ELECTRIC VEHICLE INTEGRATION IN LOW VOLTAGE DISTRIBUTION GRIDS

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by

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"Creativity is seeing what everyone else sees, but then thinking a new thought that has never been thought before and expressing it somehow"

- Neil deGrasse Tyson

Preface

The following report is the result of 11 months of effort and hard work. It is the final step to obtain my MSc in Sustainable Energy Technology. The work presented in this document is an attempt to quantify the effects of electric vehicles on the power grids. The results shown are subject to the assumptions that are incorporated in this study. I have tried to the best of my abilities to keep the report concise and to the point. This report is aimed at people who are interested in e-mobility and its effects on low voltage distribution grids.

The document contains chapters on effects of uncontrolled charging (Chapter 4) and controlled charging (Chapter 5) of electric vehicles. People with experience in the field of e-mobility will not have any difficulty in going through it. The simulation parameters and scenarios can be found in Chapter 3. It also contains the modelling equations for the grid elements. This work is carried out to answer some specific questions, that can be found in Chapter 1. This chapter also outlines the methodology and the assumptions used.

No project is the sole accomplishment of an individual. Every outcome is a result of the support and guidance received every step of the way. This project also is a team effort and I would like thank each person who has made this journey a success. Firstly, I thank my Ph.D. supervisor, Yunhe Yu for accepting me as thesis student under her project. She guided me all the way throughout these 11 months and gave me the space to try out my own ideas. I also appreciate her giving me moral support when I was not making progress. A huge amount of gratitude goes to Dr.ir. Gautham Ram Chandra Mouli for being my supervisor. I thank him for having confidence in me and making sure that I was on track. I also consider myself very fortunate to have received the help of Dr. Aditya Shekhar. He has immensely helped me in the entire work and always provided me with crucial advice and feedback whenever I was struggling. I learnt a lot from him.

Apart from them, I would like to thank my parents and my elder brother. They have seen me grow, and they are always with me. They supported me and guided me throughout my life. Finally, I would also like to thank Harsh and Annanta for being there for countless discussions over coffee and lunches. They helped me to maintain my sanity or in other words provided me with insanity whenever I needed it.

Thank you all.

Delft, October 2020

Abstract

Although electric vehicles were first used as early as the 19^{th} century, they have only recently gained popularity. By charging them with renewable sources, electric vehicles present a route to zero or low emission mobility. This is a significant reason for their recent popularity given the climate crisis. However, the integration of electric vehicles comes with a unique set of problems, such as over-loading of grid elements and under-voltages of nodes. The integration of photovoltaic generation is also another source of complexity. The focus of this thesis is to investigate the influence of electric vehicles and solar generation in low voltage power grids.

Different charging algorithms are analysed and compared to the uncontrolled charging scenario. The *price based charging* algorithm is a centralised control strategy. The other three algorithms - *average rate charging*, *nodal voltage charging*, and *smart charging* - are decentralised strategies. Each of these algorithms manipulate the charging power at different chargers in the grid according to their specific conditions.

The aforementioned algorithms are tested by performing simulations in three types of German distribution grids: rural, urban, and sub-urban. These simulations are carried out for *High PV*, *Low PV*, and *No PV* scenarios. In all three grids, there is neither over-loading of equipment nor under-voltage of nodes in the *No PV* case. The under-voltages are improved due to photo-voltaic generation. In the *High PV* case, excessive generation causes over-loading and over-voltages in the sub-urban grid. The possibility of using electric vehicles as dynamic storage elements has been explored. Based on the insights obtained from the grid simulations, the performance of different charging algorithms is analysed and compared in this thesis.

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List of Abbreviations

EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
PV	Photovoltaic (system)
PHEV	Plug-in Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
DSO	Distribution System Operator
V2G	Vehicle to Grid
G2V	Grid to Vehicle
IEA	International Energy Agency
SOC	State of Charge
RMS	Root Mean Square

1

Introduction

The increasing number of Electric Vehicles (EV) around the world has initiated a new paradigm in research of the power grids. The challenge of integrating EVs into the power grids, in a secure and more efficient way is being tackled by many researches. As people move more and more towards a cleaner mode of transport, managing the grids become complicated. Some questions that arise with EVs being part of the overall power system are :

1. *How does integrating EVs impact the present-day distribution grids ?*
2. *To what extent can the distribution grid elements (e.g. transformer, lines) handle the inclusion of EVs ?*
3. *Does the presence of renewable energy sources (e.g. solar PV) along with EVs aid or hinder the distribution grid operation?*

One additional challenge that has to be considered,is with regards to EV operation. If considered as a load, EVs add to the grid load demand, especially if they charge during peak hours. And depending on the level of penetration this extra load can be very high. Similarly, if one chooses to exploit the V2G operation, then the grid has to deal with the changes in the power flow as the EVs now behave as a source and the power flows in the opposite direction. Alongside the above mentioned questions, the dual load-source behaviour of EVs has caused the system operators and/or companies to look into the robustness of the existing grids as well as into different EV charging solutions. One can evidently anticipate that, the *smarter* the charging algorithm, the better the integration of EVs. Consequently, this thesis focuses on how different charging algorithms influence the penetration of higher number of EVs in three different types of German distribution grids. The thesis will draw a comparison between the algorithms based on how grid elements get affected under multiple scenarios.

1.1. Electric Vehicles: Battery with Wheels

1.1.1. World Outlook:

According to the global EV outlook by IEA [18], the percentage of EVs is increasing every year, in the last decade. From 17000 in 2010, the number of EVs has gone up to about 7.2 million in 2019. China, Europe and United States dominate most of the entire EV market. Figure 1.1 depicts the exponential growth in EVs all over the world. Ambitious policies by different world governments in terms of charging infrastructure deployment, in addition to the CO_2 emission regulations have given momentum to electrification of vehicles. The major polices that increased the EV numbers significantly in

2019 are namely: US states ZEV mandate; China New Energy Vehicle [NEV] mandate; EU CO_2 emissions regulations [31]. Also, by 2050, 17 other countries are on their way to phase out ICE vehicles paving the way for more EVs.
Its not only cars but there has been a significant rise in electric two-wheelers, three-wheelers and even buses and trucks. This shows that the upcoming future is going to be full electric and this will require proper regulatory frameworks, policies and strategic charging infrastructure.

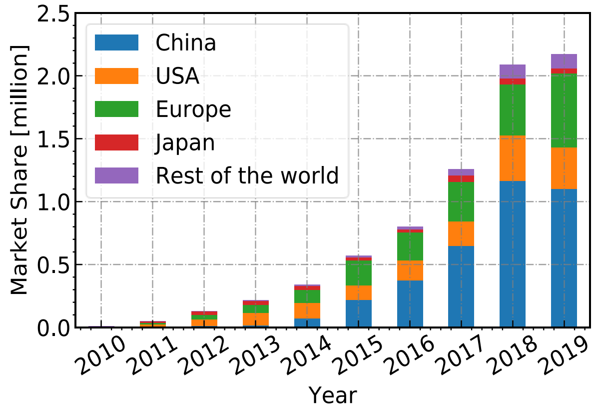


Figure 1.1: Global EV Trend [18]

1.1.2. German Outlook:

According to German federal ministry [13], 1 million electric vehicles can be seen on roads in 2020. There are many policies that provide stimulus for the people to shift to electric mobility in Germany. One such example is the *Environmental Bonus*. It consists of a specific amount of money paid to the buyer of the vehicles. If its a BEV then the amount is 4000 € where as for PHEV it is 3000 €. Similarly, 300 million € support for rolling out charging stations on major routes as well as five to ten years of vehicle tax exemption for EV owners, are some steps taken in Germany to make sure that electric mobility thrives. Figure 1.2, depicts the increasing EV numbers in Germany in the last decade. There has been a 24% increase in new EV registration in 2018 as compared to 2017 [3].

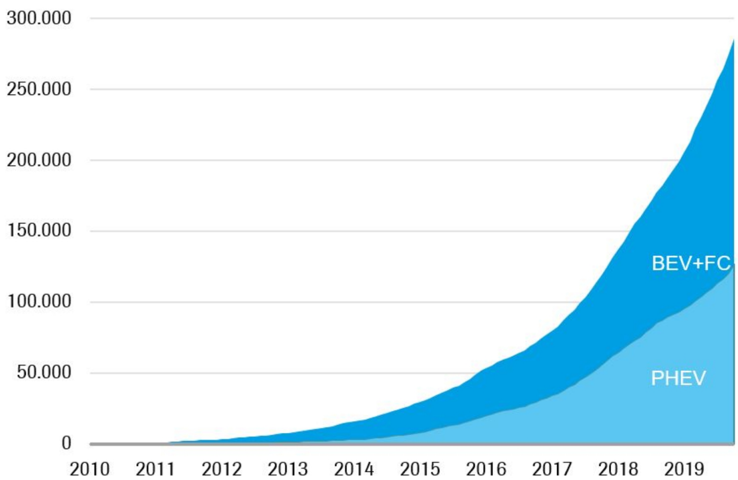


Figure 1.2: German EV Trend

1.2. Solar PV in Germany:

Germany's step toward energy transition, '*Engergiewnde*' [34], declared in 2011 focuses on moving towards renewable energy sources and phasing out the nuclear energy plants. This has led to a rapid rise in numbers of distributed energy sources in the German power network. By the end of 2022, the goal of Germany is to obtain 70% of the total power through solar PV and wind. According to IRENA, Germany is among the top 4 in the world in terms of installed PV even though the sun hours are quite less. The top 10 countries are shown in Figure 1.3.

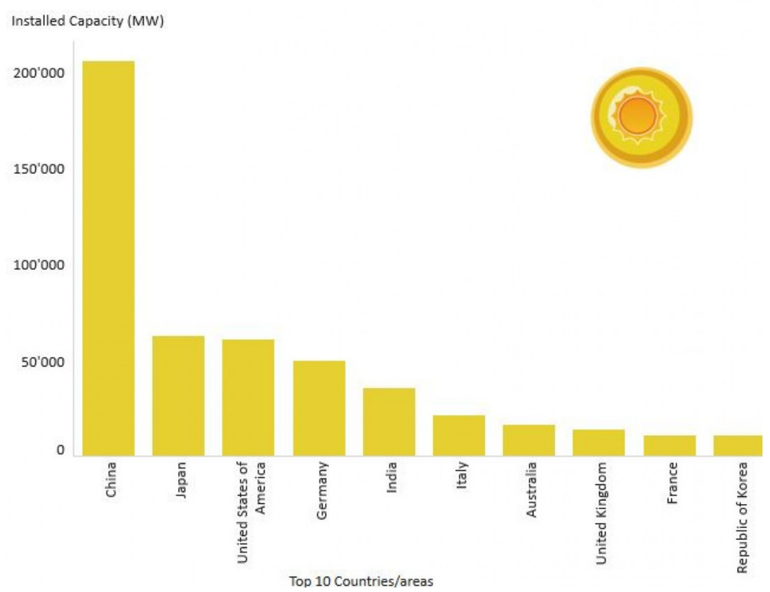


Figure 1.3: Top 10 countries in Installed Solar PV capacity

If the evolution of installed PV capacity of Germany is looked at, in Figure 1.4 [1], then it visible that, the annual capacity increased in 2010-12, and there is certain dip after 2012. But the cumulative capacity is constantly rising from 2009 to 2019.

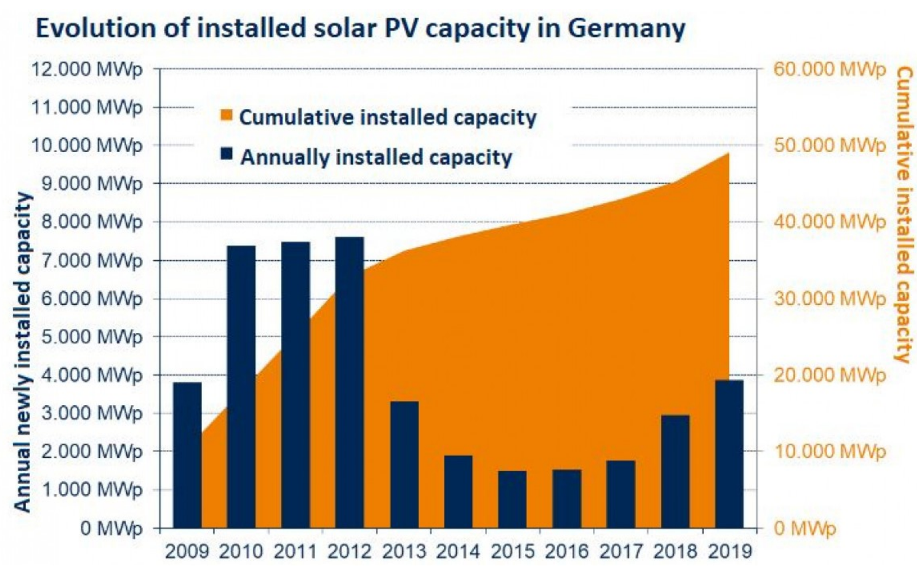


Figure 1.4: Germany's Installed Solar PV

1.3. Research Focus:

Introducing EVs in the grid, can lead to grid management problems, but on the contrary they can also be one of the solutions to resolve bottlenecks across the distribution grid. EVs provide more control as a load and as well as a power source (V2G). But increasing the EV penetration in the existing power grid can lead to adverse impacts on the grid. Shareef et al. [36] have presented the effects of EVs on the power grid . Overall, they can be summarised by the following figure.

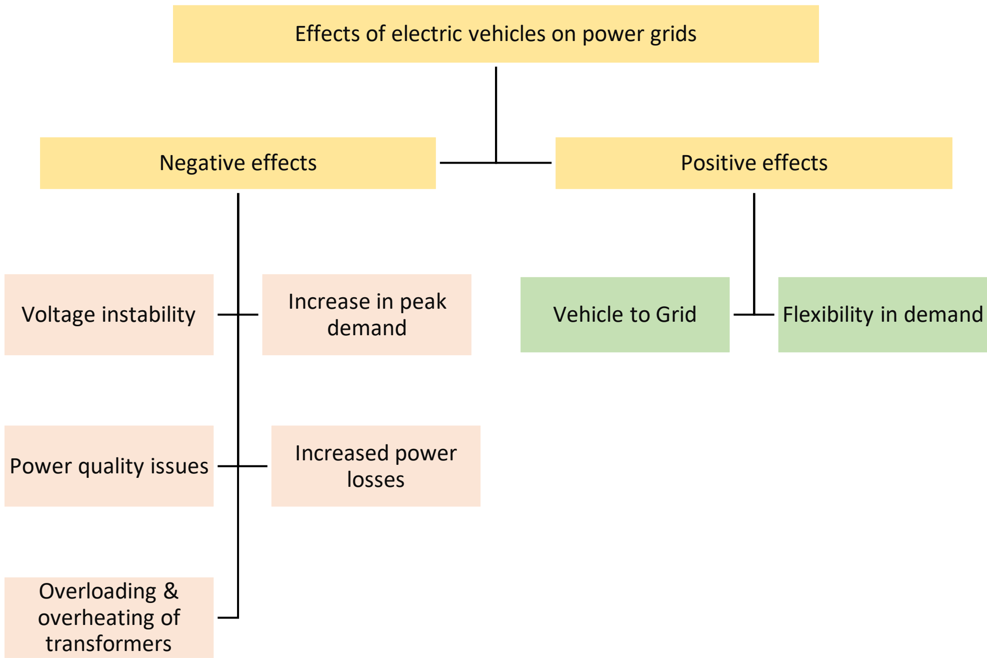


Figure 1.5: Effects of EV-Grid Integration

As the penetration of EVs increases, the distribution system operator (DSO) needs to make adjustments to grid in order to adapt to their behaviour. This can include grid expansion, optimal scheduling or more market based approaches. One of the issues that a power grid can face is *congestion*. Congestion, occurs when some elements in the grid (lines, transformers) are overloaded. It's the DSO's responsibility to make sure that the distribution grid is operating within the certified limits even when there is a power mismatch in load demand and local generation. Depending on the size of the grid, the level of EV penetration can determine the grid's efficient operation.

The focus of this thesis is to implement and compare different charging algorithms, for three different types of distribution grids, namely rural, urban and sub-urban, for different levels of EV penetration. Hence the main research objectives are:

1. ***German distribution grid evaluation:***
   - *Effect of PV penetration.*
   - *Effect of different levels of EV penetration.*
2. ***Implementation of different charging algorithms:***
   - *Analyse how different algorithms influence the operation of the power grids.*

Management of large number of EVs is the recent challenge the DSO has to tackle alongside the participation of renewable sources in the power grid. As the EVs get added to the grid, it has to accommodate the changes in the load demand, reverse power flows and other issues. Many researchers have already tackled similar problems related to EV inclusion from various perspectives, some are mentioned in section 2.3. But it is quite difficult to find solution which "works for all". Every new parameter considered, adds to the complexity of the problem. Hence it becomes quintessential to narrow down the focus and define a scope to reach a certain objective. So, this thesis work focuses on comparison and analysis of four possible charging strategies for three different low voltage distribution grids. The aim is find which algorithm effectively manages grid congestion (if any) caused by large volume of EVs. The objective of each algorithm is to manage the charging power in order to deal with possible occurrences of overloads. Improvement in voltage will be observed but it is not explicitly answered in this work.

The second aspect, and somewhat more interesting, is the presence of a large amount of PV in each of the grids. This adds another dimension to the work. It needs to be mentioned that this work does not focus on optimal use of PV in the grid, but explores the possibility of EV as a flexible storage mechanism. More detail on this can be found in chapter 4.

1.3.1. Primary Assumptions

Before moving towards the modelling and simulation certain assumptions were made. Like any other research, the results of this work are also dependent on the adopted assumptions. Changes in assumptions would results in varied outcomes and might also provide with slightly different conclusions in some cases. Furthermore, some assumptions are similar to the work done by D. Derucci in [11], as both the projects are part of the OSCD project [51], which is the work carried out by my PhD supervisor,Y.Yu. Following are the main assumptions for this study:

1. All the PV systems have an optimal tilt, and effects of cloud coverage, rain, dust etc are not considered. The PV systems will always deliver power depending on the generation profile.
2. The topology of all the grids remains unchanged. Restructuring and reinforcement is out of the scope of this work.
3. All the EV chargers modelled in chapter 3 are three phase chargers. Hence grid imbalance is not considered.
4. The EV behaviour does not change with season. This provides a better seasonal comparison of the grids.
5. EV user satisfaction is not considered, as this adds extra parameter. And the complexity will increase as the grid size increases.
6. Heat-pumps are not explicitly included in the grid modelling. The standard residential profile depicted in chapter 3 contains residential heat-pumps, but the profile is cumulative for a single household.
7. Only active power is considered for the analysis in this research work.

1.3.2. Research Methodology and Questions

The four main charging algorithms that are compared and analysed are as follows,(see chapter 5 for more detail):

1. *Average rate charging*, where the entire parking time is exploited in the charging of EVs.
2. *Price based*, where the rate of charging depends on the day ahead market price of electricity.
3. *Node voltage charging*, where the node voltage drop determines the charging current of each EV.

4. *Smart charging*, which basically is a local optimisation which calculates a charging behaviour of each charger at every node.

The optimisation approach and technique can vary based on various parameters, but at the end the required outcome is to achieve a safe, reliable and efficient grid operation. Each approach, local or central has its own pros and cons, but it is interesting to see how power grid of different sizes operate in presence of such algorithms. All the algorithms are compared to a scenario were the EVs charge unregulated. Considering all the scenarios, in total a close 300 simulations were performed in order to obtain the research outcomes.

The aforementioned simulations aim to answer the following research questions:

- **Does the increasing EV penetration cause problems in the distribution grid operation ?**
  As emphasised earlier, even if the grid can handle a certain change in load, but at what EV penetration level does the grid experiences overloading of its elements and under-voltages at the nodes ? How robust is the grid topology ?

- **How does the presence of higher PV penetration influence the grid operation ?**
  All the grids that are simulated have a very high level of PV generation. Does this cause additional issues in grid functioning ? Does EV and PV penetration complement each other ? If yes, then how ?

- **How does each algorithm impact the charging of the EVs? And is this impact similar / different for all the grids ?**
  Each algorithm in theory should perform better in terms of overloading of transformer and lines (if any) and under-voltages in the grid (if any), than the uncontrolled charging scenario. The question is, by how much ? How does every algorithm compare to each other as well as to a more complex *smart charging* approach ?

1.4. Thesis Outline:

The thesis will have the following structure. Chapter 2 focuses on the literature study and gives an overview on some current charging strategies. Chapter 3 focuses on the description of the grids and the simulation scenarios. It states the types and the characteristics of the grids and also the assumptions and data sets that are used for obtaining the above stated research goals. Chapter 4 explains in detail the uncontrolled charging scenario for all the grids and analyzes the results obtained. The next chapter elucidates all the charging algorithms used in this thesis. Finally, the main conclusions and recommendations for future work are summarised in chapter 6.

2
Theoretical Study

The purpose of this chapter is to provide an outline of the different distribution grid impacts caused by the inclusion of EV and PV generation. In addition to it, also give a review of the different charging approaches, thereby elucidating some solutions. Different charging techniques involve different entities which work towards the most favorable outcome, considering different parameters and hence, influencing the grids distinctively.

The outline of the chapter is as follows. Section 2.1 will highlight EV integration and its effects on the grid. Similarly, 2.2 will focus on PV addition in the grids. The final section will review current charging strategies presented in literature.

2.1. Impact of Electric Vehicle Integration

A conventional distribution grid is designed to accommodate a specific number of loads based on their consumption profile which typically does not change drastically which makes it easier to predict the load pattern. Even if the grid is adequate to handle changes in the load profile, it is still susceptible to overloads[16].

One such change is the introduction of different types of EVs. Existing grid demand increases with uncontrolled EV charging, particularly with higher penetration level. Higher peak loads can potentially lead to operational challenges such as grid congestion. Another aspect of the conventional grid is that it is usually operated centrally by a DSO. But, EVs, which are potentially both a source and a load depending on the operation, give more flexibility to the operator in terms of power management. In a grid, the transformer is one of the main elements, which connects the entire grid to the complete electricity network. Roe et al. [30] discusses the effects of PHEVS on the transformer. Using the thermal model, the authors calculated the loss of life and the expected life of the transformer. The comparison was drawn between two scenarios: with and without PHEVS. With PHEVs, the transformer depicted a reduced expected life. Using simulations the authors calculated that the expected life of transformer dropped from 124.3 years to 10.25 years with PHEVs. A similar study was carried out on the aging of transformers due to the high penetration of PHEVs by Turker et al. [43] on a test grid in France, where they found out that for a low voltage transformer, the aging shows a quadratic behavior in high EV penetration. Usually, transformers are designed in such a way that they can handle overloads for a short time, but if a high number of EVs are connected, then it can turn into a complication. One possible solution is upgrading the transformer [35], which is a more hardware approach and requires investments. Another solution, which more software-based is demand-side management [32]. The upside of such an approach is that it is more cost-effective and does not require power system restructuring.

Loading pattern due to uncontrolled EV charging is governed by the uncertainty in several parameters such as arrival and departure time as well State of Charge (SOC) of the vehicle. Therefore, the grid impact and potential of smart charging application can be predicted based on the probability distribution of these parameters. Moreover, an additional layer of complexity is added when there are different types of EVs, which generally is the case. This creates a necessity to model a more realistic behavior for grid connected EVs which can reduce the possibility of any unexpected changes [16]. An increase in peak demand, losses, and other problems are being tackled by utilities as the number of charging activities are increasing in the grid. The increasing EV numbers also necessitate the need for better communication within the grid. This will ensure better grid management, as the data related to charger usage, vehicle patterns, availability of the vehicles, etc. will be known to the operator. Also, EV users will have an incentive to be able to participate in electricity markets. Smart grids can be one of the many solutions which help maintain coherent information between all the entities in the grid [16].

Apart from transformer and line loading, other aspects in which EV integration affects the grid adversely are voltage and power quality issues. It is quite understood that, when the load at a certain node increases, it results in a voltage drop at that node. Higher number of EVs cause a significant increase in load (though for a short time in many cases), hence it can lead to a decrease in the nodal voltages. Similarly, if the EV which is charging is a single phase EV then this also creates unbalance of voltages in grid. Ul Haq et al. [44], conducted a study on voltage unbalance caused by single phase EV charging in an urban distribution grid. The authors noticed that the voltage unbalance violates the limit of 2% for a penetration level of 50% and above in uncontrolled charging scenario. They also compared this to a tariff-based charging scheme, which was observed to be less detrimental. A grid reinforcement strategy was proposed which includes replacing the grid transformer and reinforcing certain segments of cables, which clearly will depend upon the cost.

On the positive side, inclusion of EVs increase the storage capacity of the grid. Using V2G, power can fed in during off-peak intervals. When including RERs like solar and wind are also included in the grid, V2G acts a backup to the intermittent behaviour of these sources of energy [23]. Similarly, ancillary services like peak shaving, voltage and frequency regulation are at the operator's disposal to make sure an efficient grid operation [50]. As this thesis does not consider V2G, this section will not go into the details but this short paragraph is meant for the readers encouragement to research about the topic.

2.2. Impact of PV Integration

Given the growth in solar energy generation, the importance of including PV in the power grids is also increasing. Karimi et al. [22] identifies the impacts as voltage fluctuation i.e. rise or fall of voltage and voltage unbalance, loading of distribution transformer, feeder overloading, etc. The penetration level, the topology of the grid and location of the PV systems in the grid dictate the severity of the impacts earlier mentioned. The first and foremost issue with PV is its intermittent nature. Sue to this final electricity output obtained is highly dependent atmospheric conditions, which then creates a need for reliable forecasting methodology for accurate predictions should be present [28]. Another factor that affects the power production is the ambient temperature this becomes particularly problematic if an MPPT algorithm is used to operate the PV [5]. A higher ambient temperature will cause the open circuit voltage of the PV panels to drop, decreasing the efficiency in the process [37], which decreases the power output.

Incorporation of solar PV introduces reverse power flow in the grid. If the PV energy exceeds the local demand then the energy will move upstream via the distribution transformer, and make the entire network vulnerable to faults [42]. Ainah and Folly [4] show that the excessive upstream power flow causes overloading of the transformer and increased power losses. In addition to it over-voltage issues were also recorded. Authors in [5] have done a quite intensive review about impact of rooftop PV on distribution grids. According to them, as line losses vary with the square of current, if the mismatch is very less then the losses would be negligible otherwise in case of a larger value of mismatch, the line losses will follow a trend similar to the PV penetration trend. Similarly, a higher mismatch impinges the main network upstream of the transformer and makes the system unstable.

The continuous power fluctuation due to PV generation can affect the transformer life as well. Pezeshki et al. [29] conducted a study on typical sub-urban 200 kVA oil-immersed transformer. It was concluded that, in absence of rooftop PV, the oil and hot-spot temperatures reached larger values as compared to a scenario with PV. They also found out that a growth in PV provided an improvement in the loss of life of the transformer insulation. A similar research was carried out by authors in [45] on transformer aging. The conclusion reached was akin to the previously mentioned study that, due to PV the cumulative aging of transformer decreases and the effects are quite significant in summer season. In both the cases though, the local production was less than the load demand, hence it would be interesting to know how high PV generation affect these parameters.

The type of loads in the grid also influence the consequence of local PV generation. If the grid consists mostly of residential loads then the peak in the demand occurs mostly when there is little to no PV production i.e. in the evenings/nights. During the day as there is relatively a lower load to consume the PV power, the nodal voltages tend to rise [45]. This is can be seen from Figure 2.1, which is plot of standard residential, commercial and PV profile in winter season. It is observed that, the peak in the residential load occurs when the PV generation is close to 0. Whereas, commercial load peak occurs close to the PV peak.

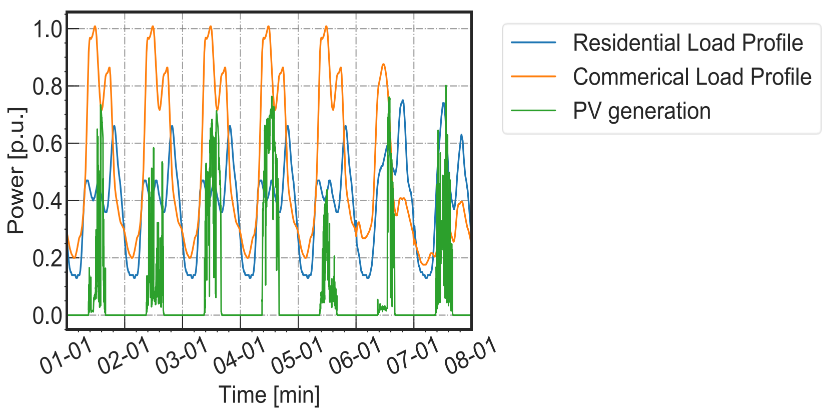


Figure 2.1: Residential and commercial load profiles along with PV generation profile

Uçar et al. [45] performed a study on voltages profiles of a common Canadian residential neighbourhood with a high PV penetration. Based on their study, the length of the feeder is one of the factors that affect the voltage rise in the grid. Feeder with a longer span, is more prone to voltage rise problems due to an increase in the impedance.

2.3. Smart Charging: Current trends and outlook

With increasing number of EVs on the road, the need for a charging strategy is increasing as well. Smart charging of EVs answers the challenges regarding management of load, grid stability, reinforcement/modifications by means of flexible shaping of EV power demand. Research into this paradigm has several perspectives. As EV charging involves several parameters like duration , volume of EVs present in the grid, topology of the grid, direction of power-flow, this makes it a multi-objective optimization. Amjad et al. [6] classify the EV charging problem into three different categories namely, charging approaches, optimization objectives and optimization strategy. The classification is shown in Figure 2.2. Please note that the figure consists of only examples, the optimization strategy and goal will change based on the focus of the research, computing power etc. One common thing between all the smart charging methods is the dependence on availability of reliable data.

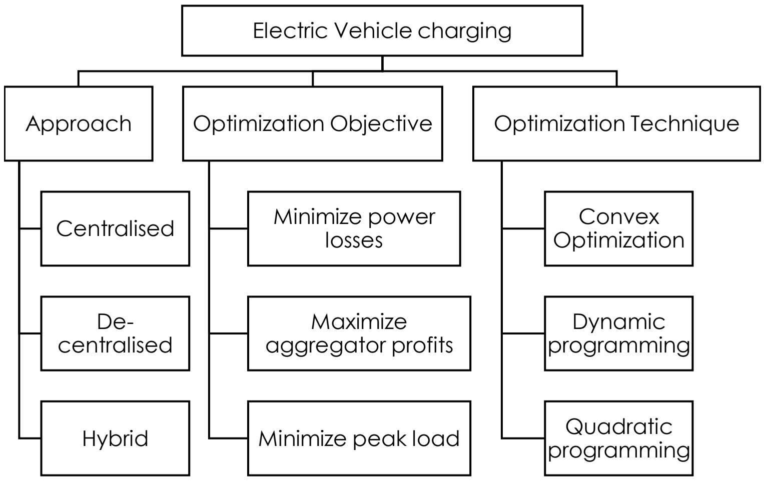


Figure 2.2: Examples of charging approaches, optimization objectives and techniques

Charging of EVs centrally is mainly managed by the aggregator or sometimes referred to as aggregator unit (AU), which is an entity acting as an intermediary between the grid operator and the user of the EVs [24]. Control of the smart charging, providing ancillary services, load distribution, these are some of the functions that the AU carries out. The central controller can aim to maximize profits of AU, reduce peak load, etc. Sortomme and El-Sharkawi [38] developed an optimal central charging strategy where the aggreagators profits are maximized.

Aswantara et al. [7] based their centralized charging approach based on EV user satisfaction and the cost of electricity. With the main objective focused on minimizing the cost of electricity, the authors investigated the effect of deviation in the user fairness level on the price of electricity. And concluded that the even for a small change in fairness level, the price was affected significantly. The authors do not take into account the effect of local generation on the price. This can further affect the charging costs as, the EV users now have more incentive to vary their charging behaviour. Authors in [27], explore the idea that EVs can be used to provide support for the grid operation in high renewable energy penetration, which introduces the need of forecasting. The optimization is focused on both G2V and V2G domains to support wind power integration in the grid. The objective function is a deterministic problem focused on reducing power imbalance in the grid. Being a deterministic optimization, the authors were able to achieve results at a higher speed. Similar central control strategy can be found in [21], where authors study real-time scheduling of EVs to minimize grid impacts and increase user satisfaction. Charging EVs centrally makes it easier to maximize the network usage to its full capacity [6]. But this approach has issues with security and privacy, plus as one entity determines everything, this increases the vulnerability of the entire structure. Some disadvantages as listed by [12] are as follows:

1. Need of large investment for better and efficient communication infrastructure.

2. High computation requirement as the data-set is quite big.

3. Possibility of high latency issues and low quality of service as the large amount of information needs to be communicated within a certain time frame.

A decentralised approach on the other hand is more flexible and scalable as compared to the centralised approach. And they do not impose a very high computational requirement [12]. As the name suggests, the control of charging and discharging is shifted from a central entity to each EV user, demanding an active participation and understanding on the user part [6]. Gan et al. [14] proposed an optimal charging strategy which is based on "valley filling" approach. Based on the day ahead market price, each EV calculated its consumption profile. In this study as well, the effect of intermittent energy sources is not considered, where EVs can provide a flexible option of optimal scheduling.

Authors in [39], developed a price based method in which they also consider the involvement of solar and wind energy sources.The main objective being reduction in electricity bill, the authors took into account the user behaviour, where the user changes his/her load patterns depending on the price. Using the price signal for the control strategy is very common in the decentralised charging of EVs. This is because of the dependence on user participation for efficient operation. And a monetary incentive proves to be a good motivation for consumer involvement.

Similar to the previous technique, this also possesses certain drawbacks. As summarized by [12],[6] and [15], some drawbacks are:

1. *Avalanche effect.* The increase in EV loads across the grid when the price falls to a low value.

2. Vulnerable to EV user behaviour.

3. Limitation in provided ancillary services. Not all services are supported by this apporach.

As a distinction can be drawn based on centralised versus decentralised EV charging approaches, a similar distinction is possible based on the optimization techniques used to solve the various objective functions which can be single or multi-objective. As it is not possible to cover every optimization technique used, some of them are mentioned here in order to encapsulate the idea. Traditional techniques like linear programming, dynamic programming , quadratic programming etc. have been explored quite popularly to integrate EVs in the grid. Another new paradigm which is fairly recent is machine learning based solutions [47] as well as data driven optimization approach [49].

2.4. Summary

To sum up, due to mass deployment of EVs in the distribution network, the grid is vulnerable to more peak demand, increase in losses and in some cases overloads. But on the positive side, EVs provide a flexible storage option that can support integration of intermittent renewable sources of energy. Similarly, inclusion of PV in high percentages leads to over-voltages and excessive reverse flows, which the grid may not be adequate enough to manage. Co-ordination between EV-PV can lead a to more efficient and reliable grid operation. Charging of EVs can be centralised, distributed or hybrid. Each algorithm focuses on a different objective function depending on the goal to be achieved. Reliable user data, systematized computation, secure communication are some of the limiting factors that can affect the charging strategies.

3
Simulation Scenarios

The following chapter covers the modelling of the loads, PV generation and EV chargers, which were used in all the grids to carry out the simulation. In addition, the scenarios which were simulated are also explained. To assess how each grid behaves differently, a comparison of the grid performance is made for summer as well as winter season. The PV generation profile, as well as the load consumption profile varies with the season, but the number of EV chargers and their power profiles are assumed to be unchanged. This is done in order to evaluate how the grids behave with changing seasons. Modelling of each component is based on certain assumptions, which are mentioned in their respective sub-sections. The tools used in this thesis are *Python* programming language and *PowerFactory* by DIgSILENT.

3.1. Scenario Definitions

3.1.1. Distribution Grids

The simulations were performed on three German distribution grids. The grids are classified into rural, urban and sub-urban category. All the grids are of meshed topology which can be seen in figures 3.1,3.2 and 3.3 . The following table summarizes the three grids:

Grid Type	**Rural Grid**	**Urban Grid**	**Sub-Urban Grid**
Number of Transformers	1	1	1
Transformer Rating [kVA]	400	400	630
Average Line Length [m]	18.9	9.5	15.82
Number of Loads	37	72	297
Number of Households	32	50	137

Table 3.1: Distribution grids summary

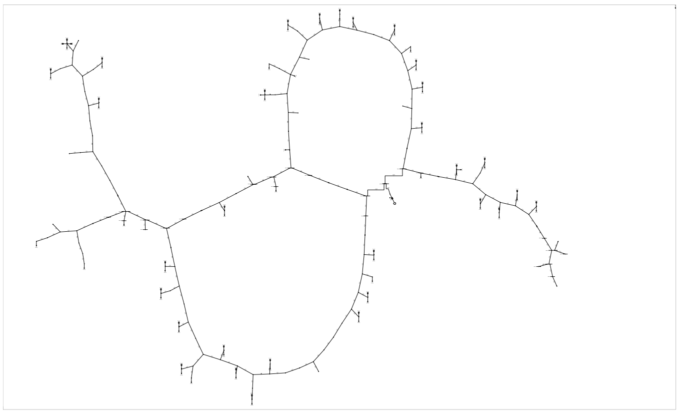


Figure 3.1: Rural Distribution Grid

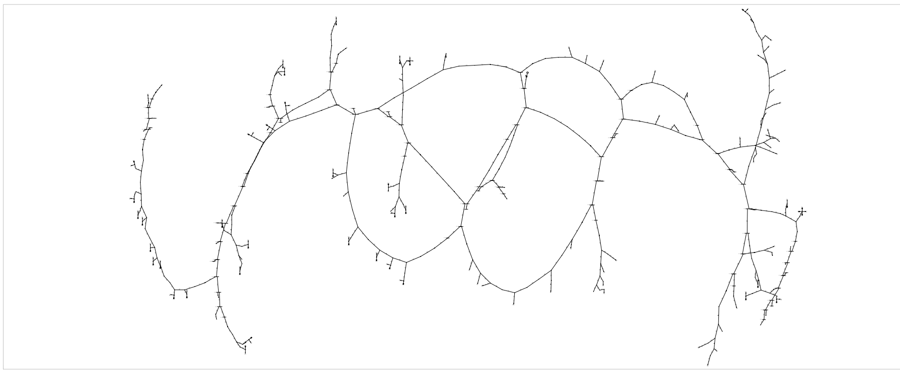


Figure 3.2: Urban Distribution Grid

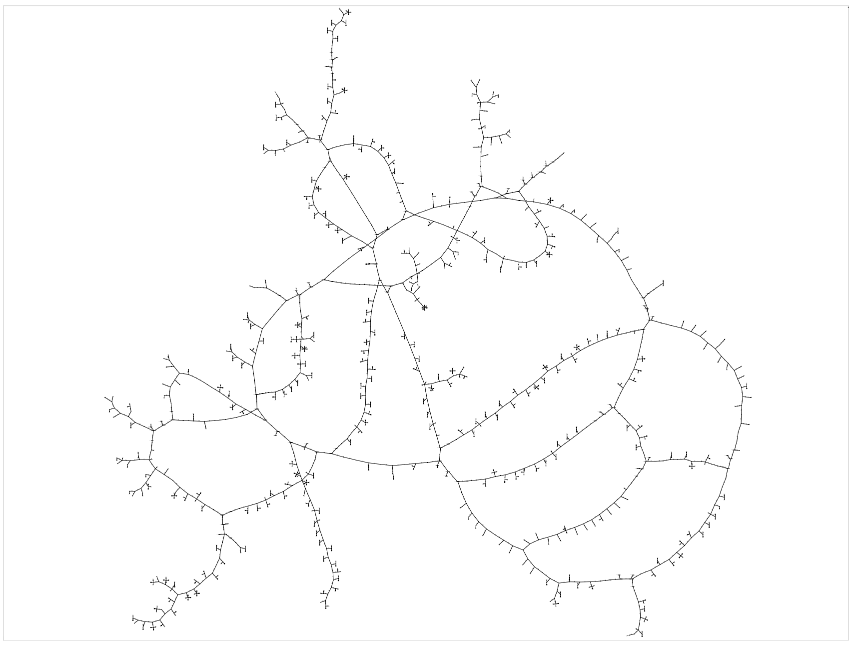


Figure 3.3: Sub-Urban Distribution Grid

3.1.2. Simulation Time

Simulation Time-Step	1 minutes
Simulation Time	7 days

Table 3.2: Simulation Interval

3.2. Electric Vehicle Modelling

The inclusion of EVs in the distribution grids is carried out in increments. The EVs are added to grid in different percentages of penetration starting from 0% upto 80%, and the scenarios are termed as shown in Table 3.3.

Scenarios	
Zero	0% of all the vehicles are electric
Present	20% of all the vehicles are electric
Future	50% of all the vehicles are electric
Far-Future	80% of all the vehicles are electric

Table 3.3: EV penetration structure

In order to imitate EV behaviour, EV chargers are modelled as loads in *PowerFactory* with a certain consumption profile. The number of EV chargers in each grid is calculated based on the number of households present in that grid. The chargers are classified into three categories, Home, Semi-public and Public. The number of a specific type of charger changes respective to the grid. Table 3.4 sums up all the charger variation in the grids.

Grid Type	**Home Charger [%]**	**Semi-Public Charger [%]**	**Public Charger [%]**
Rural	70	15	15
Urban	25	37.5	37.5
Sub-Urban	50	25	25

Table 3.4: EV charger classification in each distribution grid

The total number of EV chargers for a given percentage of penetration is calculated by (3.1),

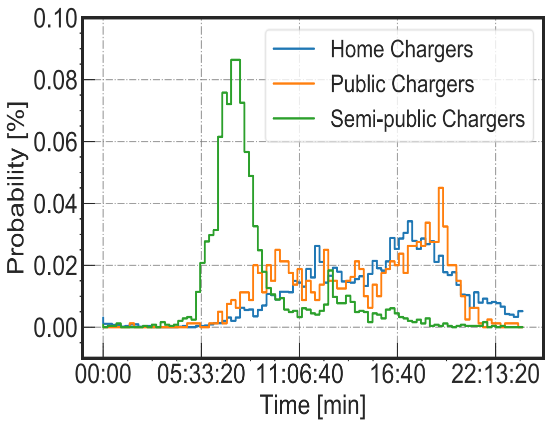
$$N_{\mathrm{c,tot}} = N_{\mathrm{c,hh}} + N_{\mathrm{c,sp}} + N_{\mathrm{c,p}} \tag{3.1}$$

where, $N_{\mathrm{c,hh}}$, $N_{\mathrm{c,sp}}$ and $N_{\mathrm{c,p}}$ are the three types, corresponding to home, semi-public and public. A data set, known as the *EV fleet* contains one week of charging information for 200 chargers per type is generated. This data set is generated with random sampling from the measured data together with the assumption of EV types. Since the EV charging information is modelled in the form of chargers, it is important to convert the amount of EVs into the corresponding number of chargers. Given the average number of cars per household ($N_{\mathrm{car,hh}}$) and total number of households (N_{hh}), the total number electric vehicle chargers of a specific type is given by (3.2).

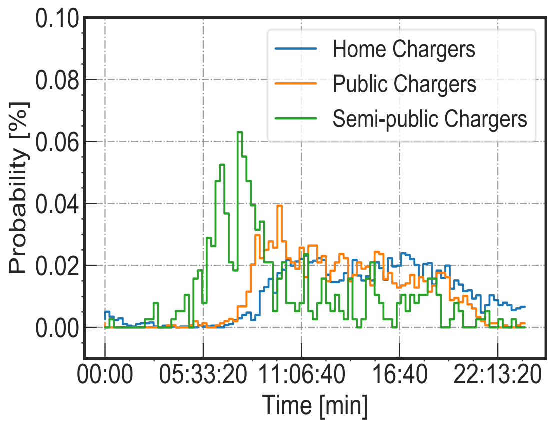
$$N_{\mathrm{c,hh}} = \gamma_{\mathrm{ev}} \cdot N_{\mathrm{car,hh}} \cdot N_{\mathrm{hh}} \cdot \alpha_{\mathrm{ce}} \cdot N_{\mathrm{ce,hh}} \tag{3.2}$$

Here, γ_{ev} takes into account different EV penetration levels as a percentage of total number of cars. The assumption for $N_{\mathrm{car,hh}}$ for different types of grids is 1.6, and N_{hh} is available from the grid data. Whereas, α_{ce} the average charging events per car per week. The value of α_{ce} is assumed to 4 and is kept constant for every grid. Whereas $N_{\text{ce,hh}}$ is the percentages of home charger distribution mentioned in Table 3.4. Similar calculation can be done for other types as well using ($N_{\text{ce,sp}}$) and ($N_{\text{ce,p}}$) as charger type percentages. In total, 14 different types of EVs were used to formulate the previously mentioned *EV Fleet*. The data set generated is dependent on the probability distribution of the arrival time t_{arr}, the parking time t_{parking} and the distance covered d_{cov} by an EV.

All these parameters vary for a weekday and a weekend. For e.g. from the distribution of t_{arr} shown in Figure 3.4, it is visible that the home chargers have higher probability of EV arrival in the evening as opposed to semi-public chargers, which experience more EVs in the morning. This probability dependent behaviour influences the grid operation during the EV penetration scenarios. Hence, for instance, looking at the rural grid charger distribution in Table 3.4, it can be inferred that, due to a higher home charger percentage, in the event of a higher local PV generation, less number of EVs would be present in the grid to utilise it.



(a) Weekday



(b) Weekend

Figure 3.4: Probability distribution of arrival time for different charger types

3.3. Photovoltaic Generation

Based on the grids received from the grid operator, it was observed that,every grid had different PV penetration levels with the PV systems being of different ratings. Also, each grid had two pre-defined operating scenarios, namely a *'High-PV'* and a *'Low-PV'* scenario. Both scenarios differ in the number of PV systems active during the simulation. In addition, to independently observe the effects of EV integration, a *'No-PV'* scenario was also simulated. Table 3.5 gives the PV penetration percentages in each scenario for every grid which is calculated using 3.3. For both the rural as well as the sub-urban grid the *'High-PV'* scenario is depicts a energy neutral scenario, with PV penetration going beyond 100% in the rural grid.

$$\gamma_{pv} = \frac{E_{pv,yearly}}{E_{load,yearly}} \tag{3.3}$$

here,
γ_{pv} : PV penetration [%]
$E_{pv,yearly}$: Yearly PV generation [MWh]
$E_{load,yearly}$: Yearly load consumption [MWh]

Grids	High PV Scenario	Low PV Scenario
Rural	122.7%	20.1%
Urban	56.03%	2.03%
Sub-Urban	99.39%	24.99%

Table 3.5: PV penetration percentages of each scenario for all grids

All the grids are located in the Lower Saxony state of Germany, hence a standard generation profile of a 1kwp is assumed, which is common for all the PV systems. The profile used is obtained using Meteonorm software [2]. The software also provides the values of the ambient temperature, wind speed which affect the PV generation and are taken into account. For obtaining the AC power generated by the PV system there are some assumptions that have been made. It is assumed that the system is south facing i.e. azimuth is 180°and has a tilt of 32°[20]. The profile for each system is calculated by multiplying the rating of the system to the standard generation profile. The following set of formulae is used to calculate AC power output of the PV system [37]:

$$T_m = T_a + \frac{T_{noct} - 20}{800} * G_M * \frac{9.5}{5.7 + w} * (1 - \frac{\eta}{0.9}) \tag{3.4}$$

$$\eta = \eta_{STC} * (1 + \kappa * (T_m - 25)) \tag{3.5}$$

$$P_{dc} = G_M * \eta * A_m \tag{3.6}$$

$$P_{ac} = P_{dc} * \eta_{inv} * \eta_{cables} \tag{3.7}$$

Here,

1. T_m: Module Temperature.
2. T_a: Ambient Temperature.
3. T_{noct}: Nominal Cell Operating Temperature. (45°C)[19]
4. G_M: Incident irradiation on the module.
5. w: Wind speed.
6. η_{STC}: Efficiency of panels under standard test conditions. (0.16)[19]
7. A_m: Area of module. (1.63 m^2)[19]
8. κ: Temperature coefficient.
9. η_{inv}: Inverter efficiency. (0.98)
10. η_{cables}: Cable efficiency. (0.98)
11. P_{dc}: DC power of the PV system.
12. P_{ac}: AC power of the PV system.

(3.4) is the Duffie-Beckamn thermal model of PV modules. It gives the module temperature depending in the incident radiation, wind-speed, ambient temperature and the NOCT of the PV module. The change in temperature is used to calculate the efficiency of the module at each time interval in (3.5). The value of the efficiency gives the output of the single panel using (3.6). Multiplying that with the inverter and cable efficiencies in (3.7) gives the final AC power of the system.
Figure 3.5, shows the standard AC profile for 1 kwp for a year. And figure 3.6 are the summer and winter season profiles for the month of July and January respectively. As expected, summer season has more generation.

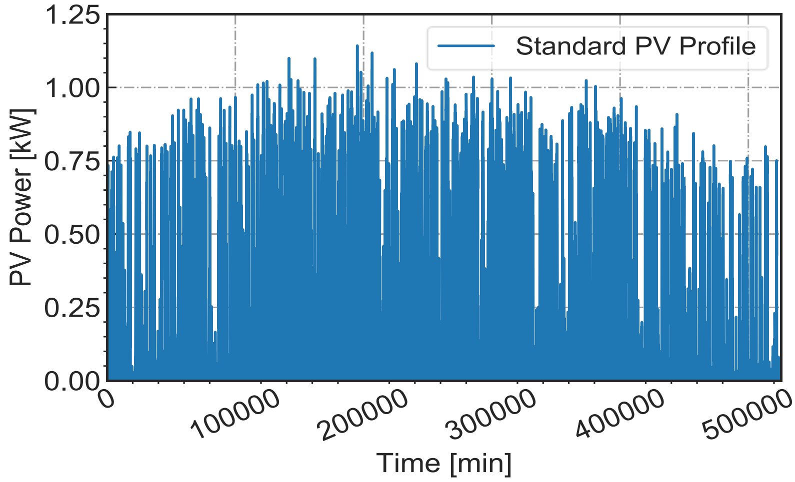


Figure 3.5: Yearly PV Production

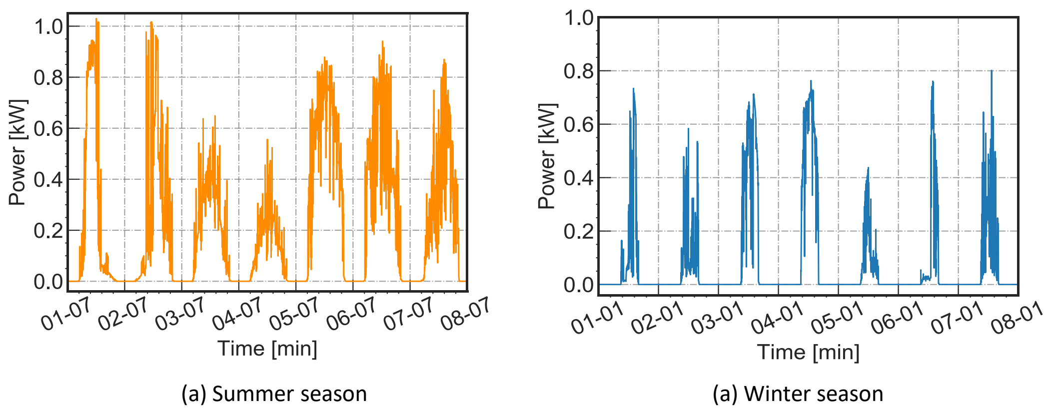


Figure 3.6: Standard PV generation profile in summer and winter seasons

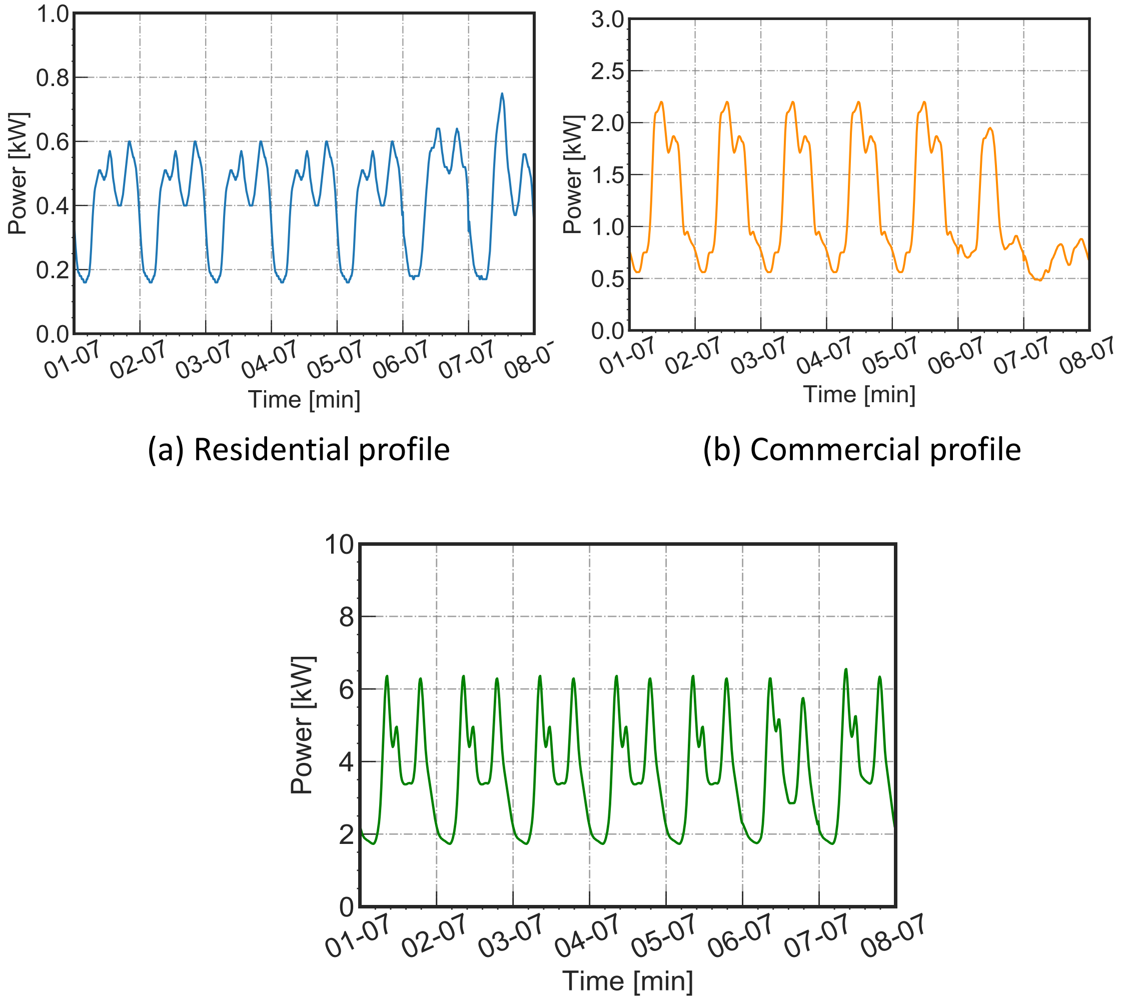
3.4. Load Modelling:

The number of loads in each grid are divided into three categories namely, household, agriculture and commercial. As the data received about the loads with the grid models was not adequate to divide the total loads in the three types, an assumption was made. The total energy consumption of the entire grid was divided into the aforementioned classification. This is shown in Table 3.6. So for example if the total consumption of the entire rural grid is 35000 kWh, then 50% i.e. 17,500 kWh is consumed by residential load and the remaining is divided equally among the rest. The load profiles (Figure 3.7) used in the thesis are the standard profiles for German loads provided by the BDEW

Grid Type	Rural Grid	Urban Grid	Sub-Urban Grid
Residential Load [%]	50	65	75
Commercial Load [%]	25	35	25
Agricultural Load [%]	25	0	0

Table 3.6: Classification of loads into different categories

(Bundesverband der Energie-und Wasserwirtschaft). All the profiles provided are for a load of 1000 kWh/a. Hence, depending upon the consumption of different loads, the profile was normalized with respect to it. Furthermore, the consumption is different for winter and summer as well as for weekend and weekday.



(a) Residential profile

(b) Commercial profile

(c) Agriculture profile

Figure 3.7: Standard profiles for types of load in summer season.

The standard load profile is calculated by 3.8 [9]:

$$F_{\mathrm{t}} = -3.92 \times 10^{-10} \cdot t^4 + 3.2 \times 10^{-7} \cdot t^3 - 7.02 \times 10^{-5} \cdot t^2 + 2.1 \times 10^{-3} \cdot t + 1.24 \tag{3.8}$$

F_t is called as dynamitization factor. And t is the day number on the day of the selected period. For e.g. $t = 1$ for January 1. The purpose of this factor is to take into account the seasonal variation in the load consumption throughout the year. From (3.8), the quarterly (15 min) standard profile is obtained by:

$$P_{hh::mm,t} = P_{hh::mm} \times F_t \tag{3.9}$$

where, $P_{hh::mm,t}$ is the quarterly power values and $P_{hh::mm}$ is the auxiliary power profile. Finally, $P_{hh::mm,t}$ was interpolated to 1 minute duration.

4

Uncontrolled Charging

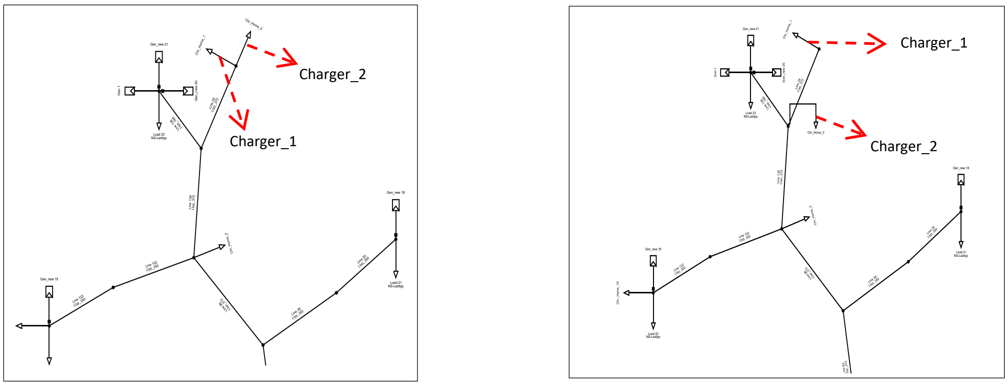
Also termed as unregulated charging, this is the simplest and quickest way to charge EVs, as this technique has no constraints and the user can charge EVs at any time of day. The EV will stop charging at 100% SOC or at departure time, whichever comes first [33]. One downside of this technique is that it causes overloading of the power equipment. For e.g. if EVs are connected during the peak of the day, then the total load demand will increase and depending upon the cumulative power asked by all the EVs at the same instance, this can cause overloads in grid elements which can lead to power congestion. Unpredictability in cost of charging is introduced by this method as, the price of electricity is not taken into account while charging [33]. However,this method does not require an algorithm as such, plus there is no need of an ICT infrastructure, making it simpler and cheaper to implement, hence it is predominantly used in most cases.

The purpose of this chapter is to evaluate the German distribution grids in the uncontrolled charging framework. At each penetration level a certain number of chargers are added to the grid, Table 4.1. The number of chargers are obtained using equations 3.1 and 3.2.

	Number of EV chargers		
Grids	**20%**	**50%**	**80%**
Rural	7	14	24
Urban	8	21	33
Sub-Urban	24	52	98

Table 4.1: EV chargers inserted in each grid in every EV penetration scenario

In order to simulate the 50% penetration scenario, additional EV chargers are integrated into the 20% penetration grid. These chargers are added at random locations. It is important to note that the locations of the chargers in th 20% scenario are not changed. For e.g., in rural grids, 7 chargers are present in the 20% penetration scenario. To simulate the 50% penetration scenario, the locations of these chargers are maintained and 7 additional chargers are randomly consigned. This was done so that the comparison between the low and high penetration scenarios is more meaningful. This can be clearly seen from Figure 1.1. In the 20% case, *Charger_1* and *Charger_2* are added to the same node. If all chargers are re-inserted for the 50% case, then the location of *Charger_2* changes. This makes it difficult to study the effects of only increasing EV penetration.



(a) 20% EV penetration

(b) 50% EV penetration

Figure 4.1: Charger locations in the grid for 20% and 50% EV penetration

Moreover, sub-urban grid, being the largest of the three, has the most number of chargers in all the cases. It is to be noted that not all the plots for all the grids are shown in the following sections. Only those which are relevant to the discussion are depicted, rest can be found in appendix.

4.1. No PV scenario:

As stated in chapter 3, EV penetration is increased from 0% to 80% in three different PV scenarios. In the *'No-PV'* scenario, the grids operate as expected. The heat map of rural grid shown in Figure 4.2, depicts the instance at which the maximum loading of the transformer occurs. As the figure is for a 80% EV penetration scenario, it can be concluded that the grid appears to be robust and can handle even more number of EVs. Figure 4.3 is the plot of transformer loading of the rural grid, it shows that even with the maximum level of EV inclusion, there is an absence of overload. The zoomed in figure represents the day which experiences the maximum loading. It is evident that the transformer loading does not even cross the 25%, in the uncontrolled charging simulations. A large number of chargers does not affect the grid operation drastically.

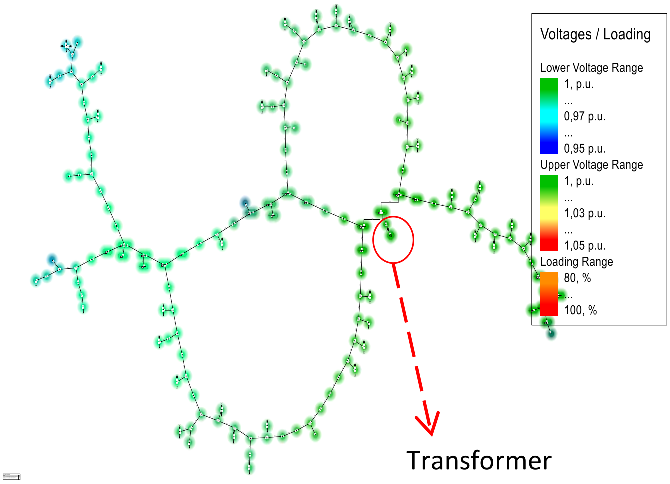


Figure 4.2: Rural grid heat map for 80% EV penetration in summer season

Figure 4.4 shows the line loading with respect to time. It is visible that, the trend is quite similar to that of the transformer loading. In terms of operation, weekdays depict more loading as compared to the weekends. This is because in weekends the commercial loads consume very less, the total loading decreases in its entirety. So the EV charging does not increase the loading to a large value. The nodal voltages in Figure 4.5 drop at the point where EVs start charging. The minimum value for nodal voltage in an entire week does not fall below 0.96 p.u.

All the above stated observations hold for urban and sub-urban grid as well. All the three German distribution grids do not experience overloads, under-voltages with increasing EV penetration. In addition, it is to be noted that the results in this section represent a benchmark for other results.

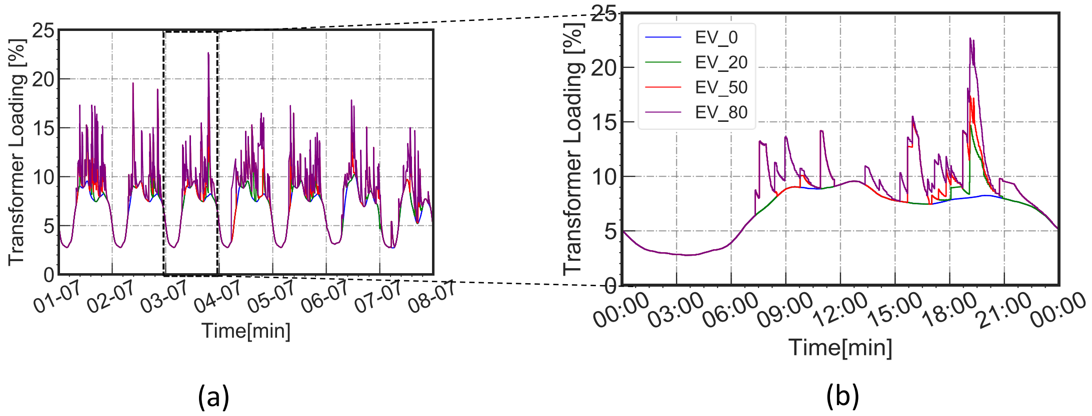


Figure 4.3: Transformer Loading in No-PV scenario in summer season for rural grid. Figure (a) is for entire week. Figure (b) is zoomed-in for a single day

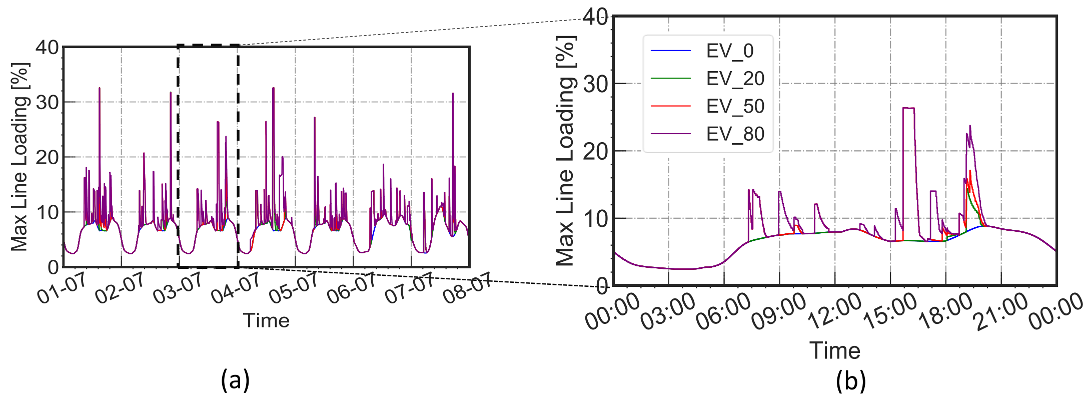


Figure 4.4: Maximum Line Loading in No-PV scenario in summer season. Figure (a) is for entire week. Figure (b) is zoomed-in for a single day

4.2. High PV and Low PV scenario:

The grids were also simulated in a *'High-PV'* and a *'Low-PV'* scenario with the penetration percentages stated in table 3.5. When the grids are simulated with only PV generation (in absence of EVs) then the results vary, especially for the *'High-PV'* scenario. As expected, when there is local generation, some amount of load is supplied by it. This reduces the loading on the transformer. The power generation in each scenario for every grid is shown in Table 4.2. However, in the *'High-PV'* case it is too high, consequently there is a mismatch of power, which leads to excessive reverse power flows

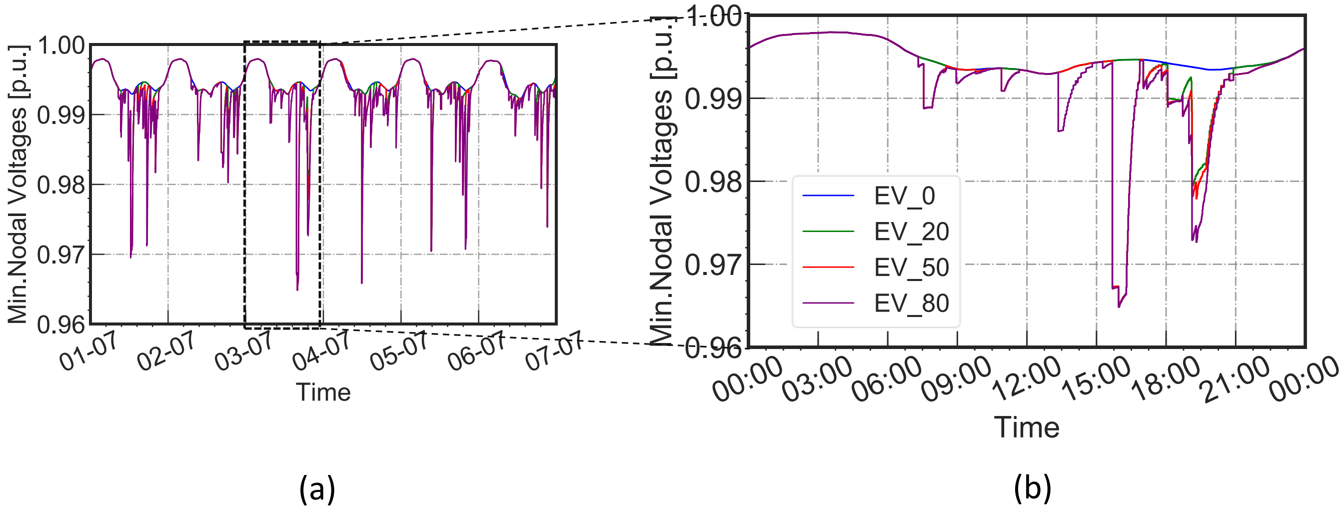


Figure 4.5: Minimum Nodal Voltages in No-PV scenario in summer season. Figure (a) is for entire week. Figure (b) is zoomed-in for a single day

	Total PV Power [kW]	
Grids	**High PV Scenario**	**Low PV Scenario**
Rural	193.89	31.72
Urban	214.5	7.8
Sub-Urban	1039.89	261.74

Table 4.2: Cumulative PV power in both scenarios for all the grids

and causes loading of the transformer. In Figure 4.6, negative transformer loading indicates reverse power flow when cumulative PV generation exceeds the total power demand in the grid. Figure 4.7 is the plot of minimum nodal voltages on the y-axis with respect to time. As seen in the zoomed plot, the minimum voltage values improve due to local PV generation.

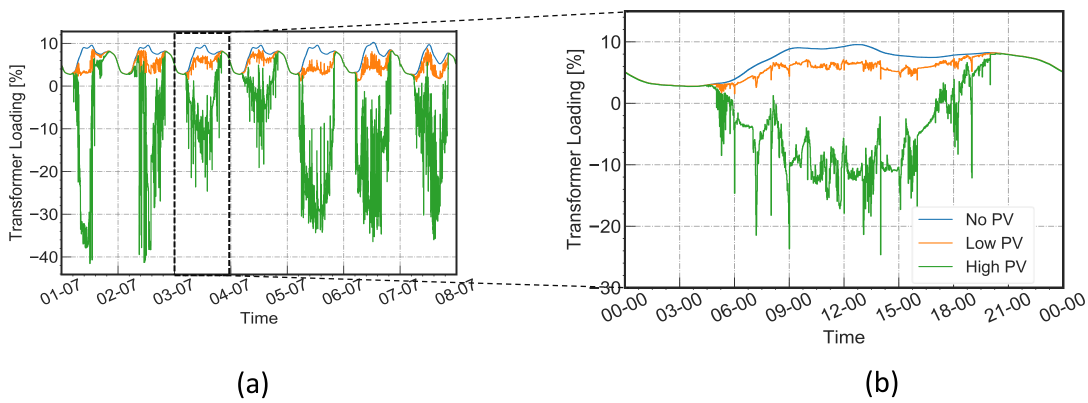


Figure 4.6: Transformer Loading in different PV scenarios in summer season. Figure (a) is for entire week. Figure (b) is zoomed-in for a single day

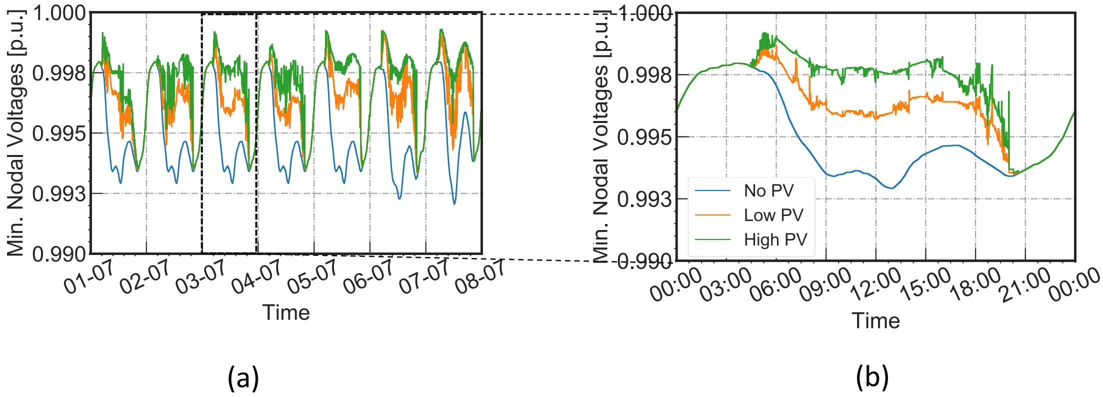


Figure 4.7: Minimum Nodal Voltages in different PV scenarios in summer season. Figure (a) is for entire week. Figure (b) is zoomed-in for a single day

In this case the sub-urban grid gets overloaded due to excessive local generation. The maximum transformer loading goes as high as 135%. This is because of a large number of PV systems present in the grid. In total. the sub-urban grid has 268 PV systems installed with different ratings. Such a large number can be because of having a more number of households in the grid. This results in over-voltages in the grid, as seen in Figure 4.8. It should be noted that for *Low PV scenario* the over-voltages do occur but the values are very close to 1 p.u., hence they are not clearly visible in the plot. The consequence of a higher local generation can be seen in Figure 4.9, which shows the heat-map of the sub-urban grid for an instance where overloading and over-voltages occur due to PV generation.

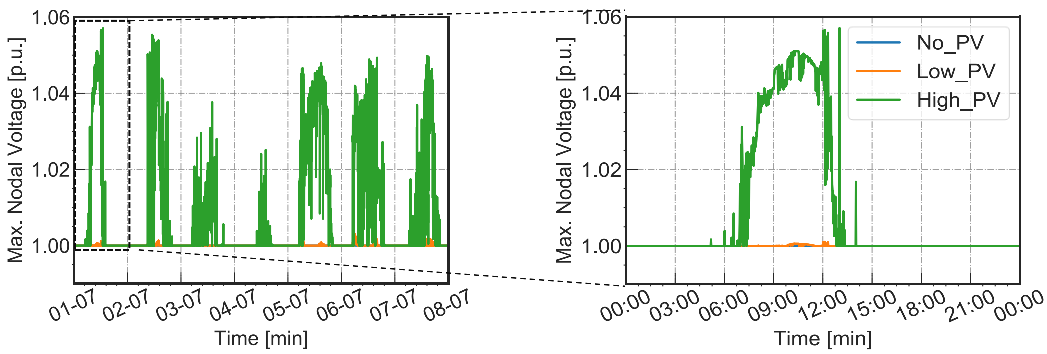


Figure 4.8: Maximum Nodal Voltages in different PV scenarios in summer season for Sub-Urban grid. Figure (a) is for entire week. Figure (b) is zoomed-in for a single day

4.3. Result analysis and discussion:

In total, 54 simulations were performed for uncontrolled charging of electric vehicles. The simulations for each PV scenario can be summed up by the diagram in Figure 4.10,

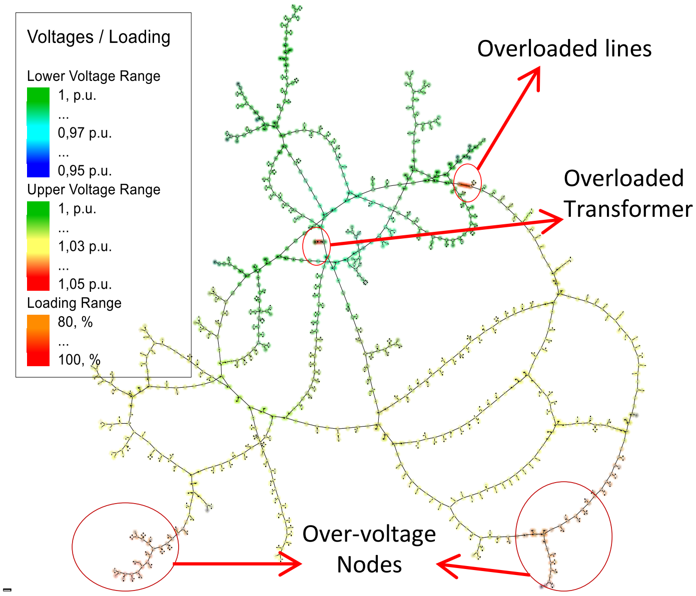


Figure 4.9: Sub-Urban Grid Overloaded due to high pv

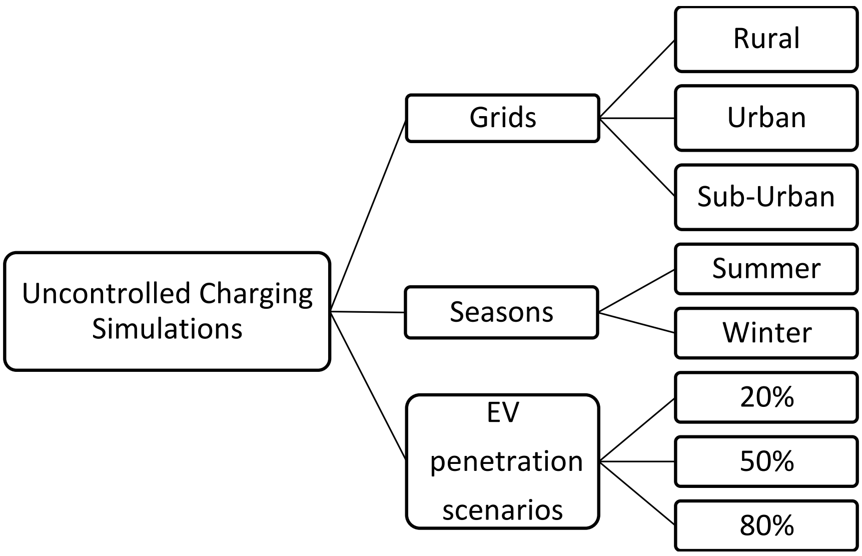
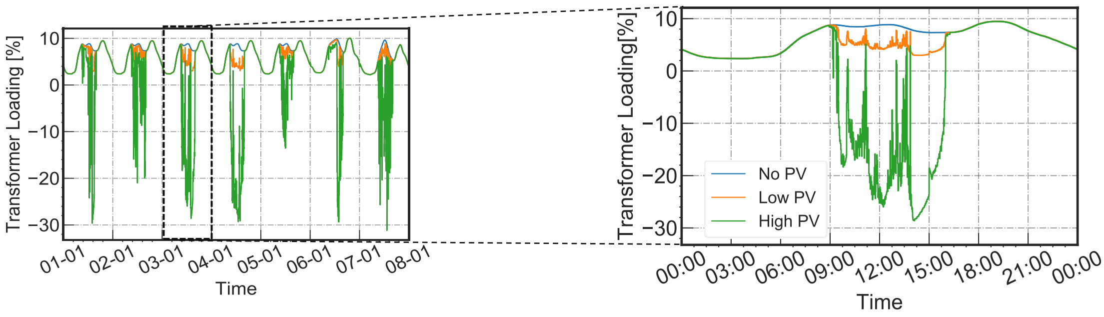


Figure 4.10: Uncontrolled charging simulations for all the grids

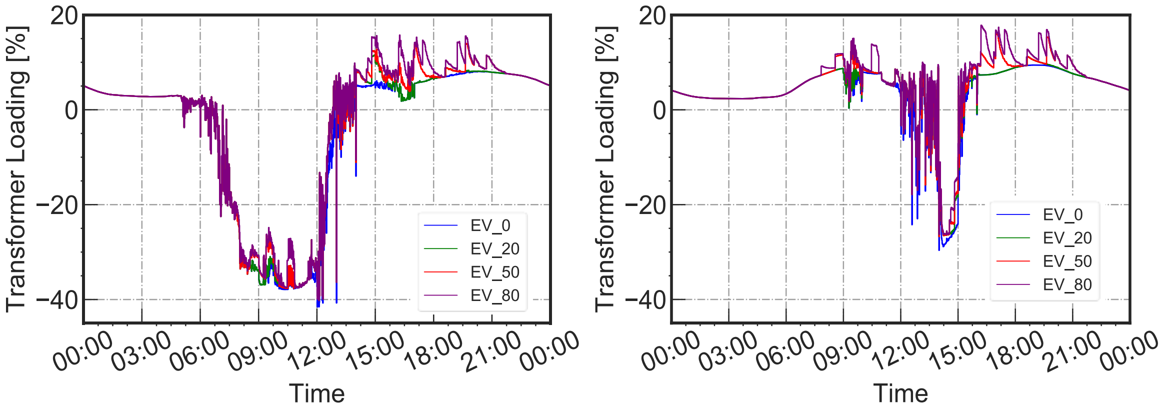
The parameters that were looked are closely were transformer & line loading, under & over voltages and power mismatch. All the grids even of different sizes gave similar trends for all the previously mentioned parameters in all the scenarios.

Figure 4.11 shows the transformer loading in the rural grid for all the three PV scenarios for the entire week in winter season. It can be seen that even with the changes in the profiles, rural grid in the winter season exhibits negative loading in the transformer. With increasing EVs in the grid, in both seasons the utilisation of PV generation is very low. This can be seen in Figure 4.12, which is a single-day plot for summer and winter season, representing transformer loading on the y-axis and time on the x-axis. This is the result of the type of EV chargers included in the grid while simulating. As explained earlier, higher home charger percentage means the more EVs will arrive in the evening as seen Figure 3.4, this in turn will result in lower consumption of PV energy.



(a) (b)

Figure 4.11: Transformer Loading in different PV scenarios in winter season. Figure (a) is for entire week. Figure (b) is zoomed-in for a single day

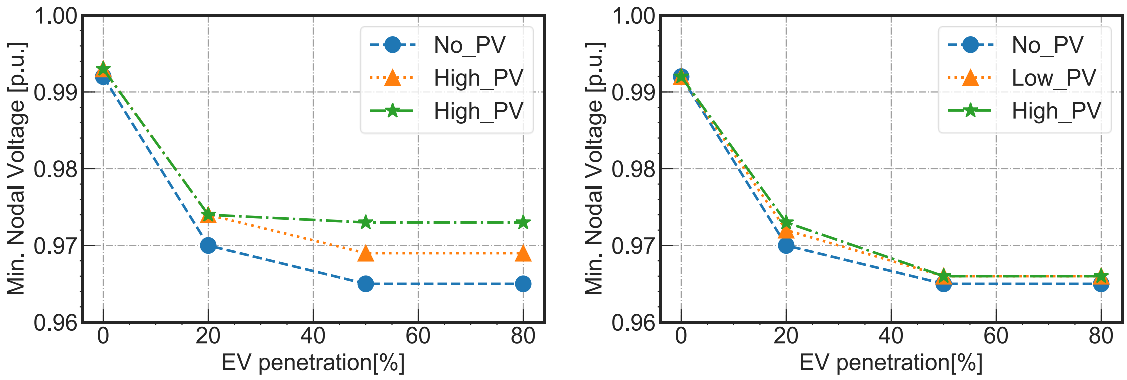


(a) Summer season (b) Winter season

Figure 4.12: Transformer Loading in High PV scenario with different EV penetration levels. Figure (a) Summer Season. Figure (b) Winter Season.

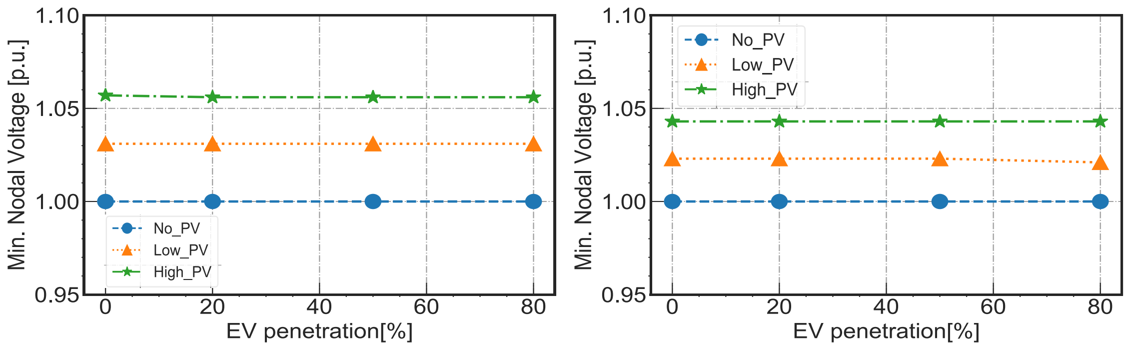
Due to the local PV production the minimum nodal voltages in the grid improve as seen in Figure 4.13. However,in winter season, this improvement is quite low as the PV generation is comparatively less. The consequences of higher generation are not only seen in the improved minimum voltages but also in the maximum values. The maximum values surpass the allowable limit. It might be argued that, the addition of EVs should help with this issue. But it is not visible as shown in Figure 4.14. The reason again being the charger percentages. All the maximum values occur at the time of maximum generation, and at that time no EVs are being charged.

It is evident that, plotting maximum value at each penetration level might not provide a clear picture. Hence to understand how the EV penetration affects the maximum voltage values the frequency of over-voltages is plotted in Figure 4.15. It is defined as the number of times the nodal voltages is above a certain allowable limit. For rural grid in summer season the value is chosen to be 1.04 p.u. and in winter it is 1.03 p.u. From the plot it is noticeable that as the EV penetration increases, the frequency of over-voltages decreases. Thus, increment in EVs aids in reducing over-voltage occurrences.



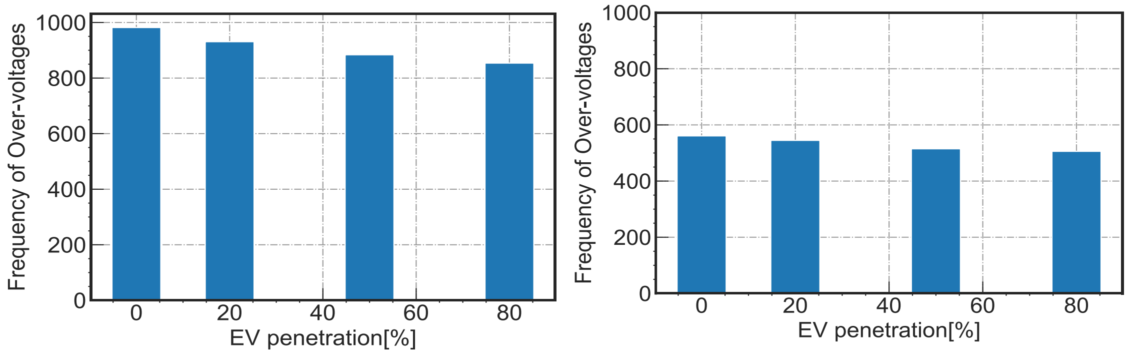
(a) Summer Season (b) Winter Season

Figure 4.13: Minimum Nodal Voltages (Rural Grid) in both seasons



(a) Summer Season (b) Winter Season

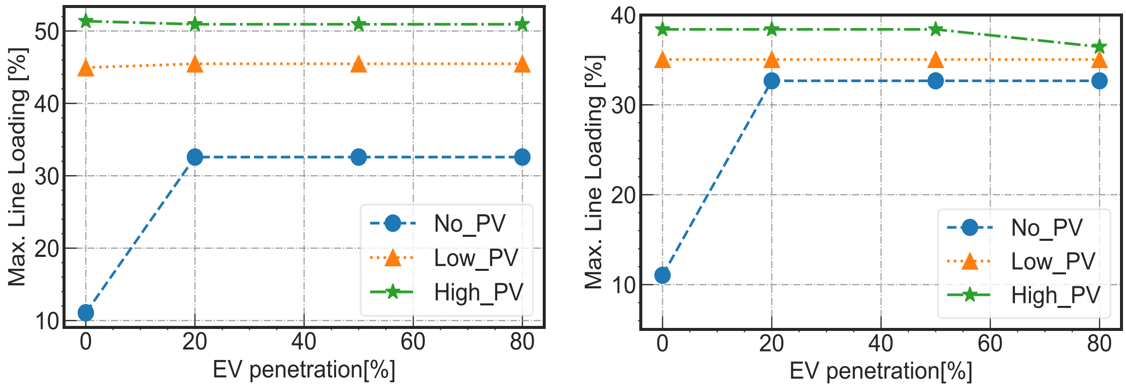
Figure 4.14: Maximum Nodal Voltages (Rural Grid) in both seasons



(a) Summer Season (b) Winter Season

Figure 4.15: Frequency of maximum Nodal Voltages (Rural Grid) in both seasons

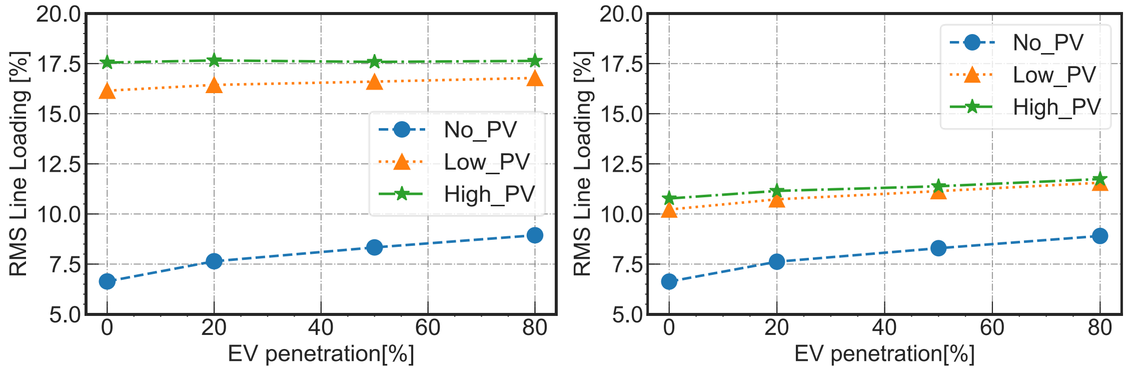
Similarly, for lines it is to be noted that the variation in the excessive line loading shown in Figure 4.16 happens to be the same line, termed as 'critical', which gets loaded at every penetration level. Figure 4.17 shows that RMS line loading as a percentage of line rating with EV penetration. The variation in RMS loading provides insight on two operational aspects: distribution losses in the system and localized generation to consumption patterns. RMS loading increases marginally by 1-2% with high EV penetration during cases with low PV genertation (Winter, Figure 4.17 (b) and Summer, Figure 4.17 (a), blue line), indicating that the corresponding impact on line losses is low. There is 10% jump for high PV generation scenario (Figure 4.17 (a), green line) that does not vary with increase in EV penetration, indicating a reverse power flow that is not consumed locally at the generation node.



(a) Summer Season

(b) Winter Season

Figure 4.16: Maximum Line Loading (Rural Grid) in both seasons



(a) Summer Season

(b) Winter Season

Figure 4.17: RMS Line Loading (Rural Grid) in both seasons

4.4. Excess PV Energy

With the simultaneous addition of the EVs and the PVs, it was observed that the in all the grids the *'High-PV'* scenario, the PV is what causes the maximum transformer as well as line loading. This implies that in each grid there is a generation mismatch, and a large amount of PV energy is left unused, as shown in Figure 4.18. The shaded area in the figure depicts the power mismatch. This introduces a challenge that can be dealt in the followings three ways:

1. The excess generated power can be exported to the upstream network. However, if the grid operators are dealing with such a high PV penetration in future, all interconnected distribution grids may exhibit similar behaviour with net excess of generated energy.

2. Power mismatches can be reduced by employing distributed energy storage elements in the

grid. While it is a popular research solution, challenges such as cost of ownership in European grids, high installation cost and space requirements need to be addressed [25] [52].

3. Locally curtail the excess generated energy with the lack of storage capacity [41] [40].

Another possible solution, that this thesis explores is using EVs to reduce this generation mismatch. The idea in itself is being studied by many researchers. Bhatti et al. [8] conducted a study on PV-EV charging in a micro-grid present in a remote island. They concluded that charging EVs using PV and energy storage is economical as compared to the charging using a generator. Similar study is carried by authors in [48], where they take into account the intermittent nature of solar energy and optimally size the PV to reduce the cost of the entire system.

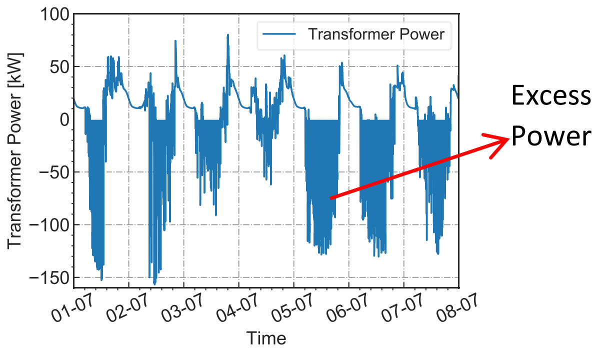


Figure 4.18: Power mismatch in rural grid in summer season

Keeping this in consideration, the thesis uses E_{pv} as a metric to quantify the impact of EV penetration in a case where there is high local generation. Mathematically, this metric is given by:

$$E_{pv} = \int_0^{T_{final}} \sum_{n=1}^{N} (P_{load,n} + P_{EV\_load,n} - P_{pv,n}) \tag{4.1}$$

where,

1. E_{pv}: Excess PV Energy [MWh].

2. $P_{load,n}$: Total base load power at n^{th} node. [kW].

3. $P_{EV_load,n}$: Total EV load power at n^{th} node [kW].

4. $P_{pv,n}$: PV power at n^{th} node [kW].

E_{PV} provides with the energy that is 'unused' after supplying all the loads. So as the EVs increase this value will. Figure 4.19 depicts the normalised E_{PV} for all the three grids. It is calculated by 4.2 where τ_{PV} is the total PV energy [MWh] produced in the respective grids in a week. For every grid with increasing EVs the E_{PV} decreases, showing the potential of EVs in reducing power mismatch in the grid. The reduction in E_{PV} happens even with uncontrolled charging. Hence one can make an hypothesis that with a proper algorithm, E_{PV} can decrease to a greater extent.

$$E_{PV normalised} = \frac{|E_{PV}|}{\tau_{PV}} \tag{4.2}$$

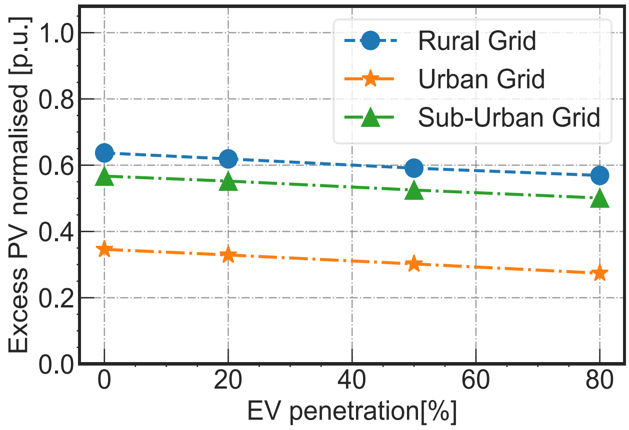


Figure 4.19: Excess PV energy for all 3 grids in summer season

4.5. Conclusion:

The simulation of four different scenarios i.e. grids with only the load, grids with EV, grids with only PV and grids with EV and PV, gave an insight into the operation of distribution grids. The introduction of EVs with different percentages of penetration increased the load as expected in all the grids but did not cause any congestion or under-voltage issue. This implies that all the grids are quite robust and can handle more EV penetration.

Introducing PV generation in both the grid indicated the presence of a *'Generation Mismatch'* as shown in section 4.2. One plausible situation that a mismatch might happen is when the grid contains less amount of storage elements. Uncontrolled charging of EVs indicated that, EVs can be one of possible solutions that if incorporated with suitable smart charging strategy can aid in reducing the excess energy in the grid. Another possible advantage of using this approach is the flexibility provided by the EVs. This reduces the potential issue with cost of storage and its space requirements.

Overall, to conclude, excessive PV penetration in the distribution grids produces an opportunity of mass deployment of EVs in the grids, which can reduce the dependence on stationary storage.

5

Controlled charging of EVs

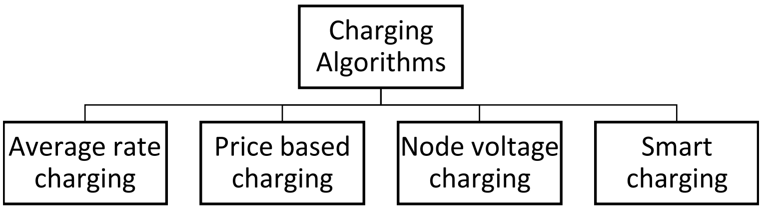


Figure 5.1: Charging algorithms

In order to draw a comparison between uncontrolled and controlled charging of EVs, four different charging algorithms were implemented for all the grids in both seasons. By having a charging algorithm, it is possible to exploit the EVs as a dynamic storage element in the grid. Even if the private ownership of EVs is increasing, the amount of time spent in charging is ~ 10% in a day [26]. This provides an opportunity to introduce incentives to use the flexibility of EVs to strengthen the grid [17]. Considering this idea, the chapter will discuss in detail all the algorithms. The structure of the chapter is as follows. Each of these algorithms will be explained in a different section consecutively. Subsequent to which, the final section will consist of result analysis and discussion. All the algorithms are part of the OSCD project [51] and are based on the work of my Phd. supervisor Y. Yu

Figure 5.1 depicts all the algorithms analyzed in this thesis. The aim of these approaches to control the charging power of electric vehicles, which differ for charger as well as car type.

5.1. Average rate charging

The first method analysed in the thesis is based on *average rate* charging. It is classified as a decentralised control strategy where the assumption is that every charger in the grid has a local controller. This approach takes into account two main parameters of the EVs i.e. *charging power* and *charging duration.* Instead of charging the EVs at the rated power, it charges with a average value based on their *arrival time* ($t_{arrival}$) , *departure time* ($t_{departure}$) and *energy demand* (E_{demand}). The average power value (($P_{average}$)) is calculated by 5.1 :

$$P_{average} = \frac{E_{demand}}{t_{departure} - t_{arrival}} \tag{5.1}$$

Even though the charging process starts as soon as an EV is connected to the EVSE, using average power, spreads the process across the parking time of the vehicle. This does not give rise to peaks in the power consumption at a specific node. The expected E_{demand} and $t_{departure}$ are provided by the user depending upon which the local controller calculates the charging power. Figure 5.2 shows the difference between the uncontrolled charging and this method. The advantage of spreading out the charging of EVs over the parking time is that the grid elements do not experience a sharp increase in the loading.

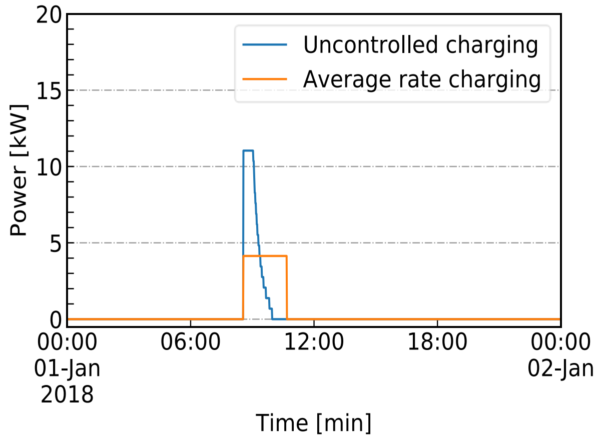


Figure 5.2: Comparison between average rate charging and uncontrolled charging.

5.2. Price based charging

Unlike the previously mentioned technique, this approach is a centralised one. Here the assumption is that a central entity (e.g. a DSO) controls the charging process based on a control signal which is given to every charger in the grid, depending on the day ahead market price. The price is obtained from the ENTSOE transparency platform [1] with an hourly time resolution. This method aims to achieve a minimized overall cost at every node. The control strategy of this algorithm is based on comparison of the hourly price value to that of the average price. If it is lower, then the EVs connected across the grid will charge at rated power. If it is higher then the EVs will charge at 50% of the rated power. Additionally, if the value is more than the third highest price value then the charging current is set to a minimum value of 6A. As opposed to average rate charging, there is a possibility of obtaining peaks in the power profile as the price can be at a lower value, which can lead to overloads and under-voltages. Also, recalculation of charging power takes place on hourly basis due to the hourly spread of the price.

The working can be demonstrated by Figures 5.3 and 5.4. The first figure shows the zoomed in hourly electricity price on 2018-07-03. From 6 a.m. to 8 a.m. the price is equal to/more than the 3^{rd} highest price. Hence any charging event between that time will be at the minimum value of 6 A. This can be corroborated from the second figure, which shows the zoomed in plot for a charging event happening on the same date, where the charging event occurs slightly after 7 a.m., and the charging

[1] https://transparency.entsoe.eu/transmission-domain/r2/dayAheadPrices/show

current is set to minimum i.e. 6 A. The price drops to 37.5 €/MWh at 8 a.m. , the current increases to half of its rated value but from 9 a.m. This is because the calculation takes place hourly. Later as the price falls below the average the remaining charging takes place at rated value of 16 A.

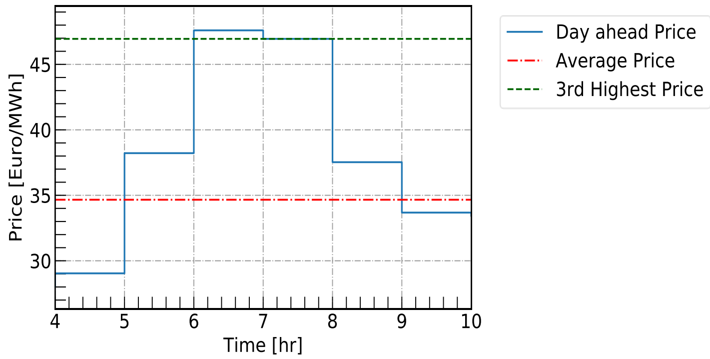


Figure 5.3: Day-Ahead prices of 2018-07-03

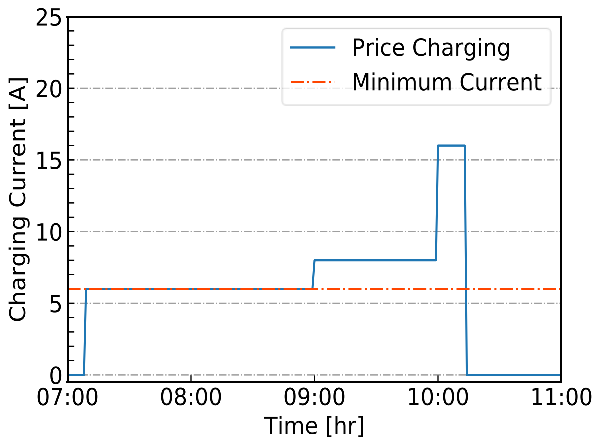


Figure 5.4: Charging current on 2018-07-03

5.3. Node voltage charging

Using this technique, EVSEs can locally change the charging power depending upon the voltage change at the nodes. This method provides a distributed control across the grids, focused mainly on maintaining the voltage between 1.05 p.u. and 0.95 p.u. When the nodal voltage is between these two points, the charging current increases in steps as shown in Figure 5.5. Please note that the values shown in the figure are an example and not actual. One major difference between this approach is the involvement of grid simulations at every point in order to calculate the nodal voltages. In both the previously mentioned cases, the output of the charging algorithm is weekly power profile for each charger, which can be incorporated in the grid model to carry out the simulations independent of the control strategy.

The algorithm varies the current inversely proportional to the voltage. In case the measured voltage is more than 1.05 then the voltage fluctuation threshold calculated in 5.2 is used to compute I_{adjust} which is the change in current needed according to the voltage change, as shown in 5.3, where $V_{node,last}$ is voltage value measured in the previous iteration. The current value is then set by adding

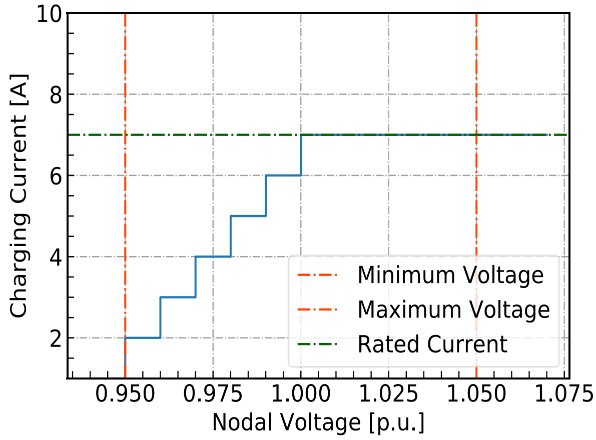


Figure 5.5: Working of nodal voltage charging

I_{adjust} to the minimum value of current i.e. 6A.

$$V_{dev} = \frac{V_{node,max} - V_{node,min}}{I_{node,max} - I_{node,min}} \tag{5.2}$$

$$I_{adjust} = \frac{V_{node,last} - V_{node,min}}{V_{dev}} \tag{5.3}$$

Here,

1. $V_{node,max}$: Maximum voltage limit, 1.05 [p.u.].
2. $V_{node,min}$: Minimum voltage limit, 0.95 [p.u.].
3. $I_{node,max}$: Maximum current value, 25 A.
4. $I_{node,min}$: Minimum current value, 6 A.

5.4. Smart charging

It is the most complex algorithm that was tested in this thesis. It is a decentralised algorithm, which analyses every node in the distribution grid, in order to optimise the EV charging process. The objective is to minimise the charging cost at each node. The technique is based on the constantly varying day ahead electricity price.

5.4.1. Algorithm Implementation

As the focus is on each node, every element connected to the node needs to be accounted for. This includes the loads, the PV systems and the EV chargers. The forecast of the loads as well as PV generation though subject to variation, is assumed to be 100% accurate. The EV data is only known when an EV arrives at the charger. Similar to the three techniques discussed in the previous sections, this algorithm also requires data like arrival time, departure time and energy demand of the EVs arriving at a specific charger. The node limitations to import as well as export power need to be known as well. In addition, the day-ahead electricity price is also of key importance and should be known.

The time instance at which an EV arrives at a charger is the trigger to start the optimization analysis. The period of optimization, also called as *optimization horizon*, is from the trigger till the departure time of the last EV that leaves. If a new EV arrives with a departure time which is later than the previous EV then, the *optimization horizon* extends to the new departure time. This can be explained with a small example. For e.g. if the optimisation starts at 14:00 with the last EV leaving at 19:00, then the current *optimization horizon* is up to 19:00. Now, assume another EV arrives at 15:00 with a departure time of 20:30, this will extend the horizon of analysis from 19:00 to 20:30 for all the connected EVs at the node. Furthermore, for the EVs already at the node, the charging process happens in two steps. First the charging will be optimised from their own arrival time to the arrival time of the new EV. And secondly, from the new arrival time to the expected departure time. This is known as *dynamic receding algorithm*.

Figure 5.6 illustrates the *dynamic receding algorithm* with an example of four chargers. The x-axis of the plot is time and the y-axis is EV connectivity status. At trigger t_i, the algorithm detects arrival of EV at charger 1, when charger 2 and charger 4 already have EVs connected. The algorithm then selects the departure time to calculate the *optimization horizon*, in this case it would be T_2^d. Then the horizon for analysis T_i becomes $T_i = T_2^d - t_i$

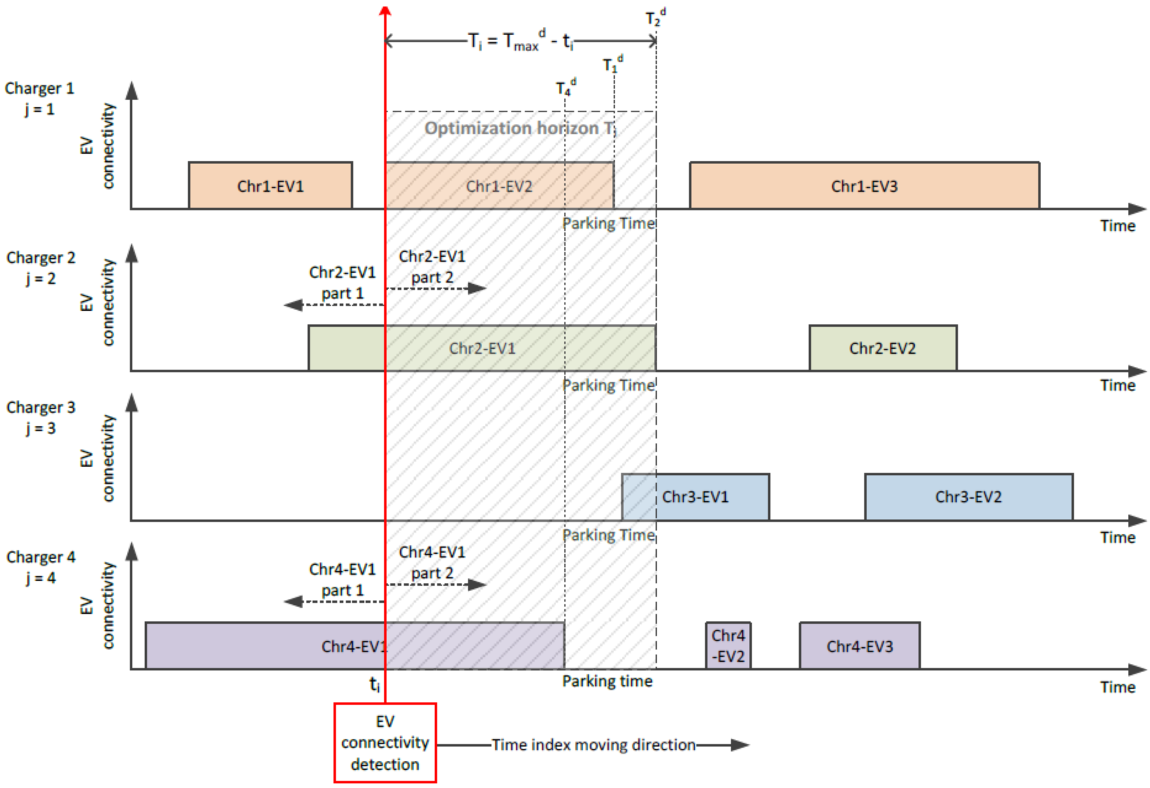


Figure 5.6: Optimization horizon illustration

5.4.2. Optimization formulation

Let J be the number of chargers connected at node n. The aim of the optimization strategy is to minimise the charging cost of i^{th} EV arriving at the node at every time step t. The optimisation variables are as follows:

- $p_{EV,i,t}$: Charging power of i^{th} EV at time t (kW).($0 < p_{EV,i,t} < P_{EV,rated}$ $\forall$ i,t)
- $i_{EV,i,t}$: Charging current of i^{th} EV at time t (A).($0 < i_{EV,i,t} < I_{EV,rated}$ $\forall$ i,t)
- $b_{EV,i,t}$: Battery energy of i^{th} EV at time t (kW).($b_{arr,i} < b_{EV,i,t} < b_{arr,i} + D_i$ $\forall$ i,t)

- $p_{PV,t}$: Used PV power at the node at time t (kW).($0 < p_{PV,t} < P_{PV,generated}$ $\forall$ t)

- $p_{import,t}$: Node imported power at the node at time t (kW).($0 < p_{import,t} < P_I^{limit}$ $\forall$ t)

- $p_{export,t}$: Node exported power at the node at time t (kW).($0 < p_{exported,t} < P_E^{limit}$ $\forall$ t)

The battery energy at arrival b_{arr} and the energy demand D_i are provided by the EV user. P_I^{limit} and P_E^{limit} are the import and export limits set up by the DSO. The power flow constraints can be written as:

$$p_{import,t} - p_{export,t} = \frac{\sum_{i=1}^{J} p_{EV,i,t}}{\eta_{charging}} + P_{load,t} - p_{PV,t} \forall t \tag{5.4}$$

$$b_{EV,i,t} = b_{arr,i} + \sum_{t=T_{arr}}^{t} p_{EV,i,t} \cdot \eta_{EV} \cdot t \forall i, t \tag{5.5}$$

$P_{load,t}$ is total load connected at the node at time t. Whereas, $\eta_{charging}$ and η_{EV} are the efficiencies of the power conversion and t is the time-step of simulation. The objective function is given by the following equation:

$$\begin{aligned} \text{Min.}C_{ch}^{op} = \sum_{i=1}^{J}(b_{arr,i} + D_i - b_{EV,i,T_{departure}}) * C_i^p + t * \sum_{t=1}^{T} p_{PV,t} * C^{PV} \\ + t * \sum_{t=1}^{T}(p_{import,t} * C^{buy} - p_{export,t} * C^{sell}) \end{aligned} \tag{5.6}$$

The equation comprises of the folowing elements:

- C_i^p: is the penalty paid to the user if the EV is not fully charged until the departure time $T_{departure}$. In this thesis the value is set to 10 €/% of SOC. In reality, this can be different for each EV user depending upon EV battery size, tariff policy etc.

- C^{buy}, C^{sell}, : are the prices at which electricity is bought and sold to the grid respectively. The former is taken from the day-ahead market price, and the latter is set to 0.02 €/kWh.

- C^{PV} : is the prices at which the EV user buys the PV energy for charging. This is set to 0 to make sure whenever there is PV generation, EV consumes most of it.

Before the charging process optimization, the EVs must meet the *acceptance criteria*, which is set to ensure safe operation. The criteria is twofold. Firstly, all the EVs connected to respective chargers should be within the power limits of the charger. Secondly, the value of b_{arr} should be above the minimum limit, which is set by the user.

In summary, all the charging methods are summed up in Table 5.1.

Sr. No.	Charging algorithm	Approach of algorithm	Charging start time	User information	Charging Power
1	Uncontrolled charging	—	Right after plugging the EV	Not required	Rated power
2	Average rate charging	De-centralized	Right after plugging the EV	Required	$P_{average}$
3	Price based charging	Centralized	Right after plugging the EV	Required	Based on the day-ahead market prices
4	Node voltage charging	De-centralized	Right after plugging the EV	Required	Based on the nodal voltage drop
5	Smart charging	De-centralized	Based on the optimization results	Required	Based on the optimization results

Table 5.1: Summary of all charging strategies

5.5. Result analysis and discussion

Taking into account all the possible scenarios for all the grids in both seasons, in total 108 grid simulations were performed. They are all summed up in Figure 5.7. The simulation results shown in this section represent the urban grid operation in the winter season. Due to the time constraint on the project, the *smart* charging algorithm was only implemented for one grid. But all other algorithms were implemented for every grid. Those results can be found in appendix B. The discussion would be focused on the urban grid for this section.

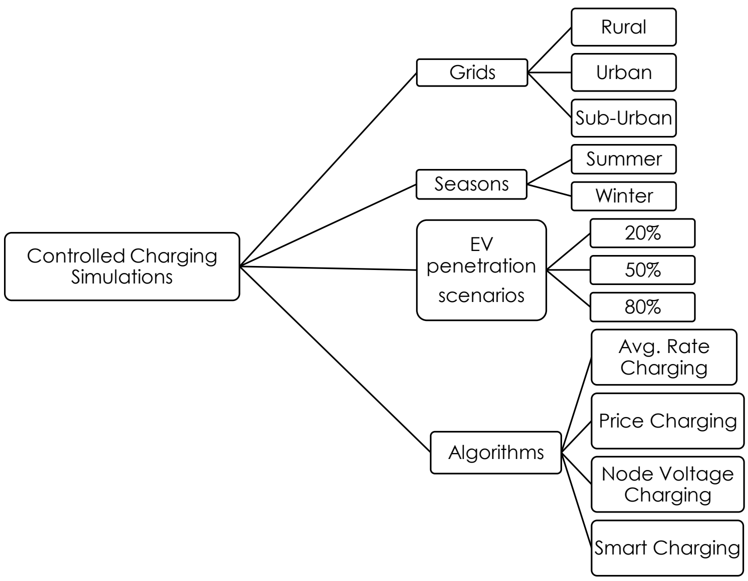


Figure 5.7: Summary of controlled charging simulations

Figure 5.8 shows the peak transformer loading with respect to EV penetration comparing all the charging strategies. *Smart charging* registers the highest peak loading at every penetration percentage, even higher than uncontrolled charging. Whereas *average power* charging has the lowest peak in all the cases. Furthermore, *price charging* and *nodal voltage charging*, both these algorithms are close to the uncontrolled charging case. The reason for which *average power* charging performs better is the simplistic nature of the algorithm. It does not depend upon external inputs other than expected energy demand and expected time of departure.

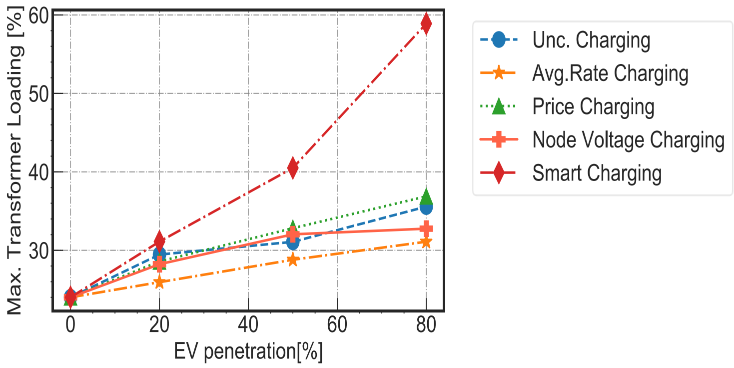


Figure 5.8: Maximum loading of transformer (Urban grid) in winter season

The *smart* charging algorithm has the day-ahead market prices as an input. Hence, whenever the price is low then all the EVs connected at that instance will charge at maximum power, which in turn will introduce sharp peaks for a short duration. Figure 5.9 shows the total EV charging power for 80% EV penetration in uncontrolled ,*smart* charging and *price charging* scenarios. The figure also shows the day-ahead market price curve. At 13:54, in the smart charging case, the transformer registers its highest peak of 58.9% due to the rise in the total EV charging power, which can be seen in the curve(green line). The peak happens when the price of electricity falls to 51.4 €/MWh, this causes all the connected EVs to charge in that time period. Another reason being, as the algorithm causes EVs to charger at a low price point, it can be seen that the charging events in uncontrolled scenario from 06:00 to 09:00 do not happen in smart charging as the price is close to 55 €/MWh. These events instead get shifted to lower price bracket i.e. 12:00 to 15:00, causing the highest peak.

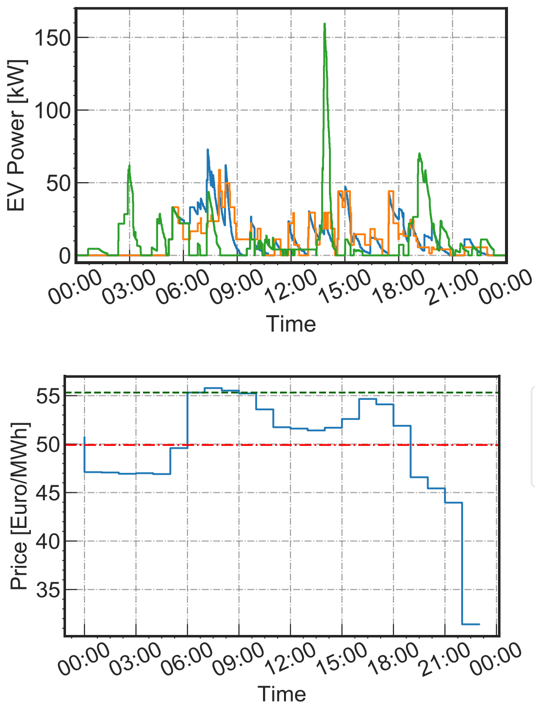


Figure 5.9: Total EV power for uncontrolled and smart charging and the change in day-ahead market price.Time range:2018-01-04:00:00:00 to 2018-01-04:23:59:00

It might be argued that, the transformer should also experience the same amount of loading when *price charging* is used, which is not the case. This is because of the conditions used in that case are different, as stated in section 5.2. As the price during the occurrence of the highest peak is more than the average price, the EVs charge at 50% power, hence the peak is absent. The RMS values for transformer loading are shown in Figure 5.10. The figure gives more information about all the charging strategies. Even though the peak values depicted a substantial difference, the difference in the RMS loading is very modest among all the schemes.

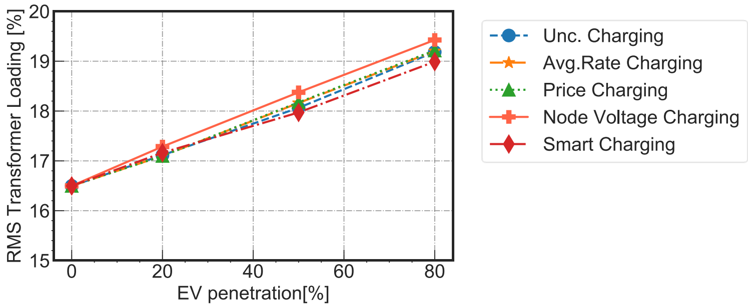


Figure 5.10: RMS loading of transformer (Urban grid) in winter season

The trend for the minimum nodal voltage values is shown in Figure 5.11. Scenario with *smart* charging experiences more drop in the voltages at each level, but this is because the loading is higher. The lowest drops are seen in the *average power* charging algorithm. This result is quite interesting because, this algorithm does not explicitly take into account the nodal voltages. But as explained in section 5.1, this algorithm does not give rise to a sharp increase in the power profile. Hence, as the voltage drops are not as extreme as compared to other scenarios. Similarly, for *nodal voltage* scheme, as the nodal voltages are always between 1.05 p.u. and 0.95 p.u., all the EVs tend to charge at large power values, causing a slightly more drop as compared to *average power* charging scheme. This can be seen in Figure 5.12.

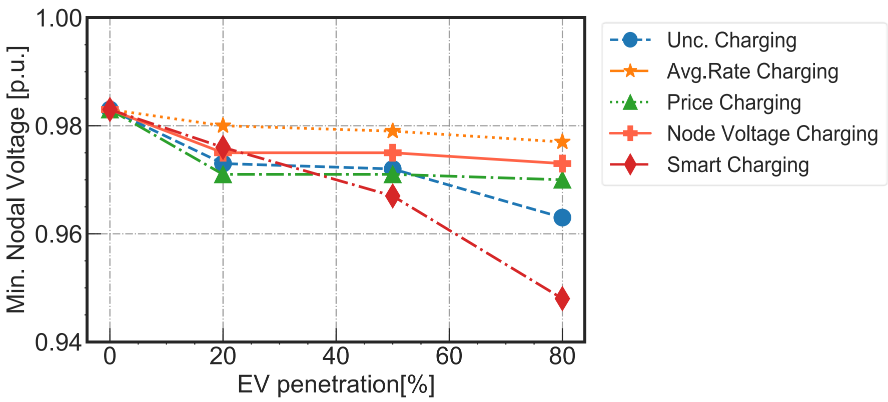


Figure 5.11: Minimum nodal voltages (Urban grid) in winter season

The *price charging* algorithm, gives results close to the uncontrolled scenario, which can be seen in all the plots shown till now. Being dependent on the day ahead market price, the peaks occur when the hourly price is less than the average price as the charging power is 100%.

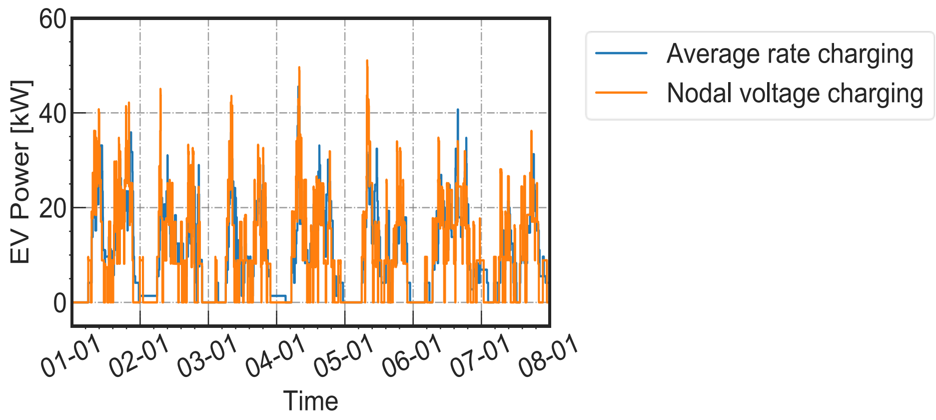


Figure 5.12: Total EV power for *nodal voltage* and *average power* charging

The *smart* charging algorithm is the only scheme which takes into account the PV production and makes sure that the EVs are charged mainly by the PV when there is local generation. As stated previously, the cost of using PV energy is set to 0, to ensure, EVs use most of the generated energy. But if we plot $E_{pv,normalised}$ as we did in Chapter 4, section 4.4, then it provides us with a conflicting outcome. Figure 5.13, is the plot of E_{pv} normalised with respect to total PV energy in the grid, 213.75 Mwh in this case. It can be seen that even though there is decrease in E_{pv} with increase in penetration, for *smart* charging the decrease is lower than expected.

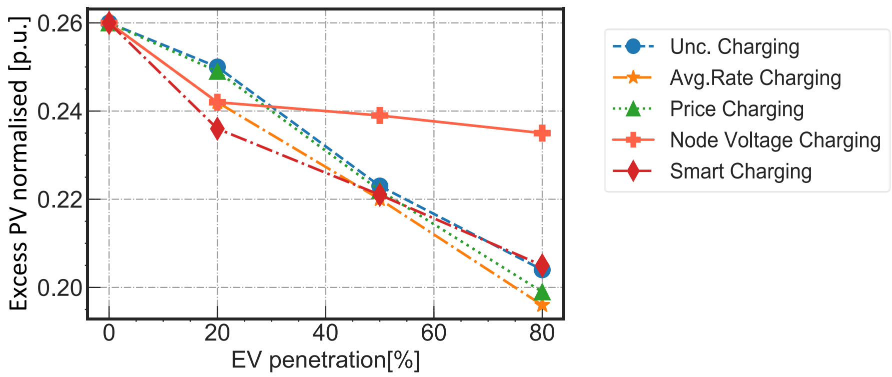


Figure 5.13: Excess PV energy in all charging algorithms implemented in Urban grid

One might assume that, given the inclusion of PV, *smart* charging should be able to use more of it for charging purposes, which is not seen happening. If we look at the transformer power for the winter week as shown in Figure 5.14, then it is clearly visible that even for 80% penetration there is a substantial amount of PV energy which is not used. The reason for this is two fold. Firstly, the arrival time of EVs. If they arrive before or after the generation, then it is not possible to charge them with PV production. Secondly, the number of PV systems in the grid. In the urban grid, there are in total 38 PV systems located at different locations. The algorithm uses PV power to charge if both the EV and PV are the same node. This happens only for a few systems. If we look at Figure 5.15 which shows total EV and PV power for a single day , then it is quite clear that charging events do happen during the time of PV generation, utilising it to charge but due to a excessive production not all of it is used.

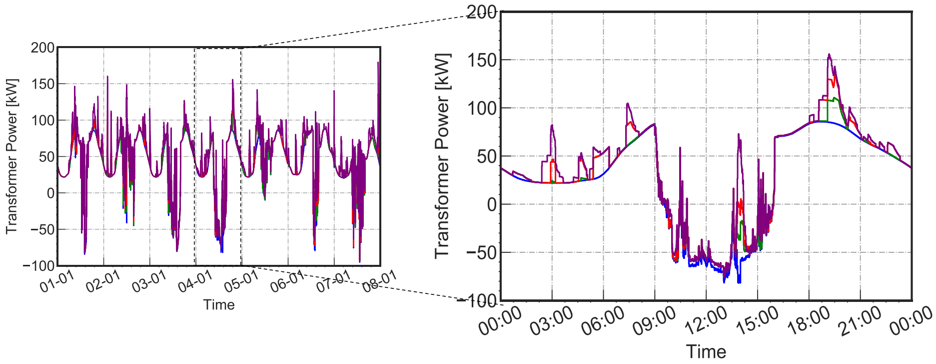


Figure 5.14: Transformer power when using *smart* charging

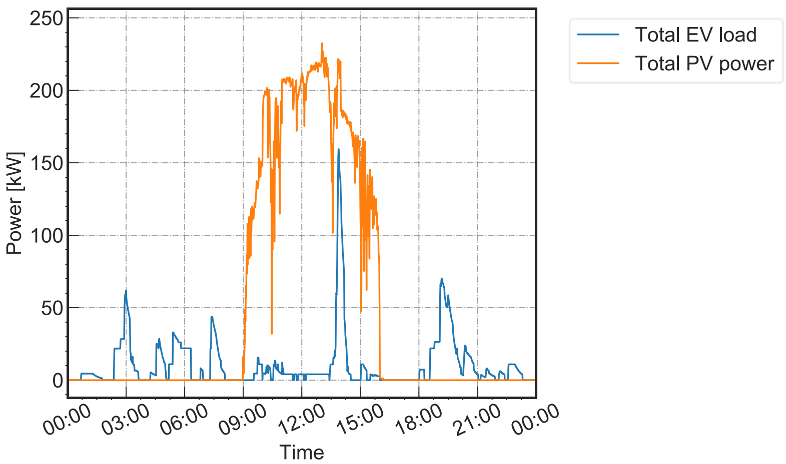


Figure 5.15: Total EV and PV power for 80% EV penetration for *smart* charging algorithm

Finally, all the charging strategies are compared on the basis of total charging costs. For simplicity, the calculations are based on the average electricity price instead of the actual, variable day-ahead market price. The total charging cost is calculated as the product of the total energy consumed by the EVs (across all penetration levels) and this average electricity price (0.37 €/kWh). The results of this comparison are shown in Figure 5.16. It can be seen that *smart* charging is the cheapest option at all penetration levels. For all other algorithms, the costs are close to the cost of uncontrolled charging. This result is intuitively appealing because the objective of the *smart* charging algorithm is cost minimization. Thus, although a more accurate cost comparison may be made by using a variable price of electricity, we can still infer that the *smart* charging algorithm yields cost savings.

One major challenge of implementing the *smart* charging is the duration of simulation. As it involves finding an optimal solution within a certain optimization time, the entire duration of simulation depends on it. An initial time limit was set to 60 seconds for the optimization to occur, which proved to be less for certain chargers. By trial and error the final time was set to 250 seconds for the urban grid. It may seem less but, it depends on the number of chargers in the grid. For e.g. for 80%

scenario, the number of chargers in the grid is 33, giving a total time of 2.5 hours. This time is added to the 4.5 hours of load flow simulation, giving a total time of 7 hours. Given the number of scenarios, this a long simulation time. For further research, it is recommended to tune the optimization to find a solution in less time.

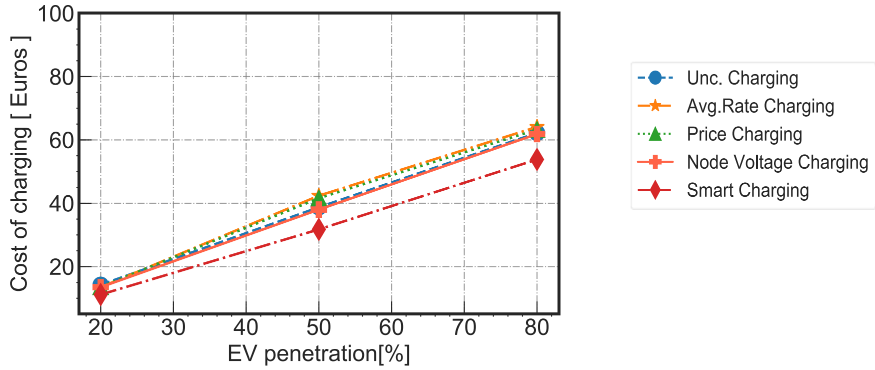


Figure 5.16: Comparison of EV charging costs for the all the charging algorithms implemented in Urban grid

5.6. Conclusion

The *average rate* charging performs better than other charging schemes. Hence it can be used for the bench-marking for the future implementation of *smart* charging algorithms. Similarly, *price charging* algorithm, due to is dependency of day ahead market price, can lead to more load peaks as compared to *average rate* and *uncontrolled* charging scenarios. But as the price is already known before hand, there is a possibility of minimising the occurrence of peaks. One possible solution is implementing a peak shaving strategy to minimise to level load profile [10]. Another strategy suggested by Van Linh et al. [46] is to have a interruption strategy in which the DSO gives a signal to switch on/off EV charging depending on congestion occurrence in the grid.

Node voltage charging is the performs better than *smart* charging and *price charging*. One might argue that, as the voltage never falls below 0.95 p.u. or rise above 1.05 p.u., the algorithm should give similar results to uncontrolled charging case. But as explained in section 5.3, the charging current is always adjusted based on the slope of the current-voltage curve (see Figure 5.5), the change in current occurs in steps instead of sharp peaks as they do in unregulated scheme. Finally,*smart* charging leads to more drastic peaks but does not cause overloads. Higher peaks happen as the charging events are shifted to the time instance of lower electricity price. Given the amount of PV systems in the grid, not a single algorithm is able to effectively reduce the excess energy in the grid. Also, it provides with a low-priced option to charge the EVs.

6 Conclusions and Recommendations

The main aim of this thesis work was to perform the grid simulations in order to quantify their performance in uncontrolled charging scenario and differentiating it with respect to four different charging schemes. By performing multiple simulations in various scenarios some conclusions were drawn, that are listed in section 6.1. Furthermore, section 6.2 will state some recommendations for future research purposes.

6.1. Conclusions

Looking at the uncontrolled charging results, none of the grids experience overloads or under-voltage issues. It can be inferred from this that all the three grids can manage EV penetration beyond the maximum level set in this thesis work. If closely looked at all the grids, then it can be seen that the grids were operating at low loading values to begin with. Hence, in order to make the grid function near its technical limits, very large loads would have to be involved. The number of EVs to make such an impact would be very significant. Hence the overloading was absent in each of the grids. Furthermore, as the calculation of EV chargers is based on the number of households in the grid, the sub-urban grid, having the most houses, experiences the highest loading percentage. All the grid topologies are robust and operationally efficient.

In the *High-PV* scenario, all the grids experience power mismatch which results in excess unused energy, termed as *Excess-PV energy*. Due to excessive local PV generation the voltage drops caused due to EV inclusion not only get improved but also violate the upper limit of 1.05 p.u.in the *Sub-urban* grids. The occurrence of over-voltages caused due to high PV generation is reduced as number of EVs increases in the grids. However, the number EVs used in this thesis is not enough to mitigate the over-voltages. Further research is required to solve this issue. Nonetheless, it can be deduced that,EV and PV appear to be complementary to each other. Both tend to balance each other out, albeit imperfectly.

Based on the strategy of algorithms, the *average rate* charging recorded the lowest values for transformer loading for all the grids. It is interesting to note that, despite the different strategies, none of the algorithms effectively minimizes the *Excess-PV energy*. In the case of *smart charging*, there is excess energy left despite the fact that PV is used for charging because of the large number of PV systems. In the other algorithms, excess energy is left simply because there is no mechanism in place to utilise it. Furthermore, *smart charging* was shown to lower charging costs based on an approximate calculation.

6.2. Recommendations

For future research, it may be interesting to use a more detailed model of PV generation. For instance, the model could account for changes in generation due to cloud coverage, rain, soiling, etc. By accounting for these changes, a more robust model may be developed.

Secondly, all the loads in this project have been modelled as 3-phase loads. In the future, it may be useful to include single phase loads as well. This is because the addition of single phase loads would allow us to evaluate the performance of the system in response to voltage and phase imbalances.

Furthermore, it may be useful to study the load distribution of the grids in more detail. For this project, the grid data received from the DSO did not explicitly state the different types of loads. As a result, we had to make assumptions about the loads. If the actual load division in each grid is known, then the results of the simulations may be more reliable. To obtain this data, it is important to have closer contact with the DSO and the other parties involved.

Finally, in this thesis, the system performance was evaluated using 3 discrete EV penetration levels. Considering the EV penetration level as a "degree of freedom", it may be useful to study the system performance by varying this parameter. Following such a study, it may be possible to recommend the type of chargers to be used in different grids to manage the excess local generation. Another aspect is the comparison of all the algorithms based cost of charging. It is recommended to use day ahead market price instead of a single average price in order to obtain more accurate result.

A

Uncontrolled Charging Simulations

A.1. Urban Grid

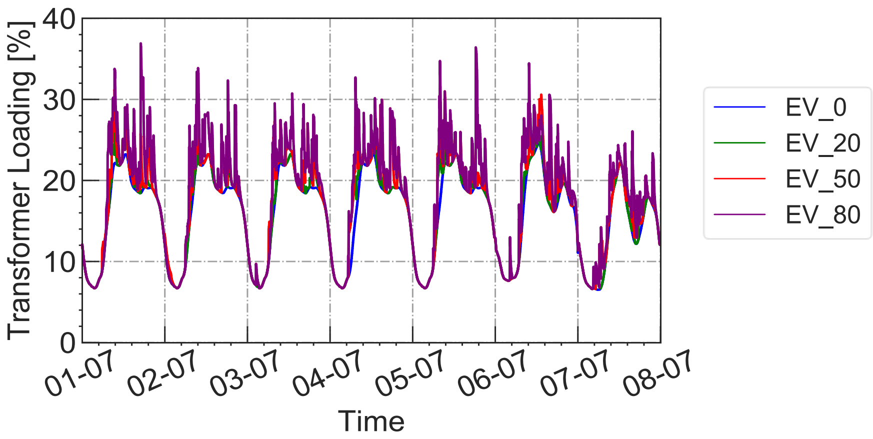


Figure A.1: Transformer Loading in No-PV scenario (urban grid) in summer season.

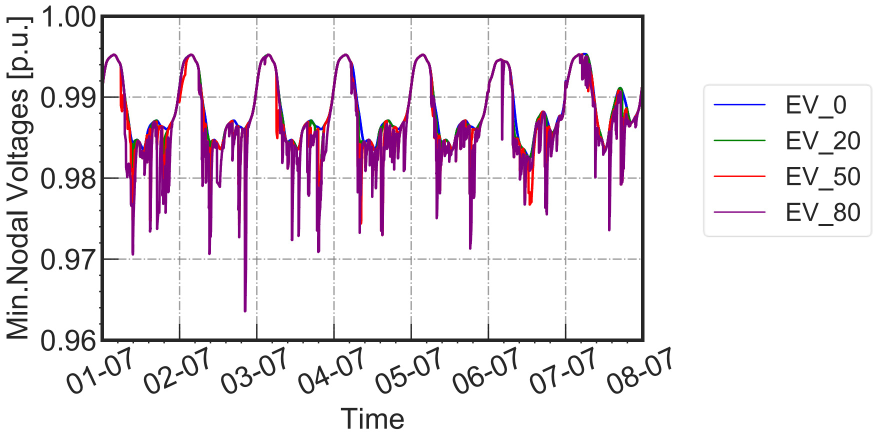


Figure A.2: Nodal Voltages in No-PV scenario (urban grid) in summer season.

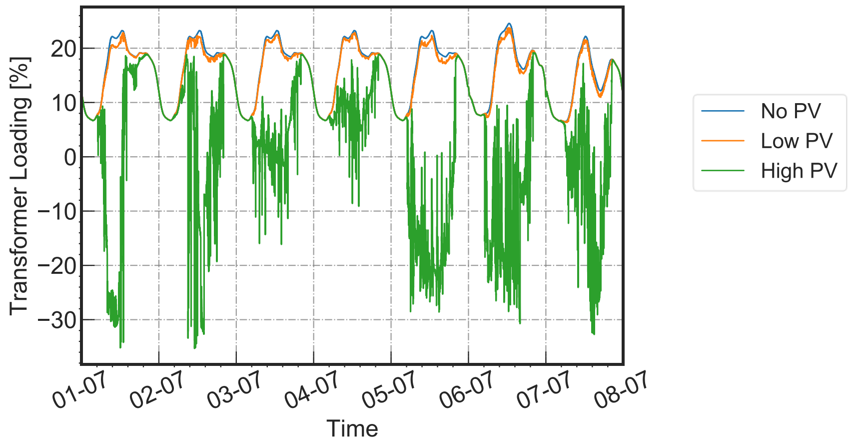


Figure A.3: Effect of PV on transformer loading (urban grid) in summer season

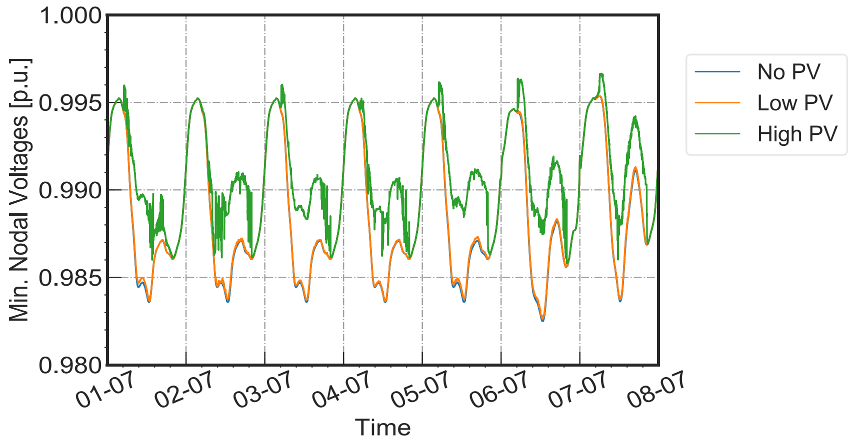


Figure A.4: Effect of PV on minimum nodal voltages (urban grid) in summer season

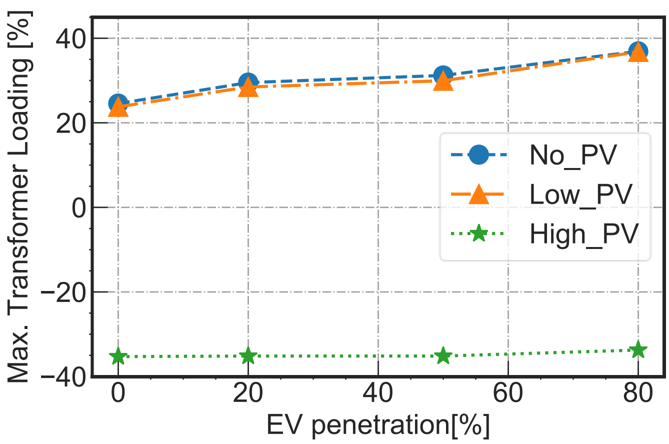


Figure A.5: Maximum transformer loading (urban grid) for all PV scenarios in summer season

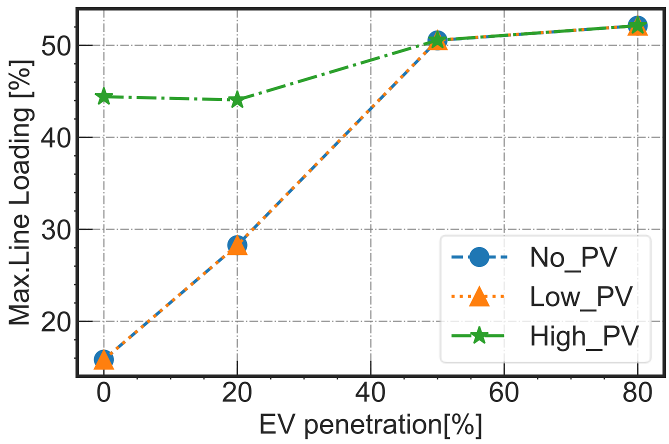


Figure A.6: Maximum line loading (urban grid) for all PV scenarios in summer season

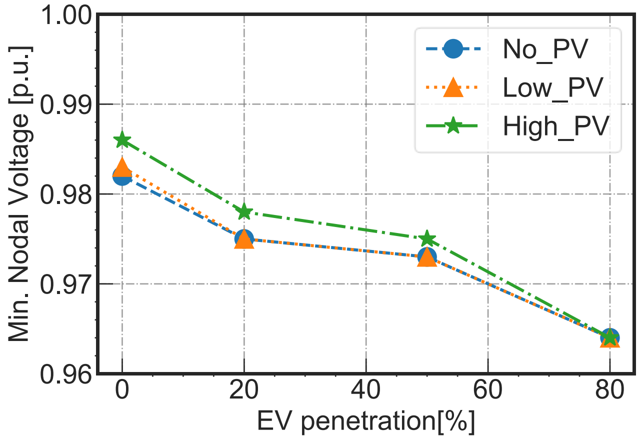


Figure A.7: Minimum nodal voltages (urban grid) for all PV scenarios in summer season

A.2. Sub-Urban Grid

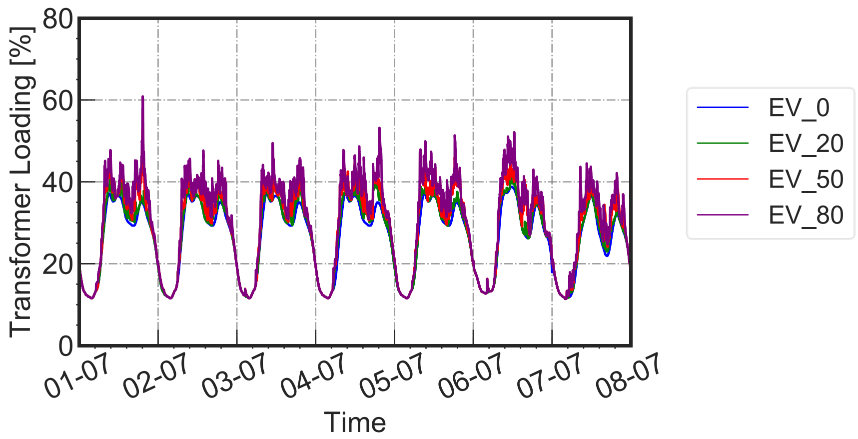


Figure A.8: Transformer Loading in No-PV scenario (sub-urban grid) in summer season.

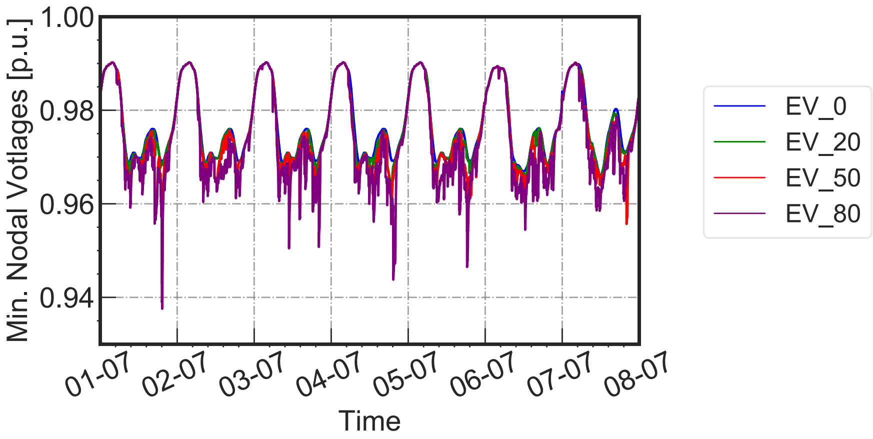


Figure A.9: Nodal Voltages in No-PV scenario (sub-urban grid) in summer season.

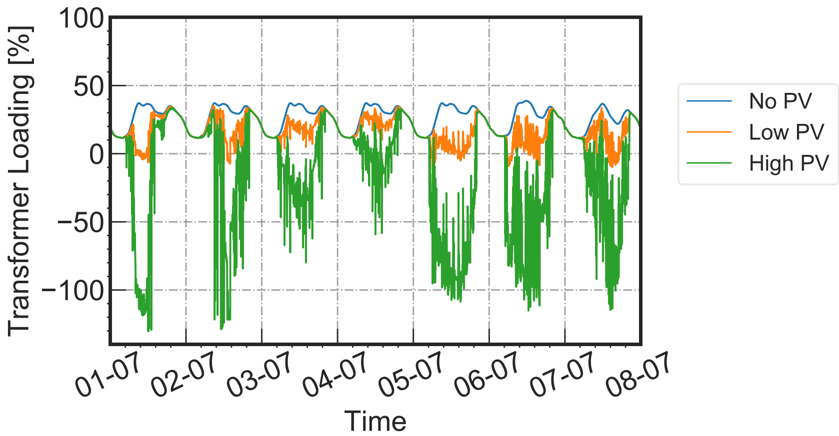


Figure A.10: Effect of PV on transformer loading (sub-urban grid) in summer season

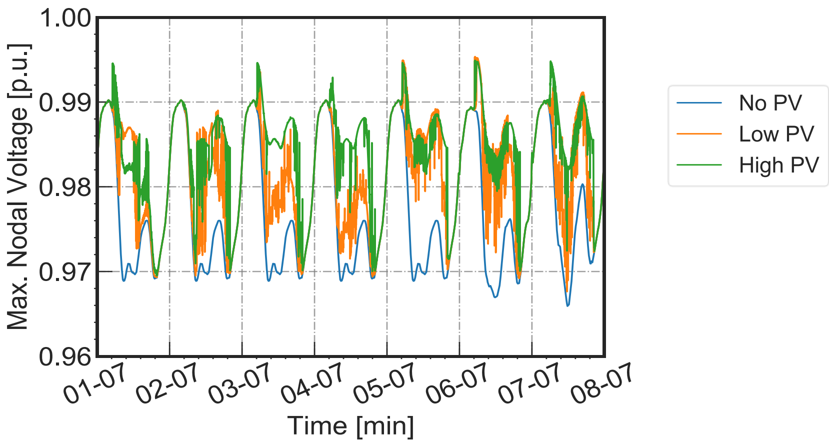


Figure A.11: Effect of PV on minimum nodal voltages (sub-urban grid) in summer season

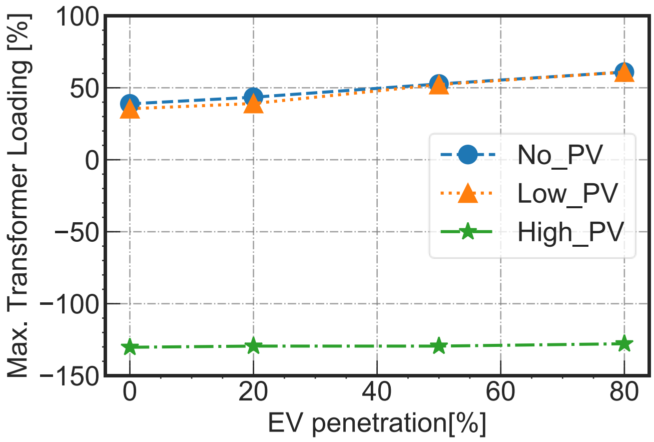


Figure A.12: Maximum transformer loading (sub-urban grid) for all PV scenarios in summer season

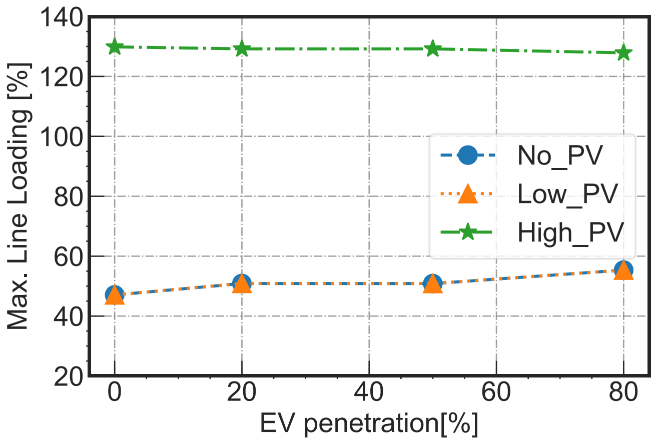


Figure A.13: Maximum line loading (sub-urban grid) for all PV scenarios in summer season

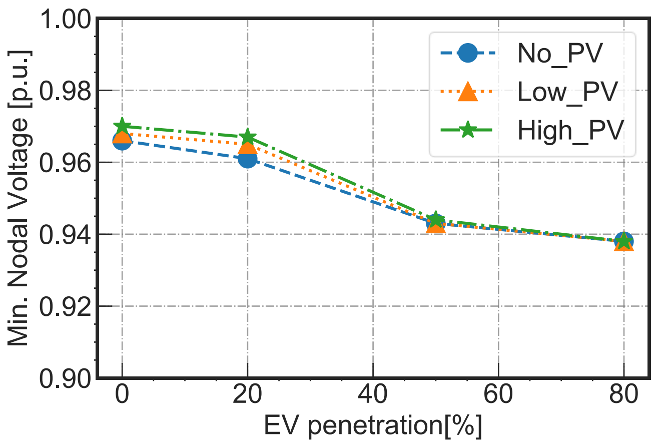
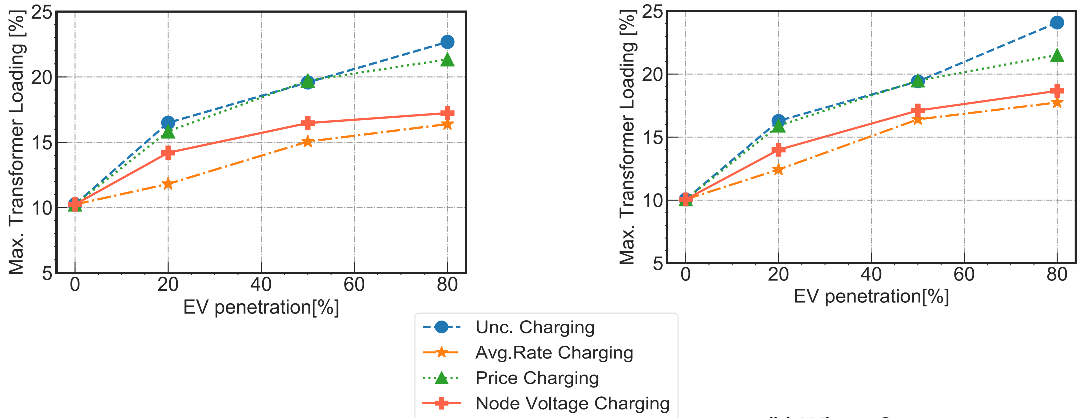


Figure A.14: Minimum nodal voltages (sub-urban grid) for all PV scenarios in summer season

B

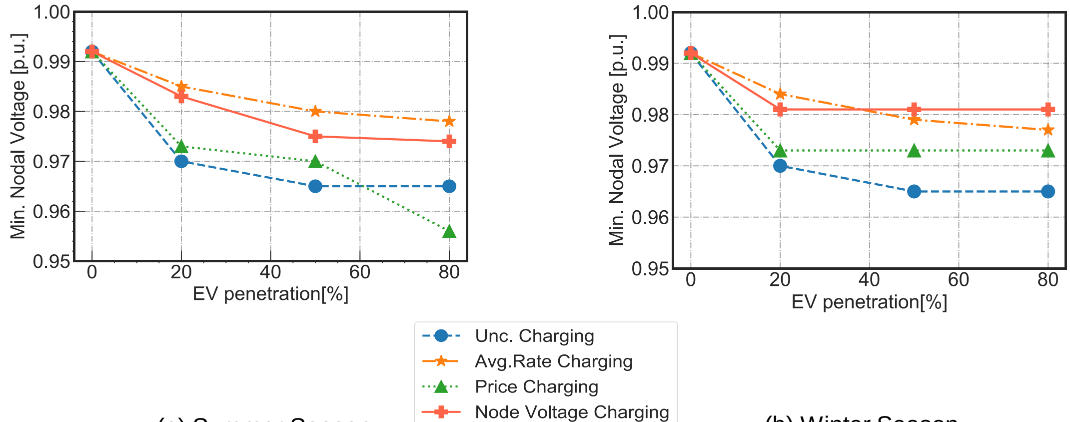
Controlled Charging Simulations

B.1. Rural Grid



(a) Summer Season (b) Winter Season

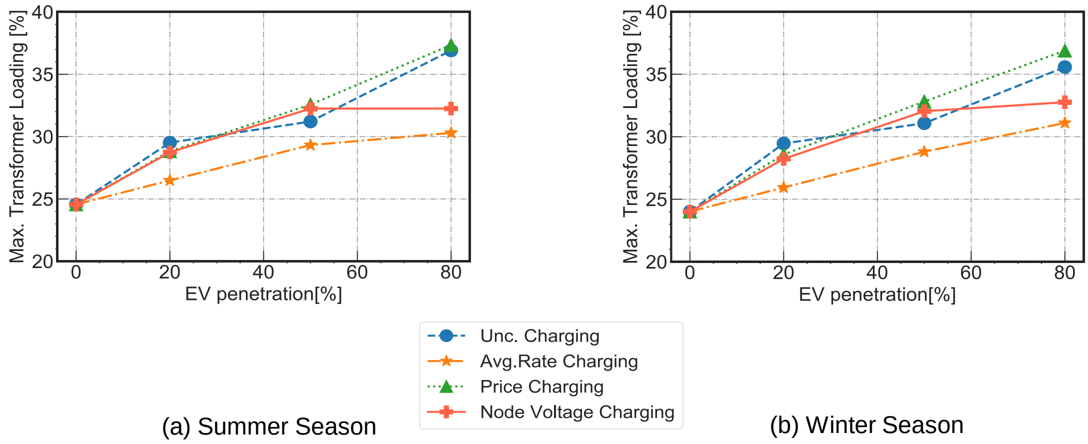
Figure B.1: Comparison of maximum transformer loading of rural grid for both seasons



(a) Summer Season (b) Winter Season

Figure B.2: Comparison of minimum nodal voltages of rural grid for both seasons

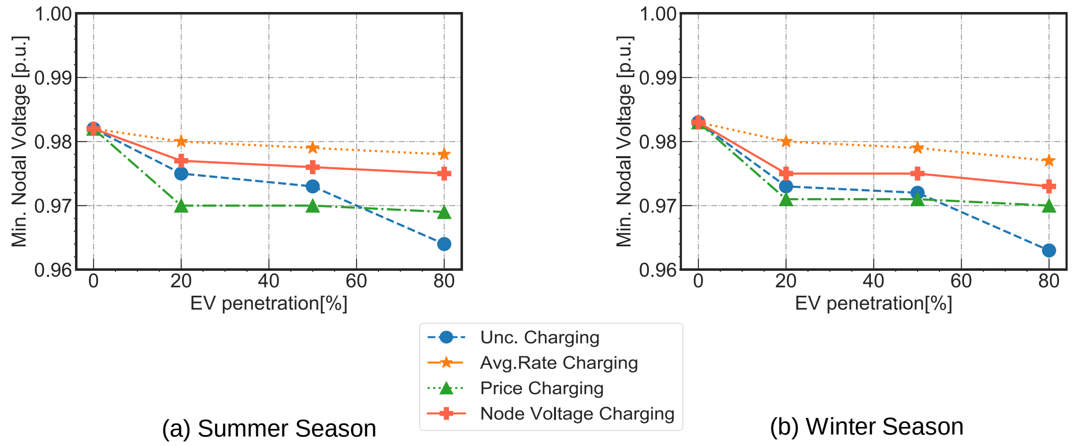
B.2. Urban Grid



(a) Summer Season

(b) Winter Season

Figure B.3: Comparison of maximum transformer loading of urban grid for both seasons



(a) Summer Season

(b) Winter Season

Figure B.4: Comparison of minimum nodal voltages of urban grid for both seasons

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