

UNIVERSITI TEKNOLOGI MARA

**MULTI-OBJECTIVE LSF-MALO
OPTIMIZATION FOR
DISTRIBUTED GENERATION
PLACEMENT IN DISTRIBUTION
SYSTEMS CONSIDERING EVCS
INTEGRATION**

**NUR ATIQA BINTI ABDUL
RAHMAN**

PhD

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NUR ATIQA BINTI ABDUL RAHMAN

Thesis submitted in fulfilment
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Doctor of Philosophy
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CONFIRMATION BY PANEL OF EXAMINERS

I certify that a Panel of Examiners has met on 23 April 2026 to conduct the final examination of Nur Atiqah binti Abdul Rahman on her Doctor of Philosophy thesis entitled “Multi-Objective LSF-MALO Optimization for Distributed Generation Placement in Distribution Systems Considering EVCS Integration” 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:

Nooritawati Md Tahir, PhD
Professor
Faculty of Electrical Engineering
Universiti Teknologi MARA
(Chairman)

Zuhaila Mat Yasin, PhD
Associate Professor
Faculty of Electrical Engineering
Universiti Teknologi MARA
(Internal Examiner)

Nor Azwan Mohamed Kamari, PhD
Senior Lecturer
Faculty of Engineering
and Built Environment
Universiti Kebangsaan Malaysia
(External Examiner)

**PROF. DR. HJH ZURAEDA BINTI
IBRAHIM**

Dean
Institute of Postgraduates Studies
Universiti Teknologi MARA

Date: 24 June 2026

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I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Teknologi MARA. It is original and is the result of my own work, unless otherwise indicated or acknowledged as referenced work. This thesis has not been submitted to any other academic institution or non-academic institution for any degree or qualification.

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Name of Student : Nur Atiqah binti Abdul Rahman

Student ID. No. : 2020397721

Programme : Doctor of Philosophy (Electrical Engineering) – EE950

Faculty : Electrical Engineering

Thesis Title : Multi-Objective LSF-MALO Optimization for
Distributed Generation Placement in Distribution
Systems Considering EVCS Integration

Signature of Student :

Date : June 2026

ABSTRACT

The rapid growth of Distributed Generation (DG) and Electric Vehicle Charging Stations (EVCS) in modern distribution networks has introduced technical and operational challenges that conventional planning and optimization approaches fail to address. While DG offers benefits such as loss reduction, improved voltage stability and enhanced sustainability, its performance is highly dependent on proper placement and sizing strategies. EVCS, on the other hand, creates voltage fluctuations, higher power losses, increased grid dependency and harmonic distortion, which significantly degrade network reliability. This research develops a new hybrid optimization technique, known as the Loss Sensitivity Factor - Mutated Ant Lion Optimizer (LSF-MALO), to address these issues. The technique combines the computational efficiency of the LSF Analytical with the global search capability of the MALO algorithm, offering both accuracy and robustness. The proposed algorithm is first validated for single objective optimization to minimize losses and improve voltage profiles and later extended into a multi-objective framework that simultaneously incorporates technical, economic and power quality aspects. A systematic assessment of distribution systems with existing charging infrastructures is conducted, explicitly incorporating both Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) operational modes to capture the real impact of EVCS under various loading and charging conditions. The algorithm is then applied to standard IEEE-33 bus and 69-bus radial distribution systems to evaluate its effectiveness. Results demonstrate that LSF-MALO outperforms existing analytical and metaheuristic approaches by achieving up to 63.75% reduction in real power losses and up to 77.5% in annual cost savings. Additionally, the proposed methodology consistently maintains Total Harmonic Distortion (THD) below the 5% standard limit, significantly minimizing grid dependency where other algorithms failed. Furthermore, the method ensures scalability and adaptability across diverse scenarios, providing a balanced trade-off between technical performance and economic feasibility. This research makes a substantial contribution by bridging methodological gaps and delivering a comprehensive optimization framework that supports reliable, efficient and sustainable distribution system planning in the era of increasing electric vehicle (EV) and renewable energy integration.

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LIST OF ABBREVIATIONS

Abbreviations

ABC-HC	Artificial Bee Colony - Hill Climbing
AC	Alternating Current
ACO	Ant Colony Optimization
ACS	Annual Cost Saving
AEL	Annual Economic Loss
AIS	Artificial Immune System
ALO	Ant Lion Optimizer
APLS	Active Power Loss Sensitivity
AVOA	African Vulture Optimization Algorithm
CAFO	Chaotic Artificial Flora Optimization
CHIO	Coronavirus Herd Immunity Optimizer
CHP	combined heat and power
CIGRE	International Council on Large Electric Systems
CSA-DC BA	Hybrid Chaotic Bat Algorithm
CSO	Competitive Search Optimization
DC	Direct Current

DG	Distributed Generation
DSTATCOM	Distribution Static Synchronous Compensator
ECOST	Expected Interruption Costs
EENS	Expected Energy Not Served
EMS	Energy Management System
EP	Evolutionary Programming
EPRI	Electric Power Research Institute
ESS	Energy Storage System
ESU	Energy Storage Unit
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
FACTS	Flexible Alternating Current Transmission System
FPA	Flower Pollination Algorithm
G2V	Grid to vehicle
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
HPSOGWO	Hybrid Particle Swarm Grey Wolf Optimization
HSBO	Hybrid Secretary Bird Optimization
IA	Immune Algorithm

IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
IGWO	Improved Grey Wolf Optimization
IHHO	Improved Harris Hawks Optimizer
IHHOA	Improved Harris Hawks Optimizer Algorithm
IIMFEP	Integrated Immune Moth Flame Evolutionary Programming
IWOA	Improved Whale Optimization Algorithm
LRI	Loss Reduction Index
LSF	Loss Sensitivity Factor
LSF-MALO	Loss Sensitivity Factor - Mutated Ant Lion Optimizer
MALO	Mutated Ant Lion Optimizer
MFO	Moth Flame Optimization
MGWO	Modified Grey Wolf Optimization
MINLP	Mixed Integer Non-Linear Programming
MOO	Multi-objective optimization
MVAR	Mega-Var
MW	Megawatt
NVSF	Network Voltage Stability Factor
PSO	Particle Swarm Optimization

PV	Photovoltaic
PVDG	Photovoltaic Distributed Generation
QOCSOS	Quasi-Oppositional Chaotic Symbiotic Organism Search
RDG	Renewable Distributed Generation
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCA	Sine Cosine Algorithm
SOC	State of Charge
SOO	Single-objective optimization
THD	Total Harmonic Distortion
V2G	Vehicle to grid
VDI	Voltage Deviation Index
VSI	Voltage Stability Index
VSM	Voltage Stability Margin
WO	War Optimization
WOA	Whale Optimization Algorithm
WOT	Whale Optimization Technique
WSM	Weighted Sum Method
WT	Wind Turbine

CHAPTER 1

INTRODUCTION

1.1 Research Background

The electrical distribution system is the critical final stage of the power grid, traditionally conceptualized as a passive network designed for unidirectional electricity flow from centralized power plants to end users. However, the modernization of the grid has fundamentally altered this traditional concept through the introduction of Distributed Generation (DG) and Electric Vehicle Charging Stations (EVCS). Conceptually, DG refers to small-scale, decentralized energy generation technologies located at or near the load centers they serve. Conversely, EVCS represents the dynamic infrastructure necessary to recharge electric vehicles, acting as massive, non-linear power consumers. The simultaneous integration of these technologies transforms the traditional one-way distribution network into an active, bi-directional system, making the strategic planning and optimization of their placement absolutely critical for maintaining overall grid stability and efficiency.

Driven by the need to mitigate the negative environmental impacts associated with conventional, fossil-fuel-dependent power generation, electrical utilities increasingly incorporate these DG technologies to offer cleaner energy alternatives and elevate the overall system's efficiency. These technologies, which include photovoltaic (PV) systems, wind turbines, and combined heat and power (CHP) units, minimize greenhouse gas emissions while simultaneously enhancing voltage stability and reducing power losses in distribution networks, making it an essential element of contemporary sustainable energy systems [1]. Recent global trends demonstrate significant adoption of DG technologies in national energy portfolios. Renewable DG sources, particularly solar photovoltaic (PV) and wind, have accounted for over 50% of electricity generation in Denmark in 2020, while contributing approximately 30% of electricity in Ireland during the same period. Looking ahead, major economies have established ambitious DG integration targets. The projections indicate that the United States and China aim to derive approximately 80% and 60% of their electricity from distributed renewable sources by 2050 [2].

The concept of DG varies across international organizations and regulatory bodies. The International Energy Agency (IEA) characterizes DG as power generation facilities directly supplying on-site consumers or providing grid support through the distribution network. On the other hand, the International Council on Large Electric Systems (CIGRE) establishes three defining criteria for DG technologies: (1) connection to local distribution networks rather than transmission systems, (2) non-centralized operational dispatch, and (3) generation capacity typically ranging between 50-100 MW. In contrast, the Electric Power Research Institute (EPRI) adopts a broader technical specification, classifying DG as generation assets with capacities spanning from several kilowatts up to 50 MW [3][4].

The integration of DG into distribution systems presents a dualistic impact, where outcomes are dependent upon proper system design and strategic implementation [5]. When appropriately planned by considering optimal sizing and location selection, DG offers substantial technical advantages, including minimized real power losses, improved voltage profile, enhanced system reliability, and superior power quality. Conversely, poor planning, such as incorrect capacity sizing or improper placement, can lead to conflicting effects, such as increased power losses, voltage instability, and diminished overall grid efficiency [6][7]. These contrasting possibilities highlight the necessity of structured deployment methodologies to ensure that DG integration maximizes its intended benefits while mitigating unintended operational challenges. Consequently, a systematic approach to DG planning is imperative to harness its full potential in modern distribution systems.

Significant research has been devoted to addressing the optimal placement of DG in distribution network using various methodological approaches. Early studies primarily utilized analytical techniques [8][9][10][11] which, while computationally efficient and conceptually straightforward, exhibit notable limitations when applied to complex scenarios. These limitations become particularly apparent in problems involving multiple control variables or expansive search spaces, where analytical methods often fail to deliver robust solutions. To overcome these challenges, metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have emerged as powerful alternatives. These techniques excel at exploring high-dimensional solution spaces and handling non-linear, multi-objective optimization problems inherent to DG placement. Despite their advantages, metaheuristic algorithms may face shortcomings such as slow

convergence rates, susceptibility to premature convergence at local optima, and limited robustness when confronted with larger systems [12]. These persistent limitations highlight the need for more advanced optimization frameworks to balance computational efficiency with solution accuracy in practical DG deployment scenarios. Recent studies highlight the superiority of hybrid optimization techniques that combine the strengths of multiple algorithms to overcome individual shortcomings [12].

However, all these approaches often neglect dynamic grid conditions, such as the impact of Electric Vehicle Charging Stations (EVCS), which introduce unpredictable load surges and harmonic distortions. The increasing integration of Electric Vehicles (EVs) into power distribution systems brings operational challenges and potential benefits. As EV adoption accelerates, the growing demand for EVCS significantly stresses existing grid infrastructure. This additional load can lead to two primary technical issues: (1) voltage instability due to increased power demand fluctuations and (2) elevated system losses that reduce overall network efficiency. Without proper charging management strategies, the grid faces heightened peak demand periods and more severe voltage variations, potentially threatening system reliability [13]. Furthermore, EVCS introduces notable power quality concerns through harmonic distortion. The power electronic converters used in these charging stations produce non-linear current waveforms that distort voltage profiles. These technical impacts underscore the need for comprehensive solutions addressing power quality and system stability concerns in EVCS-integrated networks. This gap necessitates the development of more robust, adaptive optimization frameworks capable of addressing modern grid complexities.

This study proposes a new optimization technique called Loss Sensitivity Factor–Mutated Ant Lion Optimizer (LSF-MALO) for optimal DG placement. The proposed LSF-MALO is first implemented for single-objective optimization (SOO) and subsequently extended to multi-objective optimization (MOO) to address multiple technical issues in distribution networks. To capture the challenges introduced by EVCS, a comprehensive assessment of EVCS-integrated distribution system performance is carried out. Building on this, the LSF-MALO algorithm is further formulated as a multi-objective framework to simultaneously enhance voltage stability, reduce grid dependency, and mitigate power quality issue in EVCS-integrated networks.

1.2 Problem Statement

Rapidly integrating Distributed Generation (DG) and Electric Vehicle Charging Stations (EVCS) into modern power distribution systems has introduced critical challenges that existing planning and optimization frameworks fail to address comprehensively. While DG offers significant benefits for grid sustainability and efficiency, current approaches remain inadequate in several key aspects that this research systematically investigates. The growing penetration of these technologies has revealed fundamental gaps in optimization methodologies, performance assessment frameworks and distribution system planning that require innovative solutions.

Firstly, existing methods for optimal DG placement, including analytical approaches and metaheuristics, suffer from critical limitations. While computationally efficient, analytical technique like Loss Sensitivity Factor (LSF) often lack the precision required for complex network topologies. Metaheuristic methods like Evolutionary Programming (EP) and Ant Lion Optimizer (ALO), though more adaptable, frequently exhibit premature convergence to suboptimal solutions and struggle with high-dimensional search spaces [12]. There is an urgent need for a new hybrid optimization algorithm that combines the computational efficiency of analytical methods with the robustness of metaheuristics. By bridging these complementary strengths, the proposed approach can deliver both speed and precision, offering a more reliable solution to the optimal DG placement problem in complex distribution systems.

While existing research on DG placement has progressively advanced from single-objective to multi-objective optimization frameworks, significant limitations persist in current methodologies. Many studies continue to focus narrowly on technical objectives like power loss minimization or voltage improvement, often neglecting the crucial economic dimension of DG integration and assuming identical DG type, failing to address the complex trade-offs between technical performance, financial viability, and diverse renewable energy portfolios that are essential for practical implementation. Consequently, the field still lacks a comprehensive optimization approach that can balance technical, economic, and operational objectives while accommodating mixed DG types in real-world distribution systems.

Meanwhile, the increasing penetration of Electric Vehicle Charging Stations (EVCS) into distribution systems introduces challenges such as voltage fluctuations, increased power losses, high grid dependency and harmonic distortion. Most existing

studies evaluate EVCS impacts using limited indicators, often focusing solely on load or voltage effects while overlooking broader implications for grid dependency and power quality. In this context, the measure of grid dependency is done by evaluating the net power grid of the system, P_{grid} . This indicator calculates the total active power drawn from the main utility grid by accounting for the existing base loads and the power consumed during Grid-to-Vehicle (G2V) charging, while offsetting the power supplied back to the network via Vehicle-to-Grid (V2G) discharging and local Distributed Generation (DG). Comprehensive assessments that simultaneously account for voltage stability, grid dependency, and harmonic distortion remain relatively scarce, leaving a critical gap in understanding the impact of EVCS integration on distribution system performance. Therefore, a systematic assessment of distribution system performance under various EVCS charging scenarios is necessary to capture the full extent of their impact on network performance and stability.

Finally, current DG placement methodologies present two unresolved challenges in EVCS-integrated distribution networks. First, existing approaches often lack comprehensive optimization frameworks that simultaneously reduce grid dependency while ensuring critical performance metrics such as real power loss minimization and voltage profile stability. Second, current models inadequately incorporate power quality considerations, particularly Total Harmonic Distortion (THD) mitigation, as an integrated objective alongside conventional technical goals. Ignoring grid dependency undermines the very purpose of DG, which is to supply loads locally and reduce reliance on upstream networks, while neglecting THD mitigation leads to voltage instability and equipment deterioration, ultimately lowering the overall reliability of EVCS-integrated systems. These limitations underscore the critical need for a multi-objective optimization formulation capable of addressing voltage stability, grid dependency and power quality in environments with high EVCS penetration.

Therefore, the problem statements can be summarized as follows:

- i) Current methods for optimal DG placement face major drawbacks. Analytical approaches like LSF are fast but lack precision in complex networks, while metaheuristics like EP and ALO often converge prematurely and struggle with large search spaces. A hybrid approach is needed to combine speed with robustness for more reliable DG placement.

- ii) Research on DG placement has advanced toward multi-objective frameworks, but many studies remain narrowly focused on technical goals such as minimizing losses or improving voltages. Economic factors, diverse DG types, and practical trade-offs are often overlooked, highlighting the need for a more holistic optimization approach.
- iii) The growing integration of EVCS introduces voltage fluctuations, higher losses, grid dependency, and harmonic distortion. Yet, most studies assess EVCS using limited indicators, neglecting broader impacts on grid dependency, power quality, and stability. Comprehensive evaluations across these dimensions remain scarce.
- iv) Existing DG placement models fall short in EVCS-integrated networks. They often fail to reduce grid dependency while ensuring voltage stability and loss minimization and rarely include THD as an objective. This undermines the purpose of DG and risks instability, underscoring the need for a multi-objective optimization framework addressing voltage stability, grid dependency, and power quality.

1.3 Research Objectives

Based on the problem statements identified in the previous section, the objectives of this research are:

- i) To develop the new hybrid Loss Sensitivity Factor – Mutated Ant Lion Optimizer (LSF-MALO) algorithm for optimal Distributed Generation placement in distribution systems.
- ii) To formulate the developed LSF-MALO algorithm for multi-objective optimal Distributed Generation placement considering voltage magnitude, power losses, annual economic loss and cost saving.
- iii) To assess the impacts of Electric Vehicle Charging Station (EVCS) integration on voltage stability, grid dependency, and harmonic distortion in distribution systems, considering various charging scenarios.
- iv) To implement the developed LSF-MALO algorithm for optimal DG placement in EVCS-integrated distribution systems, focusing on voltage stability improvement, grid dependency reduction, and harmonic mitigation.

Table 1.1 tabulates the mapping between the problem statement and research objectives. Problem statement 1 highlights the limitations of the current DG placement and is addressed by objective 1 through the development of the hybrid LSF-MALO algorithm to improve the robustness for reliable placement. Next, problem statement 2 identifies the narrow technical focus in existing research, and this will be addressed by objective 2, where the proposed LSF-MALO algorithm is formulated as a multi-objective framework that incorporates economic and cost-saving considerations in addition to technical aspects.

Problem statement 3 focuses on the challenge of EVCS integration, such as voltage instability, grid dependency and harmonic distortion. These issues are addressed by objective 3, which systematically evaluates EVCS impacts across multiple scenarios. Finally, problem statement 4 underlines the limitations of the DG placement model in EVCS integrated systems, especially the lack of THD consideration. Objective 4 responds by implementing the hybrid LSF-MALO algorithm in EVCS integrated systems, ensuring improved voltage stability, reduce grid dependency and harmonic mitigation.

Table 1. 1
Problem Statement Versus Research Objective Mapping

	Problem 1	Problem 2	Problem 3	Problem 4
Objective 1	/			
Objective 2		/		
Objective 3			/	
Objective 4				/

1.4 Scope and Limitations of the Study

This research begins with the development of a new hybrid metaheuristic algorithm called the Mutated Ant Lion Optimizer (MALO), which combines the strengths of Evolutionary Programming (EP) and the Ant Lion Optimizer (ALO). By hybridizing these two, MALO balances exploration and exploitation, overcoming the weaknesses of each individual method. Once formulated, MALO is then incorporated with the Loss Sensitivity Factor (LSF) to form the proposed LSF-MALO, where LSF

provides a computationally efficient analytical foundation to guide the search space, further enhancing accuracy in DG placement. The resulting algorithm is applied to minimize real power losses and improve the minimum bus voltage in distribution systems, using IEEE 33-bus and IEEE 69-bus radial networks as test systems. For the validation of this part, one type of DG unit will be used during simulation, namely solar photovoltaics (PV). The performance is systematically assessed under different numbers of DG units, multiple loading conditions, and parameter variations to ensure robustness in single-objective optimization (SOO). Comparative studies will be conducted by comparing the results obtained by the proposed algorithm with other methods like LSF analytical, EP and MALO.

Subsequently, the research will proceed to formulate a new multi-objective LSF-MALO algorithm. This will be achieved by expanding the single-objective framework into a multi-objective framework that simultaneously minimizes the total fitness function. This fitness function will accumulate key performance indicators, including improving voltage profile, reducing the total power losses and annual economic loss. The verification process will involve testing the algorithm on the same IEEE 33-bus and 69-bus systems. However, in this stage, the focus is now on integrating heterogeneous and mixed DG types (PV, wind, and diesel). The performance will also be evaluated by analyzing the achieved trade-offs in the total fitness function across different loading conditions to demonstrate the robustness and effectiveness of the algorithm in handling complex, real-world scenarios.

Next, the research will then focus on evaluating the technical impacts of EVCS integration in the distribution system. This will be achieved by modelling the different EVCS penetration scenarios with the test systems. These scenarios will include both identical (all charging stations operating in the same mode) and mixed (a mix of different charging modes) charging strategies, subject to varying penetration levels and multiple loading conditions. The impact of this penetration will be verified in the same test system of IEEE 33-bus and 69-bus systems. Key performance metrics such as voltage stability, power loss, grid dependency (power exported and imported from the main grid) and harmonic distortion will be analyzed to quantify the technical impacts of EVCS integration.

Eventually, the research will accomplish objective 4 by formulating a multi-objective LSF-MALO specifically designed for a distribution system with EVCS integration. The formulation aims to minimize the total fitness function, which

comprises real power losses, Voltage Deviation Index (VDI), grid dependency, and mitigation of Total Harmonic Distortion (THD), while maintaining a stable voltage profile. The verification of this objective will be through the implementation of the proposed multi-objective LSF-MALO into the IEEE 33-Bus and 69-Bus systems under EVCS integration. The performance will be assessed by the ability of the algorithm to effectively optimize the respective fitness function, demonstrating a targeted improvement in the system's stability and power quality.

The overall research framework of this study is summarized in **Figure 1.1**, which provides a visual workflow that maps all research objectives to their corresponding tasks, illustrating the sequential development from algorithm creation to its application in solving complex multi-objective problems in modern distribution systems.

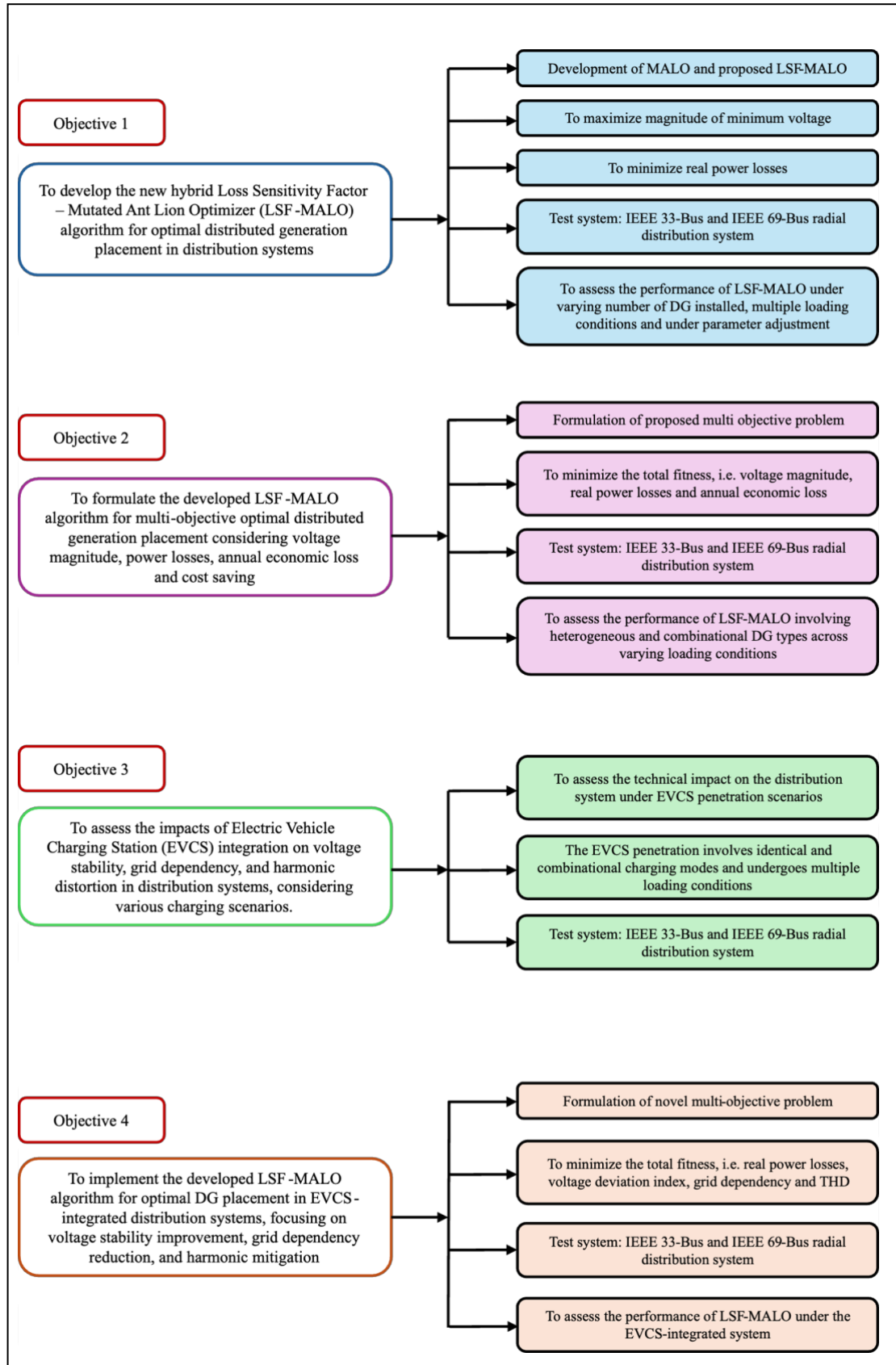


Figure 1. 1 Overall Research Framework

1.5 Significance of the Study

This study is significant in advancing both theoretical knowledge and practical applications in the field of power system optimization and distribution network planning. From a technical perspective, the proposed Loss Sensitivity Factor–Mutated Ant Lion Optimizer (LSF-MALO) provides a hybrid optimization framework that combines the computational efficiency of Loss Sensitivity Factor (LSF) with the effective global search capabilities of Mutated Ant Lion Optimizer (MALO). Through this new integration, the critical limitations of existing methods are addressed by improving the accuracy of the solution and enhancing the reliability in handling complex, non-linear problems associated with modern distribution systems.

In terms of system performance, the study contributes to a deeper understanding of Electric Vehicle Charging Station (EVCS) integration by conducting a comprehensive assessment under various penetration conditions. In addition, this work evaluates four critical performance metrics, including power loss, voltage stability, grid dependency and harmonic distortion, thus providing a more comprehensive evaluation compared to studies that only focus on a single aspect. Furthermore, comparative analysis that includes identical and mixed charging modes offers crucial insight into how different EVCS deployment strategies can impact grid performance, which is vital for planning and mitigation.

The findings of this study also hold practical relevance for utility companies and power system planners. By offering a robust tool for optimal DG placement that simultaneously considers grid dependency reduction and power quality improvement, the outcome of this study can navigate a more strategic decision-making in managing the growing penetration of EVCS while maintaining the distribution system stability and reliability. In addition, the proposed methodology provides the transition towards the sustainable and resilient distribution system by ensuring that the renewable-based DG unit is integrated effectively, fulfilling its intended role of supplying local loads, reducing fossil fuel reliance and minimizing technical losses.

Overall, this research bridges existing gaps in both optimization methodology and system assessment. It provides a valuable reference for academia, industry and policymakers by delivering a scalable and flexible optimization framework, practical insights into EVCS impacts and a foundation for developing standards and strategies for the future integration of DG resources and Electric Vehicle (EV) into the smart grid.

1.6 Organization of Thesis

This thesis is systematically structured into seven chapters, each contributing to a comprehensive exploration of the study.

Chapter One begins with the research background, which outlines the current scenario of DG and EV penetration in distribution networks, followed by a review of methodologies employed for optimal DG placement using various techniques, and the motivation for a hybrid algorithm that offers both speed and robustness. The research gap is then established, leading to the formulation of problem statements from which the research objectives are derived. These objectives are mapped against the identified problems to provide a clear direction for the study. Subsequently, the scope of work is presented, covering problem formulation, algorithm development, verification and analysis of results, and the limitations considered during experimentation. The significance of the study is then discussed, emphasizing its contribution to advancing DG placement strategies and enhancing the reliability and efficiency of EVCS-integrated distribution networks. Finally, the organization of the thesis is outlined to provide an overview of the structure and key highlights of each chapter.

Chapter Two provides an in-depth review of relevant literature, establishing the theoretical frameworks and identifying the gaps the study aims to address. The chapter begins with the introduction of DG as one of the relevant and important technologies in modern distribution systems. Later, the impact of improper DG placement on the distribution system is presented by reviewing previous articles that presented the consequences of suboptimal DG placement. This includes an increase in losses, leading to voltage instability and also leading to power quality issues. Afterwards, various techniques on optimal placement of DG are reviewed into three main categories: analytical techniques, heuristic and metaheuristic techniques, and hybrid approach. The review discusses the strengths and limitations of each approach, setting the stage for the proposed hybrid methodology. Subsequently, the impact of EVCS penetration on the distribution system is critically assessed from technical, reliability and operational aspects. The previous mitigation strategies of these impacts were also discussed to emphasize the gap. Finally, the research gaps are identified, which include the need for a more comprehensive hybrid algorithm that can tackle multi-objective frameworks that simultaneously address technical, economic and power quality criteria.

Chapter Three presents the development of the proposed optimization algorithm, the Loss Sensitivity Factor–Mutated Ant Lion Optimizer (LSF-MALO), for optimal placement and sizing of Distributed Generation (DG). The chapter begins by outlining the rationale for hybridizing two metaheuristic algorithms, namely the classical Evolutionary Programming (EP) and the modern Ant Lion Optimizer (ALO), which together form the Mutated Ant Lion Optimizer (MALO). The subsequent section explains how the analytical technique, Loss Sensitivity Factor (LSF), is mathematically formulated and integrated into MALO, resulting in the proposed LSF-MALO framework used throughout this study. The methodology then covers the problem formulation as a single-objective optimization (SOO), followed by the step-by-step development of the overall algorithm. In the results and discussion, two case studies are evaluated for each test system: the first investigates the effects of single and double DG placement under the base case scenario, while the second examines performance under multiple loading conditions. Finally, the robustness of the LSF-MALO algorithm is validated by testing its performance under varying parameter settings of the hybrid algorithm.

Chapter Four extends the single-objective optimization (SOO) formulation into a multi-objective optimization (MOO) framework using the proposed LSF-MALO algorithm, with modifications applied to its fitness function. The methodology introduces the Weighted Sum Method (WSM) to address the MOO task by incorporating an economic dimension alongside technical objectives such as voltage magnitude improvement and real power loss minimization. To achieve this, the mathematical models of Annual Economic Loss (AEL) and Annual Cost Saving (ACS) are integrated into the fitness function through WSM. The MOO-based problem formulation is then presented, followed by the adaptation of the LSF-MALO algorithm for solving MOO problems. In the results and discussion, different DG unit types are considered to evaluate their effectiveness. Three case studies are carried out for each test system: the first examines the impact of installing identical versus combinational DG types, the second directly compares the performance of these configurations, and the third validates the influence of multi-type DG placement on voltage magnitude, AEL, and ACS under varying reactive load conditions. Finally, the robustness of the MOO-based LSF-MALO is further assessed by varying the weight combinations in WSM to identify the most optimal solutions.

Chapter Five presents a comprehensive methodology for assessing the impacts of Electric Vehicle Charging Station (EVCS) integration on distribution systems. It begins with an overview of EVCS operation equipped with an Energy Management System (EMS), followed by the modelling of EVCS as static loads in the distribution network. Three performance indicators are then introduced: the Voltage Deviation Index (VDI), grid dependency, and power quality, with detailed mathematical modelling for Total Harmonic Distortion (THD) calculation. The chapter also outlines the key considerations for assessment, including EVCS locations, quantities, types, charging modes, and system loading levels, before presenting a systematic evaluation procedure. In the results and discussion, two cases are investigated for each test system: the first analyzes distribution system performance under identical and mixed charging scenarios, each comprising 20 different configurations with varying EVCS locations, quantities, types, and charging modes; the second evaluates the impact of EVCS integration under incremental loading conditions. The analysis simultaneously considers voltage stability, grid dependency, and THD to provide a holistic assessment of system performance.

Chapter Six represents the culmination of this study, focusing on the strategic placement of DG units in EVCS-integrated distribution systems through the proposed LSF-MALO algorithm. The algorithm addresses multiple objectives, with a fitness function based on the Weighted Sum Method (WSM) introduced in Chapter Four. The objectives considered include the Voltage Deviation Index (VDI) for stability enhancement, net grid power for reducing grid dependency, and Total Harmonic Distortion (THD) for power quality improvement. By incorporating these objectives, the LSF-MALO is formulated as a multi-objective optimization (MOO) approach to enhance distribution system performance under high EVCS penetration. Similar to Chapter Five, the analysis evaluates 20 different charging mode scenarios for each test system to assess the algorithm's effectiveness in determining optimal DG locations and sizes, regardless of charging conditions, while ensuring improved voltage profiles, reduced power losses, lower grid dependency, and mitigated THD. Additional analyses are conducted to validate the robustness of the proposed algorithm under incremental loading conditions.

Chapter Seven provides a comprehensive conclusion to the study by consolidating the key findings and insights obtained from the preceding chapters. It highlights the effectiveness of the proposed LSF-MALO algorithm in achieving optimal

DG placement while addressing voltage stability, power loss reduction, grid dependency, and power quality challenges in EVCS-integrated distribution systems. The chapter also discusses the broader implications of the findings for future distribution system planning, particularly under increasing penetration of EVCS and DG units. In addition, limitations encountered during the study are acknowledged to provide context for the scope of the results. Finally, the chapter proposes several recommendations and potential research directions to guide future work in advancing optimization approaches for smart and sustainable distribution systems.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Optimal placement of Distributed Generation (DG) on distribution system networks has recently been considered an important research area due to its capability in reducing power losses, enhancing voltage profile, and elevating the reliability and stability of distribution system networks [14], [15], [16]. In the last two decades, the area has shifted from analytical methods to metaheuristic optimization methods such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and hybrid approach [17][18][19]. The increasing integration of renewable sources and the introduction of smart grids further highlight the practical importance of optimal DG placement. Up to 60% power loss reduction and almost 15% improvement in voltage profile have been recorded in the literature [16][20]. This progress responds to social and environmental considerations, including lowering greenhouse gas emissions and improving energy conservation [21][22].

Despite the superiority of DG integration, determining DG capacity and optimal placement remains a complex challenge due to the nature of the task that often involves non-linear, multi-objective, and the variability of the load and generation profile [23][24][25]. The critical gaps remain in implementing multiple conflicting objectives, such as minimizing power loss, voltage deviation, enhancing the voltage profile, and reducing the economic cost, while considering various load models and system constraints [26][27][28].

The growing penetration of Electric Vehicle Charging Stations (EVCS) introduces additional complexity to the power grid, as their load demand can lead to voltage fluctuations, harmonic distortions, and an increase in grid dependency. Many studies have been conducted to find the optimal placement of EVCS. Still, a significant gap in understanding how pre-existing EVCS infrastructure impacts the optimal placement of DG remains questionable. In addition, most optimization problems often overlook the grid dependency and power quality aspects, notably Total Harmonic Distortion (THD), which is crucial in providing stable power grid operation.

This literature review systematically examines the challenges associated with optimal DG placement, starting with an introduction to Distributed Generation (DG), the importance of optimal DG placement and sizing, the impact of DG on distribution system performance, the optimization techniques and their limitations. It then explores the key objectives of the optimal DG placement, underscoring the need for a more comprehensive model that integrates technical, economic, and operational factors. Additionally, the review evaluates the influence of EVCS on DG placement, highlighting the lack of systematic studies on pre-existing EVCS infrastructure, particularly regarding charging behaviour and harmonic effects. Finally, the review identifies gaps in current methodologies, especially concerning grid dependency and power quality improvement, while introducing new techniques proposed in this research to address these shortcomings.

2.2 Overview on Distributed Generation (DG)

In distribution systems, the Distributed Generation (DG) refers to decentralized generation of electricity near the load demand or end user, which differs from the traditional centralized power generation at large power plants. It often involves small-scale energy sources that utilize both renewable and non-renewable energy sources [29][30]. Some available DG technologies currently popular include wind power, solar photovoltaic, fuel cell, gas turbines, and microturbines. DG technologies can be categorized into four types, from type 1 to type 4, based on the power injection as follows [13]:

- i) Type 1: These DG technologies only inject real power to the system and operate at unity power factor.
- ii) Type 2: These DG technologies inject both real and reactive power into the system and operate at 0 to 1 lagging power factor.
- iii) Type 3: These DG technologies only inject reactive power into the system and operate at 0 power factor.
- iv) Type 4: These DG technologies inject real but consume reactive power and operate at 0 to 1 leading power factor.

This approach has gained popularity among researchers to integrate the DG into the distribution system network. This is due to the benefits offered by the DG technologies. Since the generated electricity is close to the load demand, it significantly reduces the power losses associated with long transmission and distribution lines [30][31]. In addition, the nature of DG technologies involves various energy sources and locations, which can promote and enhance the reliability of the power supply while improving the efficiency of the distribution system network [29][32].

Regarding environmental benefits, DG incorporates renewable energy sources such as solar photovoltaics (PV) and wind turbines. This has been proven lower emissions and reduce carbon footprints compared to traditional power plants, which often use fossil fuels [29][33]. In addition to the environmental benefits, DG units' capability to operate in grid-connected and islanded modes makes them more energy independent and resilient against grid failure [29]. Concerning grid stability, DG can provide grid stability by supporting the load demands during peak periods [34]. With the power system currently shifting toward smart grid, integrating DG technologies in the distribution system can promote the development of this initiative by providing efficient monitoring, control, and management of the renewable energy resources [35]. The congestion in distribution systems can also be alleviated by integrating DG and promoting the overall performance and reliability of the grid [34].

Although DG offers many potential benefits to distribution systems, it also presents challenges that must be addressed to reap its full benefits. A well-planned and proper integration of DG successfully achieves reliable distribution systems. As the energy sector continues to change, DG will be an important tool in creating a more stable energy grid.

2.3 Impact of Improper Distributed Generation Placement on Distribution System

Improper planning for placing DGs in distribution systems can cause many technical problems and significantly influence electric distribution systems' reliability, efficiency and security. The challenges are due to fundamental alterations in power flow, protection and system stability when DGs are integrated with the existing distribution network.

One of the negative impacts of the improper placement of DG is the introduction of harmonics and flicker, which are known to degrade the power quality for the consumer. The presence of DGs intensifies these power quality problems, mainly when DGs are not located appropriately in the distribution system. This will increase voltage swell and sag, leading to a decline in grid stability and reliability [36]. Generated disturbances can influence the behaviour of power-sensitive devices and dissatisfy the customers, highlighting the necessity of strategically placing DGs to reduce these negative impacts on power quality. In addition, the poor power quality resulting from the improper placement of DG can lead to notable economic loss. Disturbances such as harmonics and voltage sag can damage the distribution system equipment and cause production losses, reaching millions of euros in the industrial sector [37]. Poor power quality can also lead to hidden costs such as rapid equipment deterioration and elevated maintenance demands, placing additional financial strain [37].

In addition to power quality issues, improper placement can also lead to severe problems for the voltage profile and stability of the system. When DG units are not adequately integrated and optimally located, they can cause poor voltage regulation, leading to voltage instability within the distribution system. The issue becomes particularly severe at higher penetration levels of DGs, where the ability of the distribution network to maintain stable voltage levels is compromised [16],[36].

The next impact that may be caused by improper DG placement is the protection challenges in distribution systems. Since the integration of DGs can modify the level and direction of fault current, it may lead to the existing protection scheme mistakenly recognizing the fault current and triggering inappropriate action, such as not properly isolating the faulty section, thus jeopardizing the protection and safety of the distribution system [38][39].

With improper placement of DG, unintentional islanding can occur and lead to false tripping of the protective devices. This is due to the power supply from DG continuing to flow to the part of the grid independently, which may lead to a safety hazard and operational efficiency [36],[40]. Additionally, the bidirectional power flow resulting from the DG integration may cause significant modifications to the distribution systems' protection strategies by introducing directional protection schemes [41].

Besides power quality and protection challenges associated with improper DG placement, the losses and efficiency of the distribution system may also be affected.

Non-optimal placement of DG can affect the system by increasing the system's loss, hindering the benefits of DG integration. The overall efficiency of the distribution system may be affected by the suboptimal power flow paths and an increase in line losses [38]. This subsequently leads to an increase in operational costs and degrades the efficiency of the distribution systems [42]. Apart from that, the integration of DG may cause the miscoordination of overcurrent relays, leading to increased time taken for fault clearance. When the fault clearance requires more time, the unwanted disconnection might occur, thus degrading the system's reliability [40],[43].

Inappropriate placement of the DG, however, could lead to substantial economic fallout due to additional investment and operational costs associated with it. When the DGs are not optimally located, extra infrastructure will be needed to support their inefficient penetration, directly imposing a substantial capital investment cost. Furthermore, suboptimal allocation of DGs reduces the initial investment's recovery time and the system's long-term operating cost, which calls for suitable placement decisions to optimize the economic benefit and system performance [42].

Network planning and operational challenges will also arise due to improper DG placement. Thermal capacity within the distribution system network and security of the power supply will be affected by DG integration. This is because the inappropriate placement leads to the distribution system components overloading, reducing operational flexibility [44]. On top of this, to secure the benefits of DG integration, thorough planning and compliance with the regulatory frameworks are obligatory so that the system integrity is not compromised [45].

Looking into the system's reliability, improper placement and sizing of DG units can largely deteriorate the reliability of the distribution system. Higher values of System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI) are usually achieved when DGs are not efficiently integrated into the system, thus resulting in a higher number of system interruptions and longer system disconnections. These perturbations increase Expected Interruption Costs (ECOST) and directly impact the system's economic behaviour [46]. Furthermore, inadequate sizing and improper DG placement can lead to overcurrent problems, voltage instability, and deteriorating distribution system reliability. These disturbances may lead to more frequent downtimes, increasing economic losses and reducing system efficiency [47]. Therefore, ensuring an appropriate DG placement is vital for the

system's stability and for preventing real financial impact generated by doubts in reliability.

Despite the significant challenges associated with improper placement of DG, including increased economic losses, overcurrent issues, poor power quality and voltage instability, careful planning is crucial to mitigating these negative impacts. Improper DG placement can lead to higher system interruption frequencies and durations, which in turn escalate ECOST, affecting the overall economic performance of the system. Additionally, overcurrent and voltage instability can compromise system reliability, leading to frequent outages and operational inefficiencies. These challenges not only stress the importance of optimal DG placement but also highlight the need for effective grid management and protection strategies to minimize the adverse effects of DG integration. Adequately addressing these challenges is essential for ensuring the stability and resilience of the distribution system.

2.4 Benefits of Distributed Generation Placement in Distribution Systems

Optimal placement and sizing of DG units in distribution systems offer significant technical benefits, primarily in reducing power losses, enhancing voltage stability, and improving the overall reliability and efficiency of the grid. These benefits are achieved by strategically locating DGs close to load centres, which minimizes the distance electricity must travel, thereby reducing losses and improving voltage profiles. Moreover, the impact on grid stability is profound as the optimal DG placement can enhance the voltage stability index and allow for better management of power flows, contributing to a more resilient and reliable distribution network.

The first technical benefit of optimally placing the DG is reducing power loss. Many studies have been conducted in the literature, proving that properly placing and sizing the DG substantially reduces power loss. For instance, a study in [48] has demonstrated a considerable loss reduction of up to 71.15% across distribution networks. Similarly, another study in [49] has also shown that the proper placement of DG resulted in a Loss Reduction Index (LRI) achieving 0.2636 p.u, significantly indicating the reduction of power loss. Additionally, the authors in [50][51] have conducted the optimal DG placement and achieved a substantial loss reduction for both real and reactive power. More literature also supported this, where the power loss has been significantly reduced through the optimal DG placement [52][53].

In addition to the power loss reduction, the voltage profile must be considered when integrating DG. A poor voltage profile can bring the system to collapse despite reduced power loss. Therefore, to achieve a balanced system, the proper placement of DG must also consider voltage profile improvement. The same literature [48] has also investigated the optimal placement of DG by considering this parameter. In addition to loss reduction, this study has presented promising results in improving the voltage stability index and average absolute voltage error across various systems. Furthermore, a recent study in [54] also found that optimal allocation and sizing of DG can improve the voltage profile and reduce power loss. As a result, improving these two parameters enhances the system's efficiency. Similarly, several recent studies, such as [55], have demonstrated promising results regarding voltage profile improvement through voltage node deviation by effectively allocating the DG into the system. The study also presented both real and reactive power reduction, together with the improvement of the investment recovery period.

Moreover, in another study [56], the optimal placement of multiple PVDGs through multi-objective approaches has also improved the voltage profile and reduced both real and reactive power loss. Further research has focused on improving the voltage profile, power loss and penalty cost minimization through optimal placement of DG, as presented in [57]. Specifically, the research in [58] combines the goals to reduce the power loss and improve the voltage profile with a weighted sum approach for optimal placement of PV DG. The research integrated multiple DG, in this case, five units, and the placement has resulted in a notable improvement in the voltage profile and reduced power loss. The study in [59] also highlights the benefits of optimal placement of DG in improving the voltage profile while minimizing the system's loss. In the study, it has been found that by optimally locating the single unit of wind-type DG, the voltage profile was improved and within the acceptable range of 0.95 p.u. to 1.05 p.u., which resulted in 27.23% improvement in the distribution system performance. Another study in [60] aimed to address the multi-objective problem by integrating multiple DG types. As a result, the bus voltage remained within acceptable limits, and the power loss was reduced by more than 50%. Another recent study [61] has combined the integration of wind-type DG with DSTATCOM to solve a multi-objective problem. Again, this has significantly improved the voltage profile, reducing power loss while maximizing the economic benefits and reducing pollution levels. Recent studies, such as [62], have incorporated a multi-objective function when integrating DG into distribution system.

The study focuses on allocating the PVDG under various scenarios, and the results demonstrate that the bus voltage remains within acceptable limits while simultaneously reducing both real and reactive power losses. Similarly, another study in [63] has adopted a multi-objective approach for optimal DG placement by integrating two types of DG, wind and PV, into the IEEE 33-bus system. The results indicate significant voltage profile improvements while reducing power loss.

Apart from minimizing power loss and improving the voltage profile, voltage stability has also gained attention as a crucial parameter in DG integration. As an essential aspect of grid stability, voltage stability can be significantly enhanced through optimal DG placement. DGs play a key role in preventing voltage collapse by improving the voltage stability index, which could otherwise lead to blackouts [64][65]. This has been proven in [48], where optimal DG placement significantly increased the voltage stability index. Furthermore, research in [66] supports this finding, showing that the optimal placement of multiple DG units, specifically of type 1 and type 2, significantly improved voltage stability while reducing energy losses. Similarly, research in [23] demonstrated that the optimal placement of both PV and wind turbine (WT) types in a radial distribution system led to an increase in the Voltage Stability Index (VSI) alongside a reduction in power loss. In a separate study [67], the authors tested the placement of DG in a practical distribution network on a remote island in Norway. The results demonstrated a significant increase in the Network Voltage Stability Factor (NVSF), with an improvement of up to 293.59%, indicating a substantial enhancement in network voltage stability while minimizing power loss. In another study [68], the optimal placement of single and two DG units was analyzed, showing significant improvements in the Voltage Stability Margin (VSM) for both real and reactive power. The study also considered other key parameters such as power loss, minimum bus voltage, and Total Harmonic Distortion (THD) in the context of DG integration. Similarly, as presented in [69], another study on optimal DG placement explored single and multiple DG integrations. The study utilized a combination of DG types 1 to 4 in its analysis, with the results indicating an improvement in voltage stability, particularly when combining types 1 and 2 DG, along with a reduction in power loss. Additional studies, such as those in [70] and [71], have also demonstrated promising results regarding the optimal placement of DG, particularly in improving voltage stability within the distribution system network.

In addition to power loss reduction, voltage profile improvement, and voltage stability, research has also considered the reliability and security of the distribution system when optimizing DG placement. These factors ensure that the grid operates efficiently and can withstand potential disturbances. DG integration enhances the reliability and security of distribution systems by providing additional power sources that can operate independently in islanding mode during grid failures [64]. This capability ensures a continuous power supply to critical loads, thereby improving the overall resilience of the distribution system and reducing the impact of potential outages [72]. Optimal DG placement can lead to substantial reductions in power losses. For instance, studies have shown loss reductions of up to 71.15% in specific test systems, directly contributing to improved system reliability [48],[73]. Additionally, optimal DG placement reduces customer interruption costs by minimizing power outages and enhancing service continuity, further boosting reliability [74]. Security enhancements related to operational constraints were also explored in [75] where the optimal placement of PV and WT DG units was integrated into the IEEE 13-bus unbalanced radial network. The integration of DG units must account for operational constraints to ensure system security, which includes maintaining acceptable voltage levels and effectively managing load uncertainties. Besides that, DG units can improve the resilience of the distribution network by providing alternative power sources during faults, thus maintaining service continuity. This was demonstrated in the study [76], which proposed a model to enhance system reliability and resilience through optimal DG placement. The study showed reduced reliability costs associated with outages and resilience costs due to natural disasters, ultimately benefiting customer service continuity. Similarly, the study in [77] supports these findings, showing that optimal DG placement enhances system reliability by reducing outage duration, resulting in a 40% reduction in SAIFI, a 25% reduction in SAIDI, and a 25% reduction in EENS values.

In addition to reliability, the security factor related to environmental and economic benefits must also be considered when integrating DG into the distribution network. Optimally locating DG units can significantly contribute to environmental sustainability by reducing greenhouse gas emissions and fossil fuel dependency. This, in turn, indirectly supports system security by promoting cleaner energy sources [78]. This has been proven in [79], where optimally locating various types of DGs through a multi-objective function demonstrated significant contributions to environmental and

economic benefits in the distribution network. Furthermore, in a different study as in [80], the optimal placement of DGs in the IEEE 26-bus system led to notable reductions in operational and maintenance costs. Specifically, the study highlighted a reduction of \$1054.16 per hour in power generation costs due to optimal DG placement. The same results were also demonstrated in [26]. The study integrates type 1 and type 2 DG in the IEEE 33-bus system under different loading scenarios, showing a reduction in total yearly economic loss, including installation, operation, and maintenance costs, proving that the optimal DG placement can maximize the economic benefits.

While significant progress has been made in understanding the technical benefits of optimal DG placement, including power loss reduction, voltage profile improvement, voltage stability, and system reliability, many studies fail to address the full spectrum of critical parameters simultaneously. A common gap in the literature is that many studies focus on a single type of DG or only consider the placement of a single DG unit, neglecting the potential benefits of integrating multiple types of DG or various units. Additionally, many studies overlook the impact of load growth or future load increments, which can influence the long-term effectiveness of DG placement. These limitations highlight the need for more comprehensive experiments and analyses considering various DG types, multiple DG units, and factors like load increment to ensure an optimal and holistic approach to DG placement in distribution systems.

2.5 Application of Optimization Technique in Distributed Generation Placement

The trend in optimization techniques for optimal DG placement in distribution systems has evolved significantly, driven by the need to enhance power quality, reduce system losses, and improve voltage profiles. Recent advancements have focused on integrating intelligent algorithms, hybrid methods, and multi-objective optimization approaches to address the complexities of modern distribution networks. These techniques offer precise solutions for optimal DG placement, enabling more efficient positioning that maximizes benefits such as power loss reduction and voltage stability. By considering both technical and economic factors, these optimization methods aim to optimize the location and sizing of DGs, contributing to the development of more innovative, resilient, and sustainable distribution systems.

Optimization Techniques: From Analytical to Hybrid Metaheuristics

The methodologies employed to solve the DG allocation problem can be broadly categorized into analytical techniques, metaheuristic algorithms, and hybrid approaches.

Analytical and Traditional Methods

Early research heavily relied on conventional mathematical approaches such as Mixed-Integer Non-Linear Programming (MINLP), Dynamic Programming (DP), and exact loss formulas [81][82][83]. While these deterministic methods guarantee convergence to a unique, global optimum and feature highly efficient computation times for small-scale radial networks, they severely lack scalability [83][84]. As distribution networks increase in size and complexity, the computational burden of these analytical methods grows exponentially, making them rigid and overly conservative for dynamic real-world grids [16][85].

General and Advanced Metaheuristics

To overcome the non-linear, multi-modal nature of modern power systems, researchers shifted toward nature-inspired metaheuristics such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and Secretary Bird Optimization (SBO) [84][86][87]. These stochastic algorithms do not require complex derivative calculations, making them highly adaptable. However, standard baseline metaheuristics often suffer from premature convergence and trapping in local optima when applied to highly multi-dimensional problems [84].

Hybrid Approaches

To balance exploration and exploitation, recent literature emphasizes hybrid algorithms that combine the rapid search space reduction of analytical tools (like the Loss Sensitivity Factor) with the optimizing power of metaheuristics (such as the LSF-WOA or ABC-HC algorithms) [88][89]. This hybridization reduces computational time by up to 40% while maintaining robust accuracy and excellent scalability in large-scale meshed networks [84][89].

Objective Function Formulations: Single vs. multi-objective

The complexity of DG planning is largely dictated by how the Objective Function (OF) is formulated.

Single-Objective Optimization (SOO)

Many foundational studies limit their focus to a single technical parameter, predominantly the minimization of total active power loss or the reduction of operational costs [81][82][90]. While straightforward, this approach fails to capture the holistic impact of DGs on the grid.

Multi-Objective Optimization (MOO)

Modern frameworks concurrently optimize multiple competing objectives, including power loss reduction, Voltage Deviation (VD) minimization, Voltage Stability Index (VSI) improvement, and economic cost and profit analysis [91][92][93]. To solve MOO problems, researchers typically employ the Weighted Sum Method (WSM), which assigns fractional coefficients to convert competing objectives into a single fitness function [86][94]. Alternatively, advanced studies utilize Pareto optimal fronts to generate a set of non-dominated, compromise solutions where no single objective can be improved without degrading another, often using fuzzy decision-making to select the final grid configuration [94][95].

Load Modelling, Reliability and Power Quality

Historically, models relied on constant power load models and assumed perfectly balanced systems [84]. Current advanced studies recognize that this fails to capture the dynamic reality of modern grids. Consequently, literature is evolving to incorporate voltage dependent load models and varying seasonal load profiles to test DG efficacy under peak, medium, and light loading scenarios [84][88]. Furthermore, while basic reliability improvements and voltage profile enhancements are frequently studied [96][97], specific power quality issues like Total Harmonic Distortion (THD) are gaining attention. Studies utilizing harmonic flow analysis have demonstrated that the integration of non-linear DGs can significantly impact voltage THD, requiring careful sizing and placement to keep distortions within IEEE tolerable limits [88].

Despite these advancements, many existing hybrid studies remain narrowly focused on technical aspects (loss reduction and voltage profiles) and overlook critical

elements such as economic constraints, grid dependency, varying load conditions, and the harmonic impacts of modern penetrations like Electric Vehicle Charging Stations (EVCS). In addition, there is a heavy reliance on deterministic data, often ignoring the stochastic, intermittent nature of renewable energy (solar/wind) and dynamic load fluctuations [16]. While recent studies have begun exploring grid restructuring to accommodate Electric Vehicle Charging Stations (EVCS) [84], investigating power quality impacts like THD mitigation [88] and pursuing economic cost savings and profit analysis [93], there is currently no single, unified framework in the literature that simultaneously co-optimizes all three. Researchers treat smart grid infrastructure (EVCS), power quality penalties (THD) and techno-economic feasibility (costs) as separate domains. Developing a comprehensive multi-objective optimization framework that concurrently targets EVCS integration, THD mitigation, and economic cost savings represents a highly relevant, unaddressed frontier for future work.

To clearly visualize the methodological gap that this research intends to fill, **Table 2.1** summarizes the respective strengths and weaknesses of the various optimization categories discussed in the literature and highlights how the proposed LSF-MALO approach bridges these structural gaps.

Table 2. 1
Comparison Of Optimization Techniques

Theme	Approach	Key Characteristics & Strengths	Limitations & Future Directions
Optimization Algorithms	Analytical Methods (e.g., MINLP, DP, Exact Loss)	Guarantee convergence to a unique, exact global optimum and feature highly efficient computation times for small-scale radial networks	Suffer from exponential computational burden and lack of scalability, rendering them rigid and overly conservative for large, complex networks
	Standard Metaheuristics (e.g., GA, PSO, WOA, SBO)	Do not require complex mathematical derivative calculations, making them highly adaptable for non-linear, multi-modal power flow problems	Inherently stochastic and frequently suffer from premature convergence and trapping in local optima when applied to highly multi-dimensional scenarios
	Hybrid Approaches (e.g., LSF-WOA, ABC-HC)	Combine analytical search space reduction (e.g., Loss Sensitivity Factor) with metaheuristic optimization. Reduces computational time	Increases the structural and coding complexity of the framework. Recommended to be expanded to highly

		significantly while maintaining robust accuracy and scalability	complex, large-scale meshed networks
Objective Function (OF) Formulations	Single-Objective Optimization (SOO)	Straightforward formulation that typically focuses strictly on the minimization of total active power loss or reduction of operational costs	Fails to capture the holistic impact of DGs on the grid, ignoring power quality, stability, and broad economic metrics
	Multi-Objective Optimization (MOO)	Concurrently optimizes competing metrics (power loss, Voltage Deviation, Voltage Stability Index, and economics) using the Weighted Sum Method (WSM) or Pareto optimal fronts	Requires complex resolution strategies, such as fuzzy decision-making or multi-criteria analysis, to select the final grid configuration from a Pareto set
Load Modelling & Power Quality	Load Modelling	Evolving from simplistic constant power load models to voltage dependent load Models and varying seasonal load profiles	Historic reliance on perfectly balanced systems and nominal profiles fails to represent real-world dynamic load fluctuations
	Power Quality (THD)	Increasing attention to the integration of non-linear DGs and their impact on voltage Total Harmonic Distortion (THD), requiring harmonic flow analysis	THD mitigation is often studied in isolation rather than integrated into broader techno-economic planning models

2.6 Impact of Electric Vehicle Charging Stations on the Distribution System

The growing use of Electric Vehicles (EVs) has led to increased penetration of Electric Vehicle Charging Stations (EVCS), which can significantly impact the distribution system's performance. This has opened new challenges in maintaining the stability and efficiency of the distribution systems. There are various impacts of the adoption of EVCS involving technical, environmental, and economic aspects of the distribution system. One of the impacts of the EVCS penetration is voltage stability issues. This is because the load increment from the charging stations can affect the voltage profile of the distribution system. This issue becomes noticeable especially in low voltage networks since the voltage limits must be within the required limits [98]. Recent studies in [99][100] have demonstrated the significant impact on the voltage profile when placing EVCS randomly in the IEEE 33-bus system. Besides the voltage

profile, the integration of EVCS might also lead to increased power losses. The consequence is due to the additional load introduced by charging stations, which heightens the energy losses, especially during peak demands [99],[101]. This has been proven by a study in [102] which utilized the stochastic Monte Carlo algorithm to simulate the various EV penetration scenarios, and the result confirmed that higher EV penetration can lead to increased power losses.

Besides these technical impacts, the reliability and operational aspects might face the same challenges. With high charging loads of EVCS, the reliability of the distribution system will be jeopardized since the critical operating parameters can be degraded, leading to customer dissatisfaction [100]. In addition, the increased integration of EVCS can contribute to the increased harmonic injection into distribution system. This issue must be addressed since it can lead to harmonic pollution if not adequately controlled. Despite some studies have shown that the harmonic distortion remains below 1%, the possibility to increase beyond the limit should not be taken for granted, as it can escalate due to the rapid growth of EVCS infrastructure [103][104][105][106][107]. Despite all these challenges faced by the integration of EVCS, the positive impact can also be seen with the shift from combustion engines to EVs, which offers environmental benefits, including the reduction in CO₂ emissions [102]. Furthermore, the penetration of EVCS can provide new ways for the distribution system to stay flexible. Electric vehicle fleets can provide services similar to energy storage, such as balancing supply and demand, significantly reducing the need for centralized storage capacities [108].

Due to the negative impacts of the EVCS penetration, many studies have been conducted to mitigate these negative impacts. One of the mitigation strategies is to find the optimal placement of EVCS through an optimization approach. This can be seen in much literature where studies have employed optimization techniques such as PSO [109][110][111], Hybrid Particle Swarm Grey Wolf Optimization (HPSOGWO) algorithm [112], Fuzzy Multi-Objective Optimization and African Vulture Optimization Algorithm (AVOA) [113], Artificial Bee Colony (ABC) [114], Competitive Search Optimization (CSO) [115], Improved Harris Hawk's Optimizer Algorithm (IHHOA) [116] and whale optimization technique (WOT) [117] either for optimal EVCS placement or optimal DG and EVCS placement simultaneously. While existing studies on optimal DG placement in distribution systems often consider both DGs and EVCS in tandem, there remains a significant gap in addressing the

optimization of DG placement specifically within systems that already integrate EVCS. Most research focuses on the simultaneous placement of DGs and EVCS, assuming these systems are implemented together from the outset. However, in real-world applications, many distribution systems already have established EVCS. The challenge shifts to optimizing DG placement within the constraints and operational conditions of these existing EVCS infrastructures.

Furthermore, the majority of the studies on finding the optimal placement of DG and EVCS mostly focus on technical performance indicators such as improvement of voltage profile and reduction of power loss. While the parameters are crucial in maintaining the distribution system stability and reliability, the broader spectrum of challenges associated with the integration of EVCS is often neglected. There exist limited studies that explore the issues of harmonic distortion despite the nature of EVCS as a nonlinear load, which can introduce harmonic injection into the distribution system, leading to power quality issues. Thus, by addressing this issue, it can represent a vital yet underexplored dimension of impact in EVCS integration. In addition, another area that is often overlooked is the grid dependency with the presence of EVCS. With the widespread deployment of EVCS, it has increased the dependency of the charging infrastructure on the grid. With high penetration levels, especially when large numbers of EVs are charged simultaneously, the demand can overlap with the current peak load conditions, which can lead to stress in the distribution systems. Despite its practical importance, grid dependency in the context of EVCS integration and its interaction with DG placement strategies remains insufficiently investigated.

2.7 Harmonic Signatures of EV Charging Levels

Electric vehicles interface with the distribution grid via power electronic converters (AC/DC rectifiers) required to charge the vehicle's DC battery. Because these converters are non-linear loads, they draw distorted current waveforms from the grid, subsequently injecting harmonic currents back into the distribution network. The specific harmonic spectrum, commonly referred to as the harmonic signature, varies significantly depending on the EV charging level and the underlying converter topology [118].

Level 1 and Level 2 chargers typically utilize single-phase connections and rely on the EV's onboard AC/DC rectifier. The harmonic signature of these slower AC

chargers is generally dominated by low-order odd harmonics, specifically the 3rd and 5th harmonic orders [119]. While the absolute current draw of a single Level 1 or Level 2 charger is relatively small, the simultaneous uncoordinated charging of multiple vehicles in a residential distribution network can aggregate these low-order harmonics, leading to severe voltage distortion and phase unbalance.

In contrast, Level 3 EV Charging Stations (EVCS) bypass the onboard electronics to supply high-power DC current directly to the battery via massive, off-board three-phase rectifiers. These commercial stations typically utilize multi-pulse topologies (e.g., 6-pulse or 12-pulse rectifiers). The harmonic signature of a Level 3 charger follows the characteristic harmonic equation. Consequently, these high-frequency DC converters typically inject dominant 5th, 7th, 11th, and 13th harmonic currents into the supply grid [120].

Consequently, the severe grid impacts associated with these distinct harmonic signatures underscore the critical necessity of incorporating Total Harmonic Distortion (THD) constraints into this study. Traditional optimization methodologies for DG placement often focus exclusively on active power losses and fundamental voltage profiles, neglecting the severe power quality degradation induced by nonlinear EVCS loads. If these harmonic injections are ignored, network planners risk severe grid instability, transformer overheating, and resonance issues. Therefore, explicitly modelling THD is essential to ensure that the proposed LSF-MALO algorithm not only maximizes network efficiency but also strictly maintains statutory power quality compliance (such as IEEE Std 519), providing a robust, safe, and realistic optimization solution for modern distribution systems.

2.8 Research Gap

Despite extensive research and studies have been conducted in the field of optimal DG placement, several limitations persist in the existing literature. Many studies have focused on reducing power losses, improving the voltage profile, and enhancing the overall performance of the distribution system. However, several research gaps remain that need to be addressed. These can be summarized into the following main points:

- i) There is a need for more comprehensive objective functions that extend beyond conventional technical aspects, such as voltage profile enhancement and power loss minimization, by incorporating economic considerations and power quality issues under realistic operating conditions.
- ii) Many existing studies oversimplify DG modelling by focusing only on a single DG technology, thereby overlooking the diversity of available DG types and limiting the applicability of their findings to real-world distribution systems.
- iii) Load conditions are often assumed to be static, without considering load variations, which reduces the robustness and adaptability of proposed DG placement strategies in dynamic and practical operating environments.
- iv) Limited research has addressed optimal DG placement in distribution systems with pre-existing EVCS. Most studies either consider simultaneous optimization of DG and EVCS placement or neglect EVCS integration altogether, which fails to represent realistic deployment scenarios.
- v) The influence of harmonic distortion introduced by EVCS as nonlinear loads has been largely overlooked, despite its significant impact on power quality, equipment performance, and overall system reliability.
- vi) The issue of grid dependency in EVCS-dominated systems remains underexplored. High penetration of EVCS can exacerbate stress on the grid, especially during peak demand, yet this challenge is seldom incorporated into DG placement research.
- vii) There is a growing need for advanced and hybrid optimization techniques capable of simultaneously addressing multi-dimensional objectives and constraints in DG placement problems, aligning with the trend in recent literature toward more sophisticated metaheuristic and hybrid approaches.

2.9 Chapter Summary

This chapter has critically reviewed the existing literature on optimal DG placement in distribution systems, with and without the presence of EVCS. It has addressed the impact of the improper placement of DG and the key challenge with the integration of EVCS in the distribution system. The key benefits of the optimal DG placement, such as loss reduction, voltage profile improvement, and system efficiency,

were highlighted alongside the challenges, including the harmonic distortion and grid dependency. A review of optimization techniques demonstrated the growing reliance on advanced and hybrid metaheuristics for addressing multi-objective problems. The analysis of strengths and weaknesses in past research led to the identification of several gaps, which provide the basis and motivation for this study.

CHAPTER 3

DEVELOPMENT OF HYBRID LOSS SENSITIVITY FACTOR & MUTATED ANT LION OPTIMIZER ALGORITHM FOR OPTIMAL DISTRIBUTED GENERATION PLACEMENT

3.1 Introduction

This chapter presents the development of hybrid Loss Sensitivity Factor and Mutated Ant Lion Optimizer (LSF-MALO) algorithm for optimal Distributed Generation (DG) placement. The main focus here is to verify the performance of the proposed algorithm in single-objective optimization (SOO) problem under various loadings and the presence of DG in the test system. For a systematic explanation, this chapter is divided into four main sections as follows: (1) section 3.2 gives general introduction on DG technology and LSF technique; (2) section 3.3, the first part of methodology, presents development of the proposed hybrid LSF-MALO algorithm; (3) section 3.4, the second part of methodology, presents the proposed problem formulation for optimal DG placement using LSF-MALO and finally; (4) section 3.5 does the analysis on performance of the proposed algorithm under several case studies

3.2 Renewable Distributed Generation (DG) and Loss Sensitivity Factor (LSF)

This section describes the various types of DG technology which have been implemented in the previous works and followed by a brief introduction on Loss Sensitivity Factor (LSF).

3.2.1 Renewable Distributed Generation (RDG)

Distributed generation (DG) is a method that uses small-scale technologies to generate electricity close to consumer. According to the IEA [121], the definition of DG is a source of electricity that is directly linked to the distribution network in order to supply local customers and maintain the distribution network. DG typically consists of modular and occasionally renewable energy sources that offer some potential assistance to the electrical network.

When compared to conventional power generators, DG has the potential to supply electricity at lower cost while simultaneously improving system's reliability and security with minimum impact on the surrounding environment. The size of DG is typically quite small, with a range that falls between 50 MW and 100 MW [122].

DG technologies are classified into two categories: renewable energy sources and fossil fuel energy sources [123]. Wind power, solar photovoltaic (PV), micro-hydro, and biomass generators are the DG technologies that fall under renewable energy sources, which will be called as Renewable Distributed Generation (RDG) in this study. On the other hand, micro-turbines, diesel generators and small gas turbines are the examples of fossil fuel DG technologies [5].

However, the DG technologies can also be categorized in terms of the type of powers, either real or reactive power, that they will inject to or absorb from the system. These are given as follows [124]:

- i) Type 1 : Inject only active power (P_{DG}) – examples are fuel cell, solar PV and bio-gas.
- ii) Type 2 : Inject both active power (P_{DG}) and reactive power (Q_{DG}) – example is gas turbine-based synchronous generator.
- iii) Type 3 : Inject only reactive power (Q_{DG}) – example is synchronous condenser, FACTS devices and capacitor bank.
- iv) Type 4 : Inject active power (P_{DG}) but consume reactive power (negative Q_{DG}) – example is wind turbine-based induction generator.

3.2.2 Loss Sensitivity Factor (LSF)

The fundamental concept behind the Loss Sensitivity Factor (LSF) involves simplifying complex, nonlinear system equations by linearizing them around a starting operating point. This mathematical approach is historically rooted in the well-known 'Exact Loss' formula and serves to significantly narrow down the potential solution space during the optimization process. When assessing the LSF, the indices do not fall within a fixed numerical range, rather, they are evaluated relatively by organizing the computed sensitivities of all network buses into a descending hierarchy. In this framework, the optimal values correspond to the highest indices on the ranking list. The bus demonstrating the highest sensitivity to real power injection is pinpointed as the

most effective candidate for DG placement to reduce real power losses. Conversely, unsatisfactory values fall at the bottom of this ranking, representing bus locations where DG integration would offer negligible benefits to the network's overall loss reduction. [125]. The LSF technique computes the sensitivity factor at each bus in the distribution system. In this study, equation (3.1) will be used to calculate the sensitivity factor of real power loss with respect to real power injection at i -th bus:

$$\gamma_i = \frac{\partial P_L}{\partial P_i} = 2 \sum_{j=1, j \neq i}^N (\alpha_{ij} P_j - \beta_{ij} Q_j) \quad (3.1)$$

Where, γ_i is the LSF index at i -th bus, P_L is the total real power losses in the system, P_i is the net real power injection at i -th bus, P_j and Q_j are the net real and reactive power injection at j -th bus (i.e. those buses other than bus i), N is the number of buses in the system and α_{ij} and β_{ij} are the parameters calculated based on bus voltages and bus impedance matrix.

Before calculating the LSF indices, the test system is simulated using load flow analysis to obtain the required parameters for the calculation, such as bus voltages (magnitudes and angles), real power losses, net real and reactive power injections at all buses and bus impedance matrix. Afterwards, the LSF indices are calculated for each bus and arranged in descending order to form a priority list. The priority list will then be used to provide a list of candidate buses for DG locations before sizing algorithm takes place. A detail procedure for calculating the LSF indices will be explained in the later section and illustrated in **Figure 3.4**.

3.2.3 The LSF Analytical Flow Process

While this research utilizes the LSF indices primarily as an initial filtering stage for the proposed hybrid algorithm, the standalone LSF Analytical method is also employed as a deterministic benchmark for comparative analysis. The procedure for executing the complete LSF Analytical analysis to identify both the optimal location and sizing for DG units involves a systematic sequence of steps:

- i) **Initial Assessment:** The algorithm initiates by running a baseline load flow analysis to evaluate the system's initial parameters and reliability metrics.
- ii) **Candidate Placement:** Utilizing the descending LSF priority list, a single DG unit is assigned to the top-ranked candidate bus, followed by a new load flow computation.
- iii) **Constraint Verification:** The system checks that the voltage magnitudes at all buses remain strictly within the predefined maximum and minimum acceptable limits.
- iv) **Iterative Sizing:** Provided the voltage constraints are satisfied, the capacity of the DG unit is determined using a direct mathematical approach. Guided by the hierarchy of the LSF priority list, a DG unit is assigned to the selected bus, and its capacity is incrementally scaled upward from an initial 0 MW. This iterative sizing continues until the system reaches the specific DG capacity that yields the maximum reduction in total power losses.
- v) **Loss Evaluation:** The total power losses for the updated configuration are calculated and compared against the prior state to determine if an overall reduction was achieved.
- vi) **Data Storage:** If the newly computed system loss is lower than the previous iteration, this improved configuration is saved as the optimal solution, and the older values are discarded.

3.3 Methodology Part 1: Algorithm Development

This section presents the development of hybrid algorithm using Ant Lion Optimizer (ALO) and Evolutionary Programming (EP). Throughout this study, the proposed hybrid algorithm is called as Mutated Ant Lion Optimizer (MALO) and will be incorporated with LSF technique for solving the DG placement problem.

3.3.1 Ant Lion Optimizer Algorithm

Since the proposed MALO algorithm is mainly based on the original ALO, this section presents the original algorithm which will become the basis for hybridization with EP afterwards. The ALO is one of the nature-inspired algorithms that was developed by Seyedali Mirjalili in 2015 [126]. This algorithm replicates the natural

phenomenon of antlions preying on ants, with antlions waiting inside their pits to trap the ants. This is illustrated in **Figure 3.1**. The main components of ALO consist of ALO operators, random walks of ants, antlions' traps, building traps by antlions, sliding ants towards antlions, catching ants and rebuilding traps, updating ants' positions and elitism.

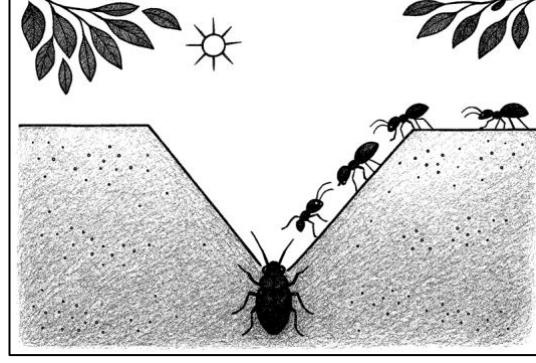


Figure 3. 1 An Antlion Inside The Pit Waiting To Trap Ants [126]

ALO operators

The population of ants and antlions are the ALO operators or search agents. In the algorithm, the ants, walking randomly within the search space, are similar to particles in Particle Swarm Optimization (PSO) or individuals in Genetic Algorithm (GA). It is also assumed that the antlions are hiding somewhere in the search space [126]. The positions of ants and antlions within the search space are saved in two separate matrices of $\mathbf{M}_{\text{Ant}}$ and $\mathbf{M}_{\text{Antlion}}$ respectively, while their fitness is saved in two vectors of $\mathbf{M}_{\text{OA}}$ for ants and $\mathbf{M}_{\text{OAL}}$ for antlions. The order of the position matrices of $\mathbf{M}_{\text{Ant}}$ and $\mathbf{M}_{\text{Antlion}}$ is M by N , with M and N represent the number of search agents (ants and antlions) and the number of dimensions respectively.

Random walks of ants

The ants are assumed to move stochastically in nature when searching for food. This behaviour of movement is called random walk and every ant in the population will update its position based on such behaviour. The random walk of an ant at t -th iteration is represented by equation (3.2):

$$X(t) = [0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1, \dots, \text{cumsum}(2r(t_n) - 1)] \quad (3.2)$$

Where, *cumsum* computes the cumulative sum, n is the maximum number of iterations, t represents the random walk step or iteration, and $r(t)$ is a stochastic function defined as in equation (3.3):

$$r(t) = \begin{cases} 1 & \text{if } rand > 0.5 \\ 0 & \text{if } rand \leq 0.5 \end{cases} \quad (3.3)$$

Where, *rand* is a random number generated with a uniform distribution in the range of $[0, 1]$.

Later, the ants will update their positions with random walks at each stage of optimization. Nonetheless, due to the search space boundary, equation (3.2) cannot be used straight away. This means that the random walks must be kept within the search space throughout the optimization. For this reason, the random walk equation is normalised via equation (3.4):

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i - c_i^t)}{(d_i^t - a_i)} + c_i \quad (3.4)$$

where a_i is the minimum random walk of i -th variable, d_i is the maximum of random walk in i -th variable, c_i^t is the minimum of i -th variable at t -th iteration, and d_i^t indicates the maximum of i -th variable at t -th iteration. To ensure the existence of a random walk in the search space, equation (3.4) should be applied at each iteration [126].

Effect of antlions' traps on random walks

In ALO, if the ants are the ones that perform the random walks, the antlions, on the other hand, create the traps. The random walks of the ants are affected by the antlions' traps. Equations (3.5) and (3.6) are used to model this effect:

$$c_i^t = Antlion_j^t + c^t \quad (3.5)$$

$$d_i^t = Antlion_j^t + d^t \quad (3.6)$$

Where, c^t is the minimum of all variables at t -th iteration, d^t is the vector including the maximum of all variables at t -th iteration, c_i^t is the minimum of all variables for i -th ant,

d_i^t is the maximum of all variables for i -th ant and $Antlion_j^t$ indicates the position of the selected j -th antlion at t -th iteration.

Building traps by antlions (selection of antlions)

In building a trap, an antlion will be selected to represent its hunting capability. The selection of the antlion is based on roulette-wheel selection. Based on this method, whichever antlions that have fitter solutions should possess a higher chance of getting selected for catching the ant. Thus, for each ant in the population, the roulette-wheel antlion will be selected so that it can catch the ant every time the ant performs the random walk around it.

Sliding ants towards antlions

After performing random walk, the ant is expected to arrive at the antlion's trap. When this happens, the antlion shoots sand outward the centre of the pit, causing the ant to slide down and prevent it from escape. To model this situation, the radius of the ant's position is reduced through equations (3.7) and (3.8) which mimic the sliding process of the ant inside the pit.

$$c^t = \frac{c^t}{I} \quad (3.7)$$

$$d^t = \frac{d^t}{I} \quad (3.8)$$

Where, c^t is the minimum of all variables at t -th iteration, d^t is the vector including the maximum of all variables at t -th iteration and I is a ratio that controls the sliding of ants towards the antlion and is calculated using the following equation:

$$I = 10^w \frac{t}{T} \quad (3.9)$$

where t is the current iteration, T is the maximum number of iterations, and w is a constant defined based on the current iteration and is used to adjust the exploitation accuracy. The value for w is set dynamically as follows: $w = 2$ when $t > 0.1T$, $w = 3$ when $t > 0.5T$, $w = 4$ when $t > 0.75T$, $w = 5$ when $t > 0.9T$, and $w = 6$ when $t > 0.95T$.

Catching ants and rebuilding traps by antlions

As the ant slides down and reaches the bottom of the pit, the antlion catches and pulls it into the sand before it is consumed. In ALO, the ant can only be caught if its fitness is better than its corresponding antlion. Hence, the antlion, after catching and consuming the ant, will update its position to the latest ant's position that it has caught. Through this way, the antlion will have greater chance for catching the next ants in the next optimization stage. The position update for antlion to mimic the process of catching ant is given by equation (3.9):

$$Antlion_j^t = Ant_i^t ; \quad \text{if } f(Ant_i^t) > f(Antlion_j^t) \quad (3.9)$$

Where, t is the current iteration, $Antlion_j^t$ is the position of selected j -th antlion at t -th iteration and Ant_i^t is the position of i -th ant at t -th iteration.

Elitism and updating ants' positions

The purpose of elitism is to maintain the best solution obtained at any stage of optimization. In the case of ALO, the best solution is represented by the fittest antlion in the population, which is called as elite antlion. This means that at every current iteration, the algorithm keeps updating its elite antlion before entering the next iteration, thus, ensuring a global optimum solution.

In addition to the roulette-wheel antlion, the elite antlion should also be able to affect the movement of all ants at every iteration. Hence, it is assumed that each ant in the population performs the random walk around both the roulette-wheel antlion and the elite antlion simultaneously. As a result, the ant will update its position based on the random walk around both antlions as in equation (3.10):

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (3.10)$$

Where, R_A^t is the random walk around the antlion selected via roulette-wheel at t -th iteration, R_E^t is the random walk around the elite antlion at t -th iteration and Ant_i^t is the updated position of i -th ant at t -th iteration. **Figure 3.2** summarizes the ALO algorithm as explained above.

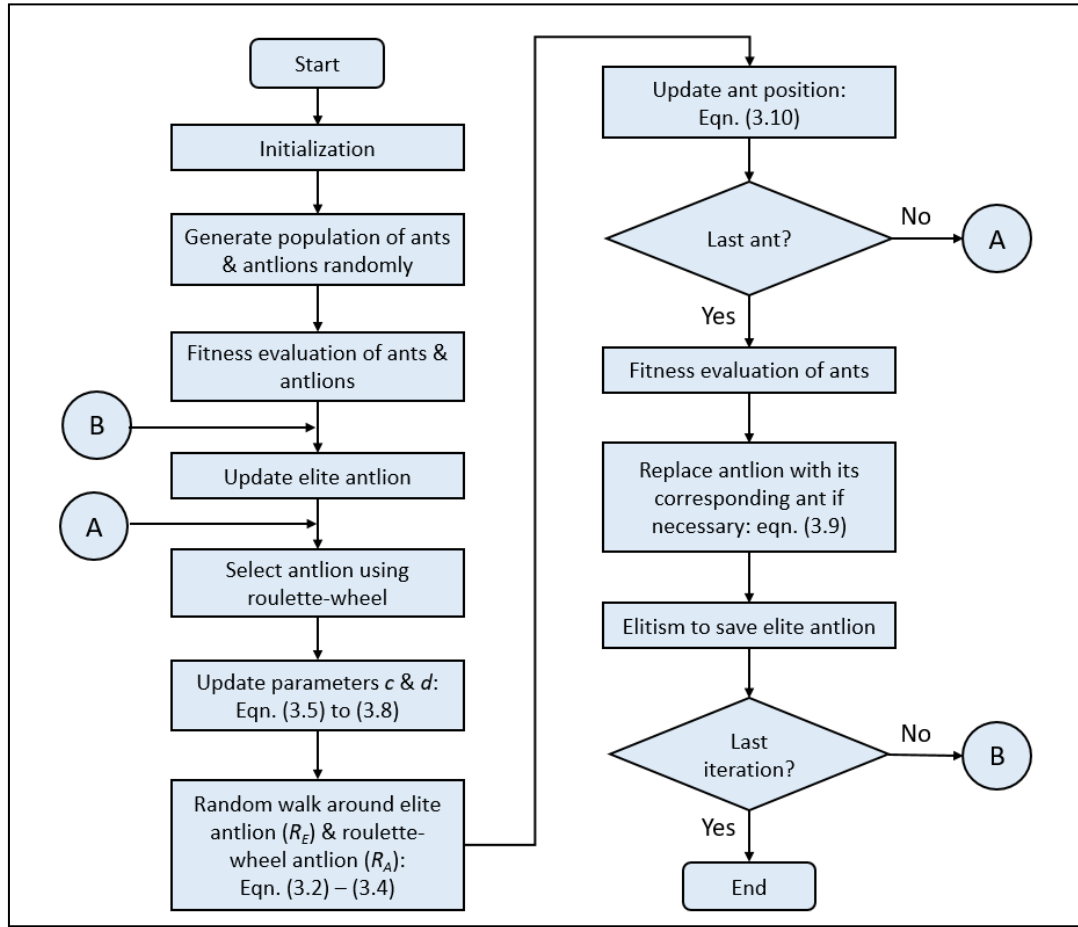


Figure 3. 2 Ant Lion Optimizer (ALO) Algorithm

3.3.2 Proposed Mutated Ant Lion Optimizer

This section explains the reason for hybridizing both ALO and EP to produce an improved algorithm, namely the Mutated Ant Lion Optimizer (MALO). As discussed in Chapter 2, hybridization is the process of combining two existing techniques in order to eliminate some of the drawbacks associated with each technique. The process also reduces the search space, improves computational time, and reduces the likelihood of the solution becoming stuck in local optima. The fundamental algorithm for the proposed MALO will be almost the same as that of ALO, with the inclusion of mutation operator from EP. The mutation technique is used to boost population diversity and reduces the tendency of the algorithm towards local optima [127]. Although the mutation operator can also be found in Genetic Algorithm (GA), the one from EP is chosen because its reproduction operator is more heuristic and simpler when mapping the solution, while also providing better convergence [128].

In this study, the EP's mutation operator will be used to generate a hybrid solution, called as 'mutated' antlion, in addition to the existing roulette-wheel and elite antlions. This means that the new position of an ant is obtained by performing random walk around the three antlions, instead of two as in the original ALO. As a result, the sole dependence on the elite antlion will be reduced and the algorithm will be able to explore for other regions within the search space. Furthermore, through this process, a variety of solutions can be obtained, and this will prevent the algorithm from becoming stuck in local optima. The MALO's mutation and solution update work as follows.

- i) At first, an antlion is chosen from the current antlion population. It is called as parent antlion.
- ii) Next, Gaussian distribution-based mutation is carried out to produce offspring antlion or mutated antlion using equation (3.11) [129].

$$mutated_{antlion_i} = parent_{antlion_i} + N(0, \sigma_i^2) \quad (3.11)$$

Where, $N(0, \sigma_i^2)$ denotes the Gaussian random variable with mean and standard deviation are zero and σ_i ; $parent_antlion_i$ and $mutated_antlion_i$ are the positions of i -th parent antlion and i -th mutated antlion respectively. The calculation of the standard deviation, σ_i is based on EP algorithm which is given by equation (3.12):

$$\sigma_i = \beta [\max(parent_{antlion}) - \min(parent_{antlion})] \left(\frac{f_i}{f_{max}} \right) \quad (3.12)$$

Where, β is the mutation scale in the range of $[0,1]$, $\min(parent_antlion)$ and $\max(parent_antlion)$ are the minimum and maximum values of parent positions from the current antlion population respectively, f_i is the fitness of i -th parent antlion and f_{max} is the maximum fitness of the current antlion population.

- iii) The random walk is then performed by an ant around the mutated antlion (R_M^t) in addition to the elite antlion (R_E^t) and the roulette-wheel antlion (R_A^t). These three random walks are calculated as in equations (3.13) to (3.24). It begins with the cumulative sum of the random walks around the three antlions as represented by equations (3.13) to (3.15).

$$X_E^t = [0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1, \dots, \text{cumsum}(2r(t_n) - 1] \quad (3.13)$$

$$X_A^t = [0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1, \dots, \text{cumsum}(2r(t_n) - 1] \quad (3.14)$$

$$X_M^t = [0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1, \dots, \text{cumsum}(2r(t_n) - 1] \quad (3.15)$$

Afterwards, the effects of the antlions' trap on the random walks are represented as in equations (3.16) to (3.21).

$$c_E^t = \text{elite}_{antlion}^t + c^t \quad (3.16)$$

$$d_E^t = \text{elite}_{antlion}^t + d^t \quad (3.17)$$

$$c_A^t = \text{roulette}_{antlion}^t + c^t \quad (3.18)$$

$$d_A^t = \text{roulette}_{antlion}^t + d^t \quad (3.19)$$

$$c_M^t = \text{mutated}_{antlion}^t + c^t \quad (3.20)$$

$$d_M^t = \text{mutated}_{antlion}^t + d^t \quad (3.21)$$

Where, X_E^t , X_A^t and X_M^t are the cumulative sums for the random walks around the elite antlion, the roulette-wheel antlion and the mutated antlion respectively; c^t and d^t are the parameters to represent the antlions' trap; elite_antlion^t , $\text{roulette_antlion}^t$ and mutated_antlion^t are the current positions of the elite antlion, the roulette-wheel antlion and the mutated antlion respectively.

Later, the normalized random walks around the three antlions, which will be used for ant's position update, are represented as in equations (3.22) to (3.24).

$$R_E^t = \frac{(X_E^t - a_E) \times (d_E^t - c_E^t)}{(b_E - a_E)} + c_E^t \quad (3.22)$$

$$R_A^t = \frac{(X_A^t - a_A) \times (d_A^t - c_A^t)}{(b_A - a_A)} + c_A^t \quad (3.23)$$

$$R_M^t = \frac{(X_M^t - a_M) \times (d_M^t - c_M^t)}{(b_M - a_M)} + c_M^t \quad (3.24)$$

Where, R_E^t is the normalized random walk around the elite antlion at t -th iteration; R_A^t is the normalized random walk around the antlion selected by roulette-wheel at t -th iteration; R_M^t is the normalized random walk around the mutated antlion at t -th iteration; a_E , a_A and a_M are the minimum random walks from equations (3.13), (3.14) and (3.15); and, b_E , b_A and b_M are the maximum random walks from equations (3.13), (3.14) and (3.15) respectively.

- iv) After the random walks have been performed around the three antlions, each ant at t -th iteration will update its position via equation (3.25).

$$Ant_i^t = \frac{R_A^t + R_E^t + R_M^t}{3} \quad (3.25)$$

Where, Ant_i^t is the updated position of i -th ant at t -th iteration. With this new update equation for ants' positions, there will be variety of solutions at every stage of optimization, thereby reducing the algorithm's sole dependence on elite antlion and ensuring local optima prevention.

The overall algorithm for the proposed MALO is presented in **Figure 3.3**.

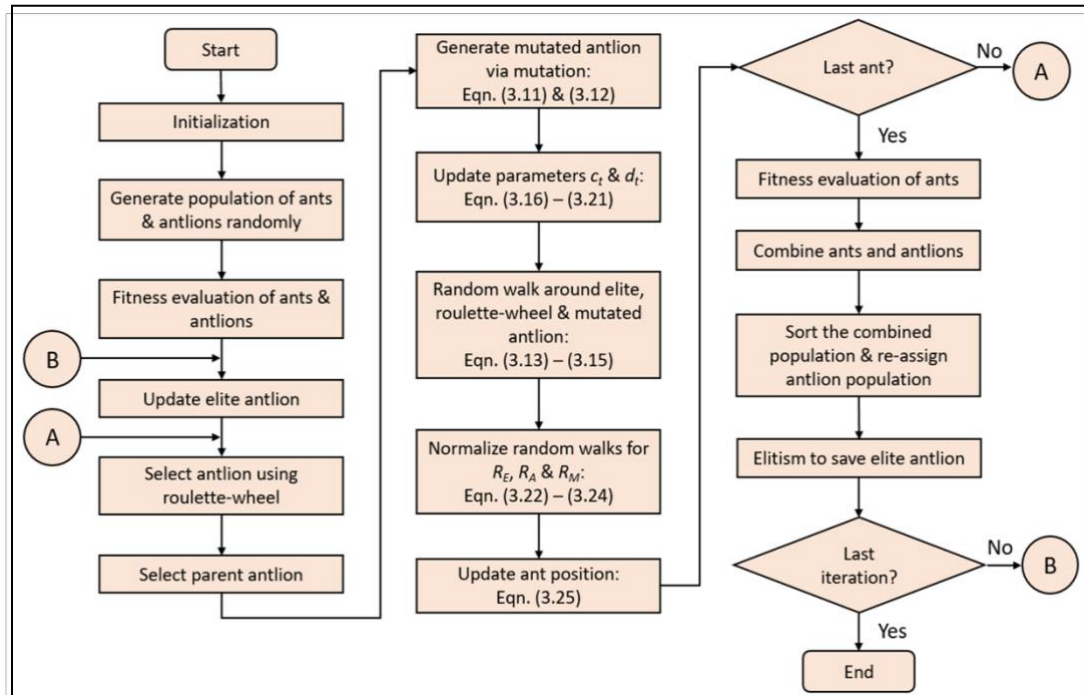


Figure 3. 3 Proposed Mutated Antlion Optimizer (MALO) Algorithm

The algorithm as in **Figure 3.3** works as follows:

- i) Initialization requires the setting of essential parameters of the algorithms such as population size, maximum iteration, lower and upper boundaries of decision variables and mutation scale, β .
- ii) Generation of population will generate randomly the initial positions of ants and antlions, i.e. the initial values of decision variables within the specified boundaries. This is performed as follows: $X = X_{LB} + (X_{UB} - X_{LB}) * rand$; where X , X_{LB} , X_{UB} and $rand$ are the initial position, lower boundary, upper boundary and random number between 0 and 1, respectively.
- iii) Fitness evaluation will evaluate the fitness values of the randomly generated population of ants and antlions.
- iv) The elite antlion is selected based on the fitness value. Whichever individual antlion that has the fittest solution will be assigned as the elite antlion.
- v) Roulette-wheel selection is then performed to choose the second antlion from the current antlion population.
- vi) Next, the third antlion is chosen starting with the first antlion from the current antlion population. This will be the parent antlion to be used in the mutation process.
- vii) Based on the parent antlion, the mutated antlion is produced by mutation using equations (3.11) and (3.12).
- viii) Afterwards, the antlion's traps for the three antlions (c_t and d_t) are updated using equations (3.16) to (3.21).
- ix) Then, each ant will perform random walk around the three antlions, namely the elite, roulette-wheel and mutated antlions, using equations (3.13) to (3.15).
- x) Normalization of the random walks is then performed to obtain R_E , R_A and R_M using equations (3.22) to (3.24).
- xi) Based on the normalized random walks, the position of the ant is updated using equation (3.25).
- xii) The steps from (v) until (xi) will be repeated until all ants have updated their positions.
- xiii) After all ants have updated their positions, their fitness values are evaluated using their updated positions.
- xiv) At this step, another characteristic of EP algorithm is adapted in addition to the mutation, which is the selection of new parent antlions. First of all, there are two

different populations, namely the antlion population and ant population. Both populations are combined and sorted based on the fitness values: the topmost will have the fittest solution while the bottommost will have the worst solution. To maintain the original population size (assuming M is the population size), the top M individuals from the combined population will be retained for the next iteration, hence they become the next population of parent antlions, while the bottom M individuals will be discarded.

- xv) The steps from (iv) to (xiv) will be repeated until the termination criterion, in this case the maximum iteration, is met.
- xvi) Once the maximum iteration has been reached, the algorithm stops immediately. The best solution can be found from the final elite antlion at the maximum iteration.

3.4 Methodology Part 2: Proposed Problem Formulation

This section presents the proposed problem formulation for optimal DG placement using MALO algorithm and LSF technique. It begins with a brief explanation on load flow analysis in distribution system, incorporation of optimal DG placement problem with MALO algorithm and overall LSF-MALO algorithm for solving optimal DG placement problem.

3.4.1 Load Flow Analysis in Distribution System

The use of load flow analysis in distribution system is of necessary when evaluating the fitness during optimization. Because of the proposed MALO algorithm will have real power losses as its fitness, simulating the test system using load flow analysis will facilitate the process of fitness evaluation in MALO. The primary goal in optimal DG placement and sizing is to minimize total power losses and to improve voltage magnitude at all buses in the system. The total power losses for an N -bus distribution system can be expressed as in equation (3.26) [130]:

$$P_{Loss} = \sum_{i=1}^N \sum_{j=1}^N [\alpha_{ij}(P_i P_j + Q_i Q_j) + \beta_{ij}(Q_i P_j - P_i Q_j)] \quad (3.26)$$

Where,

$$\alpha_{ij} = \frac{r_{ij}}{V_i V_j} \cos(\delta_i - \delta_j) \quad (3.27)$$

$$\beta_{ij} = \frac{r_{ij}}{V_i V_j} \sin(\delta_i - \delta_j) \quad (3.28)$$

$$Z_{ij} = r_{ij} + jx_{ij} \quad (3.29)$$

Where, Z_{ij} is the line impedance between bus i and bus j , r_{ij} is the line resistance between bus i and bus j , x_{ij} is the line reactance between bus i and bus j , V_i is the voltage magnitude at bus i , V_j is the voltage magnitude at bus j , δ_i is the voltage angle at bus i , δ_j is the voltage angle at bus j , P_i and Q_i are the active and reactive power injections at bus i and P_j and Q_j are the active and reactive power injections at bus j .

The calculation of real power losses via load flow analysis is subjected to several constraints of the test system. These include the real and reactive generation-demand balance constraints as in equation (3.30) and (3.31), real and reactive power limit of generators as in equation (3.32) and (3.33), and voltage limit constraint as in equation (3.34).

$$P_{Gi} - P_{Di} = \sum_{j=1}^N V_i V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] \quad (3.30)$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^N V_i V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] \quad (3.31)$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (3.32)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad (3.33)$$

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (3.34)$$

Where, G_{ij} is the line conductance between bus i and bus j , B_{ij} is the line susceptance between bus i and bus j , P_{Gi} and Q_{Gi} are the real and reactive power generation by generator at bus i , P_{Di} and Q_{Di} are the real and reactive power demand by load at bus i and V_i is the voltage magnitude at bus i .

3.4.2 Incorporating DG Placement Problem with Optimization Algorithm

The implementation of the proposed MALO algorithm requires a proper determination of the key optimization components, such as control variables, constraints, fitness and objective function. These are explained as follows.

- i) Control variables and solution – the real power and the power factor of DG units, i.e. P_{DG} and PF_{DG} , will be the control variables in the MALO algorithm. Depending on the type of DG units used in the test system (type 1 to type 4), each solution in the algorithm can have different values of PF_{DG} between 0 and 1. In general, every solution in the algorithm can be represented as in equation (3.35):

$$Antlion_i = [P_{DG1}, \dots, P_{DGk}, \dots, P_{DGN}, PF_{DG1}, \dots, PF_{DGk}, \dots, PF_{DGN}] \quad (3.35)$$

Where, $Antlion_i$ is the i -th solution of MALO population, which is also the position of i -th antlion; P_{DGk} and PF_{DGk} are the real power and power factor of k -th DG unit, and N is the number of DG units placed in the system. Hence, there will be $2N$ number of control variables for a given i -th solution.

Because the MALO algorithm has two types of populations, the ants and antlions, there will be two population matrices produced at every stage of optimization. These are given in equations (3.36) and (3.37).

$$\mathbf{M}_{Ant} = \begin{bmatrix} Ant_1 \\ \vdots \\ Ant_i \\ \vdots \\ Ant_M \end{bmatrix} = \begin{bmatrix} P_{DG1}^1 & \dots & P_{DGN}^1 & PF_{DG1}^1 & \dots & PF_{DGN}^1 \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^i & \dots & P_{DGN}^i & PF_{DG1}^i & \dots & PF_{DGN}^i \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^M & \dots & P_{DGN}^M & PF_{DG1}^M & \dots & PF_{DGN}^M \end{bmatrix} \quad (3.36)$$

$$\mathbf{M}_{Antlion} = \begin{bmatrix} Antlion_1 \\ \vdots \\ Antlion_i \\ \vdots \\ Antlion_M \end{bmatrix} = \begin{bmatrix} P_{DG1}^1 & \dots & P_{DGN}^1 & PF_{DG1}^1 & \dots & PF_{DGN}^1 \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^i & \dots & P_{DGN}^i & PF_{DG1}^i & \dots & PF_{DGN}^i \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^M & \dots & P_{DGN}^M & PF_{DG1}^M & \dots & PF_{DGN}^M \end{bmatrix} \quad (3.37)$$

Where, M is the population size, i.e. the number of ants or antlions in their respective populations, Ant_i is the position of i -th ant in the ant population and $Antlion_i$ is the position of i -th antlion in the antlion population. Throughout the optimization, every ant and antlion will update their positions, in this case the P_{DG_i} and PF_{DG_i} , based on two ways; (1) random walks around elite, roulette-wheel and mutated antlions for ant's position update and; (2) selection of new parent antlions for antlion's position update.

- ii) Constraints – in order to limit the algorithm's search space and to facilitate its searching process, defining the appropriate set of constraints related to the system is of necessary. This set of constraints can be in the form of equality and non-equality constraints. For the purpose of this study, the equality constraints are those of the generation-demand balance equations from the load flow analysis, as represented by equations (3.30) and (3.31). The non-equality constraints consist of those from the load flow analysis, which are represented by equations (3.32) to (3.34), and those specified for DG units as given in equations (3.38) to (3.40).

$$\text{DG size : } 0.005 \text{ MW} < P_{DG} < 5 \text{ MW} \quad (3.38)$$

$$\text{DG power factor : } 0 < PF_{DG} < 1 \quad (3.39)$$

$$\text{Bus voltage : } 0.95 \text{ p.u.} < V_{min} < 1.05 \text{ p.u.} \quad (3.40)$$

- iii) Fitness and objective function – One of the main focuses of this chapter, besides solving the optimal DG placement problem, is to study the behaviour of the proposed MALO algorithm in optimization. This includes its computation time and parameters dependence which will affect its convergence speed and solution optimality. Thus, for the purpose of this chapter, formulating the problem as single objective optimization (SOO) is considered sufficient. The chosen fitness for the optimal DG placement problem is the real power losses which will be calculated by load flow simulation using equation (3.26). This means that the SOO will be treated as a minimization problem. Hence, the whole optimization problem can be summarized as follows:

$$\text{minimize} \left\{ P_{Loss} = \sum_{i=1}^N \sum_{j=1}^N [\alpha_{ij}(P_i P_j + Q_i Q_j) + \beta_{ij}(Q_i P_j - P_i Q_j)] \right\} \quad (3.41)$$

Subject to:

Equality constraints : equations (3.30) to (3.31)

Non-equality constraints : equations (3.32) to (3.34) and (3.38) to (3.40).

In equation (3.41), the terms P_i , Q_i , P_j and Q_j are the real and reactive power injections at bus i and j respectively, which include the power injections by DG units at any related buses. This implies that the real power losses will be dependent of the DG sizes installed at any buses in the distribution system.

As the population of ants and antlions have been generated, their fitness will be calculated and stored in two separate vectors of **MOA** and **MOAL** as in equations (3.42) and (3.43):

$$\mathbf{M}_{OA} = \begin{bmatrix} f_1(Ant_1) \\ \vdots \\ f_i(Ant_i) \\ \vdots \\ f_M(Ant_M) \end{bmatrix} = \begin{bmatrix} P_{Loss}^1 \\ \vdots \\ P_{Loss}^i \\ \vdots \\ P_{Loss}^M \end{bmatrix} \quad (3.42)$$

$$\mathbf{M}_{OAL} = \begin{bmatrix} f_1(Antlion_1) \\ \vdots \\ f_i(Antlion_i) \\ \vdots \\ f_M(Antlion_M) \end{bmatrix} = \begin{bmatrix} P_{Loss}^1 \\ \vdots \\ P_{Loss}^i \\ \vdots \\ P_{Loss}^M \end{bmatrix} \quad (3.43)$$

As in the position update, the fitness for ants and antlions are being updated at every iteration to determine the best solution and the elite antlion. The two vectors of **MOA** and **MOAL** will determine the rank of any ants and antlions in their respective populations either they are in better group of solutions or not.

3.4.3 Overall LSF-MALO algorithm for Optimal DG Placement

This section presents the methodology for incorporating two different techniques for systematic placement of DG, namely the existing Loss Sensitivity Factor

(LSF) and the proposed MALO algorithm. The reason for incorporating the two techniques is to reduce computational time while promising optimal solution concurrently. This proposed hybrid technique has two successive tasks; (1) locating the suitable buses for DG placement via LSF and; (2) sizing multiple DG units using the proposed MALO algorithm.

Through LSF, sensitivity factor or simply LSF index is calculated for each bus using equation (3.1). It is important to note that the absolute values of the largest and smallest LSF indices are not fixed. They vary depending on the specific characteristics, topology, and loading conditions of the test system being evaluated (e.g., IEEE 33-bus versus IEEE 69-bus). Therefore, rather than relying on a universal numerical threshold, the best LSF value is relatively defined as the highest calculated index within a given system. The buses with their respective LSF indices are then arranged in descending order to form a priority list. The bus with the highest LSF index will be firstly chosen for DG placement, followed by the next buses downward. Incorporating the LSF and the MALO, hence the abbreviation LSF-MALO, will help to reduce the overall computational time during optimization. This is because only several buses in the priority list are chosen for DG integration rather than testing all buses in the test system.

Moreover, the MALO algorithm will not have too many number of control variables to be considered during optimization. Instead of lumping both DG location and size to be the control variables, like what the previous studies did, the proposed LSF-MALO performs the placement process systematically without burdening the optimization process. Hence, there will be higher possibility of getting faster convergence speed by the MALO algorithm. The overall LSF-MALO algorithm for optimal DG placement problem considering single objective optimization (SOO) is shown in **Figure 3.4**.

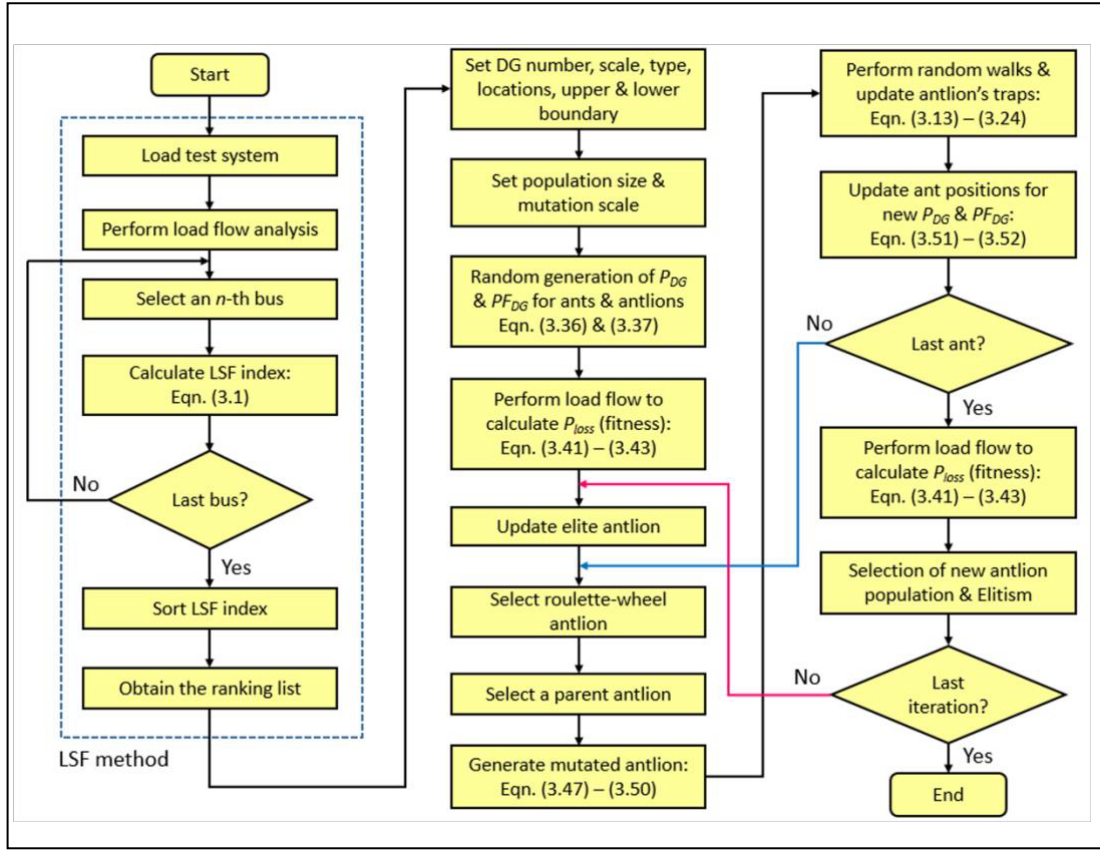


Figure 3. 4 Hybrid LSF-MALO Algorithm

The working of the hybrid algorithm as in **Figure 3.4** is explained as follows:

- i) At first, a test system is loaded to the developed program for data initialization. In this study, there are two distribution systems will be used for every simulation, namely IEEE 33-bus and IEEE 69-bus systems.
- ii) Afterwards, load flow analysis is conducted to determine bus voltages, line losses, real and reactive bus power injections and bus impedance matrix. These parameters will be used in the calculation of LSF indices in the subsequent procedure.
- iii) An n -th bus from the test system is selected and followed with the calculation of LSF index using equation (3.1).
- iv) Step (iii) is repeated until the LSF indices for all buses have been computed.
- v) The LSF indices are sorted in descending order: the topmost bus will have the highest LSF index, while the bottommost bus will have the lowest LSF index.
- vi) A ranking list is formed by selecting only several buses that have the highest LSF indices. In this study, a ranking list of 40% of the total buses is formed for DG placement in the next steps.

- vii) After that, the number of DG units (one to three), DG type (type 1 to 4), DG scale (micro to large), DG locations and lower and upper boundaries of DG size (equations (3.38) and (3.39)) are specified accordingly.
- viii) The MALO's parameters in terms of population size, mutation scale (β) and maximum iteration are set properly before optimization can be performed.
- ix) Optimization begins by randomly generating the initial values of DG's real power and DG's power factor (P_{DG} and PF_{DG}), which represent the initial positions of both ants and antlions. Hence, there will be M number of ants and antlions with different values of P_{DG} and PF_{DG} as their initial positions. This random positions of ants and antlions are stored in two separate matrices of $\mathbf{M}_{\text{Ant}}$ and $\mathbf{M}_{\text{Antlion}}$ as shown in equations (3.36) and (3.37) respectively. In addition, the randomly generated positions must fulfil the constraints as specified in equations (3.38) and (3.39). In this study, the following equations are implemented for random generation:

$$P_{DG} = P_{DG_min} + rand * (P_{DG_max} - P_{DG_min}) \quad (3.44)$$

$$PF_{DG} = rand \quad (3.45)$$

Where, $rand$ is a random number between 0 and 1.

- x) Afterwards, the DG units for each ant and antlion are installed in the test system by substituting their real and reactive power injections (P_{DG} and Q_{DG}) at the selected bus locations. The Q_{DG} for the ants and antlions is calculated as follows:

$$Q_{DG} = P_{DG} \tan[\cos^{-1}(PF_{DG})] \quad (3.46)$$

- xi) Next, the calculation of fitness, which is the real power losses (P_{loss}) as in equation (3.41), is then performed by simulating load flow analysis in the test system. If the minimum voltage magnitude, V_{min} for any ants or antlions is outside the range as specified by equation (3.40), their positions will be re-generated. This means that only those positions of ants and antlions that result in V_{min} within the range are accepted for the next processes.
- xii) Steps (x) and (xi) are repeated until the fitness values of all ants and antlions have been computed. The calculated fitness for both populations are stored in two separate vectors of $\mathbf{M}_{\text{OA}}$ and $\mathbf{M}_{\text{OAL}}$ as shown in equations (3.42) and (3.43).

- xiii) Later, the elite antlion is selected from the current antlion population ($\mathbf{M}_{\text{Antlion}}$) based on the fitness values stored in $\mathbf{M}_{\text{OAL}}$: whichever antlion that has the lowest P_{loss} will be assigned as the elite.
- xiv) The second antlion is then selected from $\mathbf{M}_{\text{Antlion}}$ based on roulette-wheel selection.
- xv) The third antlion is produced through mutation using equations (3.47) to (3.50), which are the modified versions of equations (3.11) and (3.12).

$$P_{DG_M}^i = P_{DG}^i + N(0, \sigma_{i_P}^2) \quad (3.47)$$

$$PF_{DG_M}^i = PF_{DG}^i + N(0, \sigma_{i_{PF}}^2) \quad (3.48)$$

$$\sigma_{i_P} = \beta [\max(P_{DG} \in \text{Antlion}) - \min(P_{DG} \in \text{Antlion})] \left(\frac{P_{\text{loss}}^i}{P_{\text{loss}}^{\max}} \right) \quad (3.49)$$

$$\sigma_{i_{PF}} = \beta [\max(PF_{DG} \in \text{Antlion}) - \min(PF_{DG} \in \text{Antlion})] \left(\frac{P_{\text{loss}}^i}{P_{\text{loss}}^{\max}} \right) \quad (3.50)$$

Where, $P_{DG_M}^i$ and $PF_{DG_M}^i$ are the DG's real power and power factor for i -th mutated antlion, P_{DG}^i and PF_{DG}^i are the position of i -th parent antlion, σ_{i_P} and $\sigma_{i_{PF}}$ are the standard deviations for DG's real power and power factor, P_{loss}^i and $P_{\text{loss}}^{\max}$ are the i -th real power losses and maximum power losses, $\max(P_{DG} \in \text{Antlion})$ and $\max(PF_{DG} \in \text{Antlion})$ are the maximum DG's real power and power factor in the current antlion population, $\min(P_{DG} \in \text{Antlion})$ and $\min(PF_{DG} \in \text{Antlion})$ are the minimum DG's real power and power factor in the current antlion population.

- xvi) Next, random walks by i -th ant around the three antlions (elite, roulette-wheel and mutated antlions) and antlion's traps update are performed based on equations (3.13) to (3.24). Subsequently, the resulted random walks are normalized to produced R_E , R_A and R_M .
- xvii) The position of i -th ant is updated using equations (3.51) for P_{DG} and (3.52) for PF_{DG} , which are the modified versions of equation (3.25).

$$Ant_{i,P}^t = P_{DG,new}^i = \frac{R_{AP}^t + R_{EP}^t + R_{MP}^t}{3} \quad (3.51)$$

$$Ant_{i,PF}^t = PF_{DG,new}^i = \frac{R_{APF}^t + R_{EPF}^t + R_{MPF}^t}{3} \quad (3.52)$$

Where, $Ant_{i,P}^t$, $Ant_{i,PF}^t$ are the updated positions of i -th ant for P_{DG} and PF_{DG} , R_{EP}^t , R_{AP}^t , R_{MP}^t are the normalized random walks for P_{DG} around the elite, roulette-wheel and mutated antlions, R_{EPF}^t , R_{APF}^t , R_{MPF}^t are the normalized random walks for PF_{DG} around the elite, roulette-wheel and mutated antlions.

- xviii) The selection of roulette-wheel antlion from step (xiv) until ant's position update in step (xvii) are performed repeatedly until all ants in the current ant population ($\mathbf{M}_{Ant}$) successfully update their positions.
- xix) Evaluation of fitness (P_{Loss}) for the ants is performed as in steps (x) and (xi).
- xx) Afterwards, both populations of ants and antlions ($\mathbf{M}_{Ant}$ and $\mathbf{M}_{Antlion}$) are combined as in equation (3.53). Likewise, their fitness vectors ($\mathbf{M}_{OA}$ and $\mathbf{M}_{OAL}$) are combined as in equation (3.54). This means that the combined matrix and vector have $2M$ number of rows.

$$\mathbf{M}_{Combine} = \begin{bmatrix} \mathbf{M}_{Ant} \\ \mathbf{M}_{Antlion} \end{bmatrix} \quad (3.53)$$

$$\mathbf{F}_{Combine} = \begin{bmatrix} \mathbf{M}_{OA} \\ \mathbf{M}_{OAL} \end{bmatrix} \quad (3.54)$$

- xxi) The ants and antlions in the combined population ($\mathbf{M}_{Combine}$) and their fitness in the combined vector ($\mathbf{F}_{Combine}$) are then sorted with the topmost has the lowest P_{Loss} while the bottommost has the highest P_{Loss} . Next, the new population of antlions and their fitness are defined such that the top M positions and fitness from $\mathbf{M}_{Combine}$ and $\mathbf{F}_{Combine}$ will be the new antlions and the new fitness for the next iteration. These are given as in equations (3.55) and (3.56).

$$\mathbf{M}_{Antlion} = \mathbf{M}_{Combine}(1:M, :) \quad (3.55)$$

$$\mathbf{M}_{OAL} = \mathbf{F}_{Combine}(1:M) \quad (3.56)$$

- xxii) The steps from (xiii) to (xxi) are repeated until maximum iteration has been reached.
- xxiii) After reaching the maximum iteration, the algorithm terminates itself and the best DG size in terms of P_{DG} and PF_{DG} is given by the final position of the elite antlion.

3.5 Result and Discussion

For the purpose of verification, experiment was conducted on two radial distribution systems. The first one is IEEE 33-bus system, which has 33 branches as illustrated in **Figure 3.5**. The system has a total load of 3.72 MW and 2.3 MVAR [131]. Later, the second test system is IEEE 69-bus system, which has 68 branches as shown in **Figure 3.6**. The total load demand for the system is 3.8 MW and 2.69 MVAR [132].

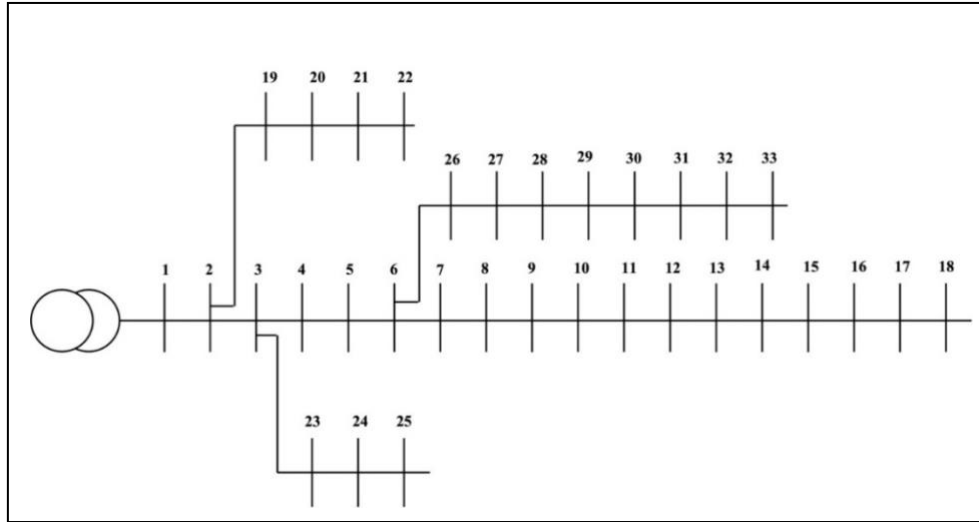


Figure 3. 5 IEEE 33-Bus System

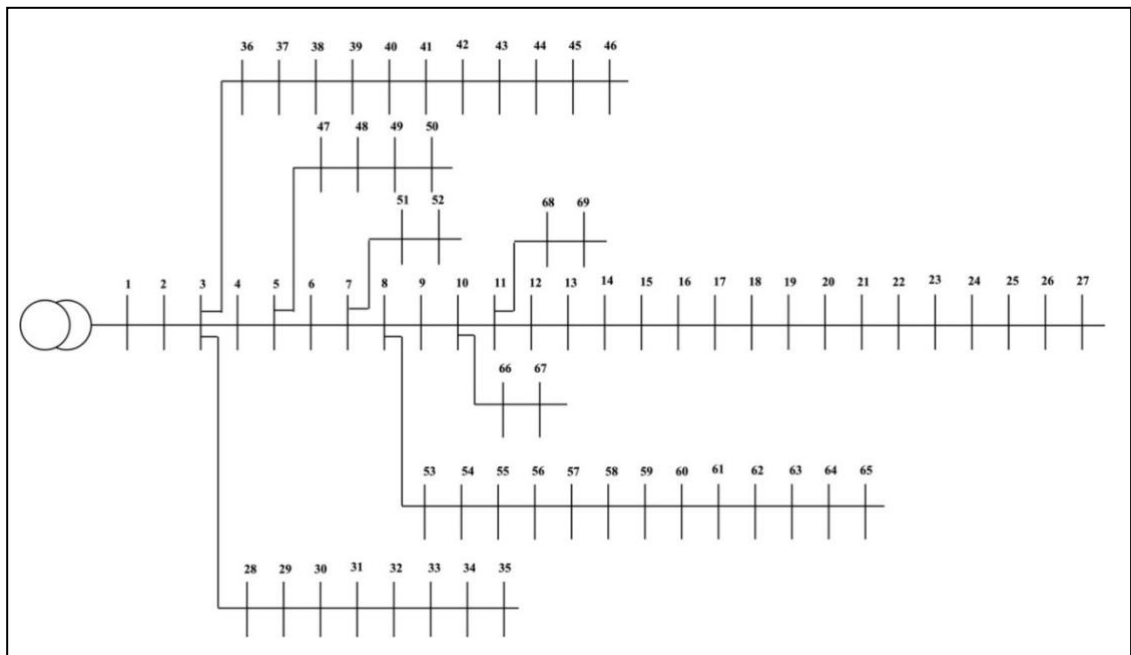


Figure 3. 6 IEEE 69-Bus System

The proposed algorithm was implemented in MATLAB software and simulation was run using the developed source codes. In this chapter, the main purpose is to verify the capability of the LSF-MALO in optimal DG placement problem and to see its performance under different settings of the algorithm's parameters. Hence, there are three (3) cases of analysis under this section as follows:

- Case 1: Effects of different number of DG units installed at base case scenario
- Case 2: Effects of DG placement under multiple loadings
- Case 3: Performance of LSF-MALO algorithm under parameter changes

To see its robustness in solving the problem, each of the cases will involve both IEEE 33-bus system and IEEE 69-bus system. The DG units used in all cases are of solar panel type (type 1 DG) with their injected real power of P_{DG} and unity power factor. In Case 1 and 2, there are four methods used for performance comparison such as the proposed LSF-MALO, LSF Analytical, EP and MALO. The LSF Analytical is a conventional and non-metaheuristic algorithm for DG placement [133], while EP and MALO are metaheuristic optimization algorithms used for DG sizing without the use of LSF indices as what the proposed technique does. For Case 1, the aim of analysis is to see the effects of different number of DG units placed in the test system, in this case, single and double DG placement. Next in Case 2, because the loads in distribution system have varying demand, the effects of DG placement under multiple loadings are analysed to further verified the proposed technique's robustness. Lastly, in Case 3, it is essential to investigate the MALO algorithm's ability in solving the optimization problem under various settings of its parameters, which are population size and mutation scale, β .

3.5.1 Effects of single and double DG placement in IEEE 33-bus system using different methods – base case scenario

At first, the effects of single and double DG placement on voltage magnitude and real power losses at base case condition in IEEE 33-bus system is investigated. **Table 3.1** and **Table 3.2** tabulate the results.

Table 3. 1
Effects Of DG Placement On Minimum Voltage Magnitude (V_{min}) And Real Power Losses (P_{loss}) In IEEE 33-Bus System With Single DG Unit Installed – Base Case Scenario

Methods	DG bus number	P_{DG} (MW)	P_{loss} (MW)	ΔP_{loss} (%)	V_{min} (p.u)	ΔV_{min} (%)	Time (s)
Without DG	-	-	0.1831	-	0.9185	-	-
LSF-MALO	6	2.5706	0.0853	53.41	0.9566	4.14	11.27
LSF Analytical	6	2.5025	0.0854	53.38	0.9556	4.04	4.68
EP	32	1.9706	0.1242	32.16	0.9473	3.14	10.77
MALO	32	1.2889	0.1068	41.69	0.9381	2.13	11.28

Table 3. 2
Effects Of DG Placement On Minimum Voltage Magnitude (V_{min}) And Real Power Losses (P_{loss}) In IEEE 33-Bus System With 2 DG Units Installed – Base Case Scenario

Methods	DG bus number	P_{DG} (MW)	ΣP_{DG} (MW)	P_{loss} (MW)	ΔP_{loss} (%)	V_{min} (p.u)	ΔV_{min} (%)	Time (s)
Without DG	-	-	-	0.1831	-	0.9185	-	-
LSF-MALO	6	1.2784	2.8480	0.0881	51.87	0.9519	3.64	18.85
	5	1.5696						
LSF Analytical	6	2.5025	5.3380	0.1353	26.10	0.9799	6.69	8.08
	5	2.8355						
EP	32	1.8279	2.5037	0.1095	40.20	0.9515	3.59	19.22
	5	0.6758						
MALO	32	1.0052	2.7415	0.0817	55.35	0.9497	3.40	19.64
	5	1.7363						

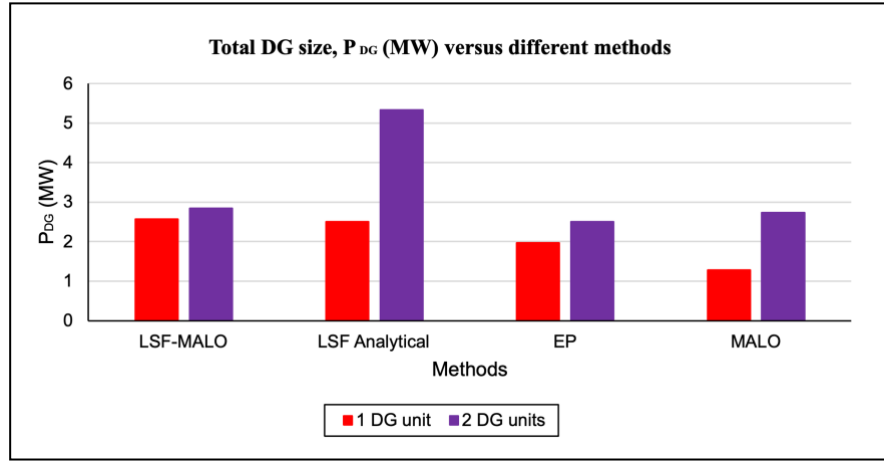
Based on **Table 3.1** and **Table 3.2**, the locations for DG placement depend on the methods used. Because they use LSF indices, the LSF-MALO and LSF Analytical have the same locations for the installed DG units, which are bus 6 for single DG placement and bus 5 and 6 for double DG placement. On the other hand, the EP and MALO have the same locations of bus 32 for single DG placement and bus 5 and 32 for double DG placement.

For the purpose of comparative analysis, the LSF Analytical method is

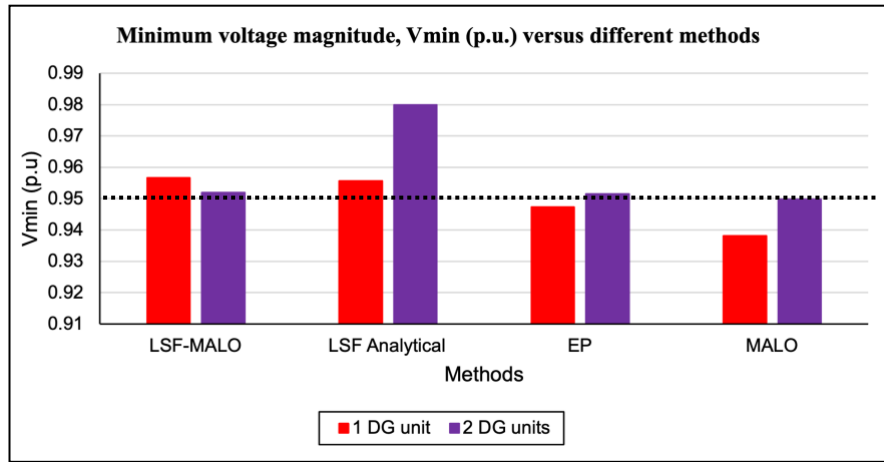
employed as a deterministic benchmark. In this technique, the DG locations (bus numbers) are identified by ranking the LSF indices in descending order and selecting the highest priority buses. Subsequently, a DG unit is assigned to the selected bus, and its capacity is incrementally scaled upward from an initial 0 MW. This iterative sizing continues until the system reaches the specific DG capacity that yields the maximum reduction in total power losses. Consequently, because it relies on direct mathematical calculation rather than iterative population generation, its computational time is inherently shorter than that of the metaheuristic approaches.

The proposed LSF-MALO demonstrates a decent performance in terms of minimum voltage magnitude (V_{min}) and percentage of power losses reduction (ΔP_{loss}). The resulted V_{min} is above the minimum level of 0.95 per-unit (p.u.) with considerable power losses reduction of 50% and above. Based on **Table 3.1** and **Table 3.2**, it yields to 0.9566 p.u. of V_{min} and 53.41% of ΔP_{loss} for single DG placement and 0.9519 p.u. of V_{min} and 51.87% of ΔP_{loss} for double DG placement. The LSF Analytical results in almost similar V_{min} and ΔP_{loss} as the proposed technique in single DG placement, which are 0.9556 p.u. and 53.38% respectively. However, its power losses reduction for double DG placement is not as high as the LSF-MALO, which is 26.10%. The remaining two methods, the EP and MALO, yield to unstable performance in terms of V_{min} and ΔP_{loss} . With ΔP_{loss} of at least 30%, which is considerable, their V_{min} values are below 0.95 p.u. in single DG placement, which is undervoltage. The EP reflects a good performance in the case of double DG placement, however, with V_{min} and ΔP_{loss} of 0.9515 p.u. and 40.2% respectively. On the contrary, the MALO still results in undervoltage of 0.9497 p.u. of V_{min} . As shown in Table 3.1, LSF-MALO (11.27 s) and MALO (11.28 s) share nearly identical execution times because both dedicate similar computational effort to iterative load flow analysis during sizing. However, LSF-MALO delivers superior solution quality by successfully converging on the global optimum, while MALO becomes trapped in a local optimum.

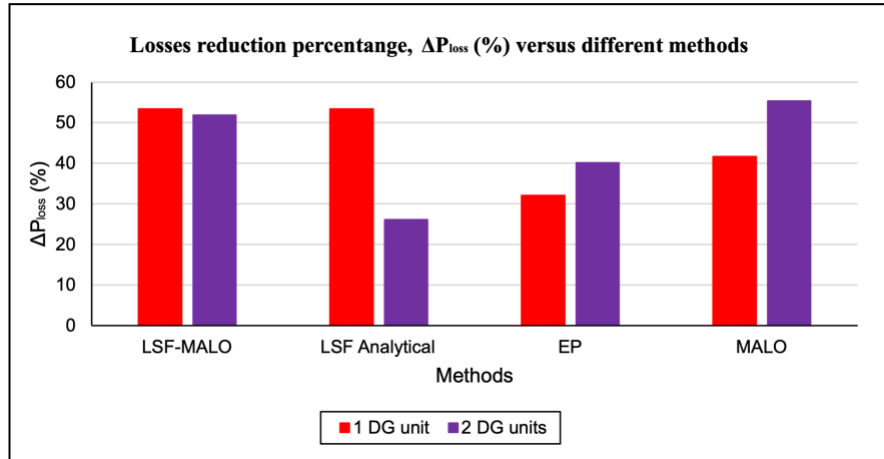
Clearer depictions from **Table 3.1** and **Table 3.2** are given in **Figure 3.7(a)** for total DG size, **Figure 3.7(b)** for V_{min} and **Figure 3.7(c)** for ΔP_{loss} . Firstly, based on **Figure 3.7(a)**, there is no much difference for LSF-MALO in terms of total DG's real power injection (ΣP_{DG}) between single DG placement (one DG unit installed) and double DG placement (two DG units installed). This is true for the EP as well. The LSF Analytical and MALO, on the other hand, have a large difference of ΣP_{DG} between single and double DG placement.



(a) Total DG's Injected Real Power



(b) Minimum Voltage Magnitude, V_{min}



(c) Losses Reduction Percentage, ΔP_{loss}

Figure 3. 7 Comparison Between 1 DG Unit And 2 DG Units Placement In IEEE 33-Bus System For Different Methods - (a) Total DG's Real Power Injected, (b) Minimum Voltage Magnitude, V_{min} and (c) Losses Reduction Percentage, ΔP_{loss}

In terms of V_{min} and ΔP_{loss} as shown in **Figure 3.7(b)** and **3.7(c)**, the LSF-MALO demonstrates that single DG placement (one DG unit installed) is sufficient to have a stable voltage magnitude (above 0.95 p.u., represented by the dotted black line) and considerable power losses reduction (above 50%). As can be seen, the resulted V_{min} and ΔP_{loss} by single DG placement is higher than that of double DG placement (two DG units installed). The EP and MALO, on the other hand, have the opposite results to that of the proposed technique.

They need double DG placement in order to have a better performance of the system. Finally, the LSF Analytical results in different performance between single and double DG placement. Its double DG placement yields to better V_{min} , but not as good as its single DG placement in terms of ΔP_{loss} .

On overall, for IEEE 33-bus system at base case scenario, the proposed LSF-MALO has successfully identified the optimal number and size of DG units to be installed in the system: one DG unit with 2.5706 MW of P_{DG} . With this size and number, the system will have stable voltage magnitude of at least 0.9566 p.u. with a considerable losses reduction of 53.41%. In addition, the LSF-MALO is the only method that ensures a consistent and stable improvement on V_{min} and ΔP_{loss} as compared to other methods.

3.5.2 Effects of single and double DG placement in IEEE 69-bus system using different methods – base case scenario

Next, the effects of single and double DG placement on voltage magnitude and real power losses at base case condition in IEEE 69-bus system is investigated. **Table 3.3** and **Table 3.4** tabulate the results.

Based on **Table 3.3** and **Table 3.4**, the locations for DG placement depend on the methods used. The LSF-MALO and LSF Analytical have the same location for the first DG unit, which is bus 61, but different location for the second DG unit, namely bus 65 for LSF-MALO and bus 62 for LSF Analytical. In addition, the EP and MALO have different locations for both DG units, which are bus 33 and 56 for EP and bus 9 and 55 for MALO.

Table 3. 3

Effects Of DG Placement On Minimum Voltage Magnitude (V_{min}) And Real Power Losses (P_{loss}) In IEEE 69-Bus System With Single DG Unit Installed – Base Case Scenario

Methods	DG bus number	P_{DG} (MW)	P_{loss} (MW)	ΔP_{loss} (%)	V_{min} (p.u)	ΔV_{min} (%)	Time (s)
Without DG	-	-	0.2178	-	0.9099	-	-
LSF-MALO	61	1.8397	0.0789	63.75	0.9784	7.53	19.89
LSF Analytical	61	1.8365	0.0790	63.75	0.9783	7.52	23.13
EP	56	2.7916	0.1495	31.33	0.9454	3.90	21.11
MALO	55	2.4249	0.1534	29.56	0.9363	2.90	21.23

Table 3. 4

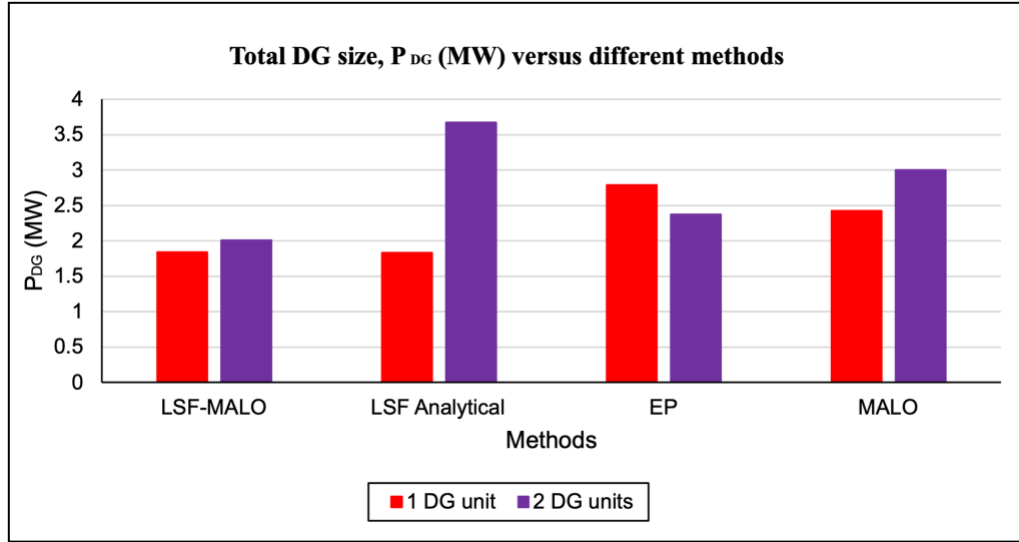
Effects Of DG Placement On Minimum Voltage Magnitude (V_{min}) And Real Power Losses (P_{loss}) In IEEE 69-Bus System With 2 DG Units Installed – Base Case Scenario

Methods	DG bus number	P_{DG} (MW)	ΣP_{DG} (MW)	P_{loss} (MW)	ΔP_{loss} (%)	V_{min} (p.u)	ΔV_{min} (%)	Time (s)
Without DG	-	-	-	0.2178	-	0.9099	-	-
LSF-MALO	61	1.0049	2.0098	0.0885	59.38	0.9964	9.51	36.04
	65	1.0049						
LSF Analytical	61	1.8365	3.673	0.1832	15.86	1.0387	14.15	37.32
	62	1.8365						
EP	56	2.3663	2.3713	0.1474	32.31	0.9402	3.33	36.53
	33	0.0050						
MALO	55	1.5029	3.0058	0.1523	30.05	0.9358	2.85	34.48
	9	1.5029						

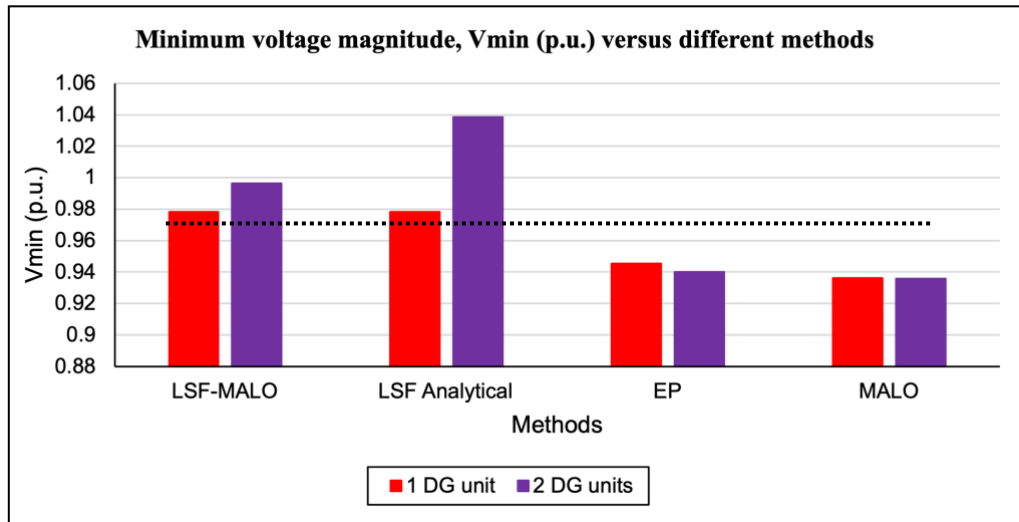
The proposed LSF-MALO demonstrates a decent performance in terms of minimum voltage magnitude (V_{min}) and percentage of power losses reduction (ΔP_{loss}). The resulted V_{min} is above the minimum level of 0.95 per-unit (p.u.) with considerable power losses reduction of 59% and above. Based on **Table 3.3** and **Table 3.4**, it yields to 0.9784 p.u. of V_{min} and 63.75% of ΔP_{loss} for single DG placement and 0.9964 p.u. of V_{min} and 59.38% of ΔP_{loss} for double DG placement. The LSF Analytical results in almost similar V_{min} and ΔP_{loss} as the proposed technique in single DG placement, which are 0.9783 p.u. and 63.75% respectively. However, its power losses reduction for double DG placement is not as high as the LSF-MALO, which is 15.86%. The remaining two methods, the EP and MALO, yield to unstable performance in terms of V_{min} and ΔP_{loss} . Although their ΔP_{loss} percentages are at least 29%, which is considerable, their V_{min} values are below 0.95 p.u., which is undervoltage. For instance, based on **Table 3.4**, the two methods result in V_{min} and ΔP_{loss} as follows: 0.9402 p.u.

and 32.31% by EP and 0.9358 p.u. and 30.05% by MALO.

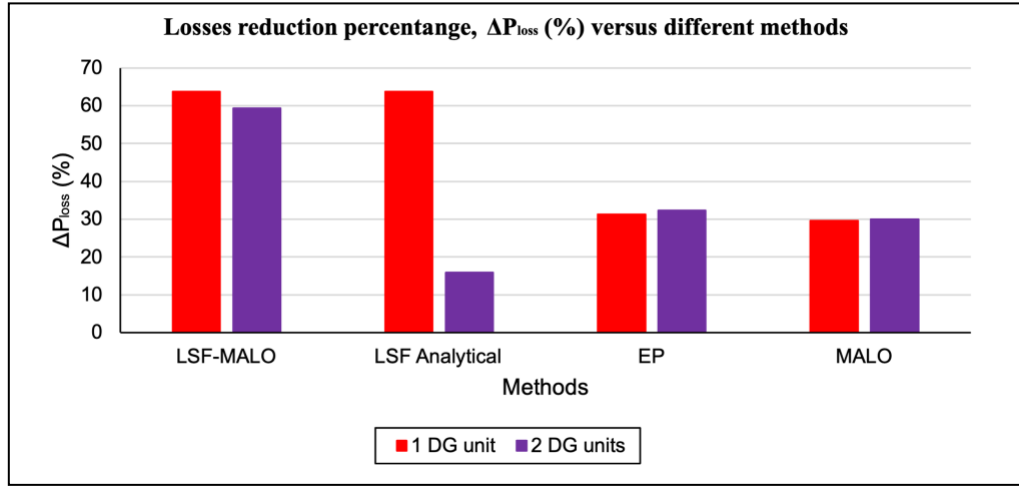
Clearer depictions from **Table 3.3** and **Table 3.4** are given in **Figure 3.8(a)** for total DG size, **Figure 3.8(b)** for V_{min} and **Figure 3.8(c)** for ΔP_{loss} . Firstly, based on **Figure 3.8(a)**, there is no much difference for LSF-MALO in terms of total DG's real power injection (ΣP_{DG}) between single DG placement (one DG unit installed) and double DG placement (two DG units installed). There is a moderate difference of ΣP_{DG} between single and double DG placement for the EP and MALO. The LSF Analytical, however, has a large difference of ΣP_{DG} between single and double DG placement.



(a) Total DG's Injected Real Power



(b) Minimum Voltage Magnitude, V_{min}



(c) Losses Reduction Percentage, ΔP_{loss}

Figure 3. 8 Comparison Between 1 DG Unit And 2 DG Units Placement In IEEE 69-Bus System For Different Methods - (a) Total DG's Real Power Injected, (b) Minimum Voltage Magnitude, V_{min} And (c) Losses Reduction Percentage, ΔP_{loss}

In terms of V_{min} and ΔP_{loss} as shown in **Figure 3.8(b)** and **3.8(c)**, the LSF-MALO demonstrates that single DG placement (one DG unit installed) is sufficient to have a stable voltage magnitude (above 0.95 p.u.) and considerable power losses reduction (above 60%). As can be seen, the resulted ΔP_{loss} by single DG placement is higher than that of double DG placement (two DG units installed). The EP and MALO, on the other hand, have the opposite results to that of the proposed technique. There is no much difference in V_{min} and P_{loss} between single and double DG placement as obtained by the two methods. Finally, the LSF Analytical results in different performance between single and double DG placement. Its double DG placement yields to better V_{min} , but not as good as its single DG placement in terms of ΔP_{loss} .

On overall, for IEEE 69-bus system at base case scenario, the proposed LSF-MALO has successfully identified the optimal number and size of DG units to be installed in the system: one DG unit with 1.8397 MW of P_{DG} . With this size and number, the system will have stable voltage magnitude of at least 0.9784 p.u. with a considerable losses reduction of 63.75%. In addition, the LSF-MALO is the only method that ensures a consistent and stable improvement on V_{min} and ΔP_{loss} as compared to other methods.

3.5.3 Effects of DG placement under multiple loadings in IEEE 33-bus system

Section 3.5.1 and 3.5.2 have verified the performance of LSF-MALO at base case scenario, yet it is still insufficient to reflect a more practical situation of distribution system. In practice, the loads in the system can have a changing trend of demand over certain period of time, which can affect the overall performance of the system. To know how far it can go, the developed LSF-MALO algorithm must be tested until the maximum limit of the system's loading has been reached.

In this section, the effects of DG placement with two DG units installed in IEEE 33-bus system under multiple loadings are analysed. The multiple loadings are from base case to 100% of reactive loading. The same four methods of DG placement, namely the LSF-MALO, LSF Analytical, EP and MALO are used for the purpose of comparison. **Table 3.5** tabulates the results.

Table 3. 5
DG Locations, DG Sizes And Their Effects On Voltage And Losses In IEEE 33-Bus System With 2 DG Units Installed - Multiple Loadings Scenario

Loading (%)	Method	DG location (bus no.)	DG size, P_{DG} (MW)	ΔP_{loss} (%)	V_{min} (p.u.)
Base case	LSF-MALO	5, 6	1.5696, 1.2784	51.87	0.9519
	LSF Analytical	5, 6	2.8355, 2.5025	26.10	0.9799
	EP	5, 32	0.6758, 1.8279	40.20	0.9515
	MALO	5, 32	1.7363, 1.0052	55.35	0.9497
25%	LSF-MALO	5, 6	1.4933, 1.6596	50.51	0.9521
	LSF Analytical	5, 6	2.8355, 2.5025	21.81	0.9777
	EP	5, 32	1.0398, 1.4497	47.33	0.9450
	MALO	5, 32	1.1660, 1.1660	50.58	0.9422
50%	LSF-MALO	6, 25	2.6732, 1.3783	49.24	0.9540
	LSF Analytical	5, 6	3.0020, 2.6690	18.22	0.9745
	EP	5, 32	0.6754, 1.8935	34.72	0.9429
	MALO	5, 32	1.1744, 1.1744	47.75	0.9376
75%	LSF-MALO	6, 25	3.1748, 1.3102	43.33	0.9561
	LSF Analytical	5, 6	3.0020, 2.6690	18.34	0.9698
	EP	5, 32	2.4693, 0.7213	46.21	0.9378
	MALO	5, 32	1.1819, 1.1818	44.86	0.9329
100%	LSF-MALO	6, 25	3.1506, 1.2859	41.53	0.9505
	LSF Analytical	5, 6	2.8355, 2.5025	18.48	0.9651
	EP	5, 32	0.7520, 1.5676	37.01	0.9294
	MALO	5, 32	1.1857, 1.1857	41.99	0.9280

In terms of DG placement locations, the proposed LSF-MALO has different locations for different loadings. For instance, based on **Table 3.5**, the DG units are placed at bus 5 and 6 when the system is at base case and 25% of loading. As the loading increases from 50% to 100%, the locations for DG placement change to bus 6 and 25. This is different for the rest of the methods, however. Without a change on DG placement locations, the LSF Analytical has bus 5 and 6, while the EP and MALO have bus 5 and 32 for all situations of the system starting from base case to 100%.

Clearer depictions from **Table 3.5** are given in **Figure 3.9** for total DG's real power injection (ΣP_{DG}), **Figure 3.10** for minimum voltage magnitude (V_{min}) and **Figure 3.11** for percentage of power losses reduction (ΔP_{loss}).

With regard to V_{min} and ΔP_{loss} as shown in **Figure 3.10** and **Figure 3.11** respectively, the LSF-MALO ensures a stable voltage magnitude of at least 0.95 p.u. with considerable power losses reduction at all system's loadings. Based on **Table 3.5**, the LSF-MALO results in V_{min} of between 0.9505 p.u. and 0.9561 p.u. and ΔP_{loss} of between 41.53% and 51.87%. The best improvement on V_{min} is shown by LSF Analytical, with magnitude of between 0.96 p.u. and 0.98 p.u. at all loading conditions. However, its power losses reduction is the lowest, which is between 18.22% and 26.10%. Even though they have a considerable power losses reduction, the EP and MALO are unable to ensure a stable voltage magnitude as V_{min} starts to reduce below 0.95 p.u. when the loading increases from 25% to 100%.

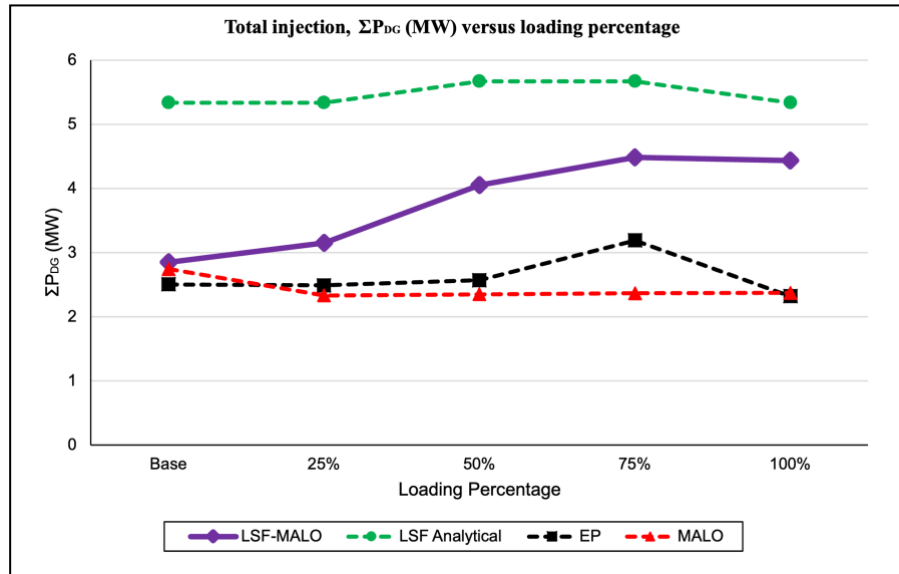


Figure 3. 9 Total Injection (ΣP_{DG}) By DG Units In IEEE 33-Bus System Under Multiple Loadings

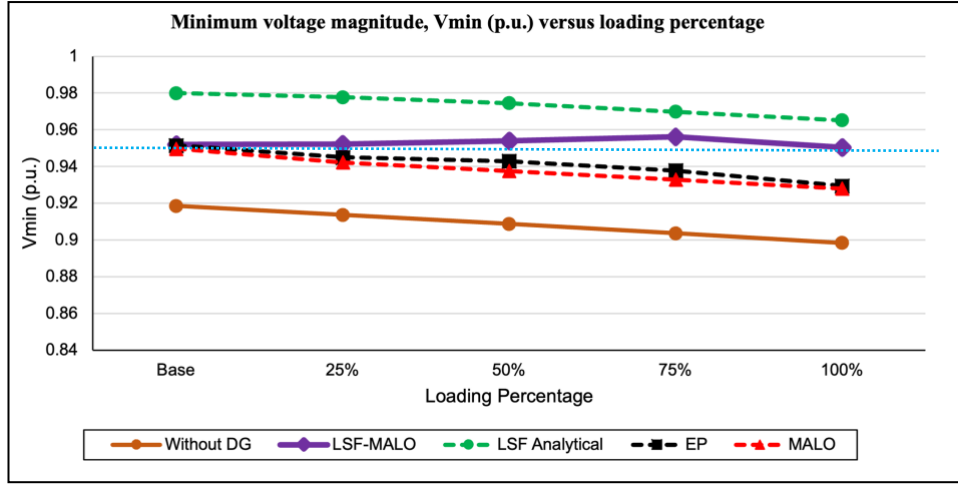


Figure 3. 10 Effect Of DG Placement On Minimum Voltage Magnitude (V_{min}) Under Multiple Loadings In IEEE 33-Bus System

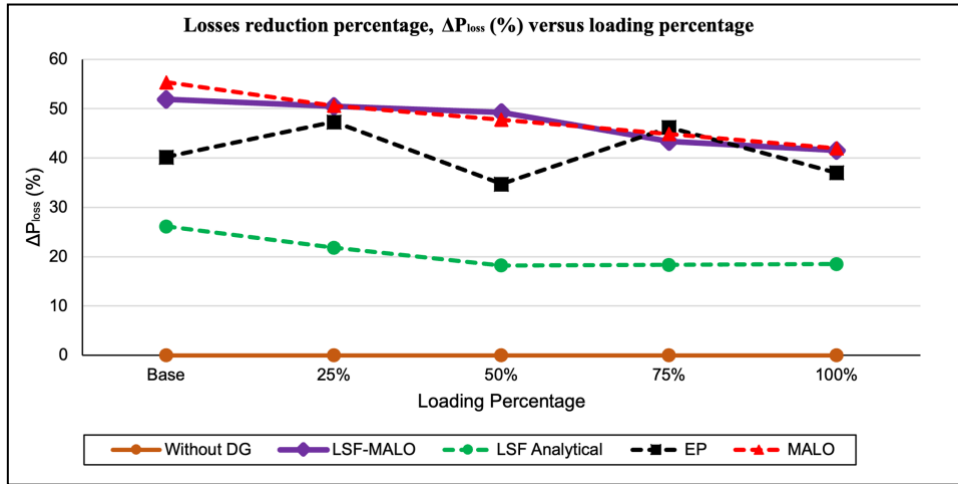


Figure 3. 11 Effect Of DG Placement On Losses Reduction Percentage (ΔP_{loss}) Under Multiple Loadings In IEEE 33-Bus System

On overall, the LSF-MALO has successfully determined the adequate sizes of DG units based on system's loading. The considerable change in ΣP_{DG} reflects that the proposed technique is able to fulfil the system's demand while maintaining a stable V_{min} of at least 0.95 p.u. with considerable ΔP_{loss} at all loading conditions.

3.5.4 Effects of DG placement under multiple loadings in IEEE 69-bus system

Despite with such a proven performance of LSF-MALO at base case scenario, it is still inadequate to reflect a more practical situation of distribution system. In practice, the loads in the system can have a changing trend of demand over certain

period of time, which can affect the overall performance of the system. Thus, the developed LSF-MALO algorithm must be tested until the maximum limit of the system's loading has been reached.

In this section, the effects of DG placement with two DG units installed in IEEE 69-bus system under multiple loadings are analysed. The multiple loadings are from base case to 100% of reactive loading. The same four methods of DG placement, namely the LSF-MALO, LSF Analytical, EP and MALO are still used for the purpose of comparison. **Table 3.6** tabulates the results.

Table 3. 6
DG Locations, DG Sizes And Their Effects On Voltage And Losses In IEEE 69-Bus System With 2 DG Units Installed - Multiple Loadings Scenario

Loading (%)	Method	DG location (bus no.)	DG size, P_{DG} (MW)	ΔP_{loss} (%)	V_{min} (p.u.)
Base case	LSF-MALO	61, 65	1.0049, 1.0049	59.38	0.9964
	LSF	61, 62	1.8365, 1.8365	15.86	1.0387
	Analytical				
	EP	33, 56	0.0050, 2.3663	32.31	0.9402
	MALO	9, 55	1.5029, 1.5029	30.05	0.9358
25%	LSF-MALO	61, 65	0.9827, 0.8388	61.12	0.9881
	LSF	61, 62	1.8365, 1.8365	15.85	1.0387
	Analytical				
	EP	33, 56	0.0050, 2.3663	32.29	0.9402
	MALO	9, 55	1.5029, 1.5029	30.02	0.9357
50%	LSF-MALO	61, 65	1.0049, 1.0049	59.28	0.9964
	LSF	61, 62	1.8365, 1.8365	15.83	1.0387
	Analytical				
	EP	33, 56	0.0050, 2.3663	32.36	0.9402
	MALO	9, 55	1.5029, 1.5029	30.00	0.9357
75%	LSF-MALO	61, 65	1.0591, 0.7025	61.88	0.9721
	LSF	61, 62	1.8365, 1.8365	15.82	1.0387
	Analytical				
	EP	33, 56	0.0050, 2.3663	32.33	0.9402
	MALO	9, 55	1.5057, 1.5057	29.97	0.9358
100%	LSF-MALO	61, 65	1.0049, 1.0049	59.17	0.9964
	LSF	61, 62	1.8365, 1.8365	15.80	1.0387
	Analytical				
	EP	33, 56	0.0050, 2.3663	32.30	0.9402
	MALO	9, 55	1.5029, 1.5029	29.94	0.9357

In terms of DG placement locations, the proposed LSF-MALO has the same locations for all loadings. For instance, based on **Table 3.6**, the DG units are placed at bus 61 and 65 from base case to 100% of loading. This is true for the rest of the methods with LSF Analytical has DG locations at bus 61 and 62, EP has bus 33 and 56 and MALO has bus 9 and 55.

Graphical illustrations from **Table 3.6** are given in **Figure 3.12** for total DG's real power injection (ΣP_{DG}), **Figure 3.13** for minimum voltage magnitude (V_{min}) and **Figure 3.14** for percentage of power losses reduction (ΔP_{loss}).

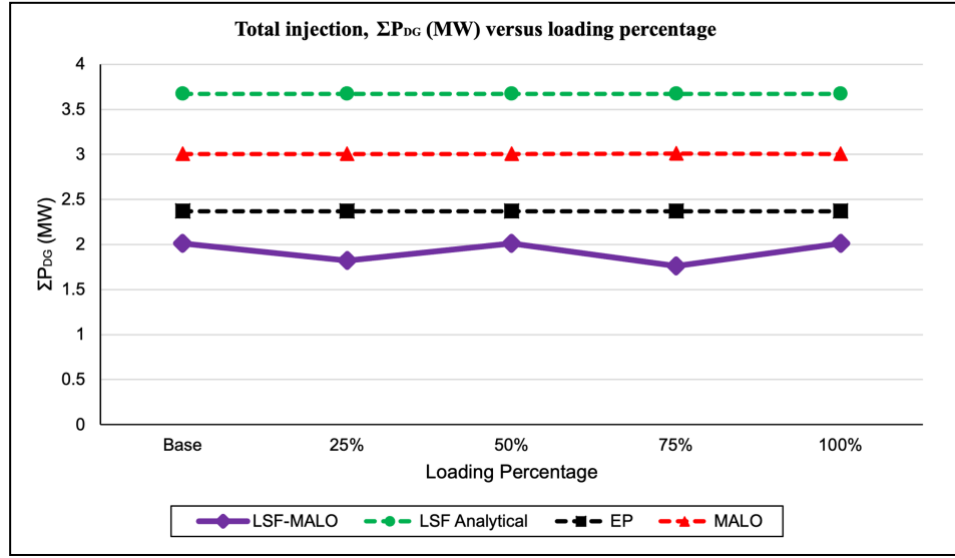


Figure 3. 12 Total Injection (ΣP_{DG}) By DG Units In IEEE 69-Bus System Under Multiple Loadings

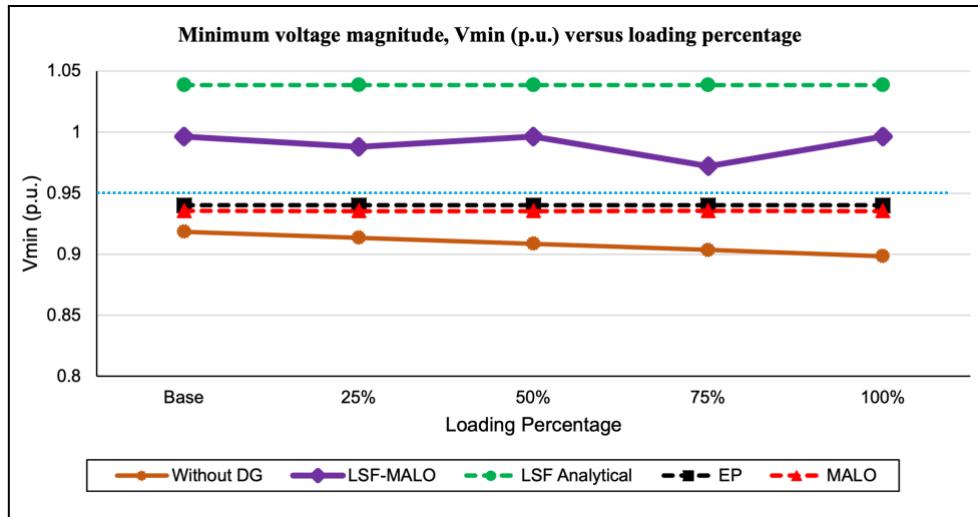


Figure 3. 13 Effect Of DG Placement On Minimum Voltage Magnitude (V_{min}) Under Multiple Loadings In IEEE 69-Bus System

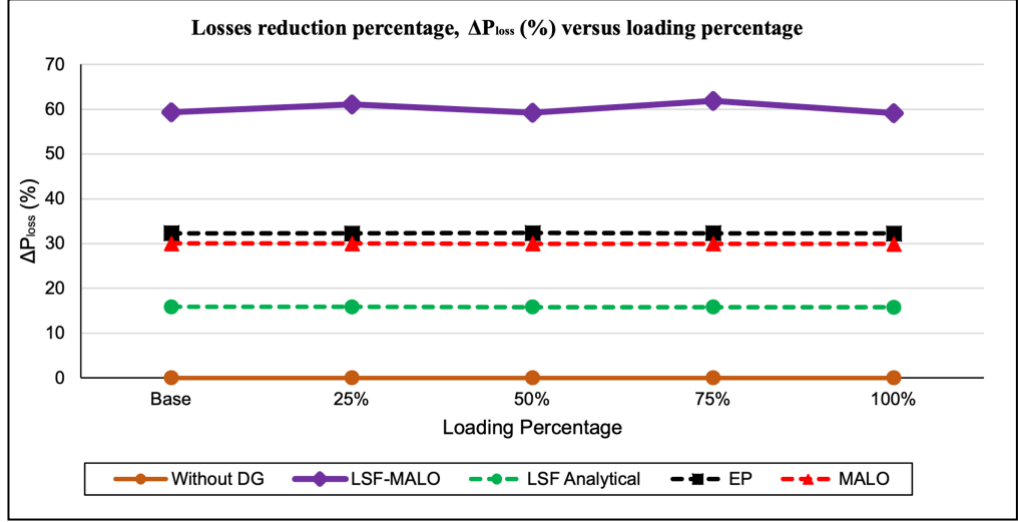


Figure 3. 14 Effect Of DG Placement On Losses Reduction Percentage (ΔP_{loss}) Under Multiple Loadings In IEEE 69-Bus System

Firstly, in term of ΣP_{DG} as in **Figure 3.12**, the LSF-MALO results in adequate DG sizes in response to the change in system's loading. It can be observed that the ΣP_{DG} changes between 1.5 MW and 2 MW as the loading increases from base case to 100%. By adding the size of both DG units from **Table 3.6**, the largest ΣP_{DG} of roughly 2 MW is obtained at base case, 50% and 100% of loading, while the smallest ΣP_{DG} of 1.76 MW is obtained at 75% of loading. However, whether the smallest or largest DG sizes, they are still below the total DG sizes produced by the rest of the methods. The LSF Analytical, EP and MALO result in constant values of ΣP_{DG} at all loadings as follows: 3.67 MW by LSF Analytical, which is the largest total DG size, 2.37 MW by EP and 3 MW by MALO.

With regard to V_{min} and ΔP_{loss} as shown in **Figure 3.13** and **Figure 3.14** respectively, the LSF-MALO ensures a stable voltage magnitude of at least 0.95 p.u. with considerable power losses reduction at all system's loadings. Based on **Table 3.6**, the LSF-MALO results in V_{min} of between 0.9721 p.u. and 0.9964 p.u. and ΔP_{loss} of roughly between 59% and 61%. The best improvement on V_{min} is shown by LSF Analytical, with magnitude of almost 1.04 p.u. at all loading conditions. However, its power losses reduction (ΔP_{loss}) is the lowest, which is roughly 15.8%. Even though they have a considerable power losses reduction, the EP and MALO are unable to ensure a stable voltage magnitude as their V_{min} values are below 0.95 p.u. from base case to 100% of loading. On overall, the LSF-MALO has successfully determined the adequate sizes of DG units based on system's loading. The change in ΣP_{DG} reflects that the proposed technique is able to fulfil the system's demand while maintaining a stable V_{min} of at least

0.95 p.u. with considerable ΔP_{loss} at all loading conditions.

3.5.5 Performance of LSF-MALO algorithm under parameter changes

In this section, an experiment to investigate the dependence of LSF-MALO on mutation scale (β) and population size was conducted. It was performed on IEEE 69-bus system at 50% of loading with two different cases; (1) varying β values with constant population size and; (2) varying population size with constant β . The results for the experiment are tabulated in **Table 3.7** and illustrated in **Figure 3.15** and **Figure 3.16**. In **Table 3.7**, the DG size (P_{DG}) are found by averaging the normalized random walks of R_E (around elite antlion), R_A (around roulette-wheel antlion) and R_M (around mutated antlion) according to equation (3.51).

Table 3. 7
Effects Of Mutation Scale, β And Population Size On LSF-MALO Performance In IEEE 69-Bus System

Case	β	Population size	P_{DG} (MW)	R_E	R_A	R_M	P_{loss} (MW)	Time (s)
Varying β , constant population size	0	20	1.4896	1.9494	2.4051	0.1144	0.0793	41.81
	0.1	20	1.2122	1.0843	2.0944	0.4579	0.0815	40.62
	0.2	20	1.0639	1.3450	1.7664	0.0802	0.0827	41.89
	0.3	20	1.3175	1.8811	2.0620	0.0096	0.0824	41.74
	0.4	20	1.2431	1.8811	1.8927	-0.0444	0.0821	41.04
	0.5	20	1.2169	1.8811	1.8681	-0.0983	0.0817	40.94
	0.6	20	1.2146	1.8811	1.8232	-0.0606	0.0817	41.54
	0.7	20	1.3218	1.9156	2.3078	-0.2580	0.0827	41.55
	0.8	20	1.3474	1.9156	2.4384	-0.3118	0.0825	40.68
	0.9	20	1.2676	1.9156	2.2530	-0.3657	0.0815	41.84
	1	20	1.2405	1.9156	2.2255	-0.4197	0.0812	40.97
Varying population size, constant β	0.5	5	0.8085	0.8905	0.9776	0.5573	0.0846	10.44
	0.5	10	1.3429	1.6127	2.0611	0.3551	0.1001	20.36
	0.5	15	0.5771	0.7534	0.6384	0.3395	0.0811	31.14
	0.5	20	0.6301	0.4252	1.5635	-0.0983	0.0817	40.94
	0.5	25	0.3743	0.1434	1.1725	-0.1932	0.0801	52.28
	0.5	30	0.5289	0.1434	1.6364	-0.1930	0.0817	61.97
	0.5	35	0.5280	0.1434	1.6336	-0.1929	0.0814	72.44
	0.5	40	0.5354	0.1434	1.3145	0.1483	0.0807	82.81
	0.5	45	0.6657	0.1434	1.7053	0.1483	0.0823	93.71
	0.5	50	0.6203	0.1434	1.5693	0.1483	0.0816	103.41

In the first case, the population size was fixed at 20 because it ensures sufficient diversity to test the mutation scale (β) while maintaining a reasonable execution time, avoiding the diminishing returns and heavy computational burden of larger populations. Throughout these experiments, the quantity and placement of the DG units are not randomized. To maintain consistency and isolate the effects of parameter changes, the quantity and location of DG are fixed at two units, located at buses 61 and 65, as established in the previous section.

In the previous sections, there is no mention of parameters that might affect the performance of the optimization techniques used in DG placement problem. In fact, the proposed LSF-MALO relies on two parameters, namely mutation scale (β) and population size. The mutation scale (β) determines the percentage of mutation used in producing an offspring antlion. There will be no difference between parent and offspring antlions if $\beta = 0$; however, there will be total difference between the two if $\beta = 1$. Hence, a value of β between $[0, 1]$ indicates the amount of difference in percentage between the parent and offspring solutions. Another parameter is the population size, which is the number of antlions, or precisely the number of search agents used to find the optimal solution. In this case, the population size is varied between five and fifty number of search agents.

Based on **Table 3.7**, for all β values and population size, the LSF-MALO algorithm results in an almost constant fitness (P_{loss}) of 0.08 MW, except at $\beta = 0.5$ and population size = 10 where P_{loss} is 0.1 MW. This means that at 50% of loading in IEEE 69-bus system, the optimal solution as found by the LSF-MALO will have fitness value of roughly 0.08 MW. However, the optimal solution is not unique. From **Table 3.7**, the values of P_{DG} , R_E , R_A and R_M are different for any different values of β and population size even though their fitness values are almost the same. For example, there are two solutions when the fitness is 0.0815 MW, first is when $\beta = 0.1$, population size = 20, $P_{DG} = 1.2122$ MW, $R_E = 1.0843$, $R_A = 2.0944$ and $R_M = 0.4579$, and second is when $\beta = 0.9$, population size = 20, $P_{DG} = 1.2676$ MW, $R_E = 1.9156$, $R_A = 2.2530$ and $R_M = -0.3657$. Another two solutions can be found when the fitness is 0.0817 MW, with the first solution happens when $\beta = 0.5$, population size = 20, $P_{DG} = 0.6301$ MW, $R_E = 0.4252$, $R_A = 1.5635$ and $R_M = -0.0983$, and the second one is $\beta = 0.5$, population size = 30, $P_{DG} = 0.5289$ MW, $R_E = 0.1434$, $R_A = 1.6364$ and $R_M = -0.1930$. These multiple optimal solutions are essential, especially in the case of DG placement problem, since the lowest size of DG units can be obtained for the same fitness values.

As can be seen in **Table 3.7**, all solutions, either varying β or population size, are optimal solutions. However, the only solutions that lead to the lowest size of DG units are those that have $\beta = 0.2$, population size = 20 and $P_{DG} = 1.0639$ MW in the case of varying β and; $\beta = 0.5$, population size = 25 and $P_{DG} = 0.3743$ MW in the case of varying population size, as highlighted in the table.

Clearer depictions for the effects of β and population size on optimal solutions are shown in **Figure 3.15** and **Figure 3.16** respectively. It is clear that the change in both parameters affect significantly the normalized random walks of R_E (green line), R_A (purple line), R_M (red line) and the DG size of P_{DG} (thick black line).

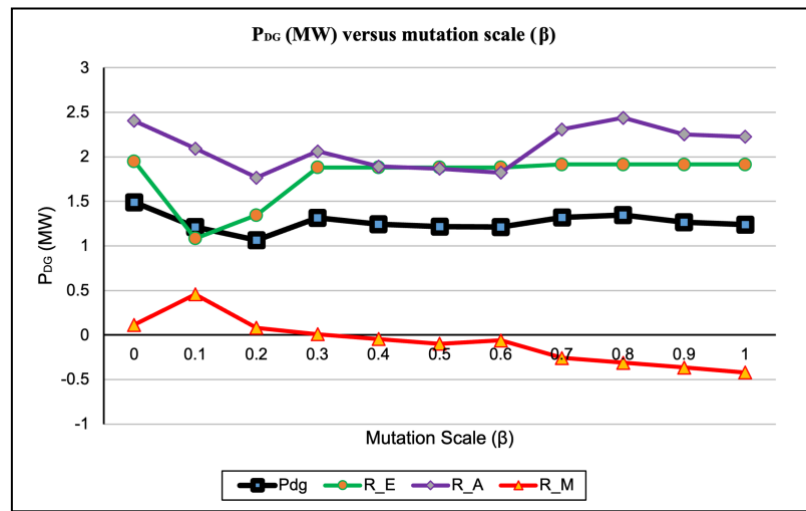


Figure 3. 15 Effect Of Mutation Scale, β On DG Size (P_{DG}), Elite's Random Walk (R_E), Roulette-Wheel's Random Walk (R_A) And Mutated's Random Walk (R_M) In IEEE 69-Bus System

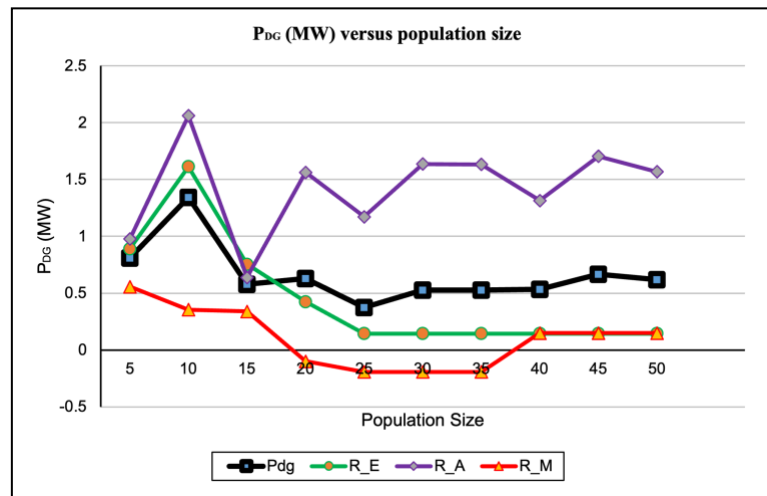


Figure 3. 16 Effect Of Population Size On DG Size (P_{DG}), Elite's Random Walk (R_E), Roulette-Wheel's Random Walk (R_A) And Mutated's Random Walk (R_M) In IEEE 69-Bus System

Based on **Figure 3.15** and **Figure 3.16**, the increase in β and population size reflects different patterns of the normalized random walks and DG size. As β increases from 0 to 1, R_E changes between 1 and 2, R_A changes between 1.5 and 2.5 and R_M changes between -0.5 and 0.5. Their changes result in corresponding change in P_{DG} between 1 MW and 1.5 MW. Likewise, as population size increases from 5 to 50, R_E changes between 0 and 1 (except at population size of 10), R_A changes between 0.5 and 2 and R_M changes between -0.5 and 0.5. These changes result in corresponding change in P_{DG} between 0.5 MW and 1.5 MW. However, it is also noticed that the change in P_{DG} is more affected by the change in population size than the change in β . The trend of P_{DG} (thick black line) as in **Figure 3.16** (varying population size) has more fluctuation than that of **Figure 3.15** (varying β). This also signifies that the optimal solution is more affected if the number of search agents employed during optimization is varied.

Based on the analysis, it is crucial to properly set the two parameters of β and population size during initialization of the algorithm. Results have shown that any settings on both parameters yield to almost the same fitness values, but that is not the case. In optimal DG placement problem, another factor that should be considered besides providing stable voltage profiles is the cost of DG units. Lower cost can be obtained if the DG units have smaller MW ratings and this is attainable provided that the optimization algorithm can search for multiple optimal solutions. Based on **Table 3.7** and **Figure 3.16**, the lowest DG size that can be obtained by LSF-MALO is $P_{DG} = 0.3743$ MW at $\beta = 0.5$ and population size = 25.

This section also justifies the significance of incorporating mutation element into the original Ant Lion Optimizer (ALO) algorithm, namely, to provide solution variety and avoiding local optima problem. Solution variety ensures multiple optimal solutions for the same fitness values. The proposed LSF-MALO algorithm is able to search for global optimum solutions by producing several optimal solutions at different values of β and population size.

3.6 Chapter Summary

In brief, this chapter has successfully developed a hybrid algorithm for optimal DG placement in distribution system, namely the Loss Sensitivity Factor Mutated Antlion Optimizer (LSF-MALO). The algorithm has been presented in a comprehensive flowchart with complete mathematical formulation in accordance to DG placement problem. The aim of the optimization is to minimize power losses while maintaining stable voltage profiles and adequate size of DG units at the right locations in the system. Experiment and analysis were conducted on two distribution systems, namely the IEEE 33-bus and IEEE 69-bus system, for the purpose of verification. The analysis has discovered several important findings. Firstly, it was justified in section 3.5.1 and 3.5.2 that the proposed LSF-MALO was able to determine adequate size and suitable location for DG placement, with one DG unit of 2.5706 MW at bus 6 for IEEE 33-bus system and one DG unit of 1.8397 MW at bus 61 for IEEE 69-bus system. Secondly, in section 3.5.3 and 3.5.4, the proposed algorithm was further tested under multiple reactive loadings from base case to maximum. This is to verify the robustness of LSF-MALO in ensuring stable voltage profiles with low power losses at whatever conditions of the system. From this analysis, it was justified that the proposed algorithm resulted in minimum voltage magnitude of at least 0.95 p.u., high percentage reduction in power losses of at least 50% with the lowest size of DG units as compared to other methods. Finally, in section 3.5.5, the influence of mutation operator (β) and number of search agents on the algorithm performance were validated. By properly adjusting the two parameters, the proposed LSF-MALO resulted in multiple optimal solutions with the same fitness value. From the analysis, the most optimal solution was achieved at $\beta = 0.5$ and population size = 25, with the lowest size of DG unit = 0.3743 MW. Hence, the purpose of hybridizing ALO and EP to produce MALO algorithm, which was then combined with LSF technique to become LSF-MALO, have been sufficiently validated and justified.

CHAPTER 4

MULTI-OBJECTIVE LSF-MALO TECHNIQUE FOR OPTIMAL DISTRIBUTED GENERATION PLACEMENT WITH COST SAVING

4.1 Introduction

Chapter 3 has implemented the Loss Sensitivity Factor and Mutated Ant Lion Optimizer (LSF-MALO) in single objective optimization (SOO) problem for real power losses minimization with enhanced voltage magnitude. However, the proposed problem formulation overlooks the economic aspects of Distributed Generation (DG) placement. Moreover, the previous chapter only considered one type of DG unit in the problem, specifically type 1, which represents solar PV units. The other types of DG unit like diesel generators and wind turbines were not included in the analysis. Therefore, this chapter extends the proposed method to tackle multi-objective optimization challenges, hence multi-objective optimization (MOO) problem, considering both the economic implications of DG installation and the impact of various types of DG unit.

4.2 Methodology

This section presents the proposed methodology for multi-objective LSF-MALO implementation in optimal Distributed Generation (DG) placement problem. It begins with the concept of annual economic loss (AEL) and annual cost saving (ACS) in the context of distribution system, the principle of Weighted Sum Method (WSM) in multi-objective optimization problem and the development of multi-objective LSF-MALO algorithm for optimal DG placement with cost saving.

4.2.1 Annual Economic Loss and Annual Cost Saving

Placement of DG units in distribution system will not be a promising preventive action if the service provider does not receive some economic benefits in terms of yearly profit and cost saving, albeit it does provide technical improvement such as reduced power losses and enhanced voltage profiles. The key principle in solving multi-

objective optimal DG placement problem is to maximize yearly profit (hence, reducing the annual cost) while ensuring minimum power losses with stable voltage profiles as well. With these aims achieved, the overall system efficiency and dependability shall increase.

In a distribution system with DG units being installed, the overall system cost is mostly determined by cost of energy loss and price of the DG units. The summation of these two is noted as annual economic loss (AEL). The cost of energy loss represents the yearly cost incurred due to total real power losses in the system, while the price of the DG units will be determined based on their total generated power and cost per kilo-Watt generated. Hence, the multi-objective optimization problem aims to reduce the power losses and improve voltage profiles (the technical aspect) and minimizing AEL (the economic aspect). As a result of DG penetration in the system, it is expected to have a cost saving from the reduced power losses. The difference between two AELs, before and after DG placement, will give the equivalent cost saving per year, which is noted as annual cost saving (ACS).

The AEL for one year, which is equivalent to 8,760 hours, can be calculated as in (4.1):

$$AEL = P_{loss} \times C_e \times 8760 \quad (4.1)$$

Where, P_{loss} is the total real power losses and C_e is the cost of energy loss in RM per kWh.

In addition, the cost of DG installation is represented by (4.2):

$$C_i = \frac{C_{DG} \times \sum_{i=1}^{N_{DG}} P_{DGi}}{L_{DG}} \quad (4.2)$$

Where, C_{DG} is the cost of DG per kilo-Watt (kW) generated including its operation and maintenance costs, N_{DG} is the number of DG units installed, P_{DGi} is the real power generation by i -th DG unit (or the DG size) and L_{DG} is the DG unit's years of life span.

The economic parameters and specific unit costs utilized in this study are explicitly defined in the Malaysian context (Ringgit Malaysia, RM). The unit cost (C_{DG})

for each DG technology, which encompasses capital installation, operation, and maintenance costs along with the cost of energy loss (C_e), is tabulated in **Table 4.1**. These values were adopted from a combination of academic literature and current market data.

Table 4. 1
Economic Parameters And Unit Costs For DG Integration

Economic Parameter	Cost (RM/kWh)	Reference
Cost of energy, C_e	0.218	[134]
Solar PV, C_{DG}	0.1901	[135]
Wind turbine, C_{DG}	0.9050	[136]
Diesel Generator, C_{DG}	1.54	[137]

In this chapter, the AEL for both conditions, namely with and without DG, will be calculated to determine the annual cost saving (ACS) as a result of DG placement in the system. The yearly ACS is calculated as in (4.3):

$$ACS = AEL_{Pre} - AEL_{Post} \quad (4.3)$$

With AEL_{Pre} and AEL_{Post} are calculated as in (4.4) and (4.5) respectively:

$$AEL_{Pre} = P_{loss} \times C_e \times 8760 \quad (4.4)$$

$$AEL_{Post} = [P_{loss} \times C_e \times 8760] + C_i \quad (4.5)$$

Where, AEL_{Pre} and AEL_{Post} are the annual economic loss without and with DG placement respectively, and C_i is the cost of DG installation as represented by (4.2).

4.2.2 Weighted Sum Method for Multi-Objective Optimal DG Placement

A more conventional approach for multi-objective optimization (MOO) problem is by treating several fitness functions to be a single, unified objective function, which is known as the Weighted Sum Method (WSM) [138]. In this approach, each fitness function will be assigned with a specific weight value indicating their level of

importance in optimization. For instance, if there are N number of fitness functions, then the unified fitness function, f_{wsm} (which is also referred to as weighted-sum fitness) can be described as in (4.6) to (4.7):

$$f_{wsm} = w_1 f_1 + w_2 f_2 + \dots + w_i f_i + \dots + w_N f_N \quad (4.6)$$

$$\therefore f_{wsm} = \sum_{i=1}^N w_i f_i \quad (4.7)$$

And:

$$\sum_{i=1}^N w_i = 1 \quad (4.8)$$

Where, f_{wsm} is the weighted-sum fitness function, f_i is the individual fitness function and w_i is the individual weight value assigned to each fitness. As in (4.8), the summation of all weight values must equal to 1. By implementing this technique, the MOO problem is equivalently transformed into SOO problem with multiple number of objectives at the same time.

In the context of optimal DG placement problem, there are three fitness functions to be considered in the problem formulation, namely the minimum bus voltage magnitude (V_{min}), total real power losses (P_{loss}) and annual economic loss (AEL). Two of the fitness functions, P_{loss} and AEL , must be solved under minimization problem while the fitness V_{min} will be under maximization problem. Hence, there will be a mix of two different optimization problems to be considered concurrently. However, the weighted-sum fitness function, f_{wsm} can only be formulated either as a minimization or maximization problem. This study assigns the highest priority (Rank 1) to total real power loss (P_{loss}) to maximize system efficiency and minimize operational costs. Minimum voltage magnitude (V_{min}) is ranked second; while essential for stability, increasing it beyond statutory limits offers less value than reducing power loss. Finally, Annual Economic Loss (AEL) is ranked third, prioritizing fundamental technical integrity over secondary financial metrics.

For the purpose of this study, the f_{wsm} will be formulated as a minimization problem by converting the maximization of V_{min} into negative weighted fitness [139]. Hence, the overall minimization of fitness function will be as in (4.9):

$$\text{Minimize } \{f_{wsm} = w_1 P_{loss} - w_2 V_{min} + w_3 AEL\} \quad (4.9)$$

Where, w_1 , w_2 and w_3 are the individual weight values for P_{loss} , V_{min} and AEL respectively.

The three weights from (4.9) can be assigned in several ways, either by heuristic approach or through calculation. The latter one is more accurate and will be implemented in this study through R-method [140]. The R-method was originally used to ranking the non-dominated solutions for Pareto-optimal solution. It was designed to logically assign the weights to objectives, making it easier to assess the performance of different solutions. It also helps in choosing the best compromised solution from a set of Pareto-optimal options in multi-objective optimization problems.

The determination of the individual weights (w_1 , w_2 and w_3) based on R-method is described in the following procedure:

- i) The priority of fitness functions (V_{min} , P_{loss} and AEL) is determined by ranking them based on their importance. If two or more fitness functions are deemed equally important, they will be assigned with an average rank.
- ii) The weight of the ranks is then calculated based on (4.10):

$$w_j = \frac{\left(\frac{1}{\sum_{k=1}^j \left(\frac{1}{r_k} \right)} \right)}{\sum_{j=1}^n \left(\frac{1}{\sum_{k=1}^j \left(\frac{1}{r_k} \right)} \right)} \quad (4.10)$$

Where:

- w_j : weight of j -th fitness function ($j = 1, 2, 3, \dots, n$)
- r_k : rank of k -th fitness function ($k = 1, 2, 3, \dots, j$)
- n : number of fitness functions

- iii) The calculated weight values are verified by ensuring their summation equals to 1, as in (4.8).

The mathematical example to illustrate the calculation of the weights are given as follows. In this case, n is set to 3 as there are three fitness functions to be considered (P_{loss} , V_{min} and AEL).

$$w_1 = \frac{\left(\frac{1}{1/1}\right)}{\frac{1}{1/1} + \left(\frac{1}{1/1 + 1/2}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3}\right)} = 0.4521$$

$$w_2 = \frac{\left(\frac{1}{1/1 + 1/2}\right)}{\frac{1}{1/1} + \left(\frac{1}{1/1 + 1/2}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3}\right)} = 0.3014$$

$$w_3 = \frac{\left(\frac{1}{1/1 + 1/2 + 1/3}\right)}{\frac{1}{1/1} + \left(\frac{1}{1/1 + 1/2}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3}\right)} = 0.2465$$

Hence, the finalized objective function for WSM based multi-objective optimal DG placement is represented in (4.11):

$$\text{Minimize } \{f_{wsm} = 0.4521 \cdot P_{loss} - 0.3014 \cdot V_{min} + 0.2465 \cdot AEL\} \quad (4.11)$$

4.2.3 Proposed Problem Formulation and Development of Multi-Objective LSF-MALO Algorithm

This section explains the proposed multi-objective LSF-MALO algorithm for optimal DG placement in distribution system. The overall flowchart is presented in **Figure 4.1**.

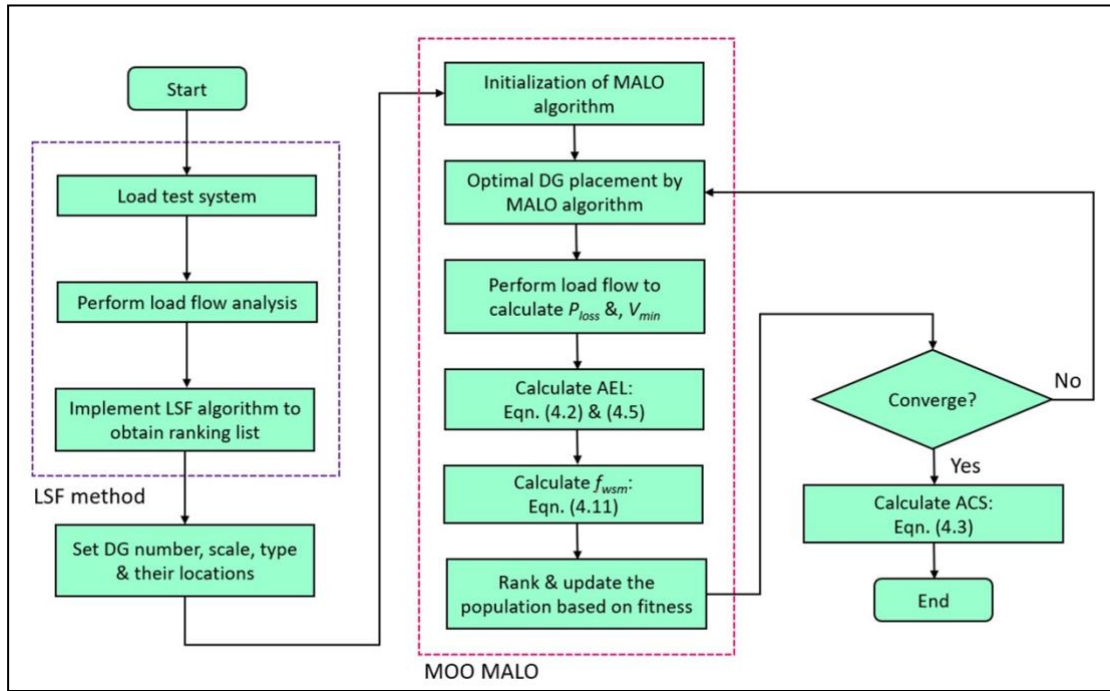


Figure 4. 1 Multi-Objective LSF-MALO Algorithm For Optimal DG Placement

The procedure for MOO LSF-MALO is described as follows:

- i) As in Chapter 3, the LSF-MALO algorithm begins with the determination of LSF indices for bus ranking. The calculation of LSF indices is performed exactly as in (3.1) of Chapter 3.
- ii) Afterwards, the suitable locations for DG placement are identified based on the LSF ranking list. The number of DG units and their types (diesel generator, solar photovoltaic and wind turbine) are also specified at the selected locations.
- iii) Next, the LSF-MALO algorithm is implemented to conduct the MOO for optimal sizing of DG units. The algorithm starts with the initialization of essentials parameters, namely the population size and mutation scale. Then, it proceeds to generate initial population of ants ($\mathbf{M}_{Ant}$) and antlions ($\mathbf{M}_{Antlion}$) as in (4.12) and (4.13). In both equations, M indicates the population size for the ants and antlions.

$$\mathbf{M}_{\text{Ant}} = \begin{bmatrix} Ant_1 \\ \vdots \\ Ant_i \\ \vdots \\ Ant_M \end{bmatrix} = \begin{bmatrix} P_{DG1}^1 & \dots & P_{DGN}^1 & PF_{DG1}^1 & \dots & PF_{DGN}^1 \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^i & \dots & P_{DGN}^i & PF_{DG1}^i & \dots & PF_{DGN}^i \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^M & \dots & P_{DGN}^M & PF_{DG1}^M & \dots & PF_{DGN}^M \end{bmatrix} \quad (4.12)$$

$$\mathbf{M}_{\text{Antlion}} = \begin{bmatrix} Antlion_1 \\ \vdots \\ Antlion_i \\ \vdots \\ Antlion_M \end{bmatrix} = \begin{bmatrix} P_{DG1}^1 & \dots & P_{DGN}^1 & PF_{DG1}^1 & \dots & PF_{DGN}^1 \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^i & \dots & P_{DGN}^i & PF_{DG1}^i & \dots & PF_{DGN}^i \\ \vdots & & \vdots & \vdots & & \vdots \\ P_{DG1}^M & \dots & P_{DGN}^M & PF_{DG1}^M & \dots & PF_{DGN}^M \end{bmatrix} \quad (4.13)$$

- iv) In the optimization algorithm, the different types of DG units (solar photovoltaic, wind turbine and diesel generator) are distinguished based on their injected real power, P_{DG} and power factor, PF_{DG} . Based on these two variables, the corresponding reactive power injection or absorption, Q_{DG} will be calculated via (4.14) to (4.16).

Solar photovoltaic (PV) (unity power factor):

$$[P_{DG}, PF_{DG}] \Rightarrow \therefore Q_{DG} = 0, \quad PF_{DG} = 1 \quad (4.14)$$

Wind turbine (leading power factor):

$$[P_{DG}, PF_{DG}] \Rightarrow \therefore Q_{DG} = P_{DG} \tan(\cos^{-1} PF_{DG}), \quad 0 \leq PF_{DG}(\text{lead}) \leq 1 \quad (4.15)$$

Diesel Generator (lagging power factor):

$$[P_{DG}, PF_{DG}] \Rightarrow \therefore Q_{DG} = P_{DG} \tan(\cos^{-1} PF_{DG}), \quad 0 \leq PF_{DG}(\text{lag}) \leq 1 \quad (4.16)$$

- v) At fitness evaluation stage, there will be three steps of determination for individual fitness. At first, the load flow simulation is conducted to determine the minimum voltage magnitude, V_{min} . Later, the real power losses, P_{loss} is

calculated from the load flow results via (3.26) of Chapter 3. Finally, the annual economic lost, AEL_{Post} with DG placement is calculated through (4.5).

- vi) After that, the WSM approach is used to determine the weighted-sum fitness, f_{wsm} based on (4.11). This is done for all ants and antlions in the population in which they will be ranked according to their f_{wsm} .
- vii) The ants and antlions are ranked such that the best of them with minimum f_{wsm} will be placed at the topmost, while the worst one with maximum f_{wsm} will be at the bottommost. This is shown in (4.17) and (4.18).

$$\mathbf{M}_{\text{Ant}} = \left[\begin{array}{c|c} Ant_1 & f_{wsm}^1 \\ \vdots & \vdots \\ Ant_i & f_{wsm}^i \\ \vdots & \vdots \\ Ant_M & f_{wsm}^M \end{array} \right] \Rightarrow \begin{array}{l} \text{Best Ant} \\ \\ \\ \text{Worst Ant} \end{array} \quad (4.17)$$

$$\mathbf{M}_{\text{Antlion}} = \left[\begin{array}{c|c} Antlion_1 & f_{wsm}^1 \\ \vdots & \vdots \\ Antlion_i & f_{wsm}^i \\ \vdots & \vdots \\ Antlion_M & f_{wsm}^M \end{array} \right] \Rightarrow \begin{array}{l} \text{Best Antlion} \\ \\ \\ \text{Worst Antlion} \end{array} \quad (4.18)$$

- viii) Later, the solutions produced by ants and antlions are updated as follows. At first, the ant positions are updated according to (4.19) and (4.20). Next, the current antlion positions are updated by combining their existing positions ($\mathbf{M}_{\text{Antlion}}$) with the updated ant positions ($\mathbf{M}_{\text{Ant}}$). This is done through (4.21). After sorting the combined matrix ($\mathbf{M}_{\text{Combine}}$) based on fitness values, the updated antlion positions are defined as in (4.22).

$$Ant_{i,P}^{new} = P_{DG,new}^i = \frac{R_{AP}^t + R_{EP}^t + R_{MP}^t}{3} \quad (4.19)$$

$$Ant_{i,PF}^{new} = PF_{DG,new}^i = \frac{R_{APF}^t + R_{EPF}^t + R_{MPF}^t}{3} \quad (4.20)$$

$$\mathbf{M}_{\text{Combine}} = \left[\begin{array}{c} \mathbf{M}_{\text{Ant}} \\ \mathbf{M}_{\text{Antlion}} \end{array} \right] \quad (4.21)$$

$$\mathbf{M}_{\text{Antlion}} = \mathbf{M}_{\text{Combine}}(1:M, :) \quad (4.22)$$

Where, $Ant_{i,p}^{new}$, $Ant_{i,pf}^{new}$ are the updated positions of i -th ant for P_{DG} and PF_{DG} , R_{EP}^t , R_{AP}^t , R_{MP}^t are the normalized random walks for P_{DG} around the elite, roulette-wheel and mutated antlions, R_{EPF}^t , R_{APF}^t , R_{MPF}^t are the normalized random walks for PF_{DG} around the elite, roulette-wheel and mutated antlions.

- ix) The optimization repeats from step (iv) to (viii) until it achieves convergence.
- x) Only after the termination criterion is met, the annual cost saving (ACS) will be calculated via (4.3) for the best solution.

Hence, the overall formulation of multi-objective optimization (MOO) problem can be summarized as follows:

$$\text{Minimize } \left\{ f_{wsm}(P_{DG}, PF_{DG}) = 0.4521 \cdot P_{loss} - 0.3014 \cdot V_{min} + 0.2465 \cdot AEL \right\} \quad (4.23)$$

Subject to constraints:

$$\text{DG size : } 0.005 \text{ MW} < P_{DG} < 5 \text{ MW} \quad (4.24)$$

$$\text{DG power factor : } 0 < PF_{DG} < 1 \quad (4.25)$$

$$\text{Bus voltage : } 0.95 \text{ p.u.} < V_{min} < 1.05 \text{ p.u.} \quad (4.26)$$

$$\text{DG number : } 1 < N_{DG} < 3 \quad (4.27)$$

$$\text{DG type : } T_{DG} = 1, 3 \text{ and } 4 \quad (4.28)$$

For the purpose of this study, a maximum of three DG units will be allowed for placement in distribution system as represented in (4.27). The constraint for DG type as in (4.28) indicates three types of DG units to be considered, namely the solar PV, wind turbine and diesel generator.

4.3 Results and Discussion

As in Chapter 3, the experiment will involve two test systems: the IEEE 33-bus and 69-bus radial distribution systems. The analysis will assess both technical and economic aspects of the distribution networks before and after optimization. These include voltage magnitude, real power losses, annual economic loss, and annual cost savings. At first, the analysis evaluates the performance of the multi-objective LSF-MALO in a base case scenario, considering both identical and combinational DG types. Identical DG type refers to the implementation of the same category of DG units across the system, either they are all solar PV units, all wind turbines or all diesel generators. On the other hand, combinational DG type involves a mixture of different categories of DG units, such as a combination of solar PV units and diesel generators.

Subsequently, the proposed method's ability to maintain desired results is further tested under various reactive loadings, ranging from the base case to 100% of maximum loading, with 20% increments. Finally, the impact of varying weight values, as specified in equation (4.11), is investigated to observe any changes in the optimization solution. For the purpose of this study, different number of DG units will be used for different test systems. Two DG units will be implemented in IEEE 33-bus system, while three DG units will be implemented in IEEE 69-bus system. This is summarized in **Table 4.2**.

Table 4. 2
Summary Of DG Units Implemented In IEEE 33-Bus And 69-Bus Systems

Test System	DG penetration type	Number of DG units	Types of DG integrations	Symbol
IEEE 33-bus system	Identical	2	2 solar PVs	PV-PV
		2	2 wind turbines	Wind-Wind
		2	2 diesel generators	Diesel-Diesel
	Combinational	2	1 solar PV 1 diesel generator	PV-Diesel
		2	1 solar PV 1 wind turbine	PV-Wind
		2	1 wind turbine 1 diesel generator	Wind-Diesel
IEEE 69-bus system	Identical	3	3 solar PVs	PV-PV-PV
		3	3 wind turbines	Wind-Wind-Wind
		3	3 diesel generators	Diesel-Diesel-Diesel
	Combinational	3	1 solar PV 1 wind turbine 1 diesel generator	PV-Wind-Diesel
		3	2 solar PVs 1 diesel generator	PV-PV-Diesel
		3	2 solar PVs & 1 wind turbine	PV-PV-Wind

4.3.1 Effects of Identical and Combinational DG Types in IEEE 33-Bus System

Table 4.3 tabulates the results after multi-objective optimal DG placement was implemented in the IEEE 33-bus system, considering identical DG types. In this scenario, two DG units of the same category are integrated into the test system at specific load buses.

Based on **Table 4.3**, the LSF-MALO technique consistently provides the best results in terms of reducing power losses (P_{loss}) and increasing minimum voltage magnitudes (V_{min}) across different DG integrations, either PV-PV, Diesel-Diesel or Wind-Wind integration.

By using PV-PV integration, the best performance results from LSF-MALO technique with P_{loss} reduced to 0.086 MW, V_{min} improved to 0.960 p.u. and AEL reduced to RM165,014.00, which is equivalent to RM184,617.00 of ACS (52.8% of cost reduction). The next acceptable performance results from MALO technique with P_{loss} of 0.152 MW, V_{min} of 0.960 p.u. and ACS of RM59,919.00, which is equivalent to 17.1% of cost saving. The LSF Analytical technique results in the lowest percentage of cost saving, while the EP technique was unable to provide V_{min} above 0.95 p.u.

The LSF-MALO technique with Diesel-Diesel integration is the most effective DG placement for the IEEE 33-bus system, providing the highest cost savings and substantial reduction in power losses and improvement on voltage magnitude. This type of DG shows superior performance in terms of ACS , with the LSF-MALO technique providing the highest cost saving percentage of 63.3% (equivalent to RM221,172.00), an improved V_{min} of 0.970 p.u. and a reduced P_{loss} of 0.067 MW as well. This is followed by the EP, LSF Analytical and MALO techniques with cost saving percentages of 55.6%, 20.9% and 17.1% respectively.

The Wind-Wind integration shows a moderate performance for the LSF-MALO technique compared to the solar PV and diesel units, while the LSF Analytical and MALO techniques did not perform well, leading to increased AEL and negative cost savings.

On the other hand, **Table 4.4** tabulates the results after optimal DG placement in the IEEE 33-bus system, considering combinational DG types. In this scenario, two DG units of different category are integrated into the test system at specific load buses using the following combinations: Wind-Diesel, PV-Diesel and PV-Wind.

Table 4. 3

Voltage Magnitude, Power Losses And Annual Economic Loss Using Optimal DG Placement In IEEE 33-Bus System - Base Case Scenario With Identical DG Types

IDENTICAL DG TYPE									
Method	DG bus	DG type	P_{DG} (MW)	Q_{DG} (MVar)	P_{loss} (MW)	V_{min} (p.u.)	AEL (RM)	ACS (RM)	% ACS
Without DG	-	-	-	-	0.183	0.918	349,631	-	-
LSF-MALO	6	PV	2.003	0.000	0.086	0.960	165,014	184,617	52.8
	5	PV	1.357	0.000					
LSF Analytical	6	PV	2.836	0.000	0.167	0.987	318,328	31,303	9.0
	5	PV	3.169	0.000					
EP	11	PV	1.066	0.000	0.099	0.943	189,352	160,279	45.8
	13	PV	0.418	0.000					
MALO	11	PV	1.730	0.000	0.152	0.960	289,712	59,919	17.1
	13	PV	0.999	0.000					
Without DG	-	-	-	-	0.183	0.918	349,631	-	-
LSF-MALO	6	Diesel	1.462	0.578	0.067	0.970	128,459	221,172	63.3
	5	Diesel	2.250	0.889					
LSF Analytical	6	Diesel	2.836	1.121	0.144	0.996	276,539	73,092	20.9
	5	Diesel	3.169	1.252					
EP	11	Diesel	1.173	0.464	0.081	0.952	155,345	194,286	55.6
	13	Diesel	0.485	0.192					
MALO	11	Diesel	1.728	0.683	0.132	0.970	289,712	59,919	17.1
	13	Diesel	0.997	0.394					
Without DG	-	-	-	-	0.183	0.918	349,631	-	-
LSF-MALO	6	Wind	2.030	-0.667	0.139	0.952	266,205	83,426	23.9
	5	Wind	1.385	-0.455					
LSF Analytical	6	Wind	2.836	-0.932	0.267	0.974	510,532	-160,901	-46.0
	5	Wind	3.169	-1.041					
EP	11	Wind	0.894	-0.294	0.129	0.934	247,349	102,282	29.3
	13	Wind	0.234	-0.077					
MALO	11	Wind	2.063	-0.678	0.429	0.960	819,691	-470,060	-134.4
	13	Wind	1.825	-0.600					

Table 4. 4

Voltage Magnitude, Power Losses And Annual Economic Loss Using Optimal DG Placement In IEEE 33-Bus System - Base Case Scenario With Combinational DG Types

COMBINATIONAL DG TYPE									
Method	DG bus	DG Type	P_{DG} (MW)	Q_{DG} (MVar)	P_{loss} (MW)	V_{min} (p.u.)	AEL (RM)	ACS (RM)	% ACS
Without DG	-	-	-	-	0.183	0.918	349,631	-	-
LSF-MALO	6	Diesel	1.852	0.732	0.085	0.968	162,476	187,155	53.5
	5	Wind	2.026	-0.666					
LSF Analytical	6	Wind	2.836	-0.932	0.175	0.984	334,724	14,907	4.3
	5	Diesel	3.169	1.252					
EP	11	Wind	0.005	-0.002	0.092	0.947	176,763	172,868	49.4
	13	Diesel	1.362	0.538					
MALO	11	Wind	1.729	-0.568	0.162	0.958	310,331	39,300	11.2
	13	Diesel	0.998	0.394					
Without DG	-	-	-	-	0.183	0.918	349,631	-	-
LSF-MALO	6	PV	1.139	0.000	0.078	0.963	148,530	201,100	57.5
	5	Diesel	2.536	1.002					
LSF Analytical	6	Diesel	2.836	1.121	0.141	0.995	269,307	80,324	23.0
	5	PV	3.169	0.000					
EP	11	Diesel	1.231	0.487	0.090	0.947	172,384	177,247	50.7
	13	PV	0.161	0.000					
MALO	11	Diesel	1.723	0.681	0.130	0.966	247,845	101,786	29.1
	13	PV	0.992	0.000					
Without DG	-	-	-	-	0.183	0.918	349,631	-	-
LSF-MALO	6	PV	1.170	0.000	0.120	0.954	228,852	120,779	34.5
	5	Wind	2.394	-0.787					
LSF Analytical	6	Wind	2.836	-0.932	0.214	0.978	409,202	-59,571	-17.0
	5	PV	3.169	0.000					
EP	11	Wind	0.005	-0.002	0.109	0.941	207,467	142,164	40.7
	13	PV	1.300	0.000					
MALO	11	Wind	1.487	-0.489	0.228	0.959	247,845	101,786	29.1
	13	PV	1.596	0.000					

Table 4.4 demonstrates that the optimal DG placement using combinational DG types significantly improves the voltage magnitude (V_{min}), power losses (P_{loss}), annual economic loss (AEL) and annual cost saving (ACS) as well. In this case, the LSF-MALO technique stands out as the most effective across different combinations of DG types.

By having a Wind-Diesel integration, the LSF-MALO technique provides the best improvement to the system, where the V_{min} was improved to 0.968 p.u., P_{loss} was

significantly reduced to 0.085 MW and AEL was greatly reduced to RM162,476.00, resulting in 53.5% of ACS (equivalent to RM187,155.00). This is followed by EP technique with ACS of 49.4%, however, at voltage magnitudes of below 0.95 p.u. for all DG type combinations. The LSF Analytical and MALO techniques provide promising V_{min} and P_{loss} , but their ACS percentages are not as high as the proposed technique.

The PV-Diesel integration is the most effective compared to the previous one. As can be seen in **Table 4.4**, the LSF-MALO technique results in improved V_{min} of 0.963 p.u., reduced P_{loss} of 0.078 MW and the highest ACS percentage of 57.5%, which is equivalent to RM201,100.00.

A moderate performance is shown by the PV-Wind integration, where the LSF-MALO technique provides a quite considerable ACS percentage of 34.5% with moderate V_{min} and P_{loss} of 0.954 p.u. and 0.12 MW respectively. The MALO technique provides the second-best performance in every aspect of the performance, with improved V_{min} , reduced P_{loss} and fair ACS percentages. The LSF Analytical technique shows the best improvement on V_{min} for all types of DG combination, however, this is not true for the ACS percentage where it results in negative cost saving of -17% for PV-Wind integration. The EP technique provides significant ACS percentage as that of LSF-MALO, yet, the resulted V_{min} is still below 0.95 p.u.

4.3.2 Comparison between Identical and Combinational DG Types in IEEE 33-Bus System

The effectiveness of DG implementation between identical and combinational DG types will be assessed in this section. The corresponding graphical illustrations, based on **Table 4.3** and **Table 4.4**, on minimum voltage magnitude (V_{min}), annual economic loss (AEL), and annual cost saving (ACS) are presented in **Figure 4.2** to **Figure 4.4**.

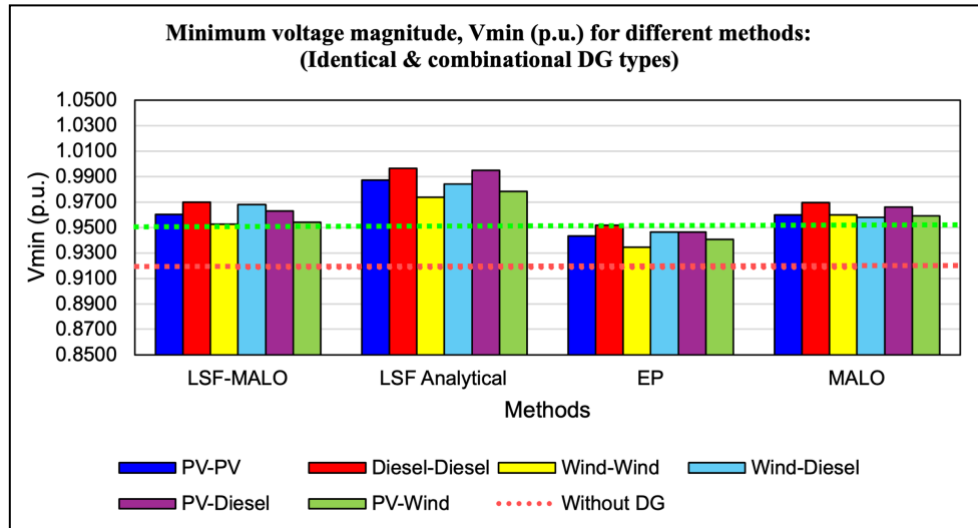


Figure 4. 2 Minimum Voltage Magnitude By All Methods – IEEE 33-Bus System

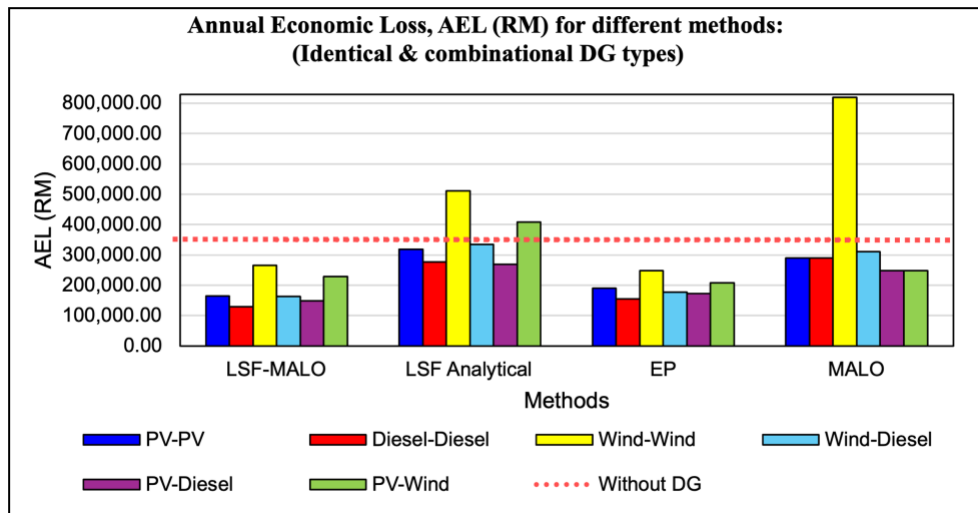


Figure 4. 3 Annual Economic Loss By All Methods – IEEE 33-Bus System

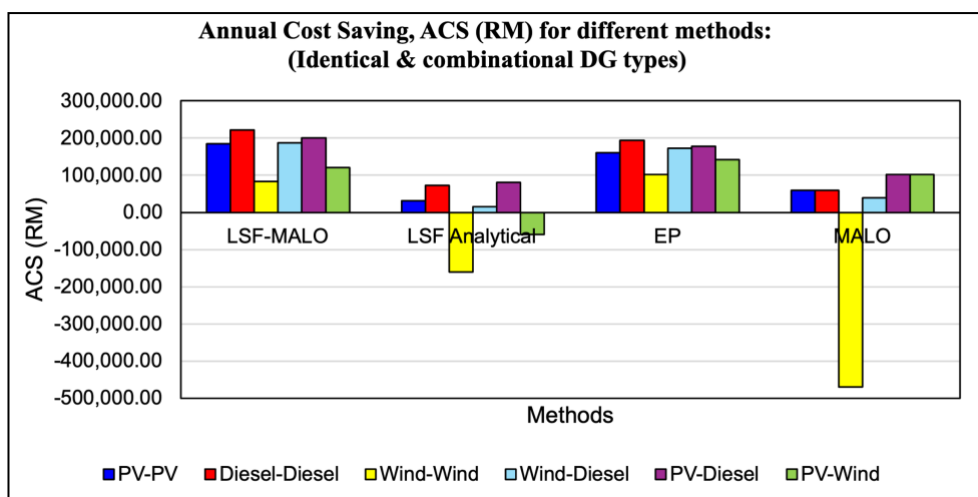


Figure 4. 4 Annual Cost Saving By All Methods – IEEE 33-Bus System

From **Figure 4.2**, the optimal DG placement by all methods results in an improved magnitude of V_{min} compared to the scenario without DG placement (The dotted red line represents the baseline scenario without DG integration, while the dotted green line indicates the 0.95 p.u. minimum acceptable statutory voltage limit.). However, the most effective technique is the LSF Analytical method, as the V_{min} magnitudes using any types of DG integrations are well above 0.95 p.u. This is followed by the MALO and LSF-MALO techniques, which show almost the same trend of voltage improvement, with V_{min} magnitudes slightly above 0.95 p.u. using any types of DG integrations. The EP technique, on the other hand, was unable to improve the voltage for most of the DG integrations, except for the Diesel-Diesel integration (red bar), which shows a very slight improvement above 0.95 p.u.

From **Figure 4.3**, the optimal DG placement by most of the methods also results in reduced AEL compared to the one without DG placement (dotted red line). In this case, the LSF-MALO and EP techniques reflect almost similar trend of AEL reduction using any types of DG integrations. They managed to reduce the AEL below RM300,000.00 using Wind-Wind (yellow bars) or PV-Wind (green bars) integrations, and below RM200,000.00 using the rest of the DG integrations. As a result, the corresponding cost savings, ACS by these two methods are the highest, well above RM150,000.00, either by using PV-PV (blue bars), Diesel-Diesel (red bars), Wind-Diesel (light blue bars) or PV-Diesel (purple bars) integrations, as shown in **Figure 4.4**.

In contrast, the Wind-Wind integration (yellow bars) by LSF Analytical and MALO techniques failed to reduce the AEL below the scenario without DG integration, as can be seen in **Figure 4.3**. This has resulted in negative cost savings (ACS), which is translated as a cost waste, as shown in **Figure 4.4**. In addition, even though the rest of the DG integrations by both methods offer cost savings, the amount cannot go as high as the LSF-MALO and EP techniques. At most RM100,000.00 of ACS can be offered by MALO technique using either PV-Diesel (purple bar) or PV-Wind (green bar) integrations, while the rest of the DG integrations have ACS much below RM100,000.00 for most of them.

The Diesel-Diesel integration shows a promising improvement in terms of voltage magnitude and cost saving. Through LSF-MALO, LSF Analytical and MALO techniques, this type of DG integration offers V_{min} magnitudes of well above 0.95 p.u., and through LSF-MALO technique, it offers an ACS higher than RM200,000.00. However, it is a non-renewable DG technology, which can cause high greenhouse gas

emissions. Therefore, the use of Diesel-Diesel integration should be minimized. Based on the analysis, the PV-PV, Wind-Diesel and PV-Diesel integrations using LSF-MALO technique can ensure voltage magnitudes of above 0.95 p.u. with considerable cost savings of above RM150,000.00 as well.

4.3.3 Multi-type DG Placement in IEEE 33-Bus System under Changing Loadings

In the previous sections, the performance of DG placement was evaluated at base case condition, where the reactive loadings in the system was kept constant. Reactive power flow is crucial for maintaining overall system stability, ensuring proper voltage profiles, and minimizing power losses. An increase in reactive power consumption by loads can significantly impact the distribution network, causing voltage magnitudes to drop below 0.95 p.u. and simultaneously increasing power losses. Hence, to observe the robustness of the proposed method, the multi-objective LSF-MALO algorithm is further tested under changing reactive loadings from base case to 100% of maximum loading.

The graphical illustrations on minimum voltage magnitude (V_{min}), annual economic loss (AEL) and annual cost saving (ACS) under changing reactive loadings for IEEE 33-bus system are shown in **Figure 4.5** to **Figure 4.7**. In the figures, only the top ten of DG integrations that show the best performance, in terms of V_{min} , AEL and ACS , are included in the graphs.

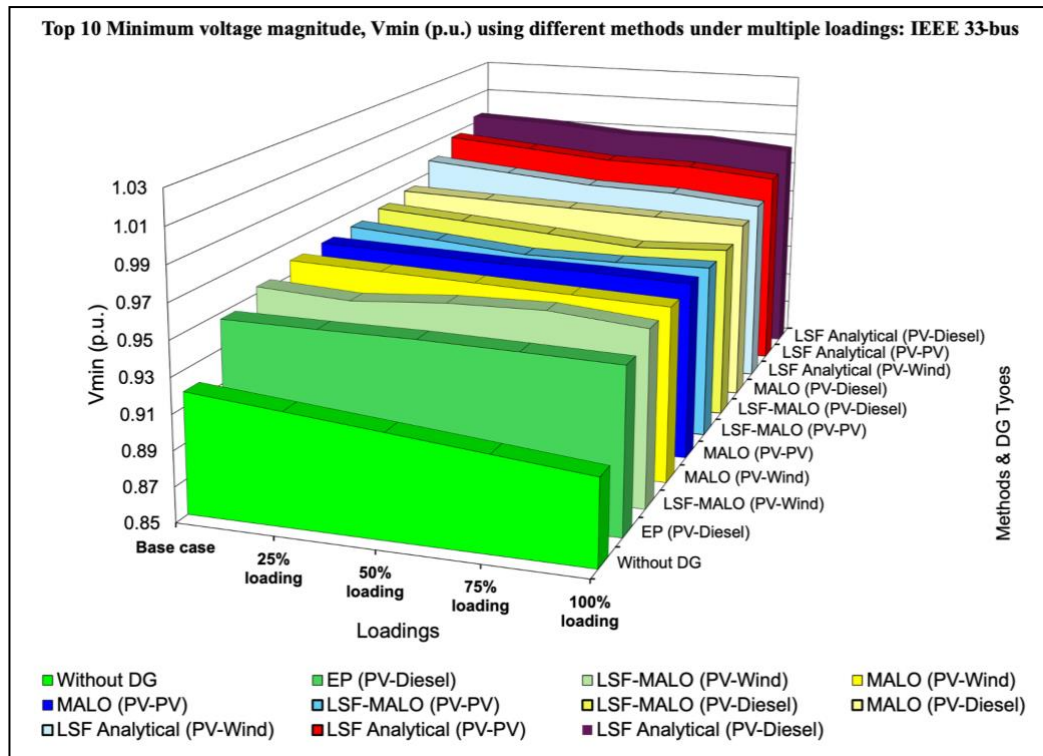


Figure 4. 5 Minimum Voltage Magnitude Under Changing Loadings By Different Methods – IEEE 33-Bus System

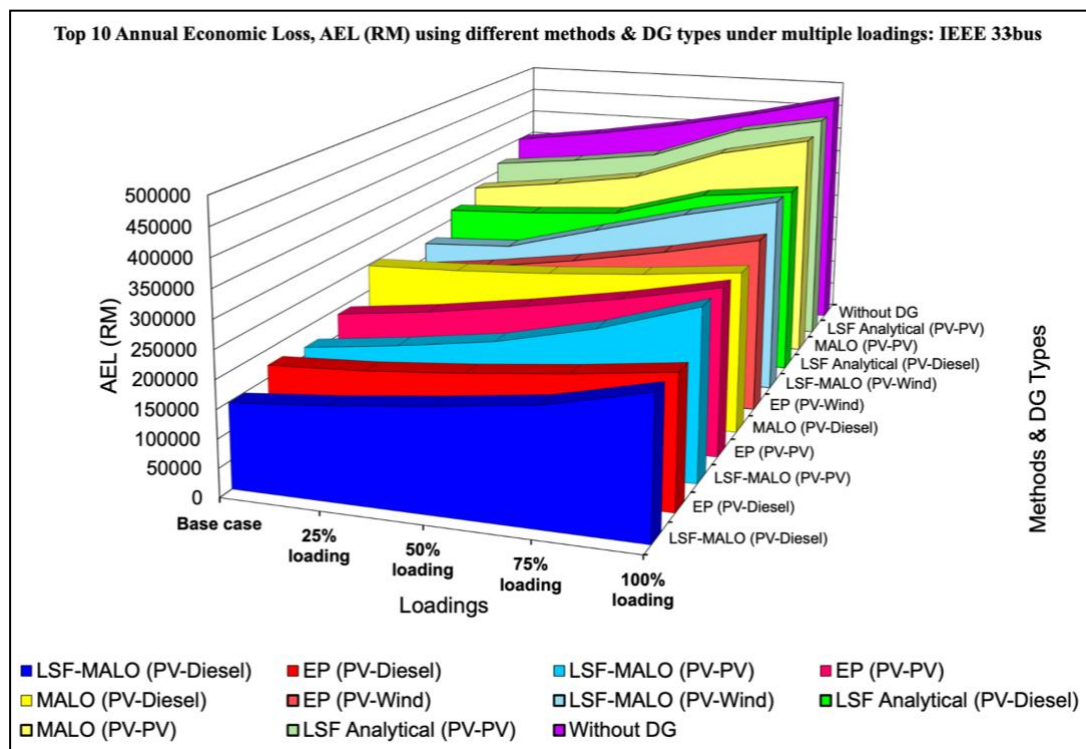


Figure 4. 6 Annual Economic Loss Under Changing Loadings By Different Methods – IEEE 33-Bus System

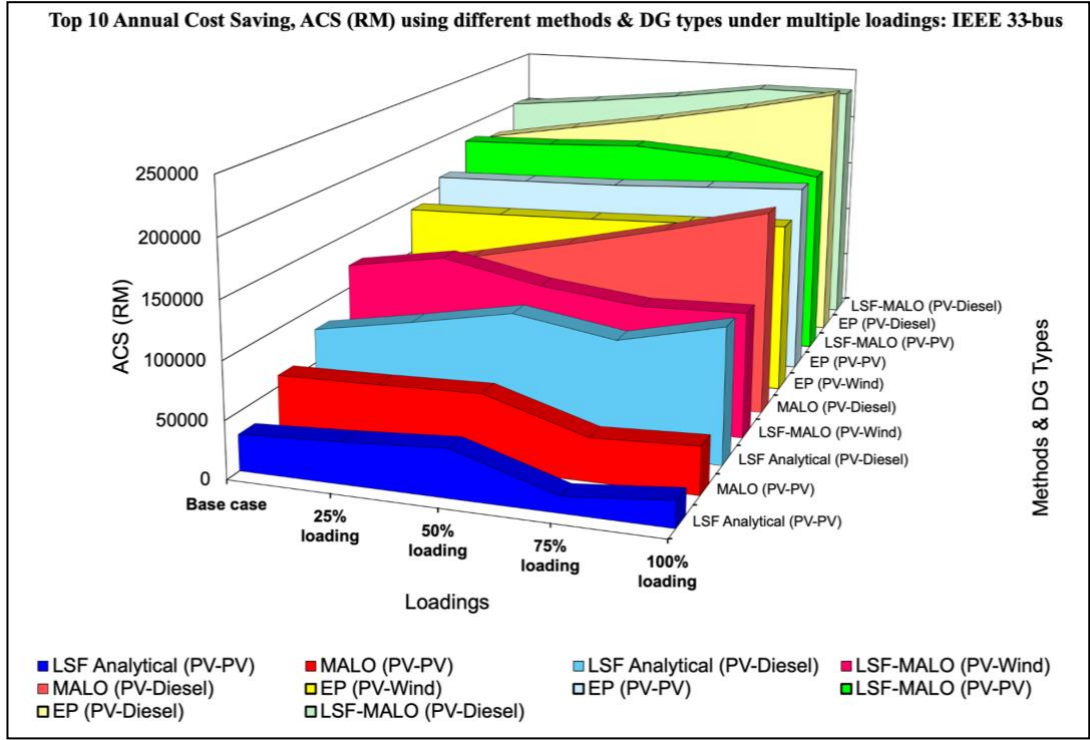


Figure 4. 7 Annual Cost Saving Under Changing Loadings By Different Methods – IEEE 33-Bus System

Figure 4.5 presents the top ten of V_{min} graphs using different methods and different types of DG integrations. As can be observed, all methods improve the magnitudes of V_{min} above the scenario without DG placement. The LSF Analytical approach dominates the top three DG integrations (PV-diesel, PV-PV, and PV-wind integrations), achieving a V_{min} close to 1.00 p.u. for all loading percentages, which is higher than the other methods. Following this, the MALO and LSF-MALO techniques, particularly with PV-Diesel and PV-PV integrations, maintain V_{min} above 0.95 p.u. for all loading percentages. In contrast, the EP technique is the least effective, with V_{min} slightly below 0.95 p.u.

Later, the top ten of AEL graphs for all methods are shown in **Figure 4.6**. All methods, with various types of DG integrations, successfully reduce the AEL below the scenario without DG placement. The proposed LSF-MALO and EP techniques, particularly with the PV-Diesel integration, offer the lowest AEL of below RM200,000.00, even under changing load conditions. However, the AEL for the EP technique is slightly higher than that of the LSF-MALO, especially from the base case to 75% of the loading percentage. Even with PV-PV integration, both methods provide satisfactory AEL values of below RM250,000.00 from the base case to 75% loading.

These findings result in higher cost savings by LSF-MALO and EP techniques,

using PV-Diesel and PV-PV integrations, as observed in **Figure 4.7**. With the PV-Diesel integration, the two methods offer the *ACS* values between RM200,000.00 and RM250,000.00, while the PV-PV integration results in the *ACS* between RM150,000.00 and RM200,000.00 – which are considered as considerable cost savings.

Despite the LSF Analytical approach showing a steady trend of V_{min} regardless of loading percentages, it does not guarantee economical DG placement. Among the top ten of *AEI* graphs as in **Figure 4.6**, the LSF Analytical technique, using PV-Diesel and PV-PV integrations, results in the highest and third-highest *AEI*. The cost can exceed RM250,000.00 at the base case and go beyond RM300,000.00 at 100% loading. Consequently, its cost saving is the lowest, below RM50,000.00, as shown in **Figure 4.7**.

4.3.4 Effects of Identical and Combinational DG Types in IEEE 69-Bus System

Table 4.5 tabulates the results after optimal DG placement in the IEEE 69-bus system, considering identical DG types. In this scenario, three DG units of the same category are integrated into the test system at specific load buses.

Based on **Table 4.5**, the proposed LSF-MALO technique consistently provides the best results in terms of reducing power losses (P_{loss}) and improving minimum voltage magnitudes (V_{min}) across different types of DG integrations.

By using PV-PV-PV integration, the best performance results from LSF-MALO technique with P_{loss} reduced to 0.105 MW, V_{min} improved to 0.978 p.u. and AEL reduced to RM199,538.00, which is equivalent to RM216,340.00 of ACS (52% of cost reduction). The next acceptable performance results from MALO technique with P_{loss} of 0.204 MW, V_{min} of 0.957 p.u. and ACS of RM26,738.00, which is equivalent to 6.4% of cost saving. The LSF Analytical technique results in negative cost saving of -100.7%, while the EP technique was unable to provide V_{min} above 0.95 p.u.

Next, the LSF-MALO technique with Diesel-Diesel-Diesel integration is the most effective approach for the IEEE 69-bus system, providing the highest cost savings and substantial reduction in power losses and improvement on voltage magnitude. This type of DG integration shows superior performance in terms of ACS , with the LSF-MALO technique providing the highest cost saving percentage of 77.5% (equivalent to RM322,230.00), an improved V_{min} of 0.976 p.u. and a reduced P_{loss} of 0.049 MW as well. This is followed by EP, MALO and LSF Analytical techniques with the cost saving percentages of 41.9%, 27.3% and -76.7% respectively.

The Wind-Wind-Wind integration shows a moderate performance for the LSF-MALO technique compared to the previous two DG integrations. However, this type of DG integration via LSF Analytical and MALO methods reflects an inefficient performance, leading to increased AEL , increased P_{loss} and negative cost savings as observed in **Table 4.5**.

On the other hand, **Table 4.6** tabulates the results after optimal DG placement in the IEEE 69-bus system, considering combinational DG types. In this scenario, three DG units of different category are integrated into the test system at specific load buses using the following combinations: PV-Diesel-Wind, PV-PV-Diesel and PV-PV-Wind

Table 4. 5
Mitigation On Voltage Profiles, Power Losses And Annual Cost Saving Using
Optimal DG Placement In IEEE 69-Bus System - Base Case Scenario With
Identical DG Type

IDENTICAL DG TYPE									
Method	DG bus	DG Type	P_{DG} (MW)	Q_{DG} (MVar)	P_{loss} (MW)	V_{min} (p.u.)	AEL (RM)	ACS (RM)	% ACS
Without DG	-	-	-	-	0.218	0.910	415,878	-	-
LSF-MALO	61	PV	1.484	0.000	0.105	0.978	199,538	216,340	52.0
	62	PV	1.267	0.000					
	49	PV	0.837	0.000					
LSF Analytical	61	PV	1.837	0.000	0.437	0.991	834,470	418,592	-100.7
	62	PV	1.837	0.000					
	64	PV	1.670	0.000					
EP	56	PV	2.393	0.000	0.152	0.941	289,641	126,237	30.4
	33	PV	0.677	0.000					
	10	PV	0.005	0.000					
MALO	56	PV	2.648	0.000	0.204	0.957	389,140	26,738	6.4
	33	PV	1.470	0.000					
	10	PV	2.256	0.000					
Without DG	-	-	-	-	0.218	0.910	415,878	-	-
LSF-MALO	61	Diesel	1.973	0.780	0.049	0.976	93,648	322,230	77.5
	62	Diesel	1.328	0.525					
	64	Diesel	2.260	0.893					
LSF Analytical	61	Diesel	1.837	0.726	0.384	0.994	734,961	319,083	-76.7
	62	Diesel	1.837	0.726					
	64	Diesel	1.670	0.660					
EP	56	Diesel	2.474	0.978	0.126	0.948	241,532	174,346	41.9
	33	Diesel	0.718	0.284					
	10	Diesel	0.005	0.002					
MALO	56	Diesel	2.012	0.795	0.158	0.958	302,256	113,622	27.3
	33	Diesel	1.367	0.540					
	10	Diesel	2.299	0.909					
Without DG	-	-	-	-	0.218	0.910	415,878	-	-
LSF-MALO	61	Wind	2.160	-0.710	0.200	0.972	382,749	33,129	8.0
	49	Wind	1.514	-0.498					
	50	Wind	2.447	-0.804					
LSF Analytical	61	Wind	1.837	-0.604	0.699	0.983	1,334,602	918,724	-220.9
	62	Wind	1.837	-0.604					
	64	Wind	1.670	-0.549					
EP	56	Wind	1.573	-0.517	0.177	0.930	338,348	77,529	18.6
	33	Wind	0.005	-0.002					
	10	Wind	0.589	-0.194					
MALO	56	Wind	3.540	-1.164	0.407	0.957	778,067	362,189	-87.1
	33	Wind	2.843	-0.935					
	10	Wind	2.272	-0.747					

Table 4. 6
Mitigation On Voltage Profiles, Power Losses And Annual Cost Saving Using
Optimal DG Placement In IEEE 69-Bus System - Base Case Scenario With
Combinational DG Type

COMBINATIONAL DG TYPE									
Method	DG bus	DG Type	P_{DG} (MW)	Q_{DG} (MVar)	P_{loss} (MW)	V_{min} (p.u.)	AEL (RM)	ACS (RM)	% ACS
Without DG	-	-	-	-	0.218	0.910	415,878	-	-
LSF-MALO	61	PV	1.972	0.000	0.099	0.973	190,042	225,836	54.3
	49	Diesel	1.327	0.524					
	50	Wind	2.259	-0.743					
LSF Analytical	61	PV	1.837	0.000	0.424	0.991	810,645	-394,767	-94.9
	62	Diesel	1.837	0.726					
	64	Wind	1.670	-0.549					
EP	56	PV	2.298	0.000	0.150	0.939	285,763	130,115	31.3
	33	Diesel	0.464	0.184					
	10	Wind	0.005	-0.002					
MALO	56	PV	2.374	0.000	0.253	0.950	483,250	-67,372	-16.2
	33	Diesel	2.382	0.941					
	10	Wind	1.976	-0.649					
Without DG	-	-	-	-	0.218	0.910	415,878	-	-
LSF-MALO	61	PV	1.972	0.000	0.097	0.973	186,389	229,488	55.2
	49	PV	1.327	0.000					
	50	Diesel	2.259	0.893					
LSF Analytical	61	PV	1.837	0.000	0.393	0.993	750,288	-334,410	-80.4
	62	PV	1.837	0.000					
	64	Diesel	1.670	0.660					
EP	56	PV	2.303	0.000	0.159	0.953	304,371	111,507	26.8
	33	PV	1.125	0.000					
	10	Diesel	1.912	0.755					
MALO	56	PV	1.302	0.000	0.140	0.940	266,839	149,039	35.8
	33	PV	0.622	0.000					
	10	Diesel	1.691	0.668					
Without DG	-	-	-	-	0.218	0.910	415,878	-	-
LSF-MALO	61	PV	1.972	0.000	0.102	0.973	195,198	220,680	53.1
	49	PV	1.327	0.000					
	50	Wind	2.259	-0.743					
LSF Analytical	61	PV	1.837	0.000	0.497	0.989	950,288	-534,410	-128.5
	62	PV	1.837	0.000					
	64	Wind	1.670	-0.549					
EP	56	PV	2.426	0.000	0.148	0.941	283,285	132,592	31.9
	33	PV	0.329	0.000					
	10	Wind	0.005	-0.002					
MALO	56	PV	2.378	0.000	0.245	0.950	467,379	-51,500	-12.4
	33	PV	2.380	0.000					
	10	Wind	1.973	-0.648					

Table 4.6 demonstrates that the optimal DG placement using combinational DG types significantly improves the voltage magnitude (V_{min}), power losses (P_{loss}), annual economic loss (AEL) and annual cost saving (ACS) as well. In this case, the LSF-MALO technique stands out as the most effective across different types of DG integrations, and it is followed by the EP technique. The different types of DG integrations by the LSF-MALO and EP techniques appear to provide a balanced improvement in both technical and economic aspects.

Based on **Table 4.6**, the PV-Diesel-Wind integration via the proposed LSF-MALO technique provides the best improvement to the system; the V_{min} was improved to 0.973 p.u., P_{loss} was significantly reduced to 0.099 MW and AEL was greatly reduced to RM190,042.00, resulting in 54.3% of ACS (equivalent to RM225,836.00). This is followed by the EP technique with ACS of 31.3%, however, at voltage magnitudes of below 0.95 p.u. The LSF Analytical and MALO techniques provide promising magnitudes of V_{min} , however, their performance on P_{loss} and AEL is worse than that of without DG condition. The losses increases and ACS percentages are negative for these two methods.

The PV-PV-Diesel integration via LSF-MALO approach provides a comparable performance as that of its PV-Diesel-Wind integration, with an ACS percentage of 55.2%, an improved V_{min} of 0.973 p.u. and a reduced P_{loss} of 0.097 MW. Likewise, its PV-PV-Wind integration also results in almost comparable performance, with ACS percentage of 53.1%, V_{min} magnitude of 0.973 p.u. and P_{loss} value of 0.102 MW. Hence, for IEEE 69-bus system, the LSF-MALO is the most effective technique for the integration of all DG types in the system.

The other methods reflect some inconsistencies in their results. As observed in **Table 4.6**, the LSF Analytical approach results in negative cost savings for all types of DG integrations, the EP technique suffers from undervoltage (V_{min} less than 0.95 p.u.) when PV-Diesel-Wind and PV-PV-Wind integrations were employed, while the MALO technique has a mixed performance for different types of DG integrations.

4.3.5 Comparison between Identical and Combinational DG Types in IEEE 69-Bus System

The effectiveness of DG implementation between identical and combinational DG types will be assessed in this section. The corresponding graphical illustrations, based on **Table 4.5** and **Table 4.6**, on minimum voltage magnitude (V_{min}), annual economic loss (AEL), and annual cost saving (ACS) are presented in **Figure 4.8** to **Figure 4.10**.

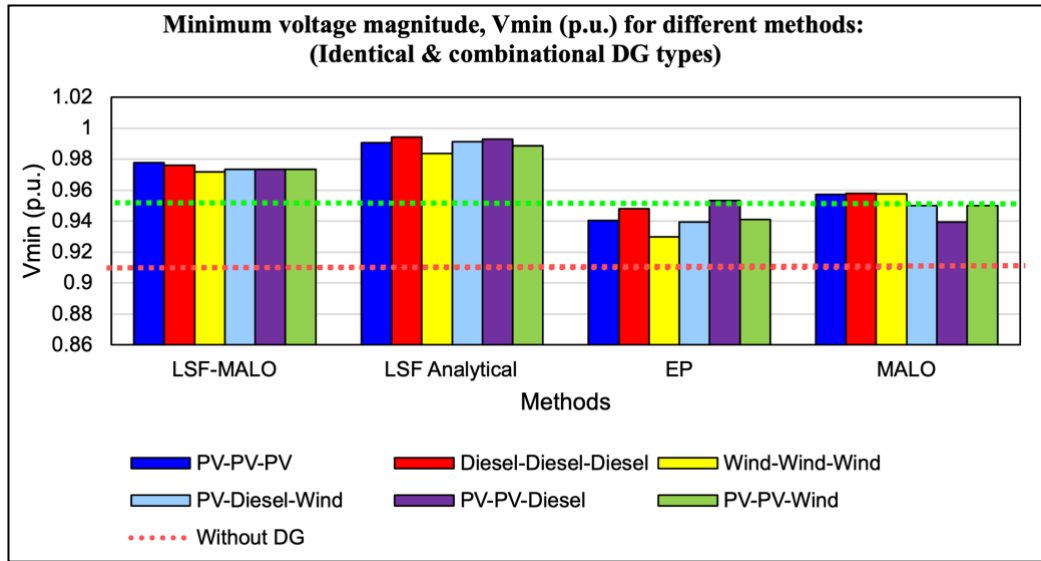


Figure 4. 8 Minimum Voltage Magnitude By All Methods – IEEE 69-Bus System

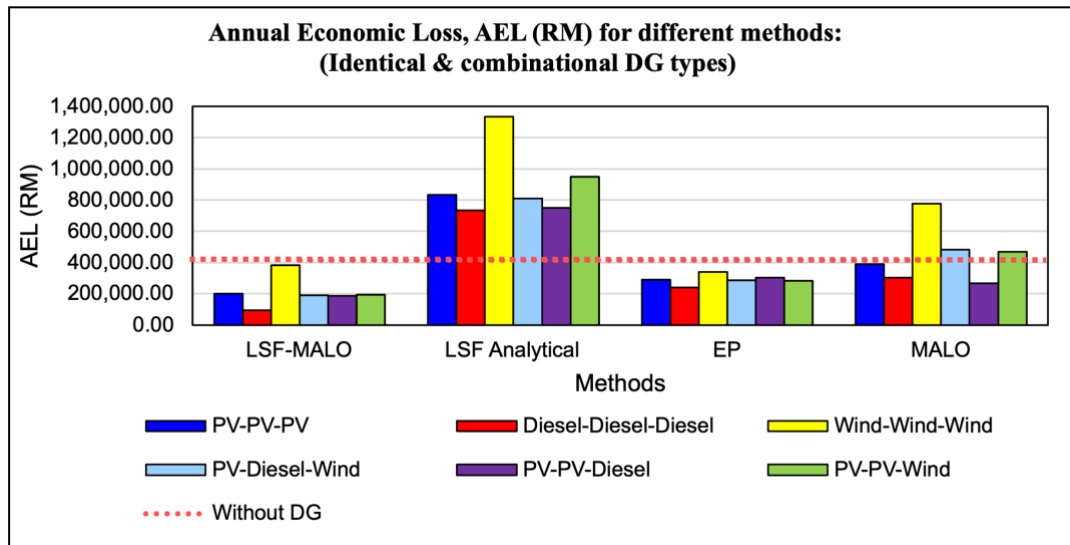


Figure 4. 9 Annual Economic Loss By All Methods – IEEE 69-Bus System

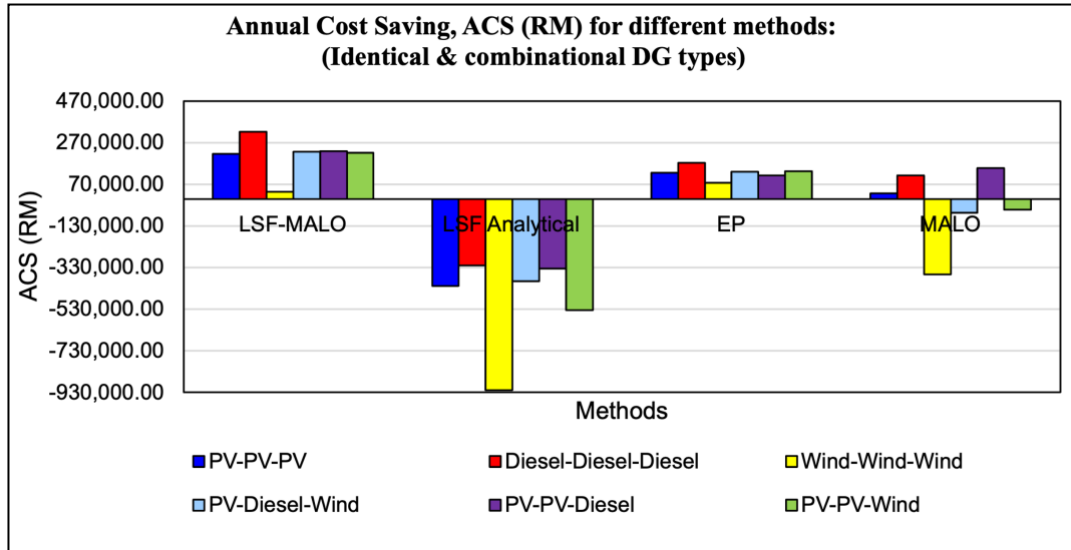


Figure 4. 10 Annual Cost Saving By All Methods – IEEE 69-Bus System

From **Figure 4.8**, the optimal DG placement by all methods results in an improved magnitude of V_{min} compared to the scenario without DG placement (dotted red line). However, the most effective technique is the LSF Analytical method, as the V_{min} magnitudes using any types of DG integrations are at least 0.98 p.u. This is followed by the proposed LSF-MALO technique, which is also able to offer stable voltage magnitudes, with V_{min} well above 0.95 p.u (dotted green line) using any types of DG integrations. The MALO technique provides a moderate performance on V_{min} with most of the DG integrations have a very slight improvement above 0.95 p.u. The EP technique, on the other hand, was unable to improve the voltage for most of the DG integrations, except for the PV-PV-Diesel integration (purple bar), which shows a very slight improvement above 0.95 p.u.

From **Figure 4.9**, the optimal DG placement by most of the methods, except the LSF Analytical technique, also results in reduced AEL compared to the one without DG placement (dotted red line). Neglecting the Wind-Wind-Wind integration (yellow bar), the proposed LSF-MALO technique offers the lowest AEL of at most RM200,000.00 using the rest of the DG integrations. This is followed by EP technique with AEL of between RM200,000.00 and RM300,000.00 except for the Wind-Wind-Wind integration. The MALO technique shows inconsistent cost reduction by using Wind-Wind-Wind (yellow bar), PV-Diesel-Wind (light blue bar) and PV-PV-Wind (green bar) integrations, where the AEL values are higher than the condition without DG integration. The worst performance is shown by the LSF Analytical, where all types of

DG integrations via this method failed to reduce the *AEL* below the scenario without DG integration.

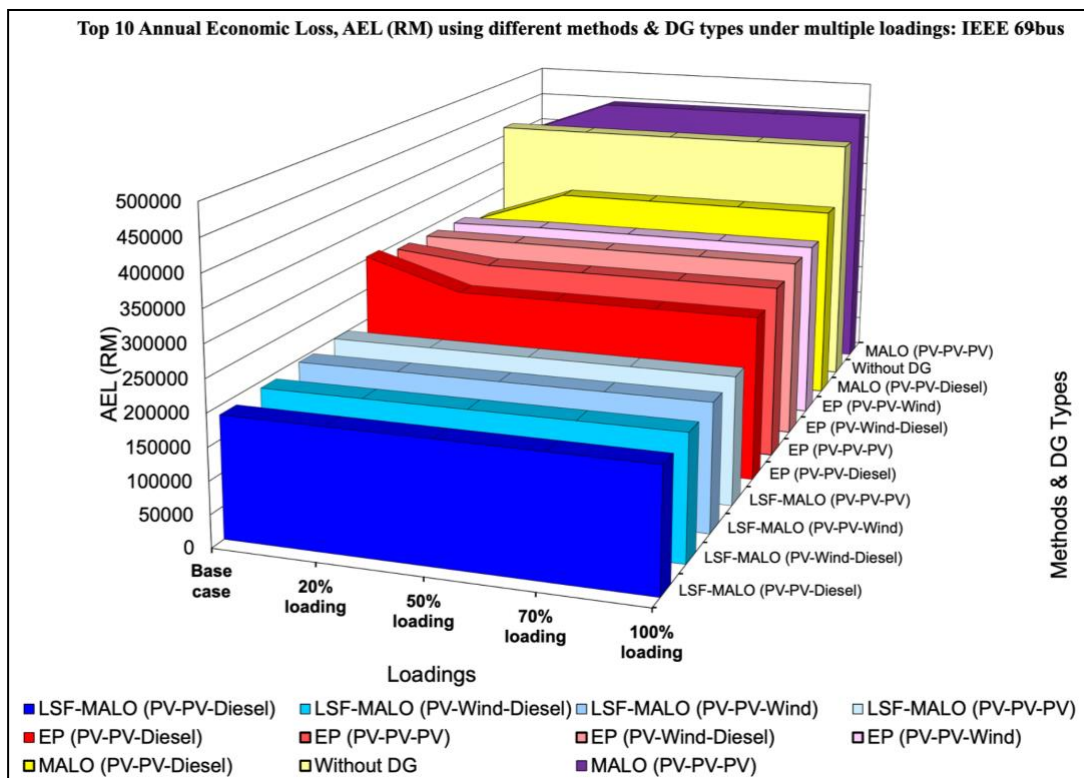
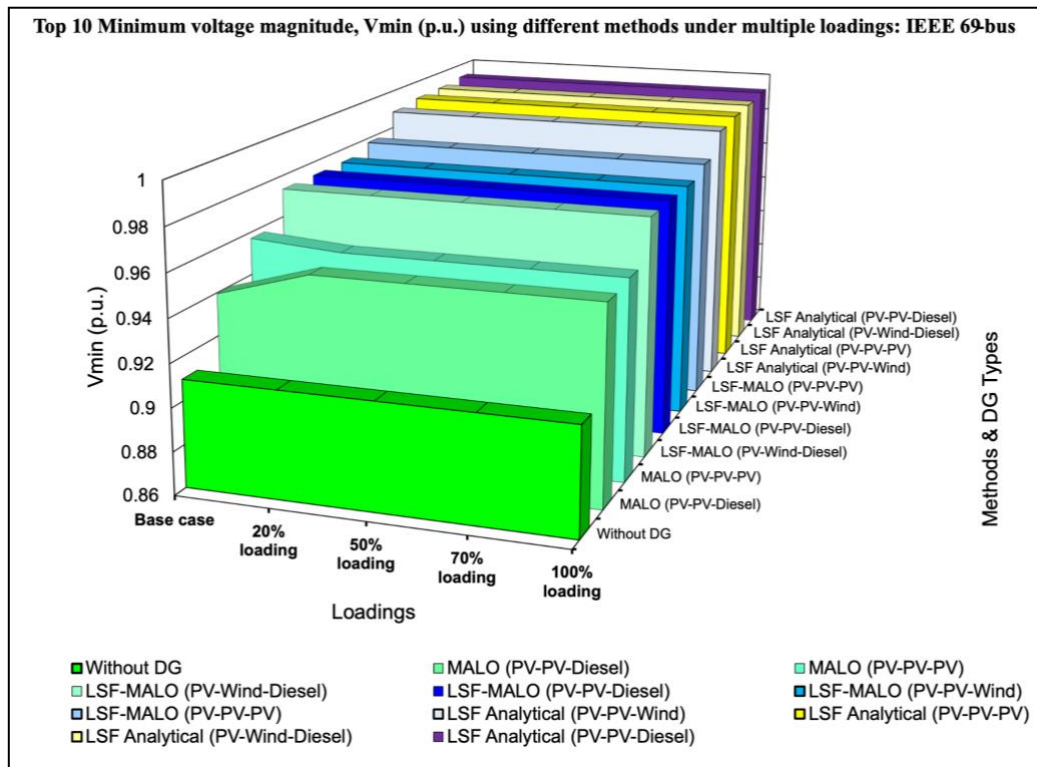
From the cost analysis, the proposed LSF-MALO results in the highest cost saving of at least RM200,000.00 using most of the DG integrations, as illustrated in **Figure 4.10**. This is followed by EP technique with *ACS* of at least RM100,000.00 excluding the Wind-Wind-Wind integration. As the *AEL* for LSF Analytical and MALO techniques reflect some inconsistencies, they have negative cost savings for most of the DG integrations, indicating a waste of cost.

On overall, the most effective DG integrations are PV-PV-PV, PV-Diesel-Wind, PV-PV-Diesel and PV-PV-Wind integrations. By using LSF-MALO technique, these four types of DG integrations are able to provide voltage magnitude above 0.95 p.u. with considerable cost saving of at least RM200,000.00. Even though the Diesel-Diesel-Diesel integration offers the highest cost saving of above RM300,000.00, it is a non-renewable DG technology, which suffers from high greenhouse gas emission.

4.3.6 Multi-type DG Placement in IEEE 69-Bus System under Changing Loadings

In the previous sections, the performance of DG placement was evaluated at base case condition, where the reactive loadings in the system was kept constant. As discussed in the previous sections regarding IEEE 33-bus system, reactive power flow is crucial for maintaining overall system stability, ensuring proper voltage profiles, and minimizing power losses. Any uncontrolled consumption of reactive power by loads can significantly impact the distribution network, which might cause extreme voltage drop and high magnitude of power losses. Therefore, to observe the robustness of the proposed method, the multi-objective LSF-MALO algorithm is further tested under changing reactive loadings in IEEE 69-bus system from base case to 100% of maximum loading.

The graphical illustrations on minimum voltage magnitude (V_{min}), annual economic loss (*AEL*) and annual cost saving (*ACS*) under changing reactive loadings for IEEE 69-bus system are shown in **Figure 4.11** to **Figure 4.13**. In the figures, only the top ten of DG integrations that show the best performance, in terms of V_{min} , *AEL* and *ACS*, are included in the graphs.



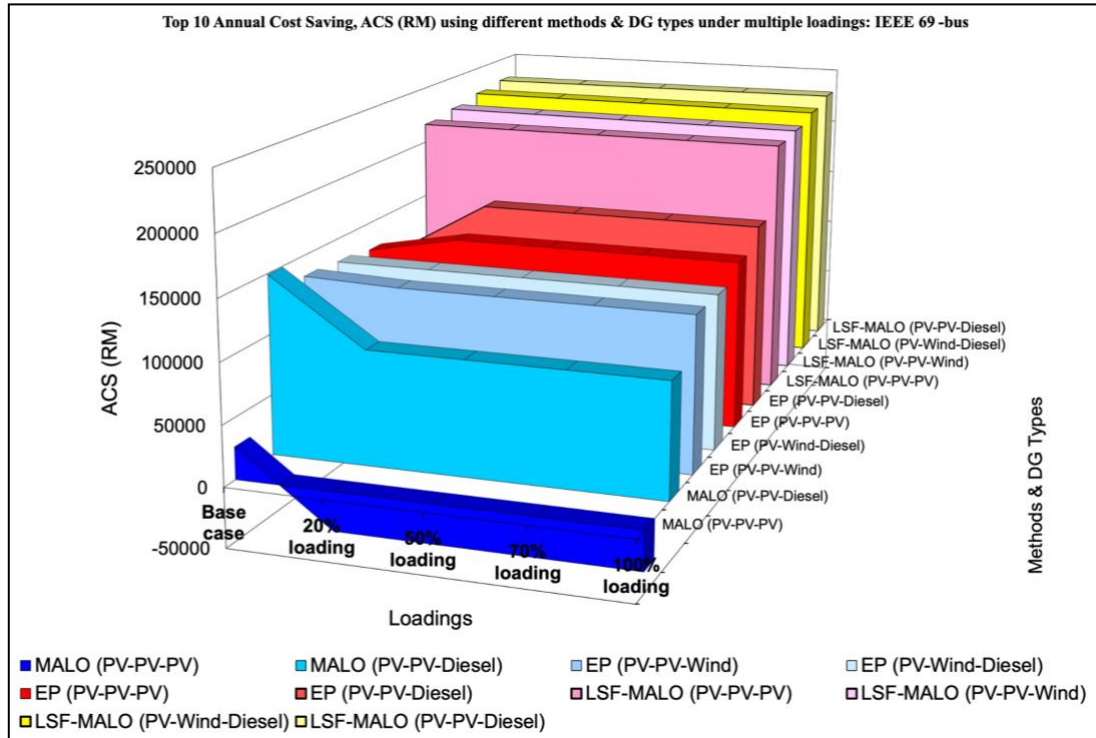


Figure 4. 13 Annual Cost Saving Under Changing Loadings By Different Methods – IEEE 69-Bus System

Figure 4.11 presents the top ten of V_{min} graphs using different methods and different types of DG integrations. As can be observed, all methods improve the magnitudes of V_{min} above the scenario without DG placement. The LSF Analytical approach dominates the top four of DG integrations (PV-PV-Diesel, PV-Wind-Diesel, PV-PV-PV and PV-PV-Wind integrations), achieving a V_{min} close to 1.00 p.u. for all loading percentages, which is higher than the other methods. Following this, the proposed LSF-MALO technique with the same DG integrations as that of the LSF Analytical, maintains V_{min} above 0.95 p.u. for all loading percentages. In contrast, the MALO technique is the least effective, with V_{min} slightly below 0.95 p.u., while the EP technique is not in the top ten, indicating the worst performance of V_{min} .

Later, the top ten of AEL graphs for all methods are shown in **Figure 4.12**. Most of the methods, with various types of DG integrations, successfully reduce the AEL below the scenario without DG placement (except for the MALO technique using PV-PV-PV integration). The proposed LSF-MALO technique offers the lowest AEL of at most RM200,000.00 via four types of DG integrations (PV-PV-Diesel, PV-Wind-Diesel, PV-PV-Wind and PV-PV-PV), even under changing load conditions. The second-best performance after the proposed method is the EP technique, with AEL of at most RM300,000.00 for the same types of DG integrations as the LSF-MALO; a rather

considerable cost gap of RM100,000.00 compared to the one obtained by the LSF-MALO technique. The least effective method is the MALO technique since it results in higher *AEI* of almost RM350,000.00 for PV-PV-Diesel integration, and the highest *AEI* of almost RM450,000.00 for PV-PV-PV integration. The LSF Analytical technique is not in the top ten of the *AEI* graphs, indicating the worst performance.

Both **Figure 4.11** and **Figure 4.12** demonstrate a direct trade-off between grid performance and financial expense. Achieving a highly stable voltage requires installing larger generators, which naturally drives up the total cost. Conversely, minimizing costs means relying on smaller generators, which leaves the grid's voltage closer to its minimum safety limit. This conflicting relationship highlights exactly why a multi-objective optimization approach is necessary. Rather than forcing a choice between a system that is dangerously weak or overly expensive, the proposed method optimally finds a practical compromise, ensuring the grid remains both technically safe and financially affordable.

These findings result in top four highest cost savings by the LSF-MALO technique, using four types of DG integrations (PV-PV-Diesel, PV-Wind-Diesel, PV-PV-Wind and PV-PV-PV), as observed in **Figure 4.13**. By using those types of DG integrations, the proposed LSF-MALO technique offers the highest cost savings with *ACS* ranging between RM200,000.00 and RM250,000.00, while the rest methods yield to *ACS* below RM150,000.00. The LSF Analytical is not in the top ten of the *ACS* graphs, indicating the method failed to provide cost saving even after DG implementation.

4.3.7 Effects of Changing Weight Values on Multi-objective LSF-MALO Performance

This section investigates the effects of changing the weight values of equation (4.9) on the multi-objective problem. The aim is to understand how variations in the weight values impact the proposed LSF-MALO algorithm's performance and its outcomes. A comparative analysis of different weight configurations, from 0 to 1, will provide insights into their effects on the placement and sizing of multi-type DG in IEEE 33-bus and 69-bus systems. After implementing the multi-objective LSF-MALO technique at 100% of maximum loading, the results are tabulated in **Table 4.7**. In the table, the highlighted rows indicate the weight configuration as determined by R-

method via equation (4.10), while the rest rows are the weight configurations randomly changed between 0 and 1.

For the results presented in **Table 4.7**, 2 and 3 DG units were injected into the IEEE 33- and 69-bus systems, respectively. Furthermore, the configuration for all injected units is identical, where every unit operates in the same charging mode and is classified as a Type 1 DG (Solar PV).

Table 4. 7
Effect Of Weight Values On Multi-Objective LSF-MALO Performance In IEEE 33-Bus And 69-Bus Systems – 100% Of Maximum Loading

Test system	Weight set	w_1 (for P_{loss})	w_2 (for V_{min})	w_3 (for AEL)	ΣP_{DG} (MW)	P_{loss} (MW)	V_{min} (p.u.)	AEL (RM)
33-bus	C1	0.1	0.2	0.7	4.3946	0.1589	0.9527	303,561
	C2	0.1	0.3	0.6	4.3946	0.1589	0.9527	303,561
	C3	0.1	0.4	0.5	4.3946	0.1589	0.9527	303,561
	C4	0.2	0.5	0.3	4.3946	0.1589	0.9527	303,561
	C5	0.2	0.6	0.2	4.3946	0.1589	0.9527	303,561
	C6	0.2	0.7	0.1	4.3946	0.1589	0.9527	303,561
	C7	0.5	0.3	0.2	4.3946	0.1589	0.9527	303,561
	C8	0.5	0.4	0.1	4.3946	0.1589	0.9527	303,561
	C9	0.6	0.3	0.1	4.3946	0.1589	0.9527	303,561
	C0	0.7	0.1	0.2	4.3946	0.1589	0.9527	303,561
	C11	0.4521	0.3014	0.2465	4.3946	0.1589	0.9527	303,561
69-bus	C1	0.1	0.2	0.7	5.4155	0.1535	0.9809	293,212
	C2	0.1	0.3	0.6	3.3597	0.0907	0.9760	173,183
	C3	0.1	0.4	0.5	3.3597	0.0907	0.9760	173,183
	C4	0.2	0.5	0.3	3.3597	0.0907	0.9760	173,183
	C5	0.2	0.6	0.2	3.5882	0.1052	0.9777	200,994
	C6	0.2	0.7	0.1	3.5882	0.1052	0.9777	200,994
	C7	0.5	0.3	0.2	3.5882	0.1052	0.9777	200,994
	C8	0.5	0.4	0.1	4.6194	0.1038	0.9773	198,398
	C9	0.6	0.3	0.1	4.6194	0.1038	0.9773	198,398
	C0	0.7	0.1	0.2	4.6194	0.1038	0.9773	198,398
	C11	0.4521	0.3014	0.2465	3.5882	0.1052	0.9777	200,994

Based on **Table 4.7**, there is no effect of changing the individual weights (w_1 , w_2 and w_3) on power losses (P_{loss}), minimum voltage magnitude (V_{min}) and annual economic loss (AEL) in IEEE 33-bus system. These three maintain the same values for all weight configurations, including the one using R-method, where P_{loss} , V_{min} and AEL are fixed at 0.1589 MW, 0.9527 p.u. and RM303,561.00 respectively. Hence, for IEEE

33-bus system, it can be deduced that there is no multiplicity of solutions by the optimization algorithm. At the same condition of the system, 100% of maximum loading in this case, the solution is unique for all settings of those individual weights.

However, the multiplicity of solutions exists in IEEE 69-bus system. Based on **Table 4.7**, different configurations of weights result in different performance on P_{loss} , V_{min} , AEL and total size of DG units (ΣP_{DG}) as well. The second, third and fourth weight configurations for IEEE 69-bus system provide the best performance with P_{loss} , V_{min} , AEL and ΣP_{DG} of 0.0907 MW, 0.976 p.u., RM173,183.00 and 3.3597 MW respectively, which are the lowest losses, stable voltage profile, the lowest cost and the smallest rating of DG units as well. The eighth, ninth and tenth weight configurations for the same test system result in comparable performance with that of R-method (highlighted row), with a slight difference in terms of AEL and ΣP_{DG} . These findings justify the significance of having proper settings of weight configurations when dealing with Weighted Sum Method (WSM) multi-objective optimization problem.

To better visualize the performance of the varying weight configurations in Table 4.6, scatter plots of Total Power Loss (P_{loss}) against Annual Cost Saving (ACS) were constructed for both test systems, as illustrated in **Figure 4.14** and **Figure 4.15**. Interestingly, the behavior of the solution space differs between the two networks. For the IEEE 33-bus system (**Figure 4.14**), the scatter plot shows a single, perfectly overlapping point for all configurations (C1 through C11). This occurs because the algorithm converged on a unique, highly robust global optimum regardless of the specific weight combinations applied, preventing any conflicting Pareto trade-offs. In contrast, the IEEE 69-bus system (**Figure 4.15**) displays a more varied solution space. In traditional multi-objective optimization, such a plot typically forms a conflicting Pareto front, where improving one objective degrades another. However, the configurations here reveal a dominating solution region. Suboptimal weight configurations (e.g., C1) result in both higher power losses and significantly lower cost savings due to the over-sizing of DG units, which increases capital costs and induces reverse power flow. Conversely, the optimal weight configurations (such as C2, C3, and C4) cluster tightly at the bottom-right of the plot. Together, these visualizations demonstrate the algorithm's capability to bypass standard Pareto conflicts and reliably converge on globally dominating solutions that simultaneously minimize power loss and maximize economic savings.

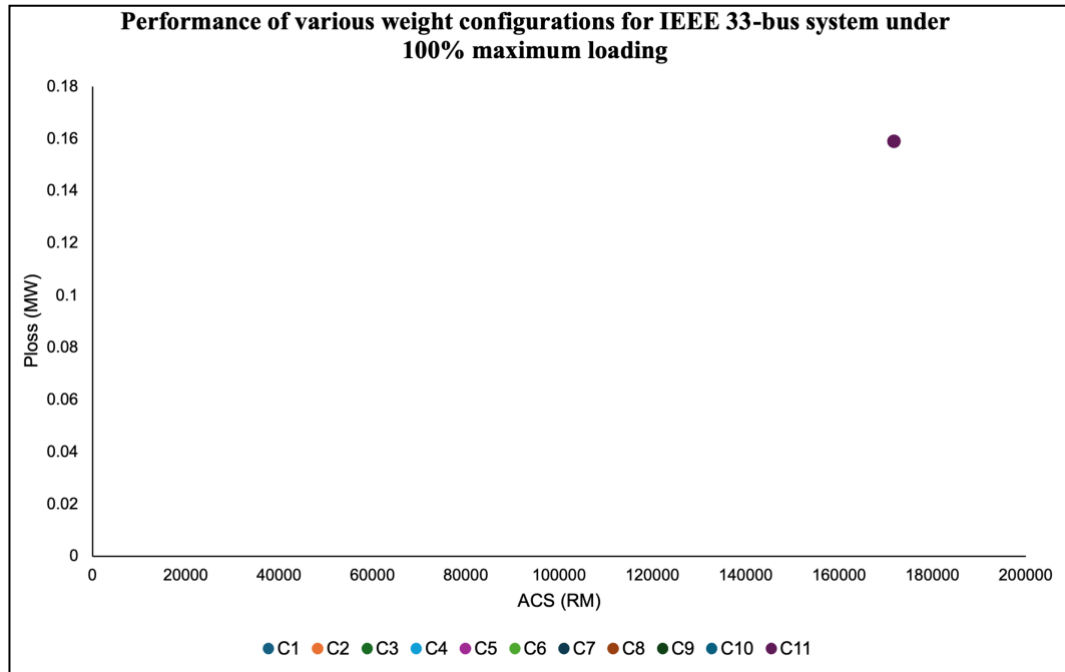


Figure 4. 14 Performance Of Various Weight Configurations For IEEE 33-Bus System Under 100% Maximum Loading

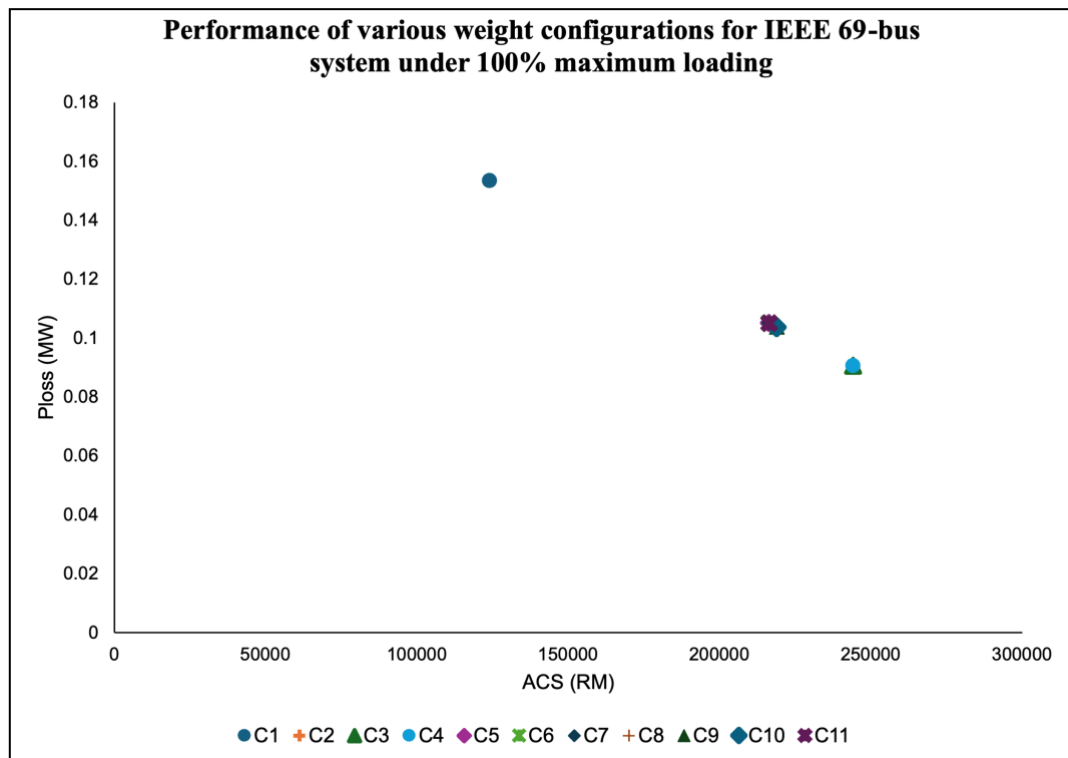


Figure 4. 15 Performance Of Various Weight Configurations For IEEE 69-Bus System Under 100% Maximum Loading

4.4 Chapter Summary

In brief, this chapter has presented an extended version of the optimization algorithm for solving the optimal DG placement problem with cost savings, namely the multi-objective LSF-MALO algorithm. The developed algorithm as in Chapter 3 has been extended and modified in this chapter for the purpose of multi-objective optimization. Unlike Chapter 3, the proposed problem formulation in this chapter considers both technical and economic aspects of DG placement in the distribution network. The technical aspect accounts for real power losses and voltage magnitude, while the economic aspect includes yearly economic loss, installation cost, and cost savings. In addition, the proposed problem formulation allows for various DG integrations into the distribution network, including identical and combinational DG integrations from three different DG categories: solar PV units, wind turbines, and diesel generators.

By formulating the LSF-MALO as a Weighted-Sum Method (WSM) multi-objective algorithm, the optimal DG placement has been successfully implemented in IEEE 33-bus and 69-bus systems. Based on the results and analysis from sections 4.3.1 to 4.3.6, the proposed LSF-MALO consistently performs well across four indicators: considerable reduction in real power losses, significant reduction in annual economic loss, improvement in voltage magnitude above 0.95 p.u., and the highest cost savings. While other methods are efficient in some cases, they can become the least effective in others.

This chapter also highlights the significance of allowing various types of DG integrations. It was found that combining solar PV with other types of DG units helps balance the improvement in both the technical and economic aspects of the distribution network, avoiding unstable voltage profiles and cost waste. Using only one type of DG integration, whether PV-PV, Diesel-Diesel or Wind-Wind, results in improvements that can be inconsistent in some cases.

Finally, the experiment on changing the individual weights of the WSM fitness equation in section 4.3.7 justifies the need to properly set the weight values. This ensures the algorithm's capability in delivering optimal solutions for any situations of the system.

CHAPTER 5

ASSESSMENT OF EVCS-INTEGRATED DISTRIBUTION SYSTEM CONSIDERING VOLTAGE STABILITY, GRID DEPENDENCY AND HARMONIC DISTORTION

5.1 Introduction

The integration of Electric Vehicles (EVs) into distribution network presents both challenges and opportunities for the overall distribution system. The demand for Electric Vehicle Charging Stations (EVCS) has increased in conjunction with the rising adoption of EVs, resulting in additional stress on the existing distribution network. The growth in demand resulting from the EV-integration may contribute to voltage instability and increase in power losses. Without an optimized charging strategy, dependency on the grid for EV charging will increase, leading to higher peak demand and greater voltage fluctuations. This heightened dependency can strain the distribution network and reduce overall system efficiency, potentially compromising grid stability and reliability [13].

The growing reliance on EVs has also introduced power quality challenges, particularly harmonic distortion, due to the non-linear nature of EVCS. These charging stations, which utilize power electronic converters, generate significant harmonic currents [141]. The integration of such non-linear loads can distort the voltage waveform, leading to non-linear voltage profiles. Excessive harmonic distortion not only affects voltage stability but can also lead to equipment damage. The rise in current due to harmonic components increases the thermal stress on distribution equipment, potentially elevating temperatures beyond safe operating limits. This thermal buildup can degrade insulation materials, shorten equipment lifespan, and increase the risk of failures, ultimately compromising the reliability of the distribution system [142].

Meanwhile, the Distributed Generation (DG) such as solar photovoltaic (PV) systems has emerged as a viable alternative to alleviate the increased stress and demand imposed by the integration of EVCS into the power grid [13]. The optimal placement and sizing of DG units in the power grid can have several advantages, including enhanced voltage profiles, minimized power losses, and lower annual economic losses, as demonstrated in the preceding chapters. The integration of DG units also addresses

the increasing demand in the power grid while promoting localized energy generation. This approach reduces the need for long-distance power transmission and mitigates stress on the main grid. With the strategic placement of DG units, the overall performance of distribution network integrated with EVCS can be significantly enhanced. This includes improvements in voltage stability, power quality, and reduced grid dependency. Proper DG allocation can mitigate voltage fluctuations, minimize power losses, and counteract the adverse effects of harmonic distortion, ultimately leading to a more resilient and efficient distribution system.

This chapter focuses on assessing the performance of distribution system integrated with EVCS, analyzing key factors such as power losses, voltage profile, grid dependency, and harmonic distortion. The impact of various EVCS parameters on network performance will be evaluated to determine how different charging scenarios affect power quality and voltage stability. From this analysis, trends and critical charging scenarios can be identified, providing insights into the extent of grid dependency and potential risks to system stability. The findings derived from this chapter will serve as a critical foundation for the optimal placement of DG in EVCS-integrated distribution systems, as will be discussed in the following chapter. By thoroughly evaluating the impact of EVCS on key performance indicators such as power losses, voltage profile, grid dependency and harmonic distortion, this chapter provides a comprehensive understanding of the system's existing limitations and areas in need of improvement. These insights will help guide the strategic placement of DG units to address the identified issues, leading to improved system reliability and performance. It will ensure that the optimal DG integration in the following chapter is both technically appropriate and aligned with the operational needs of the EVCS-integrated system.

5.2 Methodology and Problem Formulation

This section presents the proposed methodology for the assessment of distribution system performance with Electric Vehicle Charging Station (EVCS) integration. It begins with the theoretical operation of EVCS in DC power system, modelling of EVCS as static load in distribution system, proposed problem formulation incorporating voltage stability, grid dependency and power quality assessment, and proposed procedures for the overall assessment.

5.2.1 DC Power System and Electric Vehicle Charging Station

The conventional infrastructure for a charging station comprises a DC bus that functions as the central energy distribution hub, supplying power to both the Electric Vehicle Charging Station (EVCS) and the grid. This DC bus also integrates other energy sources, including Distributed Generation (DG) units such as photovoltaic (PV) systems, and energy storage units (ESUs) like battery management systems. The whole DC power system is presented in **Figure 5.1**.

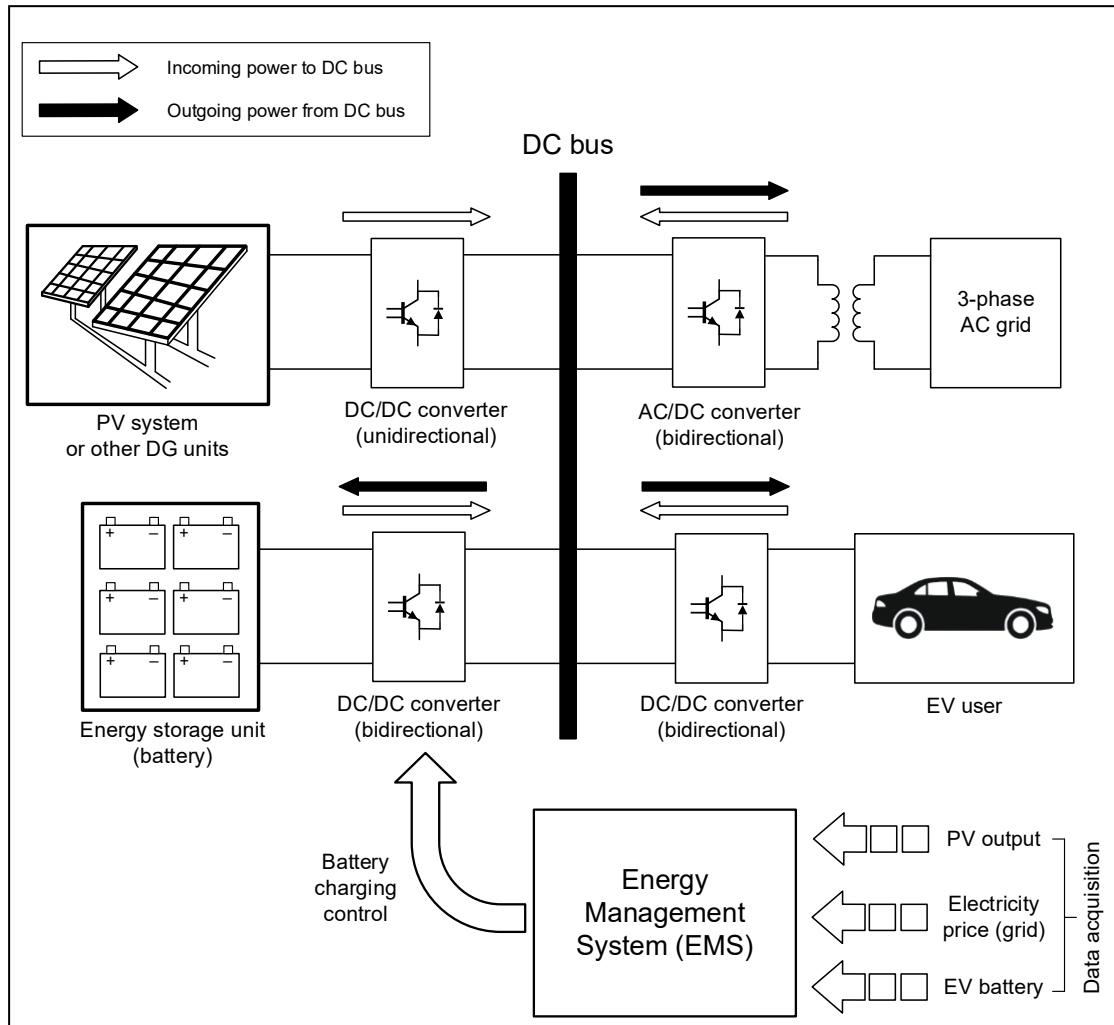


Figure 5. 1 Electric Vehicle Charging Station Infrastructure

The PV system produces DC electricity, which can either be directed to the grid through a bi-directional AC/DC converter or used locally. This bi-directional converter enables two-way power flow - either from the DC bus to the grid or from the grid to the DC bus - depending on system requirements. During peak hours, when the grid is

heavily loaded, the generated DC electricity can be used to charge EVs or batteries, thereby reducing stress on the grid. Conversely, during periods of low solar generation, power from the grid can be utilized for EV or battery charging. The DC/DC converters in the battery management system and the EVCS are also bi-directional, facilitating both charging and discharging operations based on current system conditions. If neither the grid nor the PV system can meet the EV charging demand - due to peak loads or limited solar input - the battery provides backup power. Conversely, if the battery and PV system are insufficient to support the grid during peak hours, the Vehicle-to-Grid (V2G) mode allows the EV to discharge energy back to the grid, helping to balance the load.

This entire DC power system is managed by an intelligent Energy Management System (EMS), which plays a vital role in ensuring efficient and reliable energy coordination. The EMS collects data from the PV system, the grid, and the EVCS to obtain useful information such as DC power output, real-time electricity prices, and the state of charge (SOC) of EV batteries. Using this information, the EMS will determine optimal charging and discharging strategies by issuing control signals to the battery management system. These strategies are developed based on several factors, including electricity cost, energy availability, and consumer requirements. This smart control mechanism helps to maximize energy efficiency, reduce dependency on the grid during high-tariff periods, and promote the integration of renewable energy sources for more sustainable EV charging.

It is important to emphasize that the objective of this study is not to design an intelligent energy management system for EVCS. Rather, it focuses on evaluating the overall impact of EVCS integration on distribution system performance.

5.2.2 Modelling of EVCS as Static Load in Distribution System

Electric Vehicle Charging Station (EVCS) can be classified into three groups based on their charging capacity. The charging capacity encompasses level 1 and level 2, classified as low and semi-fast charging, ranging from 1.9 kW to 19 kW. Conversely, level 3 or fast charging capability can go up to 100 kW [143]. With renewable sources such as solar photovoltaics (PV) being integrated in distribution system, Electric Vehicles (EV) can operate in two primary modes: Vehicle-to-Grid (V2G) to enhance grid infrastructure reliability, and Grid-to-Vehicle (G2V) to facilitate the charging of

EV batteries during suitable periods [144] . Electricity generation from renewable sources and EVs operating in V2G mode present several benefits, including reduced greenhouse gas emissions and improved economic stability [145] , [146], [147].

In a distribution system, the total real power demand is given as (5.1):

$$P_{dt} = P_d^1 + P_d^2 + \dots + P_d^i + \dots + P_d^{N_{bus}} \quad (5.1)$$

$$\therefore P_{dt} = \sum_{i=1}^{N_{bus}} P_d^i \quad (5.2)$$

Where, P_{dt} , P_d^i and N_{bus} are the total real power demand, real power demand at i -th bus and number of buses respectively.

The net real power demand at i -th bus considering EVCS load is given as in (5.3) [148]:

$$P_d^i = P_{ex}^i + P_{cs}^i \quad (5.3)$$

Where, P_{ex}^i and P_{cs}^i are the real powers of the existing and EVCS loads at i -th bus.

So, the total real power demand in the system with EVCS loads can be represented as in (5.4):

$$P_{dt} = \sum_{i=1}^{N_{bus}} (P_{ex}^i + P_{cs}^i) \quad (5.4)$$

The EVCS load, P_{cs}^i at i -th bus is calculated as in (5.5) [148]:

$$P_{cs}^i = (N_{G2V} \times R_C) - (N_{V2G} \times R_D) \quad (5.5)$$

Where, N_{G2V} is the number of EVs linked to EVCS in G2V mode and N_{V2G} is the number of EVs linked to EVCS in V2G mode. The charging and discharging rate are

represented by R_C and R_D respectively. Only those busses connected to EVCS will have increment or decrement in their real power loads due to charging or discharging mechanisms. The charging rate, R_C is based on the EVCS charging capacity where level 1 is 1.9 kW, level 2 is 19 kW and level 3 is 100 kW. On the other hand, the discharging rate, R_D is assumed to be around 0.42% of charging rate [148].

In this chapter, there will be two scenarios to be studied. The first scenario will focus on EVCS with participating buses employ the same charging level (level 1, level 2, or level 3). The second scenario will investigate the effects of EVCS with participating buses employing several combinations of different charging levels. Each scenario will include 20 cases for both test systems, namely the IEEE 33-bus system and IEEE 69-bus system, with variations in EVCS bus locations, number of EVCS connected to each bus, and modes (i.e. G2V or V2G) available on the selected bus.

5.2.3 Voltage Deviation Index for Voltage Stability Assessment with EVCS Integration

The first indicator to be used in the assessment of EVCS impact on distribution system is the Voltage Deviation Index (VDI). The use of VDI reflects the system performance in terms of real power losses and voltage profiles. The ideal value of VDI should be zero. Theoretically, VDI ranges from zero to a positive upper bound depending on network conditions. The optimal or best VDI value is 0, which indicates a perfect voltage profile where all buses operate exactly at the nominal voltage V_n . Consequently, higher VDI values represent the worst outcomes, indicating severe voltage deviations across the network.

Since the EVCS has the capability of charging and discharging the connected EVs, it can either draw or inject certain amount of real power from or to the system. This bi-directional power flow affects both the voltage profiles and power losses altogether.

The VDI can be calculated as in (5.6) [149]:

$$VDI = \sum_{i=1}^{N_{bus}} |V_n - V_i|^2 \quad (5.6)$$

Where, V_n is the selected nominal voltage (usually 1.00 per unit) and V_i is the voltage magnitude at bus i . Prior to calculating the VDI as in (5.6), a load flow simulation will be conducted to determine voltage magnitudes at all buses and total real power losses in the system.

Unlike the previous stages of this research (Chapters 3 and 4), which focused on resolving fundamental grid constraints specifically, minimizing total real power loss and ensuring the boundary condition of the lowest bus voltage V_{min} remained above the 0.95 p.u. In this chapter, the research introduce the Voltage Deviation Index (VDI) as a safety threshold. VDI was not implemented in the earlier stages because the primary objective was to validate the algorithm's capability to achieve baseline technical stability and economic savings. With the algorithm's robustness proven, VDI is introduced as an advanced, comprehensive metric for evaluating overall power quality and the voltage profile across the entire distribution network.

5.2.4 Net Grid Power for Grid Dependency Assessment with EVCS Integration

Besides the Voltage Deviation Index (VDI), the second indicator for the assessment of EVCS impact on distribution system is grid dependency. The grid dependency can be measured through a quantity known as the net grid power, P_{grid} . As the EVCS offers bi-directional power flow via G2V and V2G modes, there will be moments at which the distribution system either depends on the grid or contributes to the grid. A positive value of P_{grid} indicates that the distribution system is grid-dependent, meaning that the power being drawn from the grid to support the system's loads, including all the EVCS. On the other hand, the negative P_{grid} indicates that the distribution system is grid-independent since it feeds the power back to the grid instead of taking from it.

The net grid power, P_{grid} for a distribution system with EVCS can be determined as in (5.7):

$$P_{grid} = P_{dt} + P_{G2V} - P_{V2G} \quad (5.7)$$

Where, P_{dt} , P_{G2V} and P_{V2G} are the total real power demand (existing loads), total charging power (grid to EV) and total discharging power (EV to grid) respectively.

A high positive value of P_{grid} can also mean that the distribution system is strongly dependent on the grid. This might happen during the peak hour of demand curve, where the charging of EVs in addition to the existing loads put additional stress to the system. Thus, alternative, decentralized energy sources like DG are highly required to prevent voltage instability and maintaining the system's reliability as well. In contrast, the more negative P_{grid} indicates that the distribution system is more independent of the grid, meaning that it has various alternative, decentralized energy sources either from DG or the EVCS's V2G mode of operation.

Whether G2V or V2G modes, managing effectively the charging and discharging mechanisms is greatly important for any EVCS-integrated distribution system as it can improve grid efficiency and overall system performance.

5.2.5 Total Harmonic Distortion for Power Quality Assessment with EVCS Integration

The need for signal conversions from AC-to-DC for G2V mode and DC-to-AC for V2G mode has involved the power electronic converters, which are non-linear loads. Rectifier and inverter of an EVCS continuously perform their function by converting the voltage and current from both sides; the grid side and the EV side. The involvement of non-linear loads like rectifiers and inverters invites harmonic distortion in voltage and current waveforms, which can lead to high power losses and low voltage magnitudes. Hence, besides the voltage stability and grid dependency, another important indicator to assess the EVCS impact on distribution system in term of power quality is Total Harmonic Distortion (THD).

THD is an important measure to assess power quality in distribution systems. It assesses how drastically harmonic frequencies produced by non-linear loads alter the fundamental frequency of voltage or current [150]. Excessive THD in distribution networks may lead to increased power losses, equipment overheating, and a shorter lifespan for sensitive electronics [150]. With the increasing integration of renewable energy sources and EVs, understanding and mitigating THD has become critical for sustaining system reliability and compliance with power quality standards. The presence of EVCS has introduced new challenges to the harmonic profile of distribution systems [141].

In determining the THD for a distribution system, this study employs the

mathematical formulation as proposed by [151]. The research converted several power system components, such as transmission lines and loads, into their equivalent harmonic admittances and currents. The followings describe the mathematical formulation for THD analysis in power system.

Transmission lines

In [151], the research utilized the Pi-model of transmission line as in **Figure 5.2** to facilitate harmonic analysis. The line model includes a series admittance for h -th harmonic order, y_s^h and line charging admittance for h -th harmonic order, y_c^h .

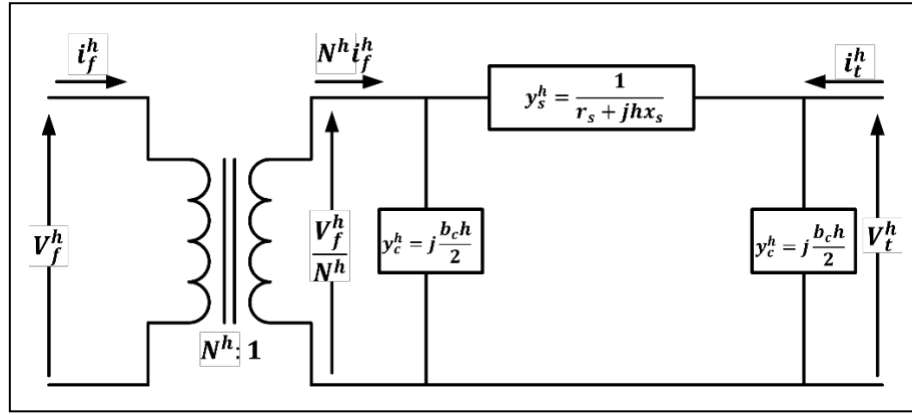


Figure 5. 2 Transmission Line Pi-Model

Based on **Figure 5.2**, the series and shunt admittance with harmonic component can be represented as in (5.8) and (5.9) respectively:

$$y_{se,k}^h = \frac{1}{r_{se,k} + h \cdot jx_{se,k}} \quad (5.8)$$

$$y_{sh,k}^h = h \frac{b_{sh,k}}{2} \quad (5.9)$$

Where, $y_{se,k}^h$ is the series admittance for h -th harmonic order for k -th transmission line, $r_{se,k}$ is the series resistance for h -th harmonic order for k -th transmission line, $x_{se,k}$ is the series reactance for h -th harmonic order for k -th transmission line, $y_{sh,k}^h$ is the shunt admittance for h -th harmonic order for k -th transmission line, $b_{sh,k}$ is the charging capacitance for k -th transmission line and h is the harmonic order.

For the purpose of simplicity, the transformer ratio is not considered in this study. Therefore, the branch admittance matrix for any k -th transmission line for h -th harmonic order can be written as:

$$\mathbf{Y}_k^h = \begin{bmatrix} y_{ff,k}^h & y_{ft,k}^h \\ y_{tf,k}^h & y_{tt,k}^h \end{bmatrix} = \begin{bmatrix} (y_{se,k}^h + jy_{sh,k}^h) & -y_{se,k}^h \\ -y_{se,k}^h & (y_{se,k}^h + jy_{sh,k}^h) \end{bmatrix} \quad (5.10)$$

The matrix elements of $y_{ff,k}^h$, $y_{ft,k}^h$, $y_{tf,k}^h$ and $y_{tt,k}^h$ are for k -th transmission line. For a distribution system with N_{line} number of transmission lines, those elements are put into four different vectors.

Linear loads:

The combination of linear and non-linear loads is represented by admittances included in the harmonic bus admittance matrix $\mathbf{Y}_{bus}^h$. Prior to deriving the equivalent matrix of $\mathbf{Y}_{bus}^h$, the representation of linear and non-linear loads in the form of admittance vectors must be obtained at first. The admittance matrix elements of linear loads for h -th harmonic order given as follows:

$$y_{load,ii}^h = \frac{1}{r_{load,i} + h \cdot jx_{load,i}} \quad (5.11)$$

$$r_{load,i} + h \cdot jx_{load,i} = \frac{|V_{base,i}|^2}{P_{load,i} - jQ_{load,i}} \quad (5.12)$$

Where, $r_{load,i} + h \cdot jx_{load,i}$ is the impedance of the linear load at bus i , $P_{load,i}$ and $Q_{load,i}$ are the real and reactive power demands at bus i respectively and h is the harmonic order.

Non-linear loads:

The non-linear loads, in this case the EVCS, are represented by harmonic current sources which are equivalent to injected (or absorbed) harmonic currents to (or from) the distribution system. These harmonic current sources for h -th harmonic order are represented by a current vector with the individual elements of the vector are found as follows:

$$I_{inj,i}^{h=1} = conj\left(\frac{P_{nl-load,i} + jQ_{nl-load,i}}{V_i}\right) = |I_{inj,1}^{h=1}| \angle \theta_{inj,1}^{h=1} \quad (5.13)$$

$$|I_{inj,i}^h| = I_{spectrum}^h \cdot |I_{inj,i}^{h=1}| \quad (5.14)$$

$$\theta_{inj,i}^h = h \cdot \theta_{inj,1}^{h=1} + \theta_{spectrum}^h \quad (5.15)$$

Where, $I_{inj,i}^{h=1}$ is the fundamental load current, $I_{inj,i}^h$ and $\theta_{inj,i}^h$ are the magnitude and phase angle of the injected (or absorbed) current for h -th harmonic order at bus- i .

Based on (5.14) and (5.15), the harmonic spectrum for the load current and phase angle are needed for calculation. Hence, the harmonic spectrum utilized in this research, which is according to [151], is presented in **Table 5.1**:

Table 5. 1
Harmonic Spectrum For Load Current And Phase Angle

Harmonic Order	Typical Harmonic Spectrum	
	$I_{spectrum}^h$	$\theta_{spectrum}^h$ (radian)
1	0	0
5	0.1824	-0.97180
7	0.1190	-1.46800
11	0.0573	-2.50559
13	0.0401	-3.06445
17	0.0193	1.94412
19	0.0139	1.19206
23	0.0094	-0.42953
25	0.0086	-1.18054
29	0.0071	-2.53876
31	0.0062	3.08627
35	0.0044	1.69995
37	0.0038	0.94876

Shunt compensator:

Besides the loads, other shunt elements like reactive power compensators, capacitor banks and DG can also be converted into their harmonic equivalent representation. The research in [151] provided the conversion of shunt capacitors into their harmonic admittances with the individual elements of the matrix is found as follows:

$$X_{c,i} = \frac{V_i^2}{Q_{c,i}} \quad (5.16)$$

$$y_{c,ii}^h = \frac{h}{-jX_{c,i}} \quad (5.17)$$

Where, $y_{c,ii}^h$ is the shunt capacitor's admittance at bus i for h -th harmonic order, $X_{c,i}$ is the shunt capacitor's reactance at bus i , V_i is the voltage magnitude at bus i and $Q_{c,i}$ is the reactive power injected at bus i by the shunt capacitor.

Harmonic bus admittance matrix:

After converting all power system components into their equivalent harmonic representations, the next step is to form a complete bus admittance matrix for every h -th harmonic order. The process begins with the formation of topology matrices, namely the 'from' and 'to' matrices, which also represent the network topology. The 'from' matrix, C_f and 'to' matrix, C_t are given in (5.18) and (5.19) respectively:

$$\mathbf{C}_f = \begin{bmatrix} C_{f,11} & \cdots & C_{f,1i} & \cdots & C_{f,1N_{bus}} \\ \vdots & & \vdots & & \vdots \\ C_{f,k1} & \cdots & C_{f,ki} & \cdots & C_{f,kN_{bus}} \\ \vdots & & \vdots & & \vdots \\ C_{f,N_{line}1} & \cdots & C_{f,N_{line}i} & \cdots & C_{f,N_{line}N_{bus}} \end{bmatrix}_{N_{line} \times N_{bus}} \quad (5.18)$$

$$\mathbf{C}_t = \begin{bmatrix} C_{t,11} & \cdots & C_{t,1i} & \cdots & C_{t,1N_{bus}} \\ \vdots & & \vdots & & \vdots \\ C_{t,k1} & \cdots & C_{t,ki} & \cdots & C_{t,kN_{bus}} \\ \vdots & & \vdots & & \vdots \\ C_{t,N_{line}1} & \cdots & C_{t,N_{line}i} & \cdots & C_{t,N_{line}N_{bus}} \end{bmatrix}_{N_{line} \times N_{bus}} \quad (5.19)$$

Where:

$$C_{f,ki} = \begin{cases} 1 & ; \text{ if } k_{th} \text{ line is away from } i_{th} \text{ bus} \\ 0 & ; \text{ if } k_{th} \text{ line is not connected to } i_{th} \text{ bus} \end{cases} \quad (5.20)$$

$$C_{t,ki} = \begin{cases} 1 & ; \text{ if } k_{th} \text{ line is toward } i_{th} \text{ bus} \\ 0 & ; \text{ if } k_{th} \text{ line is not connected to } i_{th} \text{ bus} \end{cases} \quad (5.21)$$

Later, the topology matrices are used to find the following matrices, the ‘from’ and ‘to’ admittance matrices, via equations (5.22) and (5.23):

$$\mathbf{Y}_f^h = (\mathbf{Y}_{ff}^h \mathbf{C}_f) + (\mathbf{Y}_{ft}^h \mathbf{C}_t) \quad (5.22)$$

$$\mathbf{Y}_t^h = (\mathbf{Y}_{tf}^h \mathbf{C}_f) + (\mathbf{Y}_{tt}^h \mathbf{C}_t) \quad (5.23)$$

Where, the ‘from’ admittance matrix, $\mathbf{Y}_f^h$ and ‘to’ admittance matrix, $\mathbf{Y}_t^h$ for h -th harmonic order. Thus, the harmonic bus admittance matrix $\mathbf{Y}_{bus}^h$ for h -th harmonic order can be found as follows:

$$\mathbf{Y}_{bus}^h = (\mathbf{C}_f^T \mathbf{Y}_f^h) + (\mathbf{C}_t^T \mathbf{Y}_t^h) + \mathbf{Y}_{load}^h + \mathbf{Y}_c^h \quad (5.24)$$

For slack bus, the admittance for h -th harmonic order is found via (5.25):

$$y_{slack}^h = 10^{10} + h \cdot j10^{10} \quad (5.25)$$

Total Harmonic Distortion:

Once the harmonic bus admittance matrix, $\mathbf{Y}_{bus}^h$ was formed, the bus voltages for h -th harmonic order can be calculated through (5.26):

$$\mathbf{V}_{bus}^h = (\mathbf{Y}_{bus}^h)^{-1} \mathbf{I}_{inj}^h \quad (5.26)$$

Where, $\mathbf{V}_{bus}^h$ is the vector of bus voltages for h -th harmonic order and $\mathbf{I}_{inj}^h$ is the vector of injected current by non-linear loads for h -th harmonic order. Finally, the Total Harmonic Distortion (THD) for i -th bus in the system is found via (5.27):

$$THD_i = \frac{\sqrt{\sum_{h=2}^n (|V_i^h|)^2}}{|V_i^{h=1}|} \times 100\% \quad (5.27)$$

Where, $|V_i^h|$ is the voltage magnitude of h -th harmonic order at i -th bus and n is the total number of harmonics.

Theoretically, the optimal or best THD value is 0%, which represents a perfectly pure sinusoidal waveform with zero harmonic content. Conversely, there is no mathematical upper limit for the worst THD value. However, in practical distribution networks, any value exceeding the standard 5% threshold is considered an unacceptable deterioration of power quality.

5.2.6 Consideration of Different Cases in the Assessment of EVCS Impact on Distribution System Performance

To conduct a comprehensive assessment of EVCS impact on distribution system performance, this study has selected several factors to be considered in the experiment as follows:

Locations of EVCS

The placement of EVCS units within a distribution system significantly impacts grid performance, as different buses exhibit varying levels of loadability before voltage instability occurs. This study considers two test systems to evaluate these effects. The IEEE 33-bus radial distribution system consists of 33 buses, with bus 1 serving as the slack bus and therefore excluded from EVCS integration, leaving 32 possible locations. Similarly, the IEEE 69-bus radial distribution system comprises 69 buses, with bus 1 as the slack bus, allowing EVCS placement at any of the remaining 68 buses. By analyzing

different placement scenarios, this study aims to assess the impact of EVCS locations on voltage stability, real power losses, and overall grid performance. In both test systems, the experiment will be conducted by randomly placing EVCS units at specific locations within the distribution network.

Number of EVCS per bus

Once the locations of EVCS units within the test systems are selected, the number of units to be placed at each bus will be determined, as both placement and quantity significantly impact grid performance. An excessive number of EVCS units at a single bus can lead to issues such as voltage instability, increased real power losses, and elevated Total Harmonic Distortion (THD), as these units draw power from the grid whenever EVs are charging. Conversely, an insufficient number of EVCS units may result in inefficient charging operations, potentially causing delays and limiting the availability of charging infrastructure for EVs. Therefore, assessment on the effect of location and number of EVCS units per bus is crucial to ensuring grid stability and charging efficiency.

Charging modes

Each EVCS unit operates at one of three charging levels: Level 1 (L1), Level 2 (L2), or Level 3 (L3). When EVCS units are integrated into a bus, they can either operate at the same charging level or a combination of different levels. For instance, if a bus has ten EVCS units, all units can be set to L2 charging, or a mix of L1 and L2, L2 and L3, or L1 and L3. The rationale behind analyzing these different charging modes is to determine their impact on grid performance in terms of voltage stability, power losses, and overall system efficiency. This study assesses two distinct charging modes: (1) Identical Charging Mode, where all EVCS units at a given bus operate at the same charging level (L1, L2, or L3), and (2) Mixed Charging Mode, where a combination of different charging levels is applied within the same bus. By comparing these modes, this study aims to identify how varying charging strategies influence grid stability and efficiency. The configurations are illustrated in **Figure 5.3**.

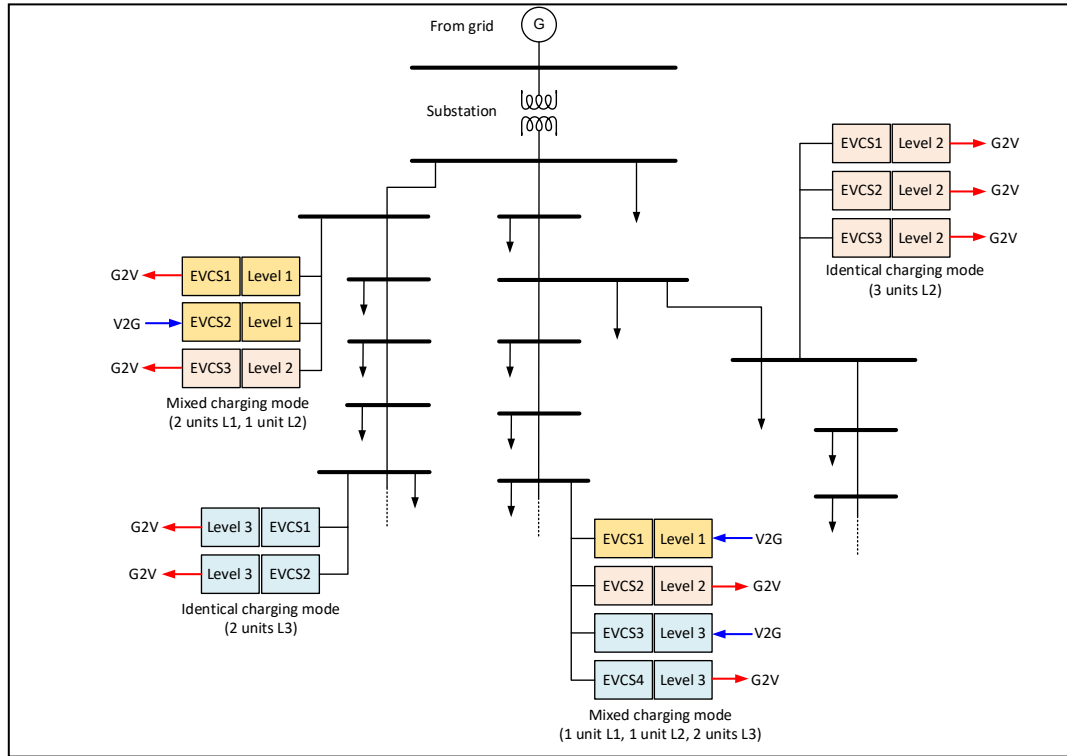


Figure 5. 3 Proposed Different Charging Modes To Be Used In Distribution System

Types of EVCS

This study incorporates two EV charging technologies: Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G). G2V enables EVs to draw power from the grid, potentially leading to increased real power losses, voltage deviations, and higher grid dependency. In contrast, V2G allows EVs to inject power back into the grid, which can help mitigate voltage drops, improve voltage stability, and support grid resilience. To achieve a comprehensive assessment of EVCS impact, each bus integrated with EVCS will be analyzed under two conditions: one with only G2V-type EVCS and another with a combination of G2V and V2G. This approach provides deeper insights into how different charging strategies influence grid performance, including voltage stability, power losses, grid dependency and Total Harmonic Distortion (THD).

System's loading

The final factor considered in assessing the impact of EVCS is the system's loading condition. The charging and discharging behaviour of EVCS units is directly

influenced by the system's load, with their effects becoming more pronounced under peak loading conditions. To capture these variations, this study evaluates EVCS impact across different loading levels, ranging from 10% to 50% of the system's maximum load. At each loading level, EVCS units will be strategically placed at various locations, with varying numbers, charging modes, and types (G2V and V2G). Their effects on voltage stability, real power losses, grid dependency, and Total Harmonic Distortion (THD) will be systematically analyzed. This assessment will provide deeper insights into how different loading conditions amplify or mitigate the impact of EVCS on overall grid performance, helping to identify critical thresholds for system stability and efficiency.

Table 5.2 summarizes all the factors considered in the proposed assessment method.

Table 5. 2
Factors Considered In The Assessment Of Distribution System Performance With EVCS Integration

Factors	Options / variables
EVCS locations	All buses except slack bus
Number of EVCS per bus	1 unit to 20 units
Charging mode	Identical and mixed charging modes
EVCS type	G2V and V2G
Loading	10% to 50% of maximum load

5.2.7 Proposed Procedures for Assessment of Distribution System Performance with EVCS Integration

This section presents the overall procedures for assessing the performance of distribution system integrated with Electric Vehicle Charging Stations (EVCS). By following the proposed assessment procedures, this research aims to provide a comprehensive understanding of the impact of EVCS on distribution system performance, facilitating the identification of potential challenges and the development of strategies to mitigate their effects.

The proposed procedures are outlined as follows:

- i) **Initialization and Test System Loading:** The program begins by initializing and loading the required test system. For this study, two standard test systems are employed: the IEEE 33-bus system and IEEE 69-bus system. These systems serve as the foundational frameworks for evaluating the impact of EVCS integration on distribution network performance.
- ii) **Pre-Load Flow Analysis:** Following the system initialization, a pre-load flow analysis is conducted using the Newton-Raphson method. This analysis is essential for determining the baseline operating conditions of the distribution network without the presence of EVCS. Key parameters such as voltage profiles at each bus, total power losses, line flows and total demand are recorded. These parameters provide a reference point for subsequent comparisons.
- iii) **Calculation of Performance Indices without EVCS:** By utilizing the results from the pre-load flow analysis, the required performance indices are computed. These include the Voltage Deviation Index (VDI) as in (5.6) which measures the extent of voltage deviations from a specified nominal value; the grid power (P_{grid}) as in (5.7) which represents the total power taken from or transferred to the grid; and the Total Harmonic Distortion (THD) as in (5.38) which is an important measure to assess power quality in distribution systems. These indices collectively characterize the system's performance prior to the integration of EVCS.
- iv) **Specifying the non-linear loads:** Non-linear loads are specified within the system to represent the EVCS loads. This step is crucial for modelling the non-linear characteristics of EVCS, which can significantly influence the system's harmonic profile and overall performance.
- v) **Integration of EVCS Loading:** The EVCS loads are integrated into the system based on different cases according to **Table 5.2**. These different scenarios are designed to reflect various real-world conditions, such as different levels of EV penetration, charging patterns, and geographical distributions of charging stations.
- vi) **Replacement of non-linear loads with EVCS Loading:** The previously declared non-linear loads are replaced with the actual EVCS loading. This step

ensures that the system model accurately reflects the impact of EVCS on the distribution network.

- vii) **Post-Load Flow Analysis:** A post-load flow analysis is performed using the Newton-Raphson method to evaluate the system's performance under the influence of EVCS. The analysis yields the related parameters such as updated voltage profiles, total power losses, line flows and total demand.
- viii) **Calculation of Performance Indices with EVCS:** The results from the post-load flow are used to determine the performance indices as in step (3). Later, they will be compared against the pre-load flow results to assess the impact of EVCS integration.
- ix) **Iterative Process for Multiple Scenarios:** Steps (i) through (viii) are repeated iteratively for all specified scenarios and cases. This iterative approach ensures a comprehensive evaluation of the distribution system's performance across a wide range of EVCS's operating conditions and its integration levels.

The summary of the proposed assessment procedures is illustrated in **Figure 5.4.**

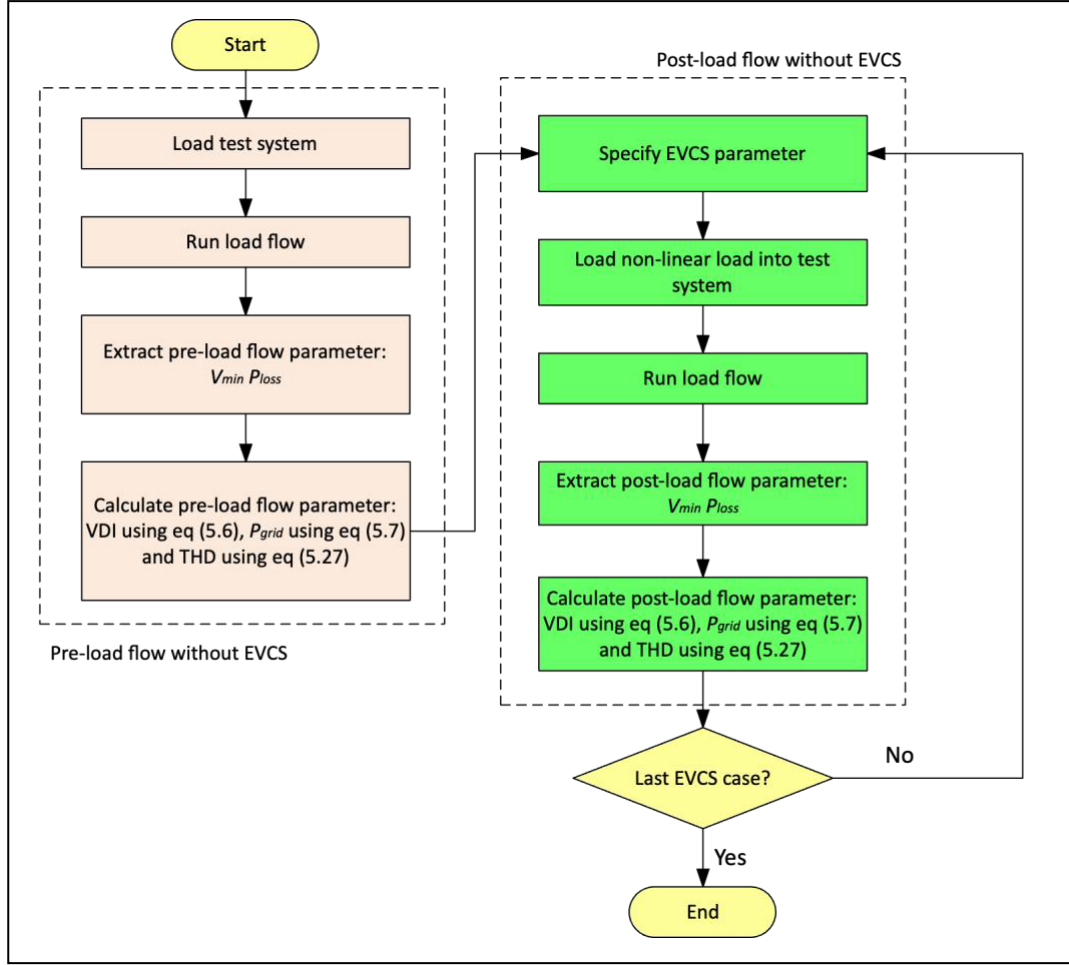


Figure 5. 4 Proposed Procedures For Assessment Of Distribution System Performance With EVCS Integration

5.3 Results and Discussions

The results and analysis will focus on evaluating the performance of distribution system with the integration of Electric Vehicle Charging Stations (EVCS). This assessment is crucial in understanding the impact of EVCS deployment on key aspects of power distribution, particularly voltage stability, grid dependency, and power quality.

Voltage stability will be assessed based on the Voltage Deviation Index (VDI), minimum voltage magnitude ($V_{\min}$), and total real power losses (P_{loss}). The VDI value quantifies fluctuations in voltage levels across the system, where higher values indicate greater instability. The minimum voltage magnitude represents the lowest recorded voltage level in the network, while the total real power losses account for the energy dissipated within the distribution system. Grid dependency will be evaluated through

the net real power drawn from the grid (P_{grid}). This metric reflects the extent to which EVCS increases reliance on external power sources, providing an indication of how charging stations influence overall grid demand. Power quality will be examined through Total Harmonic Distortion (THD), expressed as a percentage. EV chargers introduce harmonic distortions into the system, which can affect voltage and current waveforms. Higher THD values indicate a greater degree of distortion, potentially leading to operational issues regarding overall stability of the system.

To verify the findings, this study will employ two different test systems, the IEEE 33-bus and IEEE 69-bus distribution networks. Both are radial-type networks commonly used in distribution system research due to their standardized structure. By analyzing the two test systems, this study aims to provide a thorough understanding of how different network configurations respond to EVCS integration, offering valuable insights for practical applications.

5.3.1 Assessment of Distribution System Performance with Different Cases of EVCS Integration – IEEE 33-bus system

In this section, two different scenarios are analyzed: identical charging mode and mixed charging mode. As explained in subsection 5.2.6, the identical charging mode refers to a configuration where all Electric Vehicle Charging Stations (EVCS) installed at a given bus operate at the same charging level. In contrast, the mixed charging mode involves a combination of different charging levels at a single bus. Each scenario consists of twenty different cases of EVCS integration, with each case varying in terms of EVCS location (bus number), the number of installed EVCS per bus, charging mode (L1 for Level 1, L2 for Level 2, and L3 for Level 3), and EVCS type (either all Grid-to-Vehicle (G2V) or a combination of G2V and Vehicle-to-Grid (V2G)). **Table 5.3** presents the results for Scenario 1, where each EVCS bus follows an identical charging mode, while **Table 5.4** shows the results for Scenario 2, where mixed charging levels are applied at each EVCS bus.

In both tables, the upper section provides details on the different configurations of EVCS integration for each case. For example, in **Table 5.3**, Case 1 represents an integration where three buses (bus 10, bus 20, and bus 30) are equipped with EVCS, with each bus having four EVCS units operating at Level 3 (L3) charging mode, all using G2V technology, thereby following the identical charging mode. Similarly, in

Table 5.4, Case 1 for the mixed charging mode scenario maintains the same EVCS locations but with eight EVCS units per bus - four units set to Level 1 (L1) and the remaining four set to Level 2 (L2), all utilizing G2V technology.

The lower section of the tables presents the performance metrics for each case, including the Voltage Deviation Index (VDI) in per unit, minimum voltage magnitude ($V_{\min}$) in per unit, total real power losses (P_{loss}) in megawatts, net real power drawn from the grid (P_{grid}) in megawatts, and Total Harmonic Distortion (THD) in percentage. These results allow for a comprehensive evaluation of the system's performance under different EVCS integration scenarios across all twenty cases. Furthermore, based on **Table 5.3** and **Table 5.4**, graphical comparisons of the identical and mixed charging modes in terms of VDI, $V_{\min}$, P_{loss} , P_{grid} , and THD are illustrated in **Figure 5.5**, **Figure 5.6**, **Figure 5.7**, **Figure 5.8**, and **Figure 5.9**, respectively.

Table 5. 3

Voltage Stability, Power Losses, Grid Dependency And Harmonic Distortion For Distribution System Integrated With 20 Different EVCS Cases Using Identical Charging Mode – IEEE 33-Bus System

Case	EVCS Bus	Number of EVCS	Charging Mode	EVCS Type	
1	10, 20, 30	4, 4, 4	L3, L3, L3	All G2V	
2	10, 20, 30	6, 6, 6	L2, L3, L3	All G2V	
3	10, 20, 30	7, 7, 7	L3, L3, L3	5 G2V + 2 V2G	
4	10, 20, 30	8, 8, 8	L1, L1, L1	All G2V	
5	10, 20, 30	8, 8, 8	L2, L2, L2	All G2V	
6	10, 20, 30	8, 8, 8	L1, L2, L3	All G2V	
7	10, 20, 30	9, 9, 9	L2, L3, L3	7 G2V + 2 V2G	
8	10, 20, 30	10, 10, 10	L1, L2, L3	8 G2V + 2 V2G	
9	10, 20, 30	10, 10, 10	L1, L1, L1	8 G2V + 2 V2G	
10	10, 20, 30	10, 10, 10	L2, L2, L2	8 G2V + 2 V2G	
11	5, 8, 11, 16	6, 6, 3, 3	L2, L2, L3, L3	All G2V	
12	4, 7, 10, 17	8, 8, 4, 2	L2, L2, L3, L3	All G2V	
13	25, 27, 30, 33	8, 8, 5, 2	L2, L2, L3, L3	All G2V	
14	10, 15, 20, 25	8, 8, 6, 6	L2, L2, L3, L3	All G2V	
15	20, 23, 28, 30	8, 8, 8, 2	L2, L2, L3, L3	All G2V	
16	5, 8, 11, 16	15, 15, 15, 15	L2, L3, L3, L3	12 G2V + 3 V2G	
17	10, 15, 20, 25	15, 15, 15, 15	L2, L3, L3, L3	12 G2V + 3 V2G	
18	4, 7, 10, 17	15, 15, 15, 15	L2, L3, L3, L3	12 G2V + 3 V2G	
19	20, 23, 28, 30	15, 15, 15, 15	L2, L3, L3, L3	12 G2V + 3 V2G	
20	25, 27, 30, 33	15, 15, 15, 15	L2, L3, L3, L3	12 G2V + 3 V2G	
Case	VDI (p.u.)	V_{min} (p.u.)	P_{loss} (MW)	P_{grid} (MW)	THD (%)
Without EVCS	0.1042	0.9185	0.1831	3.715	0
1	0.1726	0.8962	0.3039	6.115	39.6274
2	0.1613	0.8961	0.2976	6.343	43.1011
3	0.1758	0.8953	0.3098	6.211	41.2704
4	0.1064	0.9177	0.1868	3.8062	1.4589
5	0.1277	0.9102	0.2232	4.627	14.7474
6	0.1677	0.8903	0.311	5.6494	32.897
7	0.163	0.8954	0.3014	6.4131	44.2972
8	0.16	0.8937	0.2944	5.4463	29.2685
9	0.1062	0.9178	0.1864	3.7966	1.3055
10	0.1251	0.9111	0.2187	4.5312	13.182
11	0.1838	0.8821	0.3056	5.371	28.7744
12	0.181	0.8837	0.3031	5.523	31.0042
13	0.1711	0.8884	0.3187	5.723	34.1828
14	0.1463	0.9004	0.2771	6.723	48.1734
15	0.1775	0.8905	0.3301	6.323	43.6694
16	0.706	0.7489	1.1852	10.5671	146.8182
17	0.3324	0.8314	0.6143	10.5671	121.8287
18	0.6784	0.7447	1.1294	10.5671	145.3231
19	0.3296	0.8415	0.6821	10.5671	123.1739
20	0.4838	0.7895	1.026	10.5671	139.6853

Table 5. 4
Voltage Stability, Power Losses, Grid Dependency And Harmonic Distortion For
Distribution System Integrated With 20 Different EVCS Cases Using Mixed
Charging Mode – IEEE 33-Bus System

Case	EVCS Bus	Number of EVCS	Charging Mode	EVCS Type	
1	10, 20, 30	8, 8, 8	4 L1 + 4 L2	All G2V	
2	10, 20, 30	8, 8, 8	4 L2 + 4 L3	All G2V	
3	10, 20, 30	8, 8, 8	4 L1 + 4 L3	All G2V	
4	10, 20, 30	8, 8, 8	2 L1 + 3 L2 + 3 L3	All G2V	
5	10, 20, 30	8, 8, 8	5 L2 + 3 L3	All G2V	
6	10, 20, 30	10, 10, 10	5 L1 + 5 L2	6 G2V + 4 V2G	
7	10, 20, 30	10, 10, 10	5 L2 + 5 L3	6 G2V + 4 V2G	
8	10, 20, 30	10, 10, 10	5 L1 + 5 L3	6 G2V + 4 V2G	
9	10, 20, 30	10, 10, 10	2 L1 + 4 L2 + 4 L3	8 G2V + 2 V2G	
10	10, 20, 30	10, 10, 10	6 L2 + 4 L3	8 G2V + 2 V2G	
11	5, 8, 11, 16	8, 8, 8, 8	7 L2 + 1 L3	All G2V	
12	10, 15, 20, 25	8, 8, 8, 8	7 L2 + 1 L3	All G2V	
13	4, 7, 10, 17	8, 8, 8, 8	7 L2 + 1 L3	All G2V	
14	20, 23, 28, 30	10, 10, 10, 10	8 L2 + 2 L3	All G2V	
15	25, 27, 30, 33	10, 10, 10, 10	9 L2 + 1 L3	All G2V	
16	5, 8, 11, 16	15, 15, 15, 15	8 L2 + 7 L3	12 G2V + 3 V2G	
17	10, 15, 20, 25	15, 15, 15, 15	8 L2 + 7 L3	12 G2V + 3 V2G	
18	4, 7, 10, 17	15, 15, 15, 15	8 L2 + 7 L3	12 G2V + 3 V2G	
19	20, 23, 28, 30	15, 15, 15, 15	8 L2 + 7 L3	12 G2V + 3 V2G	
20	25, 27, 30, 33	15, 15, 15, 15	8 L2 + 7 L3	12 G2V + 3 V2G	
Case	<i>VDI</i> (p.u.)	<i>V_{min}</i> (p.u.)	<i>P_{loss}</i> (MW)	<i>P_{grid}</i> (MW)	<i>THD</i> (%)
Without EVCS	0.1042	0.9185	0.1831	3.715	0.0000
1	0.1167	0.9139	0.2043	4.2166	8.0669
2	0.1881	0.8918	0.3327	6.571	47.4749
3	0.1741	0.8957	0.3067	6.1606	40.4072
4	0.1649	0.8984	0.2899	5.8798	35.6223
5	0.1716	0.8965	0.3021	6.085	39.115
6	0.1109	0.916	0.1943	3.9859	4.343
7	0.1456	0.9043	0.255	5.2572	25.155
8	0.1392	0.9064	0.2435	5.0356	21.4742
9	0.1554	0.9013	0.2727	5.5799	30.5564
10	0.1619	0.8993	0.2844	5.7851	34.018
11	0.1797	0.8857	0.3023	4.647	31.7134
12	0.157	0.8939	0.2715	4.647	30.6977
13	0.175	0.8857	0.2948	4.647	31.5917
14	0.1601	0.8964	0.2986	5.123	45.9534
15	0.1676	0.8908	0.3132	4.799	36.3654
16	0.3281	0.838	0.5506	8.0432	79.0515
17	0.2527	0.8589	0.4417	8.0432	74.783
18	0.3125	0.8379	0.5232	8.0432	78.4976
19	0.1875	0.8861	0.3595	7.6673	65.4747
20	0.2366	0.8643	0.4671	7.6673	69.2703

As can be seen in **Figure 5.5**, the VDI values of most cases exceed the condition without EVCS (as marked by the dotted-black line). This indicates that with the EVCS penetration into the system, the voltage profiles are more affected than the condition without EVCS. From Case 1 to Case 15, there is only a slight difference between identical and mixed charging modes. As in **Figure 5.5**, both modes result in VDI below 0.2 per unit for the first fifteen cases. However, the VDI values of the identical charging mode (red bars) from Case 16 to Case 20 are much higher than the mixed one (blue bars), with some of them approach 0.7 per unit. This implies that the identical charging mode can cause greater voltage disturbances, which can lead to localized voltage instability due to concentrated charging demand at specific buses. Mixed charging mode, on the other hand, helps reducing the voltage deviations by distributing the EVCS loads more evenly throughout the system. The highest VDI value by mixed charging mode is only about 0.3 per unit as shown in **Figure 5.5**. This will provide better voltage regulation and lower system stress compared to the other charging mode.

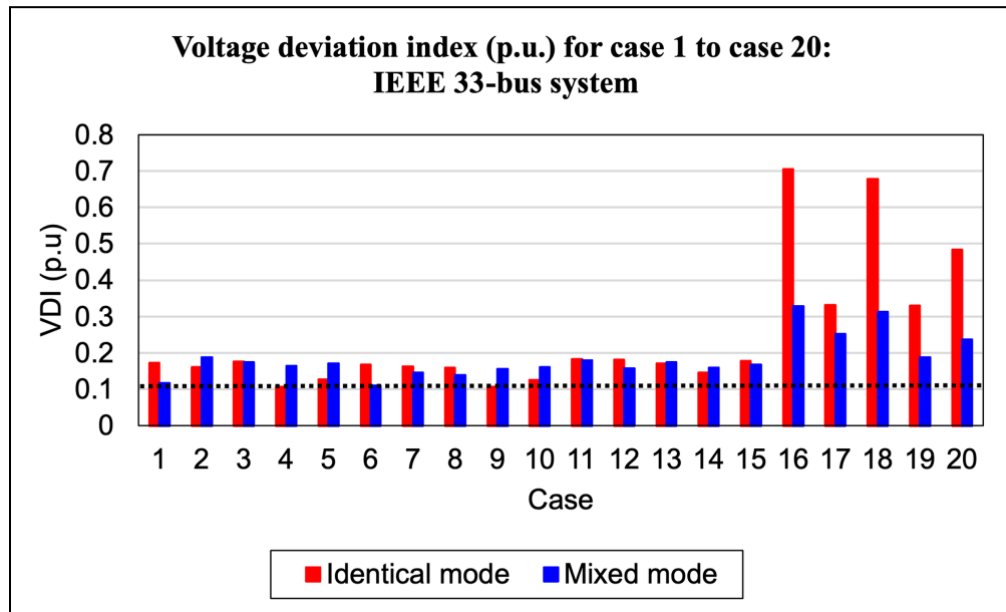


Figure 5. 5 Voltage Deviation Index (VDI) (In Per Unit) For Case 1 To Case 20 – IEEE 33-Bus System

Because of the increase in VDI values as in **Figure 5.5**, the minimum voltage magnitudes for all cases are reduced after integrating the EVCS units into the system. Based on **Figure 5.6**, all cases have minimum voltage magnitude, or $V_{\min}$, below the condition without EVCS (as marked by the dotted-black line). There is a slight

difference in $V_{\min}$ between the identical and mixed charging mode from Case 1 to Case 15, with the values of $V_{\min}$ maintained above 0.85 per unit. As Case 16 to Case 20 were implemented, the identical charging mode (red bars) faces a significant reduction in $V_{\min}$, with some of them below 0.8 per unit. Due to simultaneous higher power demand, with all EVCS units have Level 2 or 3 charging mode at multiple EVCS locations, the identical charging mode leads to greater voltage drops compared to the mixed one.

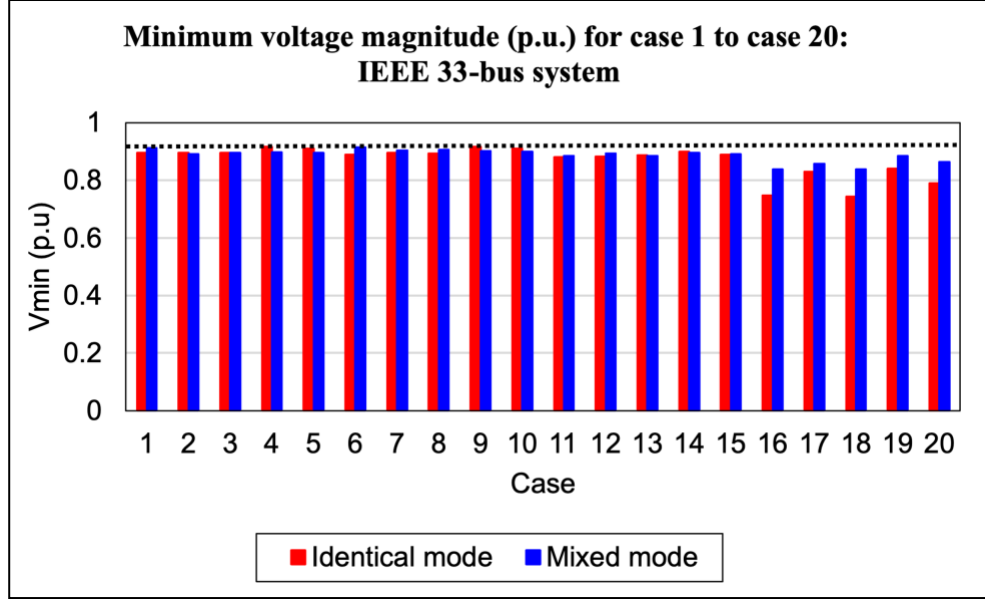


Figure 5. 6 Minimum Voltage Magnitude (In Per Unit) For Case 1 To Case 20 – IEEE 33-Bus System

A similar trend as in VDI and $V_{\min}$ can be observed for total real power losses as shown in **Figure 5.7**. With the EVCS penetration into the system, all cases exhibit an increment trend in real power losses, or P_{loss} , with respect to the condition without EVCS (as marked by the dotted-black line). The first fifteen cases have a slight difference in P_{loss} between identical and mixed charging modes, with P_{loss} between 0.2 MW and 0.4 MW. A significant increase in P_{loss} can be observed in **Figure 5.7** from Case 16 to Case 20, with the identical charging mode (red bars) surpasses 1 MW in some of the cases. Such a high increase in P_{loss} indicates an increased stress on distribution lines, which is due to concentrated charging demand at specific EVCS locations. Even though the mixed charging mode has significant increases in P_{loss} for the last five cases, they are much lower than that of the identical one, with P_{loss} maintained below 0.6 MW. In term of power losses, the mixed charging mode demonstrates a more efficient power distribution strategy than the other.

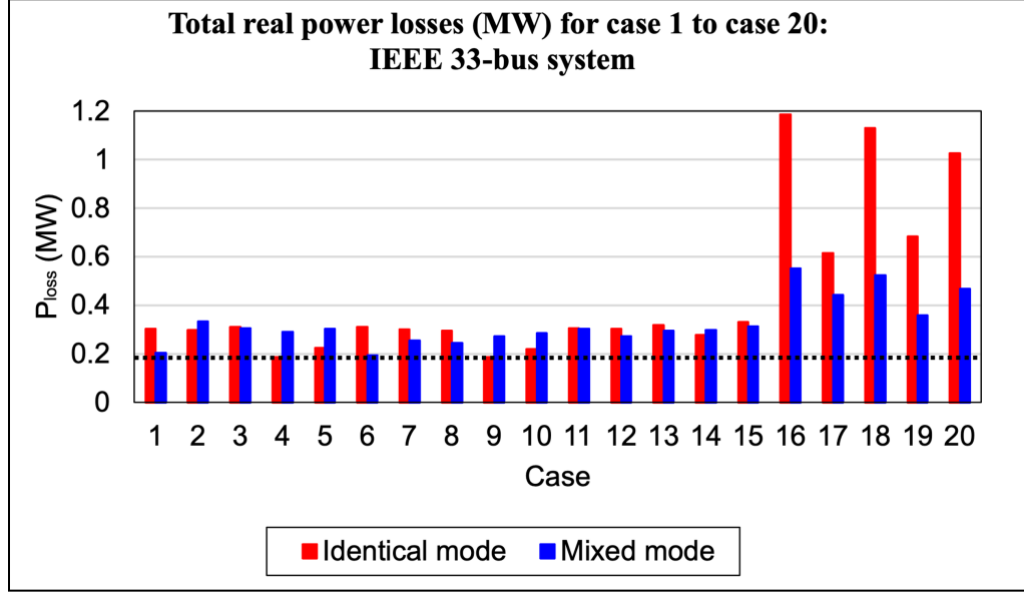


Figure 5. 7 Total Real Power Losses (In MW) For Case 1 To Case 20 – IEEE 33-Bus System

Assessment on grid dependency can be conducted by measuring the magnitude of net real power, in Megawatts, drawn by the loads from the system or grid. The net real power drawn from the grid, or P_{grid} , with the presence of EVCS is presented in **Figure 5.8**. As can be observed, all the cases have the values of P_{grid} above the condition without EVCS (as marked by the dotted-black line). This implies that the consumption of power increases with EVCS penetration into the system. The grid needs to supply more power to the loads as a result of EVCS integration. Based on **Figure 5.8**, the first fifteen cases exhibit a fluctuation in P_{grid} between identical and mixed charging modes, with P_{grid} between 4 MW and 7 MW. There are some cases where the identical charging mode requires more P_{grid} than the mixed one, and vice versa. However, the last five cases which are Case 16 to Case 20 show that the identical charging mode (red bars) has greater grid dependency than the mixed one (blue bars), with the values of P_{grid} exceed 10 MW. Such a high grid dependency indicates that the identical charging mode draws more power from the grid, thereby forcing the grid to supply more power which can increase stress on the whole system. Even though the mixed charging mode has significant increases in P_{grid} for the last five cases, the net power drawn by the loads is at most 8 MW, lower than the other charging mode. In term of net grid power, this charging mode reduces peak demand, indicating better load management.

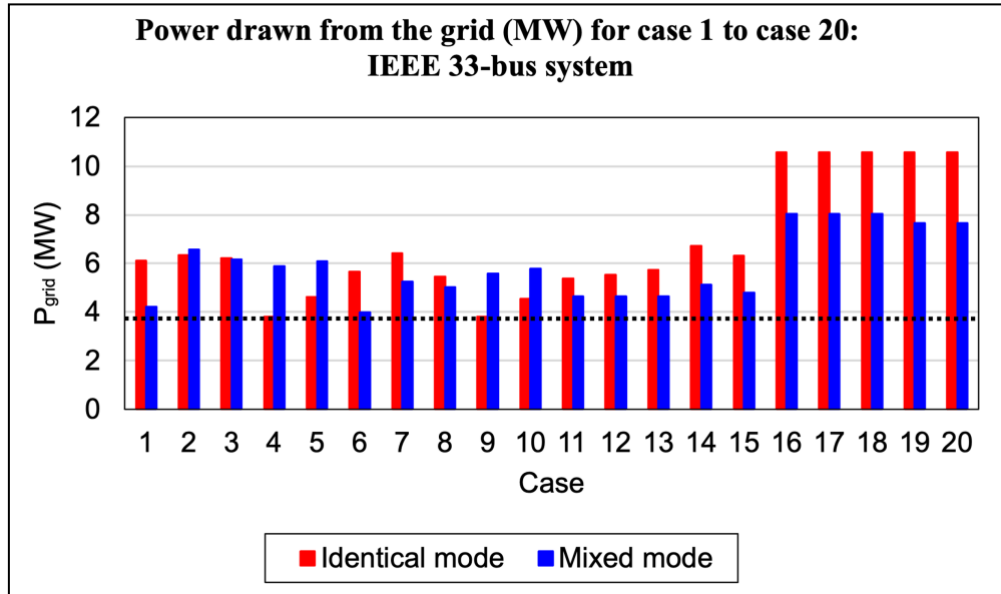


Figure 5. 8 Power Drawn From The Grid (In MW) For Case 1 To Case 20 – IEEE 33-Bus System

The aspect of power quality is measured in term of Total Harmonic Distortion (THD) in percentage. The THD trend based on the twenty different cases is shown in **Figure 5.9**. As can be observed, the EVCS penetration into the system has resulted in increased THD percentages for all cases. From Case 1 to Case 15, there are some cases where identical charging mode causes higher THD than the mixed one, and vice versa. The THD for the first fifteen cases, however, is still below 50%. Critical increase in THD can be observed in **Figure 5.9** for the last five cases. From Case 16 to Case 20, the identical charging mode (red bars) has caused the THD percentages to exceed 100%. Large-scale simultaneous EV charging, especially when all EVCS units are set to Level 2 or 3 charging mode, leads to greater harmonic distortion due to nonlinear power electronics. Even though the mixed charging mode (blue bars) exhibits a significant increase in THD for the last five cases, the percentages are maintained below 80%. Thus, in term of THD, the mixed charging mode can promise better power quality than the other one. As established earlier in this chapter, significantly high THD degrades grid reliability by causing increased power losses, severe equipment overheating, and a reduced lifespan for sensitive electronics [139].

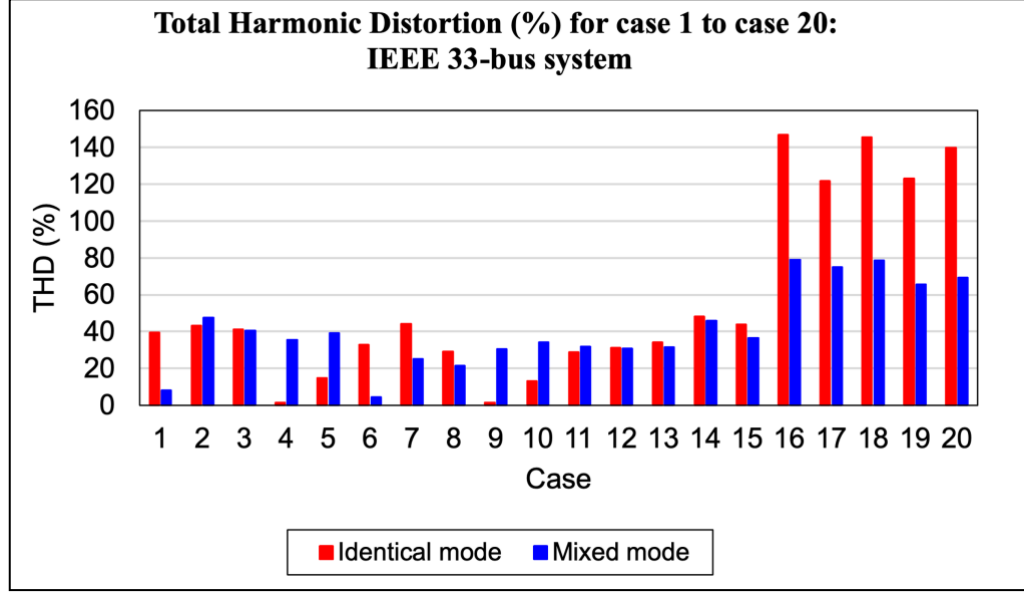


Figure 5. 9 Total Harmonic Distortion (In Percents) For Case 1 To Case 20 – IEEE 33-Bus System

5.3.2 Assessment of Distribution System Performance with EVCS Integration under Loading Increment – IEEE 33-Bus System

This section examines the impact of integrating Electric Vehicle Charging Stations (EVCS) into the distribution system while considering incremental loading levels. The objective is to assess the severity of this integration in terms of voltage stability, grid dependency, and power quality. Increment in total real power demand from 10% to 50% of maximum loading was carried out during experiment and the results in terms of Voltage Deviation Index (VDI), minimum voltage magnitude ($V_{\min}$), total real power losses (P_{loss}), net real power drawn from the grid (P_{grid}) and Total Harmonic Distortion (THD) are presented in **Figure 5.10**, **Figure 5.11**, **Figure 5.12**, **Figure 5.13** and **Figure 5.14** respectively.

In terms of voltage stability performance, the results presented in **Figure 5.10**, **Figure 5.11**, and **Figure 5.12** indicate a decline in voltage stability due to the integration of EVCS at all loading levels. Regardless of the charging mode, whether identical or mixed, the values of VDI and P_{loss} increase above the baseline condition without EVCS (black line), while the value of $V_{\min}$ decreases below the condition without EVCS. At 10% loading, the identical charging mode (red line) demonstrates slightly better performance than the mixed charging mode (blue line), exhibiting marginally lower VDI and P_{loss} , along with a slightly higher $V_{\min}$. However, as the loading level increases

from 30% to 50%, the mixed charging mode yields better results, showing lower VDI, higher $V_{\min}$, and reduced P_{loss} relative to the identical charging mode.

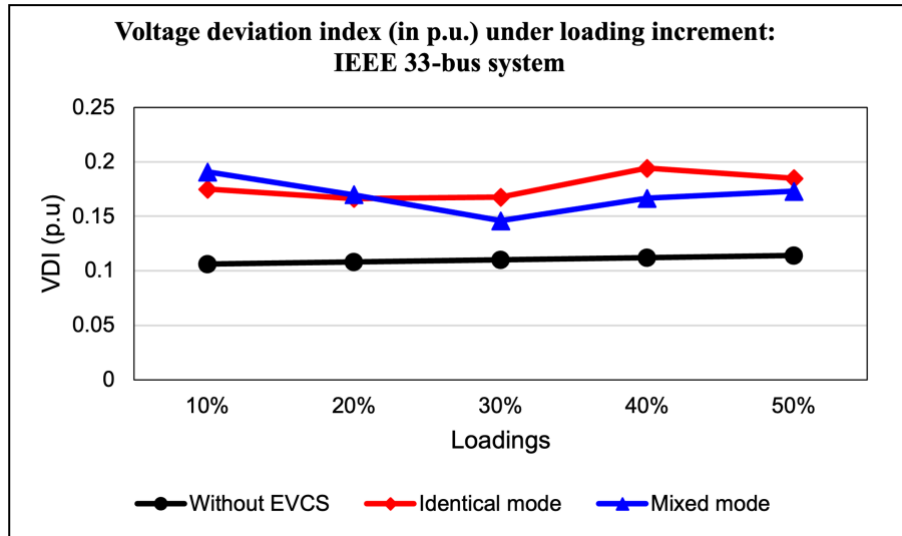


Figure 5. 10 Voltage Deviation Index (VDI) (In Per-Unit) Under Loading Increment – IEEE 33-Bus System

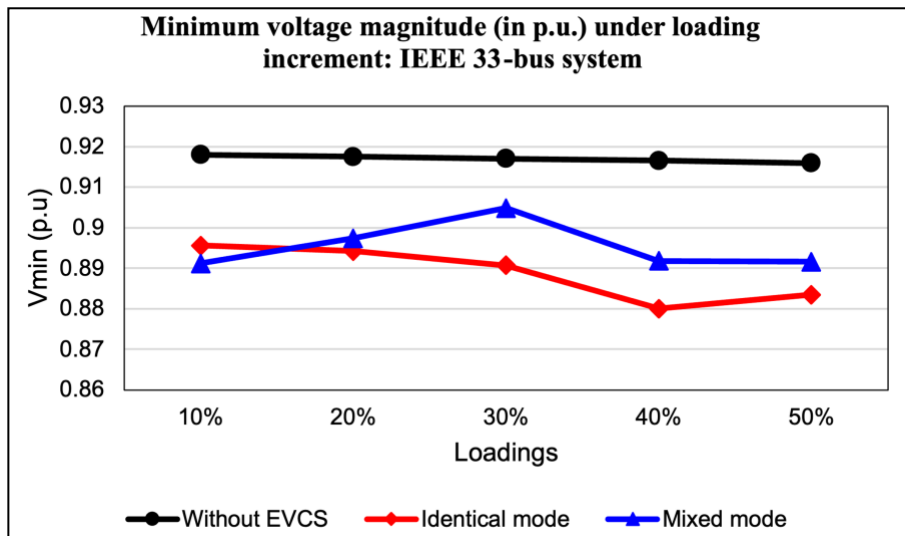


Figure 5. 11 Minimum Voltage Magnitude (In Per-Unit) Under Loading Increment – IEEE 33-Bus System

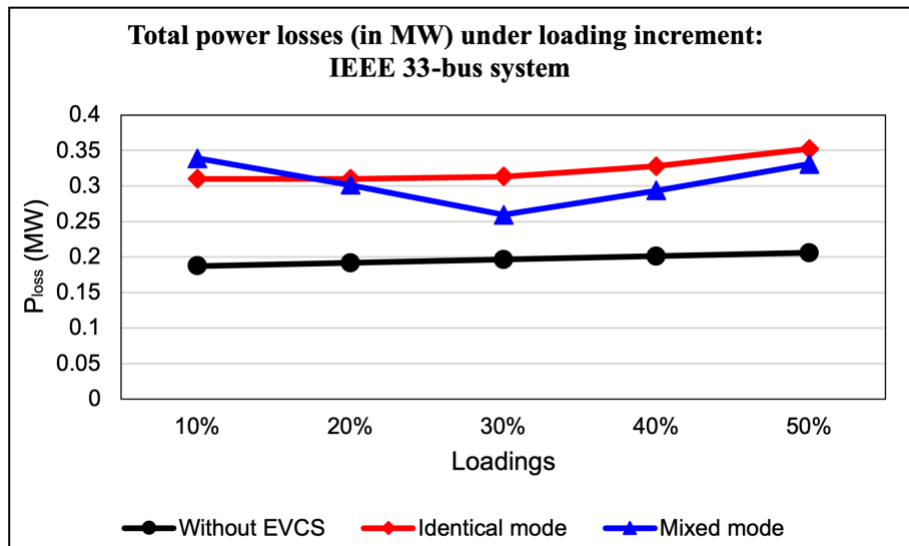


Figure 5. 12 Total Power Losses (In MW) Under Loading Increment – IEEE 33-Bus System

The integration of EVCS into the system also leads to an increase in grid dependency. As shown in **Figure 5.13**, the net real power drawn from the grid (P_{grid}) rises in comparison to the baseline condition without EVCS (black line), regardless of the charging mode. At all loading levels, both the identical and mixed charging modes require additional power from the grid, thereby increasing the grid's burden to supply power to both conventional loads and EVCS loads.

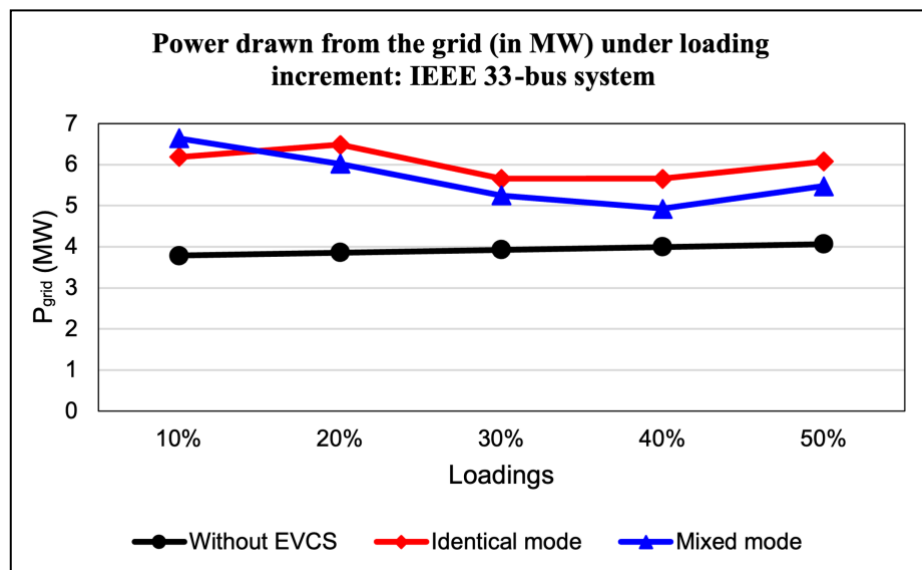


Figure 5. 13 Power Drawn From The Grid (In MW) Under Loading Increment – IEEE 33-Bus System

Similarly, the impact on power quality is evident in **Figure 5.14**, where the integration of EVCS results in an increase in THD compared to the condition without EVCS. This indicates that EVCS integration not only heightens grid dependency but also degrades power quality. At 10% loading, the identical charging mode (red line) demonstrates slightly better performance than the mixed charging mode (blue line), exhibiting marginally lower P_{grid} and THD. However, from 20% to 50% loading, the mixed charging mode performs better in terms of grid dependency, while it also shows an improvement in THD between 20% and 30% loading.

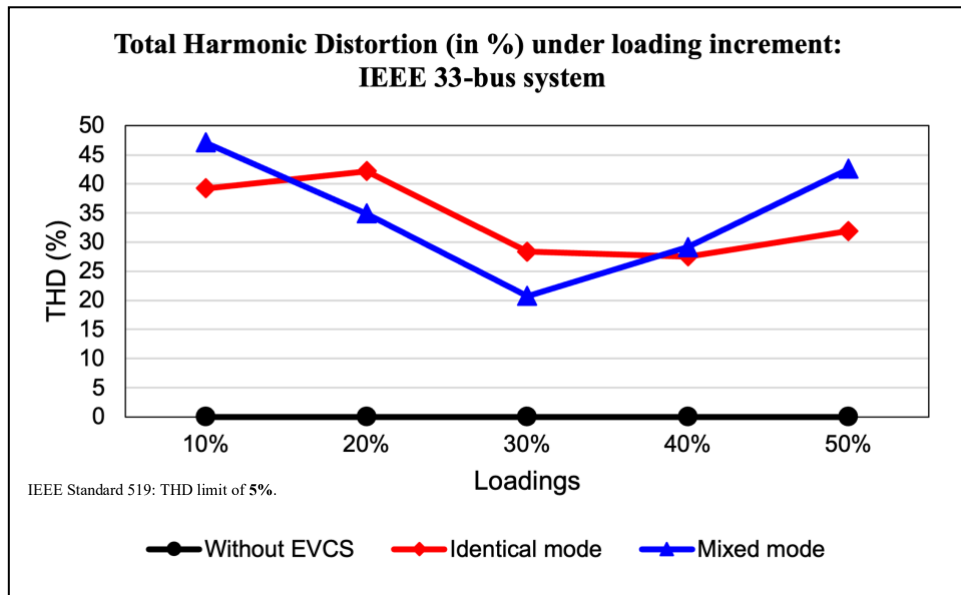


Figure 5. 14 Total Harmonic Distortion (In Percents) Under Loading Increment – IEEE 33-Bus System

5.3.3 Assessment of Distribution System Performance with Different Cases of EVCS Integration – IEEE 69-bus system

In this section, two different scenarios are analyzed: identical charging mode and mixed charging mode. As explained in subsection 5.2.6, the identical charging mode refers to a configuration where all Electric Vehicle Charging Stations (EVCS) installed at a given bus operate at the same charging level. In contrast, the mixed charging mode involves a combination of different charging levels at a single bus. Each scenario consists of twenty different cases of EVCS integration, with each case varying in terms of EVCS location (bus number), the number of installed EVCS per bus, charging mode (L1 for Level 1, L2 for Level 2, and L3 for Level 3), and EVCS type

(either all Grid-to-Vehicle (G2V) or a combination of G2V and Vehicle-to-Grid (V2G)). **Table 5.5** presents the results for Scenario 1, where each EVCS bus follows an identical charging mode, while **Table 5.6** shows the results for Scenario 2, where mixed charging levels are applied at each EVCS bus.

In both tables, the upper section provides details on the different configurations of EVCS integration for each case. For example, in **Table 5.5**, Case 1 represents an integration where six buses (bus 10, bus 20, bus 30, bus 40, bus 50 and bus 60) are equipped with EVCS, with each bus having one EVCS unit operating at Level 3 (L3) charging mode, all using G2V technology, thereby following the identical charging mode. Similarly, in **Table 5.6**, Case 1 for the mixed charging mode scenario maintains the same EVCS locations but with six EVCS units per bus - four units set to Level 2 (L2) and the remaining two set to Level 3 (L3), all utilizing G2V technology.

The lower section of the tables presents the performance metrics for each case, including the Voltage Deviation Index (VDI) in per unit, minimum voltage magnitude ($V_{\min}$) in per unit, total real power losses (P_{loss}) in megawatts, net real power drawn from the grid (P_{grid}) in megawatts, and Total Harmonic Distortion (THD) in percentage. These results allow for a comprehensive evaluation of the system's performance under different EVCS integration scenarios across all twenty cases. Furthermore, based on **Table 5.5** and **Table 5.6**, graphical comparisons of the identical and mixed charging modes in terms of VDI, $V_{\min}$, P_{loss} , P_{grid} , and THD are illustrated in **Figure 5.15**, **Figure 5.16**, **Figure 5.17**, **Figure 5.18**, and **Figure 5.19**, respectively.

Table 5. 5

Voltage Stability, Power Losses, Grid Dependency And Harmonic Distortion For Distribution System Integrated With 20 Different EVCS Cases Using Identical Charging Mode – IEEE 69-Bus System

Case	EVCS Bus	Number of EVCS	Charging Mode	EVCS Type	
1	10, 20, 30, 40, 50, 60	1, 1, 1, 1, 1, 1	L3, L3, L3, L3, L3, L3	All G2V	
2	10, 20, 30, 40, 50, 60	3, 3, 3, 3, 3, 3	L3, L3, L3, L3, L3, L3	1 G2V + 2 V2G	
3	20, 25, 40, 45, 50, 55	6, 6, 6, 1, 1, 1	L2, L2, L2, L3, L3, L3	All G2V	
4	30, 32, 36, 42, 47, 65	6, 6, 6, 1, 1, 1	L2, L2, L2, L3, L3, L3	All G2V	
5	19, 27, 29, 44, 62, 66	6, 6, 6, 1, 1, 1	L2, L2, L2, L3, L3, L3	All G2V	
6	10, 20, 30, 40, 50, 60	8, 8, 8, 8, 1, 1	L1, L1, L2, L2, L3, L3	All G2V	
7	10, 20, 30, 40, 50, 60	8, 8, 8, 8, 8, 8	L1, L1, L1, L1, L1, L1	All G2V	
8	10, 20, 30, 40, 50, 60	8, 8, 8, 8, 8, 8	L2, L2, L2, L2, L2, L2	All G2V	
9	10, 20, 30, 40, 50, 60	10, 10, 10, 10, 10, 10	L1, L1, L1, L1, L1, L1	8 G2V + 2 V2G	
10	10, 20, 30, 40, 50, 60	10, 10, 10, 10, 10, 10	L2, L2, L2, L2, L2, L2	8 G2V + 2 V2G	
11	28, 42, 47, 60, 62, 63	16, 16, 16, 16, 16, 16	L2, L2, L2, L3, L3, L3	All G2V	
12	13, 14, 21, 38, 41, 43	16, 16, 16, 16, 16, 16	L2, L2, L2, L3, L3, L3	All G2V	
13	2, 25, 26, 55, 57, 63	16, 16, 16, 16, 16, 16	L2, L2, L3, L3, L3, L3	13 G2V + 3 V2G	
14	3, 5, 29, 33, 46, 50	16, 16, 16, 16, 16, 16	L2, L2, L3, L3, L3, L3	13 G2V + 3 V2G	
15	31, 34, 38, 50, 64, 66	16, 16, 16, 16, 16, 16	L2, L2, L3, L3, L3, L3	13 G2V + 3 V2G	
16	4, 10, 26, 40, 42, 45	16, 16, 16, 16, 16, 16	L2, L2, L3, L3, L3, L3	13 G2V + 3 V2G	
17	28, 42, 47, 60, 62, 63	16, 16, 16, 16, 16, 16	L2, L2, L3, L3, L3, L3	13 G2V + 3 V2G	
18	13, 14, 21, 38, 41, 43	16, 16, 16, 16, 16, 16	L2, L2, L3, L3, L3, L3	13 G2V + 3 V2G	
19	31, 34, 38, 50, 64, 66	18, 18, 18, 18, 18, 18	L2, L2, L2, L3, L3, L3	All G2V	
20	4, 10, 26, 40, 42, 45	18, 18, 18, 18, 18, 18	L2, L2, L2, L3, L3, L3	All G2V	
Case	<i>VDI</i> (p.u.)	<i>V_{min}</i> (p.u.)	<i>P_{loss}</i> (MW)	<i>P_{grid}</i> (MW)	<i>THD</i> (%)
No EVCS	0.0922	0.9099	0.2178	3.6935	0.0000
1	0.1092	0.9049	0.2454	4.8935	12.4577
2	0.0948	0.9091	0.222	3.8855	1.9909
3	0.1127	0.9072	0.2419	4.9775	13.6865
4	0.0998	0.9044	0.2359	4.9775	13.3596
5	0.1207	0.9035	0.2582	4.9775	13.8244
6	0.1004	0.906	0.2354	4.7623	11.0136
7	0.0947	0.9092	0.2217	3.8759	1.8913
8	0.1188	0.9023	0.2613	5.5175	18.9488
9	0.0944	0.9092	0.2213	3.8567	1.6927
10	0.1158	0.9031	0.2563	5.326	16.9556
11	1.3726	0.6109	3.7737	15.1175	163.2063
12	0.1643	0.9036	0.3876	15.1175	119.1689
13	0.6939	0.7934	1.3411	13.9777	119.8798
14	0.0941	0.9098	0.26	13.9777	104.0229
15	0.2699	0.8412	0.6337	13.9777	111.1098
16	0.253	0.8837	0.4787	13.9777	115.6767
17	0.6777	0.73	1.8063	13.9777	127.5531
18	0.2798	0.8868	0.4964	13.9777	115.0629
19	0.4241	0.7986	1.0199	16.5455	143.4077
20	0.1408	0.9053	0.4076	16.5455	135.8527

Table 5. 6
Voltage Stability, Power Losses, Grid Dependency And Harmonic Distortion For
Distribution System Integrated With 20 Different EVCS Cases Using Mixed
Charging Mode – IEEE 69-Bus System

Case	EVCS Bus	Number of EVCS	Charging Mode	EVCS Type	
1	10, 20, 30, 40, 50, 60	6, 6, 6, 6, 6, 6	4 L2 + 2 L3	All G2V	
2	10, 20, 30, 40, 50, 60	6, 6, 6, 6, 6, 6,	4 L1 + 2 L3	All G2V	
3	4, 10, 26, 40, 42, 45	6, 6, 6, 6, 6, 6	5 L2 + 1 L3	All G2V	
4	13, 14, 21, 38, 41, 43	6, 6, 6, 6, 6, 6	5 L2 + 1 L3	All G2V	
5	10, 20, 30, 40, 50, 60	8, 8, 8, 8, 8, 8	4 L1 + 4 L2	All G2V	
6	10, 20, 30, 40, 50, 60	8, 8, 8, 8, 8, 8	3 L1 + 4 L2 + 1 L3	All G2V	
7	10, 20, 30, 40, 50, 60	8, 8, 8, 8, 8, 8	7 L2 + 1 L3	All G2V	
8	10, 20, 30, 40, 50, 60	10, 10, 10, 10, 10, 10	5 L1 + 5 L2	6 G2V + 4 V2G	
9	10, 20, 30, 40, 50, 60	10, 10, 10, 10, 10, 10	4 L1 + 4 L2 + 2 L3	8 G2V + 2 V2G	
10	7, 25, 26, 40, 48, 64	10, 10, 10, 10, 10, 10	5 L2 + 5 L3	6 G2V + 4 V2G	
11	16, 17, 23, 25, 38, 56	10, 10, 10, 10, 10, 10	5 L2 + 5 L3	6 G2V + 4 V2G	
12	20, 25, 40, 45, 50, 55	10, 10, 10, 10, 10, 10	5 L2 + 5 L3	6 G2V + 4 V2G	
13	30, 32, 36, 42, 47, 65	10, 10, 10, 10, 10, 10	5 L2 + 5 L3	6 G2V + 4 V2G	
14	19, 27, 29, 44, 62, 66	10, 10, 10, 10, 10, 10	5 L2 + 5 L3	6 G2V + 4 V2G	
15	34, 43, 51, 53, 65, 69	10, 10, 10, 10, 10, 10	5 L2 + 5 L3	6 G2V + 4 V2G	
16	10, 20, 30, 40, 50, 60	10, 10, 10, 10, 10, 10	5 L1 + 5 L3	6 G2V + 4 V2G	
17	2, 25, 26, 55, 57, 63	15, 15, 15, 15, 15, 15	10 L2 + 5 L3	12 G2V + 3 V2G	
18	4, 10, 26, 40, 42, 45	15, 15, 15, 15, 15, 15	10 L2 + 5 L3	12 G2V + 3 V2G	
19	28, 42, 47, 60, 62, 63	15, 15, 15, 15, 15, 15	10 L2 + 5 L3	12 G2V + 3 V2G	
20	13, 14, 21, 38, 41, 43	15, 15, 15, 15, 15, 15	10 L2 + 5 L3	12 G2V + 3 V2G	
Case	<i>VDI</i> (p.u.)	<i>V_{min}</i> (p.u.)	<i>P_{loss}</i> (MW)	<i>P_{grid}</i> (MW)	<i>THD</i> (%)
No EVCS	0.0922	0.9099	0.2178	3.6935	0.0000
1	0.1439	0.896	0.3032	7.0055	34.46
2	0.1297	0.8995	0.2793	6.1847	25.8984
3	0.1141	0.9073	0.2451	4.8635	24.3822
4	0.1316	0.9059	0.265	4.8635	25.0758
5	0.1063	0.9057	0.2407	4.6967	10.4123
6	0.1245	0.9008	0.2708	5.8739	22.6599
7	0.1348	0.8982	0.288	6.4895	29.0762
8	0.0996	0.9077	0.2298	4.2352	5.6197
9	0.1118	0.9042	0.2498	5.0689	14.2818
10	0.1296	0.9004	0.2727	5.3977	18.3911
11	0.1456	0.9041	0.2803	5.3977	19.4218
12	0.119	0.9064	0.2501	5.3977	18.1623
13	0.1031	0.9021	0.244	5.3977	17.7962
14	0.1308	0.9011	0.274	5.3977	18.3528
15	0.1159	0.8992	0.2644	5.3977	18.11
16	0.1322	0.8988	0.2836	6.3347	27.4625
17	0.3233	0.8617	0.5997	9.622	67.1941
18	0.1582	0.9032	0.3096	9.622	63.0562
19	0.2373	0.8456	0.5886	9.622	66.5112
20	0.223	0.8995	0.3917	9.622	65.9463

As can be seen in **Figure 5.15**, the VDI values of the first ten cases almost have no difference with the condition without EVCS (as marked by the dotted-black line). This indicates that with the EVCS penetration into the system, the voltage profiles are less affected as in the condition without EVCS. From Case 1 to Case 10, there is only a slight difference between identical and mixed charging modes. As in **Figure 5.15**, both modes result in VDI below 0.2 per unit for the first ten cases. However, the VDI values of the identical charging mode (red bars) for Case 11, 13, 17 and 19 are much higher than the mixed one (blue bars), with most of them exceed 0.6 per unit. This implies that the identical charging mode can cause greater voltage disturbances, which can lead to localized voltage instability due to concentrated charging demand at specific buses. Mixed charging mode, on the other hand, helps reducing the voltage deviations by distributing the EVCS loads more evenly throughout the system. The highest VDI value by mixed charging mode is only about 0.3 per unit as shown in **Figure 5.15**. This will provide better voltage regulation and lower system stress compared to the other charging mode.

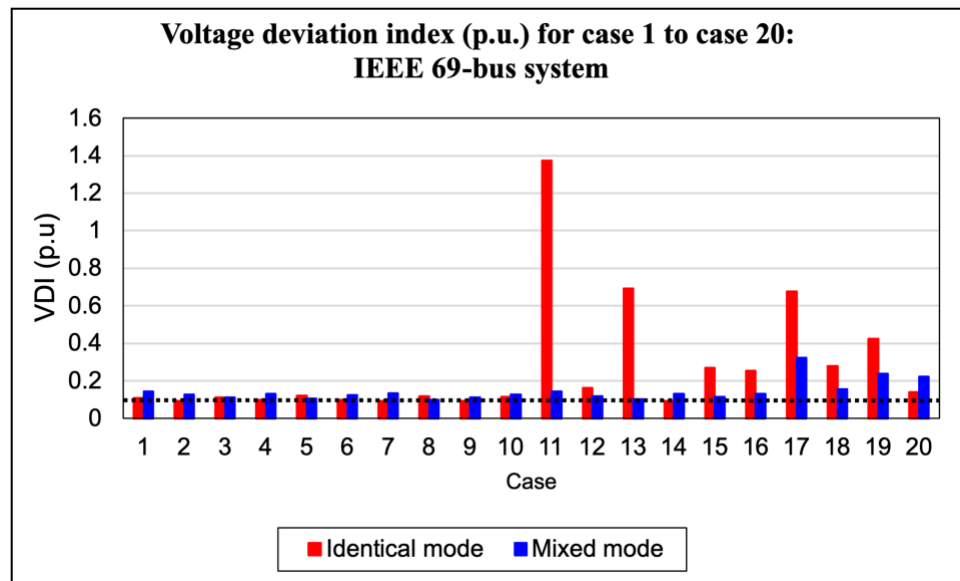


Figure 5. 15 Voltage Deviation Index (VDI) (In Per Unit) For Case 1 To Case 20 – IEEE 69-Bus System

Because of the increase in VDI values as in **Figure 5.15**, the minimum voltage magnitudes for all cases are reduced after integrating the EVCS units into the system. Based on **Figure 5.16**, all cases have minimum voltage magnitude, or $V_{\min}$, below the condition without EVCS (as marked by the dotted-black line). There is a slight

difference in $V_{\min}$ between the identical and mixed charging mode from Case 1 to Case 10, with the values of $V_{\min}$ maintained above 0.85 per unit. This is not true for Case 11, 13, 17 and 19, where the identical charging mode (red bars) faces a significant reduction in $V_{\min}$, with some of them below 0.8 per unit. Due to simultaneous higher power demand, with all EVCS units have Level 2 or 3 charging mode at multiple EVCS locations, the identical charging mode leads to greater voltage drops compared to the mixed one.

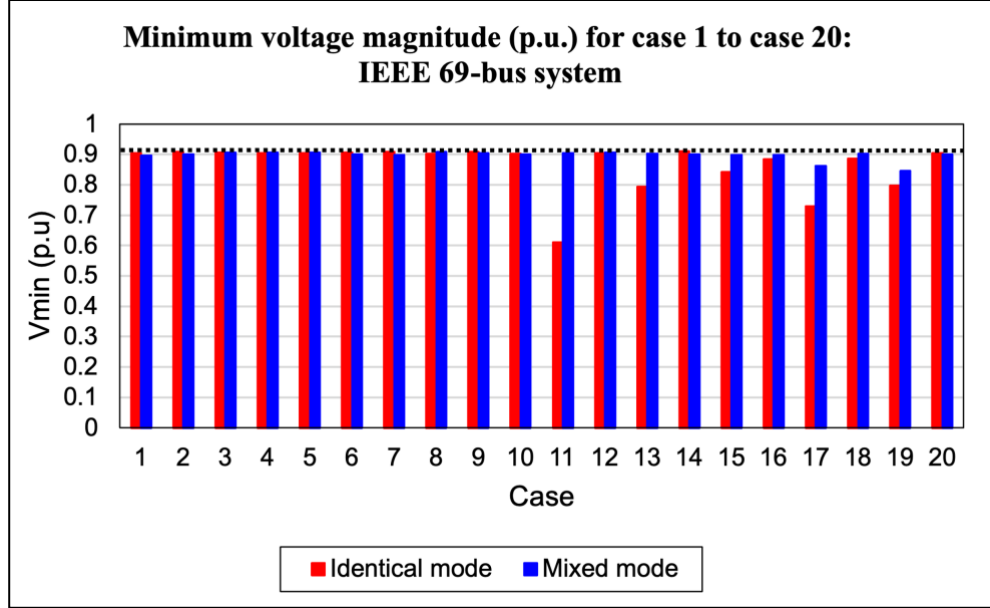


Figure 5. 16 Minimum Voltage Magnitude (In Per Unit) For Case 1 To Case 20 – IEEE 69-Bus System

A similar trend as in VDI and $V_{\min}$ can be observed for total real power losses as shown in **Figure 5.17**. With the EVCS penetration into the system, the first ten cases exhibit a very small increment in real power losses, or P_{loss} , with respect to the condition without EVCS (as marked by the dotted-black line). The first ten cases have a slight difference in P_{loss} between identical and mixed charging modes, with P_{loss} maintained below 0.5 MW. A significant increase in P_{loss} can be observed in **Figure 5.17** for Case 11, 13, 17 and 19, with the identical charging mode (red bars) surpasses 3.5 MW in Case 11 and 1.5 MW in Case 17. Such a high increase in P_{loss} indicates an increased stress on distribution lines, which is due to concentrated charging demand at specific EVCS locations. Even though the mixed charging mode has significant increases in P_{loss} for Case 17 and Case 19, they are much lower than that of the identical one, with P_{loss} maintained at almost 0.6 MW. In term of power losses, the mixed charging mode demonstrates a more efficient power distribution strategy than the other.

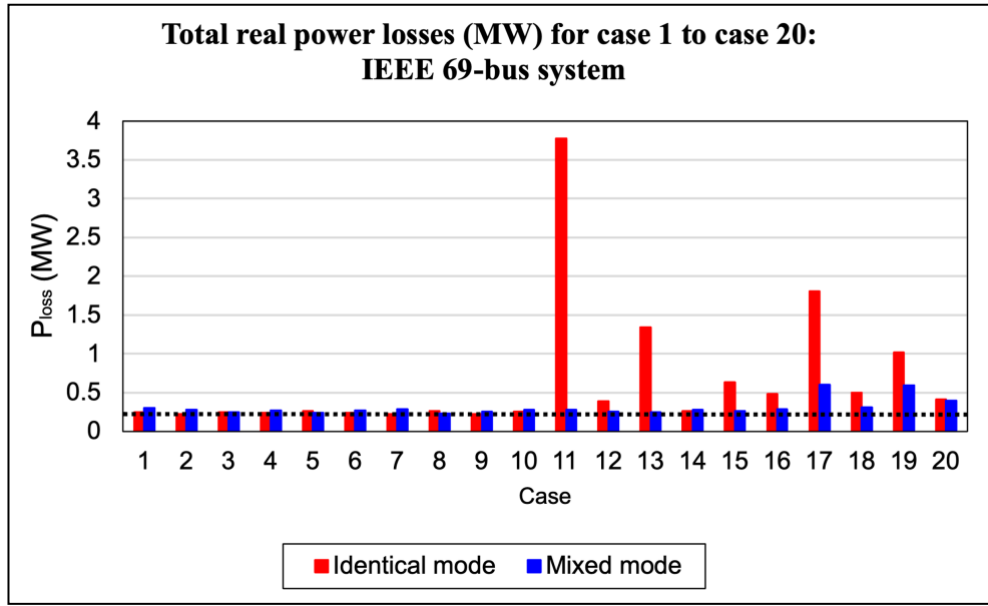


Figure 5. 17 Total Real Power Losses (In MW) For Case 1 To Case 20 – IEEE 69-Bus System

Assessment on grid dependency can be conducted by measuring the magnitude of net real power, in Megawatts, drawn by the loads from the system or grid. The net real power drawn from the grid, or P_{grid} , with the presence of EVCS is presented in **Figure 5.18**. As can be observed, all the cases have the values of P_{grid} above the condition without EVCS (as marked by the dotted-black line). This implies that the consumption of power increases with EVCS penetration into the system. The grid needs to supply more power to the loads as a result of EVCS integration. Based on **Figure 5.18**, there are obvious differences in P_{grid} between identical and mixed charging modes for Case 1, 2 and 7. In these cases, the mixed charging mode (blue bars) requires higher values of P_{grid} from 6 MW to 7 MW. However, the next ten cases which are Case 11 to Case 20 show that the identical charging mode (red bars) has greater grid dependency than the mixed one, with the values of P_{grid} exceed 10 MW. Such a high grid dependency indicates that the identical charging mode draws more power from the grid, thereby forcing the grid to supply more power which can increase stress on the whole system. Even though the mixed charging mode has significant increases in P_{grid} for the next ten cases, the net power drawn by the loads is still less than 10 MW, much lower than the other charging mode. Thus, in term of net grid power this charging mode reduces peak demand, indicating better load management.

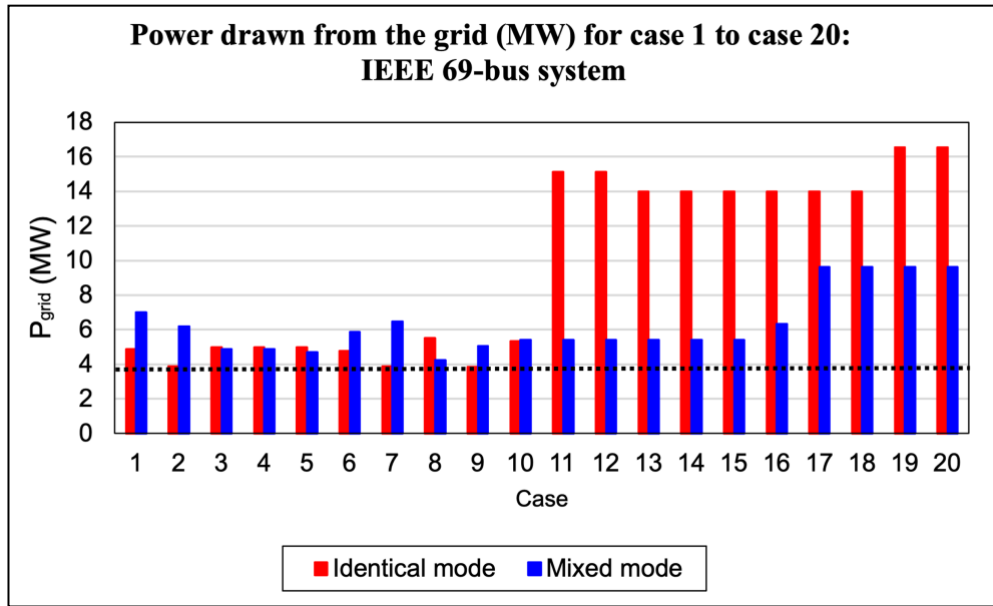


Figure 5. 18 Power Drawn From The Grid (In MW) For Case 1 To Case 20 – IEEE 69-Bus System

The aspect of power quality is measured in term of Total Harmonic Distortion (THD) in percentage. The THD trend based on the twenty different cases is shown in **Figure 5.19**. As can be observed, the EVCS penetration into the system has resulted in increased THD percentages for all cases. The THD percentages resulted from Case 1, 2, 3, 4, 6 and 7 show that the mixed charging mode (blue bars) causes higher THD than the identical one. These six cases result in THD percentages between 20% and 35% for the mixed charging mode. However, more critical increases in THD can be observed in **Figure 5.19** for the next ten cases. From Case 11 to Case 20, the identical charging mode (red bars) has caused the THD percentages to exceed 100%. Large-scale simultaneous EV charging, especially when all EVCS units are set to Level 2 or 3 charging mode, leads to greater harmonic distortion due to nonlinear power electronics. Even though the mixed charging mode (blue bars) exhibits a significant increase in THD for the last four cases, the percentages are maintained below 70%. Thus, in term of THD, the mixed charging mode can promise better power quality than the other one.

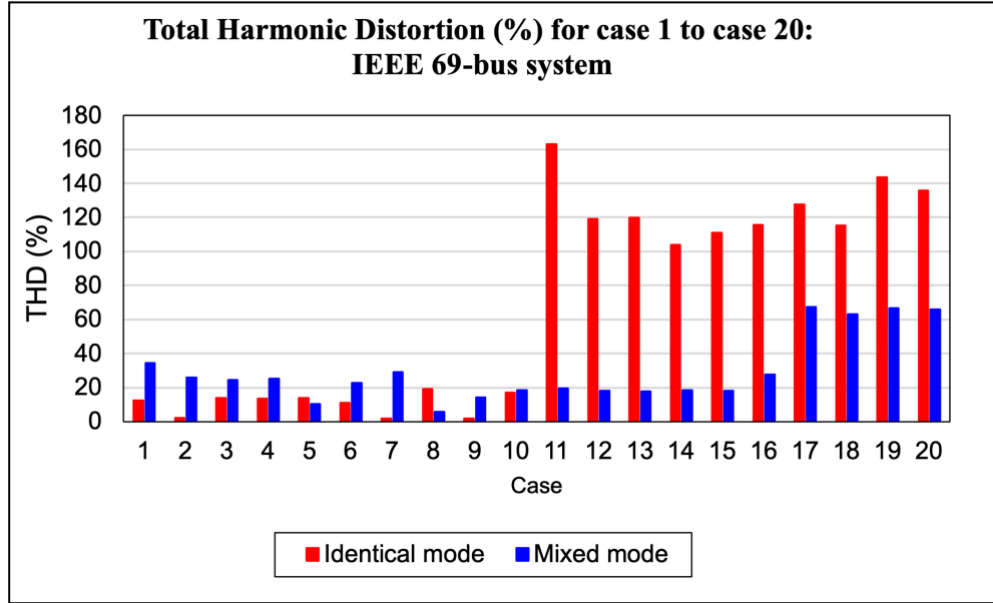


Figure 5. 19 Total Harmonic Distortion (In Percents) For Case 1 To Case 20 – IEEE 69-Bus System

5.3.4 Assessment of Distribution System Performance with EVCS Integration under Loading Increment – IEEE 69-Bus System

This section examines the impact of integrating Electric Vehicle Charging Stations (EVCS) into the distribution system while considering incremental loading levels. The objective is to assess the severity of this integration in terms of voltage stability, grid dependency, and power quality. Increment in total real power demand from 10% to 50% of maximum loading was carried out during experiment and the results in terms of Voltage Deviation Index (VDI), minimum voltage magnitude ($V_{\min}$), total real power losses (P_{loss}), net real power drawn from the grid (P_{grid}) and Total Harmonic Distortion (THD) are presented in **Figure 5.20**, **Figure 5.21**, **Figure 5.22**, **Figure 5.23** and **Figure 5.24** respectively.

In terms of voltage stability performance, the results presented in **Figure 5.20**, **Figure 5.21**, and **Figure 5.22** indicate a decline in voltage stability due to the integration of EVCS at certain loading levels. At 10%, 40% and 50% loading, regardless of the charging modes, the values of VDI and P_{loss} increase above the baseline condition without EVCS (black line), while the value of $V_{\min}$ decreases below the condition without EVCS. At 20% loading, the identical charging mode (red line) demonstrates better performance than the mixed charging mode (blue line), resulting in almost unchanged values of VDI, $V_{\min}$ and P_{loss} with respect to the condition without EVCS.

However, as the loading level increases to 30%, the mixed charging mode yields better results, showing no difference in VDI, $V_{\min}$, and P_{loss} compared to the condition without EVCS.

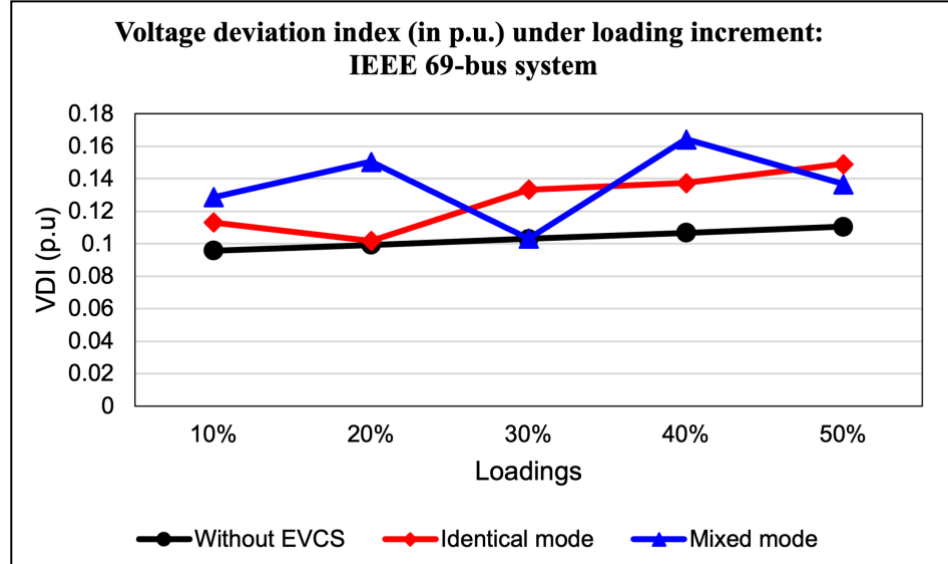


Figure 5. 20 Voltage Deviation Index (VDI) (In Per-Unit) Under Loading Increment – IEEE 69-Bus System

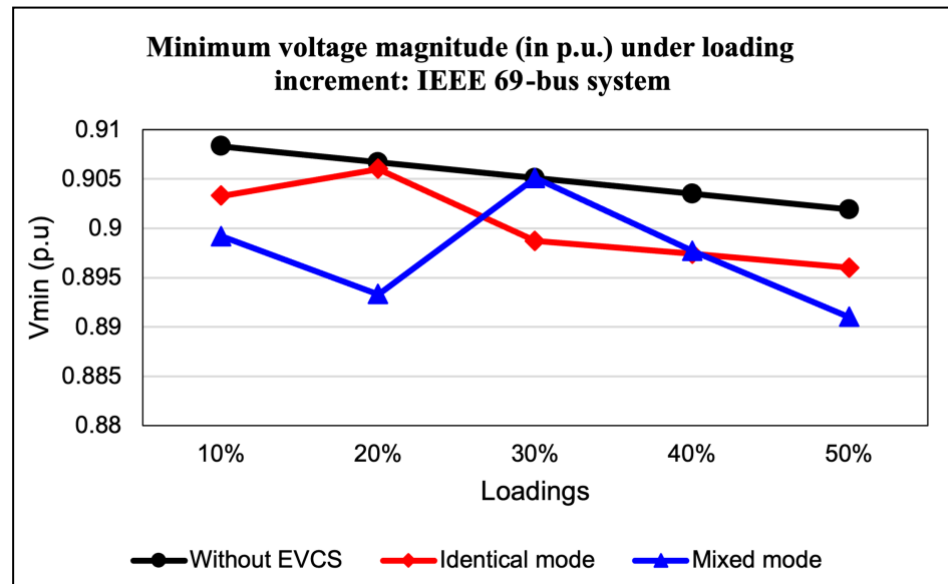


Figure 5. 21 Minimum Voltage Magnitude (In Per-Unit) Under Loading Increment – IEEE 69-Bus System

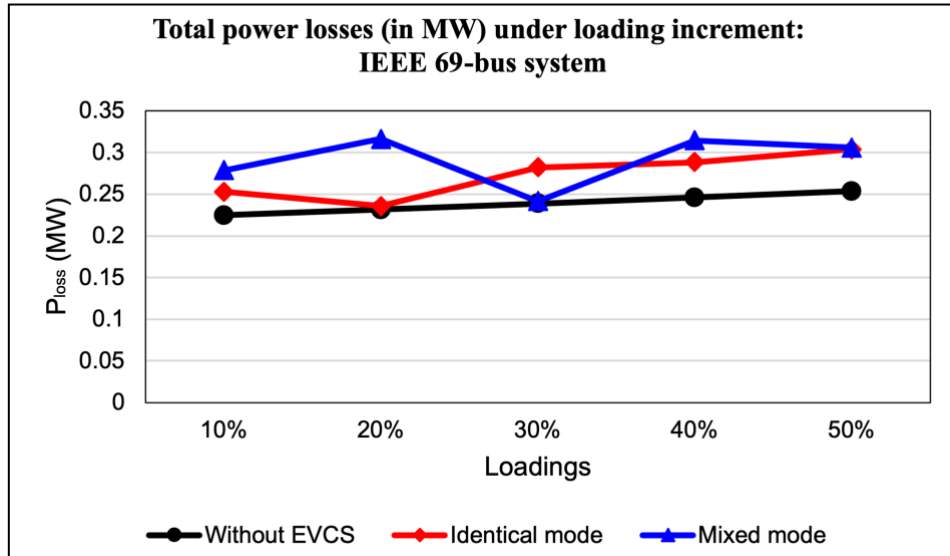


Figure 5. 22 Total Power Losses (In MW) Under Loading Increment – IEEE 69-Bus System

The integration of EVCS into the system also leads to an increase in grid dependency. As shown in **Figure 5.23**, the net real power drawn from the grid (P_{grid}) rises in comparison to the baseline condition without EVCS (black line), regardless of the charging modes. At most of the loading levels, both the identical and mixed charging modes require additional power from the grid, thereby increasing the grid's burden to supply power to both conventional loads and EVCS loads.

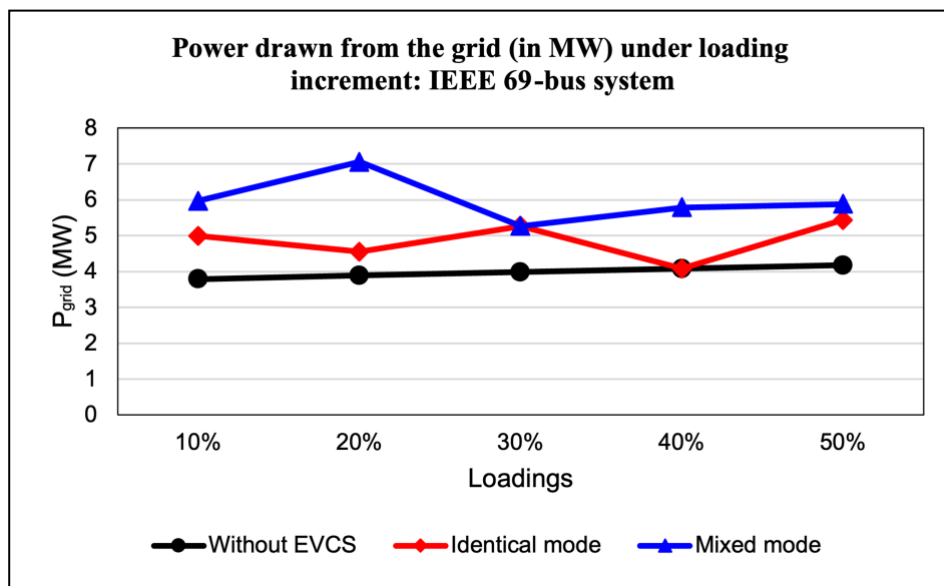


Figure 5. 23 Power Drawn From The Grid (In MW) Under Loading Increment – IEEE 69-Bus System

Similarly, the impact on power quality is evident in **Figure 5.24**, where the integration of EVCS results in an increase in THD compared to the condition without EVCS. This indicates that EVCS integration not only heightens grid dependency but also degrades power quality. At most of the loading levels, the identical charging mode (red line) demonstrates better performance than the mixed charging mode (blue line), resulting in lower P_{grid} and THD. Thus, in terms of grid dependency and power quality, the identical charging mode has less impact on the distribution system performance compared to the mixed one.

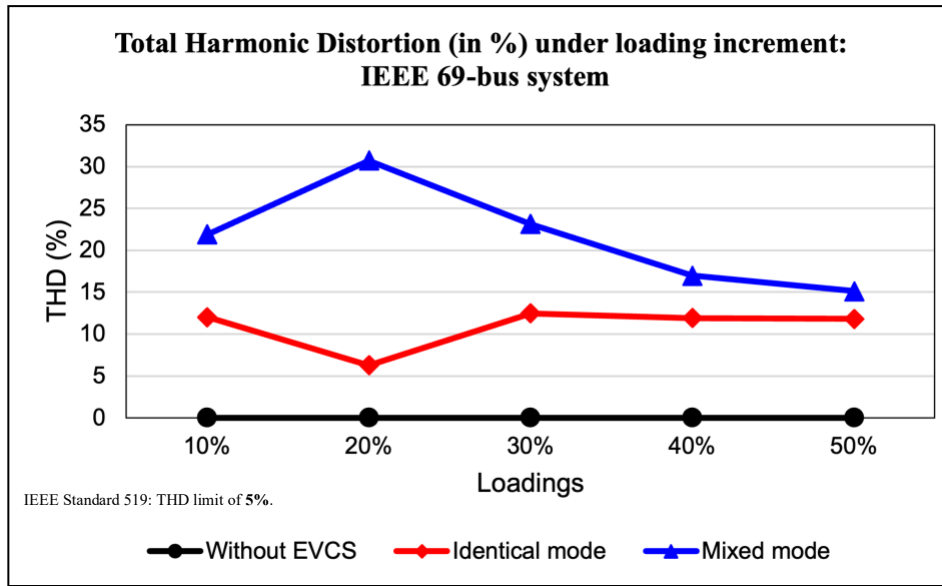


Figure 5. 24 Total Harmonic Distortion (In Percents) Under Loading Increment – IEEE 69-Bus System

5.4 Chapter Summary

On overall, the analysis of distribution system performance considering twenty different cases through two different test systems has revealed the followings. First, in the aspect of voltage stability, the identical charging mode has caused higher values of Voltage Deviation Index (VDI), lower voltage magnitudes (V_{min}), and increased power losses (P_{loss}) compared to mixed charging mode. In IEEE 33-bus system, the last five cases from Case 16 to Case 20 have resulted in the worst voltage stability performance if the identical charging mode is implemented. For IEEE 69-bus system, the four cases which are Case 11, 13, 17 and 19 have yielded to poor VDI, V_{min} and P_{loss} if the identical charging mode is used.

Secondly, in term of grid dependency, it was observed that the integration of

EVCS in power distribution network has increased the dependency on the grid. There will be more power drawn from the system to support the additional loads due to EV charging. The analysis has also revealed that some of the cases have no difference between identical and mixed charging modes, with some of them will have the identical charging mode to be more dependent on the grid than the mixed one, and vice versa. However, the identical charging mode implemented in IEEE 33-bus system for the last five cases, from Case 16 to Case 20, have forced the grid to deliver more power to the loads, thereby increasing the grid dependency significantly. In IEEE 69-bus system, the identical charging mode has also significantly increased the grid dependency for the next ten cases from Case 11 to Case 20.

Next, in term of power quality, the penetration of EVCS into distribution system has caused a serious power quality issue. The signal conversion via power electronic converters during charging and discharging mechanisms has introduced harmonic distortion in the system. The measured THD percentages across twenty different cases involving two test systems have revealed the followings. Integrating the EVCS units into distribution network can increase THD percentages to a severe level. In IEEE 33-bus system, the last five cases from Case 16 to Case 20 have resulted in THD percentages that exceed 100% if identical charging mode is used. For IEEE 69-bus system, the same result was obtained using the identical charging mode, but it involved ten cases from Case 11 to Case 20.

Further analysis involving incremental load levels from 10% to 50% of maximum loading has justified the severe impact of EVCS integration into distribution network. The findings have shown that as the loading increases, with EVCS being integrated into the system, the performance in terms of voltage stability, grid dependency and power quality decline significantly. Whether the system employed identical or mixed charging modes, there were significant drop in voltage magnitude, increase in power losses, higher magnitude of power drawn from the grid and large THD percentage. It was also found that with the increasing loading, the mixed charging mode performed better than the identical one in IEEE 33-bus system, and vice versa in IEEE 69-bus system.

From this analysis, it is obvious that integrating EVCS units into distribution system will reduce its performance in terms of voltage stability, grid dependency and harmonic distortion. The identical charging mode, with each bus will have the same charging level for all EVCS units, will cause the worst system performance in most of

the cases. Therefore, for a proper management of power distribution, mixed charging mode should be implemented to avoid unwanted disturbances such as localized voltage instability, sudden load surges due to high charging level, simultaneous operation of multiple power electronic converters and insufficient power support from the grid. To address these problems, renewable integration for decentralized energy sources, such as DG, should be considered to enhance system performance and maintain supply-demand balance.

While this chapter primarily evaluates the impacts of unidirectional EV charging, looking forward, the transition toward Vehicle-to-Grid (V2G) technology presents a significant opportunity to optimize grid performance further. By enabling EVs to discharge stored energy back into the distribution network during peak demand periods, V2G implementation could naturally lower overall Grid Dependency, effectively transforming electric vehicles from passive electrical loads into active, flexible distributed energy resources.

CHAPTER 6

OPTIMAL PLACEMENT OF DISTRIBUTED GENERATION IN EVCS-INTEGRATED DISTRIBUTION SYSTEMS USING LSF- MALO TECHNIQUE

6.1 Introduction

The rapid growth of Electric Vehicle Charging Stations (EVCS) has introduced significant technical challenges to distribution networks, as highlighted in Chapter 5. Issues such as voltage instability, increased power losses, higher grid dependency, and elevated Total Harmonic Distortion (THD) underscore the need for effective mitigation strategies. One proven approach is the optimal placement of Distributed Generation (DG) units, which can provide localized power supply, reduce reliance on the main grid, and help improve overall power quality.

Building on the findings from Chapters 3 and 4, where DG placement demonstrated strong potential for enhancing voltage stability and minimizing losses, this chapter focuses on extending the analysis to EVCS-integrated systems. The problem formulation previously used for economic objectives will be adapted to target key technical aspects: voltage stability, network efficiency, grid dependency, and harmonic mitigation.

To achieve these goals, the proposed hybrid Loss Sensitivity Factor–Mutated Ant Lion Optimizer (LSF-MALO) algorithm is developed as a multi-objective optimization (MOO) framework. By simultaneously optimizing DG location and size, the method aims to strengthen voltage profiles, lower power losses, minimize or even eliminate grid dependency, and suppress harmonics. This chapter evaluates whether strategically placed DG units can effectively offset the adverse impacts of EVCS integration and, in doing so, contribute to a more resilient and efficient distribution network capable of supporting sustainable EV adoption.

This chapter is organized as follows. Section 6.2 outlines the proposed methodology regarding the concept of DG placement in a distribution system integrated with EVCS, the formulation of new objective function using Weighted Sum Method (WSM), and the development of LSF-MALO algorithm in relation to the control variables, constraints, fitness and objective function used in the optimization

framework. Section 6.3 then presents the analysis of results obtained from the optimal DG placement in EVCS-integrated networks using the proposed algorithm. The analysis is divided into two parts: performance evaluation under different EVCS charging scenarios (cases) and performance evaluation under incremental loading, covering both the IEEE 33-bus and IEEE 69-bus radial distribution systems. Finally, Section 6.4 summarizes the key findings and compares the performance of the proposed algorithm with that of the other competing techniques used in the experiments.

6.2 Methodology

This section is organized as follows: Sub-section 6.2.1 explains the concept of DG placement in a distribution system integrated with Electric Vehicle Charging Stations (EVCS) – hence, known as EVCS-integrated distribution system. Sub-section 6.2.2 presents the formulation of a new weighted objective function – combining voltage stability, total power losses, grid dependency, and harmonic distortion – based on the Weighted Sum Method (WSM). Finally, Sub-section 6.2.3 details the development of the LSF-MALO algorithm, including the step-by-step procedure and complete problem formulation covering control variables, constraints, fitness evaluation, and the overall objective function.

6.2.1 Optimal DG Placement in EVCS-Integrated Distribution System

As reviewed in Chapter 2, most previous studies performed either optimal placement of Electric Vehicle Charging Stations (EVCS) or simultaneous optimal placement of Distributed Generation (DG) and EVCS. In such approaches, the sizes and locations of both infrastructures are treated as control variables in the optimization algorithm. This method is appropriate when planning a completely new distribution system or when both infrastructures are still at the design stage. However, it does not fully reflect the conditions faced by utilities and planners once EVCS facilities have already been deployed. In practice, the growth of EVCS penetration often faster than the deployment of DG units [152],[153], leaving utilities to retrofit DG installations into a network where the charging infrastructure is already in place.

This study addresses a different scenario. The distribution system is treated as an EVCS-integrated network with pre-existing charging facilities at various levels and

multiple stations throughout the grid. Such penetration can degrade technical and economic performance, causing issues such as higher losses, voltage instability, and harmonic distortion [141]. Therefore, the task is no longer to co-optimize both EVCS and DG placement but instead to identify the most suitable DG locations and capacities that will enhance the performance of the already EVCS-integrated system. In this context, DG units become the sole decision variables of the optimization, and their placement and sizing are determined with full consideration of system-wide performance in the post-EVCS environment.

By explicitly treating EVCS as fixed elements in the system, the proposed approach captures the operational challenges faced by utilities and planners as EV adoption accelerates. Consequently, the proposed optimization focuses on identifying DG locations and capacities that can enhance system-wide performance – improving voltage stability, reducing losses, minimizing grid dependency and mitigating harmonic levels – despite the stresses introduced by EVCS integration. This represents a significant methodological departure from most previous studies and provides insights that are more directly applicable to real-world distribution system planning.

Figure 6.1 illustrates the optimal DG placement in EVCS-integrated distribution system as proposed in this study.

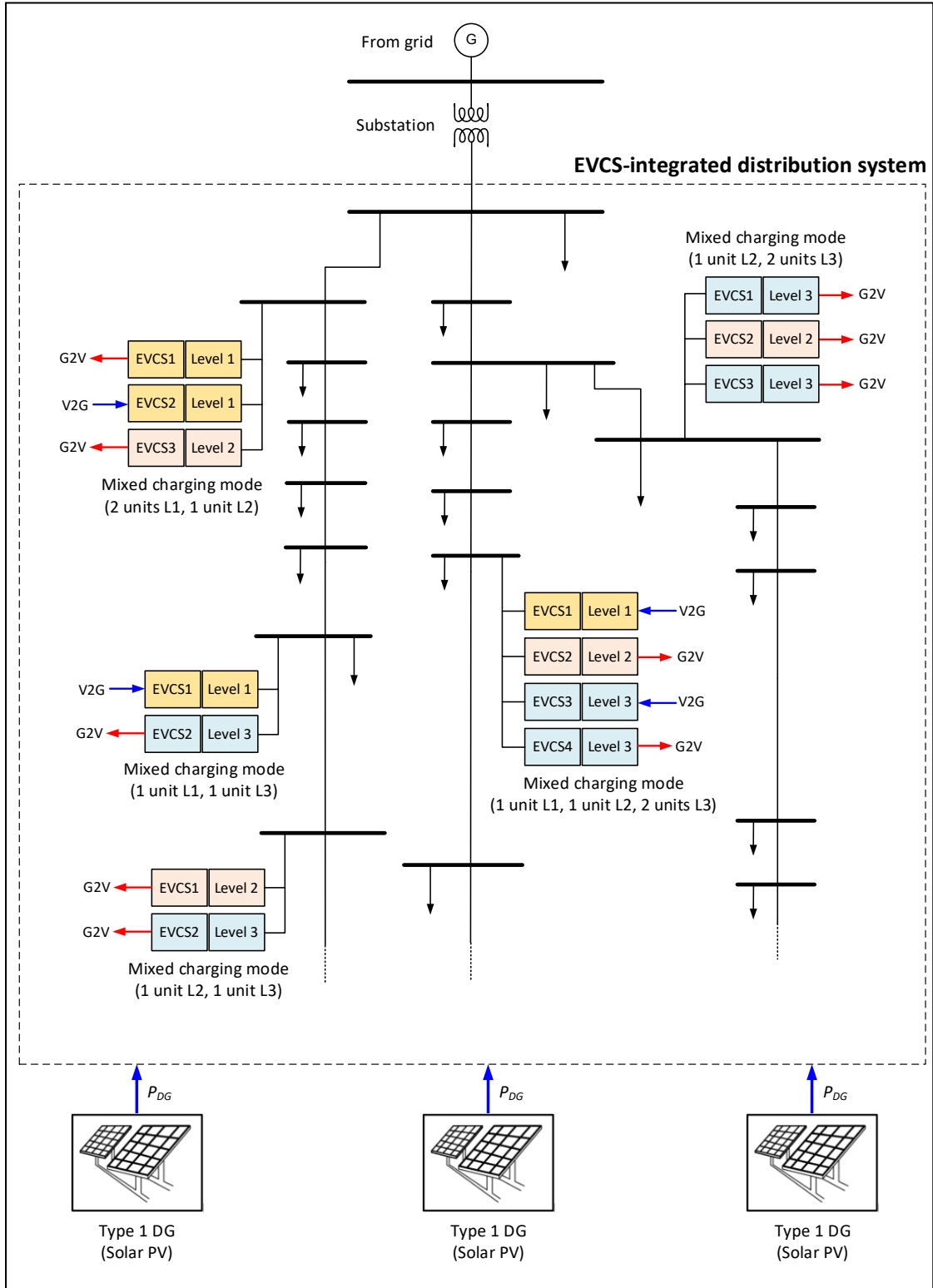


Figure 6. 1 Optimal DG Placement In EVCS-Integrated Distribution System For System-Wide Performance Improvement

6.2.2 Weighted Sum Method for Multi-objective Optimal DG Placement in EVCS-integrated Distribution Systems

In Chapter 4, the developed multi-objective optimization (MOO)–based LSF-MALO algorithm was applied to address the economic aspects of optimal DG placement, namely Annual Economic Loss (AEL) and Annual Cost Saving (ACS), alongside improvements in voltage profile and total power losses. This chapter shifts the focus to technical aspects, specifically grid dependency and harmonic distortion – through optimal DG placement. As highlighted in Chapter 5, the integration of Electric Vehicle Charging Stations (EVCS) greatly increases the distribution system’s reliance on the utility grid during charging periods. This higher grid power draw can lead to voltage instability and elevated power losses [13]. Moreover, the power electronic converters in EVCS infrastructure introduce harmonic distortion, degrading system power quality and potentially stressing sensitive equipment [150]. To mitigate these impacts, a new objective function is formulated to simultaneously improve four key aspects – voltage stability, network efficiency, grid dependency, and power quality – in EVCS-integrated distribution networks via optimal DG placement. Following the procedure in Section 4.2.2, the Weighted Sum Method (WSM) is employed to combine these four objectives into a single weighted function within the MOO-based LSF-MALO algorithm. The key performance indicators for these aspects are described below.

In term of voltage stability, the Voltage Deviation Index (VDI) will be used as one of the key performance indicators besides minimum voltage magnitude (V_{min}). The calculation of the VDI follows the mathematical formulation previously established in equation (5.6) of Chapter 5.

Next, the indicator representing the distribution network’s efficiency is the total power losses (P_{loss}). In this chapter, efficiency is not expressed using the conventional ratio of output to input power; instead, it is assessed by the reduction in power losses achieved after optimal DG placement. The method that yields the lowest P_{loss} is therefore regarded as providing the highest network efficiency. The total power losses are calculated according to the mathematical formulation previously presented in equation (3.26) of Chapter 3.

Afterwards, the grid dependency is quantified based on the net grid power (P_{grid}), which represents the net summation of real powers between existing loads (P_{dt}), G2V-type EVCS (P_{G2V}), DG units (P_{DG}) and V2G-type EVCS (P_{V2G}). This is represented as in equation (5.7) of Chapter 5. As has been explained in Section 5.2.4, Chapter 5, a distribution system is regarded as grid-dependent if P_{grid} is positive (which means that it is highly grid-dependent if P_{grid} is too positive). On the other hand, the system is said to be less grid-dependent or it is grid-independent if P_{grid} is negative.

Lastly, improvement on power quality is measured through Total Harmonic Distortion (THD). The THD at any bus i is given as in equation (5.27) of Chapter 5. The calculation of THD involves long steps which requires conversion of power system components such as transmission lines, shunt capacitors, loads and bus admittance matrix into their equivalent harmonic equations, as has been explained in Section 5.2.5, Chapter 5.

Based on the four key performance indicators, the optimization algorithm must be formulated to solve a minimization problem (since VDI, P_{loss} , P_{grid} and THD should be minimized as low as possible). Hence, the WSM-based objective function for optimal DG placement in EVCS-integrated distribution system is given in (6.1):

$$\text{Minimize } \{f_{wsm} = w_1 \cdot VDI + w_2 \cdot P_{loss} + w_3 \cdot P_{grid} + w_4 \cdot THD\} \quad (6.1)$$

Where, w_1 , w_2 , w_3 and w_4 are the individual weight values for VDI, P_{loss} , P_{grid} and THD. As in (4.10) of Section 4.2.2, Chapter 4, these weight values are determined using R-Method (with $n = 4$), which are calculated as follows:

$$w_1 = \frac{\left(\frac{1}{1/1}\right)}{\frac{1}{1/1} + \left(\frac{1}{1/1 + 1/2}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3 + 1/4}\right)} \\ = 0.3715$$

$$w_2 = \frac{\left(\frac{1}{1/1 + 1/2}\right)}{\frac{1}{1/1} + \left(\frac{1}{1/1 + 1/2}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3 + 1/4}\right)}$$

$$= 0.2476$$

$$w_3 = \frac{\left(\frac{1}{1/1 + 1/2 + 1/3}\right)}{\frac{1}{1/1} + \left(\frac{1}{1/1 + 1/2}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3 + 1/4}\right)}$$

$$= 0.2026$$

$$w_4 = \frac{\left(\frac{1}{1/1 + 1/2 + 1/3 + 1/4}\right)}{\frac{1}{1/1} + \left(\frac{1}{1/1 + 1/2}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3}\right) + \left(\frac{1}{1/1 + 1/2 + 1/3 + 1/4}\right)}$$

$$= 0.1783$$

Thus, the finalized objective function based on WSM approach is given in (6.2):

$$\text{Minimize } \{f_{wsm} = 0.3715 \cdot VDI + 0.2476 \cdot P_{loss} + 0.2026 \cdot P_{grid} + 0.1783 \cdot THD\} \quad (6.2)$$

6.2.3 Proposed Problem Formulation and Development of LSF-MALO Algorithm for Optimal DG Placement in EVCS-integrated Distribution Systems

The proposed algorithm for multi-objective optimization (MOO) based LSF-MALO as in Chapter 4, Section 4.2.3 is still applicable for this chapter, where the Weighted Sum Method (WSM) is used to obtain a unified objective function. However, instead of focusing on economic dimensions such as Annual Economic Loss (AEL) and Annual Cost Saving (ACS), this chapter implements the newly unified objective function which incorporates the elements of voltage stability, network efficiency, grid

dependency and power quality as in (6.6). In addition, the test systems will be modified to incorporate Electric Vehicle Charging Stations (EVCS) to become EVCS-integrated distribution systems.

The procedure for MOO-based LSF-MALO for optimal DG placement in EVCS-integrated distribution systems is described as follows:

- i) As in Chapter 4 the algorithm begins with the determination of LSF indices for bus ranking. In addition to this chapter, the test system incorporates EVCS via (5.5) of Chapter 5. The use of the equation is to represent the EVCS load during charging and discharging period. This means that the EVCS parameters such as locations, numbers, charging mode (in this case, mixed charging mode) and EVCS type (G2V or V2G) are specified to reflect different charging scenarios (or EVCS cases).
- ii) The calculation of LSF indices remains the same as in (3.1) of Chapter 3, however it is performed for the EVCS-integrated test system under various EVCS cases. For the purpose of this chapter, the 20 different EVCS cases as in Chapter 5 are employed to give different impacts of EVCS integration on the calculated LSF indices. Once EVCS have been integrated, load flow analysis is conducted to obtain the ranking list.
- iii) Next, the suitable locations for DG placement are identified based on the LSF ranking list. The number of DG units, their types and scale are also specified at the selected locations. For the purpose of this chapter, only type 1 DG – solar PV units – will be implemented in the proposed optimal DG placement. Thus, the number of control variables has been reduced twice since the DG unit's power factor is fixed to unity, as in (4.14) of Chapter 4. This will leave the DG unit's real power as the only control variables to be optimized by the LSF-MALO, as shown in (6.3).

$$Ant_i = [P_{DG1} \quad P_{DG2} \quad \dots \quad P_{DGN}] \quad (6.3)$$

Where, P_{DG} and Q_{DG} are the real and reactive power of DG unit, PF_{DG} is the DG unit's power factor, N is the number of DG units and Ant_i is the vector of control variables.

- iv) In addition, the number of DG units employed (N_{DG}) is fixed based on the test

system's size. In this chapter, there will be four DG units employed for IEEE 33-bus system, and six DG units for IEEE 69-bus system.

$$\text{IEEE 33-bus system: } N_{DG} = 4 \text{ units} \quad (6.4)$$

$$\text{IEEE 69-bus system: } N_{DG} = 6 \text{ units} \quad (6.5)$$

- v) Afterwards, the LSF-MALO algorithm is implemented to conduct the MOO for optimal sizing of DG units. The algorithm starts with the initialization of essential parameters, such as population size and mutation scale. The initial populations of ants ($\mathbf{M}_{Ant}$) and antlions ($\mathbf{M}_{Antlion}$) are then generated as in (4.12) and (4.13) of Chapter 4. In both equations, M is the population size of ants and antlions, Ant_i and $Antlion_i$ are the i -th solution vectors for ant and antlion population respectively.
- vi) At fitness evaluation stage, there will be four steps of determination for individual fitness. At first, the load flow simulation is conducted to determine voltage magnitudes at all buses. Voltage Deviation Index (VDI) is then calculated via (5.6) of Chapter 5. Later, the total power losses (P_{loss}) are calculated from the load flow results via (3.26) of Chapter 3. Afterwards, the grid dependency is quantified using (5.7) of Chapter 5 and finally, the harmonic level is measured by determining Total Harmonic Distortion (THD) via (5.27) of Chapter 5, which involves step-by-step conversion from (5.8) to (5.27) of Section 5.2.5, Chapter 5.
- vii) After that, the WSM approach is used to determine the weighted-sum fitness, f_{wsm} based on (6.2). This is done for all ants and antlions in the population in which they will be ranked according to their f_{wsm} .
- viii) The ants and antlions are ranked such that the best of them with minimum f_{wsm} will be placed at the topmost, while the worst one with maximum f_{wsm} will be at the bottommost. This is shown in (4.17) and (4.18) of Chapter 4.
- ix) Later, the solutions produced by ants and antlions are updated as follows. At first, the ant positions are updated according to (4.19) of Chapter 4. Next, the current antlion positions are updated by combining their existing positions ($\mathbf{M}_{Antlion}$) with the updated ant positions ($\mathbf{M}_{Ant}$). This is done through (4.21) of

Chapter 4. After sorting the combined matrix ($\mathbf{M}_{\text{Combine}}$) based on fitness values, the updated antlion positions are defined as in (4.22) of Chapter 4.

- x) The optimization process repeats from step (vi) to step (ix) until it achieves convergence.
- xi) The post load flow is conducted to obtain the post-optimization result with optimal DG placement.
- xii) The overall process is repeated for the rest of the EVCS cases.

Hence, the overall formulation of multi-objective optimization (MOO) problem for optimal DG placement in EVCS-integrated distribution systems can be summarized as follows:

$$\text{Minimize } \{f_{wsm}(P_{DG}) = 0.3715 \cdot VDI + 0.2476 \cdot P_{loss} + 0.2026 \cdot P_{grid} + 0.1783 \cdot THD\}$$

Subject to constraints as (4.24),(4.26) of Chapter 4 and as follow:

$$\text{DG power factor : } PF_{DG} = 1 \quad (6.6)$$

$$\text{DG number : } N_{DG} = \begin{cases} 4 & ; \text{ IEEE 33 – bus} \\ 6 & ; \text{ IEEE 69 – bus} \end{cases} \quad (6.7)$$

$$\text{DG type : } T_{DG} = 1 \text{ (solar PV)} \quad (6.8)$$

The overall algorithm for LSF-MALO as has been explained in the previous procedure is illustrated in **Figure 6.2**.

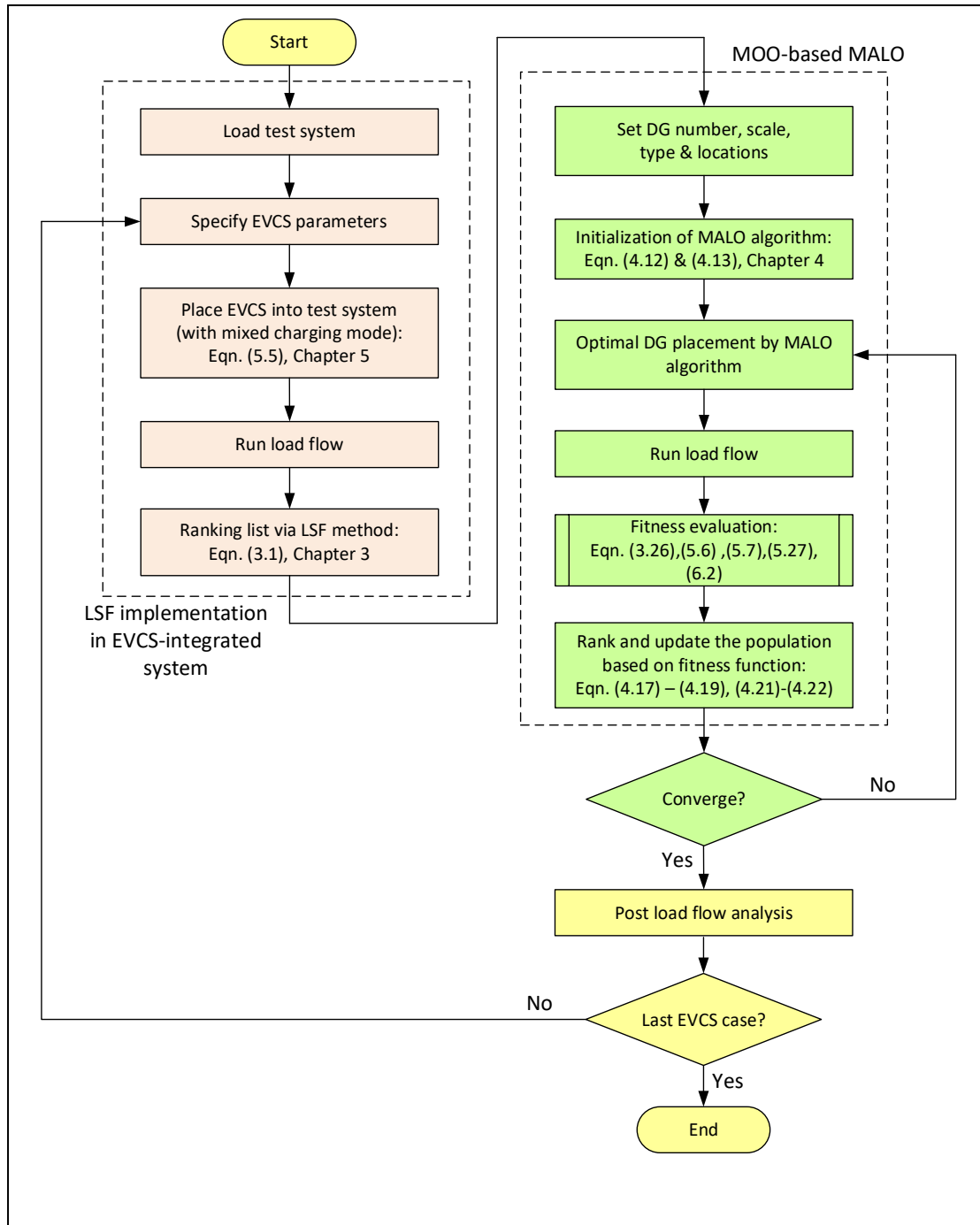


Figure 6. 2 Multi-Objective LSF-MALO Algorithm For Optimal DG Placement With EVCS Integration

6.3 Results and Discussion

The proposed LSF-MALO algorithm was evaluated on two EVCS-integrated radial distribution systems: the IEEE 33-bus and 69-bus networks. For each system, the EVCS configurations – covering location, number, charging mode, and type – are the same to those described in Chapter 5, Section 5.3. As summarized in Section 5.4, the mixed charging mode demonstrated the most promising performance in terms of voltage stability, power losses, grid dependency, and harmonic levels. Consequently, this chapter focuses on distribution systems with mixed charging mode and twenty distinct EVCS charging scenarios (or cases). The analysis is organized into two main parts:

- Optimal DG placement for EVCS-integrated radial distribution systems across the twenty EVCS scenarios.
- Optimal DG placement under incremental loading conditions.

A comparative analysis is performed using three benchmark techniques – LSF Analytical, Evolutionary Programming (EP), and MALO without LSF incorporation – to evaluate the effectiveness of the proposed LSF-MALO in determining the optimal locations and sizes of DG units. For a fair comparison, the number of DG units is kept constant: four Type-1 DG units (solar PV) are installed in the EVCS-integrated IEEE 33-bus system, and six Type-1 DG units (solar PV) in the EVCS-integrated IEEE 69-bus system. The results are assessed using five key performance indicators: Voltage Deviation Index (VDI) and minimum voltage magnitude (V_{min}) to evaluate voltage stability improvement; real power losses (P_{loss}) to assess system's efficiency in power distribution; net grid power (P_{grid}) to quantify grid dependency reduction; and Total Harmonic Distortion (THD) to measure harmonic mitigation.

6.3.1 Optimal DG placement under Different Charging Scenarios in EVCS-integrated IEEE 33-bus radial distribution system

For EVCS-integrated IEEE 33-bus radial distribution system, the number of DG units used for optimal DG placement is four, namely DG1, DG2, DG3 and DG4. **Table 6.1** presents the post-optimization results obtained from the multi-objective optimization (MOO) for optimal DG placement using the proposed LSF-MALO technique.

Table 6. 1

Optimal DG Placement Using LSF-MALO – EVCS-Integrated IEEE 33-Bus Radial Distribution System

Condition for each EVCS case					Optimal DG Placement using LSF-MALO				
EVCS Case	EVCS Buses (Bus No.)	N_{EVCS} Per Bus	Mixed Charging Mode Per Bus	EVCS Type Per Bus	DG Locations (Bus No.)	P_{DG} (MW) – Type 1 Solar PV			
						DG1	DG2	DG3	DG4
1	10, 20, 30	8	4 L1 + 4 L2	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	0.0050
2			4 L2 + 4 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
3			4 L1 + 4 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
4			2 L1 + 3 L2 + 3 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
5			5 L2 + 3 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
6	10, 20, 30	10	5 L1 + 5 L2	6 G2V + 4 V2G	6, 5, 4, 3	5.0000	0.0050	0.0050	0.0050
7			5 L2 + 5 L3	6 G2V + 4 V2G	6, 5, 4, 3	5.0000	0.0050	0.0050	0.0050
8			5 L1 + 5 L3	6 G2V + 4 V2G	6, 5, 4, 3	5.0000	0.0050	0.0050	0.0050
9			2 L1 + 4 L2 + 4 L3	8 G2V + 2 V2G	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
10			6 L2 + 4 L3	8 G2V + 2 V2G	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
11	5, 8, 11, 16	8	7 L2 + 1 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
12	10, 15, 20, 25		7 L2 + 1 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	0.0050
13	4, 7, 10, 17		7 L2 + 1 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
14	20, 23, 28, 30	10	8 L2 + 2 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
15	25, 27, 30, 33		9 L2 + 1 L3	All G2V	6, 5, 4, 3	5.0000	0.0050	0.0050	5.0000
16	5, 8, 11, 16	15	8 L2 + 7 L3	12 G2V + 3 V2G	6, 5, 4, 3	4.9382	3.5598	0.0050	4.9719
17	10, 15, 20, 25		8 L2 + 7 L3	12 G2V + 3 V2G	6, 5, 4, 3	4.3710	5.0000	0.0050	0.0050
18	4, 7, 10, 17		8 L2 + 7 L3	12 G2V + 3 V2G	6, 5, 4, 3	4.2702	2.6428	4.3959	2.6319
19	20, 23, 28, 30		10 L2 + 5 L3	12 G2V + 3 V2G	6, 5, 4, 3	4.4168	4.4969	0.0050	0.0050
20	25, 27, 30, 33		10 L2 + 5 L3	12 G2V + 3 V2G	6, 5, 4, 3	4.4963	5.0000	0.0050	0.0050

It lists the selected DG locations together with their corresponding sizes (P_{DG}) for each EVCS case or charging scenario as determined by the MOO-based LSF-MALO. The resulting distribution system performance in terms of VDI, V_{min} , P_{loss} , P_{grid} and THD across all 20 cases, after optimal DG placement, is illustrated from **Figure 6.3** to **Figure 6.7**.

Based on **Table 6.1**, the LSF-MALO produces a consistent performance in optimal DG placement across all EVCS cases. From EVCS cases 1 to 15, the algorithm alternates the DG sizes between 0.005 MW and 5 MW. For example, in case 1 the first DG unit (DG1) is sized at 5 MW while the remaining three units (DG2 to DG4) are 0.005 MW. In case 15, DG1 and DG4 are 5 MW, whereas DG2 and DG3 remain at 0.005 MW. From cases 16 to 20, the DG sizes deviate from this pattern – for instance, in case 18 the sizes are 4.2702 MW, 2.6428 MW, 4.3959 MW, and 2.6319 MW for DG1 through DG4, respectively. Overall, regardless of the EVCS locations, the DG units are consistently placed at buses 6, 5, 4, and 3. This demonstrates the system-wide perspective of the proposed algorithm, which yields a globally optimal solution for DG siting and sizing rather than a scenario-specific or locally optimal placement.

The distribution system's voltage stability performance across all 20 EVCS cases is shown in **Figure 6.3** and **Figure 6.4**, which present the VDI and V_{min} , respectively. The dotted red line in **Figure 6.3** indicates 0.1042 p.u. of VDI before the integration of EVCS and DG units into the system (no-EVCS condition), while the dotted red line in **Figure 6.4** indicates 0.95 p.u. of minimum threshold for nominal voltage magnitude. The VDI bar chart (**Figure 6.3**) clearly shows that EVCS integration causes significant voltage instability before optimal DG placement. Prior to DG installation, represented by the black bars, the VDI values are consistently higher than the no-EVCS condition (dotted red line), with instability becoming more severe in cases 16 to 20 where the VDI exceeds 0.2 p.u. This poor VDI performance is reflected in **Figure 6.4**, where the corresponding V_{min} values fall below 0.95 p.u. for cases 1 to 15 and drop even further for cases 16 to 20. After optimal DG placement, the proposed LSF-MALO (blue bars) delivers the most robust voltage stability improvement, reducing VDI to well below the no-EVCS benchmark – close to zero in most cases – and maintaining V_{min} between 0.95 p.u. and 1.00 p.u., indicating a well-regulated voltage profile. The EP technique (green bars) maintains VDI below 0.05 p.u. for most scenarios but suffers from undervoltage, with V_{min} frequently below 0.95 p.u.

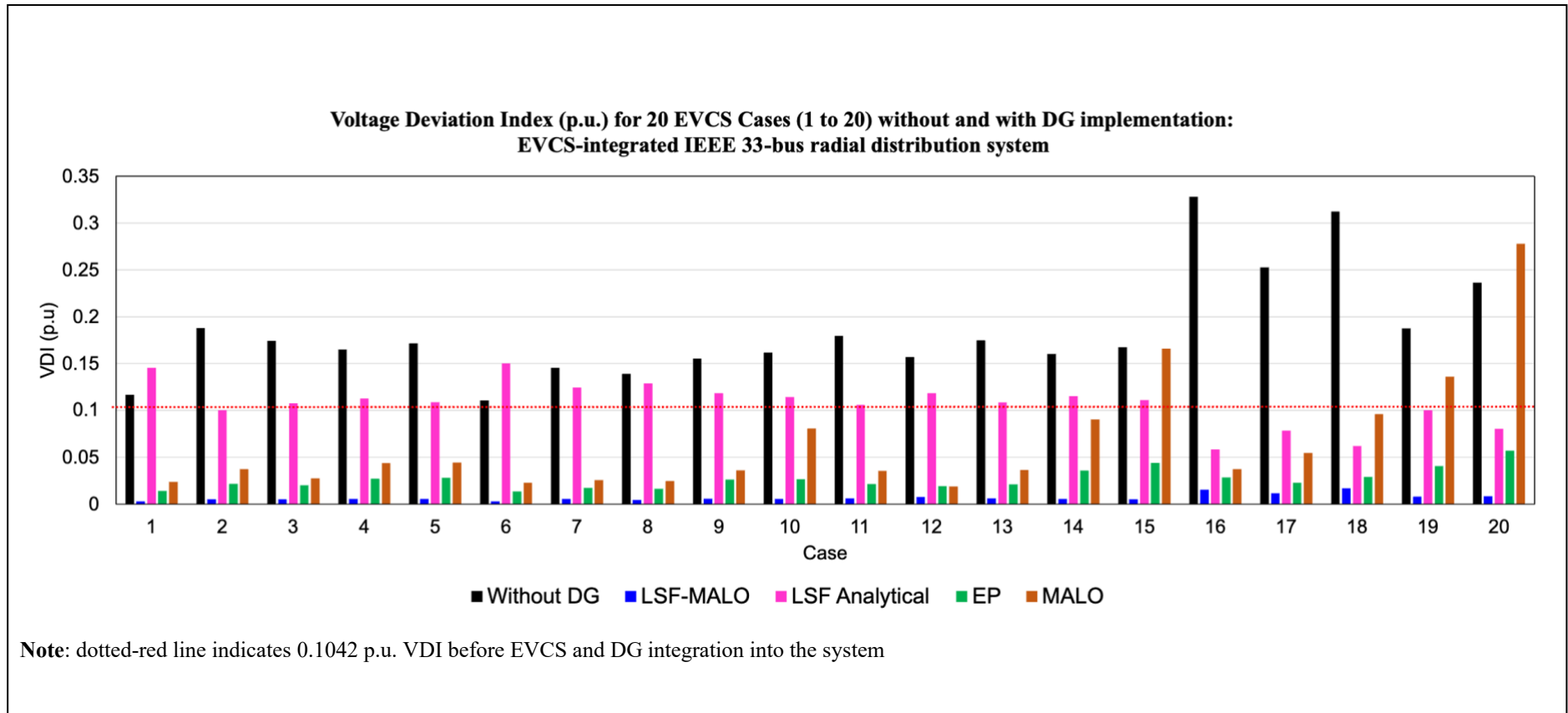


Figure 6. 3 Per-Unit Voltage Deviation Index (VDI) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 33-Bus System

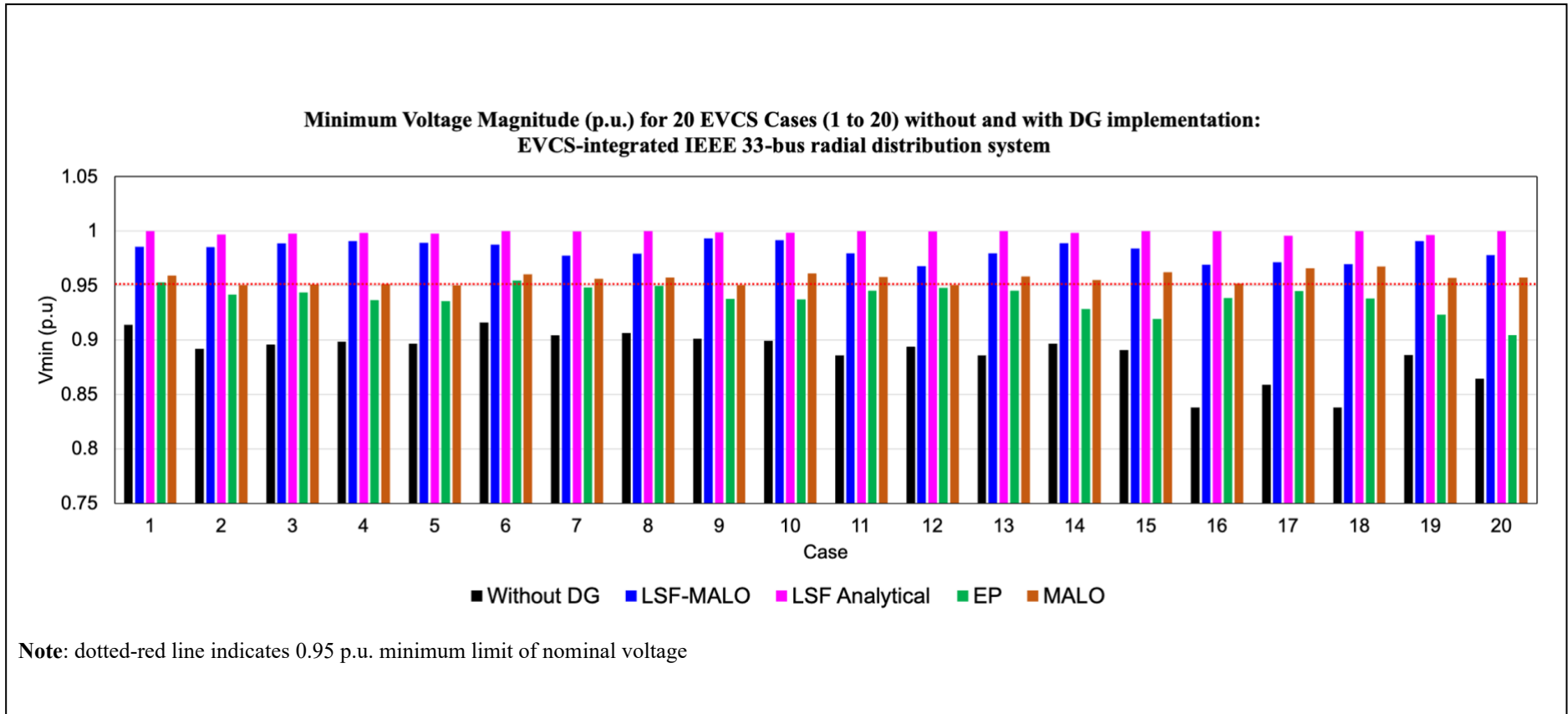


Figure 6. 4 Per-Unit Minimum Voltage Magnitude (V_{min}) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 33-Bus System

The MALO method (brown bars) generally keeps VDI under the dotted red line except in cases 15, 19, and 20, but its V_{min} fluctuates above and below 0.95 p.u., giving inconsistent voltage support. The weakest VDI performance is observed with the LSF Analytical method (pink bars), where VDI values often match or exceed the no-EVCS benchmark. However, it exhibits the highest V_{min} performance, keeping voltage magnitudes close to 1.00 p.u. across all 20 cases.

The system's ability to deliver power efficiently is indicated by the total real power losses (P_{loss}) shown in **Figure 6.5**. The dotted red line indicates 0.1831 MW of total power losses before the integration of EVCS and DG units into the system (no-EVCS condition). Clearly, EVCS integration increases losses compared to the no-EVCS condition. Across all 20 cases, the EVCS integration under pre-DG placement scenario (black bars) shows P_{loss} consistently higher than the dotted red line, confirming reduced distribution efficiency. Among the optimization methods, the EP technique (green bars) achieves the lowest P_{loss} overall. In several cases – such as 1, 3, 6, 7, 8, 9, 11, 12, and 13 – its losses are even lower than the no-EVCS benchmark (dotted red line), demonstrating highly efficient power distribution. The proposed LSF-MALO (blue bars) ranks second, with cases 1, 6, 7, 8, and 12 showing slightly lower P_{loss} than the dotted red line. Except for cases 16 and 18, it maintains P_{loss} below 0.4 MW, slightly higher than the no-EVCS condition. The MALO method (brown bars) performs comparably to LSF-MALO in many cases, but at cases 15, 19, and 20 it records noticeably higher losses above 0.6 MW. The poorest performance is delivered by the LSF Analytical approach (pink bars), where losses are consistently well above 1 MW – substantially higher than even the pre-DG scenario (black bars).

The distribution system performance in terms of grid dependency is presented in **Figure 6.6**. The dotted red line indicates 3.715 MW of net grid power before the integration of EVCS and DG units into the system (no-EVCS condition). Integration of EVCS before DG placement (black bars) clearly increases grid dependency, as the net grid power (P_{grid}) is higher than in the no-EVCS condition (dotted red line). This indicates that the grid must supply additional power not only for the existing loads but also to meet the EVCS charging demand. Grid dependency becomes particularly significant from case 16 to case 20, where P_{grid} rises well above 5 MW. Among all methods, LSF Analytical (pink bars) yields the most grid-independent results, with P_{grid} values consistently negative and exceeding |10 MW|.

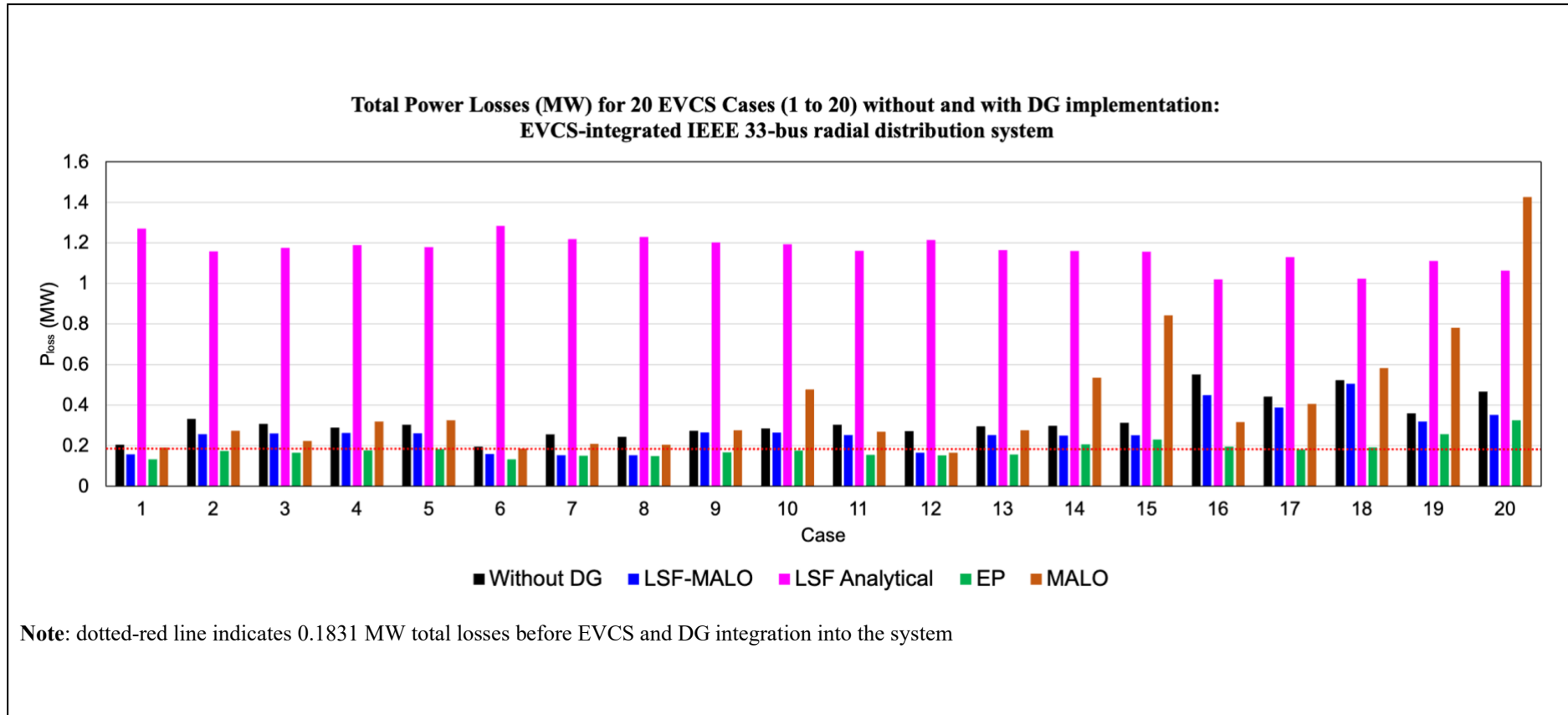


Figure 6. 5 Total Power Losses In Megawatts (P_{loss}) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 33-Bus System

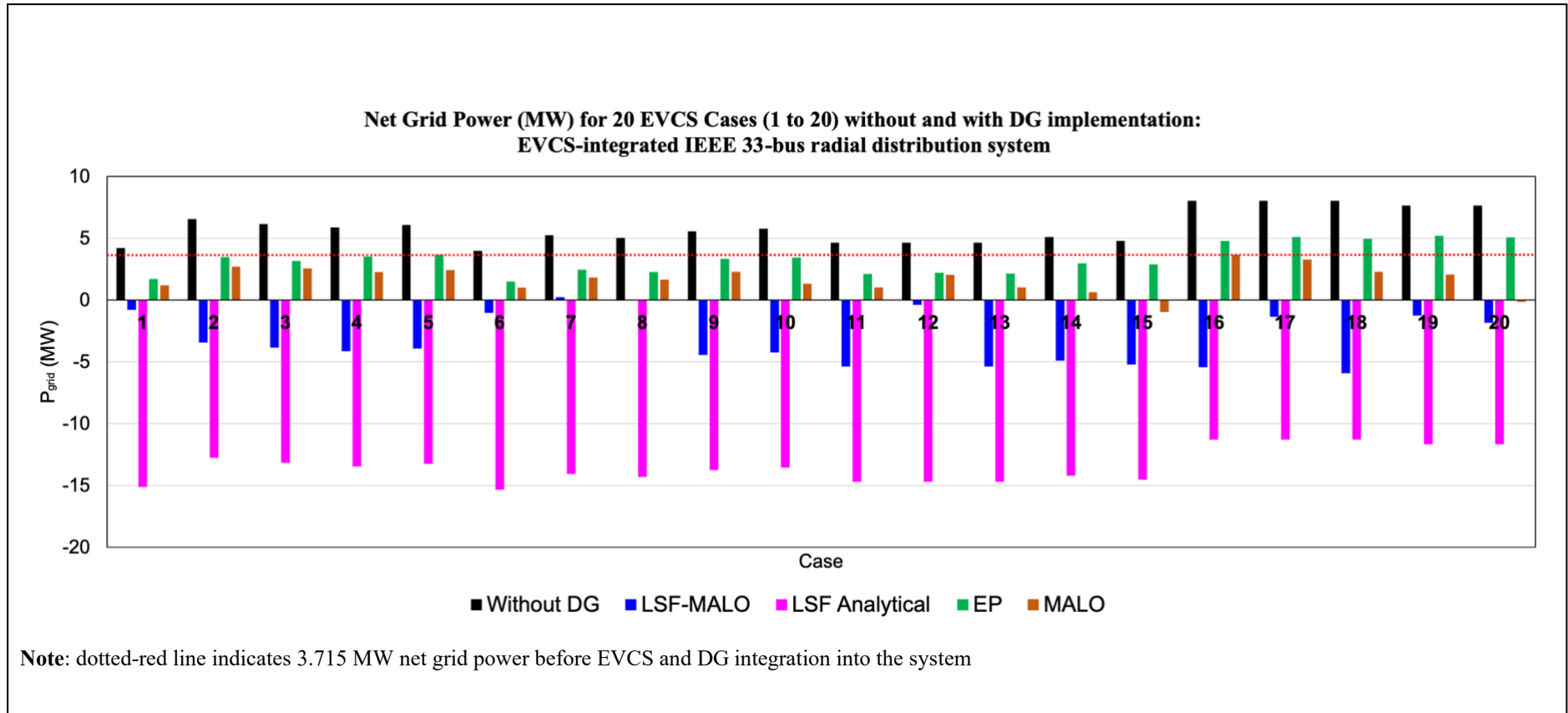


Figure 6. 6 Net Grid Power (P_{grid}) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 33-Bus System

This means the net power supplied by the installed DG units and any V2G-type EVs, after subtracting the total demand from existing loads and G2V-type EVs, exceeds 10 MW. However, such a large negative P_{grid} is not necessarily desirable, as it indicates overcompensation by the DG units, which – as discussed earlier – leads to excessively high power losses. The proposed LSF-MALO method (blue bars) achieves a more balanced outcome. It also produces negative P_{grid} values, but with a magnitude around |5 MW| across all cases. This suggests that the system is effectively grid-independent: the DG units supply enough power to meet the loads without causing the excessive power losses observed in the LSF Analytical approach. The remaining two methods, EP (green bars) and MALO (brown bars), reduce P_{grid} below the no-EVCS level (dotted red line) for the first 15 cases, thereby making the system less grid-dependent. However, they still fail to achieve full grid independence, as the grid continues to supply power to the distribution network despite the presence of multiple DG units.

The final aspect of the distribution system performance analysis is harmonic mitigation. The Total Harmonic Distortion (THD) for all 20 cases is shown in **Figure 6.7**, where the dotted red line marks the 5% maximum allowable THD. Integration of EVCS without DG placement (black bars) causes THD to rise sharply—exceeding 20% in 19 cases, except in case 6 where it remains below 5%. The proposed LSF-MALO method (blue bars) demonstrates the best THD mitigation. For the first 15 cases, it successfully keeps THD below 5%, showing that the installed DG units effectively suppress the harmonic impact of EVCS integration. The LSF Analytical method (pink bars) ranks second, maintaining THD mostly below 5% for the first 15 cases, with only slight exceedances in cases 3 and 5. By contrast, the EP (green bars) and MALO (brown bars) methods perform worst, failing to reduce THD below 5% in most cases.

This indicates that, although the two methods perform adequately in terms of voltage stability improvement, losses minimization and grid dependency reduction, their optimal DG placement is insufficient to ensure acceptable power quality. From cases 16 to 20, none of the methods can achieve THD below the 5% threshold. Even so, LSF-MALO and LSF Analytical remain the most effective, limiting THD to at most 10%, whereas EP and MALO show THD levels exceeding 10%.

Integration of EVCS without DG placement severely degrades system performance, causing high voltage instability (VDI greater than 0.2 p.u. in cases 16 to 20), V_{min} below 0.95 p.u., power losses above 0.183 MW, grid dependency exceeding 5 MW, and THD above 20%. After optimal DG placement, the proposed LSF-MALO

gives the most balanced improvement: VDI is near zero, V_{min} stays within 0.95 to 1.0 p.u., losses remain below 0.4 MW and P_{grid} hovers around $|5 \text{ MW}|$, avoiding overcompensation. LSF Analytical achieves the highest V_{min} and strongest grid independence but suffers very high losses. EP records the lowest losses yet often has undervoltage and remains grid-dependent. MALO shows moderate results but inconsistent voltage support and high losses in some cases. For power quality, only LSF-MALO and LSF Analytical keep THD below 5% for the first 15 cases and under 10% thereafter, while EP and MALO frequently exceed 10%. Overall, LSF-MALO offers the best trade-off, combining strong voltage stability, acceptable losses, adequate grid independence and effective harmonic mitigation.

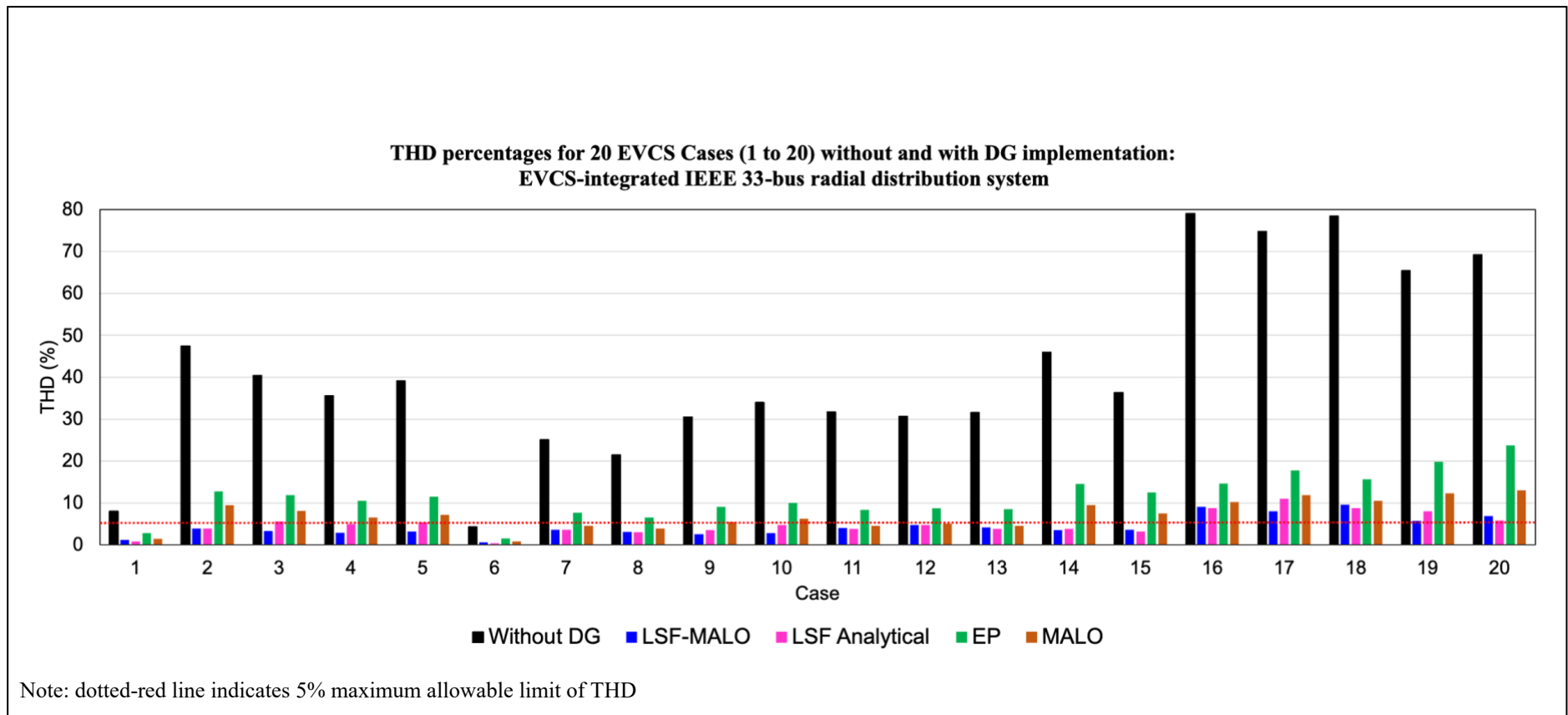


Figure 6. 7 THD Percentages For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 33-Bus System

6.3.2 Optimal DG Placement under Incremental Loading in EVCS-integrated IEEE 33-bus Radial Distribution System

This section evaluates the performance of multi-objective optimization (MOO) for optimal DG placement under incremental load growth in the EVCS-integrated IEEE 33-bus radial distribution system. Five loading levels, from 10% to 50%, are considered to reflect progressive demand increase. The aim is to assess how consistently each method solves the MOO problem and maintains good performance under rising loads. Five key indicators are used: Voltage Deviation Index (VDI) and minimum voltage magnitude (V_{min}) for voltage stability, real power losses (P_{loss}) for network efficiency, net grid power (P_{grid}) for grid dependency, and Total Harmonic Distortion (THD) for harmonic mitigation.

As shown in **Figure 6.8**, the pre-DG VDI (black line) rises from the no-EVCS benchmark of 0.1042 p.u. (dotted red line), demonstrating voltage instability. LSF-MALO (blue line) and EP (green line) keep VDI consistently below the no-EVCS level across all loadings, with near-constant trends from 10% to 50%, indicating strong voltage stability. This is followed by MALO (brown line), whose VDI remains below the dotted red line but shows a slight fluctuation at 50% loading. The weakest performer is LSF Analytical (pink line), which is only marginally stable as its VDI values fluctuate around the no-EVCS benchmark across most loading levels. **Figure 6.9** shows that, with the pre-DG VDI increases from the dotted red line, V_{min} drops sharply to around 0.90 p.u. or lower. LSF-MALO and MALO maintain consistent V_{min} between 0.95 p.u. and 0.96 p.u. across all loadings, demonstrating stable voltage profiles. LSF Analytical records the highest V_{min} (close to 1.00 p.u.) but fails to maintain low, steady VDI values. EP cannot consistently keep V_{min} at or above 0.95 p.u. across the loading levels since the voltage magnitudes at 10%, 30% and 50% are between 0.93 p.u. and 0.94 p.u.

Figure 6.10 shows the total real power losses (P_{loss}) across all loading levels. EP (green line) remains close to the no-EVCS benchmark of 0.1831 MW (dotted red line) throughout the loading range, indicating considerable losses reduction with respect to the pre-DG condition (black line). This is followed by LSF-MALO (blue line) with P_{loss} values below the pre-DG condition across all loading levels. Although the losses reduction is modest – indicating only slight gains in network efficiency – LSF-MALO and EP successfully prevent the losses from rising above the pre-DG condition or to excessive levels. MALO (brown line) shows unwanted performance since its losses are

slightly above the pre-DG condition from 10% to 50% of loading levels, while LSF Analytical (pink line) exhibits severe increase in power losses, with P_{loss} between 1.0 MW and 1.2 MW, far above the benchmark. These results highlight the poor network efficiency by MALO and, extremely poor by LSF Analytical.

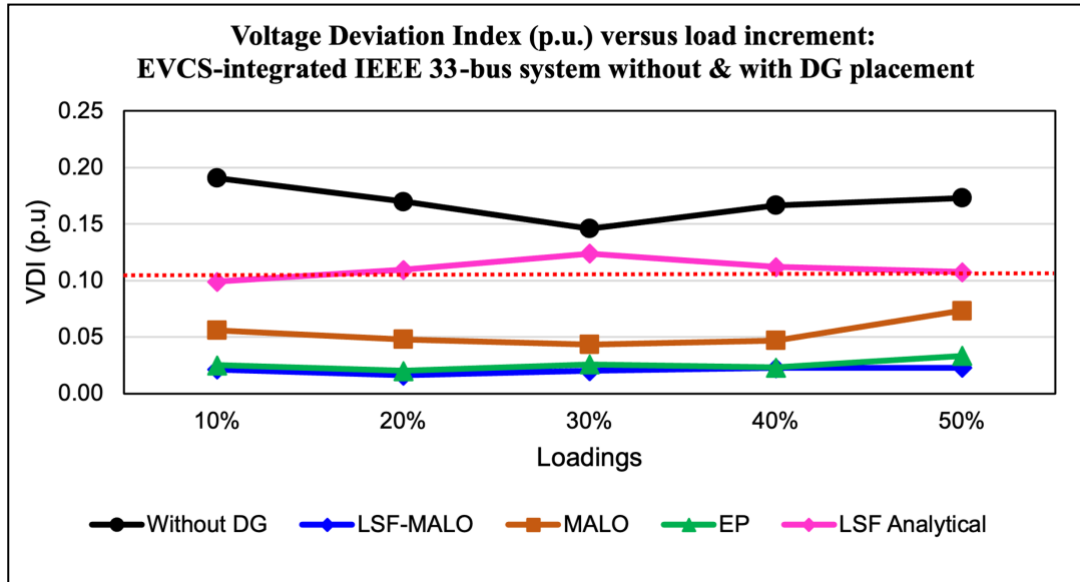


Figure 6. 8 Voltage Deviation Index (VDI) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 33-Bus Radial Distribution System

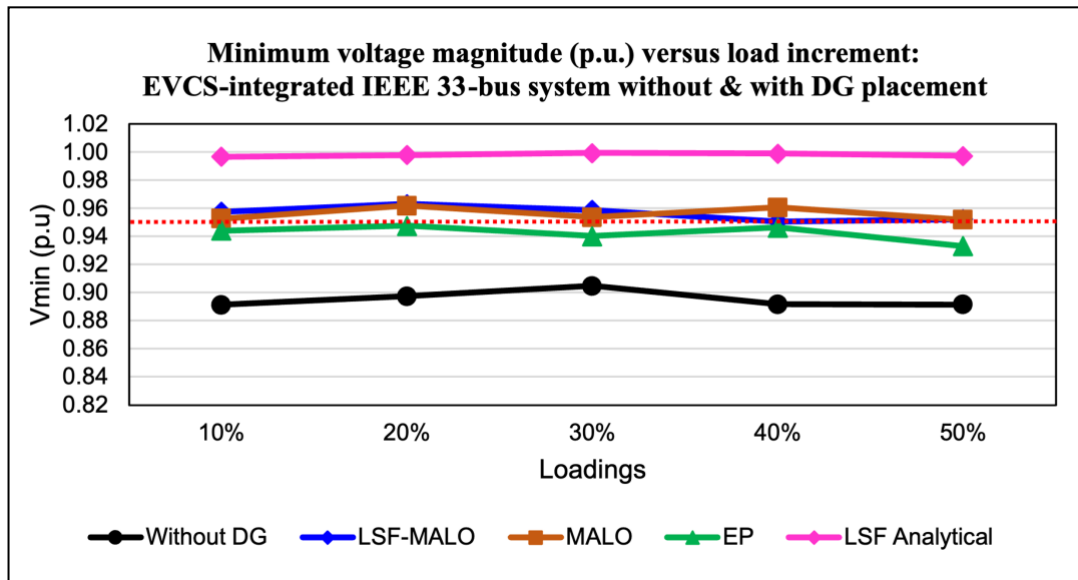


Figure 6. 9 Minimum Voltage Magnitude (V_{min}) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 33-Bus Radial Distribution System

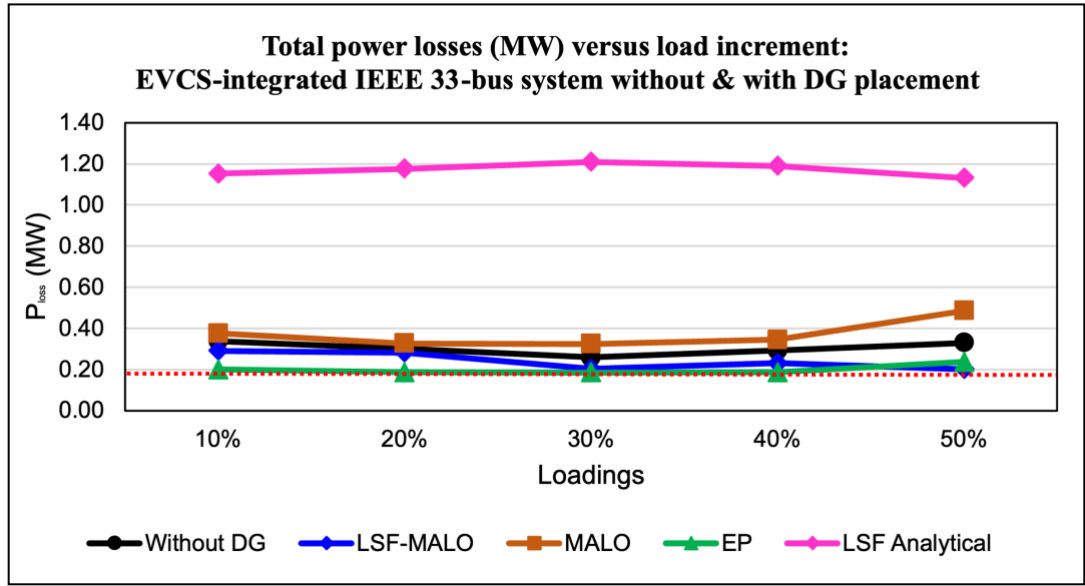


Figure 6. 10 Total Power Losses (P_{loss}) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 33-Bus Radial Distribution System

Figure 6.11 presents the grid dependency performance, showing net grid power (P_{grid}) across all loading levels. Adding EVCS before DG placement raises P_{grid} well above the no-EVCS benchmark of 3.715 MW (dotted red line), with pre-DG values (black line) ranging from 5 MW to 7 MW – indicating strong reliance on the grid. In this case, only LSF-MALO (blue line) achieves full grid independence, maintaining negative P_{grid} values at every loading level and thus fulfilling the very purpose of DG placement: supplying local loads rather than depending on the grid. By contrast, the remaining three methods, namely LSF Analytical (pink line), MALO (brown line) and EP (green line) only lower P_{grid} relative to the pre-DG scenario. Their P_{grid} remains positive, so they reduce but cannot eliminate grid dependency and therefore do not fulfil the primary objective of DG placement.

Lastly, the harmonic mitigation performance is presented in **Figure 6.12**, showing THD across all loading levels. In the pre-DG scenario (black line), harmonic level increases considerably above the 5% benchmark (dotted red line) with THD percentages between 20% and 50%, indicating severely degraded power quality after EVCS integration. In contrast, the LSF-MALO (blue line) and LSF Analytical (pink line) consistently maintain good power quality, keeping THD at or below 5% across all loading levels. EP (green line) and MALO (brown line), however, show inconsistent

performance, with THD exceeding the 5% benchmark at 10%, 20%, 40% and 50% of the loading levels.

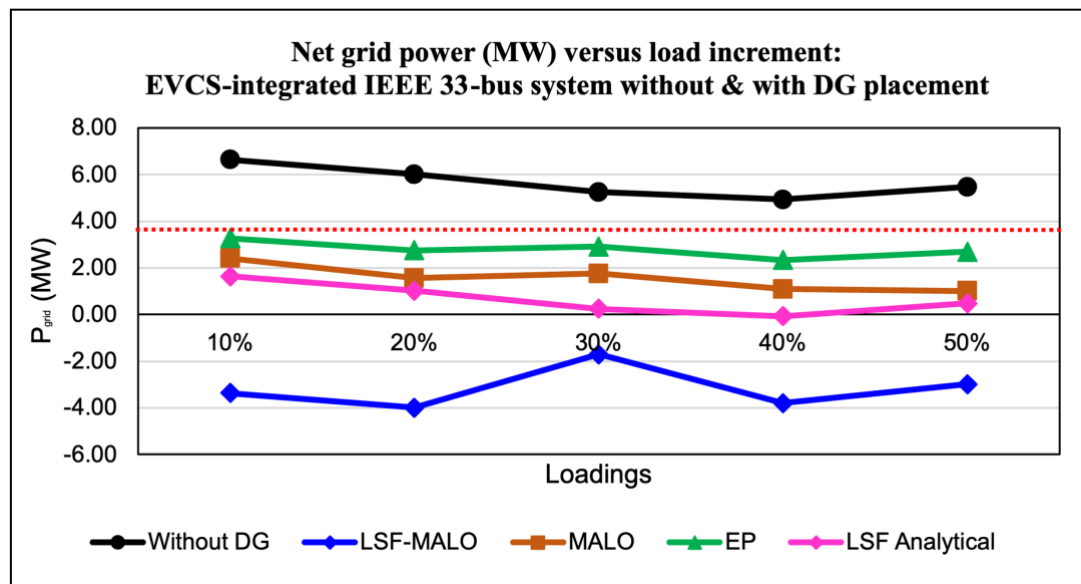


Figure 6. 11 Net Grid Power (P_{grid}) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 33-Bus Radial Distribution System

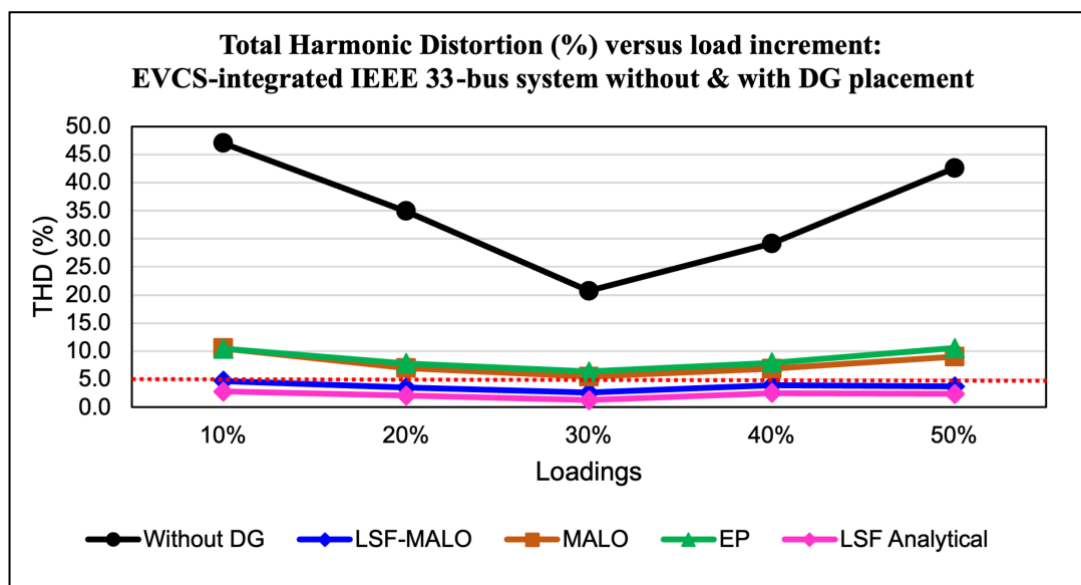


Figure 6. 12 Total Harmonic Distortion (THD) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 33-Bus Radial Distribution System

On overall, the analysis shows that each method has distinct strengths and weaknesses. LSF-MALO consistently delivers strong voltage stability with low VDI and stable V_{min} , while also achieving modest losses reduction and the only method with full grid independence, plus excellent harmonic mitigation. EP provides low VDI and the best losses reduction, but its V_{min} occasionally dips below 0.95 p.u., it cannot achieve grid independence, and its THD performance is inconsistent. MALO maintains acceptable VDI and V_{min} but suffers slightly higher losses than pre-DG, fails to achieve grid independence, and shows irregular THD. LSF Analytical records the highest V_{min} and good harmonic control, yet its VDI fluctuates around the benchmark and it suffers very high losses and underperformed grid dependence. The pre-DG case simply highlights the negative impact of EVCS integration with high losses, strong grid reliance and poor THD. Considering all five performance indicators together, LSF-MALO stands out as the most promising method.

6.3.3 Optimal DG placement under Different Charging Scenarios in EVCS-integrated IEEE 69-bus radial distribution system

For EVCS-integrated IEEE 69-bus radial distribution system, the number of DG units used for optimal DG placement is six, namely DG1 through DG6. **Table 6.2** presents the post-optimization results obtained from the multi-objective optimization (MOO) for optimal DG placement using the proposed LSF-MALO technique. It lists the selected DG locations together with their corresponding sizes (P_{DG}) for each EVCS case or charging scenario as determined by the MOO-based LSF-MALO. The resulting distribution system performance in terms of VDI, V_{min} , P_{loss} , P_{grid} and THD across all 20 cases, after optimal DG placement, is illustrated from **Figure 6.13** to **Figure 6.17**.

Based on **Table 6.2**, the LSF-MALO successfully completes the optimization for all EVCS cases, with every DG size (P_{DG}) remaining within the specified 0 to 5 MW limit. Most DG units fall between 0.01 MW and 4 MW, indicating full compliance with the DG size constraints and no occurrence of oversized units. Among the six DGs, DG6 is the least utilized, maintaining 0.01 MW in most cases except for cases 3, 4, 17, 18, 19, and 20. From cases 17 to 20, the total installed DG capacity (or the summation of P_{DG} values for all DG units) exceeds 10 MW, peaking at 16.09 MW in case 17, followed by 14.13 MW, 11.82 MW, and 11 MW in cases 19, 20, and 18 respectively, reflecting the system's higher support requirements.

Table 6. 2

Optimal DG Placement Using LSF-MALO – EVCS-Integrated IEEE 69-Bus Radial Distribution System

Condition for each EVCS case					Optimal DG Placement using LSF-MALO						
EVCS Case	EVCS Buses	N_{EVCS} Per Bus	Mixed Charging Mode Per Bus	EVCS Type Per Bus	DG Locations (Bus No.)	P_{DG} (MW) – Type 1 Solar PV					
						DG1	DG2	DG3	DG4	DG5	DG6
1	10, 20, 30, 40, 50, 60	6	4 L2 + 2 L3	All G2V	61, 50, 49, 64, 12, 40	2.71	2.06	3.00	1.60	0.01	0.01
2	10, 20, 30, 40, 50, 60		4 L1 + 2 L3	All G2V	61, 50, 49, 64, 12, 40	2.65	2.01	2.94	1.54	0.01	0.01
3	4, 10, 26, 40, 42, 45		5 L2 + 1 L3	All G2V	61, 50, 49, 64, 11, 40	0.84	0.01	0.01	2.17	3.09	1.47
4	13, 14, 21, 38, 41, 43		5 L2 + 1 L3	All G2V	61, 50, 49, 64, 11, 40	0.87	0.01	0.01	2.19	3.12	1.50
5	10, 20, 30, 40, 50, 60	8	4 L1 + 4 L2	All G2V	61, 50, 49, 64, 12, 40	1.89	1.34	2.03	1.86	1.64	0.01
6	10, 20, 30, 40, 50, 60		3 L1 + 4 L2 + 1 L3	All G2V	61, 50, 49, 64, 12, 40	2.03	1.48	2.18	2.00	1.79	0.01
7	10, 20, 30, 40, 50, 60		7 L2 + 1 L3	All G2V	61, 50, 49, 64, 12, 40	2.07	1.53	2.22	2.05	1.83	0.01
8	10, 20, 30, 40, 50, 60	10	5 L1 + 5 L2	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	1.82	1.27	0.01	1.79	0.01	0.01
9	10, 20, 30, 40, 50, 60		4 L1 + 4 L2 + 2 L3	8 G2V + 2 V2G	61, 50, 49, 64, 12, 40	1.69	1.75	0.01	1.96	0.01	0.01
10	7, 25, 26, 40, 48, 64		5 L2 + 5 L3	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	0.88	1.61	0.01	2.36	2.37	0.01
11	16, 17, 23, 25, 38, 56		5 L2 + 5 L3	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	1.88	1.34	0.01	1.85	1.64	0.01
12	20, 25, 40, 45, 50, 55		5 L2 + 5 L3	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	1.74	1.20	0.01	1.71	1.50	0.01
13	30, 32, 36, 42, 47, 65		5 L2 + 5 L3	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	0.73	1.45	0.01	2.21	2.22	0.01
14	19, 27, 29, 44, 62, 66		5 L2 + 5 L3	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	0.88	1.61	0.01	2.36	2.37	0.01
15	34, 43, 51, 53, 65, 69		5 L2 + 5 L3	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	0.86	1.59	0.01	2.34	2.35	0.01
16	10, 20, 30, 40, 50, 60		5 L1 + 5 L3	6 G2V + 4 V2G	61, 50, 49, 64, 12, 40	2.67	2.02	2.96	1.56	0.01	0.01
17	2, 25, 26, 55, 57, 63	15	10 L2 + 5 L3	12 G2V + 3 V2G	61, 50, 49, 64, 12, 40	1.62	2.26	3.18	2.93	3.87	2.23
18	4, 10, 26, 40, 42, 45		10 L2 + 5 L3	12 G2V + 3 V2G	61, 50, 49, 64, 12, 11	0.76	1.41	2.33	2.09	3.02	1.39
19	28, 42, 47, 60, 62, 63		10 L2 + 5 L3	12 G2V + 3 V2G	61, 50, 49, 64, 12, 40	2.58	2.04	2.74	2.53	2.35	1.89
20	13, 14, 21, 38, 41, 43		10 L2 + 5 L3	12 G2V + 3 V2G	61, 50, 49, 64, 12, 11	0.90	1.55	2.47	2.22	3.15	1.53

Despite variations in DG sizes, the LSF-based siting remains consistent across all 20 cases: DGs are predominantly placed at buses 61, 50, 49, 64, 12, and 40, in based on LSF priority list. This consistency highlights the system-wide perspective of the proposed algorithm, which achieves a globally optimal solution for DG siting and sizing rather than a case-specific or locally optimal outcome.

The distribution system's voltage stability performance across all 20 EVCS cases is shown in **Figure 6.13** and **Figure 6.14**, which present the VDI and V_{min} , respectively. The dotted red line in **Figure 6.13** indicates 0.0922 p.u. of VDI before the integration of EVCS and DG units into the system (no-EVCS condition), while the dotted red line in **Figure 6.14** indicates 0.95 p.u. of minimum threshold for nominal voltage magnitude. The VDI bar chart (**Figure 6.13**) clearly shows that EVCS integration causes slight voltage instability before optimal DG placement. Prior to DG installation, represented by the black bars, the VDI values are slightly higher than the no-EVCS condition (dotted red line) for the first 16 cases, with instability becoming more severe in cases 17 to 20 where the VDI exceeds 0.2 p.u. This poor VDI performance is reflected in **Figure 6.14**, where the corresponding V_{min} values fall below 0.95 p.u. for most cases and drop even further for cases 17 and 19. After optimal DG placement, the proposed LSF-MALO (blue bars) delivers the most robust voltage stability improvement, reducing VDI to well below the no-EVCS benchmark – with VDI deviates between 0.01 and 0.03 – and maintaining V_{min} between 0.95 p.u. and 1.00 p.u., indicating a well-regulated voltage profile. The EP technique (green bars) keeps VDI below the dotted red line for most scenarios, showing performance close to that of LSF-MALO. However, it experiences undervoltage in six cases (1, 14, 15, 18, 19, and 20), where V_{min} falls below the 0.95 p.u. threshold and only marginally reaches 0.95 p.u. in the remaining cases. The MALO method (brown bars) offers weaker voltage stability improvement compared with the two leading techniques. As shown in **Figure 6.13**, its VDI is slightly above the no-EVCS benchmark in 16 cases (except 11, 13, 14, and 20), indicating only moderate stability gains. This is consistent with **Figure 6.14**, where most V_{min} values hover around 0.95 p.u., though without the undervoltage issues seen in EP. The LSF Analytical method (pink bars) shows the poorest VDI performance, with 14 cases recording VDI above 0.5, reflecting severe voltage instability. Yet, it delivers excellent V_{min} results, comparable to LSF-MALO, maintaining voltage magnitudes close to 1.00 p.u. across all 20 cases.

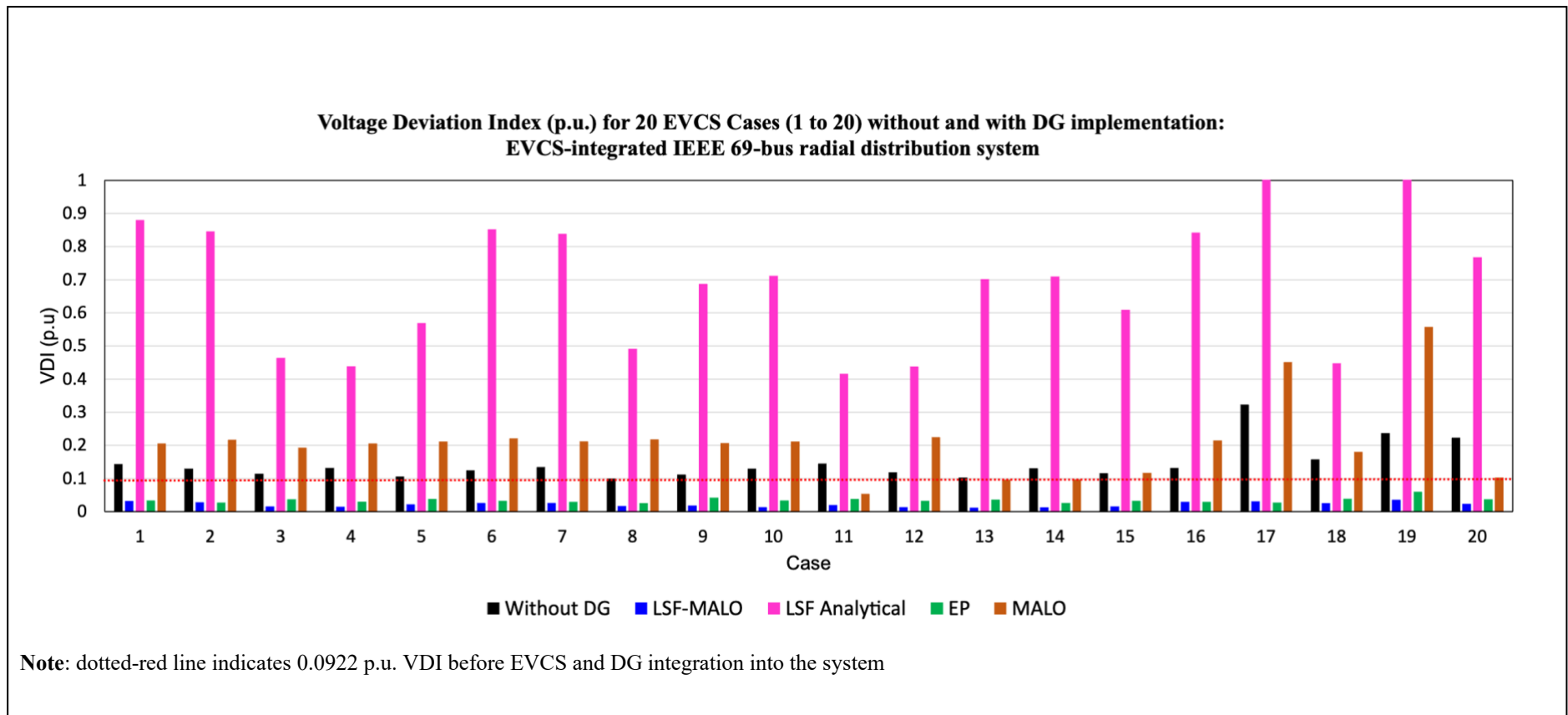


Figure 6. 13 Per-Unit Voltage Deviation Index (VDI) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 69-Bus System

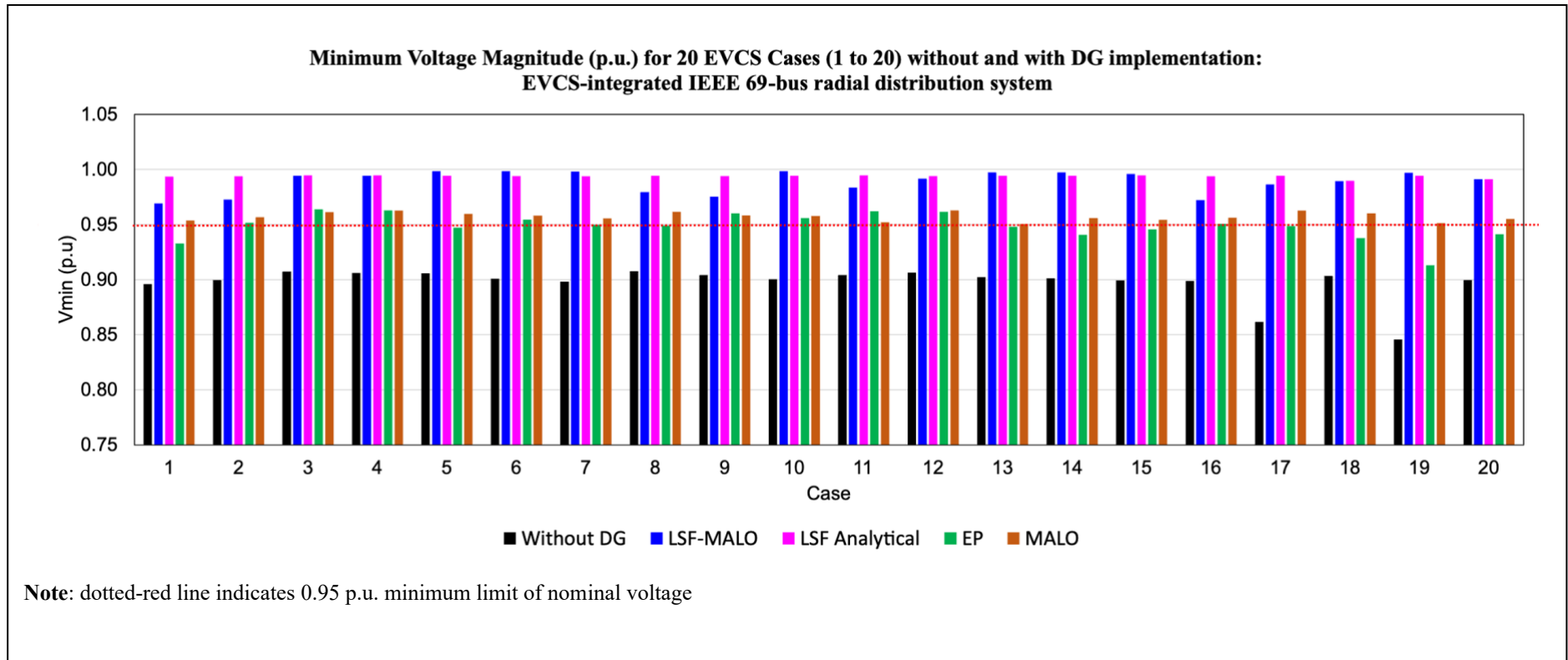


Figure 6. 14 Per-Unit Minimum Voltage Magnitude (V_{min}) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 69-Bus System

The system's ability to deliver power efficiently is indicated by the total real power losses (P_{loss}) shown in **Figure 6.15**. The dotted red line indicates 0.2178 MW of total power losses before the integration of EVCS and DG units into the system (no-EVCS condition). Clearly, EVCS integration increases losses compared to the no-EVCS condition. In the EVCS integration under pre-DG placement scenario (black bars), P_{loss} is slightly higher than the dotted red line in most cases and reaches nearly 0.60 MW in cases 17 and 19. After optimal DG placement using LSF-MALO (blue bars), losses drop noticeably, staying below 0.40 MW in most cases. In seven cases (8, 9, 10, 12, 13, 14, and 15), P_{loss} even falls below the no-EVCS benchmark, showing that LSF-MALO enables more efficient power distribution. It is the only method that achieves P_{loss} lower than the dotted red line, even if only in these seven cases. By contrast, the power losses reduced by EP (green bars) are still higher than that of the pre-DG placement scenario for about 13 cases. MALO (brown bars) performs worse, with P_{loss} consistently higher than the pre-DG condition across all 20 cases. The poorest result comes from the LSF Analytical method, where losses rise dramatically beyond 1 MW – far exceeding every other method.

The distribution system performance in terms of grid dependency is presented in **Figure 6.16**. The dotted red line indicates 3.6935 MW of net grid power before the integration of EVCS and DG units into the system (no-EVCS condition). Integration of EVCS before DG placement (black bars) clearly increases grid dependency, as the net grid power (P_{grid}) is higher than in the no-EVCS condition (dotted red line). This indicates that the grid must supply additional power not only for the existing loads but also to meet the EVCS charging demand. Grid dependency becomes particularly significant from case 17 to case 20, where P_{grid} rises to almost 10 MW. Among all methods, LSF Analytical (pink bars) yields the most grid-independent results, with P_{grid} values consistently negative and exceeding |15 MW|. This means the net power supplied by the installed DG units and any V2G-type EVs, after subtracting the total demand from existing loads and G2V-type EVs, exceeds 15 MW. However, such a large negative P_{grid} is not necessarily desirable, as it indicates overcompensation by the DG units, which – as discussed earlier – leads to excessively high power losses. The proposed LSF-MALO method (blue bars) delivers a well-balanced result, producing negative P_{grid} values in all cases, with magnitudes generally below |5 MW| except in case 17.

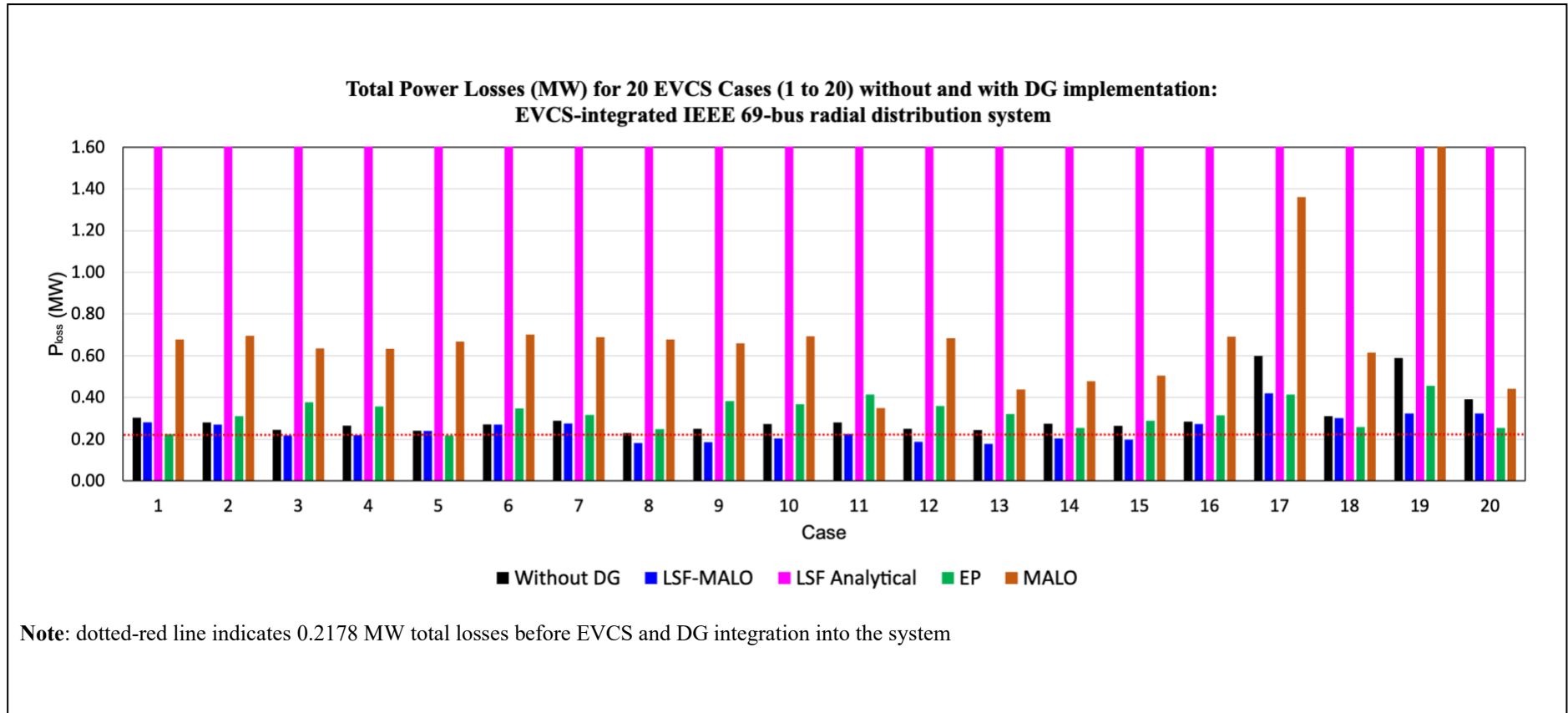


Figure 6. 15 Total Power Losses In Megawatts (P_{loss}) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 69-Bus System

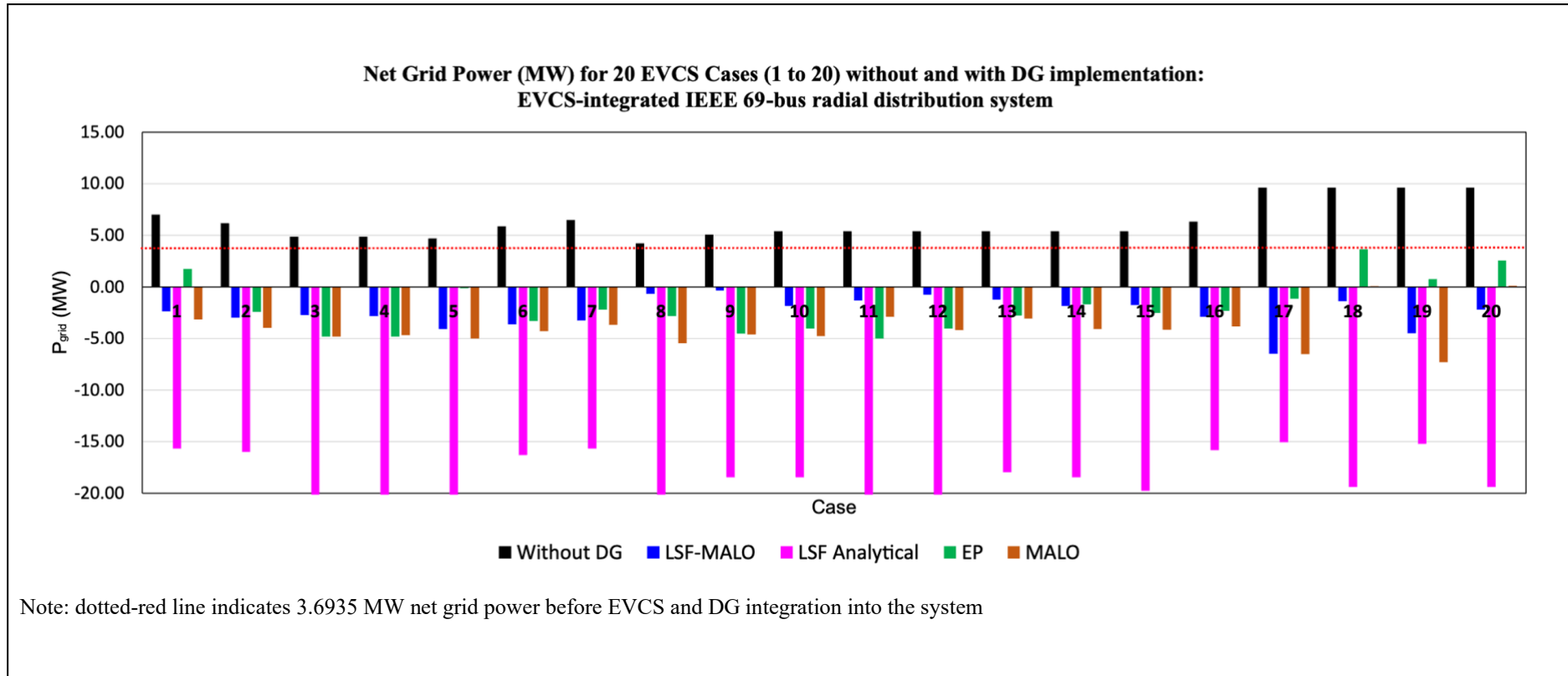


Figure 6. 16 Net Grid Power (P_{grid}) For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 69-Bus System

This indicates effective grid independence: the DG units supply sufficient power to meet the load without the excessive power losses observed in the LSF Analytical approach. The MALO method (brown bars) shows comparable performance, also achieving full grid independence by maintaining negative P_{grid} across all cases, signifying adequate DG power supply. The EP technique (green bars) achieves negative P_{grid} in 16 cases (except cases 1, 18, 19, and 20), reflecting only partial grid independence. These four exceptions show that the grid must still supply power despite multiple DG units being installed via EP.

The final aspect of the distribution system performance analysis is harmonic mitigation. The Total Harmonic Distortion (THD) for all 20 cases is shown in **Figure 6.17**, where the dotted red line marks the 5% maximum allowable THD. Integration of EVCS without DG placement (black bars) causes THD to rise sharply—exceeding 10% in 19 cases, except in case 8 where it is slightly higher than 5%. The proposed LSF-MALO (blue bars) and MALO (brown bars) demonstrates the best THD mitigation. For the first 16 cases, they successfully keep THD below 5%, showing that the installed DG units effectively suppress the harmonic impact of EVCS integration. In contrast, LSF Analytical (pink bars) and EP (green bars) cannot consistently maintain THD below 5% for the first 16 cases: some cases meet the limit, but many exceed it. This indicates that, although the two methods perform adequately in terms of voltage stability improvement, losses minimization and grid dependency reduction, their optimal DG placement is insufficient to ensure acceptable power quality. From cases 17 to 20, only LSF Analytical achieves an acceptable THD – case 19 remains below 5%. Next in rank is LSF-MALO, with THD peaking at 8% (case 18), followed by MALO at over 14% (case 18) and EP at well above 20% (case 17).

Across the 20 EVCS cases, voltage stability initially worsens after EVCS integration: VDI rises above the no-EVCS benchmark and V_{min} falls below 0.95 p.u., especially in cases 17 to 20. After optimal DG placement, LSF-MALO sharply improves voltage stability, reducing VDI to between 0.01 and 0.03 and keeping V_{min} between 0.95 and 1.0 p.u.; EP is close but shows undervoltage in six cases. MALO gives only moderate VDI improvement, while LSF Analytical has the poorest VDI yet keeps V_{min} near 1.0 p.u. EVCS integration also increases real power losses to nearly 0.60 MW in cases 17 and 19. LSF-MALO reduces losses below 0.40 MW in most cases and even beneath the 0.2178 MW no-EVCS benchmark in seven cases – better than EP, MALO and LSF Analytical, the last exceeding 1 MW. Grid dependency rises with EVCS, but

LSF Analytical yields to very large negative P_{grid} (over $|15 \text{ MW}|$), signalling oversupply and high losses. LSF-MALO achieves balanced grid independence with negative P_{grid} mostly below $|5 \text{ MW}|$, while MALO is similar and EP gives only partial independence. Harmonics worsen sharply without DGs – THD exceeds 10% in almost all cases. LSF-MALO and MALO keep THD under 5% in the first 16 cases, while EP and LSF Analytical cannot; from cases 17 to 20 only LSF Analytical stays within the limit once. Overall, LSF-MALO is the most acceptable method, delivering the best balance of voltage stability, low losses, grid independence and harmonic suppression.

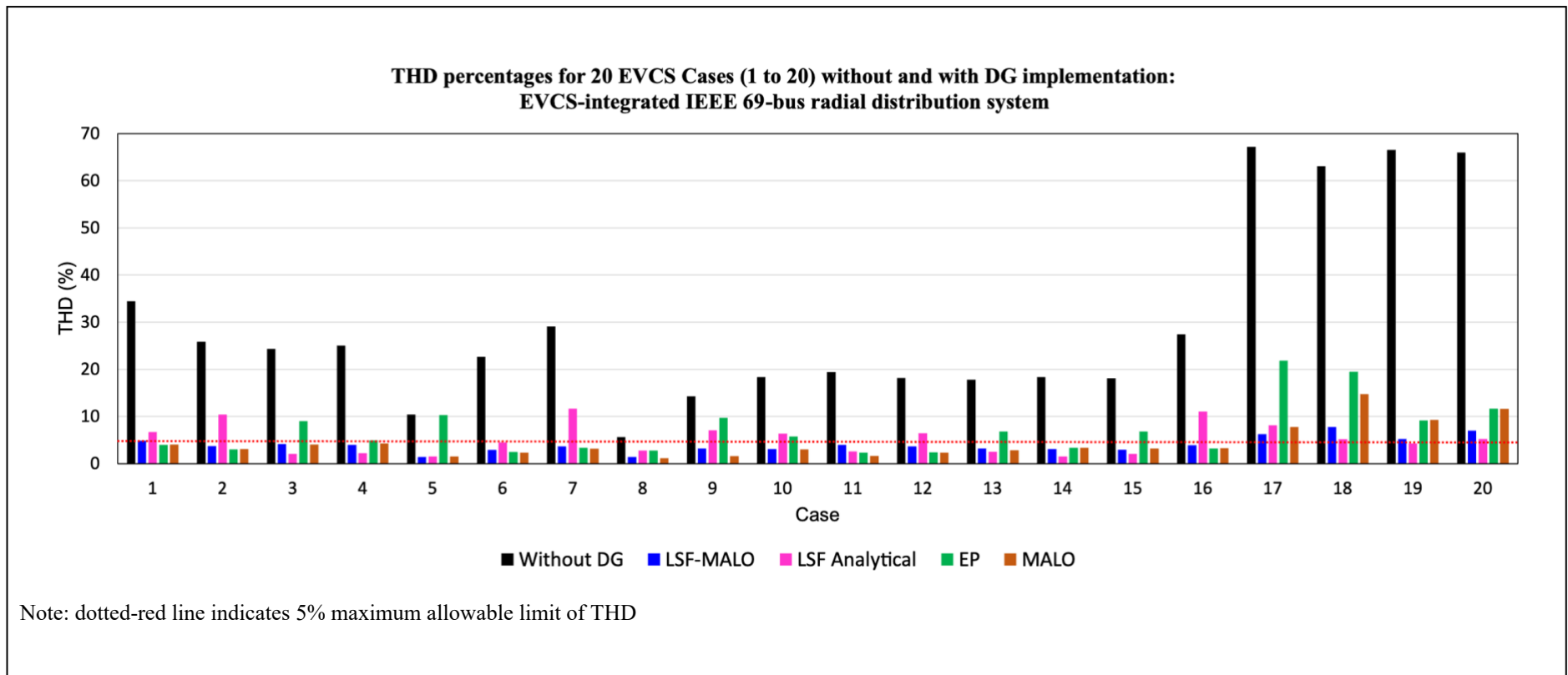


Figure 6. 17 THD Percentages For 20 EVCS Cases (1 To 20) Without And With DG Implementation – EVCS-Integrated IEEE 69-Bus System

6.3.4 Optimal DG Placement under Incremental Loading in EVCS-integrated IEEE 69-bus Radial Distribution System

This section evaluates the performance of multi-objective optimization (MOO) for optimal DG placement under incremental load growth in the EVCS-integrated IEEE 69-bus radial distribution system. Five loading levels, from 10% to 50%, are considered to reflect progressive demand increase. The aim is to assess how consistently each method solves the MOO problem and maintains good performance under rising loads. Five key indicators are used: Voltage Deviation Index (VDI) and minimum voltage magnitude (V_{min}) for voltage stability, real power losses (P_{loss}) for network efficiency, net grid power (P_{grid}) for grid dependency, and Total Harmonic Distortion (THD) for harmonic mitigation.

As shown in **Figure 6.18**, the pre-DG VDI (black line) rises slightly from the no-EVCS benchmark of 0.0922 p.u. (dotted red line), revealing slight voltage instability. LSF-MALO (blue line) and EP (green line) keep VDI consistently below the no-EVCS level across all loadings, with near-constant trends from 10% to 50%, indicating strong voltage stability. In contrast, MALO (brown line) and LSF Analytical (pink line) exhibit severe instability, with VDI fluctuating well above the no-EVCS benchmark: about 0.40 to 0.60 p.u. for MALO and 0.50 to 0.90 p.u. for LSF Analytical. **Figure 6.19** shows that, although the pre-DG VDI only slightly increases, V_{min} drops sharply to around 0.90 p.u. or lower. LSF-MALO, with its lowest VDI, maintains V_{min} between 0.95 p.u. and 1.00 p.u. across all loadings, demonstrating stable voltage profiles. LSF Analytical records the highest V_{min} (close to 1.00 p.u.) but fails to maintain low, steady VDI values. MALO barely achieves 0.95 p.u., while EP cannot consistently keep V_{min} at or above 0.95 p.u. across the incremental load levels.

Figure 6.20 shows the total real power losses (P_{loss}) across all loading levels. The pre-DG condition (black line), LSF-MALO (blue line), and EP (green line) remain close to the no-EVCS benchmark of 0.2178 MW (dotted red line), overlapping one another throughout the loading range. Although the loss reduction is modest – indicating only slight gains in network efficiency – LSF-MALO and EP successfully prevent losses from rising to excessive levels, unlike the other two methods. MALO (brown line) shows moderate fluctuation, with P_{loss} ranging from 1.0 MW to 1.5 MW, while LSF Analytical (pink line) exhibits large fluctuation, with P_{loss} between 2.5 MW and 4.0 MW, far above the benchmark. These results highlight the very poor network

efficiency by MALO and especially, by LSF Analytical.

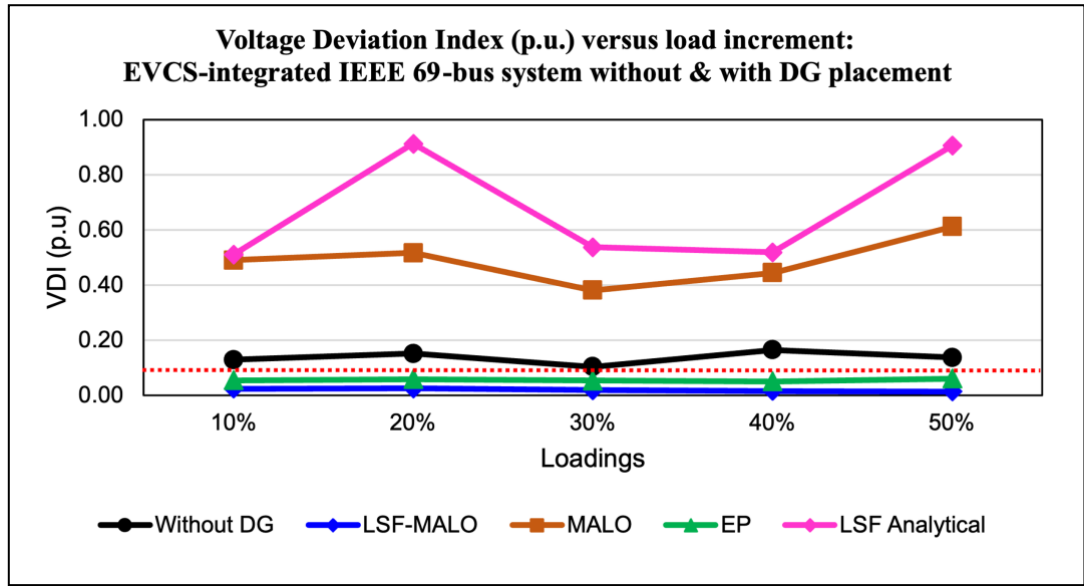


Figure 6. 18 Voltage Deviation Index (VDI) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 69-Bus Radial Distribution System

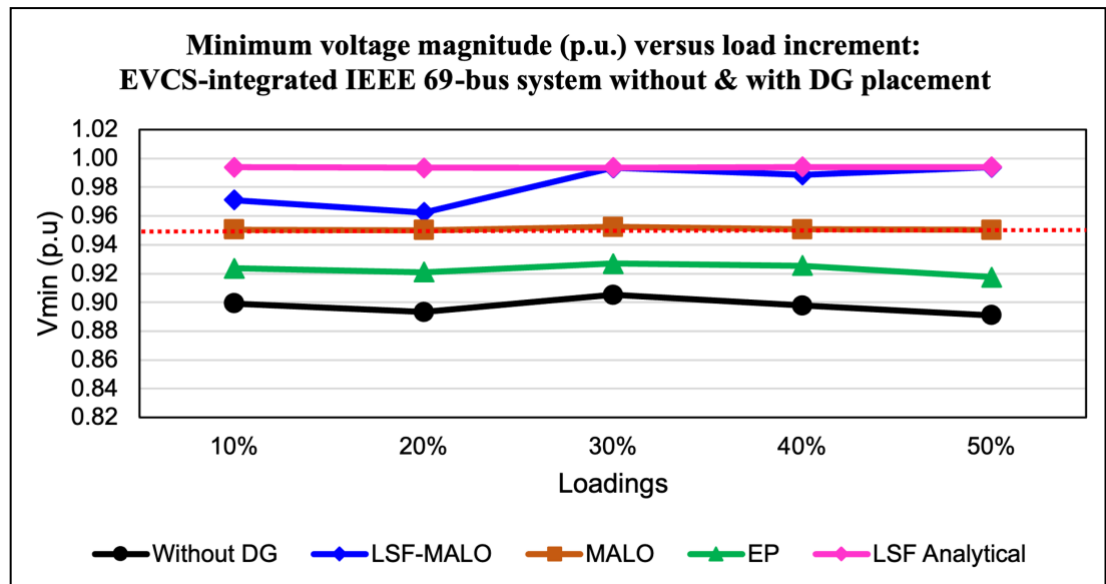


Figure 6. 19 Minimum Voltage Magnitude (V_{min}) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 69-Bus Radial Distribution System

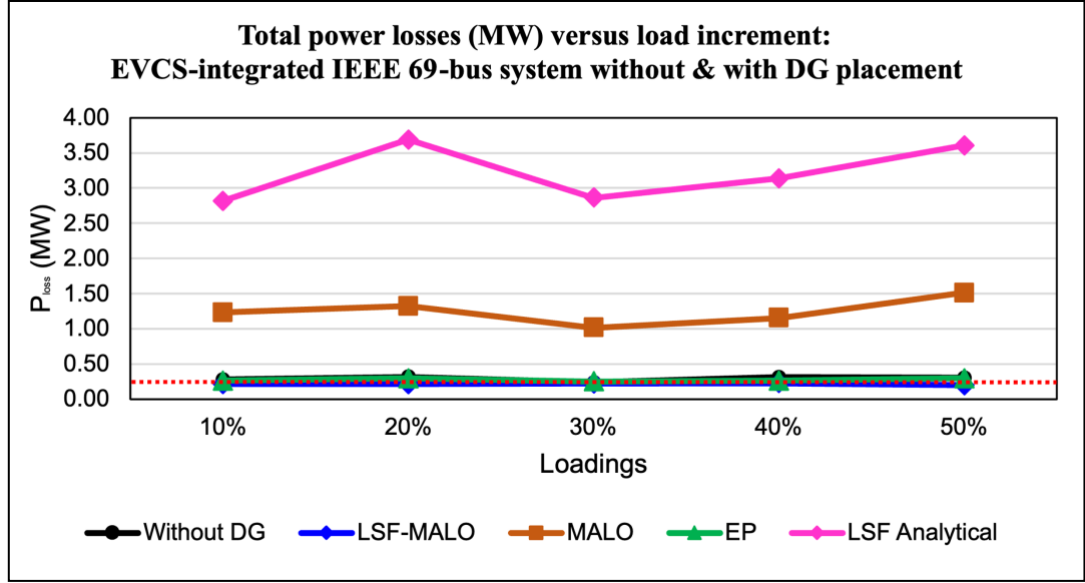


Figure 6. 20 Total Power Losses (P_{loss}) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 69-Bus Radial Distribution System

Figure 6.21 presents the grid dependency performance, showing net grid power (P_{grid}) across all loading levels. Adding EVCS before DG placement raises P_{grid} well above the no-EVCS benchmark of 3.6935 MW (dotted red line), with pre-DG values (black line) ranging from 5 MW to 7 MW – indicating strong reliance on the grid. Both LSF-MALO (blue line) and MALO (brown line) achieve full grid independence, maintaining negative P_{grid} values at every loading level and thus meeting the key goal of DG placement: supplying local loads rather than depending on the grid. By contrast, EP (green line) and LSF Analytical (pink line) only lower P_{grid} relative to the pre-DG scenario. Their P_{grid} remains positive, so they reduce but cannot eliminate grid dependency and therefore fall short of the primary objective of DG placement.

Lastly, the harmonic mitigation performance is presented in **Figure 6.22**, showing THD across all loading levels. In the pre-DG scenario (black line), THD rises dramatically between 15% and 30%, indicating severely degraded power quality after EVCS integration. In contrast, the LSF-MALO (blue line), MALO (brown line), and LSF Analytical (pink line) methods consistently maintain good power quality, keeping THD at or below 5% across all loading levels. EP (green line), however, shows inconsistent performance, with THD exceeding the 5% benchmark from 10% to 30% of the loading levels.

On overall, LSF-MALO and EP provide the best voltage stability, keeping VDI below the 0.0922 p.u. benchmark, though EP occasionally fails to maintain V_{min} at or above 0.95 p.u. LSF Analytical shows the highest V_{min} but suffers large VDI fluctuations, while MALO barely maintains 0.95 p.u. with unstable VDI. In terms of real power losses, LSF-MALO and EP stay close to the 0.2178 MW benchmark, whereas MALO fluctuates moderately (between 1 MW and 1.5 MW) and LSF Analytical performs worst (between 2.5 MW and 4 MW). For grid dependency, only LSF-MALO and MALO achieve full independence with negative P_{grid} , while EP and LSF Analytical merely reduce reliance. In harmonic mitigation, LSF-MALO, MALO and LSF Analytical maintain THD at or below 5%, but EP exceeds the limit at 10% to 30% loading. Considering all indicators, LSF-MALO stands out for its balanced strengths – stable voltage, low losses, full grid independence and strong harmonic control – making it the most promising method for optimal DG placement in the EVCS-integrated network.

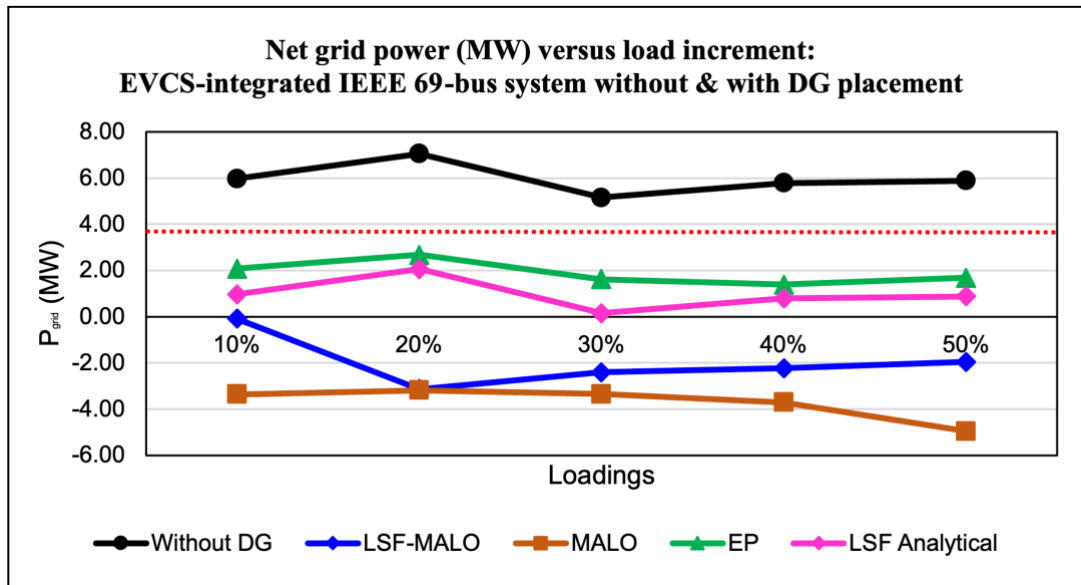


Figure 6. 21 Net Grid Power (P_{grid}) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 69-Bus Radial Distribution System

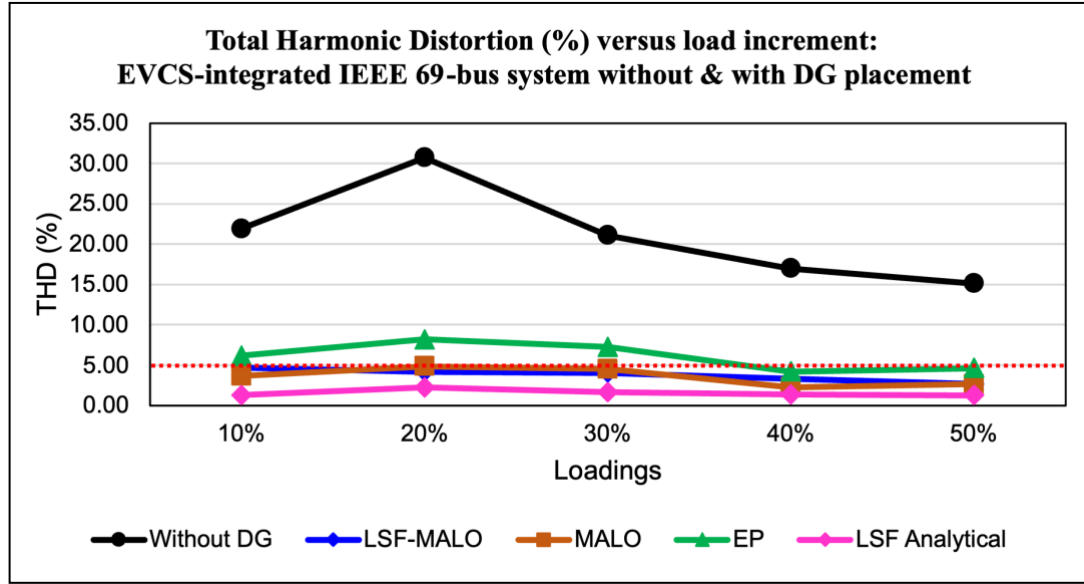


Figure 6. 22 Total Harmonic Distortion (THD) Under Incremental Loading Without And With DG Placement – EVCS-Integrated IEEE 69-Bus Radial Distribution System

6.4 Chapter Summary

The comparative evaluation of the two EVCS-integrated test systems – the IEEE 33-bus and 69-bus radial distribution networks – confirms the superiority of the proposed LSF-MALO method for optimal DG placement. In both networks, EVCS integration without DGs severely degraded performance, producing significant voltage instability (VDI often greater than 0.2 p.u.), undervoltage (V_{min} less than 0.95 p.u.), higher real power losses, increased grid dependency and excessive harmonic distortion. After DG installation, LSF-MALO consistently restored voltage stability, driving VDI close to zero and maintaining V_{min} within 0.95 to 1.0 p.u. while keeping losses below the pre-EVCS benchmarks or at least well under 0.4 MW. It was also the only technique to ensure full grid independence in both test systems without excessive overcompensation and to maintain good power quality by holding THD below 5% in most scenarios, even when load growth reached 50%. These results were achieved while respecting DG size limits and maintaining a globally optimal siting pattern that remained stable across the various EVCS cases.

Looking at the power loss reduction, specifically, the integrated LSF-MALO approach achieved a maximum power loss reduction of 35.34% for the IEEE 33-bus system and 55.53% for the IEEE 69-bus system across various EVCS scenarios, with

reduction capabilities remaining robust at up to 38.56% and 35.35%, respectively, even under maximum incremental loading conditions.

Other than that, when compared with the three benchmark techniques, the LSF-MALO approach offered the most balanced and robust performance across all key indicators. Evolutionary Programming (EP) occasionally matched LSF-MALO in voltage stability and achieved the lowest real power losses, but it suffered from undervoltage, inconsistent THD mitigation and partial grid independence. The plain MALO method (without LSF incorporation) showed acceptable VDI and V_{min} yet incurred higher losses than pre-DG conditions and failed to guarantee power quality. LSF Analytical achieved very high V_{min} and strong (but excessive) negative P_{grid} , which led to severe power losses and did not represent a practical operating point. On overall, this analysis highlights that LSF-MALO provides the best overall trade-off between voltage stability, network efficiency, controlled grid independence and harmonic suppression, demonstrating its suitability for real-world EVCS-integrated distribution networks.

In addition, the consistent superiority of this approach underscores the novelty of the proposed LSF-MALO framework, which integrates a specific mutation operator into the standard ALO and hybridizes the Loss Sensitivity Factor (LSF) as an initial filtering stage. By introducing this novel Gaussian-based mutation mechanism adapted from Evolutionary Programming, the algorithm effectively prevents premature convergence and expands search space exploration, while the LSF strategically filters candidate buses to significantly reduce the computational burden. This dual methodological novelty represents the primary contribution of this thesis, enabling the algorithm to handle the highly complex, multi-objective constraints of EVCS-integrated distribution networks more efficiently and effectively than conventional metaheuristic techniques.

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

7.1 Conclusion

This research addressed critical challenges in integrating Distributed Generation (DG) within the distribution system, both with and without Electric Vehicle Charging Station (EVCS), by developing a new hybrid optimization framework. The increasing penetration of DG and EVCS in the distribution system has introduced a more dynamic, decentralized and complex power network, which has led to the urge for more advanced optimization techniques and comprehensive performance assessment. Despite DG providing numerous benefits, such as reduced power loss, improved voltage stability and power quality, its deployment heavily depends on optimal placement and sizing strategies. In addition, the penetration of EVCS in the distribution system network has placed additional stress on grid performance due to unpredictable load variations, voltage instability, and harmonic distortion resulting from its non-linear nature.

To overcome these challenges, this research proposes a new Loss Sensitivity Factor-Mutated Ant Lion Optimizer (LSF-MALO), a hybrid optimization algorithm designed to combine the computational efficiency of LSF Analytical with the vast exploration capability of the metaheuristic approach of MALO algorithm. The LSF-MALO was initially formulated and validated for single-objective optimization (SOO) and later extended to multi-objective optimization (MOO) to incorporate technical, economic, and power quality considerations. The validation process for the proposed algorithm was conducted on two standard test systems, the IEEE 33-bus and IEEE 69-bus radial distribution networks, under diverse loading conditions and EVCS integration scenarios.

The first objective has been successfully achieved by developing the hybrid LSF-MALO, which combines analytical precision with metaheuristic exploration capabilities. Simulation results on both IEEE 33 and 69 buses have demonstrated that the proposed LSF-MALO can determine an adequate and suitable location for optimal DG placement, which reduces power loss while maintaining a stable voltage profile. The robustness of the LSF-MALO has also been verified by undergoing multiple reactive loading conditions. It has achieved robust results showing that the proposed

LSF-MALO can maintain a stable voltage profile and reduce power loss in the system's conditions. The comparative analysis has also demonstrated that the LSF-MALO provides a balanced result in reducing the power loss and maintaining the voltage profile compared to LSF Analytical, EP, and MALO techniques.

The second objective was addressed by extending the SOO framework into the MOO framework using the Weighted Sum Method (WSM). The proposed MOO framework has successfully incorporated technical and economic indicators, allowing a balanced optimization of voltage profile, loss reduction, and cost-related benefits. The combinational types of DG have demonstrated that combining solar PV with other DG units significantly helps provide a balanced improvement in both the technical and economic aspects of the distribution system network. In addition, the outcomes have also demonstrated the importance of properly determining the weight of the WSM method to ensure the optimal solution can be achieved.

The third objective was realized through a systematic assessment methodology applied to IEEE 33-bus and 69-bus systems. The findings from this assessment revealed that EVCS penetration in the distribution system network has significant impacts on system performance. This can be observed with varying severity, depending on charging scenarios, penetration levels and placement. By incorporating the Voltage Deviation Index (VDI), power loss, power grid and Total Harmonic Distortion (THD) as evaluation metrics, the assessment has provided a holistic perspective on technical challenges posed by the penetration of EVCS.

The fourth objective was successfully achieved, as the simulation results confirmed that the optimal and strategic placement of DG using the proposed LSF-MALO effectively mitigates the adverse impacts of EVCS integration. The technique has improved the VDI, reduced power losses, decreased reliance on the main grid and minimized harmonic distortion levels. Achieving balanced trade-offs across these indicators, the proposed LSF-MALO demonstrated its robustness and reliability as an optimization tool for improving the technical and power quality performance in EVCS-integrated distribution networks.

In conclusion, all four objectives were successfully achieved. This research has established the proposed LSF-MALO as a powerful and robust hybrid optimization tool, and has also provided a comprehensive framework for addressing challenges in DG placement and EVCS integration within the distribution systems. In addition, this

research offers important insights for planning and operating the distribution system, particularly with the growing integration of EVCS and renewable energy.

7.2 Research contribution

This research contributes to knowledge and practice in ways that align directly with its four objectives:

- i) A new hybrid optimization technique known as Loss Sensitivity Factor – Mutated Ant Lion Optimizer has been developed and applied to address the limitations of existing analytical and metaheuristic approaches in optimal DG placement by providing a more accurate and robust approach in loss reduction and voltage profile improvement.
- ii) A new multi-objective framework has been formulated to account for both technical and economic indicators, including voltage stability, power loss minimization, annual economic loss, and cost saving. This enables utilities and planners to achieve balance trade-offs between technical efficiency and cost-effectiveness.
- iii) A structured, systematic assessment methodology was established to evaluate the impact of EVCS integration on distribution systems. The performance metrics, including power loss, Voltage Deviation Index (VDI), grid dependency, and Total Harmonic Distortion (THD), serve as key performance indicators in this assessment, providing a holistic analysis of how different EVCS charging scenarios and penetration levels impact distribution system performance.
- iv) A new multi-objective framework addressing power loss, Voltage Deviation Index (VDI), grid dependency and Total Harmonic Distortion (THD) as key performance metrics has been formulated to mitigate the adverse effect while improving the overall system performance. The proposed multi-objective framework, focusing on EVCS-integrated system illustrates the practical capability of the LSF-MALO to support voltage stability, network efficiency, grid independence and power quality objectives simultaneously, thereby providing a valuable tool for modern distribution system planning.

7.3 Recommendations

This thesis has demonstrated the effectiveness of the proposed technique through a range of case studies, covering technical, economic and power quality aspects of distribution system planning. While the findings confirm the robustness of the approach, there remain opportunities to broaden its scope and applicability. To further strengthen and extend this research, several directions for future work are suggested as follows:

- i) The growing role of energy storage systems (ESS) and smart grid technologies offers new opportunities for distribution systems. Future research could extend the application of the LSF-MALO framework to simultaneously optimize DG, EVCS and ESS placement.
- ii) The EVCS modelling in this research was based on predefined charging scenarios. Future work should incorporate stochastic modelling of charging patterns and demand uncertainty. This would provide a more practical representation of EVCS impacts, allowing for more effective planning and control strategies.
- iii) While this research utilized IEEE 33-bus and 69-bus benchmark systems, future research should validate the proposed LSF-MALO framework on real distribution networks with practical operating constraints, diverse load profiles, and renewable generation variability. Such validation would confirm the scalability and industry applicability of the method under realistic conditions.
- iv) Future research could integrate predictive and forecasting techniques to foresee renewable generation variability, EVCS demand pattern and load behaviour. The combination of predictive analytics with the LSF-MALO optimization framework would improve its adaptability to uncertainty and support more proactive planning of distribution systems.

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APPENDICES

APPENDIX 1

IEEE 33-BUS RADIAL DISTRIBUTION SYSTEM

basemva = 100; accuracy = 0.0001; maxiter = 100;
 Bus code: 0 = load bus; 1 = slack bus; 2 = generator bus

busdata=[	Bus	Code	Voltage	Angle	----Load----		-----Generator-----				Injected
					MW	Mvar	MW	Mvar	Qmin	Qmax	Mvar
	1	1	1	0	0	0	0	0	0	0	0
	2	0	1	0	0.1	0.06	0	0	0	0	0
	3	0	1	0	0.09	0.04	0	0	0	0	0
	4	0	1	0	0.12	0.08	0	0	0	0	0
	5	0	1	0	0.06	0.03	0	0	0	0	0
	6	0	1	0	0.06	0.02	0	0	0	0	0
	7	0	1	0	0.2	0.1	0	0	0	0	0
	8	0	1	0	0.2	0.1	0	0	0	0	0
	9	0	1	0	0.06	0.02	0	0	0	0	0
	10	0	1	0	0.06	0.02	0	0	0	0	0
	11	0	1	0	0.045	0.03	0	0	0	0	0
	12	0	1	0	0.06	0.035	0	0	0	0	0
	13	0	1	0	0.06	0.035	0	0	0	0	0
	14	0	1	0	0.12	0.08	0	0	0	0	0
	15	0	1	0	0.06	0.01	0	0	0	0	0
	16	0	1	0	0.06	0.02	0	0	0	0	0
	17	0	1	0	0.06	0.02	0	0	0	0	0
	18	0	1	0	0.09	0.04	0	0	0	0	0
	19	0	1	0	0.09	0.04	0	0	0	0	0
	20	0	1	0	0.09	0.04	0	0	0	0	0
	21	0	1	0	0.09	0.04	0	0	0	0	0
	22	0	1	0	0.09	0.04	0	0	0	0	0
	23	0	1	0	0.09	0.05	0	0	0	0	0
	24	0	1	0	0.42	0.2	0	0	0	0	0
	25	0	1	0	0.42	0.2	0	0	0	0	0
	26	0	1	0	0.06	0.025	0	0	0	0	0
	27	0	1	0	0.06	0.025	0	0	0	0	0
	28	0	1	0	0.06	0.02	0	0	0	0	0
	29	0	1	0	0.12	0.07	0	0	0	0	0
	30	0	1	0	0.2	0.6	0	0	0	0	0
	31	0	1	0	0.15	0.07	0	0	0	0	0
	32	0	1	0	0.21	0.1	0	0	0	0	0
	33	0	1	0	0.06	0.04	0	0	0	0	0

]

	From bus	to bus	R (p.u)	X (p.u)	1/2B (p.u)	tr-tap (p.u)
linedata=[	1	2	0.057525912	0.029324489	0.000351684	1
	2	3	0.307595167	0.15666764	0.000065739	1
	3	4	0.228356656	0.116299674	0.000088545	1
	4	5	0.237777928	0.121103899	0.000085040	1
	5	6	0.510994811	0.441115179	0.000048400	1
	6	7	0.116798814	0.386084969	0.000118647	1
	7	8	0.44386045	0.146684835	0.000033562	1
	8	9	0.642643047	0.461704714	0.000036868	1
	9	10	0.651378001	0.461704714	0.000036214	1
	10	11	0.122663712	0.040555144	0.000121487	1
	11	12	0.233597628	0.080985502	0.000066244	1
	12	13	0.915922324	0.720633708	0.000026528	1
	13	14	0.337917936	0.444796338	0.000071274	1
	14	15	0.368739846	0.328184702	0.000067341	1
	15	16	0.465635443	0.340039282	0.000051142	1
	16	17	0.804239697	1.073775422	0.000029830	1
	17	18	0.456713311	0.358133116	0.000053160	1
	2	19	0.102323747	0.097644308	0.000244055	1
	19	20	0.938508419	0.845668336	0.000026494	1
	20	21	0.255497406	0.298485858	0.000096677	1
	21	22	0.442300637	0.584805173	0.000054388	1
	3	23	0.28151509	0.192356167	0.000082733	1
	23	24	0.560284909	0.442425422	0.000043404	1
	24	25	0.559037059	0.43743402	0.000043407	1
	6	26	0.126656834	0.064513875	0.000159656	1
	26	27	0.177319567	0.090281989	0.000114012	1
	27	28	0.660736881	0.582559042	0.000037539	1
	28	29	0.501760717	0.437122057	0.000049354	1
	29	30	0.316642084	0.161284687	0.000063862	1
	30	31	0.607952801	0.600840053	0.000041119	1
	31	32	0.193728802	0.225798562	0.000127547	1
	32	33	0.212758523	0.330805188	0.000106919	1

]

APPENDIX 2

IEEE 69-BUS RADIAL DISTRIBUTION SYSTEM

basemva = 100; accuracy = 0.0001; maxiter = 100;

Bus code: 0 = load bus; 1 = slack bus; 2 = generator bus

Busdata =

Bus	Code	Voltage	Angle	----Load----		-----Generator-----				Injected
				MW	Mvar	MW	Mvar	Qmin	Qmax	
1	1	1	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	0	0	0
4	0	1	0	0	0	0	0	0	0	0
5	0	1	0	0	0	0	0	0	0	0
6	0	1	0	0.0026	0.0022	0	0	0	0	0
7	0	1	0	0.0404	0.03	0	0	0	0	0
8	0	1	0	0.075	0.054	0	0	0	0	0
9	0	1	0	0.03	0.022	0	0	0	0	0
10	0	1	0	0.028	0.019	0	0	0	0	0
11	0	1	0	0.145	0.104	0	0	0	0	0
12	0	1	0	0.145	0.104	0	0	0	0	0
13	0	1	0	0.008	0.0055	0	0	0	0	0
14	0	1	0	0.008	0.0055	0	0	0	0	0
15	0	1	0	0	0	0	0	0	0	0
16	0	1	0	0.0455	0.03	0	0	0	0	0
17	0	1	0	0.006	0.035	0	0	0	0	0
18	0	1	0	0.006	0.035	0	0	0	0	0
19	0	1	0	0	0	0	0	0	0	0
20	0	1	0	0.001	0.0006	0	0	0	0	0
21	0	1	0	0.114	0.081	0	0	0	0	0
22	0	1	0	0.0053	0.0035	0	0	0	0	0
23	0	1	0	0	0	0	0	0	0	0
24	0	1	0	0.028	0.02	0	0	0	0	0
25	0	1	0	0	0	0	0	0	0	0
26	0	1	0	0.014	0.01	0	0	0	0	0
27	0	1	0	0.014	0.01	0	0	0	0	0
28	0	1	0	0.026	0.0186	0	0	0	0	0
29	0	1	0	0.026	0.0186	0	0	0	0	0
30	0	1	0	0	0	0	0	0	0	0
31	0	1	0	0	0	0	0	0	0	0
32	0	1	0	0	0	0	0	0	0	0
33	0	1	0	0.014	0.01	0	0	0	0	0
34	0	1	0	0.0195	0.014	0	0	0	0	0
35	0	1	0	0.006	0.004	0	0	0	0	0
36	0	1	0	0.026	0.0185	0	0	0	0	0

37	0	1	0	0.026	0.0185 5	0	0	0	0	0
38	0	1	0	0	0	0	0	0	0	0
39	0	1	0	0.024	0.017	0	0	0	0	0
40	0	1	0	0.024	0.017	0	0	0	0	0
41	0	1	0	0.0012	0.001	0	0	0	0	0
42	0	1	0	0	0	0	0	0	0	0
43	0	1	0	0.006	0.0043	0	0	0	0	0
44	0	1	0	0	0	0	0	0	0	0
45	0	1	0	0.0392 2	0.0263	0	0	0	0	0
46	0	1	0	0.0392 2	0.0263	0	0	0	0	0
47	0	1	0	0	0	0	0	0	0	0
48	0	1	0	0.079	0.0564	0	0	0	0	0
49	0	1	0	0.3847	0.2745	0	0	0	0	0
50	0	1	0	0.384	0.2745	0	0	0	0	0
51	0	1	0	0.0405	0.0283	0	0	0	0	0
52	0	1	0	0.0036	0.0027	0	0	0	0	0
53	0	1	0	0.0043 5	0.0035	0	0	0	0	0
54	0	1	0	0.0264	0.019	0	0	0	0	0
55	0	1	0	0.024	0.0172	0	0	0	0	0
56	0	1	0	0	0	0	0	0	0	0
57	0	1	0	0	0	0	0	0	0	0
58	0	1	0	0	0	0	0	0	0	0
59	0	1	0	0.1	0.072	0	0	0	0	0
60	0	1	0	0	0	0	0	0	0	0
61	0	1	0	1.244	0.888	0	0	0	0	0
62	0	1	0	0.032	0.023	0	0	0	0	0
63	0	1	0	0	0	0	0	0	0	0
64	0	1	0	0.227	0.162	0	0	0	0	0
65	0	1	0	0.059	0.042	0	0	0	0	0
66	0	1	0	0.018	0.013	0	0	0	0	0
67	0	1	0	0.018	0.013	0	0	0	0	0
68	0	1	0	0.028	0.02	0	0	0	0	0
69	0	1	0	0.028	0.02	0	0	0	0	0

]

	From bus	to bus	R (p.u)	X (p.u)	1/2B (p.u)	tr-tap (p.u)
linedata=	1	2	0.000311963	0.00074871	0	1
	2	3	0.000311963	0.00074871	0	1
	3	4	0.000935888	0.002246131	0	1
	4	5	0.015660525	0.018343403	0	1
	5	6	0.228356656	0.116299674	0	1
	6	7	0.237777928	0.121103899	0	1
	7	8	0.057525912	0.029324489	0	1
	8	9	0.030759517	0.015660525	0	1
	9	10	0.510994811	0.168896576	0	1
	10	11	0.116798814	0.043113237	0	1
	11	12	0.44386045	0.146684835	0	1
	12	13	0.642643047	0.212134598	0	1
	13	14	0.651378001	0.215254225	0	1
	14	15	0.660112955	0.218124281	0	1
	15	16	0.122663712	0.040555144	0	1
	16	17	0.233597628	0.077241951	0	1
	17	18	0.002932449	0.00099828	0	1
	18	19	0.204397925	0.067571109	0	1
	19	20	0.131398666	0.043050845	0	1
	20	21	0.213132879	0.070441165	0	1
	21	22	0.008734954	0.002870056	0	1
	22	23	0.099266513	0.03281847	0	1
	23	24	0.216065327	0.071439446	0	1
	24	25	0.467195256	0.171267492	0	1
	25	26	0.192730522	0.063702772	0	1
	26	27	0.10806386	0.035688527	0	1
	3	28	0.002745271	0.006738393	0	1
	28	29	0.039931218	0.097644308	0	1
	29	30	0.24819748	0.082046175	0	1
	30	31	0.043799555	0.014475067	0	1
	31	32	0.218997776	0.072375333	0	1
	32	33	0.523473317	0.175697361	0	1
	33	34	1.065664393	0.352268218	0	1
	34	35	0.919665876	0.291560287	0	1
	3	36	0.002745271	0.006738393	0	1
	36	37	0.039931218	0.097644308	0	1
	37	38	0.065699333	0.076742811	0	1
	38	39	0.018967329	0.022149348	0	1
	39	40	0.001123066	0.001310243	0	1
	40	41	0.454404788	0.530898028	0	1
	41	42	0.193416839	0.226048132	0	1
	42	43	0.025580937	0.029823629	0	1
	43	44	0.005740113	0.007237533	0	1
	44	45	0.067945464	0.085664942	0	1
	45	46	0.000561533	0.00074871	0	1
	4	47	0.002121346	0.005240972	0	1

47	48	0.053096042	0.129963638	0	1
48	49	0.180813549	0.442425422	0	1
49	50	0.051286659	0.125471376	0	1
8	51	0.057900267	0.029511666	0	1
51	52	0.207080803	0.069505277	0	1
9	53	0.108563	0.055279781	0	1
53	54	0.126656834	0.064513875	0	1
54	55	0.177319567	0.090281989	0	1
55	56	0.175510184	0.089408494	0	1
56	57	0.992041209	0.332988927	0	1
57	58	0.488970249	0.164092351	0	1
58	59	0.189798073	0.062766884	0	1
59	60	0.240897554	0.073124044	0	1
60	61	0.316642084	0.161284687	0	1
61	62	0.060770323	0.030946694	0	1
62	63	0.090469167	0.046045686	0	1
63	64	0.443298918	0.225798562	0	1
64	65	0.649506226	0.330805188	0	1
11	66	0.125533768	0.038121835	0	1
66	67	0.002932449	0.000873495	0	1
12	68	0.461330358	0.152487341	0	1
68	69	0.002932449	0.00099828	0	1

]

AUTHOR'S PROFILE



Nur Atiqah binti Abdul Rahman is a lecturer in Electrical Engineering with research interests in power systems and optimization techniques. She obtained her Bachelor of Engineering (Hons.) in Electrical Engineering from Universiti Teknologi MARA (UiTM) Shah Alam in 2011, followed by a Master of Science in Electrical Engineering from the same institution in 2014. She is currently serving as a lecturer at Universiti Teknologi MARA, Sarawak Branch, Samarahan Campus, where she actively contributes to teaching, research and academic development. Her expertise and commitment to the field have enabled her contributes in advancing the knowledge and skills of her students, while also pursuing impactful research in the areas of power system optimization.

LIST OF PUBLICATION:

- [1] N. A. A. Rahman, Z. A. Hamid, I. Musirin, N. A. Salim, and M. F. M. Yusoff, "Comparative studies between ant lion optimizer and evolutionary programming in optimal distributed generation placement," *International Journal of Advanced Technology and Engineering Exploration*, vol. 8, no. 75, pp. 236–246, 2021, doi: 10.19101/IJATEE.2020.762124.
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