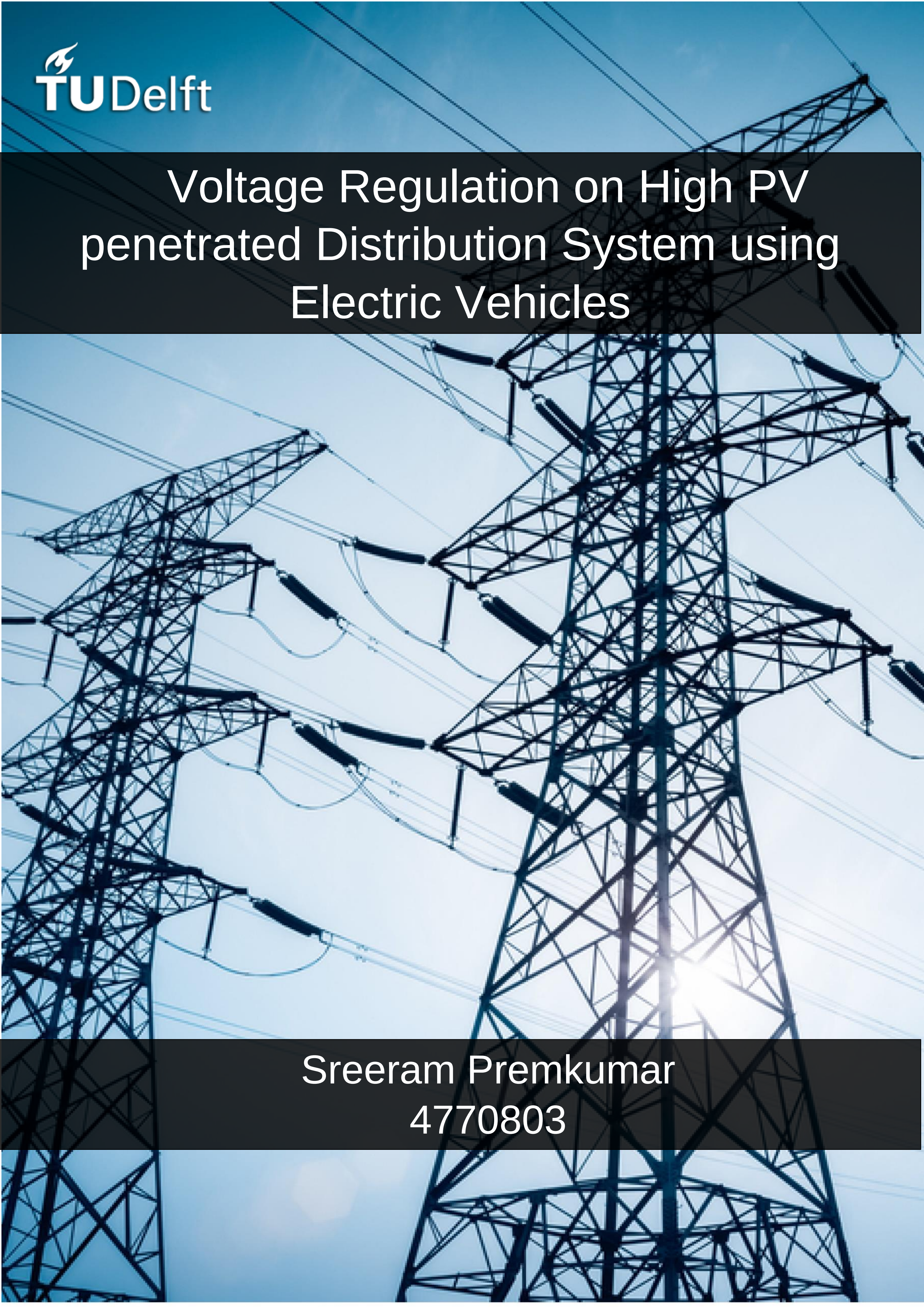
Voltage Regulation on High PV penetrated Distribution System using Electric Vehicles



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Voltage Regulation on High PV penetrated Distribution System using Electric Vehicles

by

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in partial fulfilment of the requirements for the degree of

Master of Science
in Sustainable Energy Technology

at the Delft University of Technology,
to be defended publicly on Thursday September 17, 2020 at 01:00 PM.

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Preface

This thesis is the result of my work in TU Delft over the past nine months which was improved from the idea provided by Aihui Fu. During this research, I have gained experience on working with Pandapower software and knowledge on different voltage regulation approaches. These nine months served as a path for the rise of my learning curve and also gave a unique experience. Working during a pandemic situation was quite challenging and also gave an irreplaceable experience.

I would like to express my sincere gratitude to my supervisor, Dr. Milos Cvetkovic, who has guided me from the start till the end by spending his valuable time to help me out through the process. I am really thankful for the kind and timely responses he gave me in spite of his busy schedule. I would also like to thank my thesis committee members, Prof.dr. Peter Palensky and Dr.ir. Babak Gholizad for the valuable feedback. My deepest gratitude to Aihui Fu, who has provided me with valuable suggestions and feedback and most importantly in a timely manner. This thesis would not have been possible without her priceless insights.

Last but not the least, I would like to thank my parents, who served as a pillar of support throughout my entire life both financially and mentally. I will forever be grateful to them and if not for them, I would not have been in this situation. Finally, I am thankful to my friends and group mates in the Netherlands and India. They motivated me in every step of my life, and they have played a major part in making me a respectful human being.

Sreeram Premkumar
Delft, September 7, 2020

Abstract

The penetration of renewable energy sources is increasing every year and that poses a lot of challenges in the distribution system. Since they are intermittent in nature, they cannot serve the energy demand as stand alone sources without the help of storage technologies or stable energy sources. As the RES, especially the Photo Voltaic generation units are often connected in the distribution system, their intermittent nature may result in a sudden rise or fall in overall generation. Hence the voltage has to be kept within limits to prevent the failure of the system. Storage technologies plays an important role in keeping the voltage levels under control. From the consumer perspective, the usage of electric vehicles is steadily increasing and most of the vehicles are connected to public charging stations to charge the vehicle battery. Hence there is an interaction between the EVs and distribution grids, which is utilized as a storage option here. In this research, the voltage changes due to the penetration of renewable energy sources in the distribution system is regulated by using the electric vehicles as a storage option.

This thesis tries to give an understanding on the strategy applied towards regulation of voltage in the distribution system using electric vehicles. The strategy will serve as a platform for regulating voltage using electric vehicles and it can be adapted to any such distribution network. This strategy takes into account the size and capacity of the battery, battery state of charge and the availability of electric vehicles for a given day. Consensus algorithm serves as the communication platform for information interchange between the electric vehicles connected in the network. Average consensus algorithm estimates the average state of charge of the electric vehicles connected in the distributed network and that has been used to ensure equitable contribution of power among the electric vehicles. Markov model is used to simulate the travel pattern of the electric vehicles. This provides a more realistic and accurate pattern of travel. Markov model is implemented with and without considering time of occurrence and the results shows that the pattern is more accurate when time is considered as a parameter. Considering the generated travel pattern, voltage level of the buses in the network and the output from the consensus algorithm, the voltage has been regulated.

The Electric vehicles are used for regulating the voltage when the voltage level is beyond the tolerance limits, and during other times, the electric vehicles charge their batteries. This is executed by controlling the charging and discharging cycles of the electric vehicles. The results are discussed based on different cases and the advantages and limitations of each case is explained in detail. The simulation is not robust since the availability of electric vehicles is uncertain. To make it more robust, monte carlo simulations are used. The probability of occurrence of several events has been estimated using monte carlo simulations and through the results, the availability is predicted to a certain extent. Different cases are implemented and analysed and the results shows that the availability depends on the bus, the location of the bus and the travel behaviour of the electric vehicles. Each case is discussed separately and the degree of uncertainty is reduced at the end.

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Introduction

1.1. Future of Renewable Energy

A widely known fact about conventional energy sources is the increased emission of CO_2 into the atmosphere. The CO_2 emission has found to have increased at faster rate in 2018, with 2.7% increase, which was the highest compared to the last 7 years from 2018 [1]. This has also been shown graphically in figure 1.1. As the effect of climate change is slowly grabbing people's attention, almost every country is trying to provide their best effort to prevent it by increasing the share of renewables in the global electricity production.

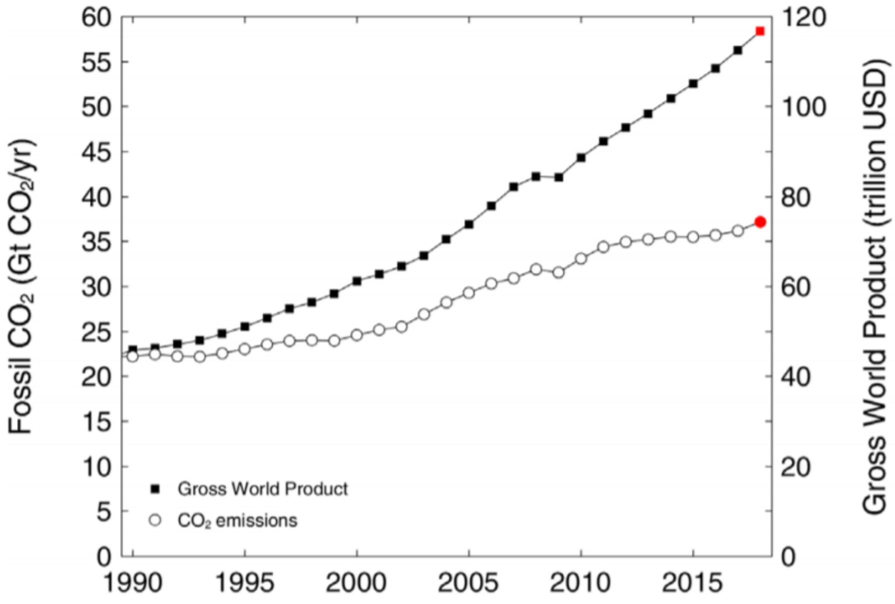


Figure 1.1: Global CO2 emissions from fossil-fuel use and industry (open circles) and Gross World Product ($ US) expressed as purchasing power parity since 1990 [1]

The percentage of renewable energy sources is steadily increasing compared to the conventional energy sources. In 2017, the renewable capacity addition was 170 GW which accounted for more than two-thirds of the global electricity growth, out of which 97 GW was from PV installations as shown in figure 1.2. Between 2017 and 2018, there has been an increase of 34.3% in PV installations, compared to the previous year [2]. It has been predicted that, over a period of 2018-2023, there will be a growth of over 1 TW of renewable capacity, which is around 46% growth over that period [6].

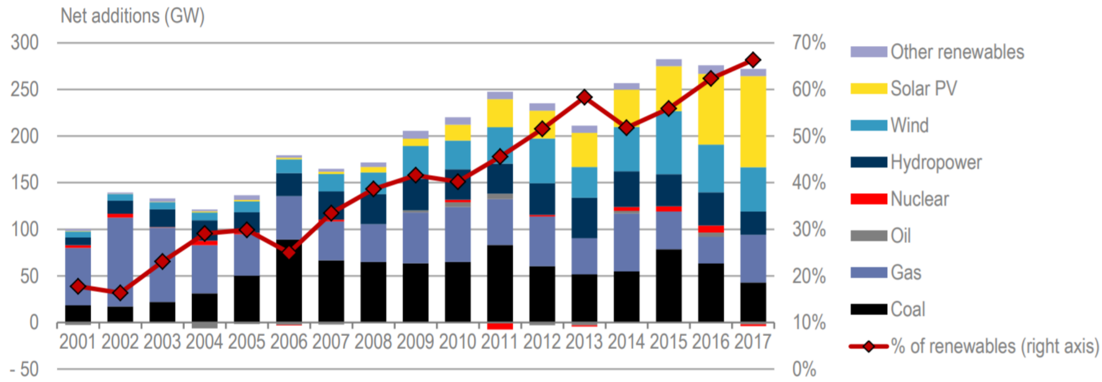


Figure 1.2: Annual net electricity capacity additions by source, 2001-17 [2]

1.2. Thesis Project

1.2.1. Thesis motivation

The technical issues that arises due to the increased penetration of Photo Voltaic (PV) power and their intermittent nature is the main motivation for this research. On most occasions, the PV systems are connected to the distribution systems. Voltage fluctuation is one of the main issues which results due to power imbalance. Every electrical system has tolerance limits for voltage. If the voltage violates these limits, it affects all the components connected to the system and in worst case scenario may also lead to a blackout. Storage technologies are necessary to minimise the effect of this issue and to prevent the occurrence of it. Batteries are the most well known form of storage units. But, using batteries just to prevent this issue leads to an additional investment cost on the batteries. Nowadays the use of electric vehicle is gaining popularity and since the batteries of electric vehicles are charged by connecting it to the charging pole which are connected to the distribution grids, they are used as a storage option in this research. The electric vehicle charges when the voltage level rises and discharges when it drops.

For an effective transfer of power and to prevent draining or overcharging of the batteries, control over the SOC level is necessary. In a distributed system, there is no central communication network. Hence the communication has to occur in a distributed way. In order to achieve this, effective communication between the neighbouring buses in the network must be established. For this purpose, an algorithm has to be chosen which facilitates this communication. Parameters such as availability, capacity and state of charge (SoC) level of the electric vehicle (EV) battery are taken into account while searching for a suitable algorithm. By effective control of charging and discharging among EVs, voltage levels in the distribution system can be maintained within limits.

Since the availability of EVs differs every time, proper analysis is required to predict and ensure the availability of EVs for voltage regulation. Travel pattern of the EVs has a huge impact on the effectiveness of the process. Travel pattern usually depends on an individual and is subject to many factors. Therefore, it is important to analyse and understand the effect of all these variables on the distribution system which results due to high PV penetration and the charging behavior of EVs.

1.2.2. Research Objectives

Main Research Goal

This thesis tries to give an understanding on the strategy applied towards regulation of voltage in the distribution system using electric vehicles. The strategy will serve as a platform for regulating voltage using electric vehicles and it can be adapted to any such distribution network. The overall thesis objective is summarized in the following statement:

How to maintain the voltage level of the distribution system using Electric vehicles in a high PV penetrated network considering the uncertain availability of Electric Vehicles while ensuring acceptable charging level of the EV batteries?

Research Questions

The main research goal in subdivided into several research questions:

1. How to maintain the SoC levels within allowable limits during charging/discharging?
2. How the power exchange among EVs can be coordinated?
3. How to make the model robust against the uncertain availability of the EVs?

1.2.3. Thesis Outline

This thesis project aims to provide the readers the understanding of the impacts of using electric vehicles for voltage regulation on a high PV penetrated distribution system. The goal of this thesis is to utilize the EV batteries to regulate the voltage and at the same time, ensure satisfactory charging of the EVs. The approach can be divided into three main focus points. The first one is to choose an appropriate algorithm to facilitate communication in a distributed system. The second is to find a way to perform voltage regulation by implementing charge and discharge control of the EV batteries. The third is to quantisize the availability of EVs considering their travel pattern. These focus points are organized in the following chapters, with the workflow illustrated in figure 1.3.

- Chapter 2: Electric Vehicles for Bidirectional Power Transfer

  This chapter provides statistics on the growth of electric vehicles and also explains about the V2G technology along with its benefits and challenges of implementation in the existing electrical system. This chapter also shows the assumptions considered in this research.

- Chapter 3: Communication in the Distributed System

  This chapter provides information on the network used in this research. The possible algorithms that may be suitable for communication are discussed. A detailed explanation on the algorithms and the reasons for selecting the algorithm are discussed. The algorithm is tested and the results are provided in this chapter.

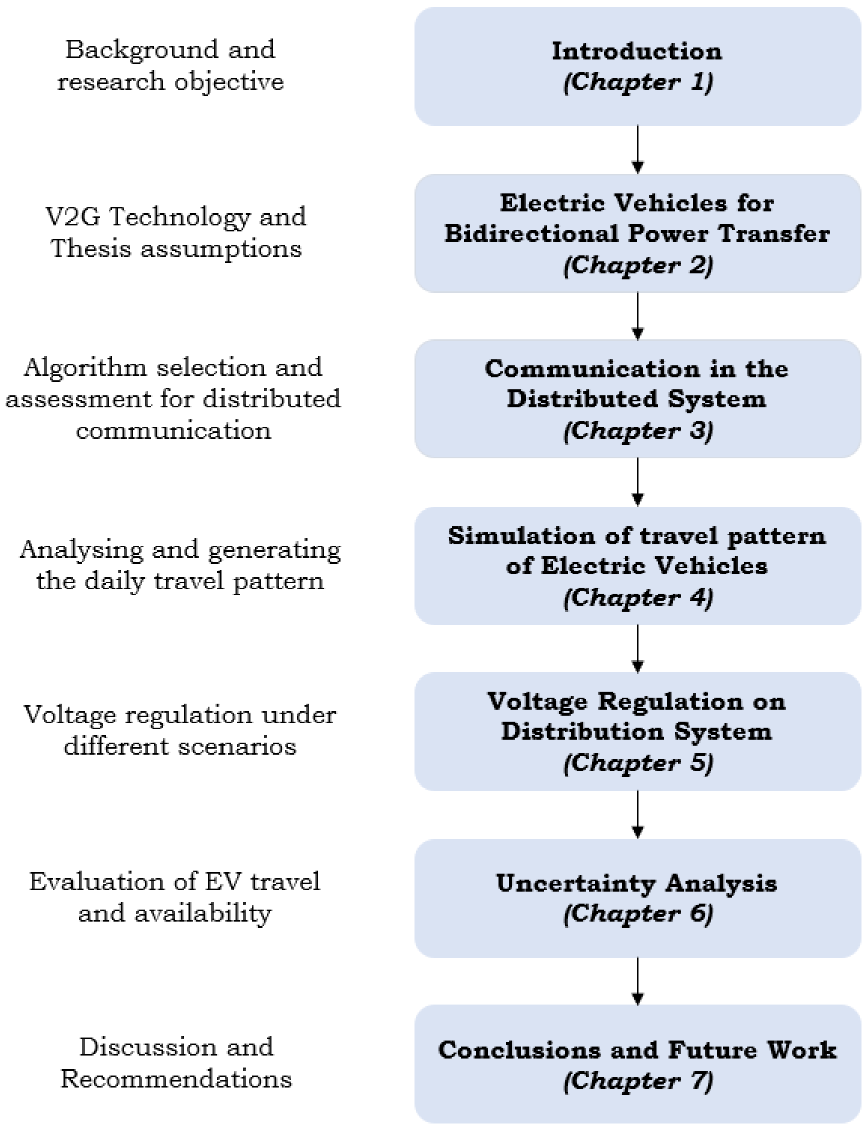


Figure 1.3: Research flow

- Chapter 4: Simulation of travel pattern of Electric Vehicles

  This chapter analyses the travel behaviour of an EV user on a normal day. This also gives a view on how the travel behaviour has been simulated and how the EV location is predicted in the simulation.

- Chapter 5: Voltage regulation on Distribution system

  This chapter describes the implementation of voltage regulation strategy in the distribution system using electric vehicles. Voltage regulation has been performed for different experimental scenarios and the results are discussed in detail. Arguments and comparisons between different scenarios are also provided.

- Chapter 6: Uncertainty Analysis

  This chapter provides a detailed analysis on the availability of EV at a particular location based on the travel pattern generated in chapter 3. This gives a description on how the

EV moves between locations and discusses about the staying probability and duration at a particular location.

- Chapter 7: Conclusions and Future Work

  The last chapter provides answers for the research questions based on the results obtained from simulations. The results are compared with the results from similar researches and the pros and cons of the results obtained is discussed. The limitations that are encountered in this research is also explained in detail. Few suggestions and recommendations are provided for further improvement of this research.

1.2.4. Research Contribution

Even though this thesis is done to satisfy research specific goals, few contents of the research can be used in other research or can be adapted to suit other researches as well. Some of the contributions are:

1. The charge/discharge control and the power distribution between the batteries and the distribution system is designed in a more generalized way. These can be adapted for any such distribution systems, as all the variables used in the model, depends on the distribution system definition. Hence, this model can be used for any kind of distributed network without much changes in the design. The travel pattern modelling is also done in a similar way, which can be used separately in any other research which requires travel pattern modelling of an user on a daily basis.
2. This model can be adapted to any other research in which the voltage of a node has to be maintained within specific limits. This can be applied in applications where the voltage has to remain constant or to be kept within narrow limits. Only minor changes are required in the model to achieve this.
3. This research provides a detailed analysis on the probability of the vehicle being in a certain location at a certain time. These results can be used in researches where the location of the vehicle is required to be known or predicted.

2

Electric Vehicles for Bidirectional Power Transfer

In this chapter, the role of electric vehicles in bidirectional power transfer is discussed. Section 2.1 provides statistical data on the growth of electric vehicles. Section 2.2 provides an overview on the V2G technology and the benefits and challenges of its implementation is explained in section 2.3. Finally, all the assumptions considered in this research are listed out is section 2.4.

2.1. Growth of Electric Vehicles

The usage of electric vehicles has been constantly rising over the past 10 years with the introduction of different kinds of EV technologies. There are 3 main types of EV technology that are currently in use. They are Battery Electric Vehicles (BEV), Plug-in Hybrid Electric Vehicles (PHEV) and Hybrid Electric Vehicles (HEV). BEVs are the most widely used form of electric vehicles and it operates with the rechargeable batteries. The power from the battery is responsible for operating the motor and all the necessary components in the electric vehicle. In this type of EV, there is no other source of power and the batteries serve as a sole unit of a power source. The charging can happen only by connecting the vehicle to an external source of power. In PHEVs, the charging can take place in two different ways. One way is to connect the EV battery to an external source and the other is by regenerative braking in some cases. Other than the battery, an alternative source is fuel will also be available in PHEVs. This alternative fuel will be gasoline in most cases. This type of EVs provide more flexibility to the user, as there are two sources of fuel to the vehicle. The energy from the battery will serve as the primary source and the gas engines helps in providing assistance to the batteries. HEVs are very similar to the PHEVs. HEVs use both electricity and gasoline for its operation, but the electricity used here is primarily generated through regenerative braking. The electricity from the regenerative braking is used to start the electric motor and when the speed of the vehicle rises, the gas engine takes over the control and increases the speed further. The coordination between the electric motor and the gas engine is managed by the internal electronic units present inside the EVs. The switching between the motor and the engine is made to ensure the optimal economical drive for the EVs.

The interest towards electric mobility has increased rapidly, especially in the last few years. The total global stock of electric vehicles has exceeded the 5 million mark in 2018

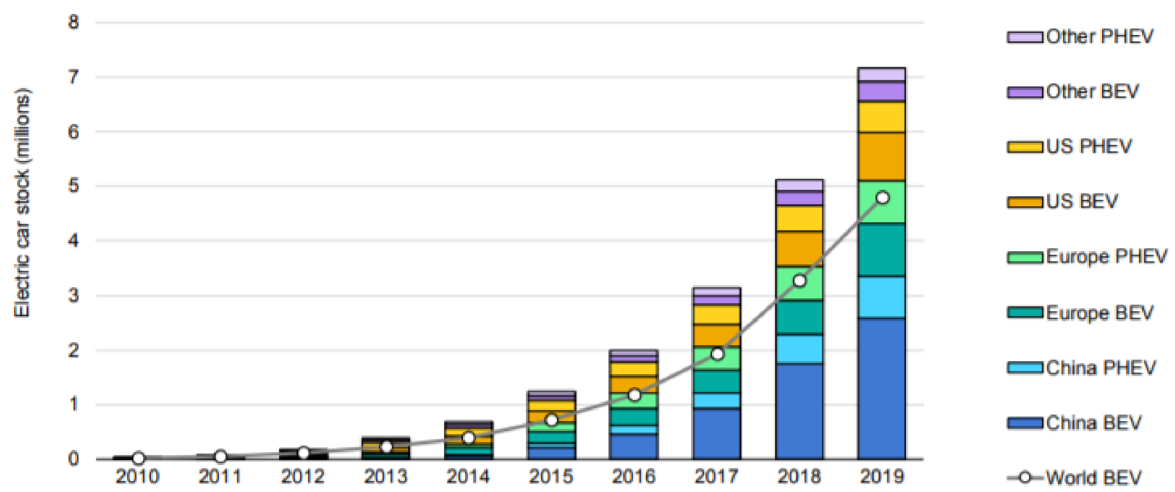


Figure 2.1: Global electric car stock, 2010-2019 [3]

which is the result of an increase of 63% of the stock of electric vehicles compared to 2017 [7]. In 2019, the sale of electric vehicles has increased further and resulted in an increase of 2.1 million globally, which is a record for the most number of EVs sold in a year. With this increase, the global stocks have reached its new peak of 7.2 million. China accounts for a major share of this sales with the sale of 2.58 million BEVs and 0.77 million PHEVs in the year of 2019. Europe also witnessed an increasing trend of electric vehicle sales with recording 1.75 million sold EVs combining the sales of BEVs and PHEVs [3]. The overall global sale of EVs and sale in different countries is shown in figure 2.1. It should also be noted that the increase in sale of electric vehicles has lead to a decrease in the amount of conventional vehicles being sold.

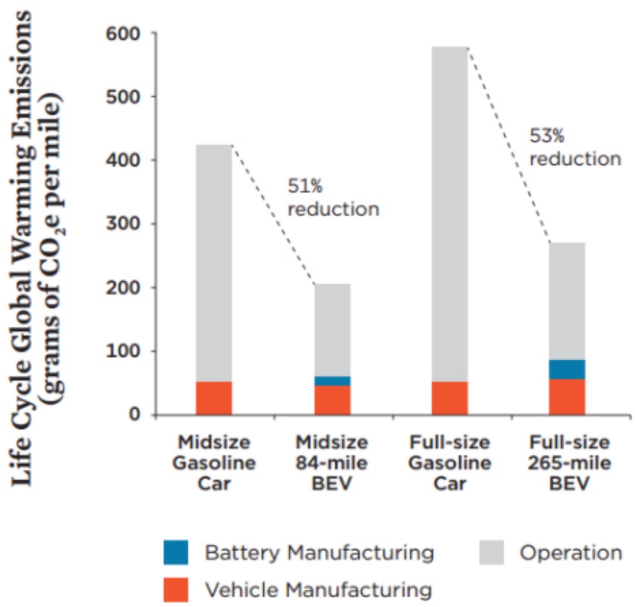


Figure 2.2: Life cycle Global Warming Emissions from the Manufacturing and Operation of Gasoline and Battery-Electric Vehicles [4]

The electric vehicles also plays a significant role in the reduction of CO_2 emissions. Though a BEV does not emit any CO_2 during its operation, there is a certain amount of emissions involved in the manufacture of its products. The overall CO_2 emission from the manufacture and operation provides the exact amount of emissions from a vehicle. In figure 2.2, the overall emission including the emission during manufacture of a gasoline vehicle and a BEV is compared. It can be seen that, when a midsize vehicle (vehicles driven 135,000 miles over their lifetime) is considered, the amount of CO_2 emitted is reduced by 51% by a BEV compared to a gasoline car. Similarly when a full-size vehicle (vehicles driven 179,000 miles over their lifetime) is considered, the CO_2 emission is reduced by 53% by a BEV compared to a gasoline car. This shows that, even with excess emission created by the manufacture of the battery, BEV emits much lesser amount of CO_2 during its operation [4]. This represents a major reason for denoting electric vehicles as the transportation for the future.

2.2. V2G Technology

Increasing integration of Renewable energy sources (RES) into the electrical grid, has raised the importance of storage technologies and hence the purpose of having bidirectional power transfer has gained attention. The Vehicle-to-Grid (V2G) is the technology that allows bidirectional transfer of electric power between the vehicle and the grid [8]. When the electric vehicles are integrated for the bidirectional transfer of power with the grid, it is referred to as a Vehicle-to-Grid system. This technology provides flexibility for power transfer and also provides a complete control over the direction and quantity of power transferred between the vehicle and the grid. Though the electric vehicles are used for travel, nearly 92% of the total vehicles remain parked even during peak hours [9]. This provides motivation for the idea of the electric vehicles supporting the grid through V2G technology. Through this technology, the electric vehicles can be used to supply the demand during peak hours and it can be charged during hours of excess or high generation. A general representation of the V2G technology is shown in figure 2.3.

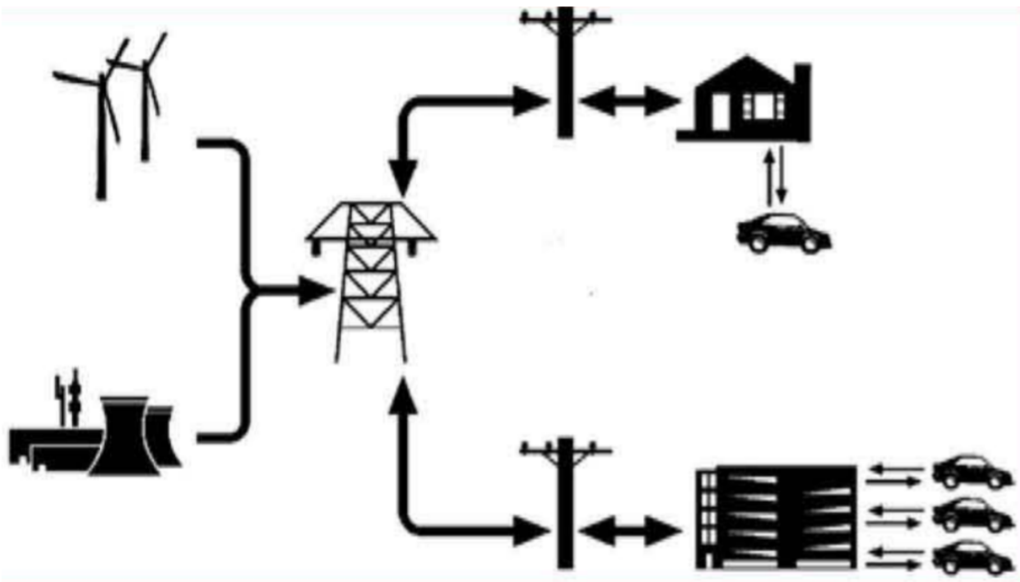


Figure 2.3: Basic schematic of V2G infrastructure

The flexibility offered by V2G technology also reduces the loading in the lines and the system. When the economic analysis is included in the system, V2G technology can also be used to control the flow of power in both directions based on the cost of power. This system increases the reliability of electricity and also increases the profit for both the users and the grid operators. Since it has complete control over the charging and discharging power and time, the charging can be pushed back to accommodate the demand based on priority. The time of charging can also be controlled based on the price of electricity to facilitate cheaper charging for the EV user. Apart from controlling the charging periods, V2G system can also be used to smoothen the fluctuations of output from wind farms [10]. These information provides enough reasons suggesting that V2G technology will be beneficial in the future electricity grid.

2.3. Benefits and Challenges of Bidirectional power transfer in Electric Vehicles

With the increase in production and sales of electric vehicles, Vehicle-to-Grid (V2G) technology has become popular due to the benefits and flexibility it provides for the grid. The electric vehicles can be used for providing several ancillary services for the grid and one of them is regulating and maintaining the voltage level of the system by bidirectional power transfer between the vehicle and the grid. This can be achieved by controlling the charging and discharging time and the amount of charge or discharge taking place at a particular time in an electric vehicle. The control can be made such that the electric vehicle battery charges when the there is higher generation or lower demand and discharges when there is higher load or lower generation. By this way, the grid can be supported at all times and it also offers flexibility for the grid and also for charging the vehicle. When PV generation is connected to the distribution system, the peak generation occurs during the mid part of the day. This is the time when there is high amount the sunlight incident on the PV modules. During this time, the generated power might be higher than the amount required for the loads connected in the network. This might result in an increase in voltage level of the distribution system. But if the EVs are charged during this time period, the extra power that has been generated can be absorbed by the EVs.

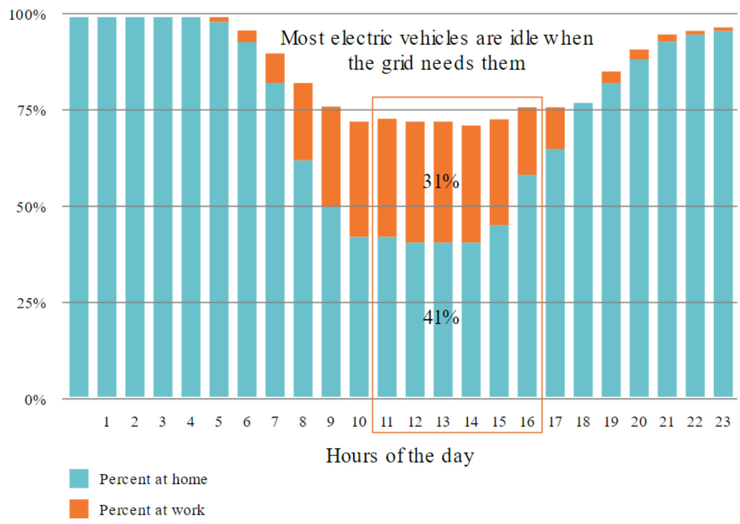


Figure 2.4: Life cycle Global Warming Emissions from the Manufacturing and Operation of Gasoline and Battery-Electric Vehicles [5]

In figure 2.4, it can be seen that, the EVs are at home during the start and end of the day. During the mid day, almost 41% of the EVs stay at home and 31% of the EVs stay at work. These numbers are not the same in all the cases, but it represents a major occurrence in behaviour of the EVs. It has to be noted that the numbers shown here, represents the percentage of vehicles that are idle at a particular location. The actual numbers might differ in different cases, but the trend is similar. Considering that more than half the total number of EVs remains idle in the afternoon, these vehicles can be used to absorb the excess power generated by the PV modules. The EVs can be charged during this period such that, the charging occurs during the period of high power generation and the EV batteries can be used to support the grid during periods of low generation or high load. This enables the grid to be more flexible irrespective of the intermittent nature of PV generation. Though the electric vehicles are considered as a mode of transport from one point to another, this shows that EVs can also be used to provide ancillary services to the grid. Apart from the services provided by the EVs, this can also reduce the cost of charging for the vehicles. Since the charging takes place during peak generation or low demand periods, the cost induced for charging can be reduced. This attracts the EVs users to charge their EVs during this period. By this way, the load during non peak hours of generation can be reduced. The EV batteries can also be used as an emergency power source when there is a power outage or a power shortage. Though active power compensation is the primary benefit of vehicle to grid technology, there are several secondary benefits as well. The electric vehicles can be used to provide reactive power support to the grid, and it can also be used to filter the current harmonics.

The Vehicle to Grid technology also has some challenges or limitations, which makes this a topic for discussion. Every battery will have a certain limitation on the number of charge or discharge cycles that it can withstand without any degradation. If the number of cycle exceeds this range, then the capacity of the power that the battery can deliver, reduces. This range, when used only for charging and discharging to the vehicle, can be maintained for several years before the battery starts to degrade. But, when it is also used to support the changes in the grid, more cycles are involved in the process. This reduces the life time of the battery and the battery degrades a lot sooner than its estimated time. This might not be the favourable scenario for the EV users. This problem is given importance and it is addressed in this research. Another challenge is to minimize energy losses involved in the bidirectional flow of electricity. Several researches has been done to test the energy losses involved in using EVs to support the grid and the research performed in [11] showed that the energy losses increases with the increase in EV penetration in the grid. It also showed that the losses increased by nearly 40% more than the actual value when the EVs were in charging mode. These are the limitations that is common with the integration of electric vehicles with the grid. If these limitations are eradicated, the use V2G technology can be increased and also provides favourable situations for the EV users to participate in the process.

2.4. Thesis Assumptions

Since there are several parameters involved in this research, it is important to specify the way in which these parameters are going to be implemented in the flow of the algorithm. For this reason, there are several assumptions considered in this research which are selected to make the process simpler and realistic at the same time. The assumptions considered in this research are given below.

- The PV capacity and power generation in two of the units are considered to be higher than the required amount to visualize the effective of the voltage regulation process.

- The EV owners are provided with a choice of participating in this process. Only the EV owners who are willing to lend their EVs for the regulation process are considered and only those EVs are assumed to take part in the process. A basic compensation is provided to the EV users for lending their vehicles.
- The EV owners are provided with the flexibility of withdrawing from the process whenever they want. No mandatory requirements are imposed on them to take part in the process. Flexibility is provided to ensure the long term enrollment of the EVs.
- Initially, each bus is assumed to have 1 EV connected to it. The EVs change their location during travel and in this case, the EVs gets connected to a different bus. Hence the distribution of EV is considered not to be uniform throughout the entire day. This is made to generate a more realistic pattern of connection, as the connection pattern is not uniform in reality.
- The EV owners who take part in the process are assumed to be employed individuals. This is considered mainly to ensure higher availability period of the EVs. The travel pattern of working individuals mainly resembles a travel between home and work most often and the EV will be parked in that there after reaching that location. Hence the parking time of the vehicle will be more compared to the travel time. This makes it suitable to make use if the EV batteries for the most part if the day.
- Here, different kinds of employed EV users are considered. This includes people working at night shifts, travelling between work places and transitioning to other locations during their travel. This provides variations and realism to the travel model.
- The EVs are assumed to start the day with the SOC of 60%. This is chosen specifically to provide room for the EVs to charge when the voltage level of the network is high and there will be adequate amount of power to supply the network in case of a voltage drop. Varying this value may not have a huge impact on the system, but it is assumed mainly to ensure safe operating conditions during the initial time periods.
- In this research, two kinds of limits are chosen to regulate the voltage. One is the voltage tolerance limits and the other is the voltage threshold limits. Voltage tolerance limit is the predefined limit for an electrical system specifying the safe operating space for the system. It differs based on the geographical region. Since European region is considered in this research, the voltage tolerance limits are specified to be ±10% from the nominal operating voltage of the system [12]. The voltage threshold limits are the limits chosen as the operating limits in this research. These are also the limits that initiates the charging and discharging process. These limits are chosen such that the corresponding values are inside the voltage tolerance limits. This is done to ensure that the operating level of voltage is well within the tolerance limits of the system.

$$V_{thr}^{d} \leq V(t) \leq V_{thr}^{c} \tag{2.1}$$

$$V_{tol}^{l} \leq V_{thr}^{d}, V_{thr}^{c} \leq V_{tol}^{u} \tag{2.2}$$

Here, V_{thr}^{c} and V_{thr}^{d} is the threshold limit for charge and discharge for respectively. V_{tol}^{l} and V_{tol}^{u} is the lower and upper tolerance limit for voltage in the network respectively

- It is assumed that the EVs are always connected to the charging pole when they are parked at home or at the work location. This assumption increases the availability of EVs for aiding in voltage regulation. When the EVs are parked at any other location, they are assumed to be parked without any connection to the charging pole.
- The travel time and the SOC level is assumed to be recorded when the EV is connected to the charging pole. The SOC value is not recorded during the travel period and hence the value before travel is retained until the end of the travel and the value is updated only after the completion of the travel.
- The time duration between two consecutive time steps is assumed to be 15 minutes. The generation data used here is also represented in 15 minute time steps. Hence, if the EV location changes in consecutive time steps, the travel duration is considered to be 15 minutes. Even if the travel ends in between two successive time steps, the location is updated only after the completion of that time step.
- The transmission losses are considered to be negligible in this research.

3
Communication in the Distributed System

In this chapter, the necessity of an algorithm for distributed communication and its selection is discussed. Section 3.1 provides a general description of the network. Section 3.2 provides an overview on the choice of control used here. Section 3.3 shows the comparison of different algorithms based on literature study. Section 3.4 provides detailed information on the selected algorithm with a description of its working. Section 3.5 provides information on the approach used to achieve equitable contribution among EVs.

3.1. Network Description

To analyse the performance of EVs in the voltage regulation process, a low voltage distribution network is considered. This distribution network consists of 27 buses with one external grid of 20 kV connected to the busbar. There is a transformer connected to the external grid to step down the voltage to consumer level voltage of 400 V. As seen in figure 3.1, the network has three main branches. The buses are connected in a linear manner in all those branches. There are six generation units connected to the network. Those units provide constant power for all the time steps. The power supplied can be considered as the power generated from conventional sources. But, to visualize the effect of high PV generation in the network, there should be PV units connected which delivers varying power based on the solar radiation incident on it. To achieve this, three of those conventional units were replaced by three PV generation units. The PV unit mentioned here is a representation of a collection of PV arrays to generate the required power. Among these three units, two units are considered to have a higher rating compared to other units. This selection is made deliberately to observe the network under high PV generation. Two units are connected in the second branch and one unit is connected in the third branch from the left. The location of these units can be seen in table 3.1. There are 14 loads distributed among various nodes of this network, which are considered as residential loads. Other than the residential loads, the EVs are also considered as loads of this network when the EV batteries need to be charged. A load mentioned in table 3.2 approximately represents a set of four residential loads together. It is assumed that there are 26 EVs connected to the network, and each EV has a different bus as its home location. As the day progresses, the EVs travel and gets connected to different buses than its initially connected bus. A simple representation of the network is shown in 3.1:

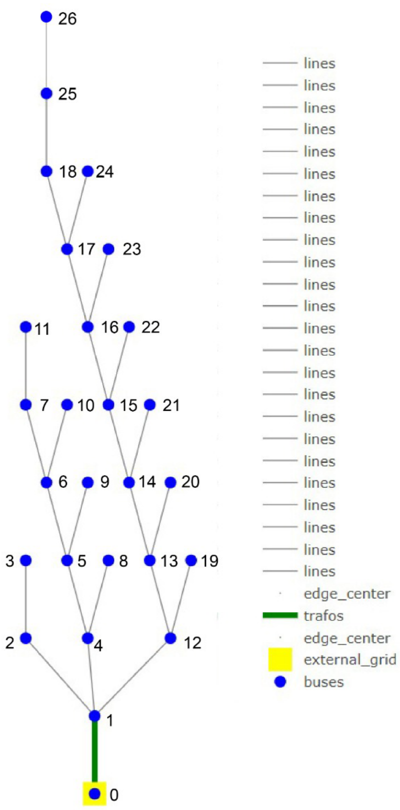


Figure 3.1: Low voltage distribution Network

Bus	Power rating	Type
8	0.41 MW_p	PV
9	0.153 MW	C
11	0.04 MW_p	PV
22	0.0158 MW	C
23	0.0253 MW	C
26	0.1 MW_p	PV

Table 3.1: Generation units connected to the network

Bus	Power [MW]
3,8,9,10,11,19	0.0051 MW
20,21,22,23,24	0.0051 MW
7,13	0.0079 MW

Table 3.2: Loads connected to the network

To simulate the PV generation behaviour for one complete day, PV generation data from [13] is used. The generation data used is for one complete day in 15 minute time steps.

It has been assumed that the three units considered here has different capacities and are placed in different directions, locations and the tilt angle and other parameters are different for different units. Hence, the generation pattern differs based on the parameters mentioned above. Figure 3.2 shows the generation profile of the PV units in the corresponding buses.

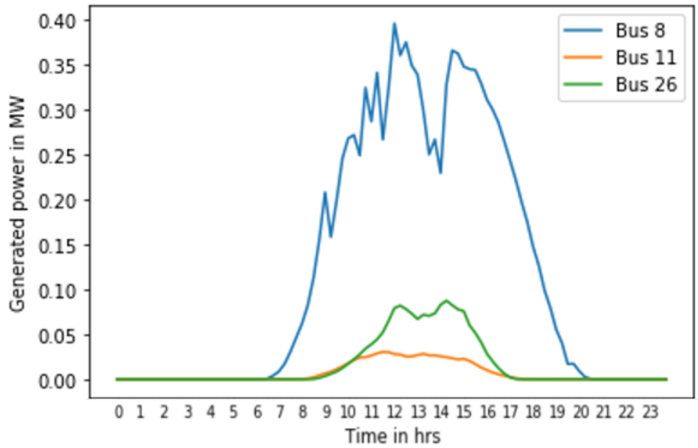


Figure 3.2: PV generation profile

Here, the duration of generation of the PV units connected at bus 8 is longer compared to others. There is no generation from the PV units before 6:00 and after 20:00 due to the absence of solar radiation. In these time periods, the load is compensated by the power generated from the conventional sources and the EV batteries. It has to be noted that, all EVs may not be used in every time step. If the EV is unavailable or has the SoC level beyond its operating limits, the corresponding EV will not be used a source to compensate the load in the network. Once the generation profile is implemented in the model, the voltage level of the network due to the increased PV generation is observed. Figure 3.3 represents the voltage profile of all the buses in the network before implementing voltage regulation algorithm.

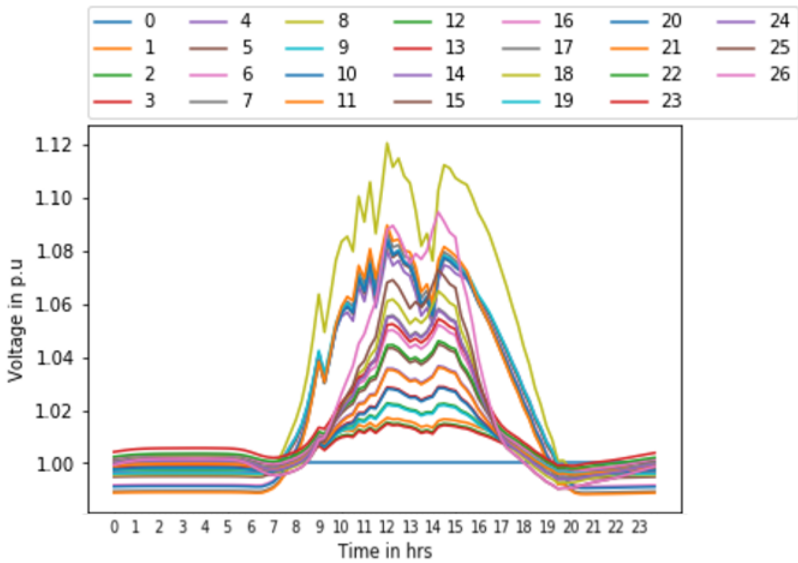


Figure 3.3: Voltage profile of the network before regulation

It can be seen that, the increased PV generation between time interval 8:00 and 17:00 has lead to the increase in voltage of the network. This voltage rise is not concentrated only on the buses where the PV units are connected, but it is also spread among its neighbouring buses. The voltage tolerance limits in the European countries are defined to be ±10% from the nominal operating voltage of the system [12]. In the voltage profile shown, few buses are violating the voltage tolerance limits of the network while some others are very close to the tolerance limits. If the network is maintained in the same state without any preventive approach, the higher voltage might lead to premature failure of the electrical components connected to the network. This includes the electrical components present in the grid, the distribution lines and the components connected to the network. This spreads throughout the network within a short period of time, and if it is not prevented, it leads to the overall failure of the system and might result in disruption of the whole system. Hence, to prevent this, the voltage of the buses in the network has to be regulated. In this research, the electric vehicle batteries are used as an element for regulating the voltage.

3.2. Centralized vs Distributed Control

In a centralized communication system, there will be a centralized communication server which receives the data from all the elements that are individually connected to the network, processes it and communicates that information throughout the network. This creates a communication link between the elements in the network and ensures efficient information transfer. Centralized communication is popular and has been implemented in several applications. Due to the advantages of distributed communication and limitations of centralized communication, distribution communication is preferred over centralized in this research. Distributed control provides autonomy to the local controllers thereby increasing the robustness of the control system. And due to this, the overall communication overhead is reduced, thus making it more scalable [14]. In addition to that, single point failures can be avoided [15] and it has better accommodation for plug and play features compared to centralized control [16]. This facilitates better integration and usage of EVs in the system. The requirement of fewer communication infrastructure improves the processing speed and provides a cost effective control compared to centralized control [17]. Hence, distributed control is preferred in this thesis. In a distributed control, there is no central communication and hence the information has to be communicated through the neighbouring elements. When a bus has two neighbouring buses, that bus will be able to communicate its information with its neighbouring buses that are physically connected to it. Particularly, in a distribution system where there are multiple storage units connected across different nodes, it is important to have communication between different nodes and different storage units. This can prevent the units from overcharging or over-discharging and also restricts the over utilization of a particular unit. Especially in this research, the communication between different units is necessary as EV batteries serves as storage units and loads. Hence, the utilization should be adjusted for every time cycle by comparing it with other EVs. This demands a need for an algorithm to collect the information from the neighbouring units and to process it. The algorithm should be able to process the information in a distributed manner and work efficiently without a centralized communication medium.

3.3. Comparison of distributed algorithms

To find an algorithm suitable for this application, several algorithms has been reviewed and tested for its feasibility in this research. First, genetic algorithm has been analysed. It is one of the well known algorithms which searches its way to reach the desired value through the process of natural selection. It can be used in a distributed manner. The commonly recognized problem with genetic algorithm is premature convergence [18][19]. Most often the sub-populations converge to the local optima instead of the global one. Though this problem can be solved by making the calculations distributed [20] and through few other methods, the probability of premature convergence increases with increase in sub-population size. Another important drawback is that, the algorithm becomes ineffective when a new individual is added to the sub-population. The new individual can be incompatible to the sub population and hence can be ignored. This is called conquest problem [21]. This is an important problem to consider in this research, as the number of EVs connected to a bus continuously varies and a new EV can be added at any instance. Migration schemes have been proposed to solve this problem, but as the size of population and sub population increases, the complexity of the problem increases. Hence it is not a trivial task to create a well designed distributed genetic algorithm, as there are several factors that influence the exploration and exploitation [21].

Secondly, Particle Swarm Optimization (PSO) algorithm is examined. PSO algorithm is known for its fast convergence. Designing PSO algorithm is relatively simple compared to genetic algorithm, as it involves fewer parameters. PSO algorithm is widely used in centralized systems and single swarm systems. When it comes to distributed systems, PSO is most often used along with other algorithms to make it a distributed particle swarm optimization algorithm. If PSO has to be used in a distributed system, it has to be modified to adapt itself to the system or it has to be combined with other algorithms. In [22], Distributed PSO is implemented using a message passing interface to transfer information between sub swarms. In [23], a single swarm PSO is extended for multiple swarms by integrating it with another model called charged PSO. In [24], PSO is combined with average consensus algorithm to make it a distributed PSO. And a similar experimentation has also been done in [25]. When PSO has to be implemented in this system, then the there will be a need for a method or another algorithm to facilitate communication between multiple swarms. This makes the design complex since two algorithm has to be synchronized. When the number of nodes increases, this becomes even more complex, forcing changes in the system parameters. Hence, in-spite of its fast convergence and other advantages, PSO is not used here due to its complexity with multiple swarms.

The reasons for not choosing these two algorithms were explained in detail, because, these are some of the widely used algorithms in similar applications. Other than these two algorithms, few other algorithms were also examined for its suitability in this model. They are Ant-colony optimization, Harmony search algorithm, Simulated annealing and Tabu search. Ant-colony optimization and Harmony search takes more iterations to converge and its complexity is proportional to the number of nodes. Most importantly, these are not very suitable for distributed networks. Tabu search might terminate at the local optimum while harmony search might skip the local optimum. Simulated annealing can be inaccurate and requires accurate designing of initial parameters. Other than that, most of these algorithms are designed to work with many parameters. But here, the only information that has to be communicated is the SoC of the EVs and the bus to which the EVs are connected.

Finally, consensus algorithm is analysed. Consensus algorithm is one of the simplest algorithms which is used to achieve an agreement on a common value among a set of various distributed units. It is most suitable for distributed networks, as the node only communicates with the other nodes which are physically connected to it. Unlike centralized algorithms, this algorithm computes the desired processes at every node without the need of any central information point [26]. Consensus algorithm works efficiently even when there are multiple unreliable nodes in the system [27]. Consensus can also be achieved in distributed systems with failures. This is an important point to consider because, the availability of EVs in a node is considered to make a node reliable here, the node is considered to be unreliable when the EVs are unavailable or if the availability of EVs are unknown. This situation occurs often as the EV constantly changes location. In this case, consensus algorithm can communicate efficiently and render high quality results. Average consensus algorithm is a type of consensus algorithm which calculates the average of the information that has been communicated between the nodes through a distributed approach [26]. When average consensus algorithm is executed in a network, only the information for which the average has to be calculated and the node to which it is connected is required. Hence there are very less parameters to model in the algorithm. This just takes the information at a particular instance of time. So, there is no need of defining initial parameters. The only initial definition that is needed for the algorithm is the definition of the network. The algorithm needs the information such as number of nodes and the network topology. These are basic information and are readily available for a well defined network. So, there is no complexity in initializing the algorithm. It is computationally efficient since it uses less parameters. The accuracy is high and the error percentage can be reduced by setting the appropriate number of iterations. Due to the above mentioned reasons, consensus algorithm is chosen to facilitate communication in this distribution system.

3.4. Consensus Algorithm: Definition and Simulation

Consensus algorithm is a way of negotiating with the neighbouring units, through which the information state of EVs can be exchanged with their neighbours [28]. Each EV updates its information by comparing it with the information state of its neighbours. When this is applied for several iterations, it is possible to make every EV converge to the same value. This means that the EVs have reached a consensus. The value that the EV converges on, will be the average value of information considering all the EVs connected to the network. Here the information exchanged is the state of charge of the EVs connected. Hence the consensus value will be the average of SoC's of all the EVs connected in the network. The main purpose of consensus algorithm here, is to establish a stable communication between the buses in the network and the EVs connected to it, by communicating with the neighbouring buses. The average SoC of the EVs connected can be estimated through this communication in a distributed manner such that an occasional arrival or departure of EVs does not affect the outcome of the control algorithm. By this way, the available storage can be utilized effectively with more dynamic and real time control. The main reason for using consensus algorithm in this research is because of the fact that, this algorithm can maintain reliability in the network which has several unreliable nodes. The information of each node can be updated using equation 3.1 [29]:

$$x_i[k+1] = x_i[k] + \sum_{j \in N_i} d_{ij}(x_j[k] - x_i[k]) \tag{3.1}$$

where i = 1.....n. $x_i[k]$ and $x_i[k+1]$ are the information updates on node i, at k and k+1 iterations respectively. d_{ij} is the communication coefficient between nodes i and j and N_i is the set of neighbouring nodes connected to node i.

For the complete system, the above equation can be represented by the equation 3.2:

$$X[k+1] = DX[k] \tag{3.2}$$

where X[k] = $[x_1[k],....,x_i[k],....,x_n[k]]^T$ and X[k+1] are the information updates at k and k+1 iterations respectively. D is the communication matrix and it describes the communication coefficient between the i^{th} node and all its neighbouring nodes. The communication coefficient d_{ij} can be given by the equation 3.3:

$$d_{ij} = \begin{cases} 2/(n_i + n_j + \epsilon) & j \in N_i \\ 1 - \sum_{j \in N_i} 2/(n_i + n_j + \epsilon) & i = j \\ 0 & otherwise \end{cases} \tag{3.3}$$

where n_i and n_j are the number of nodes connected to i and j respectively. The communication coefficient is built based on graph theory [30]. The network is represented as graph with interconnections and the information about the connected nodes is gathered from that graph. To represent the graph in a mathematical form, adjacency matrix is created. This adjacency matrix represents the connection between the nodes in the form of a matrix, thus simplifying it for further calculation. When there is no connection between the nodes i and j, the adjacency matrix element will be zero and if there is a physical connection, the value of the element will be one. Among the different methods available for d_{ij} selection, mean metropolis method is used since it ensures faster convergence [31]. The value of epsilon is generally a very small number for large systems. For large complex systems it can be considered as zero. Since the system considered here is a distribution system with less number of nodes, ϵ is considered to be 1. To represent the formation of adjacency matrix, a simple example is considered and is shown in figure 3.4.

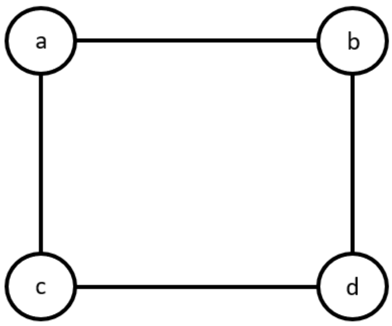


Figure 3.4: Simple example network

Here, node a and d are connected to node b and node c and similarly node b and c are connected to node a and d. This can be represented through the adjacency matrix and it is shown in equation 3.4. This matrix is then used for the calculation of communication matrix, which involves the calculation of communication coefficient for every element.

$$adjacencymatrix = \begin{array}{c} \\ \text{a} \\ \text{b} \\ \text{c} \\ \text{d} \end{array} \begin{array}{c} \begin{array}{cccc} \text{a} & \text{b} & \text{c} & \text{d} \end{array} \\ \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 \end{bmatrix} \end{array} \tag{3.4}$$

Considering this communication coefficient represented in equation 3.3, the communication matrix can be expressed as shown in equation 3.5.

$$D = \begin{bmatrix} 1-\sum_{j\in N_1} 2/(n_1+n_1+\epsilon) & \dots & \sum_{j\in N_1} 2/(n_1+n_j+\epsilon) & \dots & \sum_{j\in N_1} 2/(n_1+n_x+\epsilon) \\ \dots & \dots & \dots & \dots & \dots \\ \sum_{j\in N_i} 2/(n_i+n_1+\epsilon) & \dots & 1-\sum_{j\in N_i} 2/(n_i+n_j+\epsilon) & \dots & \sum_{j\in N_i} 2/(n_i+n_x+\epsilon) \\ \dots & \dots & \dots & \dots & \dots \\ \sum_{j\in N_x} 2/(n_x+n_1+\epsilon) & \dots & \sum_{j\in N_x} 2/(n_x+n_j+\epsilon) & \dots & 1-\sum_{j\in N_x} 2/(n_x+n_x+\epsilon) \end{bmatrix} \quad (3.5)$$

where x represents the total number of nodes in the network. The network considered in this research has 27 buses and the EVs can be connected in those buses for charging. But the availability of EVs is not static and varies depending on various factors. When it is connected to the charging pole, it can be utilized for the voltage regulation process if necessary. The EVs connected in the network can communicate with their neighbours through consensus algorithm and will converge at the average SoC value. Since the algorithm runs through all the buses, it considers all the EVs connected in those buses and the resultant value will be the average value of SoC among all the buses. In figure 3.5, it can be seen that all the buses converge to the same value and it takes around 200 iterations to reach the exact same value up to two decimal places.

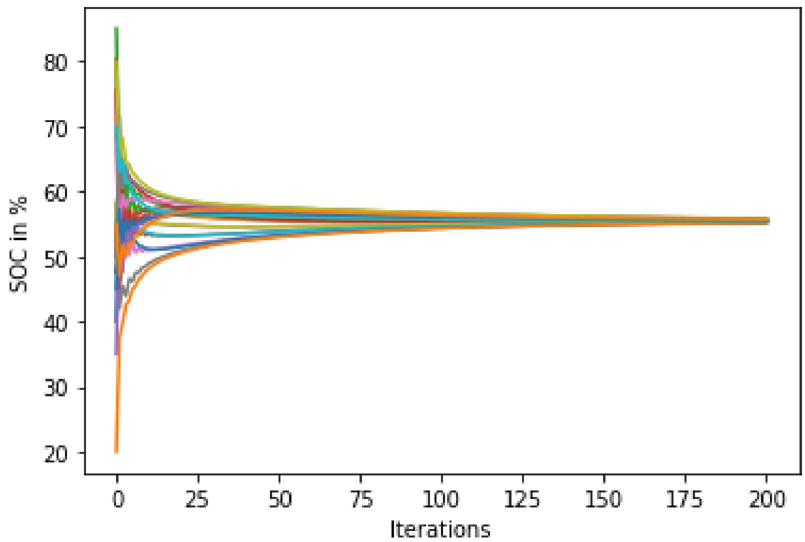


Figure 3.5: Estimation of average SoC using Consensus algorithm

For effective functioning of the algorithm, the structure and parameters of the network has to be specified properly. In a well-defined distribution system, there will always be communication links between the nodes even though it may not necessarily be direct. If the number of nodes are high and the communication links are not direct in most of the nodes, then the algorithm might take more iterations to converge to the consensus value. The convergence speed does not depend on the size of the system but the way in which the buses are connected in the system. If the buses are not closely connected or if they are connected in a linear fashion, then the iterations taken for convergence can be more compared to a closely connected system. The network used in this research is connected in a linear manner which explains the number of iterations taken for convergence. When some of the EVs are not available due to travel, then the availability of the corresponding EV is made zero in the availability matrix, such that the algorithm can still run in its usual way without much changes in the process or output. And once the EV reaches its maximum or minimum limit of SoC, it is removed from the voltage regulation process.

3.5. Calculation of Correction Factor

Once the average value of SoC is estimated, this average value is compared with the actual SoC value of the EV batteries. A correction factor is then generated which is used to adjust the utilization of the battery [32]. This ensures that the EV is utilized in a fair manner considering the SoC of a particular EV at the current instance. The estimation of correction factor during charging and discharging cycles can be represented by equations 3.6 and 3.7 respectively.

$$CF_i^c = \begin{cases} 0 & SoC_i > SoC_i^{max} \\ 1 - (\frac{SoC_i - SoC_i avg}{100}) & SoC_i \leq SoC_i^{max} \end{cases} \tag{3.6}$$

$$CF_i^d = \begin{cases} 1 + (\frac{SoC_i - SoC_i avg}{100}) & SoC_i \geq SoC_i^{min} \\ 0 & SoC_i < SoC_i^{min} \end{cases} \tag{3.7}$$

The equations for determining the correction factor differs for charging and discharging process. When an EV enters the charging process with the SoC (SoC_i) higher than the average SoC ($SoC_i avg$), then it means that the EV has a higher SoC than most of the EVs connected to the network. In this case, the contribution of the EV is decreased which provides additional capacity for other EVs to charge which has SoC levels less than the average. In similar conditions, if the EV enters the discharging process, the EV has more capacity to offer compared to most of the other EVs. Hence, the contribution of the EV is increased which prevents the EVs with lower SoC getting discharged to its minimum. This ensures the equitable utilization of EVs in both charge and discharge processes. However, this can only adjust the level of contribution of an EV battery and can communicate that information to the EVs. It cannot ensure the actual estimated level being charged or discharged, since it entirely depends on the voltage level of the bus to which the EV is connected. If the contribution for charging is increased in an EV based on the calculation of correction factor, with the voltage level of the bus being low, then the charging level might not reach the calculated contribution level, in order to maintain the voltage level of the system. Hence, the actual contribution will reach the calculated value only when the voltage of the bus is in sufficient levels.

4

Simulation of Travel Pattern of Electric Vehicles

This chapter deals with the modelling of travel pattern of the EVs. Section 4.1 provides analysis on the travel behaviour based on literature study. Section 4.2 describes the modelling of travel pattern using markov model without using the time parameter. Section 4.3 explains the travel pattern modelling as a function of time and section 4.4 provides validation of the generated model. Finally, section 4.5 explains the process of implementation of the generated travel model.

4.1. Travel Behaviour Analysis

The travel pattern of an electric vehicle is similar to that of any conventional vehicle. For a personal vehicle, the travel pattern resembles the daily working schedule of an individual person. The important assumption considered here is, the users of the EVs taking part in this process are employed individuals. Hence, during weekdays, most trips would be between home and work. This assumption is made to ensure lesser number of trips per day and other than the trip, the EV will stay parked for most part of the day. This facilitates the use of EVs for regulation as much as possible. For a normal working person, the travel begins when the person travels for his work and the vehicle will be parked in his work place till he returns back from work. According to [33], 20% of the trips start before 9:00 AM and these trips are mostly of an employed person. 20% of the trips occur between 9:00 AM and noon. Based on the research in [34], the frequency of trips is found to be high between home and work. And it also states that the vehicle is in parked state for more than 16 hrs per day. In [35], the average number of car trips per day in European countries during weekdays is found out to be 2.5 and this thesis takes this number into consideration for simulating the travel behaviour. Considering this number of trips by an average person, the car remains parked for most part of the day either connected or disconnected with the charging pole. Here, it is assumed that the EV is always connected with the charging pole when it is parked at Home or Work location, thus facilitating its use for voltage regulation. The second trip is generally a return trip and it occurs mostly between 17:00 and 19:00 and some of the trips occurs after 19:00 [34]. Once the EV user reaches home, the EV remains parked till the next day. According to [36], most of the charging takes place between 12:00 and 17:00. This is also the time where the residential loads are stable and the industrial loads reaches its peak. On a sunny day, the energy generated from the PV modules will also reach its peak during this time. Some EV users prefer overnight charging, thus to have a fully charged vehicle at the start of the day. There are two kinds of parking, active and inactive parking [34]. Active parking is the time when the car is parked after a trip that is not the last trip of the day. Inactive parking is the time when the car is parked before the first trip of the day or after the last trip of the day. In this research it is assumed that the EVs are always connected to the charging pole during inactive parking and it is connected to the charging pole during active parking, when the EV is parked at home or at work.

4.2. Travel Pattern Simulation using Markov Model

A basic travel pattern is generated based on the travel pattern data obtained from literature. This has been randomised to make it more realistic. But this is still in a more generalized form and does not include all the necessary parameters. Since the generated pattern is more random, the model does not take into account the information of the previous location before estimating the current location. This results in loss of accuracy of the pattern generated. Thus a more predictive approach was required that takes the previous location into account. To facilitate this purpose, Markov model is used. Markov models are generally used in a system that has evolutionary processes [37]. In Markov model used here, the locations of the EV are mentioned as a set of states. For each state, a set of transition probabilities are defined. These are the state transition probabilities. The state transition probability is the set of values which defines the probability of the EV to change from location i to location j, at a particular time instance [38]. So, at a specific instance of time, it is more likely that the model chooses the location which has a higher probability. First order markovian model is used here. The model can be used to predict the current state using the state transition probabilities by comparing it with the previous state. A first order markovian model only takes the previous state into account [39]. It ignores the states before that. In this research, any state other than the previous state is considered irrelevant for the prediction of the current state. Hence, higher order markovian models are not necessary for this application. A simple representation of selecting the current state based on the previous state using probabilities is given in 4.1:

$$a_{ij} = P(L_t = S_i | L_{t-1} = S_j) \tag{4.1}$$

where L_t is the current location of the EV at time t and L_{t-1} is its previous location. a_{ij} is the state transition probability for the 1st order markovian model, which gives the probability of current location being state S_i when the previous location is state S_j. These state transition probabilities are defined for all the states. It is kept the same for all the EVs for simplicity and moreover the travel pattern for most EV owners who are employed looks similar according to the consideration. There are four states considered in this markovian model. They are Home (H), Work (W), Others (O) and Intermediate (I). This is done based on the trip chain model [40]. The trip chain model contains all the necessary information related to the travel of an EV. It contains the arrival and departure location, arrival and departure times, the purpose of the trip, the purpose at the destination location, trip duration and the vehicle used for travel. When the EV is parked at home, the parking location is initialized as 'H' and similarly it is initialized as 'W' if parked at work. If the parking is in a location other than Home or Work, then the location is initialized as 'O'. It will be 'I' if the trip is in progress. Based on these four states and its state transition probability, the markovian model is developed. Here, $S_i, S_j \in$ ['H','W','O','I']. This model is capable of predicting the current state based on its previous state using state transition probabilities. The problem with the considered model is, it does not take the time of occurrence of the event into consideration. This model chooses the current state irrespective of the time at which the state is being predicted. For example, let us assume the model is predicting the location for 1:00 AM. If the most probable location is 'Work' with the previous location being 'Home', this model results in predicting the location as 'Work' irrespective of the time of the event (Going to work at 1:00 AM has the least probability when the probability is evaluated based on time). This results in the predicted location being completely irrelevant at most of the times.

4.3. Travel Pattern Simulation using Markov Model as a Function of Time

To overcome this problem, time parameter is included in the model. This improved model does not take the current location and probability of the states alone, but also takes the time of occurrence of the trip into consideration. This provides more accuracy to the prediction. After adding the time parameter, the improved model can be represented by the equation 4.2:

$$a_{ij}(t) = P(L_t = S_i(t)|L_{t-1} = S_j(t)) \tag{4.2}$$

The prediction of states now becomes a function of time and hence the state transition probability will also become a function of time. In this case, the state transition probabilities will be different for different time period considering the previous location, similar to the research performed in [41]. Considering this model, let us assume the previous state is 'Home'. If the time of prediction is 9:00 AM, the probability of the current state being 'Work' is high, whereas if the time is 2:00 AM, the probability is high to remain at 'Home'. Hence model provides a wholesome prediction considering all the essential parameters. Along with the transition between one location to another, this model also makes the EVs stay at a particular location based on probability and time. These stay probabilities are also included in the state transition probabilities mentioned in equation 4.2.

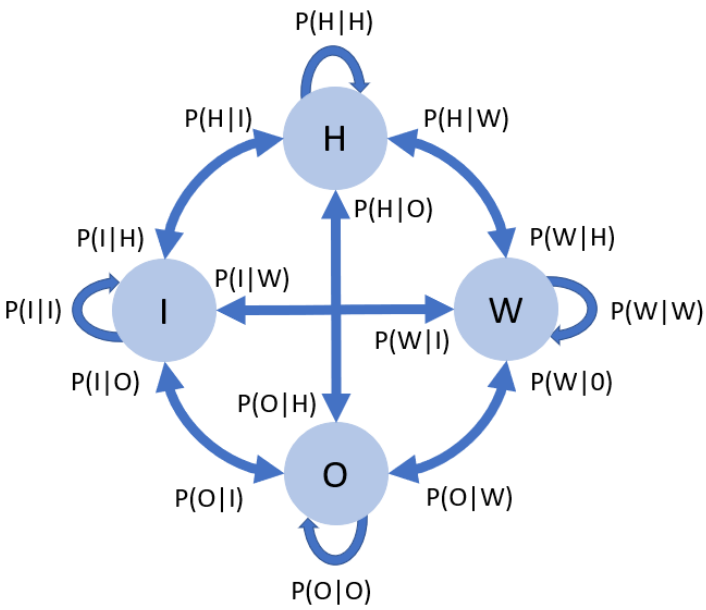


Figure 4.1: Markov chain for travel pattern simulation

This combination of stay and transition probabilities between states can be defined as a markov chain. Markov chain contains the probabilities and the states defined in the model and gives a clear visual view on the working of the model. Since both S_i and S_j belongs to the set ['H','W','O', I'], probabilities are also defined for situations where states S_i and S_j are the same. The travel pattern is generated using all these information through markov model. The representation of EV travel pattern using markov model is shown as a markov chain in figure 4.1. The transition between the four locations is represented along with the probability of transition. This also includes the probability of staying in the same location at a particular instance of time. It has to be noted that, all the probabilities mentioned in the figure are time dependent. This figure gives a general idea on the implementation of first order markov model.

4.4. Validation of the Generated Travel model

The travel model generated here, involves several assumptions and data retrieved from literature. Since the generated pattern comes from the literature data, it is important to compare the accuracy of the results generated with the literature data. For this purpose, a sample of 10 EVs is considered and the travel pattern generated for those 10 EVs is compared with the existing travel pattern data. For the ease of comparison, the travel pattern of the EVs are represented as a probability distribution based on the location of the EVs at a specific time instance. This is shown in figure 4.2 and 4.3. Figure 4.2 shows the probability of EVs at Home and work while figure 4.3 shows the probability of EVs at Other locations and travel. These results are compared with the results from [42] to estimate the accuracy of the generated model.

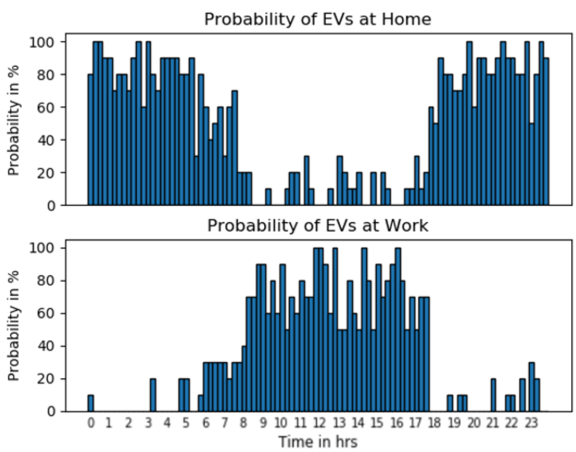


Figure 4.2: Probability of EVs at Home and Work

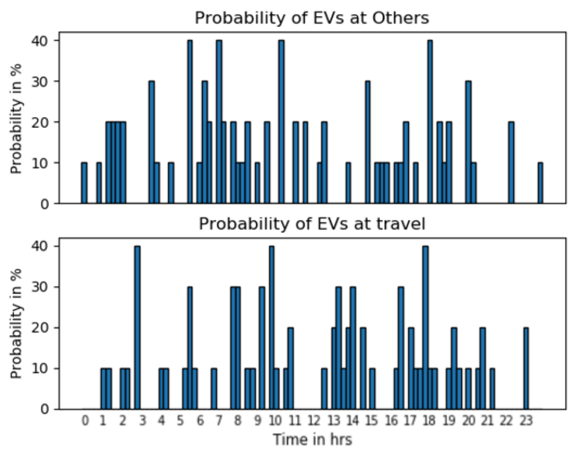


Figure 4.3: Probability of EVs at travel and Others

To numerically represent the accuracy of the pattern, mean square error determination can be used as a tool. This compares the value of two data sets and determined the percentage of deviation or error between the two samples. Here, the data set from [42] is used as the reference data and the pattern generated using the travel model specified here is compared with the reference data. The deviation is recorded for every time step and for several EVs and the only the maximum deviation is represented to discuss the accuracy of the model. The root mean square deviation can be expressed by means of equation 4.3:

$$RMSD = \sqrt{\sum_{t=1}^{T} \frac{(x_{1,t} - x_{2,t})^2}{T}} \tag{4.3}$$

where T is the length of the dataset, $x_{1,t}$ and $x_{2,t}$ are the value from the respective datasets at a time step t. Since the datasets are time relative, they are considered as time series values. For every time step, the respective value from two time series are compared and the root mean square deviation is calculated. This is calculated for both the models that are discussed in section 4.2 and section 4.3. Doing this also enables to evaluate the improvement in accuracy between the two models. While comparing time series data between the reference and the generated dataset for the model which does not consider time as a function, the maximum deviation that occurred between them turns out to be 52.04%. This means that there is an error of 52.04% between the reference and generated pattern. This shows the model is highly inaccurate when it is not considered as a function of time. Similarly, the maximum deviation is calculated after developing the model as a function of time and the result shows that the error percentage is around 28.87%. The error percentage has almost halved in the final model compared to the previous model, proving the improvement of accuracy with the model discussed in section 4.3. This error percentage is still high, but it has to be noted that the reference pattern does not have any specific assumption considered in generating the travel pattern. It is the data collected from randomly chosen vehicles, while there are several assumptions considered in the generated travel model. The assumption of EVs users working on night shifts, travelling between work places and transition to other location during its travel from Home to Work has created a major impact on the accuracy of the model. Hence, the model seems to be closely accurate when the assumptions are included in the reference model or when the assumptions are removed from the generated model. This proves that the model is realistic and is closely related to the real time travel pattern.

4.5. Travel Model Implementation

When the markov model is done predicting the location, the SoC of the EV batteries is recorded. The SoC of the EV is recorded before the start of the trip, after the end of the trip and whenever the EV is connected to the charging pole. The speed of the vehicle during the trip cannot be recorded as there is no communication with the EVs during travel. Hence, for simplicity, average driving speed of vehicles in the Netherlands is considered [43]. The average driving speed is considered based on the data collected from vehicle travel on Dutch roads. It is based on the travel of the vehicle in various locations (rural/urban) and it also considers the time of travel. According to [43], the average speed of the vehicle is estimated to be 70.8 km/h ±12.6 km/h before 9:00, 72.1 km/h ±11.5 km/h between 9:00 to 16:00 and 65.8 km/h ±22.1 km/h for the trips after 16:00. Considering these values, the approximated average speed of the vehicle on any given day and time is estimated to be 70 km/h. This value is considered in the simulation of the travel. The distance travelled is calculated using this average speed and the time taken for the trip. Since each step represents 15 minutes, when the state transition happens in the current time step compared to the previous time step, the travel duration is considered to be 15 minutes. Similarly the travel duration is calculated for all the EVs depending on its state transition step. The capacity of the EV battery depends on the manufacturer and the model of that specific EV. To create a more realistic scenario, seven different EVs with different capacities are used [44] [45] and it is shown in 4.1. These

EVs are from different manufacturers which also suits a more realistic situation. Simulating with different EV battery capacities also provides a basic understanding on the influence of battery capacity on voltage regulation to the readers and experimenters. When an EV is connected to a bus, the bus has to acknowledge the availability and it should be communicated to the neighbouring buses. To communicate the availability of EVs to the distribution system, an availability matrix is created. When the EV is connected to the charging pole and available for voltage regulation process, the value is updated as one in the availability matrix for the corresponding EV for the corresponding time step. If the EV is not connected, then the value is updated as zero. When the value is one, that particular EV is taken into account for the voltage regulation process. Whenever the value is zero, which may be due to travel or disconnection of EV from the charging pole, the EV is automatically removed from the regulation process.

Model	**Battery Capacity**	**Driving range**
BMW i3	42 kWh	345 km
Nissan Leaf	30 kWh	160 km
Tesla S 60	60 kWh	275 km
Tesla 3	75 kWh	496 km
Tesla S 85	90 kWh	360 km
Kia e-soul	39 kWh	277 km
Mercedes B	28 kWh	136 km

Table 4.1: EV model and battery specifications

When the EV is parked in a different destination other than home, it is connected to a different charging pole and hence a different bus. This is simulated in such a way that, when the vehicle is connected at a different place, the bus in which the EV is connected, is changed corresponding to its connection. This is done by dynamically changing the location of the bus of the corresponding EV during the simulation. Since the location of parking is chosen randomly based on the work location, there is a possibility of multiple EVs being connected to a single bus or no EVs connected to a bus.

When the EV is parked in an intermediate location, like a super market or a movie theatre for example, then the EV is assumed to be not connected to the charging pole. In these cases, the value of the corresponding EV is updated in the availability matrix and to process that in the simulation, the EV is made to be out of service. The process is the same when the EV is in travel. The charge or discharge cycle is selected based on the voltage level of the bus to which the EV is connected. When the voltage level of the bus is within the acceptable upper and lower limits, the EV begins to charge. The EV charges also in cases where the voltage level is higher than the required levels. If the voltage is less than the required level due to decrease in generation or increase in load, the EV battery discharges to help the voltage get back to its acceptable levels. By this way, the charging can take place without loading the lines excessively and can also support in regulating the voltage. Both charging and discharging takes place only if the SoC is within its limits to prevent overcharge or deep discharge. The availability matrix, location of the EV and its SoC is updated for every time interval for the EVs connected at all the nodes in the distribution network.

5
Voltage Regulation on Distribution System

This chapter explains in detail about the voltage regulation process implemented under different scenarios on the distribution system using EVs. Section 5.1 explains the flow of the algorithm for voltage regulation. Section 5.2 explains the experimental scenarios carried out to test the effectiveness of the voltage regulation algorithm. Finally, section 5.3 represents the effect of multiple EVs being connected to a bus and the network.

5.1. Algorithm for Voltage Regulation

The process of voltage regulation on distribution system using electric vehicles involves a lot of sub processes and several conditions in those sub processes. Based on the result derived from each condition, the algorithm chooses the direction of flow of the process. To present a easier and detailed explanation of the process flow, an algorithm is created and is shown in figure 5.1. The data used in this research is of 15 minute time steps and hence there are 96 time steps in total.

1. The process starts from 0^{th} time step.
2. After initializing the time step, the location of the EVs is updated. For this purpose, Markov model is executed, which predicts the current location based on the previous location and the time step. The location obtained from the Markov model is communicated and the bus to which the EVs are connected is estimated.
3. Using this data, the EV destination and the availability matrix is updated.
4. The SoC values of all the EVs at that time instance is scanned and updated.
5. Taking the SoC value of all the EVs, consensus algorithm is executed by initiating the communication between neighbouring buses. Based on the SoC of all the EVs, the average SoC of EVs connected is calculated.
6. To adjust the contribution of EVs based on its capacity, weight factor is calculated. This is calculated for all the EVs. This ensures a equitable contribution of all the EVs based on the capacity of the batteries. The battery with higher capacity can contribute more compared to the contribution of a battery with lower capacity. To calculate this factor, the capacity of the EV battery is compared with the average capacity of all the EVs connected in the system. The mathematical representation of weight factor is represented

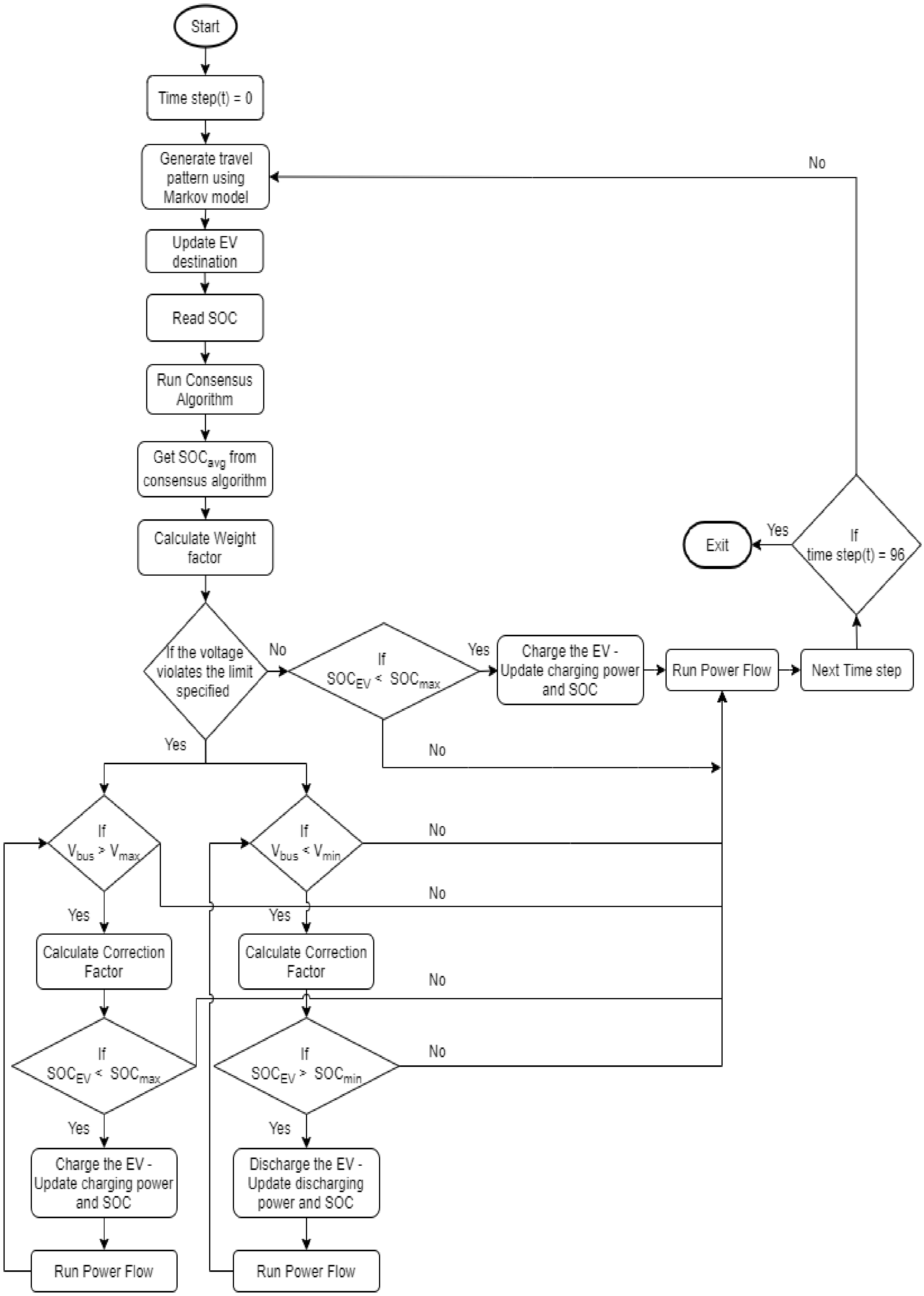


Figure 5.1: Algorithm for Voltage Regulation

in the equation 5.1. At the start of every time step, the algorithm scans every bus to estimate the EVs connected in those buses and the availability of each EV is updated in the availability matrix. If some EVs cannot be read in any of the buses, the availability of those EVs are made to be zero.

$$WF_i = 1 + (\frac{Capacity_i - Capacity_{avg}}{Capacity_{avg}}) \tag{5.1}$$

7. After calculating all the necessary variables, the voltage of the buses is checked for its safe operating levels. In this step, voltage threshold limits are specified. These limits are slightly inside the voltage tolerance limits of the system, so that a small voltage violation from the threshold limits does not lead to the violation of the tolerance limits.
8. If the voltage is within the threshold limits and the EVs connected to the bus are not charged completely, then the EVs start charging.
9. After every charge cycle, power flow calculations are executed and the voltage limits are checked before it enters into another charging cycle.
10. If the voltage is not within the threshold limits, the first check is whether the voltage is violating the upper or lower threshold limit. Based on the outcome, the EVs enter into a charge or discharge cycle.
11. When the voltage is higher than the upper threshold limit, it means that there is excess generation or less load in that particular bus. Hence, the excess power has to absorbed or used elsewhere. Here, that is used for charging the EVs connected to the bus.
12. Before starting the charging process, the contribution is adjusted based on the SoC level of the EV comparing it with the average SoC obtained from the consensus algorithm.
13. If the EV is not completely charged, the power that has to be supplied to the EV is updated using all the variables calculated before and the EVs are charged with that power.
14. Power flow calculations are executed after every cycle and the voltage levels are checked again. This loop runs until the voltage is brought back to the limits.
15. On the other hand, if the voltage level is less than the lower threshold limit, the EVs connected in the bus will discharge to recover the voltage. For this, the correction factor is calculated for every discharge cycle and the discharge power and SoC values are updated.
16. After discharge, step 14 is repeated.
17. When the voltage level in all the buses are brought back to its limits, the voltage level of the buses are updated through the power flow calculations. Then the flow proceeds to the next time step.
18. This process flow continues for all the time steps and when it reaches the 96$^{\text{th}}$ time step, the program exits the loop.
19. Here, it exits the loop because the range is specified to be one day. If this algorithm has to be executed every day continuously, then the time step is reset to zero when it reaches 96.

The flow mentioned in figure 5.1 is just one possible method of utilizing the EVs for voltage regulation. Apart from this, there are other ways to use the EVs as well. If the EV is considered to have an inverter, the EV inverter can be used to regulate the voltage by utilizing both the active power and reactive power from the inverters. The active power can be absorbed from the network when the voltage is beyond the upper limit and reactive power compensation can be used when the voltage goes below the specified range. While this method seems more appropriate, this might require a reactive power control to moderate the flow of reactive power. The inverter has to be a self commutated inverter as the line commutated inverter does not produce high reactive power. Effecient design of inverter is required since there will be an interaction with the grid. And the reactive power capacity is different for different inverters. This capacity is not high compared to the active power capacity of the inverter. This poses a limitation on the amount of reactive power that can be utilized for voltage regulation. Hence, considering the safety of the system, this method is not used here.

5.2. Experimental Scenarios of Voltage Regulation

To test the effectiveness of the voltage regulation algorithm and to examine the effect it has on the EVs, two different scenarios are implemented. These scenarios are selected mainly to observe the changes in the voltage profile of the distribution system and the state of charge of the EVs under different conditions. The main motive of observing the changes in two different scenarios is to choose a new scenario which is most suitable for both the distribution system and the electric vehicles. The scenarios that are considered to evaluate the performance of the voltage regulation algorithm are:

- Scenario 1 - Voltage level maintained close to the optimal level of 1 p.u.
- Scenario 2 - Voltage level maintained less than the optimal level (less than 1 p.u.)

Scenario 1 is to test the response of the EVs when the voltage level of the network is provided the utmost preference. In this scenario, the voltage level of the network is not compromised and the effect this has on the electric vehicles is recorded and the short comings are discussed. Scenario 2 is mainly to evaluate the changes on the distribution system and the EVs when the voltage level of the network is compromised a bit and made to operate in levels less than the optimal level. The goal of this scenario is to analyse the changes in the voltage and SoC levels compared to scenario 1 and to choose a direction of change for further improvement of the regulation algorithm. The aim of this entire procedure is to record the responses and changes during both the scenarios and to develop a better scenario suited for both the parties.

5.2.1. Scenario 1: Voltage near Optimal Level

In this research, EV batteries are used as a source for regulating the voltage when the voltage goes beyond acceptable limits. This is realized by charging the battery when the voltage level is higher than optimal and discharging the battery when the voltage goes below the tolerance limit. But at the same time, EVs are considered as loads in the system. Hence, the regulation process has to be carried out in a fair manner by not exploiting the battery too much and charging the battery to appropriate limits so that the EV owner is satisfied with the state of charge when the EV is disconnected from the charging pole. To ensure this, it is necessary to examine the response of the system when several EVs are connected to the network. To test the response of the system, three experimental scenarios are considered.

In the first scenario, efforts are made to maintain the voltage around the optimal level which is 1 p.u. So, whenever the voltage goes below 0.99 p.u the EV battery connected to that bus discharges and the battery charges when the voltage goes beyond 1 p.u. The simulation is performed by considering the travel pattern of all the EVs which are generated using the markov models for the entire day in 15 minute steps. Consensus algorithm is performed at every time step, through which the correction factor is updated for each time interval. The weight factor is calculated for each EV and is included in the power calculation.

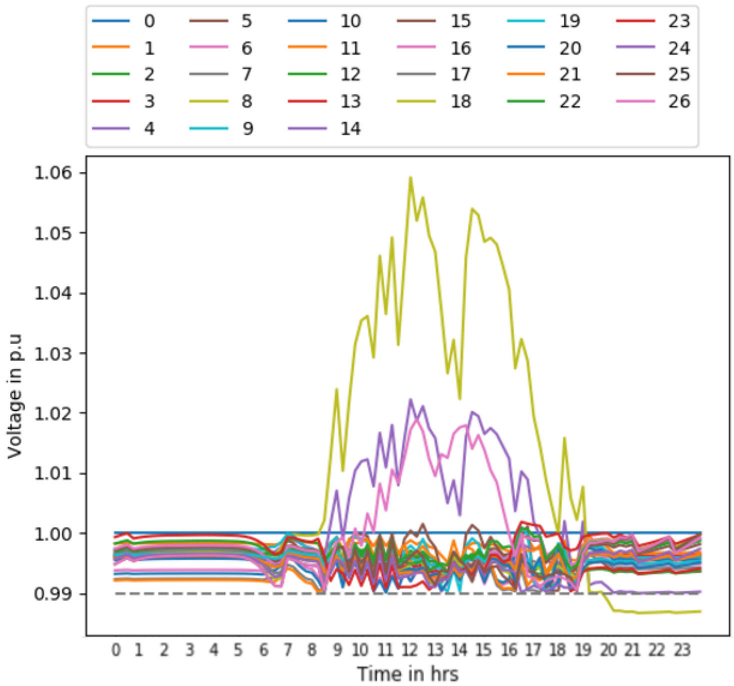
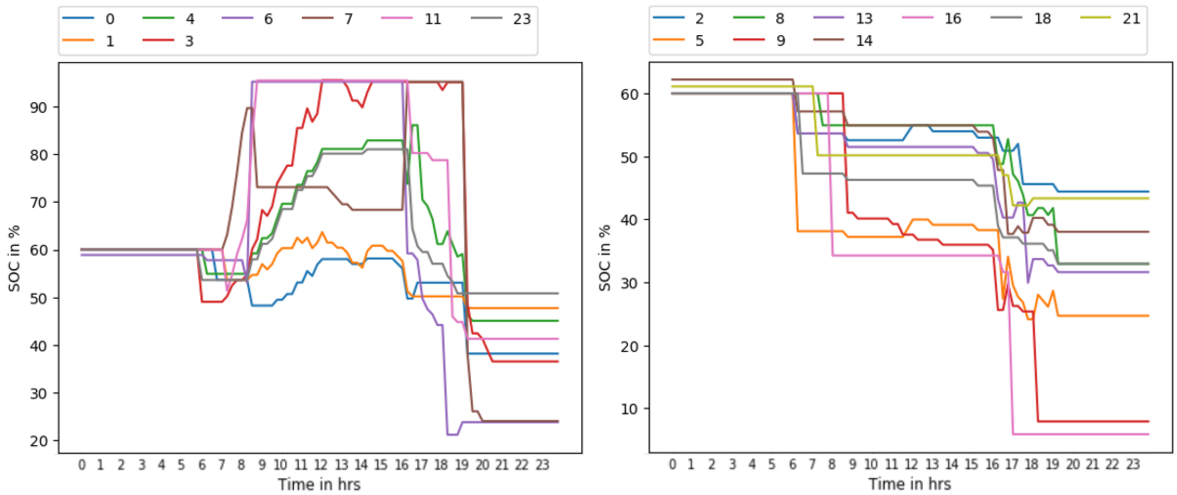


Figure 5.2: Voltage profile for scenario 1

The regulated voltage profile of the distribution network for the conditions considered in scenario 1, is shown in figure 5.2. It can be seen that, the voltage level of most buses are maintained between 0.99 p.u and 1 p.u. In few occasions, the voltage goes slightly below the lower limit. This can be due to two reasons. One is due to unavailability of EVs in that bus at that particular time instance. This can also be due to the charging of the EVs in the neighbouring bus. This will have an effect on the buses which are physically connected to it. This effect can be minimized with EVs that are available for discharge at that bus. The travel pattern generated here is close to the actual travel pattern of an individual and since the time parameter has been added in the markov model, the travel pattern generated here resembles a more realistic one. Hence the availability of EVs at a particular bus and number of EVs connected to that bus is completely random and it can only be represented as a probability distribution based on the location and time. So, when there are no EVs connected to a bus due to travel or other reasons, there is a possibility of not being able to regulate the voltage in that bus. In those cases, the control algorithm is designed to involve the EVs connected in the neighbouring buses to compensate for the unavailability of EVs in the bus considered. But this sequence happens only when the voltage level in the neighbouring buses are within acceptable limits. Hence, these EVs may help in compensating for the unavailability of EVs in the bus considered, but in some cases there is still a possibility that, it might not be enough to completely pull back the voltage within limits.

Regarding maintaining the voltage below the specified upper limit, it is quite difficult when a more realistic day is considered. The EVs are not stationary and the number of EVs connected to a bus changes during the course of the day. The PV panels are not connected to all the buses. Hence during high solar radiation, the buses which needs voltage regulation are the buses to which the PV panels are connected. So, to regulate the voltage in those buses, only the EVs connected to those buses and its neighbouring buses can be used. This provides a limitation for the amount of power that can be absorbed by charging the EVs. The other limitation is the SoC level of the EVs at that point of time and the maximum allowable SoC. If the SoC of the EVs connected is high, then it provides a limited space for the EV to charge itself to its maximum. For example, if the SoC of the EV battery is 60%, the battery can charge to a maximum of 35% to 40% more until it gets charged completely. So, when the EVs connected to the bus and its neighbouring buses gets charged to its maximum, then there is no other way to absorb the remaining power. Hence, if the generation is too high, the EVs can bring it back to the safe limits, but may not be able to bring back to the optimal level. This also means that, the EVs connected in those buses gets charged to higher value when compared to EVs connected in other buses.



(a) State of charge of charging EVs

(b) State of charge of non-charging EVs

Figure 5.3: State of charge plots for scenario 1

Figure 5.3a shows the SoC levels of several EVs connected to different buses in the distribution network. From this figure, it can be observed that, most EVs charge during the time interval between 10:00 and 16:00. This is the range when the solar power generation reaches its peak and hence the EVs has to charge to maintain the voltage within limits. It can also be seen that, EVs 3,11 and 23 charge more than the other EVs during that period. This means that those EVs are either directly connected to the buses where the PV array is connected or those are connected to its neighbouring buses. The EVs start to discharge during the time interval between 17:00 and 20:00. This can be due to two reasons. It might be the result of a travel that occurred during that time period or it might be due to the discharge caused as a response of charging of EVs in neighbouring buses. It has to be noted that, when the voltage in a bus is above the specified limits, the EVs connected to the bus charges. This will have an effect in its neighbouring buses. If the voltage level in the neighbouring buses is already low, then this charging creates a further decrease in the voltage and hence the EVs connected in those buses has to be discharged to regulate the voltage. A steep discharge curve seen in figure 5.3a, is the discharged performed to compensate the voltage reduction which was caused due to the charging of the neighbouring buses. The discharges that occurs between 6:00 to 10:00 are due to travel as there are no requirements of regulation during this period. In this case, the travel distances are short. It can be seen that, after several charge and discharge cycles, the SoC of most of the EVs settle around 35-50% at the end of the day. This is not the most suitable result, considering the charge/discharge cycles and travel. The SoC at the end of the day should at least be the same as that of the start of the day. Hence, compromise should be made on the voltage levels to satisfy the EV owners.

On the contrast to figure 5.3a, figure 5.3b shows that, almost no EVs were charged. For most of the buses, the voltage levels are already in the range between 0.99 - 1 p.u. So, when the EVs are connected to those buses, it cannot be charged because of the conditions that are specified for charging. This creates one of the most serious and important questions about the process. Though the EV owners agree to lend their vehicles for voltage regulation, the main purpose of connecting the EVs to the charging pole is to charge the EV battery. Hence, the EV owners expect their vehicles to be charged when it is disconnected from the charging port. Uncharged vehicle results in EV owners withdrawing their consent and dropping out of the voltage regulation process. To avoid this, the voltage limits should be slightly lowered, to accommodate more power to charge the EVs. This denotes that, unless the generation is increased to compensate the loads created by the EVs, the voltage has to be maintained in below par levels.

5.2.2. Scenario 2: Voltage less than Optimum level

Scenario 2 is designed to facilitate better charging of the EVs by maintaining the voltage level marginally less than the optimal value. Despite EVs being used to support the distributed network, EVs are still loads to the network and it has to be charged. As observed in scenario 1, few EVs charge to a lesser value compared to the other EVs, while maintaining the voltage of the network around 1 p.u. Charging the EV battery is the primary purpose of EVs being connected to the charging pole from the EV owner's point of view. Hence, to charge the EV batteries, the voltage level of the buses has to be compromised, to satisfy the EV owners along side the voltage tolerance limits.

To realize this scenario, the conditions are designed such that, the EV charges when the voltage of the bus is higher than 0.99 p.u and discharges when the voltage goes below 0.98 p.u. This gives a moderate space for the EVs to charge compared to scenario 1. This scenario is intended to test the improvement in charging level of the EVs with the voltage limits relaxed to a certain extent. The voltage profile of the distribution network for the conditions considered in scenario 2 is shown in figure 5.4. Similar to scenario 1, the the unavailability of EVs at that point of time in specific buses has resulted in voltage level violating the lower threshold level on few occasions. It has to be noted that, the unavailability of EVs in buses tends to have a higher effect, as the lower threshold limits are reduced. This can be validated by comparing it with scenario 1. The EVs can draw more power from the network with the limits being lowered. This means that, the charging of EVs in a bus will have more effect on the neighbouring buses with no EVs connected to it. As the charging increases, the voltage level of the neighbouring bus will continue to decrease along with the voltage of the bus at which the charging is taking place. With no EVs being connected to the neighbouring bus, a complete regulation of voltage in that bus cannot be achieved. Hence any further decrease in the limits will result in increasing the effect caused by unavailability of EVs in the neighbouring buses.

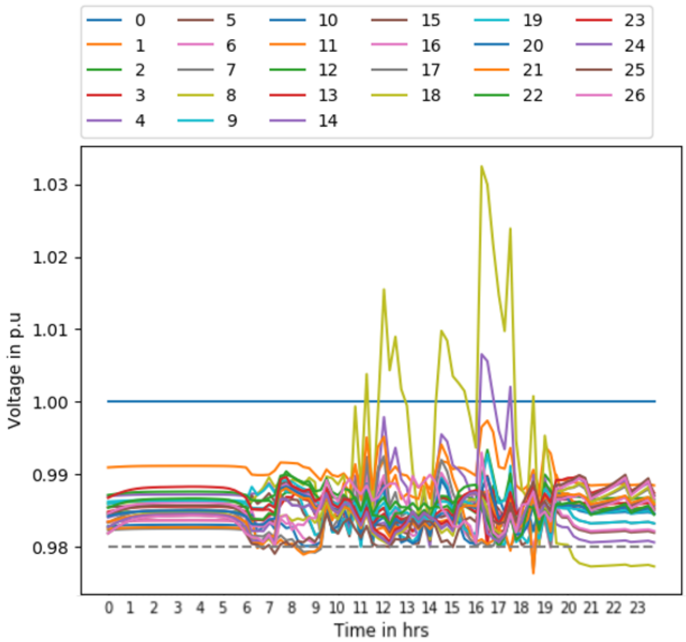
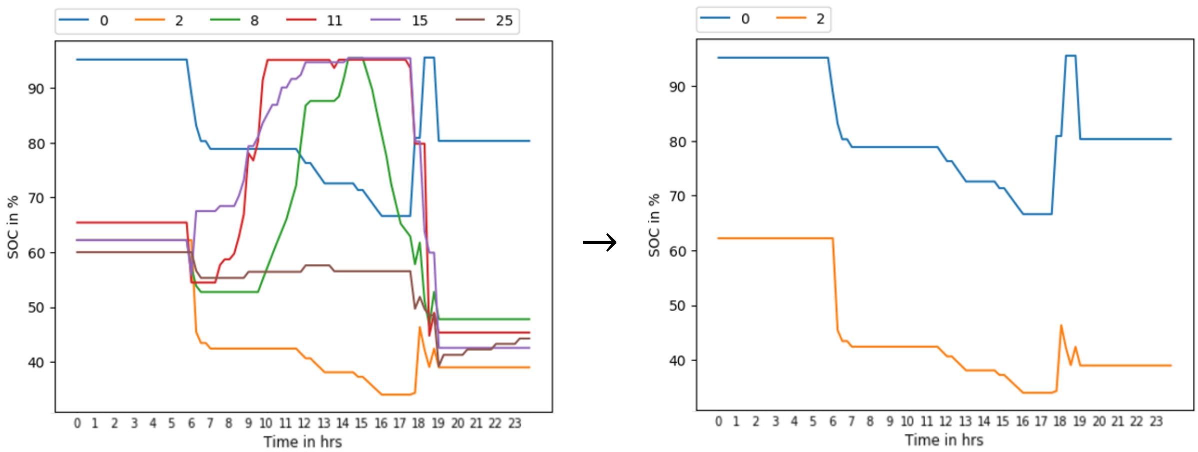


Figure 5.4: Voltage profile for scenario 2



(a) State of charge of charging EVs

(b) State of charge of EVs with the discharge effect

Figure 5.5: State of charge plots for scenario 2

In figure 5.5a, it can be seen that the SoC curves and charging patterns differ to a certain extent compared to scenario 1. While most of the EVs are charging between 8:00 and 17:00, EV 0 and 2 discharges during that period. This is the validation for the explanation provided above. As the voltage limits were lowered, the EVs had more room to charge compared to scenario 1. This has caused an increase in charging in the EVs that are connected to the buses with high voltage levels. As the EVs begins to charge, the neighbouring buses which has the voltage below the charging range, decreases. The EVs connected to it starts discharging to maintain the voltage level in those buses. This is the effect seen in EVs 0 and

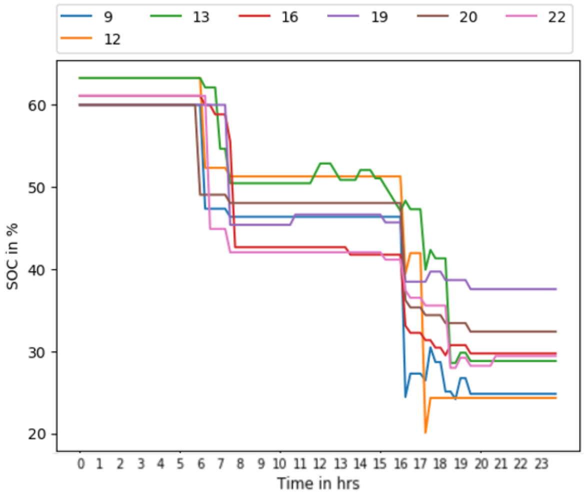


Figure 5.6: State of charge of non-charging EVs for scenario 2

2 and it is shown in figure 5.5b. It can be observed that the charging level has marginally improved compared to scenario 1. The EVs charges during high generation, while it also discharges to maintain the voltage level in the network. This creates an illusion of SoC being maintained in the same level, as the EV also discharges at different time steps. If the plot is observed carefully, the SoC of most EVs at the end of the day is closer to the SoC level at the start of the day. This denotes the discharge due to voltage changes in the network is less compared to the charging level. This increases the satisfaction rate among the EV owners as the SoC at the end of the day is more than or similar to the SoC at the start of the day. On the other hand, figure 5.6 shows the set of EVs that are uncharged or faintly charged throughout the day. The numbers are better compared to scenario 1, but it doesn't guarantee all EVs getting charged at least to its initial SoC at the end of the day. This scenario offers a sense of stability, but it might have a similar effect as scenario 1, motivating the EV owners to opt out the process. This provides enough information proving the fact that, even with voltage levels reduced, the system is not able to charge all the connected EVs.

5.2.3. Scenario 3

Scenario 2 was just an experiment to test the improvement in charging levels while the voltage limits are lowered. With scenario 2 having a positive effect on the charging profile, the voltage limits should be chosen in such a way to ensure the safe operating voltage levels in the system while facilitating charging of the EVs. Hence, a trade off should be made between the voltage level and charging level. Considering the effects of reducing the limits, that was mentioned before, the lower voltage limit is chosen to be 0.93 p.u. This value is chosen to ensure the voltage level being in safer limits despite EVs being unavailable in a bus. The charging starts with voltage level above 0.95 p.u and discharges when the level goes below 0.93 p.u. The space provided between the upper and lower limit is widened as compared to scenarios discussed before. When the limits are close to each other, frequent charge and discharge cycles was observed in figure 5.3a and 5.5a. This increases the number of cycles that the battery needs to encounter as the stress enforced on the battery increases due to the narrow range provided between the charge and discharge limits. According to [46], the battery life decreases with increase in cycle frequency. So, the cycle frequency should be kept to minimum. The frequency reduces if the limits are widened further. But any further increase in the charging limit will result in reducing the charging activity and any further decrease in the discharge limit might lead to the voltage dropping out of the safer limits. Hence these are chosen to be the optimal limits facilitating effective voltage regulation and EV charging.

Figure 5.7 shows the voltage profile for the conditions specified in scenario 3. This is similar to that of the scenarios discussed before. The important thing that has to be noted is the lesser number of fluctuations in the voltage profile compared to other scenarios. This shows that the stress to keep the voltage within limits in the system is less. This reduction in stress has resulted in a better regulation even during the periods of EV unavailability, as it can be seen that the voltage is above the discharge limits on almost all the occasions. Hence this scenario proved to be a better solution for the voltage regulation problem.

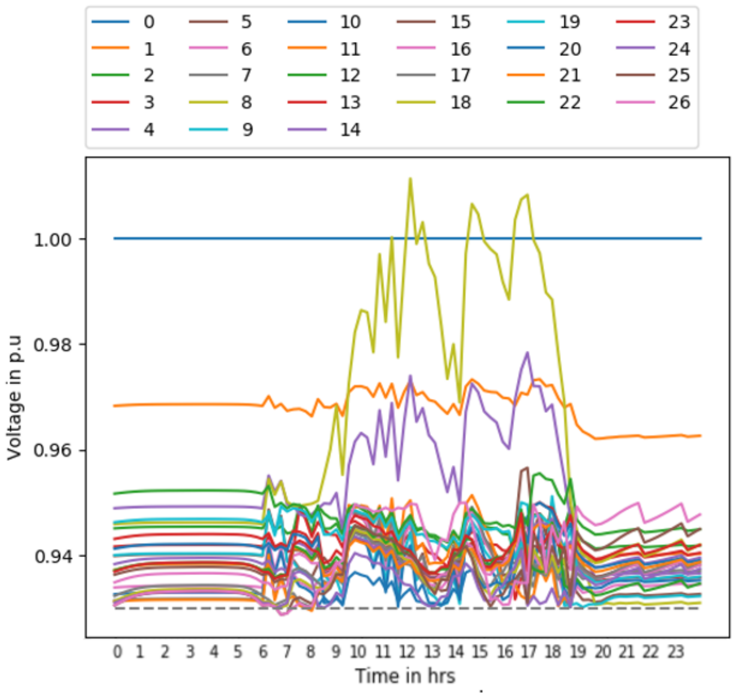
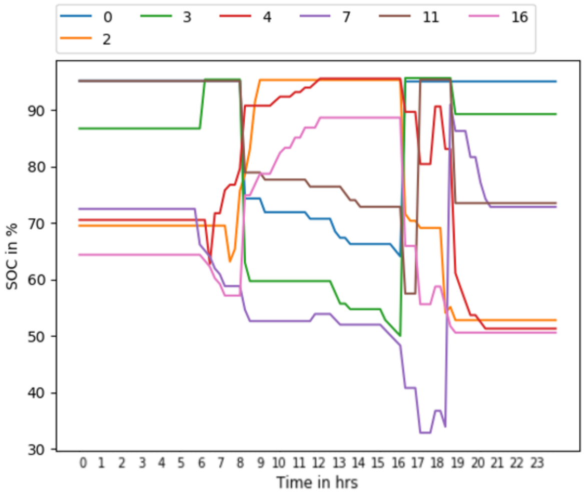
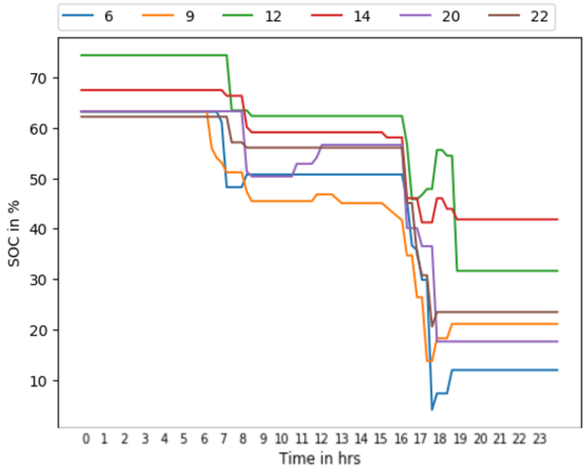


Figure 5.7: Voltage profile for scenario 3

In order to evaluate the effect of this scenario on the charging profile of the EVs, the SoC plots of the EVs for one complete day has to be analysed. Figure 5.8a and 5.8b shows the SoC plots of EVs connected to the system. In figure 5.8a, the cycle frequency is less as expected in this scenario. The SoC levels at the end of the day is higher than the level at the start of the day for most of the EVs. The SoC level is close to the initial SoC for few EVs. Hence this scenario has ensured better charging of EVs compared to other scenarios. The number of EVs that has been charged more than its initial SoC is also higher in this case. Taking everything into consideration, this is the best trade off between the charging level of EVs and safe operation of the distribution network. On the other hand, figure 5.8b shows that, few EVs still remain uncharged or charged to a marginal amount. This simulation is just for a single day. Since the pattern looks comparable, the influence of multiple EVs connected in the network is tested to show the effect of increasing the EVs connected to the network.



(a) State of charge of charging EVs



(b) State of charge of non-charging EVs

Figure 5.8: State of charge plots for scenario 3

5.3. Effect of increasing the population of Electric Vehicles

The outputs obtained so far is by considering that the there are 26 EVs connected to the network and each EV has a different bus as its home location. This means that when all the EVs are parked at home, each bus will have exactly 1 EV connected to it. Now, to test the response of the system when there are multiple EVs connected to a bus, each bus is assumed to be the home location for 2 EVs and hence there will be 2 EVs connected to a bus when they are parked at home instead of 1. Hence, the total number of EVs is twice as that of the number of buses in the network. As discussed earlier, the EVs changes their location during the course of the day and hence the number of EVs connected to a bus changes with time. In order to test the behaviour of the system with higher number of EVs, the voltage regulation algorithm is executed under similar scenarios as mentioned before. This makes it easier to compare the changes occurred in the system and in the charging of EVs with the model explained before. To compare the regulation and charging of EVs, the conditions used in scenario 3 is considered here. The voltage profile of the network considering the conditions mentioned above is shown in figure 5.9.

It can be observed that the voltage stays closer to the upper and lower limits when compared to the voltage profile in figure 5.7. This is made possible as there is a possibility of multiple EVs being connected to a bus at an instant of time. This means that there are more batteries to absorb the excess generation and to discharge in case of lower generation. This makes the scenario more suitable for distribution system when the voltage level of the system has to be strictly maintained between the specified upper and lower limits. The regulation will be better with increasing number of EVs, when the voltage regulation is given higher preference over the SOC level of the EVs. This might be the better scheme for the network, but situation of EV charging should also be given attention, as voltage regulation is only the secondary purpose of the EV batteries in this research. To examine the performance of EV batteries in this case, the SOC plot of all the EV batteries is observed. Since there are more than 50 EVs connected to the network, only the SOC of highly affected EVs is plotted and it is shown in figure 5.10.

Here, it is evident that most EVs do not charge while being connected for charging. This

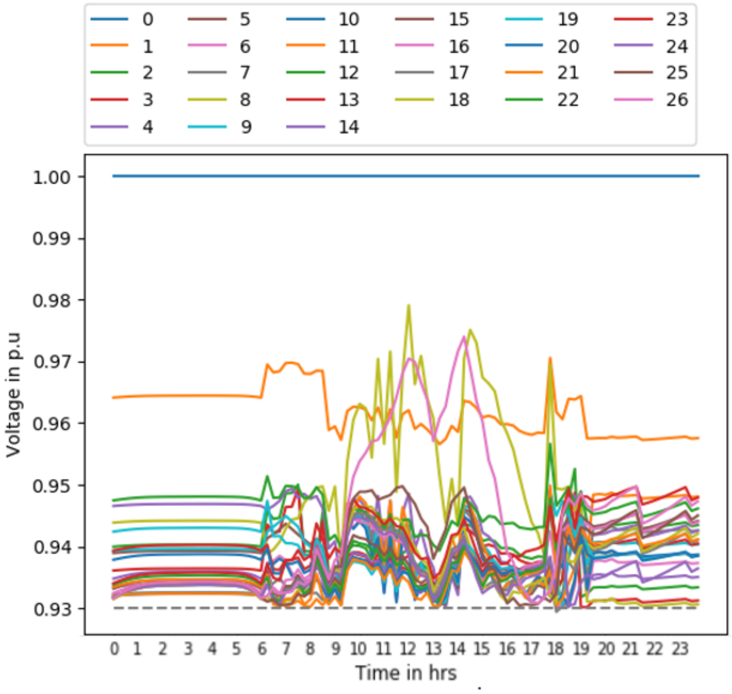


Figure 5.9: Voltage profile for the scenario with multiple EVs

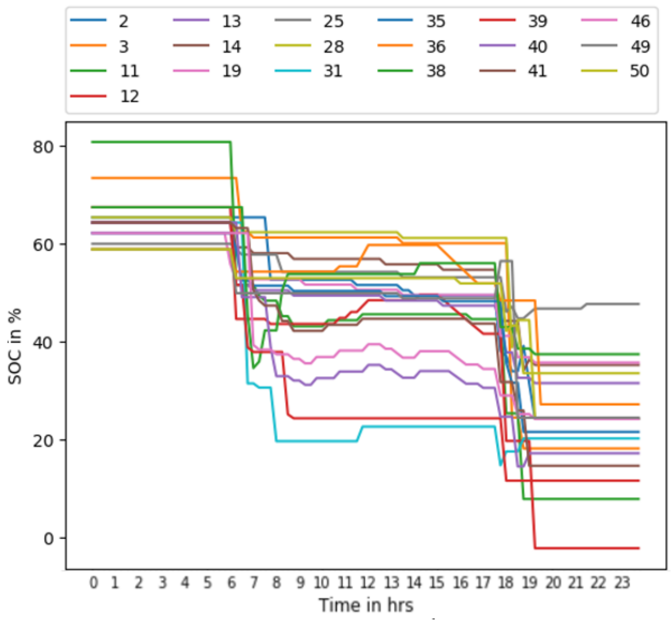


Figure 5.10: State of Charge plot of the most affected EVs

happens when there are multiple EVs connected to a bus. When multiple EVs are connected to a bus which does not have a really high voltage level, then there is a high possibility of one EV getting charged to a higher level while the other remain uncharged or several EVs getting charged to a lesser value. While few EVs are charged, majority of the EVs mentioned in figure 5.10, remains uncharged or gets charged to a minimal amount. Hence, the SOC level at the end of the day is less than the SOC at the start of the day. Even with the discharge due to travel being considered, the EV users expect their vehicles to be charged as they are connected to the charging pole for the major part of the day. So, this fails to provide a balance between the voltage level of the system and the SOC level of the EVs. But this also provides a realistic scenario. As the number of EV users are gradually increasing, there is a higher chance of more users participating the process which in turn results in multiple EVs being connected to a bus. Hence, a solution has to be proposed to avoid these kind of problems in the future.

This shows that in every scenario there are few EVs which remain uncharged throughout the day. Only the number of EVs being uncharged differs in every scenario. If this activity is prolonged for several days, the number of EVs participating in the regulation process steadily decreases. This completely negates the motivation of the EV owners to continue to involve their EVs in this process. In order to overcome this limitation, financial compensation should be provided to the EV owners to based on the charging profile of the EVs. This financial compensation should be based on the SoC at the start of the day, discharge caused by the travel, travel distance, time duration of its connection to the charging station and the SoC at the end of the day. The compensation will be based on the difference between the initial SoC and SoC at the end of the day, in cases of no travel occurrence on a particular day. There will be no compensation provided, if the final SoC is equal to or greater than the initial SoC. Even with this financial compensation scheme, choice should be given to the owners to choose the days and time during which they want to participate in this process. For example, user wishing to travel long distances during weekends, might want to charge the vehicle to its maximum, to avoid any stoppages for charging during the travel. And this also means that, the EV will not be available during the weekend. This flexibility increases the trust among the users and helps in motivating other EV owners to take part in the process. At some stage, offering flexibility might lead to a situation of total unavailability of EVs for voltage regulation. This is not the ideal situation for the DSOs. So, the number of EVs registered in the process should be increased while offering flexibility, which should be more than the amount of EVs that are required at a specific point of time. This provides options for the DSOs in cases of unavailability of majority of the EVs. There is also a limitation in this case. As the number of EVs increases, the number of EVs that remains uncharged increases. In this case, the DSOs has to choose the EVs based on the requirement while the other EVs should carry on with their usual charging. This is just one possible approach to overcome the limitations in the model. If the structure of the algorithm is optimized by adding more conditions for charging and voltage regulation, it might completely eradicate the limitations or might provide better solutions to overcome the limitations.

6

Uncertainty Analysis

This chapter describes the approach undertaken to improve system robustness against the uncertain availability of the EVs. Section 6.1 provides an overview on the approach used here. Section 6.2 describes the stay probability of the EVs in the network. Similarly, section 6.3 explains the transition probability of the EVs. Finally, section 6.4 evaluates the probability of EVs connected in different buses.

6.1. Monte Carlo Simulation

In this research, the process of voltage regulation is executed using the electric vehicles. The EVs can only be utilized when it is connected to the charging pole. Hence the certainty on the availability of EVs at any time instance cannot be guaranteed. The behaviour of EVs differ which affects their availability for the process. The Distribution system operators(DSO) don't have enough information about the availability of EVs and this creates an issue during the longer run. This information will be helpful in arranging a backup or a spinning reserve in cases of unavailability of the EVs. For this purpose, information about certainty of occurrence of a particular event becomes a necessity. It is not possible to predict the future with absolute precision and accuracy, but information on probability of occurrence of an event will be helpful in preparing the system and the operators for the upcoming time step. This helps in making the system robust for changes and also helps in preparing for the changes. Hence to obtain a degree of certainty, monte-carlo simulation is used. This is a simulation method that is used when there are uncertain parameters in the system that has to be analysed. This helps in providing a probabilistic estimation of uncertainty in the model [47]. Monte-carlo simulations can be used to improve the robustness of the system by providing a level of surety in a system with uncertain parameters which has also been proved in [48]. Here, the uncertain parameter is the availability of EVs. In other words, information on the probability of EVs being connected to a node at a specific instance of time is a scarcity. As the day progresses, the number of EVs connected to a node changes. With the knowledge of the change pattern or the probability of change, it is possible to predict the outcome in a system with extreme events. Monte-carlo simulations provides a set of possible outcomes based on the decision taken, which can be used to analyse the uncertainty and make better decisions during uncertain events. One of the reasons for using monte-carlo simulations in this research is to provide a perspective of possible outcomes and let the user make a decision, instead of providing a binary result. There are no constraints to this method, and there are no constraints to the data that has to be simulated [49]. This makes it more suitable for this analysis. To predict the availability of EVs, the probability of transition between locations, probability of stay in a particular location and probability of EVs connected to bus has to be examined. Hence monte carlo simulations has been executed to determine all these important information from the system. The simulation is executed for 100 iterations for each and every time step and for all the EVs. This facilitates in generating a more stable probability distribution pattern.

6.2. Probability of Stay

Figure 6.1 shows the probability of EVs being in a certain location at a specific instance. As discussed earlier, there are 4 locations considered here. Home, Work, Others and Intermediate. Here, it can be seen that, from 20:00 to 6:00 the probability of the EVs being at 'Home' is nearly 80%. This means that there is higher chance for the EVs to be connected to its initial location during these time period. Since the initial assumption is each bus having at least 1 EV connected to it, the probability is high for 1 EV being connected to the bus during these time steps. Since the probability is high here, the availability of EVs is not a problem in this case. The probability of being at work, other places or in an intermediate position is low in these time steps. It is evident since these are the time periods late at night and early in the morning. The probability of the EV travelling or being at work will be less during these times.

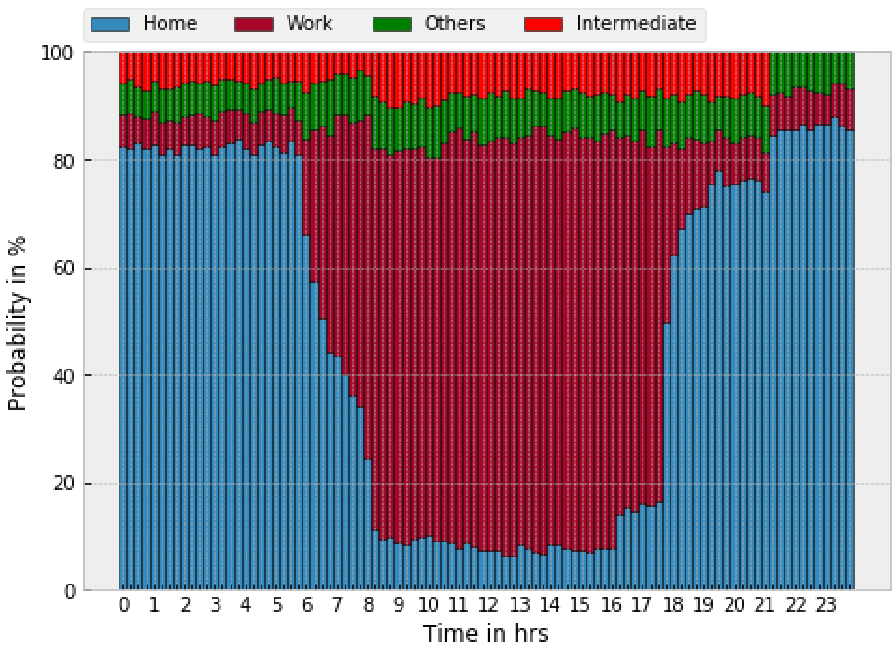
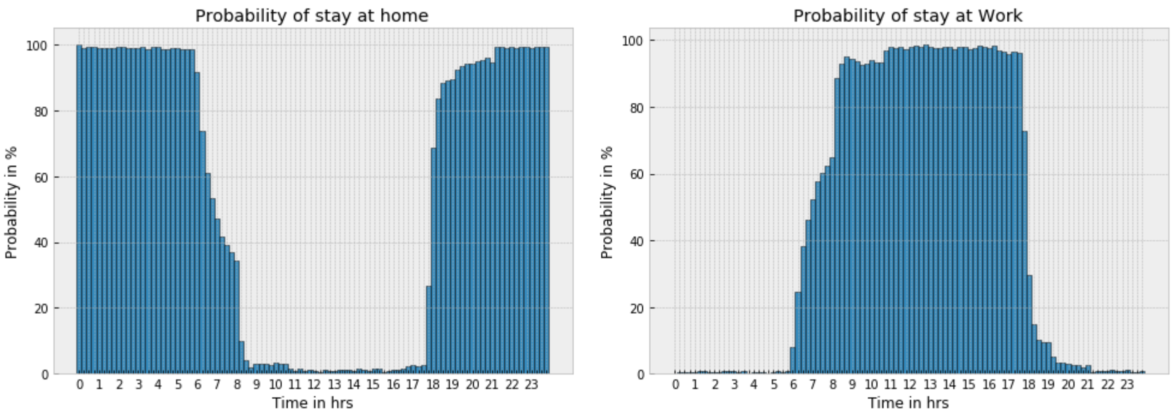


Figure 6.1: Probability of EVs in a certain location

Similarly, the probability of EVs being at work is high between 8:00 and 17:00. This high probability is mainly because of the assumptions considered in this research. Hence, after reaching the work place, the users tend to park their vehicles connected to a charging pole until they leave from work. This makes the EV available for voltage regulation in the buses to which the EVs are connected. But this probability does not mean that the EVs are equally distributed among all the buses. This does not guarantee high probability of availability of EVs in every bus. The distribution differs when the EVs travel away from home. Especially at a work location is considered, there can be many EVs connected to a bus or there can be no EVs connected to a bus. So, this high probability only denotes the EV availability in several buses and not the entire system. In the buses with multiple EVs, the regulation will be better, but it might also result in few EVs not getting charged to an appropriate amount.



(a) Probability of stay at home

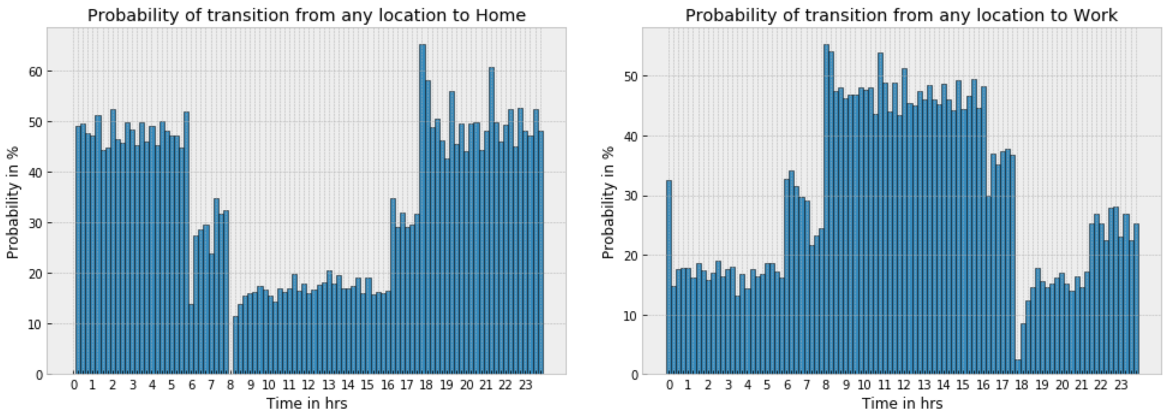
(b) Probability of stay at work

Figure 6.2: Probability of stay

Figure 6.2a and 6.2b denotes the stay probability at home and work respectively. This is not the same as that of figure 6.1. Figure 6.1 shows the probability of EV being in a certain location at a particular time step where the previous location is different from the current location. Whereas, figure 6.2a and 6.2b shows the probability of stay at home and work respectively where the current location is same as the previous location. So, this explores the probability of EV staying in a location at consecutive time steps. This provides a sense of certainty on the availability of EVs based on the previous and current state. In figure 6.2a, the probability of stay at home is nearly 100% during late night and early morning. This shows that, when an EV arrive home during this time period, the chances of staying in the same location is high. Similarly in figure 6.2b, the probability of staying at work is high in the morning till afternoon when it is already at that location. This is most often true, since the vehicles remain parked when the EV users are at work.

6.3. Probability of Transition

On the other hand, to examine the presence of EV at a particular time instance, it is important to analyse the time instances of transition from and to a location. This will provide information on the most probable time instances for EV transition. Figure 6.3a shows the transition probability from any location to home. The transition probability is around 50% from 12 AM to 5 AM. This signifies that there is a 50% chance for the vehicle to return home during these time period when it is in any other location in the previous time step. This result mainly arises due to assumption of few EV users working in shifts and hence they would be travelling back home, early in the morning. It has to be noted that, this transition probability is calculated only when the previous state is different from home. The probability of travelling back home is less during the afternoon, as the vehicle will be parked at work or will be travelling between workplaces. In figure 6.3b, the probability of vehicle going to work is around 50% in the afternoon. This value signifies that, once the vehicle reaches the work place, the probability of vehicle staying there is high as seen in figure 6.2b. In all the other time steps, the probability of transitioning to work is low. The transition to home occurs mostly when the vehicle returns back from work. Most vehicles travel back from work in the evening and this is validated by the higher probability of transition in the evening. These are the time periods which has to be noted, as this reduces the uncertainty on the availability of EVs.



(a) Probability of transition from any location to Home

(b) Probability of transition from any location to Work

Figure 6.3: Probability of transition

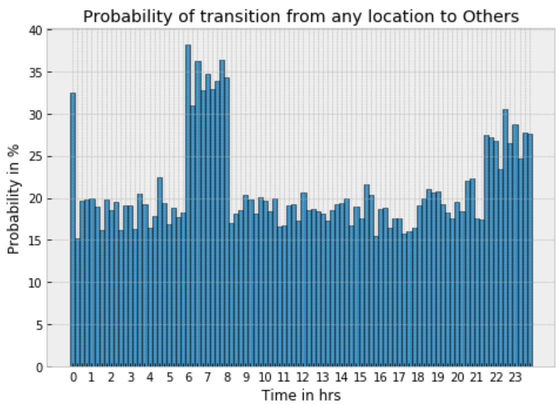


Figure 6.4: Probability of transition from any location to 'Others'

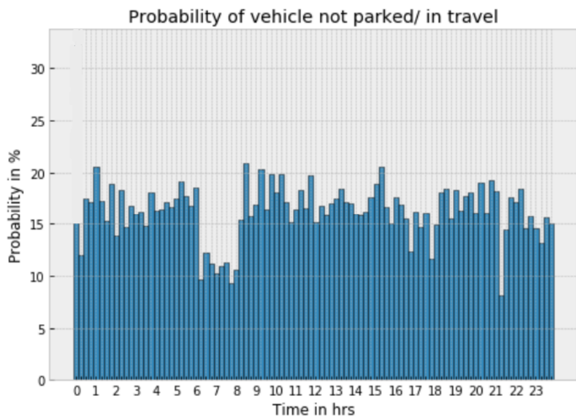


Figure 6.5: Probability of travel

Similarly, the transition to locations other than home and work are also recorded and is shown in figure 6.4. This probability is less than 40% throughout the day as it completely depends on an individual EV user and very rarely occurs in a narrow time instance. The probability is around 35% between 6 AM and 8 AM, as the transition might happen during the travel from home to work. It has be noted that, the EVs will not be available for regulation during this transition and also when it is parked in the location other than home or work. Figure 6.5 shows the probability distribution of vehicles during their travel. In this analysis, it is said to be in an intermediate position. Here, the probability is calculated whenever the EV is in an intermediate position. This probability depends on the distance and time of the travel. Since the time difference between two consecutive time steps is 15 minutes, the probability on consecutive time instances will be high only during long distance travel. Similarly, the probability of an EV being in the intermediate state increases with increase in travel distance. The even distribution of probability denotes that the transition does not happen with multiple EVs at the same time instance. It can be approximated that, when 10 EVs are considered, there are chances of 2 EVs being in travel at a time instance. This provides a view on the possibility of a vehicle being in travel at any time step.

6.4. Probability of connected EVs

After analysing all the necessary behaviour of the EV travel, it is also important to examine the probability of EVs connected to a bus, as all the previous analysis leads to this question. To evaluate this, three different cases are considered. Each bus will have a different probability distribution and it is important to discuss all the distribution patterns that occurs during a day, using monte carlo simulations. The first case of probability distribution is described in figure 6.6. Here, the probability of having at least 1 EV connected to bus 5 is high during non-working hours and low during working hours. This shows that the EVs connected to this bus, travels and gets connected to another bus during work hours. Hence, violation of voltage during work hours becomes hard to regulate as there the EVs might be unavailable for regulation for a sufficient amount of time. This provides the reason for the voltage not being regulated completely in the scenarios discussed in chapter 5. Absence of companies or workplace in bus 5 can be the practical reasons for the low probability of available EVs during work hours. On the other hand, the probability of available EVs is high during work hours compared to non work hours in figure 6.7. This shows that more EVs are getting connected to this bus during work hours. These distribution curves are just a representation of one weekday. This high probability provides a higher chance of charging the EVs when the voltage is high and higher chance of recovering the voltage levels when the voltage is below tolerance limits. This probabilities just represent the probability of EV being connected to a bus. But, the EV being available for voltage regulation depends on the SoC level of the EVs connected.

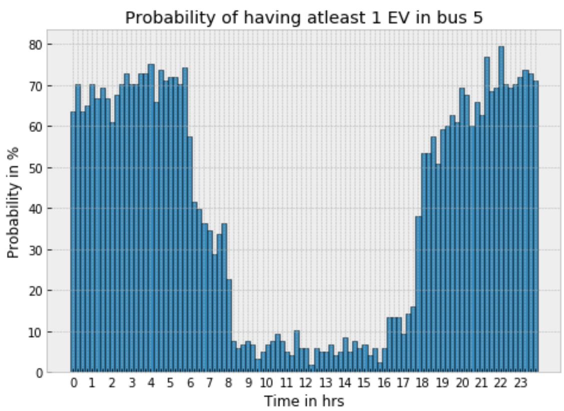


Figure 6.6: Probability of EV availability in a bus (Case 1)

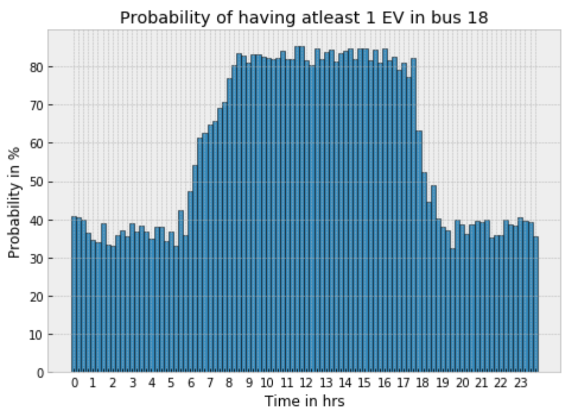


Figure 6.7: Probability of EV availability in a bus (Case 2)

If there is an entrepreneurial area in a city, there is a high probability of vehicles being there throughout the day. This kind of situation is represented in the figure 6.8. Here, it can be seen that the probability distribution is spread out equally in all the time steps. This denotes the replacement of one EV by another in a bus during travel of an EV. Hence, at least one EV stays connected to that bus at most times, resulting in high probabilities. Voltage regulation will be better in this case, while it also reduces the probability of the EVs getting charged to its maximum. These probability curves gives an in-depth analysis on the availability of EVs at different time instances and at different buses. This helps is providing a level of certainty in a system with uncertain parameters. This in turn predicts the occurrence of several events, thus making the system more robust.

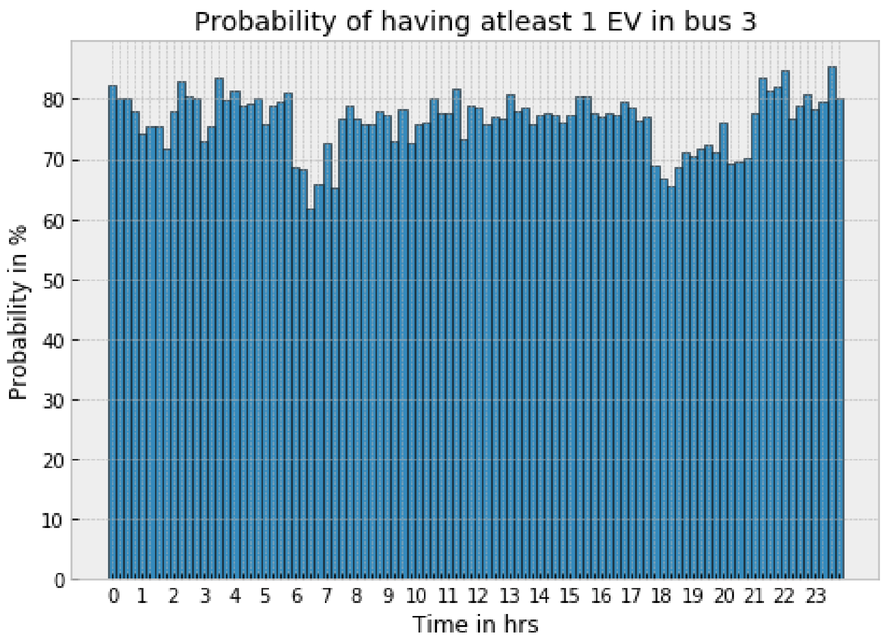


Figure 6.8: Probability of EV availability in a bus (Case 3)

7

Conclusions and Future work

7.1. Conclusions

The main aim for this research is to find an optimal way to restrict the voltage changes in the network caused due to the increased PV penetration, using the electric vehicle batteries. The evaluation is done by investigating the performance of system and the electric vehicles under various operating conditions. In this work, the main research question is:

How to maintain the voltage level of the distribution system using Electric vehicles in a high PV penetrated network considering the uncertain availability of Electric Vehicles while ensuring acceptable charging level of the EV batteries?

To facilitate distributed control in the network, consensus algorithm is used. It is proved to be effective, as the SoC of all the connected EVs is made to converge to a common value in lesser than 250 iterations. The time taken for convergence using consensus algorithm is far lesser compared to centralized control, as the latter has to process the information from all the EVs connected in the network, which in turn increases the processing time. The average consensus method has ensured equitable contribution by evaluating and implementing the correction and weight factor for most of the EVs. This does not guarantee equitable contribution by all the EVs, since the contribution during charging and discharging cycles is dependent on the voltage level of the bus to which the EVs are connected. This can be validated from the scenarios presented in chapter 5. In spite of its contribution, the consensus algorithm has maintained the SoC levels between allowable limits for most of the EVs. For few EVs, the SoC goes marginally below the specified lower limit due to the occurrence of a travel. The travel behaviour is dependent on the EV user and cannot be controlled. This answers the first sub question of this research.

Travel pattern of the EVs has been simulated to represent the realistic behaviour of the EVs. This is a very important step in this research, as the EVs are not a stationary source and are subjected to move between places. To replicate the actual travel behaviour of an EV, markov model is used. To create a markov chain, the state transition probabilities are imported from various literature and the states are predicted based on that. The markov model implemented without considering time as a function has resulted in some flaws and lacked accuracy. Then the model is improved by implementing it as a function of time. The resultant travel pattern is compared with the actual travel pattern data from the literature and it ensures the higher accuracy of predictions performed by the improved markov model.

After simulating the travel pattern, the mathematical model of charge and discharge control is designed. The charge and discharge control decides the amount of power that a EV battery has to absorb or supply during its charge and discharge cycles respectively. The correction factor, weight factor and the availability is included in the calculation of charge/discharge power. To estimate the response of the network and EVs, three experimental scenarios are considered and the results are discussed in detail. The results of the first scenario show that, most EVs remain uncharged when the voltage level of the buses is maintained around 1 p.u. It is also evident that, there are frequent charge and discharge cycles due to narrow limits and it causes frequent voltage fluctuations in the network. To improve the charging of the EVs, the charge and discharge limits are lowered to accommodate more power for the EVs to charge. This has reduced the number of EVs which remain uncharged, but even after this few EVs were charged to a lesser value and most EVs did not charge more than its initial SoC during the start of the day. This scenario is conducted as an experiment to determine the effect of charging on the EVs when the limits are reduced. Since there is an improvement in charging, the limits are further reduced in the third scenario. The selection of limits are done as a trade off between the acceptable voltage level in the network and the SoC level of the EVs. Thus in the third scenario, the limits are lowered further and the results show a significant improvement in the SoC level of the EVs. The SoC level of most of the EVs ended up being higher than the initial SoC level. Wider gap between the charge and discharge limits has also decreased the number of charging and discharging cycles encountered by the EVs, thus limiting the voltage fluctuations in the network. This scenario also ensures higher battery life as the frequency of charge/discharge cycle is less. The effect of increasing the population of EVs in the model is evaluated and the result shows that the regulation of voltage is better in this case. But the number of EVs that remained uncharged has increased and this shows the problem of increased integration of EVs in the existing model.

Since the EV batteries are a dynamic source of storage units, their availability is not a guarantee. Even when it is available, the EVs switches locations and therefore the availability of a particular EV might correspond to a different bus at different time steps. Hence to make the algorithm more robust, monte carlo simulation is used. This helped in handling the uncertain factors in the model. The uncertain parameters are modelled within the monte carlo simulation and the results present a probability analysis on various uncertain factors in the system. The results from the simulation shows that, the availability is not the same for all the buses and has a different pattern based on the location. Few buses had higher probability of availability during non-working working and few buses had high probability during work hours. This illustrates that the probability distribution depends on the location of the buses as some of the buses had a similar probabilities of availability on all time steps. This probability distribution provides analysis on the uncertain occurrences in the model and based on this information, the events can be predicted to an extent and the uncertainty is reduced.

7.2. Discussion

This research has yielded a wide variety of results both on the distribution system side as well as the EV charging/discharging side. In order to evaluate the necessity and importance of this research, the results of these research along with what they mean to current and future energy systems has to be discussed. Firstly, the integration of PV systems in the electrical power grids are increasing exponentially and this demands the need of maintaining the voltage within limits against the intermittent nature of PV power generation. While storage technologies are considered to be the primary source for regulating the generated power, investment in storage technologies increases the overall cost invested in the distribution of power. This showcases the importance of utilizing the pre-existing electric vehicles for this purpose. The number of EVs in use is also increasing and it has almost doubled during the period of 2016-2018 [1]. This creates a space for utilizing the EV batteries in this process. This research is important in showcasing an environment that can be provided for integrating higher capacities of renewable energy sources and it also shows a way of integrating EVs into the system not only as loads, but also as sources to supply power to the system.

The results from the distribution system shows that, the voltage was maintained within the tolerance limits on all time steps. However, it can be seen that, maintaining the voltage levels within the threshold limits hasn't been a simple task, especially the upper threshold limit. This has a lot to do with the availability of EVs at that instant of time. Since parameters like the availability of the EVs, the location the EVs, the SoC level of the EVs and the voltage level of the bus to which the EVs are connected should fall in place at the same time, the possibility of bringing the voltage within the upper threshold limit becomes a challenging task. Hence, this puts a limitation on the control of the voltage level in the system. The first two scenarios showed a problem of frequent voltage changes which resulted due to frequent charge and discharge cycles, but this has been minimized in the third scenario. These regulated voltage curves can be compared to voltage curves from a similar research conducted using EVs in [32] which shows that, the regulated voltage curves look smoother and it is maintained within the specified limits throughout the simulated duration. But it has to be noted that the travel, travel behaviour of the EVs and the availability of the EVs is not taken into account in that research. Even though that considered EV in their research, they considered them as more or less similar to a stationary battery. That does not reflect the realistic behaviour of the EVs. This issue is considered in this thesis and has been improved by considering the travel pattern and the availability of the EVs. And in [32] and [50], leader-follower approach has been adopted where the most critical bus is selected as the leader and the all the other buses adjusts its utilization based on the utilization of the leader. In this thesis, equal importance is given to all the buses as there is a possibility of other buses getting affected in leader-follower approach.

Regarding the EVs, different scenarios were carried out to determine the most suitable scenario for the EVs. The results from SoC plot of the EVs shows that, when the voltage regulation of the system is given a higher preference, most EVs tend to charge to a minimal value, as there is not enough power to charge the EVs while maintaining the voltage at the same time. The first two scenarios showed that it is difficult to charge all the batteries while maintaining the voltage level close to optimal (1 p.u) as the EVs are considered as additional loads in this case. Hence, a compromise had to be made between the voltage level of the buses and the SoC level of the EV batteries. And an improvement in the charging profile has been reflected in scenario 3. But, still few EVs remain uncharged due to the voltage level of the bus to which the EVs are connected. Hence, it is suggested to include a financial compensation scheme for the EV users whose EV is charged to a lower value or uncharged. This financial compensation should be based on the initial SoC during the start of the day, discharge caused by travel, travel distance, time duration of its connection to the charging station and final SoC at the end of the day. This provides a leverage for the EV users to involve their vehicles in the regulation process and also prevents the existing users from opting out of the process. Therefore, financial compensation is required along with the existing model, to encourage the EV users to continue their contribution towards voltage regulation in the distribution network. When a financial compensation scheme has to be implemented, there should be an intervention by the government or the DSO to make a decision on the range of compensation that will be provided for the EV owners. This involves a lot of parameters into consideration and it should be decided based on the effect these changes has on the future of EV integration. This part is not included in this thesis and is just given as a suggestion. It is open for future research.

7.3. Future work

There is still room for an in-depth analysis to improve the voltage regulation process by better utilization of EVs. The factors that need to be considered for improving the model are:

1. Financial Compensation

   The requirement of financial compensation has been stated. But, it cannot be simple mathematical calculation as it involves lot of different parameters. It requires information from the EVs and the network. Hence, proper economic analysis has to be made to design a well defined financial compensation scheme.

2. Robustness

   Monte carlo simulation used here, presents a probability distribution on several uncertain events. Further analysis on the steps that can be performed to counter an uncertain or low probable event is not addressed in this research. This provides a space for further analysis on improving robustness based on the outcome from monte carlo simulation.

3. Distributed algorithm

   Consensus algorithm used here only needs the network description, SoC value and connected bus for its analysis. If there are multiple parameters that has to be communicated or transferred throughout the system, then the consensus algorithm has to be remodelled or a different algorithm should be chosen for this communication. This is not addressed in this research and is open for future research.

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