motivated governments to impose restrictions on combustion-engine vehicles in high pollution scenarios. Thus, pushing car manufacturers to boost fuel efficiency and invest in electrification of their models [5].

EV market status

Nowadays, more options are available to automobile customers. In specific, around 370 electric car models were available globally in 2020 which entails a 40% increase compared to 2019. China is the country with the highest number of models available since it is the world's largest EV market. However, Europe is the fastest-growing market logging a 50% increase in the number of models from 2019 to 2020. The higher variety of car supply is pushing EVs sales [40].

There are two types of EV available in the market: (i) Battery Electric Vehicles (BEVs) and Plug-In Hybrid Electric Vehicles (PHEVs). The first one is purely powered by electricity stored in a battery while the second one is a combination of a traditional combustion engine car and a BEV, containing a gas tank, charging port, both types of engines and a battery.

The average range and battery capacity of new BEVs have been continuously growing in recent years. The new BEVs weighted average range in 2020 reached up to approximately 350km with an average usable battery capacity of 60 kWh (0,17 kWh energy consumption). However, the latest models such as "Mercedes EQS 450+" incorporates 107,8 kWh of usable energy, enabling the driver to reach a 640 km range [41]. In contrast, during the last four years, the average electric range of PHEVs has stayed fairly stable at around 50 km [40].

In terms of sales, 6,7M electric cars were sold globally throughout 2021 which represents a 108% increase in yearly sales compared to 2020, being China the top buyer with 3,3M EV. Additionally, 2,3M were purchased in Europe (+ 66% vs 2020) and 138.000 in Sweden (+ 46% vs 2020). Despite this fast growing pace, EVs only represent 1% of global private cars in use, ascending up to 1,1% in Europe, 4% in Sweden and 22% in Norway which is the global leader in relative terms [42].

The EV market share, number of EVs sold over a year relative to the total amount of cars sold, has been significantly growing over the last decade. In 2021, EVs accounted for 9% (vs 4,6% in 2020) of the total private cars sales in the world. The overall European figure reached 19% (vs 11,4% in 2020) whereof BEV registrations accounted for 54% of the total EV registrations. Norway was in the top position with a record high sales share of 86% (vs 74% in 2020), followed by Iceland with 68% (vs 45% in 2020) and Sweden with 45% (vs 32% in 2020)[42].

Sweden has the ambition to be climate neutral by 2050. For that goal, the current governmental focus is on increasing energy efficiency of vehicles and breaking dependence on fossil fuels. According to the figures presented above, the country seems to be in the right track and aims to reach a 100% EV penetration by 2050.

3 Methodology

3.1 Models overview

This study uses two different models, a reference network model simulating the LV grid in Sweden and an electricity cost optimization model that designs the electricity system up to 2050. In this thesis, modifications of the models and a feedback loop between the models are implemented in order to design a charging strategy that both helps integrate more RES by charging EVs at low-price hours and generates low power system violations in the LV grid.

The reference network model uses GIS (Geographic Information System) data on demographics to create the synthetic LV network [26]. Then, to assign adequate cable and transformer sizing to each grid cell, regulations on Swedish LV grids are included (section 3.2). The model explained above is programmed in two different software: QGIS to process the geographic information and MATLAB to populate the grid and choose the suitable grid components for each cell. Once the basic layer is created, the grid operation is simulated in section 3.4. This is done by adding electricity consumption data in two separated parts: general household consumption obtained from current consumption of average households and estimated electricity consumption from EV charging obtained from ELIN-EPOD model in section 3.3. In figure 3.1 a conceptual framework representing the interconnection between models and main data inputs is shown.

As previously mentioned, EV charging profiles are required as input to the grid simulation. For this purpose, energy optimization models programmed in GAMS (ELIN and EPOD) are utilized to simulate the energy dispatch of the system and obtain EV charging profiles. In both models, the objective is to minimize total system cost to meet power demand under certain technological and policy restrictions, such as CO_2 emissions reduction requirements [43]. ELIN is a cost-minimizing investment model which analyses the transition of the electricity system based on the current infrastructure within a 2010 – 2050 time frame. It considers both investment and running costs. In contrast, EPOD is an electricity system dispatch model that uses the output of ELIN to study a specific year. It performs minimization of the total running cost of the European generation system to identify the least-cost hourly dispatch. Both models include an add-on module to optimize the time of

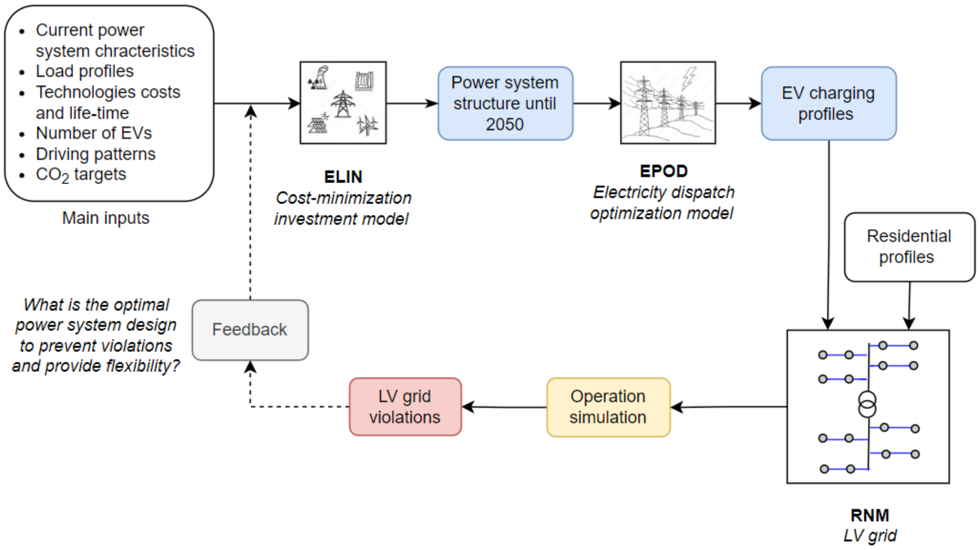


Figure 3.1: Conceptual methodology framework

charging and discharging of EVs by using their batteries as storage system [44]. An important output from EPOD model are the charging profiles for smart charging strategies that are calculated performing optimization. In contrast, charging profiles for "direct" strategy are directly obtained from driving patterns since they do not consider any price optimization.

It is important to mention that both the energy system model and reference network model have been previously created at the Energy Technology division at Chalmers and have been utilized to perform multiple research which have led to various article publications [43, 10, 45, 26, 44]. However, these models are part of the core methodology of this thesis and understanding these models is essential to comprehend the power system violations simulation. Therefore, they are further explained in the following sections prior to explaining in-depth the own crated algorithms in section 3.4 which are used to simulate the grid operation with a 10-min time resolution.

3.2 Synthetic low-voltage grid model (Reference network model)

The aim of this model is to create a fictional LV network based on current electricity demand to later in 3.4 add the EVs charging demand and check whether it would lead to power system violations. The diagram in figure 3.2 indicates the logical order followed in this section to design the current Swedish LV electricity grid. See [45] for further details in the model design.

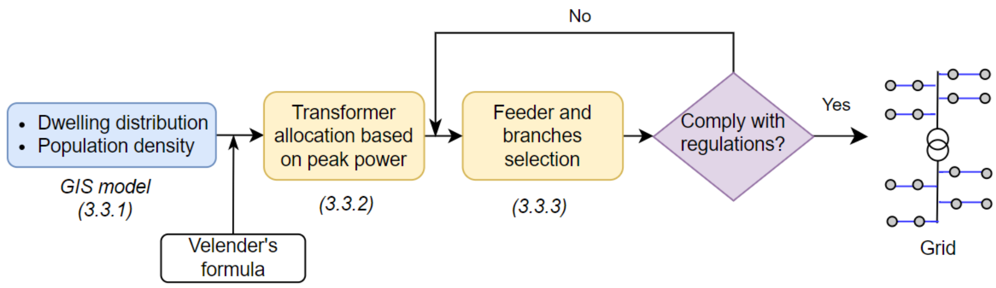


Figure 3.2: Methodology for the fictional LV network design

3.2.1 GIS model design

Geographic Information System (GIS) is a type of database widely used to analyse geographic data. Apart from the coordinates of each element in the database, it can store diverse attributes. In the file utilized in this project, each element is an inhabited **1x1km^2 square of Swedish national territory** (113.562 squares in total) and the attributes are: population density [46], kommuner (Swedish municipalities), bidding area and cars per household.

Residential energy consumption depends heavily on the type of household and heating system, houses tend to consume more energy since they are larger, hence requiring more energy to heat them up. Therefore, it is necessary for the analysis to have information on dwelling distribution (number of customers living in houses and in apartments). Dwelling and population distribution data is not typically available with high resolution. Thus, local administrative units (LAU) retrieved from [47] has been employed since it is the highest resolution available for free use in Sweden. Based on this information, a regression model is created to find the relationship between population density and share of population living in apartments. The functions considered are polynomials up to 8th order and logarithmic functions. After some data cleaning, the following function is found [45]:

$$f(\rho) = -2,5797 \cdot 10^{-8} \cdot \rho^2 + 0,000257 \cdot \rho + 0,3782 \tag{3.1}$$

where ρ denotes the population density in inhabitants per km^2 and $f(\rho)$ is the share of population living in apartments. Then, the total number of customers (NC) per cell (each $1x1km^2$ square) is calculated as:

$$NC = \frac{\rho}{2 \cdot f(\rho) + 2,7 \cdot (1 - f(\rho))} \tag{3.2}$$

where "2" stands for the average amount of residents in an apartment and "2,7" the number of residents in a house. Assuming that each household has one connection to the national LV grid, the number of apartment customers and house customers per cell are (one value per cell):

$$NC_{Apt} = NC \cdot f(\rho) \tag{3.3}$$

$$NC_{House} = NC \cdot (1 - f(\rho)) \tag{3.4}$$

Prior to do the transformer allocation process, an estimation of the **peak power energy demand** (P_{peak}) per cell is required. There are several approaches to determine this number depending on the country, however, the Velender's formula is widely used in Scandinavian countries [48]:

$$P_{peak} = P_{Apt} + P_{House} \tag{3.5}$$

$$P_{Apt} = k_{1,Apt} \cdot E_{Apt} \cdot NC_{Apt} + k_{2,Apt} \cdot \sqrt{E_{Apt} \cdot NC_{Apt}} \tag{3.6}$$

$$P_{House} = k_{1,House} \cdot E_{House} \cdot NC_{House} + k_{2,House} \cdot \sqrt{E_{House} \cdot NC_{House}} \tag{3.7}$$

where P_{Apt} and P_{House} are the peak power demand for apartments and households respectively, E_{Apt} and E_{House} are reference values for annual electricity consumption and $k_{i,j}$ are empirical coefficients. Table 3.1 shows the values applied in the formula and found in literature [48].

Table 3.1: Swedish specific model parameters for the Velender's formula

E_{Apt}	E_{House}	$k_{1,Apt}$	$k_{1,House}$	$k_{2,Apt}$	$k_{2,House}$
3,700 KWh/year	18,500 KWh/year	0,000264	0,0003	0,014	0,0375

3.2.2 Allocation of transformer quantity and size

This section describes the iterative process to allocate the suitable number and size of transformers to each cell of the GIS model which are analysed individually. Depending on the dwelling and energy demand characteristics of each cell, the model would assign different size of transformers and feeders.

Transformer allocation is carried out by solving a cost-minimization problem to reduce the total investment expenses in each cell (equation 3.8), based on peak power demand in each cell (P_{peak}) (section 3.2.1), a set of all possible transformer (Ω) (table 3.2) and cable costs (table 3.3). The algorithm finds the minimum value of $N_{Tr,i}$ (number of transformers per cell) subjected to fulfill peak power demand in each cell (equation 3.9) plus an additional margin ($\alpha = 1,8$) to consider overloading in normal operating conditions. Indeed, this is how the actual grid is designed to avoid replacing transformers every time that demand increases.

Line lengths are calculated assuming an uniform distribution of customers and transformers in each $1x1km^2$ square (equations 3.10 and 3.11). Moreover, the model considers a radial LV connection from each transformer to the final customers (see 2.1.4). A high number of small transformers distributed among the grid requires more MV cable distance, but a few high-capacity transformers need longer LV feeders, the model finds the combination that reduces the total cost. Power lines costs are highly correlated with the demographic area type, being urban grids more costly than rural grids due to the fact that are usually underground cables which entail higher working costs. Therefore, each cell is classified according to the Swedish Mapping, Cadastral and Land Registration Authority [49] as:

- City: Population density (pop/km^2) $\geq$ 1.000
- Urban: 200 $\leq$ Population density (pop/km^2) $\leq$ 1.000
- Rural: Population density (pop/km^2) $\leq$ 200

$$C_i = N_{Tr,i} \cdot C_{Tr,i} + l_{LV,i} \cdot C_{LV} + l_{MV,i} \cdot C_{MV} \quad i \in \Omega \tag{3.8}$$

$$Tr_{Cap,i} \geq \alpha \cdot P_{peak} \quad i \in \Omega \tag{3.9}$$

$$l_{LV,i} = \lambda \cdot \sqrt{\frac{A_i}{1+\lambda}} \quad i \in \Omega \tag{3.10}$$

$$l_{MV,i} = \lambda \cdot \frac{1}{\sqrt{1+N_{Tr,i}}} \quad i \in \Omega \tag{3.11}$$

where $\lambda = \frac{NC}{N_{Tr,i}}$ denotes the number of connections served per transformer, $A_i = \frac{1}{N_{Tr,i}}$ the area supplied by each transformer ,$l_{n,i}$ the resulting line lengths, $N_{Tr,i}$ the number of transformers of type i and $Tr_{Cap,i}$ the transformer capacity.

Table 3.2: Transformer cost and capacities considered in this study.

Capacity (kVA)	50	100	200	315	500	800	1250
Cost (kSEK)	32	38	54	71	102	135	195

Table 3.3: LV (400 V) and MV (12 kV, 240mm^2) line costs for different demographic areas and average sized power lines. Costs provided by the Swedish Energy Market Inspectorate [50].

Demographic classification	City	Urban	Rural
LV line cost (kSEK/km)	827	540	177
MV line cost (kSEK/km)	1.004	691	358

3.2.3 Feeder selection and number of branches

Once the number of transformers per cell has been calculated, the next step is to allocate adequate cables to feed each customer connection from the corresponding transformer. Each $1x1km^2$ cell is subdivided in a number of smaller areas equal to the number of transformers (N_{Tr}). The grid layout in the subareas assumes an uniform distribution with horizontal and vertical feeders and the transformer placed in the centre. Generally, feeders are branched into multiple ones to reach the customer. Here, the number of branches per feeder is determined by the number of customers supplied according to table 3.4, being five the maximum number of branches [26].

Table 3.4: Number of branches per feeder based on number of customers supplied by each transformer.

Customers (λ)	$\lambda < 100$	$100 < \lambda < 64$	$64 < \lambda < 36$	$36 < \lambda < 1$	$\lambda = 1$
Branches	5	4	3	2	1

Then, feeders and branches sizing are assessed following an iterative process based on national standards to supply the estimated electricity demand, this is checking parameters such as tripping criteria, voltage quality, maximum earth/supply impedance, maximum cable capacity and selecting a layout that satisfies all of them [26].

3.3 Energy system model (ELIN-EPOD)

3.3.1 Model description

As previously explained, in order to assess power grid violations when including EVs, yearly EV charging profiles indicating energy and time are required. These are obtained from the energy system models referred as ELIN and EPOD. The first one is a cost-minimization investment model designed to determine the optimal investment decisions in generation technologies for the European power system. Whereas, EPOD simulates electricity dispatch following a cost-optimization strategy based on ELIN results such as: CO_2 prices and transmission lines description. Both models have been previously used to carry out diverse studies, for instance to assess storage technologies as flexibility management strategies [44] or to study European system transformation to meet policy targets. The following paragraphs describe the characteristics of each of these two models.

ELIN model evaluates investment decisions in energy technologies every 5 years in the period 2020-2050. Each year has a time resolution of 20 representative days, this is 480 time steps. European countries are sub-divided in smaller regions to take into account transmission bottlenecks, although investing to enhance the transmission system is possible in all the investment periods. In the Nordic countries, which are part of the Nord Pool energy exchange market (See 2.1.5), these regions coincide with the actual bidding areas. The model also takes into account EV batteries as an electricity storage option, thus it optimizes the charging and discharging (if enabled) of EVs. However, only intra-day storage is allowed, hence the energy stored in EV batteries must be the same in the beginning and at the end of the day (this only applies for ELIN). The main data input to the model and its sources are included in the following list (See [44, 43] for a detailed description with specific parameters and equations):

- Information on the current European electricity supply structure retrieved from Chalmers database [51].

- Details about investment, running costs and life-time of all the technologies and fuels. The technologies are: condensing power plants with and without CCS (Carbon Capture and Storage), gas turbines, CHP (Combined Heat and Power), on-shore and off-shore wind power, solar PV and hydro-power. The fuels are: biomass, biogas, coal, gas, lignite, uranium and waste.

- CO_2 emission reduction policy targets (99% emission reduction in 2050 compared to 2019).

- Load profiles of all the regions considered in the model.

- Meteorological data for each region from year 2012 to estimate wind and solar generation.

- Number of EVs in each region, battery size and efficiency (See 3.3.2)

- Driving patterns to calculate hourly EV electricity demand that must be fulfilled (See 3.3.2).

Once the structure of the energy system has been created with ELIN, it is time to optimize the electricity dispatch with the **EPOD** model. In the present work, it is run for the year 2050 which corresponds to a 100% EV penetration but every year between 2020-2050 can be simulated. On the contrary to ELIN model, EPOD has an hourly resolution for 366 days a year (2012 was a leap year), i.e. 8.784 time-steps. The main purpose of the model is to minimize running cost of the already built generation technologies (from ELIN) and provide information on electricity prices in order to optimize charging/discharging of EVs. These are regarded as electricity storage technologies, constrained to the fulfilment of transportation demand, which is a fixed parameter given exogenously. Moreover, they can only store electricity when they are connected to the grid. The way this constraint is treated in the model is further described in section 3.3.2. In contrast to ELIN, the possibility of electricity storage between days is contemplated in EPOD as one full year is simulated. The output of the model that is of interest in this thesis is the data on **EV charging profiles**. It provides 426 different charging profiles for each region indicating the CPR demanded by each car for every hour of the year.

3.3.2 Vehicle data estimation and driving patterns

As this is a future scenario analysis, hypothesis regarding the total number of passenger vehicles are required. It is unknown how the car fleet will exactly vary in the coming decades but it is expected to grow as welfare evolves. In the present thesis, the total fleet is assumed to increase 35% linearly from 2016 to 2050. Since the total Swedish fleet amounted to 4.570.000 passenger vehicles, the number of vehicles is forecasted to reach up to 6.169.500 in year 2050. Then, a 100% EV penetration scenario is assumed for 2050, which is the year that this thesis analyses in EPOD model. Main assumptions regarding EV characteristics are indicated in table 3.5. These are based on current EV characteristics discussed in section 2.2 and expected improvement in the coming decades.

Table 3.5: Electric vehicle characteristics assumed in this study

Battery capacity	Consumption	Battery range	Max. CPR
100 kWh	0,16 kWh/Km	625 Km	6,9 kW

In terms of the **driving patterns** employed to estimate EV charging demand, the model applies input data from a previous study that measured driving behaviour of 426 combustion engine cars with GPS [52]. The sample was randomly selected among all the cars in the Västra Götaland region (west of Sweden), bewaring that it was representative in terms of car type, household income and residential area. Since no similar data is available for other regions in Europe, the model also applies this data set to other European countries driving patters. Another implicit assumption is considering that driving patterns are not going to vary in the future and EVs would be utilized for the same purposes as combustion engine cars. However, since there are still few EVs in Sweden, there is no much room for increasing accuracy in this matter.

The monitored cars completed a total number of trips of 107.910 within the period 2010-2012 and roughly 15.000 km per vehicle and year. What differentiates this measurement, hence the reason why is used in this model, is that the driving profiles were measured for several days in a row, exactly between 50-100 days each of the vehicles. Afterwards, the data was extrapolated to fulfill all the days of a year. Thus, the information was used repeatedly according to the day of the week. Then, the driving profiles are allocated to the whole Swedish fleet [44].

The model uses this driving patterns to optimize EVs charging and discharging. The dataset contains information on driving distance for each hour of the year for all the 426 cars. Transport demand fulfillment is implemented as a requirement in the model, so all the vehicles must be able to complete the hourly demanded distance. It is assumed that EV owners maximize charging at home and when driving longer distances than the battery range, they make use of fast-charging outside home location. However, only the charging taken place at home is considered to analyse power system violations since this study is focused on LV grids.

3.3.3 EV charging strategies

EVs do not require to be constantly charged at maximum power. Hence, CPR can be varied depending on external signals so that reduce load in order to avoid power system violations. Therefore, there are several charging patterns. Here, they have been clustered in three strategies, two of them are unidirectional (electricity flows from the grid to the car) and one is bidirectional, i.e. vehicle-to-grid (V2G).

- **Direct**: charging is performed immediately after plugging in the vehicle at home at maximum power up to full SoC of the battery.

- **Price optimized charging**: also known as V1G, it uses the hourly electricity price as an external signal to schedule charging to times when the price is the lowest, but ensuring that the battery will have enough SoC for the next trip. The overloading of grid components and power system violations are not considered in the simulation to produce the charging profiles. This strategy is referred to as "Smart" along the text.

- **Price optimized charging with V2G**: it follows the same principle as the previous one but allowing injecting electricity from the battery back to the grid. V2G is a new technology expected to become widely spread in the upcoming years. It is bound to serve as energy storage and support electricity grids providing emergency demand response, frequency regulation and load profile peak reduction. The last one would boost RES integration and reduce investments in electricity grid enhancement due to the increasing penetration of renewable energy [53].

Figure 3.3 shows the average charging for a week among the 426 vehicles for the three strategies presented above. A negative value means that the vehicle is discharging electricity back to the grid.

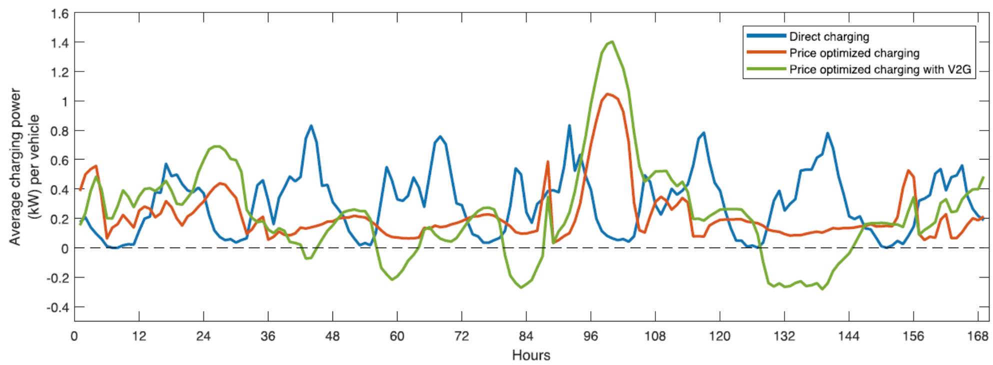


Figure 3.3: Average EV charging for a selected week and the three different charging strategies [10]

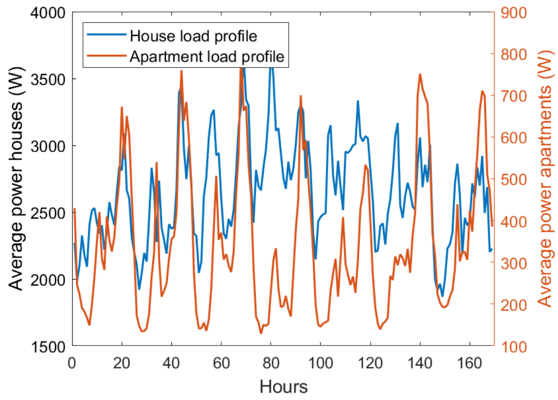
3.4 Grid operation and violations detection

3.4.1 Grid operation

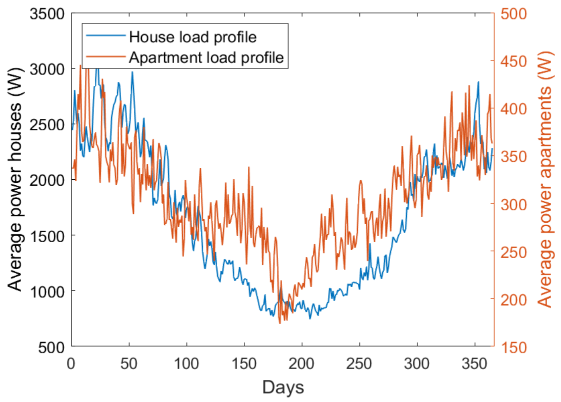
A theoretical Swedish LV network has been constructed in section 3.2, next step is to populate it with electricity demand from usual residential consumption and EV charging demand. The data inputs needed for this simulation are:

- **Residential load profiles without EVs** obtained from a study carried out by the Swedish Energy Agency in the region of Mälardalen between 2006 and 2007 [54]. The dataset contains 20 houses load profiles ($P_{House,t}$) and 15 apartments load profiles ($P_{Apt,t}$) indicating a value of demanded power for every 10-min of the year (52.560 values per year). In order to better interpret later results, it is essential to understand how residential consumption is distributed throughout the different time frames (Day, Week, Year) in Sweden. Therefore, the average power demand of the 35 residential profiles have been plotted in figure 3.4.

(a) Day



(b) Week



(c) Year

Figure 3.4: Average power of the residential load profiles for Friday 16th March 2007 (a), week 7 of the year 2007 (b) and the whole 2007 (c). Note that the house and apartment load profiles are referred to different axis to highlight consumption pattern differences.

- **Charging profiles**. EPOD model (See 3.3) provides 426 different charging profiles as output for each region of Sweden. When adding up EV electricity demand to residential demand, coincidence probability of charging events has taken into account since not all the EVs are charged simultaneously. To make an accurate estimation, a statistical charging coincidence distribution (θ^{EV}) is created by combinatorics, resulting in 10^{125} possible combinations of charging patterns and household loads. Since manipulating this data-frame would not be computationally feasible, the sample is reduced to 100 possible combinations using a bootstrap method [10]. The final structure of the charging coincidence distribution is a 3D matrix with shape 400x100x52560 that stores likelihood values for charging coincidence, sorted in ascending order of probability. The first number (400) stands for the amount of EV in a cell, 100 are the sorted charging patterns and 52.560 are all the 10-min time blocks in a year.

The next step is to calculate the power demand and voltage variation at each node of the feeder, to check whether they accomplish with the regulations or some violations occur. This is done for all the 100 sorted charging patterns. The power demand or **net load** is symbolized as $\mathbf{P_{j,t,s}}$ at each node j along the feeder for each 10-min time block in a year (t) and each one of the 100 charging patterns (s). The net load represents the future electricity demand from residential consumption and EV charging together. This is obtained by combining the EV and residential demand, considering the coincidence likelihood as follows:

$$P_{j,t,s} = NC_j \cdot (\theta^{Res} \cdot P_{Res,t} + \theta^{EV}_{t,s} \cdot P_{EV} \cdot N_{EV}) \tag{3.12}$$

where NC_j is the number of customers supplied at that feeder node, θ^{Res} the residential coincidence, $P_{Res,t}$ the average residential load profile, $\theta^{EV}_{t,s}$ the charging coincidence in column s of the θ^{EV} matrix in time t, P_{EV} the CPR (6,9 kW) and N_{EV} the number of vehicles per household which is retrieved from the GIS file for each cell. Note that only one row of θ^{EV} has been used, the one corresponding to the number of EVs in the cell. P_{Res} is calculated as:

$$P_{Res,t} = \frac{NC_{Apt} \cdot P_{Apt,t} + NC_{House} \cdot P_{House,t}}{NC_{Apt} + NC_{House}} \tag{3.13}$$

where NC_{Apt} is the number of apartment connections to the grid in the cell, NC_{House} the number of house connections to the grid, $P_{Apt,t}$ the power demand of the randomly selected apartment load profile for time t of the year and $P_{Apt,t}$ the power demand of the randomly selected house load profile for time t.

Voltage ($\mathbf{U_{j,t,s}}$) is estimated using a simplified voltage drop method [1]. The voltage at point j of the feeder at time t in the grid is calculated as:

$$\begin{aligned} U_{j,t,s} = U_N &- \frac{\lambda \cdot (\theta^{Res} \cdot P_{Res,t} + \theta^{EV}_{t,s} \cdot P_{EV}) \cdot (R_{Tr} - X_{Tr} \cdot pf)}{U_N} \\ &- \sum_{j=1}^{J} \frac{P_{j,t,s} \cdot (R_{line,j} + X_{line,j} \cdot pf)}{U_N} \end{aligned}$$

where U_N stands for the nominal voltage ($400V$), λ the number of connections per transformer, R_{Tr} the resistance of the transformer, X_{Tr} the reactance of the transformer, $R_{line,j}$ the resistance of the cable up to node j, $X_{line,j}$ the reactance

[1]The grid overloading would imply voltage reduction instead of voltage increase, therefore only surpassing the lower limit is considered (-5%)

of the cable up to node j, pf the power factor $(0,9)$ and J the set of all branches stemming from one feeder.

Once the net load and voltage drop have been calculated for each node of the feeder, the highest value of net load and the lower of voltage drop are stored. Summarizing, at this point there is a value of maximum net power and minimum voltage for every grid cell for every 10-min block of the year (t) and charging pattern (s).

3.4.2 Algorithm to detect breach of LV regulations

Grid operation has been simulated in the previous section and relevant values have been stored for each of the charging scenarios ranging from $s = 0$ with zero likelihood of charging coincidence and $s = 100$ for 100% likelihood of charging coincidence. Now, the last step is to verify whether power regulations are violated for any s index. The s index stands for the portion of charging profiles which generate power system violations, then it would be an estimation of power system violations probability. If none of the 100 charging combinations incurs in a breach of regulations, the power system violations probability would be 0%. On the contrary, for instance, if 75 of them register a violation, the probability would be assumed to be 75% [10]. For a detailed explanation of the technical implementation see Appendix B.

3.4.3 Reference network model running for power grid violations analysis

The different parts of grid operation simulation have been explained in previous sections. Here, the goal is to explain the followed order in the simulation and show how the different parts are connected to obtain power system violations for all the 52.560 time-steps in a year. Figure 3.5 shows a diagram summarizing the process. The first step is to combine the EV charging profiles from section 3.3 with residential load profiles to calculate the total electricity demand. This is used as an input to the synthetic grid built in section 3.2, which provides information on power system violations probability as explained in 3.4.1. This process is simulated for each grid cell of the Swedish power system in the GIS file (section 3.2.1). Therefore, this methodology has a geographic resolution of $1km^2$.

To make the simulation representative and reduce the impact of the residential profile allocation, each grid cell is simulated 8 times (8 years). Thus, the final value of violation probability for each cell is obtained by taking the average of the 8 simulations for every time-step of the year. Due to computational feasibility the number of simulations has to be limited, however, results with 8 simulations have been shown to converge, not being efficient to increase the number of simulations.

3.5 EV charging power rate limitation

The aim of this thesis is not only to analyse the expected power system violations in a 100% EV penetration scenario, but also to assess the optimal energy system

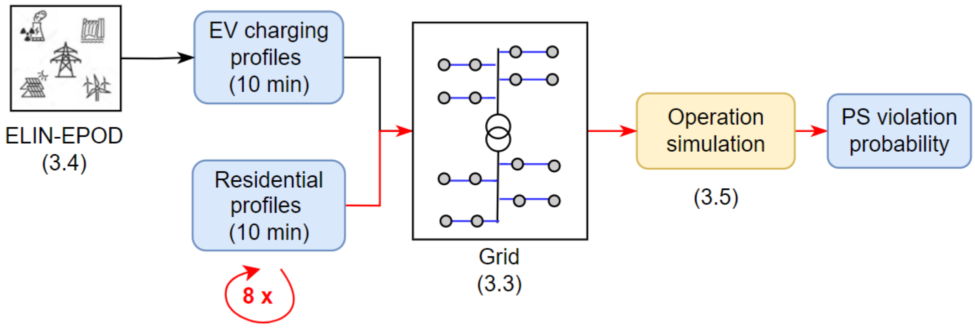


Figure 3.5: Diagram showing grid operation to obtain power system violations probability. Numbers under the boxes show the section where each block is explained. Red arrows indicate simulation repeated for 8 times.

structure and to examine possible strategies to put in place in order to reduce the grid vulnerability. A possible strategy that DSO could apply to decrease the number of violations is limiting CPR at certain vulnerable hours. This could be put in place since the LV grid is being transformed into a smart grid with seamless interconnection between DSO and customers. The vulnerable hours found in 4.1 when CPR limitation is applied are:

- Scenario with only **direct** charging allowed: reducing maximum CPR from 6,9 kW down to 3,45 kW (- 50%) from 5pm to 10pm during colder months (October, November, December, January, February and March).

- Scenario applying **smart and V2G** charging: reducing maximum CPR from 6,9 kW down to 4,83 kW (- 30%) from 6am to 10pm all the months of the year.

The implementation of this limitation requires modifying both the ELIN-EPOD model and the Reference network model. In the first one, new results for the energy system structure, electricity dispatch and charging profiles are obtained. The model performs optimization taking into account the new maximum CPR for each hour, thus having an impact on all the outcomes. Then, grid operation is simulated again with the new charging profiles to check whether this limitation has an improvement in terms of power system violations. Results can be seen in section 4.2.

4

Results

In order to simplify the results for the reader, they are divided by grid topology in city and urban according to the population density of the cells. Grid cells with more than 1000 inhabitants per square kilometre are considered as city and between 200 and 1000 are regarded as urban. This distinction is made to take into account each grid topology peculiarities. For instance, city areas are more densely populated but urban areas are usually composed of single-family dwellings which often have higher energy consumption. Note that rural grids have been excluded from the examination as explained in section 1.5. Overall, there are 2.353 km^2 of city areas and 4.485 km^2 of urban areas in the Swedish grid, according to the definition above.

In addition, the analysis examines the importance of applying "smart" charging strategies. Therefore, the model simulations have been designed to depict three charging scenarios: (i) Direct charging, where customers are allowed to charge the vehicle as they wish, (ii) Smart charging, where all the consumers apply a price-optimization charging strategy when charging, and (iii) V2G where in addition to price-optimize they are also able to inject electricity back to the grid. Thus, 2 dimensions are analysed separately in this thesis: grid topology (City / Urban) and charging strategy.

As this is a temporal analysis, the main focus is on examining the differences in power system violations in various time frames over the year. Hence, two time frames are included here: (i) year, where the minimum entity are the months over a year and (ii) day with hours as the minimum entity.

4.1 Scenario without EV charging limitation

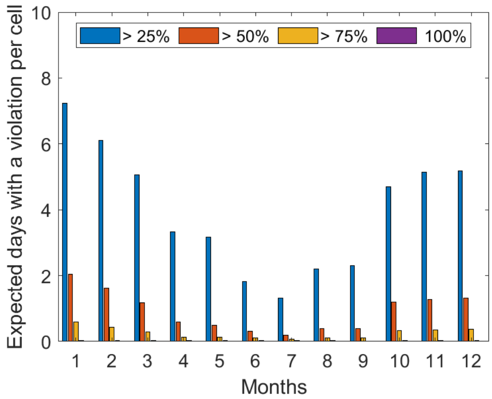
4.1.1 Year time frame

Figure 4.1 shows the expected number of days logging a power system violation per grid cell over a year. Recall that the output of the models explained in section 3.4.3 is a value of probability for power system violations occurrence. For each month, four colored bars are plotted, each of them shows the expected number of days logging a violation considering different thresholds of probability. This concept is similar to the confidence level in statistical analysis. For instance, a 75% bar could lead to a statement like "with a 75% of confidence, every January there will be X days per cell where a violation is going to be logged". In addition, plots are arranged in a matrix structure to note the differences between the dimensions being analysed: grid topology (City / Urban) in columns and charging strategy (Direct, Smart, V2G) in rows.

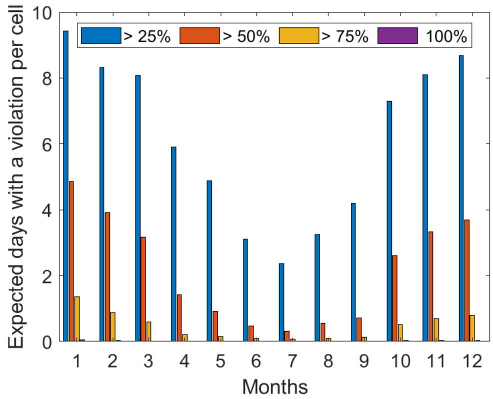
The results in Figure 4.1 show significant differences between months over a year, being the winter months the most vulnerable. This is related to the higher electricity demand from households in winter (see Figure 3.4), hence the probability of coincidence with EV charging peaks is also higher. When comparing grid topologies, urban seems to be more vulnerable reaching higher peaks than city for all the dimensions and months. This insight can be ascribed to the fact that urban areas, which are usually in the surroundings of city centres, are composed of single-family dwellings which have higher electricity peak demand and greater cars per household ratio. Not only the 25% bars but also the 50% and 75% show a considerably higher number of violations in urban areas for all the charging strategies. This suggests a lower variation in probability of violation between cells in urban grids than in city grids.

In terms of charging strategies, fewer power system violations are expected in smart charging and V2G than in direct charging. For the 25% bars, the number of days logging a violation is reduced approximately by 1-2 per cell, being more noticeable in winter months and in city than in urban areas. When looking at the 50% and 75% bars, the reduction is emphasized for winter months. However, violations are more evenly distributed throughout the year, to the point of registering more vulnerabilities in summer months compared to direct charging. This even distribution is due to the fact that vehicles are charged following a smart strategy, thus balancing energy demand from residential use and EVs to avoid peaks in the load curve. As a result, load peaks are decreased when residential demand is elevated (winter months) and can be incremented when residential demand is low (summer months). Enlarged load peaks lead to more power system violations. No significant differences are noticed between smart charging and V2G.

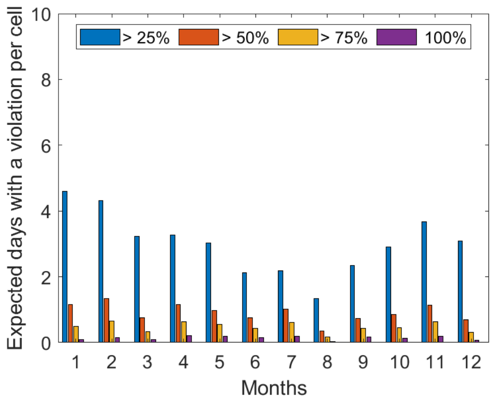
As it has been previously explained, when applying a direct EV charging strategy the likelihood of coincidence with residential electricity consumption increases. Since residential demand is higher in winter (in Sweden), power system violations are concentrated over this time of the year. However, applying a smart strategy to avoid charging EVs at the peak of residential demand or when renewable production is low, loosens the relationship between residential demand and power system violations. In order to visualize it, two heat maps for direct and smart charging are plotted in Figure 4.2. They represent the mean probability of logging a violation per cell for each day of the year. City cells and V2G strategy plots are excluded from the main text because they do not add information to the analysis, although they are included in A.3. As it can be seen, when applying a direct strategy, the days with the highest violation probability are concentrated in winter months. In fact,



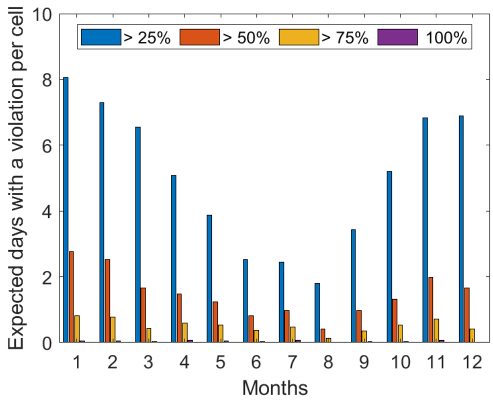
(a) City / Direct Charging



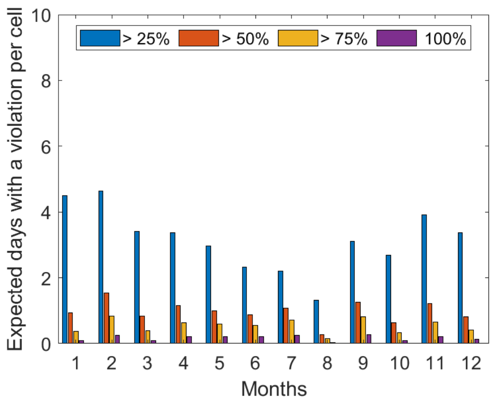
(b) Urban / Direct Charging



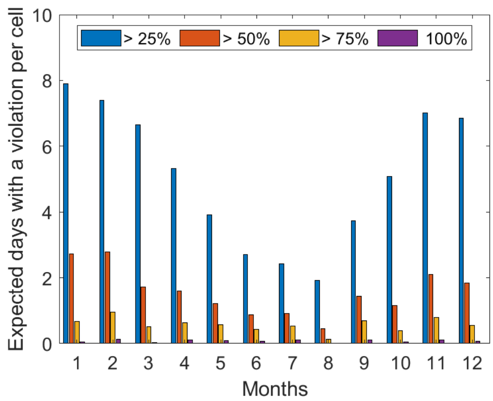
(c) City / Smart Charging



(d) Urban / Smart Charging



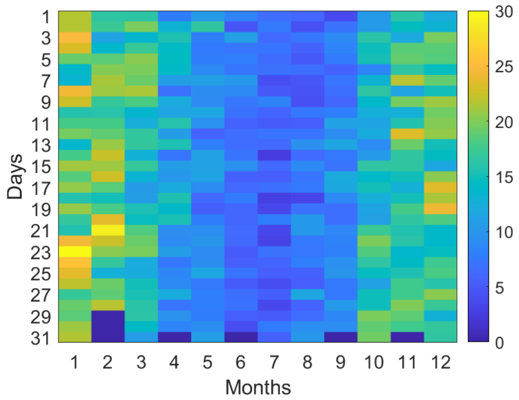
(e) City / V2G



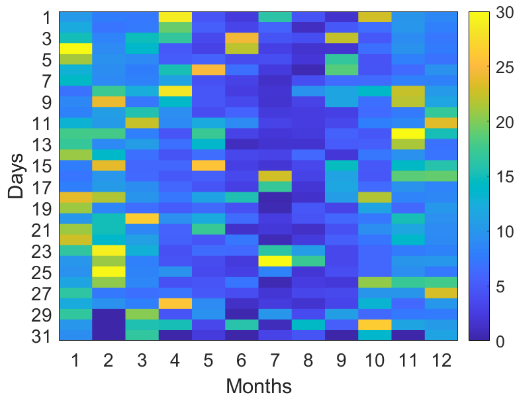
(f) Urban / V2G

Figure 4.1: Expected number of days per grid cell logging a violation throughout a year. Color bars indicate the probability threshold to consider an occurrence as a violation. For instance, for >25% only the occurrences above 25% value of probability have been counted.

the days with the highest probability are directly correlated with the days with the lowest temperatures the year that the residential demand profiles were measured (see Figure A.1). In contrast, for the smart charging case, days with highest probability of violation are scattered throughout the year. This suggests that following a smart strategy helps to reduce stress on the grid when residential demand is maximum, e.g. in winter.



(a) Urban / Direct Charging



(b) Urban / Smart Charging

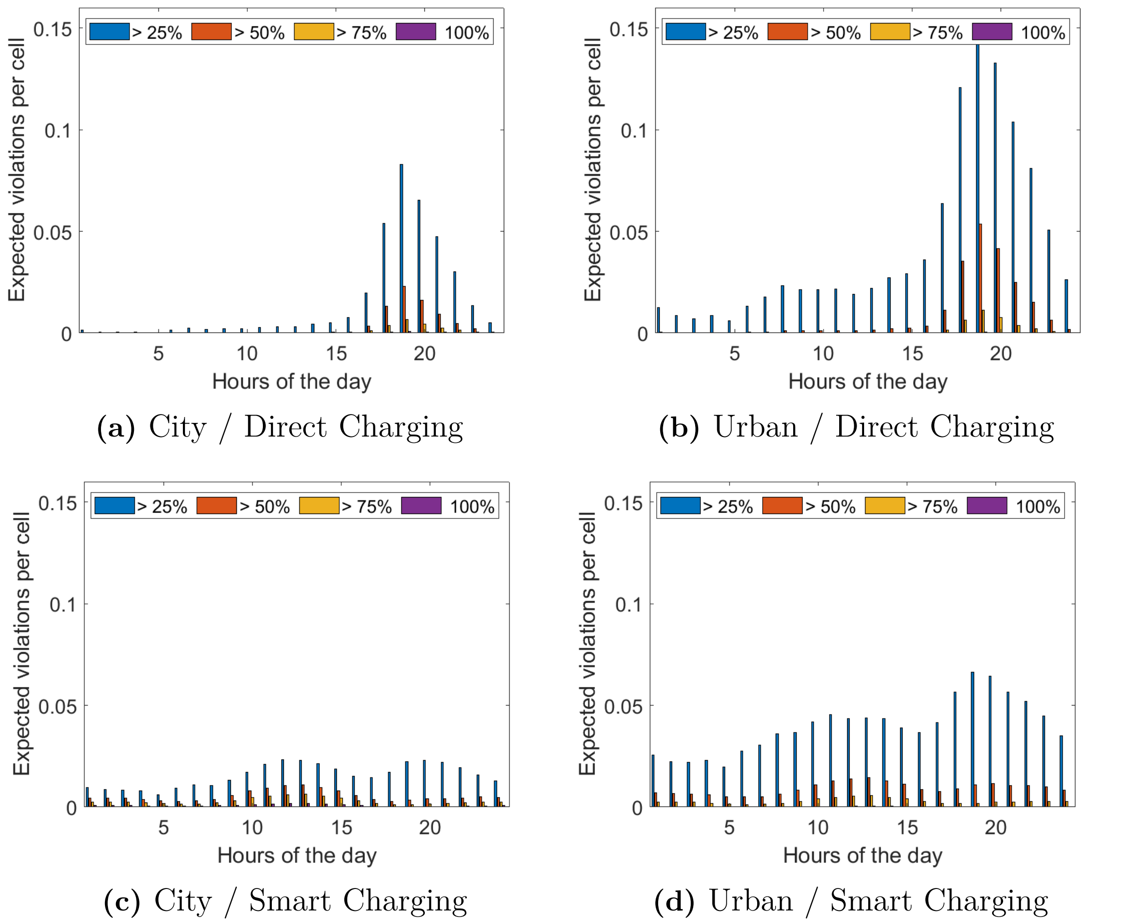
Figure 4.2: Heatmaps depicting the mean probability of logging a violation per cell for each day of the year. The left one represents a direct charging strategy for urban cells whereas the right one shows a smart charging strategy for urban cells.

4.1.2 Day time frame

In order to study the intra-day power system violations, four graphs are included in Figure 4.3. They can be read in the same way as plots in Figure 4.1 but now the horizontal axis contains the 24 hours of a day. The mean of all the cells and days of the year have been taken into account to plot the graph. Therefore, it depicts an "average" day throughout the year for the Swedish grid, being the bars the expected number of violations per cell and per hour. The first matrix column shows results for city areas whereas the second one for urban areas. Moreover, the first matrix row contains plots for a direct charging strategy and the second one for a smart charging strategy. Plots for V2G strategy are excluded in the main text because of their similarity to the smart charging strategy, therefore it does not add information to the analysis. They can be seen in A.2.

As shown in Figure 4.3, in a direct charging strategy, urban cells are expected to log more violations from an intra-day perspective reaching up to 0,15 expected violations per cell for the >25% bar at 7pm. In equal conditions and time, city cells would log 0,08 violations, which is 46% lower. A similar pattern applies to the >50% and >75% bars. This can be ascribed to the fact that the type of dwelling in urban areas usually has a higher peak power demand. It can also be noted that the violations in city areas lie mainly on the 5pm-10pm time with barely any expected violations off this range. This evening peak is a result of drivers arriving at home from work and directly plugging in the vehicle. In urban areas, while there is also a peak in the same time period, violations off this range are not negligible. This can be a consequence of residential demand being more spread out throughout the day in urban dwellings.

Regarding the charging strategies, many differences can be noted between them. Applying a smart strategy spreads the violations along the day, shaving the peaks and making more probable to log violations at low-price hours such as night hours. Furthermore, an additional smooth peak appears at midday hours when electricity prices are lower than in the evening but there is still a significant residential power demand. These results highlight the importance of developing smart charging strategies to avoid repetitive power system violations. However, in terms of grid vulnerability, no benefits from using V2G have been found compared to a smart strategy without bidirectional power flow.



(a) City / Direct Charging

(b) Urban / Direct Charging

(c) City / Smart Charging

(d) Urban / Smart Charging

Figure 4.3: Expected number of violations per grid cell for an average day. Color bars indicate the probability threshold to consider an occurrence as a violation. For instance, for >25% only the occurrences above 25% value of probability have been counted.

4.2 Scenario with EV charging limitation

The second research question focuses on charging limitations that could be implemented in order to reduce the number of power system violations. As explained in section 3.5, the approach utilized is limiting the CPR at certain hours based on results in section 4.1. There, it can be seen that for direct charging the majority of violations occur at peak hours when electricity demand from EV charging and residential use coincide. Whereas, for smart and V2G, the violations are spread over the daytime with two smooth peaks around midday and the evening. Hence, two charging limitation strategies are put into place for these scenarios:

- Scenario with only **direct** charging allowed: reducing maximum CPR from 6,9 kW down to 3,45 kW (- 50%) from 5pm to 10pm during colder months (October, November, December, January, February and March).

- Scenario applying **smart and V2G** charging: reducing maximum CPR from 6,9 kW down to 4,83 kW (- 30%) from 6am to 10pm all the months of the year.

The models have been run again with these modifications and obtained results are analysed in the present section. It is organised in the same way as the results without limitation, e.g. first it takes a look at power system violations from a year time frame to later focus on an intra-day assessment. However, as the aim is to examine the improvements with respect to the results without charging limitation, all the graphs and tables contain comparative data between the two scenarios.

4.2.1 Year time frame

The results show a significant decrease in the number of violations when applying a CPR limitation. Table 4.1 contains the total number of violations registered over a year for the different strategies, scenarios and cell topologies[1]. Note that the output from the models is a value of probability, thus a weighted sum has been used to calculate an absolute value of violations, e.g. a 3% value for violation probability has been counted as 0,03 violations. As it can be seen, for city cells the number of violations is reduced by 43,7%, 38,9% and 39,6% for direct, smart and V2G. For urban cells the reduction is not as significant in relative numbers but greater in absolute numbers since there are more urban cells in the Swedish territory.

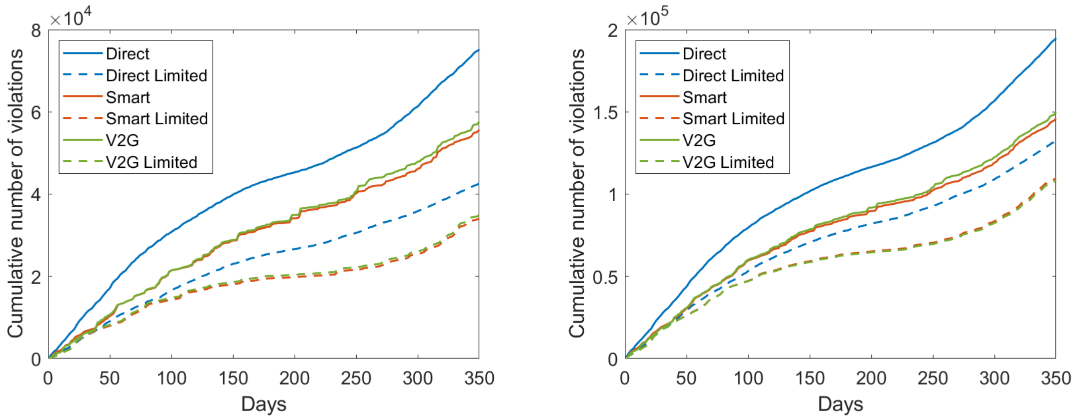
Table 4.1: Number of violations throughout a year for various scenarios

	City			Urban		
Strategy	Base	Limited	%	Base	Limited	%
Direct	79.411	44.701	-43,7%	206.750	140.050	-32,2%
Smart	57.765	35.269	-38,9%	153.190	115.060	-24,9%
V2G	59.724	36.063	-39,6%	157.230	113.520	-27,8%

To see the temporal aspect of this reduction, figure 4.4 shows the cumulative number of violations over a year for all the strategies in the limited and non-limited scenario. The value at the end of the year is the same as indicated in table 4.1. When comparing the direct strategy in the limited and non-limited case, it can be

[1]There are 2.353 city cells and 4.485 urban cells in the grid

appreciated as the lines diverge at the beginning and end of the year while they remain approximately parallel in the middle of the year. This is due to the fact that the charging limitation is in cold months when previously most of the violations were logged. When looking at smart and V2G , the lines start close together in the limited and non-limited case to later diverge in the middle of the year where the charging limitation is most effective. This is consequence of the higher grid vulnerability over summer when applying smart and V2G strategies as shown in section 4.1. It is interesting to note that by applying a charging limitation in the direct case, violations are reduced even below the smart charging strategy without limitation, thus proving to be a very effective policy.



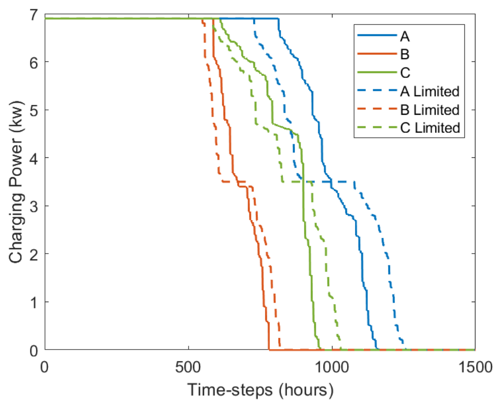
(a) City **(b)** Urban

Figure 4.4: Cumulative number of violations throughout a year. Each color represents a different charging strategy. Solid and dashed lines represent the scenario without limitation and with limitation respectively. Note that (a) and (b) have a different y-axis limit, the aim here is to highlight the shape of the curve, not to compare city vs urban grids.

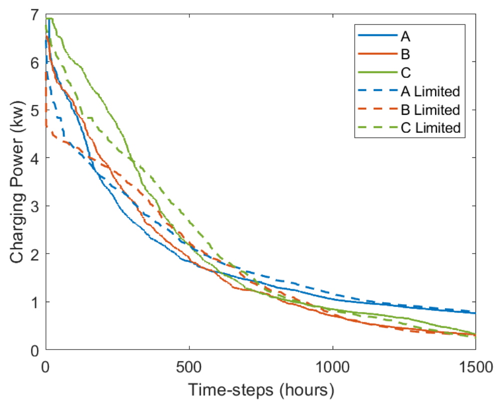
In order to see the results in a higher temporal resolution, heatmaps for city cells showing every day of the year have been included in the appendix A (Figure A.4). It is noticed how the violation probability for direct charging is significantly decreased in months with charging limitation. Even on the most susceptible days of winter with the highest residential demand for heating, the probability is reduced by a 50% factor, making the grid less exposed to drastic temperature drops. In contrast, for the smart charging case where the days with the highest probability were scattered, the probability of violations is smoothed out remaining only a few vulnerable days throughout the year.

4.2.2 Day time frame

The next step is to examine the intra-day perspective. In order to better understand the results, figure 4.5 examines how the instant CPR used by each individual driving pattern is modified between the two scenarios. It represents the CPR used by three selected cars (A, B, C) among the 426 driving patterns, independently sorted from the hour of the year with highest CPR to the lowest CPR. Only three cars are represented for ease of visualization reasons but the remaining 423 cars follow a similar trend. It is important to mention that smart and V2G charging profiles are an outcome of EPOD optimization model while direct charging profiles come from an independent model that simulates home charging according to driving patterns but without performing optimization.



(a) Direct



(b) Smart

Figure 4.5: CPR for three selected vehicles (A, B, C) sorted from the hour of the year with highest CPR to the lowest CPR. Only the first 1.500 hours with maximum CPR are shown. Each color represents a different vehicle. Solid and dashed lines represent the scenario without limitation and with limitation respectively.

One of the insights from figure 4.5a is that when using direct charging, cars are charging for a few hours per year (around 700 - 1.200 hours per year) at maximum CPR. Whereas, in a smart charging strategy, cars are plugged in for up to 5000 hours at variable CPR. Thus, smoothing out the stress on the power grid. When comparing the limited vs non-limited case, the amount of hours at high levels of CPR is reduced for each car. As the individual total energy demanded is invariant, e.g. the area below the curves is the same for each car in each scenario, the dashed line surpasses the solid line at low CPR. Another valuable insight drawn here is that the solid lines are above the dashed lines at high CPR values only for around 200 hours for the direct and 400 for smart. Taking into account the significant reduction in violations shown in figure 4.6 with respect to the no CPR limitation scenario, this suggests that there are only a few hours/days throughout the year when the grid is most vulnerable, concentrating many violations. By limiting the CPR on those occasions, a substantial amount of grid violations can be prevented.

Figure 4.6 shows the variation in total number of violations expected in the grid for every hour of an average day. A negative value means that fewer violations are expected to be logged for the limited scenario. Lower values are colored in green as it is the desired outcome and higher in red.

In the direct charging strategy (first two tables), a considerable decrease in violations within the limited interval (18-22) can be noticed, even for high thresholds of

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
> 0%	3.8	-0.4	-0.1	0.2	-0.2	-0.9	-4.0	-8.3	-10.8	-9.9	-15.0	-19.5	-24.3	-32.6	-40.7	-58.1	-145.7	-440.3	-508.5	-385.3	-273.3	-9.0	50.6	7.1
> 25%	-0.3	-0.2	-0.1	-0.1	0.0	-0.1	-0.2	-0.8	-1.3	-1.2	-1.6	-2.0	-2.8	-3.9	-5.0	-8.2	-28.7	-97.9	-139.2	-102.1	-67.1	1.1	5.2	-1.0
> 50%	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.3	-0.5	-1.2	-7.5	-29.4	-49.6	-33.9	-18.2	3.4	0.3	-0.6
> 75%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	-2.4	-8.8	-14.8	-9.8	-5.0	0.4	-0.5	-0.2
= 100%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.3	-1.3	-1.6	-1.2	-0.8	-0.1	-0.1	0.0

(a) City / Direct Charging

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
> 0%	33.1	9.1	9.4	3.1	-0.3	3.3	-9.7	-38.5	-54.6	-55.6	-67.2	-90.2	-117.5	-126.1	-143.7	-170.5	-318.5	-761.2	-793.2	-599.8	-401.2	10.5	115.3	39.1
> 25%	3.4	-0.1	0.4	0.3	-0.2	-0.4	-2.0	-7.6	-10.3	-10.5	-13.7	-15.1	-23.4	-29.0	-33.8	-47.5	-114.2	-295.4	-333.0	-265.3	-200.1	5.9	39.5	5.5
> 50%	0.3	0.0	0.0	0.0	0.0	0.0	-0.2	-0.9	-1.0	-1.1	-1.4	-1.6	-3.0	-4.2	-5.3	-8.4	-36.6	-132.4	-192.7	-141.6	-81.3	11.2	9.6	0.5
> 75%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.2	-0.3	-0.5	-1.1	-5.7	-26.7	-46.4	-29.6	-15.0	2.9	1.4	-0.1
= 100%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	-0.9	-1.6	-1.2	-0.6	0.0	0.0	0.0

(b) Urban / Direct Charging

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
> 0%	-11.8	-13.2	-11.1	-7.7	-0.3	9.8	-12.3	-20.5	-37.8	-65.9	-85.2	-103.0	-105.5	-98.3	-81.2	-52.8	-34.1	-9.7	-5.3	-26.2	-25.8	-9.5	6.0	-14.1
> 25%	-5.8	-7.4	-7.0	-4.9	-1.4	0.6	-10.4	-11.9	-17.2	-27.3	-35.7	-42.1	-43.2	-38.4	-32.1	-21.1	-13.7	-3.5	-1.2	-9.3	-11.2	-3.4	1.4	-5.9
> 50%	-3.9	-4.8	-4.4	-3.1	-1.2	0.5	-5.5	-7.0	-11.1	-17.0	-20.6	-24.0	-24.7	-21.6	-17.5	-11.6	-6.7	-3.0	-1.9	-4.2	-5.6	0.3	0.3	-3.5
> 75%	-2.5	-2.9	-2.8	-2.0	-0.8	0.3	-3.3	-4.6	-7.0	-10.3	-12.5	-14.1	-14.3	-12.5	-10.2	-6.4	-3.3	-1.5	-1.5	-2.2	-2.9	0.2	-0.2	-2.1
= 100%	-1.1	-1.2	-1.1	-0.9	-0.6	-0.3	-1.0	-1.5	-1.9	-2.9	-3.6	-4.0	-3.9	-3.5	-2.8	-1.5	-0.6	-0.3	-0.3	-0.4	-0.6	-0.2	-0.4	-1.0

(c) City / Smart Charging

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
> 0%	-22.8	-32.2	-27.0	-17.0	7.9	22.9	-8.2	-5.3	-51.2	-102.1	-153.5	-182.9	-198.7	-176.2	-136.3	-86.4	-53.2	-28.1	-34.1	-62.8	-62.6	-43.0	-1.8	-32.3
> 25%	-4.9	-8.9	-7.9	-5.2	1.9	9.2	-7.1	2.1	-7.8	-37.1	-60.2	-76.9	-78.7	-67.1	-51.9	-28.3	-10.0	1.7	6.4	-1.0	-8.3	3.3	15.0	-2.6
> 50%	-6.2	-8.3	-7.0	-4.1	0.2	8.3	-5.3	-6.6	-15.9	-29.8	-40.6	-49.1	-50.6	-43.7	-36.3	-22.4	-10.5	2.5	6.1	-1.9	-8.0	2.4	6.9	-3.7
> 75%	-4.6	-5.3	-4.9	-2.5	-0.6	1.3	-4.1	-5.9	-10.1	-15.7	-19.9	-22.0	-23.2	-20.1	-16.9	-10.2	-5.7	-1.7	-0.7	-3.5	-5.6	-1.9	0.4	-4.1
= 100%	-0.1	-0.1	0.0	0.0	0.1	0.0	-0.4	-0.3	-0.5	-1.0	-1.3	-1.5	-1.5	-1.4	-1.1	-0.7	-0.2	-0.1	0.0	-0.2	-0.2	0.2	0.2	-0.2

(d) Urban / Smart Charging

Figure 4.6: Heatmaps showing the difference in total number of violations expected in the grid for every hour of an average day between the non-limited CPR scenario and the limited scenario. For instance, hour 15 indicates violations between 2pm and 3pm. Lower values are colored in green as it is the desired outcome and higher values in red. Rows indicate the probability threshold to consider an occurrence as a violation. For instance, for >25% only the occurrences above 25% value of probability have been counted.

probability. It is remarkable how violations surge at the end of the CPR limitation period, e.g. 10pm. This suggests that even though CPR is limited, there can also be an increase in violations in this period. With this policy, peak power per car is limited, however, there can be more cars charging at the same time. The cars that in the scenario without limitation would have charged, for instance, in 3 hours now they have to charge in 6 hours. After the limiting period (from 10pm onwards) violations rise for the next 3 hours, since vehicles might not have finished charging by then. However, the surge outside the limited CPR interval is lower than the reduction within the limited CPR interval. This is a substantial finding because it means that violations can be reduced in the most vulnerable hours without significantly increasing the susceptibility at other times of the day, e.g. violations are not displaced to other hours but removed.

The lower two heatmaps depict a smart charging strategy. As it can be seen, there is a slight increase in violations on the edges of the limitation interval. The rise at 6 am can be ascribed to the combination of two factors: low electricity prices at night which increment the likelihood of more cars charging and residential demand starting to increase at the beginning of the day. However, as shown in figure A.5b a few days over the year concentrate a higher probability of violation between 1 am and 6 am. Therefore, low electricity prices due to a higher share of wind power generation on those specific days can be the reason for the increase.

4.3 Comparison of power system structure and cost

Following the third research question, this section analyses the characteristics of the optimal power system simulated for the year 2050 with the ELIN-EPOD model. In addition, it examines the differences between a scenario where EV charging limitations to prevent power system violations are in place and the base scenario without limitations. It is important to mention that ELIN-EPOD model has been run to provide information on the Swedish, Norwegian and Danish systems since they are interconnected. Running an isolated country would not lead to reliable results since these countries exchange electricity and provide backup electricity to each other. For this reason, the three systems are considered as one in this section.

As explained in section 3.3, ELIN-EPOD model optimizes the investment in power generation technologies up to year 2050 which is the year examined in this thesis. Installed power capacity in the year 2050 for a scenario allowing "smart" charging strategies but without applying EV charging limitations is shown in figure 4.7. The system is composed mainly of wind power onshore (40%) and hydropower (37%) which acts as the base-load technology. Other relevant technologies installed are: bio fuels (8%), solar power (5%), fossil fuels (5%) and wind power offshore (5%). The same analysis has been carried out for a scenario with EV charging limitations in place and no significant variations have been found. This suggests that the optimal system structure depicted in figure 4.7 provides flexibility to satisfy electricity demand even when applying demand-side management strategies with the aim of reducing LV grid violations such as temporal EV charging limitations.

In terms of total system cost including investments in generation capacities, transmission lines, running costs and CO_2 emission rights, no significant differences have been found being approximately 21.000 M€. However, the results show some differences between average marginal cost of electricity for the four scenarios.

Table 4.2 shows the average marginal costs of electricity in 2050 for the four bidding areas in Sweden. Moreover, columns include the four simulated scenarios. "Base" indicates that no temporal EV charging limitations are in place while in "Limited", these limitations are considered. As it can be seen, applying limitations to EV charging increases the average electricity price, more evidently in the southern bidding regions and for a scenario without V2G in place (+ 10% for SE3 and SE4). Therefore, in terms of electricity price, the optimal strategy to reduce power system violations (i.e. in a "Limited" scenario) would be to allow customers to use V2G. These findings are useful for DSO and grid operators to design the future Swedish

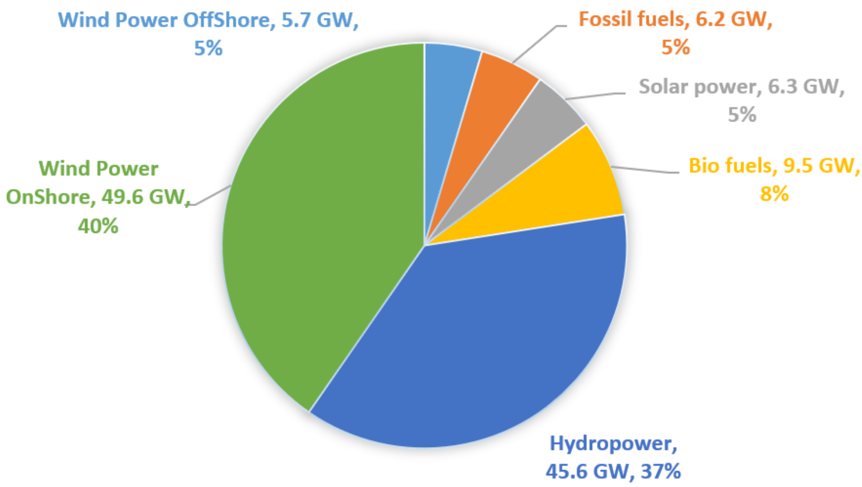


Figure 4.7: Pie chart depicting the optimal installed generation capacity in 2050 resulting from ELIN-EPOD in Sweden, Norway and Denmark together.

Table 4.2: Average marginal cost of electricity in the year 2050 for the four Swedish bidding areas in Eur/MWh. "Base" indicates a scenario without EV charging limitations, while "Limited" includes these limitations.

	Smart strategy		V2G	
Bidding area	Base	Limited	Base	Limited
SE1	71,8	70,3	76,7	77,6
SE2	76,7	76,5	89,6	90,6
SE3	109,7	120,8	115,6	117,0
SE4	110,1	121,1	115,7	117,1

power system. The installed capacity previously indicated above provides flexibility to apply strategies in order to avoid power system violations.

5

Discussion

The first question of this thesis aimed at the spatio-temporal assessment of power system violations in the Swedish LV grid. The results show that EV charging would impact significantly the electricity network, especially in winter months and peak hours when electricity demand is higher. Moreover, suburban areas have been shown to be more vulnerable than city areas, which can be ascribed to contrasting lifestyles resulting in different electricity demand patterns. In order to answer the second research question, two charging limitations have been provided and proved to be effective in reducing grid vulnerability. The third research question looks at the power system structure, questioning how it should be designed to be able to accommodate more RES and an increased EV demand while providing flexibility to apply policies to reduce grid violations. In this regard, the study suggests that a power system composed mainly of wind power and hydro power, with a few backup generation technologies is optimal to meet the previous goals.

Currently, the electricity network is designed to fulfil the usual residential demand allowing for some overloading margins. However, results show that when adding future EV charging demand in a 100% EV penetration scenario some peak loads will increase, thus leading to grid regulations being breached. Although the reference network model applies commonly used methods to create a synthetic LV grid, recently installed grids might be designed with other demand estimation methods and be adapted to withstand higher loads. Hence, results might overestimate grid vulnerability. On top of that, only residential electricity consumption is included, leading to less accurate results in areas with a large non-residential demand. Furthermore, since this study is focused on LV grids, only home charging has been considered. This can overestimate LV grid violations compared to a scenario with fast charging from a MV level outside home where less stress is placed on LV grids.

Following most studies, the evaluated power system violations are excess in thermal capacities of transformers and feeders, and voltage variations at the Point of Common Connection (PCC). Therefore, the impact from harmonics and phase unbalance is excluded from the study, what can underestimate the number and severity of the violations. Further, a stricter voltage variation limit ($\pm 5\%$) has been chosen compared to current regulations, leaving a margin to compensate for underestimating assumptions.

Temporal charging limitations to reduce grid vulnerability have been found to be effective, cutting up to 43% of yearly violations. The CPR limitation strategy has been suggested based on results since there are a few occasions in the year where each car charges at maximum CPR. Imposing restrictions on these times can reduce many grid violations. Feasibility of this measure has not been taken into account. To be applied, smart electricity grids with fast interconnection between DSOs and customers have to be deployed, so that CPR can be limited based on overall demand. Nonetheless, variable CPR while charging might have a deterioration impact on batteries.

Furthermore, the energy system composition has been shown to be flexible to accommodate EVs and various charging strategies. It is important to bear in mind that Sweden has a high availability of hydro-power which can be used instead of EVs to provide flexibility to the system to a large extent. Hence, making possible to shape EV charging demand, displacing EV charging to other hours. That is one of the reasons why the system structure does not differ noticeably between the scenario without CPR limitation and with it. Yet, other European regions more reliant on solar power would need EV charging and stationary batteries to meet its electricity storing demands. Thus, EVs would provide flexibility to the power system, not vice versa.

The results agree with previous research that a substantial EV charging demand escalation would increment peak power [9] and modify the shape of the electricity demand curve [6] heavily influenced by commuting patterns [17] if smart charging strategies are not put in place. Moreover, as indicated in [10, 12], the importance of regarding the grid vulnerability from a geographic perspective has been shown. Electricity networks are designed based on population density among other aspects and differ between regions. Sub-urban areas have been found to be more vulnerable than city areas as suggested by previous literature [10]. Results do not agree with the importance of V2G pointed out in some articles [23, 24], this study shows that a smart charging strategy without bidirectional flow is as effective as V2G when preventing power system violations in Sweden. New knowledge has been added to the literature by carrying out a temporal study from a year and day time frame. Previous studies have conducted similar temporal studies for other regions such as Australia [16] suggesting summer as the most vulnerable season. However, results from regions with contrasting weather cannot be extrapolated to Sweden. Moreover, an EV charging limitation has been proposed, analysed and shown to be effective in providing valuable knowledge to DSO and stakeholders.

6 Conclusion

As EVs increasingly become an actual part of the solution to decarbonize the energy and transport systems, it is important to understand how this high EV share will impact the future electricity grid. By modelling and simulating, this study has addressed the impact of a 100% electrified passenger vehicle fleet on the Swedish LV distribution grid from a temporal perspective. The impact has been assessed based on current regulations on thermal and voltage violations in feeder cables and transformers.

It became visible that a significant amount of power system violations would be logged, being the occurrences highly correlated with residential demand in the case of direct charging: winter months are more vulnerable than summer ones, and evenings are more susceptible than night-time. The results suggest that the coldest days in the winter are the most vulnerable for the grid. However, by applying "smart" charging strategies this correlation is alleviated and power system violations are notably reduced. In an intra-day time scope, an alarming peak in the number of violations is found between 5pm and 10pm when drivers arrive home and plug in their cars. A price-optimization strategy has shown to prevent this peaks, however, allowing EVs to discharge back to the grid (i.e. V2G) does not bring significant improvements to the grid.

On top of price-optimization strategies (smart and V2G), a temporal CPR limitation has been proposed as a grid vulnerability mitigation solution. Since most of the breaches of grid regulations are concentrated on a few occasions where EVs are charging at maximum CPR, risk of violations is significantly reduced. Limiting the maximum individual CPR at certain hours could lead to an increase in violation probability at the edges of the interval as a consequence of more cars charging at the same time since they charge slowly. However, the balance of this trade-off is positive since the decrease at limited hours is significantly higher than the increase off the limited hours. Another important conclusion of this work is that an electricity production system mainly supported by wind power and hydro power with a few backup technologies is optimal to provide flexibility in order to accommodate EVs and apply smart charging strategies.

In addition, the examination shows interesting findings in a geographical aspect since the analysis differentiates two types of urban areas based on population density. Sub-urban grids have been shown to be more vulnerable to EV charging demand what can be ascribed to two main reasons. First, urban areas contain a higher share of single-family dwellings which usually use electric heating rather than district heating, therefore the grid is more exposed to large temperature drops in winter. Second, residents in urban areas tend to own a higher number of vehicles to commute and travel to the city, hence more electricity is demanded to charge EVs.

A large amount of data has been generated with the presented models that can assist in exploring further questions. For instance, to provide specific guidelines to DSO on how to specifically reinforce the grid, a future examination could address the temporal distribution of each breach of regulations (thermal capacity and voltage variation). It could provide knowledge on violations patterns and temporal correlations. In addition, the proposed model only considers home charging, disregarding work and public charging. Furthermore, non-residential demand impact has also not been in the scope of this study. Both of these aspects could be investigated by extending the modelling framework.

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A

Appendix 1

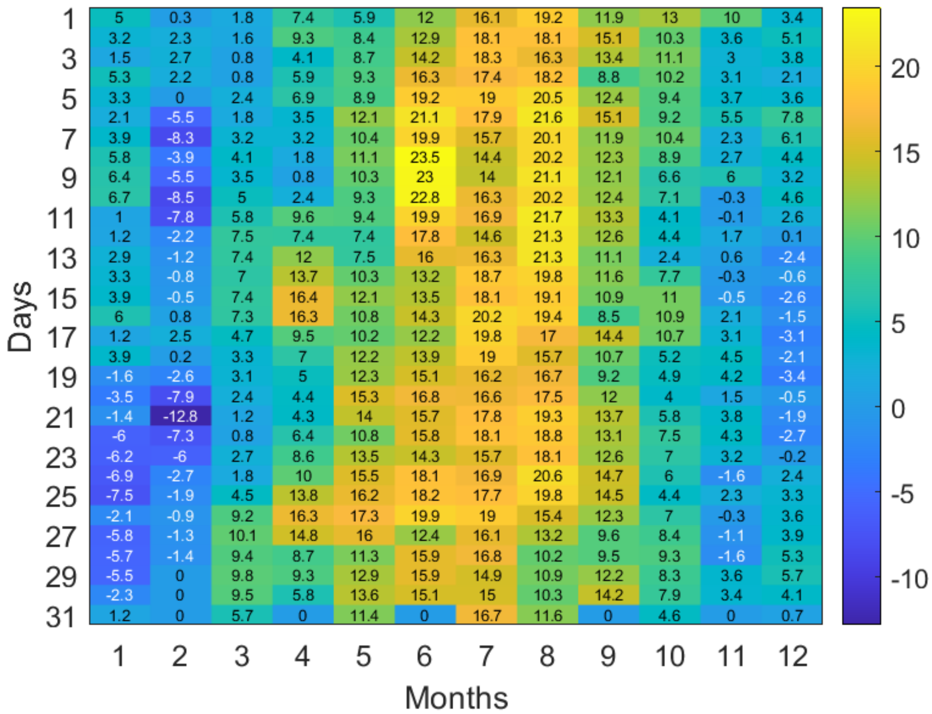
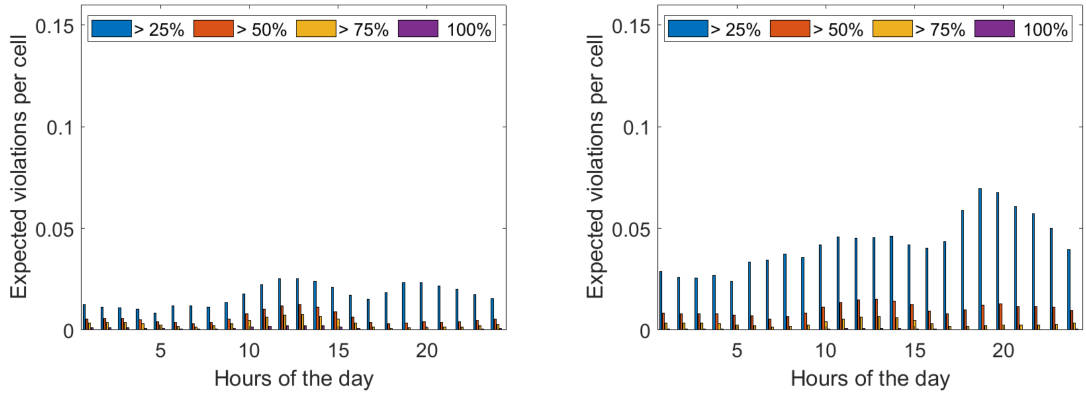
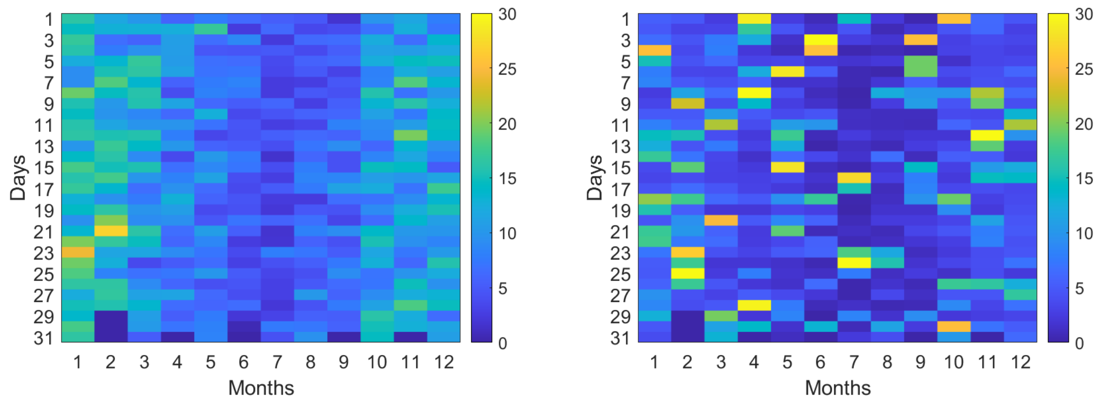


Figure A.1: Daily mean temperature in Celsius degrees in Stockholm, year 2007.

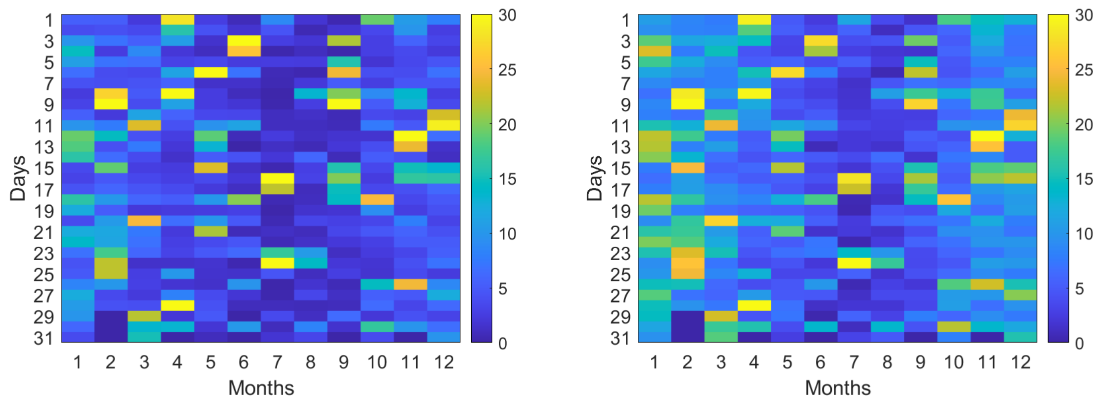


(a) City / V2G Charging **(b)** Urban / V2G Charging

Figure A.2: Expected number of violations per grid cell for an average day. Color bars indicate the probability threshold to consider an occurrence as a violation. For instance, for >25% only the occurrences above 25% value of probability have been counted.

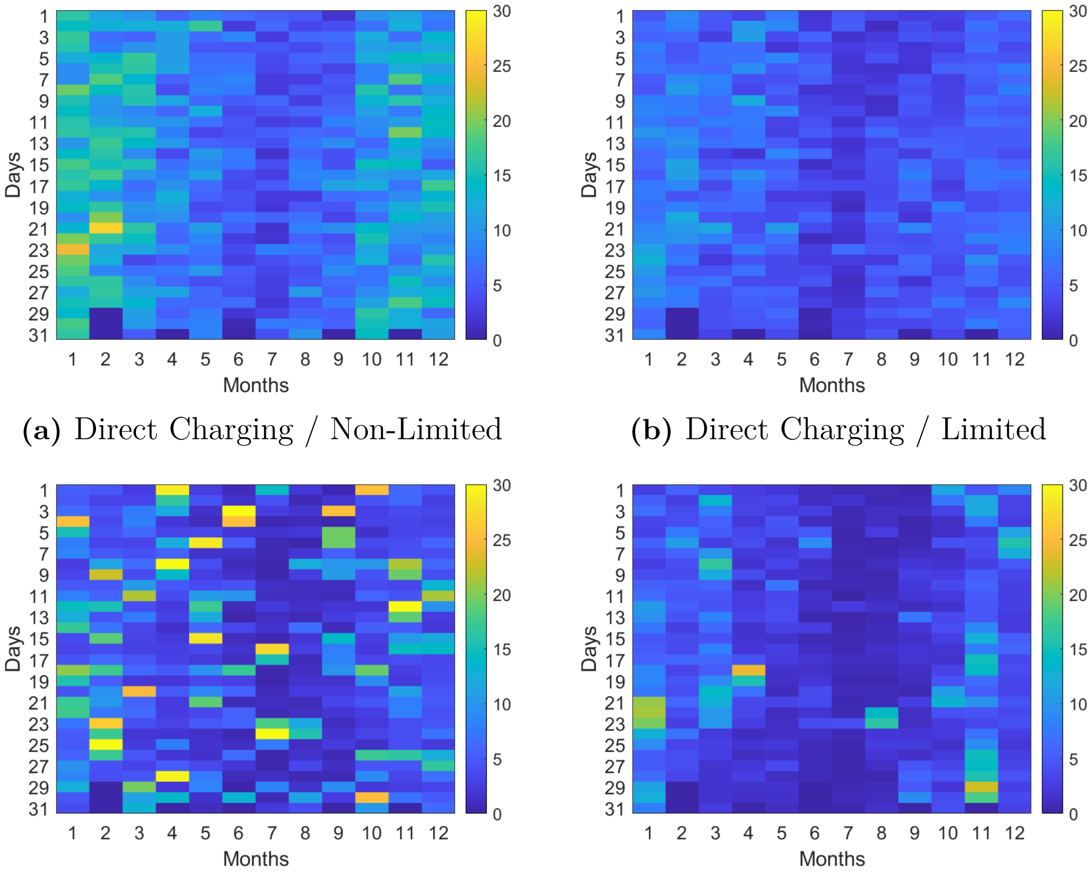


(a) City / Direct Charging **(b)** City / Smart Charging



(c) City / V2G Charging **(d)** Urban / V2G Charging

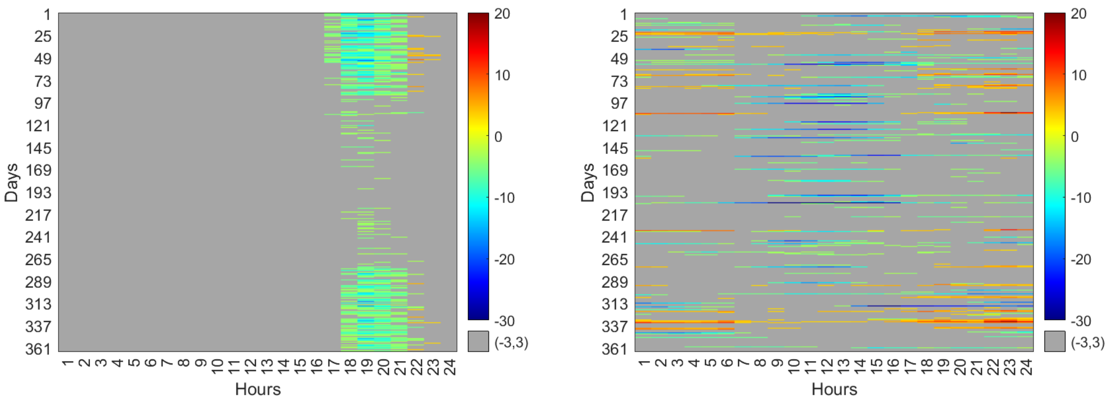
Figure A.3: Heatmaps depicting the mean probability of logging a violation per cell for each day of the year.



(a) Direct Charging / Non-Limited **(b)** Direct Charging / Limited

(c) Smart Charging / Non-Limited **(d)** Smart Charging / Limited

Figure A.4: Heatmaps depicting the mean probability of logging a violation per city cell for each day of the year. The first column represents a scenario without charging limitation while the second one with charging limitation. The first row depicts a direct charging strategy while the second one a smart charging strategy. Note that each row has a different color scale. To analyse the differences between the limited and non-limited scenario, they should be compared horizontally.



(a) Direct Charging **(b)** Smart Charging

Figure A.5: Heatmaps depicting the delta probability of violation between the limited scenario and the non-limited scenario, i.e. (Mean probability among all the cells in the limited case – Mean probability among all the cells in the non-limited case). A positive value means that more violations are expected to be logged for the limited scenario. Only city cells are represented. There is one value of probability for each hour of the year. Values between (-3%,+3%) have been colored in grey to highlight the relevant values.

B

Appendix 2

The detection of breach of LV regulations is implemented with a *binary search* algorithm. It is a search algorithm that locates a target value within a sorted array by comparing the center element of the array and discarding the segment where the target value cannot lie, repeating the process in the new segment until the target value is discovered [55]. There are three target values: thermal limit at the transformer, thermal limit in the cables and voltage drop. Thermal capacity varies with transformer and cable type, allocated during the grid design (section 3.2.1) and the lower voltage limit considered is -5% as mentioned in section 2.1.4.

Finally, when the binary search algorithm finds a s that violates any of these limits, the value of s is stored and the search is stopped for that cell and time block. The final output of the simulation is an AxB matrix containing violation probability values for each A km^2 square in the Swedish electricity network and each B time-steps in a year (52.560 in total).

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