Optimal Electric Vehicle Load Control Strategy in Malaysia Distribution Network with Distributed Energy Resources

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ABSTRACT

This thesis presents a comprehensive analysis of the impact and management of electric vehicle (EV) integration within Malaysia's low voltage (LV) distribution network, considering distributed generation (DG) resources, particularly photovoltaic (PV) systems. With the growing adoption of EVs and distributed energy resources, there is an increasing need to develop robust strategies to mitigate potential adverse effects on the distribution network. This study investigates the technical challenges posed by uncontrolled EV charging and proposes demand-side management strategies, including optimized charging schedules and distributed generation utilization, to enhance network performance.

A key aspect of this research is the development of an EV charging model based on Malaysian urban driving patterns, which incorporates variations in initial state-of-charge (SOC), user commute behaviour, and charging location preferences. The EV charging profiles were created from a database of 130 EV owners, capturing their driving and plug-in behaviours. Using load flow analysis and the Newton-Raphson method, this study examines the power demand, voltage profiles, and power losses under various EV and DG penetration scenarios. Four case studies were conducted to evaluate network impacts: (i) uncontrolled EV charging without DG, (ii) uncontrolled EV charging with full DG penetration, (iii) controlled EV charging without DG, and (iv) controlled EV charging with full DG penetration.

Simulation results indicate that, while high EV penetration increases power demand and power losses, controlled charging in conjunction with DG integration can reduce these impacts by utilizing off-peak charging times and renewable energy sources. Additionally, stochastic modelling was employed to address uncertainties in EV charging behaviour, offering a predictive framework to assess the likelihood of network impacts from variable charging demands.

This research provides key insights into the technical implications of EV integration in LV networks in urban environment and emphasizes the potential of decentralized, responsive charging strategies to enhance grid resilience. The findings support the adoption of optimized charging schedules and renewable integration policies, laying the groundwork for a sustainable, EV-compatible power infrastructure in Malaysia.

LIST OF PUBLICATIONS

The following papers were published based on work done for this thesis, or work done within the framework of the doctorate degree:

CONFERENCE PAPERS

1. N. B. Mohd Shariff, H. B. Sonder and L. Cipcigan, "Modelling charging profiles of electric vehicles on Malaysian Distribution Networks," *2022 IEEE National Power and Energy Conference (PECon)*, 2022, pp. 1-6.
2. N. B. Mohd Shariff, M. Al Essa and L. Cipcigan, "Probabilistic analysis of electric vehicles charging load impact on residential Distributions Networks," *2016 IEEE International Energy Conference (ENERGYCON)*, 2016, pp. 1-6.

JOURNAL PAPERS

1. N. B. Mohd Shariff, and L. Cipcigan, "Impact of Electric Vehicles Charging on Malaysian Low Voltage Distribution Network," [in preparation for Applied Energy].
2. N. B. Mohd Shariff, and L. Cipcigan, "Coordination of Distributed Energy Resources on Malaysia Low Voltage Distribution Network," [in preparation for Applied Energy].

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بِسْمِ اللهِ الرَّحْمٰنِ الرَّحِيْمِ

In the name of Allah, the Most Gracious, the Most Merciful

All praises to Allah SWT for His mercies, blessing and grace upon me to complete the PhD journey successfully.

This thesis marks the conclusion of a long and challenging journey that began in 2014. Over the past decade, I have faced immense trials, both academically and personally, that have shaped me into who I am today.

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This journey has been anything but ordinary, and the challenges I faced along the way have deeply shaped my life. In 2016, my sister, who had always been the pillar of strength for our family, suffered a debilitating stroke that paralyzed half her body. Just a year later, our world was turned upside down when she was diagnosed with cancer. The weight of these devastating events grew heavier in 2018, when my grandmother passed away, and my mother, already physically and emotionally drained, could no longer care for my sister. At that point, I stepped in to provide the care my sister desperately needed, balancing her condition as a stroke survivor and cancer patient. In 2019, just months after completing chemotherapy, my sister's cancer recurred, and the situation worsened as the COVID-19 pandemic took hold of the world. Despite all efforts, the cancer returned more aggressively, and by 2021, the doctors declared her condition palliative. During this heart-wrenching time, my mother, already burdened by the grief of watching her daughter suffer, began to develop dementia. The emotional and physical toll on her was immense, and I watched helplessly as she too began to decline. After years of battling both physically and emotionally, in 2022, my sister passed away, leaving a deep, irreplaceable void in our hearts. The pain of losing her, while still caring for my mother's deteriorating health, was overwhelming, yet it is through these struggles that I have found strength.

Lastly, I want to extend my deepest gratitude to my family, Mak, Nenek, Ayah, Along, Ani, Zal, and B for their prayers. May Allah bless them abundantly and grant them peace and happiness in this life and the hereafter.

And finally, I want to take a moment to thank myself. Thank you for holding on when it felt like everything was falling apart. For finding the strength to keep going, even on the days when the weight of it all seemed too much to bear. For showing up, again and again, no matter how impossible the journey felt. This journey was far from easy, it was filled with moments of doubt, heartache, and exhaustion. But through it all, I found within myself a resilience I never knew existed. I learned to trust in my own courage and to believe in my ability to finish what I started, even when the path ahead was unclear. Today, I am proud of the person I have become, the person who refused to give up, no matter how difficult the road. This accomplishment is not just a culmination of my academic efforts; it is a testament to the strength and perseverance I discovered within myself.

Sincerely,

Noraidah Binti Mohd Shariff

To my mother for all her patience, generosity, and sacrifice.
and I promise her a PhD.

For my late sister

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LIST OF ABBREVIATIONS

AM	Ante Meridiem
BESS	Battery Energy Storage System
BEV	Battery Electric Vehicle
ESS	Energy Storage System
ETOU	Enhanced Time-of-Use
DER	Distributed Energy Storage
DG	Distributed Generation
DOD	Depth of Discharge
DNO	Distribution Network Operator
DSO	Distribution System Operator
DSM	Demand Side Management
EV	Electric Vehicle
G2V	Grid-to-Vehicle
GA	Genetic Algorithm
GHG	Green House Gases
IEEE	Institute of Electrical and Electronics Engineers
kV	kilovolt
kW	kilowatt
kWh	kilowatt-hour
LV	Low Voltage
MC	Monte Carlo
MPC	Model Predictive Control
MW	Megawatt
MV	Medium Voltage
MVA	Mega Volt-Amperes
NEM	Net Energy Metering
NETR	National Energy Transition Roadmap
PHEV	Plug-in Hybrid Electric Vehicle
PM	Post Meridiem
PSO	Particle Swarm Optimisation
p.u.	per unit
PV	Photovoltaic

RT	Responsible Transition
SOC	State of Charge
TOU	Time-of-Use
TNB	Tenaga Nasional Berhad
UK	United Kingdom
UKGDN	UK Generic Distribution Network
V	Voltage
V2G	Vehicle-to-Grid

CHAPTER 1

Introduction

1.1 Background

The accelerating advancement of renewable energy technologies and the rising adoption of electric vehicles (EV) are fundamentally reshaping power distribution networks globally [1]. In Malaysia, the integration of Distributed Energy Resources (DER), including EVs, photovoltaic (PV) systems, and battery energy storage systems (BESS) presents significant opportunities to reduce carbon emissions [2]. However, these advancements also pose complex challenges, such as maintaining grid stability, managing increased load demands, and ensuring power quality [3].

As a signatory to the Paris Agreement, Malaysia has committed to reducing its greenhouse gas emissions intensity by 45% by 2030, based on 2005 levels. Achieving this target requires a substantial shift toward renewable energy sources, including solar, wind, hydro, and biomass, with solar energy projected to account for 30% of peak demand by 2035. In addition, the integration of DERs, including EVs, will play a crucial role in enhancing the flexibility and sustainability of the energy grid [4].

Simultaneously, Malaysia's energy policies, such as the National Energy Policy 2022–2040, prioritize green mobility [5]. The nation aims for EVs to constitute 38% of the market by 2030, supported by 10,000 public charging stations by 2025 [6]. Tenaga Nasional Berhad (TNB) estimates the need for 30,000 charging points to accommodate over 500,000 EVs by 2030 (see Figure 1.1) [7]. These goals highlight the increasing interdependence of EV growth and power distribution infrastructure, with urban areas facing the most significant challenges due to concentrated energy demand.

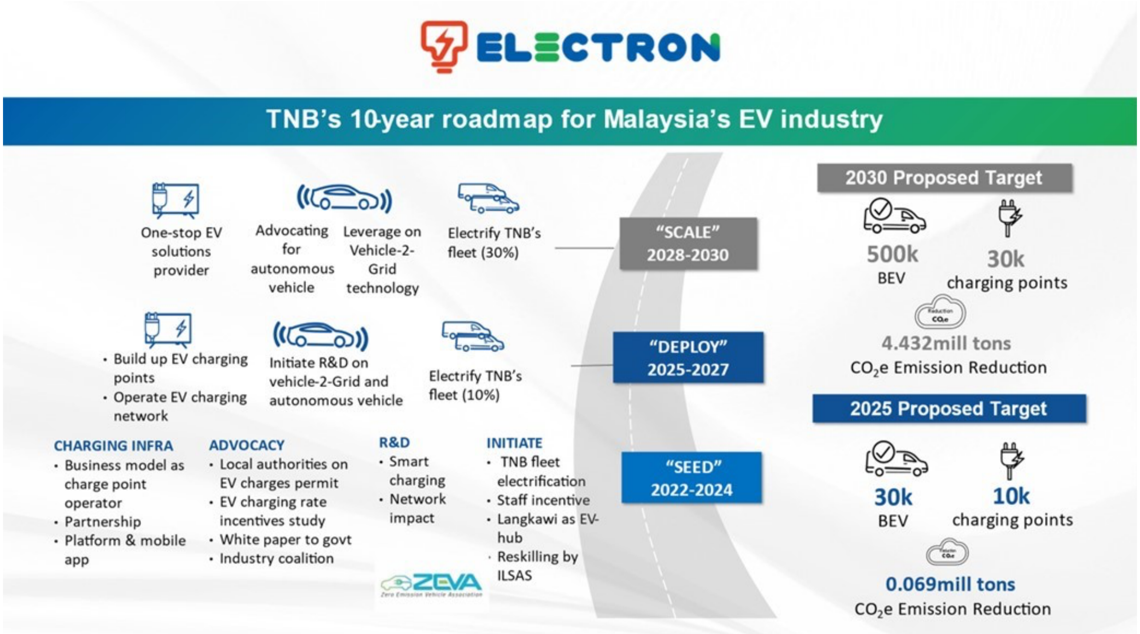


Figure 1.1: TNB's 10 year EV Roadmap for Malaysia [7].

In parallel, the National Energy Transition Roadmap (NETR), led by Malaysia's Ministry of Economy, seeks to accelerate green and sustainable growth, placing green mobility at its core [8]. The roadmap aims to unlock investment opportunities across six strategic areas, while the Responsible Transition (RT) scenario supports Malaysia's goal of achieving net-zero emissions by 2050. Refer to Figure 1.2 for potential investment opportunities and the impact of NETR's RT.

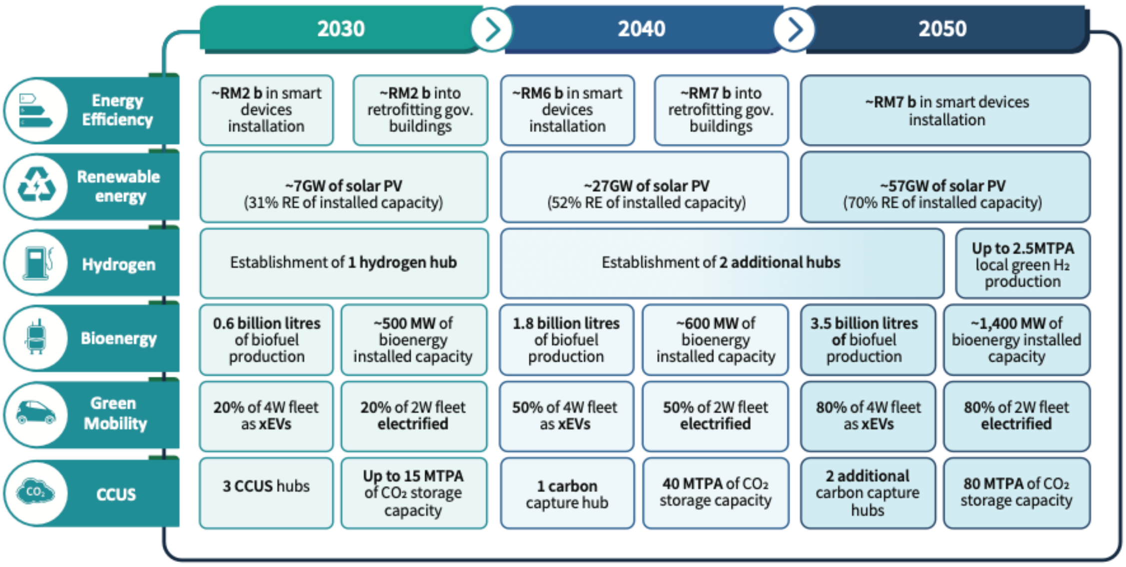


Figure 1.2: Investment opportunities and impacts of NETR's energy transition initiatives [8].

Achieving this target requires a substantial shift toward renewable energy sources, including solar, wind, hydro, and biomass, with solar energy projected to account for 30% of peak demand by 2035. The rise in renewable energy penetration, however, underscores the need for critical enablers like BESS to address the intermittent nature of renewables and maintain grid stability. The NETR introduced in 2023 emphasizes this, targeting an increase in renewable energy capacity from 4% in 2023 to 22% by 2050 and positioning BESS as a cornerstone of this transition. As DER adoption grows, including EVs, rooftop PV systems, and BESS, Malaysia's low-voltage distribution networks are experiencing dynamic power flow changes [9]. Uncoordinated integration risks operational issues such as voltage fluctuations, power losses, and network congestion, particularly in urban regions where reliability is critical [10]. Addressing these challenges is vital to ensure a resilient and efficient energy future [11].

This thesis examines the impacts of DERs on distribution networks in Malaysia, focusing on optimizing network performance with EVs and PV systems. Using stochastic modelling approaches, the research models various scenarios to identify optimal coordination strategies. The study also incorporates unique aspects of Malaysia's energy landscape, such as urban road usage for EV charging behaviour and specific network configurations, to ensure accurate simulation results. This comprehensive approach aims to enhance network hosting capacity, improve energy efficiency, and support sustainable energy management.

Existing power networks were not designed to accommodate high numbers of DER units. However, network components can only tolerate certain numbers of these low carbon technologies without immediate reinforcement.

The main questions guiding this thesis are as follows:

- What are the impacts of high penetration of DER, including EVs and PV systems, on the stability and hosting capacity of Malaysian distribution networks?
- How can realistic EV charging profiles be generated based on urban Malaysian driving patterns to better predict their effects on network demand?
- What are the potential impacts of DERs, specifically EVs and PV systems, on low-voltage sections of Malaysian distribution networks, considering the unique constraints of these networks?
- How can coordination strategies be designed to effectively integrate DERs into distribution networks, balancing demand, minimizing power losses, and preserving network reliability?

1.2 Thesis Objectives

This thesis investigates the integration of DER in power distribution networks, focusing on enhancing the resilience and efficiency of existing infrastructure. The study aims to establish a framework for optimizing the interaction between EVs, PV systems, and other DER while deferring the need for network reinforcement. The specific objectives are as follows:

1. Assessing the Impact of DER on distribution networks: Evaluating the capacity and dependability of existing distribution networks by analysing voltage profiles, power demand, and power losses when integrating DER.
2. Generating EV Charging Profiles Based on Malaysian Urban Road Characteristics: Developing detailed charging profiles for EVs that reflect the unique driving behaviours and traffic patterns in Malaysian urban environments, facilitating better integration with the grid.
3. Analysing the impact of DER on the Malaysian Distribution Network: Investigating how the presence of EVs and PV systems affects power quality, energy losses, and voltage stability within the Malaysian distribution network.
4. Coordinating DER Integration for Optimal Performance: Designing and implementing coordination strategies for the effective management of EV charging and PV generation, utilizing both centralized and decentralized control mechanisms while considering network constraints and consumer comfort. This includes monitoring EV battery state-of-charge (SOC) and ensuring the stability of the distribution network during high-load periods.

1.3 Thesis Contributions

Thesis contributions are summarized as follows:

1. Impact Analysis of DER Integration**:** A comprehensive assessment of the impacts of DER, specifically EVs and PV systems, on Malaysian distribution networks was conducted. This analysis focused on determining the hosting capacity and evaluating the effects on voltage stability and energy losses.

2. Generation of EV Charging Profiles**:** A novel methodology was developed for generating electric vehicle charging profiles tailored to the characteristics of urban roads in Malaysia. This methodology incorporates local traffic patterns and driving behaviours, enhancing the accuracy of demand forecasts.

3. Coordination Algorithms for DER Management**:** Innovative coordination algorithms were created to manage the integration of EVs and PVs within the distribution network. These algorithms optimize charging schedules to ensure efficient energy use while adhering to network constraints.

4. Stochastic Modelling for Uncertainty Management**:** The research implemented stochastic modelling techniques to address the uncertainties associated with EV charging behaviours and renewable energy generation. This approach provides a more reliable framework for evaluating the impacts of DER on distribution networks.

1.4 Thesis Structure

This thesis is organized as follows:

Chapter 2 delves into the foundational studies and relevant literature, presenting a structured review of past research. To provide a clear understanding of the various approaches, studies were organized into two main categories: deterministic and stochastic methods. Through this classification, the chapter examines the roles of EVs, and PV arrays, within the distribution network. These DER units are further analysed based on their impacts on voltage levels, energy losses, and reinforcement costs. Additionally, the chapter surveys different demand management strategies, including centralized and decentralized control, that facilitate the effective coordination of DERs.

In **Chapter 3** applies both deterministic and stochastic methods to the United Kingdom Generic Distribution Network (UKGDN), a well-established benchmark widely used in academic and industrial studies. This benchmark case study provides a controlled environment to assess the future impacts of DERs on residential demand, voltage stability, and network performance. Using data from the Customer Led Network Revolution trials and the National Grid databases, the analysis synthesizes year-long residential demand profiles at half-hourly intervals to project the potential influence of EVs and PV arrays over the next two decades. The stochastic framework developed in this chapter captures the variability of EV arrival times, initial states of charge, and PV generation patterns, demonstrating its capability to model realistic DER behaviours. The insights and validated methodology from this benchmark study form the foundation for Chapter 4, where the same approach is applied to a real Malaysian distribution network.

Chapter 4 focuses exclusively on generating EV charging profiles for the Malaysian context. The stochastic modelling framework is applied using urban road traffic data to capture commuting patterns between home and workplace. Since the study assumes home-based charging, the profiles are centred on daily office–home travel, with charging demand initiated upon vehicle arrival at residential locations. To reflect Malaysia's socio-economic structure, distinctions are made between private and government sector employees, whose differing working hours influence commuting schedules and charging behaviour. The resulting home-charging profiles provide a realistic representation of EV demand in Malaysia and form the basis for subsequent distribution network impact studies in the following chapter.

Chapter 5 builds on the EV charging profiles developed in Chapter 4 to examine their impacts on a Malaysian urban distribution network. A centralized control framework is applied to assess two charging conditions: controlled charging, where EVs with an SOC below 20% charge immediately upon arrival, and uncontrolled charging, where EVs with SOC between 20% and 80% are deferred to off-peak periods with provisions for emergency charging. The analysis evaluates effects on power demand, voltage profiles, power losses, and overall network stability.

In **Chapter 6,** the narrative shifts to a decentralized perspective, where a particle swarm optimization (PSO) algorithm is employed to balance EV and PV loads while considering user preferences, network constraints, and tariff schemes. The model incorporates enhanced time-of-use (ETOU) tariffs and the Net Energy Metering (NEM) scheme to reflect realistic economic scenarios and incentivize optimal energy usage. Simulated over a day at quarter-hourly intervals, this decentralized control algorithm enables responsive adjustments based on consumer needs and network requirements. Additionally, the optimization considers the size and location of energy storage systems (ESS) within the distribution network to further enhance flexibility and efficiency. By integrating the operational characteristics of EVs, PV systems, and ESS, the model seeks to maximize user satisfaction, measured through metrics like EV battery SOC, while maintaining grid stability. This decentralized approach underscores the potential for a consumer-centric, flexible solution to balance DER impacts, improve energy management, and support sustainable grid operations.

Chapter 7 concludes the thesis by summarizing the main findings and contributions of the research. It highlights the impacts of DERs and EV charging on distribution network performance, the development of Malaysian-based EV charging profiles, and the coordination of DERs using optimization techniques. The chapter also outlines the study's limitations and provides recommendations for future work, including the integration of ESS, Vehicle-to-Grid (V2G) applications, and advanced load control strategies to enhance grid stability and efficiency.

This structured approach in the thesis offers a comprehensive understanding of DER impacts and coordination, combining insights from predictive analysis, real-world simulations, and innovative control strategies to inform effective DER integration in modern distribution networks. Figure 1.2 shows the framework of the thesis chapters.

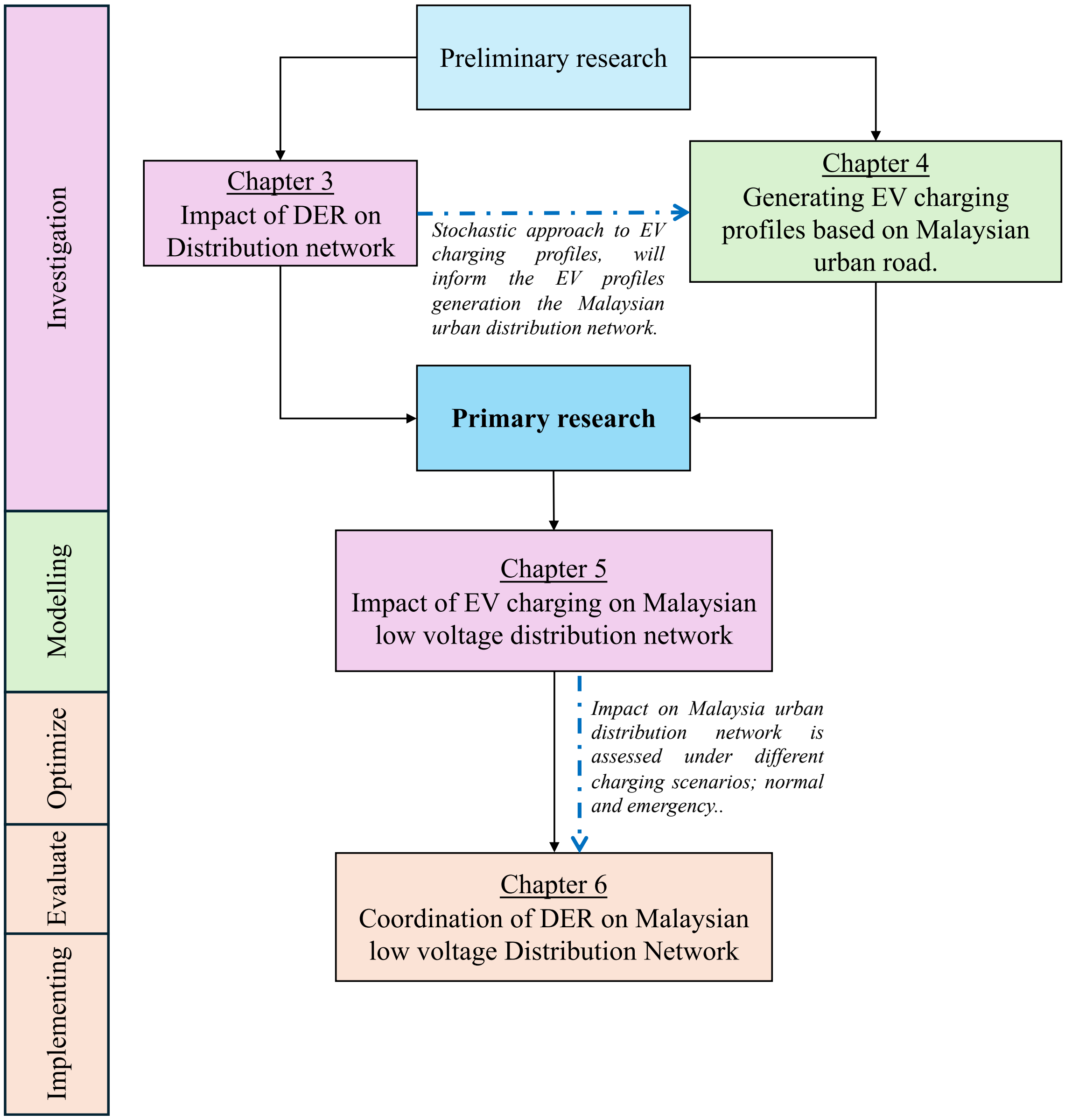


Figure 1.3: Outline of the thesis.

CHAPTER 2

Literature Review

2.1 Introduction

As the global energy landscape transforms with an increasing focus on sustainability, the integration of DER into electrical distribution networks has become a critical area of research [12]. DERs including renewable energy sources like solar PV systems, energy storage solutions, and flexible loads such as EVs offer significant opportunities for enhancing energy efficiency and grid reliability. However, their integration also poses challenges that require a comprehensive understanding of their impacts and management strategies [13].

This chapter embarks on a journey through the existing literature, exploring key studies and findings that relate to the primary objectives of this thesis. The exploration is structured around four main themes: i) the assessment of EV penetration impacts, ii) the development of charging profiles for EVs based on urban characteristics, iii) the optimization of sizing and location for DG systems, and iv) the examination of Demand Side Management (DSM) and time-of-use (TOU) tariffs. Each section highlights the contributions of previous research, setting the stage for the innovative approaches presented in this thesis.

2.2 Assessing the Impacts of EV Penetration on Distribution Networks

2.2.1 Overview of EV Integration

The advent of EVs signifies a transformative shift in both transportation and energy consumption paradigms. As the global focus intensifies on sustainability and reducing carbon emissions, the adoption of EVs is becoming increasingly prevalent. However, this surge in EV integration is accompanied by complex challenges for electrical distribution networks, as highlighted by [14]**.** These challenges necessitate a comprehensive understanding of the implications of widespread EV adoption on existing grid infrastructures.

As [15] illustrate, the increasing number of EVs presents significant operational challenges for electrical distribution systems. One of the primary concerns is the impact of EV charging on load patterns. Traditional electrical grids were not designed to accommodate the sudden influx of demand that accompanies multiple EVs charging simultaneously, especially during peak hours. This can result in elevated load levels that exceed the capacity of existing infrastructure, leading to voltage drops that may compromise the quality of electricity supply [16]**.** Such voltage drops can lead to service interruptions, potential damage to sensitive electrical equipment, and increase operational cost for both utilities and consumers [17-18].

Moreover, the integration of EVs into the grid can exacerbate existing issues related to energy losses within distribution networks. Increased load from EV charging can lead to higher resistive losses, as the energy dissipated as heat in the conductors rises with the load current [19]. This not only reduces the overall efficiency of the distribution network but also contributes to higher greenhouse gas emissions if the electricity used to charge EVs comes from fossil fuel sources [20]. Therefore, addressing these energy loss issues becomes critical for achieving the environmental benefits that EV adoption promises.

Another dimension of the challenges posed by EV integration is the potential reliability issues that may arise within the grid. As EV penetration grows, the likelihood of transformer overloading increases, particularly in densely populated urban areas where the demand for EV charging is concentrated [21]. The increased frequency of peak loads can strain transformers and other grid components, leading to a higher risk of failures or outages [22]. These reliability concerns necessitate careful planning and management to ensure that the distribution network can handle the additional stresses imposed by EVs without compromising service quality [14].

To mitigate these challenges, [14] emphasize the importance of implementing coordinated charging strategies. Such strategies involve scheduling and managing EV charging loads in a manner that aligns with the distribution network's capacity. By promoting off-peak charging, utilities can flatten the load curve, reducing peak demand pressures and enhancing voltage stability [23-24]. Additionally, implementing smart charging technologies can allow for dynamic load management, where charging rates are adjusted based on real-time grid conditions [25]. This approach not only alleviates stress on the distribution network but also provides EV owners with potential cost savings by taking advantage of lower electricity prices during off-peak hours [26].

Furthermore, the integration of DER, such as solar panels and energy storage systems, can play a vital role in supporting EV integration [27]. By generating renewable energy locally and storing it for use during peak charging times, DER can help reduce the overall load on the distribution network while contributing to a more sustainable energy ecosystem [28]. This symbiotic relationship between EVs and other DERs, such as PV and energy storage systems, can enhance grid resilience, making it better equipped to handle fluctuations in demand and supply [29-30].

The impact of EVs on voltage stability cannot be understated. The author in [31] emphasize that uncoordinated charging can exacerbate voltage deviations in low-voltage networks, potentially endangering the reliability of the entire system. To address these challenges, advanced technologies, such as smart inverters, have been proposed by [32]. Their research highlights how these technologies can enhance voltage regulation and provide necessary reactive power support, where inverters supply or absorb reactive power to maintain voltage within acceptable limits, ultimately improving overall power quality.

2.2.2 Load Management Strategies

Effective load management strategies emerge as an important aspect of integrating EVs into distribution systems. [33-42] explores demand response frameworks designed to incentivize consumers to charge their EVs during off-peak hours. This approach alleviates stress on the grid and optimizes network performance, demonstrating that intelligent management can yield both reliability and economic benefits for consumers.

Table 2.1: Summary of case studies on load management strategies.

Year	Focus area	Methodology	Key Findings	Limitations	Ref [ ]
2023	Demand Response Program for EVs	Game-theoretical model using Stackelberg formulation for EV fleet charging decision control.	The proposed time-of-use price-based scheme improves aggregator profits compared to fixed-price models, with load shifting in EV fleet charging.	Assumes fleet operator faces uncertainty in wholesale prices and consumption behaviour; does not require price elasticity model.	[33]
2023	EV Charging Load & Distribution	EV charging scheduling based on customer	Proposed EV charging scheduling reduces peak load	Limited to a case study for one distribution feeder;	[34]

	Transformer Maintenance	feedback & Deep Reinforcement Learning (DRL) for XFR maintenance.	and extends XFR life. DRL-based XFR replacement outperforms rule-based policies.	broader applicability uncertain.	
2024	Impact of EV Charging on New Zealand Networks	ABM & Monte Carlo simulation for 71 houses, 20 days.	Altruistic charging reduces peak demand & Exceedance; Selfish charging increases Exceedance. 40% EVs with Altruistic charging increases Exceedance by <20%.	Case study in NZ; may not apply globally.	[35]
2023	TOU Pricing for DSM with EVs	NoSQL database for real-time and historical data accumulation; mathematical model for tariff rate estimation	- The proposed TOU pricing model reduced peak consumption by 6-7% with an elasticity of 0.45. - Uses EVs' State-of-Charge (SOC) to optimize DSM and mitigate simultaneous EV charging.	- The model's effectiveness is dependent on accurate data and IoT infrastructure. - Tariff estimation may vary in different regions.	[36]
2018	Impact of Time-of-Use Tariffs on Peak Demand in Residential Areas	Simulation of battery operation with time-of-use and time-of-export tariffs	Home batteries may increase peak demand at low voltage substations if charging coincides with off-peak periods. Time-dependent tariffs alone do not effectively reduce peak demand.	Study focused on UK; results may not fully apply in regions with different tariff structures or energy mix.	[37]
2023	Renewable energy and EV charging impacts on local market clearing under uncertainty.	Bi-level model using hybrid stochastic-robust optimization with dynamic pricing.	- Robust conditions raise prices but reduce grid dependency. - 10.96% cost increase for 20% robustness.	- Assumes ideal behaviour. - High complexity.	[38]
2020	Grid-Connected Microgrids (MG) & EV Charging	Mixed-Integer Linear Programming (MILP)	Investigates optimal stationary ESS sizing in a charging hub MGs (CHMG) with different EV charging strategies. Results show that	Focuses on a specific CHMG near Augsburg; results may not generalize to all locations or systems.	[39]

			immediate charging of more than 65% of EVs increases ESS capacity needs, while bidirectional charging is not economically beneficial.		
2019	EV Charging & Demand Response in China	Covariance Matrix Adaptation Evolution Strategy (CMAES)	Optimizes charging service capacity and cost using a multi-objective optimization model. The approach reduces peak demand for battery swapping and cuts costs by 12%.	Focuses on battery swapping and charging infrastructure; results may not generalize to all EV systems.	[40]
2022	EV Charging, Dynamic Pricing & PV Systems	Optimization of charging strategies with dynamic electricity pricing and PV incentives	Dynamic pricing can reduce charging costs by 18.5%, while PV-based optimization reduces costs by 33.7%. PV integration increases PV energy utilization by 46% and reduces grid load.	The electricity price optimization strategy increases charging peaks; further analysis needed on price signals.	[41]
2021	Energy Management for Demand Response	Optimization-based energy management framework with Hybrid Genetic Ant Colony Optimization (HGACO)	- HGACO reduces electricity cost (up to 59%), carbon emissions (57%), and peak load (17%). - Outperforms GA, PSO, ACO, and HGPO.	- Limited to three scenarios. - Assumes full consumer participation and ideal conditions.	[42]

2.2.3 Case Studies on EV Penetration

Case studies from the UK and Malaysia provide important technical insights into the impacts of EV adoption on distribution networks. In the UK, the UK Generic Distribution Network (UKGDN) has been widely used as a test system to evaluate the effects of EV penetration [43–45]. These studies typically model low-voltage feeders under different EV uptake scenarios, incorporating diverse charging behaviours (such as immediate, delayed, and coordinated charging). Simulation results indicate that when EVs charge immediately upon arrival during evening peaks, voltage drops of up to 7–10% can occur at the end of feeders, alongside a rise in network losses by more than 15% compared to baseline conditions. Transformer loading was also shown to exceed rated capacity at penetration levels above 40–50%, raising concerns about thermal stress and asset lifetime. However, coordinated charging strategies where charging demand is shifted to off-peak hours or distributed evenly across time slots were demonstrated to reduce both losses and voltage deviations to within statutory limits. These findings confirm that without intervention, even moderate EV uptake can stress distribution infrastructure, but that targeted management strategies can preserve system resilience.

In Malaysia, several studies [46–48] have adapted local distribution models to examine the implications of EV growth under national targets. For instance, one study developed a simulation using a 33/11 kV urban distribution feeder to assess transformer loading under different EV penetration levels, showing that at 30% adoption, evening peak demand could increase by 20–25%, leading to transformer overloading in densely populated areas. Another study employed stochastic modelling of EV arrival and charging times for residential low-voltage networks, highlighting significant voltage fluctuations at penetration levels as low as 20% if unmanaged. A further study examined rural feeders with weaker infrastructure, revealing that voltage non-compliance became critical earlier than in urban networks due to longer line lengths and lower short circuit capacity. Collectively, these Malaysian studies highlight that while the nature of impacts differs between urban and rural contexts, common challenges include transformer overloading, voltage instability, and increased losses.

The technical evidence from Malaysia underscores that proactive measures such as time-of-use tariffs, coordinated charging schedules, and the integration of distributed energy resources (DER) are required to manage load growth effectively. By shifting EV charging away from peak periods, network stress can be reduced, while smart grid technologies and real-time monitoring enable better responsiveness to stochastic load patterns.

Overall, the case studies from both the UK and Malaysia demonstrate that increasing EV penetration presents quantifiable risks to voltage stability, peak loading, and network losses, but that these can be effectively mitigated through coordinated charging strategies, regulatory planning, and infrastructure upgrades tailored to local grid conditions.

2.3 Developing Charging Profiles for EVs Based on Urban Road Characteristics

2.3.1 Methodologies for Charging Profile Development

An important component of effective EV integration is the development of accurate charging profiles that reflect real-world usage patterns. In [49], the authors introduced methodologies that incorporate local traffic data and driver behaviours to create dynamic charging profiles, which can adapt to fluctuations in demand throughout the day. By leveraging real-time data analytics, this innovative approach not only enhances the accuracy of demand forecasts but also ensures that the charging infrastructure aligns with urban dynamics and reflects the unique driving patterns of different communities. In [50] further emphasized the importance of integrating geographical and temporal factors into charging profiles, noting that urban road characteristics, such as traffic density and road types, can significantly influence EV charging behaviour. Additionally, [51] developed a framework that utilizes machine learning algorithms to analyse historical charging data, allowing for more precise predictions of future charging needs based on identified trends. This framework highlights how technology can facilitate better infrastructure planning and resource allocation. Moreover, [52] underscored the significance of stakeholder engagement in the development of charging profiles, as understanding user preferences and local conditions is essential for optimizing charging station locations and operational strategies. Finally, [53] explored the role of simulation models in assessing the impact of various charging strategies on urban traffic flow, providing insights into how different charging profiles can mitigate congestion and enhance the overall efficiency of urban transportation systems. Collectively, these studies illustrate the critical need for multifaceted methodologies that consider a range of factors, from traffic patterns to user behaviours, to develop effective charging profiles for electric vehicles in urban environments.

2.3.2 Traffic Patterns and Charging Behaviour

Studies have consistently shown that urban traffic patterns significantly influence EV charging behaviour, affecting peak usage times and optimal locations for charging infrastructure. In [54], the authors delve into this connection, identifying peak usage times and optimal locations for charging infrastructure within urban environments. Their research demonstrates that understanding these interactions is important for utilities aiming to optimize grid performance and effectively plan for future capacity needs, ultimately fostering a more resilient energy system. Furthermore, in [55], the authors explore how traffic congestion influences charging habits, revealing that drivers often prefer to charge their EVs at locations that minimize their travel time, particularly during peak hours. This finding suggests that strategic placement of charging stations in high traffic areas can significantly enhance user accessibility and satisfaction.

Additionally, studies in [56] provide insights into the influence of local socioeconomic factors on EV charging patterns. Their analysis indicates that areas with higher income levels and greater access to public charging facilities tend to exhibit more favourable charging behaviours, leading to higher EV adoption rates. Moreover, in [57], the importance of incorporating real-time traffic data into the development of dynamic charging profiles is highlighted, allowing for a more adaptive response to fluctuating urban traffic conditions. By integrating advanced analytics with traffic flow data, utilities can better manage charging demands and mitigate potential grid overloads during peak times. Finally, in [58], the necessity of public awareness campaigns to educate drivers on optimal charging behaviours is emphasized, as increased awareness can lead to more strategic charging decisions that align with available infrastructure and grid capacity. Collectively, these studies underscore the intricate link between traffic patterns and charging behaviour, suggesting that a comprehensive understanding of this relationship is essential for effective EV integration into urban distribution networks.

2.3.3 Impact of Urban Infrastructure on Charging Profiles

The influence of urban infrastructure on EV charging profiles has been the focus of several studies. In [59], the authors highlight how elements such as the availability of charging stations and prevailing traffic flow patterns significantly impact charging behaviour. This integration of infrastructure factors into charging profile development is essential for creating accurate and effective demand models. Furthermore, research in [60] emphasizes the role of urban design and land use in shaping EV charging patterns, suggesting that well-planned urban environments can facilitate higher rates of EV adoption. In [61], the analysis indicates that access to public transportation options is associated with increased EV usage, as drivers are more likely to charge their vehicles in proximity to public transit hubs. Moreover, [62] explores the relationship between urban density and charging infrastructure, noting that urban areas with higher population densities tend to support more robust charging networks, ultimately improving the convenience and accessibility of charging stations. Collectively, these studies underline the necessity of considering urban infrastructure components when developing charging profiles to ensure effective EV integration into the existing energy landscape.

2.3.4 Case Studies on Charging Profiles

Real-world case studies demonstrate the effectiveness of methodologies for modelling EV charging profiles, contributing valuable insights into charging behaviour. For instance, in [63], the authors investigate how the optimal scheduling of EV charging can benefit from TOU tariffs to minimize costs and system tariffs. In their study, EV charging profiles were sourced externally, considering EV usage for purposes such as office/school commutes, family and leisure activities, shopping, and emergencies.. Moreover, a study examines the daily and seasonal profiles of the cumulative load demand for 50 EVs, amounting to 3500 kWh using HOMER software [64]. However, the authors do not specify how the EV charging profiles were generated. In [65] investigated controlled and uncontrolled EV charging strategies using the IEEE 33-bus system. For uncoordinated charging, the authors considered a time window from 5:00 PM to 9:00 PM. In the coordinated charging scenarios, three cases were analysed with varying durations: 5:00 PM to 2:00 AM, 5:00 PM to 3:00 AM, and 5:00 PM to 5:00 AM. While the study explored different timeframes for charging, it lacks an analysis of how variations in user specific SOC, diverse driving patterns, or regional demand profiles impact the charging strategies. Additionally, the mixed charging approach is not fully detailed in terms of implementation or its implications on network stability, leaving an opportunity for further exploration of localized and real-world charging scenarios.

Additionally, six road scenarios with varying intersections, modelled in AIMSUN [66], were analysed to assess energy consumption under different conditions. The scenarios aimed to assess energy or fuel consumption based on road altitudes or gradients, road conditions, and traffic management controls, as these factors significantly influence consumption. The study also explored the impact of traffic congestion, particularly in urban areas prone to peak-hour congestion. The six scenarios included: (i) long-distance highway routes, (ii) short-distance highway routes, (iii) long-distance urban routes, (iv) short-distance urban routes, (v) long-distance suburban routes, and (vi) short-distance suburban routes. However, the study does not address how these road scenarios and traffic congestion affect EV charging behaviour, including variations in SOC and charging needs. Understanding these dynamics is essential for developing optimized charging strategies tailored to urban, suburban, and highway settings. In [67], findings reveal that specific urban characteristics, such as peak traffic times, significantly impact EV charging demand, reinforcing the need for tailored charging solutions. Furthermore, while the existing literature primarily focuses on developed countries, a study in [68] highlights how lessons learned from urban areas in the UK can inform the development of charging profiles in Malaysian cities, providing a framework for future research. This collective evidence underscores the necessity of localized charging strategies that can effectively address the unique challenges of the Malaysian distribution network as EV adoption continues to rise. For a detailed summary of relevant case studies on EV charging profiles, refer to Table 2.1.

Table 2.2: Summary of case studies on EV charging profiles.

Year	Focus area	Methodology	Key Findings	Limitations	Ref [ ]
2019	Optimal scheduling with TOU tariffs.	External charging profiles for diverse EV use cases.	TOU tariffs reduce costs and system tariffs.	Does not address Malaysian specific conditions.	[63]
2024	Daily and seasonal EV load demand profiles.	HOMER software, 3500 kWh demand.	Insight into aggregate EV fleet energy needs.	Charging profile generation method unspecified.	[64]
2021	Local driving behaviours and demand forecasts.	Analysis of localised driving patterns.	Improves accuracy of EV demand forecast.	No details on SOC or time-of-day factors.	[65]
2023	Energy consumption under different road and traffic scenarios	AIMSUN simulation of six road scenarios.	Urban congestion and road types influence energy consumption.	No link to EV charging variations or SOC dynamics.	[66]
2017	Urban factors impacting EV charging demand.	Analysis of peak traffic times.	Urban peak hours significantly affect EV demand.	Limited focus on Malaysian urban contexts.	[67]
2016	Adapting UK urban strategies to Malaysia.	Comparative study of UK and Malaysia.	Framework for adapting strategies to Malaysian urban areas.	Lacks detail on Malaysia specific implementation.	[68]

2.4 Investigating Optimal Sizing and Location Strategies for DG in Distribution Network

2.4.1 Importance of Optimal Sizing and Location

As DERs such as PV systems become more prevalent, determining their optimal size and location within the distribution network has become a critical focus area for researchers and utilities alike. The integration of these resources can lead to significant enhancements in energy efficiency, reliability, and sustainability of the power supply, but only if they are deployed strategically. Studies in [69] emphasize that optimization techniques are essential to maximize the benefits of DG systems, particularly in relation to cost-effectiveness and performance.

The methodologies employed for achieving optimal sizing and location involve a range of analytical tools and simulation models. For instance, research conducted in [70] highlights the use of genetic algorithms and mixed-integer linear programming as effective strategies for identifying optimal configurations for DG installations. These techniques not only help in minimizing installation and operational costs but also ensure that the generated energy aligns with the demand profile of the local distribution network.

Moreover, the significance of site-specific factors, including geographical characteristics, load profiles, and existing infrastructure, is discussed in [71]. By considering these variables, utilities can implement more tailored and effective DER solutions that enhance grid resilience and mitigate potential disruptions. Studies have shown that neglecting the importance of optimal sizing and location can lead to suboptimal performance, as illustrated by research in [72], which found that poorly positioned DERs can exacerbate voltage fluctuations and increase energy losses within the network.

Additionally, the literature indicates that successful integration of DG systems, including PV, requires a multi-faceted approach, explicitly including demand forecasting, load management, and real-time data analytics. In [73], the authors discuss how advanced monitoring systems and smart grid technologies can provide valuable insights into network conditions, enabling more informed decision-making regarding the placement and sizing of DERs. The integration of these advanced technologies can significantly enhance the responsiveness of distribution networks to variable energy flows, allowing for better management of supply and demand dynamics.

In the context of Malaysia, while there is a growing body of literature exploring renewable energy integration, specific case studies on optimal sizing and location strategies for DG systems remain scarce. As evidenced in [74], many studies focus on theoretical frameworks without empirical validation in the Malaysian context. This gap highlights the necessity for further research that considers local conditions and regulatory frameworks, thereby providing actionable recommendations for effective DER deployment. Moreover, the absence of detailed studies on the specific challenges faced by Malaysian distribution networks underscores the need for tailored approaches that reflect the unique characteristics of the region.

The insights gathered from existing studies can provide a foundation for future research endeavours aimed at optimizing DER placement and sizing. Researchers can explore the development of customized optimization models that take into account the varying load profiles and renewable energy potentials across different Malaysian regions. This would facilitate more effective planning and implementation of DG systems, ultimately contributing to a more sustainable energy future in Malaysia.

2.4.2 Application of Particle Swarm Optimization (PSO) in Distributed Energy Resources (DER)

PSO has emerged as a powerful tool for the optimal sizing and siting of DERs, particularly in the context of PV systems. PSO is a computational method that mimics the social behaviour of birds or fish, enabling the identification of optimal solutions through collaborative searching in a multi-dimensional space. In [75], it is illustrated how PSO can effectively optimize the placement of PV installations while taking into account various grid constraints and economic factors.

The flexibility of PSO allows it to balance multiple objectives, such as minimizing costs, maximizing energy generation, and enhancing reliability. In [76] it was demonstrated that by applying PSO, the optimal locations for PV systems could be determined with a high degree of accuracy, resulting in improved overall performance of the distribution network. Their findings suggest that PSO can address the complexities involved in DER integration, making it an essential tool for utilities seeking to enhance grid efficiency.

Further studies, including those in [77], have expanded upon the basic principles of PSO by incorporating hybrid approaches, combining PSO with other optimization techniques like genetic algorithms or simulated annealing. This hybridization enhances the algorithm's convergence speed and accuracy, enabling it to handle more complex optimization problems. Such advancements are particularly relevant in densely populated urban areas where the demand for energy is high, and optimal DER placement is critical to maintaining grid stability.

In addition, PSO has been recognized for its ability to adapt to real-time data inputs, enabling dynamic optimization based on changing load patterns, renewable generation forecasts, and operational constraints [78]. This adaptability allows for dynamic optimization based on changing load patterns, renewable generation forecasts, and operational constraints. By continuously adjusting the positions of the particles in the search space, PSO can identify optimal solutions even as conditions change, ensuring that the deployment of PV systems remains aligned with current network requirements.

Several empirical studies have validated the effectiveness of PSO in various scenarios. For instance, in [79], the authors applied PSO to determine the optimal sizing and location of DG units in a distribution network, showing significant improvements in voltage stability and reduction in energy losses. Similarly, [80] explored the use of PSO for multi-objective optimization of renewable energy systems, demonstrating its capability to achieve a balance between economic viability and environmental impact. However, while PSO offers numerous advantages, it also presents challenges, such as sensitivity to initial conditions and the risk of premature convergence. These limitations have led researchers to explore modifications to the PSO algorithm to enhance its robustness and effectiveness in diverse applications [81]. By addressing these challenges, PSO can be further refined to meet the unique demands of DER integration in varying geographical and operational contexts.

Overall, the application of PSO for optimal sizing and siting of DG systems represents a promising area of research, particularly as the energy landscape evolves toward greater reliance on renewable resources. As illustrated by the findings in [82], the continued exploration and refinement of PSO methodologies can contribute significantly to the efficient and sustainable deployment of DERs in both urban and rural settings.

2.4.3 Comparative Studies on Optimization Techniques

Comparative studies have shown that PSO often outperforms a range of other optimization methods including Genetic Algorithms (GA), Differential Evolution (DE), and Ant Colony Optimization (ACO) in applications related to DERs. In [83], an analysis demonstrated that PSO provides faster convergence rates and more accurate results for the sizing and placement of DERs, reinforcing its status as a preferred optimization technique within the field.

The efficiency of PSO in finding optimal solutions has been validated through numerous empirical studies. For instance, a comprehensive evaluation by [84] highlighted that PSO consistently yields superior performance metrics, such as reduced computational time and improved solution quality, compared not only to GA but also to other evolutionary methods. This study emphasizes the ability of PSO to effectively explore the solution space while avoiding local optima, a common challenge faced by GA-based methods.

In addition, comparative research conducted by [85] showcased the versatility of PSO in handling multi-objective optimization problems associated with DER integration. This work illustrated that PSO could accommodate various conflicting objectives, such as cost minimization and emissions reduction, achieving more effective trade-offs than GA and similar algorithms. The results indicated that PSO not only achieved better compromise solutions but also facilitated faster computation times, making it a valuable tool for real-time applications.

Moreover, studies have also explored hybrid approaches that combine PSO with other optimization techniques to enhance performance further. For example, [86] introduced a hybrid PSO-GA method that leveraged the strengths of both algorithms. This approach aimed to benefit from the exploration capabilities of PSO while utilizing the exploitation advantages of GA, leading to enhanced overall performance in DER optimization tasks.

The comparative advantage of PSO extends beyond mere performance metrics; it also addresses the complexities associated with real-world applications. Research by [87] indicated that PSO's inherent parallelism allows for the simultaneous evaluation of multiple solutions, which is particularly advantageous in large-scale DER deployment scenarios. This characteristic not only accelerates the optimization process but also ensures that more potential solutions are considered, thus improving the likelihood of identifying the best configuration.

However, while PSO has proven effective in many cases, it is essential to recognize its limitations. Studies such as [88] have pointed out issues related to parameter sensitivity and the potential for premature convergence under certain conditions. These findings highlight the necessity for ongoing research to refine PSO algorithms and enhance their robustness across diverse applications.

Overall, the comparative studies underscore the prominence of PSO as a leading optimization technique in the sizing and placement of DERs. The accumulated evidence supports its application in both academic research and practical scenarios, indicating that PSO can significantly contribute to the efficient integration of renewable energy resources into distribution networks.

2.4.4 Case Studies on Optimal Sizing

Numerous case studies illustrate the practical applications of PSO in the optimal sizing of DG systems, particularly PV units. For instance, in [89], a comprehensive application of PSO to a real distribution network was conducted, demonstrating how optimal sizing not only improved energy output but also significantly reduced losses within the system. The study highlighted the efficiency gains achieved through the precise allocation of resources, reinforcing the importance of utilizing advanced optimization techniques in energy systems.

In another case study, [90] examined the impact of PSO on the sizing of renewable energy resources within a microgrid. The researchers found that by applying PSO, they could effectively determine the optimal capacities of both PV and wind generation sources, leading to enhanced system reliability and economic viability. Their results indicated that PSO facilitated a more balanced approach to resource allocation, which minimized operational costs while maximizing the contribution of renewable energy.

Furthermore, research conducted by [91] focused on the application of PSO for optimal sizing in urban areas with high demand variability. This study demonstrated that PSO could adaptively adjust the sizing parameters based on real-time load data and environmental conditions. The findings illustrated how this dynamic approach to sizing could lead to improved energy management and stability, particularly in regions where load patterns are highly unpredictable.

In [92], the authors presented a case study that applied PSO to optimize the placement and sizing of solar panels in a residential community. Their findings revealed that strategic positioning and sizing led to a remarkable reduction in energy costs for homeowners, as well as a substantial increase in overall system efficiency. The study underscored the potential for PSO to tailor solutions to specific community needs, enhancing the effectiveness of renewable energy integration.

Another significant case study was conducted in [93], where the authors employed PSO to optimize the sizing of DG units in a rural distribution network. Their results showed that implementing optimal sizing strategies not only enhanced energy security for rural consumers but also facilitated greater integration of renewable resources. This research further solidified the role of PSO in addressing the unique challenges faced by rural energy systems.

The cumulative evidence from these case studies emphasizes the practical benefits of utilizing PSO for optimal sizing in DG systems. The application of PSO not only improves energy output and operational efficiency but also promotes the sustainable integration of renewable energy resources across various types of distribution networks.

2.5 Examining the Role of Demand-Side Management and Time-of-Use Tariffs in Enhancing DER Integration

2.5.1 Role of Demand-Side Management (DSM)

DSM strategies play a crucial role in optimizing energy consumption while enhancing the reliability of electrical grids. As highlighted in [94], DSM can effectively mitigate the variability associated with renewable energy sources and the unpredictable charging patterns of EVs. By strategically managing demand, utilities can balance load fluctuations and ensure that energy supply meets consumer needs without overwhelming the distribution network.

Research indicates that effective DSM strategies not only stabilize the grid but also contribute to a more resilient energy ecosystem. For instance, [95] emphasizes the importance of real-time demand response programs, which encourage consumers to adjust their energy usage based on grid conditions. This flexibility can alleviate peak demand pressures, reducing the risk of outages and enhancing overall system reliability.

Additionally, in [96], the authors discuss how integrating DSM with advanced metering infrastructure enables utilities to gather real-time data on consumer behaviour. This data can inform tailored DSM programs that incentivize users to shift their consumption to off-peak periods, thereby optimizing energy use and minimizing costs. Such initiatives are particularly beneficial in the context of integrating DERs, as they can align energy consumption patterns with the availability of renewable generation.

Moreover, the effectiveness of DSM strategies is further underscored by [97], which examines case studies demonstrating the positive impact of demand response initiatives on reducing energy costs and improving grid performance. The research shows that by actively engaging consumers in energy management, utilities can enhance the integration of renewable sources and EVs, leading to a more sustainable energy landscape.

Overall, the literature indicates that the implementation of robust DSM strategies is essential for facilitating the seamless integration of DERs into the existing energy infrastructure. By promoting energy efficiency and encouraging flexible consumption patterns, DSM can play a pivotal role in enhancing grid stability and reliability.

2.5.2 Time-of-Use Tariffs

TOU tariffs represent a strategic approach to DSM by providing financial incentives for consumers to adjust their energy consumption habits to align with periods of lower demand. In [98], it was shown that TOU tariffs can significantly reduce peak demand, which is important for maintaining system reliability and efficiency. By encouraging off-peak charging of EVs, these tariffs help to flatten the load curve, reducing stress on the electrical grid during high demand periods.

The economic benefits of TOU tariffs extend to consumers as well. According to [99], by shifting their usage to off-peak hours, consumers can capitalize on lower electricity rates, leading to substantial savings on their energy bills. This dual advantage of enhancing grid performance while providing cost savings makes TOU tariffs an appealing strategy for both utilities and consumers.

Additionally, [100] explored the impact of TOU pricing on consumer behaviour, noting that education and awareness campaigns are important for maximizing the effectiveness of these tariffs. The study found that when consumers are informed about the potential savings associated with TOU tariffs, they are more likely to adapt their charging behaviours, resulting in increased participation in demand response programs.

Moreover, research by [101] indicated that the implementation of TOU tariffs can facilitate the integration of DERs by encouraging consumers to utilize locally generated renewable energy during off-peak hours. This alignment of generation and consumption not only enhances grid stability but also promotes the use of clean energy sources, further supporting sustainability goals.

2.5.3 Integration of DSM with DERs

The integration of DSM strategies and TOU tariffs with DERs presents a significant opportunity to enhance grid performance and reliability. In [102], a framework was proposed that combines TOU pricing with smart metering technology, which allows for real-time monitoring and control of EV charging. This integration is essential for fostering consumer engagement, as it enables users to make informed decisions about their energy consumption based on current grid conditions and pricing signals.

Furthermore, the use of smart meters in conjunction with DSM and TOU tariffs facilitates a more responsive energy system that can dynamically adapt to changes in demand and supply. As noted in [103], this level of responsiveness not only improves the efficiency of energy use but also enhances the resilience of the electrical grid by mitigating the impacts of sudden load fluctuations. By effectively coordinating EV charging with the availability of renewable energy from DERs, such as solar and wind power, utilities can optimize energy flows and reduce the reliance on fossil fuel-based generation during peak periods.

Research by [104] emphasizes that integrating DSM with DERs can lead to improved grid stability, as consumers are incentivized to adjust their consumption patterns to match the availability of locally generated renewable energy. This synergy between DSM and DERs not only maximizes the utilization of clean energy resources but also supports the transition toward a more sustainable energy future.

2.5.4 Economic Benefits of DSM

The economic implications of implementing DSM strategies and TOU tariffs are substantial and multifaceted. In [105], it was highlighted that both utilities and consumers stand to benefit from cost savings associated with reduced peak demand and lowered operational expenses. By encouraging consumers to shift their energy consumption to off-peak periods, DSM initiatives can alleviate pressure on the grid during peak times, resulting in decreased infrastructure costs for utilities and increased reliability of service.

Moreover, [106] found that a well-designed DSM framework could significantly enhance overall system efficiency, leading to further economic advantages. Their findings suggest that utilities can avoid costly investments in new infrastructure by effectively managing demand through DSM and TOU tariffs, ultimately translating into lower rates for consumers. This synergy not only promotes sustainable energy consumption but also supports the financial viability of utilities in the face of rising operational costs.

In addition, the research by [107] suggests that engaging consumers in energy management through DSM and TOU tariffs can foster a culture of energy conservation, further driving down costs and enhancing grid reliability. By providing consumers with the tools and incentives to adjust their energy usage, utilities can create a more sustainable and economically efficient energy ecosystem.

2.6 Summary

This literature review has examined a broad spectrum of studies on DERs, with particular emphasis on the penetration of EVs and PV systems into distribution networks. Beyond assessing their impacts on network performance such as voltage stability, energy efficiency, and reliability the review also considered modelling methodologies, control strategies, tariff mechanisms, and optimization techniques relevant to DER integration.

Case studies from both international contexts (e.g., the UK) and Malaysia were highlighted to illustrate the real-world challenges of large-scale EV and PV adoption. These works revealed persistent issues such as voltage fluctuations, peak demand pressures, and the complexities of managing uncertain charging behaviours. Modelling approaches varied, with deterministic methods offering insights into fixed operating scenarios, while stochastic approaches captured uncertainties in EV usage patterns. However, the literature showed that the combined effects of EV and PV integration within the specific context of Malaysian distribution networks particularly under actual charging profiles, demand response mechanisms, and national tariff schemes remain insufficiently explored.

The identified gaps therefore include: (i) the lack of locally developed EV charging profiles that reflect Malaysian driving and charging behaviours, (ii) limited studies on the simultaneous impact of EV and PV integration in Malaysian low-voltage networks, and (iii) insufficient exploration of optimization-based control strategies tailored to local tariff structures and policies.

In response, this thesis proposes to investigate these gaps by developing stochastic EV charging profiles suited to Malaysia, evaluating the cumulative impacts of EV and PV integration on local distribution networks, and designing coordinated control strategies using PSO to enhance network performance under energy tariff and net energy metering (NEM) schemes. This approach ensures that the research not only builds upon existing global knowledge but also delivers context-specific insights for Malaysia's transition toward sustainable energy systems.

CHAPTER 3

Analysis of Distributed Energy Resources on UK Generic Distribution Network

3.1 Introduction

The integration of DERs, such as EVs and PV arrays, into power distribution networks presents both transformative opportunities and complex technical challenges. As the adoption of these technologies accelerates, their impacts on network performance particularly in LV sections are becoming increasingly significant. High penetration levels of DERs introduce variability and potential disruptions that must be carefully managed to maintain network reliability, voltage stability, and efficiency. This chapter investigates these impacts, with a focus on evaluating network constraints and performance indicators under various DER scenarios.

The principal aim of this chapter is to assess the impacts of EV charging loads and PV integration on LV distribution networks, addressing network capacity constraints, voltage steady state limits, and energy losses. To achieve this, the study employs two complementary methodologies: deterministic and stochastic analyses. Together, these approaches provide a comprehensive framework for evaluating DER impacts under both controlled and uncertain conditions.

The deterministic analysis, which evaluates the impacts of EV charging loads and PV integration on the LV distribution network, is presented in this chapter. The key models, assumptions, and analytical steps are outlined to ensure clarity and transparency in the evaluation process. In parallel, a stochastic study is also conducted using data collected in 2016. While this dataset may not fully capture the most recent developments in EV adoption and charging behaviour, the underlying methodology remains valid and continues to be relevant, as it can be readily adapted to more recent datasets in future studies.

1. **Deterministic Methodology**: The deterministic analysis is designed to evaluate the hosting capacity of the LV network for uncoordinated EV charging.
    - **Inputs:** Residential demand at minimum and maximum load levels (summer and winter), fixed EV penetration levels, PV penetration levels, and projected demand growth for the years 2010, 2015, 2020, 2025, and 2030.
    - **Process:** Load flow simulations are conducted in MATLAB/Simulink using the Newton–Raphson algorithm [108]. Four case studies are defined to analyse variations in demand and seasonal conditions. EV and PV penetration levels are kept fixed, ensuring controlled scenario comparisons.
    - **Outputs:** Voltage deviation, power losses, and transformer loading are extracted as performance indicators. These outputs quantify the static network response and define benchmark conditions for evaluating DER penetration.

This deterministic approach establishes baseline scenarios, offering clear insights into the operational boundaries of the network.

2. **Stochastic Methodology**: In contrast, the stochastic methodology captures uncertainties associated with EV charging behaviours and PV generation.
    - **Inputs:** Residential load profiles from the CLNR dataset, stochastic EV charging profiles (based on vehicle type, initial state of charge, plug-in

time, and disconnection), and PV generation data. It is assumed that EVs with low state of charge immediately upon arrival at home.

- **Process:** Monte Carlo (MC) simulations are carried out using a custom MATLAB load flow algorithm. Randomized charging and generation profiles are applied across multiple iterations to model the diversity of real-world operating conditions.
- **Outputs:** Stochastic distributions of power losses, voltage variation, and feeder demand are produced. These results highlight the variability of outcomes and enable identification of potential worst-case scenarios.

The stochastic methodology thus extends beyond static scenarios, providing a more realistic assessment of DER impacts while complementing the deterministic study.

For this analysis, the LV section of the test network was modelled using MATLAB/Simulink, enabling precise simulation of both deterministic and stochastic cases. Four deterministic case studies were conducted to examine the impacts of uncoordinated EV charging under different seasonal and demand conditions:

Case Study 1: EV Charging During On-Peak Hours in Winter

Case Study 2: EV Charging During Off-Peak Hours in Winter

Case Study 3: EV Charging During On-Peak Hours in Summer

Case Study 4: EV Charging During Off-Peak Hours in Summer

These case studies enabled a structured evaluation of EV charging impacts on voltage stability, power losses, and transformer loading under varying load conditions. In addition, the LV section of a real world distribution network was modelled using a balanced load flow algorithm implemented in MATLAB [108]. This function allowed for rigorous power flow analysis of radial low-voltage networks, providing accurate assessments of network response to variable load conditions without requiring external software packages.

3.2 Network Topology

The network topology employed in this study is based on the UKGDN, chosen for its representative structure and suitability for both deterministic and stochastic analyses. The UKGDN is a well-established model that simulates a typical medium to low voltage distribution network in the United Kingdom, offering a reliable basis for understanding the potential impacts of high levels of DER integration, particularly in the LV segments.

In the UKGDN, the distribution network is supplied by a main power station with a capacity of 500 MVA [109]. Power from this station is delivered to the distribution network through two step-down transformers, each rated for 33 kV to 11 kV, thereby reducing the voltage to a level suitable for the 11 kV feeders that supply power to the LV sections (see Figure 3.1). For the purposes of this study, focus was placed on one feeder to enable a detailed examination of the LV network. The remaining feeders were combined and treated as aggregated loads to simplify the network model and focus computational resources on the LV feeder under study.

This selected feeder on the 11 kV side serves as the primary supply point for eight feeders in the LV section of the network. Each of these LV feeders has its own step-down transformer (11 kV to 0.433 kV), which further reduces the voltage for end-user consumption. However, to streamline the simulation, seven of these feeders were also lumped together, leaving only one feeder to represent the LV network for the purpose of this analysis. This approach allows for an efficient and targeted examination of DER impacts on the LV network while maintaining the network's overall structural integrity. On the LV side, the selected feeder is further subdivided into four LV segments, each serving 24 customers. Consequently, the LV feeder studied in this analysis represents a total of 96 customers, which provides a reasonable approximation of the residential load structure commonly found in distribution networks. This simplified setup allows for the integration of various DER components, such as EVs and PV arrays, to evaluate their impacts on voltage steady state limits, power quality, and hosting capacity.

For power flow analysis, bus 26 in the UKGDN was designated as the slack bus. This slack bus maintains a fixed voltage of 1.00 per-unit (p.u.), serving as a reference point for the load flow calculations. By anchoring the system voltage at this bus, the model simulates realistic network conditions while accommodating the voltage variations introduced by DERs across the distribution network.

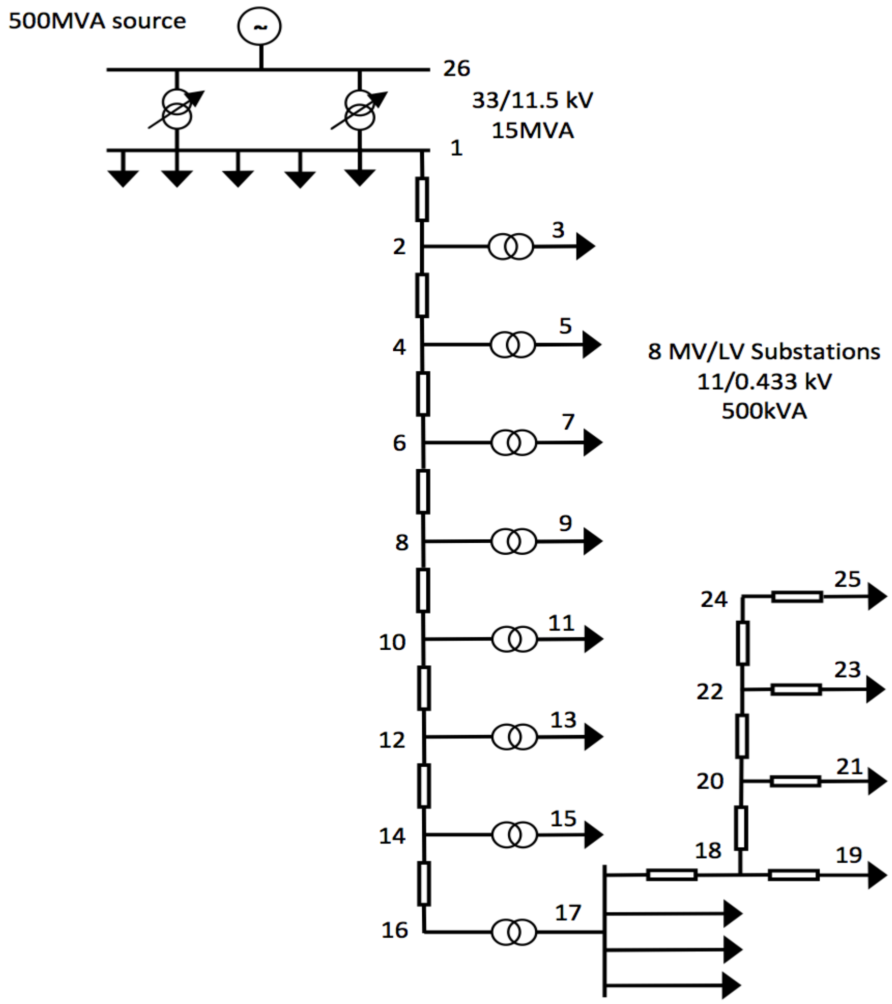


Figure 3.1: UK Generic Distribution Network [110].

In distribution networks, the impedance of lines is distributed continuously along their length, making it challenging to incorporate directly into load flow studies. This complexity increases further when considering the impedance of distribution transformers in conjunction with the lines. To facilitate analysis, all line and transformer impedances are converted to p.u. values, allowing for straightforward inclusion in the system admittance matrix. This p.u. conversion standardizes the impedance values, enabling efficient computation of power flow and network stability within the distribution network.

The impedances between various buses, including those associated with distribution lines and transformers, are provided in Table 3.1. These values represent the cumulative impedance characteristics for each segment within the test network and are critical inputs to the load flow analysis. By integrating these p.u. impedances into the system admittance matrix, the analysis ensures that each component's influence on voltage, current, and power losses is accurately captured, reflecting the actual operational behaviour of the distribution network.

Table 3.1: Per-unit values of line and distribution transformer.

Bus		**Cable size**	**Impedance**	**Length**	**Voltage**	**Per-unit**
From	To	**(mm)**	**(ohm/km)**	**(km)**	**(kV)**	**Impedance**
26	1	-	-	-	33/11	0.0399 + j0.5987
1	2	185	0.164 + j0.080	0.375	11	0.0465 + j0.0227
2	3	-	-	-	11/0.4	0.6086 + j9.1291
2	4	185	0.164 + j0.080	0.375	11	0.0465 + j0.0227
4	5	-	-	-	11/0.4	0.6086 + j9.1291
4	6	185	0.164 + j0.080	0.375	11	0.0465 + j0.0227
6	7	-	-	-	11/0.4	0.6086 + j9.1291
6	8	185	0.164 + j0.080	0.375	11	0.0465 + j0.0227
8	9	-	-	-	11/0.4	0.6086 + j9.1291
8	10	95	0.32 + j0.087	0.375	11	0.0465 + j0.0227
10	11	-	-	-	11/0.4	0.6086 + j9.1291
10	12	95	0.32 + j0.087	0.375	11	0.0465 + j0.0227
12	13	-	-	-	11/0.4	0.6086 + j9.1291
12	14	95	0.32 + j0.087	0.375	11	0.0465 + j0.0227
14	15	-	-	-	11/0.4	0.6086 + j9.1291
14	16	95	0.32 + j0.087	0.375	11	0.0465 + j0.0227
16	17	-	-	-	11/0.4	0.6086 + j9.1291
17	18	185	0.164 + j0.074	0.075	0.4	6.0741 + j2.7407
18	19	35	0.851 + j0.041	0.03	0.4	12.6074 + j0.6074
18	20	185	0.164 + j0.074	0.075	0.4	6.0741 + j2.7407
20	21	35	0.851 + j0.041	0.03	0.4	12.6074 + j0.6074
20	22	95	0.32 + j0.075	0.075	0.4	11.8519 + j2.7778
22	23	35	0.32 + j0.041	0.03	0.4	12.6074 + j0.6074
22	24	95	0.32 + j0.075	0.075	0.4	11.8519 + j2.7778
24	25	35	0.32 + j0.041	0.03	0.4	12.6074 + j0.6074

3.3 Methodology of Deterministic Studies

The deterministic approach is employed in this research to evaluate the hosting capacity of the UKGDN for uncoordinated EV charging and PV integration. This methodology systematically analyses network behaviour under predefined scenarios, focusing on the voltage stability, power losses, and loading conditions within the LV segments of the distribution network. By establishing a controlled environment, deterministic studies allow for in-depth exploration of worst-case scenarios, such as peak demand during uncoordinated EV charging, providing a clear understanding of the network's limitations and constraints.

3.3.1 Deterministic Load Profiles

In deterministic studies, load profiles represent specific, pre-defined patterns of electricity consumption within the distribution network. For this research, deterministic load profiles for both traditional residential loads and EV charging are used to simulate a fixed daily demand. This approach enables a clear understanding of the potential impacts of uncoordinated EV charging and PV integration on network performance.

3.3.1.1 Seasonal Power Demand

Seasonal load profiles for winter, summer, autumn, and spring, as produced by [111], are illustrated in Figure 3.2. The data indicates that winter and summer exhibit the highest power demand among the four seasons. Consequently, this study focuses on residential load profiles for winter and summer weekdays.

The analysed profiles show a maximum demand of 1.3 kW and a minimum demand of 0.16 kW, which have been adjusted to align with the demand metrics provided by the UKGDN in [112]. Furthermore, an annual demand increase of 1% has been factored in, starting from the year the model was published, in accordance with estimates from Distribution Network Operators (DNOs) in the UK [113].

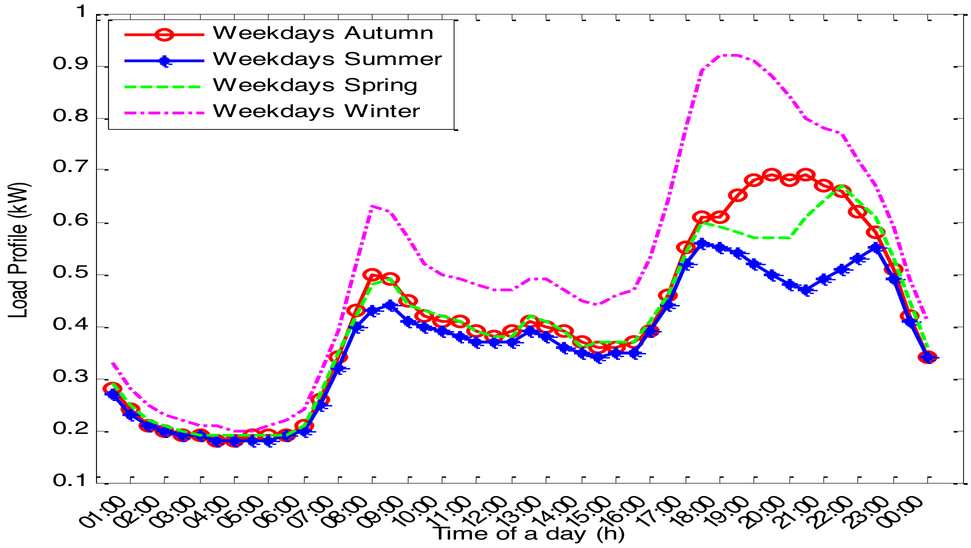


Figure 3.2: Load profiles in a day [111]

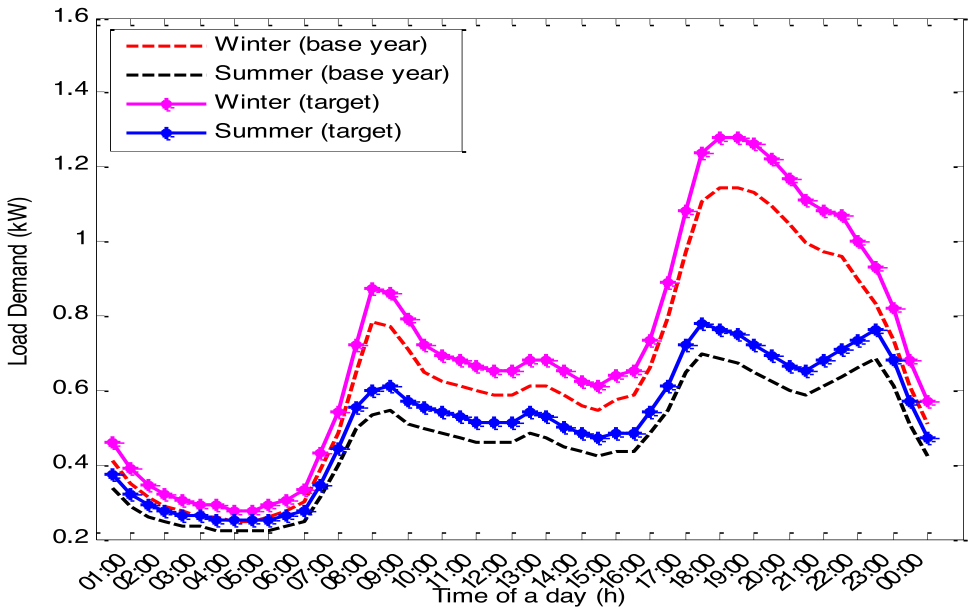


Figure 3.3: Electricity demand for the season of 2010 (base year) and 2030 (target).

3.3.1.2 Electric Vehicles Charging Profiles

For this simulation, it assumes all the EV charge at home. With slow charger station, 3 kW were used [114]. EV that use in this study were assumed having 12 kWh battery capacity [115].

With EV battery capacity and slow charger, Eq. 3.1 were used to calculated the duration of EV charging. Assuming the initial battery SOC is 0% and the disconnection of SOC when the battery reaches 100% SOC.

$$T_{duration} = \frac{1\, x\, batt_{cap}}{home_{charge}} \tag{3.1}$$

3.3.2 Load Flow Analysis

In this section, a load flow analysis is conducted to assess the impact of EV charging on the LV distribution network. The study employs the Newton-Raphson method [108], a widely used iterative technique for solving nonlinear power flow equations by updating bus voltage magnitudes and angles until convergence. This method is implemented in MATLAB to model how different charging scenarios affect network performance, specifically in terms of power losses and voltage stability [108]. By simulating both summer and winter demand, the analysis provides a comprehensive view of how EV charging influences network's ability to meet demand and maintain stability under different conditions.

3.3.3 Simulation Results of Deterministic Studies

The deterministic studies conducted in this research examine the impacts of EV charging on the distribution network under various seasonal and time-based scenarios. The simulations are structured as follows:

Case Study 1: EV Charging During On-Peak Hours in Winter

This scenario investigates the effects of EV charging during high demand periods in winter, a time characterized by peak residential and commercial loads due to heating and extended lighting requirements. The combination of on-peak winter demand and simultaneous EV charging imposes a significant load on the distribution network. This study aims to determine the implications of concentrated EV charging loads on voltage steady state limits, potential overloads, and power losses. The findings indicate that winter peak times may experience higher voltage drops and increased power losses, thereby stressing the network. These results suggest the necessity for controlled or staggered EV charging strategies during peak periods to enhance network resilience.

Case Study 2: EV Charging During Off-Peak Hours in Winter

This case study explores the network's response when EVs charge during lower-demand periods in winter, typically at night. Charging during off-peak hours can alleviate stress on the network by reducing competition with residential and commercial loads. By assessing this scenario, insights are gained into the impacts of shifting EV charging on voltage levels and line losses. The results often demonstrate improvements in power distribution efficiency and a reduction in power losses, indicating that off-peak charging in winter is an effective strategy for minimizing the impact of EVs on the network.

Case Study 3: EV Charging During On-Peak Hours in Summer

In this scenario, the focus is on EV charging during high-demand periods in summer, when air conditioning and cooling systems place substantial loads on the network. Although peak demand in summer may be slightly lower than in winter, the cumulative effect of household loads and EV charging can still strain the network. This study evaluates the interaction between summer peak demand and EV charging, with a particular emphasis on voltage drops, potential thermal stress on network components, and increased power losses. The findings provide insights into whether additional infrastructure or cooling measures may be necessary during summer on-peak hours to maintain network performance.

Case Study 4: EV Charging During Off-Peak Hours in Summer

The final scenario examines EV charging during off-peak hours in summer, typically overnight, when demand is lower. This period allows the network to accommodate additional EV loads more comfortably. By analysing off-peak summer charging, this case study highlights the advantages of aligning EV charging with periods of reduced network demand. Results typically show fewer issues related to voltage stability, minimal power losses, and better utilization of network capacity. These findings underscore the benefits of promoting off-peak charging schedules during summer to enhance power quality and mitigate strain on network resources.

Each case study provides valuable insights into optimal EV charging strategies, illustrating how peak and off-peak charging times across different seasons affect network resilience. Through the analysis of these scenarios, the study identifies methods to mitigate potential negative impacts, such as voltage instability and power losses, particularly in networks with high EV penetration.

3.3.3.1 Power Losses

Figure 3.4 and Figure 3.5 show the losses result for season winter and summer. The baseline of this graph is a year and EVs penetration versus losses. Figure 3.4 showed the highest power losses were observed during peak charging regimes. In the year 2010 with 0% EV penetration; was assumed that there are no EVs this year, it showed power losses of about 7.18%. This is pure residential power loss. In the year 2015, with 12.5% EVs penetration, power losses increased to 9.41% (about 24%) increased from the base year 2010. In the year 2020, with 25% EV penetration, power losses increased to 11.75% (about 39%) increased from the base year 2010. In the year 2025, with 50% EV penetration, losses of about 16.13% (about 55%) increased from the base year 2010. In the year 2030, with 75% EV penetration, losses of about 20.80% (about 65%) increased from the base year 2010.

Compare to off-peak charging regimes, in the year 2010 with 0% EV penetration; was assumed that there are no EVs this year, and it showed power losses of about 1.55%. This is pure residential power loss. In the year 2015, with 12.5% EVs penetration, power losses increased to 3.12% (about 50%) increased from the base year 2010. In the year 2020, with 25% EV penetration, power losses increased to 4.72% (about 67%) increased from the base year 2010. In the year 2025, with 50% EV penetration, losses of about 7.88% (about 80%) increased from the base year 2010. In the year 2030, with 75% EV penetration, losses of about 11.13% (about 86%) increased from the base year 2010.

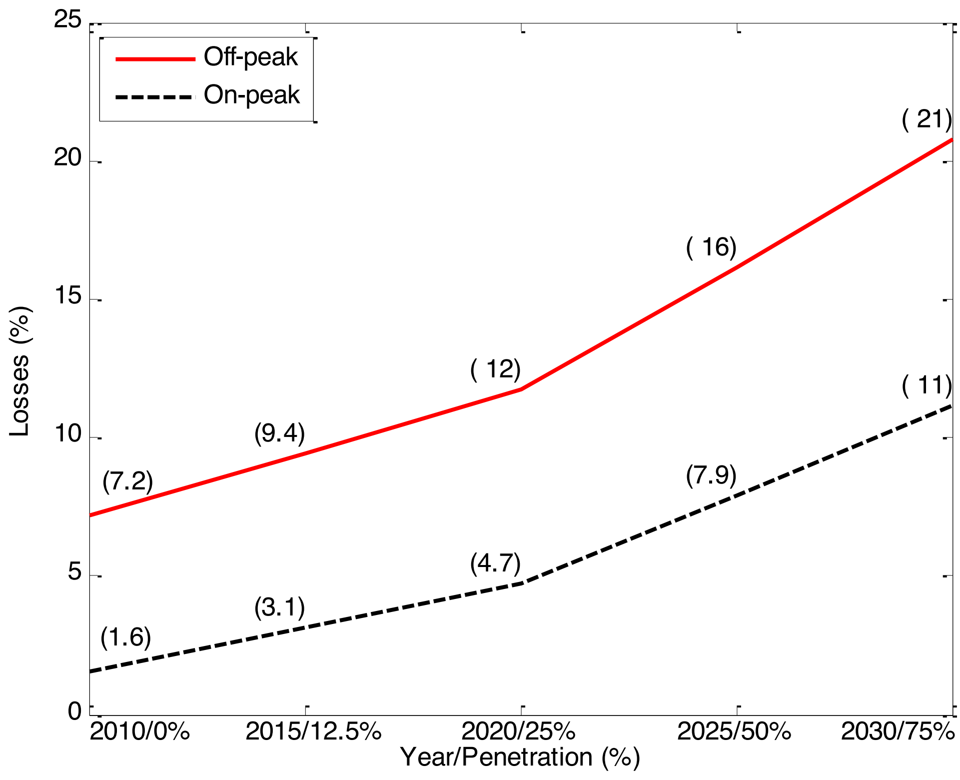


Figure 3.4: Power losses for peak and off-peak EV charging regimes (winter)

Figure 3.5, showed the highest power losses were observed during peak charging regimes. In the year 2010 with 0% EV penetration; was assumed that there are no EVs this year, and it showed power losses of about 3.94%. This is pure residential power loss. In the year 2015, with 12.5% EVs penetration, power losses increased to 5.77% (about 32%) increased from the base year 2010. In the year 2020, with 25% EV penetration, power losses increased to 7.66% (about 49%) increased from the base year 2010. In the year 2025, with 50% EV penetration, losses of about 11.27% (about 65%) increased from the base year 2010. In the year 2030, with 75% EV penetration, losses of about 15.04% (about 74%) increased from the base year 2010.

Compare to off-peak charging regimes, in the year 2010 with 0% EV penetration; was assumed that there are no EVs this year, and it showed power losses of about 1.34%. This is pure residential power loss. In the year 2015, with 12.5% EVs penetration, power losses increased to 2.89% (about 54%) increased from the base year 2010. In the year 2020, with 25% EV penetration, power losses increased to 4.47% (about 70%) increased from the base year 2010. In the year 2025, with 50% EV penetration, losses of about 16% increased follow by the year 2023, power losses reach 15%.

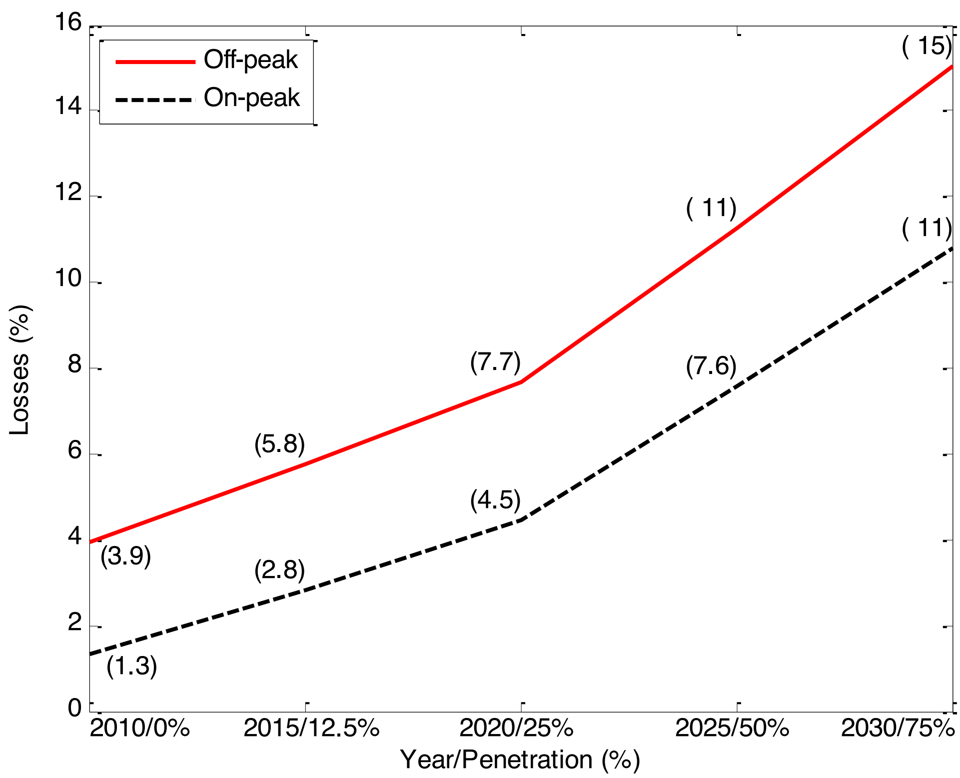


Figure 3.5: Power losses for peak and off-peak EV charging regimes (summer)

Figures 3.4 and 3.5 concluded that by the year 2030 high EVs penetration will create increasing demand for electricity and increased winter peak demand. The rise of losses for different penetration is more on winter weekdays than compared on summer weekdays. This is due to the higher residential loads in winter than in summer. Similarly, the losses are high for peak charging than compared to off-peak charging due to higher residential loads at peak load.

3.3.3.2 Voltage Profiles

Figure 3.6, showed voltage rises were observed during peak charging regimes while voltage drops were observed during off-peak charging regimes. In the year 2010 with 0% EV penetration; was assumed that there are no EVs in this year, it showed a voltage profile of about 1.0283 p.u. and in the year 2030 with 75% EV penetration showed a voltage profile of about 1.0220 p.u. This gave a 0.6% voltage drop from 2010 (base year).

Compared to on peak voltage profile trend it showed a voltage drop. In the year 2010 with 0% EV penetration; was assumed that there are no EVs in this year, it showed a voltage profile of about 0.9678 p.u. and in the year 2030 with 75% EV penetration showed a voltage profile of about 0.9428 p.u.. This gave a 2.6% voltage drop from 2010 (base year).

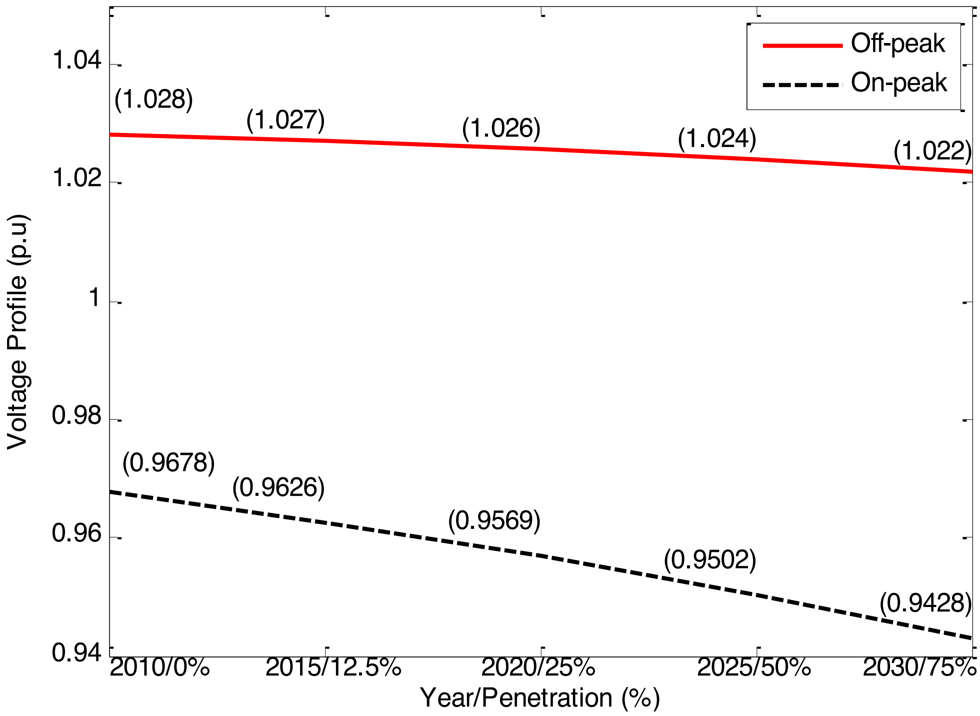


Figure 3.6: Voltage profile for peak and off-peak EV charging regimes (winter)

Figure 3.7, showed voltage rises were observed during peak charging regimes while voltage drops were observed during off-peak charging regimes. Only in the year 2010, for on-peak charging regimes gives voltage rise only in the year 2010.

In the year 2010 with 0% EV penetration; was assumed that there are no EVs in this year, it showed a voltage profile of about 1.0305 p.u. and in the year 2030 with 75% EV penetration showed a voltage profile of about 1.0247 p.u.. This gave a 0.6% voltage drop from 2010 (base year).

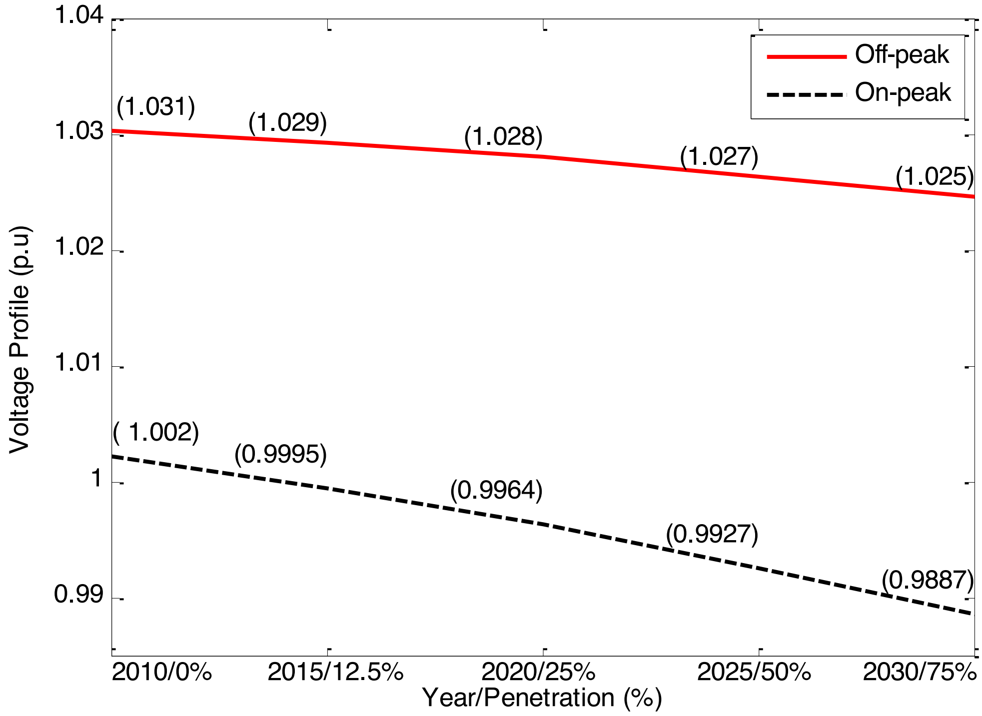


Figure 3.7: Voltage profile for peak and off-peak EV charging regimes (summer)

Compared to on peak voltage profile trend it showed voltage drop only in the year 2010 it showed voltage rises. In the year 2010 with 0% EV penetration; was assumed that there are no EVs this year, and it showed a voltage profile of about 1.0023 p.u.. In the year 2015 with 12.54% EV penetration, the voltage profile was 0.9995 p.u. and in the year 2030 with 75% EV penetration showed a voltage profile of about 0.9887 p.u.. This gave a 1.4% voltage drop from 2010 (base year).

Figure 3.6 and Figure 3.7 showed that the voltage level of the micro-grid is below the permissible limit for charging regime 1 (off-peak charging). Whereas the voltage level for charging regime 2 (peak charging) is well within the permissible limit. This is due to the lower residential loads at charging regime 2 than compared to other charging regimes.

3.4 Methodology of Stochastic Studies

In this study, stochastic studies are presented using the MC method to analyse the impact of EV battery charging on UKGDN focusing on the LV side. These studies evaluated the impact of EV battery charging on distribution transformer power demand, voltage profile, and line losses.

Realistic thirty-minute time-series profiles were constructed using actual demand and generation data to ensure that the simulations closely represent operational conditions:

Seasonal daily loads Derived from recorded UK residential load profiles (aggregated and normalised), adjusted for winter and summer demand characteristics.

EV load demands Based on empirical data from observed EV charging trials and published studies, where plug-in behaviour, charging duration, and power ratings were matched to common EV models expected in the UK market by 2030.

PV load profiles Modelled using measured PV generation data, scaled to typical household PV system sizes. The profiles reflect seasonal solar irradiation patterns, thus capturing variability between summer and winter months.

The use of these data sources ensures that the time-series profiles used in the simulations reflect actual demand and generation behaviour, rather than purely theoretical or idealised curves.

EV uptake estimations for the year 2030 were applied based on [113], and additional cases with increasing penetration of PV were simulated. One hundred MC simulations were conducted per penetration level (percentage of houses with PV) to capture uncertainty. The following factors were randomly varied across simulations:

i. EV types,
ii. EV charger locations,
iii. EV charging plug-in time and duration,
iv. PV size and location.

In this study, EV discharging was limited to 90 ± 10% SOC, in line with [116], as maintaining operation within this range reduces lithium-ion cell degradation and prolongs battery cycle life.

3.4.1 Modelled Electric Vehicles Charging Profiles

To reproduce the daily charging behaviour of individual EVs, probability distributions of plug-in times and corresponding energy requirements were combined. In this study, EVs participate only in the real-time energy market, with charging considered solely in Grid-to-Vehicle (G2V) mode. Given that UK residential loads are predominantly single-phase, users are initially expected to adopt slow charging at home (3.6 kW). Two types of EVs were modelled: Plug-in Hybrid Electric Vehicles (PHEVs) with a battery capacity of 9 kWh and Battery Electric Vehicles (BEVs) with a capacity of 24 kWh [117], reflecting earlier UK BEV models (e.g., Nissan Leaf) and ensuring consistency with the dataset used. Charging efficiencies were assumed to be 85% for PHEVs and 87% for BEVs [118].

Three main uncertainties were considered in the modelling of EV connections: plug-in time, location, and charging duration. The daily mean EV charging demand profiles from [119], illustrated in Figure 3.8, were used as a reference, with data measured during both winter and summer. Figure 3.8 shows a clear seasonal pattern: in winter, EVs tend to arrive later in the evening (around 18:30), whereas in summer, arrivals occur earlier (around 17:30). This trend reflects differences in daylight hours and residential routines. To generate realistic EV arrival times at home, a normal distribution was applied in MATLAB, parameterised by mean and standard deviation. The mean values were aligned with these observed seasonal peaks, corresponding to typical residential return-home periods. A standard deviation of two hours was adopted, ensuring that approximately 68.27% of arrivals fall within two hours of the mean and 99.7% within a six-hour window.

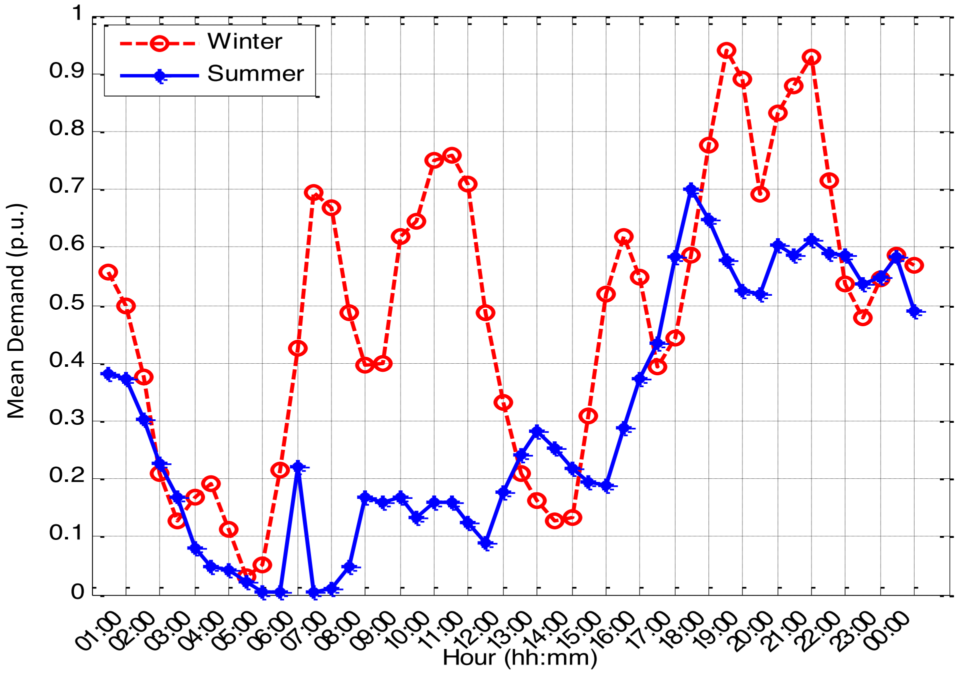


Figure 3.8: Daily mean of EV demand profiles [119].

In the MC simulations, each EV's arrival time was randomly generated by sampling from this distribution, thereby capturing the variability of household charging behaviour while maintaining consistency with observed seasonal demand patterns. The simulation results reflect the seasonal differences indicated in Figure 3.3, with later EV arrivals in winter and earlier, more evenly spread arrivals in summer. For the purposes of this study, it was further assumed that all EV owners charge their vehicles exclusively at home, reflecting dominant residential charging behaviour in the UK context (see Figure 3.9).

Data from the National Grid [120] was considered to estimate the EV uptake levels for 2030. The uptake levels for PHEV and BEV are presented in Table 3.3.

Table 3.2: EV penetration level per 96 customers in 2030 [120].

Vehicle type	**PHEV**	**BEV**
No. of EVs	54	14
EV penetration	71%	

The number of residential customers was fixed at 96 to match the LV feeder section of the UK Generic Distribution Network (UKGDN) model used in this study. This feeder is widely adopted in academic research as a representative low-voltage residential network, and therefore 96 households were considered in the simulations. The EV ownership (PHEV or BEV) was then assigned according to the penetration levels shown in Table 3.2, with customers randomly allocated using a normal distribution.

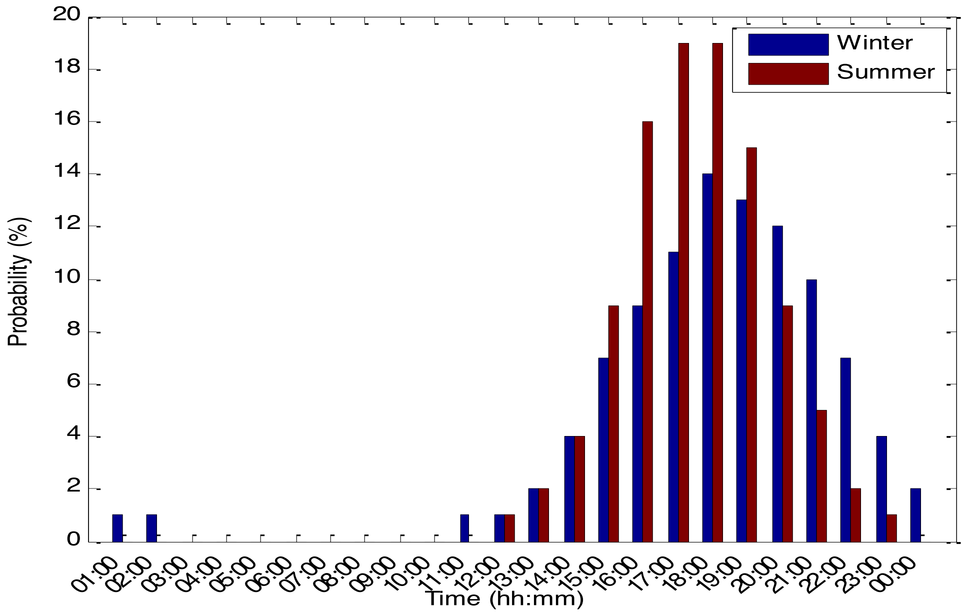


Figure 3.9: Histogram of EV arrival time at home.

The duration of EV battery charging depends on the (i) battery capacity, (ii) its SOC before the plug-in and (iii) disconnection time. Each SOC depends on the EV owner's preferences. The uncertainty of each owner's EV battery SOC at the moment of plug-in for charging was modelled as a normal distribution. For this simulation, each EV will have different initial SOC when arrived at home. The initial SOC when plugged in was assumed to be 20% ± 10%. The initial SOC is based on the mean daily energy remaining in the EV after the day's trip (on reaching home). From [121], the mean daily energy remaining for 28 trips in winter is 12kWh and for 189 trips in summer is 7kWh. Nissan Leaf with a 24 kWh battery capacity [122] was used in this simulation. Therefore, the mean daily energy remaining (i.e. initial SOC) at the end of a day trip is 50% and 20% in winter and summer respectively. For this reason, a pessimistic initial SOC of 20% is chosen.

For the battery disconnection, it was assumed that the SOC level is 80% ± 10% for preserving the life of the battery [123]. Based on 1000 MC simulations, it was found that there is only a 4% probability that the EV owner will disconnect their battery at 76% SOC (see Figure 3.10). There are a couple of extreme cases, where the EV owners have to disconnect their battery at around 70% SOC for emergency trips.

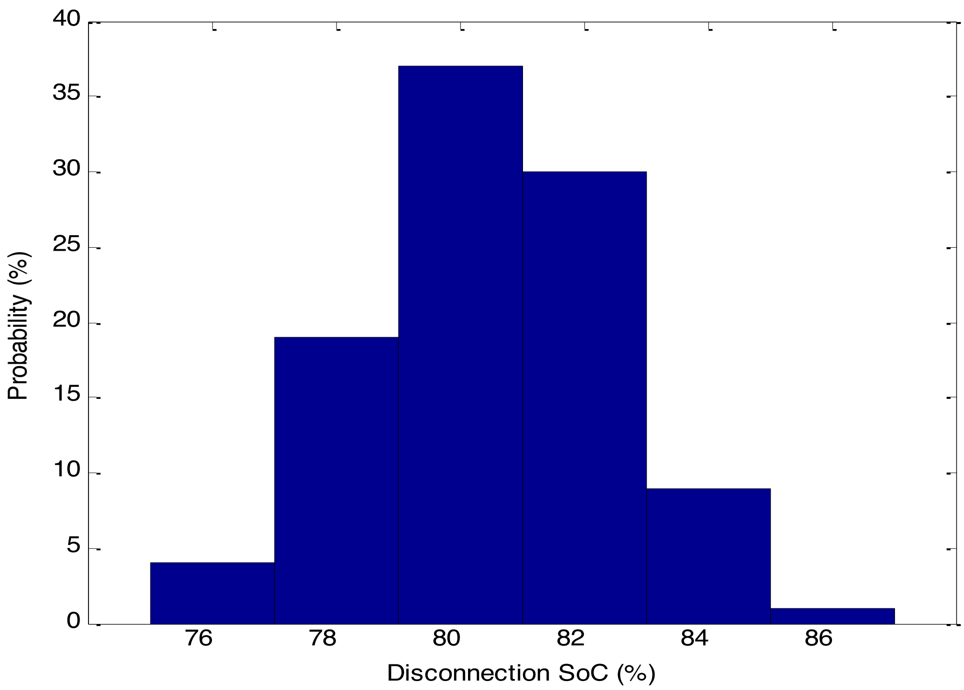


Figure 3.10: SOC probability level for EV disconnection (based on 1000 runs).

3.4.2 Photovoltaic Profiles

PV profiles were produced based on data from real trials [124]. These profiles had a resolution of thirty minutes time-series. The penetration levels for PV are presented in Table 3.3.

Table 3.3: PV penetration level per 96 customers in 2030.

PV Penetration	No. of PV (unit)
20%	19
100%	96

3.4.3 Load Flow Analysis

The stochastic impact assessment methodology employed in this study incorporates the key uncertainties associated with EV charging in electricity networks. These include EV type, charger location, plug-in time, and charging duration. To capture this stochastic behaviour, a MC simulation framework was adopted.

To ensure statistically reliable results, different EV penetration levels were investigated using 1000 independent simulation trials for each case. The selection of 1000 trials was based on a convergence analysis, where the mean values of the output indicators such as feeder demand, transformer loading, network losses, and voltage profiles stabilised with minimal variation as the number of trials increased. The standard error of the results was observed to be less than 0.01%, confirming that this number of simulations was sufficient to provide statistically accurate outcomes without incurring unnecessary computational burden.

The main steps for a single simulation of a particular feeder, across varying EV and PV penetration levels, are outlined below (see Figure 3.12). These steps are repeated for each simulation under both winter and summer scenarios:

1. Import Seasonal Load Profiles: Seasonal load profiles are imported into MATLAB 2014a and assigned to each residential customer in the feeder network.
2. Assign EVs Based on Penetration Level: For the specified penetration level, PHEVs and BEVs are randomly assigned to the customers.

3. Generate EV Charging Profiles: EV charging profiles are created based on plug-in times and required energy levels, as outlined in Section 3.4.1.
4. Define Initial and Disconnection SOC: For each season (winter and summer), every one of the 96 residential EV owners in the feeder network was assigned an initial SOC and a disconnection SOC. To illustrate this process clearly, Figure 3.11 presents the SOC allocation for the 24 customers connected at Bus 4. Bus 4 was selected purely for reference, as each of the four LV segments is structurally identical and serves 24 customers (see Section 3.2). Presenting one segment avoids unnecessary repetition while still demonstrating how SOC variability was incorporated into the MC simulations.
5. Allocate PV Profiles: PV profiles are randomly allocated to customers based on each penetration level (20% and 100%) [124].
6. Aggregate Load Profiles: Final load profiles are generated by combining seasonal load profiles, EV charging profiles, and PV profiles. The aggregated feeder load profiles are then created.
7. Execute Power Flow Analysis: A daily time-series power flow is conducted. For each 30-minute interval, a Newton-Raphson load flow algorithm is executed, and the results are recorded.

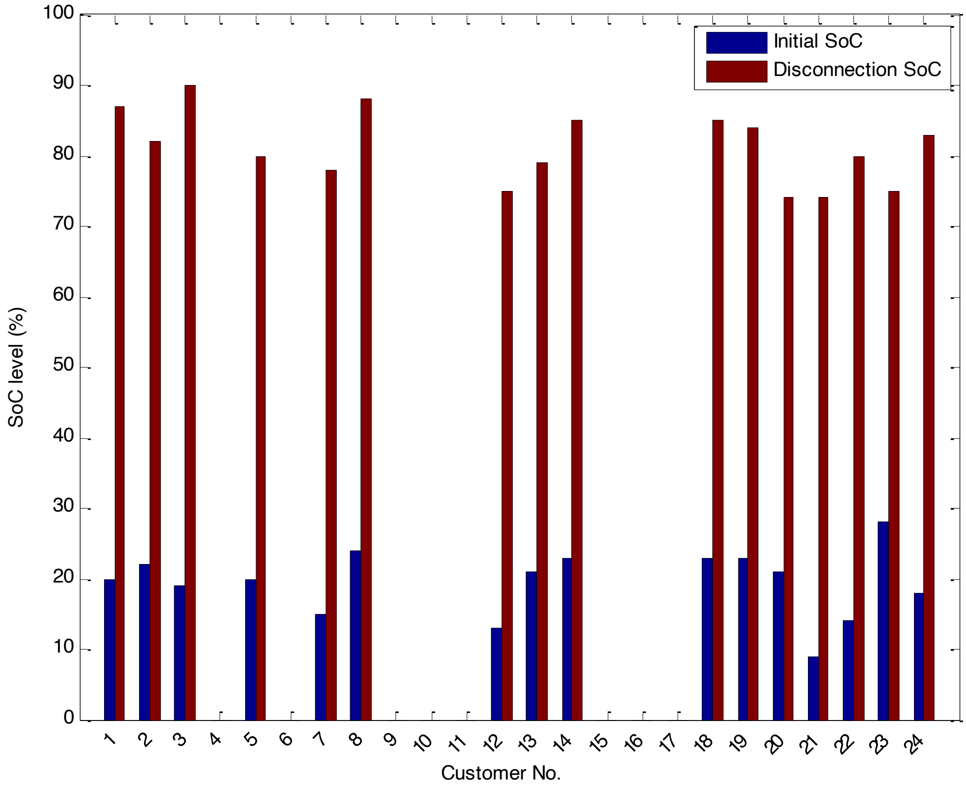


Figure 3.11: Example of initial and disconnection SOC levels for 24 residential customer at Bus 4 (seasonal case). All 96 customers were assigned SOC levels in the same manner.

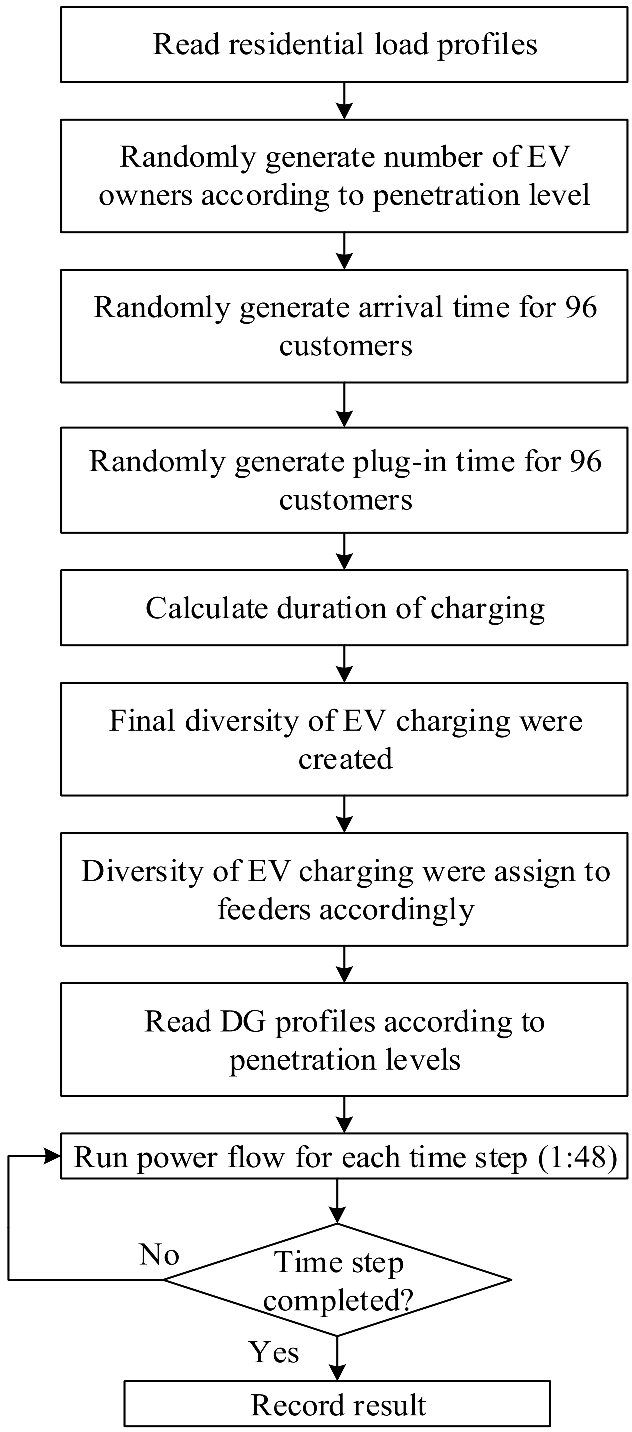


Figure 3.12: The flowchart of load flow analysis.

3.4.4 Simulation Results of Stochastic Studies

From the compiled data during the weekdays of the winter and summer season, a mean of load profiles (residential, EV and PV) was calculated for every thirty-minute load of the day. To perform a stochastic analysis, 100 load flows for each thirty-minute time series were executed generating a random mean of the final load profiles.

Figure 3.13 presents the simulation results for 96 residential customers under different EV penetration levels (0%, 12.5%, 33.3%, and 71%) during winter. These penetration values were selected to reflect typical increments adopted in related studies and to capture both moderate and high-adoption scenarios. The steady-state voltage compliance limits, defined by the distribution code as −6% (red line) and +10% (blue line) from the nominal voltage, are also indicated in the figure for reference. Voltage limit violations were observed at 71% penetration, which was therefore taken as the critical case for further analysis.

To investigate the combined impact of EVs and PV, two worst case scenarios were considered based on 71% EV penetration with varying PV levels, as defined in Tables 3.2 and 3.3:

Case 1: 71% EV penetration with 20% PV penetration

Case 2: 71% EV penetration with 100% PV penetration

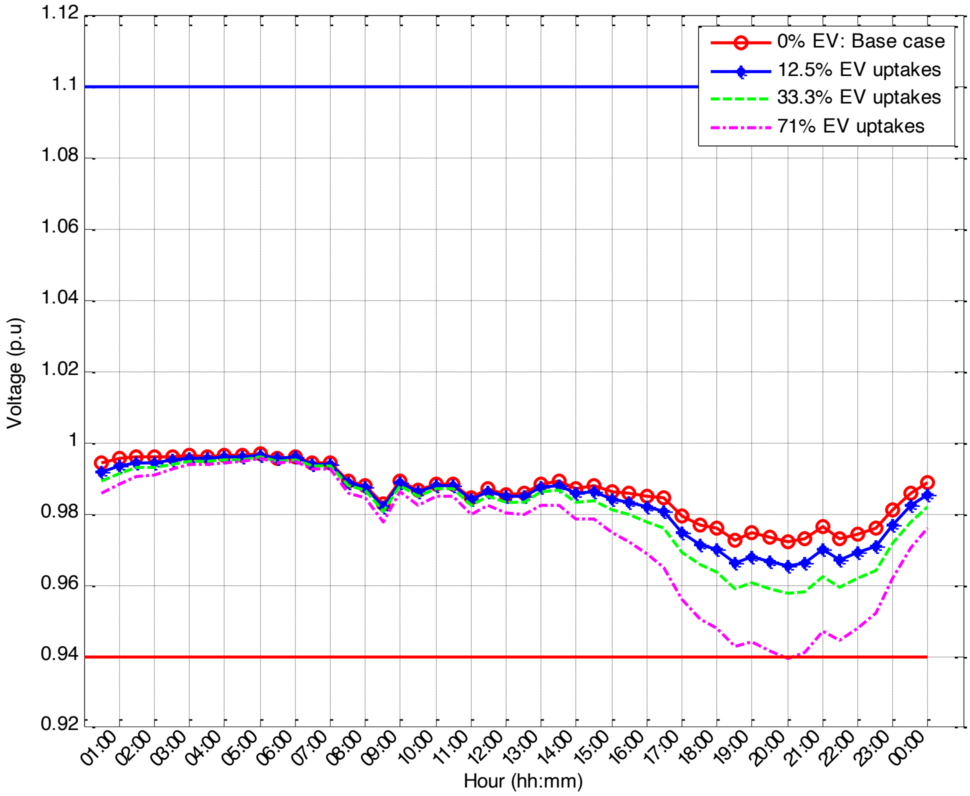


Figure 3.13: Voltage profile with different EV uptakes during winter.

3.4.4.1 Transformer Load Demand

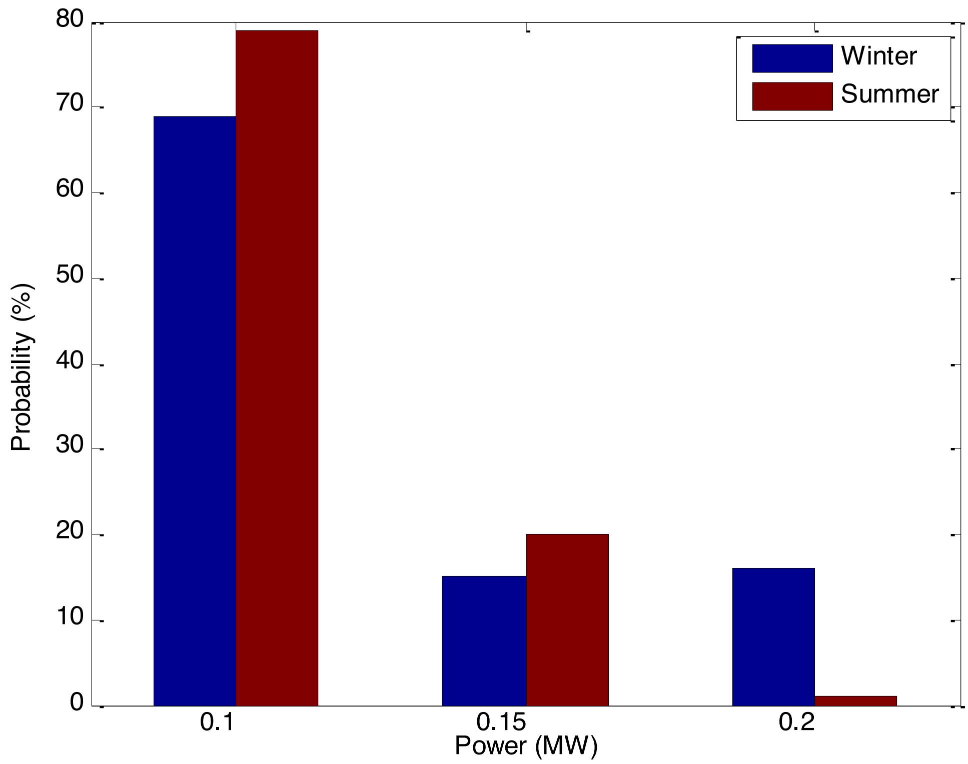
The impact of high EV penetration, in combination with PV systems, was assessed for the year 2030 under two penetration scenarios: 20% and 100% PV integration. Figure 3.14 presents histograms of the transformer power demand distribution for both winter and summer seasons.

The x-axis represents transformer power (MW), ranging from 0.15 MW to 0.20 MW, while the y-axis indicates the probability of occurrence. For the case of 20% PV penetration (Figure 3.14a), the probability of transformer demand clustering around 0.10 MW is the highest compared to other values, with winter exhibiting a slightly higher probability than summer. For 100% PV penetration (Figure 3.14b), a similar trend is observed, although the distributions broaden, reflecting the greater variability introduced by higher PV generation levels.

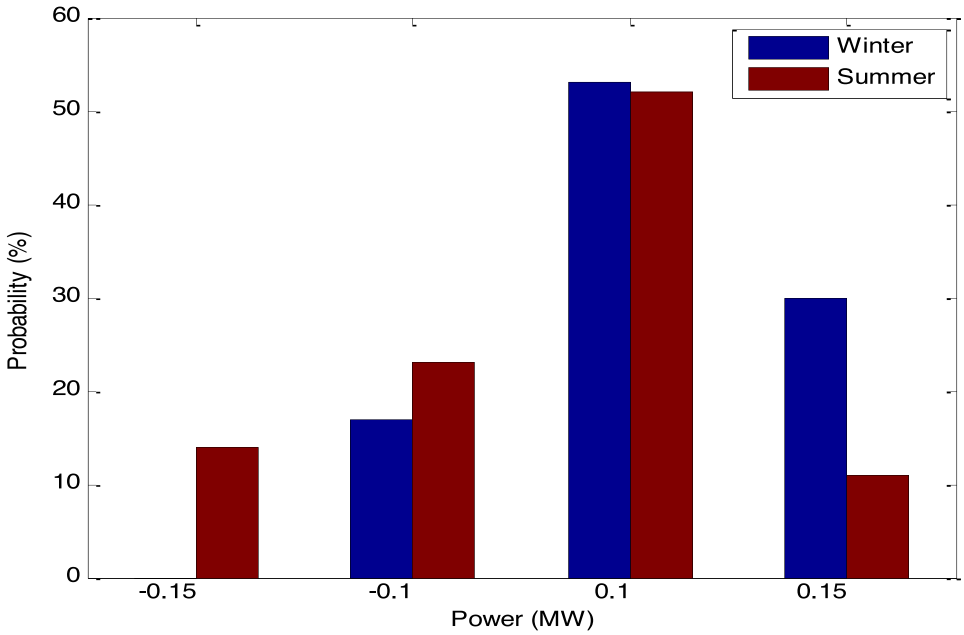
Seasonal differences are evident: during winter, reduced PV output results in higher net demand from the transformer, whereas in summer, greater PV generation shifts the probability distribution and lowers the likelihood of demand clustering at 0.10 MW.

It should be noted that EV charging loads were incorporated into the power demand calculation by superimposing the stochastically generated EV charging profiles (Section 3.3.1) onto the baseline residential demand, which corresponds to 96 customers in the network. This ensured that the histograms in Figure 3.8 reflect the combined impact of residential demand, EV charging, and PV generation on transformer loading.

To complement the probability-based results in Figure 3.8, Figure 3.14 presents the corresponding daily power demand curves for the same scenarios. While the histograms provide insights into the likelihood of different demand levels, the daily curves illustrate how these patterns evolve over time under 20% and 100% PV penetration. Together, these figures highlight both the statistical distribution and the temporal dynamics of transformer loading under high EV uptake.



(a)

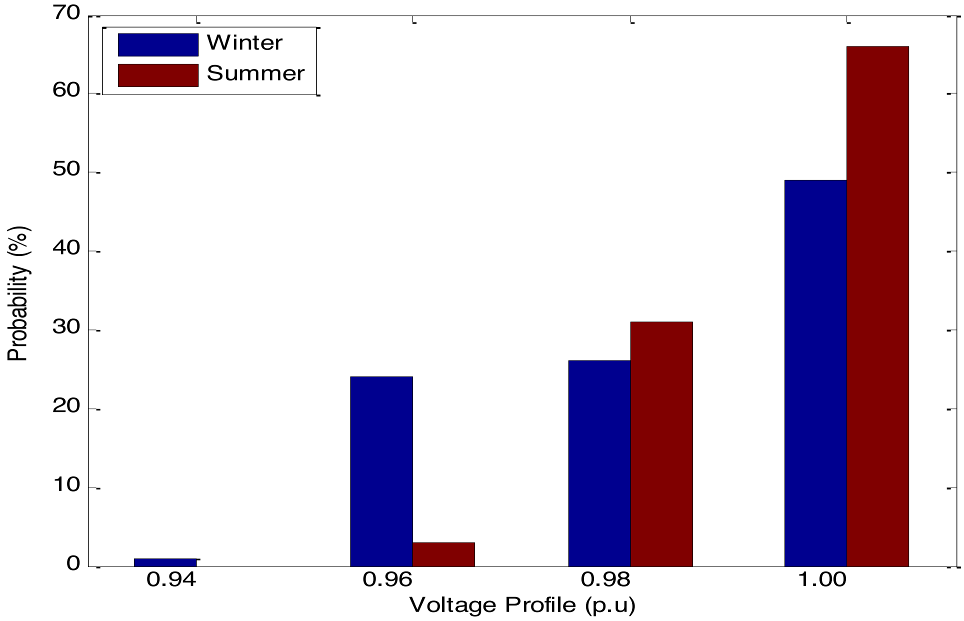


(b)

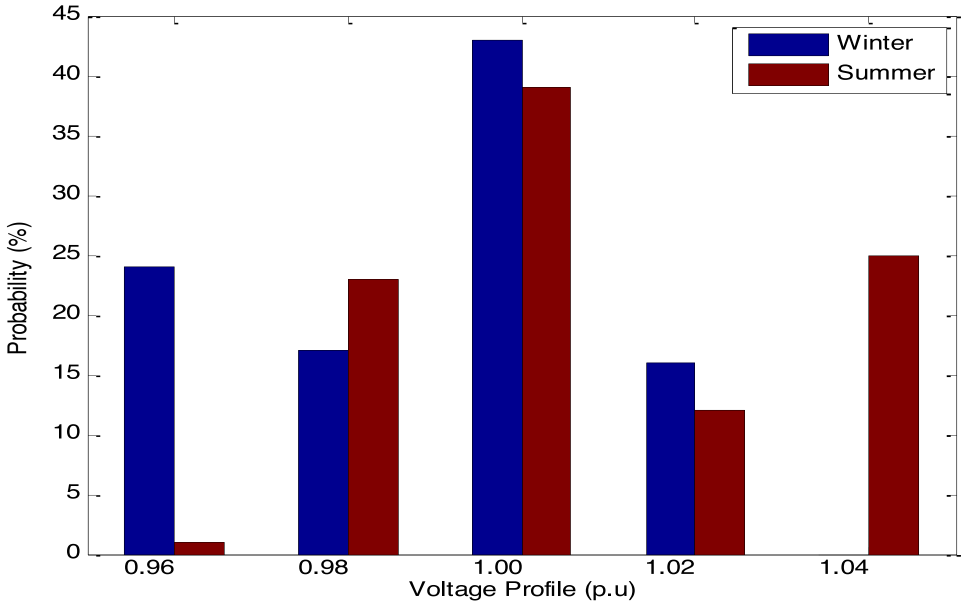
Figure 3.14: Histogram of power for (a) 20% and (b) 100% PV penetration.

3.4.4.2 Voltage Profiles

Figure 3.15 (a) shows the voltage profiles for 20% penetration. There is a 1% probability of 0.94 p.u. voltage during winter. Figure 3.15 (b) shows the voltage profiles for 100% PV penetration. There is a 24% and 1% probability of 0.96 p.u. voltage during winter and summer respectively.



(a)

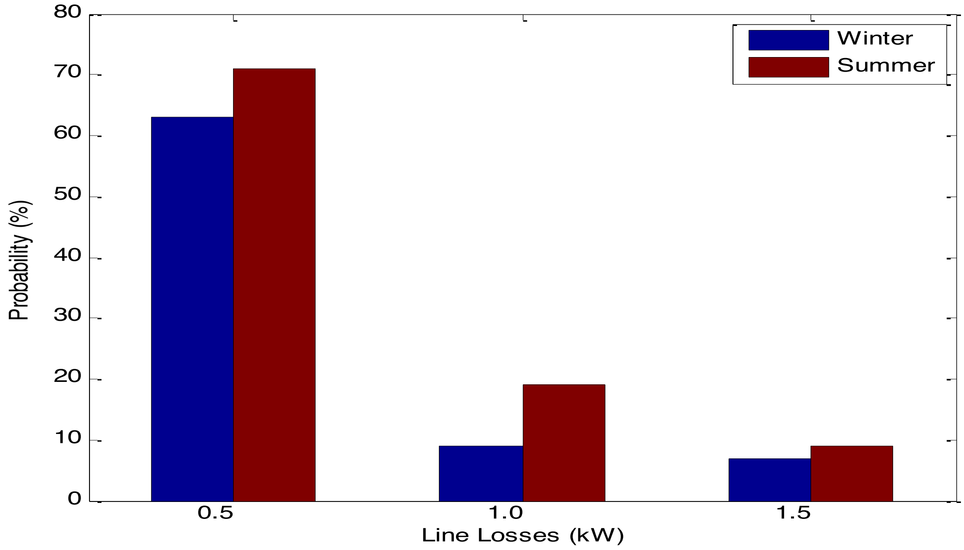


(b)

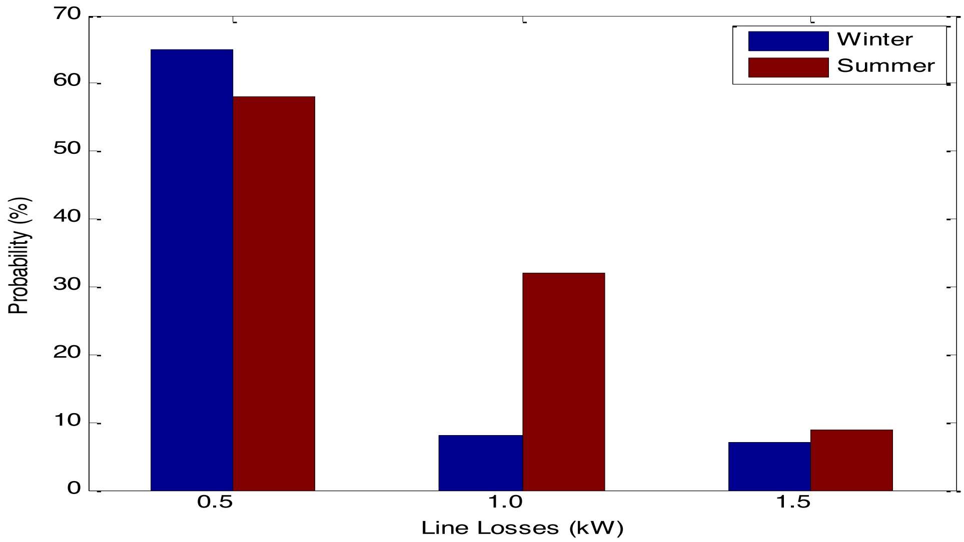
Figure 3.15: Histogram of voltage profile for (a) 20% and (b) 100% PV penetration.

3.4.4.3 Line Losses

Figure 3.16 (a) and Figure 3.16 (b) show the line losses for PV penetration of 20% and 100% respectively. At 1.5 kW, the probability of line losses is slightly higher during summer compared to winter, reflecting the increased demand from cooling appliances in the summer season.



(a)



(b)

Figure 3.16: Histogram of transformer line losses for (a) 20% and (b) 100% PV penetration.

3.5 Summary

This chapter analysed the impacts of EV charging and PV integration on distribution networks using both deterministic and stochastic approaches via the Newton-Raphson load flow method in MATLAB. Network impedances were converted to p.u.

values, and bus and line data were coded for accurate simulation of power losses and voltage profiles.

The deterministic analysis established baseline scenarios for uncoordinated EV charging on the LV section of the UKGDN, which consists of 26 buses with bus 1 as the slack bus and serves 96 customers with 3 kW chargers. Seasonal demand and EV load profiles from UKERC were applied to model daily charging behaviour. Results showed that by 2030, peak demand could increase by 65% during on-peak charging, with winter exhibiting the highest power losses and voltage drops, providing key insights into the network's static response to DER penetration.

The stochastic analysis captured uncertainties in EV types, charger locations, plug-in times, and PV sizes using MC simulations. PV penetration levels of 20% and 100% were considered, revealing that high EV penetration (71%) brought steady-state voltages close to the lower limit of 0.94 p.u., while PV integration helped stabilize voltages under significant EV uptake. Power losses were higher at high PV penetration with low EV uptake.

Overall, the combined deterministic and stochastic analyses offer a comprehensive evaluation of the LV network under varying DER scenarios, emphasizing the need for strategies such as renewable-based EV charging and smart battery management to maintain safe and efficient operation as DER adoption increases. The stochastic methodology presented here also forms the basis for the analyses in the next chapter, where these approaches are applied to the Malaysian distribution network to evaluate the impacts of EV charging under local conditions.

CHAPTER 4

Generating Electric Vehicles Charging Profile based on Urban Road Usage in Malaysia

4.1 Introduction

The rapid proliferation of EVs is reshaping the landscape of urban transportation and energy consumption worldwide. In Malaysia, the growing interest in EV adoption aligns with national goals to enhance energy sustainability, reduce carbon emissions, and promote cleaner transportation options. However, to effectively manage the integration of EVs into the existing power distribution network, it is essential to develop accurate and comprehensive charging profiles that reflect the unique characteristics of Malaysian urban environments.

This chapter focuses on generating EV charging profiles specifically tailored to the urban context of Malaysia, addressing the absence of reliable charging data in the region. By analysing user backgrounds and preferences, this research aims to model realistic charging behaviours based on factors such as commuting patterns, distances travelled, and residential characteristics. The study considers three major urban locations; Shah Alam, Petaling Jaya, and Kuala Lumpur each with distinct traffic patterns and socio-economic dynamics that influence EV usage.

To develop these charging profiles, this research employs a systematic approach that takes into account key variables such as road length, traffic convenience, and working hours in both government and private sectors. An initial assumption of a fully charged EV battery before departure enables the estimation of charging needs based on individual commuting distances and energy consumption patterns. By involving a representative sample of 130 residential units connected to the local distribution network, the analysis provides insights into the charging requirements and behaviours of EV users in urban settings.

Ultimately, this section aims to contribute valuable data to the field of electric mobility in Malaysia, informing policymakers and energy planners about the implications of EV charging on the distribution network. By establishing a foundation for understanding charging patterns, the research lays the groundwork for effective load management strategies that accommodate the evolving energy landscape, enhance grid reliability, and support the transition to sustainable transportation.

4.2 Data Inputs and Assumptions

This section describes the development of EV charging profiles based on urban commute patterns, vehicle characteristics, and user behaviour. The goal is to create an accurate representation of EV charging demands that reflect the needs of typical EV owners in urban areas of Malaysia, providing insights into load impacts on the distribution network.

4.2.1 Electric Vehicle Owner Profile Generation

To generate the EV charging profiles, this study developed a synthetic dataset representing 130 EV owners. The number of owners was chosen to match the residential distribution network under investigation, which consists of 130 houses (see Section 4.5.1 for details). The generated profiles incorporate driving patterns based on commute mode, route selection, driving technique, type of EV, charging location, plug-in time, and duration of charging. It is assumed that all EV owners primarily use their vehicles for commuting to and from work. In line with national statistics, approximately 30% of employees are assumed to work in the government sector, while the remainder are employed in the private sector in Malaysia [125].

Malaysia comprises thirteen states and three federal territories. Two federal territories are selected for analysis: Kuala Lumpur (capital), and Putrajaya, the administrative centre of the federal government. Kuala Lumpur and Putrajaya are carved out of Selangor. Selangor, situated on the west coast of Malaysia (see Figure 4.1), has the highest population among all the states [126]. The Department of Statistics reported that the population in Selangor is growing rapidly and give the highest population density in Malaysia reaching 7.62 million people per km^2 in 2030 [127]. Shah Alam is a city and the state capital of Selangor that is situated within the Petaling District. Thus, Shah Alam is selected as the area of study.

Kuala Lumpur is the capital and hence has the highest number of vehicles and population density in Malaysia [128]. As Kuala Lumpur is situated within the state of Selangor it was selected as a suitable settlement area. Putrajaya is a new federal administrative capital of Malaysia which has been set to achieve a 70% share of all travels by public transport in the area [129].

Petaling Jaya is the second biggest city in Peninsular Malaysia after Kuala Lumpur [130]. Becoming a centre of attraction in the Klang Valley area with rapid development for industries and transportation as well as an increase in population growth. For this study, Petaling Jaya was selected to represent the private sector employment area.

Figure 4.1: Map of Malaysia highlighting the study area, Selangor [131].

4.2.2 Data Collection for Electric Vehicles Travel Routes

In this chapter, a method to generate individual EV charging patterns has been developed based on the group characterisation of the driving characteristics and home plug-in behaviour of EV owners. The first input is used to define properties, such as the daily driven distance and the expected departure and arrival time, which determines the possible home charging window. The second input is used to quantify the probability of plug-in time and energy required.

Real-time commuting data is determined using *Google Maps* [132]. There is a feature provided by *Google Maps* that includes directions of location, departure and arrival times, and travel dates. Once the selections are set, the feature returns a set of results considering the route selection that has an estimation of:

i. distance between the current location to the destination,

ii. duration of time for arrival to destination, and

iii. arrival time to destination.

Three main types define the daily driving pattern: departure time, travelled distance, and arrival time. It is considered two departure times: the first departure time is in the morning starting from home to the office, and the second departure time is when the EV owners return home. The same considerations are given for arrival time, the first arrival time is when the EV owner reaches the office, and then home.

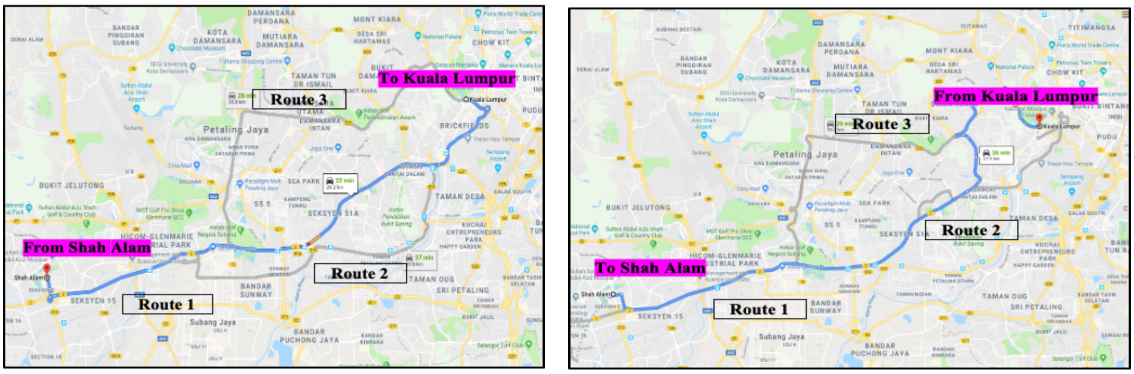
In the government sector, Staggered Working Hours (SWH) have been implemented in the federal territory of Kuala Lumpur commencing on 1st May 1998 [133]. The Government has agreed to add Staggered Hours (SH) to the existing SWH schedule in all federal government agencies in the year 2007 [134].

In the year 2017, the regulation stated that employees are given four options as to when they start and complete work (see Table 4.1) with the fulfilment of nine working hours every day [135]. As for the private sector, normal working hours start at 9:00 am and finish at 6:00 pm.

Table 4.1: Working Hours in the Malaysian Public Sector.

City	**Staggered Hours**	**Time In**	**Time Out**
Putrajaya, Kuala Lumpur	Option 1	7:30 am	4:30 pm
	Option 2	8:00 am	5:00 pm
	Option 3	8:30 am	5:30 pm
	Option 4	9:00 am	6:00 pm

The data was generated on a weekday for all 130 residential customers, corresponding to the number of houses in the distribution network under investigation. The EVs are started to drive towards a starting point, following the rules to arrive fifteen minutes earlier before *Time In*. The starting point is referred to as each working place, which is either Kuala Lumpur, Putrajaya or Petaling Jaya (see Table 4.1). Based on Google Maps data, three possible routes were identified for each location by considering specific departure and arrival times. The routes correspond to each of the selected locations: Kuala Lumpur (see Figure 4.2), Putrajaya (see Figure 4.3), and Petaling Jaya (see Figure 4.4). For commuting from office to home, there are also three possible selections to choose from.

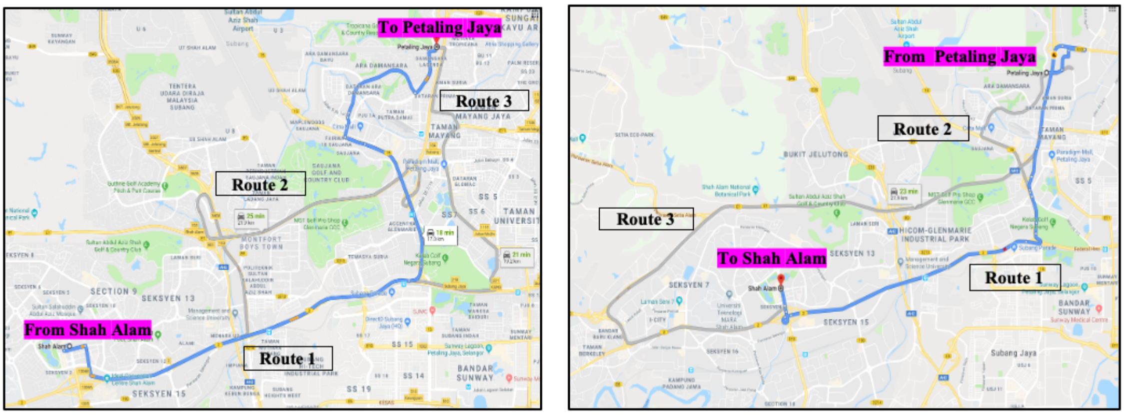


(a) (b)

Figure 4.2: Commute Routes (a) Shah Alam to Office, (b) Kuala Lumpur to Home

(a) (b)

Figure 4.3: Commute Routes (a) Shah Alam to Office, (b) Putrajaya to Home



(a) (b)

Figure 4.4: Commute Routes (a) Shah Alam to Office, (b) Petaling Jaya to Home.

It is assumed that all employees come back from the office immediately at the *Time Out*. There are six different routes for each EV owner to select during the day. The description of each route in terms of distance is shown in Table 4.2.

Table 4.2: Description of the Route Selection.

Commuting		Route	Distance, D (km)
From	**To**		
Shah Alam (home)	Kuala Lumpur (office)	1	31.9
		2	30.4
		3	30.1
Shah Alam (home)	Putrajaya (office)	1	41.1
		2	40.0
		3	39.0
Shah Alam (home)	Petaling Jaya (office)	1	21.4
		2	19.8
		3	16.6
Kuala Lumpur (office)	Shah Alam (home)	1	32.7
		2	31.7
		3	30.4
Putrajaya (office)	Shah Alam (home)	1	42.2
		2	41.7
		3	39.1
Petaling Jaya (office)	Shah Alam (home)	1	27.9
		2	21.5
		3	17.1

4.3 Modelling Electric Vehicles Charging Profiles

For producing the daily behaviour of individual EVs, there are uncertainties associated with the EV batteries:

i. The plug-in time,

ii. Initial battery SOC upon arrival at home,

iii. SOC at the end of charge,

iv. The charging duration.

4.3.1 Plug-in Time

The plug-in time starts once the EV arrives at home. In this study, it is assumed that the EV owner starts charging upon arrival. The arrival time ($T_{arrival}$) is the sum of the EV owner's work finish time (T_{end}) and the time taken for the commuting on that day (T_{taken}), given by (Eq. 4.1).

$$T_{arrival} = T_{end} + T_{taken} \tag{4.1}$$

T_{taken} is calculated using (Eq. 4.2), where D denotes the commuting distance back home (see Table 4.2) and S is the commuting speed, selected from 10 km/h, 20 km/h and 30 km/h to represent typical variations in urban traffic conditions. This simplified driving cycle, constrained to speed below 40 km/h, captures the impact of congested roads and frequent stop-go patterns commonly observed in Malaysia, which have a significant influence on EV energy consumption [136].

$$T_{taken} = \frac{D}{S} \tag{4.2}$$

4.3.2 Initial Battery State-of-Charge

The initial battery SOC depends on the length of travel. It is assumed that the initial battery SOC ($Initial_{SoC}$) before starting to commute is 100%. The initial battery SOC once arrived at the destination ($Initial_{SoC_a}$) is given by (Eq. 4.3).

$$Initial_{SoC_a} = Initial_{SoC} - Initial_{SoC_b} \tag{4.3}$$

The initial battery SOC after travelling ($Initial_{SoC_b}$) is calculated using (Eq. 4.4).

$$Initial_{SoC_b} = \frac{\sum D_t}{D_g} \tag{4.4}$$

Where D_t is the total distance for commuting, which is measured from commuting from home to office and from office to home. This is by referring to (Eq. 4.5), where the distance for commuting (D_{hf}) is obtained by referring to Table 4.2 and where the specification of EV's range of travel (D_g) is referring to Table 4.4.

$$\sum D_t = D_{hf} + D_{fh} \tag{4.5}$$

4.3.3 State-of-Charge at the End of the Charge

For the battery disconnection (End_{SoC}), it is assumed that the SOC level is 80% ± 10% for preserving the life of the battery. To generate battery disconnection, a normal distribution is used as defined by the mean and standard deviation. The mean value of the normal distribution was set at 80% and a standard deviation of 10% was considered (Eq. 4.6).

$$End_{SoC} = 80\% \pm 10\% \tag{4.6}$$

4.3.4 Charging Duration

For this parameter, all drivers charge their EVs at home with a slow charger rated at 3.6 kW (EV_c). The duration of charging ($T_{duration}$) is calculated according to (Eq. 4.7). The charging duration is based on the type of EV; either Mitsubishi i-Miev or Nissan Leaf. Equation (4.8) applied to determine the specific charging duration for each type.

$$T_{duration} = \left(End_{SoC} - Initial_{SoC_b}\right) x\ EV_c / \ EV_{bi} \tag{4.7}$$

$$EV_{bi}(x) = \begin{cases} 1, & x = 1, Mitsubishi\ i - Miev \\ 2, & x = 2, Nissan\ Leaf \end{cases} \tag{4.8}$$

4.4 Simulation Framework for Electric Vehicle Charging Load

From the compiled weekday data, aggregated load profiles comprising residential, EV, and PV components were calculated for every fifteen-minute interval of the day. The stochastic algorithm developed in Chapter 3 was employed to conduct the analysis, while the EV charging profiles in this chapter were generated based on local parameters, including working background (sector, time, and place), EV type, and commuting distance. To adequately capture the variability of charging behaviour, 1000 stochastic load flow simulations were performed for each fifteen-minute time step, and the final aggregated load profiles were derived from these stochastic realizations. The flowchart of the proposed methodology is presented in Figure 4.5.

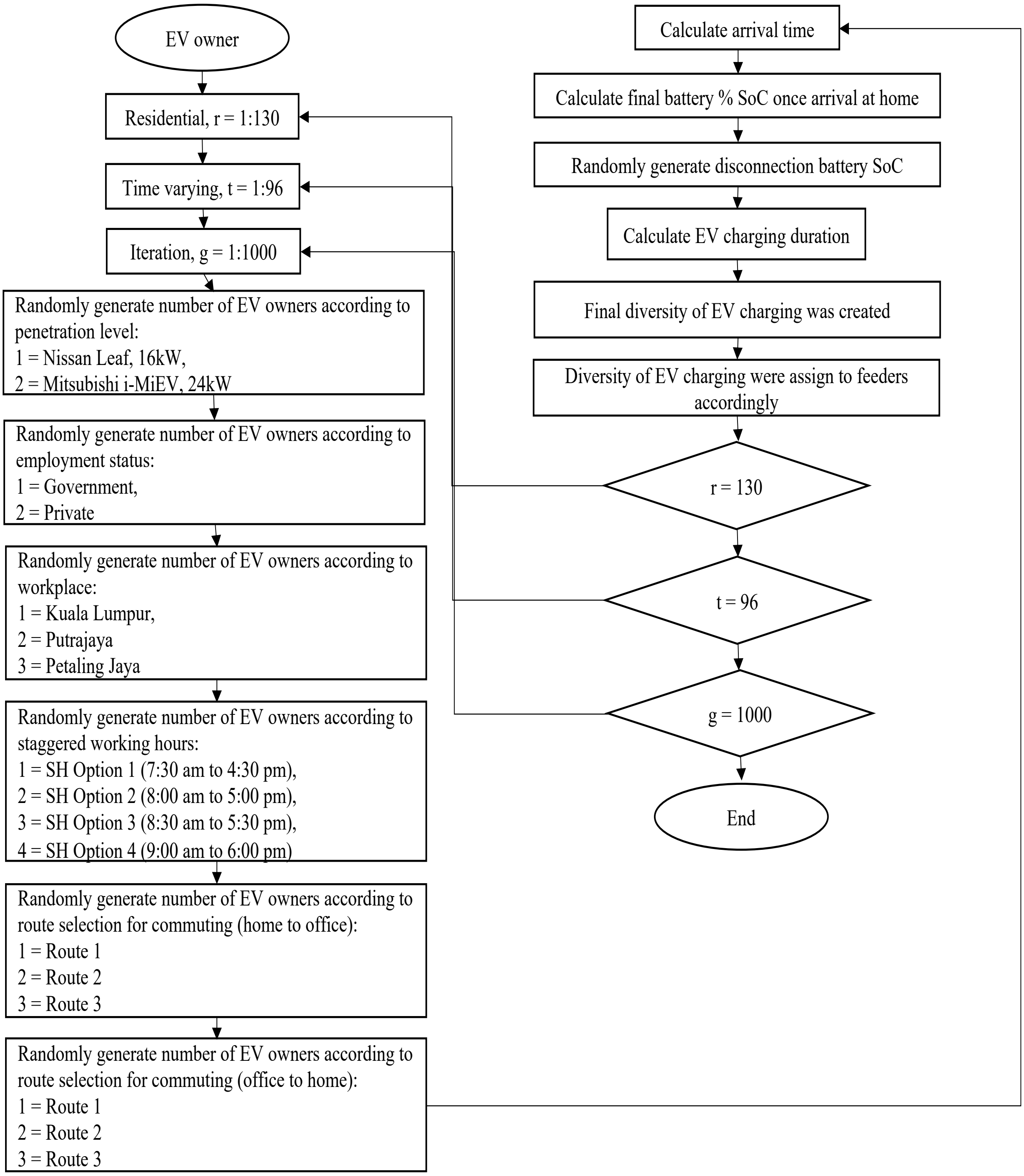


Figure 4.5: Flowchart of Monte Carlo simulation.

4.5 Network Assumptions

In this section, the foundational assumptions underlying the network modelling for this study are established, focusing on the geographical context of Shah Alam, the data sourced from TNB, the configuration of the low voltage distribution network as a single-phase four-wire radial system with six feeders, and the characteristics of the cables and transformers utilized in the network, which collectively provide a comprehensive framework for analysing the impact of EV charging and PV power contribution on the Malaysian distribution system.

4.5.1 Malaysia Network Modelling

Shah Alam was chosen as the reference network. This low voltage network data is obtained from TNB, the electric utility company in Malaysia. The given data includes the cable types, cable rating, the number of main feeders, and the transformer rating. The network is a single-phase four wire radial system with six low voltage feeders emanating from the 11/0.4 kV distribution transformer, as seen in Figure 4.6. The urban network is a single-phase radial system connected with two step-down transformers rated at 11/0.4 kV: Substations 1 and 2 have a 4-Core 300m^3 cable distributed to three feeders. Each feeder serves approximately 16 to 25 terrace houses, giving a total of 130 residential units in the network. This residential network forms the basis for the EV owner dataset described in Section 4.2.1. The sizes and types of cables used in this network are shown in Table 4.3.

Table 4.3: Cable Configurations in the Network [137].

Branch section	Cable Type
1000-kVA Transformer	240 mm^2 PVC/PVC AL
Feeder 1 to Feeder 6	300 mm^2 4-Core AL XLPE
Feeder to Nodes	185 mm^2 4-Core AL XLPE
Nodes to Houses	25 mm^2 4-Core AL XLPE

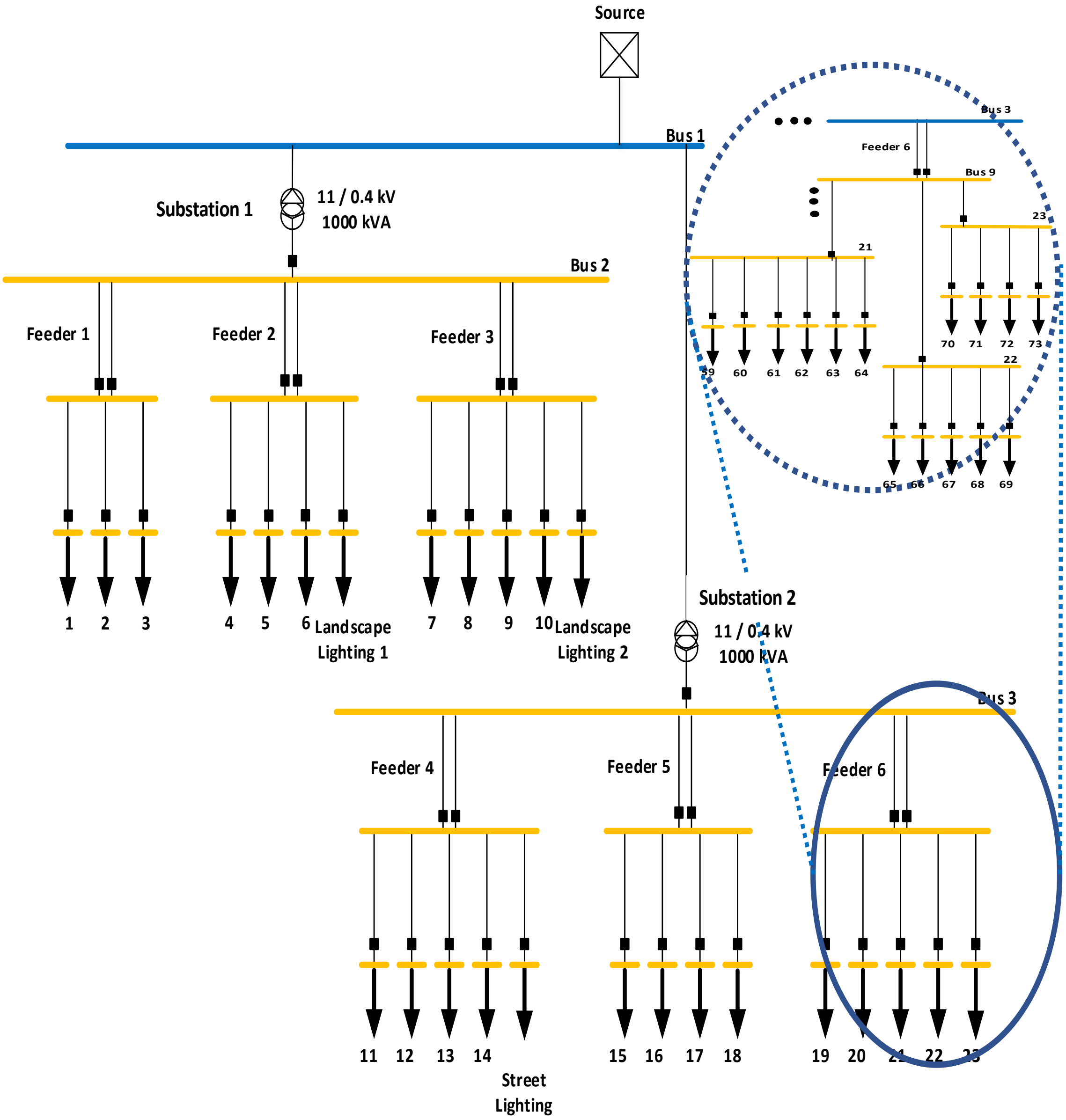


Figure 4.6: One-line diagram of the investigated distribution network.

4.5.2 Load Profiles for Residential Customers

A typical aggregated Malaysian domestic load profile as shown in Figure 4.7 is used in this study [138]. The 24-hour load profile with fifteen minutes time series is assigned to each of the houses located in the feeder. These profiles are scaled to meet the projected Malaysia electricity demand by 2030 [139]. The residential consumer demand starts to increase at about 17:00 when people start coming home after work and reaches the maximum peak demand at about 19:00, which continues until midnight. This is due to the warm weather in Malaysia where it is common for consumers to switch on their air-conditioners from the evening to night-time.

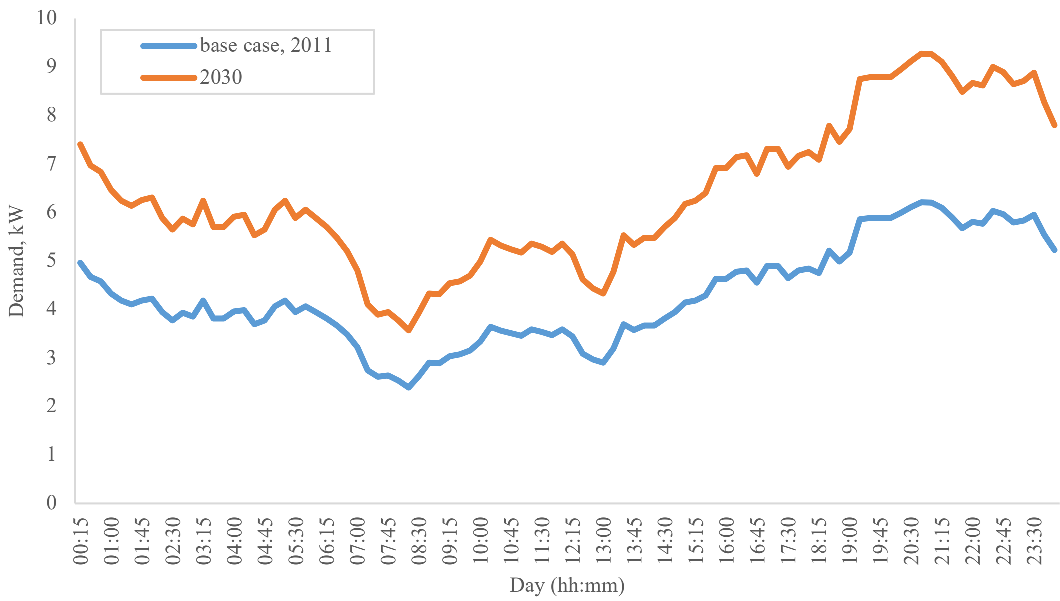


Figure 4.7**:** Residential load demand in the year 2030 for Malaysia.

4.5.3 Electric Vehicle Selection

In the context of the Malaysian residential sector, where loads are predominantly single-phase, EV users typically employ slow charging modes for home charging, with charging equipment rated at or around 3.6 kW. Two types of slow charger compatible EVs are used: Nissan Leaf and Mitsubishi i-MiEV. This selection of models is based on the EVs available in the Malaysian market [140]. The EV specifications are detailed in Table 4.4. The number of residential customers that own an EV, either Nissan Leaf or Mitsubishi i-MiEV, is based on 100% EV uptakes and randomly distributed based on the normal distribution of all customers in the network. Nissan Leaf represents 70%, whereas Mitsubishi represents a 30% adoption rate among consumers.

Table 4.4: Electric Vehicle Specifications.

Item	Nissan Leaf	Mitsubishi i-MiEV	Reference
Battery Capacity (kWh)	24	16	
Length of Travel (km)	100	160	[134]
Battery Efficiency (%)	85	85	

4.6 Simulation Results

This section presents the simulation results related to the various aspects of EV charging profiles within the low voltage distribution network. The findings are organized into the following subsections.

4.6.1 Battery Initial State-of-Charge

The initial SOC of EV batteries plays a pivotal role in shaping charging behaviour and the resulting demand on the residential distribution network. As described in Section 4.3.2, the initial SOC values for the 130 residential EVs were determined based on daily commuting patterns between home and workplace. Factors such as commuting distance, battery capacity, travel length, and efficiency were considered to estimate the remaining charge upon arrival at home.

Figure 4.8 illustrates the initial SOC values assigned to the residential EV population under study. Vehicles arriving with lower initial SOC values (e.g., below 20%) require substantially longer charging durations and higher energy input to reach their disconnection SOC threshold, thereby contributing more significantly to evening peak demand. In contrast, vehicles arriving with higher initial SOC values demand less energy and complete charging within shorter durations, exerting a smaller impact on overall network load.

The required charging duration for each vehicle was calculated using Equation (4.7), which relates the difference between the initial SOC and the disconnection SOC to the corresponding charging time and power demand. This variation in initial SOC across the EV population therefore shapes the aggregated charging profile, influencing both the magnitude and timing of electricity demand in the residential distribution network.

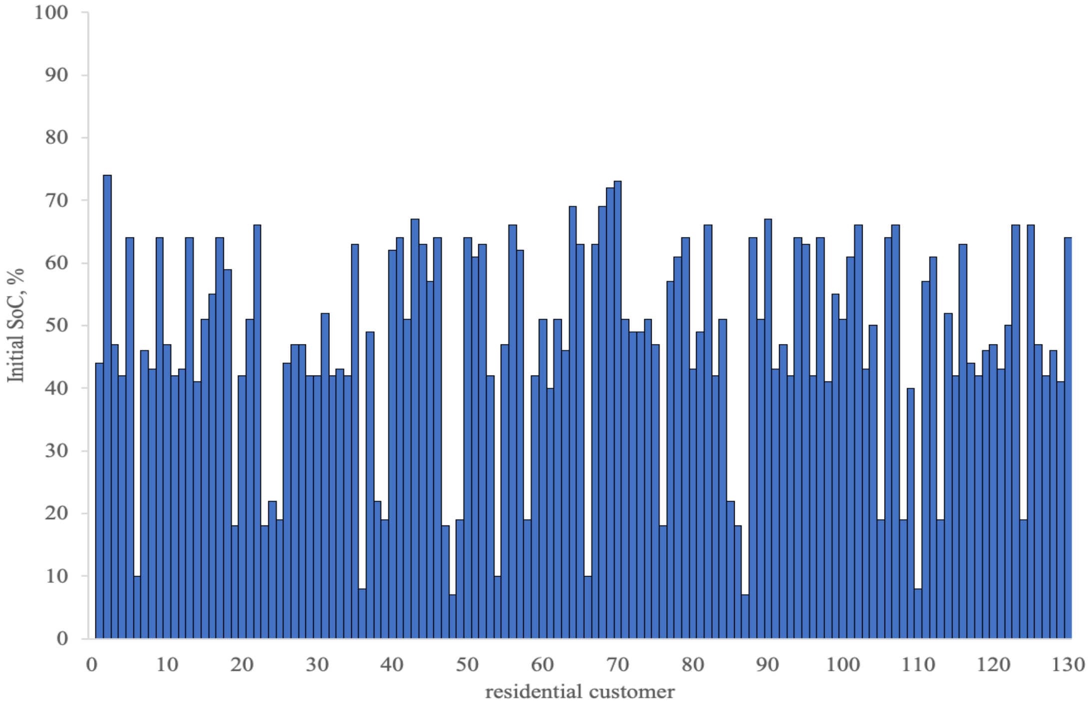


Figure 4.8: Initial SOC (%) of 130 residential EVs upon arrival at home.

4.6.2 Battery Disconnection State-of-Charge

In addition to the initial SOC, the disconnection SOC plays a critical role in determining the total charging requirements of EVs and their subsequent impact on the residential distribution network. As described in Section 4.3.3, the disconnection SOC was set at 80% ±10% to reflect realistic charging practices and battery management strategies. This assumption accounts for the common behaviour of EV users who disconnect charging before reaching 100% in order to preserve battery lifetime.

Figure 4.9 shows the distribution of disconnection SOC values for the 130 residential EVs considered in this study. For example, an EV that arrives home with an initial SOC of 20% may charge until it reaches 80%**,** requiring a larger energy input and longer charging duration compared to an EV that arrives with an initial SOC of 50%**.**

While Figure 4.9 itself illustrates only the disconnection SOC values, the effect on peak demand is reflected in the aggregated charging load profiles presented later in Section 4.6.4. Vehicles with lower initial SOC values require greater energy input to reach their disconnection threshold, thereby contributing more significantly to evening peak demand. Conversely, vehicles arriving with higher initial SOC values need less charging and exert a smaller impact on network load.

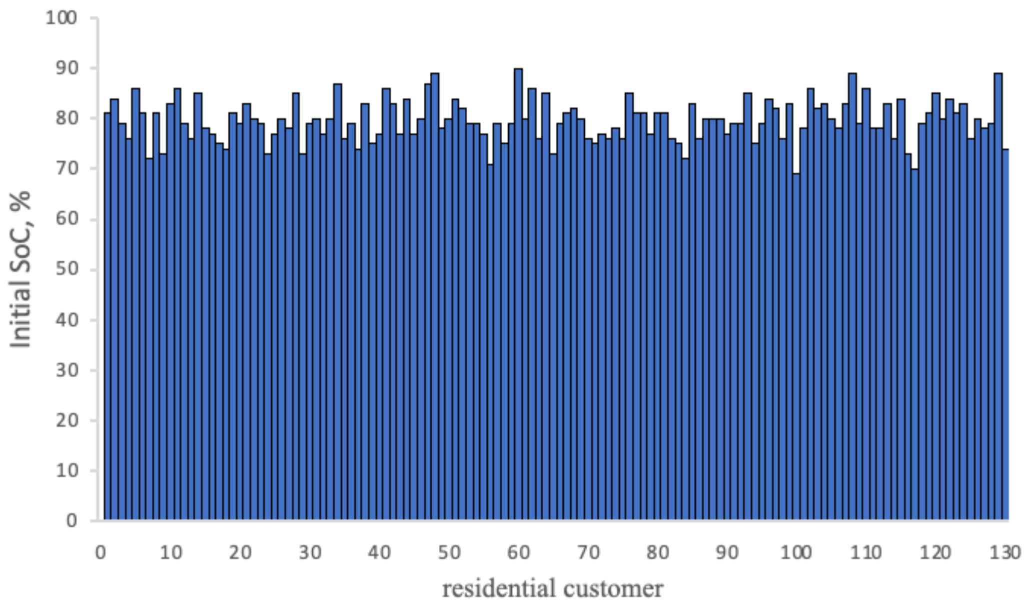


Figure 4.9: Disconnection SOC (%) of 130 residential EV customers.

4.6.3 Arriving Time

The timing of EV arrivals at home, specifically in relation to their charging needs, was evaluated in the simulations. The results demonstrate that varying arrival times can lead to different charging profiles, thereby impacting the distribution network's load patterns and overall stability. In this study, EV arrivals are deliberately modelled based on commuting patterns (home–work–home), with vehicles typically returning home between 16:30 and 19:00, as shown in the arrival distribution (see Figure 4.10). Consequently, the probability outside this window (00:15–16:15 and 19:15–23:15) is zero, since vehicles are not assumed to return home during those hours. This modelling choice is consistent with the definition of $T_{arrival}$ in Section 4.2.3.1, where the evening peak commuting period is considered the most critical scenario for residential charging demand. Other trip purposes, such as school runs, shopping, leisure, or weekend activities, were not considered, in order to maintain focus on the dominant commuting-based charging behaviour that strongly influences evening peak demand.

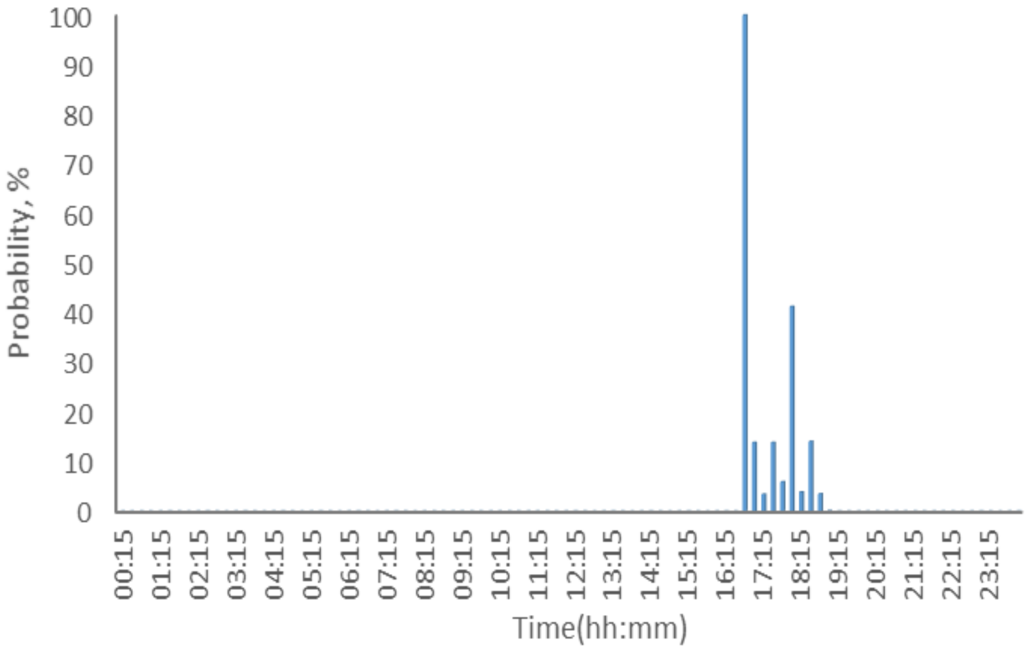


Figure 4.10: Probability of EV arrival at home.

4.6.4 Synthetic EV Charging Profiles

The simulations yielded comprehensive EV charging profiles that encapsulate the charging behaviours under various initial SOC conditions, discharging scenarios, and arrival times. These profiles offer valuable insights into effectively managing EV integration to optimize performance within the Malaysian low voltage distribution network.

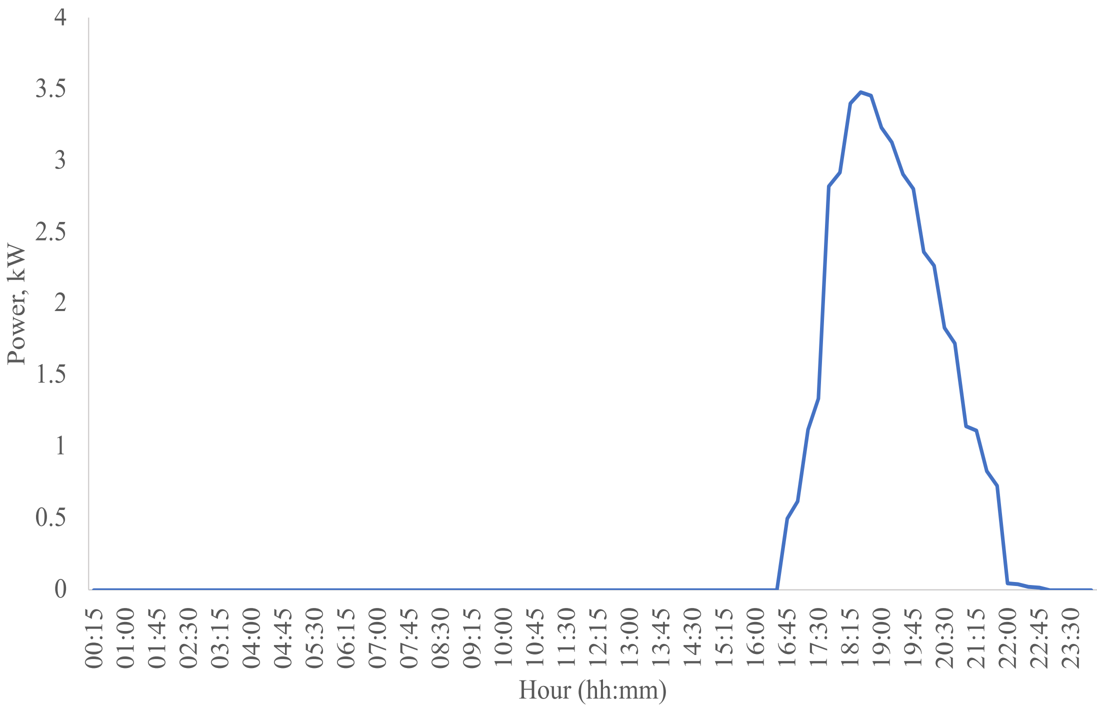


Figure 4.11: EV charging profiles.

4.7 Summary

This study comprehensively examined the impact of EVs on the Malaysian LV distribution network, utilizing a detailed simulation approach. By modelling various EV charging scenarios and incorporating different initial SOC conditions, the research highlighted the complex interplay between EV behaviour and the distribution network's performance.

The findings revealed that the initial SOC of EV batteries significantly influences charging demands, with lower initial SOC levels leading to higher energy requirements during peak charging times. Additionally, the study explored how battery disconnection SOC and arrival times affect overall charging dynamics, further emphasizing the need for tailored strategies to manage EV integration effectively.

By developing comprehensive EV charging profiles based on immediate home charging, this research establishes a foundation for evaluating their impacts on network performance amid the growing adoption of EVs in the Malaysian context.

Overall, this study underscores the importance of considering user behaviour, charging patterns, and network conditions when developing effective management strategies for EV integration. The insights gained from this research will be invaluable for utility providers and policymakers aiming to facilitate the transition to a more sustainable and efficient energy landscape in Malaysia.

CHAPTER 5

Impact of Electric Vehicles Charging on Malaysian Low Voltage Distribution Network

5.1 Introduction

In Chapter 4, a model was developed for EV charging based on a range of driving characteristics and the home plug-in behaviour patterns of EV owners, establishing a foundational understanding of EV interactions with residential charging infrastructure under various conditions.

This chapter focuses on assessing the impact of integrating EVs within the Malaysian LV Distribution Network. The same network configuration from Chapter 4 is used here to maintain continuity and provide a consistent basis for comparing the impacts of EV charging.

This study investigates two key scenarios regarding EV charging:

i. charging without any management strategies,

ii. charging with implemented control strategies.

The control of EV charging is based on the initial SOC of the battery upon the vehicles' arrival at home. Within this framework, there exists a group of EV owners recommended to charge during off-peak hours, while others within the same group may opt for immediate charging upon arrival. These scenarios facilitate an analysis of various outcomes concerning power demand, power losses, and voltage profiles throughout the network. This chapter provides valuable insights into the impact of controlled and responsive EV charging on the operational efficiency and sustainability of Malaysia's LV distribution network.

5.2 Electric Vehicle Charging Strategies

In a centralized coordination framework, utilities directly manage vehicle charging while ensuring that system constraints are maintained. This centralized control also referred to as direct control entails the Distribution System Operator (DSO) handling the charging decisions for each EV within its jurisdiction. Through this coordination, DSOs offer economic incentives to EV owners, including reduced electricity tariffs, while also enhancing grid efficiency and reliability.

To implement centralized coordination, the DSO conducts demand forecasting using data from the previous day and analyses EV users' driving patterns. Based on this information, the DSO constructs a demand profile that ensures safe and stable distribution system operation. As EV charging introduces an additional load to the system, the coordination process is designed to optimize charging times, balancing the needs of EVs with those of household loads connected to the network. Research shows that effective coordination can achieve efficient EV charging while mitigating adverse impacts on the distribution system. Key benefits include reduced power loss, lower voltage deviation, and minimized risk of system overload, all of which contribute to enhanced reliability.

In this study, ETOU tariffs are employed as a demand shifting strategy to encourage EV owners to charge during off-peak hours, thereby alleviating peak hour stress on the distribution network. This approach focuses exclusively on optimizing load distribution without delving into the cost implications of ETOU tariffs. The study demonstrates that ETOU driven charging coordination can effectively balance network load by shifting EV charging demand to off-peak times. This mitigates peak demand impacts and enhances grid stability, offering a sustainable approach to managing the operational challenges of integrating EV charging into Malaysia’s LV distribution network [141].

Figure 5.1 presents the initial battery SOC upon arrival at home for 130 residential EV users. In this figure, the red line identifies vehicles with an initial SOC below 20%, classifying them as part of Group 1. These vehicles, having a lower initial SOC, require extended charging times to reach adequate energy levels. As a result, they are prioritized for immediate charging upon arrival to maintain operability and readiness for subsequent use.

Meanwhile, vehicles falling below the green line represent those with initial SOC levels between 20% and 80%, constituting Group 2. For this group, a controlled charging strategy is recommended, wherein charging is scheduled during off-peak hours to alleviate stress on the grid and optimize energy distribution across the network. By deferring Group 2 charging to lower-demand periods, this controlled approach not only aids in managing network load but also supports effective demand side management. This structured method of immediate and scheduled charging offers a robust framework for integrating EV loads into residential networks, addressing both operational needs and grid stability.

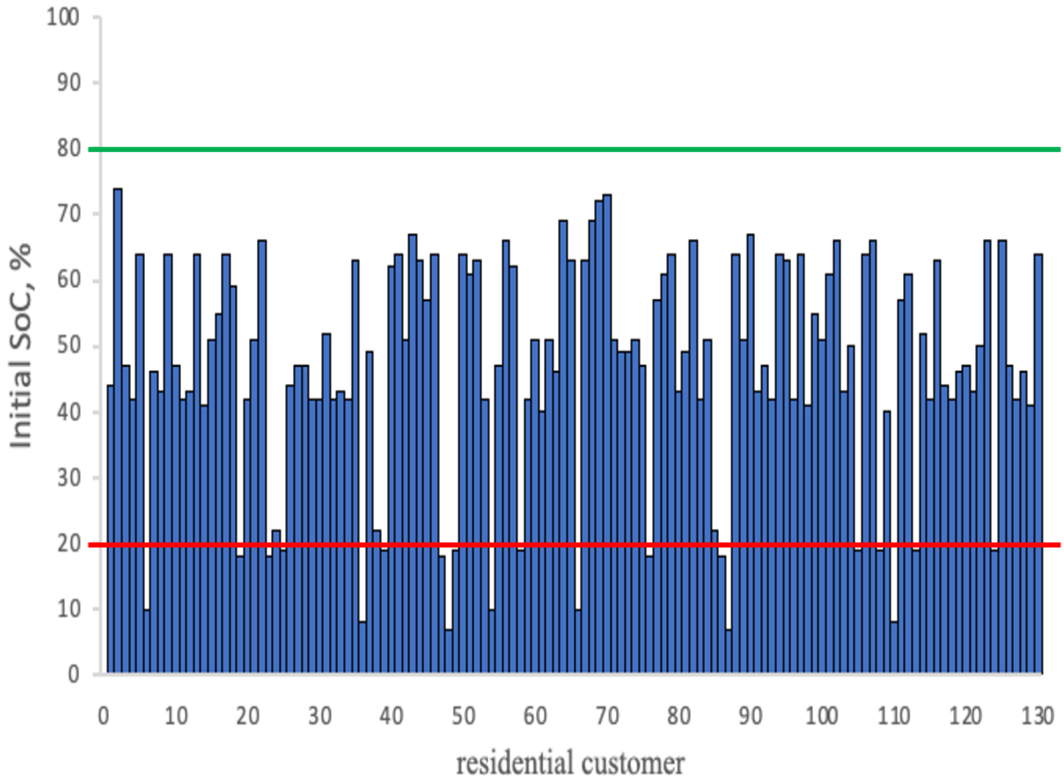


Figure 5.1: Initial battery SOC of 130 residential EVs upon arrival.

5.2.1 EV Charging Strategies

The impact of EV charging on distribution networks can be evaluated under different charging strategies, each affecting the grid in unique ways [142 - 144]. In this study, two distinct charging strategies are implemented to manage the varying demands of EV integration into the residential distribution network: *Uncontrolled Charging* and *Controlled Charging*.

Uncontrolled Charging is assigned to Group 1, which includes EVs with an initial battery SOC below 20%. These vehicles are prioritized to charge immediately upon arrival at home, allowing for gradual recharging to ensure availability for subsequent usage. Immediate charging for low SOC vehicles prevents potential operational constraints for owners who rely on daily EV use.

Controlled Charging is designated for Group 2, comprising EVs with an initial SOC between 20% and 80%, a scheduled charging approach is adopted. For this group, charging is deferred to off-peak hours, distributing demand more evenly across the day and minimizing peak load impact. This off-peak charging schedule is recommended to optimize energy distribution and reduce strain on the distribution network during peak periods, aligning with the goal of demand-side management (see Table 5.1 for off-peak charging schedules). These vehicles are programmed to charge during off-peak hours, specifically from 10:00 pm to 8:00 am, when the grid is less stressed and the demand is lower. This strategic timing helps to prevent exacerbating the emergency conditions faced by the distribution network. By shifting the charging of these EVs to periods of reduced demand, the grid can better manage existing loads and maintain overall system stability.

Table 5.1: TNB peak hours [145].

Period	Hours
On-peak	11:00 am – 12:00 pm, 2:00 p.m. – 5:00 pm
Mid-peak	8:00 am – 11:00 a.m., 12:00 p.m. – 2:00 pm
	5:00 pm – 10:00 pm
Off-peak	10:00 pm – 8:00 am

5.2.2 EV Charging Scenarios

To evaluate the effects of EV charging strategies on grid performance, two primary scenarios are examined: *Normal* and *Emergency*.

Normal Scenario Under typical conditions, both Group 1 and Group 2 EVs adhere to their defined charging schedules. EVs in Group 1, with an SOC below 20%, initiate charging upon arrival, while Group 2 vehicles charge only during off-peak hours. This scenario represents ideal adherence to recommended charging patterns, allowing for systematic load balancing and a predictable demand pattern that optimally utilizes network capacity.

EVs that arrive with a battery SOC below 20% are treated as critical and are subjected to immediate charging. This action ensures that these vehicles receive the necessary charge to remain operational, preventing any potential issues related to battery depletion. Immediate charging for these EVs occurs regardless of the time of day, as maintaining their availability is important. This strategy helps to alleviate concerns about stranded EVs and ensures that essential transportation remains accessible during emergencies.

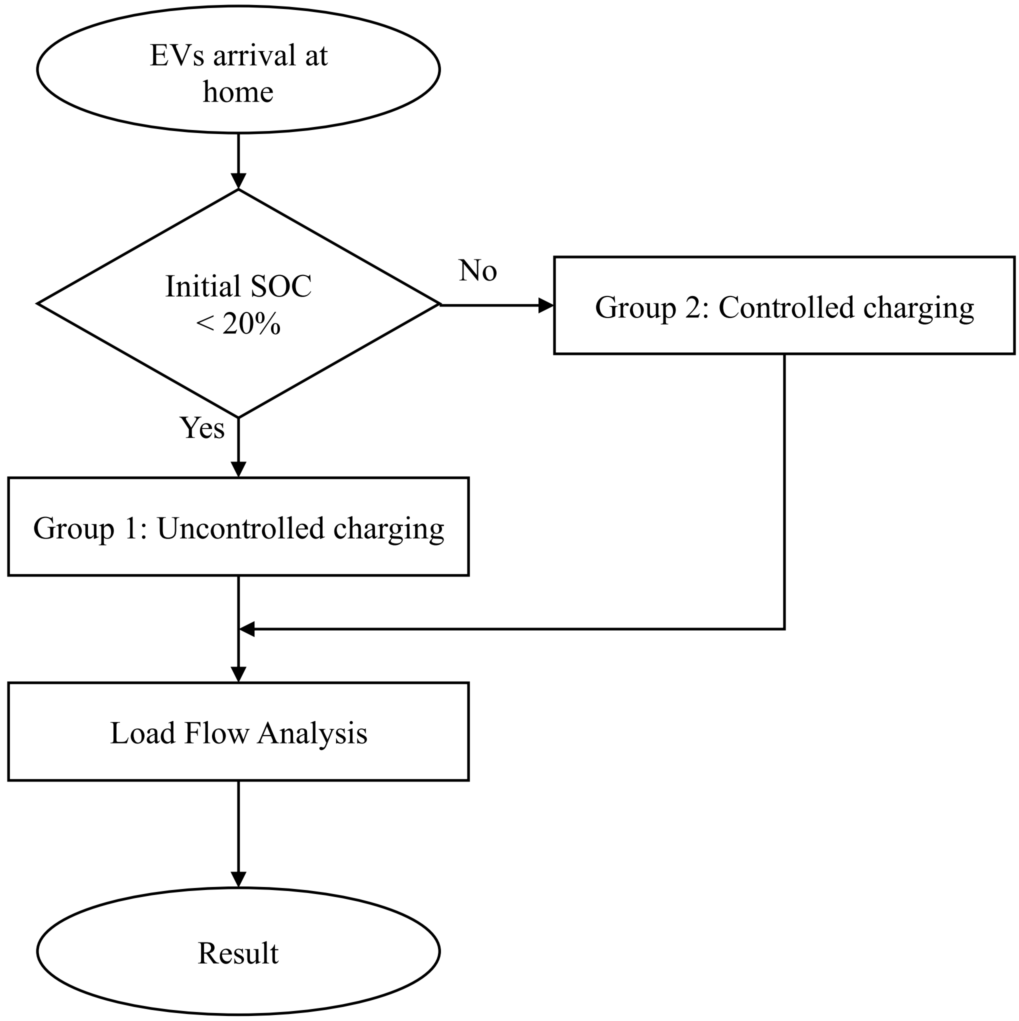


Figure 5.2: Flowchart for uncontrolled charging.

<u>Emergency Scenario</u> In contrast, the Emergency Scenario addresses conditions where certain EV owners in Group 2 elect to charge immediately upon arrival, mirroring the behaviour of Group 1. This deviation results in elevated demand during peak hours, increasing pressure on the network and potentially affecting voltage limits and reliability. Emergency scenarios simulate unexpected shifts in user behaviour, highlighting the grid's resilience under suboptimal charging distribution.

In emergency conditions, certain EV owners may prioritize charging upon arrival due to unforeseen circumstances, rather than delaying until off-peak hours. This immediate charging need could arise from a variety of urgent or unpredictable situations that require the vehicle to be readily available. For instance, an EV owner may need to charge immediately if preparing for an unscheduled night shift, an early morning commute, or a sudden medical or family emergency. Such scenarios place a premium on vehicle readiness, making immediate charging essential despite typical off-peak scheduling preferences.

Consequently, these owners choose to override the scheduled charging plan to ensure their EV has sufficient charge to fulfil immediate demands. This highlights a critical aspect of charging behaviour under emergency conditions, where the priority shifts from optimizing grid load to maintaining vehicle availability, underscoring the need for flexible charging strategies that accommodate sudden, high-priority usage requirements.

Figure 5.2 and Figure 5.3 illustrate these scenarios, with Figure 5.2 depicting the structured charging patterns of the Normal Scenario, and Figure 5.3 capturing the intensified demand profile in the Emergency Scenario where Group 2 EVs opt for immediate charging. These scenarios underscore the need for adaptive strategies to manage demand effectively under both typical and exceptional circumstances.

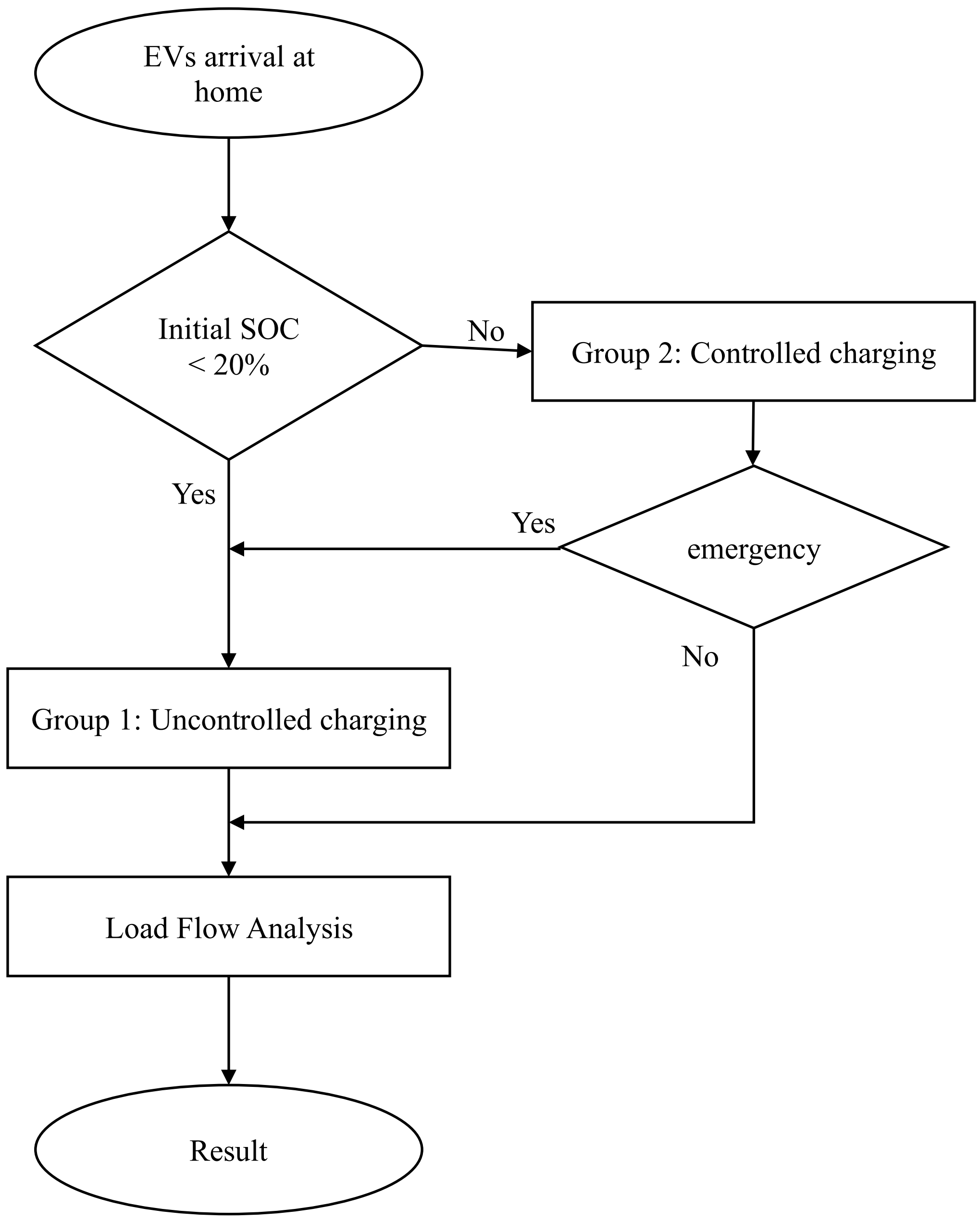


Figure 5.3: Flowchart of controlled charging.

5.2.3 Simulation Methodology for Emergency Cases

To accurately assess the impact of emergency charging conditions on the distribution network, a systematic approach was applied to simulate uncoordinated charging among a subset of EV owners from Group 2. In these scenarios, a randomized selection method was implemented using MATLAB's "rand" function, which generated uniformly distributed random numbers to identify EV owners from Group 2 who would deviate from scheduled charging times and instead charge immediately upon arriving home.

The simulation tested several levels of emergency charging penetration, incrementally increasing from 15% up to 40% of Group 2 EVs. This stratification allowed for detailed examination of how different levels of emergency charging demand influence overall network performance. The selection of EV owners for immediate charging at each penetration level was randomized using MATLAB2014a, ensuring that each specified penetration level (15%, 20%, 25%, and 40%) consisted of a unique, randomly assigned subset of Group 2. This methodology maintained the integrity of the stochastic model by incorporating variability in user behaviour, simulating real-world conditions more closely.

5.3 Simulation Results

The simulation results presented in this section provide a comprehensive analysis of the impact of EV charging on the Malaysian distribution network under both normal and emergency conditions. The evaluation focuses on key performance metrics, including voltage profiles, power demand, and power losses, derived from the load flow analysis conducted using the Newton-Raphson method. Prior to the implementation of demand-side management strategies, the power demand experienced a significant increase resulting from the concurrent charging of multiple EVs.

5.3.1 Power Demand Analysis

5.3.1.1 Normal Condition

The examination of power demand under both normal and emergency charging conditions is presented in Figure 5.4 and Figure 5.5. Figure 5.4 illustrates the power demand profile when all 130 residential EVs engage in immediate charging upon arrival at home. This scenario simulates an unrestricted, uncontrolled charging approach, where power demand increases sharply, reaching a peak of 1.2 MW around 8:00 p.m. from a baseline of approximately 0.9 MW. This surge underscores the potential grid strain introduced by unmanaged EV charging, particularly during peak evening hours, which could affect overall stability and reliability within the distribution network.

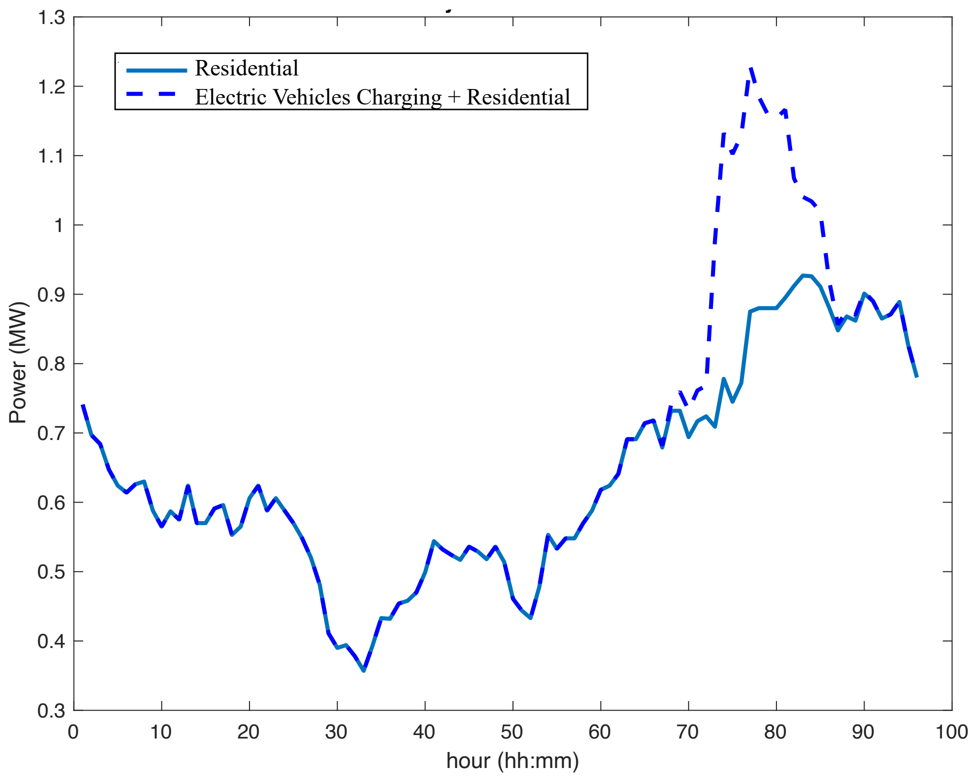


Figure 5.4: Power demand for uncontrolled charging.

In contrast, Figure 5.5 presents the controlled charging scenario, where charging activities are divided between two groups: Group 1 initiates charging immediately upon arrival, while Group 2 adheres to scheduled, off-peak charging times. These groups represent government and private sector employees who typically commute to their workplace and follow regular working hours, influencing their energy consumption patterns and charging behaviour. As described in Chapter 4, the network study focuses on a specific urban region in Selangor, Malaysia, where these employees predominantly reside. In this study, the base residential demand without EV charging is approximately 0.8 MW, supplied by a 1 MVA distribution transformer. With the integration of EV charging, the peak demand increases to 1.2 MW, thereby exceeding the transformer's rated capacity. This condition is considered representative of the study area as it reflects a realistic loading scenario for urban residential networks in Selangor, where EV penetration can push demand beyond transformer limits. Although the magnitude of peak demand rises to 1.2 MW, the timing of the peak shifts to 10:30 pm, effectively redistributing load away from the traditional residential peak period. This managed strategy illustrates the capability of DSM to alleviate grid stress, redistributing load more evenly and enhancing network reliability. By deferring Group 2 charging to off-peak hours, this approach demonstrates significant potential for mitigating peak demand issues associated with increased EV penetration in the Malaysian urban network under study.

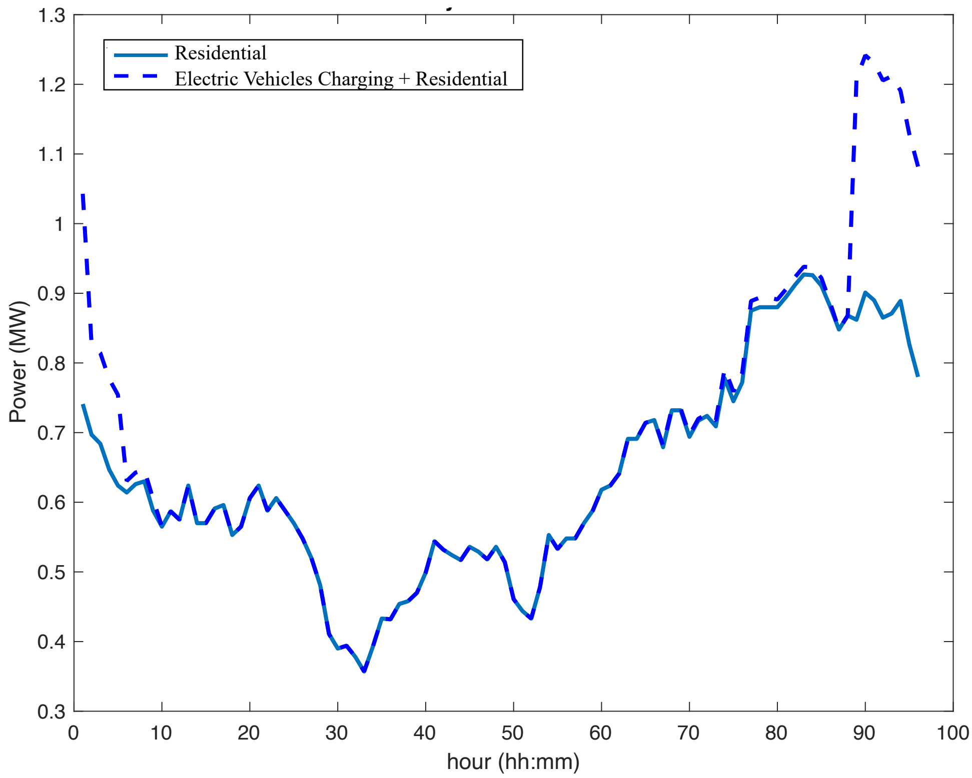


Figure 5.5: Power demand for controlled charging.

5.3.1.2 Emergency Condition

For emergency conditions, this study explores the impact of uncoordinated charging from Group 2 EVs that would typically adhere to scheduled, off-peak charging in a normal scenario. Here, the base case remains the normal condition with coordinated charging. In the emergency scenario, a fraction of EVs from Group 2 chooses to charge immediately upon arrival rather than waiting for off-peak hours. To examine the implications of this shift, penetration rates of uncoordinated charging from Group 2 are tested at four incremental levels: 15%, 20%, 25%, and 40%, with EVs randomly selected at each level.

Figure 5.6 presents the power demand associated with each penetration level, highlighting that a penetration rate of up to 25% from Group 2 still allows the distribution network to operate within its maximum demand threshold. However, as the penetration reaches 40%, power demand exceeds the established limit, posing risks to network stability and reliability. This finding underscores a critical limit at 25% for uncoordinated charging in emergency scenarios, beyond which demand management strategies become essential to avoid grid impacts. These insights emphasize the importance of managing EV charging under emergency conditions to maintain grid performance and prevent overload.

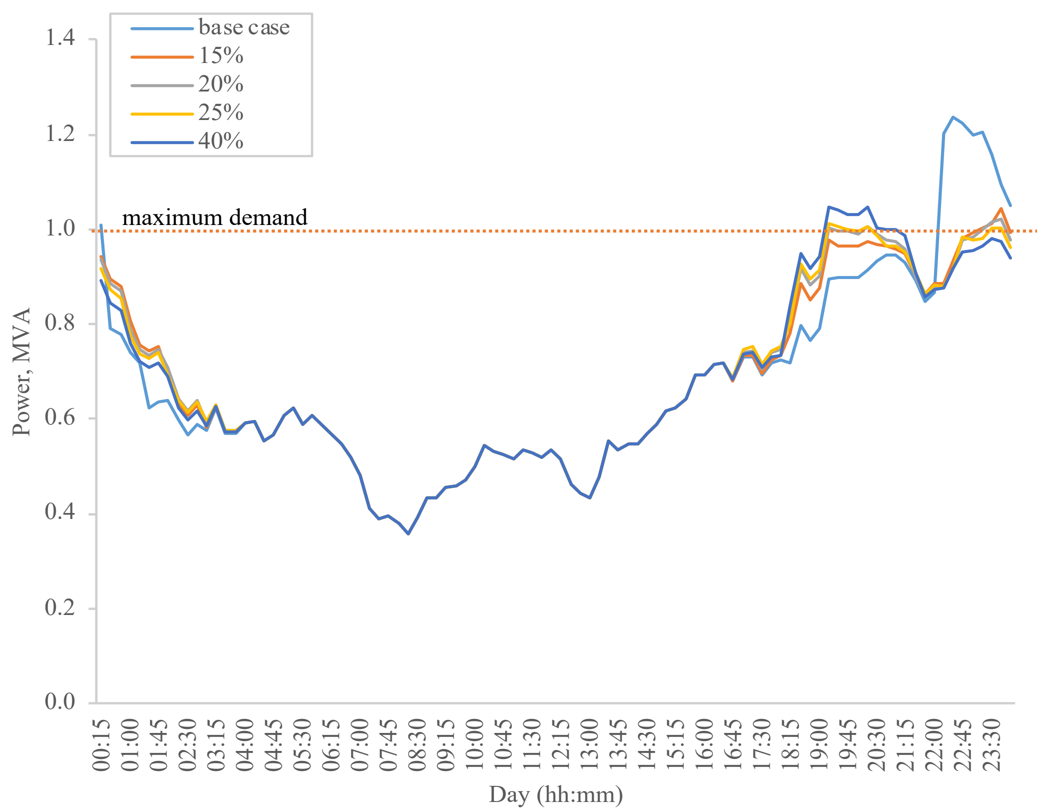


Figure 5.6: Power demand under emergency condition.

5.3.2 Voltage Profile

In each case study, the voltage value is recorded at the end of each feeder where the worst-case scenario for voltage drops occurs. The voltage profiles based on the stochastic analysis are shown in Figure 5.7. There is no indication of a voltage limit violation in the network. It should be mentioned that the nominal line to neutral voltage of 230 V at the low voltage side is within the range of +10% and −6% [146].

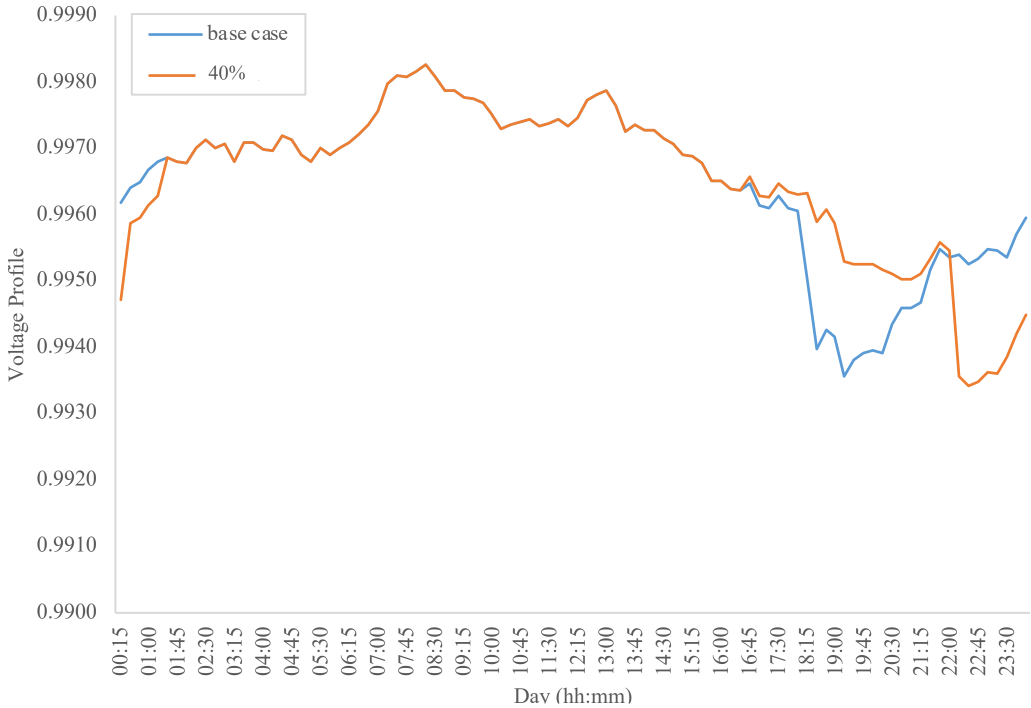


Figure 5.7: Voltage profiles.

5.3.3 Power Losses

Power losses were analysed under two scenarios: the base case (without coordination) and the coordinated charging case. Figure 5.8 indicate that at peak demand, power losses remain consistent between both cases, reaching a maximum of 0.0029 MW. However, the timing of these peak losses varies between the scenarios, aligning with shifts in peak demand. In the uncoordinated scenario, peak power losses occur earlier in the evening as all EVs initiate charging upon arrival. Conversely, in the coordinated scenario, peak losses are deferred, reflecting the distributed charging times among EV owners. This demonstrates that while coordinated charging does not reduce the magnitude of power losses directly, it does contribute to a more stable temporal distribution of demand, potentially alleviating stress on network components during critical load periods.

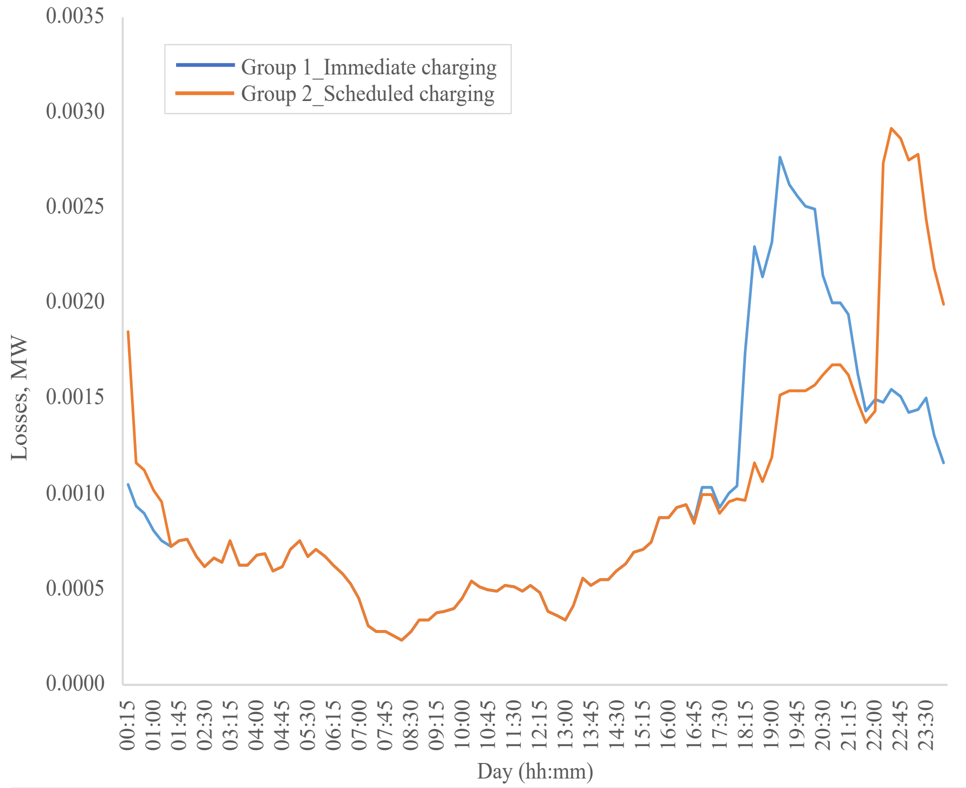


Figure 5.8: Calculated power losses in the residential distribution network with residential demand and combined EV charging load (Group 1: immediate, Group 2: scheduled).

5.4 Summary

This study evaluates the impact of EV charging on Malaysia's LV Distribution Network, focusing on both coordinated and uncoordinated charging approaches under normal and emergency conditions. In normal conditions, EVs follow a managed charging schedule based on their initial battery SOC, with coordinated charging strategies encouraging demand shifting to off-peak hours to minimize peak load impact. During emergency conditions, however, a proportion of EV users deviate from off-peak charging and opt to charge immediately upon arrival, regardless of peak periods, increasing strain on network resources.

The analysis investigates key metrics such as power demand, voltage profiles and power losses. Coordinated charging demonstrates effectiveness in shifting demand away from peak hours, thereby reducing load stress on the network. However, emergency uncoordinated charging shows potential for peak demand increases up to 20% beyond anticipated levels. While power losses remain comparable between coordinated and uncoordinated scenarios, their occurrence aligns differently, with peak losses occurring later in the coordinated scenario. Additionally, voltage drops stay within acceptable steady-state limits, affirming the network's resilience under controlled conditions. This study illustrates how coordinated EV charging, encourage through ETOU tariffs, can optimize demand patterns, reduce operational stress, and facilitate the sustainable integration of EVs into Malaysia's LV distribution network.

CHAPTER 6

Coordination of Distributed Energy Resources on Malaysia Low Voltage Distribution Network

6.1 Introduction

In Chapter 5, the study explored the potential grid impact from EVs requiring emergency charging, revealing that if even 20% of scheduled EVs were to need emergency charging, the grid would likely be unable to handle this additional demand. This highlights the need for dedicated strategies to support both scheduled and emergency EV charging.

To manage scheduled EV charging, this chapter introduces an ETOU tariff, aimed at encouraging users to shift charging activities to off-peak hours. This tariff structure reduces electricity costs during off-peak times, providing financial incentives for users while enabling the DSO to better distribute demand across the day. In addition, the NEM scheme, which has already been implemented in Malaysia, is also considered to maximise the benefits of rooftop solar PV by allowing surplus solar generation to be exported to the grid and later offset against consumption during peak hours. Together, ETOU and NEM provide both financial incentives and renewable energy optimisation, making them complementary strategies to support scheduled EV charging. However, for EVs needing immediate charging (emergency charging) upon arrival, the sudden surge in demand could exceed grid capacity. To address these peak instances, an Energy Storage System (ESS) is proposed as a supplementary power source.

The ESS is charged during low-demand periods, using surplus energy generated by DG sources, particularly solar power produced during midday under the NEM scheme. This stored energy is then available for evening emergency charging, helping to alleviate grid stress. As DG sources such as solar and wind become more prevalent, they introduce challenges in synchronizing generation with demand; solar power generation, for instance, peaks during the day, often failing to meet the evening demand from EVs. ESSs are therefore an important asset to be added to balance this mismatch, enabling the grid to effectively support both scheduled and emergency EV charging needs.

6.2 Methodology

This section outlines the methodology used to develop a decentralized control system aimed at optimizing EV charging loads, minimizing electricity costs, and ensuring network stability. The methodology comprises the design of a decentralized controller based on a PSO algorithm, the implementation of time-varying tariffs, and the evaluation of system performance in a simulated distribution network environment.

6.2.1 Electric Vehicle Charging Coordination

In centralised coordination, the utility directly controls the vehicle charging while maintaining all the system constraints. Besides, the utility offers economic benefits to EV owners by reducing the total electrical tariff. The centralised coordination is also known as direct control where the DSO manages the charging decision for each EV within its region. Through the coordination process, the DSO performs demand forecasts based on the previous day's data and EV users' driving behaviour. Then, the DSO investigates the demand profile for the safe operation of the distribution system. The EV is charging is considered as an additional load to the distribution system while the regular household loads remain connected to the system. It is found that effective coordinated charging activities can charge the EV while mitigating all the distribution system impacts. From the distribution system point of view, reduction of voltage deviation and power loss provide many advantages. These include low operation costs and fewer instances of system overload, which improve the reliability of the system.

The economic consideration is one of the major benefits of the charging coordination for the distribution system owner and EV users. If the EV charging is not coordinated properly, it will increase the charging cost as well as the energy generation demand considerably. Since the utilities are responsible for the charge of each EV, the minimisation of the EV charging cost is one of the important considerations. However, there are two types of costs associated with EV charging coordination: the energy generation cost and the EV charging cost. The energy generation cost includes the price of purchasing or producing electricity and the cost of total energy losses in the grid. Therefore, the generation cost can be minimised by reducing the total power loss in the system. On the other hand, the cost of EV charging refers to the cost of energy consumed by the EV charger.

6.2.2 Cost Minimisation Approach

The main research aims to minimise the power demand by introduce a variable electricity bill for EV users. The price benefit approach is based on supply and demand graph (see Figure 6.1).

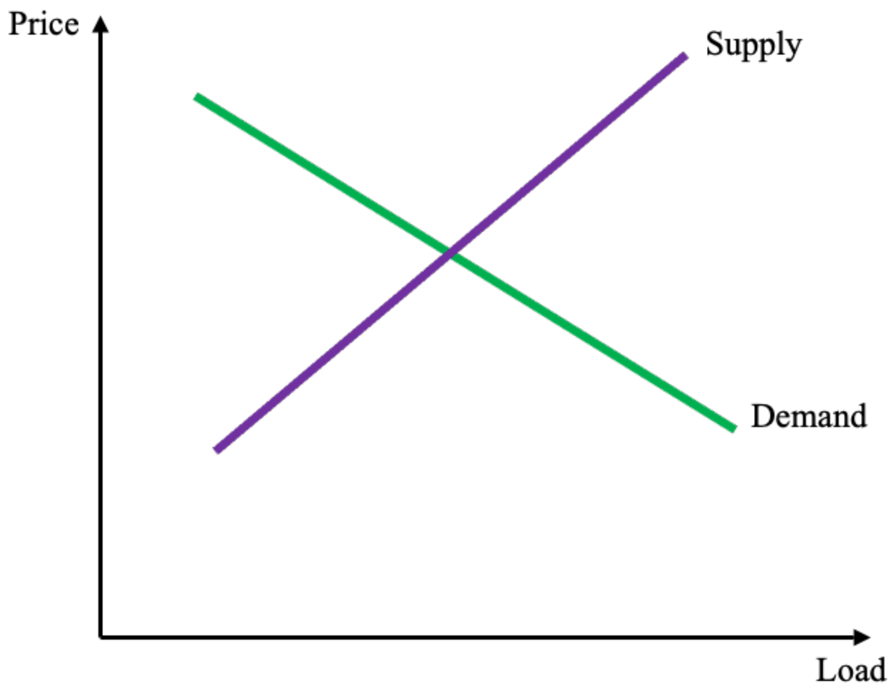


Figure 6.1: Supply and Demand Basic Graph.

Figure 6.2 shows the reference price. '*Price_old'* (with the dotted red line) is user input and is fixed for all hours, whereas '*Load_old'* is equal to the hourly loads and therefore changes from hour to hour.

The *Price_old* shows the cost of electricity before the optimisation process. After the optimal coordination of EV charging, the cost curve is reducing, referring with a new blue curve labelled as '*Price_new'*. With optimum placement of EV charging, an increment in optimum '*Load*' from '*Load_old*' to "*Load_new'*, as shown in Figure 6.2, could be achieved.

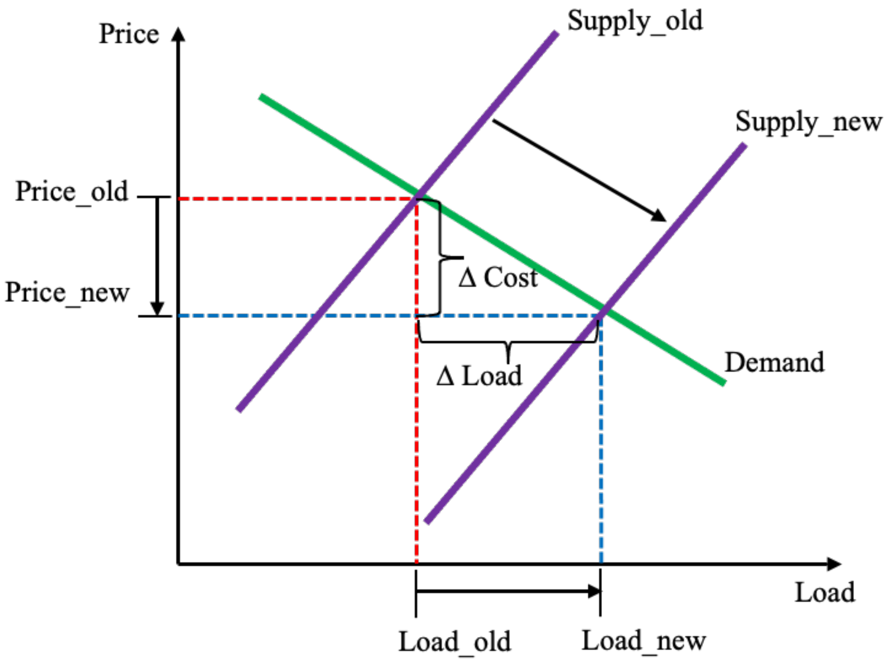


Figure 6.2: Supply and Demand Analysis Graph.

In this chapter, the concept of the ETOU tariff is presented based on the mechanism of supply and demand. The ETOU tariff has been introduced in Malaysia to provide price benefits for residents with EVs by encouraging charging during off-peak hours. In addition, the NEM scheme is highlighted for residents with rooftop solar panels, allowing them to offset their electricity consumption with surplus solar generation. The benefits and applications of the NEM scheme are further discussed in Section 6.2.2.2.

6.2.2.1 Enhanced Time-of-Use Tariff

In Malaysia, energy pricing for residential customers follows a block tariff structure, where electricity rates increase with higher consumption (see Table 6.1). This block tariff system is intended to promote energy conservation, encouraging customers to be mindful of their electricity use, as higher consumption leads to higher charges. However, since this pricing structure is not based on specific time-of-use periods, it does not incentivize shifting energy consumption to off-peak hours, a strategy that could relieve some stress from the grid during peak periods.

Table 6.1: Block tariff of TNB in Malaysia ringgit (Tariff A – Domestic Tariff) [147].

Tariff Category (kWh)	Unit price (cents/kWh)
For the first 200 kWh (1-200 kWh)	21.80
For the first 100 kWh (201-300 kWh)	33.40
For the first 300 kWh (301-600 kWh)	51.60
For the first 300 kWh (601-900 kWh)	54.60
For the next kWh (901 kWh onwards)	57.10

In 1998, TNB, Malaysia's main electricity provider, introduced the ETOU tariff as an initiative to encourage DSM [145]. Unlike the block tariff, the ETOU tariff varies rates according to peak and off-peak hours, offering customers the option to reduce costs by adjusting their energy use to off-peak periods. As shown in Table 6.2, the ETOU pricing scheme is currently offered only to commercial and industrial customers [145], where it aims to encourage a shift in high-energy activities away from peak demand times. While not yet available for residential users, expanding ETOU tariffs to this sector could foster further DSM participation, as discussed in Chapter 5, ultimately enhancing load flexibility and grid stability within the Malaysian electricity network.

Table 6.2: ETOU pricing scheme [145].

Tariff Category (kWh)	**Unit Price (RM/kWh)**
On-peak	50.00
Mid-peak	35.00
Off-peak	13.00

6.2.2.2 Net Energy Metering (NEM) Scheme

NEM scheme is designed to allow customers with solar PV installations to first utilize the energy generated by their solar PV systems. Under this scheme, any excess energy produced by the solar PV system that is not immediately consumed by the customer is exported to the power grid, where it is credited on a one-to-one basis [148]. This "*one-on-one offset*" means that for every 1 kWh of energy exported to the grid, the customer will be compensated with a credit equivalent to 1 kWh consumed from the grid. The NEM scheme therefore provides an incentive for residential and commercial customers to adopt solar PV systems, promoting renewable energy generation and supporting Malaysia's broader goals for sustainable energy development.

6.2.3 Optimisation Method

This research aimed to develop an optimal EV charging coordination strategy that balances user benefits with the goal of maintaining stable power demand on the distribution network. To achieve this, two specific tariffs were utilized: the Enhanced ETOU tariff and the NEM scheme. These tariffs support DSM and incentivize charging behaviours aligned with network stability goals.

The study employed a heuristic approach, specifically using PSO, to optimize the coordination of EV charging. PSO is a population-based. Since its inception in 1995, PSO has been enhanced and adapted through various versions tailored to address specific challenges across multiple domains. Over time, theoretical analyses and empirical studies have contributed to refining the approach, creating alternative algorithmic variants, and broadening PSO's applications across diverse research fields [149].

The basic PSO algorithm consists of a swarm of "n" particles, and the position of each particle represents a possible solution of the fitness function in D-dimensional search space. The particle changes its condition under the influence of three factors:

i. inertia weight (w),

ii. cognitive component (c_1r_1),

iii. social component (c_2r_2) (see Figure 6.3).

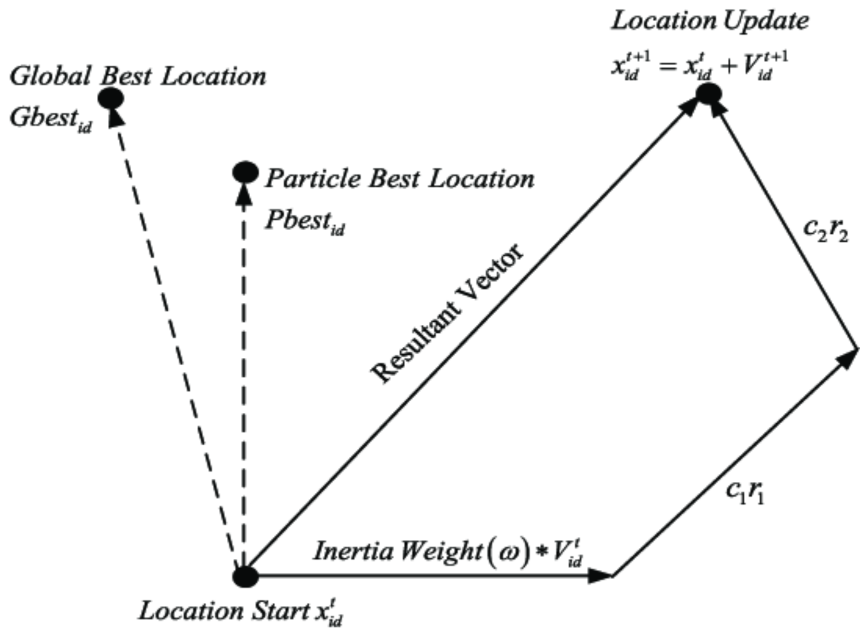


Figure 6.3: Particle Swarm Optimisation.

The movement of a particle from one iteration to the next is mathematically defined by the following formula [75].

$$v_{id}^{t+1} = wv_{id}^{t} + c_1 r_1^t (Pbest_{id}^t - x_{id}^t) + c_2 r_2^t (Gbest_{id}^t - x_{id}^t) \tag{6.1}$$

$$x_{id}^{t+1} = x_{id}^{t} + V_{id}^{t+1} \tag{6.2}$$

V_{id}^t and x_{id}^trepresents velocity and position of i^{th} particle (out of n particles) at D-dimension (out of D dimensions) in t^{th} iteration respectively. $Pbest_{id}^t$ and $Gbest_{id}^t$ represents personal and best position and global best position (i.e. group's best) of i^{th} particle (out of n particles) at D-dimension (out of D dimensions) in t^{th} iteration respectively. w represents inertial weight attached to the particle's previously attained position. c_1 and c_2 represent acceleration constants. r_1 and $r_2$represent random numbers in the range of [0,1].

The velocity update in PSO consists of three parts [75]; momentum, cognitive part and social part. Momentum is representing the tendency of particle to move in the same direction as it was moving in the previous iteration. It incorporates the effect of previous velocity on current velocity of the particle. Cognitive part is representing the pull to particle's velocity towards its own personal best (*Pbest*). Referred to as '*memory*', '*self-knowledge*' or '*remembrance*'. Social part is representing the pull to particle's velocity towards swarm's best (*Gbest*). Referred to as '*cooperation*', '*social knowledge*' or '*shared information'*. Refer to Figure 6.4 for flowchart of PSO algorithm.

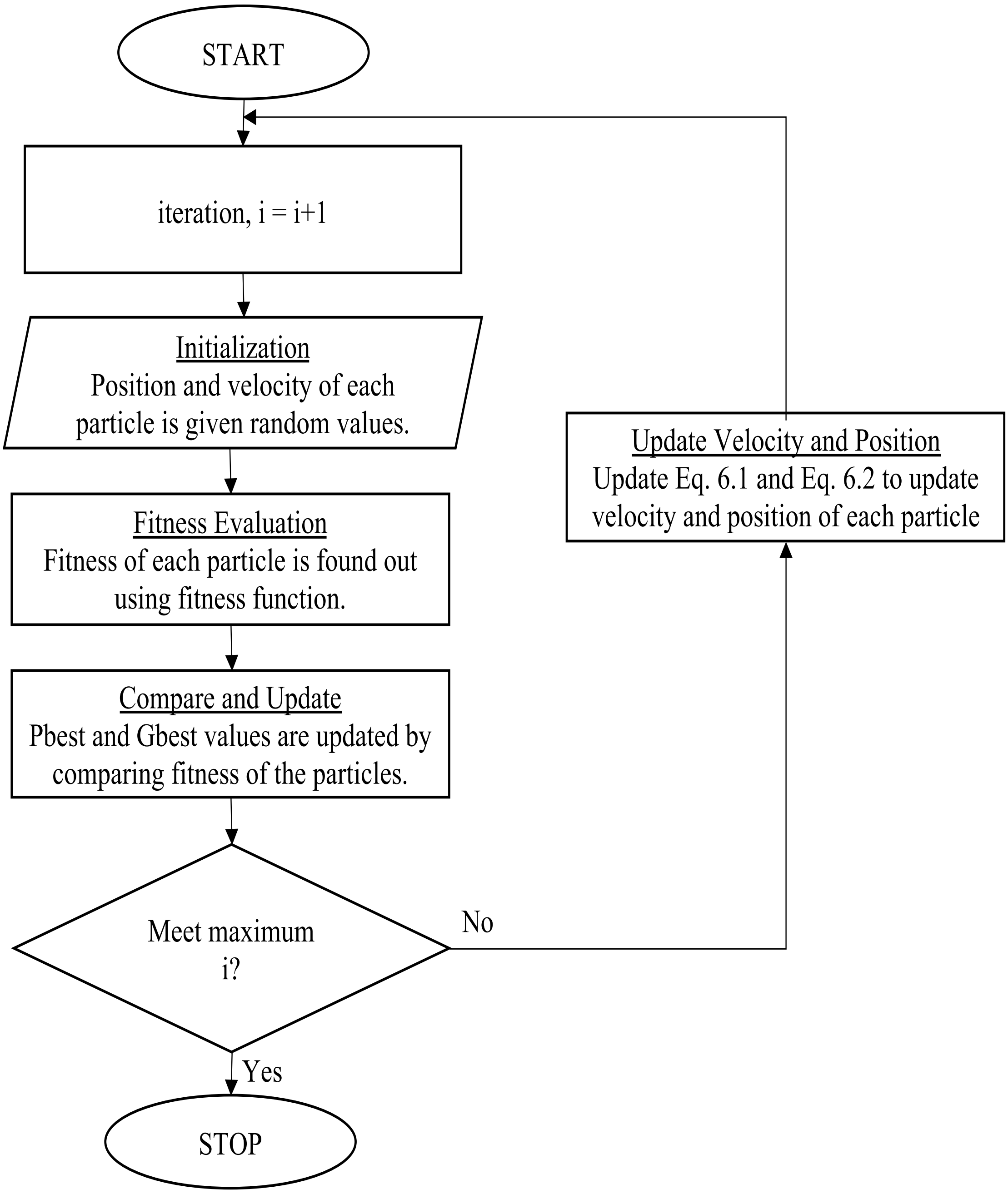


Figure 6.4: Flowchart of the PSO algorithm.

6.2.3.1 PSO based EV Allocation Algorithm

This section presents a PSO algorithm developed to determine the optimal allocation of EV charging loads across the Malaysian LV distribution network. The primary objective of the algorithm is to manage the allocation of charging demands effectively, balancing feeder loading to prevent excessive peak demand and, thereby, enhance the network's operational efficiency.

As outlined in Chapter 5, under controlled conditions, all EVs in Group 2 are scheduled to begin charging during off-peak hours, starting at 10:00 pm (see Table 5.1). This timing creates a peak demand shift to the start of the off-peak period. The PSO algorithm is implemented to optimize this peak demand by distributing EV charging initiation times throughout the off-peak window.

In this study, stochastic inputs, specifically the initial SOC of EVs, are generated randomly to reflect realistic variations. The PSO algorithm randomly selects a subset of EVs from Group 2 (as defined in Chapter 5) to begin charging at staggered times, optimizing load distribution over five designated 2-hour time windows: 10:00 pm, 12:00 am, 2:00 am, 4:00 am, and 6:00 am. By varying the charging start times, the algorithm helps smooth the demand curve and reduces the risk of localized overloading, thereby supporting a more stable and efficient charging strategy for the network.

Objective Function for EV Allocation

The objective function of the EV allocation PSO algorithm is designed to maximize the EV charging allocation within the 10:00 pm to 12:00 am time window, optimizing the number of EVs that begin charging at this designated off-peak period. The function seeks to enhance charging efficiency while avoiding undue load stress on the distribution network. By focusing on this early off-peak period, the algorithm aims to distribute charging demand across five time windows, each lasting 2 hours, starting at

10:00 pm and ending at 8:00 am. The goal is to minimizes peak load impacts while achieving an optimal balance of charging demand throughout the available time windows.

$$\max f_x = \sum_{t=1}^{T} P_{charging}(t).\, x_t \tag{6.3}$$

Mathematically, the objective function maximizes the total EV charging power allocated to each time window, represented as the summation of charging power demand, $P_{charging}$, for each time window t. To achieve this, a binary decision variable, x_t, is introduced, indicating whether EVs are assigned to begin charging during a specific time window. If $x_t = 1$, charging is allocated to time window t; otherwise, $x_t = 0$, meaning no charging is assigned to that window.

Constraints

To ensure the algorithm meets network operational limits, several constraints are considered:

1. **State of Charge (SOC) Constraints**: Each EV's initial state of charge, $SOC_{initial}$, is between 20% and 80% to qualify for charging in a scheduled, controlled manner:

$$0.2 \leq SOC_{initial,i} \leq 0.8, \forall_i \in \ EV\ fleet \tag{6.4}$$

2. **Power Demand Constraints**: The total power demand from all EVs at any time *t* must not exceed 800 MW, which represents a 20% buffer below the maximum demand capacity of 1000 MW to ensure network reliability and prevent stress on the system [150]:

$$\sum_{i=1}^{N} P_{charging,i}(t) \ll 0.8\ x\ 800MW, \forall t \tag{6.5}$$

where N represents the number of EVs, and $P_{charging,i}(t)$ is the charging power demand of EV i at time t.

3. **Charging Rate Constraints**: Charging rates for each EV, determined by their battery type (e.g., Nissan Leaf or Mitsubishi i-MiEV), must respect the maximum

capacity of each model's battery. For example, if *Pmax*, *Leaf* and *Pmax*, *MiEV* are the maximum charging rates:

$$P_{charging,i} \leq \begin{cases} P_{max,Leaf} \; if \; i \; is \; a \; Nissan \; Leaf \\ P_{max,MiEV} \; if \; i \; is \; a \; Mitsubishi \; i - MiEV \end{cases} \tag{6.6}$$

4. Voltage Constraints: The voltage at each node $V_j(t)$ in the distribution network must remain within +10% and −6% of the nominal voltage (230 V):

$$0.94 \; x \; V_{nominal} \leq V_j(t) \leq 1.1 \; x \; V_{nominal}, \forall j, \forall t \tag{6.7}$$

5. ETOU Constraints: EV charging should be prioritized for off-peak hours, where each time window tw is designated for charging:

$$x_{tw} = \begin{cases} 1 \; if \; tw \; is \; an \; off - peak \; window \\ 0 \; otherwise \end{cases} \tag{6.8}$$

where x_{tw} indicates whether charging is allocated to that time window, allowing demand to be shifted across five off-peak windows for balanced distribution.

6.2.3.2 PSO based Optimal Sizing of ESS Algorithm

In this section, the PSO algorithm employed to determine the optimal sizing and placement of an ESS within the Malaysian LV distribution network is presented. This approach is aimed at supporting additional demand arising from EV charging while alleviating peak load pressures. By strategically locating and sizing the ESS, the network's ability to accommodate increased EV loads is improved, enhancing overall grid resilience.

The primary objective of this ESS sizing algorithm is to identify an optimal ESS capacity that enables efficient peak demand management without overstressing network infrastructure. The ESS operates by storing excess energy during low-demand (off-peak) periods and discharging it during peak demand periods to relieve pressure on the network.

This process minimizes power fluctuations and enhances system stability, particularly during off-peak EV charging windows.

For further information on ESS charging and discharging strategies, see Section 6.3.1, which discusses the operational details of ESS management within the optimized EV charging framework.

Objective Function for ESS Sizing

The objective function f_{ESS} is defined to achieve these goals by balancing ESS size SESS, power loss reduction P_{loss}, and peak demand mitigation D_{peak}. Mathematically, the function is formulated as follows:

$$\max f_{ESS} = \propto . S_{ESS} + \beta . (1 - P_{loss}) + \gamma . \left(1 - D_{peak}\right) \tag{6.9}$$

Here, S_{ESS} refers to the ESS size, which should be carefully optimized to avoid being too small (which may not meet demand) or excessively large (which can lead to unnecessary costs). In this study, the ESS size is considered based on the number of houses at the transformer level. This approach aggregates the total energy storage requirements for multiple households served by a single transformer, taking into account the collective demand and optimising the storage capacity accordingly. P_{loss} represents power losses within the network; minimizing these losses is essential to enhance overall efficiency and reduce energy costs. Finally, D_{peak} corresponds to the peak demand on the network, where reducing peak values helps mitigate stress on the infrastructure, improving reliability and preventing potential overload.

The parameters α, β, and γ serve as weights that prioritize the importance of ESS size, loss reduction, and peak demand mitigation, respectively, depending on network requirements. By adjusting these values, the function provides flexibility in focusing on specific operational and efficiency goals for the distribution network.

Constraints

The constraints for the ESS sizing algorithm ensure that the ESS is capable of effectively supporting EV charging:

1. Power Demand Constraints: The ESS should provide enough support to meet peak demand without surpassing the network capacity limit P_{max}. This capacity limit is set with a buffer to prevent network overload:

$$P_{EV}(t) + P_{ESS}(t) \leq 0.8 \,.\, P_{max} \tag{6.10}$$

where $P_{EV}(t)$ is the power demand from EVs, and $P_{ESS}(t)$ is the power supplied by the ESS at time t.

2. Charging/Discharging Rate Constraints: The ESS charging and discharging rates must remain within safe operating limits, denoted by R_{min} and R_{max}, to avoid overuse:

$$R_{min} \leq P_{ESS}(t) \leq R_{max} \tag{6.11}$$

3. Voltage Constraints: The voltage at each node $V_j(t)$ in the distribution network must remain within +10% and −6% of the nominal voltage (230 V):

$$0.94\ x\ V_{nominal} \leq V_j(t) \leq 1.1\ x\ V_{nominal}, \forall j, \forall t \tag{6.12}$$

This steady-state range of −6% to +10% around the nominal voltage $V_{nominal}$ ensures network stability under normal and peak operating conditions.

6.3 Flowchart of proposed PSO algorithm

The following steps outline the procedure for determining the optimal coordination of EV charging to simultaneously minimize power loss and voltage deviation, while adhering to all system constraints:

1. **Data Input**: All relevant input data were loaded into the program, including network, bus, and line data; residential load data; distributed generation data; and

a set of EV data (Group 2). The EV data encompassed arrival times, initial battery SOC, and user-requested SOC.

2. **Initialization of Population**: For the optimization process, an initial population was generated by selecting random samples from Group 2.
3. **Sorting Battery SOC**: The initial SOC values within Group 2 were sorted in ascending order to streamline the prioritization of EVs with lower initial SOCs.
4. **Timeslot Allocation for ETOU**: In the optimization phase, two time slots of ETOU were defined. For the first time slot, initial selections were made from the generated population, while for the subsequent time slot, the remaining EVs were queued for charging.
5. **Generation of New EV Charging Profiles**: Based on the allocated timeslots, new EV charging profiles were created to match the load requirements.
6. **Fitness Function Evaluation**: A fitness function was computed using Equation (6.1), incorporating the Newton-Raphson load flow method to evaluate power loss and voltage levels across the network.
7. **Optimization for Minimal Power Loss and Voltage Deviation**: The optimization procedure iteratively identified the optimal combination of EV chargers that minimized both power loss and voltage deviation. This process continued until reaching the specified maximum iteration count.
8. **Update of EV Charging Status**: Upon convergence of the optimization process, the charging status of each EV was updated to reflect the optimal schedule.

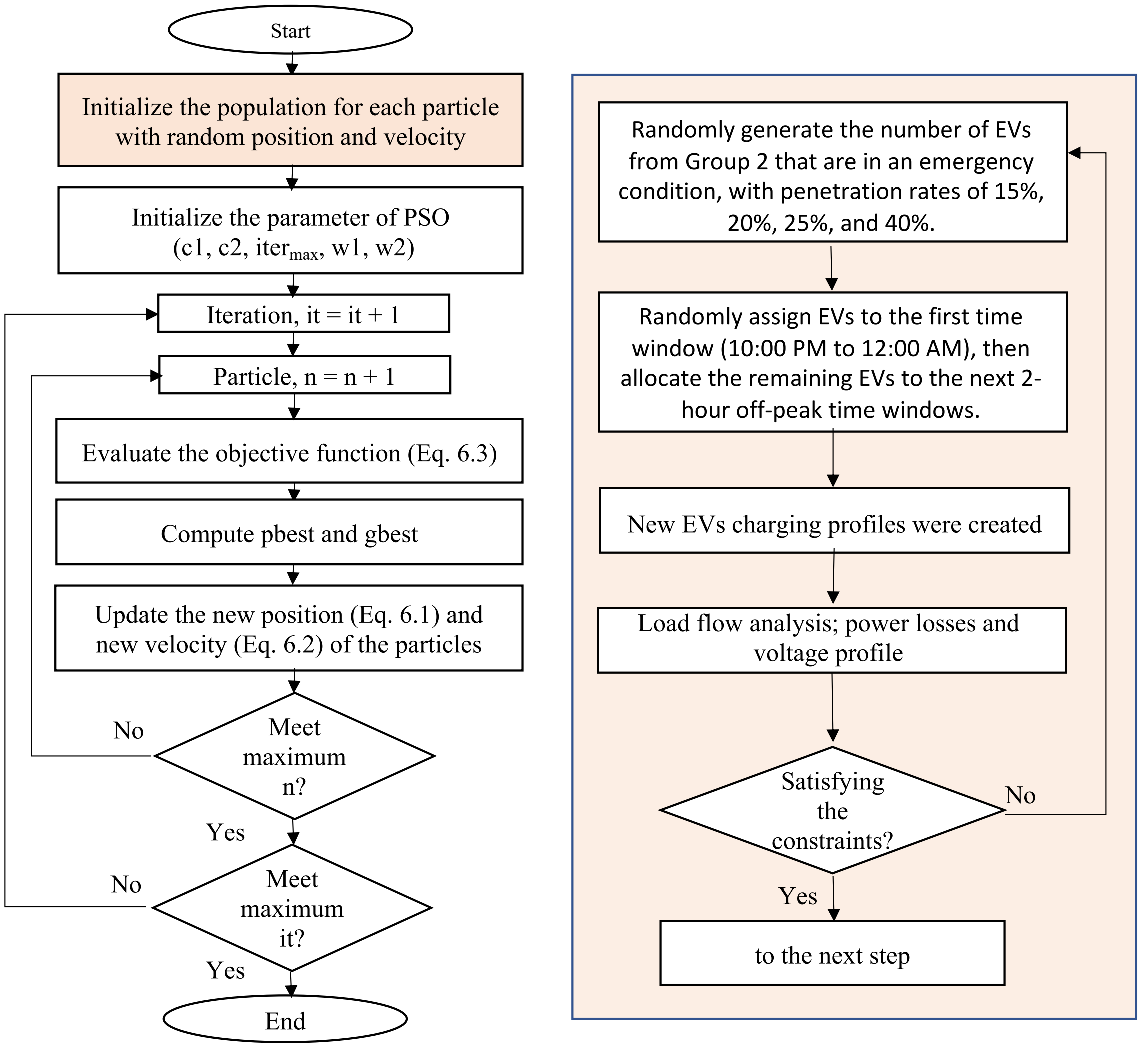


Figure 6.5: Flowchart of PSO algorithm for EV allocation.

6.3.1 Energy Storage System Modelling

In this section, the ESS model is developed to manage emergency EV charging demands during peak hours, with constraints designed to optimize ESS utilization and battery longevity. Based on the analysis in Chapter 5, emergency EV charging is required in stages to prevent the grid from surpassing its maximum demand threshold, as the network can only handle emergency charging for 15% of EVs before reaching critical demand levels. Consequently, the emergency levels are divided into four stages: L1 = 20%, L2 = 30%, L3 = 40%, and L4 = 50%, starting from 20% to manage demands incrementally.

The PSO algorithm is employed for ESS sizing, which calculates the optimal capacity needed to balance the additional EV energy demand without destabilizing the network. Using a timestep range from 6:15 PM (timestep 25) to 7:45 PM (timestep 79), the model evaluates the demand surge as EVs return home during peak hours, a period that has shown increased demand due to EV charging (as illustrated in Figure 5.4).

ESS Charging Strategy

The ESS is charged during periods when PV power generation exceeds power usage, utilizing surplus energy. This "*PV surplus*" is stored within the ESS for later use during peak hours when demand exceeds supply, as depicted in the ESS charging flowchart in Figure 6.6. This approach ensures that the ESS is charged without consuming additional grid resources, thereby maintaining grid stability during off-peak hours.

The PSO algorithm determines the optimal ESS size by calculating the maximum and minimum ESS capacity needed throughout the day, setting the ESS within these bounds.

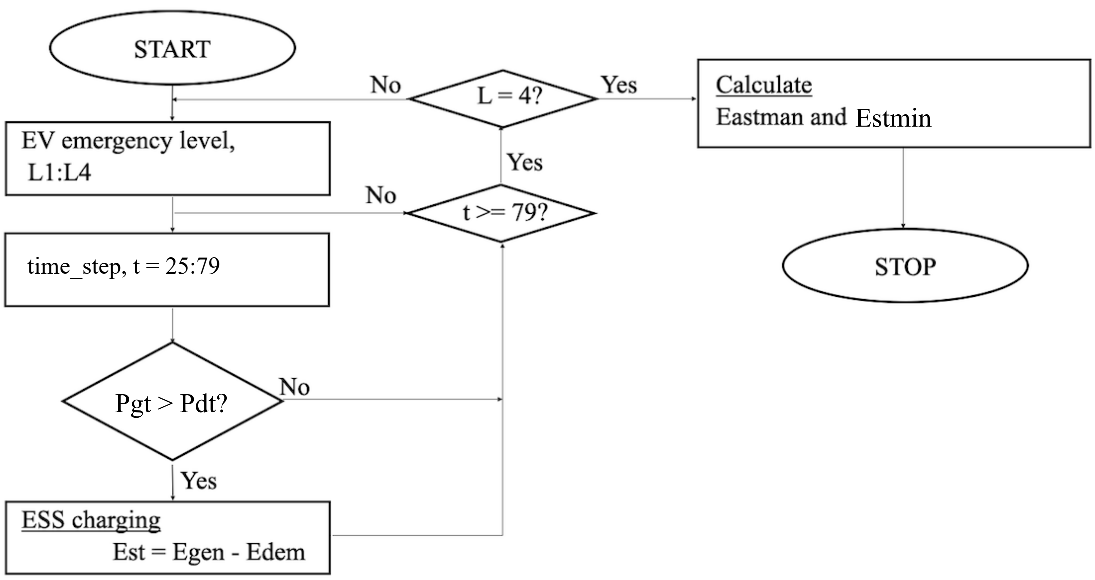


Figure 6.6: Flowchart ESS sizing.

ESS Discharging Strategy

To prolong battery life, ESS discharging occurs only when the Depth of Discharge (DOD) reaches or exceeds 80% [151]. Limiting the DOD to 80% reduces the frequency and DOD cycles, helping to minimize wear on the battery cells and extend ESS lifespan. This DOD threshold strikes a balance between maintaining an adequate power reserve for emergency demands and preserving the ESS's capacity to deliver energy in future peak periods. The ESS discharging process, detailed in Figure 6.7, demonstrates how the ESS prioritizes long-term efficiency and stability by maintaining this DOD limit.

Overall, the ESS model in this chapter aims to enhance the distribution network's resilience, supporting both scheduled and emergency EV charging demands while aligning with sustainable energy management practices.

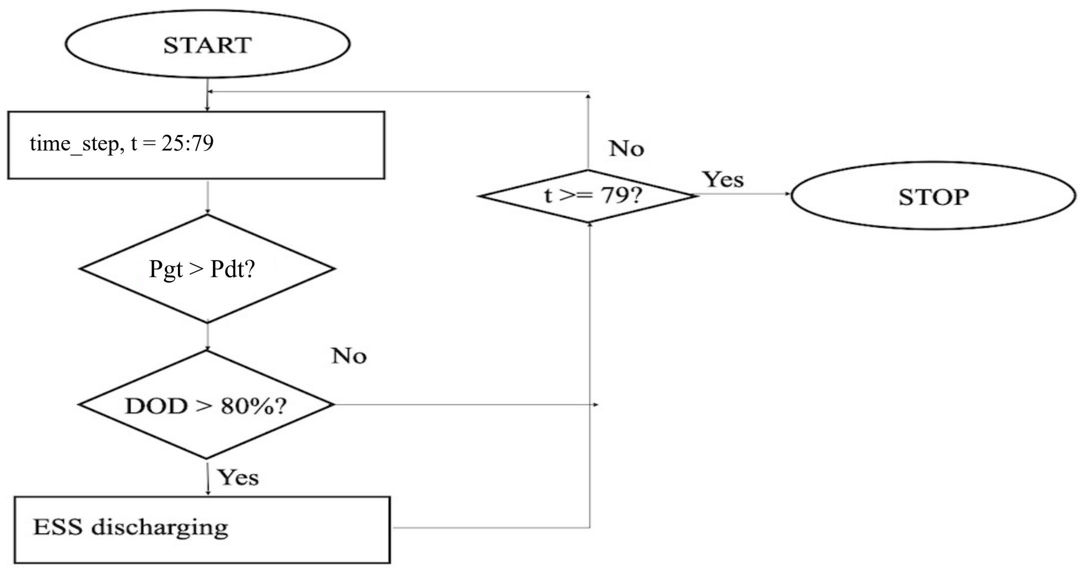


Figure 6.7: Flowchart of discharging ESS.

6.3.2 Optimal sizing of ESS based PSO

A method was designed to utilise the different electricity tariffs in EV charging cost minimisation while coordinating EV charging is made. The following steps were used to minimise the EVs charging cost by utilising the energy from electricity tariff for EVs under Group 2:

1. All the input data were inserted into the program. These data were network data, bus data, line data, residential load data, distributed generation data and a set of EVs data (Group 2). The EVs data considered the arrival time, battery SOC, and requested SOC by the users.
2. In the optimization process, the ESS location was generated randomly between P-Q bus; bus 4, 5, 6, 7, 8 or 9 (see Figure 4.6).
3. Then, the ESS size was randomly generated in between PESSmin to PESSmax.
4. After ESS size and location were generated, the ESS will discharge based on time-step that already setting follow off-peak hours where in this study in between 10:00 pm to 08:00 am.
5. The discharge of ESS is based on the status of DOD (see Figure 6.7)
6. Then, new load profile was generated.
7. The fitness function, as defined in Equation (6.1), was calculated (see Appendix B).
8. The optimisation procedure selected the optimal size of ESS, which provided the minimum power loss and voltage deviation. This iterative process was continued until the maximum iteration number was reached.
9. Once the optimisation process had converged, it updated optimal size and location of ESS.

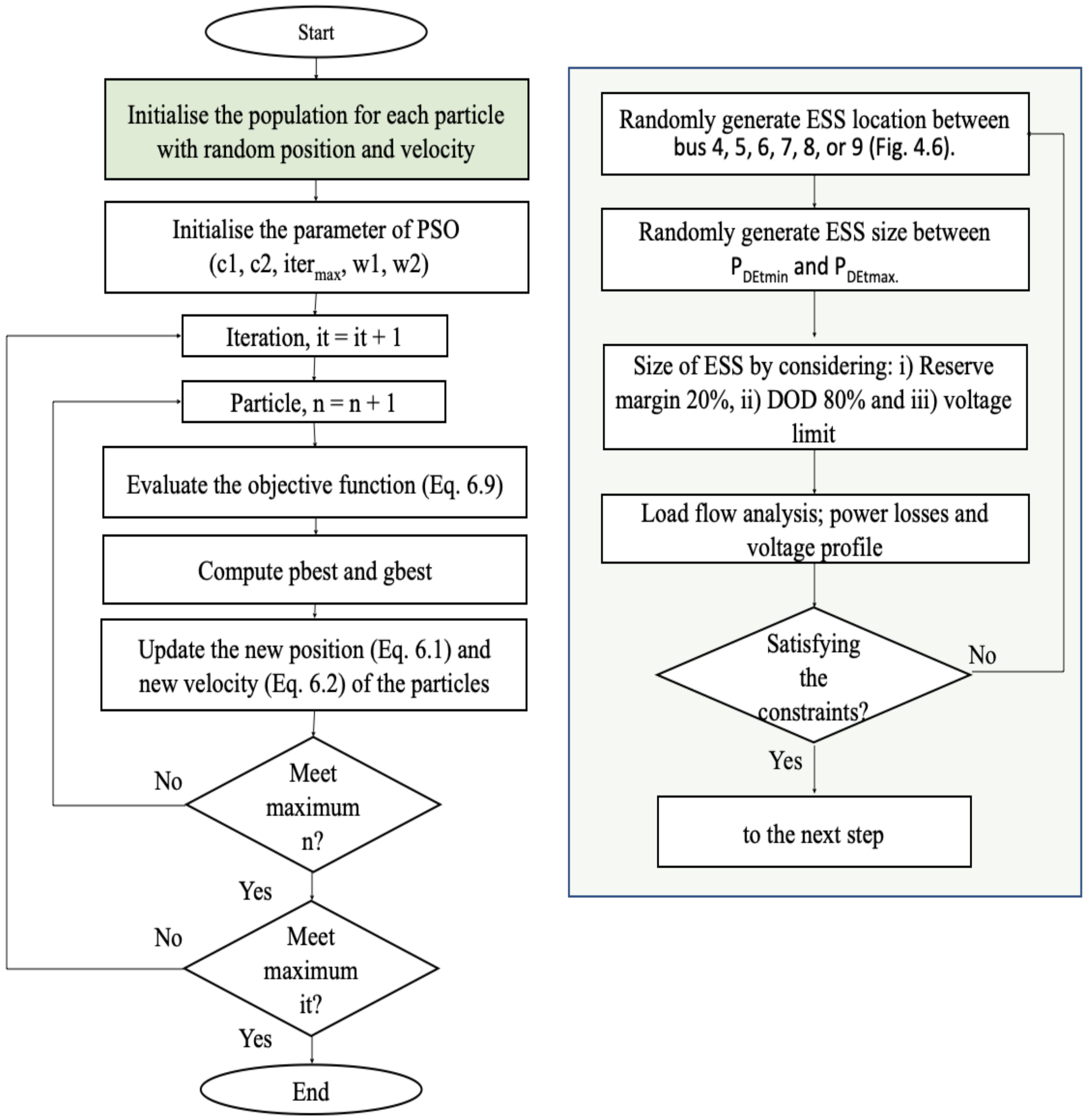


Figure 6.8: Flowchart of the PSO algorithm for ESS sizing.

6.4 System Modelling

This section presents the development of the system model used to simulate and analyse the decentralized EV charging control strategy in the distribution network. The model incorporates key elements such as power flow analysis, DER integration, and demand-side management to ensure a comprehensive understanding of the impacts on the distribution network.

6.4.1 Test System

The test system used in this study remains consistent with the configuration outlined in Chapter 5. This continuity allows for direct comparison across various scenarios and provides a stable baseline for evaluating the impacts of EV integration and control strategies on the Malaysian LV distribution network.

6.4.2 Energy Storage System

The ESS is modeled to store excess energy during off-peak periods, making it available for redistribution during peak demand. This capability aids in load leveling and supports voltage stability across the network. Furthermore, the ESS works in conjunction with the ETOU tariffs and the NEM scheme, as discussed in earlier sections, to encourage DSM by redistributing loads effectively.

6.4.3 Electric Vehicle Driving Pattern

The EV driving pattern used in this chapter builds on the analysis from Chapter 5, which categorizes EVs into two distinct groups: Group 1 and Group 2. In this chapter, Group 2 is examined in greater detail, especially concerning emergency charging scenarios. For Group 2, four levels of emergency charging demand have been defined to manage the grid's capacity effectively during peak hours. These emergency levels are as follows:

- **L1**: 20% of Group 2 vehicles require emergency charging.
- **L2**: 30% of Group 2 vehicles require emergency charging.
- **L3**: 40% of Group 2 vehicles require emergency charging.
- **L4**: 50% of Group 2 vehicles require emergency charging.

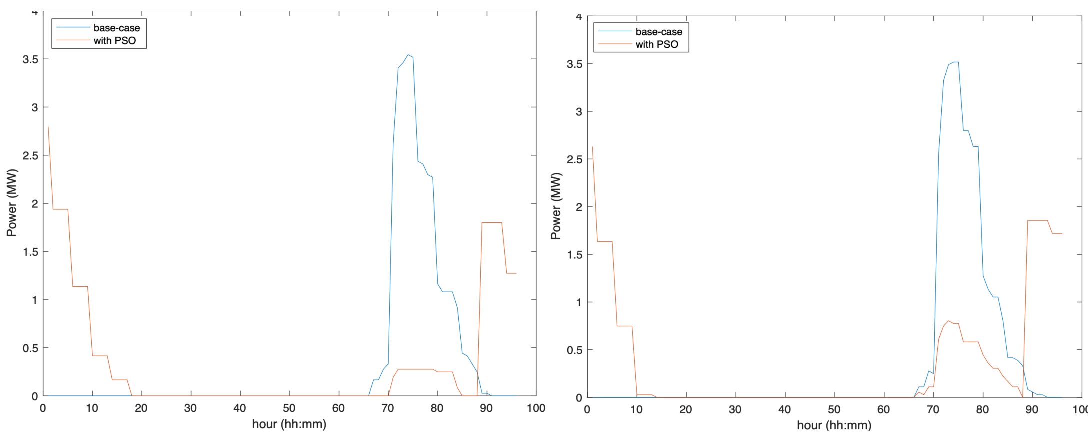
Each emergency level reflects varying intensities of immediate charging requirements, with L1 representing a lower strain on the network and L4 posing the highest demand. This classification allows for a more controlled approach to managing grid load, optimizing charging schedules to prevent overstressing the network. By incorporating these emergency stages, the proposed ESS and PSO based control strategies can dynamically adjust to real-time demand, ensuring reliable support for EV users while maintaining network stability.

6.5 Simulation Result

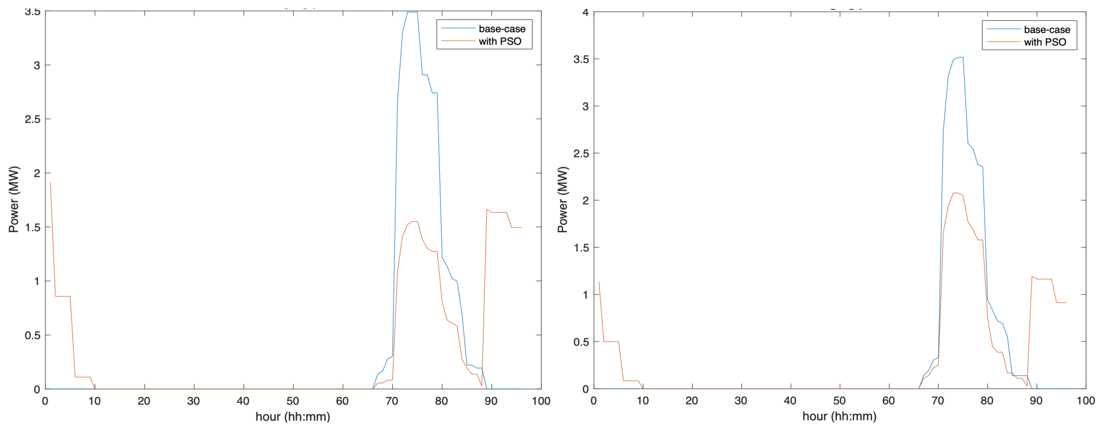
This section discusses the results of the simulation carried out to evaluate the effectiveness of the decentralized control strategy in optimizing EV charging profiles, minimizing power demand during peak hours, and maintaining grid stability. The findings focus on the generated EV charging profiles, the technical impacts on the distribution network, and the power demand patterns observed under various charging scenarios.

6.5.1 Electric Vehicle Charging Profiles

The results demonstrate that emergency charging significantly increases electricity demand. As the emergency level rises, the additional load from EVs intensifies, leading to peak demand periods that can stress the distribution network. This trend is illustrated in Figure 6.9, showing distinct demand profiles for each emergency level.



(a) (b)



(c) (d)

Figure 6.9: EV charging profiles for emergency levels (a) 20% Emergency, (b) 30% Emergency, (c) 40% Emergency, and (d) 50% Emergency.

6.5.2 Technical Impact

This section evaluates the technical impacts of the decentralized EV charging control system on the distribution network. The decentralized model aims to optimize EV charging behaviour to align with grid stability and efficiency goals, which is assessed through metrics such as power demand, voltage profile, voltage unbalance, power losses, and current flow distribution.

6.5.2.1 Power Demand

Figure 6.10 illustrates the power demand across all emergency charging scenarios, specifically Levels 1 through 4 (L1 to L4). The data demonstrates that even in the most extreme case, where 50% of EVs from Group 2 require emergency charging (L4), the total power demand remains comfortably within 20% of the threshold maximum demand. This finding highlights the effectiveness of the proposed strategies in managing load during peak charging periods. Moreover, the analysis indicates that EV owners can coordinate their charging preferences effectively, even when they choose to charge their vehicles after midnight. This flexibility allows them to fully charge their EV batteries without exceeding grid capacity. As a result, both the DSO and the EV owners benefit from this arrangement; the DSO avoids the risk of reaching maximum demand thresholds, while EV owners can take advantage of lower electricity rates during off-peak hours. This mutually beneficial scenario underscores the viability of implementing demand-side management strategies to optimize energy consumption while ensuring grid stability.

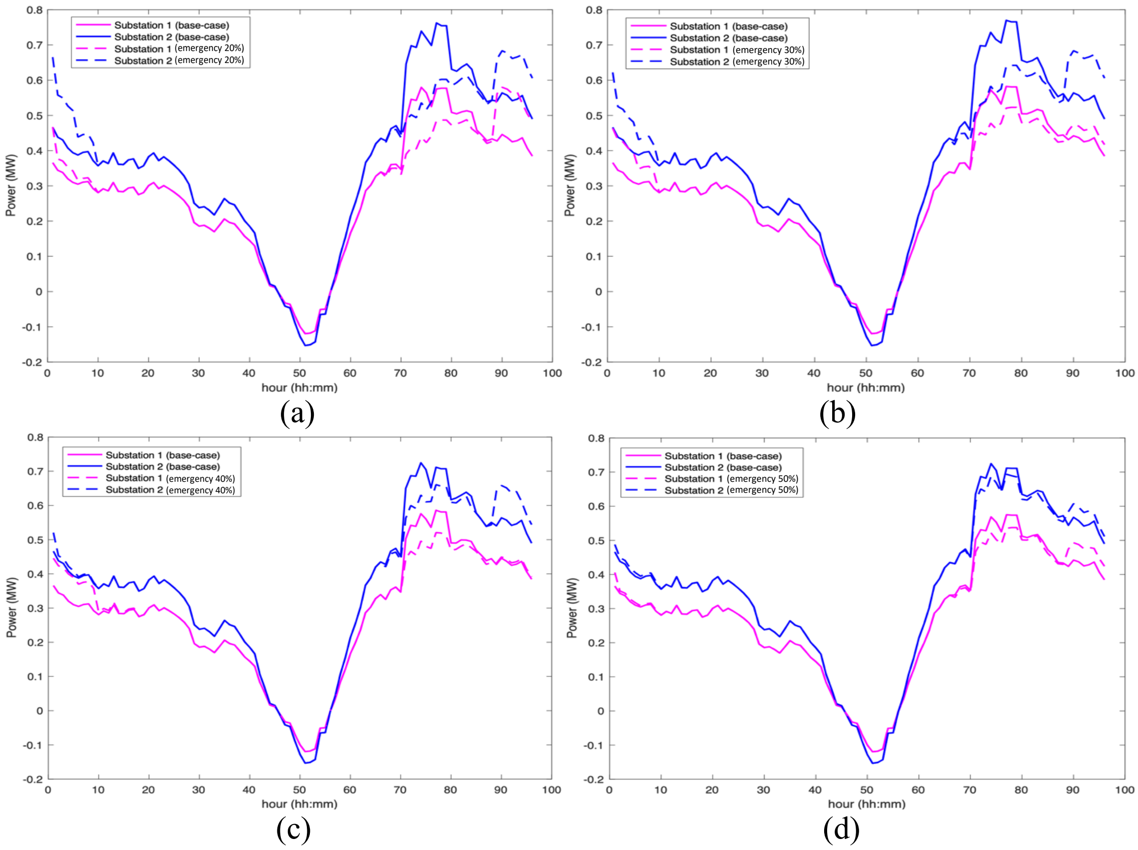


Figure 6.10: Power Demand EV for emergency levels (a) 20% Emergency, (b) 30% Emergency, (c) 40% Emergency, and (d) 50% Emergency.

6.5.2.2 Voltage Profile

The voltage profile analysis across all emergency charging levels (L1 to L4) shows that the distribution network maintains voltages within steady-state limits, even at the highest demand level, L4, where 50% of EVs from Group 2 require charging. As illustrated in Figure 6.11, voltages across key nodes remain stable under all conditions, confirming the effectiveness of the proposed control strategy in preventing voltage drop.

This stability is especially beneficial in high EV adoption areas, ensuring the network can handle peak charging loads without significant voltage deviations. Overall, these results underscore the reliability of the demand-side management strategies in supporting grid stability and maintaining acceptable voltage levels across the network during various charging demands.

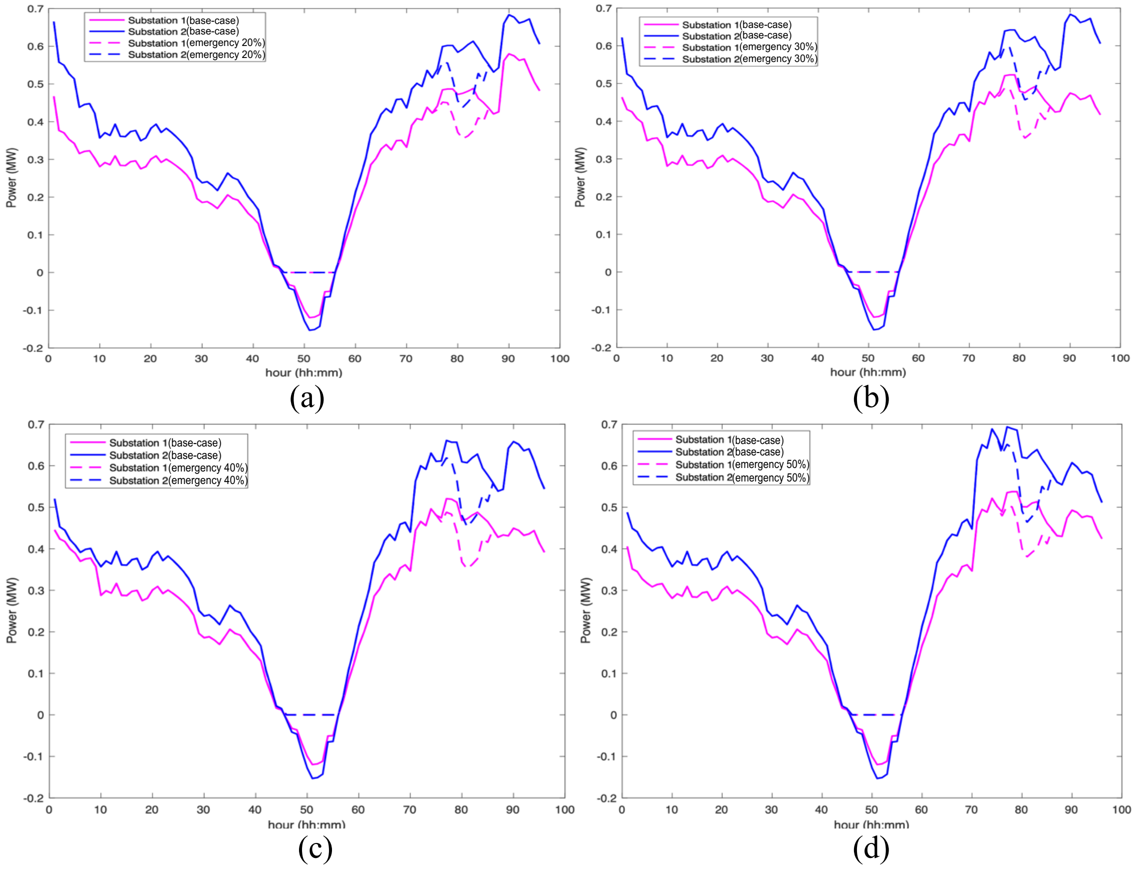


Figure 6.11: Voltage Profile for emergency levels (a) 20% Emergency, (b) 30% Emergency, (c) 40% Emergency, and (d) 50% Emergency.

6.5.2.3 Power Losses

This section examines the impact of the decentralized EV charging control model on power losses within the distribution network. Figure 6.12 illustrates that the proposed control model significantly reduces power losses, particularly during peak charging periods, by evenly distributing charging loads across the network. This reduction in losses leads to improved system efficiency, and a more cost effective power distribution framework. These results highlight the effectiveness of decentralized control strategies in maintaining an efficient and resilient distribution network as EV integration grows.

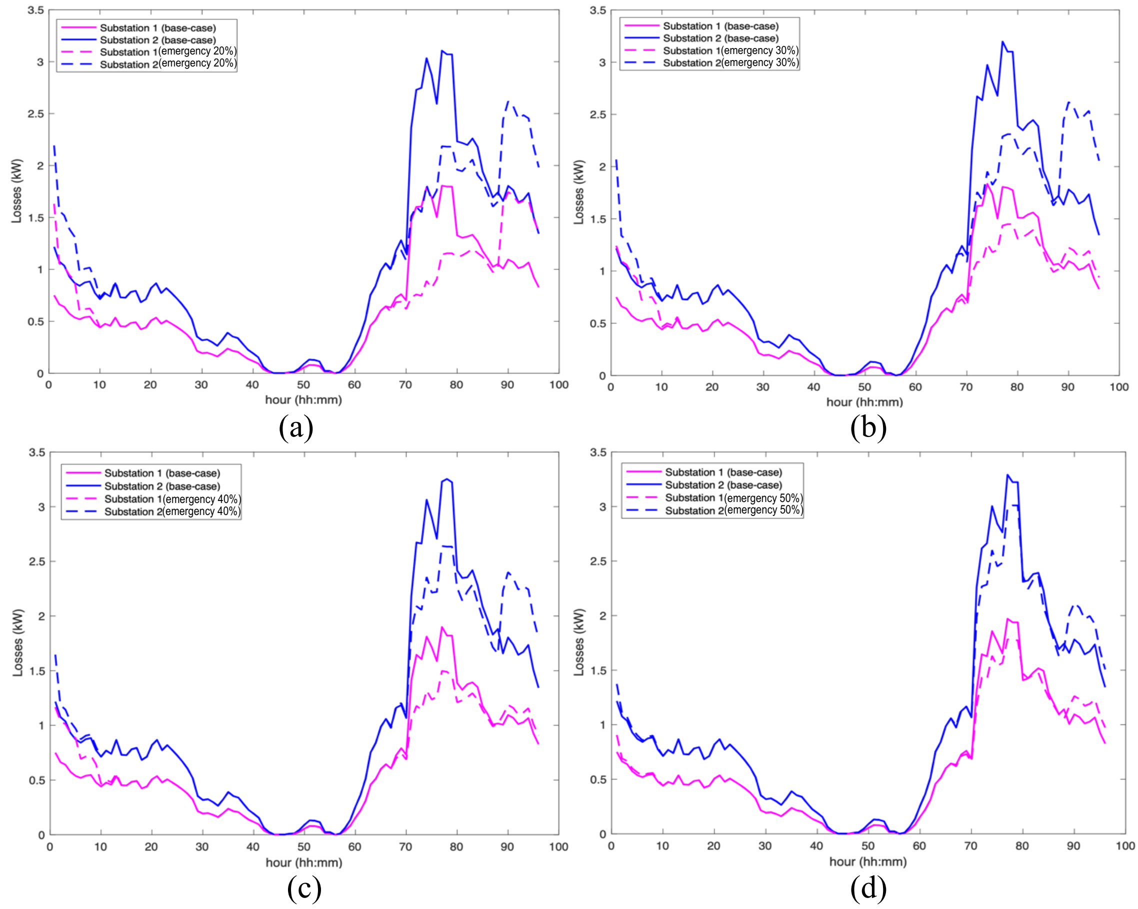


Figure 6.12: Power Losses for emergency levels (a) 20% Emergency, (b) 30% Emergency, (c) 40% Emergency, and (d) 50% Emergency.

6.5.3 Electricity Bill Analysis under Demand Side Management Strategies

The analysis of economic impacts reveals substantial savings for consumers through the implementation of DSM strategies. Table 6.3 presents the monthly electricity costs under various scenarios. Without any DSM measures, the annual electricity bill amounts to RM5,936.14. However, with the application of the ETOU tariff, this annual cost decreases to RM3,191.30, resulting in a notable 46% savings. This tariff structure incentivizes consumers to shift their energy usage to off-peak hours, effectively reducing costs while accommodating EV charging needs.

Moreover, when utilizing the NEM scheme, the annual bill further declines to RM2,963.84, yielding a significant 50% savings. The NEM scheme enables consumers to offset their energy consumption by generating their own power, such as through solar panels, thus enhancing overall cost efficiency. These findings highlight the significant economic advantages of integrating DSM and NEM strategies, illustrating their potential to lower electricity expenses for consumers while promoting sustainable energy practices within the distribution network.

Table 6.3: Monthly Electricity Bill Comparison Before and After Applying ETOU and ETOU+NEM Schemes.

Month	Fixed Tariff	ETOU Tariff	ETOU Tariff + NEM scheme
	Base Case	**Case 1**	**Case 2**
Jan	506.43	271.04	251.72
Feb	445.98	244.81	227.36
Mar	506.43	271.04	251.72
Apr	486.28	262.30	243.60
May	506.43	271.04	251.72
Jun	486.28	262.30	243.60
Jul	506.43	271.04	251.72
Aug	506.43	271.04	251.72
Sep	486.28	262.30	243.60
Oct	506.43	271.04	251.72
Nov	486.28	262.30	243.60
Dec	506.43	271.04	251.72
Total Bill, RM	**5,936.14**	**3,191.30**	**2,963.84**
Yearly saving, %		**46**	**50**

6.6 Summary

This chapter explored the impact of implementing DSM strategies and decentralized control models on the distribution network's performance, focusing on key parameters such as power demand, voltage profile, power losses, and economic implications.

The analysis revealed that even under peak charging conditions, the total power demand remained well within acceptable limits, demonstrating the effectiveness of the proposed control strategies. Voltage profile assessments confirmed that voltage levels across the network stayed stable, ensuring power quality was maintained despite high electric vehicle penetration.

Additionally, significant reductions in power losses were achieved through the decentralized EV charging control model, enhancing system efficiency, reducing energy waste, and improving cost-effectiveness in power distribution.

The economic impacts of these strategies were also substantial. The implementation of ETOU tariffs and the NEM scheme resulted in annual electricity bill reductions of 46% and 50%, respectively. These findings emphasize the financial advantages of integrating DSM and renewable energy solutions, showcasing their capacity to lower electricity costs while promoting sustainable practices.

Overall, this chapter demonstrates the critical role of innovative demand-side management and decentralized control in optimizing distribution network performance and enhancing economic viability in the context of increasing electric vehicle adoption.

CHAPTER 7

Conclusions and Recommendations for Further Work

7.1 Conclusions

This chapter consolidates the key findings and contributions of this research, which investigated the integration of DERs and EV charging demands within Malaysia's power distribution network. The study aimed to understand the effects of DERs, such as solar PVs and battery storage, on the distribution network and to model EV charging profiles that reflect the distinct urban road conditions in Malaysia. By analysing power losses, voltage profiles, and peak demand impacts, the research offers insights into the challenges and opportunities that DERs and EVs bring to the Malaysian grid.

7.1.1 Impact of Distributed Energy Resources on Distribution Network

This research examined the impact of distributed energy resources, specifically EVs and PVs, on a generic distribution network in the UK. Utilizing load flow analysis conducted through MATLAB, the study assessed the effects of varying residential load profiles, specifically minimum and maximum load conditions on key parameters such as power losses, voltage profiles, and overall demand.

The findings indicate that the integration of EVs and PVs leads to notable changes in the distribution network's performance. Under maximum load conditions, the presence of PV systems significantly reduces power losses by providing localized generation, which alleviates the burden on the grid during peak demand periods. This localized generation can enhance voltage profiles, maintaining acceptable voltage levels throughout the network, thereby improving overall reliability and reducing the risk of voltage sags.

Conversely, during minimum load conditions, the presence of EVs presents unique challenges. While EVs contribute to increased demand, particularly during off-peak hours, their impact on power losses is contingent upon the charging strategy employed. The analysis revealed that uncontrolled charging could exacerbate voltage drop issues, necessitating advanced demand-side management techniques to optimize charging times and mitigate adverse effects on the grid.

Overall, the research underscores the critical importance of integrating DERs into distribution network planning and operation. The findings suggest that effective management of EV charging and PV generation can lead to significant improvements in network efficiency and reliability, paving the way for a more resilient and sustainable energy system.

7.1.2 Generating Electric Vehicles Charging Profile based on Malaysia Urban Road

Given the lack of existing EV charging data profiles in Malaysia, this research developed a model to simulate EVs charging profiles based on two key factors: (1) user background and (2) user preferences. The user background component focused on road length and traffic convenience, particularly for EVs with an assumed maximum travel range of 100 km. The study considered three different destination locations; Petaling Jaya, Putrajaya, and Kuala Lumpur, starting from Shah Alam, Selangor, which served as the initial residential location. The research accounted for varied working hours, differentiating between government sector employees, who follow distinct working hours, and private sector employees.

The charging profile model assumes that all EVs have a fully charged battery (100%) when leaving home in the morning. After commuting to their respective workplaces, the research determined the charging requirements for each individual based on their journey distance and energy consumption. The study encompassed 130 residential units connected to a real distribution network.

The generated profiles reflect the diverse charging needs of users based on their commuting patterns. For instance, employees traveling longer distances or facing higher traffic congestion displayed a higher demand for mid-day or evening charging. The variation in work schedules, particularly between government and private sector workers, also contributed to different charging times and demand peaks throughout the day. These insights provide a foundation for planning and optimizing future charging infrastructure in urban areas, ensuring that the distribution network can accommodate EV growth while maintaining stability and efficiency. However, this analysis was limited to a generic UK distribution network and did not account for region-specific consumer behaviours or dynamic operational conditions. As such, further research is required to validate the findings under actual Malaysian network configurations and demand patterns.

7.1.3 Impact of Distributed Energy Resources on Malaysian Distribution Network

Following the development of EV charging profiles in Chapter 4, this research applied these profiles to the Malaysian LV distribution network to assess the impact of EV charging on the grid. Load flow analysis was conducted using MATLAB2014a, utilizing the Newton-Raphson method to study critical parameters, including power losses, voltage profiles, and overall power demand when EV charging loads were introduced.

The analysis revealed that the integration of EV charging significantly influences the performance of the distribution network. As EV charging loads are applied, the study observed an increase in power demand, particularly during peak commuting hours. This additional load leads to increased power losses within the network, with the magnitude of losses varying depending on the density of EV adoption in specific residential areas.

Voltage profiles also showed degradation in certain network sections, particularly in areas farther from the distribution substation, where voltage drops became more pronounced due to the higher demand.

However, the results also suggest that strategic planning and advanced load management techniques, such as staggered charging schedules or demand response mechanisms, could mitigate the negative impacts of EV charging on the network. Optimizing charging times based on real-time grid conditions could help reduce power losses and maintain voltage stability, ensuring the network operates efficiently even with the growing presence of distributed energy resources like EVs.

This study underscores the need for proactive measures in Malaysia's power distribution planning, particularly as the country prepares for increased EV adoption and the associated demands on the grid. Proper integration of EV charging infrastructure, combined with the use of DERs, will be essential in maintaining a stable and efficient distribution network. However, the analysis was limited to a single LV distribution network model and assumed immediate home-charging behaviour; further studies with diverse network topologies and stochastic charging patterns would provide a more comprehensive understanding of DER impacts in Malaysia.

7.1.4 Coordination of Distributed Energy Resources on Malaysia Power Distribution Network

This research introduced a DSM strategy to optimize the coordination of DERs in Malaysia’s power distribution network. Key elements include the use of a demand management approach known as “ETOU” to encourage EV charging during off-peak hours, alongside the integration of an ESS to store surplus solar energy generated during the day for use at night. PSO algorithm was employed to effectively manage both EV charging and energy storage sizing, ensuring balanced load distribution and efficient energy utilization.

The PSO algorithm was applied to determine optimal EV charging schedules based on the initial SOC of each vehicle. The charging schedule was divided into three time windows: the first for EVs with an initial SOC of less than 20%, the second for EVs with an SOC between 20% and 80%, and the third for EVs with an SOC above 80%. This tiered approach ensures that EVs in most need of charging are prioritized, helping to prevent excessive load on the distribution network during peak periods.

In addition, the PSO algorithm was used to determine the optimal sizing of the energy storage system to support 130 residential users. The ESS stores unused solar power generated during the day, providing an alternative energy source for night-time use, reducing dependence on grid power, and alleviating peak loads. By optimizing the ESS size, the study ensures that it effectively supports household energy needs while maximizing the use of renewable energy.

Overall, the coordination of DERs through demand-side management and strategic energy storage sizing improves the stability and efficiency of Malaysia's distribution network. This approach highlights the importance of intelligent load control strategies as Malaysia moves toward an energy system that is both sustainable and adaptable to the demands of increasing EV adoption and renewable integration. However, it is important to note that the findings are derived from simulation models with assumed user behaviours and PV generation patterns, which may not fully capture real-world uncertainties or large-scale implementation challenges.

7.2 Recommendations for Further Work

This research identified several potential avenues for future work to optimize the integration and management of DERs, EVs, and Vehicle-to-Grid (V2G) technology within Malaysia's power distribution network. From an electrical engineering perspective, these recommendations focus on enhancing grid stability, optimizing load flow, and improving the performance of the distribution network under increased DER penetration.

7.2.1 Advanced Modelling of V2G and ESS Coordination for Voltage Stability and Frequency Regulation

Future research should investigate the coordinated use of V2G and ESS for voltage stabilization and frequency regulation within LV and MV networks. By enabling EVs to discharge during periods of voltage dips or frequency fluctuations, V2G technology can provide ancillary services that improve network stability. Detailed simulations that model voltage and frequency dynamics under different V2G scenarios would be invaluable, particularly in the context of urban and suburban Malaysian grids with varying load demands and DER penetration levels.

7.2.2 Design and Implementation of Real-Time Load Control Algorithms Using V2G and DERs

Developing real-time, adaptive load control algorithms that optimize DER integration, including V2G, would enhance the efficiency of power flow management and minimize losses. Future work could involve the use of advanced techniques such as model predictive control (MPC) or machine learning algorithms to dynamically adjust EV charging, discharging, and ESS operations in response to real-time grid conditions. Such algorithms could help ensure efficient energy distribution and improve overall power quality by reducing instances of overloading and voltage drop across residential and commercial areas.

7.2.3 Optimal Sizing and Placement of ESS and V2G Charging Stations to Minimize Power Losses

Determining the optimal sizing and placement of ESS and V2G charging stations within the distribution network is critical for minimizing power losses and enhancing voltage profiles. Using optimization techniques like PSO algorithm, future studies could identify the most effective locations and capacities for ESS and V2G stations, particularly in high-density EV areas. This would allow for distributed support across the grid, reducing the burden on centralized generation and enhancing local reliability while ensuring that the power losses remain within permissible limits.

These recommendations aim to advance the technical capabilities of Malaysia's distribution network in managing DER and V2G technology, enhancing grid resilience, and ensuring efficient power delivery under the demands of an evolving energy landscape.

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APPENDIX A

MATLAB Coding for EV Charging Profiles in Malaysia

```
for jj = 1:NN;

ev_owner = zeros(1,130);    % no of customers
Nel = numel(ev_owner);      % matrix size
Rindices = randperm(Nel);   % ran random
ev_owner(Rindices(1:91)) = 1;       % 1 = Nissan Leaf
ev_owner(Rindices(92:130)) = 2;     % 2 = Mitsubishi i-MiEV

ev_sector = zeros(1,130);       % no of customers
Nel = numel(ev_sector);         % matrix size
Rindices = randperm(Nel);           % ran random
ev_sector(Rindices(1:91)) = 3;      % 3 = Government
ev_sector(Rindices(92:130)) = 4;

working_at_p = [5, 6];   % 5 = Kuala Lumpur, 6 = Putrajaya

for g = 1:130;

   if ev_sector(:,g) == 3;
      working_at(:,g) = working_at_p(randi(numel(working_at_p)));
   elseif ev_sector(:,g) == 4;
      working_at(:,g) = 7;          % 7 = Petaling Jaya
   end;

end;

% Working Hours
working_hours_p = [11, 12, 13, 14];

% Working hours
% 11 : 7:30am ~ 4:30pm
% 12 : 8:00am ~ 5:00pm
% 13 : 8:30am ~ 5:30pm
% 14 : 9:00am ~ 6:00pm
% 15 : 8:30am ~ 5:30pm

for g = 1:130;

   if ev_sector(:,g) == 3;             % 3 = Government
      working_hours(:,g) = working_hours_p(randi(numel(working_hours_p)));
   elseif ev_sector(:,g) == 4;    % 4 = Private
      working_hours(:,g) = 15;
   end;

end;

% Route Selection

route_sa_kl = [81,82,83];
```

```
route_sa_p = [91,92,93];
route_sa_pj = [101,102,103];

route_kl_sa = [31,32,33];
route_p_sa = [41,42,43];
route_pj_sa = [51,52,53];

sa_kl_r1 = 27.5;
sa_kl_r2 = 28.2;
sa_kl_r3 = 28.8;

sa_p_r1 = 39;
sa_p_r2 = 40;
sa_p_r3 = 50.6;

sa_pj_r1 = 16.6;

% from Work to Home
kl_sa_r1 = 25.2;
kl_sa_r2 = 29.3;
kl_sa_r3 = 30.8;

p_sa_r1 = 39.1;
p_sa_r2 = 41.7;
p_sa_r3 = 42.2;

pj_sa_r1 = 17.1;
pj_sa_r2 = 21.5;
pj_sa_r3 = 27.9;

t_length_kl_r1 = sa_kl_r1 + kl_sa_r1;
t_length_kl_r2 = sa_kl_r2 + kl_sa_r2;
t_length_kl_r3 = sa_kl_r3 + kl_sa_r3;

t_length_p_r1 = sa_p_r1 + p_sa_r1;
t_length_p_r2 = sa_p_r2 + p_sa_r2;
t_length_p_r3 = sa_p_r3 + p_sa_r3;

t_length_pj_r1 = sa_pj_r1 + pj_sa_r1;
t_length_pj_r2 = sa_pj_r1 + pj_sa_r2;
t_length_pj_r3 = sa_pj_r1 + pj_sa_r3;

for g = 1:130;

   if working_at(:,g) == 5;      % 5 = Kuala Lumpur
      working_route(:,g) = route_kl_sa(randi(numel(route_kl_sa)));
   elseif working_at(:,g) == 6;   % 6 = Putrajaya
      working_route(:,g) = route_p_sa(randi(numel(route_p_sa)));
   elseif working_at(:,g) == 7;   % 7 = Petaling Jaya
      working_route(:,g) = route_pj_sa(randi(numel(route_pj_sa)));
   end;
end;
```

```
% route commuting to work
for g = 1:130;

   if working_at(:,g) == 5;        % 5 = Kuala Lumpur
      working_route_g(:,g) = route_sa_kl(randi(numel(route_sa_kl)));
   elseif working_at(:,g) == 6;    % 6 = Putrajaya
      working_route_g(:,g) = route_sa_p(randi(numel(route_sa_p)));
   elseif working_at(:,g) == 7;    % 7 = Petaling Jaya
      working_route_g(:,g) = route_sa_pj(randi(numel(route_sa_pj)));
   end;
end;

% Speed
% EVspeed_71 = 10km/j
% EVspeed_72 = 20km/j
% EVspeed_73 = 30km/j

 ev_speed_p = [71, 72, 73];
 ev_speed = ev_speed_p(randi(numel(ev_speed_p),1,130));

% PRO+CESS
% Step 1 - EVs Arrival Time

workingHours1 = round(normrnd(66,2,[1 130])); % 4:30pm , time_step 15 minutes
workingHours2 = round(normrnd(68,2,[1 130])); % 5:00pm from 68 to random
workingHours3 = round(normrnd(70,2,[1 130])); % 5:30pm
workingHours4 = round(normrnd(72,2,[1 130])); % 6:00pm

% working route is also divided into three for each road.

for g = 1:130;

   if working_route(:,g) == 31;
      final_route(:,g) =  30.4;
   elseif working_route(:,g) == 32;
      final_route(:,g) = 31.7;
   elseif working_route(:,g) == 33;
      final_route(:,g) =  32.7;
   elseif working_route(:,g) == 41;
      final_route(:,g) = 39.1;
   elseif working_route(:,g) == 42;
      final_route(:,g) =  41.7;
   elseif working_route(:,g) == 43;
      final_route(:,g) = 42.2;
   elseif working_route(:,g) == 51;
      final_route(:,g) =  17.1;
   elseif working_route(:,g) == 52;
      final_route(:,g) = 21.5;
   elseif working_route(:,g) == 53;
      final_route(:,g) =  27.9;
   end;
end;
```

```
 for g=1:130;
     if ev_speed(:,g) == 71;
         final_speed(:,g) = 10;   % 20km/j
     elseif ev_speed(:,g) == 72;
         final_speed(:,g) = 20;   % 40km/j
     elseif ev_speed(:,g) == 73;
         final_speed(:,g) = 30;   % 60km/j
     end;
 end;

final_speed = round(normrnd(30,6,[1 130]));

for g = 1:130;

    if working_hours(:,g) == 11;
        arrival_time_i(:,g) = workingHours1(:,g) + (round(final_route(:,g) /
final_speed(:,g)));
    elseif working_hours(:,g) == 12;
        arrival_time_i(:,g) = workingHours2(:,g) + (round(final_route(:,g) /
final_speed(:,g)));
    elseif working_hours(:,g) == 13;
        arrival_time_i(:,g) = workingHours3(:,g) + (round(final_route(:,g) /
final_speed(:,g)));
    elseif working_hours(:,g) == 14;
        arrival_time_i(:,g) = workingHours4(:,g) + (round(final_route(:,g) /
final_speed(:,g)));
    elseif working_hours(:,g) == 15;
        arrival_time_i(:,g) = workingHours3(:,g) + (round(final_route(:,g) /
final_speed(:,g)));
    end;
 end;

% arrival_time                    % EVs start charging
ev_start = arrival_time_i;
integ_s(:,:,jj) = ev_start;
integ_ss = squeeze(integ_s(:,:,:));

% Step 2 - EVs Battery SoC status
for g = 1:130;
    if working_route(:,g) == 31;
    initial_SoC(:,g) = round((t_length_kl_r1/160)*100);
    elseif working_route(:,g) == 32;
    initial_SoC(:,g) = round((t_length_kl_r2/160)*100);
    elseif working_route(:,g) == 33;
    initial_SoC(:,g) = round((t_length_kl_r3/160)*100);
    elseif working_route(:,g) == 41;
    initial_SoC(:,g) = round((t_length_p_r1/160)*100);
    elseif working_route(:,g) == 42;
    initial_SoC(:,g) = round((t_length_p_r2/160)*100);
    elseif working_route(:,g) == 43;
    initial_SoC(:,g) = round((t_length_p_r3/160)*100);
    elseif working_route(:,g) == 51;
```

```
    initial_SoC(:,g) = round((t_length_pj_r1/160)*100);
    elseif working_route(:,g) == 52;
    initial_SoC(:,g) = round((t_length_pj_r2/160)*100);
    elseif working_route(:,g) == 53;
    initial_SoC(:,g) = round((t_length_pj_r3/160)*100);
    end;
end;

% initial_SoC
total_SoCs(:,:,jj) = initial_SoC;
total_SoC = squeeze(total_SoCs(:,:,:));

% final_SoC = 80; % discharge battery SoC = 80%
final_SoC = round(normrnd(80,5,[1 130]));   % discharge battery SoC = 80%
total_endSoCs(:,:,jj) = final_SoC;
total_endSoC = squeeze(total_endSoCs(:,:,:));

batt_cap1 = 24;          % Nissan Leaf
batt_cap2 = 16;          % Mitsubishi i-MiEV  changed from 9 to 16
on_board = 3.6;

% Step 3 - EVs charging duration
for g = 1:130;
  if ev_owner(:,g) == 1;
      batt_charge(:,g) = (((final_SoC(:,g) - initial_SoC(:,g))*0.01)*batt_cap1)/on_board;
  elseif ev_owner(:,g) == 2;
      batt_charge(:,g) = (((final_SoC(:,g) - initial_SoC(:,g))*0.01)*batt_cap2)/on_board;
  end;

% end;

batt_charge_s = round(batt_charge);

time_step = 4;   % for 15 minutes

% ajakkkk = batt_charge_s * time_step

batt_time_s(:,g) = batt_charge_s(:,g) * time_step;

% batt_time_s(:,g) = ajakkkk(:,g);
ev_end(:,g) = ev_start(:,g) + batt_time_s(:,g);

end;
```

APPENDIX B

MATLAB Coding for EV Charging Scheduling

E.1 Normal condition

```
for st1 = 1:57;
    if EVs_initial_SoCn(2,st1) < 20;
```

```
      Group11(:,st1) = EVs_initial_SoCn(:,st1);
   elseif EVs_initial_SoCn(2,st1) >= 20 & EVs_initial_SoCn(2,st1) <= 100;
      Group12(:,st1) = EVs_initial_SoCn(:,st1);
   end;
end;

for st1 = 58:130;
   if EVs_initial_SoCn(2,st1) < 20;
      Group21(:,st1) = EVs_initial_SoCn(:,st1);
   elseif EVs_initial_SoCn(2,st1) >= 20 & EVs_initial_SoCn(2,st1) <= 100;
      Group22(:,st1) = EVs_initial_SoCn(:,st1);
   end;
end;

% % to sorting EVs to two group.
for st1 = 1:57;
   if initial_SoC(st1) < 20;
      Group_11(:,st1) = initial_SoC(st1);
   elseif initial_SoC(st1) >= 20 & initial_SoC(st1) <= 100;
      Group_12(:,st1) = initial_SoC(st1);
   end;
end;

for st2 = 58:130;
   if initial_SoC(st2) < 20;
      Group_21(:,st2) = initial_SoC(st2);
   elseif initial_SoC(st2) >= 20 & initial_SoC(st2) <= 100;
      Group_22(:,st2) = initial_SoC(st2);
   end;
end;

Count_std1_1 = nonzeros(Group_11);
Count_std1_2 = nonzeros(Group_12);

Count_std2_1 = nonzeros(Group_21);
Count_std2_2 = nonzeros(Group_22);

Count_std11_1 = numel(Count_std1_1);
Count_std11_2 = numel(Count_std1_2);

Count_std22_1 = numel(Count_std2_1);
Count_std22_2 = numel(Count_std2_2);

EVs_St1_G1 = nonzeros(Group11);
EVs_St1_G2 = nonzeros(Group12);
EVs_St2_G1 = nonzeros(Group21);
EVs_St2_G2 = nonzeros(Group22);

reshapes_st1_1 = reshape(EVs_St1_G1,2,Count_std11_1);
reshapes_st1_2 = reshape(EVs_St1_G2,2,Count_std11_2);

reshapes_st2_1 = reshape(EVs_St2_G1,2,Count_std22_1);
```

```
reshapes_st2_2 = reshape(EVs_St2_G2,2,Count_std22_2);

EV_SOC_11 = sortrows(reshapes_st1_1');
EV_SOC_12 = sortrows(reshapes_st1_2');

EV_SOC_21 = sortrows(reshapes_st2_1');
EV_SOC_22 = sortrows(reshapes_st2_2');

% B = reshape(A,[],2)
% bab = sortrows(pso_st_2,[2,1]);

for def = 1:130;
   if initial_SoC(def) < 20;
      EVs_groups(:,def) = 1;
   elseif initial_SoC(def) >= 20 & initial_SoC(def) <= 100;
      EVs_groups(:,def) = 2;
   end;
end;

Group_1 = Count_std11_1 + Count_std22_1;
Group_2 = Count_std11_2 + Count_std22_2;

ev_start = arrival_time_i;
integ_s(:,:,jj) = ev_start;
integ_ss = squeeze(integ_s(:,:,:));

EVs_owner_s = 1:130;

EVs_group_SoC = [EVs_owner_s
                 initial_SoC
                 EVs_groups];
```

E.2 Emergency condition

```
% to set EV owner that will charge emergency even they under Group 2
% (initial SoC in between 20%-100%)

akaun = Count_std11_2 + Count_std22_2;
percentage = 80;   % emergency
percentage_value = round((percentage/100) * akaun);

ev_condition = zeros(1,akaun);                    % no of customers
Nel = numel(ev_condition);                        % total bil matrix size
Rindices = randperm(Nel);                         % ran random
ev_condition(Rindices(1:percentage_value)) = 123;       % 123 = Emergency
ev_condition(Rindices(percentage_value+1:akaun)) = 456;  % 456 = Normal

tatak = Count_std11_2 + 1;
asdk = ev_condition(1:Count_std11_2);
dskl = ev_condition(tatak:akaun);

for ug = 1:Count_std11_2;
```

```
    if asdk(:,ug) == 123;
        E_Group11(:,ug) = reshapes_st1_2(:,ug);
    elseif asdk(:,ug) == 456;
        E_Group12(:,ug) = reshapes_st1_2(:,ug);
    end;
end;

for ugu = 1:Count_std22_2;
    if dskl(:,ugu) == 123;
        E_Group21(:,ugu) = reshapes_st2_2(:,ugu);
    elseif dskl(:,ugu) == 456;
        E_Group22(:,ugu) = reshapes_st2_2(:,ugu);
    end;
end;

E_Group_11 = E_Group11(2,:); %    Group Emergency from Substation 1
E_Group_12 = E_Group12(2,:); %    Group Normal from Substation 1

E_Group_21 = E_Group21(2,:); %    Group Emergency from Substation 2
E_Group_22 = E_Group22(2,:); %    Group Normal from Substation 2

E_Count_std1_1 = nonzeros(E_Group_11); % E
E_Count_std1_2 = nonzeros(E_Group_12); % N

E_Count_std2_1 = nonzeros(E_Group_21); % E
E_Count_std2_2 = nonzeros(E_Group_22); % N

E_Count_std11 = nonzeros(E_Group11); %
E_Count_std12 = nonzeros(E_Group12); %

E_Count_std21 = nonzeros(E_Group21); %
E_Count_std22 = nonzeros(E_Group22); %

E_Count_std11_1 = numel(E_Count_std1_1); %
E_Count_std11_2 = numel(E_Count_std1_2); %

E_Count_std22_1 = numel(E_Count_std2_1); %
E_Count_std22_2 = numel(E_Count_std2_2); %

E_Count_std111 = numel(E_Count_std11);  %
E_Count_std112 = numel(E_Count_std12);  %

E_Count_std221 = numel(E_Count_std21);  %
E_Count_std222 = numel(E_Count_std22);  %

E_reshapes_st1_1 = reshape(E_Count_std11,2,E_Count_std11_1); %
E_reshapes_st1_2 = reshape(E_Count_std12,2,E_Count_std11_2); %

E_reshapes_st2_1 = reshape(E_Count_std21,2,E_Count_std22_1); %
E_reshapes_st2_2 = reshape(E_Count_std22,2,E_Count_std22_2); %

E_EV_SOC_11 = sortrows(E_reshapes_st1_1'); %
```

```
E_EV_SOC_12 = sortrows(E_reshapes_st1_2'); %

E_EV_SOC_21 = sortrows(E_reshapes_st2_1'); %
E_EV_SOC_22 = sortrows(E_reshapes_st2_2'); %

for def = 1:130;
   if initial_SoC(def) < 20;
      EVs_groups(:,def) = 1;
   elseif initial_SoC(def) >= 20 & initial_SoC(def) <= 100;
      EVs_groups(:,def) = 2;
   end;
end;

Group_1 = Count_std11_1 + Count_std22_1 + E_Count_std11_1 + E_Count_std22_1;
Group_2 = E_Count_std11_2 + E_Count_std22_2;

ev_start = arrival_time_i;
integ_s(:,:,jj) = ev_start;
integ_ss = squeeze(integ_s(:,:,:));

EVs_owner_s = 1:130;

EVs_group_SoC = [EVs_owner_s
                 initial_SoC
                 EVs_groups];
```

APPENDIX C

EV Charging Scheduling

C1. MATLAB for EV Scheduling for Decentralised with ETOU Tariff

```
time_step = max_load_demand;

Load_data_pso =
csvread('/Users/mac/Work/data_bus1.csv',0,time_step,[0,time_step,164,time_step]);
Gen_data_pso =
csvread('/Users/mac/Work/data_gen1.csv',0,time_step,[0,time_step,164,time_step]);

pso_st_1 = E_reshapes_st1_2';      % Group 2 from Substation 1
pso_st_2 = E_reshapes_st2_2';      % Group 2 from Substation 2

beb = sortrows(pso_st_1,[2,1]);   % sort initial SoC descending
bab = sortrows(pso_st_2,[2,1]);   % sort initial SoC descending

% beb = sortrows(pso_st_1,[-2,1]);   % sort initial SoC descending
% bab = sortrows(pso_st_2,[-2,1]);   % sort initial SoC descending

for kln = 1:2;
   if ESSlocation_s(:,kln) == 2;
      group1_pso = beb(1:ESSsize_s(:,kln),:);   % selection of EVs for charging based
on PSO algorithm
```

```
   elseif ESSlocation_s(:,kln) == 3;
      group2_pso = bab(1:ESSsize_s(:,kln),:);    % selection of EVs for charging based
on PSO algorithm
   end;
end;

bebeb = sortrows(group1_pso,[1,1]);    % sort EVs owner escending
babab = sortrows(group2_pso,[1,1]);    % sort EVs owner escending

total_size_pso = ESSsize_s (:,1) + ESSsize_s (:,2);
combine_resd_EVs = vertcat(bebeb,babab);   % to combine matrix

EV_value_a = 3.6 * N;

value_EVs = ones(1,total_size_pso);
value_EVss = EV_value_a * value_EVs;

resd_EVs_PSO = [combine_resd_EVs(:,1)'     % no. of selected residential
             value_EVss]';             % no. of

total_resd_EVs = 1:165;
value_resd_EVs = zeros(1,165);

EVs_data_pso = [ total_resd_EVs
              value_resd_EVs]';

% to create EVs profiles 165x1
for loop_pso1 = 1:165;
   for keyl = 1:total_size_pso;
      if EVs_data_pso(loop_pso1,1) == resd_EVs_PSO(keyl,1);
         EVs_data_pso(loop_pso1,2) = resd_EVs_PSO(keyl,2);
      else;
      end;
   end;
end;

Final_EVS_data = EVs_data_pso(:,2);

Total_load_pso = Load_data_pso + Final_EVS_data;

busdata(:,5) = Total_load_pso;
busdata(:,7) = Gen_data_pso;

busdata;
```

C2. MATLAB for Optimal Size and Location of ESS Malaysia LV Distribution Network

```
NoP = 20;        % no. of particle, 20

busESS       = [4, 5, 6, 7, 8, 9];
```

```
busESS_demand  = [4, 5, 6, 8, 9, 10];
busESS_Fdemand = [busESS;busESS_demand]';
busdata4 = busdata_final4(:,:,iil);

size_1 = min_ESS_size
size_2 = max_ESS_size
min_percent = 0.01;
max_percent = 0.8;

Demand_feeder1;   % Load at 4
Demand_feeder2;   % Load at 5
Demand_feeder3;   % Load at 6
Demand_feeder4;   % Load at 8
Demand_feeder5;   % Load at 9
Demand_feeder6;   % Load at 10

% Generating no of ESS
no_of_ESS = 1;      % randi([1 6],1)

for kk = 1:NoP;

busdata = busdata4;

% Generating location of ESS
ESSlocation_s = busESS(randperm(numel(busESS),no_of_ESS)) ;

while(1);
 while(1)
  while(1)

% Generating sizing of ESS
ESSsize_s = randi([size_1 size_2],1,no_of_ESS) * 0.000001;
% ESSsize_s = randi([size_1 size_2],1,no_of_ESS) * 0.0001;
for hklk = 1:no_of_ESS;
    if ESSlocation_s(:,hklk) == 4;
        Pload_1(:,hklk) = busESS_Fdemand(1,2);
    elseif ESSlocation_s(:,hklk) == 5;
        Pload_1(:,hklk) = busESS_Fdemand(2,2);
    elseif ESSlocation_s(:,hklk) == 6;
        Pload_1(:,hklk) = busESS_Fdemand(3,2);
    elseif ESSlocation_s(:,hklk) == 7;
        Pload_1(:,hklk) = busESS_Fdemand(4,2);
    elseif ESSlocation_s(:,hklk) == 8;
        Pload_1(:,hklk) = busESS_Fdemand(5,2);
    elseif ESSlocation_s(:,hklk) == 9;
        Pload_1(:,hklk) = busESS_Fdemand(6,2);
    end;
end;

Pload_1;
loves = [Pload_1
        ESSsize_s]';
```

```
for ess_no = 1:no_of_ESS;

   if Pload_1(:,ess_no) == 4;
      Pload_(:,ess_no) = Demand_feeder1;
   elseif Pload_1(:,ess_no) == 5;
      Pload_(:,ess_no) = Demand_feeder2;
   elseif Pload_1(:,ess_no) == 6;
      Pload_(:,ess_no) = Demand_feeder3;
   elseif Pload_1(:,ess_no) == 8;
      Pload_(:,ess_no) = Demand_feeder4;
   elseif Pload_1(:,ess_no) == 9;
      Pload_(:,ess_no) = Demand_feeder5;
   elseif Pload_1(:,ess_no) == 10;
      Pload_(:,ess_no) = Demand_feeder6;
   end
end

Pload_;

loves = [Pload_1
       ESSsize_s
       Pload_]';
```

C3. MATLAB Coding for Constraint of PSO EV Decentralised Charging

```
% constraint #1 : Demand load at substation 1 & 2 not higher than 0.8 MW
Pload_1 = DAB(1);
Pload_2 = DAB(2);

  if (Pload_1 < 0.8) && (Pload_2 < 0.8);
     break;
  end;
   end;

% constraint #3 : Voltage
Vmm = Vm(:,:);
Vaa = zeros (1,165);
Vab = 0.94 + Vaa;
Vmin = Vab;
Vac = zeros (1,165);
Vad = 1.10 + Vac;
Vmax = Vad;

   if (Vmm >= Vmin) & (Vmm <= Vmax);
      break;
   end;

end;

z(kk,:)  = [ESSlocation_s ESSsize_s real(SLT)];
```

```
x(kk,:)  = [ESSlocation_s ESSsize_s];
ff(kk,:) = [real(SLT)];

end ;
```

C4. MATLAB Coding for Constraint of PSO ESS Size and Location

```
for loopij = 1:no_of_ESS;
   if Pload_1(:,loopij) == 4;
      pESSmin_1(loopij) = min_percent * Pload_(:,loopij);
      pESSmax_1(loopij) = max_percent * Pload_(:,loopij);
   elseif Pload_1(:,loopij) == 5;
      pESSmin_1(loopij) = min_percent * Pload_(:,loopij);
      pESSmax_1(loopij) = max_percent * Pload_(:,loopij);
   elseif Pload_1(:,loopij) == 6;
      pESSmin_1(loopij) = min_percent * Pload_(:,loopij);
      pESSmax_1(loopij) = max_percent * Pload_(:,loopij);
   elseif Pload_1(:,loopij) == 8;
      pESSmin_1(loopij) = min_percent * Pload_(:,loopij);
      pESSmax_1(loopij) = max_percent * Pload_(:,loopij);
   elseif Pload_1(:,loopij) == 9;
      pESSmin_1(loopij) = min_percent * Pload_(:,loopij);
      pESSmax_1(loopij) = max_percent * Pload_(:,loopij);
   elseif Pload_1(:,loopij) == 10;
      pESSmin_1(loopij) = min_percent * Pload_(:,loopij);
      pESSmax_1(loopij) = max_percent * Pload_(:,loopij);
   end;
end;

pESSmin_1;
pESSmax_1;

loves = [Pload_1
       ESSsize_s
       Pload_
       pESSmin_1
       pESSmax_1]';

   if no_of_ESS == 1;
      if(ESSsize_s(:,1) > pESSmin_1(:,1)) && (ESSsize_s(:,1) < pESSmax_1(:,1));
         break;
      end;
   elseif no_of_ESS == 2;
      if(ESSsize_s(:,1) > pESSmin_1(:,1)) && (ESSsize_s(:,1) < pESSmax_1(:,1));
        if(ESSsize_s(:,2) > pESSmin_1(:,2)) && (ESSsize_s(:,2) < pESSmax_1(:,2));
         break;
        end;
      end;
   elseif no_of_ESS == 3;
      if(ESSsize_s(:,1) > pESSmin_1(:,1)) && (ESSsize_s(:,1) < pESSmax_1(:,1));
        if(ESSsize_s(:,2) > pESSmin_1(:,2)) && (ESSsize_s(:,2) < pESSmax_1(:,2));
          if(ESSsize_s(:,3) > pESSmin_1(:,3)) && (ESSsize_s(:,3) < pESSmax_1(:,3));
```

```
            break;
          end;
        end;
      end;
    elseif no_of_ESS == 4;
      if(ESSsize_s(:,1) > pESSmin_1(:,1)) && (ESSsize_s(:,1) < pESSmax_1(:,1));
        if(ESSsize_s(:,2) > pESSmin_1(:,2)) && (ESSsize_s(:,2) < pESSmax_1(:,2));
          if(ESSsize_s(:,3) > pESSmin_1(:,3)) && (ESSsize_s(:,3) < pESSmax_1(:,3));
            if(ESSsize_s(:,4) > pESSmin_1(:,4)) && (ESSsize_s(:,4) < pESSmax_1(:,4));
              break;
            end;
          end;
        end;
      end;
    elseif no_of_ESS == 5;
      if(ESSsize_s(:,1) > pESSmin_1(:,1)) && (ESSsize_s(:,1) < pESSmax_1(:,1));
        if(ESSsize_s(:,2) > pESSmin_1(:,2)) && (ESSsize_s(:,2) < pESSmax_1(:,2));
          if(ESSsize_s(:,3) > pESSmin_1(:,3)) && (ESSsize_s(:,3) < pESSmax_1(:,3));
            if(ESSsize_s(:,4) > pESSmin_1(:,4)) && (ESSsize_s(:,4) < pESSmax_1(:,4));
              if(ESSsize_s(:,5) > pESSmin_1(:,5)) && (ESSsize_s(:,5) <
pESSmax_1(:,5));
                break;
              end;
            end;
          end;
        end;
      end;
    elseif no_of_ESS == 6;
      if(ESSsize_s(:,1) > pESSmin_1(:,1)) && (ESSsize_s(:,1) < pESSmax_1(:,1));
        if(ESSsize_s(:,2) > pESSmin_1(:,2)) && (ESSsize_s(:,2) < pESSmax_1(:,2));
          if(ESSsize_s(:,3) > pESSmin_1(:,3)) && (ESSsize_s(:,3) < pESSmax_1(:,3));
            if(ESSsize_s(:,4) > pESSmin_1(:,4)) && (ESSsize_s(:,4) < pESSmax_1(:,4));
              if(ESSsize_s(:,5) > pESSmin_1(:,5)) && (ESSsize_s(:,5) <
pESSmax_1(:,5));
                if(ESSsize_s(:,6) > pESSmin_1(:,6)) && (ESSsize_s(:,6) <
pESSmax_1(:,6));
                  break;
                end;
              end;
            end;
          end;
        end;
      end;
    end;
      end;

busdata(ESSlocation_s(1,:),7) = ESSsize_s(:,(1:no_of_ESS))' +
busdata4(ESSlocation_s(1,:),7);
```