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Efficient BESS Scheduling in AC Microgrids via Multiverse Optimizer: A Grid-Dependent and Self-Powered Strategy to Minimize Power Losses and CO₂ Footprint

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Abstract: This paper presents a novel energy management system for AC microgrids that integrates a parallel implementation of the Multi-Verse Optimizer (MVO) with the Successive Approximations method for power flow analysis. The proposed approach optimally schedules battery energy storage systems (BESSs) in both grid-connected and islanded modes, aiming to minimize energy losses and reduce CO₂ emissions. Numerical evaluations on a 33-node AC microgrid demonstrate significant improvements: in the grid-dependent mode, energy losses drop from 2484.57 kWh (base case) to 2374.85 kWh, and emissions fall from 9.8874 Ton(CO₂) to 9.8693 Ton(CO₂). Under the self-powered configuration, energy losses and emissions are curtailed from 2484.57 kWh to 2373.53 kWh and from 16.0659 Ton(CO₂) to 16.0364 Ton(CO₂), respectively. The results highlight that the proposed method outperforms existing metaheuristics in solution quality and consistency. This work advances microgrid scheduling by ensuring technical feasibility, reducing carbon footprint, and maintaining voltage stability under diverse operational conditions.

Keywords: AC microgrids; multi-verse optimizer (MVO); battery energy storage; CO₂ emissions minimization; energy loss reduction; dual-mode operation; power flow analysis



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1. Introduction

Alternating current (AC) microgrid (MG) systems have emerged as a fundamental paradigm in modernizing electrical infrastructures, particularly in addressing the challenges of integrating distributed generation and meeting operational flexibility requirements [1]. In the current energy transition context, these systems offer a technically and economically viable solution for managing the increasing penetration of fluctuating renewable sources while ensuring power supply quality and reliability [2].

A key enabler of modern MGs is the technological evolution of battery energy storage systems (BESSs). According to recent data from the U.S. Department of Energy (2023), the global installed capacity of BESSs has surpassed 206 GW [3], reflecting their rapid deployment across diverse geographical and operational contexts. This growth is primarily attributed to their capacity to provide critical ancillary services such as generation-demand balancing, frequency regulation, and power quality enhancement [4].

In parallel, the optimal energy management of MGs, especially regarding the coordination of distributed energy resources (DERs), has been a central theme in the

specialized literature [5,6]. Among the various approaches, metaheuristic techniques have gained prominence for their effectiveness in addressing the nonlinearities and high dimensionality inherent to these problems [7]. However, recent studies have highlighted persistent limitations in current control schemes, particularly in the comprehensive integration of BESSs within energy management systems (EMSs) [8,9].

Addressing these gaps, recent research in DER optimization has increasingly focused on minimizing technical losses in distribution and transformation stages and operation costs [10], as well as reducing CO₂ emissions associated with energy generation and DER operation. Metaheuristic approaches such as Particle Swarm Optimization (PSO), Vortex Search Algorithm (VSA), Chu & Beasley Genetic Algorithm (CBGA), Ant Lion Optimization (ALO), and JAYA have shown promising results in EMS applications for AC MGs [11,12]. These methods enable the optimal dispatch of distributed generators, reducing energy losses and emissions while complying with operational constraints in both grid-dependent and self-powered modes. Nevertheless, EMS strategies that focus solely on generation control without effectively coordinating energy storage often lead to wasted surplus energy [4]. Storing this excess for later use during peak demand can significantly enhance MG efficiency, reduce losses, and improve system performance [13].

In this context, several studies have proposed BESS-centric EMS strategies aimed at both reducing CO₂ emissions and mitigating energy losses. For instance, ref. [14] introduces the Opposition-Based Learning Grey Wolf Optimizer (GWO) for managing hybrid renewable-conventional MGs, focusing on minimizing grid carbon footprint and transmission losses. This method outperformed alternatives, such as PSO, CSA, GWO, and GGWO, in convergence speed and efficiency. However, its scope was limited to grid-dependent mode, leaving a critical gap in addressing standalone operation, an increasingly relevant scenario in real-world applications.

Similarly, in [15], the authors proposed an optimization approach to determine the optimal placement and sizing of BESSs in distribution networks. The goal was to reduce reverse power flow from high DG penetration and manage peak shaving during high-demand periods. GA, PSO, and the Salp Swarm Algorithm (SSA) were used for optimization. Tests on 33- and 69-bus systems showed PSO and SSA performed best. However, battery dispatch was approximated using the Fourier series, which may not yield truly optimal BESS configurations.

Complementing these efforts, in [16], the optimal power dispatch problem is addressed using the Monte Carlo method. The study formulates a multi-objective nonlinear optimization problem to minimize active power losses and improve voltage deviations, considering operational constraints such as line capacity, voltage limits, generator capacities, and transformer tap settings. The approach is tested on 30- and 118-bus systems, showing better solution quality compared to GA and PSO. Although statistical analysis is provided, convergence times are not discussed, limiting insights into the computational load.

In line with this perspective, recent studies have developed EMS strategies for the optimal operation of BESSs in AC MGs, with an increasing focus on reducing energy losses and CO₂ emissions [17]. These works apply diverse methodologies—such as convex optimization, metaheuristics, and linear programming—to enhance the environmental performance of MGs [18–20]. Metaheuristic techniques, in particular, have been recognized for their simplicity, robustness, and effectiveness, enabling practical EMS implementations with lower system complexity. Building on these advantages, this study adopts metaheuristic optimization as the core approach to maximize the contribution of BESSs while minimizing technical losses and environmental impact.

The work reported in [21] provides a performance comparison between the proposed adapted version of the PSO method and classical optimization techniques, such as GA. It

reports key indicators such as the best result, average performance, and computation time, offering a solid foundation for evaluating optimization quality and efficiency. However, the analysis does not include the standard deviation of the results, which is a critical metric to assess the variability and repeatability of the solutions. Including this statistical measure would enhance the reliability of the findings and support broader validation of the algorithm's consistency across multiple runs. In [22], a comprehensive and well-structured methodology for the optimal integration and operation of BESSs in grid-connected AC distribution networks was presented, demonstrating strong performance in reducing both energy losses and CO₂ emissions. The authors correctly include statistical metrics such as the best, average, and standard deviation of the results, ensuring transparency and repeatability in the evaluation. The operation of batteries is effectively optimized through a PSO-based strategy that responds to hourly variations in load and PV generation. However, the main limitation of the study lies in its exclusive focus on the grid-connected (On-Grid) mode. The methodology does not analyze the behavior of the microgrid under isolated (Off-Grid) conditions, which is essential for realistic energy management in microgrids that frequently switch between operational states. As a result, the proposed approach, while solid, is only applicable to active distribution networks and does not fully capture the operational versatility required in modern microgrids.

In [23], the authors propose a two-stage energy management system (EMS) for a grid-connected photovoltaic (PV) charging station integrated with a battery energy storage system (BESS). The first stage performs a day-ahead optimization to minimize CO₂ emissions and electricity costs, while the second stage uses model predictive control (MPC) to manage real-time uncertainties in PV generation and electric vehicle (EV) connections. The proposed method demonstrates clear benefits, including a 36% reduction in emissions and a 33% decrease in energy costs compared to a conventional EMS. However, the study presents several limitations. First, it lacks a statistical analysis of solution variability, such as standard deviation, which is crucial for validating the repeatability of the proposed approach. Second, the evaluation is limited to a simplified mononodal network, whereas real-world distribution systems are multi-nodal and subject to power flow constraints. The study also omits the analysis of voltage and current limitations in the lines, which are essential for ensuring reliable and secure operation. Moreover, the EMS is only assessed in grid-connected mode, ignoring the traditional dual-mode nature of microgrids, which can operate both in on-grid and islanded (off-grid) modes. This restricts the practical applicability of the proposed method to more complex and realistic microgrid scenarios.

In the specialized literature, multiple tools based on exact methods and commercial software have been proposed to address the problem of energy management in battery systems [24–26]; however, these solutions often rely on specialized software, such as GAMS, which requires costly licenses and presents restrictions that hinder their practical implementation in environments where flexibility, replicability, and low cost are essential [27]. Moreover, deterministic methods or those based on specialized software tend to fall into local optima as the solution space grows or becomes more complex, limiting their ability to solve nonlinear and high-dimensional problems typical in modern electrical networks. In contrast, sequential programming methods, such as metaheuristic techniques, offer more robust and adaptable algorithms that maintain strong exploratory performance across complex solution spaces. These algorithms can be implemented in widely used engineering languages like MATLAB, facilitating their adaptation, integration with other analysis tools, and application by electric utilities, academic institutions, and research centers. For all these reasons, this research was based on sequential programming software, specifically on metaheuristic optimization techniques, which, according to the state of the

art, constitute a well-established and widely studied approach for energy management in electrical networks.

In response to the growing need for advanced energy management systems that can optimize BESS operation in AC MGs while aiming to address the specific limitations identified in the current state-of-the-art literature, this work introduces an innovative EMS designed to minimize both energy losses and CO₂ emissions through intelligent battery storage optimization. Unlike previous approaches that often neglect statistical robustness, grid constraints, or dual-mode operation, the proposed solution integrates a comprehensive optimization strategy that considers technical and environmental requirements. At its core lies the Multi-Verse Optimizer (MVO), a powerful metaheuristic algorithm particularly well-suited to handle the multi-objective and nonlinear nature of EMS problems [28], enabling effective navigation of trade-offs between system efficiency and sustainability in real-world MG scenarios.

This study develops a comprehensive framework where MVO determines optimal battery charge/discharge cycles while accounting for power flow dynamics through Successive Approximation. What sets this approach apart is its dual focus, not just on traditional operational metrics but specifically on reducing both energy waste and carbon footprint. The methodology undergoes rigorous tuning to ensure peak performance, with comparative analysis against vortex search and genetic algorithms conducted under identical conditions for fair evaluation.

Validation occurs on a realistic 33-node MG testbed that mirrors actual operating conditions. By using real solar generation and load profiles from Medellín, Colombia, the system demonstrates its effectiveness across two crucial scenarios: grid-dependent operation, where it minimizes losses during energy exchange, and self-powered mode, where it strategically deploys diesel generation to maintain power quality while constraining emissions. The extensive testing regimen, comprising 100 independent simulations, provides robust evidence of the system's capabilities.

The results reveal clear advantages of the MVO-based approach, with significant reductions in energy losses and consistently lower CO₂ emissions in both connected and islanded modes. Its robust and repeatable performance, along with high computational efficiency, suggests strong potential for real-world implementation. This dual-mode capability represents an important advancement over typical single-mode optimization studies, offering MG operators a more versatile tool for maintaining reliability during both normal and emergency conditions.

This work delivers significant contributions both academically and for the energy sector. From an academic perspective, it proposes a novel mathematical formulation for the optimal scheduling of BESS in AC microgrids operating in both grid-connected and islanded modes. The model incorporates detailed technical constraints, such as power balance, voltage limits, and current capacities, often oversimplified in previous studies. Additionally, it introduces a master-slave optimization architecture combining the MVO algorithm with a power flow analysis based on Successive Approximations, enabling efficient and repeatable resolution of complex multi-objective problems.

For the energy sector, the study provides a robust and applicable tool for enhancing microgrid planning and operation. Its validation on a realistic 33-node system with actual demand and PV generation profiles demonstrates its practical relevance. The proposed strategy effectively reduces energy losses and CO₂ emissions while ensuring compliance with system stability and security standards. These features make it a valuable solution for energy planners and system operators aiming to integrate storage and renewable energy in modern distribution networks, contributing to smarter and more sustainable energy management.

In particular, the dual emphasis on loss minimization and emissions reduction reflects two critical priorities in current power systems. Losses directly impact the efficiency of electricity delivery, while emissions are a growing environmental concern, especially in densely populated or highly polluted regions such as Medellín [29] or Shanghai [30], where seasonal air quality thresholds may be exceeded. By modeling photovoltaic generation under Maximum Power Point Tracking (MPPT) mode, the framework ensures full utilization of the available solar resource. In this context, the optimization strategy not only balances power flow and storage behavior but also enables the efficient and complete use of renewable energy within the operational limits of the system.

The remainder of this paper is organized as follows: Section 2 introduces the mathematical modeling of the AC MG, operating under both grid-dependent and self-powered modes, incorporating a comprehensive set of constraints to reflect realistic operation in the presence of DERs. Section 3 details the proposed master–slave optimization framework based on MVO/SA. Section 4 describes the test system setup, including the comparison algorithms and the optimizer parameters selected through a systematic tuning process, while Section 5 presents and analyzes the simulation results. Finally, Section 6 summarizes the main conclusions and outlines directions for future research.

2. Mathematical Formulation

This section presents the mathematical formulation developed to optimize the operation of BESSs within AC MGs. The proposed model seeks to minimize energy losses and CO₂ emissions, incorporating the technical constraints of a distributed generation environment with energy storage. The location and sizing of the BESS units are assumed to be known beforehand. Model validation is carried out based on the self-powered and grid-dependent scenarios reported in [31].

2.1. Objective Functions

The optimization problem seeks to minimize the following composite function (E_{loss}), concerning power losses due to the Joule effect:

$$E_{\text{Loss}} = \min(f_{\text{loss}}) = \min \left(\sum_{h \in \Omega_{\mathcal{H}}} \sum_{l \in \Omega_{\mathcal{L}}} R_l |I_l|^2 \Delta h \right), \quad (1)$$

$$\{\forall h \in \Omega_{\mathcal{H}}, \forall l \in \Omega_{\mathcal{L}}\}$$

In this expression, R_l represents the resistance of the distribution line l , and I_l is the magnitude of the current flowing through the line.

Lastly, the emissions function (E_{missions}) seeks to reduce the environmental impact of the system:

$$E_{\text{missions}} = \min(f_{\text{CO}_2}) = \min \left(\sum_{h \in \Omega_{\mathcal{H}}} \sum_{i \in \Omega_{\mathcal{N}}} P_{i,h}^{\text{cg}} C E_i^{\text{cg}} \Delta h + \sum_{h \in \mathcal{H}} \sum_{i \in \Omega_{\mathcal{N}}} P_i^{\text{dg}} C_h^{\text{dg}} C E_i^{\text{dg}} \Delta h \right), \quad (2)$$

$$\{\forall h \in \Omega_{\mathcal{H}}, \forall i \in \Omega_{\mathcal{N}}\}$$

In this equation, $P_{i,h}^{\text{cg}}$ represents the active power generated by a conventional generator at node i during period h , and $C E_i^{\text{cg}}$ is the corresponding emission coefficient. This coefficient depends on the type of energy source used, such as electricity from the main grid, diesel-based distributed generation, or natural gas, and is introduced into the model as a constant factor representing CO₂ emissions per unit of energy (in this particular case, kg/kWh). The period duration Δh defines the time interval in which electrical variables remain constant. Similarly, $P_{i,h}^{\text{dg}}$ denotes the active power supplied by the DG at node

i during period h , while C_h^{dg} refers to the expected electricity production curve of the DG. The emission coefficient CE_i^{cg} is also applied here to estimate CO₂ emissions from distributed generators.

It is important to note that in the proposed model, the emission factor for each generation source can be adjusted depending on its characteristics. For instance, distributed generators that rely on fossil fuels (e.g., diesel) will have a positive emission coefficient, while clean sources, such as photovoltaic (PV) systems, are assigned a zero emission factor since they do not emit CO₂ during operation [32]. In the context of this paper, PV generation is the only distributed source used, and therefore, it does not contribute to emissions in the simulation results.

The sets $\mathcal{N}$, $\mathcal{L}$, and $\mathcal{H}$ refer to the nodes, lines, and hourly periods considered in the microgrid.

2.2. Model Constraints

The operation of the DG and BESS within an AC MG is subject to constraints based on equipment limitations and network operation. These include loadability and voltage limits, power balance, and the minimum and maximum active power output of DG and BESS operation. It is worth noting that, in this study, only active power injection from the DG is considered, as this reflects their typical mode of operation.

2.2.1. Active and Reactive Power Constraints

Nodal active power balance:

The first constraint presented in (3) establishes the active power balance in the electrical network, ensuring power equilibrium at each node of the system during every time period.

$$P_{i,h}^{cg} + P_{i,h}^{dg} \pm P_{i,h}^B - P_{i,h}^d = v_{i,h} \sum_{j \in \mathcal{N}} Y_{ij} v_{j,h} \cos(\theta_{i,h} - \theta_{j,h} - \varphi_{ij}), \quad (3)$$

$$\{\forall h \in \Omega_{\mathcal{H}}, \forall i \in \Omega_{\mathcal{N}}\}$$

In this constraint, $P_{i,h}^B$ is the active power supplied by a BESS at node i over period h , and $P_{i,h}^d$ is the power demand at node i during hour h . $v_{i,h}$ and $v_{j,h}$ are the voltage magnitudes at nodes i and j , and Y_{ij} is the magnitude of the admittance between them. $\theta_{i,h}$ and $\theta_{j,h}$ represent the voltage angles at nodes i and j , while φ_{ij} is the admittance angle of the line connecting the two nodes.

Nodal reactive power balance:

Constraint (4) performs a similar role to the previous one but focuses on the reactive power balance of the system.

$$Q_{i,h}^{cg} - Q_{i,h}^d = v_{i,h} \sum_{j \in \Omega_{\mathcal{N}}} Y_{ij} v_{j,h} \sin(\theta_{i,h} - \theta_{j,h} - \varphi_{ij}), \quad (4)$$

$$\{\forall h \in \Omega_{\mathcal{H}}, \forall i \in \Omega_{\mathcal{N}}\}$$

The new terms, $Q_{i,h}^{cg}$ and $Q_{i,h}^d$, represent the reactive power supplied by conventional generators and the reactive power demand at node i during hour h , respectively.

A unit power factor is assumed for generation in this initial analysis, focusing only on active power. Reactive power control is left for future work.

2.2.2. Operational Limits

Active and reactive power limits for conventional generation:

The constraints in (5) define the limits of active and reactive power generation by conventional generators each hour based on their nominal capacities within the grid.

$$P_i^{cg,\min} \leq P_{i,h}^{cg} \leq P_i^{cg,\max}, \quad Q_i^{cg,\min} \leq Q_{i,h}^{cg} \leq Q_i^{cg,\max}, \quad (5)$$

$$\{\forall i \in \Omega_{cg}, \forall h \in \Omega_H\}$$

where $P_i^{cg,\min}$ is the minimum active power to be injected by the conventional generator at node i , and $P_i^{cg,\max}$ is the maximum active power to be injected by the generator at node i . Similarly, $Q_i^{cg,\min}$ is the minimum active power to be injected by the conventional generator at node i , and $Q_i^{cg,\max}$ is the maximum active power to be injected by the generator at node i .

Active power constraints for distributed generation:

In the same way, Equation (6) sets a limit for the power supplied by the DG at node i during hour h .

$$P_i^{dg,\min} \leq P_{i,h}^{dg} \leq P_i^{dg,\max} G_h^{dg}, \quad (6)$$

$$\{\forall i \in \Omega_B, \forall h \in \Omega_H\}$$

Here, $P_i^{dg,\min}$ is the minimum active power to be injected by the distributed generator at node i , and $P_i^{dg,\max}$ is the maximum active power to be injected. This constraint considers the PV generation curve in p.u., determined by the technology used and radiation conditions in the study region, which vary each hour and are represented by G_h^{dg} .

BESS operating limits:

On the other hand, Equation (7) defines the charging and discharging power limits of the BESS in the microgrid. It ensures that the power exchanged by the battery at node i and hour h stays within the allowable range.

$$P_{B,i}^{charg_max} \leq P_{i,h}^B \leq P_{B,i}^{disch_max}, \quad (7)$$

$$\{\forall i \in \Omega_N, \forall h \in \Omega_H\}$$

In this case, $P_{i,h}^B$ is the power absorbed or supplied by the battery, $P_{B,i}^{charg_max}$ is the maximum charging power, and $P_{B,i}^{disch_max}$ is the maximum discharging power.

For the calculation of BESS power limits, the equations in (8) define the maximum charging and discharging powers as a function of the battery capacity C_i^B , and the charging (tc_i^B) and discharging (td_i^B) time intervals at node i :

$$P_{B,i}^{dischmax} = \frac{C_i^B}{td_i^B}, \quad P_{B,i}^{chargmax} = -\frac{C_i^B}{tc_i^B}, \quad (8)$$

$$\{\forall i \in \Omega_B\}$$

With this in mind, charging power is assumed to be negative, while discharging power is positive.

In this sense, the state of charge (SoC) of each battery over time is updated by Equation (9), considering the charge/discharge coefficient ϕ_i^B , power $p_{i,h}^B$, and time step Δt :

$$SoC_{i,h}^B = SoC_{i,h-1}^B - \phi_i^B p_{i,h}^B \Delta t, \quad (9)$$

$$\{\forall i \in \Omega_B, \forall h \in \Omega_H\}$$

The coefficient ϕ_i^B defined in Equation (10) depends on the battery's charging/discharging times and power limits:

$$\phi_i^B = \frac{1}{td_i^B P_{B,i}^{dischmax}} = \frac{1}{tc_i^B P_{B,i}^{chargmax}}, \quad (10)$$

$$\{\forall i \in \Omega_B, \forall h \in \Omega_H\}$$

To calculate the state of charge at any given time, it is necessary to know the initial state of charge of the battery:

$$SoC_{i,h=0}^B = SoC_i^0, \quad (11)$$

$$\{\forall i \in \Omega_B\}$$

If a final SoC is required at the end of the day, it is set by (12)

$$SoC_{i,h=24}^B = SoC_i^f, \quad (12)$$

$$\{\forall i \in \Omega_B\}$$

Finally, the SoC must remain within the operational bounds, as stated in Equation (13):

$$SoC_i^{B,min} \leq SoC_{i,h}^B \leq SoC_i^{B,max}, \quad (13)$$

$$\{\forall i \in \Omega_B, \forall h \in \Omega_H\}$$

where $SoC_i^{B,min}$ and $SoC_i^{B,max}$ represent the minimum and maximum state of charge limits of the battery, respectively.

2.2.3. Network Constraints

Voltage regulation limits:

In the case of nodal voltages, Equation (14) ensures that they remain within the limits defined by grid regulations.

$$V_i^{min} \leq v_{i,h} \leq V_i^{max}, \quad (14)$$

$$\{\forall i \in \Omega_N, \forall h \in \Omega_H\}$$

For this, $v_{i,h}$ denotes the voltage at node i during period h , while V_i^{min} and V_i^{max} represent the minimum and maximum allowable levels. Voltage deviations are limited to $\pm 10\%$ (0.1 p.u.) of the nominal system voltage.

Current limits for distribution lines:

In the case of line currents, constraint (15) sets the limits for current flow through each line to ensure safe operation and prevent infrastructure damage. $I_{ij,h}$ represents the current flowing through the line connecting nodes i and j during period h , while I_{ij}^{max} is the maximum allowable current for that line based on its technical specifications.

$$|I_{ij,h}| \leq I_{ij}^{max}, \quad (15)$$

$$\{\forall i \in \Omega_N, \forall h \in \Omega_H\}$$

where $I_{ij,h}$ represents the current flowing through the line connecting nodes i and j during period h , while I_{ij}^{max} is the maximum allowable current for that line based on its technical specifications.

2.2.4. Operational Constraints for Self-Powered Mode

When operating in self-powered mode, the previously defined equations remain valid. However, additional constraints are required to reflect this operational condition.

Energy trading:

In Equation (16), $P_{i,h}^{\text{slack}}$ denotes the power supplied by the conventional generator at node i at time h :

$$0 \leq P_{i,h}^{\text{slack}}, \quad (16)$$

$$\{\forall h \in \Omega_H\}$$

Since the slack bus is connected to a fossil or distributed generator, the system cannot absorb power—as there are no storage units or external grids for energy export. This constraint ensures that generation nodes only inject power into the microgrid.

Power range of the diesel generator:

Furthermore, Equation (17) sets the operational limits of the slack generator in islanded mode:

$$\text{If } P_{i,h}^{\text{slack}} > 0, \quad P_{i,h}^{dg,\min} \leq P_{i,h}^{\text{slack}} \leq P_{i,h}^{dg,\max}, \quad (17)$$

$$\{\forall h \in \Omega_H\}$$

In this study, a diesel generator is connected at the slack bus, with a minimum injection threshold of 40% and a maximum of 80% of its nominal capacity [33]. These constraints ensure that the generator remains off when not required and operates only within safe limits, contributing to its longevity.

3. Master–Slave Optimization Framework

To evaluate the effectiveness and robustness of the proposed PMVO-based scheduling strategy, a comparative analysis was conducted using two additional metaheuristic algorithms: the Parallel Vortex Search Algorithm (PVSA) and the Chu & Beasley Genetic Algorithm (CBGA). All algorithms were integrated with the exact power flow solver and tested under identical conditions. This multi-algorithm comparison forms the basis of the experimental framework described in Section 4 and supports the performance benchmarking presented in Section 5.

3.1. Master Stage: Multi-Verse Optimizer (MVO)

The Multi-Verse Optimizer (MVO) is a metaheuristic optimization algorithm inspired by concepts from cosmology, particularly the multi-verse theory. This theory postulates the existence of multiple parallel universes (multi-verses) that may interact through mechanisms such as white holes, black holes, and wormholes. These mechanisms have been adapted into an optimization framework to efficiently explore and exploit the search space in solving complex optimization problems [34].

3.1.1. Foundations of the Algorithm

In the MVO algorithm, each potential solution to the optimization problem is conceptualized as a universe. A set of candidate solutions is, thus, referred to as a multi-verse. The quality or fitness of each universe is quantified by an objective function that the algorithm seeks to minimize or maximize. MVO simulates the dynamic evolution of these universes through three main operators derived from cosmological analogies:

1. White holes: Universes with high fitness (inflation rate) probabilistically share their components with others, mimicking the emission of matter and energy;
2. Black holes: Universes with low fitness are more likely to absorb components from others, analogous to the gravitational absorption of black holes;

3. Wormholes: Allow universes to perform local searches by perturbing their positions relative to the best-known solution, encouraging the exploitation of promising regions.

These operators are integrated to balance the global exploration and local exploitation of the search space throughout the optimization process.

3.1.2. Mathematical Representation

Let the solution space be defined by d decision variables, with each bounded within a minimum and maximum limit denoted as $U_{Min}(j)$ and $U_{Max}(j)$, respectively, for the j -th variable. In the context of this problem, U_{Min} and U_{Max} represent the lower and upper power limits that the batteries can deliver to or absorb from the MG. A population of n candidate solutions (universes) is initialized as

$$U_{i,j} = (U_{Max}(j) - U_{Min}(j)) \cdot \text{rand} + U_{Min}(j), \quad (18)$$

where $U_{i,j}$ is the j -th component of the i -th universe, and rand is a uniformly distributed random number in $[0, 1]$. This results in an initial population matrix:

$$\mathbf{U} = \begin{bmatrix} U_{1,1} & U_{1,2} & \cdots & U_{1,d} \\ U_{2,1} & U_{2,2} & \cdots & U_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ U_{n,1} & U_{n,2} & \cdots & U_{n,d} \end{bmatrix}. \quad (19)$$

In the context of the optimal operation of a BESS, each particle $U_{i,j}$ represents the charging or discharging power assigned to the BESS units within the AC microgrid.

Figure 1 presents the encoding scheme used to model the 24 h operational schedule of each BESS unit. Each row, composed of 24 time-indexed elements, represents the hourly power profile of a specific BESS unit, where each element indicates the normalized charging or discharging power at a given time step.

h=1	h=2	...	h=23	h=24	h=1	h=2	...	h=23	h=24	h=1	h=2	...	h=23	h=24
0.5	0.7	...	0.3	0.5	0.5	0.35	...	0.7	0.5	0.5	0.2	...	0.4	0.5
→ BESS A ←					→ BESS B ←					→ BESS C ←				

Figure 1. Coding scheme for determining the operation of the BESS.

The first and last elements are emphasized to incorporate boundary conditions, assuming an initial and final state of charge (SoC) of 50%, as recommended by the IEEE standard [35]. This structure allows the MVO algorithm to evaluate each particle as a complete and feasible operational schedule for the BESS system.

3.1.3. Objective Function

Each universe is evaluated using a scalar objective function $f : \mathbb{R}^d \rightarrow \mathbb{R}$. The goal of the MVO is to identify the universe with the optimal objective function value. Let $OF_i = f(U_i)$ be the objective function value for the i -th universe, and define the following:

$$OF_i = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix}. \quad (20)$$

Assuming a minimization problem, the best solution is selected as

$$\text{Best}_U = U_{i^*}, \quad \text{with } i^* = \arg \min_i (OF_i), \quad (21)$$

$$\text{Best}_{OF} = \min_i (OF_i), \quad (22)$$

In this case, the objective functions (OF_i) correspond to energy losses or CO₂ emissions, which means that the problem is formulated as a minimization. The best universes—i.e., (Best_U), the candidate solutions—are those that achieve the lowest values for these aspects (Best_{OF}), thereby attaining a higher level of technical and environmental efficiency in the MG.

3.1.4. Exploration: White Hole and Black Hole Mechanism

To perform exploration, the MVO algorithm uses a probabilistic mechanism that replaces the components of each universe with those from better universes based on the normalized inflation rate (NIR) concept. The NIR for each universe is computed as

$$\text{NIR}_i = \frac{OF_i}{\max(OF_1, OF_2, \dots, OF_n)}. \quad (23)$$

Then, the j -th component of universe U_i is updated as

$$U_{i,j} = \begin{cases} U_{k,j}, & \text{if } r_1 < \text{NIR}_i, \\ U_{i,j}, & \text{otherwise,} \end{cases} \quad (24)$$

where U_k is a universe selected via roulette wheel selection based on NIR values, and $r_1 \in [0, 1]$ is a random number.

3.1.5. Exploitation: Wormhole Mechanism

The wormhole mechanism guides the search toward the current best solution. It is governed by two dynamic parameters:

- Wormhole Existence Probability (WEP), which increases linearly with iterations:

$$\text{WEP} = \text{WEP}_{\text{Min}} + \text{iter} \cdot \left(\frac{\text{WEP}_{\text{Max}} - \text{WEP}_{\text{Min}}}{\text{iter}_{\text{Max}}} \right), \quad (25)$$

- Travel Distance Rate (TDR), which decreases nonlinearly to refine the local search:

$$\text{TDR} = 1 - \left(\frac{\text{iter}^{1/p}}{\text{iter}_{\text{Max}}^{1/p}} \right), \quad (26)$$

where p is a user-defined constant (typically, $1 \leq p \leq 6$), and iter is the current iteration number.

The wormhole-based update is applied as

$$U_{i,j} = \begin{cases} \text{Best}_{U,j} + \text{TDR} \cdot ((U_{\text{Max}}(j) - U_{\text{Min}}(j)) \cdot r_4 + U_{\text{Min}}(j)), & \text{if } r_3 < 0.5, \\ \text{Best}_{U,j} - \text{TDR} \cdot ((U_{\text{Max}}(j) - U_{\text{Min}}(j)) \cdot r_4 + U_{\text{Min}}(j)), & \text{otherwise,} \end{cases} \quad (27)$$

where $r_3, r_4 \in [0, 1]$ are random values. This operator is applied probabilistically only when a randomly drawn value r_2 satisfies $r_2 < \text{WEP}$.

3.1.6. Boundary Control and Termination

All updated values are subjected to boundary constraints to ensure feasibility:

$$U_{i,j} \in [U_{Min}(j), U_{Max}(j)] \quad \forall i, j. \quad (28)$$

The algorithm proceeds iteratively, applying exploration and exploitation operators in each generation. The process continues until a predefined number of iterations $iter_{Max}$ is reached or another convergence criterion is satisfied.

3.1.7. Algorithm Summary

The structure of the MVO algorithm is presented in Algorithm 1.

Algorithm 1 MVO (Multi-Verse Optimizer) Algorithm Pseudocode

Require: MG parameters, DER power limits (U_{min} , U_{max})

for $iter = 1$ **to** $iter_{max}$ **do**

if $iter == 1$ **then**

1. Generate the initial population of MVO (U_i) randomly;
2. Evaluate the objective function for each individual in the population and store this value in OF_i (Slave stage);
3. Sort U and OF_i from minimum to maximum value;
4. Select the universe and its objective function located in the first position of U and OF_i as incumbent ($Best_U$ and $Best_{OF}$);

else

5. Apply the exploration and exploitation strategy to universes different from the incumbent;
6. Verify the boundary values of the elements that compose the universes;
7. Evaluate the objective function for each individual in the population and store this value in OF_i ;
8. Sort U_i and OF_i from minimum to maximum value;
9. Select the universe and its objective function located in the first position of U and OF_i as incumbent ($Best_U$ and $Best_{OF}$);

end if

if Any stopping criterion has been met? **then**

10. Finish optimization process;
 11. Print $Best_U$ and $Best_{OF}$ as the solution to the problem;
- Break;**

else

Continue;

end if

end for

This algorithmic framework is suitable for high-dimensional, non-convex, and multimodal optimization problems, demonstrating strong performance across various engineering and scientific applications.

3.2. Slave Stage: Load Flow Problem via Successive Approximations

In the proposed optimization-based solving approach, the MVO algorithm functions as the master stage, generating candidate operating schedules for the battery energy storage system (BESS) over a 24 h horizon. Each particle represents a potential combination of hourly charging and discharging power values for the BESS.

The slave stage is responsible for evaluating the technical feasibility and overall performance of each candidate solution provided by the MVO, considering both the objective function and constraints. This evaluation is carried out through a sequential, hour-by-hour power flow analysis using the Successive Approximation (SA) method [36].

The SA method is an approximate numerical technique used to solve the Load Flow Problem (LFP). It operates iteratively, without requiring derivatives or the matrix inversion of non-diagrid-dependental blocks, making it computationally more efficient compared to methods like Newton–Raphson (NR) and Fixed-Point Iteration (FPI) [37]. The iterative process is described by the following formulation:

$$\mathbb{V}_d^{t+1} = -\mathbb{Z}_{dd} \left[\mathbb{Y}_{ds} \mathbb{V}_s + \text{diag}^{-1}(\mathbb{V}_d^{t,*}) \mathbb{S}_d^* \right] \quad (29)$$

where $\mathbb{Z}_{dd}$ is the impedance matrix (inverse of $\mathbb{Y}_{dd}$), and $\mathbb{Y}_{ds}$ represents the admittances between the generation and demand nodes. The process starts with the slack node voltage ($|\mathbb{V}_s| = 1 \text{ p.u.}$, $\delta_s = 0^\circ$) and iterates until convergence, incorporating the conjugate of the complex power demand $\mathbb{S}_d^*$.

Figure 2 depicts the step-by-step iterative algorithm employed in the Successive Approximations method, represented as a structured flowchart.

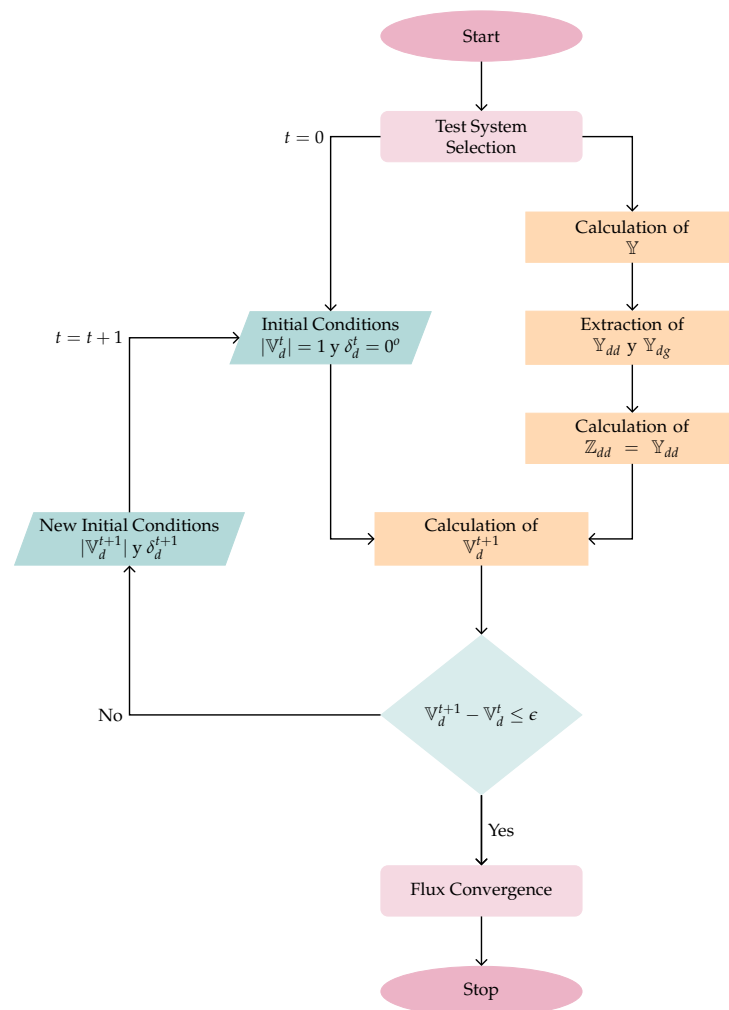


Figure 2. Flowchart of the LFP solution using the Successive Approximations method.

On the other hand, the evaluation procedure involves the following steps:

1. **Data preparation for each hour:** For every time step $h \in \{1, 2, \dots, 24\}$, gather the following information:
 - The electrical demand at each load bus;
 - The power generation profile from photovoltaic (PV) sources;
 - The BESS charging or discharging schedule proposed by the MVO algorithm.

2. **Execution of load flow analysis:** Apply the Successive Approximation (SA) method to solve the network's load flow equations and obtain the voltage levels and line load flows at each node.

$$\mathbb{V}_{d,h}^{t+1} = -\mathbb{Z}_{dd} \left[\mathbb{Y}_{ds} \mathbb{V}_{s,h} + \text{diag}^{-1}(\mathbb{V}_d^{t,*}) \mathbb{S}_{d,h}^* \right] \quad (30)$$

3. **Operational constraint validation:** Each candidate solution generated by the optimization algorithms (PMVO, PVSA, and CBGA) is validated through an hourly power flow analysis based on the Successive Approximations method. This evaluation ensures compliance with all technical and operational constraints, including (i) maintaining voltage levels within acceptable bounds at each bus ($\pm 10\%$), (ii) ensuring that current flows remain within the thermal ratings of the distribution lines, and (iii) verifying that the BESS units operate within their charging and discharging power limits. Additionally, in the self-powered mode, the diesel generator is constrained to operate strictly within its predefined dispatch range in accordance with its rated capacity and technical requirements. It is also ensured that this generator does not store energy since, by design, it can only inject active power into the system. To guarantee that candidate solutions are technically feasible, all battery-related constraints, such as minimum and maximum SoC levels, charging/discharging power bounds, and initial and final SoC values, are directly encoded into the decision variables. This approach restricts the search space to physically admissible schedules and avoids the generation of infeasible operating states. If any violation of operational, voltage, current, or diesel generator power constraints is detected, penalty terms are incorporated into the objective function to discourage the selection of such solutions during the optimization process.
4. **Incorporation of penalty terms:** If any constraint violations are detected, corresponding penalty terms are added to the objective function to penalize infeasible solutions. This evaluation is performed using the fitness functions described in (1) and (2). The penalization used is explained below:

To manage constraint violations within the optimization process, the proposed strategy incorporates penalty terms directly into the objective function. This mechanism modifies the evaluation of candidate solutions by penalizing infeasibilities, thereby guiding the search toward viable regions of the solution space.

- **Penalty-adjusted evaluation:** Each solution is assessed using a penalized objective, denoted as the adjusted fitness (f_{Eval}), which merges the original cost metric (f_{Obj}) with an aggregated penalty component (Φ):

$$f_{\text{Eval}} = f_{\text{Obj}} + \Phi \quad (31)$$

This formulation ensures that solutions violating constraints receive degraded evaluations, making them less likely to persist in the optimization process.

- **Penalties in grid-connected operation:** When operating in grid-connected mode, constraint breaches primarily relate to load balancing and voltage regulation:

$$\Phi = \alpha_1 \cdot \delta_{\text{Current}} + \alpha_2 \cdot \delta_{\text{Voltage}} \quad (32)$$

- δ_{Current} : Quantifies the deviation from permissible branch current limits;
- δ_{Voltage} : Measures voltage violations across the system;
- α_1, α_2 : Tunable penalty weights, chosen to ensure constraint violations significantly degrade solution quality.

- Penalties in islanded operation: In scenarios without grid support, further constraints become active, particularly concerning local generation and energy exchange via the slack bus:

$$\Phi = \alpha_1 \cdot \delta_{\text{Current}} + \alpha_2 \cdot \delta_{\text{Voltage}} + \alpha_3 \cdot \delta_{\text{Pslack}} + \alpha_4 \cdot \delta_{\text{Diesel}} \quad (33)$$

- δ_{Pslack} : Quantifies the energy injected from the microgrid into the slack node during islanded operation, where the slack corresponds to the diesel generator;
- δ_{Diesel} : Captures instances where the diesel generator operates outside its nominal range;
- α_3, α_4 : Penalty coefficients calibrated to prioritize feasibility in isolated mode.

Penalty coefficients are deliberately set to high values to ensure that any constraint violation results in a significant degradation in the fitness function, effectively discarding infeasible solutions early in the optimization process and preserving the robustness of the search. In this particular case, the penalty weights were tuned heuristically, with all coefficients set to 1000 in grid-dependent mode and increased to 1500 in self-powered mode to enforce stricter feasibility requirements.

Furthermore, the power balance is satisfied through the application of the power flow algorithm, which evaluates the nodal injections based on the operational states of distributed generators, storage units, and loads. The power output limits of the photovoltaic generators are inherently respected by their operation under MPPT control. Additionally, the proposed encoding structure ensures compliance with both the maximum charge/discharge power and the state-of-charge bounds of the batteries, thus guaranteeing the physical feasibility of each candidate solution generated by the optimization methodologies.

5. **Fitness function evaluation:** After completing the simulations for all 24 h, the total energy losses and CO₂ emissions of the MG are quantified. Additionally, any penalties resulting from constraint violations are incorporated into the overall fitness value. As the magnitude of detected violations increases, indicating technical feasibility, the objective function value also increases. Consequently, such solutions are discarded both as viable candidates and as potential stepping points in the convergence path, prompting the initiation of a new optimization cycle focused on feasible regions of the search space.
6. **Fitness feedback to MVO:** The final value of the fitness function is returned to the master stage, allowing it to update and refine the search for more optimal BESS scheduling strategies in subsequent iterations.

This framework allows for a detailed and dynamic assessment of MG performance under various BESS operating strategies. The SA method ensures efficient resolution of the power flow problem, while the MVO enhances voltage stability, system reliability, and technical and environmental performance.

4. Test System Description and Experimental Setup for Algorithmic Benchmarking

This section presents the technical configuration used to evaluate the proposed optimization framework. First, we describe the 33-node AC microgrid test system, including load profiles, PV generation data, and BESS characteristics, under both grid-connected and self-powered modes. Then, we detail the experimental setup used for benchmarking the optimization strategies, including parameter tuning, simulation conditions, and criteria for fair comparison across all tested methods.

4.1. Test System

This study evaluates the operational performance of a 33-node AC MG test system under both grid-dependent and self-powered modes [38], as illustrated in Figure 3. The analysis incorporates realistic power generation and demand profiles for Medellín, Colombia, derived from operational data provided by Empresas Públicas de Medellín (EPM) [39] and solar irradiance datasets from NASA [35].

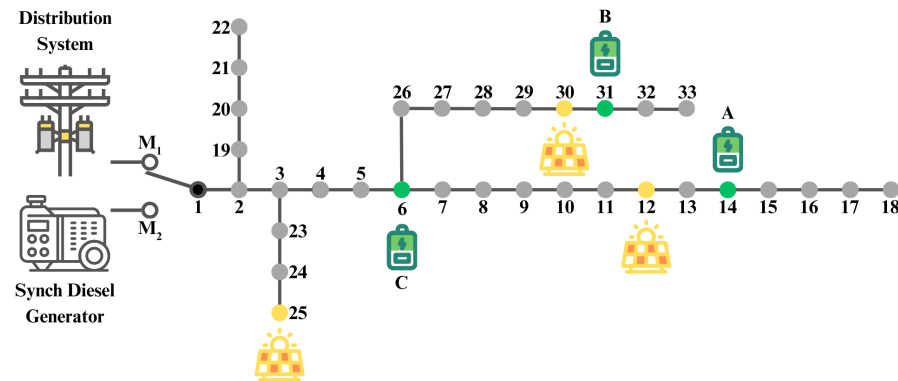


Figure 3. Topological schematic of the 33-node AC microgrid test system in dual-operation modes: Grid-dependent (M_1) and self-powered (M_2).

This 12.66 kV test system (100 kW base) features a 33-node architecture with 32 distribution lines. The slack bus (Bus 1) operates with dual functionality:

- Acts as PCC (Point of Common Coupling) in grid-dependent mode;
- Switches to diesel generator control in self-powered mode.

The diesel generator connected at the Point of Common Coupling (PCC) has a nominal capacity of 4000 kW, with its dispatch constrained between 1600 kW and 3200 kW (40% to 80% of rated capacity) to ensure reliable performance and extend operational lifespan [33]. This slack bus configuration accurately represents the microgrid's dual-mode operation: in grid-connected mode, Bus 1 acts as the PCC, balancing active and reactive power by exchanging energy with the upstream network to maintain voltage stability; in islanded mode, the diesel generator assumes the slack role, regulating power balance internally without external support. The operational limits prevent the generator from running at zero load or full capacity continuously, avoiding damage and maintenance issues. Consequently, the control algorithm must carefully coordinate energy storage and renewable sources to meet demand while keeping the diesel generator within its safe operating range. This strategy reflects realistic constraints typical of isolated power systems and ensures reliable, efficient microgrid operation.

Complete line parameters, including resistance and reactance per kilometer, as well as load demands and current limits, are provided in Table 1 [40].

Table 1. Technical parameters of the 33-node AC microgrid test system.

Line l	From Node i	To Node j	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kVAr)	$I_{ij}^{\max}$ (A)
1	1	2	0.0922	0.0477	100	60	385
2	2	3	0.4930	0.2511	90	40	355
3	3	4	0.3660	0.1864	120	80	240
4	4	5	0.3811	0.1941	60	30	240
5	5	6	0.8190	0.7070	60	20	240
6	6	7	0.1872	0.6188	200	100	110
7	7	8	1.7114	1.2351	200	100	85
8	8	9	1.0300	0.7400	60	20	70

Table 1. Cont.

Line l	From Node i	To Node j	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kVAr)	$I_{ij}^{\max}$ (A)
9	9	10	1.0400	0.7400	60	20	70
10	10	11	0.1966	0.0650	45	30	55
11	11	12	0.3744	0.1238	60	35	55
12	12	13	1.4680	1.1550	60	35	55
13	13	14	0.5416	0.7129	120	80	40
14	13	15	0.5910	0.5260	60	10	25
15	15	16	0.7463	0.5450	60	20	20
16	16	17	1.2890	1.7210	60	20	20
17	17	18	0.7320	0.5740	90	40	20
18	18	19	0.1640	0.1565	60	40	20
19	19	20	1.5042	1.3554	90	40	20
20	20	21	0.4095	0.4784	90	40	20
21	21	22	0.7089	0.9373	90	40	20
22	3	23	0.4512	0.3083	90	50	85
23	23	24	0.8980	0.7091	420	200	85
24	24	25	0.8960	0.7011	420	200	40
25	6	26	0.2030	0.1034	60	25	125
26	26	27	0.2842	0.1447	60	25	110
27	27	28	1.0590	0.9337	60	20	110
28	28	29	0.8042	0.7006	120	70	110
29	29	30	0.5075	0.2585	200	600	95
30	30	31	0.9744	0.9630	150	70	55
31	31	32	0.3105	0.3619	210	100	30
32	32	33	0.3410	0.5302	60	40	20

The test system integrates three PV generation units with the following distribution:

- Bus 12: 1125 kW rated capacity;
- Bus 25: 1320 kW rated capacity;
- Bus 30: 999 kW rated capacity.

All photovoltaic systems operate under MPPT during the entire simulation horizon. Figure 4 presents the characteristic daily profiles of both solar generation and load demand for the Medellín case study. All values are expressed as percentages relative to the total installed capacity of PV generation available in the system and the total installed demand capacity supplied by the slack node or the corresponding distribution substation.

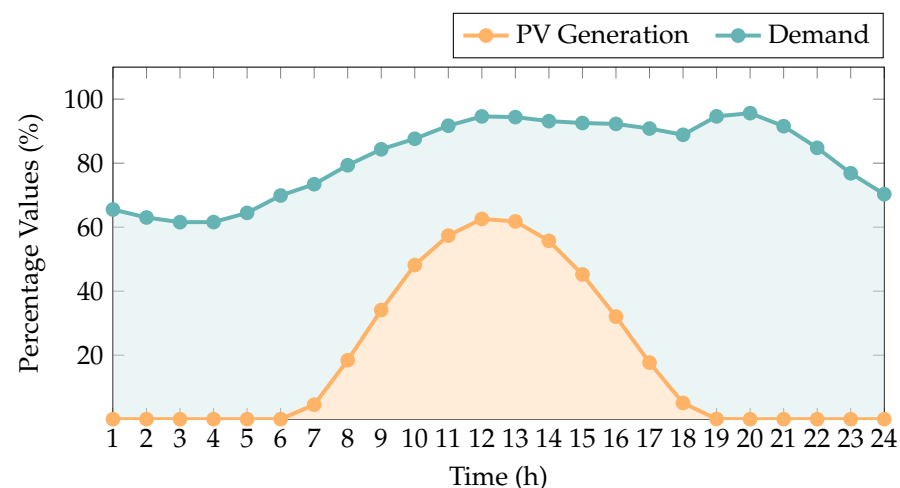


Figure 4. Daily profiles of photovoltaic production and power demand in Medellín, Colombia.

The system includes three lithium-ion BESS units positioned at Buses 6, 14, and 31, as detailed in [41] and categorized as follows:

- **Type A:** 1000 kW h capacity (4-h charge/discharge);
- **Type B:** 1500 kW h capacity (4-h charge/discharge);

- **Type C:** 2000 kW h capacity (5-h charge/discharge).

All BESS units operate within a 10% to 90% SoC range, with the initial/final SoC fixed at 50% to ensure operational stability and battery longevity, as per IEEE recommendations [42,43].

For voltage regulation, all bus voltages must maintain $\pm 10\%$ deviation tolerance from the nominal 12.66 kV value, complying with Colombian standard NTC 1340 [44].

The system exhibits distinct emission profiles across operational modes, with measured CO₂ intensities of 0.1644 kg/kWh (grid-dependent) versus 0.2671 kg/kWh (self-powered) [32].

An important observation is that both operating modes are evaluated using the same test system, reflecting realistic microgrid conditions where the physical infrastructure remains unchanged regardless of grid connectivity [45]. The primary distinction lies in the source of grid support: the utility grid in the connected mode and a local synchronous diesel generator in the self-powered mode [46]. This setup enables a consistent comparison of the proposed optimization strategies, as each mode introduces a distinct solution space. Consequently, performance differences can be attributed solely to the operating conditions, allowing for a fair assessment in terms of solution quality, average performance, variability, and computational effort.

4.2. Input Parameters and Control Variables

The master optimization stage (PMVO) requires the following input data, as summarized in Table 2:

- **Active and reactive power demand profiles** at each node, represented by $P_j^d(t)$ and $Q_j^d(t)$, where $j \in 1, \dots, 33$ and $t \in 1, \dots, 24$;
- **Photovoltaic generation profiles** $P_j^{PV}(t)$ at nodes $j = 12, 25, 30$, derived from local solar irradiance measurements;
- **Technical specifications of BESS units**, including rated energy capacity $E_{\max}$ and round-trip efficiency η ;
- **State of charge (SoC) constraints**, defined by $\text{SoC}_j^{\min} \leq \text{SoC}_j(t) \leq \text{SoC}_j^{\max}$;
- **Initial SoC values** for each node equipped with a BESS.

The decision variables optimized by the PMVO correspond to the hourly charging and discharging powers, $P_{\text{bess},j}(t)$, for the BESS units installed at nodes $j = 6, 14, 31$, over a 24 h time horizon.

Table 2. Summary of input data and control variables for the proposed optimization model.

Parameter	Symbol	Source / Value
Active Demand	$P^d(t)$	IEEE 33-bus benchmark + load profile
Reactive Demand	$Q^d(t)$	IEEE 33-bus benchmark + PF assumptions
PV Generation	$P^{PV}(t)$	Scaled irradiance (Medellín, Colombia)
Initial SoC	SoC^0	50% of $E_{\max}$
BESS SoC Limits	$\text{SoC}^{\min}, \text{SoC}^{\max}$	10–90% of $E_{\max}$
BESS Energy Capacity	$E_{\max}$	1000/1500/2000 kWh
Charging efficiency	η	0.95

Each candidate solution generated by the PMVO encodes the hourly state-of-charge values, $\text{SoC}_j(t)$, which serve as the primary control variables of the optimization. The charging and discharging power profiles, as well as the resulting battery currents, are implicitly defined by the temporal evolution of SoC. To evaluate the feasibility of each solution under AC power flow constraints, the Successive Approximation (SA) method is applied to compute the corresponding nodal voltages.

The simulation covers a 24 h period with an hourly resolution. At each time step, the load and photovoltaic generation profiles are updated, and the optimization algorithm determines the charging or discharging strategy for the three BESS units. These decisions are subject to constraints on the state of charge, power limits, and network feasibility, with the latter verified through the SA method.

4.3. Comparison of Optimization Methodologies and Parameter Calibration

All optimization approaches were calibrated using a PSO algorithm with a swarm size of 100 particles. Both the cognitive and social coefficients were set to 1.494, while the inertia weight decreased linearly from 1 to 0. The stopping condition was defined as a maximum of 300 iterations. This algorithm has been widely adopted in the literature to improve energy management strategies in systems incorporating distributed energy resources [47]. In this study, its role is to identify the optimal parameter set that allows each control strategy to reach its highest performance.

During the tuning process, tailored parameter configurations were defined for each optimization method under both grid-dependent and self-powered conditions. Specifically, for the MVO algorithm, the grid-dependent scenario employed a population size (N_i) of 100 agents and a maximum of 1964 iterations (T_{Max}). The inertia weight varied linearly from 0 to 1 (WEP_{Min} and WEP_{Max}), with the exponential constant (p) set to 10. In contrast, the self-powered configuration used 200 agents, 2000 iterations, the same inertia range, and a reduced exponential constant of $p = 8$.

To assess the effectiveness of the PMVO/SA-based EMS, comparative analyses were carried out against two alternative metaheuristic algorithms: the Chu & Beasley Genetic Algorithm (CBGA) [48] and the Vortex Search Algorithm (VSA) [49]. All methods were implemented using the same power flow solver (SA), ensuring a consistent evaluation framework.

For the Chu & Beasley Genetic Algorithm, the grid-dependent configuration used 10 individuals (N_i) over 2000 iterations (T_{Max}), applying three mutation operations per generation (N_m). In the self-powered mode, the population size was increased to 200 individuals with 4000 iterations, while the number of mutations per generation was reduced to one.

Regarding the Vortex Search Algorithm, the grid-dependent setup employed a population (N_i) of 100 individuals and a maximum of 1000 iterations (T_{Max}), while the self-powered case utilized 233 individuals and 4000 iterations. The decay rate (χ) was adapted to each scenario, with values of -9.0645 for the grid-dependent mode and -11.4285 for the self-powered case.

Moreover, to significantly accelerate computations, this study incorporates a parallel processing scheme into the proposed optimization methodologies, giving rise to the Parallel Vortex Search Algorithm (PVSA) and Parallel Multi-Verse Optimizer (PMVO). These enhanced versions leverage all available CPU cores to simultaneously evaluate multiple BESS operation schemes per iteration using the Successive Approximations (SAs) method [50], dramatically reducing computation time by distributing power flow analyses across multiple threads [51,52]. In contrast, the Chu & Beasley Genetic Algorithm (CBGA) maintains a sequential approach, evaluating only one solution per iteration due to its inherent structure, underscoring the superior efficiency of the parallelized methods for large-scale optimization problems [48].

To ensure robustness, consistency, and reproducibility, all optimization algorithms were executed under identical conditions, using the same power flow solver, system configuration, demand and PV generation profiles, and tuning methodology. Each method was tested over 100 independent runs in both grid-connected and self-powered modes. The performance evaluation reports the best, average, and standard deviation values for

energy losses and CO₂ emissions, as well as the average computation time per method. Additionally, violin-scatter plots are included to illustrate the variability and distribution of the results.

In this analysis, two approaches were considered: (i) a scenario without BESS operation (base case) and (ii) a scenario with BESS actively operated using the proposed optimization methodologies. In the base case scenario, the BESS units are excluded from operation and remain inactive throughout the daily simulation horizon. The system relies solely on grid connection, diesel generator dispatch during islanded hours, and PV generation operating under MPPT control. This configuration serves as a reference to quantify the benefits of intelligent BESS scheduling. By comparing both scenarios, the analysis demonstrates how the optimized coordination of battery dispatch improves the technical and environmental performance of the microgrid while ensuring compliance with all operational constraints.

5. Results and Discussion

Tables 3 and 4 present the performance metrics obtained in both the grid-dependent and self-powered configurations of the 33-node test system. These results correspond to a 24 h evaluation horizon, during which the proposed optimization methodology was executed jointly with the load flow calculation using the SA method. The tables summarize the best and average outcomes, along with their respective standard deviations, for energy losses and CO₂ emissions. The results obtained through the proposed PMVO-based methodology are compared with the base case (without BESS scheduling) and with two alternative optimization approaches (CBGA and PVSA).

Table 3. Performance results for the 33-node grid-dependent test system over a 24 h evaluation horizon.

Method	Energy Loss (kWh)		Emissions (TonCO ₂)		Performance Metrics	
	Best	Avg. $\pm \sigma\%$	Best	Avg. $\pm \sigma\%$	Avg. Time (s)	Rank
Base Case	2484.5741	–	9.8874	–	–	–
CBGA	2383.4955	2392.9080 $\pm$ 0.3253	9.8708	9.8721 $\pm$ 0.0085	2.7427	3
PVSA	2375.3347	2392.9807 $\pm$ 0.6240	9.8694	9.8725 $\pm$ 0.0255	38.4663	2
PMVO	2374.8497	2391.8690 $\pm$ 0.3974	9.8693	9.8719 $\pm$ 0.0172	90.4112	1

In the grid-dependent configuration (Table 3), the PMVO algorithm yielded the best performance for all indicators. It achieved the lowest energy loss with a best value of 2374.8497 kWh and the lowest emissions at 9.8693 TonCO₂. Furthermore, its average values also surpassed the other methods, maintaining relatively low variability (0.3974% for energy and 0.0172% for emissions). Although the PVSA showed a comparable performance, particularly in its best-case scenario, its average results were slightly less efficient and more dispersed.

Table 4. Performance results for the 33-node self-powered test system over a 24 h evaluation horizon.

Method	Energy Loss (kWh)		Emissions (TonCO ₂)		Performance Metrics	
	Best	Avg. $\pm \sigma\%$	Best	Avg. $\pm \sigma\%$	Avg. Time (s)	Rank
Base Case	2484.5741	–	16.0659	–	–	–
CBGA	2396.5347	2408.1874 $\pm$ 0.2062	16.0427	16.0454 $\pm$ 0.0068	5.5936	3
PVSA	2374.2757	2384.2941 $\pm$ 0.3722	16.0365	16.0393 $\pm$ 0.0149	248.7784	2
PMVO	2373.5262	2380.1794 $\pm$ 0.2989	16.0364	16.0386 $\pm$ 0.0113	155.5360	1

A similar pattern is observed in the self-powered configuration (Table 4). The PMVO produced the most favorable outcomes again, reducing energy losses to the best value of 2373.5262 kWh and emissions to 16.0364 TonCO₂. The average performance remained

superior across both metrics with low dispersion. All optimization strategies significantly outperformed the base case regarding both technical and environmental indicators, validating the positive impact of BESS scheduling regardless of the selected method.

An important aspect to highlight is the execution time of the algorithms. While PMVO required slightly more computational time compared to CBGA and PVSA, it consistently outperformed them in both operational and environmental objectives. However, this increased execution time is not a drawback in this context. Since the planning problem addressed here is executed offline and not in a real-time environment, the solution time is not a critical constraint. BESS operations are scheduled within a vast planning horizon (e.g., hourly or daily forecasts), allowing for more computationally intensive algorithms without compromising practical feasibility. The standard deviations (σ) reported quantify the variability of each algorithm's performance over 100 independent runs. A low σ value indicates consistent convergence behavior and high robustness of the optimization strategy, which is particularly important in microgrid applications where repeatable scheduling enhances operational reliability. The PMVO algorithm consistently achieved the lowest standard deviations in both energy losses and CO₂ emissions, confirming its repeatability and stability across multiple executions. For example, in the self-powered mode, PMVO achieved $\sigma = 0.2989\%$ for energy losses and $\sigma = 0.0113\%$ for emissions, outperforming PVSA and CBGA in both metrics. This stability reinforces the suitability of PMVO for planning applications where dependable outcomes are as important as optimal performance.

In terms of overall ranking, PMVO ranked first in both scenarios, followed by PVSA and CBGA. This reinforces the robustness and reliability of the PMVO algorithm in addressing the multi-objective problem formulated for energy loss and emissions minimization. The consistent dominance of PMVO across both configurations demonstrates its adaptability and superior search capabilities under different operational conditions of the microgrid.

Figures 5 and 6 illustrate the relative improvements achieved by each method in terms of energy loss and CO₂ emissions reduction for the 33-node test system under both grid-dependent and self-powered configurations over a 1-week evaluation horizon.

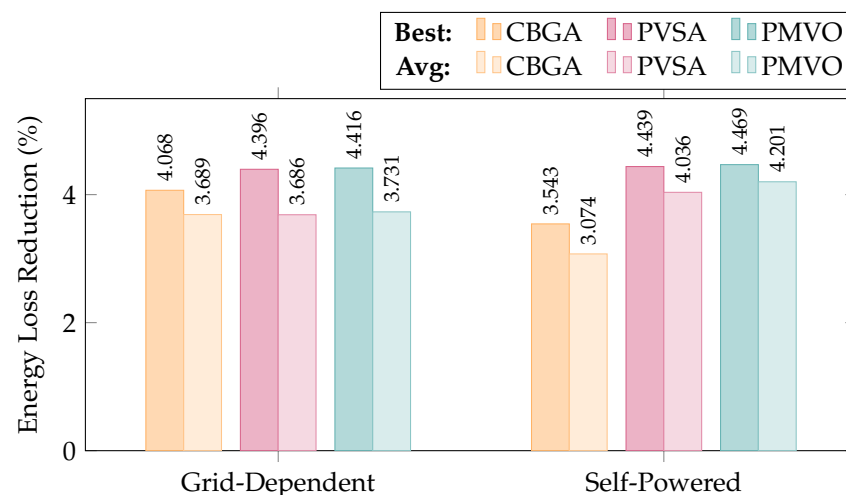


Figure 5. Energy loss reduction: Best and average results for the 33-node system in grid-dependent and self-powered modes over a 24 h evaluation horizon.

In Figure 5, it is evident that PMVO consistently attains the highest percentage reductions in energy losses, both in the best and average cases. Under the grid-dependent mode, the PMVO algorithm achieves a best-case reduction of 4.416%, followed closely by

PVSA (4.396%) and CBGA (4.068%). A similar pattern is observed in the average results, with PMVO achieving 3.731%, outperforming PVSA (3.866%) and CBGA (3.669%). In the self-powered mode, the advantage of PMVO becomes even more pronounced, with a best-case reduction of 4.469%, surpassing PVSA (4.439%) and CBGA (3.543%). The average values reflect the same tendency, confirming the robustness of PMVO under varying conditions.

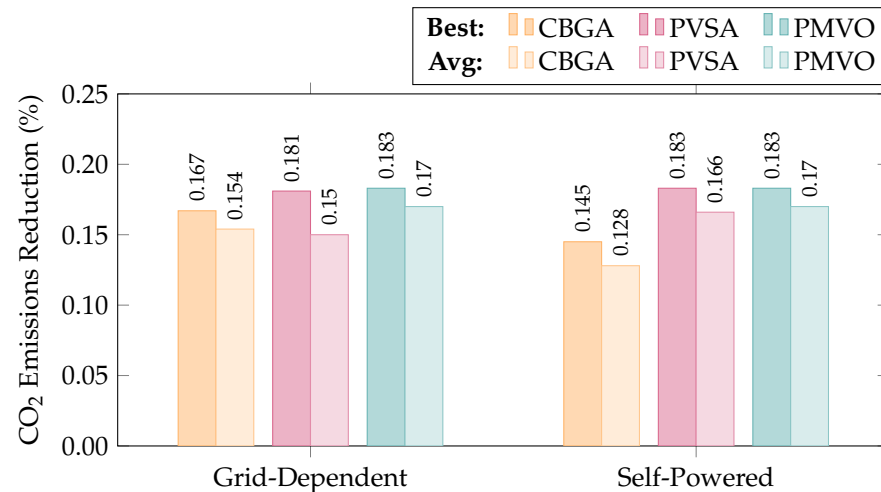


Figure 6. CO₂ emissions reduction: Best and average results for 33-node system in grid-dependent and self-powered modes over a 24 h evaluation horizon.

Figure 6 presents the corresponding reductions in CO₂ emissions. Although the absolute values are smaller due to the nature of the emissions metric, the comparative performance remains consistent. In the grid-dependent case, PMVO leads with a best-case reduction of 0.183%, while PVSA and CBGA follow with 0.181% and 0.167%, respectively. The average values reinforce this trend, with PMVO, again, ahead at 0.17%. For the self-powered configuration, PMVO and PVSA tie in the best-case results at 0.183%, and PMVO achieves the highest average at 0.17%, compared to 0.166% for PVSA and 0.128% for CBGA.

Figure 7 provides a complementary perspective on the performance of the evaluated algorithms through violin-scatter plots. These plots depict the distribution of the optimization outcomes for each method across multiple runs under both operational modes. The left side of each violin represents the grid-dependent case, and the right side shows the self-powered configuration.

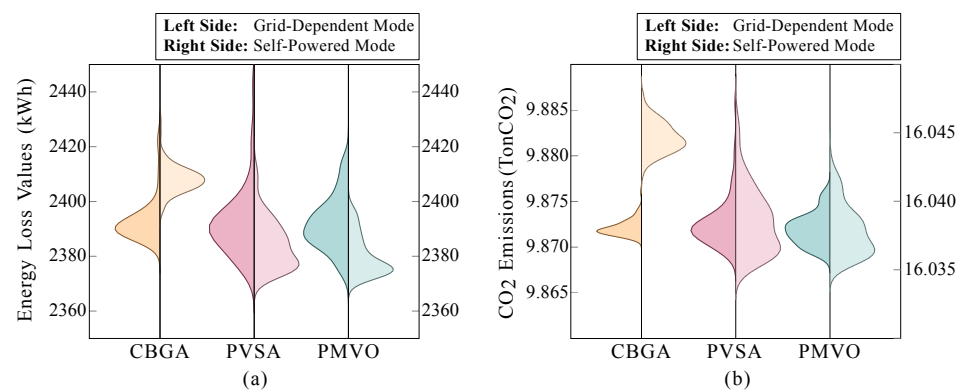


Figure 7. Violin-scatter plot comparing the implemented methodologies for the 33-node system under grid-dependent and self-powered modes over a 24 h evaluation horizon. (a) Energy loss. (b) CO₂ emissions.

Figure 7a illustrates the spread of energy loss values. The PMVO algorithm exhibits the narrowest distribution in both configurations, reflecting its stable convergence behavior and lower outcome variability. This visual result is coherent with the low standard deviation values previously reported in Tables 3 and 4. In contrast, the CBGA and PVSA methods show wider violins, especially in the self-powered mode, suggesting more dispersed solutions and less predictable performance. Figure 7b compares the distributions for CO₂ emissions. Once again, PMVO yields the most compact distribution, indicating consistently optimized behavior for environmental criteria. The violin shapes confirm the observations made from numerical indicators: PVSA provides competitive results but exhibits slightly higher variability, while CBGA shows more scattered emissions values.

These violin-scatter plots offer a visual confirmation of the robustness and reliability of the PMVO approach. The plots highlight that not only does PMVO achieve the best average and best-case performance, but it also maintains tighter distributions across optimization runs, which is an important feature in practical planning contexts where reproducibility and consistency are desirable.

It is worth reiterating that although the PMVO algorithm involves a longer computational time, the nature of the BESS scheduling problem (executed offline within a broad planning window) renders the solution time a non-critical factor. Therefore, selecting a strategy that guarantees higher quality and consistency in the solutions, such as PMVO, is more valuable than prioritizing minimal computation time.

5.1. Voltage Regulation Performance Analysis Under Best PMVO Solution

Figures 8 and 9 present the hourly voltage regulation profiles for a 33-node distribution system optimized using the PMVO algorithm under the two operational modes. Each curve corresponds to the optimal voltage regulation profile obtained when minimizing one of the two evaluated objective functions: energy losses and CO₂ emissions, respectively. Although the vertical axis represents voltage regulation (in %), these profiles illustrate the system's voltage behavior resulting from two distinct optimization goals. In both cases, the voltage deviations remain consistently below the critical 10% limit, confirming the algorithm's effectiveness in maintaining power quality regardless of the selected objective.

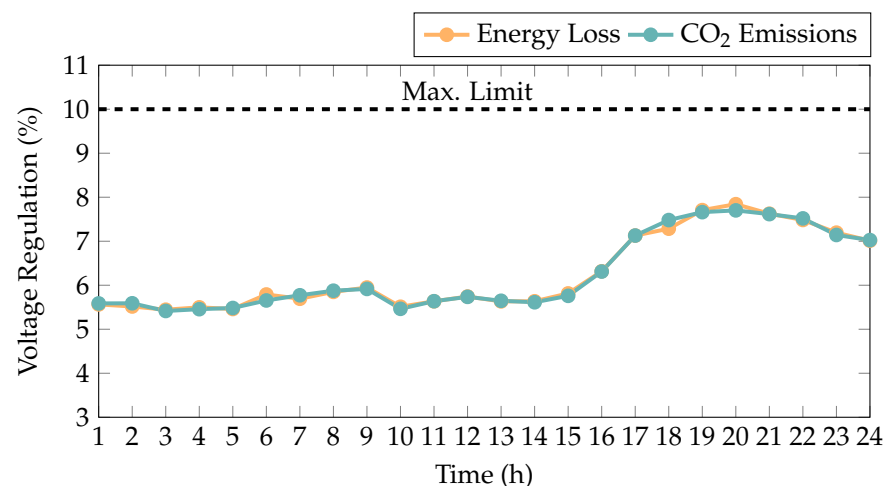


Figure 8. Voltage regulation performance achieved by the PMVO algorithm in a representative daily scenario for the 33-node system in grid-dependent mode over a 24 h evaluation horizon.

In the grid-dependent configuration (Figure 8), the system benefits from the external grid's support, allowing the PMVO to maintain voltage regulation between 5.4% and 7.8%. Notably, from hour 1 to hour 16, both the energy loss and CO₂ emission curves exhibit stable and overlapping behavior, suggesting that the algorithm identifies operating points with

joint benefits for both objectives. A slight rise is observed from hour 17 to hour 20, where voltage regulation approaches its highest values (a peak at 7.84% for energy losses and 7.70% for emissions), likely due to increased demand during night peak hours. However, the algorithm effectively constrains the rise within the permissible operational margins.

In contrast, the self-powered scenario (Figure 9) represents a more restrictive condition where the system operates without grid support. Despite this limitation, the PMVO algorithm maintains robust voltage regulation, ranging from approximately 5.4% to 7.74%, exhibiting only a marginal deviation from the grid-dependent case. As in the previous mode, hours 17–20 represent the most demanding interval, but the algorithm ensures compliance with the voltage regulation standard. The slight differences observed (particularly the slightly lower performance in the early hours) reflect the added constraint of managing local resources without external reinforcement.

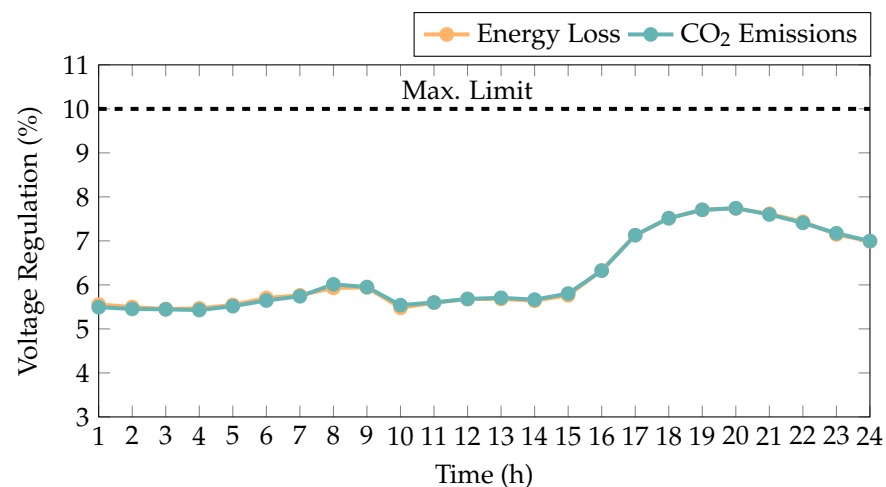


Figure 9. Voltage regulation performance achieved by the PMVO algorithm in a representative daily scenario for the 33-node system in self-powered mode over a 24 h evaluation horizon.

Comparing both operational modes reveals that the PMVO algorithm maintains a consistent and technically sound voltage regulation profile, with no hour surpassing the 10% regulatory threshold in either case. From a practical perspective, this analysis suggests that PMVO offers a reliable solution for voltage regulation across diverse microgrid configurations.

5.2. Loadability Performance Under Best PMVO Solution

Figures 10 and 11 display the hourly peak current loading across network lines, expressed as a percentage of their rated limits, for the 33-node distribution system optimized via the PMVO algorithm under both operational modes. Each curve represents the system response when minimizing a specific objective function—energy losses or CO₂ emissions. While the vertical axis shows the current loading level, the profiles themselves are the result of distinct optimization criteria.

In the grid-dependent configuration (Figure 10), none of the lines surpassed the 100% limit, validating the fact that the power flow remains within secure operational margins. However, certain branches exhibited values approaching the upper boundary, such as lines 13, 14, and 30, which registered loadabilities above 90%. Line 13 reached approximately 99.99%, suggesting that this particular line consistently bears high power transfer and may require infrastructure reinforcement or active control strategies. Conversely, the minimum loadability values—most notably observed in lines 17, 21, and 32—fell below 45%, indicating segments with underutilized capacity that could be leveraged for load redistribution if system flexibility permits.

In the self-powered mode (Figure 11), the loadability profile remained qualitatively similar, yet minor fluctuations can be observed. While line 13 slightly decreased its loading to 99.95%, the general high-load pattern on lines 13 to 15 and 30 persisted. Variations in load distribution, particularly visible in lines 25 to 29, showed marginal differences between the two modes. Despite this, the overall profile demonstrates the capability of PMVO to adapt to decentralized generation while preserving the integrity of the network. The lowest value continued to appear in line 32, consistent with the grid-dependent case, highlighting the persistent underuse of this branch in both strategies.

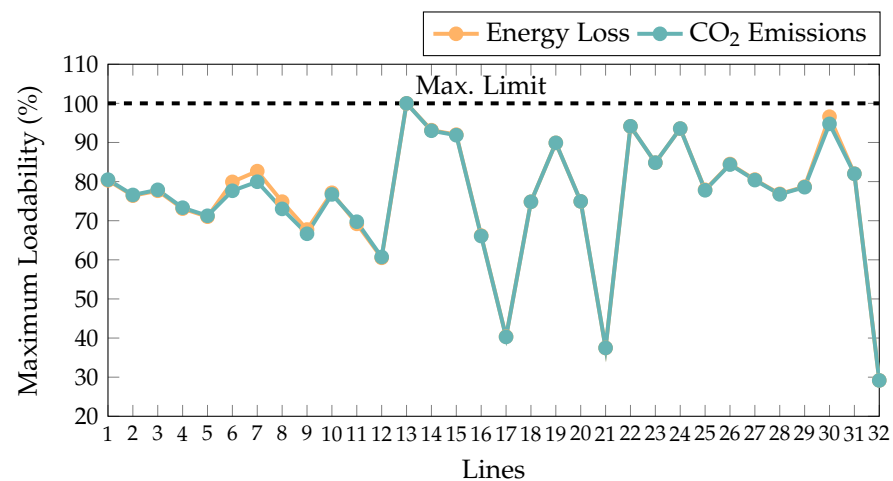


Figure 10. Maximum loadability performance achieved by the PMVO algorithm in a representative daily scenario for the 33-node system in grid-dependent mode over a 24 h evaluation horizon.

The minimal discrepancies in loadability between the energy loss and CO₂ emission scenarios support the robustness of the PMVO algorithm in ensuring that the optimization does not compromise operational safety.

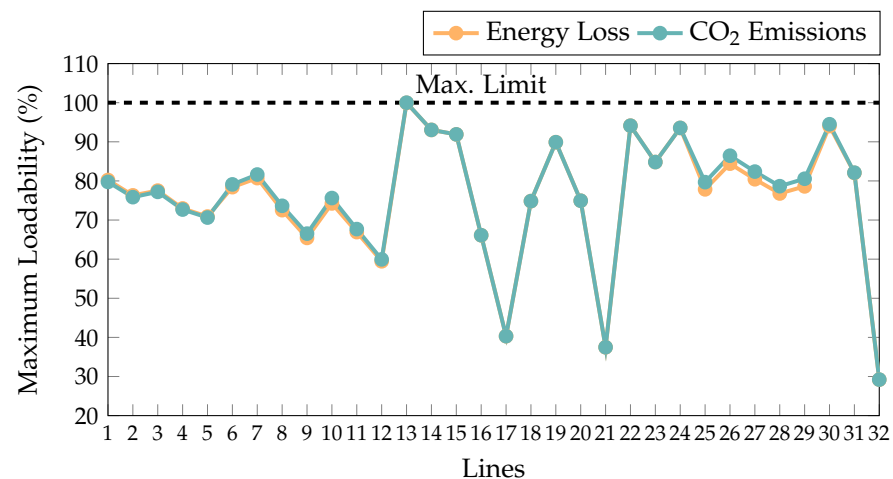


Figure 11. Maximum loadability performance achieved by the PMVO algorithm in a representative daily scenario for the 33-node system in self-powered mode over a 24 h evaluation horizon.

5.3. SoC Performance Under Best PMVO Solution

Figures 12 and 13 illustrate the hourly state-of-charge (SoC) profiles of the BESS units throughout the 24 h horizon under the optimal dispatch strategies determined by the PMVO algorithm in both operational modes. Each curve corresponds to an optimal solution obtained by minimizing either energy losses or CO₂ emissions, although the vertical axis reflects the SoC level (%). The results reveal different charging patterns that align with

the underlying optimization goals while still complying with operational constraints and ensuring reliable system performance.

Regarding the batteries' conditions, in the grid-dependent configuration (Figure 12), all BESS units maintain their SoC within the allowable range (10–90%), with distinct charge and discharge phases clearly observable. A synchronized depletion occurs during the early morning hours (00:00–08:00), followed by a coordinated charging interval during mid-day, peaking around 15:00–17:00. BESS C shows a more aggressive discharge pattern, reaching the lower bound precisely at hour 7, which suggests it is prioritized for higher utilization. BESS B maintains relatively stable behavior, avoiding deep discharges and helping to smooth transitions in SoC levels.

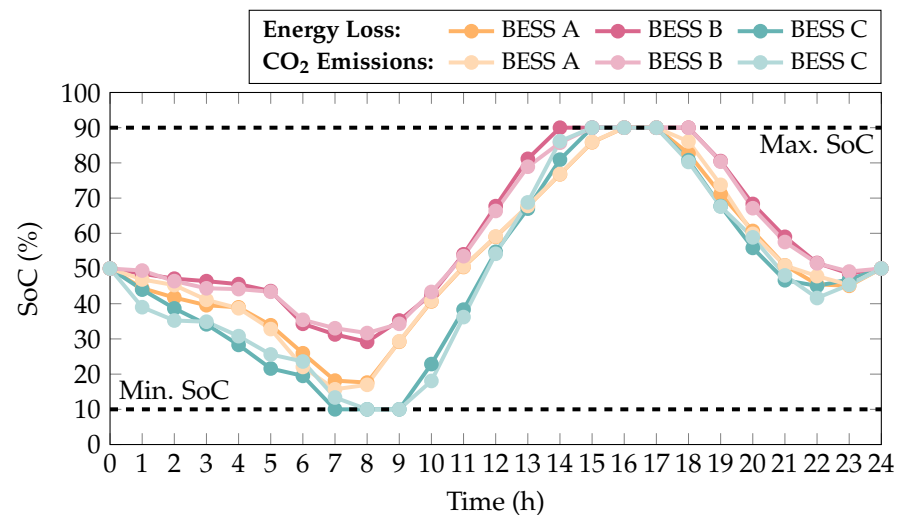


Figure 12. SoC profile as the solution achieved by the PMVO for a representative day of operation in the grid-dependent mode over a 24 h evaluation horizon.

In the self-powered mode (Figure 13), the storage operation becomes more sensitive due to the absence of external grid support. The early-hour SoC levels are notably lower compared to the grid-dependent case, reflecting the increased autonomy of the system. Again, BESS C reaches the lower SoC threshold, confirming its role in providing fast-acting support. The charging trajectory across all BESS units is slightly delayed but still ensures full recovery within operational boundaries by mid-afternoon.

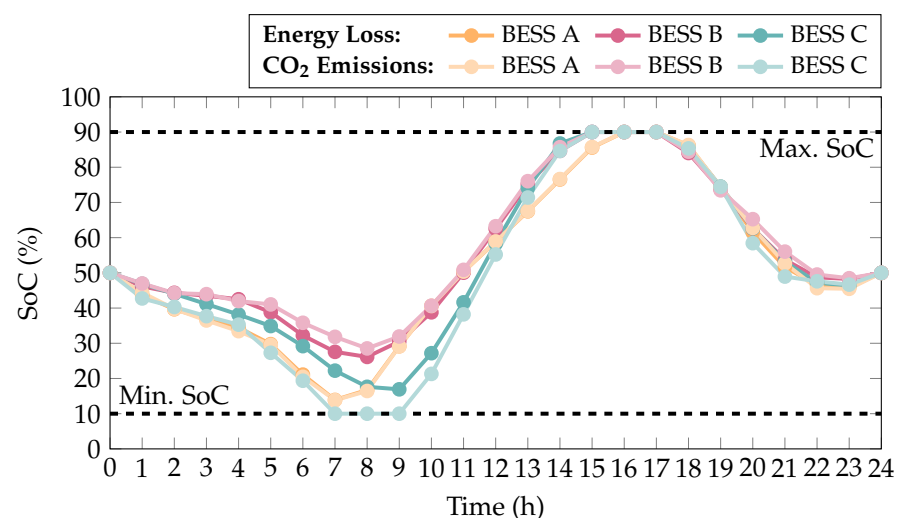


Figure 13. SoC profile as the solution achieved by the PMVO for a representative day of operation in the self-powered mode over a 24 h evaluation horizon.

The behavior across both modes highlights that the PMVO algorithm enforces constraint satisfaction while achieving adequate storage coordination. There is no evidence of excessive cycling or limit violations, which implies the strategy is compatible with long-term asset reliability.

5.4. Validation of the Methodology on a 136-Bus Microgrid

To further validate the proposed PMVO approach, it was applied to a 136-bus microgrid [53] over a full week, encompassing both grid-connected and islanded modes. This larger, more complex system tests the algorithm's robustness and flexibility across different microgrid sizes.

Figure 14 shows the 136-bus microgrid layout, where node 1 serves as the slack bus, connected either to the main grid or a 4000 kW diesel generator operating between 40% and 80% capacity, following the same constraints as the 33-bus system. Three PV units rated 1125, 1320, and 999 kW are located at nodes 106, 88, and 47. The base values are 13.8 kV and 100 kVA, with environmental parameters consistent with Section 4.1.

The system includes three lithium-ion BESS units with the same characteristics as those described in Section 4.1, located at buses 89, 75, and 35, respectively. The selection of these nodes was based on their higher power demand levels, which makes them critical points in the network. By placing storage systems at these locations, the BESS can effectively support the local load and alleviate stress on the distribution network, particularly during peak demand or islanded operation.

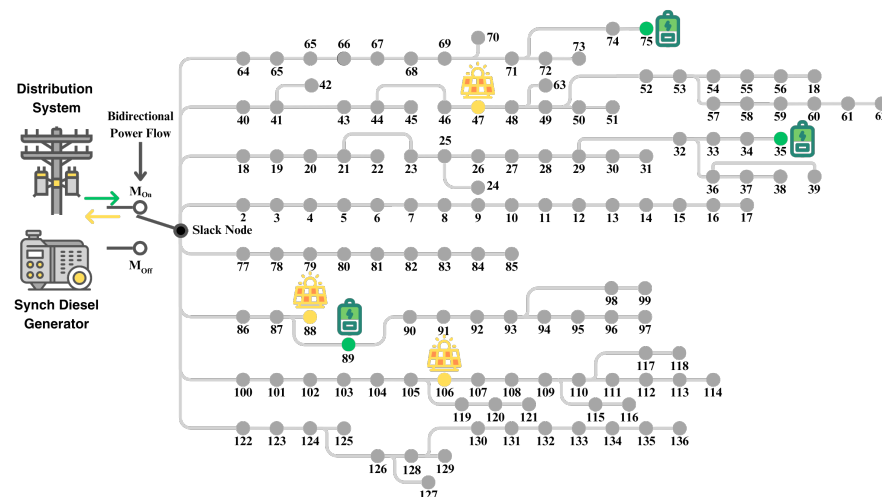


Figure 14. Topological schematic of the 136-node AC microgrid test system in dual-operation modes: Grid-dependent (M_1) and self-powered (M_2).

The technical parameters of the 136-node microgrid (MG) employed in this study are presented in Table A1, located in Appendix A. The description of these parameters follows the same criteria as those detailed in Table 1. For this MG, the maximum allowable voltage deviation is $\pm 10\%$ of the nominal voltage.

The load profile used in this study was sourced from a Colombian distribution company, while the PV generation profile was produced through an artificial neural network (ANN) trained with climatic data from a specific region in Colombia [27]. This ANN was developed by incorporating real meteorological variables, including time, temperature, solar radiation, humidity, and atmospheric pressure, and was employed to simulate hourly PV generation and power demand profiles over a representative 7-day period. Figure 15 shows the weekly load variation, where the “regular” curve represents the typical demand pattern observed on Monday, Tuesday, Thursday, and Friday. The remaining curves illustrate the distinctive behavior of the other days of the week.

Meanwhile, Figure 16 presents the corresponding photovoltaic generation profiles for each day.

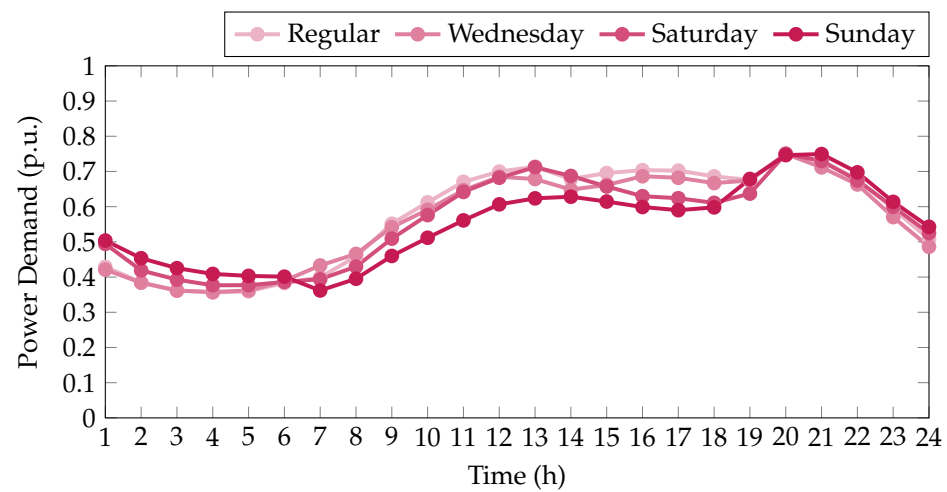


Figure 15. Representative daily load curves for a typical operational week.

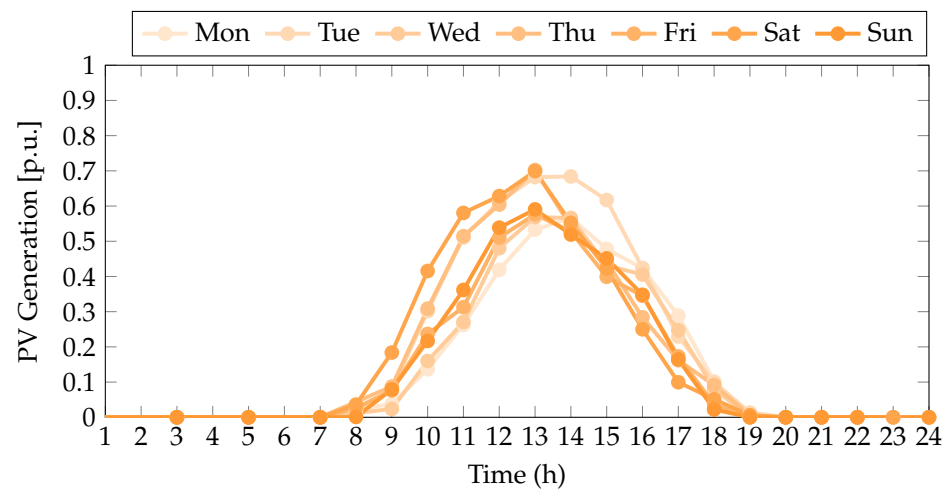


Figure 16. Daily PV generation profiles for a typical operational week.

Table 5 summarizes the results obtained by applying the PMVO to the 136-node microgrid under grid-connected operation. The table reports the values of the different objective functions considered in this work, including the baseline cases for each day of the week and the corresponding outcomes achieved by the PMVO.

Table 5. Performance results for the 136-node grid-dependent test system.

Objective Function	Case	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Energy Loss (kWh)	Base Case	2458.3857	2407.2377	2355.2850	2444.1375	2463.2519	2304.2519	2213.9967
	PMVO	2444.6646	2392.7391	2341.8054	2431.0729	2449.4778	2293.3203	2206.3791
	Time	93.7884	90.8853	89.3680	90.1772	90.6644	90.7031	92.5636
Emissions (TonCO ₂)	Base Case	40.0421	39.4684	39.2509	39.7717	40.0717	38.8444	38.1597
	PMVO	40.0399	39.4665	39.2487	39.7694	40.0695	38.8427	38.1580
	Time	89.7078	90.5946	88.0271	88.3221	88.8445	88.4533	90.3868

In terms of energy losses, the PMVO achieved an average weekly reduction of 87.5718 kWh, representing a technical improvement of 0.5261% compared to the base case. Daily absolute reductions ranged from 7.6175 kWh to 14.4985 kWh. The standard

deviation over the week was approximately 2.8377%, reflecting the stable and consistent performance of PMVO under varying operating conditions.

In addition, the proposed methodology required an average execution time of 91.1643 s per day to solve the energy loss minimization problem, i.e., approximately 1.52 min. This result highlights the practicality of the approach for day-ahead or short-term operational planning.

Similarly, in the case of CO₂ emissions, the PMVO achieved a weekly average reduction of 14.3062 kgCO₂ compared to the base scenario, representing an average improvement of 0.0052%. Daily absolute reductions ranged from 1.6691 to 2.2718 kgCO₂. With a weekly standard deviation of approximately 1.7562%, these results highlight the robustness and consistency of the PMVO under different operational scenarios.

The average computation time required to solve the CO₂ emissions minimization problem was approximately 89.1909 s per day (1.49 min), which is consistent with the execution time observed for energy loss minimization. These results confirm the practicality and scalability of the proposed optimization framework for multi-objective operation planning in both real-time and day-ahead contexts.

To further evaluate the robustness of the proposed methodology under more restrictive conditions, the PMVO was also applied to the same 136-node microgrid operating in self-powered (islanded) mode. Table 6 presents the results obtained in this scenario, including daily performance for each objective function and the corresponding baseline cases.

Table 6. Performance results for the 136-node self-powered test system.

Objective Function	Case	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Energy Loss (kWh)	Base Case	136.4297	133.7218	135.2536	136.7316	136.9853	129.0127	125.3783
	PMVO	135.2337	133.5115	134.86347	136.4138	136.9544	127.7908	125.3518
	Time	380.4747	378.2386	378.7801	385.7859	393.8756	403.8317	407.5802
Emissions (TonCO ₂)	Base Case	14.9350	14.3373	14.6324	14.6519	14.9657	14.2166	14.1764
	PMVO	14.9347	14.3372	14.6321	14.6516	14.9656	14.2160	14.1753
	Time	164.7517	159.9047	158.8186	160.2062	159.5723	160.1344	159.0750

In terms of energy losses, the PMVO achieved a weekly average reduction of 3.3938 kWh compared to the base case, which corresponds to a technical improvement of approximately 0.3635%. Daily absolute reductions ranged from 26.5283 Wh to 1.1961 kWh. The low standard deviation of approximately 3.3871% across the week indicates that the energy loss reductions were consistently achieved each day, regardless of operational variability.

Regarding execution time, the methodology required an average of 389.7953 s per day (approximately 6.49 min) to solve the energy loss minimization problem. Although this represents a higher computational demand compared to the grid-connected case, it remains reasonable for offline planning or short-term scheduling in more constrained systems.

For CO₂ emissions, the PMVO reported a weekly average reduction of 2.8774 kgCO₂, representing an average improvement of 0.0028%. The standard deviation, measured at 2.2336%, suggests stable behavior in emissions reduction throughout the week, with the algorithm adapting effectively to day-to-day variations in system conditions.

The corresponding average computation time for solving the emissions minimization problem was 160.3519 s per day (approximately 2.67 min), which is consistent across the week and aligned with the performance observed in the energy loss case. These results confirm that the proposed framework maintains its effectiveness and computational feasibility even in isolated microgrid conditions, reinforcing its applicability for diverse operational contexts.

Figures 17 and 18 illustrate the weekly performance of the PMVO algorithm in terms of daily energy loss and CO₂ emission reductions for the 136-node system under both grid-dependent and self-powered configurations.

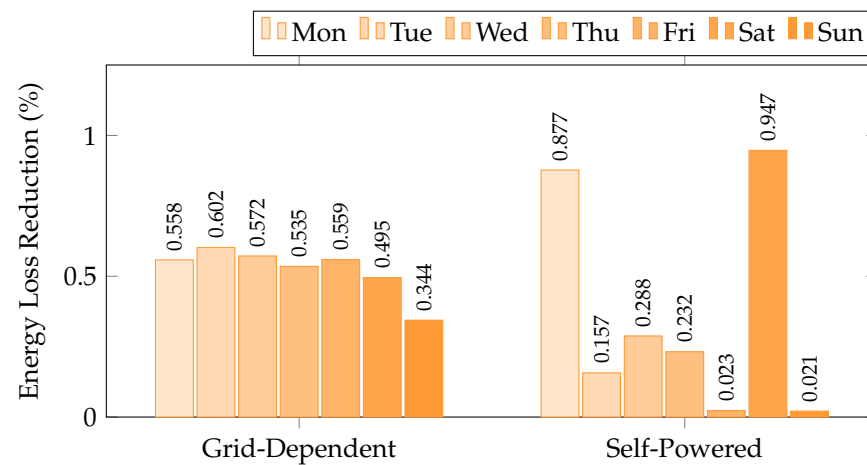


Figure 17. Energy loss reduction: Results for a 136-node system in grid-dependent and self-powered modes over a 1-week evaluation horizon.

In Figure 17, PMVO demonstrates noticeable variability in daily energy loss reductions depending on the operation mode. In the grid-dependent configuration, the reductions fluctuate between 0.344% (Sunday) and 0.602% (Tuesday), whereas, in the self-powered mode, the range is broader, from as low as 0.021% (Sunday) to a peak of 0.947% (Saturday). The weekly average energy loss reduction for the grid-dependent case is approximately 0.5236%, with a standard deviation of 0.0815%, indicating relatively stable but modest performance across the week. In contrast, the self-powered mode yields a higher variability, with a weekly mean of 0.3636% and a standard deviation of 0.3391%, reflecting the influence of local generation dynamics and load profiles on the performance of PMVO.

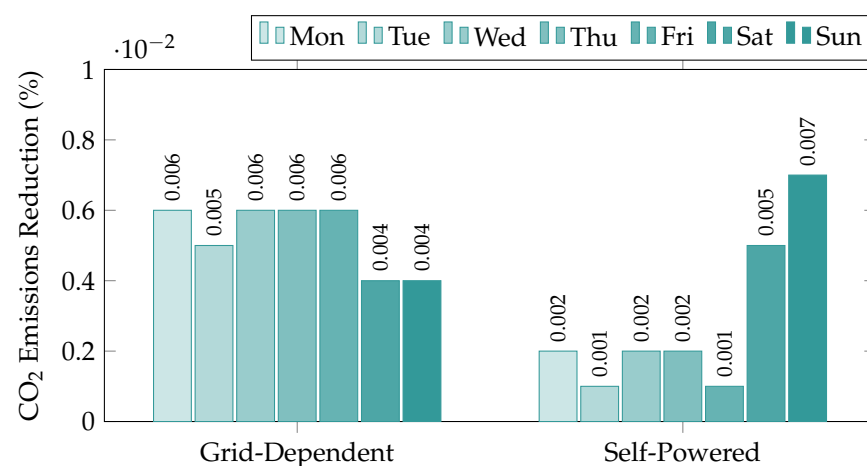


Figure 18. CO₂ emissions reduction: Results for a 136-node system in grid-dependent and self-powered modes over a 1-week evaluation horizon.

Figure 18 presents the corresponding CO₂ emission reductions. Although the absolute values are lower due to the nature of the metric, the overall trend aligns with the observed pattern in energy losses. In the grid-dependent configuration, reductions range from 0.004% to 0.006%, with a weekly average of 0.0053% and a standard deviation of 0.0009%, indicating stable performance throughout the week. In contrast, the self-powered mode exhibits greater variability, with values spanning from 0.001% to 0.007%, a weekly

average of 0.0029%, and a higher standard deviation of 0.0021%. This increased dispersion reflects the effects of intermittent power flows and the absence of centralized dispatch control.

These results highlight that the algorithm's performance, both in terms of energy loss and CO₂ emission reductions, is strongly influenced by the specific configuration of the distribution network, particularly the placement of photovoltaic generators and battery systems. It is worth noting that the 136-node test system originally lacked both PV generation and storage units; consequently, these components were assigned to arbitrary locations within the network. While the reported outcomes demonstrate the algorithm's potential, they could likely be enhanced through an optimized siting strategy for DERs, a topic beyond the scope of this study but identified as a direction for future research.

Figure 19 displays the hourly voltage regulation of a 136-node distribution network optimized with the PMVO algorithm under both grid-connected and self-powered configurations, using daily operational profiles over a full week to capture typical load and generation fluctuations.

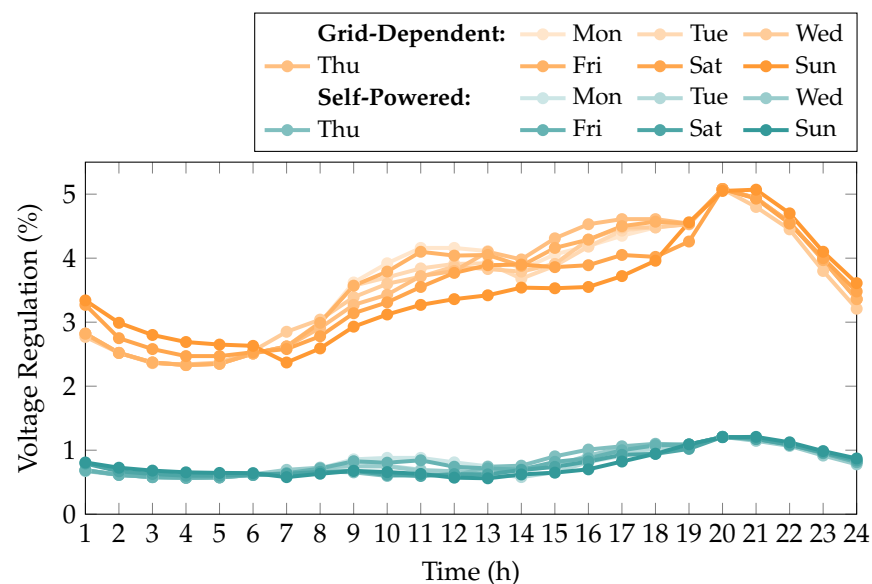


Figure 19. Voltage regulation performance achieved by the PMVO algorithm in a representative weekly scenario for a 136-node system in grid-dependent and self-powered modes.

In the grid-connected mode, voltage regulation remains within 2.3% to 5.08%, always below the 10% operational limit. The lowest deviations occur in the early morning hours (1–6), with regulation levels near 2.3–2.6% due to lower demand and system stress. Voltage deviations increase gradually during the day, peaking consistently at hour 20 with a maximum of 5.08%, reflecting evening peak demand. Despite day-to-day variability, the algorithm maintains a narrow voltage band with minimal fluctuations between days, demonstrating robustness against variable operating conditions.

Under the self-powered scenario, voltage regulation is even more constrained, ranging from 0.57% to 1.21%, with similar daily trends. These lower values stem from a different voltage reference related to slack-less operation. Peak deviations occur, again, near hour 20, with all days converging at around 1.208%, confirming the repeatability of this peak pattern.

The results confirm that the PMVO algorithm effectively controls voltage within safe operational limits over a larger, more complex network, achieving a similar regulation quality to that previously demonstrated in a 33-node system. The use of detailed daily profiles covering multiple days illustrates the algorithm's capacity to handle typical variability and suggests its suitability for integration into EMS frameworks with frequent updates. This implies that the

approach can adapt to forecast uncertainties and changing conditions, providing reliable voltage regulation in both grid-supported and islanded microgrid configurations.

Figure 20 presents the maximum loadability percentages of the 136-node distribution system for each day of the week under grid-connected and self-powered configurations based on the optimal dispatch of BESS, which is found by the PMVO algorithm.

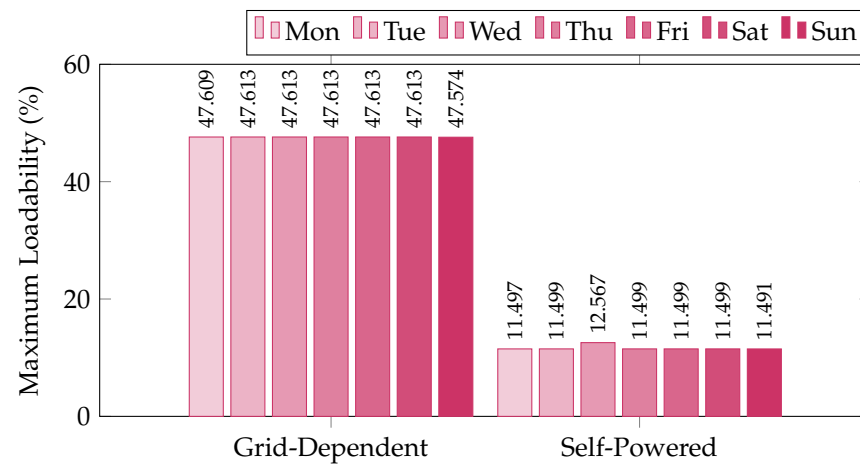


Figure 20. Maximum loadability performance achieved by the PMVO algorithm in a representative weekly scenario for a 136-node system in grid-connected and self-powered modes.

In the grid-dependent mode, the system exhibits relatively stable maximum loadability values of around 47.6% across all days, well below the 100% operational limit, indicating a comfortable margin against line overloads. This consistent performance suggests that the algorithm effectively balances power flows, preventing any single line from reaching critical loading levels. The minor day-to-day variations (less than 0.05%) reflect the system's response to typical daily demand and generation patterns without compromising safety or reliability.

Under the self-powered configuration, maximum loadability values are significantly lower, ranging from 11.5% to 12.6%. This reduction is expected since the system operates relying solely on local generation and storage, limiting power transfers over the lines and, thus, reducing line stress. Slightly higher values observed midweek (Wednesday) indicate minor load shifts but remain far from critical levels, showcasing the algorithm's adaptability to different operating modes while preserving network integrity.

Overall, the PMVO algorithm maintains line loadings at safe, moderate levels regardless of the operation mode, demonstrating its capability to manage power flows effectively in a large-scale network. The stable and repeatable loadability profile over the week highlights the robustness of the dispatch strategy against demand variability. These results reinforce the scalability of the approach and suggest that it can reliably ensure operational security in complex microgrids under varying configurations.

The SoC profiles in Figure 21 demonstrate the coordinated operation of BESS units within safe operating limits (10–90%) under grid-dependent mode over the course of a full week of operation, accounting for the variability of both demand and generation. Analysis reveals three distinct operational strategies: BESS C serves as the primary flexible resource with aggressive cycling (minimum 10% SoC on Day 2); BESS B maintains stable operation (SoC > 35%) for grid stabilization; and BESS A provides intermediate support with adaptive cycling (27.38% discharge on Day 3). All units exhibit synchronized daily patterns with midday solar charging and evening discharge while maintaining complementary weekly operation that balances battery health preservation with grid support requirements. The system achieves optimal performance through this tiered operational approach, where each BESS unit fulfills specific grid support functions according to its cycling characteristics.

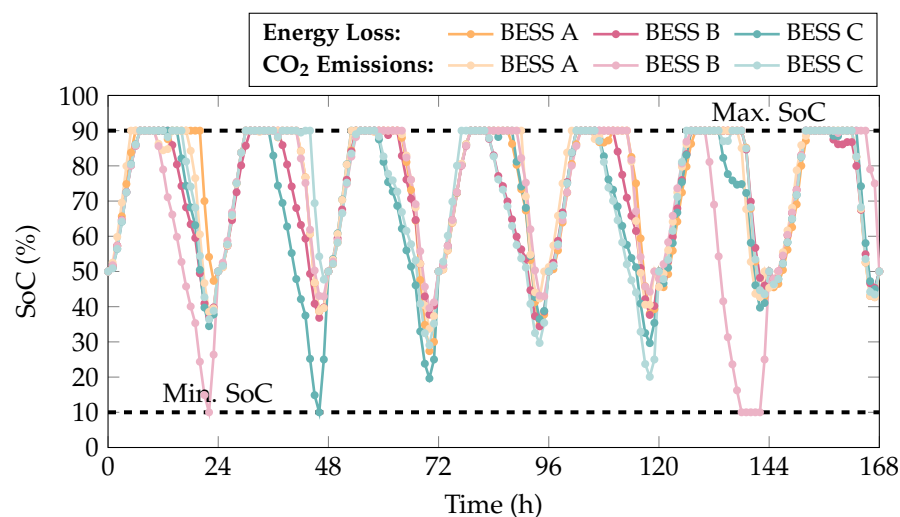


Figure 21. SoC profile as the solution achieved by the PMVO for a representative week of operation for a 136-node system in the grid-dependent mode.

The SoC profiles in Figure 22 reveal distinct operational strategies for BESS units in self-powered mode with the objective of minimizing energy losses, with all systems maintaining safe operating limits (10–90%). BESS A demonstrates moderate cycling with gradual charge–discharge patterns, typically operating between 30–90% SoC, except for a strategic deep discharge to 10% during hours 79–81 to address critical system needs. BESS B shows more aggressive utilization, frequently charging to 90% capacity and undergoing periodic deep discharges (reaching 10% during hours 154–160), suggesting its role as the primary energy buffer. BESS C exhibits intermediate behavior with regular full recharge cycles but avoids extreme depletion, except for the period between hours 57 and 69.

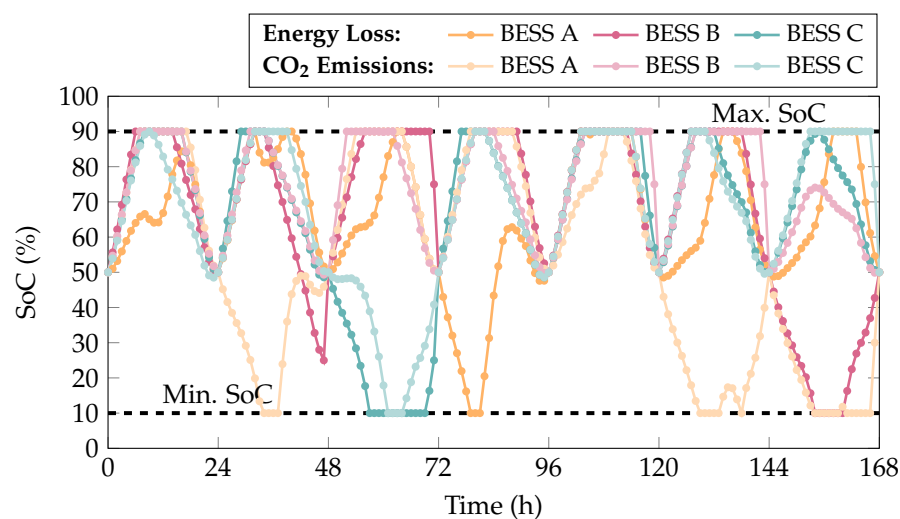


Figure 22. SoC profile as the solution achieved by the PMVO for a representative week of operation for a 136-node system in the self-powered mode.

On the other hand, for the objective function focused on minimizing emissions, Figure 22 illustrates different SoC dynamics. BESS A displays a highly fluctuating SoC pattern, with frequent charging and discharging cycles, indicating a reactive strategy to counter emission peaks. BESS B maintains prolonged discharge intervals, especially between hours 0–16 and 52–117, likely aimed at supporting the system during high-demand or high-emission periods. In contrast, BESS C shows smoother transitions with a significant charging period between hours 57 and 72, possibly aligning with lower-emission windows.

This behavior suggests that BESS C pursues a more balanced trade-off between operational stability and emission reduction.

Notably, the weekly operation shows consistent alignment with renewable generation patterns, strategic depth-of-discharge allocation based on unit function, and adaptive responses to changing grid conditions while maintaining safe operating limits. This configuration demonstrates an effective multi-objective optimization strategy that simultaneously addresses grid stability, renewable integration, and battery longevity requirements.

These results further support the scalability of the proposed technique, demonstrating its applicability to larger networks without compromising performance. Moreover, the method has shown strong adaptability to scenarios with high variability in both renewable generation and demand, making it a robust tool for the optimal operation of microgrids under dynamic and realistic conditions. This operational flexibility is particularly valuable in modern systems, where uncertainty and variability play a central role in decision-making.

6. Conclusions

This work presented an optimization energy management framework for an AC microgrid using the MVO. The master–slave strategy combined MVO in the master stage with a Successive Approximations (SAs) power flow approach in the slave stage, enabling a robust search for optimal battery energy storage system scheduling. Two operating conditions were addressed: (i) grid-dependent and (ii) self-powered. The key conclusions are as follows:

- Technical and environmental performance: Numerical tests on a 33-node microgrid revealed that the proposed Parallel MVO consistently led to the best performance in both energy losses and CO₂ emissions reduction. In the grid-dependent scenario, energy losses were reduced to approximately 2374.85 kWh from a base of 2484.57 kWh, while CO₂ emissions were cut to near 9.8693 TonCO₂ from 9.8874 TonCO₂. For the self-powered mode, losses reached about 2373.53 kWh (compared to 2484.57 kWh in the base case), and emissions were held at 16.0364 TonCO₂ (down from 16.0659 TonCO₂). Compared to other metaheuristics, the PMVO exhibited lower standard deviation values, reflecting high consistency and reliability.
- Voltage regulation and loadability: The PMVO-based dispatch ensured that all voltage magnitudes and line currents remained within prescribed limits. Even under the self-powered mode, where grid support was absent, voltage regulation stayed below the 10% threshold, and no line exceeded 100% of its thermal rating.
- BESS scheduling: The daily charge and discharge cycles for each BESS unit indicated efficient usage of storage capacity. No state-of-charge violations were observed, and batteries were charged in periods of available surplus generation and discharged mainly during higher load intervals. This helped reduce technical losses and emissions without compromising power quality.

In addition to the primary tests on the 33-node system, the proposed methodology was further validated on a large-scale 136-bus microgrid to demonstrate scalability and robustness. The results confirmed that the PMVO algorithm maintains its superior performance even under significantly more complex topologies and operating scenarios. Specifically, the algorithm successfully minimized both energy losses and emissions while adhering to operational constraints, such as voltage profiles and thermal line limits, across a higher-dimensional decision space. This extended validation highlights the algorithm's adaptability and positions it as a viable solution for real-world deployment in medium- to large-scale microgrid applications.

6.1. Limitations

- The model assumes fixed active power factors, and reactive power support was excluded. Including reactive power control could further enhance voltage stability.
- Real-time operational changes were not considered; a day-ahead schedule was assumed.
- The computational effort, although not critical in offline scenarios, may be significant for larger networks or real-time applications.
- Energy losses and CO₂ emissions, although consistent, are modest in absolute terms. This outcome is not due to deficiencies in the proposed methodology but rather reflects the physical and operational constraints of the test microgrid. Specifically, the system is characterized by limited photovoltaic generation capacity, and the BESS units have fixed location, power rating, and charge/discharge operation schedules. These restrictions significantly narrow the search space available to the optimization algorithm, thus constraining the potential for further performance improvements. As such, the reported results should be interpreted as the best possible outcomes within a constrained infrastructure scenario.

6.2. Future Work

Research can include real-time or rolling-horizon implementations that integrate uncertainty in load and renewable generation forecasts. Exploring the addition of demand response mechanisms, reactive power dispatch, and dynamic transitions between operating modes would expand the solution space. Furthermore, it is possible to incorporate more complex cost functions, maintenance aspects, and grid constraints to address broader challenges in microgrid operation while enhancing the reliability of dispatch solutions.

Furthermore, to enhance the effectiveness of the proposed energy management strategy, future work will focus on evaluating more flexible and expanded configurations. This includes increasing the PV generation capacity and relocating and resizing BESS units. Additionally, future research will explore the use of power electronic interfaces for coordinated control of both active and reactive power, aiming to maximize the technical and environmental benefits of optimized microgrid operation.

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Appendix A. Technical Data of the 136-Node AC Test System

Table A1. Technical parameters of the 136-node AC test system.

First Half							Second Half						
Line <i>l</i>	From Node <i>i</i>	To Node <i>j</i>	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kVAr)	Line <i>l</i>	From Node <i>i</i>	To Node <i>j</i>	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kVAr)
1	1	2	0.33205	0.76653	0.000	0.000	69	69	70	0.55914	0.29412	83.015	33.028
2	2	3	0.00188	0.00433	47.780	19.009	70	69	71	0.05816	0.13425	217.917	86.698
3	3	4	0.22324	0.51535	42.551	16.929	71	71	72	0.70130	0.36890	23.294	9.267
4	4	5	0.09943	0.22953	87.022	34.622	72	72	73	1.02352	0.53839	5.075	2.019
5	5	6	0.15571	0.35945	311.310	123.855	73	71	74	0.06754	0.15591	72.638	28.899
6	6	7	0.16321	0.37677	148.869	59.228	74	74	75	1.32352	0.45397	405.990	161.524
7	7	8	0.11444	0.26417	238.672	94.956	75	1	76	0.01126	0.02598	0.000	0.000
8	7	9	0.05675	0.05666	62.299	24.786	76	76	77	0.72976	1.68464	100.182	42.468
9	9	10	0.52124	0.27418	124.598	49.571	77	77	78	0.22512	0.51968	142.523	60.417
10	9	11	0.10877	0.10860	140.175	55.768	78	78	79	0.20824	0.48071	96.042	40.713
11	11	12	0.39803	0.20937	116.813	46.474	79	79	80	0.04690	0.10827	300.454	127.366
12	11	13	0.91744	0.31469	249.203	99.145	80	80	81	0.61950	0.61857	141.238	59.873
13	11	14	0.11823	0.11805	291.447	115.952	81	81	82	0.34049	0.33998	279.847	118.631
14	14	15	0.50228	0.26421	303.720	120.835	82	82	83	0.56862	0.29911	87.312	37.013
15	14	16	0.05675	0.05666	215.396	85.695	83	82	84	0.10877	0.10860	243.849	103.371
16	16	17	0.29379	0.15454	198.586	79.007	84	84	85	0.56862	0.29911	247.750	105.025
17	1	18	0.33205	0.76653	0.000	0.000	85	1	86	0.01126	0.02598	0.000	0.000
18	18	19	0.00188	0.00433	0.000	0.000	86	86	87	0.41835	0.96575	89.878	38.101
19	19	20	0.22324	0.51535	0.000	0.000	87	87	88	0.10499	0.13641	1137.280	482.108
20	20	21	0.10881	0.25118	30.127	14.729	88	87	89	0.43898	1.01338	458.339	194.296
21	21	22	0.71078	0.37388	230.972	112.920	89	89	90	0.07520	0.02579	385.197	163.290
22	21	23	0.18197	0.42008	60.256	29.458	90	90	91	0.07692	0.17756	0.000	0.000
23	23	25	0.30326	0.15952	230.972	112.920	91	91	92	0.33205	0.76653	79.608	33.747
24	25	24	0.02439	0.05630	120.507	58.915	92	92	93	0.08442	0.19488	87.312	37.013
25	25	26	0.04502	0.10394	0.000	0.000	93	93	94	0.13320	0.30748	0.000	0.000
26	26	27	0.01876	0.04331	56.981	27.857	94	94	95	0.29320	0.29276	74.001	31.370
27	27	28	0.11823	0.11805	364.665	178.281	95	95	96	0.21753	0.21721	232.050	98.369
28	28	29	0.02365	0.02361	0.000	0.000	96	96	97	0.26482	0.26443	141.819	60.119
29	29	30	0.18954	0.09970	124.647	60.939	97	93	98	0.10318	0.23819	0.000	0.000
30	30	31	0.39803	0.20937	56.981	27.857	98	98	99	0.13507	0.31181	76.449	32.408
31	29	32	0.05675	0.05666	0.000	0.000	99	1	100	0.00938	0.02165	0.000	0.000
32	32	33	0.09477	0.04985	85.473	41.787	100	100	101	0.16884	0.38976	51.322	21.756
33	33	34	0.41699	0.21934	0.000	0.000	101	101	102	0.11819	0.27283	59.874	25.381
34	34	35	0.11372	0.05982	396.735	193.960	102	102	103	2.28608	0.78414	9.065	3.843
35	32	36	0.07566	0.07555	0.000	0.000	103	102	104	0.45587	1.05236	2.092	0.887
36	36	37	0.36960	0.19442	181.152	88.563	104	104	105	0.69600	1.60669	16.735	7.094
37	37	38	0.26536	0.13958	242.172	118.395	105	105	106	0.45774	1.05669	1506.522	638.634
38	36	39	0.05675	0.05666	75.316	36.821	106	106	107	0.20298	0.26373	313.023	132.694
39	1	40	0.33205	0.76653	0.000	0.000	107	107	108	0.21348	0.27737	79.831	33.842
40	40	41	0.11819	0.27283	1.254	0.531	108	108	109	0.54967	0.28914	51.322	21.756
41	41	42	2.96288	1.01628	6.274	2.660	109	109	110	0.54019	0.28415	0.000	0.000
42	41	43	0.00188	0.00433	0.000	0.000	110	108	111	0.04550	0.05911	202.435	85.815
43	43	44	0.06941	0.16024	117.880	49.971	111	111	112	0.47385	0.24926	60.823	25.784
44	44	45	0.81502	0.42872	62.668	26.566	112	112	113	0.86241	0.45364	45.618	19.338
45	44	46	0.06378	0.14724	172.285	73.034	113	113	114	0.56862	0.29911	0.000	0.000
46	46	47	0.13132	0.30315	458.556	194.388	114	109	115	0.77711	0.40878	157.070	66.584
47	47	48	0.06191	0.14291	262.962	111.473	115	115	116	1.08038	0.56830	0.000	0.000
48	48	49	0.11444	0.26417	235.761	99.942	116	110	117	1.09933	0.57827	250.148	106.041
49	49	50	0.28374	0.28331	0.000	0.000	117	117	118	0.47385	0.24926	0.000	0.000
50	50	51	0.28374	0.28331	109.215	46.298	118	105	119	0.32267	0.74488	69.809	29.593
51	49	52	0.04502	0.10394	0.000	0.000	119	119	120	0.14633	0.33779	32.072	13.596
52	52	53	0.02626	0.06063	72.809	30.865	120	120	121	0.12382	0.28583	61.084	25.894
53	53	54	0.06003	0.13858	258.473	109.570	121	1	122	0.01126	0.02598	0.000	0.000
54	54	55	0.03002	0.06929	69.169	29.322	122	122	123	0.64910	1.49842	94.622	46.260
55	55	56	0.02064	0.04764	21.843	9.260	123	123	124	0.04502	0.10394	49.858	24.375
56	53	57	0.10881	0.25118	0.000	0.000	124	124	125	0.52640	0.18056	123.164	60.214
57	57	58	0.25588	0.13460	20.527	8.702	125	124	126	0.02064	0.04764	78.350	38.304
58	58	59	0.41699	0.21934	150.548	63.819	126	126	127	0.53071	0.27917	145.475	71.121
59	59	60	0.50228	0.26421	220.687	93.552	127	126	128	0.09755	0.22520	21.369	10.447
60	60	61	0.33170	0.17448	92.384	39.163	128	128	129	0.11819	0.27283	74.789	36.564
61	61	62	0.20849	0.10967	0.000	0.000	129	128	130	0.13882	0.32047	227.926	111.431
62	48	63	0.13882	0.32047	226.693	96.098	130	130	131	0.04315	0.09961	35.614	17.411

Table A1. Cont.

First Half							Second Half						
Line <i>l</i>	From Node <i>i</i>	To Node <i>j</i>	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kVAr)	Line <i>l</i>	From Node <i>i</i>	To Node <i>j</i>	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kVAr)
63	1	64	0.00750	0.01732	0.000	0.000	131	131	132	0.09192	0.21220	249.295	121.877
64	64	65	0.27014	0.62362	294.016	116.974	132	132	133	0.16134	0.37244	316.722	154.842
65	65	66	0.38270	0.88346	83.015	33.028	133	133	134	0.37832	0.37775	333.817	163.199
66	66	67	0.33018	0.76220	83.015	33.028	134	134	135	0.39724	0.39664	249.295	121.877
67	67	68	0.32830	0.75787	103.770	41.285	135	135	136	0.29320	0.29276	0.000	0.000
68	68	69	0.17072	0.39409	176.408	70.184							

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