Electric Vehicle Coordination through Dynamic Virtual Power Plants

By

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Abstract

The integration of electric vehicles (EVs) in distribution grids is a possible solution to reaching the goal of a reliable and sustainable environment and electrifying the transportation system. EV integration is widely implemented by introducing the virtual power plant (VPP) concept in which EVs can be clustered and controlled together. In this way, one single VPP or aggregator model can be used to solve challenges in the grid such as issues related to power quality, system losses, and peak demand management.

This thesis will analyse the conventional single VPP model and show the limitations of conventional models, which have inadequate use of EVs to solve grid issues. To overcome issues associated with conventional models, this thesis proposed a dynamic VPP algorithm that can cluster EVs into several different VPPs based on the EVs' present state of charge and plug-out time. After the formation of different VPP clusters, the EV coordination and V2G optimization of each VPP cluster is formulated as a mixed integer nonlinear optimization model to maximize customer satisfaction while subjected to grid constraints.

The proposed methodology was evaluated by MATLAB and Open-DSS simulation, and the results indicated that the proposed methodology has better grid performance than the results of the conventional single fixed VPP model.

Statement of Candidature

I certify that the work presented in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirement for a degree to any other university or institution other than Macquarie University.

I also certify that this thesis is an original piece of research, and it has been written by me. Any help and assistance that I have received in my research work and preparation of this thesis itself have been appropriately acknowledged.

Adithya Ravikumar

1/07/2022

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List of Publications

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List of Abbreviations

EV – Electric Vehicle

VPP – Virtual Power Plant

DVPP – Dynamic Virtual Power Plant

SOC – State of Charge

p.u – Per Unit

kW – Kilowatts

DER – Distributed Energy Resources

LV – Low Voltage

Chapter 1

Introduction

1.1 Background

With the rise of climate change, countries around the globe need to use more eco-friendly technologies and discard fossil fuel-based technologies. One such technology that will replace the internal combustion engine of present automobiles is the electric vehicle (EV). The integration of EVs into the power grid will cause additional power demand and an increase in transformer loading and power line capacity. To efficiently manage this disruption without any drastic physical changes to power grids, coordinated charging strategies are necessary. There are applications and solutions through which EVs can be coordinated for better operations of the grid, and it is also important that EV charging be done optimally to avoid curtailments of EV batteries, power losses in the LV network and other negative impacts related to EV charging. Currently, virtual power plants (VPPs) are playing a major role in the balance of power grids, where all distributed energy resources are combined together to both act as a source and a load demand, which has helped utilities gain more profits. Moreover, current research focuses on the integration of EVs and VPPs and addresses the problems caused due to the inflexibility of decentralised energy sources in power grids. Hence, the concept of EV management as a fleet used in VPPs has many benefits, and its feasibility has been studied [1]. A VPP is useful for both customers and utilities. A VPP is a collection of distributed energy resources (DER) connected by a control system, and it acts as a single entity in the power system that can be either static or dynamic [2]. The DER can use distribution generation, storage units and flexible loads. There are two different types of VPPs: commercial VPPs and technical VPPs [3]. Commercial VPPs are used for market participation and trade, whereas technical VPPs are used for balancing the power system or commercialization and profit [4]. Figure 1 shows the structure of a VPP where different renewable energy sources are connected together using a control system in which the individual DER is controlled. This research thesis will use this VPP concept as a dynamic VPP to balance the power system and improve its performance.

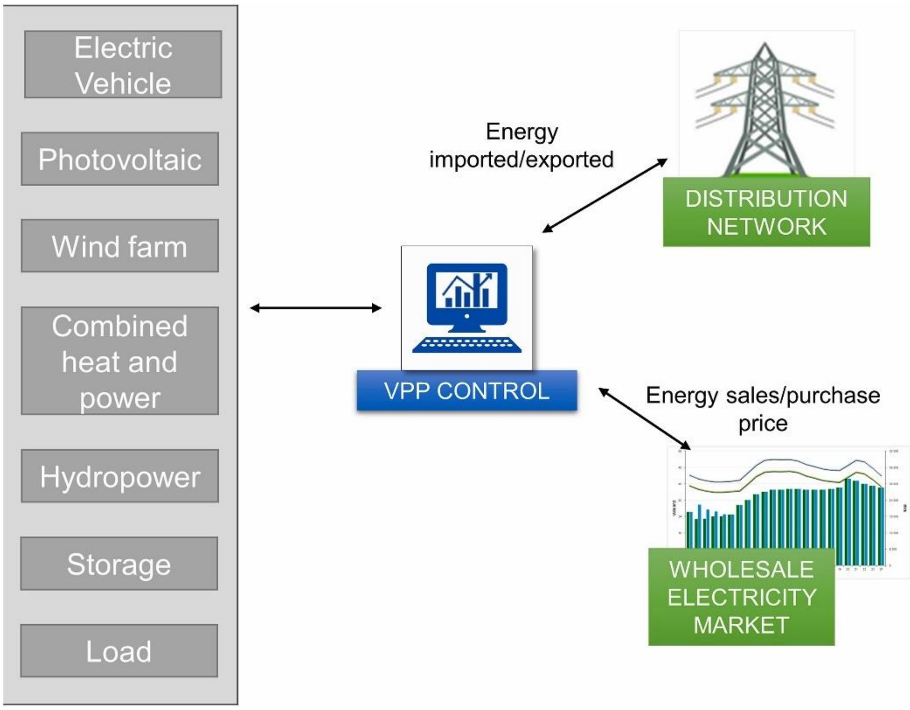

Figure 1: VPP and its interaction with DER and markets [4]

1.2 Motivation of Research

At the UN climate change conference (COP26) that took place in Glasgow, a declaration was signed by governments and businesses to commit to rapidly accelerating the transition to zero emissions globally by the year 2040, and by the year 2035, EVs will have to lead markets globally [5]. Moreover, automotive manufacturers will also work towards the goal by introducing 100% of cars and vans as zero emission vehicles [5]. There are just eight more years for this transition to ending the manufacturing of fossil fuel-based vehicles and manufacturing EVs at a large scale, which is going to start from 2030. Hence, sooner or later more EVs will be connected to the grid. EVs often get charged in residential areas and cause additional load demand in the residential distribution power grid [6]. This rise in demand creates power system overloading, poor grid performance, and voltage violations. This may require real-time control strategies to coordinate EVs and DER [7]. To solve the above-mentioned grid issues such as the mitigation of grid overloading, reduction of power losses and maintenance of desired bus voltage, different real-time coordination techniques are proposed in the literature [8–10]. EV management strategies also focus on the discharging of EVs due to their ability to act as a power source, a capability that can be used for peak shaving [11] [12], which will benefit grid operators.

Over the last decade, the concept of the VPP has been gradually becoming more popular, especially in the integration of DER and EVs to the distribution grid. The focus of this thesis is to develop a dynamic virtual power plant (DVPP) algorithm that will improve the grid performance through the effective control and coordination of EVs. The proposed optimised strategy will control the operation of EVs in DVPPs. This flexible framework addresses the adverse impacts of voltage violations and power losses in residential and distribution power networks. Additionally, customer satisfaction is also considered, as the welfare of the EV owner is important when the owner's EV is participating through V2G technology and the reliability of the presented energy management system for different scenarios are evaluated.

1.3 Research objectives

The main objective of this thesis is to investigate the impact and effectiveness of the proposed dynamic VPP model compared to the present-day VPP model, which is used in the improvement of grid performance and user preference. Special focus is placed on the flexibility and control of the algorithm to model, operate and plan EV coordination as well as to ensure better customer satisfaction and coordinated voltage regulation and to support power system operations.

1.4 Problem Statement

This thesis focuses on the problems and limitations of the present-day VPP and aggregator model, where a certain number of participating EVs will always have to come under the control of a single fixed VPP or aggregator, which results in less flexibility in the usage of EVs and reduces the grid performance. Moreover, this type of VPP model also fails to satisfy most EV customers' preferences.

1.5 Research Contribution

The main contributions of this research are listed below:

- Development of a DVPP algorithm using the concept of a multi-agent distribution network, average consensus protocol and K-means clustering.

- Development of a flexible optimization algorithm to control and model the VPPs for higher EV penetrations. The optimization algorithm controls the flexible movement of the EVs between the VPPs while considering constraints such as the SOC and plug-out time of the EV.

- Implement and control the charge/discharge capabilities of EVs while considering user preferences.

1.6 Thesis Overview

This thesis consists of five chapters, including the introduction and the chapter that highlights the background of VPPs. The following chapters are structured as follows:

Chapter 2 describes the literature review of methodologies used by previous research papers that use charge and discharge management strategies, which use fixed aggregators and the VPP model, and discusses the limitations of these methodologies.

Chapter 3 discusses the development of methodologies of the three different scenarios and the design of residential distribution grids in Open-DSS. In this chapter, the first scenario is the performance of the grid during the uncoordinated charging of PEV. The second scenario is developed using the present-day VPP model, and the objective function for customer satisfaction is formulated as mixed integer non-linear programming; it is formulated in the general algebraic modelling system (GAMS) and is solved using KNITRO solver. The simulation was carried out using MATLAB, where the design of the grid was done in Open-DSS, and the grid control was implemented using MATLAB. Scenario three is the proposed methodology in which DVPPs are used for dynamically clustering EVs into different VPPs. Furthermore, the optimization of these dynamic VPPs is done for each individual VPP. Hence, when the dispatch takes place, the optimization will take place for every minute for all the VPP. This dynamic clustering algorithm is carried out and simulated using MATLAB.

In Chapter 4, the results of all three scenarios are presented, and the grid performance is shown using system power consumption, system power losses, and voltage profile. The results of the sensitivity analysis for the effects of EV penetration are also presented.

In Chapter 5, the final conclusion and future work will be discussed.

Chapter 2

Literature Review

2.1 Introduction

The accommodation of EVs in the low voltage residential distribution grid without major changes to the power network is possible by using coordinated EV management strategies. The focus of this chapter is to review different strategies that use a single aggregator or single VPP model, and it summarises work on the effects of EV coordination and scheduling strategies on the grid. This chapter will further discuss optimal coordinated EV charging strategies and literature pertaining to the use of EV batteries to support distribution grids. However, there many studies that focus on EV charging strategies, which improve frequency regulation and reactive power support, but this literature exclusively focusses on improvements to user satisfaction, power losses, voltage profile and mitigating grid overloading.

2.2 Single and Multiple Virtual Power Plant-based Model in a Distribution Grid

Research has been conducted on managing EVs in a distribution grid using the VPP model, which aggregates all the EVs into a huge smart power storage facility where the charge and discharge of their batteries occurs through a smart hardware software platform [13]. This model allows the storage of additional electricity generated from renewable energy sources, but the energy management method proposed in [13] only addresses the energy demands of the power grid. When energy consumption predictions of EVs for the future for EV coordination is considered, one unaddressed issue is the overloading of the grid during EV coordination. In [14], a VPP model-based energy management system that integrates both EV parking lots and a PV system is proposed to solve the issue of solar PV output as well as grid issues caused by the charging of EVs. The energy management system in [14] was used to improve the bus voltage from 0.90 p.u to 0.95 p.u, and the reduction of the active power flow is managed well under the maximum capacity of the grid; however, the limitation of this method will be present when EVs will be used for demand management rather than as an additional source like a PV system to both satisfy EV and load demand, as the energy management system is heavily reliant on the PV source for solving grid constraints and issues. Further, it does not take into consideration the scenario of solving grid issues without the use of additional energy sources. To handle the large number of EVs for optimal operations, a Stackelberg game algorithm with multiple VPPs is proposed in [15], which aims to reduce the EV charging station operation cost and smooth the power flow in the grid. In [15], the shifting of EV demand is based on the cost of electricity rather than using grid constraints like voltage and the maximum power capacity of the grid. The multiple VPP concept is used for the purpose of effectively handling a large number of EVs for charging. The VPP was introduced as a solution to address the integration of DER and the grid [16]. The author in [17] proposes a global energy management framework that takes advantage of EVs to support the grid and maximize the owner's benefits. The simulation results of [17] show an improvement in reducing the aggregate load and EV demand. The issues associated with this method are that the type and battery capacity of all the EVs considered in the simulation are of the same model with no diversity in the type of EV, and the simulation results of [17] do not show a significant reduction of power losses.

2.3 Optimal EV Coordination Strategies

The authors in [18] developed an architecture for real-time EV coordination by having a prediction unit and optimization unit, which will maximize the customer satisfaction and minimize the operational cost. Additionally, an aggregator is also in place to collect EV information. The optimization unit uses the current and future power demands and regulates power demand based on the present customer demands and current future power system load. The research in [19] aims to improve the grid voltage, power losses and transformer overloading as well as increase customer satisfaction by satisfying the requested SOC and plug-out times. The research uses the single aggregator model and formulates its objective function and maximizes the total customer satisfaction function by optimizing the charging rates of the EV, where the aggregator will decide on which EV to be charged. The improvements in the voltage profile are not significant, as the aggregator is only able to maintain a voltage drop of 0.9 p.u.

The use of a multi-agent architecture instead of a single aggregator architecture for demand reduction in order to avoid transformer overloading is tested using a laboratory micro-grid [20]. The multi-agent architecture has two layers: one layer is the coordinator agent, which monitors grid constraints, and the other layer is the local area agent, which monitors the EV agents and its SOC and plug-out time. The transformer overloading is avoided by the EV demand reduction requested by the coordinator agent. Additionally, this multi-agent architecture is realised in the form of an EV aggregator, where the aggregator is comprised of three different agents. Another research [21] focuses on minimizing power losses and reducing the generation cost through an aggregator, where the delivery charging power will be maximized, and the losses and generation cost will be minimized, and all three factors are formulated as one objective function. Two different optimization techniques will be used for every 5 min time slot for EV scheduling and will get updated for the same time period.

The authors in [22] show the minimization of power losses and the improvement of voltage profile by a real-time scheduling scheme that has a power-voltage levelling factor where the sum of the voltage deviation of all the nodes in the grid is based on the base load and will be used to schedule the EV loads based on the calculated voltage deviation, and power losses are minimized through system load levelling. All the forecast and scheduling in this research are implemented as a single aggregator.

A vehicle-to-grid technology is introduced and investigated by the author in [24] to get the optimal coordination of EV charging. The proposed optimization model includes the departure and estimated arrival time of the EV, and the SOC is also considered to get accurate charging schedules for the EV. All these parameters are included in the mathematical model within the optimization problem. The main aim of the objective function for this study is to minimize the cost of energy and reduce the EVs' energy curtailment while considering the abovementioned constraints/parameters. The study presented an effective method for overcoming uncontrolled/random EV charging.

The research in [25] introduces optimal EV charging with the additional aim of mitigating the overloading of transformers. This paper uses reinforcement learning that aims at simultaneously maximizing local objectives such as price paid, maintaining user-specific SOC, minimizing energy costs and avoiding transformer overloads. This multi-agent reinforcement learning architecture achieved the best performance in both dynamic and time-of-use tariffs among the evaluated algorithms. Another research with a similar aim of avoiding unfair usage of the distribution transformer capacity is resolved using a two-step coordination strategy that is proposed in [27]. The main aim is to minimize the total energy procurement cost of the smart neighbourhood and at the same time to consider 30 different constraints related to EVs, energy storage and power sharing constraints. This optimization is the first step, and the second step will prevent the increase of costs to the individual households. Hence, this methodology will promote a smoother induction of EVs and other types of loads.

There are charging strategies that maintain the voltage levels in the distribution grid, but reference [26] does not consider EV reactive power support; instead, a volt-var control device is considered for the status of the volt-var devices. An optimization algorithm for the EV charging schedule is formulated and solved, and the proposed methodology is demonstrated in a three-phase unbalanced electrical distribution network. Hence, in using this methodology the overall energy cost is reduced and the technical limits are not violated in the distribution network. However, this methodology only adds additional constraints to the charging of EVs for better operation of the low voltage grid, and EVs have no role in mitigating those technical constraints.

EV charging coordination with multiple energy sources will require a flexible energy management strategy. The paper in [23] introduces a two-stage scheme to coordinate the EV charging and allocate the power among the PV, battery, and grid with the usage of game theory in energy management. The first stage deals with power allocation among the PV, battery, and grid with respect to the total available charging power. The second stage is the EV charging coordination, which was implemented in a distributed manner. The utilization of battery by the energy management has reduced the burden on the grid, and simultaneously the preference of the individual EVs is considered based on the urgency of charging, which is the main achievement of the proposed charging strategy.

Research has also been done on the mitigation of voltage unbalance by phase switching in EVs and simultaneously reducing transformer overload. The paper in [28] presents a coordination approach where the dynamic load transfer takes place within three phases in which the EVs are connected to the respective phases. Additionally, the voltage profile is improved by using the same phase shifting method, a heavily loaded phase where the EV is connected and will be transferred to a lightly loaded phase. This research is similar to previous research [23] on the minimization of voltage unbalance factor and power loss. Similarly, in this research, the same issues are being resolved but with two different coordination strategies by using a central controller and three transfer switches. This transfer switch with the reactive power support of the EV is a hybrid scheme to improve the voltage profile. This hybrid method is more effective in a highly unbalanced system.

2.4 Coordinated Electric Vehicle Management for Distribution Grid Support

EVs impose capacity issues on the grid operator [11]. To solve this issue, [11] proposed a coordinated management system for EVs with functions to support the power grid. To prevent undervoltage and overloading situations, multiagent system architecture-based coordinated EV management was proposed. This paper also proposed a methodology called flexible bid, which represents both demands shifting and V2G for residential EVs. The active bidding provides the EV owners with full decision-making authority and autonomy, thereby increasing their participation. The objective function is optimized to minimize the electricity cost of the EV owner while complying with local grid constraints. The EV charging and discharging are done by coordination, and the optimization is done by the EV aggregator, which results in electricity cost minimization. Moreover, decision-making authority is given to the EV owner by utilizing the multiagent system architecture.

EV management is also done to reduce grid congestion due to uncoordinated EVs. The research in [29] proposes a charging coordinated strategy V2G and G2V. Based on the level of SOC, the coordination strategy is formulated. Particle swarm optimization is used to formulate the strategy to avoid grid congestion. The results show that all the EVs can be integrated without congesting the grid. The congestion analysis is carried out using 800 EVs. Similar issues are also solved by the research in [30], which introduces a robust virtual battery, and to optimally schedule the EVs a distribution locational marginal price method is introduced to prevent network congestion. This is a price-based framework in which higher prices will be issued to households for high power consumption. This method will have an interaction between the distribution system operator and the energy management system at the prosumer level and makes schedules for the EVs. The optimization model's aim is to minimize the cost of all participating prosumers by abiding the network constraints.

The paper in [31] focused on improvements in energy coordination between EV charging stations and the distribution system to improve the quality of service. The quality of service of the charging station is represented through six constraints, and for a better operational model of distribution system power balance, security constraints are also used to maximize the welfare of the EV charging station. The energy management method is based on a supply function game model. Thus, the interactive EV charging station and distribution system operator can reduce the peak load and improve the voltage profile of the network.

The study in [32] focused on reducing the peak demand and came up with a charge-discharge scheduling for peak demand management and minimizing the cost for EV owners. The charge-discharge scheduling strategy is implemented through a mixed integer programming approach. The proposed model has considered the uncertainty associated with the predicted demand and EV usage the next day. However, the maximum cost for the EV owners is higher when the EV penetration is higher. This is because more EVs in the network creates higher energy demand, and while the system constraints are in place, the aggregated peak demand cannot exceed the peak demand constraint.

A decentralized strategy to mitigate the peak demand problem is proposed in [33]. Different scenarios are modelled by having the same constraints that are common to both EV and commercial loads. The scheduling is done such that the operation cost is minimum while observing a set of constraints. The authors in [34] proposed coordinated charging-discharging management to determine the schedule of the EV on a daily basis in order to charge the EV using the curtailed PV. The scheduling is determined by the information exchange between the home energy management system and the grid energy management system. This scheme helps reduce the operational cost of the residence and avoid PV curtailment. The grid operator will send the expected PV curtailment to the home energy management system, and the resident will generate the provisional EV schedule; the operator will use the provisional schedule to decide on the minimization of PV curtailment with the consideration of the voltage constraints of the grid.

2.5 Conclusion

This chapter is divided into three parts. The first part deals with the literature review of a VPP as an aggregator, and the limitations of the methodology were discussed. The research gaps in the literature [13]-[17] are as follows:

- overloading of the grid during the EV coordination in [13] is unaddressed with a major focus only on energy demand.
- The limitation of the method used in [14] is that the energy management system is heavily reliant on a PV source for solving the grid constraint issues.
- The method used in [15] shifts the EV demand using electricity cost, and it neglected using the grid constraints and power capacity of the grid.
- In [16][17], the method did not show any significant reduction in power losses, and there is no diversity in the type of EVs considered in simulation.

The second part of the literature was to review different optimal coordination strategies. The research gaps in the literature [18]-[28] are:

- The results shown in [20]-[22] for improving the voltage profile were not successful in getting better results for far bus voltage nodes where the voltage drop is close to 0.90 p.u, and the methods used in all these papers did not consider the EV discharging to tackle this problem, especially for the buses far away from the source.
- One of the limitations is the improvement of the voltage profile and power losses, which is achieved by the methods in [18][19][23]-[28] where the traditional aggregator model is applied. As a result, the methodology has to add additional control and optimization schemes with more constraints or control volt-var devices just to maintain the voltage profile and power losses, which is still a more complex solution with unwanted additional constraints. This can be further simplified and effectively handled by improving the architecture of the energy management framework.

The third part of the literature deals with EV coordination management strategies with the purpose of supporting the distribution grids, and their gaps are as follows:

- The studies in [30]-[33] that involve the forecasting of EV loads make general assumptions, which will not guarantee customer satisfaction as much as a real-time model. The upcoming chapter will discuss in detail the solutions for the above-mentioned limitation.

Chapter 3

Research Methodology

3.1 Introduction

This thesis focuses on the problem and limitations of the present-day VPP and aggregator model where a certain number of participating EVs will always have to come under the control of a single fixed VPP or aggregator, which results in less flexibility in the usage of EVs; as a result, this model reduces the grid performance. Moreover, this type of VPP model will also fail to satisfy most of the EV customers' preferences. An energy management system is required for the coordination of EVs in a low voltage residential distribution grid. In this case, the energy management system for coordinating the EVs is modelled in MATLAB, which will function as a control system for the EVs. The residential low voltage distribution grid is modelled in Open-DSS software; this power system's modelling software has the ability to perform time-series analysis of low voltage distributed power systems. MATLAB will have the control algorithm based on the VPP or DVPP model to coordinate the EVs in the Open-DSS. In this chapter, three scenarios are presented: Scenario A is uncoordinated EV charging, Scenario B is coordinated EV charging-discharging through the present-day VPP model, and Scenario C is EV coordination through the proposed DVPP methodology.

A VPP is generally defined as the aggregation of distributed generation, and through coordination it acts as a power plant [44]. In the last decade, EVs have been generally considered as DER, and the VPP aggregates these EVs and controls their total output power [45]. This kind of aggregation is the same for Scenario B (controlled EV strategy). The scenario where the aggregation of EVs is using a single aggregator, as in the case of scenario B, can also be called one fixed VPP model because the aggregator behaves the same as a single fixed VPP. Even though this method is still being used, there are limitations considering the grid performance and stability of the power network. In this chapter, a new concept called a dynamic virtual power plant (DVPP) is introduced for EV clustering. This chapter discusses this proposed methodology and observes the improvements in grid performance. The advantages of the DVPP model over the traditional VPP model used for EV aggregation are discussed.

3.2 EV coordination management for three different scenarios

Three scenarios are outlined in this section: Scenario A is uncoordinated EV charging, Scenario B is coordinated EV charging and discharging where customer satisfaction and grid performance are analysed, and the method used in Scenario B is used as the main performance benchmark model against the proposed method, which is Scenario C. The proposed method used in Scenario C is DVPP. Moreover, this section explains in detail the DVPP method and the other benchmarking techniques used in the analysis.

3.3 Scenario A (Uncoordinated EV)

The uncoordinated EV charging case scenario will be considered as the worst-case scenario. EV charging data from UK domestic EV charging will be considered for the simulation. In this case, the V2G is not considered as a functionality of the EV. The impacts of the uncoordinated EV charging will be seen when the EV will start charging immediately when plugged in. To overcome the grid issue of Scenario A, Scenario B is introduced.

3.4 Scenario B (Coordinated EV charging and discharging strategy)

The objective of this study is to focus on a scenario where there are multiple EV owners with different user preferences participating in the V2G and G2V operations. The user preferences have to be satisfied, and the grid constraints have to be maintained. This scenario will be known as Scenario B, whereas for the uncoordinated case it will be called Scenario A, and the use of the proposed algorithm for EV coordination will be called Scenario C. The Scenario B objective function and constraints are taken from the paper [42]. This is done to compare the results from the method used by [42] and the results from the proposed algorithm, which is explained in the next chapter, which will show how the result from the proposed algorithm is much better than the method used in [42]. This paper has implemented two different coordination strategies with the same constraints: one is fixed charge-rate coordination, and the other is variable charge-rate coordination. This thesis uses the fixed charge rate coordination strategy to maximize the customer satisfaction and to improve the grid performance. The difference between the fixed and variable charging strategy is that the variable charging strategy will have a variable charging function, where each EV is assumed as an active variable load, but a fixed charge-rate will have a fixed charging capacity and during the charging process the charger will charge the EV at constant power as per the standard power outlet. Furthermore, in [42] the total customer satisfaction is maximized in two ways: one is by optimizing the EV charging rate, which is the variable charge-rate coordination strategy, and the other is performing optimization of the objective function with fixed charging rates. The research [42] presented the objective function for EV coordination for the variable charging rate case and did not modify the objective function equation and constraints for the fixed charging rate. In Scenario B, the objective function for the EV coordination is done as a single EV aggregator and is expressed as follows:

$$Max\left(f(t)\right) = \sum_{e=1}^{Nev} \lambda_1 \left(1 - \frac{SOC(e)}{SOC_{req}(e)}\right) + \lambda_2 \left(1 - \frac{T(e)}{T_{req}(e)}\right) \; p_e^{ev} \triangle t \qquad (1)$$

$$e = 1,2, \ldots\ldots Nev$$

$SOC(e) - State\ of\ Charge\ of\ the\ eth\ EV$

$SOC_{req}(e) - state\ of\ charge\ requested\ by\ the\ user\ of\ the\ eth\ EV$

$T(e) - Remaining\ available\ time\ for\ charging\ the\ eth\ EV$

$T_{req}(e) - Plug - out\ time\ of\ the\ eth\ EV$

$p_e^{ev} - Power\ Consumed\ by\ the\ eth\ EV$

$\triangle t - Duration\ of\ the\ time\ period\ in\ minutes$

$Nev - Number\ of\ EVs\ at\ the\ \triangle t\ time\ slot$

$\lambda 1\ and\ \lambda 2 - weights$

3.4.1 Grid Constraints

In this thesis, there are two types of grid support services: one is to prevent the overloading of the grid, and the other is to maintain the optimum voltage of the grid. For scenario B, the aggregator will continuously monitor the grid conditions, and based on the load demand the EV aggregator will coordinate the EVs. So, the objective function equation (1) is subjected to the following constraints:

$$Pmax \leq \sum P_e^{ev} + \sum Pload \qquad (2)$$

$$V_{min} \leq V_b(\triangle t) \leq V_{max} \qquad (3)$$

$$SOC_e(t) \geq SOC_{req} \qquad (4)$$

$Pmax - Maximum\ Power\ Transfer\ Limit$

$\sum P_e^{ev} - Sum\ of\ total\ power\ consumed\ by\ EV\quad s\ coordinated$

$\sum Pload - Load\ demand\ of\ the\ residents$

$V_{min} - Minimum\ Voltage\ limit$

$V_b(\triangle t) - Voltage\ of\ bus - b\ at\ time\ t$

$V_{max} - Maximum\ voltage\ limit$

$SOC_e(t) - State\ of\ charge\ of\ eth\ EV\ at\ time\ t$

3.5 Proposed Model - Scenario C (Coordinated EV using the DVPP strategy)

A new concept called the dynamic virtual power plant (DVPP) is introduced for EV aggregation. A methodology for this DVPP is formed and the improvements in grid performance were observed. The advantages of the DVPP model over the traditional VPP model used for EV aggregation will be discussed.

3.5.1 Concept and Modelling of Dynamic Virtual Power Plants

A DVPP is a form of real-time clustering where the DER can be clustered into different VPPs, and each DER can be sent into a VPP through a common parameter. Unlike the traditional VPP [46] or even multiple VPP concept [47] where the selected DER or EVs have to remain under the same VPP once assigned, in the DVPP concept any DER or EV can move from one VPP to another VPP based on the user-assigned constraints and parameters. The DVPP is based on a concept called the distributed real-time clustering algorithm [48]. Unlike the paper in [48], where the chosen parameter for the clustering is the capacity of the battery and power demand of the microgrid, in this thesis two parameters are defined as variables to represent the SOC of the EV and the time remaining for plugging-out the EV. The real-time dynamic clustering algorithm in this chapter is developed using two concepts: one is the K-means clustering algorithm and the other concept is called the average-consensus algorithm.

3.5.1.1 K-Means Clustering

K-means clustering is a portioning of datasets such that the variance within the created cluster is minimized [49]. The basic steps of the K-means clustering are extracted from [50] and are presented as follows:

1. Having N different objects, with each having a measurement on P variables.
2. Specify the number of clusters K.

3. Initialize the centroids $C_{1,}\ C_2, C_3, C_4, C_5, \dots \dots .. C_K$ by the random selection of K data points.

4. Then, using squared Euclidean distance, each N objects will be compared with the randomly initialized using the formula below:

$$d^2(x_i, x^k) = \sum_{i=1}^{N} min\ ||x_i - x_j^k|| \qquad j = 1,2 \dots N \tag{5}$$

$x_i - The\ state\ of\ ith\ EV\ (e.g. SOC\ or\ Plug - out\ time)\ in\ Kth\ cluster$
$x_j^k - The\ centroid\ value\ of\ the\ kth\ cluster$
$i, j - EV\ number$

5. Each object is now allocated to their respective centroids.

The step six formula will calculate the average of the state value in their respective cluster. This is done to get the new centroid value, which is done to make sure the accuracy of clustering improves. The formula of this is given below as equation 6.

6. Then, a new centroid is calculated again with the formula below:

$$C^K = \frac{1}{|N_K|} \sum_{i=1}^{N} x_i \tag{6}$$

$N_k - Number\ of\ EVs\ in\ Kth\ cluster$

$x_i - state\ of\ the\ ith\ EV$

7. Repeat step 3 to 6 until no object can be re-allocated.

3.5.1.2 Graph Theory and Consensus Algorithm

The graph theory is used to portray the multiagent system network topology and the interaction between the agents. In this thesis, the agent is the EV. The information between EV agents is sent in a bidirectional way. This graph theory will be used in a consensus algorithm that deals with the cooperative control of the EV agents. In the consensus algorithm, consensus is defined as an agreement between agents on a shared variable or common goal by interaction as a group. When the condition is satisfied, it is said that the agents have reached a consensus. This consensus aspect will be used and will replace equation 6 of the k-means algorithm.

3.5.1.3 Continuous Time Consensus Protocol

A consensus algorithm is used to collectively make agents reach an agreement by applying system dynamics to the information state of each agent. In this thesis, continuous time consensus [51] is used, and the equation of the protocol is given below.

$$\dot{x}_i = \sum_{j \in N_i} A_{ij}(x_j - x_i) \qquad (7)$$

$x_i - The\ state\ of\ ith\ EV\ (e.g. SOC\ or\ Plug - out\ time)\ in\ Kth\ cluster$

$x_j - The\ state\ of\ the\ jth\ EV\ whicn\ is\ neighbouring\ to\ the\ ith\ EV\ in\ Kth\ cluster$

$N_i - Number\ of\ EVs\ that\ are\ neighbouring\ to\ ith\ EV$

In this equation, A_{ij} is the adjacency matrix [51], which is derived from the network topology of the multiagent system or EV. x_i and x_j are the initial states of the two neighbouring EV agents.

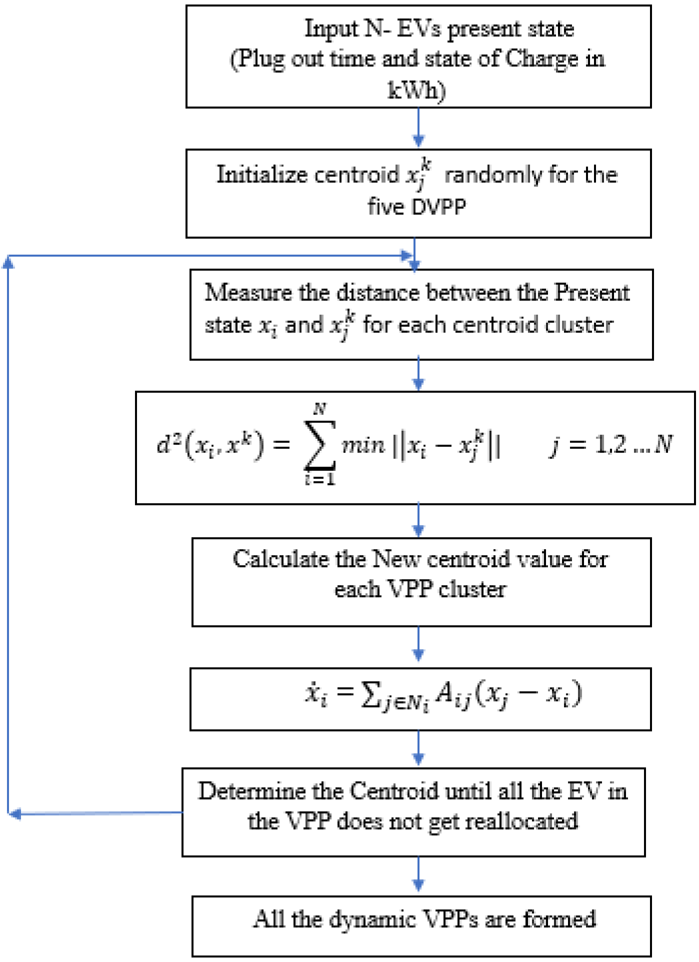

Figure 2: Flow Chart for the working of the DVPP algorithm

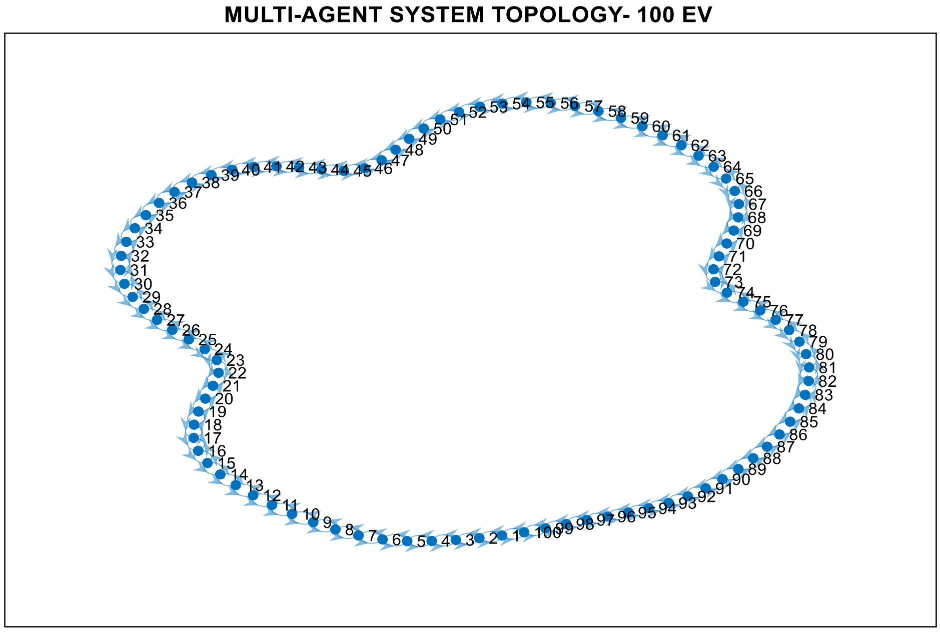

Figure 3: Multi-agent system topology using the graph theory

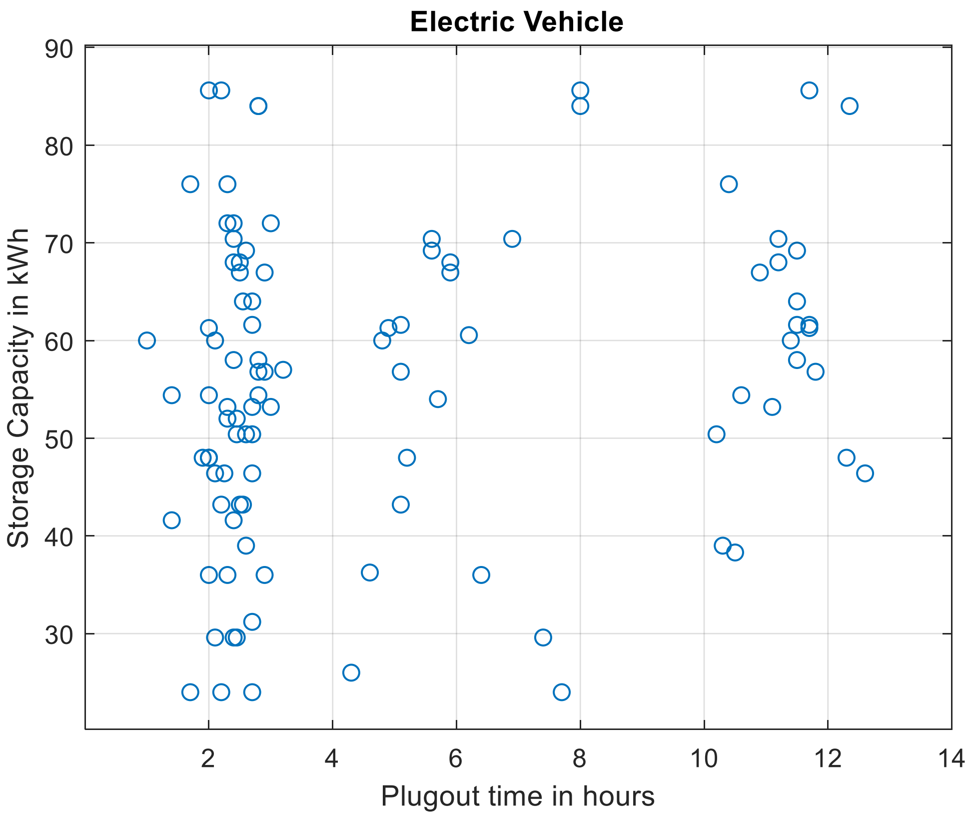

Figure 4: 100 EVs' data inform the Present SOC in kWh and Plug-out time

The real-time clustering algorithm is the combination of the two concepts where the DVPPs will use equation (5) and equation (7). Equation (5) will act as the equation to initially partition the data, and then to make this clustering algorithm work on a real-time basis, equation (6) of the K-Means clustering is substituted with the concept of continuous consensus protocol, which is given by equation (7). Hence, the DVPPs work by using equations (5) and (7). For a better understanding of the algorithm, see Figure 2.

Figure 3 and Figure 4 illustrate the working of this real-time DVPP concept where the data of 100 EVs are portioned into five different VPPs. The adjacency matrix will be formed through the formation of the EV agents in a graph theory format. As can be seen from Figure 3, the present state of the EV information for partitioning the EVs into five different VPPs are SOC in kWh and plug-out time. Then, based on the data in Figure 4 and by using equations 5 and 7 the EV will start to dynamically form VPPs. Figure 5 shows how the EVs with different plug-out times use equation 7 to form a consensus value. Similarly, the EVs with different storage capacity values do a similar operation, which is seen in Figure 6.

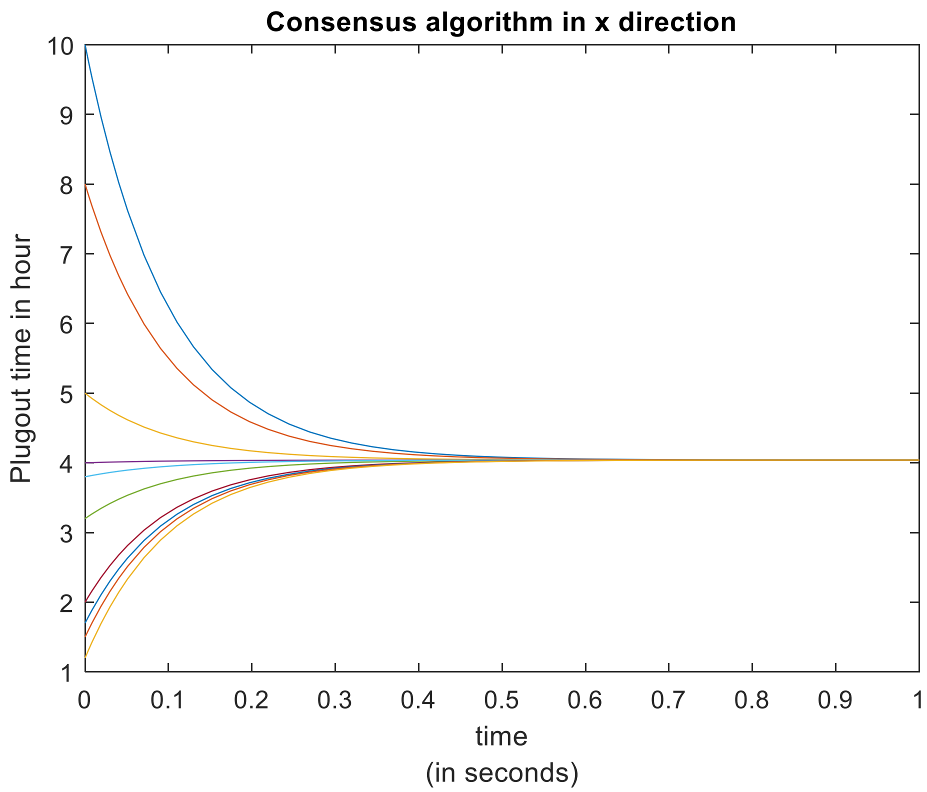

Figure 5: Consensus algorithm for the plug-out time of EVs

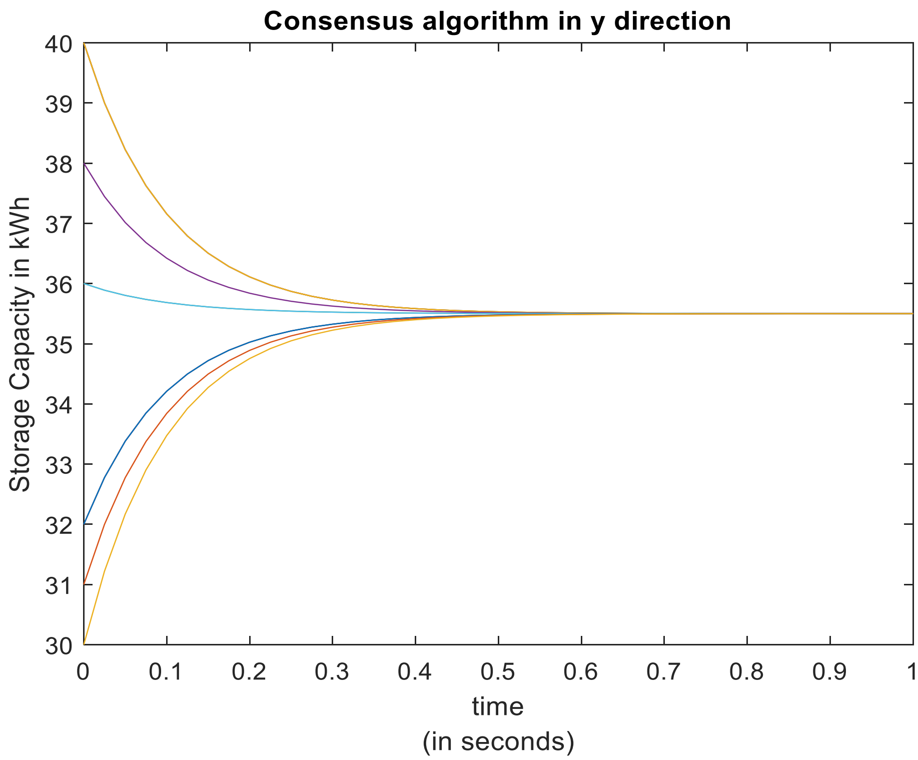

Figure 6: Consensus algorithm for the storage capacity of EVs

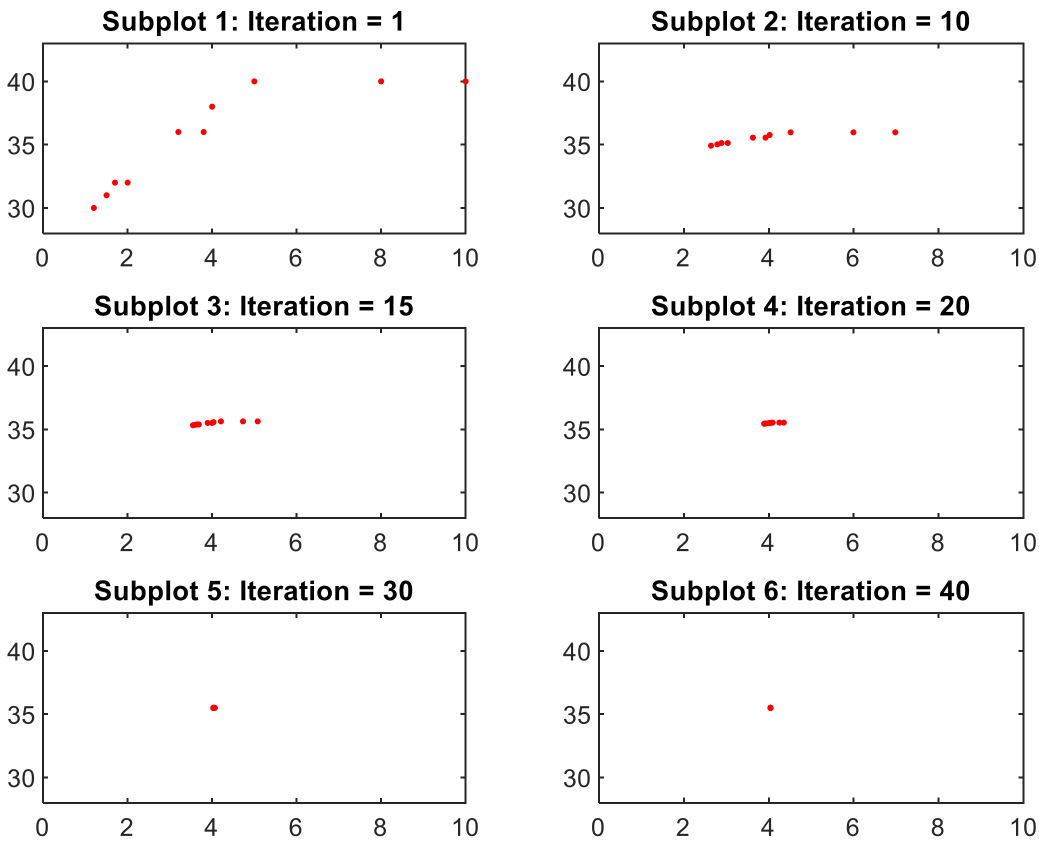

Figure 7: Set of EVs in the process of forming a VPP

To understand this process even more clearly, Figure 7 shows the set of EVs after the partitioning of data into five different sets of initial random centroid, and some set of EVs in subplot 1 that are considered close to a centroid is chosen based on equation 5. Then, through continuous time consensus protocol equations it can be seen that the EVs are getting closer and closer and trying to meet at a certain point to form a VPP as seen from subplot 2 to subplot 6. Hence, this process will repeat multiple times once the dynamic VPP algorithm will not have any EVs to be allocated again, and this might take at least 40 iterations to reach such a stage. The same process will happen for the other VPPs at the same time. This methodology for forming DVPPs and coordinating the EV charging and discharging will be denoted as Scenario C in this thesis. The results section will show how Scenario C improves the grid performance and the satisfaction of the owner better than Scenario B and Scenario A.

3.6 Conclusion

In this chapter, the concept of DVPP is introduced, and this concept was modelled as Scenario C in MATLAB. The methodology for this scenario is developed using two concepts: K-Means clustering and average consensus protocol. A detailed illustration about the working of DVPP was shown. EV management using DVPP modelling is considered as Scenario C. Further, the two different scenarios for the EV charging strategy model are Scenario A and Scenario B. One scenario is the uncoordinated EV charging, and the other scenario is the coordinated EV charging and discharging. The EV coordination for both Scenario B and Scenario C are done by a mixed integer non-linear objective equation, which is a function of time, and the equation contains the SOC, time period and power of EV, and this equation is subjected to grid constraints. The results of the different models of EV charging and discharging are shown in the next chapter. The performance of these models is compared, where Scenario B is the benchmark model and Scenario C is the proposed model.

Chapter 4

Results

4.1 Introduction

Based on the input data, the simulation is run for 24 hours in a discrete period of every 1 minute. It is considered that 100 out of 150 households have an EV with a V2G facility, and in total there are 100 EVs that can participate in the grid. The VPP is developed under a MATLAB environment and open distribution system simulator (Open-DSS) and applies numerical algorithms and mathematical calculations by software to solve the objective function and optimization algorithms. The objective function is formulated to maximize the total customer satisfaction considering two weighting factors: user SOC preference and user preference for charging or discharging time of the EV. This problem is formulated as a mixed integer non-linear programming-based optimization model, and this will also be subjected to grid constraints. Scenario B, which uses the one fixed VPP model or aggregator model, will coordinate these EVs according to the methodology presented in Chapter 3. The aggregator will get the grid constraints and the details of the EVs that are plugged in during that time slot, and then the optimization will run for equation 1. Based on the optimized result, the aggregator will send a dispatch signal to charge, discharge or remain idle for that particular one-minute time slot. For scenario C, instead of a fixed single VPP it has a DVPP where all the EVs will have access to all the information and states of all the other EVs. Based on that, VPP clustering will take place. In this thesis, the number of DVPP is 5, and based on the grid constraints each VPP will decide on its own to run the optimization model (equation 1) or not, and each VPP will send its dispatch signal to their respective EV within its cluster, and the dispatch will take place every one minute. This dynamic aggregation of EVs is implemented into one local computer that will interact with all the EVs and cluster the EVs based on their current states and user preferences. Each VPP will then decide to charge or discharge its EVs based on the system's load demands. As for uncoordinated charging Scenario A, there is no V2G functionality, as there is only charging function; therefore, it is a worst-case scenario. The system power consumption, system power losses and voltage profile of the far bus are studied and compared for all three scenarios in this chapter. Furthermore, sensitivity analysis based on the effects of EV penetration is performed specifically for the methodology in Scenario B and Scenario C and their grid performance results are analysed.

4.2 Simulation Setup

4.2.1 Design of a Residential Distribution Grid in Open-DSS

The Open-DSS, which stands for open distribution system simulator, is power system simulation software used for distribution system design [35]. In this thesis, the simulations are performed using the same residential distribution grid design for all the scenarios. The IEEE European low voltage distribution system [36] is modified into a 150-bus low voltage distribution system. The circuit diagram and its components are illustrated in Figure 8. The circuit includes one source connected to a step-down transformer with voltages 11/0.415 kV and a rated capacity as 300 KVA. The data for the load and the line are available in Appendix A. Figure 8 shows the line and is highlighted in green with bus number 131 and 132, and the distribution line is a three-phase line. The loads are represented in the form of blue circles, and all 150 loads are residential households that are connected to 150 buses each. The system's base frequency is 50 Hz.

4.2.2 Load Profile

The load profile of household 1 in the 150-bus low voltage grid for phase A, phase B, and phase C are shown in Figure 8. This 3-phase load profile is taken from the IEEE European low voltage test feeder, and the load shape is of one-minute resolution for over 24 hours, which is in total 1440 minutes, which equals 1440 data points for every 150 households. The total aggregate of the demand without EVs is shown in Figure 9.

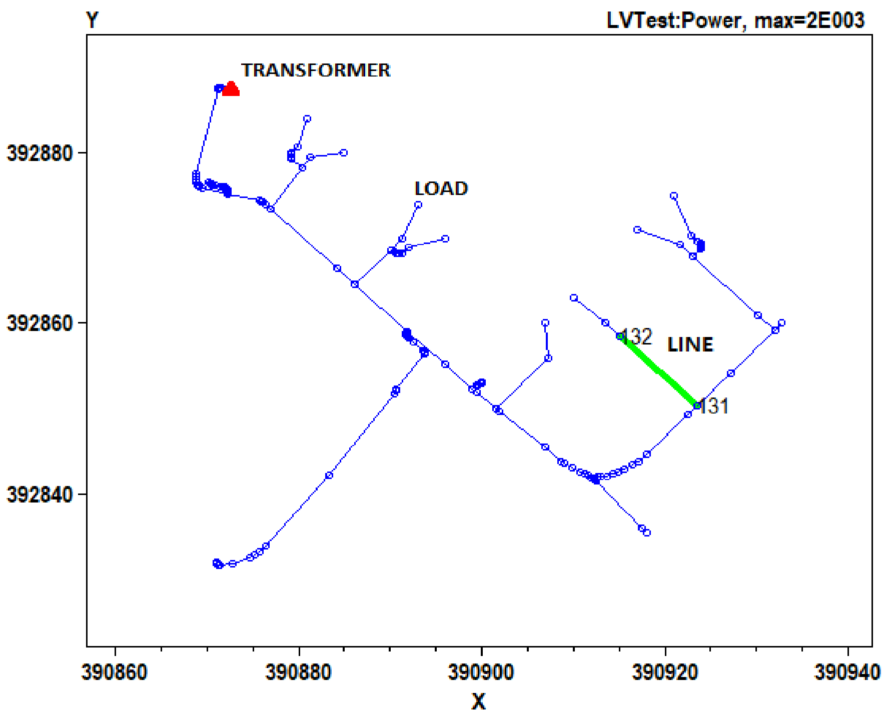

Figure 8: 150-bus low voltage distribution system

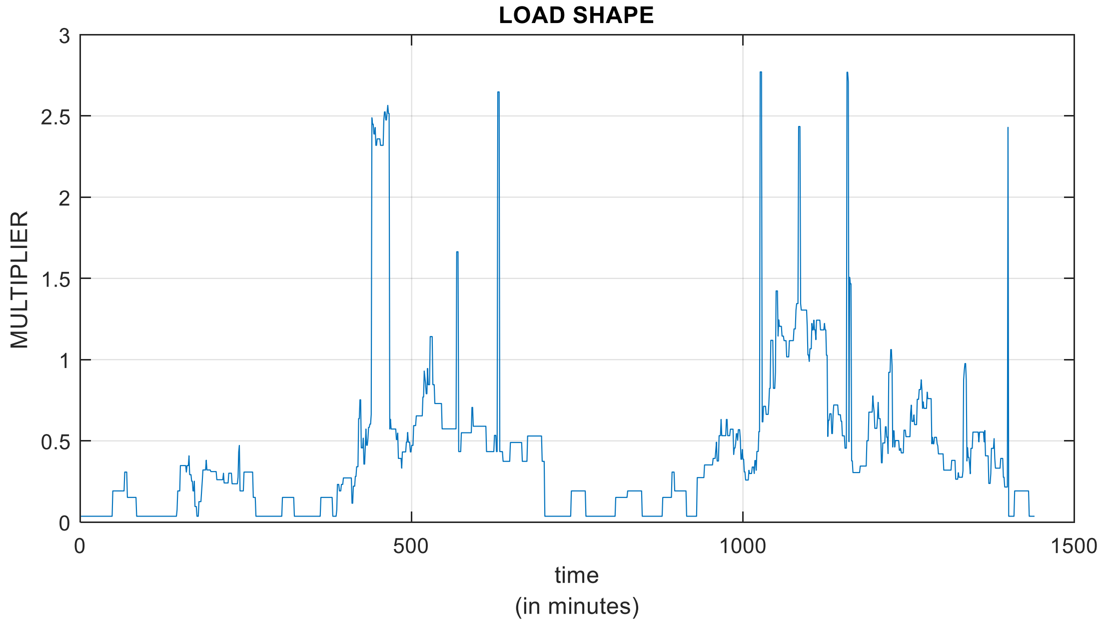

Figure 9: Load profile of LOAD-1 (Household-1) in the 150-BUS low voltage system

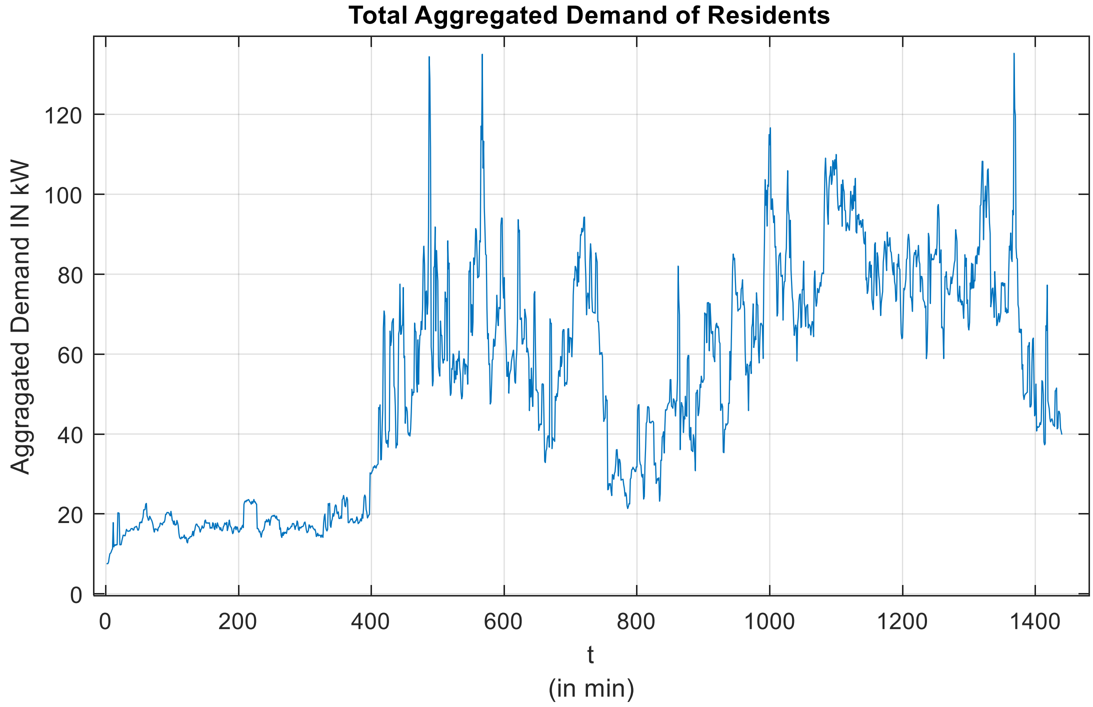

Figure 10: Total demand of all the 150-load demand (150 households) in the grid

This is used for the time-series simulations for all the scenarios in this thesis. The loads are modelled as PQ constant. The base kW value of all 150 loads is specified as 2 kW [37]. There are 100 different load profiles, and these load profiles are input to each of the 150 loads in the residential grid. Figure 10 shows the y-axis as a multiplier value, and all the 150 loads for each minute will have the kW value as the multiplier value and are multiplied by a base value to get the actual power consumption for that minute.

4.2.3 EV Modelling and EV Data

The EV travel data and their availability are taken from the UK Department of Transport electric charge point analysis 2017: Domestic as given in [38]. The data [38] provide the details of monitored EVs such as the energy supplied in kWh, the plug-in duration and the time and date of plugging in the EV. The initial SOC value of the EV when plugged in is taken from the "smart grid smart city" EV trial data [39]. The data are selected based on the energy supplied value taken from [38] and are corelated with the charging amount value taken from the [39]. Based on those, the initial SOC values are estimated, whereas the final user preferred SOC values are randomly generated. The EV battery capacities are considered from 30–107 kWh [40], which represent the battery capacity in today's market. The typical charger rating is 3.8 kW–11.5 kW [41] for home charging through a standard charging outlet. The lower minimum threshold of EV batteries is considered as 20% SOC. Figure 11 shows the number of EVs plugged in for each minute for the entire 24 hours or 1440 minutes of the day.

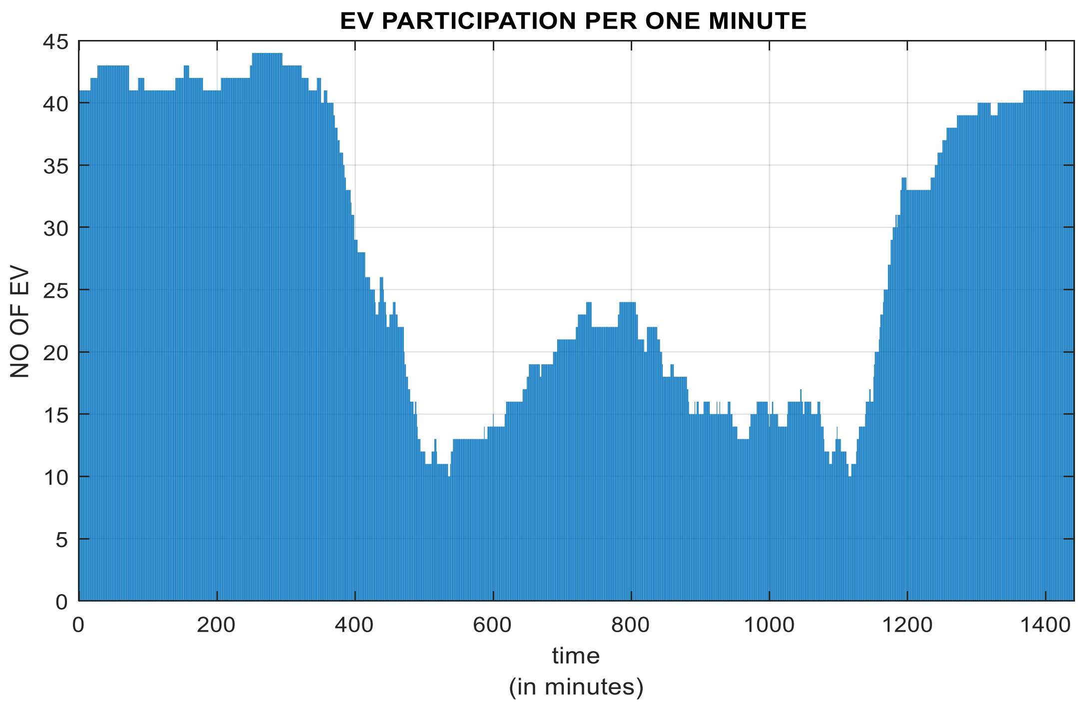

Figure 11: Number of EVs plugged in per one minute resolution for 24 hours in a day

The EVs are modelled as a battery in Open-DSS, as there are no options for having an EV as a device in the Open-DSS software. There are 100 EVs in total that belong to the 100 individual residential houses, and all the houses have V2G capability. Further, the EVs are capable of bidirectional (V2G/G2V) operation based on their plug-in and plug-out time. The V2G and G2V operation of EV is controlled by Open–DSS using MATLAB. Whenever the EV is plugged out the program in MATLAB will make sure that the specific EV does not participate. The list of definitions and assumptions are given in Table 1.

S.NO	Definitions and Assumptions
1	The EV owner will input their requested SOC and plug-out time during the plug-in time.
2	The 24-hour day is divided into a one-minute time slot. In total, there are 1440 time slots in a day.
3	At each one-minute time slot, when the EV gets plugged in, the grid operator will automatically get the initial SOC, battery capacity, and charger type details.
4	Even if the EV reaches its final SOC during charging, the EV will still be used for V2G operations until it gets plugged out.
5	EVs are not allowed to be disconnected before their plug-out time.
6	The coordination algorithm will run for every one-minute time slot and will control the EVs that are connected during that time slot. Hence, the coordination algorithm will run for 1440 minutes of simulation time.
7	The coordination algorithm process will update every one minute whenever an EV is plugged in or plugged out.

Table 1: List of definitions and assumptions

4.3 Computation Implementation of OPEN-DSS, MATLAB and GAMS

As mentioned above, the test grid is implemented in Open-DSS with various different load profiles and EVs connected to the grid. To coordinate these EVs charge-discharge, the power is considered constant for each simulation period of 1 minute. The algorithm is implemented in a MATLAB model to act as an aggregator; hence, the decision-making authority will lie with the aggregator to charge or discharge the individual EVs. For the coordination and optimization to take place for every simulation period, the objective function (1) and its constraints (2) are formulated in General Algebraic Modelling System (GAMS). This software is used to solve mathematical

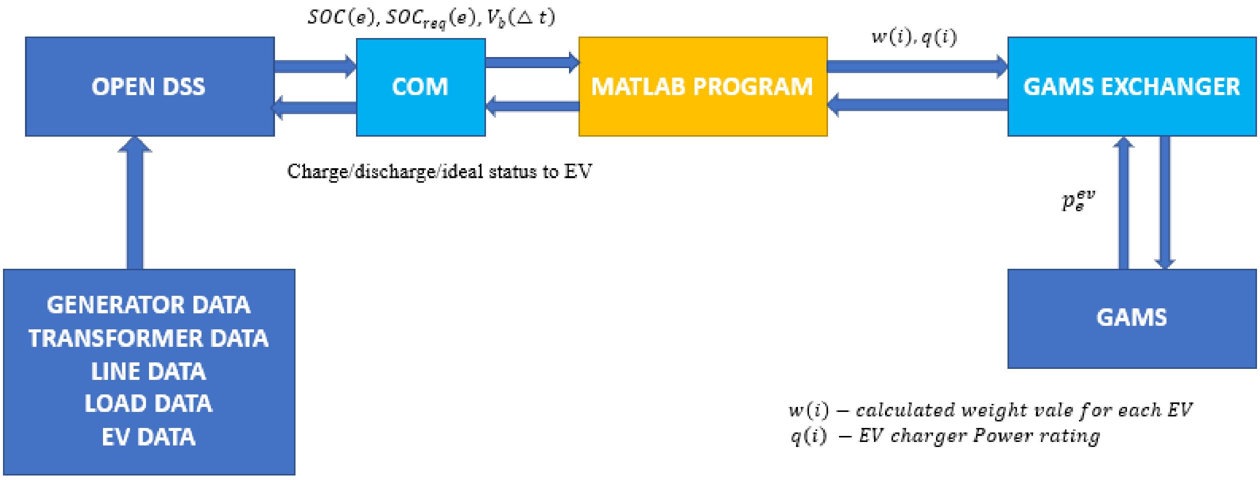

Figure 12: Integration of Open-DSS, MATLAB and GAMS

programming problems. GAMS is used for solving linear, nonlinear, and mixed-integer optimization problems [43]. The equation (1) is formulated as a mixed integer non-linear optimization problem. GAMS will always require a solver to solve the problem formulated. For this equation, KNITRO solver is used. Figure 12 shows that both open-DSS and GAMS are connected to MATLAB through two interfaces called COM and GAMS exchange, which is denoted by blue blocks. These two interfaces will exchange the data between MATLAB and other outside applications like Open-DSS and GAMS. MATLAB is chosen for EV coordination because the dispatching of EVs is done using MATLAB, so GAMS is used to solve the optimization problem, then MATLAB will receive the solution of the optimized problem from GAMS through the GAMS data exchanger.

Similarly, a COM interface is used to interface both MATLAB and Open-DSS. COM stands for Component Object Model and is used specifically for external programs like MATLAB, Python, etc... [35] to control the distribution grid in Open-DSS. Hence, MATLAB will control the EVs in Open-DSS for every minute in 1440 simulation time, and MATLAB with GAMS will also solve the optimization at the same time for the whole 1440 simulation time.

4.4 Grid Performance Comparison of Scenario A and Scenario B

To overcome the problems associated with the un-coordination case of Scenario A, Scenario B is introduced to coordinate the EV and improve the grid conditions. Moreover, customer satisfaction is one of the most important aspects of Scenario B and will be discussed in detail in the next chapter. This chapter, however, will focus on Scenario B improvements in the grid like transformer overloading, power losses and improvements of weak bus voltage. From Figure 13, it is clearly seen that the system power consumption for Scenario B is always less than 200 kW. This proves that the EV coordination in Scenario B can maintain power below a certain level without any cause of overloading of the transformer. When trying to see the improvements for power losses, it can be difficult because there are higher instances of power losses from Scenario B also, but it is still less than Scenario A. When comparing the average value of power losses, Figure 14 of Scenario A is 10.6 kW, whereas the average power losses for Scenario B are 9.18 kW, which is still an improvement from the

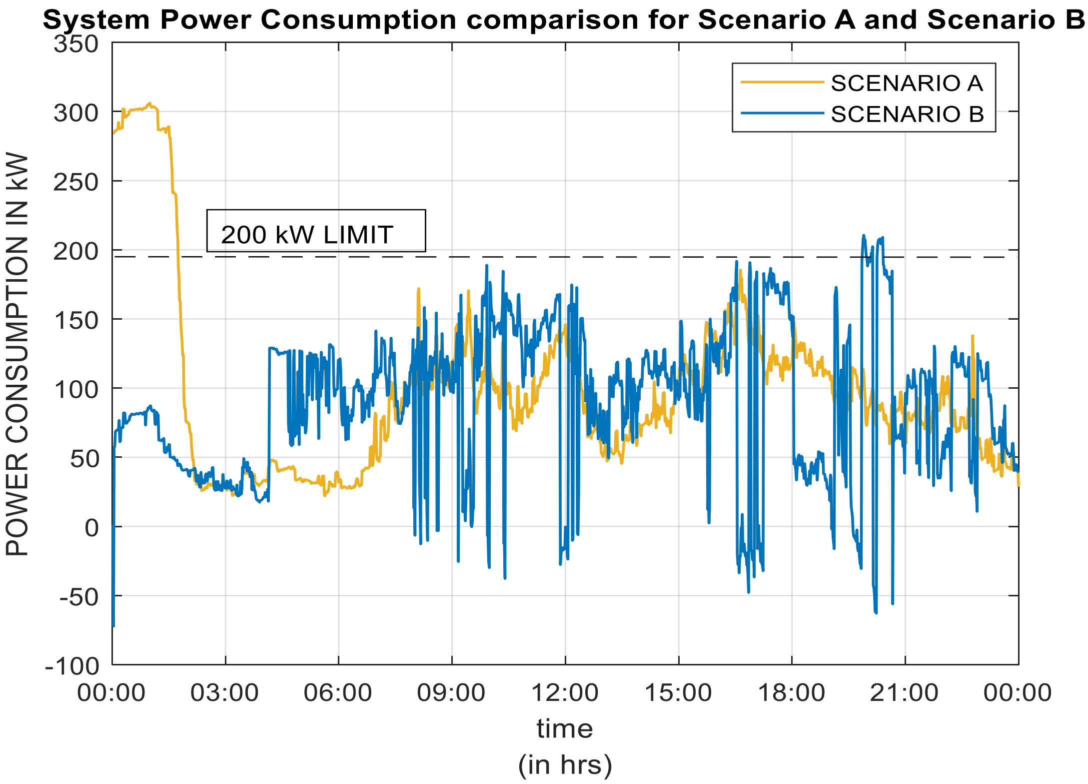

Figure 13: Scenario A **(**Uncoordinated EV) vs Scenario B (Coordinated EV) system power comparison

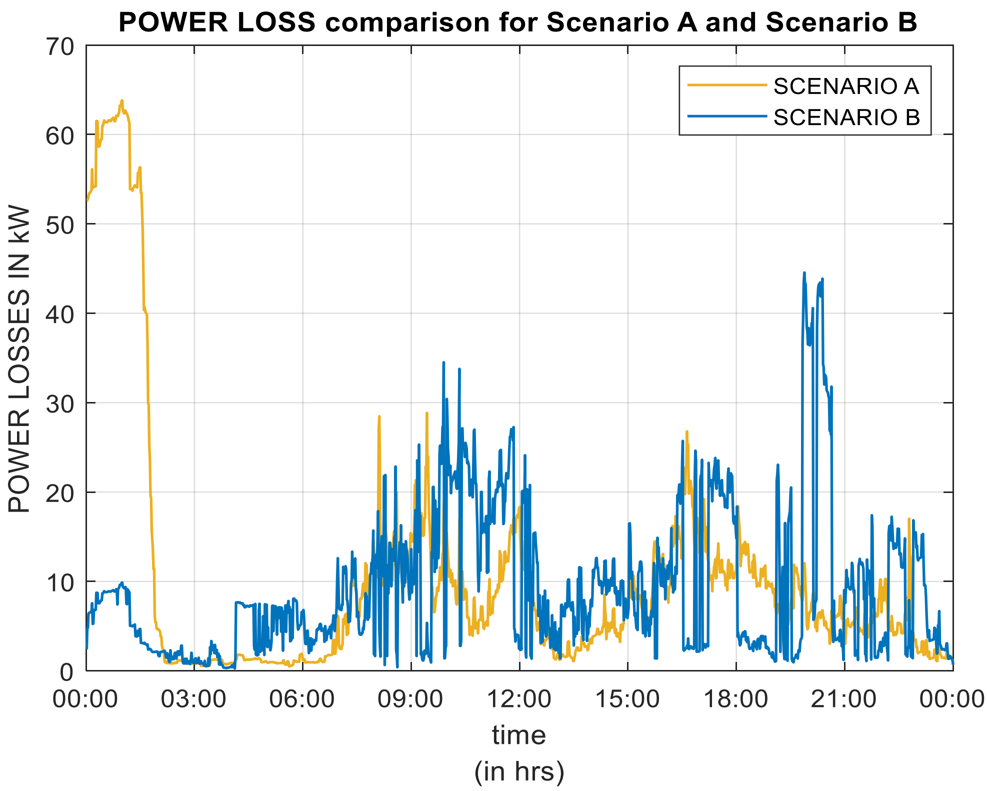

Figure 14: System Power Losses for Scenario A **(**Uncoordinated EV) vs Scenario B (Coordinated EV)

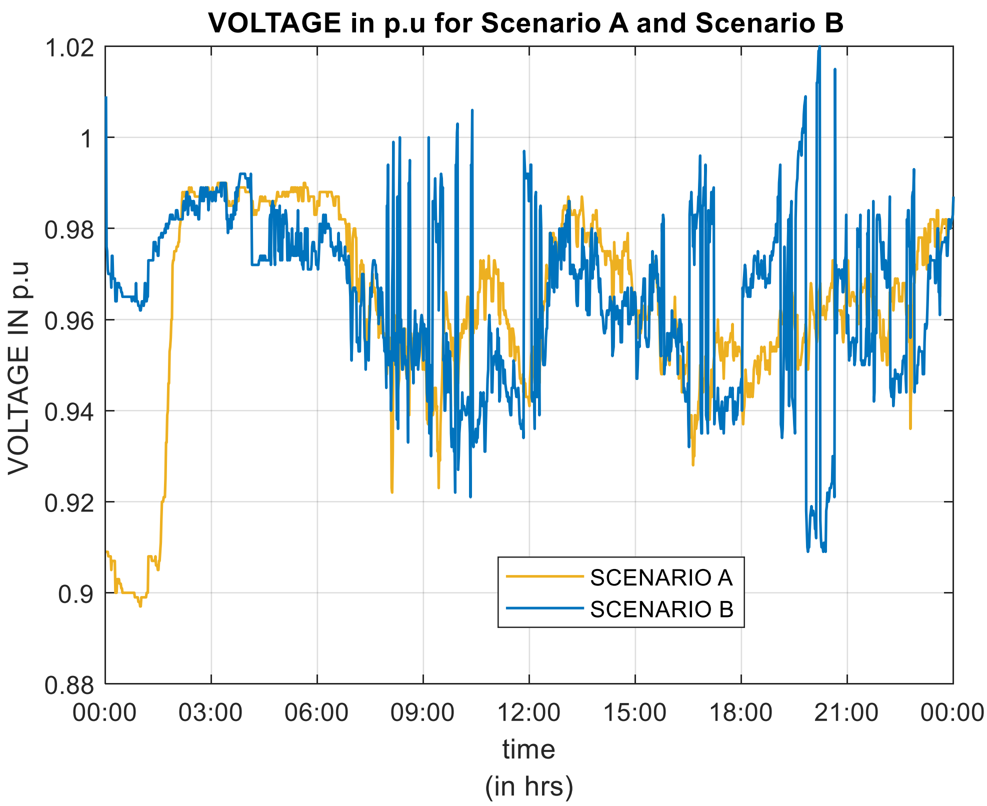

Figure 15: Scenario A **(**Uncoordinated EV) vs Scenario B (Coordinated EV) far bus-96 voltage comparison

uncoordinated case. Similarly, there are improvements in voltage deviation of the far bus-96. The highest voltage deviation of Scenario A is 0.90 pu, but when compared to Scenario B the highest deviation is 0.92, which is a significant improvement as seen in Figure 15.

4.5 Grid Performance Results for Scenario C

The plots shown in this section include system power consumption, power losses of the system and the far bus voltage profile of the grid. The simulation results are run for three different cases: Scenario A is for uncoordinated EVs, which does not have any algorithm or optimization, Scenario B is for EVs coordinated using one fixed VPP and optimization, whereas Scenario C is EV coordination using DVPP and optimization based on customer satisfaction. This demonstrates how the Scenario C method is much better than the Scenario B method. Now, in the power loss graph in Figure 16 it can be seen that the case with the least power loss is Scenario C. Even if we compare the average power loss, for Scenario A it is 10.59 kW, Scenario B is 9.1 kW, and Scenario C is 5.98 kW, so Scenario C is still less than other two cases. To understand the power loss graph, we need to see the system power consumption plots, as this will give us a better idea of why Scenario B has higher losses than Scenario C. Figure 17 shows that there are instances where the power consumption and power discharge of the EVs are much higher during the times 12:00

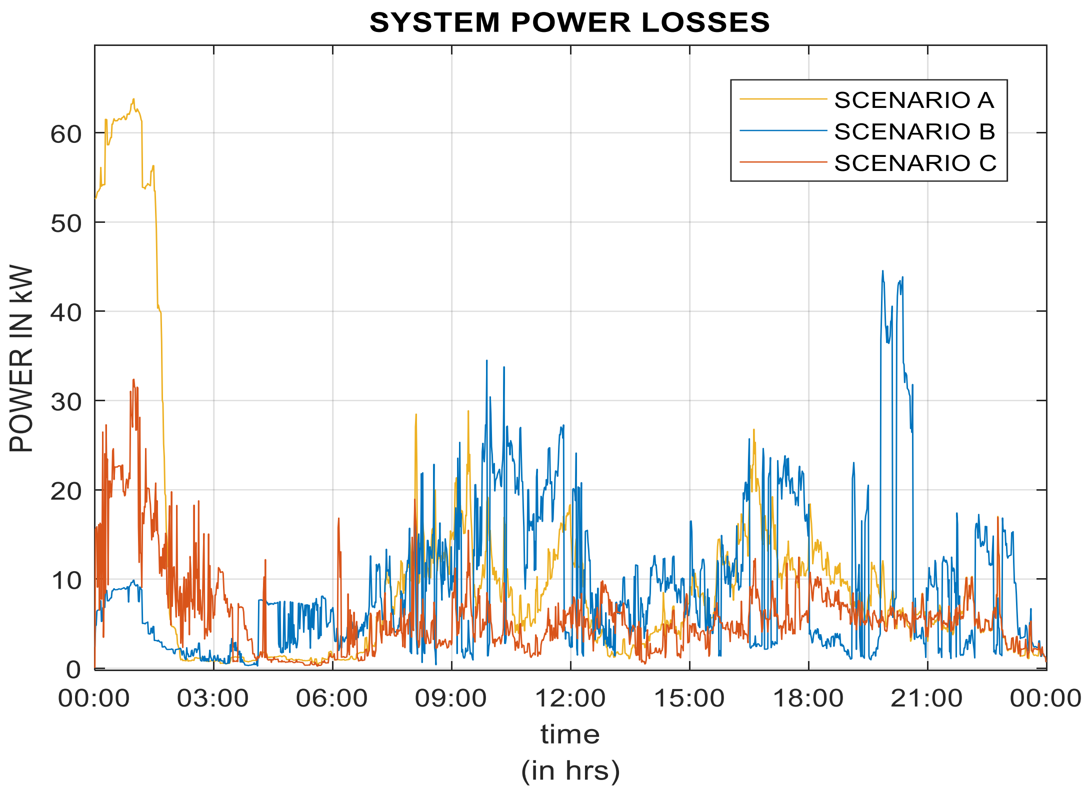

Figure 16: Power Loss for Scenario A (Uncoordinated EV), Scenario B (Fixed VPP model), Scenario C (DVPP model)

hrs, 16:00 hrs–20:00 hrs. The reason for this is because the load demand during these times is higher, and EVs try to reduce the load demand during this time. Also, when the time to plug out the EVs from the grid gets near, the EVs that have less power due to discharge will try to get charged back quickly by consuming more power. How is Scenario C able to manage this much better than Scenario B and what makes Scenario C better? We know that in Scenario B, the optimization model is run by one single aggregator/single VPP. But Scenario C has EVs, which will automatically get clustered into five VPPs. Based on the system demand requirements and the customer preferences, only selected VPPs will operate to get charged or discharged, and some VPPs will just remain idle based on the system constraints. Hence, this aspect of Scenario C makes the use of EVs more flexible as the decision does not lie with one VPP, and the decision making for EV dispatch will be done by five different individual VPPs. Hence, the unnecessary charge and discharge of EVs can be eliminated. Certain VPPs are optimized to support the load demand, whereas in Scenario B the EVs are under one VPP or aggregator; hence, it is limited to a fixed/single VPP or aggregator and does not have the flexibility of the dynamic VPP to control the EV charge and discharge operations. Moreover, this single fixed VPP model is only dependent on the objective function variable (e.g., electricity price, weight factor,

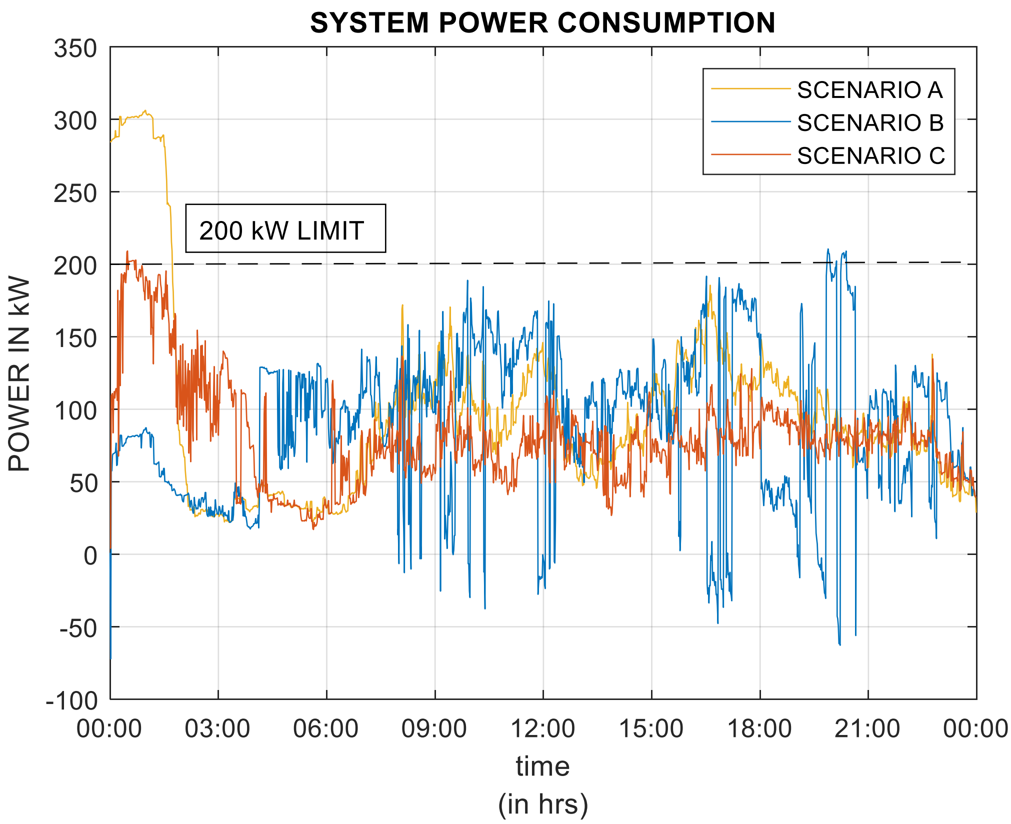

Figure 17: System power consumption for Scenario A (Uncoordinated EV), Scenario B (Fixed VPP model), Scenario C (DVPP model)

grid constraints, etc) and does not include the state and nature of EVs (like EV storage capacity) when coordinating the EVs. However, Scenario C will cluster the EVs based on its states and storage capacity into different VPP groups, and it will further optimize those individual groups of VPPs and provide more flexibility to control the charging strategies leading to improved grid performance. Figure 18 shows the voltage profile where Scenario C performs much better than Scenario B and Scenario A. But there is only one instance where Scenario C is not able to maintain 0.95 pu, which is between 1:00 and 2:00 hrs. The reason is that according to the VPP algorithm, higher plug-out times and higher capacities will be grouped together and charged at the time, which inevitably has to deviate due to the larger number of EVs with similarly higher capacities and the plug-out time gets introduced into the system. Moreover, Figure 18 shows bus-96, which is specifically chosen because this is the farthest bus away from the source and the transformer.

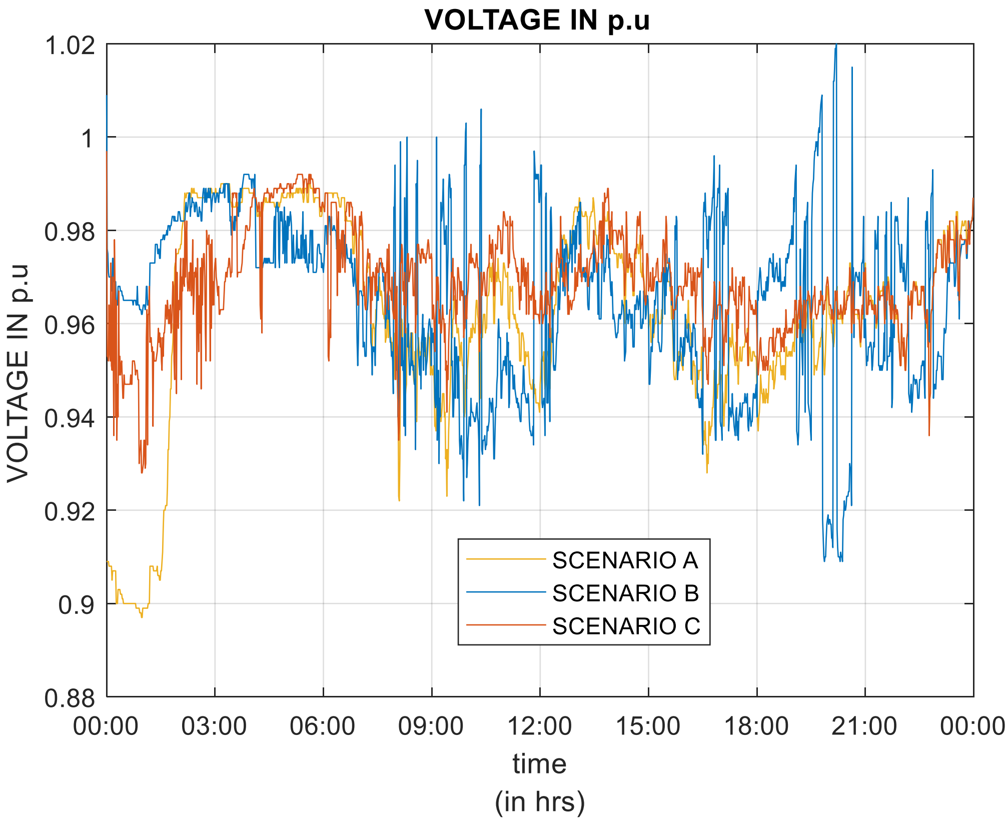

Figure 18: Voltage profile in Bus 96 for Scenario A (Uncoordinated EV), Scenario B (Fixed VPP model), Scenario C (DVPP model)

4.6 Illustration and Verification of DVPP Clusters

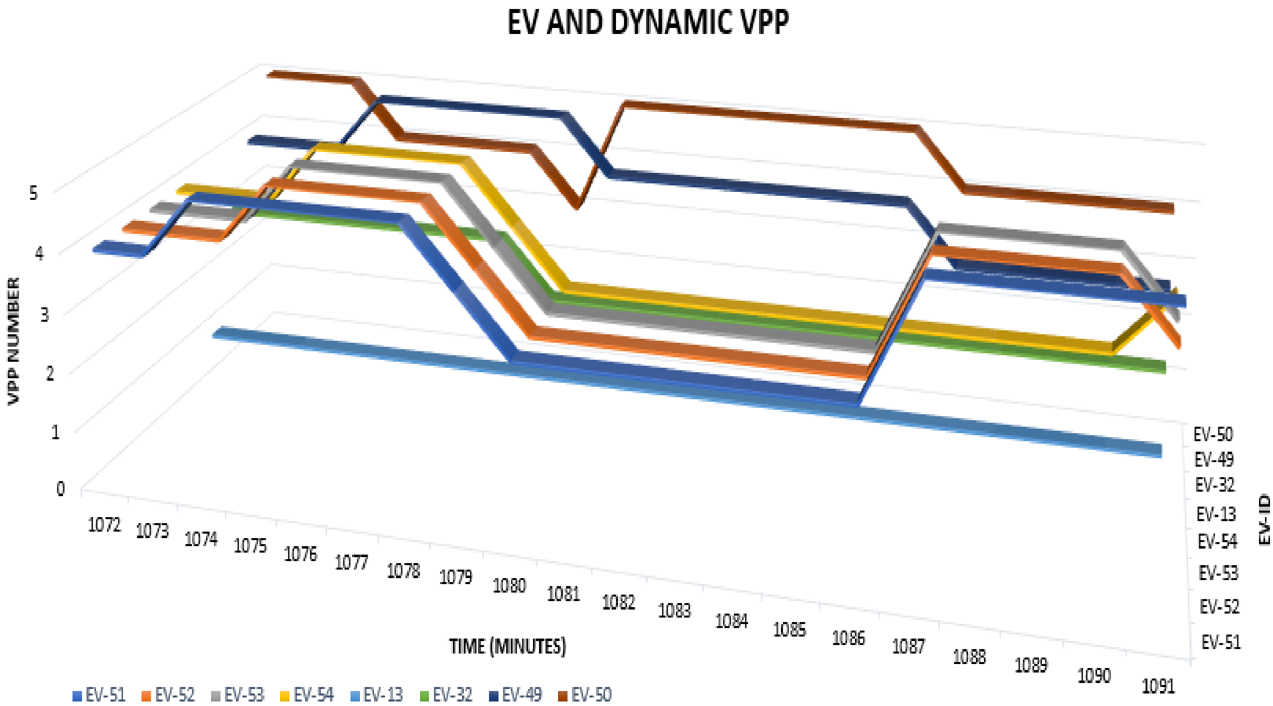

Figure 19: Clustering of specific EVs into different VPPs for the time slot between the 1072nd minute until the 1091st minute from Scenario C.

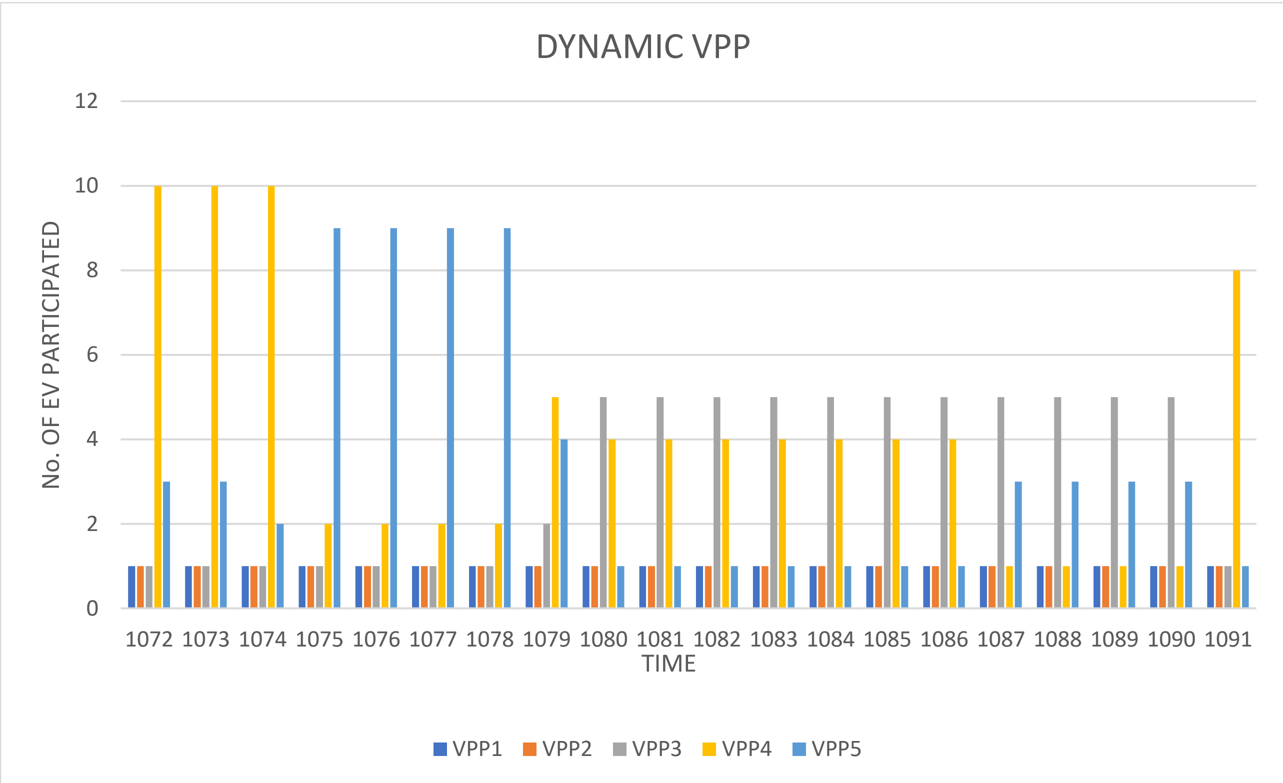

Figure 20: Number of EVs participating in each VPP cluster for time slot 1072 until 1091 minute from Scenario C

Figure 19 represents the way each EV moves from one VPP cluster to another VPP cluster when their present states of EV change continuously for every minute due to the charging and discharging activity of all EVs. For instance, take EV-51. At the 1072nd minute it is plugged in and the dynamic VPP algorithm sends that particular EV to VPP-4 and then at the 1074th minute EV-51 goes to VPP-5 and stays in VPP-5 until the 1079th minute. Then, due to the charging and discharging activity of all the EVs, the algorithm then sends this EV to VPP-3 at the 1086th minute and then back to VPP-5. Hence, based on the system requirements and constraints, the DVPP algorithm will cluster the EVs on a different VPP for each time slot as shown in Figure 19. Figure 20 shows the number of EVs participating in the VPP clustering; for instance, at the 1072nd minute VPP-4 has a higher number of EVs than the rest of the other VPPs, whereas after some of the EVs get plugged out the number of EVs in VPP-4 reduces to 2, and the number of EVs in VPP-5 goes up to 9. This clustering is highly dependent on the grid requirements and the present status of the EVs. The main idea of using this dynamic VPP algorithm is to simultaneously improve the grid performance as well as the customer requirements.

4.7 Effects of EV Penetration on Grid Performance and User Preference

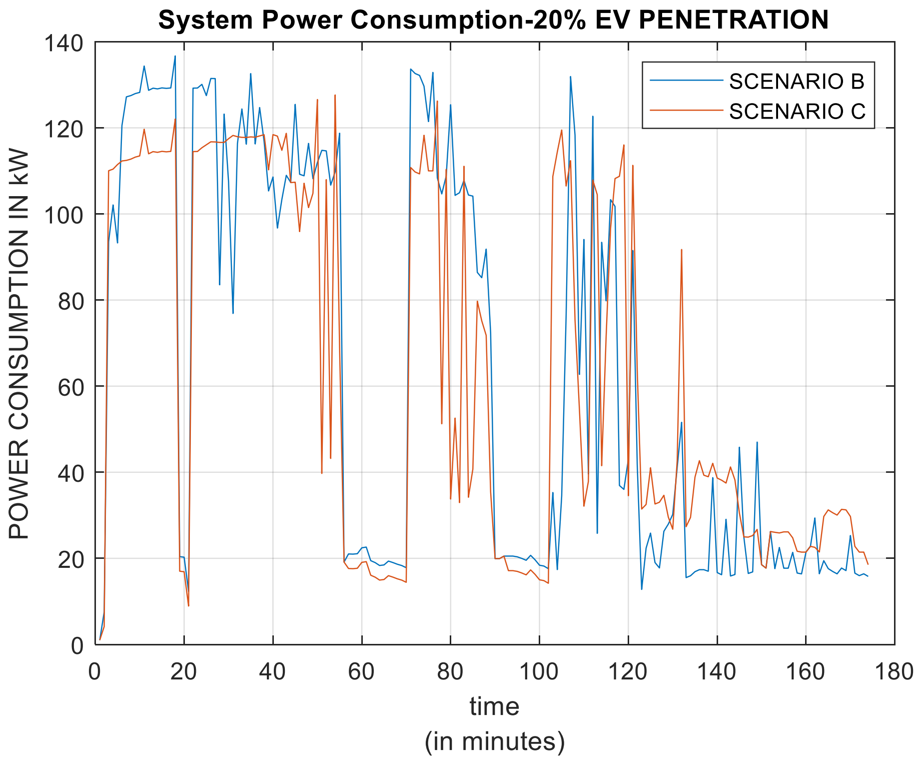

Figure 21: System Power Consumption for 20% EV Penetration Scenario B (Fixed VPP model) and Scenario C (DVPP model)

In this section, a different set of simulations was performed with simulation reduced from 1440 minutes to 180 minutes, which is three hours. This time was chosen to do a sensitivity analysis and to see how well the algorithm deals with a situation where more EVs are to be charged at a very short plug-in duration and with limits on the system power consumption until 150 kW. Hence, the plug-in duration for this analysis is chosen between two to three hours, and the penetration of EVs will be starting from 20% and will gradually be adding 10% to every time for analysis until 70% and will check for how each penetration analysis sees the grid performance and user preference effects. In this section, only two scenarios will be compared: Scenario B and Scenario C because Scenario B has the methodology used by previous literature, and Scenario C has the proposed methodology, which is the DVPPs for EV coordination. Figure 25, Figure 27, and Figure 29 follow the same pattern where the system power consumption of Scenario C is higher than Scenario B. Yet, Figure 22, Figure 26, Figure 28, and Figure 30 all show that the power losses are lower for Scenario C when compared with Scenario B despite the instances where Scenario C consumes more power at certain times than Scenario B. To reach the user SOC requirements, the dynamic VPP algorithm technique has managed to lower the power losses of the grid successfully for 20%, 40%, 50% and 60% EV penetration.

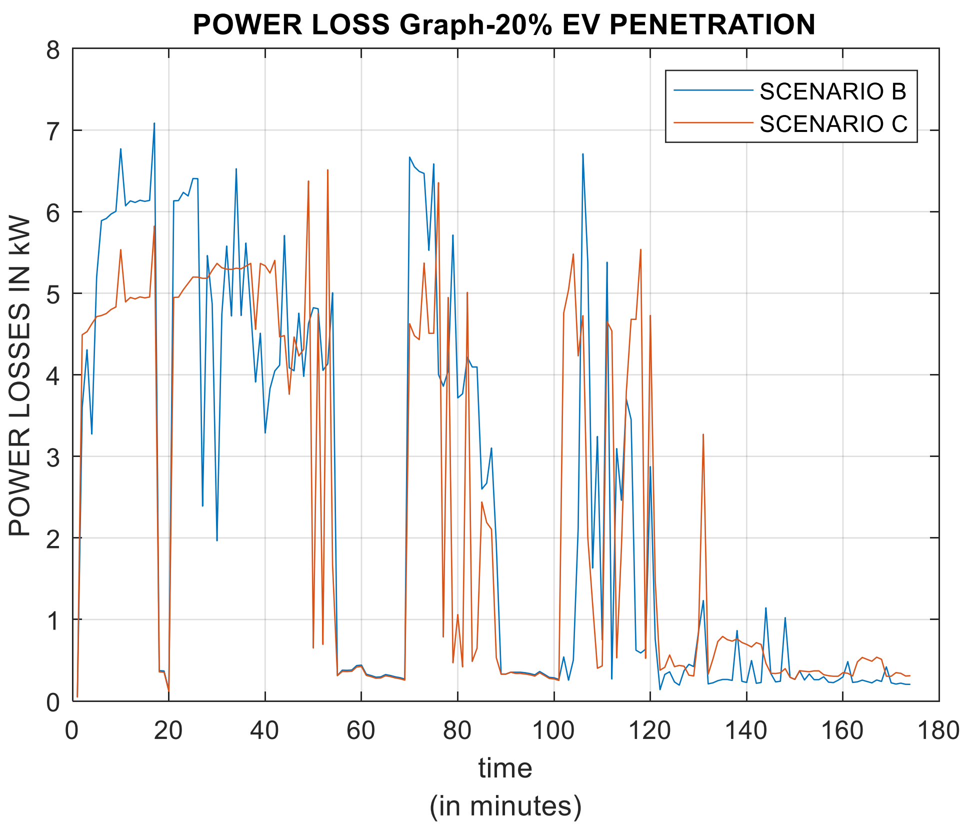

Figure 22: Power Loss for 20% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

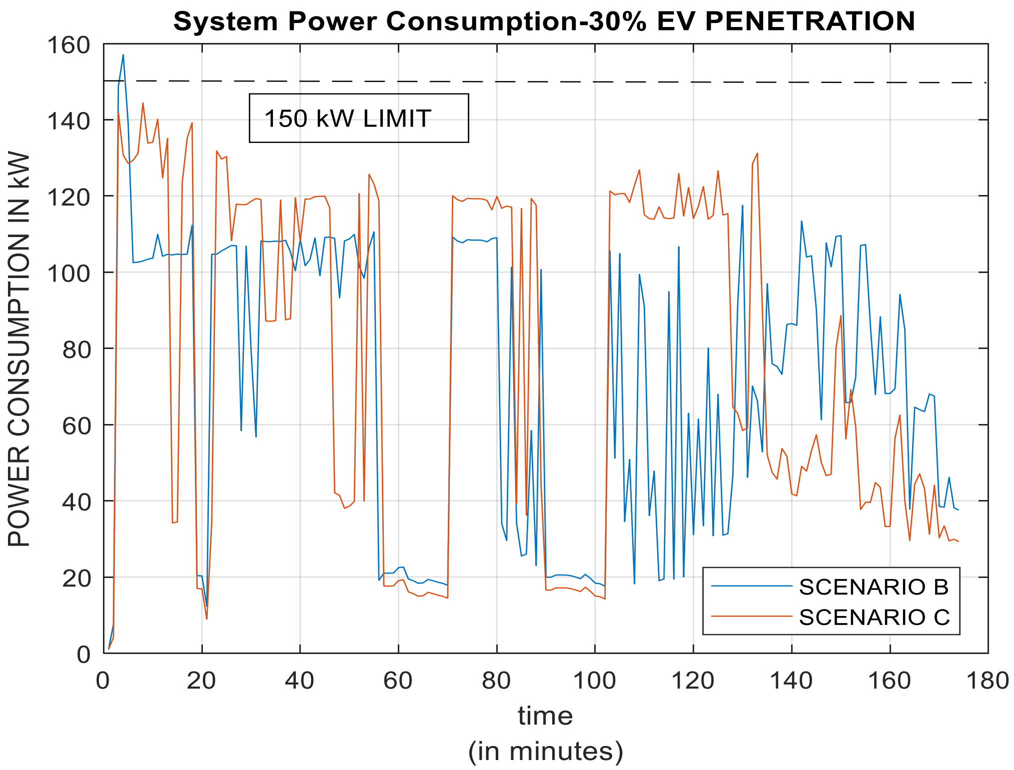

Figure 23: System Power Consumption for 30% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

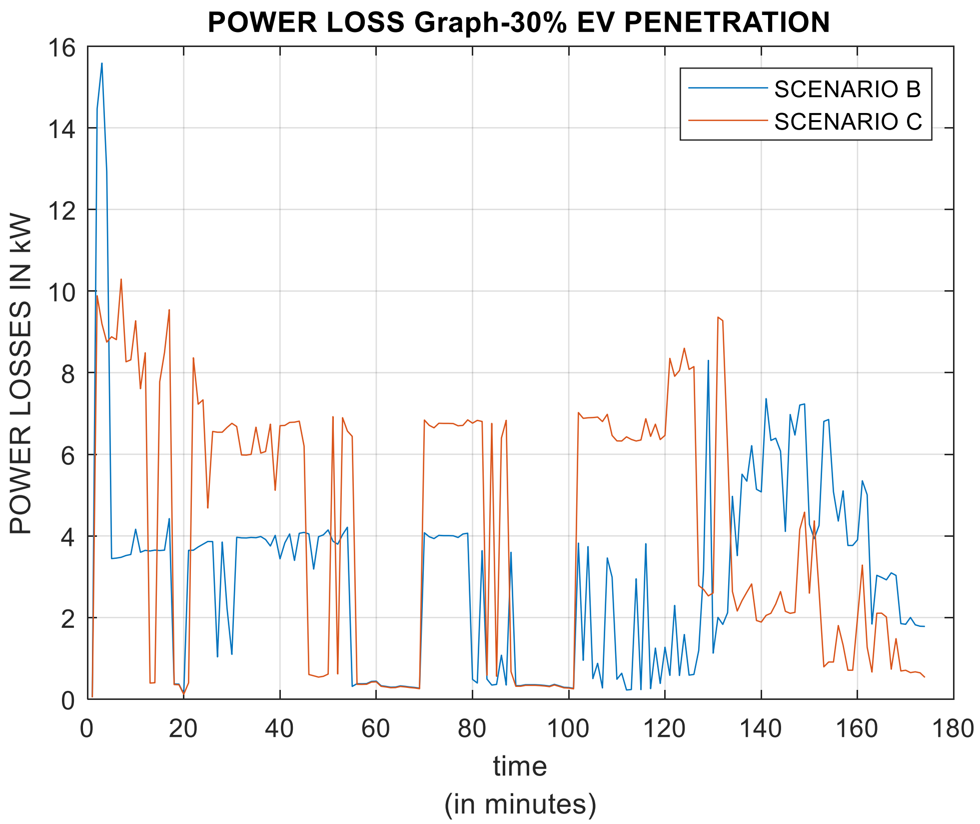

Figure 24: System Power Losses for 30% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

For 30% penetration, Scenario B (fixed VPP model) has better grid performance than Scenario C (DVPP model), which explains why the power losses for Scenario B are much better than Scenario C. When looking at the 30% penetration case for user satisfaction from Figure 33, out of 30 EVs, 23 get satisfied for Scenario C, whereas for Scenario B only 17 EVs get satisfied or reach the user preferred SOC, which means that for Scenario B almost 43% of EVs did not meet the user SOC requirements, which is a large number. Hence, when looking into this aspect, Scenario C attempts to make sure that all the grid constraints and user requirements are still met when compared with Scenario B. The 40% EV penetration for scenario C (DVPP model) has lower power losses and slightly higher power consumption, but when analysing the number of EVs satisfied for scenario C only 19 out of 40 EVs have reached the desired user SOC, but Scenario B has been able to get 23 out of 40 EVs satisfied. The reason for this might be due to the power consumption level seen in Figure 25 between 140 and 180 minutes. The power consumption for Scenario B increases, whereas Scenario C decreases. This is because the EVs in Scenario C have discharged and have started supplying the load demand, whereas Scenario B still continues to consume energy from the grid and supply it to the EVs and residential loads.

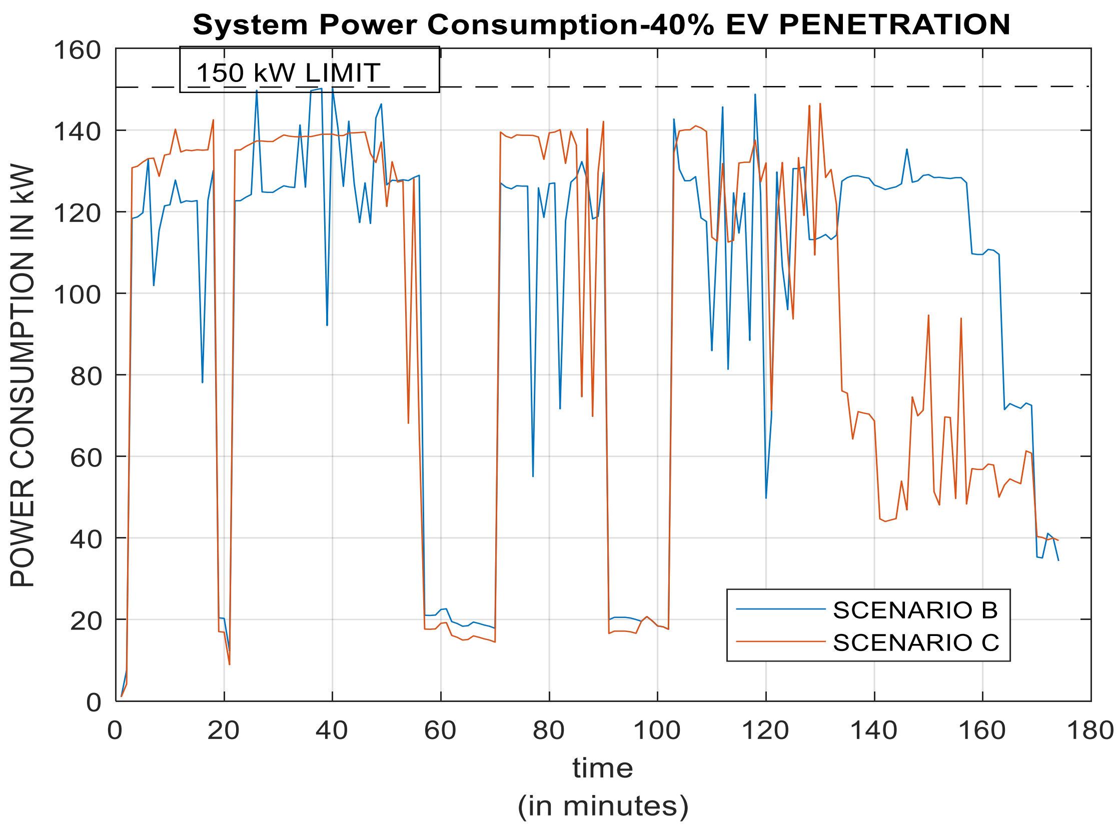

Figure 25: System Power consumption for 40% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

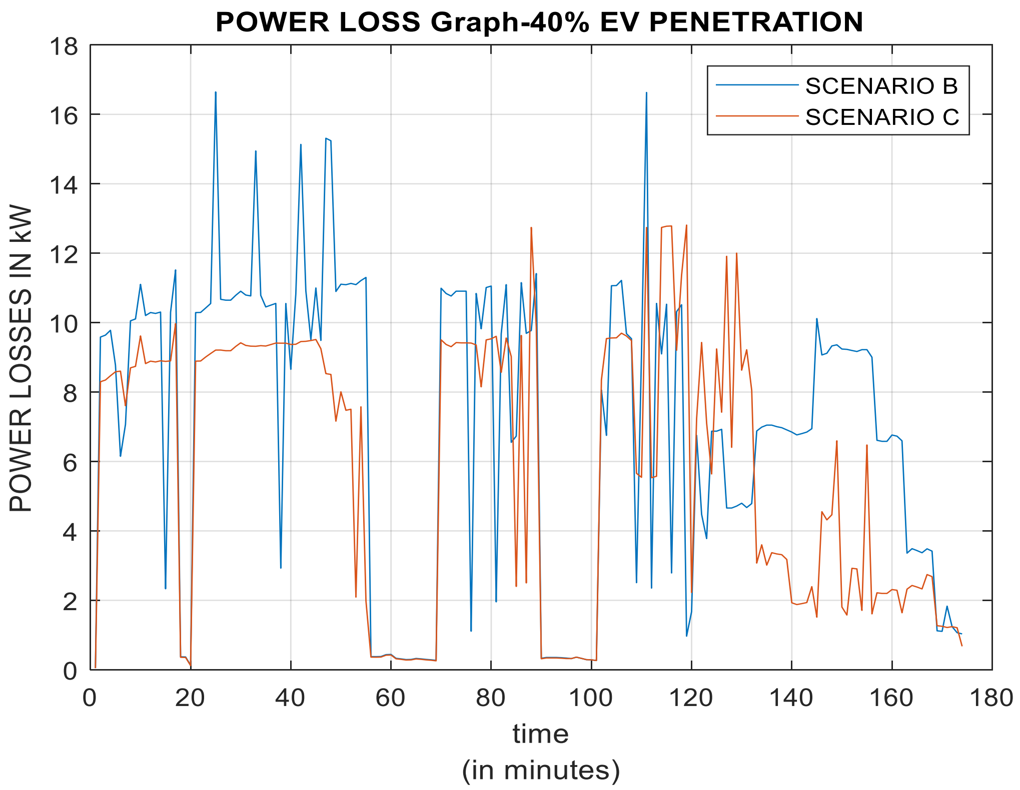

Figure 26: System Power Losses for 40% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

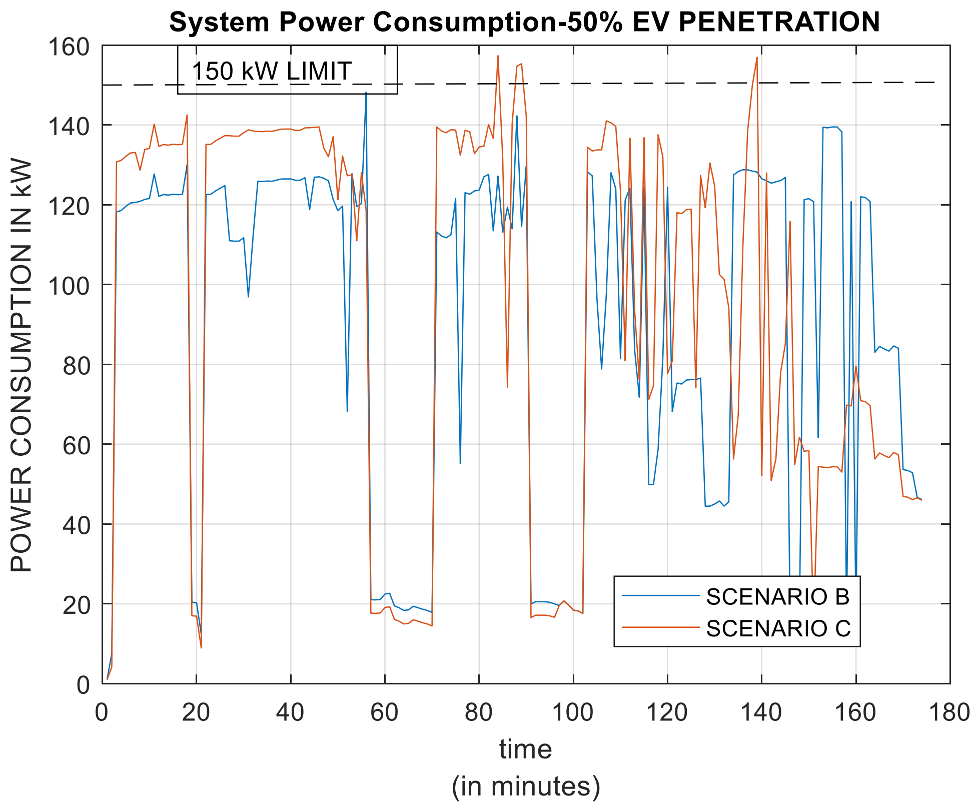

Figure 27: System Power consumption for 50% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

When analysing the power consumption of the system for 20%, 30%, 40%, 50% and 60% EV penetration levels from Figure 21, Figure 23, Figure 25, Figure 27, and Figure 29 for Scenario C (DVPP model), the power consumption levels are always lower between the time period of 140 minutes and 180 minutes. Except for the 70% penetration case during the 140th minute, the power consumption of Scenario C is much higher than Scenario B (fixed VPP model). Again, this pattern only shows that there are EVs discharging during this time, and especially for the user satisfaction as seen in Figure 33 the 40% and 50% penetration shows much fewer EVs satisfied compared to Scenario B (fixed VPP model), where one of the VPPs in Scenario C has decided to discharge its EV rather than consume power from the grid, and the other remaining VPPs are staying idle. There is a clear failure of both the dynamic VPP algorithm and Scenario B, which uses the single fixed VPP method or aggregator method where the grid performance is poor, and Scenario C exceeds the limits fixed by the algorithm to maintain the system power levels below 150 kW. Furthermore, Scenario B is also a failure in this case because the user satisfaction for the 70% penetration case is almost same as the 30% penetration case. This is because the sensitivity analysis for the 70% penetration case has stricter constraints where more EVs need to be charged at a short period of 2–3 hours, which makes it difficult to meet all the requirements of the grid for both Scenario B and Scenario C.

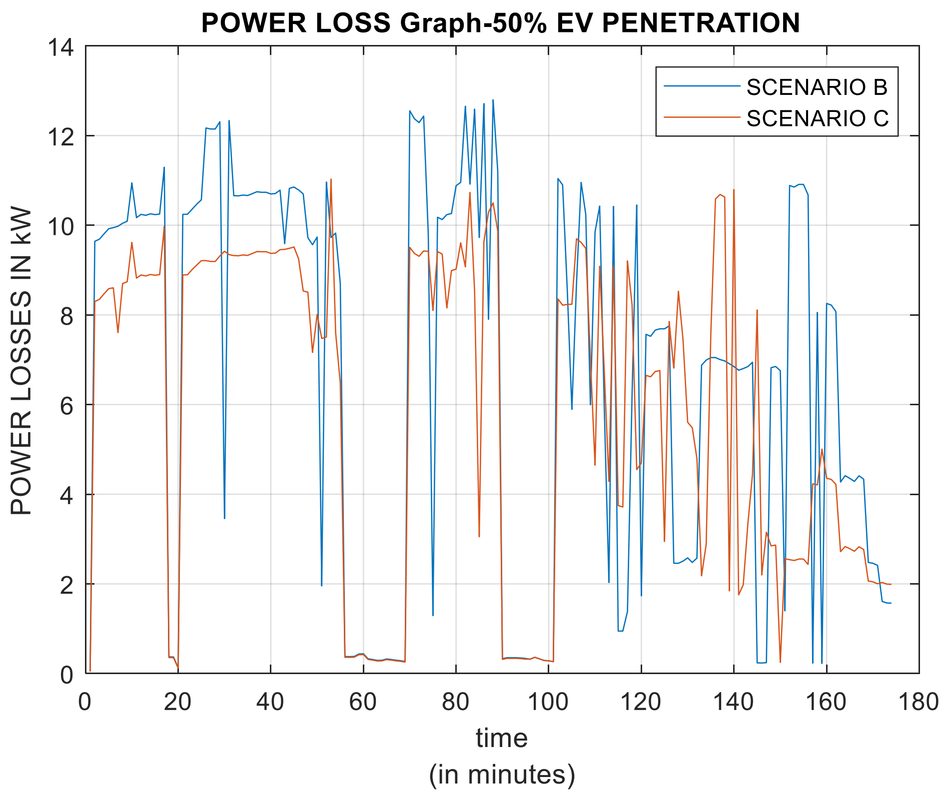

Figure 28: System Power Loss for 50% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

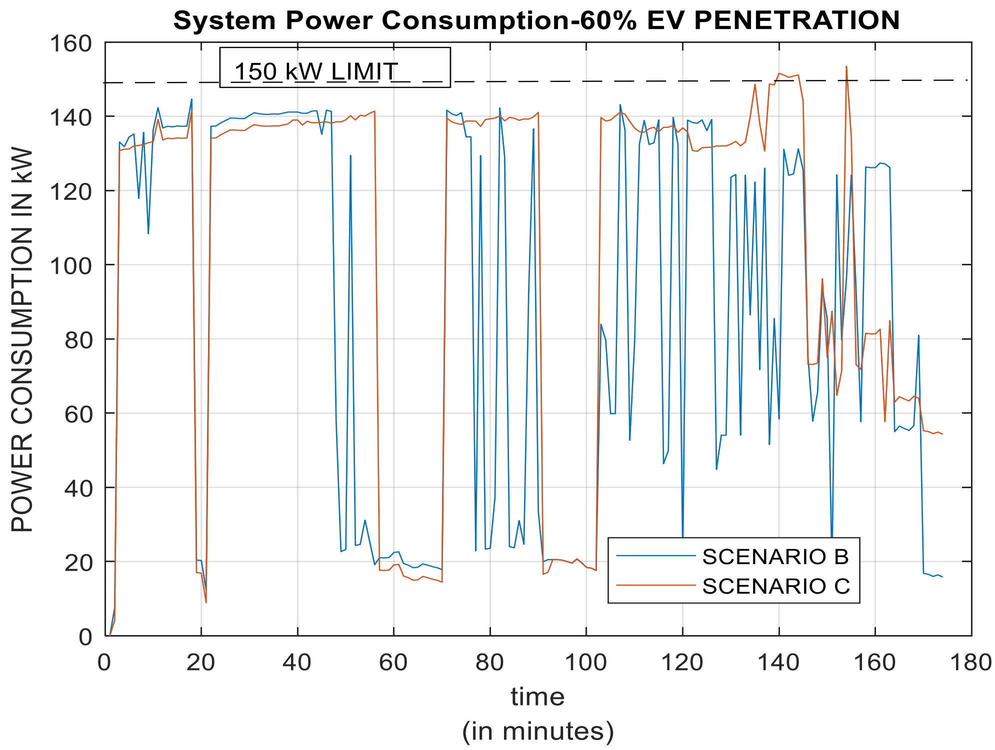

Figure 29: System Power consumption for 60% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

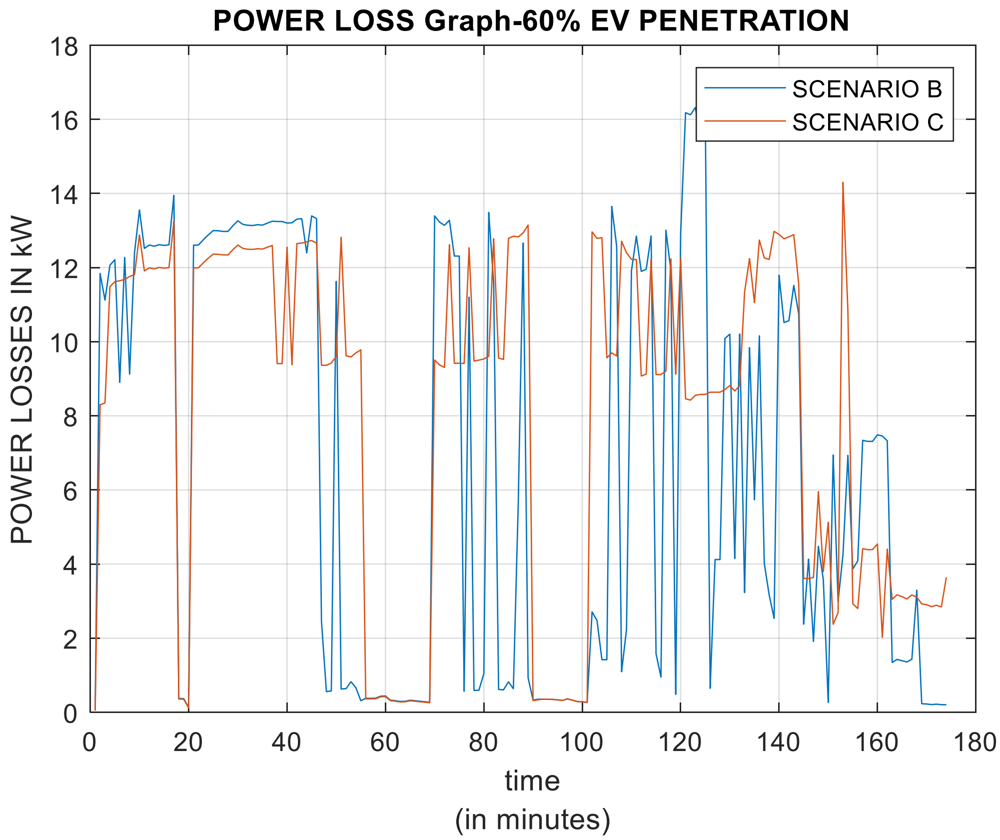

Figure 30: System Power Losses for 60% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

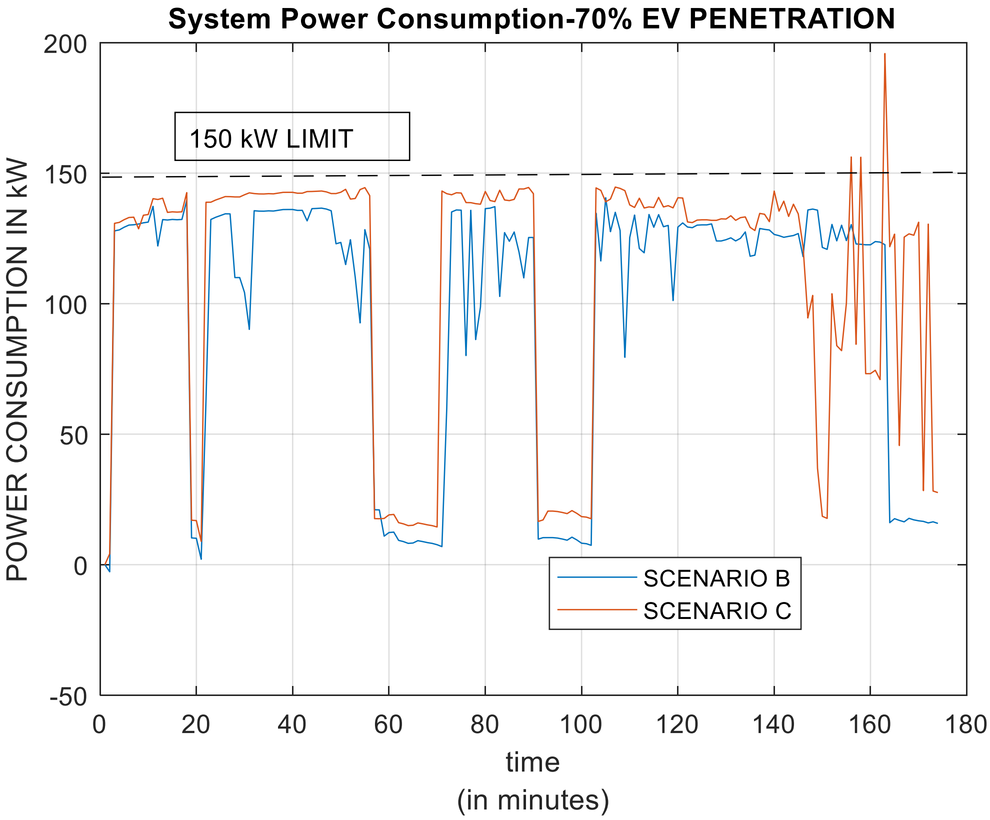

Figure 31: System Power consumption for 70% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

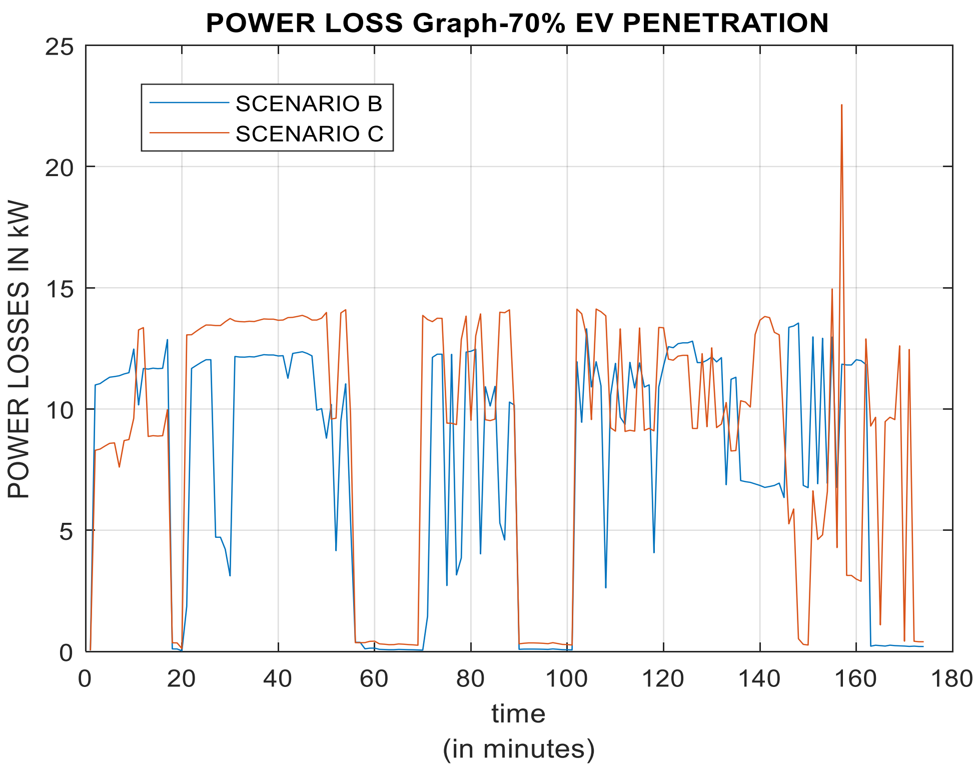

Figure 32: System Power consumption for 70% EV Penetration Scenario B (Fixed VPP model), Scenario C (DVPP model)

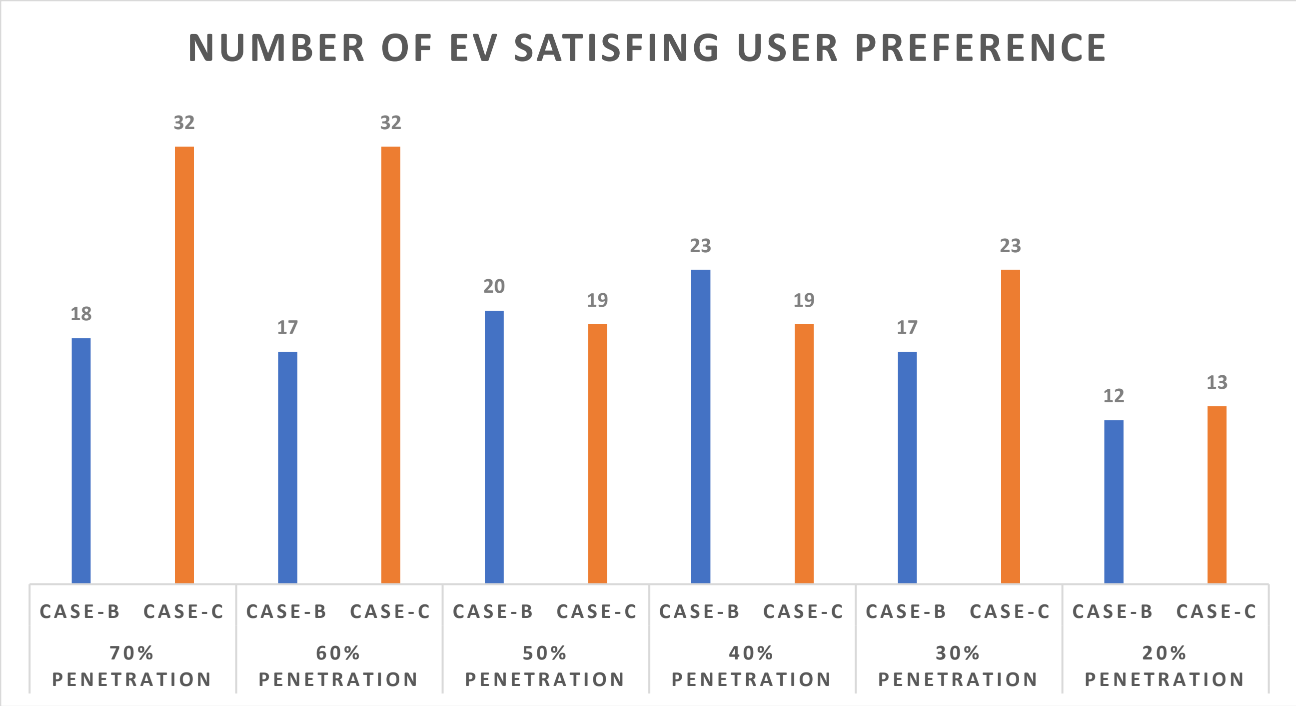

Figure 33: Number of user satisfaction for different penetration levels

S.NO	EV PENETRATION LEVELS	SCENARIO B (kW)	SCENARIO C (kW)
1	20%	1.86	1.12
2	30%	2.96	2.23
3	40%	6.90	5.81
4	50%	7.16	5.97
5	60%	8.66	8.02
6	70%	7.67	8.85

Table 2: Average power losses for different penetration levels

The user satisfaction for different EV penetration levels can be analysed from Figure 33, which shows the number of EVs that have been satisfied for six different penetration levels. Overall, it can be seen that except for the 40% and 50% penetration levels, all the other penetration levels for Scenario C (DVPP model) have higher satisfaction levels than Scenario B (fixed VPP model). The reason for the decrease in satisfaction levels for 40% and 50% in Scenario C is explained above. Hence, it can be seen that even for customer satisfaction levels Scenario C (DVPP model) is much better than Scenario B (fixed VPP model). When comparing the grid performances on an overall scale, in terms of power losses from Table 2, Scenario C is much better than Scenario B because for different penetration levels Scenario C's power losses are lower than Scenario B, except for the 70% penetration, where the Scenario C algorithm fails to perform.

4.8 Conclusion

In this chapter, the results of three different scenarios for EV charging strategies are modelled and simulated. Scenario A is uncoordinated EV charging, Scenario B is coordinated EV charging and discharging using a fixed VPP model, and Scenario C is EV coordination by the DVPP model.

The results show that Scenario A has higher power losses and voltage deviations when compared with Scenario B. Moreover, Scenario A is prone to transformer overloading, whereas Scenario B overcomes these issues and makes sure the power consumed by the grid is maintained below a certain value, which in this case is 200 kW. The analysis also showed that whenever the household demand rises the coordination algorithm is able to shift the EVs from G2V operation to V2G operations without much of an impact to the grid.

The result from the proposed methodology is compared with the results of Scenario B, where this methodology is taken from previous literature in order to show the limitations of the method used currently in Scenario B and the advantages of using Scenario C, which provides much better grid improvements and customer satisfaction. Furthermore, sensitivity analysis is done by adding more constraints to both Scenario B and Scenario C, and grid performance and customer satisfaction are analysed for different EV penetrations.

It can be concluded overall that the DVPPs bring more improvements in terms of less power loss and a better voltage profile to low voltage residential distribution grids than the traditional single VPP or single aggregator model that is used at present.

Chapter 5

Final Conclusion and Future Work

5.1 Conclusion

A DVPP model for EV coordination has been proposed in this thesis to support a residential low voltage distribution grid. Furthermore, the DVPP is used to improve the performance of the grid by reducing power losses, preventing undervoltage and limiting the system's power consumption to certain levels that will be decided by the operator. The EV dispatch is coordinated and optimized by these DVPPs by themselves instead of relying on a single fixed VPP or any aggregator. The optimization is performed to maximize the customer satisfaction by simply satisfying the user's SOC preference while complying with the grid constraints.

In contrast to most fixed VPP models, the proposed methodology gives the EV the freedom to move from one VPP to another VPP based on the present state of the EV. This allows the EVs to move to VPP clusters that have EVs with similar energy levels and plug-out times to come together and satisfy their objectives as well as make themselves more reliable for grid support. In addition, the nature of the DVPP is that it allows to operate in real time without any unnecessary use of computation techniques to determine future prediction results, and the DVPP clustering takes place based only on the present state and condition of the EV; if the present state of the EV is changed, this will quickly affect the clustering.

The simulation results show that the proposed methodology can effectively reduce power loss and prevent major under voltages when compared to the power losses and under voltages shown by the conventional fixed VPP model. For detailed analysis of the effect of EV penetration up to 60% EV penetration, the grid performance is higher for the DVPP model compared with the fixed VPP model. But after 70% EV penetration, the model fails to achieve its necessary objectives. However, even for the 70% penetration level the DVPP model is able to mitigate any capacity issues and is still able to show better customer satisfaction.

5.2 Future Work

The future research of the author will be focused on incorporating real-time pricing and time of use tariffs to the system, and the objective will be to make EV owners reduce their electricity bills and also earn money if the EV owner decides to participate in grid support activity.

Second, future research will also focus on the use of the DVPP in low voltage residential grids for voltage regulations through reactive power support.

Third, future work will be focused on the incorporation of renewable energy resources and using DVPP for power sharing, where a DVPP with higher power can share its energy to another DVPP that is power deficient.

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APPENDIX A

LINE DATA

Name	nphases	R1	X1	R0	X0	C1	C0	Units
2c_.007	3	3.97	0.099	3.97	0.099	0	0	km
2c_.0225	3	1.257	0.085	1.257	0.085	0	0	km
2c_16	3	1.15	0.088	1.2	0.088	0	0	km
35_SAC_XSC	3	0.868	0.092	0.76	0.092	0	0	km
4c_.06	3	0.469	0.075	1.581	0.091	0	0	km
4c_.1	3	0.274	0.073	0.959	0.079	0	0	km
4c_.35	3	0.089	0.0675	0.319	0.076	0	0	km
4c_185	3	0.166	0.068	0.58	0.078	0	0	km
4c_70	3	0.446	0.071	1.505	0.083	0	0	km
4c_95_SAC_XC	3	0.322	0.074	0.804	0.093	0	0	km

- Refer to reference [37] for the rest of the data as to large to fit in this thesis.

APPENDIX B – MATLAB CODE

Note – This Appendix not included the entire code, this present code has lot of codes which are called from other MATLAB files and those files are used as functions and are not included in this appendix due to the size limit of this thesis.

```
clc;
clear all;
close all;

DSSCircObj = actxserver('OpenDSSEngine.DSS');

if ~DSSCircObj.Start(0),
    disp('Unable to start the OpenDSS Engine')
    return
end

DSSText = DSSCircObj.Text;

DSSText.Command = 'Compile (C:\GAMS\38\testmap.dss)';
DSSCircuit = DSSCircObj.ActiveCircuit;
DSSSolution=DSSCircuit.Solution;

DSSText.Command = 'Set mode=daily number=1 time=(0,0) stepsize=1m';

DSSText.Command = 'Set maxcontroliter=1000';


     simulationSteps = 1;
    voltageBusNames = DSSCircuit.AllNodeNames; %names of each bus per phase
    Elementnames = DSSCircuit.ALLElementNames;

    minVoltages = zeros(simulationSteps,1);
    minDistances = zeros(simulationSteps,1);
    minDistanceNames = cell(simulationSteps,1);
    maxVoltages = zeros(simulationSteps,1);
    maxDistances = zeros(simulationSteps,1);
    maxDistanceNames = cell(simulationSteps,1);
    absoluteMinVoltage = 2;
    absoluteMaxVoltage = 0;

 disp('Simulation started');

for ii=1:simulationSteps

  ii
%.......................Reading the data from the grid and exporting to VPP
algorithm...

DSSActiveClass = DSSCircuit.ActiveClass;
DSSCircuit.SetActiveClass('storage');
Storagelist = DSSActiveClass.AllNames;


storagedata
a;
socstorage
```

```
socp;


% %....................DYNAMIC VPP ALGORITHM......................

na=100;
A_array = zeros(1,na); %create an array of [0 0 0 ...0]
rw = [1 1];
cm = [2 na];
index = sub2ind(size(A_array), rw, cm);
A_array(index) = 10; %this will generate an array of [0 1 0 ... 0]
A = zeros(na); %Adjacency matrix for directed graph initialization
for k = 1:na
if k == 1
A(1,:) = A_array;
else
A(k,:) = circshift(A(k-1,:),1); %circular shift to create adjacency matrix for
directed cycle
end
end
A;

G = digraph(A)
plot(G)

tout =  [470    476 440 882 1005 837  534   587 489 1046    1060    359     1098
444 445 473 488 818 897 865 1012    1078    350  382    350     841 863 845 806
913 386 1320   421  928  861 943 997  941 924 414 494 1048  1079    1074    490
600 1086    1073    1141    1114    1103    1151    1146    1111    1198    1177
1184    429     368     322     294     394     377     384     332     414 403
374 393 72   72   94     370    484 441 479 471 470 398 458 461 428 398 501 517
518 742 946 880 809 742 999 892 809 883 953 667 844 179 159];

tin =   [1178   1172    1166    720 723 735 1302    1331    1251    866 892 1151
450 1272    1165    1151     206    248 693 649 928 940 1172    1234    1190
619 617 587 542 643 1091    600 1159    781 783 823 823     857 864 1152    1244
895    905  924        1240 1368    942    971 973 982 1001    1004    1026
1027    1045    1051    1070    1257    1190    1096    1098    1126    1127
1140    1142    1152    1153    1160    1161    1176    1176    1192    1186
1183    1179    17   27 86   140    152 1145    1130    251 345 355 434 436 670
592 515 436 687 538 455 511 539    487  652 1139    1119];

b = [2.2;  2.4;    2.9;    2.7;    2.2;    2.7;    2.0;    2.6;    2.3;    3;
2.8;    2.8;    2.8;    2.1;    2;  2.7;    2.7;    2.5;    2.4;    2.6;    2.4;
2.3;    2.3;    2.8;    2;  2.7;    2.1;    2.3;    2.4;    2.5;    2.25;   2;
2.7;    2.45;   2.3;    2;  2.9;    2.4;    1;  11.7;   11.5;   2.55;   2.9;
2.5;    11.5;   11.2;   2.4;    1.7;    2.8;    2.2;    1.7;    2.45;   2;  1.4;
2.55;   2.1;    1.9;    10.2;   10.3;   11.1;   10.6;   11.8;   11.5;   11.4;
10.5;   11.7;   11.5;   10.9;   11.2;   5.6;    5.6;    5.7;    10.4;   12.35;
11.7;   7.7;    7.4;    6.4;    4.3;    5.1;    12.6;   12.3;   2.45;   2.6;
2.7;    1.4;    5.1;    4.6;    4.8;    4.9;    5.1;    5.2;    5.9;    5.9;
6.2;    6.9;    3;  3.2;    8;  8];

c = [ 1  ;   2   ;   3   ;   4   ;   5   ;   6   ;   7   ;   8   ;   9   ;   10
;   11  ;   12  ;   13  ;   14  ;   15  ;   16  ;   17  ;   18  ;   19  ;   20
;   21  ;   22  ;   23  ;   24  ;   25  ;   26  ;   27  ;   28  ;   29  ;   30
;   31  ;   32  ;   33  ;   34  ;   35  ;   36  ;   37  ;   38  ;   39  ;   40
;   41  ;   42  ;   43  ;   44  ;   45  ;   46  ;   47  ;   48  ;   49  ;   50
;   51  ;   52  ;   53  ;   54  ;   55  ;   56  ;   57  ;   58  ;   59  ;   60
;   61  ;   62  ;   63  ;   64  ;   65  ;   66  ;   67  ;   68  ;   69  ;   70
;   71  ;   72  ;   73  ;   74  ;   75  ;   76  ;   77  ;   78  ;   79  ;   80
;   81  ;   82  ;   83  ;   84  ;   85  ;   86  ;   87  ;   88  ;   89  ;   90
```

```
;   91   ;   92   ;   93   ;   94   ;   95   ;   96   ;   97   ;   98   ;   99   ;
100];

socr = [82 ;  94  ;90;    55; 60; 60; 90; 90; 90; 30; 55; 86; 70; 77; 80; 85;
65; 86; 64; 35; 30; 37; 88; 75; 73; 57; 61; 63; 50; 50; 83; 87; 79; 43; 50; 47;
65; 59; 43; 88; 84; 57; 51; 61; 84; 82; 38; 66; 40; 64; 55; 60; 40; 66; 68; 60;
66; 86; 88; 89; 84; 82; 80; 82; 83; 81; 87; 85; 80; 43; 75; 54; 86; 86; 89; 64;
68; 54; 64; 47; 90; 90; 55; 45; 43; 53; 44; 48; 66; 46; 52; 51; 77; 57; 85; 83;
57; 70; 90; 87];

kwrateddata
socstorage

f;
socp;

list= [a b c];


f=size(b);
g=size(a);
m=zeros(1,3);

 for j=1:100
        if tout(j)>tin(j)
           if ii>=tin(j) && ii<=tout(j)
              m(j,:)=list(j,:);
           else
               m(j,:)=0;
           end
        end

        if tin(j)>tout(j)
            if ii>=tin(j) || ii<=tout(j)
                m(j,:)=list(j,:);
            else
                m(j,:)=0;
            end
        end
 end
x= m(:,:);
x( all(~x,2), : ) = [];
x;


K = 5;
max_iterations = 60;

centroid = zeros(K,size(x,2));
centroid = x(1:K,:,:);

for i=1:max_iterations

    K = size(centroid,1);
    k_lable = zeros(size(x,1),1);
    m = size(x,1);

    for i=1:m
        k = 1;
         min_dist = sum((x(i,:) - centroid(1,:)).^ 2);
    for j=2:K
```

```
        dist = sum((x(i,:) - centroid(j,:)).^ 2);
        if(dist < min_dist)
          min_dist = dist;
          k = j;
        end
    end
    k_lable(i) = k;

    end

end

    [m n o] = size(x);
    centroid = zeros(K,n,o);

for i=1:K

        idx = k_lable;

        xi= x(idx == i,:);
        n = size(xi,1);

        t_initial = 0;
        t_final = 2.0;
        a = xi(:,1);
        b = xi(:,2);
        %c = xi(:,3);
        %calculating ode45 to compute state x
          [t,xi] = ode45(@(t,xi) Cx(t,xi,n),[t_initial t_final],a);


         %% ydot Calculations
         [t,y]= ode45(@(t,y) Cy(t,y,n),[t_initial t_final],b);

   e = (xi(end));
   f = (y(end));
   g = 0  ;         %(z(end));
   centroid(i,:,:) = [e f g];

end

    T = table(k_lable,x(:,1),x(:,2),x(:,3));
    T.Properties.VariableNames = {'VPP' 'Capacity' 'Plugout_time' 'EV_ID'};
    vppinev=k_lable;
    %sz = size(vppinev);
    filename=['evppsone',num2str(ii),'.xlsx'];
    xlswrite(filename,vppinev);
    C = zeros(sz);
    C = [C ; {k_lable}]

  vppone=zeros(size(x,1));
  for i=1:size(x,1)
        if(k_lable(i) == 1)
            vppone(i) =(ev_id(i));
        end

  end
        vpponestorages=vppone(vppone~=0);
        vpponestorages;
        vpponestorages1= vpponestorages.';
```

```
 vpptwo=zeros(size(x,1));
 for i=1:size(x,1)
       if(k_lable(i) == 2)
           vpptwo(i) =(ev_id(i));
       end

 end
       vpptwostorages=vpptwo(vpptwo~=0);
       vpptwostorages;
       vpptwostorages2=vpptwostorages.';



  vppthree=zeros(size(x,1));
  for i=1:size(x,1)
       if(k_lable(i) == 3)
           vppthree(i) =(ev_id(i));
       end

  end
       vppthreestorages=vppthree(vppthree~=0);
       vppthreestorages;
       vppthreestorages3= vppthreestorages.';


 vppfour=zeros(size(x,1));
for i=1:size(x,1)
       if(k_lable(i) == 4)
           vppfour(i) =(ev_id(i));
       end

 end
       vppfourstorages=vppfour(vppfour~=0);
       vppfourstorages;
       vppfourstorages4= vppfourstorages.';

 vppfive=zeros(size(x,1));
for i=1:size(x,1)
       if(k_lable(i) == 5)
           vppfive(i) =(ev_id(i));
       end

 end
       vppfivestorages=vppfive(vppfive~=0);
       vppfivestorages;
       vppfivestorages5= vppfivestorages.';

   a12=zeros(1,100);

for j=1:100
       if tout(j)>tin(j)
          if ii>=tin(j) && ii<=tout(j)
             r12(j,:)= 1;
          else
              r12(j,:)=0;
          end
       end

       if tin(j)>tout(j)
           if ii>=tin(j) || ii<=tout(j)
```

```
                r12(j,:)=1;
            else
                r12(j,:)=0;
            end
        end
 end

 a12 = r12.';
 size(a12);

kwrateddata
socstorage

f;
socp;

for i=1:100

      b12(i) = (0.8*( 1- (socp(i)/socr(i))) + 0.2*(1 - ((tout(i)-ii)/tout(i))))
;

end
b12;
for i=1:100

    if b12(i) == 0
     b12(i)=0.001;
     w(i) = a12(i)*b12(i);
    else
     w(i) = a12(i)*b12(i);
    end
      zk(i) = a12(i)*f(i);
end


w;
zk;

powerev=zk(zk~=0);
evkw= powerev.';


w;
weights=w(w~=0);
fullwt= weights.';
x(:,3);

size(fullwt);
size(evkw);
size(x(:,3));
%size(k_lable);
 %y=(1:size(x(:,3))).';
    T = table(k_lable,x(:,3),evkw,fullwt);
   T.Properties.VariableNames = {'VPP' 'EV_ID' 'Power' 'Weights'};
 l=[k_lable , x(:,3), evkw ,fullwt];
  %l=[y,x(:,3), evkw ,fullwt];
 Pmax=25;
%

% %%%%%%%%%%%%%%%%%%%%%%--VPP-1-OPTIMIZATION
e=l(l(:,1)==1,:);
```

```
a=zeros(size(e,1));
n1=size(e,1);
k1=size(e,1);
q1=e(:,3);
w1=e(:,4);
[p] = customer_driver(n1,k1,q1,w1,Pmax);
a1 = p.';
a21= e(:,2).';
a31=a1.*a21;
a41=a31(a31~=0);
vpponestorages1= a41;
%%%%%%%%%%%%%%%%%%%%%%--VPP-2-OPTIMIZATION

f=l(l(:,1)==2,:);
b =zeros(size(f,1));
n2=size(f,1);
k2=size(f,1);
q2=f(:,3);
w2=f(:,4);
[p] = customer_driver(n2,k2,q2,w2,Pmax);
b1 = p.';
b21 = f(:,2).';
b31 = b1.*b21;
b41=b31(b31~=0);
 vpptwostorages2= b41;
%%%%%%%%%%%%%%%%%%%%%--VPP-3- OPTIMIZATION

g=l(l(:,1)==3,:);
n3=size(g,1);
k3=size(g,1);
q3=g(:,3);
w3=g(:,4);
[p] = customer_driver(n3,k3,q3,w3,Pmax);
c1 = p.';
c21 = g(:,2).';
c31 = c1.*c21;
c41=c31(c31~=0);
 vppthreestorages3= c41;
%%%%%%%%%%%%%%%%%%%--VPP-4-OPTIMIZATION

h=l(l(:,1)==4,:);
n4=size(h,1);
k4=size(h,1);
q4=h(:,3);
w4=h(:,4);
[p] = customer_driver(n4,k4,q4,w4,Pmax);
d1 = p.';
d21 = h(:,2).';
d31= d1.*d21;
d41=d31(d31~=0);
vppfourstorages4 = d41;
% % %%%%%%%%%%%%%%%%%%--VPP-5-OPTIMIZATION
%
i=l(l(:,1)==5,:);
n6=size(i,1);

if n6 <= 17

    r=i(1:n6,:);
    n51=size(r,1);
    k51=size(r,1);
    q51=r(:,3);
```

```
    w51=r(:,4);
    [p] = customer_driver(n51,k51,q51,w51,Pmax);
    e1 = p.';
    e21 = r(:,2).';
    e31 = e1.*e21;
    e41=e31(e31~=0);

%   vpponestorages1= e41;
%   vpptwostorages2= zeros(size(e41,2),1).';
%   vppthreestorages3= zeros(size(e41,2),1).';
%   vppfourstorages4= zeros(size(e41,2),1).';
%   vppfivestorages5= zeros(size(e41,2),1).';
    vppfiveone_opt = e41;
    vppfivetwo_opt = zeros(size(e41,2),1).';
    vppfivethree_opt = zeros(size(e41,2),1).';
    vppfivefour_opt  = zeros(size(e41,2),1).';
    vppfivefive_opt  = zeros(size(e41,2),1).';

elseif n6 >= 18 && n6 <= 34
     r=i(1:17,:);
    n51=size(r,1);
    k51=size(r,1);
    q51=r(:,3);
    w51=r(:,4);
    [p] = customer_driver(n51,k51,q51,w51,Pmax);
    e1 = p.';
    e21 = r(:,2).';
    e31 = e1.*e21;
    e41=e31(e31~=0);
    %vpponestorages1= e41;
    vppfiveone_opt= e41;

    t=i(18:n6,:);
    n52=size(t,1);
    k52=size(t,1);
    q52=t(:,3);
    w52=t(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    q1 = p.';
    q21 = t(:,2).';
    q31 = q1.*q21;
    q41=q31(q31~=0);
    % vpptwostorages2=  q41;
     vppfivetwo_opt= q41;


%   vppthreestorages3= zeros(size(e41,2),1).';
%   vppfourstorages4= zeros(size(e41,2),1).';
%   vppfivestorages5= zeros(size(e41,2),1).';

    vppfivethree_opt = zeros(size(e41,2),1).';
    vppfivefour_opt  = zeros(size(e41,2),1).';
    vppfivefive_opt  = zeros(size(e41,2),1).';

elseif n6 >= 35 && n6 <= 51

    r=i(1:17,:);
    n51=size(r,1);
    k51=size(r,1);
    q51=r(:,3);
    w51=r(:,4);
    [p] = customer_driver(n51,k51,q51,w51,Pmax);
```

```
    e1 = p.';
    e21 = r(:,2).';
    e31 = e1.*e21;
    e41=e31(e31~=0);
     %vpponestorages1= e41;
    vppfiveone_opt= e41;

    t=i(18:34,:);
    n52=size(t,1);
    k52=size(t,1);
    q52=t(:,3);
    w52=t(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    q1 = p.';
    q21 = t(:,2).';
    q31 = q1.*q21;
    q41=q31(q31~=0);
     %vpptwostorages2= q41;
    vppfivetwo_opt= q41;

    s=i(35:n6,:);
    n52=size(s,1);
    k52=size(s,1);
    q52=s(:,3);
    w52=s(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    f1 = p.';
    f21 = s(:,2).';
    f31 = f1.*f21;
    f41=f31(f31~=0);
    %vppthreestorages3 = f41;
    vppfivethree_opt= f41;

%   vppfourstorages4= zeros(size(e41,2),1).';
%   vppfivestorages5= zeros(size(e41,2),1).';
%
     vppfivefour_opt = zeros(size(e41,2),1).';
     vppfivefive_opt = zeros(size(e41,2),1).';
% %
elseif n6 >= 52 && n6 <= 68

    r=i(1:17,:);
    n51=size(r,1);
    k51=size(r,1);
    q51=r(:,3);
    w51=r(:,4);
    [p] = customer_driver(n51,k51,q51,w51,Pmax);
    e1 = p.';
    e21 = r(:,2).';
    e31 = e1.*e21;
    e41=e31(e31~=0);
      %vpponestorages1= e41;
    vppfiveone_opt= e41;

    t=i(17:34,:);
    n52=size(t,1);
    k52=size(t,1);
    q52=t(:,3);
    w52=t(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    q1 = p.';
    q21 = t(:,2).';
```

```
    q31 = q1.*q21;
    q41=q31(q31~=0);
      %vpptwostorages2= q41;
    vppfivetwo_opt= q41;

    s=i(35:51,:);
    n52=size(s,1);
    k52=size(s,1);
    q52=s(:,3);
    w52=s(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    f1 = p.';
    f21 = s(:,2).';
    f31 = f1.*f21;
    f41=f31(f31~=0);
    % vppthreestorages3 = f41;
    vppfivethree_opt= f41;

     s1=i(52:n6,:);
    n52=size(s1,1);
    k52=size(s1,1);
    q52=s1(:,3);
    w52=s1(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    g1 = p.';
    g21 = s1(:,2).';
    g31 = g1.*g21;
    g41=g31(g31~=0);
     %vppfourstorages4= g41;
     vppfivefour_opt = g41;
     %vppfivestorages5= zeros(size(e41,2),1).';
       vppfivefive_opt = zeros(size(e41,2),1).';

elseif n6 >= 69 && n6 <= 85


    r=i(1:17,:);
    n51=size(r,1);
    k51=size(r,1);
    q51=r(:,3);
    w51=r(:,4);
    [p] = customer_driver(n51,k51,q51,w51,Pmax);
    e1 = p.';
    e21 = r(:,2).';
    e31 = e1.*e21;
    e41=e31(e31~=0);
     %vpponestorages1= e41;
    vppfiveone_opt = e41;

    t=i(18:34,:);
    n52=size(t,1);
    k52=size(t,1);
    q52=t(:,3);
    w52=t(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    q1 = p.';
    q21 = t(:,2).';
    q31 = q1.*q21;
    q41=q31(q31~=0);
     vppfivetwo_opt = q41;
      %vpptwostorages2= q41;
```

```
    s=i(35:51,:);
    n52=size(s,1);
    k52=size(s,1);
    q52=s(:,3);
    w52=s(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    f1 = p.';
    f21 = s(:,2).';
    f31 = f1.*f21;
    f41=f31(f31~=0);
     %vppthreestorages3 = f41;
    vppfivethree_opt= f41;

     s1=i(52:68,:);
    n52=size(s1,1);
    k52=size(s1,1);
    q52=s1(:,3);
    w52=s1(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    g1 = p.';
    g21 = s1(:,2).';
    g31 = g1.*g21;
    g41=g31(g31~=0);
    %vppfourstorages4= g41;
    vppfivefour_opt = g41;

    s2=i(69:n6,:);
    n52=size(s2,1);
    k52=size(s2,1);
    q52=s2(:,3);
    w52=s2(:,4);
    [p] = customer_driver(n52,k52,q52,w52,Pmax);
    h1 = p.';
    h21 = s2(:,2).';
    h31 = h1.*h21;
    h41=h31(h31~=0);
    %vppfivestorages5= h41;
    vppfivefive_opt = h41;
end



kwrateddata
  f ;

 size(vppfiveone_opt,2);
vppfiveone_sumopt = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppfiveone_opt,2)

        if ( i == vppfiveone_opt(j))
            vppfiveone_sumopt(j) = f(i);

   %      else
    %           vppfiveone_sumopt(j) = 0
        end
    end
end

vppfiveone_sumopt;
```

```
vppfiveonekwsum = sum(vppfiveone_sumopt,'all');

vppfivetwo_sumopt = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppfivetwo_opt,2)

        if ( i == vppfivetwo_opt(j))
            vppfivetwo_sumopt(j) = f(i);

   %      else
   %          vppfivetwo_sumopt(j) = 0;
        end
    end
end

vppfivetwo_sumopt;
vppfivetwokwsum = sum(vppfivetwo_sumopt,'all');

vppfivethree_sumopt = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppfivethree_opt,2)

        if ( i == vppfivethree_opt(j))
           vppfivethree_sumopt(j) = f(i);
    %      else
    %          vppfivethree_sumopt(j) = 0;
        end
    end
end

vppfivethree_sumopt;
vppfivethreekwsum = sum(vppfivethree_sumopt,'all');

vppfivefour_sumopt = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppfivefour_opt,2)

        if ( i == vppfivefour_opt(j))
            vppfivefour_sumopt(j) = f(i);
    %      else
    %          vppfivefour_sumopt(j) = 0;
        end
    end
end
 vppfivefour_sumopt;
 vppfivefourkwsum = sum(vppfivefour_sumopt,'all');

 vppfivefive_sumopt = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppfivefive_opt,2)

        if ( i == vppfivefive_opt(j))
            vppfivefive_sumopt(j) = f(i);
    %     else
    %          vppfivefive_sumopt(j) = 0;
        end
    end
end
 vppfivefive_sumopt;
 vppfivefivekwsum = sum(vppfivefive_sumopt,'all');
```

```
%%....................EV-CHARGE-DISCHARGE CONTROL........................


   DSSText.Command='select transformer.TR1';
   DSSCircuit.SetActiveElement('transformer.TR1');
   temptr=DSSCircuit.ActiveElement.Powers;
   temptrkw = temptr(1,1);
   transinkW(ii)= temptrkw;

ev;
 kwrateddata
  f;


for i=1:100
    for j=1:size(vpponestorages1,2)

        if ( i == vpponestorages1(j))
            vpponesum(j) = f(i);

   %       else
     %         vpponesum(j) = 0;
        end
    end
end

vpponesum;
vpponekwsum = sum(vpponesum,'all');
 vpptwosum = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vpptwostorages2,2)

        if ( i == vpptwostorages2(j))
            vpptwosum(j) = f(i);

      %   else
      %       vpptwosum(j) = 0;
        end
    end
end

vpptwosum;
vpptwokwsum = sum(vpptwosum,'all');

vppthreesum = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppthreestorages3,2)

        if ( i == vppthreestorages3(j))
            vppthreesum(j) = f(i);
       %  else
       %      vppthreesum(j) = 0;
        end
    end
end
```

```
vppthreesum;
vppthreekwsum = sum(vppthreesum,'all');

 vppfoursum = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppfourstorages4,2)

        if ( i == vppfourstorages4(j))
            vppfoursum(j) = f(i);
        % else
        %     vppfoursum(j) = 0;
        end
    end
end
 vppfoursum;
 vppfourkwsum = sum(vppfoursum,'all');

 vppfivesum = zeros(size(e41,2),1).';
for i=1:100
    for j=1:size(vppfivestorages5,2)

        if ( i == vppfivestorages5(j))
            vppfivesum(j) = f(i);
      %   else
       %      vppfivesum(j) = 0;
        end
    end
end
 vppfivesum;
 vppfivekwsum = sum(vppfivesum,'all');


    loadtot
    demandkw;

   kwload(1)=7.546;
   kwload(ii) = demandkw;


  maxpower= 150;

  requiredkw = maxpower - demandkw;

  vsum = [vpponekwsum  vpptwokwsum   vppthreekwsum  vppfourkwsum vppfivekwsum
(vpponekwsum+vpptwokwsum)  (vpponekwsum+vppthreekwsum)
(vpponekwsum+vppfourkwsum) (vpponekwsum+vppfivekwsum)
(vpptwokwsum+vppthreekwsum)  (vpptwokwsum+vppfourkwsum)
(vpptwokwsum+vppfivekwsum) (vppthreekwsum+vppfourkwsum)
(vppthreekwsum+vppfivekwsum)  (vppfourkwsum+vppfivekwsum)
(vpponekwsum+vpptwokwsum+vppthreekwsum)
(vpponekwsum+vppthreekwsum+vppfourkwsum)
(vpponekwsum+vppfourkwsum+vppfivekwsum) (vpptwokwsum+vppthreekwsum+vppfourkwsum)
(vppthreekwsum+vppfourkwsum+vppfivekwsum)
(vpponekwsum+vpptwokwsum+vppthreekwsum+vppfourkwsum)
(vpptwokwsum+vppthreekwsum+vppfourkwsum+vppfivekwsum)
(vppthreekwsum+vppfourkwsum+vppfivekwsum+vpponekwsum)
(vppfourkwsum+vppfivekwsum+vpponekwsum+vpptwokwsum)
(vpponekwsum+vpptwokwsum+vppthreekwsum+vppfourkwsum+vppfivekwsum) ];

  if (demandkw > 18)
  [val,idx]=min(abs(vsum));
```

```
  minVal=vsum(idx);
  else
  [val,idx]=min(abs(vsum-requiredkw));
   minVal=vsum(idx);
  end
idx;

 if(idx == 1)
     q= [vpponestorages1];

 elseif(idx == 2)
     q= [vpptwostorages2];

 elseif(idx == 3)
      q= [vppthreestorages3];

 elseif(idx == 4)
      q= [vppfourstorages4];

 elseif(idx == 5)
      q= [vppfivestorages5];

 elseif(idx == 6)
      q= [vpponestorages1  vpptwostorages2];

 elseif(idx == 7)
      q= [vppthreestorages3 vpponestorages1];

 elseif(idx == 8)
      q= [vpponestorages1 vppfourstorages4];

 elseif(idx == 9)
      q= [vpponestorages1 vppfivestorages5];

 elseif(idx == 10)
      q= [vpptwostorages2  vppthreestorages3];

  elseif(idx == 11)
      q= [vpptwostorages2 vppfourstorages4];

   elseif(idx == 12)
      q= [vpptwostorages2 vppfivestorages5];

 elseif(idx == 13)
      q= [vppthreestorages3  vppfourstorages4];

  elseif(idx == 14)
      q= [vppthreestorages3  vppfivestorages5];

  elseif(idx == 15)
      q= [vppfourstorages4  vppfivestorages5];

   elseif(idx == 16)
      q= [vpponestorages1  vpptwostorages2 vppthreestorages3];

  elseif(idx == 17)
      q= [vpponestorages1 vppthreestorages3 vppfourstorages4];

  elseif(idx == 18)
      q= [vpponestorages1 vppfourstorages4 vppfivestorages5];
```

```
  elseif(idx == 19)
      q= [vpponestorages1 vppthreestorages3 vppfourstorages4];

   elseif(idx == 20)
      q= [vpptwostorages2 vppthreestorages3 vppfourstorages4];

  elseif(idx == 21)
      q= [vppthreestorages3  vppfourstorages4  vppfivestorages5];

  elseif(idx == 22)
      q= [vpponestorages1  vpptwostorages2 vppthreestorages3 vppfourstorages4];

  elseif(idx == 23)
      q= [vpptwostorages2 vppthreestorages3 vppfourstorages4 vppfivestorages5];

  elseif(idx == 24)
      q= [vppthreestorages3 vppfourstorages4 vppfivestorages5 vpponestorages1];

  elseif(idx == 25)
     q= [vpponestorages1  vpptwostorages2 vppfourstorages4 vppfivestorages5];

   elseif(idx == 26)
     q= [vpponestorages1  vpptwostorages2 vppthreestorages3  vppfourstorages4
vppfivestorages5];

 end

q;


 c= zeros(1,size(ev,2));
 z=zeros(1,size(ev,2));

for i=1:size(q,2)
     for j=1:size(ev,2)
if (q(i)==ev(j))
    c(j)=ev(j);
else
    c(j)=0;

end
     end
 z=z+c;
end
z;

   s= strings(size(1,100));
   formatSpec = '%s';
   if (demandkw <= 18 && temptrkw <= 125 )
       A1='charge';

   elseif(demandkw > 18)

       A1='discharge';

   else

       A1='charge';
```

```
   end


       A2='idling';



   for i=1:100

       if (z(i) == i)
           s(i)= sprintf(formatSpec,A1);
       else
           s(i)= sprintf(formatSpec,A2);
       end

   end
  % disp('EVs to be charged,discharges or remain ideal=');
   s;

dispatchfunction; % code to dispatch individual EVs
 DSSText.Command = 'solve';


 Loss=DSSCircuit.Losses;
 realloss=Loss(1);
realLossesinkW(ii)=realloss/1000;
time(ii)=ii;

DSSCircuit.AllBusVmagPu;

voltagedata

end

disp('Simulation finished');

filename = 'load demand.xlsx';
xlswrite(filename, kwload);

figure;
plot(time, kwload)
 title('Demand Graph');
grid on; xlabel({'t','(in min)'});ylabel('Aggragated Demand IN kW');



function xdot = Cx(t,x,n)
         na=100;
A_array = zeros(1,na); %create an array of [0 0 0 ...0]
rw = [1 1];
cm = [2 na];
index = sub2ind(size(A_array), rw, cm);
A_array(index) = 10; %this will generate an array of [0 1 0 ... 0]
A = zeros(na); %Adjacency matrix for directed graph initialization
for k = 1:na
if k == 1
A(1,:) = A_array;
else
```

```
A(k,:) = circshift(A(k-1,:),1); %circular shift to create adjacency matrix for
directed cycle
end
end

          xdot = zeros(n,1);
          for i=1:n
          for j = 1:n
          xdot(i) = A(i,j)*(x(j)-x(i))+ xdot(i);

          end
          end
          end

         function ydot = Cy(t,y,n)

          na=100;
A_array = zeros(1,na); %create an array of [0 0 0 ...0]
rw = [1 1];
cm = [2 na];
index = sub2ind(size(A_array), rw, cm);
A_array(index) = 10; %this will generate an array of [0 1 0 ... 0]
A = zeros(na); %Adjacency matrix for directed graph initialization
for k = 1:na
if k == 1
A(1,:) = A_array;
else
A(k,:) = circshift(A(k-1,:),1); %circular shift to create adjacency matrix for
directed cycle
end
end
          ydot = zeros(n,1);
          for i=1:n
          for j = 1:n
          ydot(i) = A(i,j)*(y(j)-y(i))+ ydot(i);

          end
          end
          end
```