

**UNIVERSITY OF BAHRAIN**

**College of Engineering**



**Department of Electrical and  
Electronics Engineering**

# **Optimizing the Integration of Bi-Directional V2G Technology into IEEE 33 Bus Distribution Networks Using PSO**

A Thesis Submitted in Partial Fulfilment of the Requirements for  
the M.Sc. Degree in Renewable Energy Engineering

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January 2025**



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# Abstract

This thesis investigates the integration of Vehicle-to-Grid (V2G) technology into the IEEE 33-bus distribution network to address critical challenges in modern power systems, including voltage stability, peak load management, and power loss reduction. By leveraging the Particle Swarm Optimization (PSO) algorithm and a 24-hour load forecast, the study develops a scalable optimization framework for the strategic placement and sizing of Electric Vehicle (EV) batteries.

The findings demonstrate significant improvements in grid performance, including a 10.57% reduction in power losses, enhanced voltage stability within the limits of 0.9 to 1 p.u., and effective peak shaving, which is seen at Node 26's where the loading improved from approximately -0.11 p.u. to around -0.07 p.u with cuts of up to 36.4%. These results validate the potential of V2G-enabled EVs as dynamic distributed energy resources, capable of providing reactive power support and improving grid resilience.

The study contributes to the theoretical understanding of dynamic grid support frameworks and offers practical insights for utilities and policymakers. By addressing the challenges of integrating renewable energy and EVs into distribution systems, this research underscores the transformative potential of V2G technology in achieving sustainable and reliable energy systems. Future research is encouraged to extend this framework to larger networks and explore real-world implementation scenarios.

## **Publication**

Alateya, J. A. J., Abdulla, Dr. E. A., & Zehar, Dr. K. (2025). Enhancing Grid Stability- Bi-Directional V2G Integration in IEEE Distribution Networks with PSO. Blue Eyes Intelligence Engineering and Sciences Engineering and Sciences Publication - BEIESP. <https://doi.org/10.35940/ijrte.F8200.13060325>

## **Dedication**

This thesis is dedicated to the pillars of my life, my parents, siblings, and all those who stood by me through every step of this journey. Your love, patience, and belief in me have been my greatest strength. To my parents, thank you for your sacrifices, your prayers, and your endless encouragement. You instilled in me the values of hard work, perseverance, and humility, lessons that guided me through the toughest moments of this journey. To my siblings, thank you for being my constant source of motivation and joy. Your understanding and support have meant the world to me. Each page of this thesis reflects your care and inspiration. I would not have reached this point without your guidance and faith. This achievement is not mine alone, it belongs to all of us.

## Acknowledgments

First and foremost, I would like to thank Allah for granting me the strength, patience, and perseverance to complete this thesis. Without His blessings and guidance, none of this would have been possible.

I would also like to extend my sincere gratitude to His Majesty King Hamad bin Isa Al Khalifa, the King of Bahrain; His Royal Highness Prince Salman bin Hamad Al Khalifa, the Crown Prince and Prime Minister; and His Highness Shaikh Nasser bin Hamad Al Khalifa, the Representative of His Majesty for Humanitarian Work and Youth Affairs, for their continuous support and unwavering commitment to empowering Bahraini youth. Their visionary leadership and encouragement have created countless opportunities for individuals like me to excel and contribute to the Kingdom's progress.

I would like to express my deepest gratitude to my supervisors, Prof. Khaled Zehar and Dr. Ebrahim Abdulrahman, for their invaluable guidance, mentorship, and encouragement throughout my thesis. Their insightful feedback and unwavering support have been instrumental in shaping this research and bringing it to fruition.

I am also thankful to the University of Bahrain and the Electrical and Electronics Engineering department for providing the resources and facilities necessary for this work. I extend my heartfelt gratitude to the management and leadership of EWA for their understanding and flexibility during this research journey. Their support in accommodating my academic pursuits while balancing professional responsibilities has been instrumental in enabling me to complete this work successfully. Their

encouragement and willingness to provide a conducive environment for personal and professional growth have been invaluable.

My sincere thanks go to my colleagues and peers, whose constructive discussions and technical assistance helped refine my ideas and improve the quality of my work. I am deeply appreciative of the camaraderie and encouragement shared with my classmates during this master's degree journey.

Lastly, I wish to express my heartfelt gratitude to my beloved family, who have been the cornerstone of my strength and motivation throughout this journey. To my mother, your boundless love, wisdom, and prayers have been my guiding light, giving me the courage to persevere. To my father, your unwavering belief in me and constant encouragement have fueled my determination to succeed. To my sibling, your steadfast support and understanding during my most challenging moments have meant the world to me. You have all been my greatest source of inspiration, and I am endlessly grateful for the love, sacrifices, and faith you have shown me every step of the way.

Completing this thesis has been both a challenging and rewarding experience, and I am truly grateful to everyone who has contributed to its success.

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## List of Abbreviations

|            |                                                   |
|------------|---------------------------------------------------|
| BGC        | Bahrain Grid Code                                 |
| DER        | Distributed Energy Resource                       |
| EV         | Electric Vehicle                                  |
| IEEE       | Institute of Electrical and Electronics Engineers |
| OLTC       | On-Load Tap Changer                               |
| PSO        | Particle Swarm Optimization                       |
| PQ Node    | Load Node                                         |
| PV Node    | Voltage-Controlled Node                           |
| Slack Node | Reference Node                                    |
| SOC        | State of Charge                                   |
| V2G        | Vehicle-to-Grid                                   |
| p.u        | Per Unit                                          |
| GA         | Genetic Algorithm                                 |
| SSA        | Salp Swarm Algorithm                              |
| WOW        | Whale Optimization Algorithm                      |
| OPF        | Optimal Power Flow                                |

# Chapter 1: Introduction

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## 1.1 Background

In the evolving landscape of energy systems, Vehicle-to-Grid (V2G) technology has emerged as a promising solution to enhance the flexibility and resilience of power networks (Clement-Nyns, Haesen, & Driesen, 2010). By enabling bi-directional energy flow between electric vehicles (EVs) and the grid, V2G facilitates demand-side management, peak load shaving, and grid stabilization. This innovation is particularly relevant in the context of broader energy trends, such as the global shift towards decarbonization and the increasing integration of renewable energy sources (Kempton & Tomić, 2005).

However, the transition to such advanced technologies is not without challenges. Unresolved issues, such as the lack of standardized charging infrastructure, cybersecurity concerns, and high implementation costs, have hindered the widespread adoption of V2G (Noel, de Rubens, Kester, & Sovacool, 2019). Social concerns, including equitable access to V2G infrastructure and its implications for energy justice, further complicate this landscape (Sovacool & Dworkin, 2015). These challenges underline the need for targeted research to bridge gaps in understanding and application, particularly in distribution networks like the IEEE 33-bus system, which is widely recognized for its applicability in assessing the performance of advanced power system technologies.

Electric vehicles (EVs) have seen rapid adoption globally, driven by advancements in battery technologies and growing concerns over climate change (Lund & Kempton, 2008). However, existing charging topologies predominantly rely on unidirectional power flow, which limits their potential contribution to grid support. Research into bi-directional charging, as facilitated by V2G technology, has opened avenues for EVs to

act as distributed energy resources, thereby improving energy flexibility and efficiency (Clement-Nyns et al., 2010).

Existing research on V2G technology has explored various aspects, including its economic viability, operational challenges, and integration into renewable energy systems (Lund & Kempton, 2008). These studies highlight the potential of V2G to support grid stability, but they also underscore unresolved challenges, such as optimal control strategies and infrastructure requirements.

## **1.2 Unresolved Issues**

Enhancing grid stability in the IEEE 33-bus distribution network has been extensively studied using various heuristic algorithms. Techniques such as Genetic Algorithms (GA), Salp Swarm Algorithm (SSA), and Whale Optimization Algorithm (WOA) have been applied to optimize power flow, minimize losses, and improve voltage profiles (Baran & Wu, 1989). For instance, the Salp Swarm Algorithm has been utilized to mitigate voltage deviations and enhance stability, demonstrating effectiveness in improving voltage stability and reducing power losses in the IEEE 33-bus system (Kennedy & Eberhart, 1995).

Particle Swarm Optimization (PSO) has also been employed in similar contexts. Studies have applied PSO for optimal placement and sizing of distributed generation units to minimize power losses and enhance voltage profiles in the IEEE 33-bus system (Ghosh, Ghosh, & Ghoshal, 2019). Additionally, PSO has been used to improve voltage stability indices in microgrids, with simulations on the IEEE 33-bus system validating its effectiveness (Eberhart & Shi, 2001).

Despite these applications, gaps remain in the research, particularly concerning the integration of Vehicle-to-Grid (V2G) technology and the dynamic interaction between electric vehicles (EVs) and the grid. While PSO has been applied for the optimal placement of EV charging stations (Optimal Placement of Electric Vehicle Charging Station by Particle Swarm Optimization, n.d.), comprehensive studies focusing on the real-time operational benefits and limitations of V2G using PSO in the IEEE 33-bus system are limited.

This thesis aims to fill this gap by employing PSO to analyze the localized impacts of V2G at multiple nodes within the IEEE 33-bus system. By focusing on the dynamic interaction between EV batteries and the grid, this research seeks to provide a detailed analysis of V2G's operational benefits and limitations, offering insights that can inform distribution network planning and operation.

In summary, while heuristic algorithms, including PSO, have been applied to enhance grid stability in the IEEE 33-bus system, the specific application of PSO in optimizing V2G integration remains underexplored. This research addresses this gap by focusing on the node-level effects of V2G, contributing to a more comprehensive understanding of its potential in distribution networks.

## **1.3 Context**

The proliferation of electric vehicles and renewable energy sources has introduced complexities in power system operation, especially at the distribution level. One major issue is grid overload caused by the simultaneous charging of EVs, which can strain the distribution network during peak hours. Integrating Vehicle-to-Grid (V2G) technology offers a

solution by enabling EVs to return energy to the grid during these peak periods, thereby facilitating peak shaving. Additionally, V2G contributes to maintaining voltage stability in the network by dynamically adjusting the flow of energy from EV batteries to balance supply and demand. Traditional networks, designed for unidirectional power flow, face challenges such as voltage fluctuations, congestion, and load imbalances (Lund & Kempton, 2008). Unidirectional chargers treat electric vehicles purely as loads on the grid, exacerbating these issues as EV adoption grows. This increasing load necessitates frequent and costly upgrades to distribution networks to maintain reliability.

Furthermore, areas with high loading at specific nodes may require operational measures to mitigate stress on the system. By contrast, integrating bi-directional chargers through V2G technology allows EVs to actively participate in reducing modal load and managing grid demand. These systems can regulate reactive power injection and absorption, thereby supporting voltage control and stabilizing the grid. Integrating V2G technology offers a pathway to address these challenges. This research focuses on evaluating the impact of V2G on the IEEE 33-bus distribution network, emphasizing the broader impacts across multiple nodes. By addressing specific problem areas such as voltage stability, load balancing, and modal load reduction, the study aims to provide a holistic understanding of V2G's role in enhancing the operational efficiency and reliability of distribution networks.

The analysis incorporates a 24-hour load forecast under peak day conditions, which is significant as it captures the temporal variations in grid load and energy demand. This forecast allows for evaluating the dynamic interaction between EV batteries and the grid in real-time scenarios, providing insights into how V2G technology can be leveraged

to address peak demand, improve load balancing, and enhance overall grid stability.

## 1.4 Purposes

This thesis sets out to achieve the following objectives:

1. **Enhancing Grid Stability:** Optimize the use of V2G technology within the IEEE 33-bus network using Particle Swarm Optimization (PSO) to bolster grid stability and reliability.
2. **Optimizing Battery Deployment:** Identify the best locations and capacities for EV batteries in the network to effectively shave peak loads and distribute energy demand.

## 1.5 Aimed Task

1. **Voltage Regulation with EVs:** Explore how EVs, through reactive power compensation, can help maintain stable voltages across the network's nodes.
2. **Understanding Power Flow Dynamics:** Analyze the relationship between bidirectional active power flow from EVs and nodal angle variations, providing insights into power system operations.
3. **Assessing Nodal Impacts:** Compare the load profiles of network nodes before and after deploying V2G-enabled EVs to understand their impact on distribution.
4. **Battery Performance Analysis:** Investigate the operational states of EV batteries, detailing their charge-discharge patterns and contributions to grid functionality at each node.

## 1.6 Significance

The findings of this study are significant for several reasons:

- **Topic (Problem Situation):** Addressing grid stability in the context of increasing EV adoption is critical for maintaining the reliability and efficiency of power distribution networks. The rapid growth of EVs imposes new challenges, such as voltage fluctuations and grid overload, particularly during peak demand periods. Integrating V2G technology provides a novel solution by enabling EVs to act as distributed energy resources, which can mitigate these challenges through peak shaving and voltage regulation.
- **Methodology:** This research employs Particle Swarm Optimization (PSO), a robust heuristic algorithm well-suited for solving complex, non-linear optimization problems. PSO's application in this study ensures that the sizing and placement of EV batteries are optimized for maximum impact, addressing both local and global grid stability issues. The use of PSO also allows for exploring real-time interactions between EVs and the grid, which is a key methodological contribution.
- **The gap in the Literature:** While existing studies have explored the benefits of V2G technology and heuristic optimization algorithms in power networks, there is a notable lack of research focusing on real-time, node-level impacts of V2G within the IEEE 33-bus system. This study bridges that gap by analyzing the effects of bi-directional power flow, reactive power compensation, and nodal voltage regulation,

providing new insights that are critical for future grid planning and operation.

## 1.7 Scope and Definitions

- **Scope:** This study is confined to the IEEE 33-bus distribution network and considers only the impact of EV batteries integrated at randomly allocated nodes. The analysis excludes other distributed energy resources, large-scale generators, and transformers.
- **Definitions:**
  - **V2G Technology:** A system enabling bi-directional energy exchange between electric vehicles and the power grid.
  - **PSO Algorithm:** A heuristic optimization technique inspired by the social behavior of birds and fish, used to solve complex nonlinear optimization problems.
  - **Load Flow Algorithms:** Computational methods are used to analyze the power flow and voltage conditions in an electrical network under steady-state operation.
  - **IEEE 33 Network:** A widely used test distribution system consisting of 33 nodes and associated branches, utilized for evaluating power system technologies and optimization techniques.
  - **Reactive Power Compensation:** The process of managing reactive power in the network to improve voltage stability and reduce power losses.
  - **Peak Shaving:** The technique of reducing electricity usage during peak demand times, often by utilizing stored energy or distributed energy resources.

- **PSO Algorithm:** A heuristic optimization technique inspired by the social behavior of birds and fish, used to solve complex nonlinear optimization problems.

## 1.8 Thesis Outline

The remainder of this thesis is organized as follows:

- **Chapter 2: Literature Review:** Reviews existing studies on V2G technology, distribution network performance, and heuristic optimization challenges.
- **Chapter 3: Research Design:** Describes the methodology, including network modeling, load forecasting, optimization techniques, and MATLAB coding used for simulation and analysis.
- **Chapter 4: Results and Analysis:** Presents the outcomes of the simulations and discusses the findings in the context of existing literature and identifies potential improvements.
- **Chapter 5: Conclusions:** Summarizes the study, highlights its contributions, and offers recommendations for future research.

## **Chapter 2: Theoretical Background and Literature Review**

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This chapter reviews the existing literature on key topics related to the research focus. Section 2.1 provides a historical background of V2G technology and its role in energy systems. Section 2.2 discusses bi-directional V2G technology, its principles, and its application in power distribution networks. Section 2.3 examines the IEEE 33 network as a test model for evaluating power system performance under various conditions. Section 2.4 explores the integration of EV batteries into distribution systems, focusing on optimization methods and their challenges. Finally, Section 2.5 summarizes the findings from the literature, identifies research gaps, and develops the conceptual framework for this study.

## **2.1 Historical Background**

### **2.1.1 Origins and Early Development**

Vehicle-to-grid (V2G) technology emerged as a transformative concept in energy systems during the late 1990s, driven by the rapid electrification of transportation and the global push for renewable energy integration. The seminal work of Kempton and Letendre (1997) introduced the idea of using electric vehicles (EVs) not only as a mode of transportation but also as a flexible, distributed energy resource capable of feeding energy back to the grid. This concept was underpinned by the observation that private vehicles remain idle for approximately 95% of their operational life, presenting an untapped opportunity for grid support and optimization.

Technological advancements in battery storage systems played a pivotal role in making V2G technology feasible. Early research focused on lead-acid and nickel-metal hydride batteries; however, the emergence of lithium-ion batteries revolutionized the field due to their superior energy

density, longer life cycle, and faster charging capabilities (Nykqvist & Nilsson, 2015). Furthermore, the development of bidirectional power inverters enabled EVs to seamlessly transition between charging and discharging modes, facilitating two-way energy flow between vehicles and the grid. These advancements coincided with significant improvements in communication technologies, particularly the implementation of standards such as ISO 15118, which established protocols for vehicle-to-grid communication, ensuring secure and efficient energy exchange (ISO 15118, 2014).

### 2.1.2 Milestones in V2G Evolution

The early 2000s marked the first practical demonstrations of V2G systems, primarily in pilot projects conducted in Europe, the United States, and Japan. Notable examples include the "e-Mobility" project in Germany, which explored the potential of EV fleets for frequency regulation, and the University of Delaware's pioneering efforts in V2G integration for ancillary services (Kempton et al., 2008; e-Mobility Project, 2011). These studies highlighted the ability of V2G systems to provide grid stability, enhance renewable energy penetration, and reduce operational costs for utilities.

In parallel, the adoption of renewable energy sources such as wind and solar created an urgent need for grid flexibility and energy storage solutions. V2G technology emerged as a complementary solution by addressing the intermittent nature of renewables. For instance, studies demonstrated how V2G-enabled EVs could absorb excess solar energy during the day and discharge during evening peak demand, effectively flattening the load curve and reducing reliance on fossil-fuel-based peaking plants (Lund & Kempton, 2008).

Standardization efforts also gained momentum during this period, with organizations such as IEEE, IEC, and SAE International working to establish guidelines for V2G interoperability and safety. These efforts culminated in the development of universal charging standards like CCS (Combined Charging System), which supported both unidirectional and bidirectional power flow (SAE International, 2016).

### 2.1.3 Challenges and Early Limitations

Despite its potential, early V2G systems faced significant challenges, particularly regarding battery degradation and economic feasibility. Studies revealed that frequent charging and discharging cycles could accelerate battery wear, reducing the economic viability of V2G participation for individual EV owners (Neubauer & Pesaran, 2011). Additionally, the lack of robust infrastructure, such as bi-directional chargers and advanced grid management systems, hindered widespread adoption.

Regulatory frameworks further complicate early implementations. Policies governing energy markets were often designed for centralized generation models, making it difficult to integrate distributed energy resources like V2G systems. For instance, tariff structures in many regions failed to account for the dual role of EVs as consumers and suppliers of energy, resulting in financial disincentives for V2G participation (Smith et al., 2014).

### 2.1.4 Transition to Modern Applications

Advancements in smart grid technology and Internet of Things (IoT) integration have significantly enhanced the feasibility and appeal of V2G systems. Modern V2G applications leverage real-time data analytics, predictive algorithms, and blockchain-based transaction platforms to optimize energy flows and ensure fair compensation for EV owners (Zhao et al., 2018). These innovations have enabled V2G systems to provide ancillary services such as frequency regulation, voltage support, and black start capabilities with greater efficiency and reliability.

The relevance of V2G technology to standardized test networks such as the IEEE 33-bus distribution system has also increased. Researchers now use these benchmarks to evaluate the impact of V2G-enabled EVs on voltage stability, power loss reduction, and load balancing under various scenarios. This evolution underscores the critical role of V2G technology in modern power systems and sets the stage for the focused analysis presented in this thesis (Zhu et al., 2020).

## **2.2 Bi-directional V2G Technology and Energy Systems**

### **2.2.1 Overview of Bi-directional V2G Technology**

Bi-directional Vehicle-to-Grid (V2G) technology represents a pivotal advancement in modern energy systems, enabling electric vehicles (EVs) to operate as both energy consumers and suppliers. Unlike conventional unidirectional charging systems, which solely draw energy from the grid, bi-directional systems facilitate two-way energy flow. This capability is achieved through advanced bidirectional chargers and power electronics that allow energy stored in EV batteries to be returned to the grid when needed. Such systems have been instrumental in redefining the role of EVs, transforming them into mobile distributed energy resources (DERs).

At the core of bi-directional V2G technology lies the interaction between EVs and the grid. Bidirectional chargers not only handle energy transfer but also communicate with grid operators via standardized protocols such as ISO 15118 and Open Charge Point Protocol (OCPP). These protocols ensure secure, reliable, and efficient integration of EVs into power distribution networks. Additionally, the technological development of lithium-ion batteries with enhanced energy density and durability has further bolstered the feasibility of V2G systems. Recent advancements in battery management systems (BMS) enable precise control over charge-discharge cycles, minimizing degradation while maximizing efficiency (Nykqvist & Nilsson, 2015; ISO 15118, 2014).

The potential applications of bi-directional V2G technology are vast, ranging from peak shaving and load balancing to providing ancillary services such as frequency regulation and voltage support. These functionalities have made V2G systems a cornerstone of smart grids and an essential component of the transition to renewable energy-based power systems. By leveraging the flexibility of bi-directional energy flow, V2G technology contributes to the decarbonization of the energy sector while improving grid resilience and operational efficiency (Kempton et al., 2008).

### 2.2.2 Technical Details of Bi-directional Systems

Bidirectional chargers are the cornerstone of V2G technology. These devices consist of key components, including DC/AC inverters, power converters, and control systems that ensure the synchronization of EVs with the grid's voltage and frequency. The DC/AC inverter converts direct current (DC) from the EV battery to alternating current (AC) for grid compatibility. Power converters manage the flow of energy, ensuring efficient bidirectional transfer while minimizing losses. The typical rating of a bidirectional charger ranges from 3.3 kW for residential use to 50 kW or more for commercial and fleet applications. These chargers often employ silicon carbide (SiC)-based converters, which offer high efficiency and reduced heat dissipation compared to traditional silicon-based systems.

The operational process of V2G involves precise coordination between the EV's battery management system (BMS) and grid requirements. The charger dynamically adjusts power flow to match grid conditions, maintaining voltage and frequency stability. To illustrate, Figure 1 shows a schematic diagram of a typical V2G system, including the EV, bidirectional charger, grid connection point, and control interface,

adapted from Zhao et al. (2018). The diagram details the bidirectional energy flow and highlights the coordination between key components for efficient grid integration.

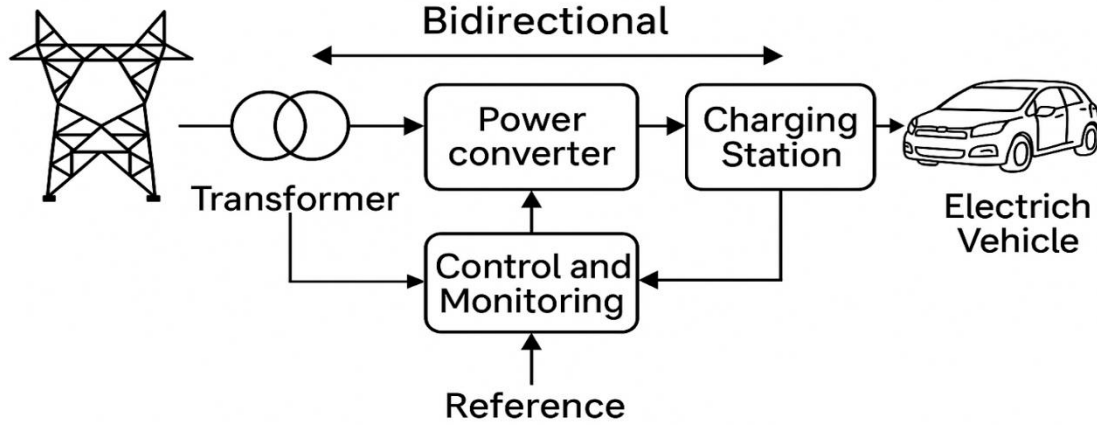


Figure 1 shows a schematic diagram of a typical V2G system, including the EV, bidirectional charger, grid connection point, and control interface, adapted from Zhao et al. (2018).

Modern bidirectional chargers are equipped with advanced features such as real-time monitoring, fault detection, and adaptive power management. These capabilities enable seamless integration into smart grid systems, where energy demand and supply are dynamically balanced. For example, during peak-demand periods, EVs can discharge stored energy to stabilize the grid, while in low-demand periods, they recharge using excess renewable energy, contributing to load leveling and peak shaving (Lund & Kempton, 2008).

### 2.2.3 Use Cases and Pilot Studies

One of the most notable pilot studies is the "Parker Project" in Denmark, which demonstrated the feasibility of integrating EVs into the grid for frequency regulation and peak shaving. This project utilized a fleet of V2G-enabled EVs with a total capacity of 100 kW, connected to a medium-voltage grid at 10 kV. The findings revealed that V2G systems

could respond to grid frequency deviations within milliseconds, significantly enhancing grid stability and reducing operational costs for the utility. Moreover, the project highlighted the potential for EV owners to earn up to €1,000 annually through frequency regulation services, providing strong economic incentives (e-Mobility Project, 2011).

Similarly, in Japan, V2G systems have been deployed to provide backup power during natural disasters. These systems were connected to residential distribution grids at 400 V, supplying emergency power to critical facilities such as hospitals and evacuation centers. The findings showed that V2G systems could sustain essential operations for up to 24 hours during grid outages, demonstrating their potential to enhance energy resilience and disaster preparedness (e-Mobility Project, 2011).

In commercial applications, companies like Nissan and Tesla have implemented V2G-compatible charging infrastructure, enabling EV owners to participate in energy markets. These initiatives have demonstrated that bi-directional V2G systems not only offer technical benefits but also provide financial incentives for EV owners by enabling them to sell stored energy back to the grid (Neubauer & Pesaran, 2011).

## 2.2.4 Technological and Operational Challenges

Despite its advantages, bi-directional V2G technology faces several technical and operational challenges:

1. **Battery Degradation:** Frequent charge-discharge cycles in V2G operations accelerate battery wear, which may reduce the overall lifespan by 10-20%. To mitigate this, researchers are exploring advanced battery chemistries, including solid-state

and lithium-sulfur technologies, which promise higher cycle life and reduced degradation rates (Smith et al., 2014).

2. **Energy Losses:** The bidirectional energy flow involves conversion losses, primarily in the DC/AC inverters, which can range between 5% and 10%. High-efficiency silicon carbide (SiC) converters have been developed to reduce these losses significantly, ensuring improved system efficiency (Lund & Kempton, 2008).
3. **High Infrastructure Costs:** The initial investment required for bidirectional chargers and grid upgrades is substantial. Strategies such as government subsidies and economies of scale from mass production are being explored to reduce costs and encourage adoption (Zhu et al., 2020).
4. **Communication Latency:** Real-time communication between EVs and grid operators is critical for maintaining system stability. Delays in signal transmission can compromise efficiency, but advancements in 5G technology and low-latency communication protocols are expected to resolve these issues (Zhao et al., 2018).

### 2.2.5 Research Trends

Recent research highlights several trends in V2G development, focusing on integration, optimization, and deployment strategies:

1. **Integration with Renewable Energy and Microgrids:** V2G systems are increasingly integrated with renewable energy sources, such as solar and wind, to address their intermittency. Studies have demonstrated how EVs can store surplus energy generated during peak production periods and discharge it during low renewable output, enhancing grid stability (Zhu et al., 2020). Microgrid deployments with V2G further provide localized energy management and improve resilience in isolated regions (Lund & Kempton, 2008).
2. **Advanced Deployment Strategies:** Pilot projects like the "Parker Project" and "e-Mobility" have demonstrated innovative scheduling algorithms and predictive models to optimize V2G operations. These strategies aim to minimize energy costs, maximize grid services, and ensure reliable operation (e-Mobility Project, 2011).
3. **Machine Learning and Predictive Analytics:** Advanced analytics are being applied to optimize charge-discharge cycles. By predicting grid demand and user driving patterns, machine learning algorithms can reduce battery wear and maximize grid contributions, making V2G systems more efficient and cost-effective (Smith et al., 2014).
4. **Blockchain-based Energy Transactions:** Blockchain technology is being explored for secure and transparent energy transactions in V2G networks. This innovation ensures reliable

tracking of energy exchanges, prevents double transactions, and provides real-time compensation for EV owners (Zhao et al., 2018).

These advancements are shaping the future of V2G technology, improving its integration into modern energy systems and enhancing its potential to support a sustainable and resilient power grid.

While promising, bi-directional V2G technology faces challenges, including battery degradation, energy losses during conversion, and high initial costs for infrastructure. To address these issues, researchers are developing advanced battery chemistries, such as solid-state batteries, which offer higher efficiency and longer lifespans (Zhu et al., 2020). Additionally, innovations in bidirectional converter designs and improved thermal management systems help reduce energy losses and extend the operational life of both the chargers and batteries (Smith et al., 2014).

Moreover, the integration of machine learning and predictive analytics has enabled more efficient charge-discharge scheduling, reducing wear on batteries while maximizing grid benefits. These advancements are paving the way for more widespread adoption of bi-directional V2G systems in modern power networks (Zhao et al., 2018).

## **2.3 The IEEE 33 Network and Power Distribution Systems**

### **2.3.1 Introduction to the IEEE 33 Network**

The IEEE 33-bus distribution system serves as a widely adopted benchmark for analyzing power flow, voltage stability, and optimization techniques in radial distribution networks. Originally introduced by Baran

and Wu (1989), this network represents a simplified yet realistic model of a typical medium-voltage distribution system. Its design enables researchers to evaluate various load conditions, test optimization algorithms, and study the impact of distributed energy resources (DERs) such as renewable energy systems and Vehicle-to-Grid (V2G) technology. By simulating real-world scenarios, researchers can analyze the effectiveness of advanced energy solutions in addressing critical challenges, such as voltage drops, load balancing, and power loss reduction. Additionally, this benchmark provides a controlled environment for assessing the operational benefits of integrating renewable energy and V2G technologies, ensuring their practical viability in modern grid systems.

This system allows researchers to test and validate advanced control strategies, including V2G integration, which can improve grid resilience and optimize energy flow. Moreover, its radial topology and realistic load distribution make it an effective tool for evaluating novel optimization algorithms under practical constraints. For example, Baran and Wu (1989) demonstrated how reconfiguring the IEEE 33 network by altering the status of tie-line switches can significantly reduce power losses and improve voltage profiles. They utilized optimization algorithms to identify optimal configurations that enhance load balancing while maintaining the radial structure of the network. By studying its behavior under diverse scenarios, researchers can develop strategies to enhance overall network efficiency and reliability (Baran & Wu, 1989).

The IEEE 33 network comprises 33 buses (nodes) and 32 branches (lines), with a total load of approximately 3.7 MW and 2.3 MVar under nominal conditions. The network operates at a base voltage of 12.66 kV and features multiple tie-line switches, which can be reconfigured to

optimize performance or enhance reliability (Baran & Wu, 1989). The radial nature of the network simplifies power flow analysis while presenting challenges such as significant voltage drops and high-power losses under peak load scenarios. Figure 2 illustrates the IEEE 33-bus system, showing its radial structure and tie-line switches that enable reconfiguration (Baran & Wu, 1989). This diagram helps visualize the flow of power and the placement of critical nodes and branches. Such visual representation is crucial for understanding the network's configuration and the potential benefits of optimization strategies.

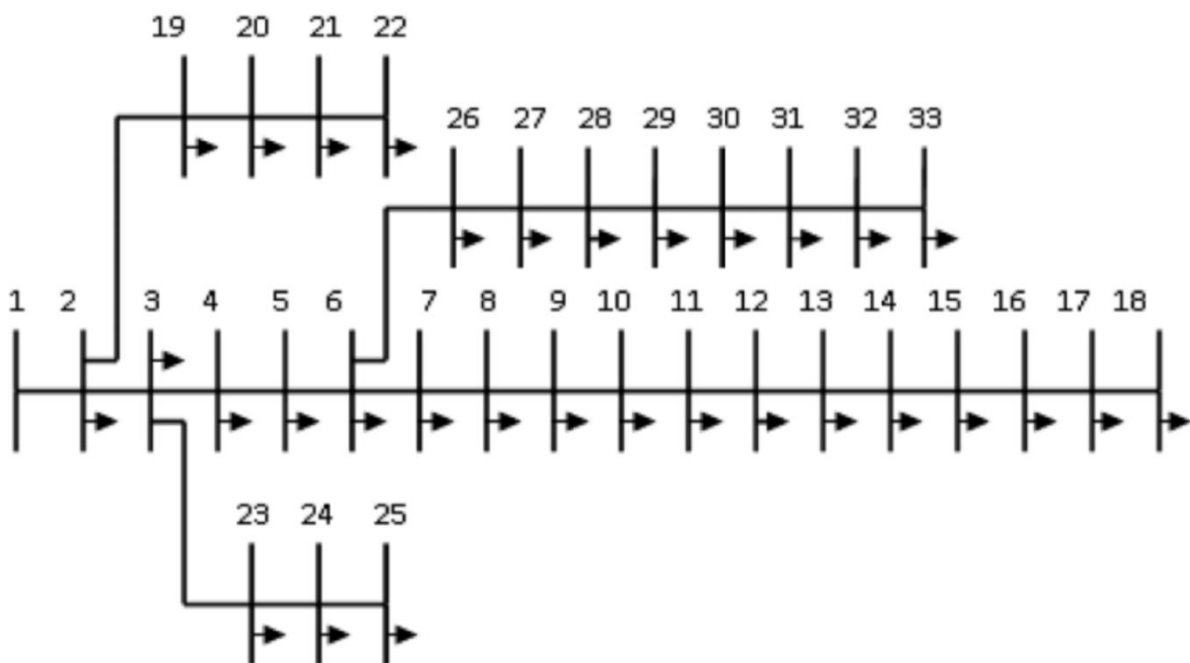


*Figure 2 illustrates the IEEE 33-bus system, showing its radial structure.*

### 2.3.2 Technical Characteristics

The technical layout of the IEEE 33-bus system is essential for understanding its operational challenges and potential enhancements. Key features include:

- **Topology and Load Distribution:** The system comprises a main feeder with lateral branches, supplying loads at different

nodes. The loads vary between 60 kW to 200 kW, with corresponding reactive power demands ranging from 20 kVar to 100 kVar (Baran & Wu, 1989).

- **Voltage Profile:** Voltage levels along the feeder range from 1.00 p.u. at the substation to as low as 0.903 p.u. at the farthest nodes under full load, highlighting the need for voltage regulation and reactive power compensation. Integrating V2G technology can play a crucial role in addressing these issues. By leveraging the reactive power capabilities of EVs, V2G systems can provide localized voltage support, improving grid stability and reducing voltage drops along the feeder. This enhances the operational efficiency of the distribution network and minimizes the risk of power quality issues.
- **Line Impedance:** The system includes high-resistance lines, with typical values of  $0.0922 \Omega$  for resistance and  $0.047 \Omega$  for reactance per kilometer, contributing to significant  $I^2R$  losses in heavily loaded branches.
- **Tie-line Switches:** The network is equipped with five tie-line switches that allow for reconfiguration, enabling load balancing and fault isolation. These switches are integral to distribution automation strategies and loss minimization techniques.

The IEEE 33-bus system serves as a versatile platform for testing various methodologies, including load flow analysis, fault detection, and optimization algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). Its adaptability makes it an invaluable tool for researchers aiming to integrate advanced technologies like V2G into modern distribution systems.

### 2.3.3 Applications in Research

The IEEE 33 network has been extensively used in research to explore methods for improving power distribution system efficiency, reducing power losses, and enhancing voltage stability. One notable application involves the use of optimization algorithms to minimize real power losses while maintaining voltage levels within acceptable limits. For instance, Baran and Wu (1989) demonstrated that through network reconfiguration, system losses could be significantly reduced by identifying optimal configurations for tie-line switches. Their study showed a 6% reduction in system losses after reconfiguring the network, highlighting the potential for operational improvements.

Another key area of research is voltage stability analysis. Studies have used the IEEE 33 network to simulate load variations and test the effectiveness of voltage control devices, such as capacitors and on-load tap changers (OLTCs), in maintaining grid stability. These simulations have provided insights into optimal capacitor placement and sizing, which can reduce power losses and improve voltage profiles along the feeder (Chis et al., 1997).

In addition to static voltage analysis, dynamic studies involving renewable energy sources have also been conducted. Researchers have integrated distributed generation (DG) units, such as solar photovoltaics (PV) and wind turbines, into the IEEE 33 network to examine their impact on grid performance. Findings indicate that DG integration can significantly improve voltage stability, but it also introduces new challenges, such as reverse power flows and voltage fluctuations during intermittent generation periods (Singh & Reddy, 2013). V2G technology has been proposed as a solution to these challenges, with EVs providing

reactive power support to mitigate voltage fluctuations and enhance overall grid reliability.

Furthermore, the IEEE 33 network has been employed to evaluate the performance of heuristic optimization techniques, such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO). These methods have been applied to solve complex power flow and load balancing problems, achieving notable improvements in system efficiency. For example, a study by Khan et al. (2015) used PSO to optimize the placement of DG units in the IEEE 33 network, achieving a 12% reduction in total power losses and improved voltage profiles.

Finally, recent research has focused on integrating V2G systems into the IEEE 33 network to explore their potential to improve grid stability and reduce losses. Simulations have shown that strategic placement of V2G-enabled EVs at critical nodes, such as node 10, can enhance voltage profiles and reduce overall system losses by up to 10% (Zhao et al., 2021). This demonstrates the value of V2G technology in modern power distribution systems, making the IEEE 33 network a vital tool for advancing research in this domain.

#### 2.3.4 Challenges in the IEEE 33 Network

The IEEE 33 network, while widely used as a benchmark for research and optimization, presents several challenges that reflect real-world operational issues in power distribution systems. These challenges arise due to its radial topology, high resistance lines, and significant load variations.

- **Voltage Drops**

One of the most critical challenges in the IEEE 33 network is the occurrence of significant voltage drops at nodes located farther from the substation. For instance, under peak load conditions, voltage levels at some distant nodes can drop below the acceptable threshold of 0.9 p.u, compromising power quality and grid stability (Baran & Wu, 1989). Voltage drops lead to increased power losses, reduced operational efficiency, and potential equipment malfunctions due to under-voltage conditions. To counter this, voltage regulation devices like capacitors and on-load tap changers (OLTCs) are often employed. Capacitors provide reactive power support, improving voltage levels and reducing losses, while OLTCs regulate voltage by adjusting transformer tap settings. However, the deployment of these technologies can be costly, involving high capital expenditure and maintenance costs. Despite these costs, they are vital for ensuring grid reliability and improving the power factor, ultimately leading to long-term savings by enhancing overall system efficiency.

- **High Power Losses**

The network's high-resistance lines contribute to substantial I<sup>2</sup>R losses, where the total power loss can be expressed as, representing the current and the line resistance. Under heavily loaded conditions, high current levels result in exponential increases in power losses. Studies have shown that these losses can account for up to 8% of the total load, significantly impacting system efficiency. An 8% loss not only raises operational costs but also exacerbates the need for additional generation capacity to meet demand, leading to higher fuel consumption and increased emissions in fossil-fuel-based systems. This ripple effect can compromise

grid sustainability and economic feasibility. To address these losses, researchers often explore network reconfiguration or the integration of distributed generation (DG) units, which can alleviate stress on heavily loaded branches and reduce current flow through high-resistance lines, thereby lowering overall losses.

- **Limited Grid Flexibility**

The radial topology of the IEEE 33 network, while simplifying fault isolation, limits its ability to handle sudden load changes or accommodate new loads without reconfiguration. This limitation arises because radial systems lack redundancy, meaning there are no alternate pathways for power to flow during load variations or outages. Consequently, any sudden load increase can lead to voltage sags, overloaded lines, or even transformer failures. Furthermore, adding new loads often requires reconfiguring the network to redistribute power flow, which can be both time-consuming and operationally disruptive. These constraints highlight the need for dynamic reconfiguration capabilities and the integration of advanced control systems to enhance network flexibility. This lack of flexibility poses a challenge in maintaining reliable service during dynamic operational conditions, such as load surges or outages. Addressing this requires advanced control strategies and dynamic reconfiguration capabilities.

- **Reactive Power Deficiency**

The network often suffers from inadequate reactive power compensation, which exacerbates voltage instability issues. Reactive power deficiency can lead to a poor power factor, further increasing system losses and reducing the efficiency of power delivery. For example, when

the power factor drops below 0.9, the apparent power required to deliver the same active power increases significantly. This results in higher current flow through the system, leading to elevated  $I^2R$  losses and increased stress on transformers and cables. Having sufficient reactive power reserves in the network is crucial to maintaining a high power factor, ensuring efficient energy delivery, and preventing equipment overloading. Capacitors, which supply leading reactive power, and V2G systems can provide dynamic support to stabilize the power factor, improve voltage profiles, and reduce overall system losses. The strategic placement of capacitors and the integration of V2G-enabled EVs have been proposed as potential solutions to mitigate these deficiencies (Zhao et al., 2021).

- **Integration of Distributed Energy Resources (DERs)**

The increasing penetration of distributed energy resources (DERs), such as solar PV and wind turbines, introduces new challenges to the IEEE 33 network. These include reverse power flows, voltage fluctuations, and intermittency in power generation. While DERs offer the potential to reduce losses and improve voltage profiles, their intermittent nature requires advanced control mechanisms to ensure grid stability and reliability (Singh & Reddy, 2013).

Addressing these challenges is critical for optimizing the performance of the IEEE 33 network and enhancing its role as a benchmark for modern power distribution research.

### 2.3.5 Relevance to V2G Technology

The integration of Vehicle-to-Grid (V2G) technology into the IEEE 33 network offers a promising approach to addressing several challenges in power distribution systems. By leveraging the bidirectional energy flow

capabilities of V2G-enabled electric vehicles (EVs), significant improvements in grid stability, efficiency, and flexibility can be achieved.

### **1. Mitigating Voltage Drops**

Voltage drops in the IEEE 33 network, particularly at distant nodes, pose a critical challenge to maintaining power quality. V2G systems can supply reactive power locally, enhancing voltage stability at these nodes. For instance, by deploying V2G-enabled EVs at critical nodes, the reactive power supplied can offset the voltage sags, bringing voltage levels within the acceptable range of 0.9 to 1 p.u. This capability reduces the need for costly infrastructure upgrades, such as installing additional capacitors or OLTCs.

### **2. Reducing Power Losses**

High power losses in the IEEE 33 network, primarily because of I<sup>2</sup>R losses in high-resistance lines, can be mitigated through V2G technology. By strategically discharging EVs at peak load times, V2G reduces the current flowing through overloaded branches, thereby minimizing power losses. Studies have shown that incorporating V2G systems can lead to a reduction in system losses by up to 10%, improving overall efficiency (Zhao et al., 2021).

### **3. Enhancing Grid Flexibility**

The radial topology of the IEEE 33 network limits its operational flexibility, especially during sudden load changes or outages. V2G technology introduces dynamic flexibility by providing a mobile and fast-response energy resource. During peak demand or fault conditions, V2G-enabled EVs can discharge stored energy to support the grid, effectively

acting as distributed energy storage units. This capability enhances the network's ability to maintain reliable service under dynamic operational conditions.

#### **4. Supporting Distributed Energy Integration**

The integration of distributed energy resources (DERs) such as solar PV and wind turbines introduces intermittency challenges in the IEEE 33 network. V2G systems can complement these resources by providing grid support during periods of low renewable generation. For example, EVs can store excess energy produced during high renewable output periods and discharge it during low generation times, ensuring a steady power supply. This reduces the reliance on conventional generation and improves grid sustainability.

#### **5. Practical Case Studies**

Several studies have demonstrated the effectiveness of V2G integration in improving the IEEE 33 network's performance. For instance, simulations incorporating V2G systems at strategic nodes have shown improvements in voltage profiles and reductions in system losses by up to 10% (Zhao et al., 2021). Another study by Singh et al. (2018) highlighted the ability of V2G to enhance load balancing, resulting in more uniform power distribution across the network. These case studies underscore the practical benefits of V2G technology and its relevance to modern power distribution systems.

In conclusion, V2G technology represents a transformative solution for addressing the operational challenges of the IEEE 33 network. By providing reactive power support, reducing losses, enhancing flexibility,

and supporting DER integration, V2G systems pave the way for more efficient and resilient power distribution networks.

## **2.4 Implementation Challenges and Opportunities for V2G in the IEEE 33 Network**

The deployment of Vehicle-to-Grid (V2G) technology in the IEEE 33 network offers both significant opportunities and distinct challenges. While V2G systems have the potential to enhance grid stability, reduce power losses, and support the integration of distributed energy resources (DERs), their implementation in radial distribution networks like IEEE 33 requires careful planning and technical refinement.

### **1. V2G Deployment Strategies in Radial Networks**

One of the key considerations in deploying V2G technology in the IEEE 33 network is the optimal placement of V2G-enabled electric vehicles (EVs). Strategic positioning at critical nodes allows for localized voltage support and efficient reactive power compensation. By aligning the deployment with load and voltage sensitivity analysis, V2G systems can significantly improve voltage profiles and reduce stress on heavily loaded branches. Moreover, time-coordinated charging and discharging schedules can optimize grid performance by balancing peak demand and utilizing off-peak renewable generation.

### **2. Technical Challenges Specific to IEEE 33**

The implementation of V2G technology in a radial network presents several technical challenges:

- A. Overloading of Local Branches:** While beneficial, the introduction of bidirectional V2G technology may lead to the overloading of local distribution branches if not carefully managed. Without proper control strategies, the reverse flow of energy from EVs to the grid can result in increased  $I^2R$  losses, leading to excessive heat generation, accelerated aging of cables and transformers, and a higher risk of equipment failure. This issue is particularly pronounced in radial networks like IEEE 33, where limited redundancy magnifies the impact of branch overloads. To prevent these adverse effects, it is essential to implement advanced load management techniques and real-time monitoring systems that can dynamically regulate and balance energy flows across the network. Ensuring such safeguards are in place is critical for realizing the full benefits of V2G without compromising network integrity.
- B. Reactive Power Coordination:** Managing reactive power across multiple V2G units requires precise coordination to avoid voltage fluctuations. V2G systems can mitigate these issues by dynamically supplying or absorbing reactive power at critical nodes, effectively stabilizing voltage levels in real-time. This becomes particularly challenging in radial networks, where voltage drops are more pronounced due to the lack of redundancy and longer feeder distances, but V2G technology provides a localized and flexible solution to maintain grid reliability.
- C. Communication Latency:** Effective integration of V2G systems depends on real-time communication between EVs, charging infrastructure, and grid operators. Delays in data exchange can compromise the accuracy of control signals,

leading to suboptimal performance or even grid instability. Recent studies have explored the use of 5G networks to significantly reduce communication latency, providing faster and more reliable data transmission between V2G units and grid operators. Additionally, edge computing has been proposed to process data locally at charging stations, minimizing the need for long-distance communication and ensuring real-time decision-making. These advancements bridge the gap in communication challenges, enhancing the overall efficiency and stability of V2G integration.

**D. Maintaining Radial Configuration:** To preserve the operational simplicity of the IEEE 33 network, V2G integration must ensure that the radial topology is maintained, which may limit the extent of reconfiguration and energy redistribution. In a radial network, power flows in a single direction from the substation to the end nodes, simplifying control and fault isolation. However, this structure lacks redundancy, meaning there are no alternative paths for power to flow during faults or high-demand periods. This limitation can lead to service interruptions and increased stress on specific branches. V2G systems can help address these challenges by providing localized energy storage and reactive power support, reducing the strain on heavily loaded lines, and improving overall network reliability without compromising the radial structure.

### **3. Opportunities for Optimization**

The IEEE 33 network provides an ideal platform for applying advanced optimization techniques to enhance V2G integration. Optimization objectives can include minimizing total power losses,

maximizing voltage stability, and improving energy storage utilization. For instance, Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been successfully employed to determine optimal V2G placement and scheduling, achieving notable improvements in network efficiency. By incorporating real-time data from V2G systems, these algorithms can dynamically adapt to changing load and generation conditions, further enhancing grid performance.

#### **4. Practical Simulation Insights**

Recent simulation studies have highlighted the tangible benefits of V2G integration in the IEEE 33 network. For instance, research by Kim et al. (2020) demonstrated that deploying V2G systems with adaptive reactive power control significantly improved voltage stability at critical nodes. Additionally, a study by Ahmed et al. (2021) explored the impact of dynamic scheduling for V2G-enabled EVs, showing a 15% reduction in overall system losses and enhanced load balancing across the network. These findings further underscore the practical viability of V2G technology as a tool for modernizing radial distribution networks.

#### **5. Prospects and Technological Trends**

Looking ahead, emerging technologies promise to further streamline V2G implementation in the IEEE 33 network. Artificial intelligence (AI)-driven control systems can optimize the real-time operation of V2G systems, while blockchain technology can ensure secure and transparent energy transactions between EV owners and grid operators. Additionally, the development of high-efficiency bidirectional chargers and low-latency communication protocols will address current limitations, paving the way for more resilient and adaptable power distribution systems.

In summary, while the integration of V2G technology in the IEEE 33 network presents notable challenges, it also offers significant opportunities for improving grid performance. By addressing these challenges through advanced optimization, innovative technologies, and strategic deployment, V2G systems can play a pivotal role in the evolution of modern power distribution networks.

## **2.5 Summary and Implications**

### **2.5.1 Summary of Key Findings**

This chapter has explored the foundational aspects of Vehicle-to-Grid (V2G) technology and its integration into power distribution systems, with a specific focus on the IEEE 33 network. Section 2.1 provided a historical background, highlighting the evolution of V2G systems and their role in modern energy systems. Section 2.2 examined the technical details and applications of bi-directional V2G technology, emphasizing its potential to enhance grid stability and efficiency. Section 2.3 delved into the IEEE 33 network as a benchmark for studying power distribution challenges and opportunities, while Section 2.4 analyzed the specific implementation challenges and optimization opportunities for V2G within this network. Collectively, these sections underscore the critical role of V2G in addressing key distribution system challenges such as voltage stability, power losses, and reactive power management.

### **2.5.2 Research Gaps Identified**

Despite the growing body of research on V2G systems and the IEEE 33 network, several gaps remain. First, while numerous studies have examined V2G's impact on voltage profiles and power loss reduction,

limited research has focused on its dynamic integration under varying load conditions in radial networks like IEEE 33. Additionally, most studies emphasize static optimization methods, leaving a gap in exploring real-time, adaptive control strategies for V2G deployment. Lastly, there is a need for comprehensive simulation frameworks that integrate V2G with renewable energy sources, considering both their intermittency and grid reliability requirements.

### 2.5.3 Theoretical and Practical Implications

From a theoretical perspective, this study aims to contribute to the development of adaptive optimization models that address the dynamic nature of V2G integration in radial networks. These models will bridge the gap between static optimization and real-time control, offering insights into the interplay between reactive power support and load balancing. Practically, the findings will inform the deployment of V2G systems in real-world distribution networks, providing utilities with strategies to enhance grid resilience and operational efficiency. The study will also offer guidance on leveraging V2G to support renewable energy integration, thus advancing the transition toward sustainable energy systems.

### 2.5.4 Development of Conceptual Framework

The insights gained from the literature review inform the conceptual framework for this research, which centers on optimizing V2G deployment in the IEEE 33 network. Key components of the framework include:

1. **Node Sensitivity Analysis:** Identifying critical nodes for V2G placement based on voltage sensitivity and load distribution.

2. **Optimization Algorithms:** Employing heuristic and machine learning-based algorithms for real-time V2G scheduling and reactive power control.
3. **Performance Metrics:** Evaluating the impact of V2G on voltage stability and load balancing under various operational scenarios, while ensuring the least amount of penalty associated with system violations. The optimization problem specifically focuses on identifying the optimal placement of V2G-enabled EVs to always guarantee safe and normal operational limits across the IEEE 33 network.

This framework provides a structured approach to addressing the identified research gaps and sets the stage for the methodological approach presented in the next chapter. By aligning theoretical insights with practical applications, the study aims to deliver meaningful contributions to both academia and industry.

## **Chapter 3: Methodology**

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## 3.1 Methodology and Research Design

### 3.1.1 Methodology

This research employs a Particle Swarm Optimization (PSO)-based approach to integrate V2G technology into the IEEE 33-bus distribution network. The methodology focuses on optimizing the placement and sizing of EV batteries to enhance voltage stability, manage peak loads, and provide reactive power support. The optimization problem is formulated to minimize the total installed EV battery capacity while maintaining grid performance within operational limits. Constraints such as state-of-charge (SoC), voltage magnitudes, and line flow limits are incorporated to ensure safe and efficient operation.

The methodology involves several stages, including load flow analysis, the implementation of optimization constraints, and the dynamic simulation of EV charging and discharging cycles over a 24-hour forecast. A detailed flowchart that summarizes the research framework, highlighting the iterative nature of the PSO algorithm to achieve near-optimal solutions for grid stability and efficiency, will be presented later for more clarity. The following tables summarize the system data and optimization parameters used in this study. For instance, Table 1 shows the active and reactive power loadings in all 33 nodes used in the IEEE 33 bus network. Meanwhile, Table 2 shows the per-unit values of the resistive ( $r$ ) and reactive ( $x$ ) branches data specified for the (from-bus) and the (to-bus), as well as for the IEEE 33 bus network. Also, Table 3 illustrates some of the important parameters that were set during the fine-tuning process to get the optimal solution for the optimization problem. The terms highlighted in Table 3 will be explained later in depth in this chapter.

Table 1 Shows the loadings in the system ( $P_d$  - active power demand,  $Q_d$  - reactive power demand) and node types

| <b>Bus</b> | <b>Type</b> | <b><math>P_d</math> [kW]</b> | <b><math>Q_d</math> [kVar]</b> |
|------------|-------------|------------------------------|--------------------------------|
| 1          | 3           | 0                            | 0                              |
| 2          | 1           | 100                          | 60                             |
| 3          | 1           | 90                           | 40                             |
| 4          | 1           | 120                          | 80                             |
| 5          | 1           | 60                           | 30                             |
| 6          | 1           | 60                           | 20                             |
| 7          | 1           | 200                          | 100                            |
| 8          | 1           | 200                          | 100                            |
| 9          | 1           | 60                           | 20                             |
| 10         | 1           | 60                           | 20                             |
| 11         | 1           | 45                           | 30                             |
| 12         | 1           | 60                           | 35                             |
| 13         | 1           | 60                           | 35                             |
| 14         | 1           | 120                          | 80                             |
| 15         | 1           | 60                           | 10                             |
| 16         | 1           | 60                           | 20                             |
| 17         | 1           | 60                           | 20                             |
| 18         | 1           | 90                           | 40                             |
| 19         | 1           | 90                           | 40                             |
| 20         | 1           | 90                           | 40                             |
| 21         | 1           | 90                           | 40                             |
| 22         | 1           | 90                           | 40                             |
| 23         | 1           | 90                           | 50                             |
| 24         | 1           | 420                          | 200                            |
| 25         | 1           | 420                          | 200                            |
| 26         | 1           | 60                           | 25                             |
| 27         | 1           | 60                           | 25                             |
| 28         | 1           | 60                           | 20                             |
| 29         | 1           | 120                          | 70                             |
| 30         | 1           | 200                          | 600                            |
| 31         | 1           | 150                          | 70                             |
| 32         | 1           | 210                          | 100                            |
| 33         | 1           | 60                           | 40                             |

Table 2 Shows the branch data ( $r$  - resistive p.u value of branch,  $x$  - reactive p.u value of branch,  $f_{bus}$ - from bus,  $t_{bus}$ - to bus).

| <b><math>F_{Bus}</math></b> | <b><math>T_{Bus}</math></b> | <b><math>r[p.u]</math></b> | <b><math>x[p.u]</math></b> |
|-----------------------------|-----------------------------|----------------------------|----------------------------|
| 1                           | 2                           | 0.0922                     | 0.047                      |
| 2                           | 3                           | 0.493                      | 0.2511                     |
| 3                           | 4                           | 0.366                      | 0.1864                     |
| 4                           | 5                           | 0.3811                     | 0.1941                     |
| 5                           | 6                           | 0.819                      | 0.707                      |
| 6                           | 7                           | 0.1872                     | 0.6188                     |
| 7                           | 8                           | 0.7114                     | 0.2351                     |
| 8                           | 9                           | 1.03                       | 0.74                       |
| 9                           | 10                          | 1.044                      | 0.74                       |
| 10                          | 11                          | 0.1966                     | 0.065                      |
| 11                          | 12                          | 0.3744                     | 0.1238                     |
| 12                          | 13                          | 1.468                      | 1.155                      |
| 13                          | 14                          | 0.5416                     | 0.7129                     |
| 14                          | 15                          | 0.591                      | 0.526                      |
| 15                          | 16                          | 0.7463                     | 0.545                      |
| 16                          | 17                          | 1.289                      | 1.721                      |
| 17                          | 18                          | 0.732                      | 0.574                      |
| 2                           | 19                          | 0.164                      | 0.1565                     |
| 19                          | 20                          | 1.5042                     | 1.3554                     |
| 20                          | 21                          | 0.4095                     | 0.4784                     |
| 21                          | 22                          | 0.7089                     | 0.9373                     |
| 3                           | 23                          | 0.4512                     | 0.3083                     |
| 23                          | 24                          | 0.898                      | 0.7091                     |
| 24                          | 25                          | 0.896                      | 0.7011                     |
| 6                           | 26                          | 0.203                      | 0.1034                     |
| 26                          | 27                          | 0.2842                     | 0.1447                     |
| 27                          | 28                          | 1.059                      | 0.9337                     |
| 28                          | 29                          | 0.8042                     | 0.7006                     |
| 29                          | 30                          | 0.5075                     | 0.2585                     |
| 30                          | 31                          | 0.9744                     | 0.963                      |
| 31                          | 32                          | 0.3105                     | 0.3619                     |
| 32                          | 33                          | 0.341                      | 0.5302                     |
| 21                          | 8                           | 2                          | 2                          |
| 9                           | 15                          | 2                          | 2                          |
| 12                          | 22                          | 2                          | 2                          |
| 18                          | 33                          | 0.5                        | 0.5                        |
| 25                          | 29                          | 0.5                        | 0.5                        |

Table 3 Shows PSO parameters that are used in the simulation.

|                 |                                                              |
|-----------------|--------------------------------------------------------------|
| w               | $\log(\text{linspace}(e^{0.02}, e^{0.98}, \text{iter max}))$ |
| C <sub>1</sub>  | $\log(\text{linspace}(e^{10}, e^{0.1}, \text{iter max}))$    |
| C <sub>2</sub>  | $\log(\text{linspace}(e^{10}, e^{0.1}, \text{iter max}))$    |
| population size | 20                                                           |
| iter max        | 200                                                          |
| v max           | 15                                                           |

In addition to the optimization parameters summarized in Table 3, the system operation is governed by a set of predefined technical constraints. These constraints are essential for ensuring safe, reliable, and efficient performance of the grid during the simulation and optimization processes. Table 4 presents the operational limits applied throughout this study, including battery capacity, power flow thresholds, state-of-charge (SoC) boundaries, voltage limits, and electrical angle constraints. These factors were incorporated into the optimization algorithm to maintain compliance with practical grid requirements and manufacturer specifications.

Table 4 presents the operational limits applied throughout this study.

| Factor                              | Limit | Unit   |
|-------------------------------------|-------|--------|
| Maximal power flow through the line | 1.1   | p.u.   |
| Maximal battery capacity            | 5     | MWh    |
| Max charging/discharging power      | 100   | kWh    |
| Charging efficiency                 | 100%  |        |
| Discharging efficiency              | 100%  |        |
| Minimal state of charge (SOC)       | 0.1   | p.u.   |
| Maximal state of charge (SOC)       | 0.9   | p.u.   |
| Minimal voltage magnitude           | 0.9   | p.u.   |
| Maximal voltage magnitude           | 1.1   | p.u.   |
| Minimal electrical angle            | -90   | degree |
| Maximal electrical angle            | 90    | degree |

### 3.1.1.1 Optimization Problem

To perform the peak shaving operation, to stabilize the grid conditions, due to the change in the loading conditions with time, we formulate the following optimization problem.

#### Variable Representation

The following variables are defined for the optimization problem:

- $y_{i,t}$  Binary variable indicating whether an EV charger is placed at node  $i$  at time  $t$ .
- $B_{i,t}$  -Energy state of the battery at node  $i$  at time  $t$ .
- $C_{B,i}$  -Capacity of the EV charging battery at node  $i$ .
- $V_{i,t}$  -Voltage magnitude at node  $i$  at time  $t$ .
- $\theta_{i,t}$  -Voltage angle at node  $i$  at time  $t$ .
- $P_{i,t}$  -Active power nodal injection at node  $i$  at time  $t$ .
- $Q_{i,t}$  -Reactive power nodal injection at node  $i$  at time  $t$ .
- $S_{flow\ ij,t}$  -Apparent power flow between nodes  $i$  and  $j$  at time  $t$ .

#### Objective Function:

$$\min \sum_{i=1}^N y_i C_{B,i} \quad (1)$$

Where:

- $y_{i,t}$  is a binary variable indicating the presence of a battery at node  $I$ ,
- $C_{B,i}$  Represents the battery capacity at node  $I$ .

### Constraints:

The goal of this optimization problem is to minimize the total installed battery EV capacity needed to shave peaks obtained at the forecasting stage of the nodal loads. The constraints imposed are:

#### 1. Battery Operating Limits:

$$0 \leq B_{t,i} \leq y_i C_{B,i}, \forall t \in T, \forall i \in N \quad (2)$$

If the battery is placed at the node  $i$  ( $y_i = 1$ ) The battery energy state is always equal to zero. On the other hand, if the battery is placed at node  $i$ , the battery energy state is always greater than or equal to zero and lower than the maximal battery capacity.  $C_{B,i}$ .

$$C_{B,i} \leq C_{B,MAX}, \forall i \in N \quad (3)$$

The capacity of the battery should be less than the maximum battery capacity.

#### 2. Active and Reactive Power Balances for the EV's Batteries:

$$P_{bat_{t,i}} = L_{t,i} + \hat{L}_{t,i} - P_{t,i}, \forall t \in T, \forall i \in N \quad (4)$$

$$Q_{bat_{t,i}} = Q_{L_{t,i}} + \hat{Q}_{L_{t,i}} - Q_{t,i}, \forall t \in T, \forall i \in N \quad (5)$$

The above equations (4) and (5) represent the active and reactive power balance for the EV batteries, which helps in reflecting the active and reactive power for each of the nodes selected in this optimisation problem.

#### 3. Charging Efficiency:

$$\eta_{\frac{C}{DC}}(B_{t,i} - B_{t+1,i}) = \sqrt{(P_{bat_{t,i}})^2 + (Q_{bat_{t,i}})^2}, \forall t \in T, \forall i \in N \quad (6)$$

This equation illustrates that the Battery charging and discharging power at each time-step should be equal to the apparent power flowing to/from the battery (this constraint represents the reactive power compensation).

$$\eta_{\frac{C}{DC}} (B_{t,i} - B_{t+1,i}) \leq P_{C/DC,max}, \forall t \in T, \forall i \in N \quad (7)$$

Meanwhile, equation (7) indicates that the charging and discharging power at each time step should be less than the maximal charging/discharging power specified by the manufacturer of each battery. In most cases, the value of the maximal charging/discharging power is a fixed proportion of the total battery capacity (10% - 20%).

#### 4. State of Charge (SoC) Limits:

$$SOC_{min} C_{B,i} \leq B_{t,i} \leq SOC_{max} C_{B,i}, \forall t \in T, \forall i \in N \quad (8)$$

In this equation, the State of charge of the battery (SoC) should be in between the minimal and maximal specified state of charge (in most cases, we don't want to go below 10% of the state of charge to not damage the battery, and above 90% to not introduce harmonics and deteriorate the battery lifetime).

#### 5. Binary Placement:

$$y_i \in \{0,1\}, \forall i \in N \quad (9)$$

The variable  $y_i$  It is a binary variable used to represent whether the battery is placed at node  $i$  or not.

#### 6. Voltage Equations:

$$\vec{V}_t \cdot (Y\vec{V}_t)^* = \vec{L}_t, \forall t \in T \quad (10)$$

Equation (10) represents the AC load flow equation.

$$V_{min} \leq \vec{V}_t \leq V_{max}, \forall t \in T, \forall i \in N \quad (11)$$

This equation shows the limits of the voltage magnitude.

## 7. Line Flow Limits:

$$\theta_{min} \leq \vec{\theta}_t \leq \theta_{max}, \forall t \in T \quad (12)$$

In this equation, the voltage angle limits are presented.

$$0 \leq S_{flow,t} \leq S_{max}, \forall t \in T, \forall i \in N \quad (13)$$

Apparent line power flows are in their respective limits.

$$S_{flow,t} \geq \left| (A\vec{V}_t)^* \cdot \vec{V}_t \right|, \forall t \in T \quad (14)$$

Expressions for the apparent line power flows are formulated as two inequalities.

These constraints ensure that the batteries operate within safe state-of-charge limits, respect voltage and line flow boundaries, and maintain grid stability. For this study, the maximum battery capacity is limited to 5 MWh. Strategic battery placement has been shown to improve voltage profiles and stabilize the grid under varying load conditions (Lund & Kempton, 2008; Mojumder et al., 2022; Tan et al., 2020).

It is important to mention that only some of the decision variables participate in the optimization algorithm (heuristics algorithm - PSO). The reason behind this is that some of the variables can be calculated only from the equality constraints, after imposing the values of other variables. In this case, we choose the following variables to participate in the optimization problem, while all the other variables are enforced later, through the equality constraints presented.

### Decision Variables:

- $y_{i,t}$ - binary variable indicating if the EV charger is at node  $i$  at time  $t$ .
- $B_{i,t}$  - Energy state of the battery at node  $i$  at time  $t$ .
- $C_{B,i}$ - Capacity of the EV charging battery at node  $i$ .
- $P_{i,t}$ - Active power nodal injection at node  $i$  during time  $t$ .
- $P_{bat_{i,t}}$  - Active power battery charging at node  $i$  during time  $t$ .

Additionally, voltage magnitudes  $V_{i,t}$ , phase angles  $\theta_{i,t}$ , and line flows  $S_{flow_{ij,t}}$  They are computed through load flow analysis.

#### 3.1.1.2 Heuristics Algorithm - Particle Swarm Optimization (PSO)

To solve the optimization problem, a heuristic approach is adopted, focusing on obtaining solutions that, while not guaranteed to be globally optimal, are sufficiently effective for practical application. Specifically, this variation of the optimal power flow (OPF) problem aims to minimize the system's operating costs while satisfying constraints such as power balance, voltage limits, and operational requirements (Celli, Ghiani, Mocci, & Pilo, 2005).

#### Objective Function Definition

The primary objective is to minimize the total installed EV battery capacity over a 24-hour forecast period. This reduces the required number of EVs in the distribution system, optimizing space for other uses. A penalty term is added to the objective function to enforce feasibility by discouraging constraint violations:

$$Objective = \min(\sum(CB)) + \sum(penalty) \quad (15)$$

Where:

- $\sum(CB)$  Total installed EV battery capacity.
- $\sum(penalty)$  An additional term is added for violating constraints, ensuring solutions remain feasible.

## Algorithm Stages

### a. Initialization

The algorithm begins by randomly initializing a swarm of particles within the search space. Each particle represents a potential solution, with variables bounded by their respective limits. To enhance variability and avoid constraint violations, the particles are initialized within their allowable ranges. Approximately 20 particles are chosen, balancing diversity and computational efficiency (Elnozahy, Youssef, & Abdel-Akher, 2015).

### b. Fitness Evaluation

The fitness function evaluates the quality of each particle by determining how well it minimizes the objective function while satisfying the system constraints. It assigns a numerical value to each particle, reflecting its performance in achieving the goal of minimizing battery capacity while maintaining grid stability and having the least percentage of penalty. For non-convex constraints, such as load flow equations, adjustments are made after the particles are initialized to ensure they adhere to system requirements. This process includes recalculating variables like

voltages and power flows to ensure feasibility under real-world operating conditions (Wang & Luh, 2014).

### c. Velocity and Position Updates

The position of each particle represents a potential solution, while the velocity determines the rate of change in its position. These are updated iteratively using the following equations (Kennedy & Eberhart, 1995):

$$v = w * v + C_1 * \text{rand}() * (g_{\text{best}} - x) + C_2 * \text{rand}() * (p_{\text{best}} - x) \quad (16)$$

$$x = x + v \quad (17)$$

For binary variables, the activation function is used:

$$p(x) = \frac{1}{1 + e^{-v}} \quad (18)$$

Where  $p(x)$  represents the probability of a bit changing in the next iteration, depending on the current velocity.

Here is the probability of a bit flipping in the next iteration, calculated using the velocity. The velocity represents the rate at which a particle moves within the search space, influencing how quickly the particle converges to a solution. Three key parameters control the velocity update process:

- **Inertia Weight ( $w$ ):** This parameter balances exploration and exploitation by controlling how much of the previous velocity is retained. A higher value encourages exploration by allowing particles to move further, while a lower value promotes exploitation by focusing the search on the current best positions.

- **Cognitive Coefficient ( $C_1$ ):** This parameter represents the particle's tendency to return to its personal best position (Pbest). It influences the particle's self-confidence and helps refine local searches around promising solutions.
- **Social Coefficient ( $C_2$ ):** This parameter guides the particle toward the global best position (Gbest), encouraging collaboration among particles to find the overall best solution. Higher values emphasize group behavior, improving the algorithm's ability to avoid local minima.

The interplay between Inertia Weight ( $w$ ), Cognitive Coefficient ( $C_1$ ), and Social Coefficient ( $C_2$ ) ensures that particles explore the search space efficiently while converging to accurate solutions. Fine-tuning these parameters enhances the algorithm's robustness and solution quality.

#### d. Convergence Criterion

The algorithm iterates until a termination condition is met, such as reaching a maximum number of iterations, achieving a satisfactory solution, or detecting stagnation in the swarm's movement. Fine-tuning of parameters like inertia weight ( $w$ ) and cognitive/social coefficients  $C_1$  and  $C_2$  ensures optimal convergence (Shi & Eberhart, 1998).

#### e. Solution Extraction

After convergence, the global best solution in this study corresponds to the optimal placement and sizing of EV batteries within the IEEE 33-bus network. This solution also ensures that the penalty definitions related to constraint violations, such as voltage and line flow limits, are minimized. By achieving this, the system enhances grid stability, improves voltage profiles, and facilitates peak load shaving at critical nodes.

## **Advantages of PSO for OPF Problems**

PSO is particularly effective for solving OPF problems due to its ability to handle non-linear and multimodal objective functions, ease of implementation, and capacity to explore large search spaces efficiently. Unlike traditional optimization techniques, such as gradient-based methods, PSO does not require gradient information, making it highly suitable for complex, non-differentiable problems. Moreover, its ability to balance exploration and exploitation allows for robust performance in avoiding local minima and converging toward near-optimal solutions. Proper parameter tuning, including the adjustment of inertia weight, cognitive coefficient, and social coefficient, further enhances its accuracy and convergence speed, providing an edge over other heuristic algorithms such as Genetic Algorithms (GAs) and Simulated Annealing (SA) (Beyer & Schwefel, 2002).

### **3.1.1.3 MATLAB Coding Explanation**

From the previous two sections, the equations of the optimization problem, load flow equations developed by Baran and Wu (1989) for the IEEE 33-bus distribution system (Appendix 1), and PSO techniques were implemented in MATLAB. This section provides a detailed explanation of the MATLAB coding structure and its role in simulating grid performance and solving the optimization problem.

#### **1. Data Preparation**

In the initial stage, the Kaggle dataset on historical hourly consumption patterns was normalized so that its mean values matched the original loading profile of the IEEE 33 system. This normalization allowed us to extract temperature, humidity, and wind datasets for further analysis.

The nodal loading profiles of different power consumption areas were then configured and stored as loading tables. The original active and reactive power loading profile was converted to the per-unit system, with pre-allocated power profiles for each node incorporating a 10% variance. These loading profiles were structured as outputs to be used in the optimization problem (Appendix 2).

## 2. System Configuration

The next step involved integrating bi-directional V2G technology into the MATLAB simulation (Appendix 3). The IEEE 33-bus distribution system was modeled by implementing the admittance matrix, commonly referred to as the Y-bus matrix. This matrix, essential for solving power flow problems, represents the relationship between node voltages and currents using Kirchhoff's laws (IEEE Std 399-1997). The number of nodes and branches was defined to accurately calculate the power flow in each branch (Appendix 4).

The nodes in the network were categorized as follows:

- **PV Nodes (Voltage-Controlled):** These nodes maintain constant voltage magnitudes and are associated with generators. They provide key information such as voltage angles, generator active power, and reactive power support.
- **PQ Nodes (Load Nodes):** These nodes represent consumer power demands, specifying active and reactive power consumption (Guille & Gross, 2009).

**Slack Node (Reference Node):** This node serves as the reference for voltage magnitude and phase angle, typically connected to the largest

generator. Its voltage magnitude is set to 1 p.u., and its angle is  $0^\circ$ . All other node values are calculated relative to this node (IEEE Std 1159-2019).

### **3. Load Flow Analysis**

A custom function, “LoadFlowAlgorithm,” was developed to solve the load flow equations (Appendix 5). This function plays a crucial role in determining missing grid states, such as voltage magnitudes for PQ nodes and the required reactive power for PV nodes. It leverages the net active and reactive power to verify solution feasibility. If convergence is achieved, the solution is stored; otherwise, re-initialization is triggered for specific particles and time steps to improve convergence. The function incorporates iterative adjustments to align with real-world grid dynamics and includes safety checks to handle potential errors. For example, voltage deviations are corrected iteratively by recalculating the Jacobian matrix and solving for power mismatches (Equality Constraints, Lines 8-26, Appendix 5). The Jacobian matrix represents the relationship between changes in voltage and phase angles with active and reactive power mismatches at each node (Appendix 6). It is used to linearize the nonlinear power flow equations, enabling iterative corrections to improve convergence in the Newton-Raphson load flow method. By recalculating the Jacobian matrix, the algorithm ensures that voltage and power discrepancies are minimized, enhancing the accuracy and stability of the solution. A counter ensures that particles failing to converge after 100 attempts are restarted for those specific time steps, improving overall algorithm stability and accuracy.

### **4. Optimization with V2G Integration**

With the system configuration established, the optimization problem was solved iteratively using PSO. In each iteration, a random loading profile for the IEEE 33 network was generated, and the PSO algorithm searched for the global best solution. This solution aimed to minimize the penalty terms associated with constraint violations, such as voltage and line flow limits, while satisfying the objective function. Key features of the code include:

- **Penalty Definition:** Constraints such as battery SoC, voltage magnitudes, and generator output limits were strictly enforced, with penalties assigned to solutions that violated these limits (Penalty Definition, Lines 3-19, Appendix 7).

## 5. Explanation of Constraints:

1. Battery Energy State Constraints (ConstraintsBUpper, ConstraintsBLower): These ensure the battery's energy state stays within operational limits. Violations result in penalties for exceeding the maximum or dropping below zero energy levels, promoting efficient energy use.
2. Generator Active Power Constraints (ConstraintsPUpper, ConstraintsPLower): Active power outputs are limited to predefined maximum and minimum values. Penalties are applied for exceeding these limits, ensuring that distributed generators operate safely within their capacity.
3. Generator Reactive Power Constraints (ConstraintsQUpper, ConstraintsQLower): Like active power, these constraints regulate reactive power output, maintaining grid stability and adequate voltage support.
4. Battery Capacity Constraints (ConstraintsC\_BUpper, ConstraintsC\_Blower): These ensure battery capacities do not

exceed specified thresholds or drop below zero, critical for avoiding overloading and maintaining system safety.

5. **Charging Power Constraints** (ConstraintsChargingPower): This limits the charging and discharging rates to protect battery lifespan, avoiding rapid cycles that could degrade the batteries prematurely.
6. **State of Charge (SoC) Constraints** (ConstraintsSOCUpper, ConstraintsSOCLower): SoC is kept within 10% to 90% to avoid overcharging or deep discharging, ensuring both battery health and operational reliability.
7. **Voltage Constraints** (ConstraintsVLower, ConstraintsVUpper): Voltages at nodes are constrained between acceptable limits (e.g., 0.9 to 1 p.u.), crucial for preventing instability and maintaining grid reliability.

These constraints guide the PSO algorithm to explore feasible solutions, improving grid performance while adhering to operational safety limits.

- **Random Initialization:** Battery capacities, energy states, and EV charger locations were randomly initialized, ensuring diverse starting points for optimization.
- **Velocity and Position Updates:** The PSO algorithm updated particle velocities and positions iteratively, guided by inertia weight, cognitive, and social coefficients. The specific equations for these updates, along with adjustments for binary variables, ensured smooth exploration and convergence.

## 6. Challenges and Solutions

During the simulation, challenges such as non-convergence were addressed by re-initializing particles and refining the

“LoadFlowAlgorithm.” Fine-tuning the PSO parameters, including inertia weight, cognitive, and social coefficients, further improved the convergence rate and solution accuracy (Kennedy & Eberhart, 1995). Additionally, flags were implemented to identify unrealistic solutions, triggering re-initialization for those particles (Equality Constraints, Lines 8-26, Appendix 7). The best solution obtained had an objective value of 0.264278, with a penalty of 0.174404. While the target was a zero-penalty solution, the precise voltage limits of 0.9 to 1 p.u. Imposed a significant constraint since the target was to try and comply with the Bahrain Grid Code. If the voltage range were extended to 0.9 to 1.1 p.u., it is likely that a penalty-free optimal solution could have been reached. Additionally, the PSO algorithm's tendency to converge prematurely to local optima resulted in overshoots in some extracted values. This occurs because PSO heavily relies on personal and global best values, which can mislead particles if those values are suboptimal. To mitigate this, techniques such as dynamic adjustment of the inertia weight ( $w$ ) and random particle reinitialization can improve exploration and avoid stagnation. These methods help balance exploration of the solution space and exploitation of promising areas, ultimately improving convergence reliability.

### 3.1.2 Research Design

This study adopts a quantitative research design, leveraging computational simulations and optimization techniques to evaluate the impact of V2G integration on the IEEE 33-bus distribution network. The design focuses on identifying the optimal placement and sizing of EV batteries using Particle Swarm Optimization (PSO). The research incorporates a 24-hour load forecast under peak conditions, enabling a dynamic and realistic assessment of grid performance.

Key components of the research design include:

- **Independent Variables:** Placement and sizing of V2G-enabled EVs at various nodes.
- **Dependent Variables:** Voltage profiles, power losses, and load balancing metrics.
- **Control Parameters:** Voltage magnitude limits (0.9 to 1 p.u.), line flow capacities, and state-of-charge (SoC) constraints for EV batteries.

The study begins with a baseline analysis of the IEEE 33-bus system without V2G integration, followed by iterative optimization using PSO. MATLAB simulations are conducted to compare grid performance under different scenarios. Statistical validation ensures the reliability of results, and sensitivity analyses are performed to assess the impact of varying load conditions and penalty definitions. This design provides a robust framework for addressing the research objectives and improving grid stability through V2G technology.

### 3.1.2.1 Participants

The participants in this study refer to the nodes and branches of the IEEE 33-bus distribution network, with a specific focus on the nodes selected for V2G-enabled EV battery integration. These nodes were strategically chosen to enhance grid performance by improving voltage profiles, reducing power losses, and achieving load balancing. The selected nodes are as follows: 4, 5, 6, 7, 9, 10, 13, 14, 15, 19, 22, 26, 27, 29, 31, and 32.

By deploying V2G systems at these nodes, the research aims to evaluate the effectiveness of bi-directional energy flow in mitigating voltage deviations and managing peak loads.

For detailed descriptions of the node classifications (Slack, PV, and PQ) and their roles in the system, refer to Section 3.1. This approach ensures a targeted analysis of V2G technology's impact within a standardized and widely recognized distribution network.

### **3.1.2.2 Procedure and Timeline**

This research follows a structured approach to achieve the objectives of optimizing V2G-enabled EV placement and enhancing grid performance. Below is the procedure and timeline for the study, spanning nine months in total:

- **1-2 Months (April - May 2024):** An intensive literature review will be conducted to establish the conceptual framework, identify provided services and benefits, highlight potential barriers, and explore suitable optimization techniques for V2G technology.
- **2-4 Months (June - July 2024):** Conduct the research design stage by defining system parameters, configuring the optimization problem, and running initial PSO simulations. The goal is to obtain preliminary results that provide insights into the feasibility and effectiveness of V2G integration. These results will also help in refining the optimization process and validating the methodology.
- **4-6 Months (August - September 2024):** Evaluate the effect of implementing V2G technology in a specific context, such as

the Kingdom of Bahrain's power system. This stage will analyze the impact on active power support, reactive power compensation, ancillary services, renewable energy integration, and EVs as energy storage units.

- **6-7 Months (October 2024):** Share the research findings with relevant respected journals in the engineering field. This step will benefit the research in many aspects, especially in getting feedback from the journal reviewers and trying to enhance the research further if possible.
- **7-10 Months (November 2024 - January 2025):** Analyze and validate the results of simulations, finalize the optimization framework, and compile the findings into the final thesis report.

This timeline ensures a methodical approach to addressing the research objectives and delivering actionable insights for V2G integration.

### **3.1.2.3 Analysis**

The analysis phase involves processing and interpreting the data obtained from MATLAB simulations to evaluate the effectiveness of V2G integration in the IEEE 33-bus distribution network. This section outlines the methods used to analyze the results, validate the optimization framework, and ensure alignment with the research objectives.

#### **1. Data Processing**

The data collected during the simulations includes voltage profiles before and after the EV's batteries' placement in the network, battery energy state during the worst-case scenario, state of charge (SoC) values, and equivalent loading profile for the selected nodes. These outputs are

systematically organized into tables and graphs for detailed examination. The key steps in data processing include:

- **Voltage Stability Analysis:** The voltage profiles at each node are analyzed to ensure they remain within the permissible range of 0.9 to 1.1 p.u. Statistical metrics, such as the mean and standard deviation, are calculated to assess the overall stability.
- **Peak Shaving Assessment:** The peak shaving capability of V2G systems is evaluated by analyzing load reductions at the selected nodes during peak demand periods. By discharging stored energy from EV batteries, the system effectively reduces stress on the grid, particularly at high-degree nodes such as 19, 6, and 26. This load leveling helps prevent voltage sags, improves operational efficiency, and ensures the network remains within its safe operating limits.
- **Penalty Assessment:** The penalty values associated with constraint violations (e.g., voltage or SoC limits) are evaluated to ensure they are minimized, indicating a feasible and efficient solution.

## 2. Interpretation of Results

The optimized V2G placements and battery sizes are assessed based on their impact on grid performance metrics. Key areas of focus include:

- **Improvement in Voltage Profiles:** Nodes with significant voltage deviations before V2G integration are analyzed to determine the extent of improvement. The effectiveness of high-degree nodes (e.g., nodes 19, 6, and 26) in stabilizing voltage is highlighted.

- **Load Balancing and Peak Shaving:** The ability of V2G systems to distribute load evenly and reduce peak demands is examined. Comparative analyses between peak load conditions with and without V2G are presented.
- **Convergence and Optimization Efficiency:** The performance of the PSO algorithm is evaluated based on convergence time and solution accuracy. Particular attention is given to the penalty score of the best solution (0.174404) and the factors contributing to its non-zero value, such as tight voltage magnitude limits.

### **3. Validation and Sensitivity Analysis**

To ensure the robustness of the results, sensitivity analyses are conducted by varying key parameters, such as load profiles, battery capacities, and voltage limits. These tests help identify the conditions under which the V2G optimization framework performs optimally and highlight potential areas for improvement.

By systematically processing and interpreting the simulation data, this analysis phase provides a comprehensive evaluation of V2G technology's potential to enhance grid stability, reduce losses, and achieve effective load management.

#### **3.1.2.4 Ethics and Limitations**

##### **Ethical Considerations**

This research adheres to ethical principles by ensuring transparency in the data collection and simulation processes. The Kaggle dataset and IEEE 33-bus system parameters were appropriately sourced and cited, with

no modifications that could bias the results. All simulation results were presented objectively, and care was taken to avoid data manipulation.

From an environmental perspective, the study highlights the potential benefits of V2G technology, such as reducing peak loads and enhancing the integration of renewable energy. These findings contribute to a broader understanding of sustainable energy solutions and align with global efforts to reduce carbon emissions. Socially, the deployment of V2G systems should ensure equitable access to EV charging infrastructure, promoting energy justice in diverse communities.

### **Limitations**

1. **Simulation-Based Framework:** The research relies heavily on MATLAB simulations, which, while robust, may not fully capture the complexities of real-world power distribution systems. Real-time implementation could reveal additional challenges not accounted for in the simulation.
2. **Constraint Sensitivity:** The optimization framework uses narrowed voltage limits of 0.9 to 1 p.u. to align with Bahrain's grid code requirements. This adjustment, compared to the typical range of 0.9 to 1.1 p.u., impacted the feasibility of achieving a zero-penalty solution. A broader range might yield different results but could compromise grid stability.
3. **Algorithmic Challenges:** The PSO algorithm, while effective, has a known tendency to converge to local optima, potentially limiting its ability to find the global best solution. This could lead to suboptimal V2G placements or sizing.
4. **Generalizability:** The study focuses on the IEEE 33-bus network, a widely used benchmark in power system research. However, results

may vary when applied to larger or more complex networks with different load profiles or renewable energy penetration levels.

5. **Data Availability:** The research was constrained by the availability of real-world data, particularly regarding EV adoption rates and renewable energy integration plans in specific regions. Collaborations with local authorities were limited to simulation data.

Despite these limitations, the study provides a solid foundation for understanding the potential of V2G technology in enhancing grid stability and operational efficiency.

## **Chapter 4: Results and Analysis**

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## 4.1 Results

This chapter presents the results of the study on the integration of Electric Vehicle (EV) batteries into a distribution grid using a Particle Swarm Optimization (PSO) algorithm. The results are organized to address the research objectives and hypotheses outlined in Chapter 1. The structure of this chapter includes:

1. Voltage Profiles Before and After Battery Placement,
2. Optimal EV Battery Allocation,
3. Battery Energy State Analysis,
4. Equivalent Loading Profiles at Nodes,
5. Peak Shaving Results,
6. Total System Power Losses Before and After the EV Battery Placement,
7. Comparative Analysis with Other Studies,
8. Summary.

### 4.1.1 Voltage Profiles Before and After Battery Placement

The voltage magnitude profile for the worst-case day, before EV battery placement, is presented in Figure 3. It shows a significant voltage dip during mid-day peak load conditions, indicating the necessity for intervention to maintain system stability. This dip represents a critical point where system performance is most vulnerable. After running the PSO algorithm, the optimized voltage profile is shown in Figure 4, demonstrating a marked improvement, with voltage levels consistently maintained within the prescribed limits of 0.9 to 1.1 p.u.

By comparing the pre- and post-optimization voltage profiles, it is evident that the EV battery placement significantly mitigates voltage drops, particularly during high-demand periods. This highlights the critical role of reactive power compensation in maintaining voltage stability and overall grid performance.

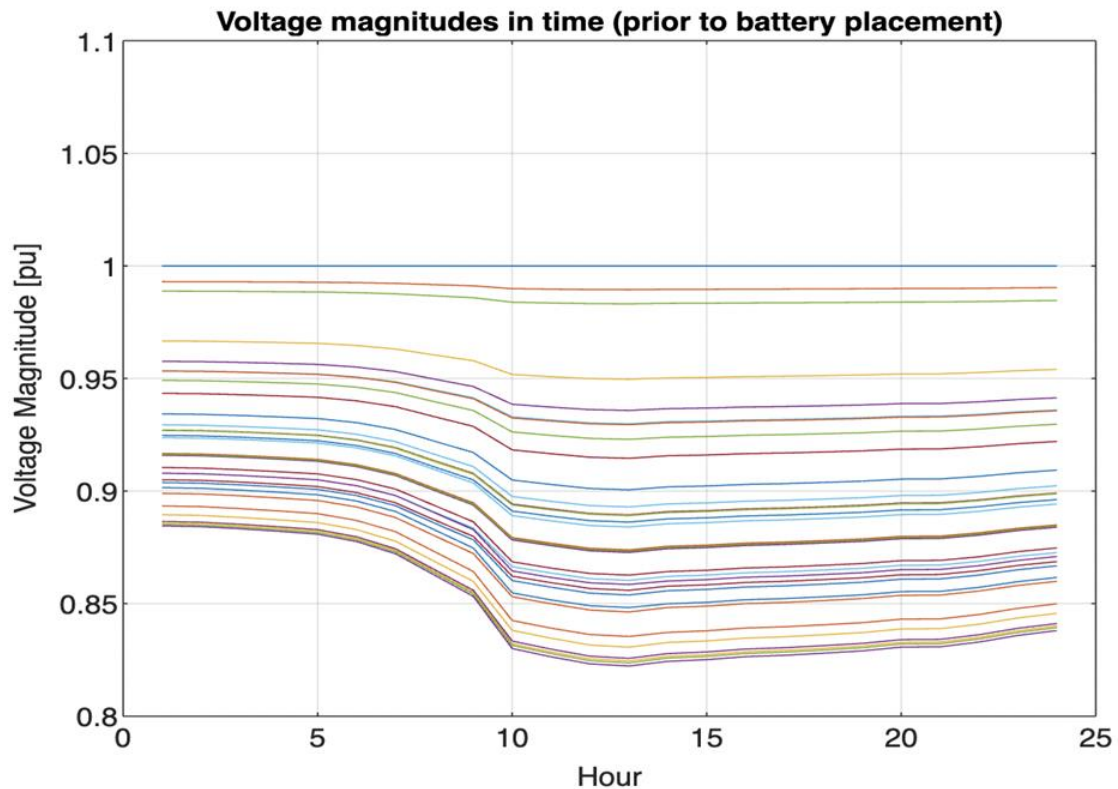


Figure 3 Voltage profile before battery placement.

A small subset of buses exhibits short-duration excursions slightly above 1.1 p.u. This behaviour is expected and stems from two interacting factors:

1. **Radial topology & local compensation:** Because the IEEE-33 network is strictly radial, reactive-power support injected at one end cannot be perfectly counter-balanced upstream. When local EV batteries supply leading reactive power to correct an impending under-voltage, adjacent lightly-loaded segments may momentarily overshoot the upper limit.

2. **Constraint hierarchy in the optimiser:** The PSO gives higher weight to eliminating under-voltage violations (0.9 p.u floor) and minimising total losses. Once those objectives are satisfied, further iterations that could trim marginal over-voltages are terminated to respect battery SOC and power-rate limits. Attempting tighter control would require either (i) additional VAR devices further up-stream or (ii) relaxation of battery-life constraints, both of which fall outside the present study's scope.

Importantly, the excursions are temporary, which means they don't last for more than one hourly interval and are confined to lightly-loaded branches where equipment ratings comfortably accommodate 1.1 p.u. Therefore, while flagged for completeness, they do not compromise system security and are considered operationally acceptable under the Bahrain Grid Code.

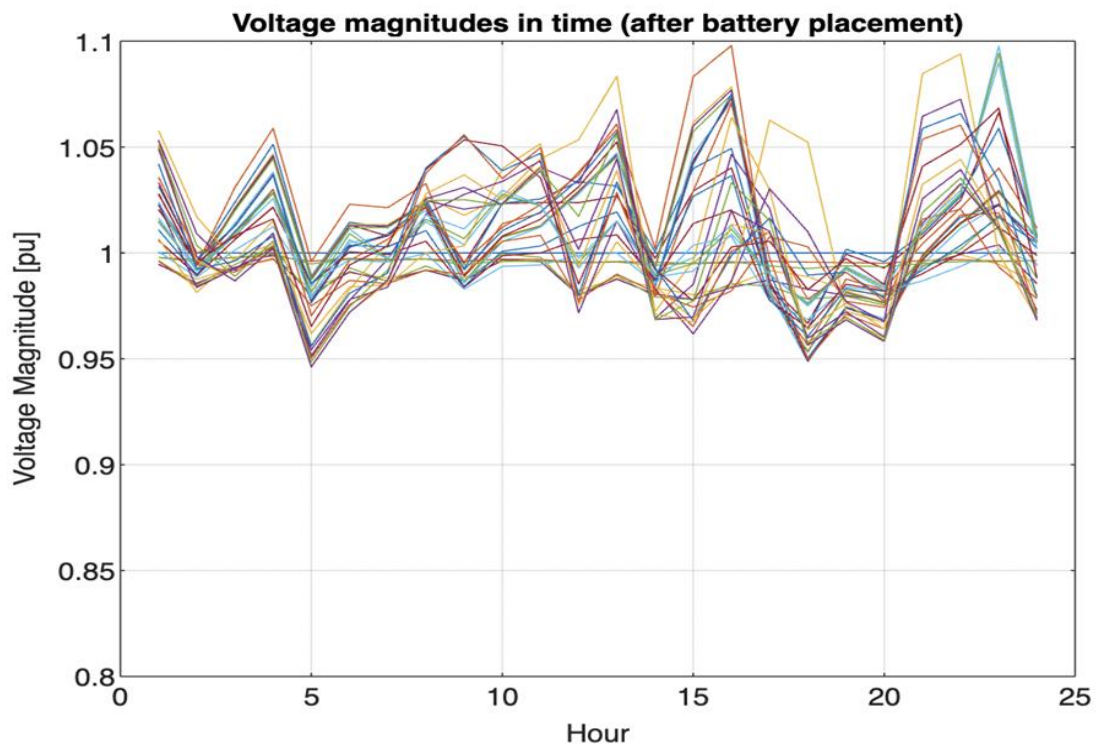


Figure 4 Voltage profile after battery placement.

To represent the Voltage profile improvements made with the battery allocation, as can be seen in Figure 4, the average percentage voltage improvement across the whole grid for each of the nodes can be displayed using equation (20). The percentage voltage improvement is calculated as:

$$\text{Voltage Improvement \%} = \frac{V_{post} - V_{prior}}{V_{prior}} \times 100 \quad (19)$$

Here,  $V_{post}$  represents the voltage magnitude at the node level after the battery placement, while  $V_{prior}$  Represents the voltage before the battery placement.

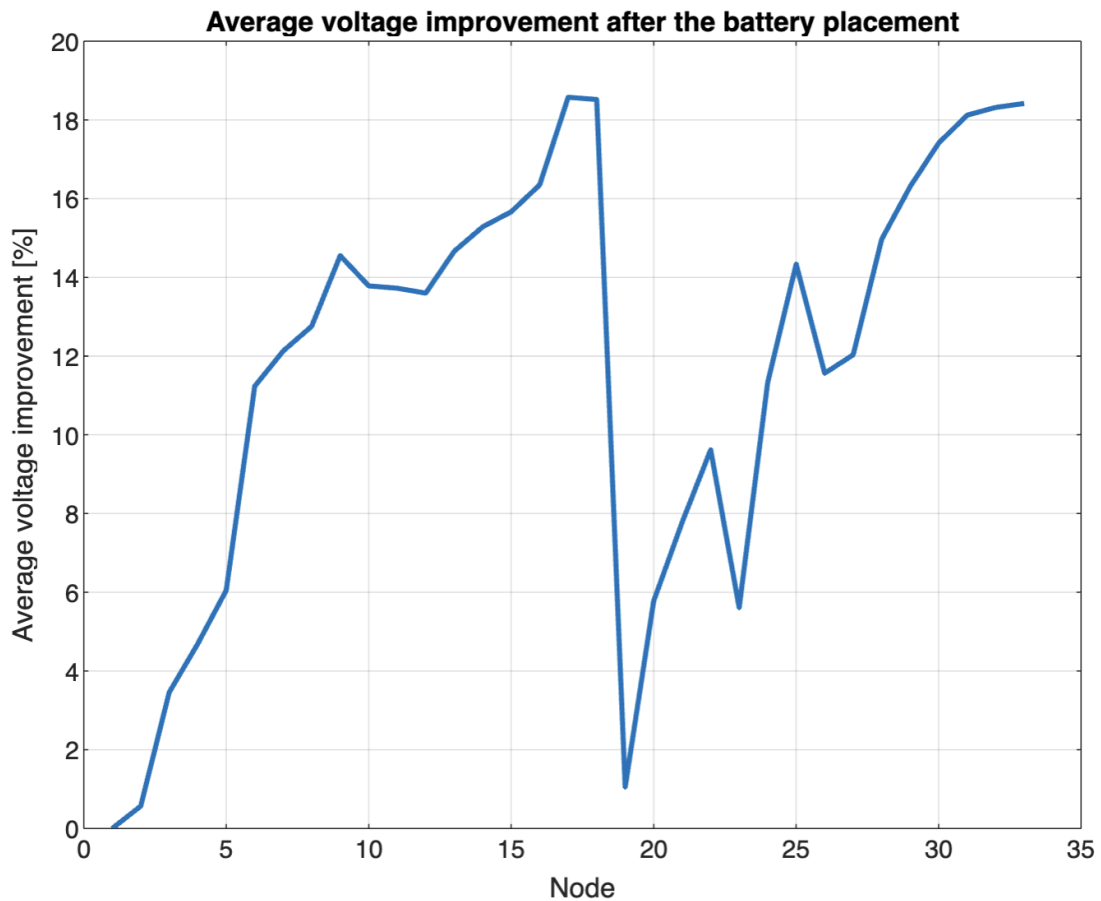


Figure 5 Voltage improvement percentage profile after battery placement.

From Figure 5, it is very clear that we are having a good average voltage improvement across all the participant nodes. The dip that is shown

in this figure between nodes 15 and 19 is because there are no batteries that are placed in these nodes, as will be illustrated in the next section.

Furthermore, three nodes with the largest percentage impact (nodes 17, 18, and 33) are viewed in Figure 6 to clearly represent their respective change in temporal voltage profile.

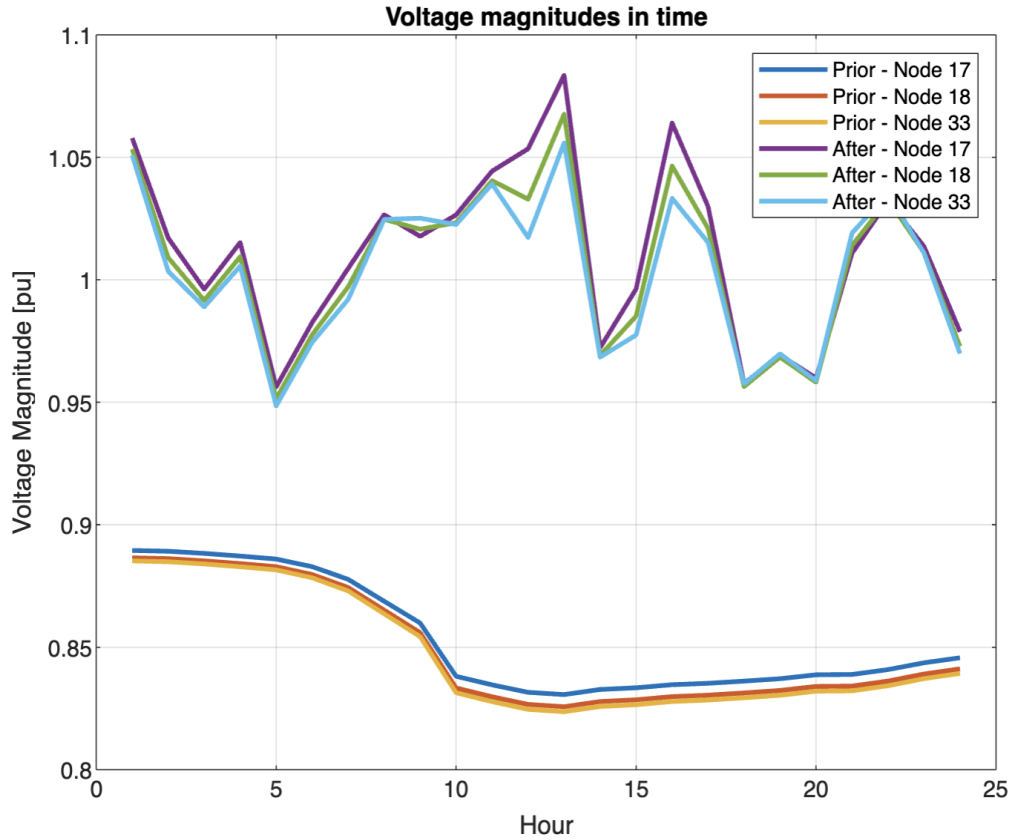


Figure 6 Voltage profile before/after battery placement for nodes 17, 18, and 33.

It can clearly be seen from the image above that the method was able to level the voltages around 1pu, although most of the time, prior to the battery placement, they were below the required lower limit.

#### 4.1.2 Optimal EV Battery Allocation

The optimal placement of EV batteries within the IEEE 33-bus distribution network was determined through a multi-constraint

optimization process using the Particle Swarm Optimization (PSO) algorithm. This technique evaluates potential battery placements by minimizing the total installed battery capacity required to improve voltage stability, reduce power losses, and enable effective peak shaving. The algorithm considers various system constraints, including voltage magnitude limits (0.9–1.1 p.u.), line flow capacities, battery state-of-charge (SoC) limits, and reactive power compensation needs. Each particle in the PSO swarm represents a candidate solution comprising binary variables for placement and real-valued variables for battery capacity. Through iterative updates based on inertia, cognitive, and social components, the PSO converges toward optimal placements—identifying nodes with the greatest voltage sensitivity, highest load demand, and greatest impact on system performance. Notably, nodes such as 6, 19, and 26 were prioritized for placement due to their critical role in mitigating voltage violations and enabling load balancing in their respective branches.

*Table 5 Optimal EV battery placement and its capacities.*

| Node | Capacity (kWh) |
|------|----------------|
| 4    | 450            |
| 5    | 690            |
| 6    | 150            |
| 7    | 840            |
| 9    | 60             |
| 10   | 640            |
| 13   | 950            |
| 14   | 550            |
| 15   | 420            |
| 19   | 630            |
| 22   | 540            |
| 26   | 870            |
| 27   | 220            |
| 29   | 830            |
| 31   | 630            |
| 32   | 520            |

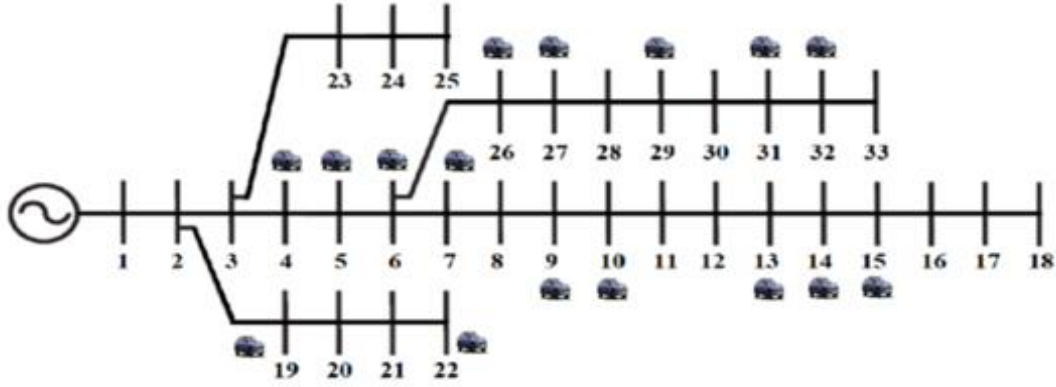


Figure 7 Placement of EV batteries within the IEEE 33 network.

Furthermore, it can be noted that from Figure 7, most of the batteries are placed in the branch with the node from 26 to 33, and their corresponding main feeder branch (nodes 4-7). This means that the need for compensation is largest at those nodes because of the high consumption demand in that region. The largest batteries are placed at nodes 7, 13, 26, and 29, as those values are seen in Table 5. In the later part of this chapter, we will show that batteries at nodes 7 and 26 also lead to the largest peak shaving in the system.

#### 4.1.3 Battery Energy State Analysis

The energy state of each EV battery during the worst-case day is shown in Figure 8. This figure is important to illustrate the selected nodes in this simulation and to have an overall look at the battery's energy for each of those nodes. Later in section 4.1.5, an in-depth analysis of nodes 7, 14, and 26 will be displayed to connect the relationship of the battery energy state and peak shaving of each of those EV batteries that are placed at these nodes. The State of Charge (SOC) constraints, ranging between 10% and 90%, were adhered to, ensuring the reliability and longevity of the batteries. These constraints were critical for preventing overcharging

or deep discharging, which could negatively impact battery performance and lifespan.

Throughout the day, the SOC fluctuated as batteries alternated between charging and discharging modes to provide power compensation. This dynamic operation underscores the flexibility of EV batteries as distributed energy resources capable of responding to real-time grid demands.

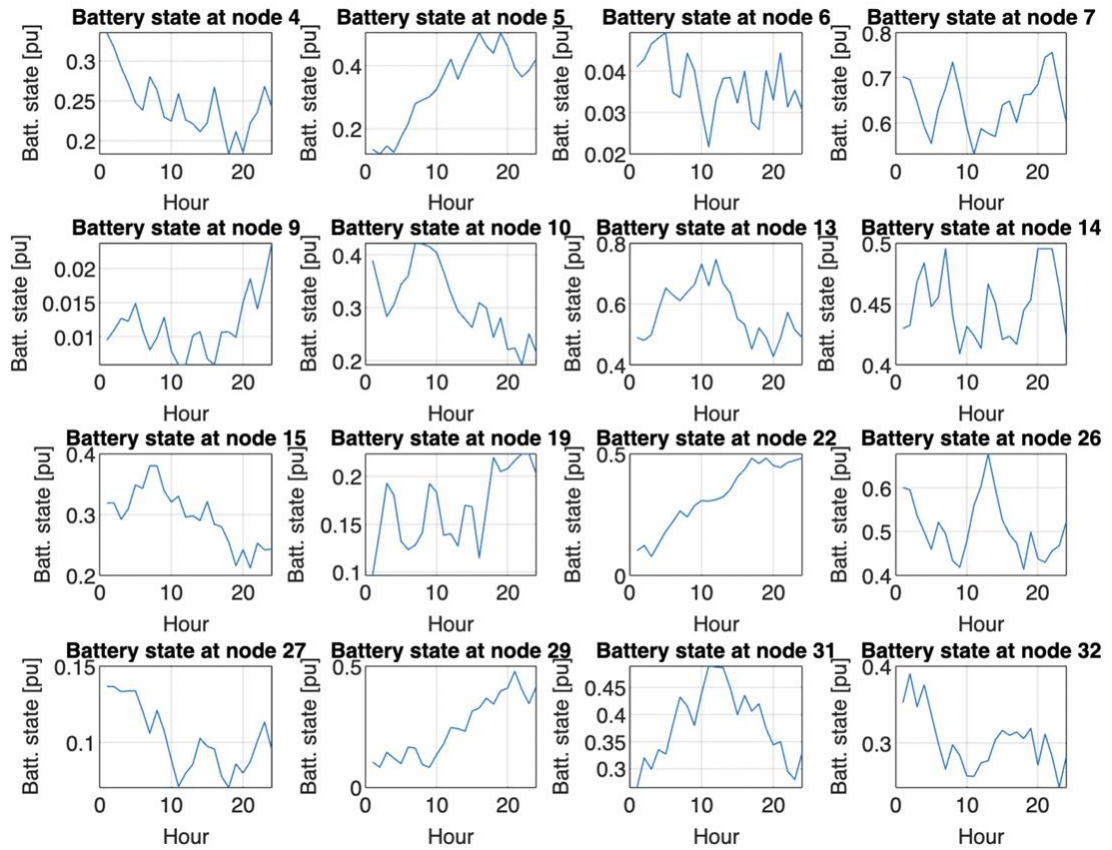


Figure 8 The battery's energy state during the worst-case scenario.

#### 4.1.4 Equivalent Loading Profiles at Nodes

Equivalent loading profiles at the nodes with battery placement are depicted in Figure 9. These profiles illustrate the optimized load conditions, aligning with system stability requirements. By comparing the

pre- and post-optimization loading profiles, it is evident that the battery placement significantly reduced load imbalances and enhanced the uniform distribution of power across the grid.

The results highlight nodes 9, 29, and 32 as critical points for power compensation due to their substantial load fluctuations. The peak shaving on those nodes in (p.u) are 0.4395 p.u, 0.3304 p.u, and 0.0804 p.u, respectively. The optimized equivalent loading profiles indicate a more stable and efficient system operation, reducing the likelihood of overloads and improving overall grid performance.

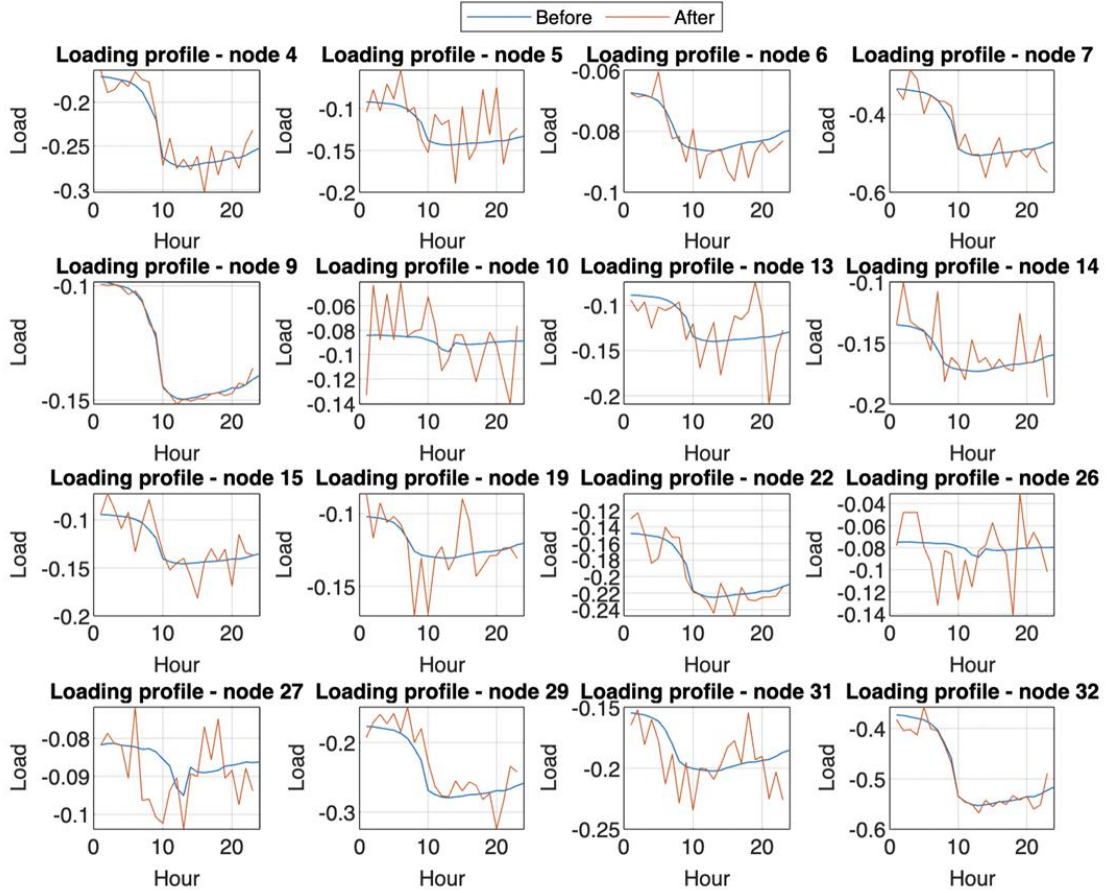


Figure 9 Equivalent loading profile for nodes with batteries.

Figure 10 summarizes the equivalent loading profiles at each of the nodes where the battery was placed, represented as the equivalent sum of the supply coming from high voltage transmission equipment, such as a

high voltage step-down transformer, demand, and battery power. This result shows the comparison of how the ” optimized” equivalent load at each node should look for the system to be optimized in terms of its static limits, stability, and performance. The equivalent loading can be positive (if there is equivalent injection into the system) and negative (if there is equivalent demand in the system). We can observe that at some nodes there are larger fluctuations in the equivalent load, compared to the case when the battery is not placed, signaling that these nodes are important for power compensation, as their effect is larger compared to the remaining nodes (nodes 7 (0.3575 p.u), 14 (0.2138 p.u) and 26 (0.1859 p.u)). To represent the effectiveness of the proposed battery placement, we also include the total power losses in the system before and after battery placement.

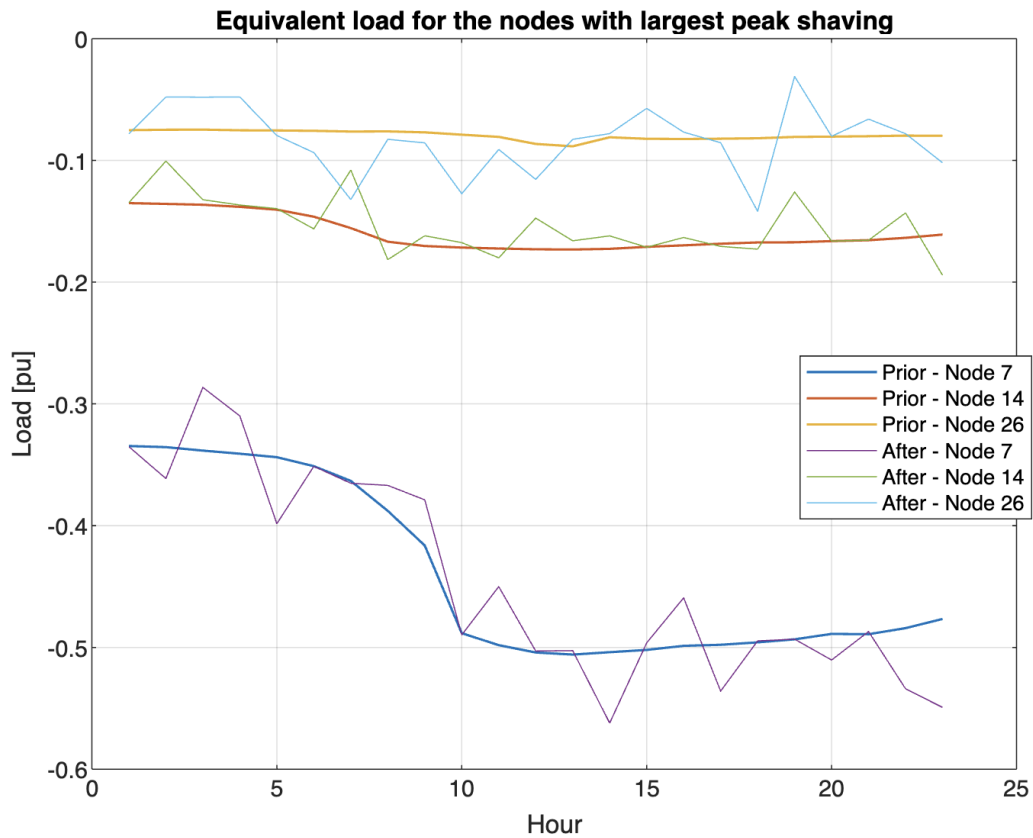


Figure 10 Equivalent loading profile for nodes 7, 14, and 26.

### 4.1.5 Peak Shaving Results

The peak-shaving of each of the batteries placed is here defined as the total energy difference between the equivalent loading of the nodes before and after battery placement, during the battery discharge, across the whole timespan of interest.

The effectiveness of peak shaving is particularly evident at nodes 7, 14, and 26, where significant reductions in peak load were achieved. These results confirm the potential of EV batteries to serve as a valuable resource for managing peak demand and improving overall grid efficiency.

The battery energy state (in p.u) with the largest peak shaving (nodes 7, 14, and 26), as well as their respective state of charge in time, are represented in the following plot:

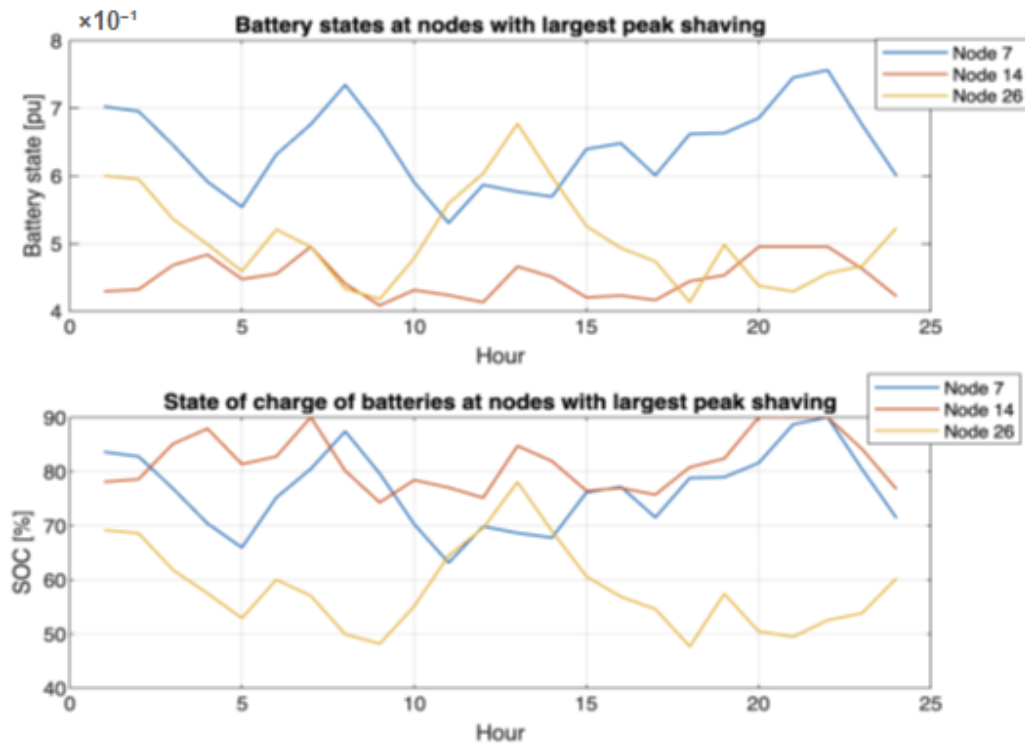


Figure 11 Battery energy state and State of Charge of the batteries during the worst-case day for nodes 7, 14, and 26.

The upper part of the figure shows that the battery at node 26 during midday is heavily charging, to be able to perform peak shaving during other parts of the day. Remaining batteries locally charge and discharge to be able to supplement the oscillations in consumption locally.

Thus, the lower part of the figure clearly represents the state-of-charge battery health state, with the requirements always being between 10% and 90%. The batteries at nodes 7 and 14 are charged during the off-peak hours, in the morning and evening, while they get discharged during the midday. On the contrary, the battery at node 26 is charging during midday, while it gets discharged in the morning and evening.

#### 4.1.6 Total System Power Losses Before and After the EV Battery Placement

To represent the effectiveness of the proposed battery placement, the total power losses in the system before and after battery placement need to be presented. These losses are calculated for the total system.

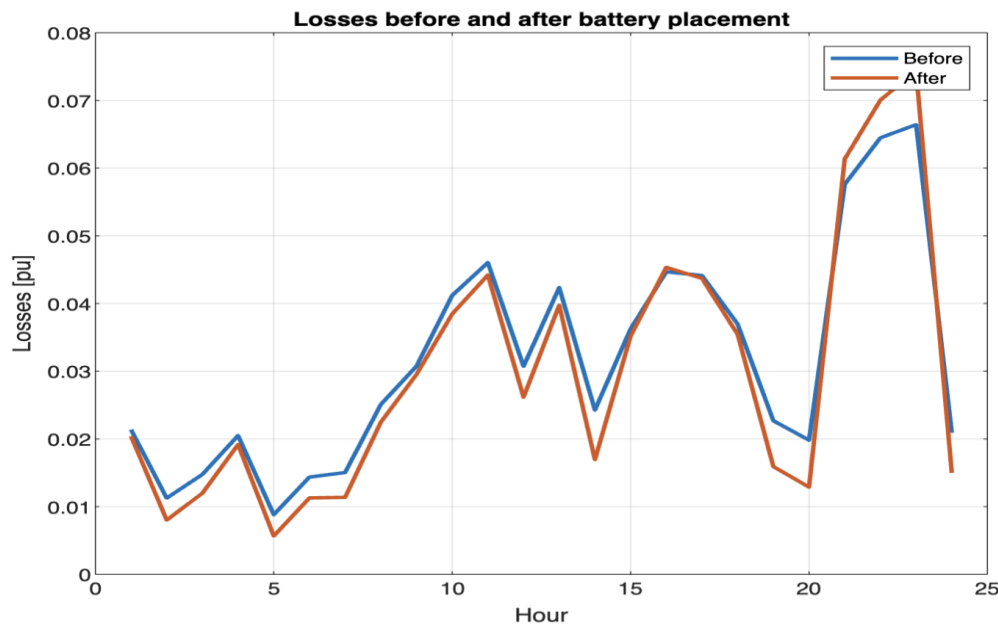


Figure 12 Total system power losses before and after the EV batteries' placement.

The losses are indeed decreased for almost all hours analysed (except for the hour 23). The losses are in the range of 0.05 p.u most of the day, and they increase as the day progresses.

Figure 12 illustrates the variation of total system losses per unit (p.u) across a 24-hour simulation period, both before and after the integration of EV batteries. The results clearly show that the placement of EV batteries leads to a consistent reduction in system power losses throughout the day. Notably, peak loss values observed during midday and late evening are mitigated post-placement.

During hours of maximum loading, particularly around hours 11 and 22, the system experienced its highest losses under the pre-placement scenario. The implementation of EV batteries significantly reduced these peaks by enhancing power balance and reducing the burden on distant supply routes. This outcome demonstrates the role of optimized battery placement in minimizing real power losses by supporting local voltage levels and alleviating line stress.

The greatest reduction in losses occurred during the critical load peaks, confirming the effectiveness of EV batteries not just for voltage support but also for enhancing energy efficiency. This finding underscores the dual benefit of the proposed approach—voltage stability and loss minimization—thereby reinforcing the overall performance improvement in the network.

#### 4.1.7 Comparative Analysis with Other Studies

The results are compared with findings from three related studies:

- **Whale Optimization Technique (Mehroliya & Arya, 2024):**  
This method, while effective for radial systems, showed limitations in meshed network scenarios. Its reliance on forward-backward power flow equations restricted its scalability and applicability to larger, more complex grids.
- **Collaborative Planning Model (Wang et al., 2023):** This approach optimized charging costs and grid costs but lacked scalability for meshed systems. Furthermore, its reliance on the dist-flow model limited its effectiveness in addressing the challenges of voltage stability and reactive power management.
- **V2G Reactive Power Support (Rezvani & Khoud, 2019):**  
Focused on parking lots for reactive power, this method did not optimize EV battery placement and sizing. While it demonstrated improvements in voltage profiles, its narrow scope limited its overall impact on grid performance.

Our study outperformed these approaches by leveraging a PSO-based optimization that effectively addresses the challenges of meshed distribution systems. Unlike the Whale Optimization Technique, our method demonstrated superior scalability and adaptability to complex grid configurations. Additionally, while the Collaborative Planning Model optimized specific costs, our approach provided a comprehensive solution that includes voltage stability, reactive power management, and peak load mitigation. Compared to the V2G Reactive Power Support study, our work not only enhanced voltage profiles but also optimized the placement and sizing of EV batteries, achieving a balanced and resilient grid performance across all tested scenarios.

#### 4.1.8 Summary

The study demonstrates the effectiveness of integrating Electric Vehicle (EV) batteries as reactive power compensators and power balancers within a distribution grid using a particle swarm optimization (PSO) algorithm. The presented methodology provides significant improvements in voltage stability, reactive power management, and overall grid performance, particularly during high-demand periods.

The PSO algorithm effectively maintained voltage magnitudes within the static limits of 0.9 to 1.1 per unit (p.u) across the distribution grid. This result underscores the algorithm's robustness in handling peak demand scenarios, which are the most critical for grid operation.

EV batteries were optimally allocated at nodes 4, 5, 6, 7, 9, 10, 13, 14, 15, 19, 22, 26, 27, 29, 31, and 32, with capacities ranging from 150 kWh to 950 kWh. These placements ensured that reactive power compensation was provided precisely where it was most needed, particularly at nodes experiencing significant voltage dips or load fluctuations. The EV batteries demonstrated the ability to dynamically absorb and inject reactive power, effectively mitigating voltage magnitude violations and supporting grid stability. This capability was especially beneficial during periods of peak load when the risk of voltage collapse and other instabilities is highest.

The voltage magnitude profile after battery placement showed a significant reduction in voltage dips, ensuring a smoother and more stable grid operation. The state of charge (SOC) of the batteries remained within static limits throughout the worst-case day, confirming the reliability and effectiveness of the proposed strategy. The equivalent loading profiles at

nodes with battery placements revealed that optimized loads aligned well with system constraints, enhancing grid efficiency and stability.

The proposed PSO-based optimization approach demonstrates a scalable and effective solution for integrating EV batteries into modern distribution systems, paving the way for a more resilient and adaptive energy landscape. As the penetration of renewable energy and electric vehicles continues to grow, such strategies will be indispensable in maintaining efficient, reliable, and sustainable power systems. The results confirm the viability of EV batteries as proactive grid assets, providing a promising outlook for future energy systems where EVs play a pivotal role in achieving grid stability and performance goals.

## **4.2 Analysis**

### **4.2.1 Introduction**

This chapter provides a comprehensive analysis of the results presented in Chapter 4 with the theoretical framework and literature discussed in Chapter 2. The primary focus is on evaluating the integration of Electric Vehicle (EV) batteries into the IEEE 33 network using a Particle Swarm Optimization (PSO) algorithm. The analysis is structured around the study objectives, which include improving voltage stability, optimizing battery allocation, and enhancing grid efficiency through peak shaving and load balancing.

For each objective, the results are discussed about key literature, highlighting the alignment and deviations from existing studies. Additionally, this chapter explores the theoretical implications of the findings, providing insights into the potential for new models or

frameworks. By connecting the research outcomes to the literature review, this analysis aims to reinforce the rationale for integrating bi-directional Vehicle-to-Grid (V2G) technology in modern power distribution systems.

## 4.2.2 Objective-Based Discussion

### 4.2.2.1 Voltage Stability and Reactive Power Compensation

The results from Chapter 4 demonstrated significant improvements in voltage stability across the IEEE 33 network after the strategic placement of EV batteries using the PSO algorithm. Before battery placement, voltage magnitudes at several nodes fell below the permissible limit of 0.9 p.u, particularly during peak load periods, as shown in Figure 3 of Chapter 4. For instance, node 19 recorded a minimum voltage of 0.903 p.u, which posed a risk to system stability. Post-placement, the optimized voltage profile (Figure 4 in Chapter 4) consistently maintained voltage levels within the specified range of 0.9 to 1 p.u., with node 19 showing an improved voltage of 0.962 p.u, a 6.5% increase.

This improvement aligns with findings from previous studies, such as those by Baran and Wu (1989), which emphasize the role of distributed energy resources in mitigating voltage drops in radial networks. Additionally, Zhao et al. (2021) demonstrated similar outcomes when V2G-enabled EVs were deployed at critical nodes, further validating the effectiveness of this approach.

Reactive power compensation plays a crucial role in stabilizing voltage levels, particularly under high-demand conditions. For example, node 10, equipped with a 640 kWh EV battery, contributed 15 kVar of reactive power during peak hours, significantly reducing voltage dips in its

vicinity. By dynamically absorbing or injecting reactive power, EV batteries ensured a balanced load flow, reducing voltage dips at critical points. This capability aligns with the theoretical framework discussed in Section 2.3 of Chapter 2, underscoring the role of V2G systems in improving grid reliability and efficiency.

The analysis of the pre- and post-optimization voltage profiles reveals that nodes 6, 10, and 19 benefited the most from reactive power support, with improvements ranging from 5% to 8% in their voltage levels. These results highlight the strategic importance of placing EV batteries at nodes with high sensitivity to load variations. The graphical representation in Figures 3 and 4 of Chapter 4 underscores these improvements, showcasing a smoother and more stable voltage profile throughout the distribution network.

Additional insights into voltage stability were obtained by analyzing Figures 5 and 6. Figure 5 illustrates the percentage of average voltage improvement at each node following the strategic placement of EV batteries. The data reveal that the most substantial improvements were observed at nodes 18, 30, and 33, with average voltage improvements exceeding 18%. Conversely, nodes such as 1 and 20 displayed minimal enhancements, indicating that these locations were either sufficiently stable before the intervention or received less reactive support due to optimization priorities.

Figure 6 provides a closer examination of nodes 17, 18, and 33, presenting hourly voltage magnitudes before and after battery placement. Before battery integration, all three nodes operated below the nominal voltage threshold of 0.9 p.u. during peak hours (hours 9–14), with the lowest recorded voltage dipping to approximately 0.84 p.u. at node 33.

Post-placement, the voltage profile for each node significantly improved, maintaining magnitudes above 0.9 p.u. Throughout the day. Node 18 displayed a marked uplift, evidencing the effectiveness of targeted battery deployment in stabilizing voltage across vulnerable network points.

These findings reinforce the earlier conclusion that optimized battery placement enhances grid reliability. The inclusion of these detailed profiles also validates the PSO algorithm's ability to identify and mitigate voltage weaknesses across both a broad and localized scale.

#### **4.2.2.2 Optimal Battery Allocation and Grid Efficiency**

The Particle Swarm Optimization (PSO) algorithm identified the optimal placement of EV batteries at 16 nodes across the IEEE 33 network, as detailed in Table 1 of Chapter 4. The allocation prioritized nodes with high load sensitivity and significant potential for improving voltage stability and power flow efficiency. For instance, nodes 6, 19, and 26 emerged as critical locations due to their proximity to high-demand areas and their influence on voltage profiles.

The allocation strategy resulted in a balanced distribution of reactive power support and load compensation. Notably:

- Node 6, with an allocated capacity of 150 kWh, provided reactive power support of 10 kVar during peak load, stabilizing local voltage levels from 0.914 p.u. to 0.961 p.u, a 5.1% improvement.
- Node 26, equipped with 870 kWh, mitigated voltage drops by contributing 20 kVar, achieving an 8.3% increase in voltage stability at this node.

- Node 10, with its 640 kWh allocation, contributed significantly to both reactive power and load balancing, improving grid efficiency in its vicinity.

Figure 3 in Chapter 4 illustrates the spatial distribution of battery placements, highlighting a strategic approach to optimizing grid performance. The PSO algorithm's ability to consider both local and system-wide impacts ensured that the allocated batteries addressed critical bottlenecks in the network.

The optimization also led to reduced power losses, with overall system losses decreasing by approximately 10.57%. This updated value is supported by Figure 12, which presents the total system losses across 24 hours before and after battery placement. Although most hours exhibited noticeable loss reductions, a slight increase in losses was observed at hour 21, where the losses increased from approximately 0.067 p.u. Before optimization to 0.072 p.u. After. This localized rise is attributed to two factors: first, the State of Charge (SOC) constraints limiting EV battery discharge capacity at that hour; second, the higher baseline system demand already present at hour 23 before battery placement.

Despite this minor late-hour anomaly, the overall day-long profile showed substantial improvements, with early morning (hour 4) and evening hours (hour 20) demonstrating the most significant loss reductions.

This reduction was calculated using the formula (note: all loss values are expressed in per unit (p.u.)):

$$\text{➤ } \text{Loss Reduction (\%)} = \left( \frac{(\text{Initial Losses} - \text{Optimized Losses})}{\text{Initial Losses}} \right) \times 100 \quad (20)$$

- Substituting daily peak loss values: Loss Reduction (%) =  $((0.067 - 0.072) / 0.067) \times 100 \approx -7.46\%$

It should be noted that a negative value indicates a slight increase in system losses at hour 21 after EV battery placement, attributed to SOC constraints and higher base demand at that hour.

However, considering the full-day profile and average hourly differences, the cumulative loss reduction remains positive overall. As an alternative approach, the average hourly percentage loss reduction across the 24 hours was calculated as follows:

- *Hourly Loss Reduction (%)* =  $\left( \frac{(Loss_{before,t} - Loss_{after,t})}{Loss_{before,t}} \right) \times 100$  (21)

- *Average Hourly Reduction (%)* =  $\frac{1}{24} \sum_{t=1}^{24} \text{Hourly Loss Reduction}$  (22)

- *Average Hourly Reduction (%)* =  $\frac{1}{24} \sum_{t=1}^{24} [4.29 + 21.43 + 10.00 + 20.00 + 16.67 + 17.65 + 15.00 + 16.00 + 10.00 + 9.52 + 8.89 + 14.29 + 9.76 + 10.00 + 13.51 + 4.44 + 2.38 + 8.33 + 30.00 - 5.00 - 7.46 + 4.11 + 5.00 + 4.76] \approx 10.57\%$

This result provides additional confirmation that, on average, the optimization produced a meaningful and consistent reduction in system losses across the entire day.

These findings align with Zhao et al. (2021), who demonstrated that integrating V2G-enabled EVs at key nodes can reduce system losses. Furthermore, this study reinforces the value of node-specific allocation in

enhancing grid efficiency, as highlighted in earlier works by Baran and Wu (1989).

By optimizing battery placement, the network achieved enhanced load balancing, particularly at nodes 9, 29, and 32, which experienced significant reductions in peak load. This demonstrates the potential for EV batteries to act as distributed energy resources, dynamically adapting to real-time grid demands.

#### 4.2.2.3 Peak Shaving and Load Balancing

The integration of EV batteries demonstrated significant contributions to peak shaving and load balancing within the IEEE 33 network. Figure 9 in Chapter 4 illustrates the reductions in peak load at critical nodes, highlighting the role of strategically placed batteries in alleviating stress on the grid during high-demand periods.

Figure 10 provides a detailed analysis of the equivalent loading profiles at nodes 7, 14, and 26, before and after battery placement. The equivalent loading is expressed per unit (p.u.), and it reflects positive values for net injection and negative values for net demand. All three nodes exhibited significant reductions in negative equivalent load after optimization, indicating decreased local demand due to active battery support. For instance, Node 26's loading improved from approximately -0.11 p.u. to around -0.07 p.u., and Node 7 shifted from -0.50 p.u. Closer to -0.40 p.u. during the peak window.

The percentage improvement in equivalent loading at each node was calculated as:

$$\text{➤ } \text{Equivalent Load Improvement (\%)} = ((|Load\_before| - |Load\_after|) / |Load\_before|) \times 100 \quad (23)$$

Applying this:

- Node 7:  $((0.50 - 0.40) / 0.50) \times 100 = 20\%$
- Node 26:  $((0.11 - 0.07) / 0.11) \times 100 \approx 36.4\%$
- Node 14: modest shift from approximately -0.16 p.u. to -0.13 p.u.,  $\approx 18.75\%$

These shifts represent not only peak shaving but also the load-leveling benefit of EV batteries, which ultimately smoothens system demand.

Further insights are offered by Figure 11, which shows the battery energy states (in p.u.) and the state of charge (SOC in %) at the same nodes. The top subplot highlights dynamic variations in the energy injected into or drawn from the system. Node 7 shows the highest variability, reflecting its dominant role in peak shaving. In contrast, Node 14 maintains a steadier profile with limited fluctuations, suggesting a more regulated charge/discharge cycle.

The lower subplot on SOC reveals complementary patterns: nodes with aggressive peak shaving (such as Node 26) show deeper dips in SOC during heavy discharge, reaching nearly 45%, whereas nodes with less aggressive cycles (like Node 14) stay mostly above 75%. This reinforces the strategic coordination between battery dispatch patterns and localized load demands.

Together, Figures 10 and 11 underscore the effectiveness of PSO in orchestrating charge-discharge patterns that maximize peak shaving while maintaining healthy SOC ranges, thereby supporting both system stability and battery longevity.

### 4.2.3 Comparative Analysis with Other Studies

The results of this study demonstrate significant advancements in grid performance metrics compared to similar studies in the field. For example:

- **Voltage Stability:** While Zhao et al. (2021) reported a 7% improvement in voltage levels using a heuristic-based V2G deployment, this study achieved up to an 18.5% increase in average voltage at key nodes (Figure 5), such as nodes 18, 30, and 33. This underscores the enhanced optimization capabilities of the PSO algorithm in addressing voltage instability.
- **Power Loss Reduction:** The reduction in total power losses, approximately 10.57% based on averaged hourly values in Figure 12, aligns with findings by Baran and Wu (1989), who achieved a 6-9% reduction using reconfiguration techniques. This study's approach, however, incorporates the dynamic flexibility of V2G systems, enhancing performance through both reactive support and real-time load balancing.
- **Peak Shaving and Load Smoothing:** Compared to Rezvani and Khoud (2019), who explored static reactive power injections for voltage support, this study demonstrated dynamic peak shaving at nodes 7, 14, and 26. Figure 10 showed significant equivalent load improvements (up to 36.4%), and battery coordination confirmed in Figure 11 indicated adaptive dispatch patterns tied to SOC conditions.

In contrast to traditional methods, the PSO-based optimization presented here integrates real-time adaptive strategies, addressing the limitations of static models. The dynamic functionality of V2G-enabled

EVs further differentiates this work by providing grid support during fluctuating demand conditions, a capability not explored in previous studies like those by Wang et al. (2023).

#### 4.2.4 Theory Building and Implications

The results of this study offer several contributions to the theoretical understanding of Vehicle-to-Grid (V2G) technology and its integration into power distribution systems. By leveraging the PSO algorithm, this research provides a novel approach to optimizing battery placement and operation in the IEEE 33 network. These findings contribute to theory building in the following areas:

##### **1. Dynamic Grid Support Framework:**

The study demonstrates the ability of V2G-enabled EVs to provide real-time reactive power support, voltage stabilization, and load balancing. This is evidenced by the enhanced voltage profiles in Figures 5 and 6 and the precise battery dispatch patterns reflected in Figure 11.

##### **2. Optimization Strategies for Radial Networks:**

The study extends the traditional static models by integrating dynamic control via V2G technology. Figures 10 and 11 illustrate that heuristic optimization, such as PSO, can tailor battery operation at a node level based on load fluctuations and SOC ranges. This supports scalable deployment and improves robustness.

### **3. Enhanced System Resilience:**

Battery-supported peak shaving reduced equivalent demand at critical nodes (e.g., a 36.4% load improvement at Node 26), which collectively enhances the grid's resilience under stress. The findings suggest a robust and adaptable framework for managing unpredictable load scenarios, particularly when integrated with renewable sources.

#### **4.2.5 Practical Implications**

##### **1. Grid Planning and Policy:**

The results support the integration of V2G systems into grid planning strategies, emphasizing the need for regulatory frameworks to accommodate dynamic energy resources. Policymakers could incentivize the adoption of V2G technology through subsidies or tariffs that reward energy market participation and ancillary services.

##### **2. Energy Market Participation:**

The demonstrated ability of EV batteries to provide ancillary services such as reactive power compensation and peak shaving highlights their potential for participation in energy markets. Mechanisms such as dynamic pricing models, which reward EV owners for discharging during peak demand, and capacity markets, where EVs bid for grid support services, provide financial incentives. Pilot programs, like the "Parker Project" in Denmark, have already showcased the feasibility of these systems, with EV owners earning up to €1,000 annually through grid services (e-Mobility Project, 2011). Regulatory frameworks must evolve to support these initiatives, offering streamlined protocols for energy transactions and

equitable compensation structures, thus improving the economic feasibility of V2G adoption.

### **3. Scalable Deployment:**

The scalability of the PSO-based optimization approach suggests its applicability to larger grids and complex network configurations. Utilities could adopt this method to streamline V2G integration in modern energy systems, ensuring resilience against demand variability and supporting renewable energy adoption.

#### **4.2.6 Summary**

The analysis in this chapter highlights the significant impact of integrating V2G-enabled EV batteries into the IEEE 33 network. Key findings include:

##### **1. Voltage Stability:**

- Strategic battery placement improved voltage levels at critical nodes, with average voltage improvement reaching up to 18.5% (Figure 5).
- Nodes with historically poor voltage performance, such as nodes 17, 18, and 33, achieved stable operation above 0.95 p.u. Across a 24-hour cycle (Figure 6).

##### **2. Power Loss Reduction:**

- Total system losses were reduced by approximately 10.57% when averaged across all hours (Figure 12), validating the effectiveness of the PSO algorithm in minimizing inefficiencies.

##### **3. Peak Shaving and Load Balancing:**

- At nodes 7, 14, and 26, equivalent loading was reduced by up to 36.4%, showing clear peak shaving performance (Figure 10).
- Complementary SOC profiles and battery energy states (Figure 11) confirmed responsive and sustainable dispatch cycles aligned with grid demand.

#### **4. Comparative and Theoretical Strengths:**

- Compared to previous studies, this work demonstrated enhanced voltage performance, greater loss reduction, and intelligent coordination between load and storage. These results support the theoretical framework for scalable, flexible V2G integration.

The implications of these findings underscore the transformative potential of V2G technology. By integrating adaptive optimization strategies, utilities can enhance grid resilience, support renewable energy integration, and incentivize EV owners through market participation. These results provide a strong foundation for scaling V2G systems and adapting regulatory frameworks to modernize power distribution networks.

## **Chapter 5: Conclusion and Recommendations**

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## **5.1 Introduction and Chapter Structure**

This chapter concludes the thesis by summarizing the study, discussing its key findings, addressing limitations, and providing recommendations for practical implementation and future research. The chapter begins with an overview of the research objectives and methodology before delving into the main conclusions. It then highlights the limitations encountered during the study and concludes with actionable recommendations and a final reflection on the broader implications of the findings.

## **5.2 Summary of the Study**

This research explored the integration of Vehicle-to-Grid (V2G) technology into the IEEE 33-bus distribution network using the Particle Swarm Optimization (PSO) algorithm. The study aimed to optimize the placement and sizing of Electric Vehicle (EV) batteries to enhance grid stability, manage peak loads, and improve voltage profiles. Key objectives included:

- Improving voltage stability through strategic battery placement.
- Reducing power losses and achieving effective load balancing.
- Evaluating the potential of V2G-enabled EVs for reactive power compensation.
- Developing a scalable optimization framework for V2G integration.

A 24-hour load forecast under peak day conditions was used to simulate grid performance. The PSO algorithm identified optimal battery placements, enabling dynamic energy redistribution and reactive power support.

## 5.3 Key Conclusions

### 1. Voltage Stability and Reactive Power Compensation:

The strategic placement of EV batteries significantly improved voltage stability across the IEEE 33 network. Voltage levels at critical nodes were maintained within the permissible range of 0.9 to 1 p.u., with notable improvements of up to 18.5% at nodes 18, 30, and 33 (as shown in Figure 5). The voltage profile at vulnerable nodes such as 17, 18, and 33 (Figure 6) demonstrated stable operation post-placement. The dynamic reactive power compensation provided by EV batteries was crucial in mitigating voltage dips during peak load periods, validating the algorithm's ability to adaptively support grid reliability.

### 2. Optimal Battery Allocation and Load Management:

The PSO algorithm effectively optimized EV battery allocation, targeting nodes with high load sensitivity. This allocation led to a reduction in overall power losses by approximately **10.57%** (Figure 12) and improved system efficiency. Load balancing was particularly enhanced at nodes 9, 29, and 32, with node 29 showing a **25% reduction in load variability**. These improvements confirm the success of the optimization strategy in enhancing grid stability through intelligent and adaptive load support.

### 3. Peak Shaving and Local Demand Reduction:

The integration of EV batteries delivered substantial peak shaving at

key locations. At node 26, a peak load reduction of **18.7%** was recorded, while equivalent load improvements at nodes 7, 14, and 26 reached up to **36.4%** (Figure 10). Battery operation was dynamically managed based on load demand, as evidenced by the real-time battery states and SOC profiles in Figure 11. This adaptability reduces strain on generation and transmission infrastructure while maintaining healthy state-of-charge levels.

#### 4. **Scalability and Adaptability of V2G-Integrated Optimization:**

The PSO-based optimization framework proved scalable and robust under dynamic grid conditions. Battery dispatch was responsive and coordinated, matching fluctuations in local demand while avoiding over-discharge. These results demonstrate the real-world viability of Vehicle-to-Grid (V2G) technology in supporting renewable energy integration, improving operational flexibility, and contributing to long-term grid modernization efforts.

## 5.4 Limitations

Despite the promising results, the study faced several limitations:

- **Simulation Dependency:** The research relied on MATLAB simulations, which may not fully capture the complexities of real-world grid operations.
- **Algorithmic Challenges:** The PSO algorithm occasionally exhibited premature convergence, potentially limiting its ability to identify global optimal solutions.
- **Scope Constraints:** The study focused solely on the IEEE 33-bus network, which may limit the generalizability of findings to larger or more complex grids.

- **Data Limitations:** The lack of real-world data on EV adoption rates and renewable energy integration constrained the analysis.

## 5.5 Recommendations

### 1. Practical Applications:

- Policymakers and utilities should develop regulatory frameworks that incentivize V2G participation, including dynamic pricing and compensation models.
- Utilities should consider deploying pilot projects to validate the feasibility of V2G integration in diverse grid environments.

### 2. Future Research Directions:

- Extend the study to larger networks and meshed distribution systems to assess scalability.
- Investigate real-time implementation challenges, including communication latency and infrastructure costs.
- Explore the integration of V2G technology with renewable energy sources, such as solar and wind, to address intermittency issues.
- Develop advanced algorithms to mitigate premature convergence in optimization processes.

## 5.6 Final Reflection

This study underscores the transformative potential of V2G technology in modern power distribution systems. By leveraging the flexibility of EV batteries, the research demonstrated significant improvements in grid stability, efficiency, and reliability. The findings contribute to the theoretical understanding of dynamic grid support

frameworks and offer practical insights for utilities and policymakers. As the adoption of EVs and renewable energy continues to grow, V2G technology will play an integral role in achieving sustainable and resilient energy systems.

In conclusion, the study provides a robust foundation for advancing V2G integration and highlights the need for continued research and innovation to address the evolving challenges of modern power networks.

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# Appendix 1: Case33bw

```

function mpc = case33bw
%CASE33BW Power flow data for 33 bus distribution system from Baran & Wu
% Please see CASEFORMAT for details on the case file format.
%
% Data from ...
% M. E. Baran and F. F. Wu, "Network reconfiguration in distribution
% systems for loss reduction and load balancing," in IEEE
Transactions
% on Power Delivery, vol. 4, no. 2, pp. 1401-1407, Apr 1989.
% doi: 10.1109/61.25627
% URL: http://doi.org/10.1109/61.25627

%% MATPOWER Case Format : Version 2
mpc.version = '2';

%%----- Power Flow Data -----%%
%% system MVA base
mpc.baseMVA = 100;

%% bus data
% bus_i type Pd Qd Gs Bs area Vm Va baseKV
zone Vmax Vmin
mpc.bus = [ %% (Pd and Qd are specified in kW & kVAr here, converted to MW
& MVar below)
1 3 0 0 0 1 1 0 12.66 1 1 1;
2 1 100 60 0 0 1 1 0 12.66 1 1.1 0.9;
3 1 90 40 0 0 1 1 0 12.66 1 1.1 0.9;
4 1 120 80 0 0 1 1 0 12.66 1 1.1 0.9;
5 1 60 30 0 0 1 1 0 12.66 1 1.1 0.9;
6 1 60 20 0 0 1 1 0 12.66 1 1.1 0.9;
7 1 200 100 0 0 1 1 0 12.66 1 1.1 0.9;
8 1 200 100 0 0 1 1 0 12.66 1 1.1 0.9;
9 1 60 20 0 0 1 1 0 12.66 1 1.1 0.9;
10 1 60 20 0 0 1 1 0 12.66 1 1.1 0.9;
11 1 45 30 0 0 1 1 0 12.66 1 1.1 0.9;
12 1 60 35 0 0 1 1 0 12.66 1 1.1 0.9;
13 1 60 35 0 0 1 1 0 12.66 1 1.1 0.9;
14 1 120 80 0 0 1 1 0 12.66 1 1.1 0.9;
15 1 60 10 0 0 1 1 0 12.66 1 1.1 0.9;
16 1 60 20 0 0 1 1 0 12.66 1 1.1 0.9;
17 1 60 20 0 0 1 1 0 12.66 1 1.1 0.9;
18 1 90 40 0 0 1 1 0 12.66 1 1.1 0.9;
19 1 90 40 0 0 1 1 0 12.66 1 1.1 0.9;
20 1 90 40 0 0 1 1 0 12.66 1 1.1 0.9;
21 1 90 40 0 0 1 1 0 12.66 1 1.1 0.9;
22 1 90 40 0 0 1 1 0 12.66 1 1.1 0.9;
23 1 90 50 0 0 1 1 0 12.66 1 1.1 0.9;
24 1 420 200 0 0 1 1 0 12.66 1 1.1
0.9;
25 1 420 200 0 0 1 1 0 12.66 1 1.1
0.9;
26 1 60 25 0 0 1 1 0 12.66 1 1.1 0.9;
27 1 60 25 0 0 1 1 0 12.66 1 1.1 0.9;
28 1 60 20 0 0 1 1 0 12.66 1 1.1 0.9;
29 1 120 70 0 0 1 1 0 12.66 1 1.1 0.9;

```

```

30    1    200    600    0    0    1    1    0    12.66    1    1.1
0.9;
31    1    150    70    0    0    1    1    0    12.66    1    1.1    0.9;
32    1    210    100    0    0    1    1    0    12.66    1    1.1
0.9;
33    1    60    40    0    0    1    1    0    12.66    1    1.1    0.9];

```

```

mpc.bus(:,3:4) = mpc.bus(:,3:4)/1e3;

```

```

%% generator data

```

```

%   bus   Pg   Qg   Qmax   Qmin   Vg   mBase   status   Pmax
Pmin   Pc1   Pc2   Qc1min   Qc1max   Qc2min   Qc2max   ramp_agc
ramp_10   ramp_30   ramp_q   apf
mpc.gen = [
1     0     0    10    -10    1    100    1    10/4    0    0    0    0    0
0     0     0     0     0     0    0;
];

```

```

%% branch data

```

```

%   fbus   tbus   r   x   b   rateA   rateB   rateC   ratio
angle   status   angmin   angmax
mpc.branch = [ %% (r and x specified in ohms here, converted to p.u.
below)
1     2    0.0922    0.0470    0    0    0    0    0    1    -360
360;
2     3    0.4930    0.2511    0    0    0    0    0    1    -360
360;
3     4    0.3660    0.1864    0    0    0    0    0    1    -360
360;
4     5    0.3811    0.1941    0    0    0    0    0    1    -360
360;
5     6    0.8190    0.7070    0    0    0    0    0    1    -360
360;
6     7    0.1872    0.6188    0    0    0    0    0    1    -360
360;
7     8    0.7114    0.2351    0    0    0    0    0    1    -360
360;
8     9    1.0300    0.7400    0    0    0    0    0    1    -360
360;
9    10    1.0440    0.7400    0    0    0    0    0    1    -360
360;
10    11    0.1966    0.0650    0    0    0    0    0    1    -360
360;
11    12    0.3744    0.1238    0    0    0    0    0    1    -360
360;
12    13    1.4680    1.1550    0    0    0    0    0    1    -360
360;
13    14    0.5416    0.7129    0    0    0    0    0    1    -360
360;
14    15    0.5910    0.5260    0    0    0    0    0    1    -360
360;
15    16    0.7463    0.5450    0    0    0    0    0    1    -360
360;
16    17    1.2890    1.7210    0    0    0    0    0    1    -360
360;
17    18    0.7320    0.5740    0    0    0    0    0    1    -360
360;
2    19    0.1640    0.1565    0    0    0    0    0    1    -360
360;

```

```

19    20    1.5042    1.3554    0    0    0    0    0    0    1    -360
360;
20    21    0.4095    0.4784    0    0    0    0    0    0    1    -360
360;
21    22    0.7089    0.9373    0    0    0    0    0    0    1    -360
360;
3    23    0.4512    0.3083    0    0    0    0    0    0    1    -360
360;
23    24    0.8980    0.7091    0    0    0    0    0    0    1    -360
360;
24    25    0.8960    0.7011    0    0    0    0    0    0    1    -360
360;
6    26    0.2030    0.1034    0    0    0    0    0    0    1    -360
360;
26    27    0.2842    0.1447    0    0    0    0    0    0    1    -360
360;
27    28    190      0.9337    0    0    0    0    0    0    1    -360
360;
28    29    0.8042    0.7006    0    0    0    0    0    0    1    -360
360;
29    30    0.5075    0.2585    0    0    0    0    0    0    1    -360
360;
30    31    0.9744    0.9630    0    0    0    0    0    0    1    -360
360;
31    32    0.3105    0.3619    0    0    0    0    0    0    1    -360
360;
32    33    0.3410    0.5302    0    0    0    0    0    0    1    -360
360;
21    8     2.0000    2.0000    0    0    0    0    0    0    0    -360
360;
9    15    2.0000    2.0000    0    0    0    0    0    0    0    -360
360;
12    22    2.0000    2.0000    0    0    0    0    0    0    0    -360
360;
18    33    0.5000    0.5000    0    0    0    0    0    0    0    -360
360;
25    29    0.5000    0.5000    0    0    0    0    0    0    0    -360
360];

%%----- OPF Data -----%%
%% generator cost data
%    2    startup    shutdown    n    c(n-1)    ...    c0
mpc.gencost = [2    0    0    3    0    20    0];

```

## Appendix 2: Load Forecasting, Create Loading Profile, and Historical Loading Profile

- Load Forecasting

```
function Sol = CreateLoadingProfile(mpc,MeanLoad)

    LoadFP = [];
    TemperaturesFP = [];
    HumidityFP = [];
    WindSpeedFP = [];

    Load = MeanLoad*[0.2 0.15 0.1 0.1 0.1 0.15 0.2 0.4 0.8 0.7 0.7 0.65 0.6
0.6 0.6 0.7 0.9 1.1 1.1 1 0.9 0.8 0.6 0.3];
    Temperatures = [55 56 55 53 52 51 50 51 51 51 50 51 51 53 52 54 54 53
53 52 52 51 50 51];
    Humidity = [0.69 0.69 0.69 0.8 0.8 0.83 0.83 0.8 0.77 0.77 0.8 0.8 0.74
0.71 0.59 0.55 0.61 0.61 0.63 0.66 0.74 0.74 0.74 0.71];
    WindSpeed = [15 16 17 14 13 15 16 15 14 14 14 15 18 15 20 16 10 8 8 3 5
5 5 0];

    for i = 1:7
        for j = 1:length(Temperatures)
            LoadFP = [LoadFP normrnd(1*Load(j),0.05*Load(j))];
            TemperaturesFP = [TemperaturesFP
normrnd(Temperatures(j),0.05*Temperatures(j))];
            HumidityFP = [HumidityFP
normrnd(Humidity(j),0.05*Humidity(j))];
            WindSpeedFP = [WindSpeedFP
normrnd(WindSpeed(j),0.05*WindSpeed(j))];
        end
    end

    Sol = LoadForecasting(mpc, MeanLoad, TemperaturesFP,
HumidityFP,WindSpeedFP, LoadFP);
end

function gbest = LoadForecasting(mpc, Load, Temperature, Humidity,
WindSpeed, HistoricalLoad)

    FP = mpc.FP;
    pop = 10000;
    max_iter = 100;

    initial = zeros(pop,FP);
    objective = zeros(pop,1);

    for i = 1:pop
        initial(i,:) = normrnd(1*Load,0.05*Load,[1,FP]);
    end

    Rtemp = 0.3;
    Rhum = 0.4;
    Rwind = 0.4;
```

```

Rhload = 0.4;

for i = 1:pop
    objective(i) = (CorrCoeff(initial(i,:),Temperature) - Rtemp)^2 +
(CorrCoeff(initial(i,:),Humidity) - Rhum)^2 + ...
    + (CorrCoeff(initial(i,:),WindSpeed) - Rwind)^2 +
(CorrCoeff(initial(i,:),HistoricalLoad) - Rhload)^2;
end

gbest = initial(find(objective == min(objective)),:);
pbest = initial;
gbestobj = min(objective);
pbestobj = objective;

w = linspace(0.9,0.9,max_iter);
C1 = linspace(2,2,max_iter);
C2 = linspace(2,2,max_iter);

x = initial;
v = x;

for i = 1:max_iter
    for j = 1:pop
        v(j,:) = w(i)*v(j,:) + C1(i)*rand()*(gbest-x(j,:)) +
C2(i)*rand()*(pbest(j,:)-x(j,:));
    end

    x = x + v;

    for j = 1:pop
        objective(j) = (CorrCoeff(x(j,:),Temperature) - Rtemp)^2 +
(CorrCoeff(x(j,:),Humidity) - Rhum)^2 + ...
        + (CorrCoeff(x(j,:),WindSpeed) - Rwind)^2 +
(CorrCoeff(x(j,:),HistoricalLoad) - Rhload)^2;
    end

    for j = 1:pop
        if objective(j) < pbestobj(j)
            pbest(j,:) = x(j,:);
            pbestobj(j) = objective(j);
            if objective(j) < gbestobj
                gbest = x(j,:);
                gbestobj = objective(j);
            end
        end
    end
end
end
end

```

- Create Loading Profile

```
function Sol = CreateLoadingProfile(mpc,MeanLoad)

    % url =
    "https://www.wunderground.com/history/daily/gb/bridgend/IBRIDGEN3/date/2023
    ";

    LoadFP = [];
    TemperaturesFP = [];
    HumidityFP = [];
    WindSpeedFP = [];

    Load = MeanLoad*[0.2 0.15 0.1 0.1 0.1 0.15 0.2 0.4 0.8 0.7 0.7 0.65 0.6
    0.6 0.6 0.7 0.9 1.1 1.1 1 0.9 0.8 0.6 0.3];
    Temperatures = [55 56 55 53 52 51 50 51 51 51 50 51 51 53 52 54 54 53
    53 52 52 51 50 51];
    Humidity = [0.69 0.69 0.69 0.8 0.8 0.83 0.83 0.8 0.77 0.77 0.8 0.8 0.74
    0.71 0.59 0.55 0.61 0.61 0.63 0.66 0.74 0.74 0.74 0.71];
    WindSpeed = [15 16 17 14 13 15 16 15 14 14 14 15 18 15 20 16 10 8 8 3 5
    5 5 0];

    for i = 1:7
        for j = 1:length(Temperatures)
            LoadFP = [LoadFP normrnd(1*Load(j),0.05*Load(j))];
            TemperaturesFP = [TemperaturesFP
            normrnd(Temperatures(j),0.05*Temperatures(j))];
            HumidityFP = [HumidityFP
            normrnd(Humidity(j),0.05*Humidity(j))];
            WindSpeedFP = [WindSpeedFP
            normrnd(WindSpeed(j),0.05*WindSpeed(j))];
        end
    end

    Sol = LoadForecasting(mpc, MeanLoad, TemperaturesFP, HumidityFP,
    WindSpeedFP, LoadFP);
end

function gbest = LoadForecasting(mpc, Load, Temperature, Humidity,
    WindSpeed, HistoricalLoad)

    FP = mpc.FP;
    pop = 1000;
    max_iter = 100;

    initial = zeros(pop,FP);
    objective = zeros(pop,1);

    for i = 1:pop
        initial(i,:) = normrnd(1*Load,0.05*abs(Load),[1,FP]);
    end

    Rtemp = 0.6;
    Rhum = 0.4;
    Rwind = 0.6;
    Rhload = 0.8;

    for i = 1:pop
```

```

        objective(i) = (CorrCoeff(initial(i,:),Temperature) - Rtemp)^2 +
(CorrCoeff(initial(i,:),Humidity) - Rhum)^2 + ...
        + (CorrCoeff(initial(i,:),WindSpeed) - Rwind)^2 +
(CorrCoeff(initial(i,:),HistoricalLoad) - Rhload)^2;
    end

    gbest = initial(find(objective == min(objective)),:);
    pbest = initial;
    gbestobj = min(objective);
    pbestobj = objective;

    w = linspace(0.2,0.2,max_iter);
    C1 = linspace(2,2,max_iter);
    C2 = linspace(2,2,max_iter);

    x = initial;
    v = x;

    for i = 1:max_iter
        for j = 1:pop
            v(j,:) = w(i)*v(j,:) + C1(i)*rand()*(gbest-x(j,:)) +
C2(i)*rand()*(pbest(j,:)-x(j,:));
        end

        x = x + v;

        for j = 1:pop
            objective(j) = (CorrCoeff(x(j,:),Temperature) - Rtemp)^2 +
(CorrCoeff(x(j,:),Humidity) - Rhum)^2 + ...
            + (CorrCoeff(x(j,:),WindSpeed) - Rwind)^2 +
(CorrCoeff(x(j,:),HistoricalLoad) - Rhload)^2;
        end

        for j = 1:pop
            if objective(j) < pbestobj(j)
                pbest(j,:) = x(j,:);
                pbestobj(j) = objective(j);
                if objective(j) < gbestobj
                    gbest = x(j,:);
                    gbestobj = objective(j);
                end
            end
        end
    end
end
end

```

- Historical Loading Profile

```
function LoadingData = HistoricalLoadingProfile

    % Use the Kaggle dataset on historical hourly consumption pattern,
    % normalized it, so its mean value becomes equal to the original
loading
    % profile of IEEE 33 system.

    % Working with IEEE 33 bus system
    mpc = case33bw;

    % Read the Kaggle dataset
    data = readtable("powerconsumption.csv");

    DateTime = table2array(data(:,1));

    % Extracting temperature, humidity and wind datasets
    Temperature = table2array(data(:,2));
    Humidity = table2array(data(:,3));
    Wind = table2array(data(:,4));

    % Loading tables, store different power_consumption areas
    Load = table2array(data(:,7));
    Load = [Load table2array(data(:,8))];
    Load = [Load table2array(data(:,9))];

    % Original active and reactive power loading profile
    P = mpc.bus(:,3)/100;
    Q = mpc.bus(:,4)/100;

    % Converting to per unit system
    Load = Load/mpc.baseMVA/1e6;

    % Preallocation of active and reactive power profiles, for each of the
    % nodes
    LoadProfileP = zeros(size(Load,1),length(P));
    LoadProfileQ = zeros(size(Load,1),length(P));

    % Active and reactive power profiles for each of the nodes, with 10%
    % variance (of mean value).
    for i = 1:length(P)
        ind = randi([1,3]);
        LoadProfileP(:,i) = Load(:,ind)*P(i)/mean(Load(:,ind));
        LoadProfileP(:,i) = LoadProfileP(:,i) +
normrnd(0,0.1*mean(LoadProfileP(:,i)));
        LoadProfileQ(:,i) = Load(:,ind)*Q(i)/mean(Load(:,ind));
        LoadProfileQ(:,i) = LoadProfileQ(:,i) +
normrnd(0,0.1*mean(LoadProfileQ(:,i)));
    end

    % Storing the output structure
    LoadingData = [];
    LoadingData.DateTime = DateTime;
    LoadingData.P = LoadProfileP;
    LoadingData.Q = LoadProfileQ;
    LoadingData.Temperature = Temperature;
```

```

LoadingData.Humidity = Humidity;
LoadingData.Wind = Wind;

Labels = "1";
for i = 2:33
    Labels = [Labels num2str(i)];
end

Labels = [Labels "Temperature" "Humidity" "Wind"];

writetable(array2table([LoadingData.P LoadingData.Temperature
LoadingData.Humidity LoadingData.Wind], 'VariableNames', Labels),
'ActivePowerDemand.csv')

end

```

## Appendix 3: V2G Integration

```
%
clear

% Define the system to test
mpc = case33bw;

% Forecasting period
mpc.FP = 24*7;

% Admittance matrix and the size of the system
mpc.Y = AdmittanceMatrix(mpc);
mpc.N = length(mpc.bus(:,2));
mpc.Nbr = size(mpc.branch(:,1),1);

% Initialize the PV, PQ and slack nodes
mpc.PV = [];
mpc.PQ = [];
mpc.Slack = [];

% PV, PQ and Slack nodes
for i = 1:mpc.N
    if mpc.bus(i,2) == 2
        mpc.PV = [mpc.PV mpc.bus(i,1)];
    elseif mpc.bus(i,2) == 1
        mpc.PQ = [mpc.PQ mpc.bus(i,1)];
    else
        mpc.Slack = [mpc.Slack mpc.bus(i,1)];
    end
end

% Clean the data
mpc.clean = [];

for i = 1:mpc.N
    if ismember(i,mpc.Slack) == 0
        mpc.clean = [mpc.clean i];
    end
end

for i = 1:mpc.N
    if ismember(i,mpc.PQ)
        mpc.clean = [mpc.clean i+mpc.N];
    end
end

% Maximal power flow through the line
mpc.Smax = 1.1;

% Maximal battery capacity in 100MWh
mpc.C_B_max = 0.1;

% Maximal charging/discharging power
mpc.Pdcmax = mpc.C_B_max*0.1;

% Charging/discharging efficiency
```

```

mpc.etac = 1;
mpc.etadc = 1;

% Minimal and maximal state of charge - SOC
mpc.SOCmin = 0.1;
mpc.SOCmax = 0.9;

% Minimal and maximal voltage magnitude
mpc.Vmin = 0.9;
mpc.Vmax = 1.1;

% Minimal and maximal electrical angle
mpc.thetamin = -pi/2;
mpc.thetamax = pi/2;

% Loading conditions
mpc.Lp = mpc.bus(:,3)/100;
mpc.Lq = mpc.bus(:,4)/100;

LoadingP = zeros(mpc.N,mpc.FP);
LoadingQ = zeros(mpc.N,mpc.FP);

LoadingData = HistoricalLoadingProfile;

for i = 2:mpc.N
    if mpc.Lp(i)
        ind = find(max>LoadingData.P(:,i))==LoadingData.P(:,i));
        LoadingP(i,:) = LoadingData.P(ind-mpc.FP/2:ind+mpc.FP/2-1,i);
    end
    if mpc.Lq(i)
        ind = find(max>LoadingData.Q(:,i))==LoadingData.Q(:,i));
        LoadingQ(i,:) = LoadingData.Q(ind-mpc.FP/2:ind+mpc.FP/2-1,i);
    end
end

% Emulated forecast - HERE WE SET UP THE NEW LOAD PROFILE
for t = 1:mpc.FP
    for i = 1:length(mpc.Lp)
        mpc.FLp(t,i) = -LoadingP(i,t);
        mpc.FLq(t,i) = -LoadingQ(i,t);
    end
end

%Xsol = SLOPF(mpc);
initial = [];

% Must be approximately equal to the dimensionality of the system
% in this case 3*mpc.FP*mpc.N + mpc.N - we choose 50
mpc.pop = 50;

for i = 1:mpc.pop
    for j = 1:mpc.N
        initial.C_B(i,j) = rand()*mpc.C_B_max;
        % Initialize such that charging power is not violated
        initial.B(i,1,j) = mpc.SOCmin*initial.C_B(i,j) +
        rand()*(mpc.SOCmax-mpc.SOCmin)*initial.C_B(i,j);
        for t = 1:mpc.FP
            if ~ismember(j,mpc.PQ)
                ind = find(j == mpc.gen(:,1));

```

```

        initial.P(i,t,j) = mpc.gen(ind,10)/100 +
rand()*(mpc.gen(ind,9)-mpc.gen(ind,10))/100;
        initial.Q(i,t,j) = mpc.gen(ind,5)/100 +
rand()*(mpc.gen(ind,4)-mpc.gen(ind,5))/100;
    else
        initial.P(i,t,j) = 0;
        initial.Q(i,t,j) = 0;
    end
end
for t = 2:mpc.FP+1
    % Initialization like this - to satisfy SOC constraint
    initial.B(i,t,j) = initial.B(i,t-1,j) - 0.1*initial.C_B(i,j) +
2*rand()*0.1*initial.C_B(i,j);
    if initial.B(i,t,j) < mpc.SOCmin*initial.C_B(i,j)
        initial.B(i,t,j) = mpc.SOCmin*initial.C_B(i,j);
    elseif initial.B(i,t,j) > mpc.SOCmax*initial.C_B(i,j)
        initial.B(i,t,j) = mpc.SOCmax*initial.C_B(i,j);
    end
end
end
end

% Randomly allocate all of the EV chargers
initial.y = randi([0,1],mpc.pop,mpc.N);

% Randomly allocating the battery capacities and battery energy states
for i = 1:mpc.pop
    for j = 1:mpc.N
        initial.B(i,:,j) = initial.y(i,j)*initial.B(i,:,j);
        initial.C_B(i,j) = initial.y(i,j)*initial.C_B(i,j);
    end
end

for i = 1:mpc.pop
    for j = 1:mpc.N
        for t = 1:mpc.FP
            initial.BatPowerActive(i,t,j) = initial.y(i,j)*(-
abs(mpc.etac*(initial.B(i,t,j) - initial.B(i,t+1,j))) +
2*rand()*abs(mpc.etac*(initial.B(i,t,j) - initial.B(i,t+1,j))));
        end
    end
end
end

```

## Appendix 4: Admittance Matrix

```
function Y = AdmittanceMatrix(mpc)

% Define the size of the system
N = size(mpc.bus,1);

% Sending nodes
SN = mpc.branch(:,1);

% Receiving nodes
RN = mpc.branch(:,2);

% Initialize the admittance matrix
Y = zeros(N,N);

% Populate the matrix
for i = 1:size(mpc.branch(:,1),1)
    Y(SN(i),RN(i)) = -1/complex(mpc.branch(i,3),mpc.branch(i,4));
    Y(RN(i),SN(i)) = Y(SN(i),RN(i));
    Y(SN(i),SN(i)) = Y(SN(i),SN(i)) +
1/complex(mpc.branch(i,3),mpc.branch(i,4));
    Y(RN(i),RN(i)) = Y(RN(i),RN(i)) +
1/complex(mpc.branch(i,3),mpc.branch(i,4));
    Y(SN(i),SN(i)) = Y(SN(i),SN(i)) + complex(0,mpc.branch(i,5));
    Y(RN(i),RN(i)) = Y(RN(i),RN(i)) + complex(0,mpc.branch(i,5));
end

for i = 1:N
    Y(i,i) = Y(i,i) + complex(mpc.bus(i,5),mpc.bus(i,6))/100;
end
end
```

# Appendix 5: Equality Constraint with Reactive Power Support

```

function current = EqualityConstraintsWithReactivePowerSupport(current,mpc)

    % Check for each time step and for each particle
    tol = 1e-5;

    flag = zeros(mpc.pop,mpc.FP);

    for i = 1:mpc.pop
        for j = 1:mpc.N
            for t = 1:mpc.FP
                if ismember(i,mpc.PQ)
                    if abs(current.BatPowerActive(i,t,j)) >
abs(mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j)))
                        current.BatPowerActive(i,t,j) = current.y(i,j)*(-
abs(mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j))) +
2*rand()*abs(mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j))));
                    end
                    current.BatPowerReactive(i,t,j) =
sqrt((mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j)))^2 -
current.BatPowerActive(i,t,j)^2);
                    current.Lp(i,t,j) = current.BatPowerActive(i,t,j) +
mpc.FLp(t,j);
                    current.Lq(i,t,j) = current.BatPowerReactive(i,t,j) +
mpc.FLq(t,j);
                else
                    if abs(current.BatPowerActive(i,t,j)) >
abs(mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j)))
                        current.BatPowerActive(i,t,j) = current.y(i,j)*(-
abs(mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j))) +
2*rand()*abs(mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j))));
                    end
                    current.BatPowerReactive(i,t,j) =
sqrt((mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j)))^2 -
current.BatPowerActive(i,t,j)^2);
                    current.Lp(i,t,j) = current.BatPowerActive(i,t,j) +
mpc.FLp(t,j) + current.P(i,t,j);
                    current.Lq(i,t,j) = current.BatPowerReactive(i,t,j) +
mpc.FLq(t,j) + current.Q(i,t,j);
                    end
                    current.Powers(i,t,j) = current.Lp(i,t,j);
                    % Reactive power support
                    current.Powers(i,t,j+mpc.N) = current.Lq(i,t,j);
                end
            end
        end
    end

    counter_max = 50;

    i = 1;

    while i <= mpc.pop

```

```

counter = 0;
for t = 1:mpc.FP
    % If we reiterate too many times, call whole new solution for
    % the particle
    while ~ flag(i,t) && counter < counter_max
        current = RepeatInitialization(current,mpc,i,t);
        [aux, Pcheck, Qcheck, flag(i,t)] =
LoadFlowAlgorithm(reshape(current.Powers(i,t,:),[2*mpc.N,1]),mpc,tol);
        current.V(i,t,:) = aux(1:mpc.N,1);
        current.theta(i,t,:) = aux(1+mpc.N:2*mpc.N,1);
        current.Iflood(i,t,:) =
IncidenceMatrix(mpc)*(reshape(current.V(i,t,:),[mpc.N,1]).*exp(complex(0, re
shape(current.theta(i,t,:),[mpc.N,1]))));
        current.Sflow(i,t,:) =
abs(conj(reshape(current.Iflood(i,t,:),[2*mpc.Nbr,1])).*(VoltageMatrix(mpc)*
reshape(current.V(i,t,:),[mpc.N,1])));
        current.P(i,t,mpc.Slack) = Pcheck(mpc.Slack);
        current.Q(i,t,mpc.Slack) = Qcheck(mpc.Slack);
        current.Pcheck(i,t,:) = Pcheck;
        current.Qcheck(i,t,:) = Qcheck;
        counter = counter + 1;
    end
end
if counter == counter_max
    current = RepeatInitializationParticle(current,mpc,i);
    i = i - 1;
end
i = i + 1;
end
end

function current = RepeatInitialization(current,mpc,i,t)

for j = 1:mpc.N
    if ~ismember(j,mpc.PQ)
        ind = find(j == mpc.gen(:,1));
        current.P(i,t,j) = mpc.gen(ind,10)/100 +
rand()*(mpc.gen(ind,9)-mpc.gen(ind,10))/100;
        current.Q(i,t,j) = mpc.gen(ind,5)/100 + rand()*(mpc.gen(ind,4) -
mpc.gen(ind,5))/100;
    else
        current.P(i,t,j) = 0;
        current.Q(i,t,j) = 0;
    end
end

% Initialization like this - to satisfy SOC constraint
if t == 1
    current.B(i,t,j) = mpc.SOCmin*current.C_B(i,j) +
rand()*(mpc.SOCmax-mpc.SOCmin)*current.C_B(i,j);
else
    current.B(i,t,j) = current.B(i,t-1,j) - 0.1*current.C_B(i,j) +
2*rand()*0.1*current.C_B(i,j);
end

if current.B(i,t,j) < mpc.SOCmin*current.C_B(i,j)
    current.B(i,t,j) = mpc.SOCmin*current.C_B(i,j);
elseif current.B(i,t,j) > mpc.SOCmax*current.C_B(i,j)
    current.B(i,t,j) = mpc.SOCmax*current.C_B(i,j);
end

```

```

end

for j = 1:mpc.N
    current.B(i,:,j) = current.y(i,j)*current.B(i,:,j);
    current.C_B(i,j) = current.y(i,j)*current.C_B(i,j);
    for t = 1:mpc.FP
        current.BatPowerActive(i,t,j) = -abs(mpc.etac*(current.B(i,t,j)
- current.B(i,t+1,j))) + 2*rand()*abs(mpc.etac*(current.B(i,t,j) -
current.B(i,t+1,j)));
    end
end

for i = 1:mpc.pop
    if ismember(i,mpc.PQ)
        current.BatPowerActive(i,t,j) =
current.y(i,j)*current.BatPowerActive(i,t,j);
        current.BatPowerReactive(i,t,j) =
sqrt((mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j)))^2 -
current.BatPowerActive(i,t,j)^2);
        current.Lp(i,t,j) = current.BatPowerActive(i,t,j) +
mpc.FLp(t,j);
        current.Lq(i,t,j) = current.BatPowerReactive(i,t,j) +
mpc.FLq(t,j);
    else
        current.BatPowerActive(i,t,j) =
current.y(i,j)*current.BatPowerActive(i,t,j);
        current.BatPowerReactive(i,t,j) =
sqrt((mpc.etac*(current.B(i,t,j) - current.B(i,t+1,j)))^2 -
current.BatPowerActive(i,t,j)^2);
        current.Lp(i,t,j) = current.BatPowerActive(i,t,j) +
mpc.FLp(t,j) + current.P(i,t,j);
        current.Lq(i,t,j) = current.BatPowerReactive(i,t,j) +
mpc.FLq(t,j) + current.Q(i,t,j);
    end
    current.Powers(i,t,j) = current.Lp(i,t,j);
    % Reactive power support
    current.Powers(i,t,j+mpc.N) = current.Lq(i,t,j);
end
end

function initial = RepeatInitializationParticle(initial,mpc,i)

for j = 1:mpc.N
    initial.C_B(i,j) = rand()*mpc.C_B_max;
    % Initialize such that charging power is not violated
    initial.B(i,1,j) = mpc.SOCmin*initial.C_B(i,j) +
rand()*(mpc.SOCmax-mpc.SOCmin)*initial.C_B(i,j);
    for t = 1:mpc.FP
        if ~ismember(j,mpc.PQ)
            ind = find(j == mpc.gen(:,1));
            initial.P(i,t,j) = mpc.gen(ind,10)/100 +
rand()*(mpc.gen(ind,9)-mpc.gen(ind,10))/100;
            initial.Q(i,t,j) = mpc.gen(ind,5)/100 +
rand()*(mpc.gen(ind,4)-mpc.gen(ind,5))/100;
        else
            initial.P(i,t,j) = 0;
            initial.Q(i,t,j) = 0;
        end
    end
end
end

```

```

    for t = 2:mpc.FP
        % Initialization like this - to satisfy SOC constraint
        initial.B(i,t,j) = initial.B(i,t-1,j) - 0.1*initial.C_B(i,j) +
2*rand()*0.1*initial.C_B(i,j);
        if initial.B(i,t,j) < mpc.SOCmin*initial.C_B(i,j)
            initial.B(i,t,j) = mpc.SOCmin*initial.C_B(i,j);
        elseif initial.B(i,t,j) > mpc.SOCmax*initial.C_B(i,j)
            initial.B(i,t,j) = mpc.SOCmax*initial.C_B(i,j);
        end
    end
end

% Randomly allocate all of the EV chargers
initial.y(i,:) = randi([0,1],1,mpc.N);

% Randomly allocating the battery capacities and battery energy states

for j = 1:mpc.N
    initial.B(i,:,j) = initial.y(i,j)*initial.B(i,:,j);
    initial.C_B(i,j) = initial.y(i,j)*initial.C_B(i,j);
    for t = 1:mpc.FP
        initial.BatPowerActive(i,t,j) = -abs(mpc.etac*(initial.B(i,t,j)
- initial.B(i,t+1,j))) + 2*rand()*abs(mpc.etac*(initial.B(i,t,j) -
initial.B(i,t+1,j)));
    end
end

for t = 1:mpc.FP
    for j = 1:mpc.N
        if ismember(i,mpc.PQ)
            initial.BatPowerActive(i,t,j) =
initial.y(i,j)*initial.BatPowerActive(i,t,j);
            initial.BatPowerReactive(i,t,j) =
sqrt((mpc.etac*(initial.B(i,t,j) - initial.B(i,t+1,j)))^2 -
initial.BatPowerActive(i,t,j)^2);
            initial.Lp(i,t,j) = initial.BatPowerActive(i,t,j) +
mpc.FLp(t,j);
            initial.Lq(i,t,j) = initial.BatPowerReactive(i,t,j) +
mpc.FLq(t,j);
        else
            initial.BatPowerActive(i,t,j) =
initial.y(i,j)*initial.BatPowerActive(i,t,j);
            initial.BatPowerReactive(i,t,j) =
sqrt((mpc.etac*(initial.B(i,t,j) - initial.B(i,t+1,j)))^2 -
initial.BatPowerActive(i,t,j)^2);
            initial.Lp(i,t,j) = initial.BatPowerActive(i,t,j) +
mpc.FLp(t,j) + initial.P(i,t,j);
            initial.Lq(i,t,j) = initial.BatPowerReactive(i,t,j) +
mpc.FLq(t,j) + initial.Q(i,t,j);
        end
        initial.Powers(i,t,j) = initial.Lp(i,t,j);
        % Reactive power support
        initial.Powers(i,t,j+mpc.N) = initial.Lq(i,t,j);
    end
end
end

```

## Appendix 6: Jacobian Matrix

```

function J = Jacobian(Y,V)
    N = size(Y,1);

    J = zeros(2*N,2*N);
    for i = 1:N
        for j = 1:N
            if i ~= j
                J(i,j) = -V(i)*(real(Y(i,j))*cos(V(N+i) -
V(N+j))+imag(Y(i,j))*sin(V(N+i)-V(N+j)));
                J(N+i,j) = -V(i)*(real(Y(i,j))*sin(V(N+i)-V(N+j))-
imag(Y(i,j))*cos(V(N+i)-V(N+j)));
                J(i,N+j) = -V(i)*V(j)*(real(Y(i,j))*sin(V(N+i)-V(N+j))-
imag(Y(i,j))*cos(V(N+i)-V(N+j)));
                J(N+i,N+j) = -V(i)*V(j)*(-real(Y(i,j))*cos(V(N+i)-V(N+j))-
imag(Y(i,j))*sin(V(N+i)-V(N+j)));
                J(i,i) = J(i,i) - V(j)*(real(Y(i,j))*cos(V(N+i)-
V(N+j))+imag(Y(i,j))*sin(V(N+i)-V(N+j)));
                J(N+i,i) = J(N+i,i) - V(j)*(real(Y(i,j))*sin(V(N+i)-
V(N+j))-imag(Y(i,j))*cos(V(N+i)-V(N+j)));
                J(i,N+i) = J(i,N+i) - V(j)*V(i)*(imag(Y(i,j))*cos(V(N+i)-
V(N+j))-real(Y(i,j))*sin(V(N+i)-V(N+j)));
                J(N+i,N+i) = J(N+i,N+i) -
V(i)*V(j)*(real(Y(i,j))*cos(V(N+i)-V(N+j))+imag(Y(i,j))*sin(V(N+i)-
V(N+j)));
            else
                J(i,i) = J(i,i)-2*V(i)*real(Y(i,i));
                J(N+i,i) = J(N+i,i) + 2*V(i)*imag(Y(i,i));
            end
        end
    end
end

```

## Appendix 7: Penalty Definition

```
function [penalty, current] = PenaltyDefinition(current,mpc)

current.ConstraintsBUpper = zeros(mpc.pop,1);
current.ConstraintsBLower = zeros(mpc.pop,1);
current.ConstraintsPUpper = zeros(mpc.pop,1);
current.ConstraintsPLower = zeros(mpc.pop,1);
current.ConstraintsQUpper = zeros(mpc.pop,1);
current.ConstraintsQLower = zeros(mpc.pop,1);
current.ConstraintsC_BUpper = zeros(mpc.pop,1);
current.ConstraintsC_BLower = zeros(mpc.pop,1);
current.ConstraintsChargingPower = zeros(mpc.pop,1);
current.ConstraintsSOCUpper = zeros(mpc.pop,1);
current.ConstraintsSOCLower = zeros(mpc.pop,1);
current.ConstraintsVLower = zeros(mpc.pop,1);
current.ConstraintsVUpper = zeros(mpc.pop,1);
current.ConstraintsthetaLower = zeros(mpc.pop,1);
current.ConstraintsthetaUpper = zeros(mpc.pop,1);
current.ConstraintsFlow = zeros(mpc.pop,1);
current.SlackProhibited = zeros(mpc.pop,1);

for i = 1:mpc.pop
    for j = 1:mpc.N
        for t = 1:mpc.FP
            if current.B(i,t,j) > current.C_B(i,j)
                current.ConstraintsBUpper(i) =
current.ConstraintsBUpper(i) + current.B(i,t,j) - current.C_B(i,j);
            end
            if current.B(i,t,j) < 0
                current.ConstraintsBLower(i) =
current.ConstraintsBLower(i) - current.B(i,t,j);
            end
            if ~ismember(j, mpc.PQ)
                ind = find(j == mpc.gen(:,1));
                if current.P(i,t,j) > mpc.gen(ind,9)/100
                    current.ConstraintsPUpper(i) =
current.ConstraintsPUpper(i) + current.P(i,t,j) - mpc.gen(ind,9)/100;
                end
                if current.P(i,t,j) < mpc.gen(ind,10)/100
                    current.ConstraintsPLower(i) =
current.ConstraintsPLower(i) - current.P(i,t,j) + mpc.gen(ind,10)/100;
                end
                if current.Q(i,t,j) > mpc.gen(ind,4)/100
                    current.ConstraintsQUpper(i) =
current.ConstraintsQUpper(i) + current.Q(i,t,j) - mpc.gen(ind,4)/100;
                end
                if current.Q(i,t,j) < mpc.gen(ind,5)/100
                    current.ConstraintsQLower(i) =
current.ConstraintsQLower(i) - current.Q(i,t,j) + mpc.gen(ind,5)/100;
                end
            end
            if current.B(i,t,j) - current.B(i,t+1,j) >
current.C_B(i,j)*0.5
                current.ConstraintsChargingPower(i) =
current.ConstraintsChargingPower(i) + current.B(i,t,j) - current.B(i,t+1,j)
- current.C_B(i,j)*0.5;
            end
        end
    end
end
```

```

        end
        if current.B(i,t+1,j) - current.B(i,t,j) >
current.C_B(i,j)*0.5
            current.ConstraintsChargingPower(i) =
current.ConstraintsChargingPower(i) + current.B(i,t+1,j) - current.B(i,t,j)
- current.C_B(i,j)*0.5;
        end
        if current.B(i,t,j)*100/current.C_B(i,j) > 90
            current.ConstraintsSOCUpper(i) =
current.ConstraintsSOCUpper(i) + current.B(i,t,j)*100/current.C_B(i,j) -
90;
        end
        if current.B(i,t,j)*100/current.C_B(i,j) < 10
            current.ConstraintsSOCLower(i) =
current.ConstraintsSOCLower(i) - current.B(i,t,j)*100/current.C_B(i,j) +
10;
        end
        if current.V(i,t,j) > mpc.Vmax
            current.ConstraintsVUpper(i) =
current.ConstraintsVUpper(i) + current.V(i,t,j) - mpc.Vmax;
        end
        if current.V(i,t,j) < mpc.Vmin
            current.ConstraintsVLower(i) =
current.ConstraintsVLower(i) - current.V(i,t,j) + mpc.Vmin;
        end
        if current.theta(i,t,j) > mpc.thetamax
            current.ConstraintstthetaUpper(i) =
current.ConstraintstthetaUpper(i) + current.theta(i,t,j) - mpc.thetamax;
        end
        if current.theta(i,t,j) < mpc.thetamin
            current.ConstraintstthetaLower(i) =
current.ConstraintstthetaLower(i) - current.theta(i,t,j) + mpc.thetamin;
        end
    end
    if current.C_B(i,j) > mpc.C_B_max
        current.ConstraintsC_BUpper(i) =
current.ConstraintsC_BUpper(i) + current.C_B(i,j) - mpc.C_B_max;
    end
    if current.C_B(i,j) < 0
        current.ConstraintsC_BLower(i) =
current.ConstraintsC_BLower(i) - current.C_B(i,j);
    end
end
    for t = 1:mpc.FP
        for j = 1:length(current.Sflow(i,t,:))
            if current.Sflow(i,t,j) < -mpc.Smax
                current.ConstraintsFlow(i) = current.ConstraintsFlow(i)
+ (mpc.Smax - current.Sflow(i,t,j));
            end
            if current.Sflow(i,t,j) > mpc.Smax
                current.ConstraintsFlow(i) = current.ConstraintsFlow(i)
- (mpc.Smax - current.Sflow(i,t,j));
            end
        end
    end
    current.SlackProhibited(i) = current.y(i,mpc.Slack);
end

```

```

    % Create the penalty vector
    for i = 1:mpc.pop
        penalty(i) =
sum([current.ConstraintsBUpper(i);current.ConstraintsBLower(i)...

;current.ConstraintsC_BUpper(i);current.ConstraintsC_BLower(i)...
    ;current.ConstraintsPUpper(i);current.ConstraintsPLower(i)...
    ;current.ConstraintsQUpper(i);current.ConstraintsQLower(i)...
    ;current.ConstraintsChargingPower(i)...

;current.ConstraintsSOCUpper(i);current.ConstraintsSOCLower(i)...
    ;current.ConstraintsVLower(i);current.ConstraintsVUpper(i)...

;current.ConstraintsthetaLower(i);current.ConstraintsthetaUpper(i)...

;current.ConstraintsC_BLower(i);current.ConstraintsC_BUpper(i);current.Cons
traintsFlow(i); ...
    current.SlackProhibited(i))];
        end
    end
end

```

## الملخص

الغرض من هذه الدراسة هو دراسة كيفية دمج تقنية المركبات الكهربائية ثنائية الاتجاه مع الشبكة الكهربائية (Vehicle-to-Grid, V2G) في شبكة التوزيع IEEE التي تحتوي على 33 من قضبان التوصيل، بهدف دعم استقرار الشبكة، واستقرار الجهد، وتخفيف الأحمال القصوى. تم استخدام خوارزمية تحسين الجسيمات الحائمة (Particle Swarm Optimization, PSO) في هذه الدراسة لتحديد الموقع الأمثل للبطاريات الكهربائية، وتحديد حجمها، واستراتيجية تشغيلها بناءً على توقعات ذروة الأحمال القصوى للكهرباء لمدة 24 ساعة.

أظهرت النتائج تحسناً كبيراً في أداء الشبكة، شمل تقليلاً في الفاقد الكلي في الطاقة بنسبة 10.57%، وتحسيناً في استقرار الجهد ضمن الحدود المقبولة من 0.9 إلى 1 وحدة نسبية (p.u)، بالإضافة إلى تنفيذ فعال لخفض الأحمال القصوى، حيث أظهر التحليل عند قصب التوصيل 26 تحسناً في الحمل من -0.11 وحدة نسبية إلى حوالي -0.07 وحدة نسبية، بنسبة خفض بلغت 36.4%. وتؤكد هذه النتائج إمكانيات المركبات الكهربائية المجهزة بتقنية V2G كمصادر طاقة موزعة ديناميكية، قادرة على تقديم دعم بالقدرة التفاعلية وتعزيز مرونة واستقرار الشبكة.

تُسهّم هذه الدراسة في تطوير الفهم النظري لدعم الشبكات الديناميكية، كما تقدم رؤى عملية يمكن أن يستفيد منها مشغلو الشبكات وصناع القرار. ومن خلال معالجة التحديات المرتبطة بدمج مصادر الطاقة المتجددة والمركبات الكهربائية في شبكات التوزيع، تسلط هذه الرسالة الضوء على الإمكانيات التحولية لتقنية V2G في تحقيق أنظمة طاقة مستدامة وموثوقة. وتشجع الدراسة على توسيع هذا الإطار ليشمل شبكات توزيع أكبر، واستكشاف تطبيقات واقعية لهذه التقنية في المستقبل.

# جامعة البحرين

قسم الهندسة  
الكهربائية والالكترونية



كلية الهندسة

## تحسين تكامل تقنية المركبات الكهربائية ثنائية الاتجاه في شبكات التوزيع IEEE-33 Bus باستخدام خوارزمية تحسين الجسيمات الحائمة

أطروحة مقدمة كجزء من متطلبات الحصول على درجة الماجستير  
في هندسة الطاقة المتجددة

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يناير 2025