UNIVERSITI TEKNOLOGI MARA

OPTIMAL ELECTRIC VEHICLE CHARGING STATION PLACEMENT AND NETWORK RECONFIGURATION FOR ENHANCED DISTRIBUTION SYSTEM PERFORMANCE

NUR AINA FATINI BINTI ROSLAN

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NUR AINA FATINI BINTI ROSLAN

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CONFIRMATION BY PANEL OF EXAMINERS

I certify that a Panel of Examiners has met on 24 July 2026 to conduct the final examination of Nur Aina Fatini Binti Roslan on her Master of Science thesis entitled "Optimal Electric Vehicle Charging Station Placement and Network Reconfiguration for Enhanced Distribution System Performance" in accordance with Universiti Teknologi MARA Act 1976 (Akta 173). The Panel of Examiners recommends that the student be awarded the relevant degree. The Panel of Examiners was as follows:

Mahanijah Md Kamal, PhD
Associate Professor
Faculty of Electrical Engineering
Universiti Teknologi MARA
(Chairman)

Nor Zulaily Mohamad, PhD
Senior Lecturer
Faculy of Electrical Engineering
Universiti Teknologi MARA
(Internal Examiner)

Wardiah Mohd Dahalan, PhD
Associate Professor
Institute of Marine Engineering
Technology
Universiti Kuala Lumpur Malaysia
(External Examiner)

PROF DR HJH ZURAEDA IBRAHIM
Dean
Institute of Postgraduate Studies
Universiti Teknologi MARA

Date: 15 August 2026

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Name of Student	:	Nur Aina Fatini Binti Roslan
Student ID. No.	:	2024429884
Programme	:	Master of Science (Electrical Engineering) – CEEE750
Faculty	:	Electrical Engineering
Thesis Title	:	Optimal Electric Vehicle Charging Station Placement and Network Reconfiguration for Enhanced Distribution System Performance
Signature of Student	:	. ……..
Date	:	August 2026

ABSTRACT

The rapid growth of electric vehicle (EV) adoption has accelerated the deployment of electric vehicle charging stations (EVCS), creating significant technical challenges in distribution networks, particularly increased active power losses and voltage profile degradation. To address these challenges, this study proposes an integrated optimization framework for optimal EVCS placement and network reconfiguration in radial distribution systems. A Hybrid Particle Swarm Optimization–Multi-Verse Optimization (HPSOMVO) algorithm is developed to minimize total active power losses while maintaining network operational constraints. The proposed approach is validated using the IEEE 33-bus and IEEE 69-bus test systems under varying EVCS capacity levels, with additional assessment incorporating photovoltaic (PV) integration. The performance of HPSOMVO is compared with established optimization techniques, including Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Multi-Verse Optimization (MVO), Grey Wolf Optimizer (GWO), and Evolutionary Programming (EP). The results demonstrate that the proposed HPSOMVO algorithm effectively minimizes the increase in active power losses caused by EVCS integration, limiting the loss increase to 76.04% and 6.81% for the IEEE 33-bus and IEEE 69-bus systems, respectively. Subsequently, coordinated network reconfiguration further reduces the active power losses by 14.30% and 48.27%, while the integration of photovoltaic (PV) systems provides additional reductions of 24.10% and 46.34%, respectively, together with improved voltage profiles and enhanced network stability. Overall, the proposed hybrid optimization framework provides an effective, robust, and scalable solution for EV-integrated distribution networks, consistently achieving lower active power losses and superior overall performance compared with the benchmark optimization algorithms.

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LIST OF SYMBOLS

Symbols

H	Hours
k	Thousand/Kilo
A	Current
V	Voltage
kW	Kilowatt
MW	Megawatt
p.u.	Per unit

LIST OF ABBREVIATIONS

Abbreviations

EVs	Electric Vehicles EVs
EVCS	Electric Vehicle Charging Stations
DNR	Distribution Network Reconfiguration

LIST OF NOMENCLATURES

Nomenclatures

PQ	Power Quality
IEEE	Institute of Electrical and Electronics Engineers
AC	Alternating Current
DC	Direct Current
GWO	Grey-Wolf Optimization
HPSOMVO	Hybrid Particle Swarm Optimization–Multi-Verse Optimization
PSO	Particle Swarm Optimization
MVO	Multi-Verse Optimization

CHAPTER 1
INTRODUCTION

1.1 Research Background

The global transition toward sustainable energy systems has accelerated the electrification of the transportation sector, with electric vehicles (EVs) emerging as a main factor in reducing greenhouse gas emissions and dependence on fossil fuels. The transportation sector accounts for a significant portion of global carbon dioxide (CO_2) emissions, and large-scale EV deployment is widely recognised as an effective pathway to support carbon neutrality goals and long-term environmental sustainability (Tracking Transport 2020, 2020; Ahmad F. I., 2022). Consequently, EV adoption has increased rapidly over the past decade across various vehicle categories, including passenger cars, commercial vehicles, and two-wheelers.

As more electric vehicles enter the market, the number of Electric Vehicle Charging Stations (EVCSs) has increased accordingly, and these stations require substantial grid power to support user charging needs. According to recent global reports illustrated in Figure 1.1, the number of EVs in operation has surpassed tens of millions worldwide, while public charging infrastructure continues to expand to accommodate this growth (Zeb, 2020). The availability, capacity, and geographical distribution of EVCSs play an important role in enhancing charging accessibility, improving user confidence, and supporting the long-term viability of electric mobility.

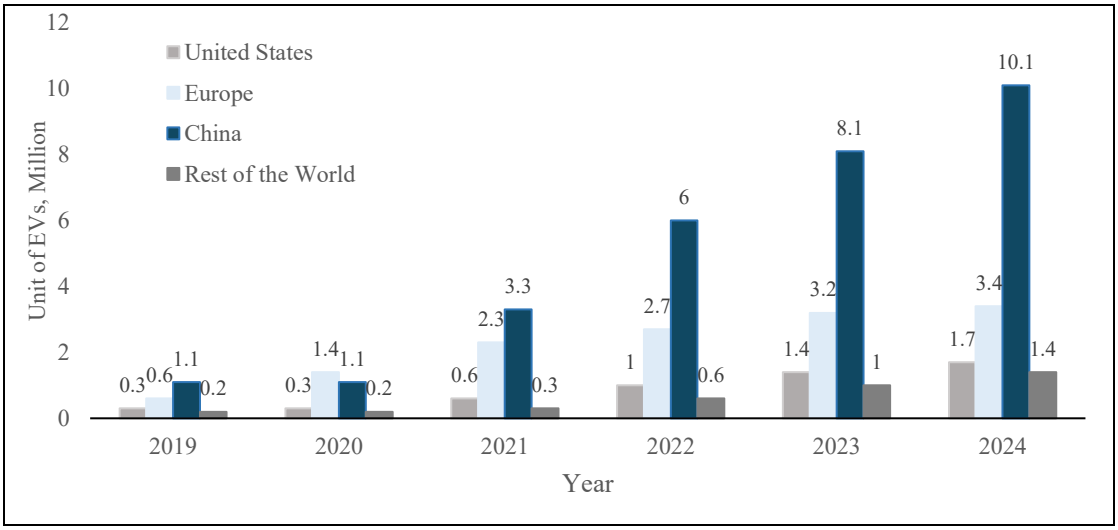


Figure 1.1 EV Sales For 10 Years (2015-2024)

EVCSs are predominantly connected to low- and medium-voltage distribution networks, making distribution systems the backbone of EV charging infrastructure. The integration of EV charging demand introduces new operating characteristics into distribution networks due to the high-power rating of chargers and the unpredictable pattern of charging behaviour. As EV penetration increases, charging activities become a significant component of system load, alters power flow patterns, voltage profiles, and overall network performance (Moupuri, 2020).

In recent years, various approaches have been explored to improve the operational performance of distribution networks under increasing EV penetration. Placing EVCSs in the right locations has become increasingly important as more EVs connect to the grid. When EVCSs are installed at suitable points in the network, they help maintain stable voltage levels, reduce technical losses, and avoid overloading on heavily used feeders. Proper placement also helps distribute the load more evenly and improves overall system performance. As the number of EV users continues to grow, strategically locating EVCSs is essential to ensure reliable and efficient operation of distribution networks (Anna Pinnarelli, 2025).

In addition to appropriate EVCS placement, photovoltaic (PV) generation can also provide support to distribution networks experiencing higher loading from EV charging by supplying real-power injection during daytime periods. When installed at suitable feeder locations, PV helps reduce net power drawn from the upstream network and can contribute to lower technical losses and improved voltage conditions. However, because PV output is intermittent and generally insufficient to meet fast-charging demand on its own, it serves as a complementary resource rather than a primary supply for EV charging (Arvind R. Singh, 2024).

From an operational perspective, distribution network reconfiguration adds flexibility for managing dynamic and widely distributed EV charging. Proper reconfiguration by altering the open and closed states of sectionalizing and tie switches, balances feeder loading, lowers technical losses, and strengthens voltage profiles without major upgrades (Deeum, 2023; Chakraborty, 2023; Altaf, 2023). Recent studies show that integrating EVCS placement with network reconfiguration can significantly enhance distribution system efficiency and resilience, particularly under high EV penetration (Golla, 2022; Kumar, 2024; Habib, 2024). Such coordinated planning

provides a systematic framework for developing future-ready distribution networks capable of accommodating the rapid growth of electric mobility.

1.2 Motivation for This Work

The increasing adoption of electric vehicles has introduced additional loading on distribution networks, particularly when charging stations of different sizes are connected at locations that do not align with feeder capacity or voltage limits. Poor placement of EVCSs can lead to higher technical losses, voltage deviations, and localized overloading. At the same time, existing feeder topology may not adequately support these added demands without operational adjustments. Distribution network reconfiguration and PV support offer practical means to redistribute power flows and reduce network stress. These considerations motivate the need to identify suitable EVCS locations and to apply appropriate reconfiguration measures supported by PV integration, so that the distribution network can continue to operate efficiently as EV penetration increases.

Based on these concerns, this study defines the problem of determining appropriate EVCS locations and accompanying network reconfiguration, with PV support, to minimize active power loss while keeping all bus voltages within statutory limits.

1.3 Problem Statement

Although the effects of EVCS placement and network topology on distribution system performance are well recognised, determining appropriate EVCS locations and adapting feeder configuration in a coordinated manner remains challenging in practice. Existing approaches often address these components separately.

Locating public EVCSs typically considers practical placement factors such as traffic flow, proximity to high-attraction destinations (points of interest), population distribution, and user charging behaviour to ensure accessibility and convenience. However, while these factors are important for planning, EVCS placement must also consider the technical capability of the distribution network, including feeder loading capacity, transformer loading margins, and acceptable bus-voltage limits. Failure to

consider these technical constraints may result in excessive active power losses, voltage deviations, feeder congestion, and reduced system reliability.

To address these challenges, optimization techniques have been widely adopted to determine technically suitable EVCS locations within distribution networks. By formulating EVCS placement as an optimization problem, candidate locations can be systematically evaluated based on system performance indices such as active power loss minimization and voltage profile improvement. However, most previous studies rely on a single metaheuristic optimization algorithm, such as PSO, GA, ACO, or MVO, which often exhibit limitations including premature convergence, slow convergence speed, or insufficient exploration capability when solving complex, highly constrained optimization problems. These limitations may reduce the ability to obtain high-quality global solutions, particularly under increasing EV penetration and larger search spaces.

Although optimization techniques have been extensively applied to determine suitable EVCS locations, many previous studies rely on single metaheuristic algorithms, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Multi-Verse Optimization (MVO). While these algorithms have demonstrated satisfactory performance, they often suffer from limitations including premature convergence, slow convergence speed, and an imbalance between exploration and exploitation, particularly when solving highly constrained and high-dimensional optimization problems. To overcome these limitations, hybrid metaheuristic algorithms have increasingly been introduced by combining the strengths of different optimization techniques. Despite the promising performance reported by existing hybrid approaches, many still exhibit limitations in solution quality, convergence consistency, computational efficiency, or adaptability under different operating conditions and network complexities. Therefore, there remains a need to investigate more suitable combinations of optimization techniques that can further improve the robustness and effectiveness of EVCS placement in modern distribution systems.

Nonetheless, placement alone is insufficient. EVCS allocation determines where new demand is connected to the network, yet the existing radial topology is not routinely adapted to accommodate the resulting changes in power flows. In many practical distribution systems, feeder configurations remain fixed or are only adjusted locally, which may lead to sub-optimal power loss performance and reduced voltage margins

under increasing EV penetration and distributed generation. Recent studies on Distribution Network Reconfiguration (DNR) have shown that network topology significantly influences loss minimization and voltage regulation performance, indicating that inadequate consideration of feeder switching can limit overall system efficiency (Çelik, 2024).

The integration of distributed generation such as PV systems further increases the analytical complexity of distribution network operation. Additional power injections and bidirectional power flows introduced by PV systems may alter voltage profiles and feeder loading conditions. Without systematic optimization of feeder switching together with EVCS placement and PV integration, the distribution network may operate away from its optimal condition, resulting in higher technical losses and possible voltage constraint violations.

Although previous studies have investigated EVCS placement and distribution network reconfiguration separately, limited research has integrated these strategies within a unified optimization framework while simultaneously considering photovoltaic (PV) integration. Since EVCS placement, feeder reconfiguration, and distributed generation collectively influence power flow, voltage profile, and active power losses, optimizing these components independently may not achieve the overall optimal network performance. Therefore, there is a need for a coordinated optimization framework that simultaneously determines appropriate EVCS locations, optimal feeder configurations, and the effects of PV integration to improve distribution system performance while satisfying operational constraints.

1.4 Research Objectives

The objectives of this study are:

a) To determine the optimal placement of Electric Vehicle Charging Stations (EVCSs) in a distribution network by minimizing total active power losses using the hybrid Particle Swarm Optimization–Multi-Verse Optimization (HPSOMVO) algorithm.

b) To develop an optimal network reconfiguration that integrates the selected EVCS locations and photovoltaic (PV) systems by minimizing power loss using HPSOMVO algorithm.

1.5 Research Question

This study aims to answer the following research questions:

i) How does the optimal placement of EVCSs affect active power losses and bus voltage profiles in a radial distribution network?

ii) How does distribution network reconfiguration with PV integration improve the performance of the distribution network after the optimal EVCS locations have been determined?

iii) To what extent does the proposed Hybrid PSO–MVO (HPSOMVO) algorithm provide better optimization performance than conventional optimization algorithms in solving the EVCS placement and network reconfiguration problems?

1.6 Significance of Study

The increasing integration of electric vehicle charging stations (EVCSs) and renewable energy resources into distribution networks presents new operational challenges that require effective planning and optimization strategies. This study contributes to the development of a more efficient, reliable, and sustainable distribution network by proposing a coordinated framework for optimal EVCS placement and distribution network reconfiguration with photovoltaic (PV) integration using the Hybrid Particle Swarm Optimization–Multi-Verse Optimization (HPSOMVO) algorithm.

From a scientific perspective, this study contributes to the existing body of knowledge by developing a coordinated optimization framework that simultaneously addresses EVCS placement, distribution network reconfiguration, and PV integration. Unlike conventional approaches that treat these problems independently or employ a single optimization technique, the proposed HPSOMVO algorithm combines the exploration capability of Multi-Verse Optimization (MVO) with the exploitation capability of Particle Swarm Optimization (PSO) to achieve a more balanced and robust optimization process. The findings provide additional insight into the application of hybrid metaheuristic algorithms for solving complex distribution network optimization problems.

From a technical perspective, the proposed framework improves distribution network performance by identifying optimal EVCS locations and network configurations that minimize active power losses while maintaining all bus voltages within statutory operating limits. The incorporation of PV generation further enhances voltage profile performance, improves feeder utilization, and supports more efficient network operation under increasing EV penetration levels. The comparative evaluation against established optimization algorithms also demonstrates the effectiveness and robustness of the proposed HPSOMVO algorithm in terms of convergence behaviour and solution quality.

From a practical perspective, the outcomes of this study provide useful guidance for utility companies, distribution network operators, and energy planners in planning future EV charging infrastructure. The proposed methodology offers a systematic decision-support tool for identifying technically suitable EVCS locations and feeder reconfiguration strategies while considering distribution network constraints. This can assist in improving network planning, reducing operational losses, and supporting the reliable integration of large-scale EV charging demand.

From an environmental and societal perspective, the integration of PV generation within the proposed optimization framework promotes greater utilization of renewable energy resources and supports the transition towards cleaner and more sustainable electricity systems. By improving the efficiency of distribution network operation while facilitating higher EV adoption, this study contributes to national and global sustainability initiatives, particularly the United Nations Sustainable Development Goal (SDG) 7: Affordable and Clean Energy and SDG 13: Climate Action.

1.7 Scope and Limitations

This study focuses on the optimal placement of Electric Vehicle Charging Stations (EVCSs) and the optimal reconfiguration of radial distribution networks with photovoltaic (PV) integration using a hybrid optimization framework. The proposed methodology is validated on the IEEE 33-bus and IEEE 69-bus radial distribution test systems under different EV penetration levels to evaluate its effectiveness in improving distribution network performance.

Figure 1.2 presents the overall research methodology, which consists of four main phases. The first phase, Knowledge Acquisition, establishes the theoretical foundation of the study through a comprehensive review of EVCS integration, optimal EVCS placement, distribution network reconfiguration, and PV integration to understand their impacts on active power losses and voltage profiles. The second phase, Development of Algorithms, involves the development of a hybrid optimization algorithm to address two research objectives: (i) determining the optimal placement of EVCSs and (ii) performing optimal distribution network reconfiguration with PV integration. The third phase, Simulation and Validation, evaluates the proposed methodology using MATLAB R2021a on the IEEE 33-bus and IEEE 69-bus test systems through a series of structured simulation cases. Finally, Data Evaluation and Analysis assesses the performance of the proposed approach by comparing it with established optimization algorithms based on convergence behaviour, active power loss reduction, voltage profile improvement, solution quality, and overall network performance.

To ensure a consistent and tractable analysis, several assumptions are adopted throughout this study. The distribution network is assumed to operate under balanced, radial, and steady-state conditions. EV charging demand is represented using predefined EV penetration scenarios, with each EVCS modelled as an aggregated charging load. Load demand and PV generation are assumed to be known and remain constant for each simulation case. Furthermore, the locations and capacities of PV systems are predetermined based on previous studies and are not treated as optimization variables. PV units are modelled as constant active power sources operating at unity power factor, while the effects of solar irradiance variation, temperature changes, and reactive power control are neglected.

The scope of this study is limited to the technical assessment of distribution network performance under steady-state operating conditions. Dynamic characteristics, including time-varying EV charging behaviour, stochastic load variations, intermittent PV generation, battery degradation, demand response strategies, electricity market participation, and real-time operational uncertainties, are beyond the scope of this research. In addition, practical planning considerations such as installation costs, land availability, traffic density, charging station accessibility, consumer charging preferences, and regulatory constraints are not incorporated into the optimization

process. The study also assumes normal operating conditions and does not consider fault analysis, contingency assessment, protection coordination, or system reliability evaluation. These aspects provide opportunities for future research to further enhance the applicability of the proposed optimization framework in real-world distribution networks.

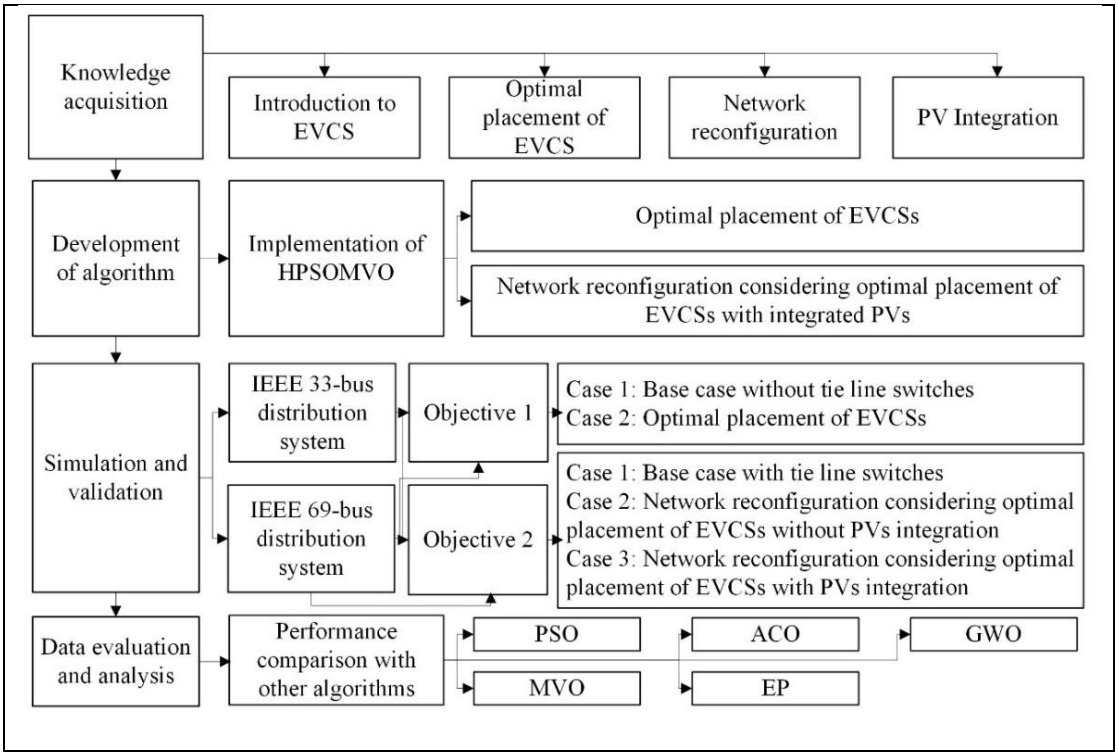


Figure 1.2 Research Framework

1.8 Thesis Outline

This report contains five chapter describing the overview of Optimal Electric Vehicle Charging Station Placement and Network Configuration for an Effective Operation in Distribution System using HPSOMVO including reference.

Chapter 1: Introduction

This chapter present the research background on the rapid growth of EVs and the resulting impact of EVCSs and PV integration on distribution network performance. It then outlines the motivation for the study by highlighting the technical challenges associated with improper EVCS placement and fixed feeder topology under increasing loading conditions. The problem statement identifies the key research gaps in

coordinated EVCS allocation and network reconfiguration, followed by the research objectives and research questions. The chapter also discusses the significance of the study and finally defines the scope and limitations to clarify the boundaries and assumptions of the research.

Chapter 2: Literature Review

This chapter provides a comprehensive review of previous studies related to the integration of EVCSs in distribution networks. It begins by discussing the fundamental characteristics of distribution systems and the key performance indices used in network planning. The review then examines EV charging demand, charging technologies, and the impacts of EVCS placement on network performance. The role of PV systems as distributed generation and their effects on losses and voltage profile are subsequently analysed. Next, DNR is reviewed as an operational strategy to enhance system performance. The chapter also highlights existing studies that integrate EVCS, PV, and reconfiguration, followed by a comparative review of conventional, metaheuristic, and hybrid optimization techniques. Finally, the chapter summarise the key findings and limitations from the literature to identify the research gaps that motivate the proposed work.

Chapter 3: Methodology

This chapter presents the overall research framework, which consists of knowledge acquisition, algorithm development, simulation and validation, and data evaluation. The chapter then explains the proposed HPSOMVO framework for optimal EVCS placement and distribution network reconfiguration with integrated PV support. Detailed system modelling for the IEEE 33-bus and IEEE 69-bus test systems, including EVCS and PV representations, is provided together with the mathematical formulation of the optimization problems, objective functions, decision variables, and operational constraints. The implementation procedures for both optimization stages are subsequently outlined, followed by a description of the comparative algorithms used for benchmarking. Finally, the chapter summarizes the methodology and clarifies how the proposed approach is validated.

Chapter 4: Result and Discussion

This chapter presents and analyses the simulation results obtained from the proposed HPSOMVO framework.

The chapter begins with the description of the case studies and simulation parameters used in the analysis. The optimization results are then presented according to the research objectives, including EVCS placement results, power loss reduction, voltage profile improvement, and convergence behaviour. A comparative analysis with several conventional metaheuristic optimization techniques is also provided to evaluate the performance of the proposed algorithm. Finally, the chapter discusses the significance of the obtained results and summarizes the key findings.

Chapter 5: Conclusion

This chapter summarizes the overall findings of the research and presents the main contributions of the proposed optimization framework. The conclusions are made based on the results obtained from the optimal EVCS placement and optimal network reconfiguration with PV integration in radial distribution networks.

The chapter first discusses the achievement of the research objectives and highlights the effectiveness of the HPSOMVO algorithm in improving distribution network performance. The study is then summarized in terms of power loss reduction, voltage profile improvement, and coordinated planning of EVCS and network configuration. Finally, recommendations for future work are provided to suggest possible extensions of the proposed research, including the consideration of more realistic operating conditions and further improvement of the optimization framework.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This chapter presents a comprehensive review of the background and prior research related to the integration of Electric Vehicle Charging Stations (EVCSs) in power distribution networks. The review begins by examining the characteristics of distribution system such as radial topology, high resistance to reactance ratio, and sensitivity to voltage and power losses affect their response to increasing EV charging demand. The chapter also outlines the performance indices and operational constraints widely used in optimization-based distribution planning, providing a basis for evaluating EVCS impacts and comparing methodological approaches. The review further explores research on EV charging demand, charging technologies, and EVCS placement, and how these aspects affect distribution network performance. The chapter also discusses the role of photovoltaic (PV) systems, where properly located PV units can reduce losses and support voltage, although high penetration may cause voltage rise or operational challenges. Distribution Network Reconfiguration (DNR) is reviewed as an operational strategy to redistribute power flow, reduce losses, and improve voltage conditions. Studies that combine EVCS, PV, and network reconfiguration are also highlighted, although fully integrated frameworks remain limited.

Finally, the chapter provides an overview of optimization approaches applied in distribution system studies. Existing literature highlights the varying strengths and limitations of conventional, metaheuristic, and hybrid optimization methods when addressing nonlinear, multi-objective, and constrained planning problems. This review of existing methods provides the basis for identifying the gaps and methodological requirements addressed later in the chapter.

2.2 Distribution Network Background and Performance Indicators

2.2.1 Distribution Network Characteristics

Electric power distribution networks represent the final stage of power delivery to end users and exhibit structural and electrical characteristics that are fundamentally different from transmission systems. These characteristics significantly influence system operation, planning, optimization, and the integration of emerging technologies such as EVCS and DG. Figure 2.1 illustrates the structural and electrical differences between transmission and distribution networks.

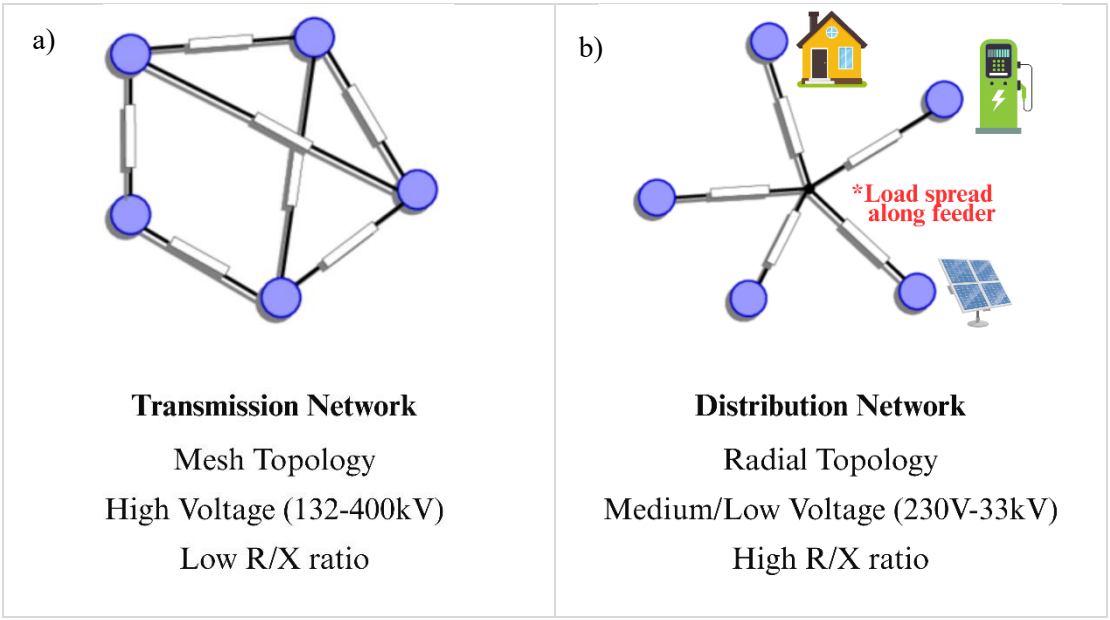


Figure 2.1 Transmission Network (a) And Distribution Network (b)

Most practical distribution systems are operated in a radial topology, where each load bus is supplied through a single path from the substation. This configuration is preferred due to its simplicity, low protection cost, and ease of fault isolation and coordination. However, the absence of alternative power paths makes radial networks more vulnerable to voltage deviations and reliability issues under heavy loading or high penetration of new loads such as EVCS (Al-Anbarri, 2024).

Recent studies confirm that radial operation remains dominant even in modern active distribution networks, as protection and control schemes are still largely designed around radial feeders (Hasanvand, 2025).This radial nature necessitates specialized

load-flow and optimization methods, particularly when network reconfiguration is considered as a loss-reduction strategy.

A defining electrical characteristic of distribution networks is their high resistance-to-reactance (R/X) ratio, in contrast to transmission systems where reactance dominates. The short line lengths, smaller conductor sizes, and lower voltage levels of distribution feeders contribute to this condition. As a result, active power flows have a pronounced impact on voltage magnitude, making conventional transmission-oriented power-flow methods less effective. Several recent studies highlight that the high R/X ratio exacerbates voltage instability and loss sensitivity, especially under high loading or renewable integration (Ghaffarianfar, 2018). This characteristic is particularly critical for EV-integrated networks, where active power demand increases sharply and dynamically.

Due to their radial structure and high R/X ratio, distribution networks are highly sensitive to voltage drops, especially at buses located far from the substation. Voltage drop in distribution feeders is directly proportional to line impedance and load current, causing end-user voltage levels to deviate significantly during peak demand conditions. Recent works emphasize that voltage regulation is more challenging in distribution systems than in transmission networks, and improper placement of high-power loads such as EVCS can lead to unacceptable voltage profiles (Panneerselvam, 2023). Consequently, coordinated strategies involving network reconfiguration, reactive power support, and distributed generation are increasingly required.

Distribution systems experience significantly higher power losses compared to transmission networks, primarily due to higher line resistance, longer cumulative feeder lengths, and lower operating voltages. Studies consistently report that distribution losses account for the largest share of total system losses, often exceeding transmission losses by a considerable margin (Mahato, 2024). Recent optimization-based studies demonstrate that power losses in radial distribution networks are highly sensitive to load location and feeder configuration, validating the effectiveness of network reconfiguration and optimal asset placement as loss-mitigation measures (Gupta, 2016).

2.2.2 Performance Indices in Distribution Network

Performance indices are commonly used in distribution network studies to evaluate system efficiency and reliability. Although various indices such as voltage deviation and voltage stability have been applied in past research, this study focuses specifically on real power loss minimization as the primary objective. Operational constraints such as bus voltage limits and branch current limits are also incorporated to ensure safe and reliable system operation throughout the optimization process.

2.2.2.1 Real Power Loss Minimization

Real (active) power loss minimization is one of the most extensively used performance indices in distribution network optimization. Due to relatively low operating voltages and higher current magnitudes, distribution systems experience disproportionately high I^2R losses compared to transmission systems. Consequently, reducing real power losses directly enhances network efficiency, lowers operational costs, and improves asset utilization.

Recent studies have demonstrated that optimization-based approaches incorporating loss minimization as a primary objective can significantly improve network performance. For example, coordinated reactive power compensation and distributed generation (DG) placement strategies have been shown to achieve substantial reductions in feeder losses while maintaining voltage limits (Getahun, 2025). Similarly, reconfiguration-based optimization techniques consistently outperform static network configurations in minimizing losses across varying load conditions (Tahir, 2018). These findings validate the importance of loss minimization as a core performance index in distribution network planning.

2.2.2.2 Voltage Profile Improvement and Voltage Deviation Reduction

Voltage profile quality is a fundamental indicator of power quality and system reliability in distribution networks. Voltage deviation is typically quantified as the deviation of bus voltages from the nominal value (1.0 p.u.), with acceptable limits generally defined between 0.95 and 1.05 p. u (Iqbal, 2025). Long radial feeders and

uneven load distribution often result in significant voltage drops, particularly at buses located far from the substation.

Numerous studies integrate voltage deviation minimization either as a standalone objective or in combination with power loss reduction. Optimal DG allocation has been shown to significantly improve voltage profiles by reducing voltage drops and enhancing minimum bus voltages (Eiada, 2021). Furthermore, multi-period voltage optimization frameworks demonstrate that coordinated control of voltage-regulating devices effectively minimizes voltage deviations under fluctuating load and renewable generation scenarios (Jiang, Multi-period Voltage Optimization of Active Distribution Network with Distributed Power, 2018). These results highlight voltage deviation reduction as an essential performance metric in active distribution networks.

2.2.2.3 Operational Constraints

In addition to performance objectives, operational constraints are essential to ensure safe and reliable system operation. Commonly enforced constraints include bus voltage magnitude limits and branch current or thermal loading limits. These constraints prevent excessive voltage deviations, feeder congestion, and equipment overloading, thereby ensuring compliance with grid codes and operational standards.

Modern optimization frameworks explicitly incorporate such constraints to maintain solution feasibility. Studies on EV charging coordination highlight that neglecting voltage and branch loading limits can lead to transformer overloading and unacceptable voltage violations (Aliffianto, 2021). Similarly, network reconfiguration strategies that simultaneously minimize losses while respecting operational constraints have been shown to significantly enhance system reliability and security (Salau, 2020).

2.3 Electric Vehicle and Electric Vehicle Charging Station

2.3.1 Electric Vehicle Charging Demands and Charging Types

The adoption of electric vehicles has increased rapidly in recent years and has led to a clear increase in electricity demand at the distribution network level. This growth is mainly influenced by improvements in battery technology, reduction in battery cost, government incentives, and stricter environmental policies (Global EV

Outlook 2024, 2024). As the number of EVs increases, EV charging demand becomes an additional load in distribution systems, especially in urban and residential areas.

EV charging demand is different from conventional residential loads because it is highly dependent on user behaviour, charging time, and charging location. Several studies have shown that uncoordinated EV charging can increase peak demand, overload distribution transformers, and cause congestion in distribution feeders, even when the overall network capacity is adequate (Sortomme, 2011). This problem becomes more serious when many EVs are connected within a small area, resulting in concentrated charging demand at specific buses in the distribution network.

For power system analysis and planning, EV charging stations are therefore commonly modelled as additional loads connected to specific buses in the distribution network. The characteristics of these loads depend strongly on the charging technology used, charging power level, and charging control strategy. As a result, the selection and deployment of EV charging technologies have a direct influence on system losses, voltage profile, and overall network performance. The impact of EV charging on distribution networks is closely related to the charging technology employed. Figure 2.2 illustrates the main types of EV charging technologies and methods based on previous studies (What is Conductive Charging and how does it work in the context of EV Charging Stations?, 2023; Shen, 2024; al. X. M., 2020; Mehrjerdi, 2021; al. A. T., 2019).

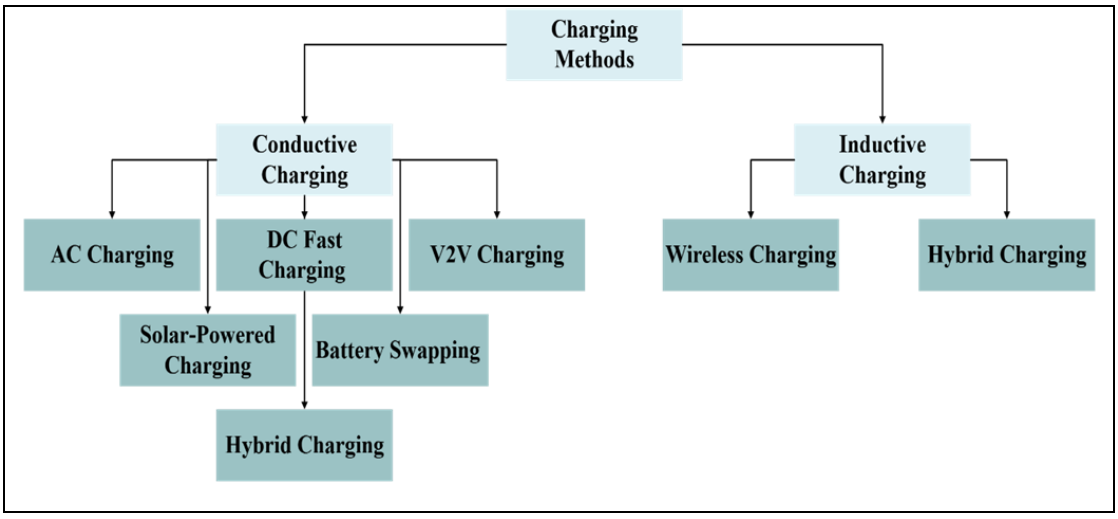


Figure 2.2 Charging Methods

Among these, conductive charging, also known as plug-in charging, is the most widely used method. In this approach, electrical energy is transferred from the grid to the EV through a physical cable and plug. Conductive charging can be implemented using standard household outlets or dedicated EVCS, making it suitable for existing distribution infrastructure (What is Conductive Charging and how does it work in the context of EV Charging Stations?, 2023).

Conductive charging is generally divided into three levels based on voltage and power rating, as shown in Table 2.1. Level 1 charging operates at 120 V and provides low charging power, which is suitable for overnight charging at residential locations. Level 2 charging operates at 230–240 V and is commonly used in residential, workplace, and public charging locations due to its moderate charging speed. Level 3 charging, also known as direct current (DC) fast charging or supercharging, supplies direct current directly to the vehicle battery and allows fast charging, with up to 80% of the battery charged within 20–30 minutes and power ratings of up to 350 kW (al. M. S., 2022; Tejeida-Padilla, 2024).

Table 2.1
Details of EV Charging levels (Tejeida-Padilla, 2024)

	Level 1 and 2	**Level 2**	**Level 3**	**Supercharging**
	Residential Charging	**Work and Public Charging**	**DC Fast Charging**	**Tesla Supercharger**
Voltage	120V 1-Phase AC	208 or 240 V 1-Phase AC	208 or 480 V 3-Phase DC	480 V
Amps	12-16 Amps	12-80 Amps (Typ. 32 Amps)	< 125 Amps (Typ. 60 Amps)	< 500 Amps
Charging Load	1.4 to 1.9 KW	2.5 to 19.2 KW (Typ. 7 KW)	< 90 KW (Typ. 50 KW)	70 to 250 KW
Charging Time	3-5 Miles of Range per hour	10-20 Miles of Range per hour	80% Charge in 20–30 mins	80% Charge in 20–30 mins

However, DC fast charging introduces considerable stress on distribution networks due to its sudden and high-power demand characteristics. This can cause voltage drops, increased line losses, transformer overheating, and harmonic distortion if the stations are not properly planned (Dantas, 2025). Therefore, proper placement and sizing of DC fast charging stations are required to avoid excessive stress on network components. Ultra-fast chargers are especially important for heavy-duty electric

vehicles such as buses and trucks, where charging time must be minimised. However, chargers with power ratings above 350 kW often exceed the capacity of low-voltage networks and may require dedicated substations and additional protection equipment (al. M. S., 2021). Energy storage systems are often suggested to help reduce peak demand and improve network stability.

Apart from grid-based charging, vehicle-to-vehicle (V2V) charging allows direct energy transfer between EVs using bidirectional power converters. This method is useful in emergency situations or areas with limited charging infrastructure (al. X. M., 2020). However, V2V charging requires proper coordination and control to ensure safe and stable operation. When applied in fleet systems, V2V charging can support load sharing and demand response applications (al. X. M., 2020).

In addition, EVs can support bidirectional charging, commonly referred to as vehicle-to-everything (V2X). Figure 2.3 illustrates the development from unidirectional grid-to-vehicle charging (V1G) to more advanced V2X applications. V1G is the basic charging mode where EVs only draw power from the grid (Hu, 2025). V2G allows EVs to supply power back to the grid and can support peak load reduction and other grid services (Hu, 2025). Vehicle-to-home (V2H) and vehicle-to-building (V2B) enable EVs to act as mobile energy storage units for local energy use. Studies have shown that combining V2H with photovoltaic systems and battery storage can reduce energy costs and improve power supply reliability during outages (Borge-Diez, 2021). These charging modes support the role of EVs as active components in smart grids, although appropriate communication and control frameworks are required for large-scale implementation.

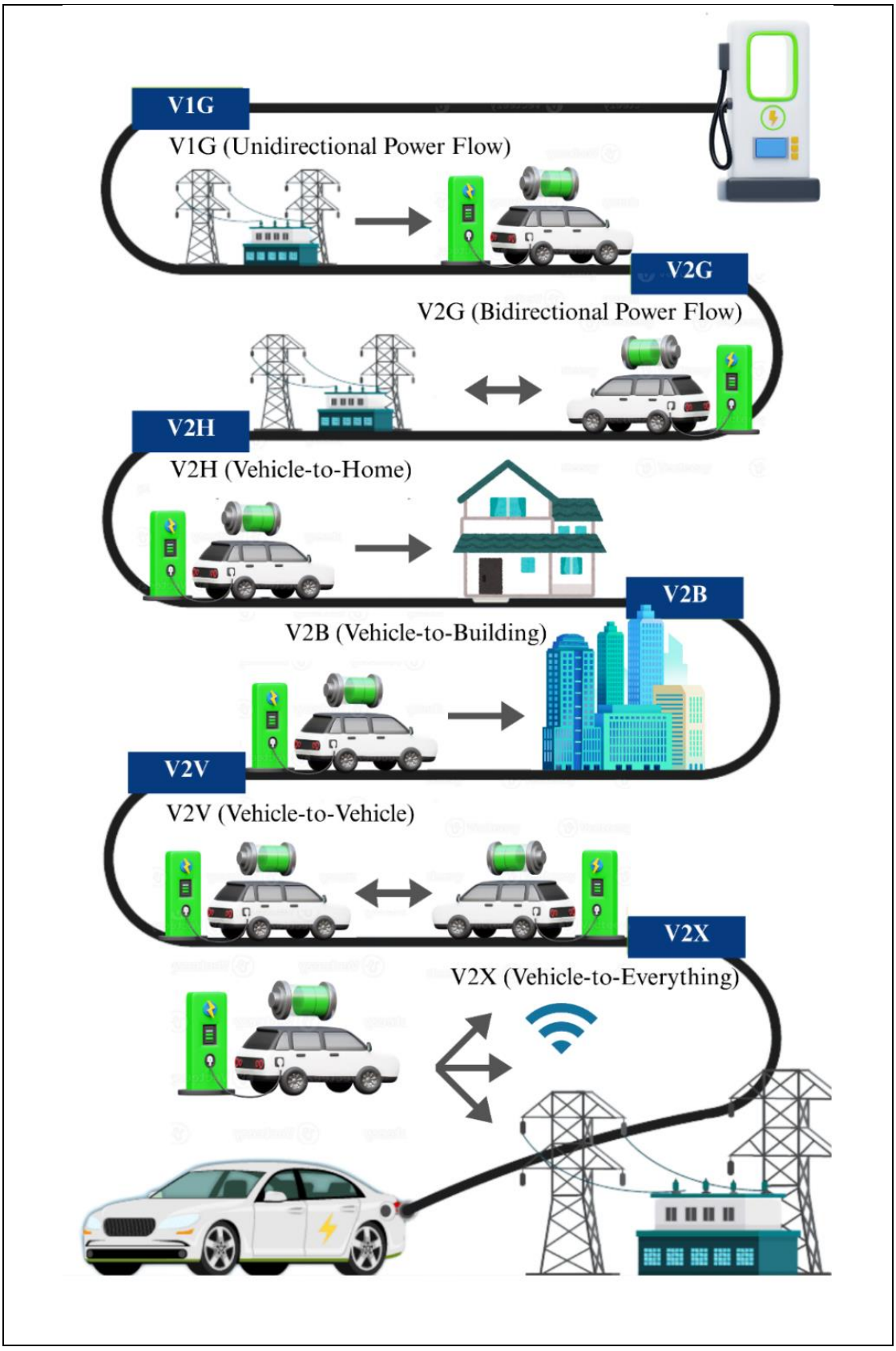


Figure 2.3 Evolution of EV Charging Models

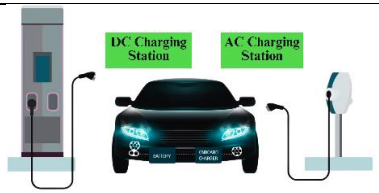
Solar-powered charging stations use photovoltaic panels to supply energy to EVs, either directly or through the grid with energy storage support. This approach reduces dependence on conventional grid supply and helps reduce peak load in the distribution network. When combined with battery storage, solar charging stations can operate in off-grid or hybrid modes, which is suitable for remote areas. However, uncontrolled solar power injection may cause reverse power flow and voltage rise issues and therefore requires proper inverter control and energy management strategies (al. M. D., 2022; al. H. A., 2023).

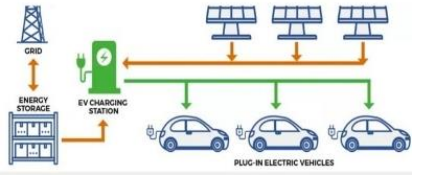
Battery swapping is another charging method where a depleted EV battery is replaced with a fully charged one at a designated station. This method significantly reduces charging time and is suitable for fleet-based applications such as taxis and delivery vehicles (Mehrjerdi, 2021). However, battery swapping shifts the charging load to centralised charging facilities, and uncoordinated charging at these facilities may cause concentrated loading in the distribution network (Mehrjerdi, 2021).

Hybrid charging systems combine grid supply, renewable energy sources, and battery storage systems to improve charging reliability. These systems are useful in areas with weak grid connections. Hybrid charging stations can reduce peak demand and improve power supply continuity during grid outages, particularly in rural or isolated areas (al. A. T., 2019). However, proper energy management is required to ensure stable integration with the distribution network. Table 2.4 summarises the main EV conductive charging technologies and their operating characteristics

Besides conductive charging, inductive charging is also employed as an alternative method. Inductive charging transfers energy wirelessly using electromagnetic fields between a charging pad and the vehicle. Static inductive charging occurs when the vehicle is parked, while dynamic inductive charging allows charging during vehicle movement. Dynamic inductive charging is suitable for electric buses and freight vehicles as it reduces charging downtime and onboard battery size (Shen, 2024). However, inductive charging requires careful planning to manage power quality and network impact.

Table 2.2
Summary of EV Charger Technology and Operating Characteristic

Technology	Technical Specifications	Key Performance	Constraints	Power Flow	Charger Technologies Architecture
AC Charging	Up to 22 kW via OBC	Optimal dwell time utility	High recharge duration/OBC loss	Unidirectional (G2V)	
DC Fast Charging	Up to 350 kW via off-board converter	Minimized recharge time, T_{charge}	High grid demand / battery stress (C-rate)	Unidirectional (G2V)	
V2V Charging	Bidirectional DC-DC power transfer	Mobile emergency energy supply	Limited infrastructure / donor SoC dependency	Bidirectional (V2V)	
Solar Charging	PV array and BSS integration to electric vehicle supply equipment (EVSE)	Maximized renewable energy utilization.	Intermittency (solar irradiance)	Decentralized	
Battery Swapping	Automated mechanical battery exchange	Near-instantaneous replenishment	Standardization requirement	Offline	

Technology	Technical Specifications	Key Performance	Constraints	Power Flow	Charger Technologies Architecture
Hybrid Charging	Intelligent control of PV/grid/storage input	Demand charge reduction	Complexity of EMS	Hybrid (RE, G2V)	

2.3.2 Impacts of EVCS Integration on Distribution Network

The connection of EVCS introduces additional electrical demand to distribution networks and directly affects their operating conditions. When EVCS are connected without proper planning or coordination, the resulting charging demand may significantly alter power flow patterns, leading to several technical challenges related to feeder loading, power losses, voltage profile, and system stability.

One of the most reported impacts of EVCS integration is the increase in feeder loading and line current flow. High charging demand, particularly during peak hours, can cause distribution feeders and transformers to operate close to or beyond their rated limits. Studies using probabilistic load modelling have shown that uncoordinated EV charging can lead to feeder congestion and transformer overloading, especially in residential and urban networks with high EV penetration (al. S. a., 2022). This effect becomes more severe when fast-charging stations are connected at weak buses or at the end of long radial feeders, where current flow is already high.

The increase in current flow due to EVCS connection also leads to higher real power losses in distribution networks. Several studies have demonstrated that power losses rise noticeably with increasing EV charging demand, mainly due to the quadratic relationship between line current and losses. Optimization-based studies have shown that improper placement of EVCS can significantly increase total network losses, while optimal placement can effectively mitigate this impact (Das, 2023; Jamatia, 2022; Srinivas, 2022). These findings indicate that EVCS location and capacity play a crucial role in loss minimization.

Voltage drop and voltage profile degradation are also major concerns associated with EVCS integration. The high-power demand of charging stations, particularly DC fast chargers, can cause substantial voltage drops at nearby buses. Research has shown that voltage deviations become more definite under high EV penetration levels and during simultaneous charging periods (Ahmad F. a., 2022; Bukit, 2024). In radial distribution networks, buses located far from the substation are more vulnerable to voltage violations when EVCS are connected. Without appropriate control or compensation, voltage levels may fall below acceptable operational limits, affecting power quality and customer equipment.

In addition to voltage deviation, EVCS integration can affect overall system stability, especially in weak or heavily loaded feeders. Several studies report that fast-charging stations introduce sudden load variations, which may reduce voltage stability margins and increase the risk of voltage collapse under stressed conditions (Pal, 2021; apoor, 2024). The problem is further aggravated in networks with limited reactive power support and low short-circuit capacity. Weak buses experience larger voltage fluctuations due to their reduced ability to withstand sudden changes in load demand.

Overall, findings from previous studies clearly indicate that EVCS integration has a significant influence on feeder loading, power losses, voltage performance, and system stability. These impacts highlight the need for systematic planning approaches that consider optimal EVCS placement, charging coordination, and network reconfiguration to ensure reliable and efficient operation of EV-integrated distribution networks.

2.4 EVCS Placement in Distribution Network

Strategic siting and correct sizing of EVCS in distribution networks are essential to maintain efficient and reliable grid operation as EV penetration increases. Poor placement or inappropriate charger capacity can lead to technical problems such as increased losses, voltage decline, and reduced stability, especially in radial distribution systems.

Accordingly, optimal EVCS placement helps limit the increase in power losses by reducing unnecessary current flow and preventing feeder overload. When charging stations are placed far from load centres or in weak parts of the network, additional current must travel longer distances, increasing line losses due to the quadratic relationship between current and losses. Optimally placing EVCS closer to load centres or strong buses helps shorten current paths and minimise these losses.

Additionally, the minimum bus voltage level in a distribution network is strongly influenced by where EVCS are located and how large they are. EV charging represents additional load that can cause voltage drops at nearby buses, especially under high demand or clustered charging patterns. Siting EVCS at network locations with better voltage support or dividing charging loads across multiple buses can improve the minimum bus voltage and maintain voltage profile within acceptable operating limits.

Research shows that optimal placement of EVCS coupled with distributed generation improves voltage magnitude and mitigates violations of voltage limits (Grammenou, 2024).

Moreover, voltage stability can be enhanced through proper EVCS siting and sizing. Voltage stability refers to the ability of the network to maintain acceptable voltage levels under varying loading conditions. When large EVCS loads are connected to weak buses or heavily loaded feeders, voltage stability margins shrink and the risk of voltage collapse increases. Strategic EVCS placement, often combined with network support (e.g., distributed generation), helps preserve voltage stability by balancing load distribution and reducing stress on weak network nodes. Studies have shown that optimal positioning of EVCS together with supporting resources leads to improved voltage stability indices and overall system resilience (Devisree Chippada, 2022).

Finally, choosing appropriate charger capacities is also important because oversized stations can draw excessive current, increasing both losses and voltage drop. Conversely, undersized chargers may concentrate demand at specific hours, creating peak load issues. Research on combined optimal siting and sizing of charging stations indicates that jointly determining location and capacity reduces power losses and minimises voltage deviations compared to uncoordinated installations (Liang Chen, 7).

2.4.1 Purpose of EVCS Placement Optimization

Strategic siting and correct sizing of EVCS in distribution networks are essential to maintain efficient and reliable grid operation as EV penetration increases. Poor placement or inappropriate charger capacity can lead to technical problems such as increased losses, voltage decline, and reduced stability, especially in radial distribution systems.

First, optimally locating EVCS helps to reduce power losses by avoiding excessive current flow in distribution feeders. When charging stations are placed far from load centres or in weak parts of the network, additional current must travel longer distances, increasing line losses due to the quadratic relationship between current and losses. Careful placement near load centres or strong buses can lower current flows and reduce these losses, as confirmed by recent studies that show optimal EVCS siting

reduces overall network losses compared to non-optimized installation (Saheb Ghanbari Motlagh, 2026).

Second, the minimum bus voltage level in a distribution network is strongly influenced by where EVCS are located and how large they are. EV charging represents additional load that can cause voltage drops at nearby buses, especially under high demand or clustered charging patterns. Siting EVCS at network locations with better voltage support or dividing charging loads across multiple buses can improve the minimum bus voltage and maintain voltage profile within acceptable operating limits. Research shows that optimal placement of EVCS coupled with distributed generation improves voltage magnitude and mitigates violations of voltage limits (Grammenou, 2024).

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2.4.2 Summary of Key Finding and Limitations

Based on the reviewed literature, several consistent findings can be identified regarding the integration and optimal placement of EVCS in distribution networks. Most studies agree that optimal EVCS placement significantly improves network performance compared to random or unplanned installation. Proper siting of EVCS helps to reduce real power losses by avoiding excessive current flow in weak feeders and improves the overall voltage profile by maintaining bus voltages within acceptable limits. These improvements are commonly observed when EVCS placement is coordinated with system operating conditions and network constraints.

Another important finding is that the EVCS placement problem is highly nonlinear and constrained in nature. The objective functions, such as loss minimisation, voltage deviation reduction, or voltage stability enhancement, are influenced by power flow equations, network topology, and operational limits. As a result, classical optimisation methods often face difficulties in handling multiple objectives and constraints simultaneously. This has led many researchers to adopt metaheuristic and hybrid optimisation techniques, which show better flexibility and robustness when solving complex EVCS planning problems (Liang Chen, 7).

However, several limitations are also reported in past studies. The performance of optimal EVCS placement solutions is highly dependent on network characteristics, such as network size, loading level, and line parameters citation. Solutions that perform well in small or standard test systems may not provide the same level of improvement when applied to larger or heavily loaded networks. In addition, different objective function formulations can lead to different optimal solutions, making direct comparison between studies difficult.

Furthermore, many existing works assume fixed EV charging demand citation or simplified charging behaviour, which may not fully represent real-world charging patterns. This simplification can affect the accuracy of the results, especially under high EV penetration levels. Overall, while optimal EVCS placement is proven to enhance voltage performance and minimise the increase in losses, its effectiveness is influenced by modelling assumptions, network conditions, and the chosen optimisation framework.

Among various performance indicators considered in EVCS placement optimization, active power loss minimization is one of the most widely adopted objectives in distribution network studies. This is because EVCS integration introduces additional load demand, which increases feeder current and consequently increases technical losses due to the relationship between current magnitude and power dissipation. Minimizing active power losses helps improve network efficiency, reduce thermal stress on distribution components, and indirectly enhance voltage performance. Therefore, this study selects active power loss minimization as the primary objective function for determining optimal EVCS locations, while voltage constraints are incorporated to ensure acceptable network operating conditions.

2.5 PV System Integration in Distribution Network

2.5.1 PV as Distributed Generation in Distribution Network

PV systems are commonly classified as DG because they are installed at the distribution level and operate close to end users, unlike conventional centralised power plants that are located far from load centres (Saad, 2018).

The integration of PV as DG enables local power supply to distribution loads, which reduces the dependence on upstream transmission networks and lowers the loading of primary substations during periods of high solar generation. By injecting active power directly into distribution feeders, PV systems can significantly reduce the amount of current flowing from the grid, which leads to lower thermal stress on conductors and improved feeder utilisation (Getie, 2020). The presence of PV-based DG alters the conventional unidirectional power flow in radial distribution networks, causing power to flow from downstream buses back toward the substation under certain operating conditions (Chen Q. B., 2024). This change in power flow behaviour creates a positive impact on bus voltage magnitudes, as the injection of real power from PV systems increases voltage levels at the point of common coupling, particularly for buses located far from the substation (Chen Q. B., 2024).

Consequently, PV systems are increasingly viewed not only as energy sources but also as active elements that influence voltage regulation, feeder loading, and overall operational performance of distribution networks (Maghami, 2023).

2.5.2 Impacts of PV Integration on Losses and Voltage Profile

One of the most widely reported benefits of PV integration is the reduction of power losses in distribution networks, as local generation decreases the current flowing through feeders and transformers. Studies based on radial distribution systems show that strategically placed PV units can significantly reduce real power losses by shortening the electrical distance between generation and load points (Pokhrel, 2021).

In addition to loss reduction, PV integration contributes to the improvement of voltage profiles by supporting weak buses and reducing voltage drops along long distribution feeders. Simulation studies using IEEE test systems confirm that properly sized PV installations can improve voltage magnitude uniformity across the network,

resulting in better compliance with statutory voltage limits (Jiang, Multi-period Voltage Optimization of Active Distribution Network with Distributed Power, 2018). Nevertheless, when PV penetration becomes excessively high, especially during low load conditions, voltage rise may occur due to surplus active power injection at downstream buses (Gang, 2019).

High PV penetration has also been shown to increase the operating frequency of voltage regulating devices such as on-load tap changers and voltage regulators, which may accelerate equipment ageing and maintenance requirements (De Negreiros, 2023). Under high loading conditions, PV systems provide effective voltage support by injecting power near load centres, which helps to mitigate undervoltage issues commonly observed during peak demand periods (De Negreiros, 2023). Studies conducted on Southeast Asian distribution networks further indicate that PV integration during peak load periods can improve voltage stability while simultaneously reducing technical losses, if penetration levels are properly controlled (Nguyen Huy Tien, 2023)

Overall, the literature demonstrates that PV integration offers substantial benefits in terms of loss reduction and voltage profile enhancement. However, careful planning, sizing, and penetration control are essential to prevent voltage rise and operational challenges in distribution networks (Reinaldo, 2020).

2.6 Distribution Network Reconfiguration

2.6.1 Concept of Network Reconfiguration

Distribution Network Reconfiguration (DNR) is a planned process that changes the physical topology of a distribution network through controlled switching operations. The main aim of reconfiguration is to improve system performance, such as reducing power losses, improving voltage profile, balancing feeder loads, and increasing system reliability, while still ensuring continuous electricity supply to consumers.

The idea of DNR was first introduced by (Merlin, 1975), where the objective was to reduce real power losses in distribution systems. A branch-and-bound method was used to solve the DC load flow reconfiguration problem, which became the foundation for later studies. After that, (Hong, 1989) improved this method by applying

AC load flow analysis together with an optimal flow pattern, resulting in better loss reduction performance for practical distribution networks.

In real distribution systems, two main types of switches are used, namely sectionalizing switches and tie switches. Sectionalizing switches are installed along feeders and are normally kept closed during normal operation. These switches are used to isolate faulty sections or to support reconfiguration during maintenance works. Tie switches are usually installed between feeders and remain open under normal conditions. During reconfiguration, selected tie switches can be closed to create alternative supply paths, allowing load transfer between feeders and reducing feeder overloading (S. Civanlar, 1988).

Work in (S. Civanlar, 1988) later introduced the branch exchange method, which provided a simpler and faster approach to perform reconfiguration for power loss reduction. This method was further improved by (Wu, 1989) using approximate load flow calculations. Their work also introduced the widely used IEEE 33-bus test system, which is commonly applied to study loss reduction and load balancing through reconfiguration.

The main function of DNR is to change power flow paths in the network. By opening and closing selected switches, current can be redirected to different branches, which directly affects line losses, voltage drop, and feeder loading. For example, transferring part of the load from a heavily loaded feeder to a lightly loaded feeder can reduce current flow in overloaded lines, leading to lower losses and better voltage levels at buses located far from the substation.

One important constraint in DNR is the requirement to maintain a radial network structure. Most distribution networks operate in radial form because it simplifies protection coordination and fault isolation. If reconfiguration creates closed loops, it may cause circulating currents and protection problems. Therefore, every switching action must be carefully selected to ensure the network remains radial while achieving the desired operational improvements (Gholami, 2020).

With the increase in system size and number of switches, DNR is commonly treated as an optimization problem. The objective is to find the best combination of switch statuses that gives the best system performance while satisfying operational

constraints. Due to the large number of possible switching combinations, many studies apply heuristic and metaheuristic methods, such as genetic algorithm and simulated annealing, to obtain good solutions within reasonable computation time (K. Nara, 1992; Mishra, 2017; Ayodeji Olalekan Salau, 2020).

Although early DNR studies mainly focused on power loss reduction, recent research has expanded the objectives of reconfiguration. DNR is now also used to improve voltage profile, control active and reactive power flows, enhance reliability indices, and manage branch current limits.

The effect of DNR can be clearly explained using a simple example, as shown in Figure 2.4. Consider a small distribution network with four buses and five lines (L1–L5), where L1 to L4 are normally closed and L5 is normally open. Even though the network has a looped physical layout, it operates in a radial manner. When L5 is closed, three other lines (L2, L3, and L4) must be opened to maintain radial operation. Each resulting configuration produces different current flow directions and voltage profiles, especially at the end buses. This example clearly shows how network topology changes can directly influence system performance.

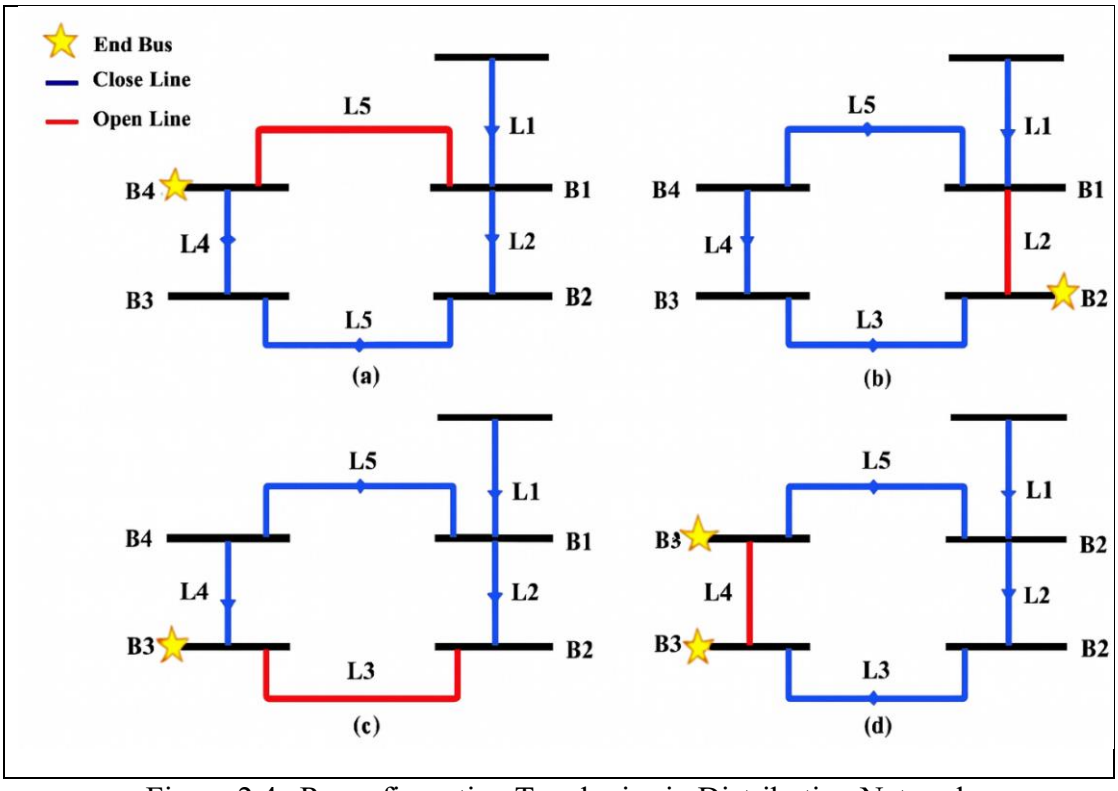


Figure 2.4 Reconfiguration Topologies in Distribution Network

2.7 Integrated Framework: EVCS, Network Reconfiguration, PV

2.7.1 Reconfiguration with EVCS Integration

Research has indicated that the presence of EVCS can shift feeder load profiles, particularly during peak charging times when multiple EVs are connected to the network simultaneously (Ng, 2023). Such changes in load characteristics can cause issues related to overloading of specific feeders and lead to unbalanced system operation. For example, a study by (Mohd Nor N. F., 2022) demonstrated that the increased load due to EVCS requires a reassessment of the feeder's configuration to accommodate dynamic charging demands, thus ensuring reliable supply and preventing overload situations. In fact, it has been shown that optimal reconfiguration after EVCS integration can effectively mitigate voltage drops and the loss increase caused by these new loads (Chong, 2024). The ability of reconfiguration strategies to reduce the negative impact of EVCS has been a subject of active investigation, suggesting that carefully designed switching strategies can enhance system resilience and minimize power losses (Chong, 2024).

2.7.2 Reconfiguration with PV integration

The injection of PV power into the grid impacts the voltage distribution across buses, potentially leading to overvoltage issues during high solar generation periods (Rahman M. A., 2023). Studies have highlighted that network reconfiguration can help mitigate these issues by enhancing the voltage profile and reducing line losses, especially when the output from PV systems varies throughout the day (Zainuddin, 2024). Study by (Lee, 2022) showed that reconfiguring the network in response to varying PV generation helps manage power flow more efficiently, ensuring that the grid remains stable even as PV penetration increases. Furthermore, reconfiguration can help in optimally dispatching power from PV units, allowing for better utilisation and improved voltage regulation (Siti Hajar, 2025).

2.7.3 Studies Combining EVCS Placement and Network Reconfiguration

Recent research has suggested that the simultaneous placement of EVCS and network reconfiguration results in better network performance than treating these

elements separately. Studies by (Ali M. A., 2022) indicate that coordinated planning of EVCS installation and network reconfiguration optimises the load distribution, which significantly reduces overall system losses and enhances operational efficiency. In fact, reconfiguration, when combined with well-planned EVCS deployment, can improve the power quality by balancing the load more effectively (Hassan, 2024). On the other hand, non-integrated solutions where EVCS placement and network reconfiguration are handled separately tend to lead to suboptimal results, as they fail to justify the interactions between these two factors.

2.7.4 Studies Combining EVCS Placement, Network Reconfiguration and PV

There is limited research that simultaneously considers the integration of EVCS, PV systems, and network reconfiguration. However, some studies have highlighted the potential benefits of combining these technologies. For example, study by (Mohd Nor N. F., 2023) states that combining PV systems with EVCS placement and reconfiguration leads to a more balanced grid with reduced system losses. However, the challenge of balancing loss reduction with voltage stability remains an ongoing concern. Study by (Rahman M. A., 2024) found that while such integration can significantly improve grid performance, the trade-offs between maintaining voltage stability and reducing losses are not always clear, and a more consistent methodology is needed (Ahmad R. e., 2025). Furthermore, integrated planning often encounters difficulties in optimally coordinating the placement of both EVCS and PV systems, which can affect the overall success of the reconfiguration process.

Among the reviewed studies, references (Mohd Nor N. F., 2023) and (Rahman M. A., 2024) are the most closely related to the present research because they considered EVCS integration, PV systems and distribution network reconfiguration within the same study. However, these studies did not investigate the use of a Hybrid PSO–MVO algorithm for coordinating the optimization process. In addition, limited attention was given to combining the population-diversification capability of MVO with the efficient solution-refinement capability of PSO. Therefore, the present study extends the existing literature by developing a Hybrid PSO–MVO approach for the coordinated consideration of EVCS placement, PV integration and distribution network reconfiguration.

2.8 Comparative Optimization Techniques Used in Literature

2.8.1 Overview of Optimization Approaches in Distribution Planning

The integration EVCS and network reconfiguration problems are known to be nonlinear, constrained, and multi-objective in nature. These problems often involve complex factors such as time-dependent load variations and the nonlinear nature of power flows, particularly when considering renewable energy sources (Pasha, 2024). As such, they require efficient optimization techniques capable of handling multiple conflicting objectives, such as minimizing losses, improving voltage stability, and reducing operational costs. Given the wide variety of constraints, such as voltage limits, power demand, and capacity of the network, these problems often cannot be solved by simple analytical methods and require advanced optimization techniques (Jamil, 2025).

2.8.2 Conventional (Mathematical) Optimization Techniques

Conventional optimization techniques have been extensively utilized in the optimization of distribution systems, including the placement of EVCS, network reconfiguration, and overall power system planning. These techniques are based on mathematical programming methods that formulate the problem as an optimization model with objective functions and constraints. The commonly used conventional optimization techniques in distribution planning include Linear Programming (LP), Nonlinear Programming (NLP), Mixed-Integer Linear Programming (MILP), and Mixed-Integer Nonlinear Programming (MINLP). Each of these approaches has its own strengths and weaknesses depending on the nature of the optimization problem.

LP is one of the simplest and most widely used optimization methods for solving problems with linear objective functions and constraints. LP involves optimizing a linear objective subject to a set of linear constraints. This method is very efficient and is particularly suitable for problems where all relationships are linear, such as when optimizing the distribution of power without considering the nonlinear effects of system losses or other factors (Ismail, 2023). However, the major limitation of LP arises when dealing with real-world systems that contain nonlinear relationships, such as the power losses in networks or voltage stability, which are inherently nonlinear. (Ismail, 2023) In

such cases, LP's simplifications often fail to capture the complexity of the system, leading to suboptimal results.

NLP is an extension of LP that allows for the inclusion of nonlinear objective functions and constraints. NLP is particularly useful in power distribution systems where nonlinearities, such as voltage and power loss characteristics, are significant (Goh C. S., 2022). NLP allows for more flexibility in modelling real-world systems and can provide better results for optimization problems involving nonlinear relationships. However, the challenge with NLP lies in its susceptibility to local optima. The objective function in NLP problems often has multiple local minima, and without proper initialization or advanced techniques like global search strategies, the algorithm may converge to suboptimal solutions (Goh C. S., 2022). Additionally, solving large NLP problems can be computationally expensive and time-consuming.

MILP combines the simplicity of linear programming with the ability to handle discrete decision variables, such as binary or integer variables. MILP is particularly suitable for problems that involve discrete decisions, such as network reconfiguration or determining the placement of EVCS (Vargas, 2024). For example, in distribution network reconfiguration, MILP can be used to model the on/off states of switches. While MILP provides a powerful tool for solving complex combinatorial optimization problems, its major drawback is the high computational burden, especially for large-scale systems with many variables. As the problem size grows, MILP models require significant computational resources and time, making them less practical for real-time applications (Hussain, 2023)

MINLP is a more advanced form of optimization that allows both nonlinear objective functions and discrete decision variables. MINLP is useful for problems that involve both nonlinearities and discrete choices. While MINLP can handle highly complex problems, it suffers from the same issues as NLP in terms of local optima and the computational difficulty of solving large-scale problems. The addition of integer variables further increases the complexity, as MINLP problems are often NP-hard and require advanced solution techniques such as branch-and-bound or outer-approximation methods, which can be computationally expensive and slow (Abdullah, 2023).

In summary, conventional optimization techniques like LP, NLP, MILP, and MINLP are widely applied in distribution system optimization, but each comes with

limitations. LP is efficient but ineffective for nonlinear problems, NLP handles nonlinearities but suffers from local optima, MILP is useful for discrete variables but computationally expensive, and MINLP is highly flexible but difficult to solve for large-scale systems. These limitations highlight the need for alternative methods, such as metaheuristics or hybrid optimization techniques, to overcome the increasing complexity of modern distribution systems.

2.8.3 Motivation for Using Metaheuristic Optimization Techniques in Distribution Network Planning

The optimization problems associated with EVCS placement, distribution network reconfiguration, and PV integration are characterized by nonlinear power flow relationships, discrete decision variables, multiple operational constraints, and a large search space. For example, EVCS placement requires determining suitable installation locations among numerous possible buses, while network reconfiguration involves identifying optimal combinations of switch states while maintaining radial network operation. These characteristics make the optimization problems highly complex and difficult to solve using conventional mathematical techniques.

Although conventional optimization methods such as Linear Programming (LP), Nonlinear Programming (NLP), Mixed Integer Linear Programming (MILP), and Mixed Integer Nonlinear Programming (MINLP) have been widely applied, their performance is often limited when handling large-scale nonlinear and mixed-integer distribution network problems. These methods generally require mathematical simplification, convex formulation, or accurate initial solutions, which may reduce their effectiveness when dealing with non-convex objective functions and complex constraints.

Therefore, metaheuristic optimization techniques have gained significant attention in distribution system planning due to their ability to search large solution spaces without requiring gradient information or mathematical convexity assumptions. These algorithms are particularly suitable for EVCS placement and network reconfiguration problems because they can effectively handle discrete variables, nonlinear objective functions, and multiple constraints simultaneously. Furthermore, metaheuristic methods provide flexibility in integrating different objectives, such as

loss minimization, voltage improvement, and operational constraints, within a single optimization framework.

However, despite their advantages, individual metaheuristic algorithms may still experience limitations, including premature convergence, insufficient exploration capability, sensitivity to parameters, or slow convergence when applied to complex distribution network optimization problems. Therefore, hybrid optimization approaches have been increasingly investigated to combine the complementary strengths of different algorithms and achieve improved optimization performance.

2.8.4 Metaheuristic Optimization Techniques

Metaheuristic algorithms, including Genetic Algorithm (GA), Differential Evolution (DE), Simulated Annealing (SA), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), as well as Multiverse Algorithm (MVA) and Particle Swarm Optimization (PSO), are widely used to tackle complex and large-scale optimization problems. These methods are particularly useful when traditional optimization techniques cannot efficiently solve problems involving nonlinear, constrained, and multi-objective.

GA remains one of the most widely used optimization methods, known for its ability to explore large solution spaces efficiently. However, it may suffer from slow convergence, particularly when the problem involves complex interactions or a vast solution space (Bharati, 2024). Study by (Tan, 2022) have shown how GA can be applied for EVCS placement, but they also noted that it may struggle with finding optimal solutions in large-scale systems.

DE is known for its ability to maintain diversity in the population, thus helping to avoid premature convergence. DE has been successfully applied to a range of optimization problems, including power system optimization (Baskar, 2023). However, according to study by (Shao, 2024), DE can be highly sensitive to the choice of parameters, which may reduce its performance in certain complex applications.

SA has been widely used for optimization problems with many local minima. It allows the search process to explore different areas of the solution space by accepting worse solutions under certain conditions. In power systems, SA has been shown to work well in finding near-optimal solutions for reconfiguration problems. However, SA may

face difficulty when dealing with large-scale systems, requiring extensive tuning to maintain efficiency (Goh T. e., Simulated Annealing for Optimal Placement of Renewable Energy Sources in Power Networks, 2023).

ACO works well for pathfinding and optimization problems involving discrete decisions, like network reconfiguration. Study by (Xie, 2024) highlighted that ACO can become inefficient in large-scale systems due to its computational demands, particularly when many variables need to be considered, such as those in EVCS placement.

GWO mimics the hunting behaviour of grey wolves. It is well known for its strong exploration capabilities and has been applied in various power system optimization problems, including distribution network design (Abidin, 2023). However, GWO tends to suffer from premature convergence, especially when the search space is complex or large (Abidin, 2023).

WOA is inspired by the hunting strategies of humpback whales. It has been widely used due to its ability to balance exploration and exploitation effectively (Kannan, 2023). However, WOA can suffer from premature convergence when applied to complex systems, particularly in large, multi-objective optimization problems (Nguyen, 2024).

MVO is a relatively recent population-based metaheuristic inspired by the concept of multiple universes and the interaction between different solutions. Each candidate solution is represented as a universe, where the inflation rate represents solution quality. Through mechanisms such as white hole, black hole, and wormhole operators, MVO provides an effective balance between exploration and exploitation during the optimization process.

The strong exploration capability of MVO enables it to investigate diverse regions of the search space and reduce the probability of becoming trapped in local optima. Previous studies have demonstrated the effectiveness of MVO in solving distribution network problems, including EVCS placement and network reconfiguration (Goh T. e., Multiverse Algorithm for Optimal Placement of EVCS and Network Reconfiguration, 2024). However, similar to other population-based algorithms, excessive exploration may reduce convergence speed, particularly when high-quality solutions have already been identified. Therefore, additional exploitation mechanisms may be required to improve solution refinement and convergence accuracy.

PSO is a population-based metaheuristic algorithm inspired by the collective movement behaviour of birds and fish. The algorithm uses a group of particles, where each particle represents a possible solution, and updates its position based on individual experience and information shared among the population. The main advantages of PSO include its simple implementation, limited number of control parameters, and fast convergence capability, which make it attractive for distribution system optimization problems such as EVCS placement and network reconfiguration (Chen J. e., Particle Swarm Optimization for Power System Optimization with EVCS Integration, 2023).

Several studies have applied PSO for EVCS planning and distribution network optimization due to its ability to efficiently search for optimal locations and sizing solutions. However, PSO performance is highly dependent on population diversity. During later optimization stages, particles may converge prematurely toward local optima, particularly when solving large-scale nonlinear problems with multiple constraints. This limitation reduces its capability in exploring unexplored regions of the search space and may lead to suboptimal solutions (Radha Thangaraj, 2011).

2.8.5 Hybrid Optimization Approaches Used in Previous Literature

Hybrid optimization approaches combine multiple algorithms to leverage the strengths of each, aiming to enhance both the exploration and exploitation capabilities of the search process. These methods are particularly useful for solving complex optimization problems where a single algorithm may struggle to balance global search efficiency with convergence speed. By combining the robustness of metaheuristic algorithms with the precision of traditional mathematical optimization techniques, hybrid methods can achieve better performance in finding high-quality solutions for complex problems (Rashid, 2023).

The motivation for hybrid methods stems from the need to improve the global search ability while ensuring fast convergence to the optimal or near-optimal solutions. Metaheuristic algorithms such GA, PSO, and ACO are known for their strong exploration capabilities but may face issues like slow convergence or premature trapping in local optima when applied to large, complex systems (Ali R. e., 2024). By combining these with more traditional mathematical techniques, such as LP or NLP,

hybrid approaches are able to refine solutions more precisely, thus balancing exploration with exploitation (Mansor, 2024).

For example, hybridizing GA with PSO has been shown to improve the convergence speed of the optimization process while still maintaining a broad search capability (Rahman M. e., 2023). Such combinations take advantage of GA's ability to handle large solution spaces and PSO's strength in fine-tuning solutions in a more efficient manner. In power system optimization problems these hybrid methods have proven to be effective, offering a way to find high-quality solutions faster than using a single optimization technique alone (Chen J. e., Optimizing Distribution Systems with Hybrid Algorithms: A Case Study on EVCS Placement, 2023).

Hybrid approaches aim to obtain high-quality solutions with reduced computational effort and are widely applied in power system optimization problems such as loss minimization and EVCS planning. Recent studies have applied hybrid techniques specifically for EVCS placement and network configuration. For example, hybrid GA–Simulated Annealing (S. D. Nugraha, 2025), PSO–GWO–Cuckoo Search (B. Vinod Kumar, 2024). Overall, these studies indicate that hybrid optimization techniques are effective tools for EVCS placement and network configuration problems.

2.8.6 Motivation and Advantages of Hybrid PSO-MVO Algorithm

Hybrid optimization approaches have been introduced to overcome the limitations associated with individual metaheuristic algorithms by combining complementary search characteristics. In this study, the combination of Particle Swarm Optimization (PSO) and Multi-Verse Optimization (MVO) is selected because both algorithms possess different but complementary strengths.

PSO demonstrates strong exploitation capability due to its velocity and position updating mechanism, allowing particles to rapidly move toward promising solutions. However, its limited population diversity may cause premature convergence when solving complex nonlinear optimization problems. Conversely, MVO provides strong exploration capability through its multi-universe search mechanism, enabling a wider investigation of the solution space and reducing the likelihood of being trapped in local

optima. Nevertheless, MVO may require additional exploitation capability to improve convergence accuracy during the final optimization stage.

Therefore, combining PSO and MVO provides a potential balance between exploration and exploitation. The exploration ability of MVO allows the optimization process to identify promising regions of the search space, while PSO improves solution refinement by accelerating convergence toward high-quality solutions. This complementary relationship is particularly suitable for EVCS placement and network reconfiguration problems, which involve nonlinear power flow equations, discrete decision variables, and multiple operational constraints.

Based on this motivation, this study develops a Hybrid PSO-MVO (HPSOMVO) algorithm using a sequential hybrid strategy. The proposed approach aims to achieve better convergence performance and solution quality compared with individual optimization algorithms by utilizing the global search capability of MVO and the fast convergence characteristics of PSO.

2.9 Summary of Literature Review and Research Gap

2.9.1 Summary of Literature Findings

From the reviewed studies, the integration of EVCSs has a significant impact on distribution system performance. High EV penetration increases power demand, which can lead to higher feeder losses, voltage drop, and stress on transformers if not properly managed. Many researchers reported that uncontrolled EV charging may worsen voltage profile and increase active power losses, especially in radial distribution networks.

Optimal placement and sizing of EVCSs have been widely studied as an effective solution to reduce system losses and improve voltage stability. Properly located charging stations can distribute the load more evenly along the feeders and reduce excessive voltage drop at weak buses. Several optimization techniques such as PSO, GA, ACO, and MVO have been applied, and results show that optimal EVCS planning can significantly enhance system performance compared to random placement.

In addition, PV integration has been shown to support voltage improvement and reduce feeder losses, depending on its location, size, and operating condition. When PV is installed near load centres or EVCS locations, it can supply part of the demand locally, reduce power flow from the substation, and improve voltage magnitude along the feeder. However, the performance of PV integration depends on generation level and load variation.

Network reconfiguration is also proven to be an effective operational strategy to improve distribution system performance. By changing the status of sectionalizing and tie switches, power flow can be redistributed to reduce losses, balance feeder loading, and enhance voltage profile. Many studies confirm that reconfiguration can further improve results when combined with optimal EVCS placement.

Furthermore, comparative optimization studies show that different algorithms produce different performance results in terms of convergence speed, accuracy, and solution quality. The effectiveness of each technique depends on problem formulation, objective function, and system constraints. Hence, hybrid optimization methods are increasingly explored to achieve better performance.

2.9.2 Justification for Selecting Active Power-Loss Minimization

Active power-loss minimization is selected as the primary objective because the integration of EVCS increases feeder demand and branch current, particularly during peak charging periods. Since active power losses in a distribution network are proportional to the square of the branch current, additional EVCS demand can significantly reduce network operating efficiency and increase feeder loading. Power loss therefore provides a direct and measurable indicator for comparing different EVCS locations and network configurations. Previous EVCS placement and distribution network reconfiguration studies have also commonly adopted active power loss as a principal technical objective [insert relevant references]. In this study, voltage limits, branch-current limits, power balance and radiality requirements are maintained as operational constraints. Therefore, the reduction in power loss is achieved without compromising acceptable voltage and secure network operation.

2.9.3 Research Gaps

As many existing works focus on EVCS placement, network reconfiguration and PV integration in isolation, several key research gaps are still present. Although previous studies have investigated EVCS placement, PV integration, and network reconfiguration, most existing works consider these aspects separately or only combine two components. Studies simultaneously considering EVCS placement, PV integration, and network reconfiguration under a unified optimization framework remain limited. Furthermore, many existing studies rely on individual metaheuristic algorithms, where limitations such as premature convergence and insufficient exploration capability may affect solution quality for complex distribution optimization problems.

Moreover, limited studies have provided detailed justification for hybrid algorithm development specifically for EV-integrated distribution networks. The complementary relationship between PSO and MVO has not been extensively explored, particularly for coordinated EVCS placement and network reconfiguration problems. Therefore, this research investigates the application of a Hybrid PSO-MVO algorithm to improve optimization performance by combining global exploration capability and convergence efficiency.

2.9.4 Contribution of the Study

Based on the identified gaps, this study contributes to several important aspects. First, this research develops a hybrid PSO-MVO algorithm to determine the optimal placement of EVCSs in distribution networks. The proposed hybrid method aims to minimize active power losses while improving voltage profile to ensure all bus voltages remain within statutory limits. By combining the strong exploration capability of MVO and the fast convergence characteristic of PSO, the algorithm is expected to provide better solution quality and convergence performance.

Second, this study designs an optimal network reconfiguration framework that considers the optimal EVCS placement together with PV integration. The coordinated optimization of EVCS placement, PV capacity, and network reconfiguration allows a more realistic and practical evaluation of distribution system performance under different operating conditions.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodology and the research development process used to meet the study objectives. It includes key sections on the proposed research framework, system modelling and problem formulation, the proposed optimization algorithm, network reconfiguration modelling and optimization implementation. The Hybrid Particle Swarm Optimization–Multi-Verse Optimization (HPSOMVO) algorithm is applied to solve two sequential optimization problems: (i) optimal EVCS placement and (ii) optimal distribution network reconfiguration considering the identified EVCS locations. PV integration is subsequently incorporated as an additional planning scenario to evaluate its contribution in improving voltage performance and reducing network losses.

3.2 Proposed Framework

Figure 3.1 presents the framework of the proposed HPSOMVO in this study. The framework integrates optimal EVCS placement and optimal network reconfiguration considering optimal EVCS placement with integrated PVs to enhance the operational performance of radial distribution networks.

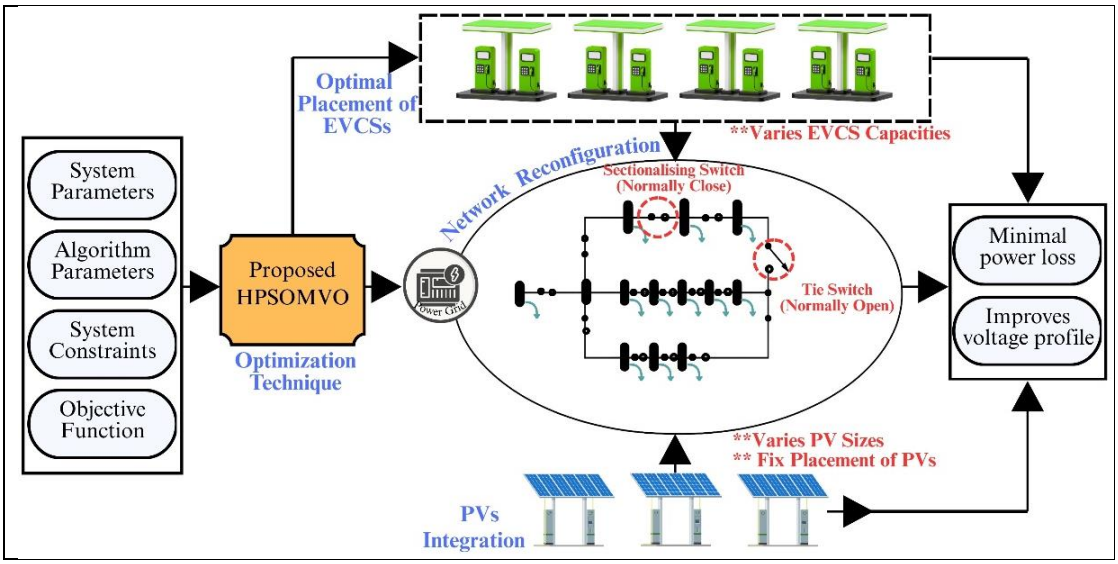


Figure 3.1 Proposed Framework

The optimization framework begins with the definition of system parameters, algorithm parameters, operational constraints, and objective functions, which serve as inputs for the proposed HPSOMVO algorithm. The optimization process is implemented using a sequential two-stage strategy to reduce computational complexity and improve solution reliability. In the first stage, EVCS placement is optimized independently to determine technically suitable locations and capacities while minimizing active power losses and maintaining voltage constraints. The obtained EVCS configuration represents the additional demand condition imposed on the distribution network.

In the second stage, network reconfiguration is performed based on the optimal EVCS locations obtained from the first stage. This approach allows the switching optimization to focus on improving the feeder topology under the actual charging demand scenario rather than simultaneously searching for EVCS locations and switch configurations, which significantly increases the dimensionality of the optimization problem. After obtaining the optimal network configuration, PV generation is integrated as a supporting resource to evaluate its additional contribution in reducing losses and improving voltage performance.

The sequential framework therefore provides a practical planning approach where EVCS deployment decisions are determined first, followed by operational adjustment through network reconfiguration and renewable energy support. This

approach is suitable for distribution planning studies because EVCS installation represents a long-term infrastructure decision, whereas network reconfiguration represents an operational strategy that can be adjusted according to changing system conditions.

3.3 System Modelling

Two radial distribution systems, namely the IEEE 33-bus and IEEE 69-bus test systems, are selected to evaluate the effectiveness and scalability of the proposed optimization framework. These systems are widely adopted in distribution network studies because they represent practical radial feeders with different network sizes and complexity levels.

The IEEE 33-bus system is selected as a benchmark small-scale distribution network due to its simple topology, limited number of branches, and widespread application in studies involving power loss minimization, network reconfiguration, distributed generation placement, and EV integration. It provides an appropriate platform for evaluating the effectiveness of the proposed algorithm under a controlled network condition.

The IEEE 69-bus system is additionally considered to examine the performance of the proposed method in a larger and more complex radial network. Compared with the IEEE 33-bus system, the IEEE 69-bus network contains more buses and branches, resulting in a larger search space and higher optimization complexity (Wu, 1989). Therefore, evaluating both systems allows the robustness and scalability of HPSOMVO to be assessed under different network conditions. Details of the system are explained in Section 3.3.1. The EVCS and PV modelling used in the study are explained in Section 3.3.2 and 3.3.3 respectively.

3.3.1 Distribution System Modelling

i. IEEE 33 Bus Distribution System

The IEEE 33-bus distribution test system includes 37 branches, 32 sectionalizing switches, and 5 tie switches are shown in Figure 3.2. The parameters of test systems were taken from (Hany S. E. Mansour, 2021). Total

active and reactive loads of the test system are 3.72 MW and 2.3 MVar, respectively. The branches 33, 34, 35, 36, 37 are tie branches which builds the primary loops.

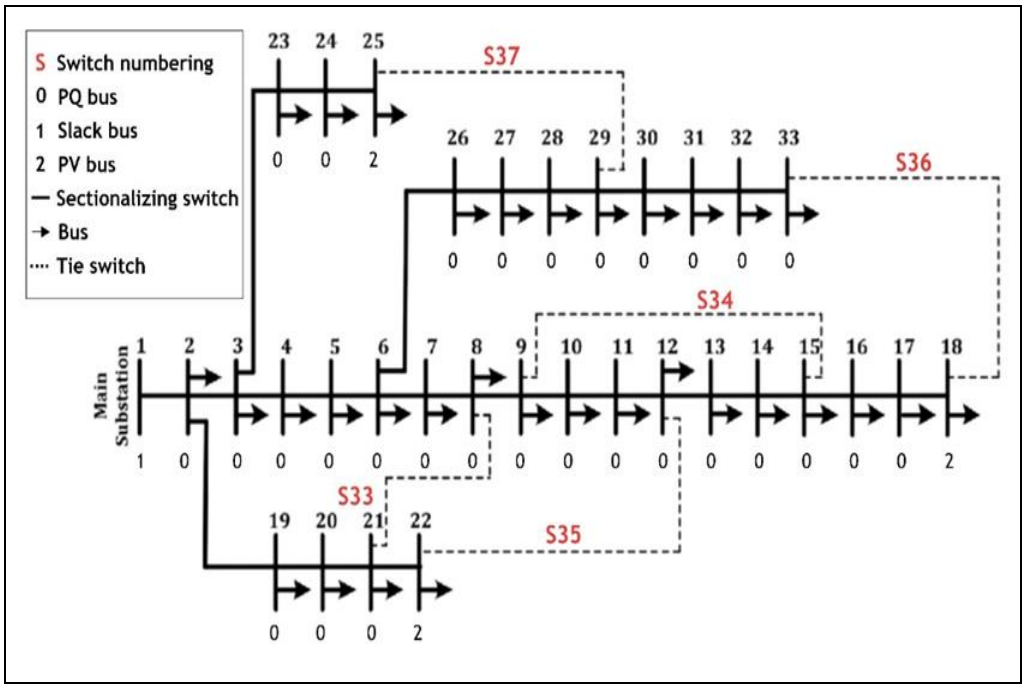


Figure 3.2 IEEE 33-Bus Distribution Network

ii. IEEE 69 Bus Distribution System

The IEEE 69-bus distribution test system, which represents a medium-scale network as illustrated in Figure 3.3, is employed to further evaluate the performance of the proposed algorithm in a larger network. The test system includes 73 branches, 68 sectionalizing switches, and 5 tie switches. It has 3.802 MW and 2.695 MVar of active and reactive loads, respectively. The branches 69, 70, 71, 72, 73 are tie branches which builds the primary loops.

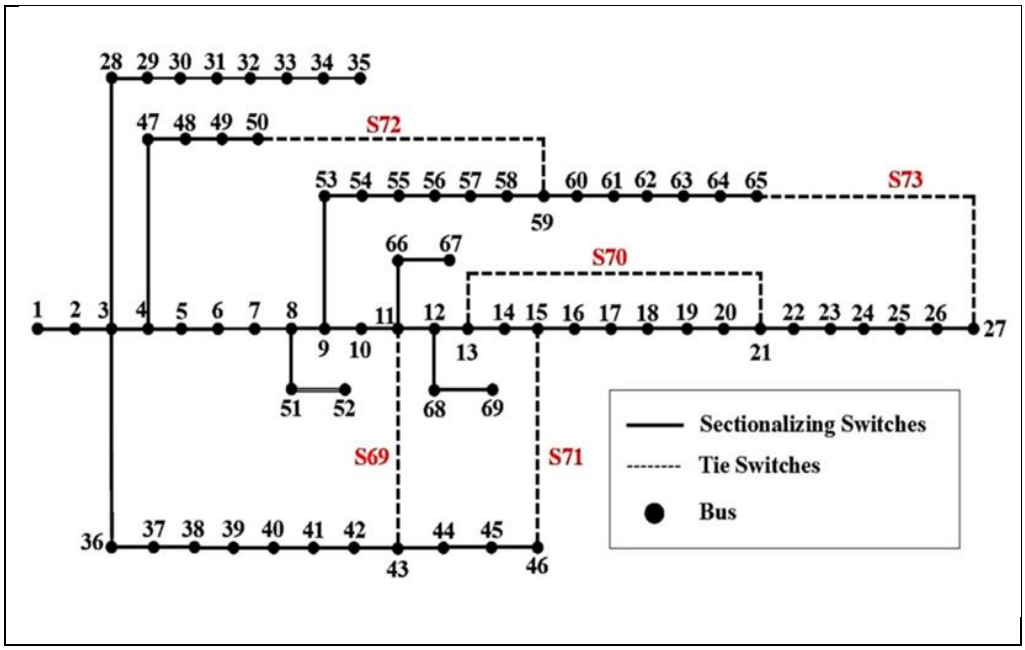


Figure 3.3 IEEE 69-Bus Distribution Network

3.3.2 EVCS Modelling

In this study, 10 EVCSs are considered for the IEEE-33 and IEEE-69 bus distribution networks to represent a moderate-to-high EV penetration scenario. The selected number provides sufficient loading impact to clearly observe changes in voltage profile and power losses while still maintaining realistic network operation. Using too few EVCS units may not significantly affect the system, whereas an excessively large number may lead to unrealistic overloading.

EVCS capacities of 0.15 MW, 0.35 MW, and 0.48 MW are adopted to represent aggregated fast-charging stations at the distribution level. According to Table 2.1 in Section 2.3.1, typical DC fast chargers operate around 50–90 kW, with some superchargers reaching 70–250 kW per charger. When multiple chargers are installed at a single station and operate simultaneously, the total station demand can reach hundreds of kilowatts, which justifies the selected capacity levels of 0.15MW (low aggregated charging demand), 0.35MW (medium aggregated charging demand), and 0.48MW (high aggregated charging demand) for the study. This aggregated modelling approach is widely used in distribution network studies to realistically assess the impact of EVCS on voltage profiles and feeder losses, particularly in test systems such as the IEEE-33 and IEEE-69 bus networks (Ahmad F. I., 2022).

3.3.3 PV Modelling

The PV modelling is not treated as an optimisation variable, instead, fixed PV placement with varying ratings is adopted to examine the secondary impact of PV integration on voltage profile improvement and system loss reduction after network reconfiguration.

In the network model, PV units are integrated as constant active power injections, at selected buses. The PV units are assumed to operate at unity power factor, supplying only real power (Q = 0), which is consistent with common distribution-level PV modelling practices and avoids introducing additional reactive power control complexity. Variations in solar irradiance, temperature effects, and dynamic PV behaviour are not considered, as the focus of this work is on steady-state performance assessment. The placement and sizing of PV units in the test systems is summarized in Table 3.1. The placement of PV units is adopted based on the optimal DG locations reported in (Rehman, 2023), while the PV capacities are determined according to typical commercial building rooftop installation sizes, ranging from 100kW to 300kW.

Table 3.1
Placement and Sizing of PV Units in Test Systems

No	Test System	Bus Location	PV Size, MW
1	IEEE 33-bus system	14, 24, 30	0.3, 0.2, 0.1
2	IEEE 69-bus system	11, 18, 61	0.3, 0.2, 0.1

3.4 Optimization Problem Formulation

As stated in Section 3.3, two optimization problems are solved sequentially: Objective 1 (optimal EVCS placement) and Objective 2 (optimal network reconfiguration considering the optimal EVCS placement from Objective 1 with integrated PVs). The objective function, decision variable and constraints for both objectives were explained in Section 3.4.1 and 3.4.2 respectively.

3.4.1 EVCS Placement Optimization Problem

A. Objective Function

The first optimization objective is to identify the optimal placement and capacities of EVCS in the distribution network considering minimum power losses. This objective function is defined as:

$$\min_{x, P_{EVCS}} \quad f1 = \mathrm{P}_{loss} = \sum_{l=1}^{N_l} \mathrm{P}_l \tag{3.1}$$

where

- P_{loss} is the total real power loss of the distribution network obtained from load-flow analysis,
- N_l is the number of branches, and
- P_l is the real power loss of branch l.

The total power loss is computed using Newton–Raphson load flow after integrating the EVCS loads at the selected buses.

B. Decision Variables

Two decision variables are considered in this study:

i. EVCS Bus Locations

ii. $$X = [x1,\ x2,\ \ldots,\ x_k] \tag{3.2}$$

where $x_k \in 2, 3, \ldots, N_b$ denotes the bus number at which the k^{th} EVCS is installed, excluding the slack bus.

iii. EVCS Capacities

$$P_{EVCS} = [P_1, P_2, \ldots, P_k] \tag{3.3}$$

where each EVCS capacity is selected from a predefined discrete set:

$$P_k \in \{0.15, 0.35, 0.48\}\ p.u. \tag{3.4}$$

A priority-based capacity allocation strategy is adopted, whereby bus (typically upstream buses) is assigned larger charging capacities. This approach aligns with real-world planning considerations, as downstream buses are more voltage-sensitive and therefore require smaller charging capacities to maintain acceptable voltage limits.

C. Constraints

Three constraints are considered in this optimization problem:

i. Bus Voltage Limits

$$V_i^{min} \leq V_i \leq V_i^{max}, \quad \forall_i \in \{2, \ldots, N_b\} \tag{3.5}$$

where $V_i^{\min} = 0.90\ p.u.$ and $V_i^{\max} = 1.05\ p.u.$

ii. Unique EVCS Placement

$$x_i \neq x_j \tag{3.6}$$

$$\forall i \neq j \tag{3.7}$$

ensuring that no two EVCS are placed on the same bus.

iii. Network Operating Constraints

- Load flow convergence must be achieved.
- Branch current and power flow limits are implicitly enforced through feasible load-flow solutions.

3.4.2 Network Reconfiguration Optimization Problem

A. Objective Function

The second optimization problem focuses on determining the optimal network reconfiguration through tie-switch selection, considering fixed EVCS placement and capacities (obtained from 3.4.1A). The same objective function as the first optimization problem is used, i.e. minimum power losses. The objective function of minimum power loss is defined as:

$$\min_{s} f2 = P_{loss} = \sum_{l=1}^{N_l'} P_l \tag{3.8}$$

where

- $s = [s_1, s_2, \ldots, s_m]$ denotes the selected tie-switches to be opened,
- s_m represents the index of a branch (tie-switch) to be opened
- N_l' is the number of branches after reconfiguration, and
- P_l is the real power loss of branch l.

B. Decision Variable

The decision variables for network reconfiguration are:

Switch Configuration Vector

$$s = [s_1, s_2, \ldots, s_m] \tag{3.9}$$

The number of open switches is fixed to maintain a radial network structure.

C. Constraints

The network reconfiguration problem is subject to five constraints:

i. Radiality Constraint

$$\text{Rad}(s) = 1 \tag{3.10}$$

This constraint ensures that the voltage magnitude at each bus remains within acceptable operating limits. The voltage at bus i denoted by V_i must lie between the minimum allowable voltage $V_i^{\min}$ and the maximum allowable voltage $V_i^{\max}$.

ii. Branch Loading Limits

$$| I_l | \leq I_l^{\max}, \forall l \tag{3.11}$$

This constraint ensures that the current flowing through each branch or distribution line does not exceed its maximum allowable current capacity.

The branch current magnitude $|I_l|$ must be less than or equal to the rated current limit $I_l^{\max}$. In EVCS integration studies, excessive charging demand may increase line currents and lead to overloading conditions.

iii. Fixed EVCS Integration

EVCS locations and capacities are fixed and treated as additional real power loads:

$$P_i^{\text{new}} = P_i^{\text{base}} + P_i^{\text{EVCS}} \tag{3.12}$$

iv. Non-Overlapping Constraint

Switch positions are restricted to non-EVCS buses to avoid operational conflicts.

3.5 Optimization Algorithm Used

This section explains the optimization methods used in this study. It describes the proposed hybrid algorithm HPSOMVO, which is the main method used to solve the EVCS placement and network reconfiguration problems. Then, it introduces several other optimization algorithms that are used for comparison. These comparison methods provide a fair basis for evaluating the performance of the proposed hybrid algorithm under consistent test conditions.

3.5.1 Proposed HPSOMVO Algorithm

The optimization framework as discussed in Section 3.2, are solved using a HPSOMVO algorithm, which integrates the fast convergence and strong exploitation capability of PSO with the superior global exploration mechanisms of the MVO algorithm. PSO efficiently refines candidate solutions by guiding particles toward promising regions based on velocity and position updates influenced by personal and global best solutions. However, PSO alone may suffer from premature stagnation when diversity in the population decreases. In contrast, MVO employs White Hole, Black Hole, and Wormhole mechanisms that enhance population diversity and enable effective global search, although it exhibits relatively slower convergence.

3.5.1.1 Overview of PSO Operators

The PSO component updates particle velocities and positions based on personal and global best solutions. The velocity update rule is given by:

$$v_{ij}^{(t+1)} = w \times v_{ij}^{(t)} + c_1 \times r_1 \times (P_{ij} - x_{ij}^{(t)}) + c_2 \times r_{2,} \times (g_{j,} - x_{ij}^{(t)}) \quad (3.13)$$

where:

- $v_{i,d}^{t+1}$is the velocity of particle $i$in dimension $d$at iteration $t + 1$,
- $w$is the inertia weight controlling the influence of the previous velocity,
- $c_1$and $c_2$are the cognitive and social acceleration coefficients, respectively,
- $r_1$and $r_2$are random numbers uniformly distributed in $[0, 1]$,
- $pBest_{i,d}$is the personal best position of particle $i$in dimension d,
- $gBest_d$is the global best position in the swarm for dimension d,
- $x_{i,d}^t$is the current position of particle $i$in dimension d.
- The position of each particle is updated as:

$$x_{i,d}^{(t+1)} = x_{i,d}^{(t)} + v_{i,d}^{(t+1)} \quad (3.14)$$

The inertia weight w is often linearly decreased over iterations to balance global and local search performance:

$$w = w_{\max} - (\frac{iter}{itmax})(w_{\max} - w_{\min}) \quad (3.15)$$

To enhance stability in discrete optimization problems, a damped PSO operator is applied with a probability of 0.3:

$$x_{i,d} = x_{i,d} + 0.2V_{i,d} \quad (3.16)$$

3.5.1.2 Overview of MVO Operators

The MVO component introduces two key operators:

A. White Hole Operator

In the white–black hole mechanism, universes with superior fitness values probabilistically transfer their parameters to inferior universes. Specifically,

universes with higher inflation rates function as white holes, while those with lower inflation rates act as black holes that receive information. For universe $i$and dimension d, this information exchange process allows better solution attributes to guide poorer solutions toward improved regions of the search space, thereby enhancing the global exploration capability of the algorithm.

$$x_{i,d} = \begin{cases} x_{\text{donor},d}, & \text{if } rand < IR_i \\ x_{i,d}, & \text{otherwise} \end{cases} \tag{3.17}$$

The inflation rate IR_i is defined as:

$$IR_i = \frac{f_i - f_{\min}}{f_{\max} - f_{\min}} \tag{3.18}$$

Donor universes are selected using roulette wheel selection based on fitness.

B. White Hole Operator

The wormhole existence probability (WEP) guides universes toward the global best solution:

$$WEP = WEP_{\min} + \left(\frac{iter}{Max_iter}\right)(WEP_{\max} - WEP_{\min}) \tag{3.19}$$

The travelling distance rate ($\mathcal{TDR}$) is given by:

$$\mathcal{TDR} = 1 - \left(\frac{iter}{MaxIt}\right)^{1/6} \tag{3.20}$$

The wormhole position update is expressed as:

$$x_{i,d} = \begin{cases} gBest_d + \mathcal{TDR} \cdot U(0,1), & rand < 0.5 \\ gBest_d - \mathcal{TDR} \cdot U(0,1) \end{cases} \tag{3.21}$$

This mechanism strengthens exploitation in later iterations.

3.5.1.3 Hybridization Strategy of PSO-MVO

To combine the strengths of both algorithms, the proposed hybrid strategy adopts a stage-based integration approach. During the early iterations, MVO operators are mainly applied to explore the global search space and diversify candidate solutions

through probabilistic universe exchange and wormhole-based movements. As the optimization progresses, PSO update rules are gradually given more emphasis to fine-tune the best candidate solutions using velocity and position updates.

Fitness evaluation is performed after each update cycle, where PSO updates personal best and global best positions, while MVO updates the best and worst universes based on inflation rates. This coordinated information sharing helps improve convergence stability and solution quality during the optimization process. The algorithm terminates when the maximum number of iterations is reached or when successive improvements in the fitness value fall below a predefined threshold.

Previous studies have shown that the HPSOMVO framework performs well in complex power system optimization problems, producing better objective values and more stable convergence compared to standalone PSO and MVO algorithms [128]. Sections 3.5.2.1 and 3.5.2.2 further explain the application of the proposed HPSOMVO framework for the two optimization objectives in this study.

3.5.1.4 Constraints Handling Strategy

There are two constraints handling for HPSOMVO:

A. Discrete Mapping

To ensure feasibility, candidate solutions are repaired using a constraint-handling mechanism that:

- Rounds values to the nearest integer,
- Bounds solutions within the permissible range,
- Replaces duplicated bus indices through random resampling.

This process is summarized as:

$$x_k \leftarrow \text{unique}(\text{round}(x_k)) \tag{3.22}$$

B. Termination Criteria

The optimization process terminates when either:

- The maximum number of iterations $MaxIt$ is reached, or
- The standard deviation of the fitness values over the last five iterations satisfies:

$$\text{std}(f_{t-4:t}) < 10^{-3} \tag{3.23}$$

This early stopping criterion prevents unnecessary computations once convergence is achieved.

3.5.1.5 Algorithm Parameters

The parameter selection of HPSOMVO is based on commonly adopted values reported in previous PSO and MVO applications, with additional adjustment through preliminary testing to achieve a balance between convergence speed and solution diversity. Table 3.2 summarizes the main parameters used in the HPSOMVO algorithm.

The population size of 20 is selected to provide sufficient candidate solutions for exploring the search space while maintaining reasonable computational efficiency, considering that EVCS placement and network reconfiguration involve discrete decision variables. Increasing population size improves exploration capability but significantly increases computational burden due to repeated load flow calculations.

The maximum iteration number of 200 is selected to ensure sufficient opportunity for convergence, as metaheuristic algorithms require multiple search cycles to improve solution quality. The inertia weight range of 0.9–0.4 follows the common PSO strategy, where higher initial inertia promotes global exploration and gradual reduction improves local exploitation in later iterations.

The cognitive and social coefficients are set to 2, which are widely used PSO parameters to provide balanced influence between individual experience and global information sharing. For the MVO component, the WEP range of 0.2–1.0 is adopted to gradually increase exploitation ability throughout the optimization process. The PSO application probability of 0.3 is selected to allow MVO-based exploration during early iterations while gradually introducing PSO-based refinement for solution improvement.

These parameters provide a compromise between exploration capability, convergence behaviour, and computational efficiency, which is important for solving nonlinear and mixed-integer distribution network optimization problems. The inertia weight, introduced by (Shi, 1998), helps the algorithm move from global exploration to local exploitation. The WEP range, based on the MVO by (Mirjalili, 2016), gradually increases the exploitation ability.

Table 3.2
Main Parameters in HPSOMVO Algorithm

Parameter	Value
Population size	20
Maximum iterations	200
Inertia weights	0.9-0.4
Cognitive coefficient	2
Social coefficient	2
WEP	0.2-1.0
PSO application probability	0.3

3.5.2 Optimization Implementation for Each Objective

This section describes the optimization procedures for Objectives 1 and 2. Both procedures were implemented with the proposed HPSOMVO by using parameters as stated in Section 3.5.4.1

3.5.2.1 EVCS Placement Optimization Procedure (Objective 1)

The optimal placement of EVCSs is formulated as a constrained, nonlinear optimization problem and solved using the proposed HPSOMVO algorithm. Figure 3.4 illustrates the flowchart of the EVCS placement optimization.

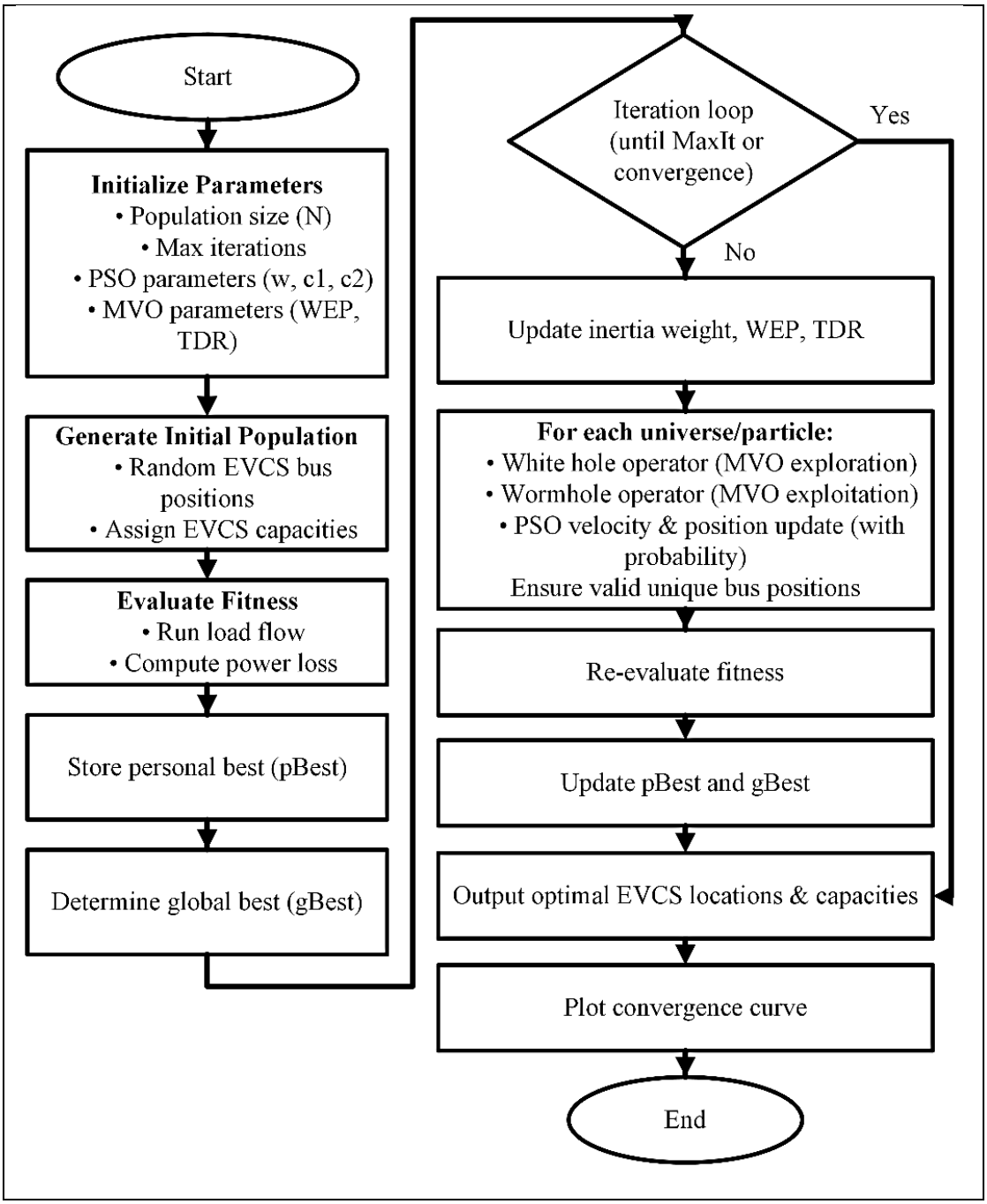


Figure 3.4 Flowchart for Objective 1

An initial population of candidate solutions is first generated, where each solution represents a set of discrete EVCS bus locations with predefined charging capacities. A Newton–Raphson load flow is then performed to evaluate each candidate solution, and the corresponding total active power loss is calculated as the objective function. The personal best (pBest) and global best (gBest) solutions are subsequently identified to guide the optimization process.

During each iteration, the algorithm adaptively updates the inertia weight of PSO together with the Wormhole Existence Probability (WEP) and Travelling Distance Rate (TDR) of MVO. The hybrid optimization process combines the search mechanisms of both algorithms. First, the white hole operator of MVO promotes global exploration by allowing candidate solutions to exchange information with higher-quality universes, thereby increasing population diversity and reducing the likelihood of premature convergence. Next, the wormhole operator performs local exploitation by moving candidate solutions towards the current best universe, enabling further refinement of promising regions in the search space. In parallel, the PSO velocity and position update is applied with a predefined probability to accelerate convergence using the information stored in the personal best (pBest) and global best (gBest) solutions. This probabilistic integration allows the algorithm to exploit the rapid convergence capability of PSO while preserving the exploration strength of MVO.

Following each update, the candidate solutions are repaired to ensure that all EVCS locations remain valid integer bus numbers without duplication. The updated solutions are then re-evaluated through load flow analysis, after which pBest and gBest are updated accordingly. This iterative process continues until the maximum number of iterations, or the convergence criterion is satisfied. Finally, the algorithm outputs the optimal EVCS locations and charging capacities with the minimum active power loss, and the convergence curve is generated to illustrate the optimization performance.

3.5.2.2 Network Reconfiguration Optimization Procedure (Objective 2)

Following the determination of optimal EVCS placement, a second optimization stage is performed to identify the optimal distribution network reconfiguration through tie-switch selection. This stage aims to further minimize system power losses and ensure bus voltage remain under statutory limit. The flowchart is shown in Figure 3.5.

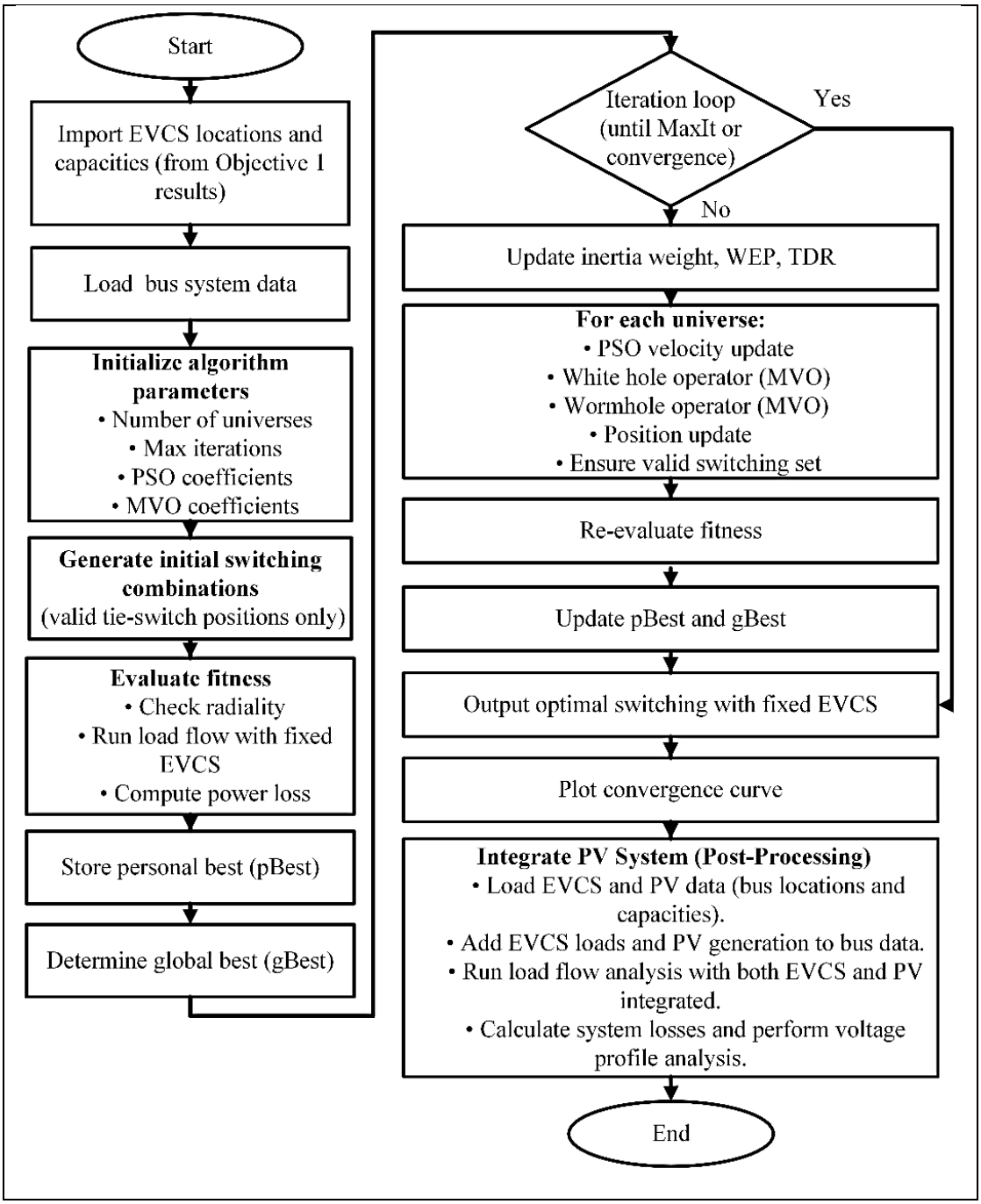


Figure 3.5 Flowchart for Objective 2

The optimal EVCS locations and capacities obtained from Objective 1 are fixed and embedded into the distribution network. An initial population of candidate solutions is first generated, where each solution represents a set of discrete tie-switch configurations for network reconfiguration. Each candidate topology is evaluated by performing radiality checks to ensure feasible distribution network operation. Infeasible configurations are penalized, while feasible solutions undergo Newton–Raphson load flow analysis to calculate the total active power loss, which is used as the objective

function. The personal best (pBest) and global best (gBest) solutions are then identified to guide the optimization process.

During each iteration, the HPSOMVO algorithm adaptively updates its optimization parameters, including the inertia weight of PSO, Wormhole Existence Probability (WEP), and Travelling Distance Rate (TDR) of MVO. The hybridization mechanism combines the exploration capability of MVO with the exploitation capability of PSO to efficiently search for the optimal switching configuration. The white hole operator of MVO enhances global exploration by enabling information exchange between candidate topologies and better-performing solutions, allowing the algorithm to investigate diverse switching combinations and avoid premature convergence. Meanwhile, the wormhole operator improves local exploitation by directing candidate solutions towards the current best topology, enabling refinement around promising search regions. In parallel, the PSO velocity and position updating mechanism is incorporated with a predefined probability to accelerate convergence by utilizing the information from the personal best (pBest) and global best (gBest) solutions. This adaptive integration enables HPSOMVO to achieve a balance between wide exploration of possible network configurations and rapid convergence towards an optimal solution.

After each position update, the switch indices are repaired to ensure valid discrete switching operations while maintaining radial network topology and operational constraints. The updated configurations are subsequently re-evaluated through radiality verification and load flow analysis, where the pBest and gBest solutions are updated based on the obtained objective function value. The optimization process continues until the maximum iteration limit, or convergence criterion is achieved. Finally, the optimal switching configuration with the minimum active power loss is selected as the reconfigured network topology.

Subsequently, the PV system is integrated as a post-processing step without modifying the obtained optimal reconfiguration solution, allowing the additional impact of renewable energy integration to be assessed. The PV generation is incorporated into the bus data together with the fixed EVCS loads, followed by a final load flow analysis to evaluate the resulting active power losses and voltage profile improvement while ensuring compliance with the predefined operational limits.

3.5.3 Comparative Optimization Techniques

This subsection introduces several well-known optimization algorithms that are used to compare with the proposed HPSOMVO algorithm. These algorithms have been widely applied in power system optimization, and they provide meaningful benchmarks to evaluate whether the proposed method performs better, similar, or worse under the same testing conditions.

3.5.3.1 Ant Colony Optimization Algorithm

ACO is a population-based metaheuristic inspired by the foraging behaviour of real ants, where artificial agents (ants) construct solutions based on pheromone trails that represent the quality of previous solutions. Over time, pheromone reinforcement allows promising paths to attract more ants, gradually converging toward an optimal solution. The algorithm balances exploration and exploitation through parameters such as α (pheromone importance), β (heuristic importance), and ρ (evaporation rate). ACO is particularly effective for combinatorial and discrete optimization problems such as routing or placement optimization (Marco Dorigo, 2004).

3.5.3.2 Grey Wolf Optimization Algorithm

GWO is another nature-inspired optimization method, modelled on the hunting strategy and social hierarchy of grey wolves. The algorithm divides the population into four groups including alpha (best), beta (second best), delta (third best), and omega (the rest), to simulate leadership in hunting. The best three wolves guide the movement of others, ensuring an effective balance between global exploration and local exploitation. GWO has gained popularity for its simplicity and strong performance in continuous and nonlinear optimization problems (Seyedali Mirjalili, 2014).

3.5.3.3 Evolutionary Programming Algorithm

EP is an evolutionary algorithm inspired by natural evolution and adaptive behaviour. It focuses primarily on mutation and selection rather than crossover, making it distinct from other evolutionary algorithms like Genetic Algorithms (GA). Each

individual in EP generates offspring through mutation, often using a Gaussian distribution, and both parents and offspring compete based on their fitness. The best individuals survive to form the next generation, maintaining both diversity and adaptive capability. EP is especially effective for nonlinear and continuous optimization due to its self-adaptive mutation strategies, which allow dynamic control of the search process.

3.5.3.4 Summary of Comparative Optimization Techniques

To ensure a fair comparison among these techniques, all algorithms are tested under the same experimental conditions, including an equal population size of 20, a maximum of 200 iterations, identical stopping criteria (fitness variation below 0.001 for five consecutive iterations), and the same optimization objective and constraints, such as minimizing power loss in a standard IEEE 33 and 69-bus distribution system. This standardization eliminates bias and allows performance to be evaluated purely based on algorithmic efficiency, convergence behaviour, and solution quality.

3.6 Summary of Methodology

This study presents a structured optimization framework for the coordinated integration of EVCS, network reconfiguration, and PV systems in radial distribution networks. The framework is designed to address two primary optimization problems aligned with the research objectives: (1) optimal EVCS placement to minimize total real power losses, and (2) optimal network reconfiguration considering the determined EVCS locations and integrated PV units to improve network performance while maintaining statutory voltage limits.

To solve the nonlinear, non-convex, and mixed-integer nature of the problem, a hybrid PSO–MVO algorithm is developed. The main contribution is a stage-based hybrid method that combines PSO's fast convergence with MVO's strong global search capability to achieve a balanced optimization process.

The optimization framework is implemented sequentially. In the first stage, EVCS placements are optimized subject to minimum power loss, and voltage and operational constraints. In the second stage, network reconfiguration is performed through tie-switch selection while maintaining fixed EVCS parameters (based on the

optimal placement). Radiality, voltage limits, and branch loading constraints are strictly enforced throughout the process. PV integration is subsequently incorporated to evaluate its supplementary impact on voltage profile and loss reduction. The proposed methodology is validated through simulation studies using the IEEE 33-bus and IEEE 69-bus test systems, with load flow analysis embedded within the optimization loop. For performance assessment, the proposed HPSOMVO framework is comparatively evaluated against established optimization techniques, including PSO, ACO, GWO, MVO, and EP, based on predefined evaluation criteria.

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the results and discussion of the proposed optimization framework. The performance of the HPSOMVO algorithm is evaluated based on two main tasks: (i) optimal placement of electric vehicle charging stations (EVCSs), and (ii) distribution network reconfiguration with EVCS and photovoltaic (PV) integration. The analysis is carried out using the IEEE 33-bus and IEEE 69-bus radial distribution systems under different simulation scenarios.

The chapter begins with a description of the case study and simulation setup. The results are then presented according to the research objectives, followed by a comparative analysis to assess the effectiveness of the proposed method. A discussion is provided to interpret the findings, and the chapter concludes with a summary of the key outcomes.

4.2 Case Study

To evaluate the effectiveness of the proposed optimization framework, simulation studies were conducted on two widely used benchmark systems, namely the IEEE 33-bus and IEEE 69-bus radial distribution networks. These test systems were selected due to their different feeder lengths and loading characteristics, allowing the proposed method to be assessed under both relatively small-scale and medium-scale network conditions.

The analysis was structured according to the two research objectives and implemented through multiple operating scenarios to systematically evaluate system performance. Table 4.1 summarize the case studies adopted for each objective.

Table 4.1
Simulation Cases for Objective 1 and 2

Objective	Case Study	Description
Objective 1	Case 1	Base case without tie line switches
	Case 2	Optimal placement of EVCS
Objective 2	Case 1	Base case with tie line switches
	Case 2	Network reconfiguration using optimal placement of EVCS without integrated PVs
	Case 3	Network reconfiguration using optimal placement of EVCS with integrated PVs

The case study for Objective 1 investigates the direct impact of EVCS integration on system losses and voltage conditions and evaluates the effectiveness of the optimization process in mitigating these effects. In contrast, the case study for Objective 2 analyses the individual and combined contributions of EVCS integration, network reconfiguration, and PV support to overall network performance.

To validate the robustness of the proposed HPSOMVO algorithm, its performance was compared with several established metaheuristic optimization techniques i.e Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Multi-Verse Optimization (MVO), Grey Wolf Optimization (GWO), and Evolutionary Programming (EP). The comparison focuses on solution quality, convergence characteristics, and key network performance indicators such as total active power loss and bus voltage levels. All simulations were conducted under steady-state operating conditions to ensure fair and consistent comparison across different algorithms and scenarios.

4.3 Result for Objective 1: Optimal EVCS Placement

Table 4.2 summarises the results obtained for Objective 1 under two operating cases for the IEEE 33-bus and IEEE 69-bus distribution systems. Case 1 represents the base operating condition without EVCS integration, while Case 2 considers the optimal placement of ten EVCSs using six optimization algorithms. The results are compared in terms of EVCS locations, active power loss, and minimum and maximum bus voltages. For Case 2, the ten EVCSs consist of three high-capacity stations rated at 0.48 MW, three medium-capacity stations rated at 0.35 MW, and four low-capacity stations

rated at 0.15 MW. In the EVCS placement column, the first three listed buses correspond to the 0.48 MW EVCSs, the following three buses correspond to the 0.35 MW EVCSs, and the remaining four buses correspond to the 0.15 MW EVCSs. The Case 1 results provide the reference operating condition for evaluating the effects of EVCS integration and the performance of the different placement solutions obtained in Case 2. Detailed analyses of the EVCS locations, active power losses, voltage performance, and convergence behaviour are presented in the subsequent subsections.

A. EVCS Placement Result

Table 4.2
Summary of Optimization Results for Objective 1

IEEE 33-system				
		Case 1		
Algorithms	**EVCS Placement**	**Power Loss, MW**	**Minimum Voltage, p.u.**	**Maximum Voltage p.u.**
Base	-	0.1348	0.9738	0.9933
		Case 2		
HPSOMVO	2, 3, 5, 6, 20, 22, 24, 25, 28, 29,	0.2373	0.9547	0.9897
ACO	2, 3, 6, 19, 21, 24, 27, 28, 30, 31	0.2624	0.9481	0.9897
PSO	2, 7, 20, 22, 23, 24, 25, 27, 28, 33	0.2467	0.9483	0.9897
MVO	2, 3, 5, 11, 20, 24, 25, 29, 30, 32	0.2580	0.9483	0.9897
GWO	2, 4, 5, 12, 19, 23, 25, 27, 32, 33,	0.2887	0.9483	0.9897
EP	2, 3, 4, 6, 9, 21, 24, 27, 30, 31,	0.2543	0.9483	0.9897
IEEE 69-system				
		Case 1		
Algorithms	**EVCS Placement**	**Power Loss, MW**	**Minimum Voltage, p.u.**	**Maximum Voltage p.u.**
Base	-	0.2246	0.9093	1.000
		Case 2		
HPSOMVO	2, 4, 31, 37, 38, 39, 44, 45, 52, 67	0.2399	0.9003	1.000
ACO	2, 9, 33, 36, 37, 40, 43, 47, 50, 69	0.2419	0.9046	1.000
PSO	4, 5, 29, 31, 33, 38, 55, 59, 66, 69	0.2583	0.9041	1.000
MVO	2, 28, 31, 42, 43, 45, 46, 53, 54, 69	0.2782	0.9016	1.000
GWO	3, 7, 28, 29, 33, 37, 43, 49, 50, 53	0.2628	0.9003	1.000
EP	3, 4, 30, 31, 32, 37, 39, 41, 44, 69	0.2520	0.9017	1.000

Table 4.2 shows that the six optimization algorithms select different combinations of EVCS locations for the IEEE 33-bus and IEEE 69-bus distribution systems. Although the number of EVCSs and their capacity groups are fixed, the selected buses are different for each algorithm because each method uses a different search process. This shows that more than one feasible placement can satisfy the system operating limits. However, the effect of each placement on the network is not the same because the selected buses influence how the additional charging demand is distributed along the feeders.

The quality of the selected locations cannot be judged only from the bus numbers. Instead, each placement must be evaluated using the load-flow results, especially the resulting active power loss, while ensuring that all bus voltages remain within the allowable limits. Among the solutions obtained from the six algorithms, HPSOMVO gives the best-performing EVCS placement for both test systems because it produces the lowest active power loss while satisfying the voltage constraints.

The EVCS locations obtained using HPSOMVO also show a general capacity-based placement pattern across both systems. Most of the higher-capacity EVCSs are placed nearer to the substation or along feeder paths with lower impedance, while most of the lower-capacity EVCSs are located farther along the network. This arrangement helps to avoid placing large charging loads at the weakest or most distant parts of the feeder, where the additional demand could cause higher current flow and larger voltage drops. However, this pattern is not followed by every selected bus because the final solution is based on the overall performance of the whole network rather than the distance of each bus alone.

The other optimization algorithms also produce feasible EVCS placement solutions, but their selected bus combinations lead to different levels of network performance. This shows that the location of the EVCSs plays an important role even when the total number and capacities of the charging stations remain unchanged. The detailed effects of the different placement solutions on active power loss, voltage performance, and convergence behaviour are discussed in the following subsections.

B. Power Loss Analysis

The total active power loss for Objective 1 under Case 1 (base case without tie-line switches) and Case 2 (optimal EVCS placement) is tabulated in Figure 4.1 and Figure 4.2 for IEEE 33-system and IEEE 69-system respectively.

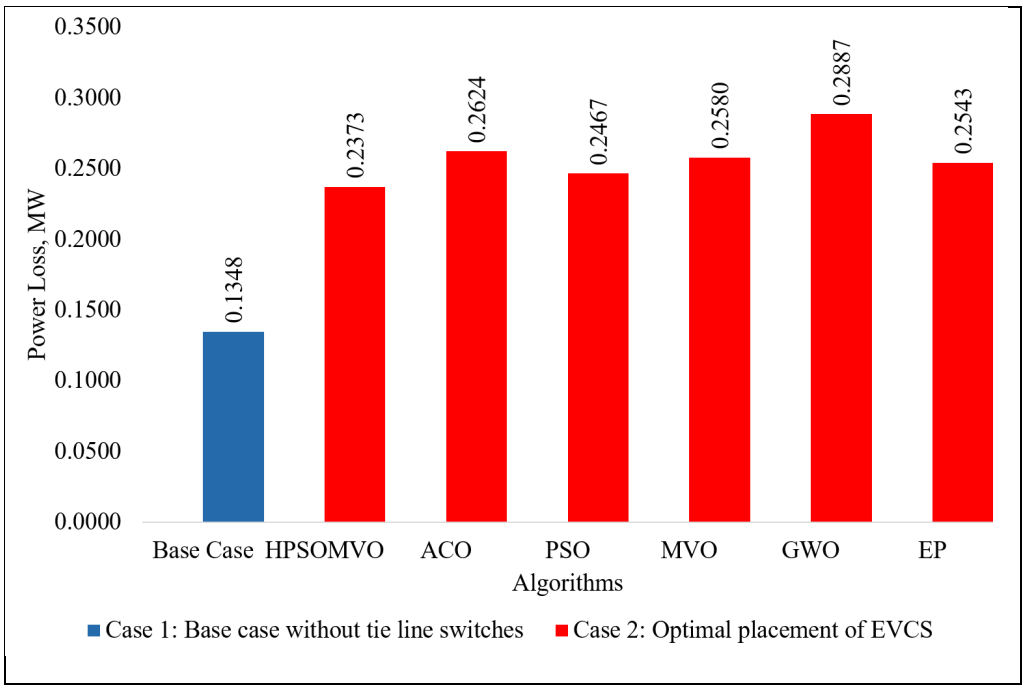


Figure 4.1 Objective-1 Power Loss for IEEE 33-System

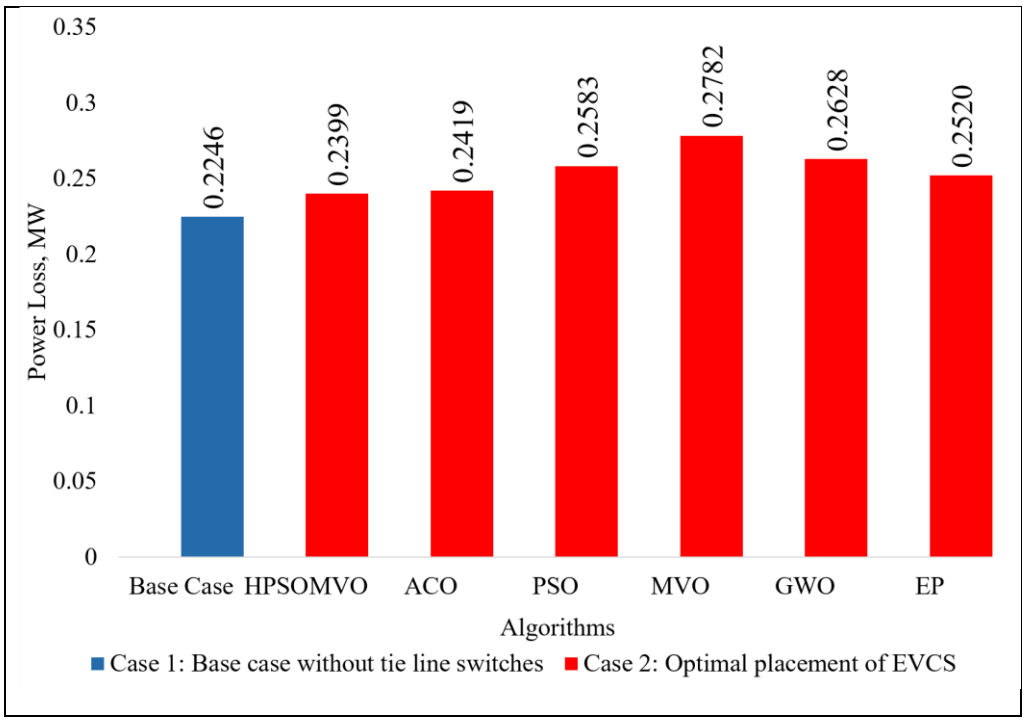


Figure 4.2 Objective-1 Power Loss for IEEE 69-System

For Case 1, both the IEEE 33-bus and IEEE 69-bus distribution systems record identical power losses across all optimization algorithms, as no EVCS integration or optimization is applied. The power losses are 0.1348 MW and 0.2246 MW for the IEEE 33-bus and IEEE 69-bus systems, respectively, representing the baseline operating conditions of each network.

When EVCSs are integrated in Case 2, the total active power loss increases in both test systems regardless of the optimization algorithm employed. This increase is expected because EVCSs introduce additional charging demand, resulting in higher feeder currents and consequently greater I^2 R losses. However, the magnitude of the increase depends on the effectiveness of each optimization algorithm in determining suitable EVCS locations.

Among all evaluated techniques, the proposed HPSOMVO algorithm achieves the lowest total power loss in both test systems, as presented in Figure 4.1. For the IEEE 33-bus system, HPSOMVO records a power loss of 0.2373 MW, while the standalone PSO, ACO, MVO, GWO, and EP algorithms produce comparatively higher losses under the same EVCS loading conditions. Similarly, for the IEEE 69-bus system, HPSOMVO also provides the minimum power loss compared with the benchmark algorithms. These results indicate that the hybrid search strategy effectively identifies EVCS locations that distribute the additional charging demand more uniformly across the network, thereby reducing excessive feeder loading and limiting power loss.

A more pronounced improvement is observed in the IEEE 69-bus system. Owing to its longer feeder length, larger number of buses, and higher cumulative line impedance, the network is inherently more sensitive to additional EV charging demand than the IEEE 33-bus system. Consequently, strategic EVCS placement has a greater influence on power flow distribution and feeder current, allowing the proposed HPSOMVO algorithm to achieve larger reductions in active power loss. This demonstrates that the proposed hybrid algorithm remains effective across different network sizes and is particularly advantageous for larger radial distribution systems where the optimization search space is more extensive.

C. Voltage Performance Analysis

The variation of minimum bus voltage obtained for Objective 1 under Case 1 (base case without tie-line switches) and Case 2 (optimal EVCS placement) is presented in Figure 4.3 and Figure 4.4 for the IEEE 33-bus and IEEE 69-bus systems, respectively.

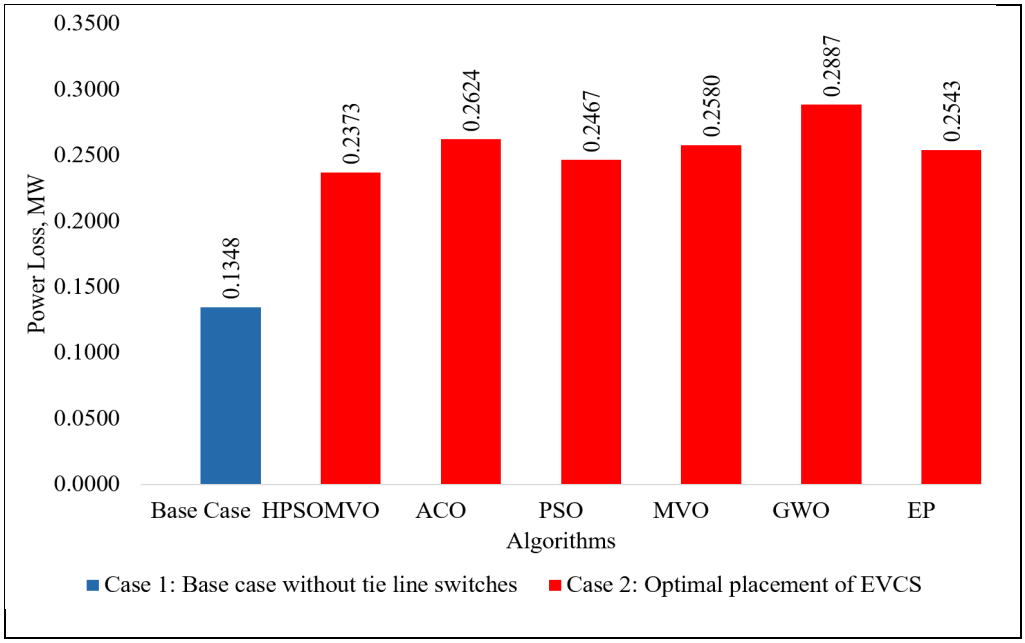


Figure 4.3 Objective-1 Minimum Voltage for IEEE 33-System

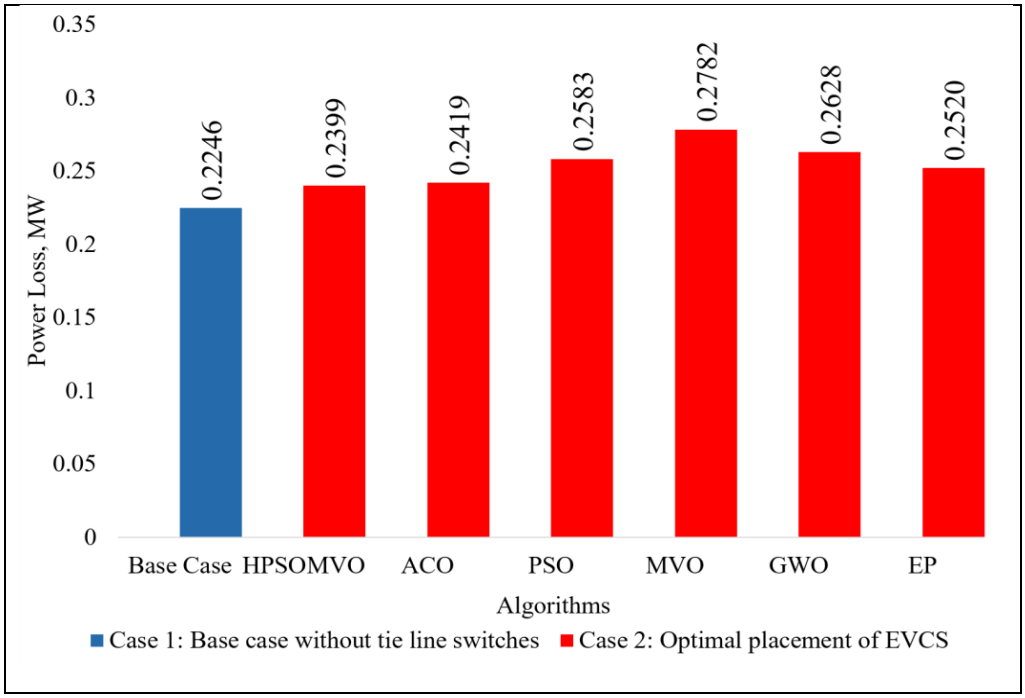


Figure 4.4 Objective-1 Minimum Voltage for IEEE 69-System

In Case 1, all optimization algorithms produce identical minimum voltage values of 0.9738 p.u. for the IEEE 33-bus system and 0.9093 p.u. for the IEEE 69-bus system, since no additional EVCS loading is introduced. These values represent the initial operating conditions of the respective distribution networks. The lower minimum voltage observed in the IEEE 69-bus system compared with the IEEE 33-bus system is mainly due to its larger network size, longer feeder length, and higher cumulative branch impedance, which results in greater voltage sensitivity along the radial feeder.

In Case 2, the integration of EVCS causes a reduction in minimum bus voltage for all optimization algorithms due to the increased active and reactive power demand, which leads to higher branch currents and additional voltage drops throughout the distribution system. For the proposed HPSOMVO algorithm, the minimum voltage decreases to 0.9547 p.u. in the IEEE 33-bus system while maintaining acceptable operating limits. Similarly, the IEEE 69-bus system also demonstrates competitive voltage performance after EVCS placement. Although the voltage reduction is more noticeable in the IEEE 69-bus system due to its larger and more complex feeder structure, HPSOMVO can maintain the voltage profile within the allowable statutory limits.

The proposed HPSOMVO algorithm demonstrates superior voltage performance compared with the benchmark optimization techniques by identifying more effective EVCS locations that minimize voltage degradation. This improvement is attributed to the hybrid optimization mechanism, where the Multi-Verse Optimization (MVO) component enhances global exploration of the search space, enabling the identification of promising EVCS placement regions, while the Particle Swarm Optimization (PSO) component improves solution refinement through local exploitation. The combined exploration and exploitation capability allows HPSOMVO to avoid unsuitable EVCS placements at weak buses that may cause severe voltage drops, particularly in larger distribution systems.

The improvement achieved in the IEEE 69-bus system is more significant because the network contains more buses, longer feeder sections, and a wider range of voltage-sensitive locations. Therefore, optimal EVCS placement has a greater influence on reducing voltage deviation compared with

the IEEE 33-bus system. The results demonstrate that HPSOMVO provides better adaptability and robustness for different distribution network configurations, maintaining acceptable voltage levels while accommodating additional EV charging demand.

Similarly, the maximum bus voltage results for Objective 1 under Case 1 and Case 2 are presented in Figure 4.5 and Figure 4.6 for the IEEE 33-bus and IEEE 69-bus systems, respectively.

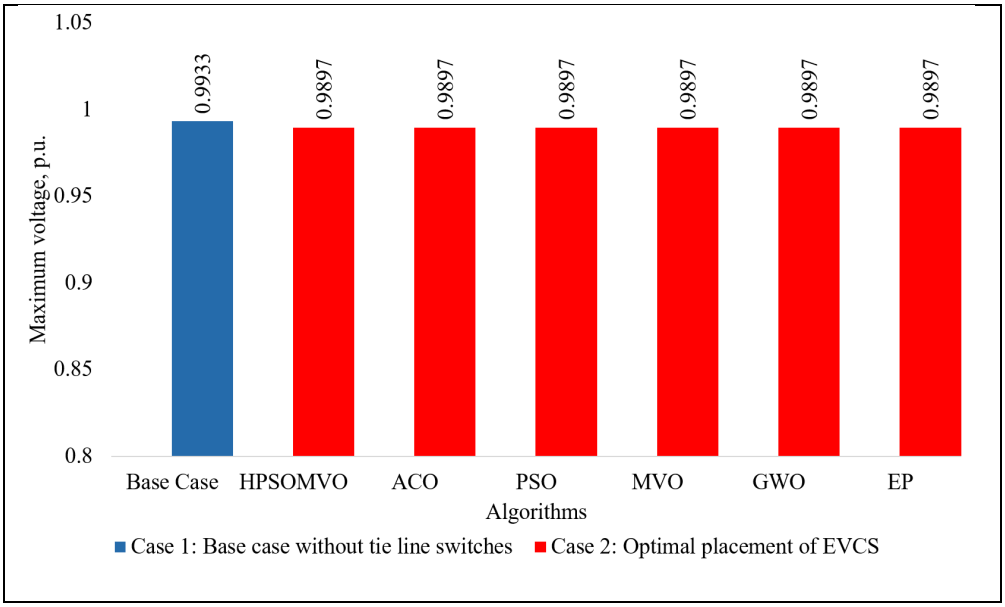


Figure 4.5 Objective-1 Maximum Voltage for IEEE 33-System

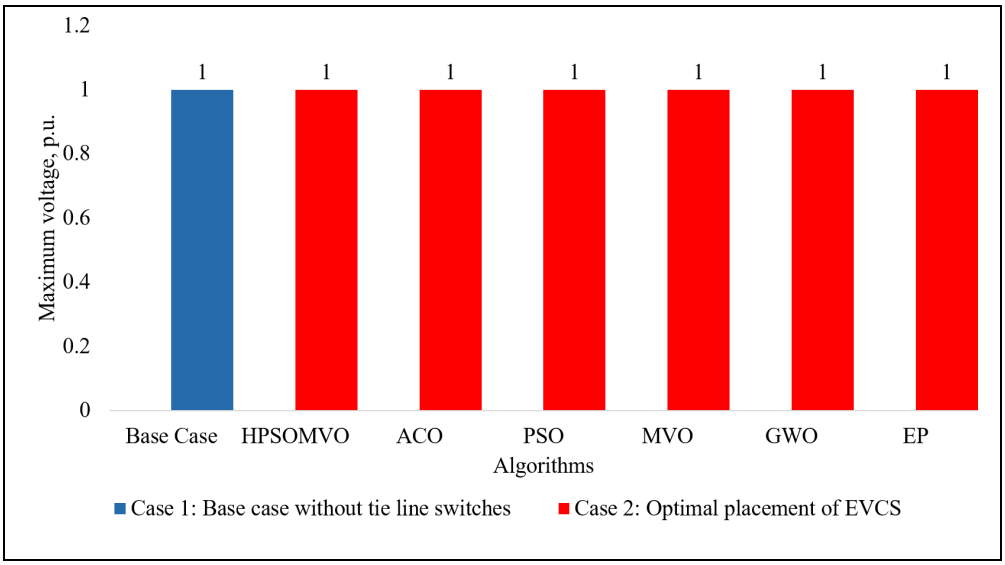


Figure 4.6 Objective-1 Maximum Voltage for IEEE 69-System

In Case 1, the maximum voltage values are 0.9933 p.u. for the IEEE 33-bus system and 1.0000 p.u. for the IEEE 69-bus system, representing the normal operating conditions before EVCS integration. After EVCS placement in Case 2, only minor variations in the maximum voltage are observed for all optimization algorithms. This indicates that the additional EV charging demand mainly influences voltage-sensitive buses located farther from the substation, while buses with stronger voltage support and lower electrical distance remain relatively unaffected.

The proposed HPSOMVO algorithm maintains a maximum voltage profile comparable to the benchmark optimization methods, with no occurrence of overvoltage conditions in either distribution system. This demonstrates that the optimal EVCS placement determined by HPSOMVO effectively distributes the charging demand without creating excessive voltage rise at any bus. Unlike voltage reduction, which is highly influenced by increased feeder loading and branch impedance, the maximum voltage is less sensitive to EVCS integration because the added charging load primarily causes voltage drops rather than voltage increases.

The consistent maximum voltage performance observed in the IEEE 69-bus system, where the maximum voltage remains at approximately 1.0000 p.u. for all algorithms, further confirms the robustness of the proposed method in larger distribution networks. Although the IEEE 69-bus system has a more complex radial structure with longer feeder sections and higher impedance accumulation, HPSOMVO successfully identifies EVCS locations that avoid abnormal voltage conditions. The results indicate that the proposed hybrid exploration and exploitation strategy provides a reliable EVCS placement solution that preserves overall voltage stability while accommodating increased charging demand.

D. Convergence Analysis

The convergence behaviour of the optimization algorithms for Case 2 (Objective 1) is illustrated in the Figure 4.7 and 4.8 for IEEE 33-system and IEEE 69-

system respectively. The figure shows the variation of the fitness value (total active power loss) with respect to the number of iterations.

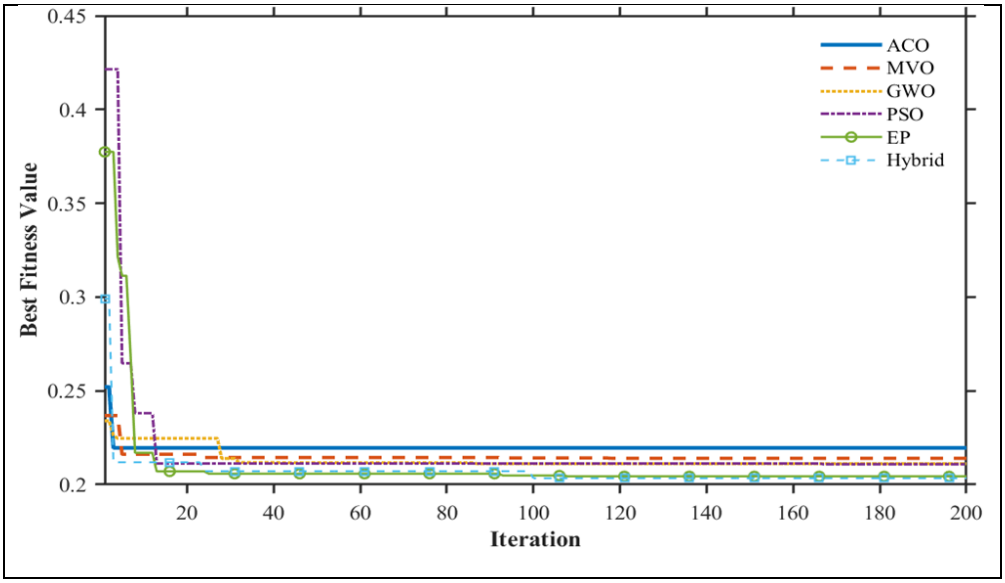


Figure 4.7 Objective-1 Convergence Curve of Case 2 for IEEE 33-System

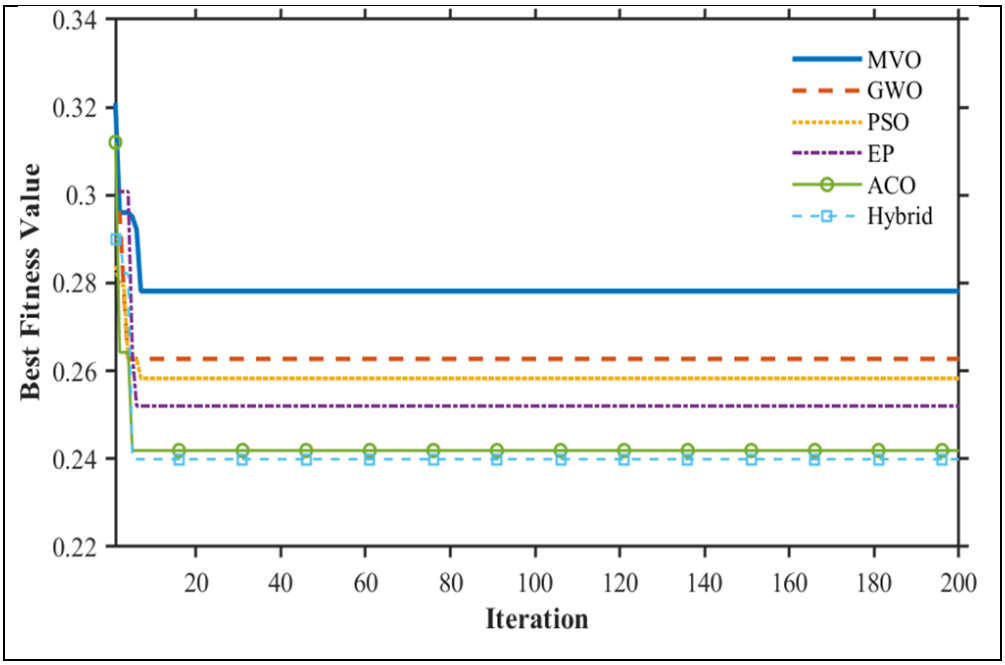


Figure 4.8 Objective-1 Convergence Curve of Case 2 for IEEE 69-System

Overall, all algorithms exhibit a rapid reduction in fitness value during the initial iterations, followed by gradual convergence towards stable solutions. However, noticeable differences are observed in their convergence speed, stability, and final solution quality.

During the early stage of the optimization process (approximately Iterations 1–20), all algorithms demonstrate a significant decrease in fitness value, indicating effective exploration of the search space. The proposed HPSOMVO algorithm achieves a rapid reduction in fitness while maintaining a smooth convergence trajectory. In comparison, PSO and EP also show fast initial convergence due to their strong exploitation capability, whereas ACO, MVO, and GWO exhibit relatively slower improvement as they continue exploring candidate solutions.

In the middle stage (approximately Iterations 20–60), the superiority of the proposed hybrid algorithm becomes more apparent. The convergence curves of PSO and EP begin to stabilise, indicating a tendency to converge prematurely towards local optima. Although ACO, MVO, and GWO continue improving, their convergence rates become slower and their final fitness values remain higher. In contrast, HPSOMVO maintains continuous improvement throughout this stage, demonstrating that the integration of MVO's global exploration capability with PSO's fast local exploitation enables the algorithm to balance exploration and exploitation more effectively than the standalone methods.

During the final stage (Iterations 60–200), all algorithms approach convergence and their fitness values become relatively stable. Nevertheless, the proposed HPSOMVO consistently achieves the lowest final fitness value for both the IEEE 33-bus and IEEE 69-bus systems, confirming its ability to obtain higher-quality solutions while maintaining stable convergence behaviour. The smoother convergence curve also indicates that the hybrid algorithm avoids premature stagnation and continues refining candidate solutions until convergence is achieved. Although similar convergence trends are observed for both test systems, the convergence behaviour in the IEEE 69-bus system is relatively slower than that of the IEEE 33-bus system due to the larger network size and increased optimization search space. The proposed HPSOMVO maintains stable convergence and consistently outperforms the benchmark algorithms.

4.4 Result for Objective 2 (Optimal Network Reconfiguration)

Table 4.3
Summary of Optimization Results for Objective 2

Algorithms	Switch Configurations	Power Loss, MW	Minimum Voltage, p.u.	Maximum Voltage p.u.
IEEE 33-Bus Distribution System				
		Case 1		
Base	33 34 35 36 37	0.0976	0.9518	0.9933
		Case 2		
HPSOMVO	10 14 15 27 33	0.2034	0.9199	0.9897
ACO	7 14 16 35 37	0.2196	0.9129	0.9892
PSO	6 8 14 15 37	0.2265	0.9233	0.9897
MVO	7 10 13 16 37	0.2140	0.9296	0.9897
GWO	7 11 14 16 28	0.2111	0.9026	0.9891
EP	11 17 28 33 34	0.2044	0.9316	0.9892
		Case 3		
HPSOMVO	Same as Case 2	0.1639	0.9465	0.9904
ACO		0.1630	0.9460	0.9904
PSO		0.1730	0.9453	0.9904
MVO		0.1690	0.9413	0.9904
GWO		0.1687	0.9402	0.9904
EP		0.1677	0.9416	0.9904
IEEE 69-Bus Distribution System				
		Case 1		
Algorithms	**EVCS Placement**	**Power Loss, MW**	**Minimum Voltage, p.u.**	**Maximum Voltage p.u.**
Base	-	0.0874	0.9625	1.000
		Case 2		
HPSOMVO	12 19 42 54 61	0.1241	0.9419	1.000
ACO	11 18 41 54 61	0.1459	0.9419	1.000
PSO	18 41 44 57 61	0.1452	0.9422	1.000
MVO	12 20 41 58 61	0.1353	0.9419	1.000
GWO	12 20 41 55 62	0.1631	0.9419	1.000
EP	14 56 61 69 71	0.1335	0.9419	1.000
		Case 3		
HPSOMVO	Same as Case 2	0.0848	0.9462	1.000
ACO		0.0846	0.9638	1.000
PSO		0.0911	0.9630	1.000
MVO		0.0916	0.9624	1.000
GWO		0.1027	0.9618	1.000
EP		0.0880	0.9632	1.000

Table 4.3 summarises the optimization results obtained for Objective 2 using six optimization algorithms for the IEEE 33-bus and IEEE 69-bus distribution systems. Three operating cases are considered. Case 1 represents the base network condition with the original open-switch configuration and without EVCS or PV integration. Case 2 considers optimal network reconfiguration after the integration of the EVCS locations

obtained from Objective 1, without PV integration. Case 3 evaluates the reconfigured network after the integration of both EVCSs and PV systems.

The results are compared in terms of the selected open-switch configurations, active power losses, and minimum and maximum bus voltages. The detailed discussion is presented in the subsequent subsections, covering the optimal network reconfiguration results, active power-loss analysis, voltage-performance analysis, and convergence analysis.

A. Optimal Network Reconfiguration Results

Table 4.3 shows that the six optimization algorithms produce different open-switch configurations for the IEEE 33-bus and IEEE 69-bus distribution systems. In Case 1, both systems operate using their original radial configurations. In Case 2, new open-switch combinations are determined after considering the optimal EVCS locations obtained from Objective 1. The different solutions indicate that several feasible radial configurations can satisfy the network operating constraints.

Each open-switch configuration creates a different path for power to flow from the substation to the connected loads and EVCSs. Through network reconfiguration, selected tie switches are closed while suitable sectionalizing switches are opened to maintain radial operation. This process changes the feeder structure and allows the load to be supplied through alternative paths. As a result, heavily loaded branches can be relieved, and the feeder currents can be distributed more effectively.

The suitability of a switch configuration cannot be determined from the switch numbers alone. It must be evaluated based on the resulting active power loss while ensuring the operating constraints are satisfied. Although all six algorithms obtain feasible configurations, the resulting network performance differs because each configuration produces a different power-flow pattern.

In Case 3, the switch configurations obtained from the network reconfiguration process are retained while PV systems are integrated into the networks. The reconfigured feeder structure provides improved power-flow paths, while the local PV generation supplies part of the demand and reduces the

power drawn from the substation. The detailed effects of network reconfiguration and PV integration on active power loss and voltage performance are discussed in the following subsections.

B. Power Loss Analysis

The total active power loss for Objective 2 is illustrated in Figure 4.9 and Figure 4.10 for IEEE 33-system and IEEE 69-system respectively. The figures compare the results for Case 1, Case 2, and Case 3 using the six optimization algorithms.

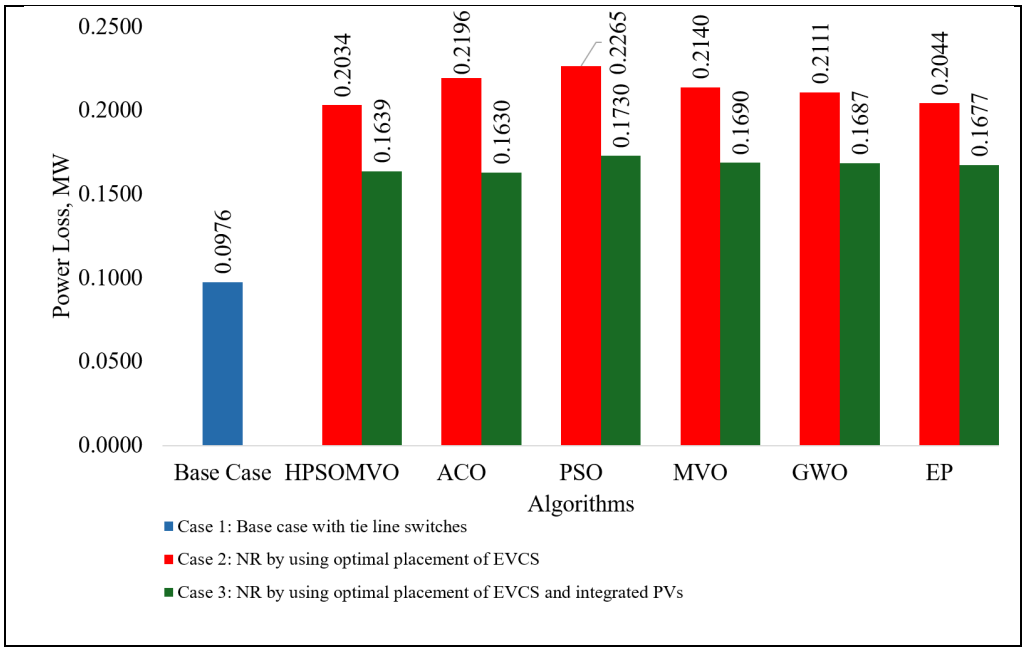


Figure 4.9 Objective-2 Power Loss for IEEE 33-System

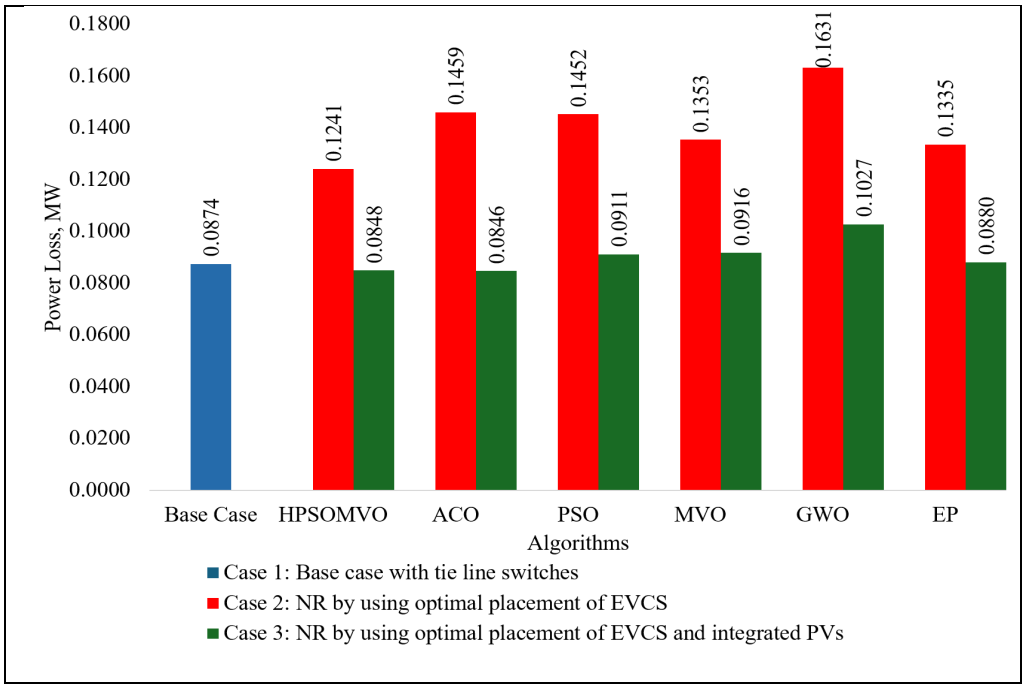


Figure 4.10 Objective-2 Power Loss for IEEE 69-System

In Case 1, all algorithms produce the same active power loss because no optimization is performed and both systems operate under their original network configurations without EVCS or PV integration. These values represent the reference operating conditions for evaluating the effects of EVCS integration, network reconfiguration, and PV support.

In Case 2, the integration of EVCSs increases the total network demand and feeder currents, causing the active power losses to increase compared with the base case. Nevertheless, the optimized network reconfiguration helps to reduce the effect of this additional charging demand. The different loss values obtained by the algorithms indicate that the selected network configuration has a direct influence on the resulting system performance.

Compared with Objective 1, where only the EVCS locations are optimized under the original network configuration, Objective 2 provides an additional improvement by allowing the feeder structure to be reconfigured. The comparison between Objective 1, Case 2 and Objective 2, Case 2 therefore shows the contribution of network reconfiguration in further reducing active power losses after optimal EVCS placement. This confirms that EVCS placement alone does not provide the full possible improvement because the

original feeder configuration may not be the most suitable for the new charging demand.

Among the evaluated algorithms, the proposed HPSOMVO produces the best or highly competitive active power-loss results for both test systems, subject to confirmation of the corrected data. This indicates that the hybrid algorithm is able to identify effective network configurations after considering the EVCS locations obtained from Objective 1.

In Case 3, PV systems are integrated into the reconfigured networks, resulting in a further reduction in active power losses. The PV units supply part of the demand locally, thereby reducing the amount of power transferred from the substation through the feeder branches. The lower branch currents consequently reduce the associated losses. Therefore, the comparison between Cases 2 and 3 shows the additional contribution of PV integration after network reconfiguration.

The improvement is generally more noticeable in the IEEE 69-bus system because its longer feeder paths and higher accumulated line impedance. Thus, its losses more sensitive to the distribution of loads and local generation. Consequently, the combined application of optimal EVCS placement, network reconfiguration, and PV integration provides greater opportunity for reducing active power losses in the larger network.

C. Voltage Performance Analysis

The minimum bus voltage results for Objective 2 are presented in Figure 4.11 and Figure 4.12 for the IEEE 33-bus and IEEE 69-bus systems, respectively.

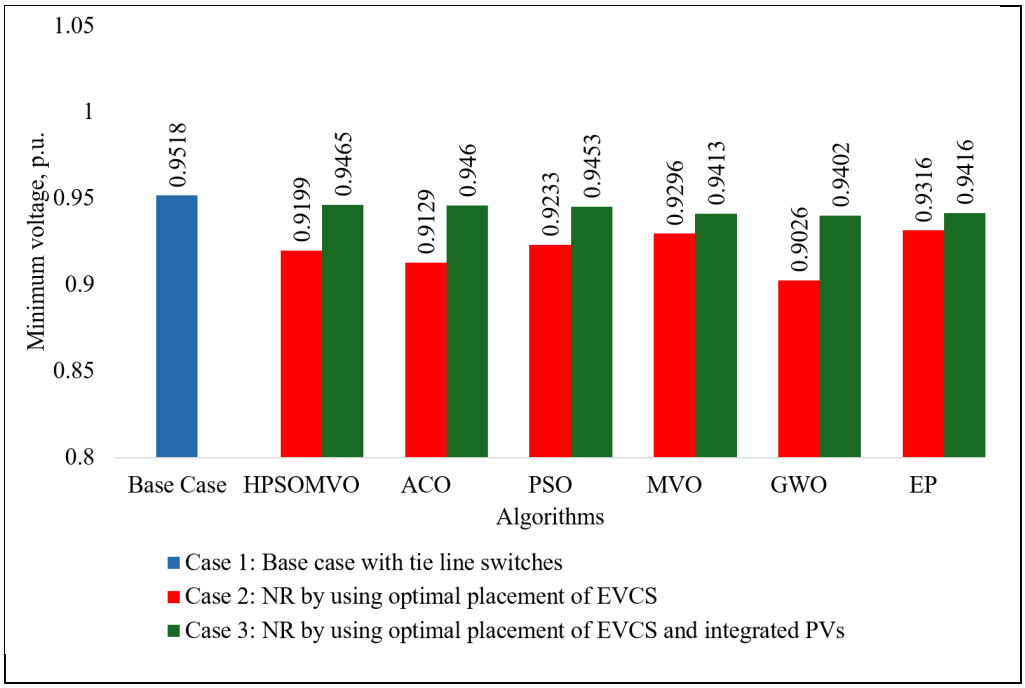


Figure 4.11 Objective-2 Minimum Voltage for IEEE 33-System

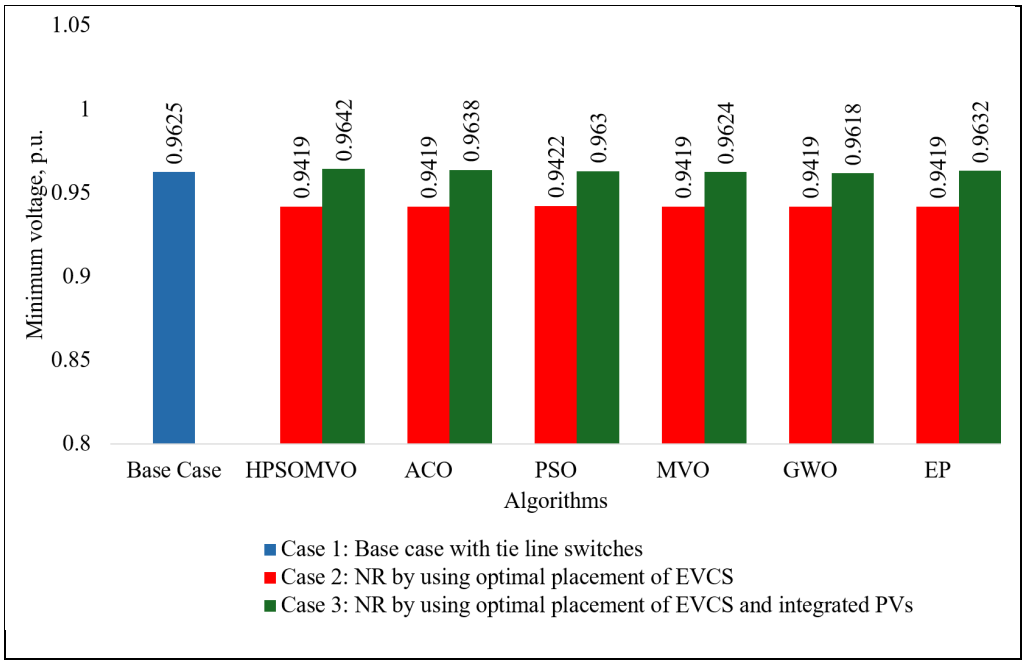


Figure 4.12 Objective-2 Minimum Voltage for IEEE 69-System

As shown in Figure 4.11 and Figure 4.12, the minimum bus voltage results for Objective 2 are presented for the IEEE 33-bus and IEEE 69-bus systems, respectively. In Case 1, all optimization algorithms produce identical minimum voltage values of 0.9518 p.u. for the IEEE 33-bus system and 0.9625

p.u. for the IEEE 69-bus system, representing the reference condition after considering tie-line switches without EVCS and PV integration.

Compared with Objective 1, the implementation of network reconfiguration provides additional flexibility in power flow management by optimizing the feeder configuration. In Case 2, although EVCS integration still results in voltage reduction due to the additional charging demand, the impact is mitigated through the optimized switching configuration. For the IEEE 33-bus system, the proposed HPSOMVO achieves a minimum voltage of 0.9199 p.u., while the IEEE 69-bus system maintains a minimum voltage of approximately 0.9419 p.u. These results indicate that network reconfiguration improves the system's capability to accommodate EVCS loading by redistributing power flow through a more favourable radial configuration.

When PV integration is introduced in Case 3, further improvement in minimum voltage is observed for both systems. The proposed HPSOMVO achieves a minimum voltage of 0.9465 p.u. for the IEEE 33-bus system, which is closer to the reference condition compared with Case 2. Similarly, the IEEE 69-bus system achieves minimum voltage values of approximately 0.962–0.964 p.u. The improvement demonstrates the complementary effect of PV integration with network reconfiguration, where optimized switching reduces feeder stress while local renewable generation provides additional voltage support.

Similarly, the maximum bus voltage results for Objective 2 under Case 1 to 3 are presented in Figure 4.13 and Figure 4.14 for the IEEE 33-bus and IEEE 69-bus systems, respectively.

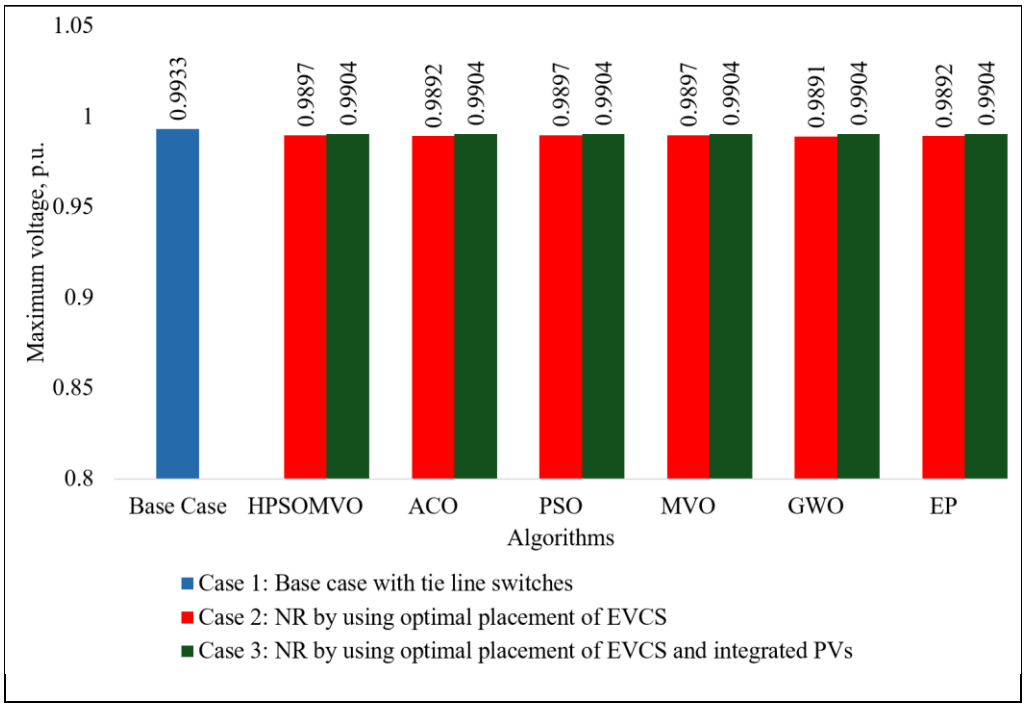


Figure 4.13 Objective-2 Maximum Voltage for IEEE 33-System

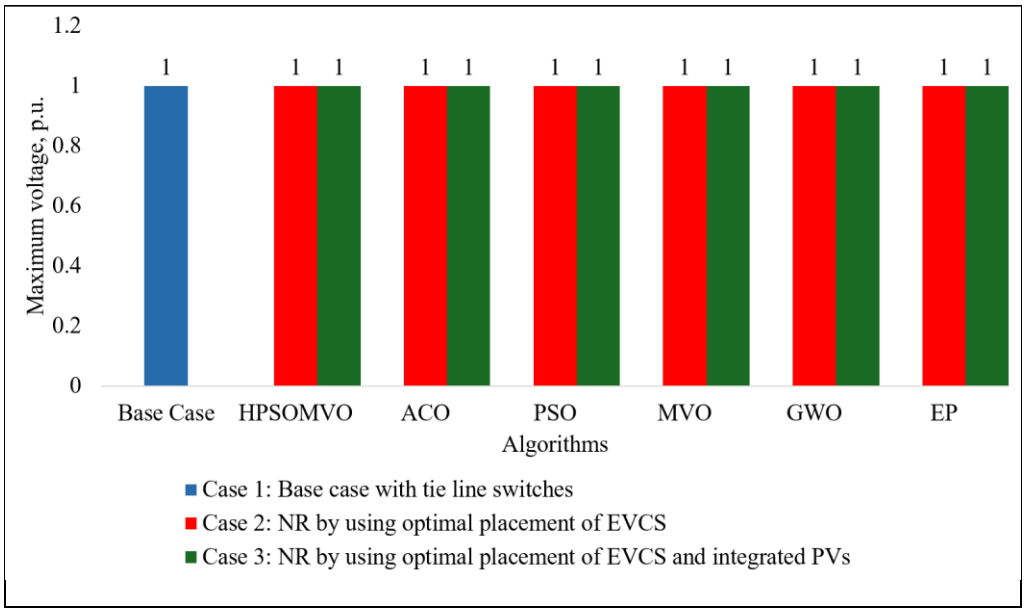


Figure 4.14 Objective-2 Maximum Voltage for IEEE 69-System

In Case 1, the maximum voltage values are 0.9933 p.u. for the IEEE 33-bus system and 1.0000 p.u. for the IEEE 69-bus system, representing the reference operating condition after considering tie-line switches without EVCS and PV integration.

Compared with Objective 1, the inclusion of network reconfiguration provides additional control over power flow distribution but does not

significantly influence the maximum voltage values. In Case 2, after incorporating EVCS with optimized network configuration, only a slight reduction in maximum voltage is observed. For the IEEE 33-bus system, HPSOMVO achieves a maximum voltage of 0.9897 p.u., while similar values are obtained by the other optimization algorithms. This indicates that the optimized switching configuration primarily improves the operating condition of voltage-sensitive buses rather than significantly affecting buses that already maintain higher voltage levels.

In Case 3, the integration of PV results in a slight increase in maximum voltage for both systems compared with Case 2. For the IEEE 33-bus system, HPSOMVO achieves a maximum voltage of 0.9904 p.u., while the IEEE 69-bus system maintains a maximum voltage of approximately 1.0000 p.u. across all optimization methods. The limited variation demonstrates that PV integration provides additional voltage support without causing excessive voltage rise, indicating appropriate coordination between PV generation and network reconfiguration.

Overall, the maximum voltage results confirm that the proposed HPSOMVO-based network reconfiguration strategy successfully maintains voltage stability under different operating conditions. Although reconfiguration and PV integration improve system flexibility and support voltage recovery, their impact is more significant on minimum voltage improvement rather than maximum voltage enhancement. No overvoltage condition is observed in either distribution system, demonstrating that the proposed approach effectively accommodates EVCS and PV integration while maintaining operation within acceptable voltage limits.

D. Convergence Analysis

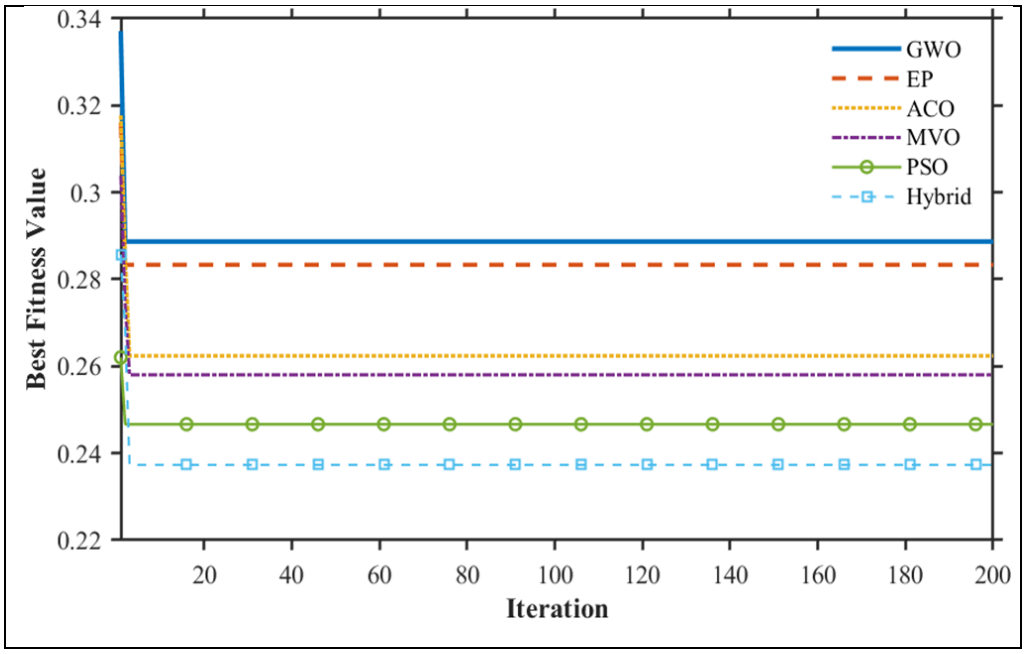


Figure 4.15 Objective-2 Convergence Curve of Case 2 for IEEE 33-System

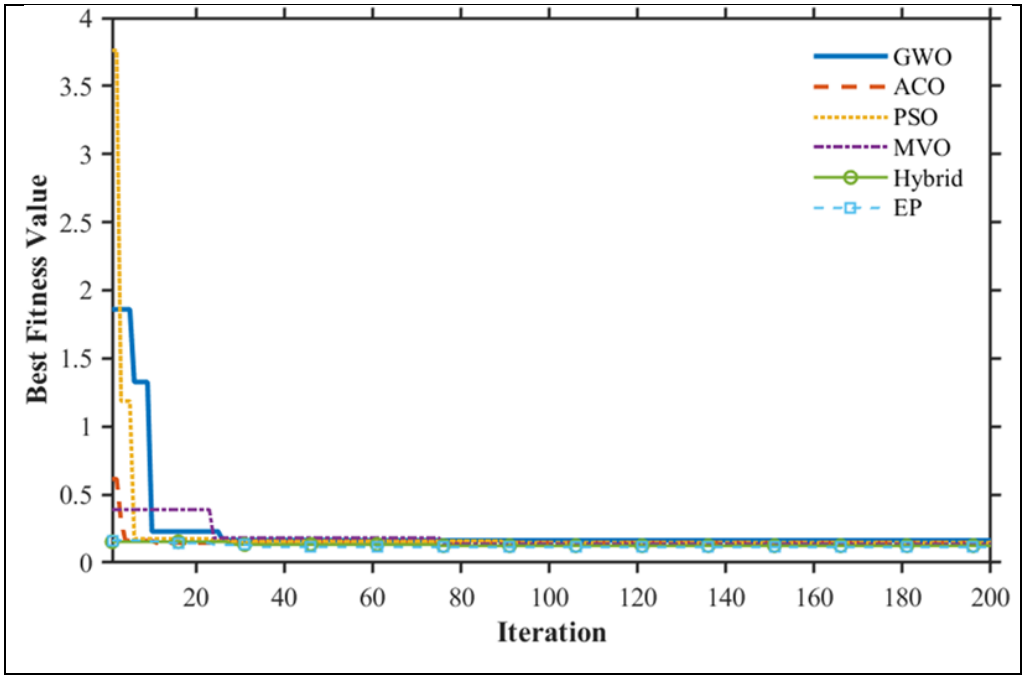


Figure 4.16 Objective-2 Convergence Curve of Case 2 for IEEE 69-System

As shown in Figure 4.15 and Figure 4.16, the convergence characteristics of the proposed HPSOMVO algorithm for Objective 2 are presented for the IEEE 33-bus and IEEE 69-bus systems, respectively. In Objective 2, the optimization process involves determining the optimal network configuration while considering EVCS placement and PV integration, resulting in a more

complex search space compared with Objective 1 due to the additional switching variables.

For the IEEE 33-bus system, all optimization algorithms show a reduction in fitness value during the initial iterations as they search for improved switching configurations. The benchmark algorithms demonstrate different convergence behaviours, where some methods experience faster initial improvement but tend to stabilize at higher fitness values due to limited refinement capability. In comparison, the proposed HPSOMVO achieves a lower fitness value throughout the optimization process and maintains a smooth convergence trend, indicating its ability to identify favourable network configurations while avoiding premature convergence.

Similarly, the IEEE 69-bus system presents a more challenging optimization problem due to the larger number of branches, possible switching combinations, and increased network complexity. As shown in Figure 4.16, several algorithms exhibit higher initial fitness values and require more iterations to achieve stable solutions. Although PSO, GWO, MVO, ACO, and EP demonstrate improvement during the optimization process, their convergence behaviour shows either slower refinement or higher final fitness values compared with HPSOMVO. The proposed algorithm begins with a competitive fitness value and gradually converges towards the best solution with minimal fluctuations, demonstrating better search capability for large-scale reconfiguration problems.

The superior convergence performance of HPSOMVO is attributed to its hybrid optimization strategy, which effectively balances global exploration for identifying promising switching configurations and local exploitation for refining the optimal solution. This capability becomes more significant for the IEEE 69-bus system, where the larger solution space increases the possibility of obtaining suboptimal configurations. Overall, the convergence results confirm that HPSOMVO provides a more stable and reliable optimization process for network reconfiguration while considering EVCS and PV integration.

4.5 Performance Comparison of Objective 1 and Objective 2

Tables 4.4 and 4.5 summarize the optimization results obtained for the IEEE 33-bus and IEEE 69-bus distribution systems under Objectives 1 and 2 using the six optimization algorithms. The results are compared in terms of switch configuration, active power loss, and percentage loss reduction. Objective 1 focuses on optimal EVCS placement under the existing switch configuration, while Objective 2 determines the optimal network reconfiguration based on the optimal EVCS locations obtained from Objective 1.

Table 4.4
Summary of Result for IEEE 33-System

Algorithms	Objective 1			Objective 2				
	Case 1	Case 2	(Case 1 vs Case 2)	Case 1	Case 2	Case 3	(Case 2-Obj1) vs Case 2	(Case 2-Obj1) vs Case 3
	Power Loss, MW		Loss Increases, %	Power Loss, MW			Loss Reduction %	Loss Reduction %
Base	0.1348	-	-	0.0976	-	-		-
HPSOMVO	-	0.2373	76.04	-	0.2034	0.1639	14.29	30.93
ACO	-	0.2624	94.66	-	0.2196	0.1630	16.31	37.88
PSO	-	0.2467	83.01	-	0.2265	0.1730	8.19	29.87
MVO	-	0.2580	91.39	-	0.2140	0.1690	17.05	34.50
GWO	-	0.2887	114.17	-	0.2111	0.1687	26.88	41.57
EP	-	0.2543	88.65	-	0.2044	0.1677	19.62	34.05

Table 4.5
Summary of Result for IEEE 69-System

Algorithms	Objective 1			Objective 2				
	Case 1	Case 2	(Case 1 vs Case 2)	Case 1	Case 2	Case 3	(Case 2-Obj1) vs Case 2	(Case 2-Obj1) vs Case 3
	Power Loss, MW		Loss Increases, %	Power Loss, MW			Loss Reduction %	Loss Reduction %
Base	0.2246	-	-	0.0874	-	-		-
HPSOMVO	-	0.2399	6.81	-	0.1241	0.0848	48.27	64.65
ACO	-	0.2419	7.70	-	0.1459	0.0846	39.69	65.03
PSO	-	0.2583	15.00	-	0.1452	0.0911	43.79	64.73
MVO	-	0.2782	23.86	-	0.1353	0.0916	51.37	67.07
GWO	-	0.2628	17.00	-	0.1631	0.1027	37.94	60.92
EP	-	0.2520	12.20	-	0.1335	0.0880	47.02	65.08

Tables 4.4 and 4.5 compare the performance of the six optimization algorithms under Objectives 1 and 2 for the IEEE 33-bus and IEEE 69-bus distribution systems. Under Objective 1, the comparison between Cases 1 and 2 shows the effect of EVCS integration and the ability of each algorithm to determine suitable EVCS locations. Under Objective 2, the comparison between Objective 1 Case 2 and Objective 2 Case 2 shows the improvement obtained through network reconfiguration, while the

comparison with Objective 2 Case 3 shows the overall improvement after PV integration.

For the IEEE 33-bus system, the integration of EVCSs under Objective 1 increases the active power loss from the base value of 0.1348 MW. Among the six algorithms, HPSOMVO produces the lowest Case 2 loss of 0.2373 MW and the lowest power-loss increase of 76.04%. This indicates that HPSOMVO identifies the best-performing EVCS locations among the evaluated algorithms in limiting the additional losses caused by EV charging. Under Objective 2, network reconfiguration further reduces the HPSOMVO loss from 0.2373 MW to 0.2034 MW, corresponding to a reduction of 14.29%. Although some benchmark algorithms achieve larger percentage reductions, HPSOMVO produces the lowest actual loss after reconfiguration, showing that the selected network configuration provides better overall performance.

With PV integration in Objective 2 Case 3, the HPSOMVO loss is further reduced to 0.1639 MW. This represents an overall reduction of 30.93% compared with Objective 1 Case 2. ACO records a slightly lower final loss of 0.1630 MW, while GWO achieves the highest overall percentage reduction of 41.57%. However, the larger percentage reduction obtained by some algorithms is partly influenced by their higher initial losses under Objective 1. Therefore, both the percentage reduction and the final active power loss should be considered when evaluating the overall performance.

For the IEEE 69-bus system, a similar trend is observed. Under Objective 1, HPSOMVO produces the lowest active power loss of 0.2399 MW after EVCS integration, corresponding to the lowest loss increase of 6.81% from the base value of 0.2246 MW. This shows that HPSOMVO is also effective in selecting EVCS locations for the larger distribution system. Following network reconfiguration under Objective 2 Case 2, the loss is reduced substantially to 0.1241 MW, representing a reduction of 48.27% compared with Objective 1 Case 2. HPSOMVO again produces the lowest actual power loss among the six algorithms after reconfiguration.

After PV integration in Case 3, the HPSOMVO loss is further reduced to 0.0848 MW, giving an overall reduction of 64.65% compared with Objective 1 Case 2. ACO produces a slightly lower final loss of 0.0846 MW, while MVO records the highest overall percentage reduction of 67.07%. Nevertheless, the HPSOMVO result remains

very close to the lowest final loss and demonstrates strong performance across both stages of Objective 2.

Overall, the comparison demonstrates the achievement of both research objectives for the two test systems. Under Objective 1, HPSOMVO produces the lowest active power loss after optimal EVCS placement for both networks. Under Objective 2, network reconfiguration provides further loss reduction, with HPSOMVO again producing the lowest Case 2 losses. PV integration provides an additional improvement in Case 3, although ACO produces marginally lower final losses. The results therefore show that the coordinated use of optimal EVCS placement, network reconfiguration, and PV integration can significantly improve the operating efficiency of both radial distribution systems.

4.6 Summary of Result and Discussion

The results and discussion demonstrate that the proposed coordinated optimization framework effectively minimizes the impact of EVCS integration on radial distribution networks through the sequential implementation of optimal EVCS placement, network reconfiguration, and PV integration. Although EVCS deployment inevitably increases network loading and active power losses, the proposed HPSOMVO algorithm successfully limits these increases by identifying favourable EVCS locations. The subsequent network reconfiguration further reduces active power losses by improving power flow distribution, while PV integration provides additional loss reduction and enhances the voltage profile. Comparative analyses using the IEEE 33-bus and IEEE 69-bus systems show that HPSOMVO consistently achieves competitive and, in most cases, superior performance compared with the benchmark algorithms in terms of power loss minimization, voltage regulation, and convergence characteristics. The findings confirm that the hybrid exploration and exploitation mechanism of HPSOMVO provides robust and reliable optimization performance, demonstrating its suitability for coordinated EVCS planning and distribution network reconfiguration in modern power systems with increasing EV penetration.

CHAPTER 5
CONCLUSION

5.1 Introduction

This section summarizes and concludes all the findings of the study and relate it to the objectives of the research. Continuous study in this area is also suggested based on the outcome of this research.

5.2 Conclusion

This thesis presented an optimization framework for the integration of Electric Vehicle Charging Stations (EVCS) in distribution networks by considering optimal EVCS placement and optimal network reconfiguration with photovoltaic (PV) support. A hybrid optimization technique, namely Hybrid Particle Swarm Optimization–Multi-Verse Optimization (HPSOMVO), was developed to address the nonlinear and mixed-integer characteristics of the problem. The proposed method was validated using the IEEE 33-bus and IEEE 69-bus test systems and benchmarked against several established optimization algorithms.

The two objectives of this research, as stated in Chapter 1, have been successfully achieved. The following discusses the outcomes for each objective:

A. Objective 1: To determine the optimal placement of EVCSs) in a distribution network by minimizing total active power losses while ensuring that all bus voltages remain within statutory limits, using the hybrid PSO-MVO) algorithm.

To achieve this objective, a hybrid optimization framework based on the HPSOMVO algorithm was developed to determine the optimal locations of multiple EVCS units with predefined capacity levels. The optimization process aimed to minimize incremental power losses introduced by EV charging demand while maintaining voltage limits under the existing radial network structure.

The main contribution of this objective lies in the development of a coordinated EVCS placement strategy that systematically allocates charging stations across electrically suitable buses to balance feeder loading. The results demonstrated that improper EVCS placement can significantly increase feeder losses and degrade voltage profiles, particularly in longer radial networks. However, the proposed method successfully identified well-distributed EVCS locations that minimized additional power losses while maintaining all bus voltages within statutory limits. Compared with other metaheuristic techniques, HPSOMVO consistently achieved better loss performance and stable convergence characteristics.

Therefore, Objective 1 was successfully achieved, validating the effectiveness of the proposed optimization framework for strategic EVCS placement in distribution networks.

B. Objective 2: To develop an optimal network reconfiguration that integrates the selected EVCS locations and PV systems by minimizing power loss under statutory voltage limits, using HPSOMVO algorithm.

The second objective focused on enhancing system performance through optimal network configuration under EVCS loading conditions. Unlike Objective 1, which addressed placement decisions, this stage concentrated on structural modification of the distribution network by determining the most suitable tie-switch operations. The HPSOMVO algorithm was applied to search for an optimal radial configuration while satisfying operational constraints, including radiality, voltage limits, and branch loading conditions.

The primary contribution of this objective is the establishment of a coordinated network reconfiguration framework that systematically redistributes feeder loading to reduce excessive current flow in critical branches. The results confirmed that proper switching decisions significantly influence loss reduction, especially in larger radial systems. The optimized configurations obtained using HPSOMVO demonstrated improved power flow distribution and more balanced voltage profiles compared to conventional metaheuristic

methods. Furthermore, the integration of PV provided additional local support, enhancing the effectiveness of the reconfigured network structure.

In conclusion, this study successfully developed an optimization framework for EVCS-integrated distribution networks using the proposed HPSOMVO algorithm. The framework addressed optimal EVCS placement and network reconfiguration with PV support to reduce power losses and maintain acceptable voltage levels. The results from the IEEE 33-bus and IEEE 69-bus systems show that proper planning of charging station locations and network configuration is important to improve system performance under increasing EV demand. The proposed hybrid algorithm demonstrated stable convergence and effective coordination between placement and reconfiguration decisions. Overall, the developed framework provides a practical approach to support the integration of electric vehicles in modern distribution networks.

5.3 Future Work

Further studies related to the optimal integration of EVCS in distribution networks that have not been comprehensively covered in this thesis would help improve the overall performance and applicability of the proposed optimization framework. The following are some recommended studies that can be carried out:

i. Although the proposed HPSOMVO algorithm has demonstrated effective performance in determining optimal EVCS placement and network reconfiguration, future work may extend the current single-objective formulation to a multi-objective optimization framework. Additional objectives, such as minimizing installation and operating costs, reducing greenhouse gas emissions, improving system reliability, maximizing renewable energy utilization, and enhancing voltage stability, can be considered simultaneously to provide more practical planning solutions for distribution network operators. Furthermore, adaptive parameter tuning or hybrid learning mechanisms may be incorporated to improve the convergence speed, robustness, and scalability of the proposed algorithm for larger and more complex distribution systems.

ii. The present study assumes fixed EVCS charging demand and predetermined PV generation under steady-state operating conditions. Future studies should

consider time-varying EV charging demand, stochastic renewable generation, and load uncertainty to better represent realistic network operation. In addition, Battery Energy Storage Systems (BESS) may be integrated with EVCSs and PV systems to mitigate renewable intermittency, reduce peak demand, improve voltage regulation, and enhance operational flexibility. Coordinated optimization of EVCSs, PV systems, and BESS would enable more efficient energy management and increase the resilience of future active distribution networks.

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AUTHOR'S PROFILE



Nur Aina Fatini Binti Roslan obtained Bachelor of Engineering (Hons) Electrical Engineering in 2024 from University Teknologi Mara, Shah Alam and currently pursuing her MSc in Electrical Engineering also at Universiti Teknologi Mara.

LIST OF PUBLICATIONS

JOURNAL PUBLICATION

Roslan, N.A.F., H. Mohamad, K. Naidu, N.A. Salim, and Z.M. Yasin, Electric Vehicle Diversity: A Comprehensive Review of Impacts on Distribution Networks, Charging Infrastructure, and Regulatory Perspectives. Submitted to Journal of Traffic and Transportation Engineering (English Edition), 2026. Status: Under Review.

CONFERENCE PUBLICATIONS

Mohamad, H., N.A.F. Roslan, K. Naidu, N.A. Salim, and Z.M. Yasin, Optimal Placement of Electric Vehicle Charging Station Using Ant Colony Optimization. In 2025 IEEE 5th International Conference on Power Engineering Applications (ICPEA), Bandar Baru Bangi, Malaysia, 2025, pp. 101–106. doi:10.1109/ICPEA65539.2025.11234567.

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