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Optimizing Energy Management in AC Microgrids: A Comparative Study of Metaheuristic Algorithms for Minimizing Energy Losses and CO_2 Emissions

Héctor Pinto Vega [1], Luis Fernando Grisales-Noreña [2], Vanessa Botero-Gómez [3,*]

[1] *Universidad de Talca, Facultad de Ingeniería, Departamento de Ingeniería Eléctrica, Curicó, Chile; hpinto18@alumnos.utalca.cl (H.P.V.)*
[2] *Grupo de Investigación en Alta Tensión—GRALTA, Escuela de Ingeniería Eléctrica y Electrónica, Universidad del Valle, Cali 760015, Colombia; grisales.luis@correounivalle.edu.co (L.F.G.-N.)*
[3] *Department of Mechatronic Engineering, Faculty of Engineering, Instituto Tecnológico Metropolitano, Medellín 050030, Colombia; vanessabotero@itm.edu.co (V.B.-G.)*

Abstract This study tackles the energy management problem for wind distributed generators in AC microgrids (MGs) operating in both connected and isolated modes. A mathematical formulation is proposed to minimize energy losses and CO_2 emissions, incorporating technical and regulatory constraints to reflect real-world MG operations. The solution methodology combines the Population-Based Genetic Algorithm (PGA) with an hourly power flow analysis based on the successive approximation (SA) method. To validate the proposed approach, a comprehensive comparison is conducted against three widely used metaheuristic algorithms: Particle Swarm Optimization (PSO), JAYA, and the Generalized Normal Distribution Optimizer (GNDO). Employing a rigorous statistical framework, including ANOVA and Tukey HSD tests, the algorithms' performance is evaluated through 100 independent runs per objective and configuration, using a 33-node AC MG with variable generation and demand as the test scenario. Results demonstrate that PGA consistently outperforms other algorithms, achieving lower mean values and variance in both energy loss and emission minimization. GNDO, by contrast, shows higher variability and less effective optimization. Then, to further validate the strong performance and adaptability of the PGA, it is applied to a 69-node MG, where it achieves significant reductions in both emissions and energy losses. This work not only underscores the robustness and adaptability of PGA for sustainable microgrid management but also establishes a standardized framework for evaluating optimization algorithms in energy systems.

Keywords Metaheuristic Optimization, Microgrid, Algorithm Comparison, Energy Loss Minimization, CO_2 Emissions Reduction

AMS 2010 subject classifications: 90C59, 90C90, 49M37, 68W20, 94C15.

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1. Introduction

The increasing integration of distributed renewable energy sources, particularly wind energy, has driven the development of MGs to enhance energy efficiency and resilience in modern power systems [1]. Wind energy offers two significant advantages over photovoltaic (PV) generation: (i) its ability to produce energy continuously throughout the day and (ii) the absence of concentrated peak generation during specific hours (e.g., 13:00–14:00 for PV systems). This avoids the issue of overgeneration, which can adversely impact the electrical system by disrupting voltage and frequency regulation. Such disruptions often necessitate generation curtailment, leading to wasted regional energy potential and an increased dependence on battery storage systems. The latter further elevate

*Correspondence to: Vanessa Botero-Gómez (Email: vanessabotero@itm.edu.co).

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electrical grids' investment and operational costs, making wind energy a more favorable option in specific scenarios [2].

The MGs, defined as localized clusters of distributed energy resources capable of operating either connected to the main grid or in isolated (islanded) mode, provide flexibility in power distribution and enhance system reliability [3]. However, operating MGs with a high penetration of renewable energy sources, such as wind generators (WGs), presents significant challenges in maintaining system stability and meeting performance objectives. These challenges are particularly critical when seeking to minimize energy losses and reduce environmental emissions associated with conventional generation—two essential factors for grid operators and the well-being of electrical grid users [4]. Addressing these issues is the primary focus of this research.

One primary challenge in the operation of MGs is optimizing power flow to achieve a balance between operational efficiency and environmental impact. This study addresses two critical objectives within this context: minimizing active power losses across the network and reducing CO_2 emissions from power generation sources. Reducing energy losses is crucial for enhancing the efficiency of power delivery and mitigating the strain on network infrastructure, which is particularly relevant in MGs with distributed wind generation under various operational scenarios [5]. Additionally, reducing CO_2 emissions aligns with global efforts to combat climate change by transitioning toward more sustainable energy systems [6].

An analysis of the literature reveals several works addressing the optimal operation of wind-distributed generators in electrical grids, focusing on reducing energy losses and CO_2 emissions. One such example is the work presented in [7] where the authors address the problem of integration and operation of distributed WGs in an 83-node electrical system, focusing on minimizing system losses while adhering to voltage and power constraints. The proposed solution employs a master-slave methodology [8]; a Genetic Algorithm (GA) is used in the master stage to determine the optimal placement of WGs, and the Primal-Dual Interior-Point Method (PDIPM) is applied in the slave stage to manage generator operations and perform power flow analysis. A key contribution of this work is the application of the PDIPM to optimize the energy generated by wind turbines. Despite this, the study does not consider the telescopic behavior of distribution networks or the current limits in these lines, which limits the realistic representation of the system.

The study presented in [9] focused on minimizing energy losses in 33- and 69-node test systems by determining the optimal placement and operation of WGs within the electrical networks. To achieve this, the authors utilized a GA to optimize both parameters. The analysis incorporated voltage constraints and ensured the balance of active and reactive power in the proposed network, reducing system losses exceeding 30% for both active and reactive power. Nonetheless, the study did not include the power limitations of generation equipment or the current constraints of electrical lines, which are essential considerations in real-world systems.

The study reported in [10] explores the optimal power flow problem in distributed generation systems (DGS) integrating thermal, wind, and solar technologies. A multi-objective optimization approach, ACNSDE, derived from NSGA-II and combining GA and Differential Evolution (DE) techniques, is proposed to enhance technical, economic, and environmental performance. Tests conducted on a 30-node network with thermal, wind, and solar generators and a 57-node network without renewables show that ACNSDE reduces costs more effectively than NSGA-II. At the same time, the latter performs better in minimizing emissions and power losses. Despite these advantages, the study does not account for generation and demand variability, which limits its applicability to real-world scenarios. Additionally, it lacks a statistical analysis to demonstrate the performance of the proposed solution methodology compared to the methods used for comparison.

The authors in [11] proposed an Advanced Prioritized Deep-Q-Network (AP DQN) algorithm to optimize energy production of wind and PV generators in AC MGs, integrating advanced techniques such as a multi-headed attention mechanism and prioritized experience replay to improve decision-making. This approach, similar to other methodologies reviewed in this work, addresses critical challenges in energy management by enhancing system reliability and reducing energy losses and emissions. The AP DQN algorithm achieved excellent results in objective functions and reliability compared to traditional methods; however, its reliance on discrete decision-making and the lack of optimization in the reward function present areas for improvement. These gaps align with the broader need for research identified in the state-of-the-art reviews, emphasizing the importance of refining methodologies to better account for variability, scalability, and computational efficiency in real-world scenarios.

Additionally, in order to provide a broad and rigorous perspective on previous research aimed at enhancing various performance indicators in MGs through the intelligent management of WGs, Table 1 is presented. This table summarizes the reviewed studies, the methodologies applied, the test systems employed, and the economic indicators targeted for optimization.

Table 1. Summary table of recent research on optimization problems involving intelligent WGs management

Research	Proposed methodology	Test system	Objective function
[12]	RUNge Kutta Optimizer (RUN)	IEEE 57 bus system	Energy losses, Voltage Stability
[13]	PSO-GWO hybrid algorithm	IEEE 30 bus system	Operational costs
[14]	Adaptive Lightning Attachment Procedure Optimizer (ALAPO)	IEEE 57 bus system	Energy loss, Voltage Stability
[15]	Enhanced Slime Mould Algorithm (ESMA)	IEEE 30 bus system	Operational costs, Emissions costs
[16]	Multi-objective Snow Ablation Optimizer (MOSAO)	IEEE 30 bus system	Operational costs, Voltage Stability, Energy Losses
[17]	Barnacles Mating Optimizer (BMO)	IEEE 30, 57 bus systems	Operational costs, Energy losses and Emissions
[18]	Improved Salp Swarm Algorithm (ISSA)	IEEE 30, 57, 118 bus systems	Operational costs
[19]	Improved Differential Evolution algorithm (IDE)	IEEE 30 bus system	Operational costs, Energy losses and Emissions

The state-of-the-art review conducted in this work on the energy management of WGs in AC MGs or electrical grids highlights that this is a developing field, with limited studies available in the literature. This underscores the need for further research and development to address the challenges and opportunities within this domain. In contrast, the energy management of distributed PV generators in AC MGs has been widely studied [20, 21, 22], with solution methodologies primarily focused on optimization tools based on sequential programming to reduce costs and simplify the use of commercial software. Among these, metaheuristic optimization techniques have gained significant attention and have been extensively explored in recent years. Drawing on this knowledge, this paper develops solution methodologies tailored to the addressed problem, achieving excellent results in energy loss and CO_2 emission reductions while ensuring adequate repeatability of the solutions for grid operators.

The integration of technical and environmental considerations, such as energy losses and emissions reduction, remains an area requiring further exploration in the energy management of WGs in AC MGs. This research seeks to address this gap by proposing an optimization approach that concurrently considers energy losses and CO_2 emissions as core performance metrics in MG operation. A comprehensive mathematical formulation of these objectives is developed, incorporating all constraints specific to MGs operating with distributed WGs. This model ensures that power flow and emissions are optimized in both grid-connected and isolated operational modes, providing a robust framework for sustainable MG management.

To address the non-linear optimization problem associated with energy management of wind-distributed generators in AC MGs, aimed at reducing energy losses and CO_2 emissions, and to provide solutions to the challenges and needs identified in the state-of-the-art review, a hybrid methodology is proposed. This methodology combines the PGA for managing the energy output of WGs within the MG and an hourly power flow method based on the SA technique to solve the power flow problem. This approach accounts for variable generation and demand, enabling the evaluation of the proposed wind power schemes regarding the objective function and constraints. For comparison, additional metaheuristic algorithms (PSO, JAYA, and the GNDO) were also employed, using the same power flow method. These algorithms were selected for their proven effectiveness in solving complex, non-linear optimization problems in power systems [3, 23, 24, 25]. An adapted 33-bus MG is used as the test scenario, considering both grid-connected and isolated operation modes. The scenario also accounts for emissions associated with energy purchases from the electrical grid and power production through diesel fuel.

To identify the optimization methodology with the best performance, each algorithm was executed 100 times by considering the MG operation in both operation modes, allowing for a comparative analysis aimed at identifying the most effective solution approach for both grid-connected and isolated MG operational modes in terms of quality and repeatability of solution, by employing a rigorous statistical framework, including ANOVA and Tukey HSD tests.

As main academic and power sector contributions, this paper presents a comprehensive approach for optimizing the operation of AC MGs, allowing system operators to prioritize, according to their needs, the minimization of either technical energy losses or CO_2 emissions. From an academic perspective, a robust mathematical model is developed that accurately represents the operational dynamics of distributed wind generators under both grid-connected and isolated modes, incorporating technical and environmental constraints. In addition, an adapted version of PGA is proposed, introducing improvements in generational replacement strategy, real-valued recombination and mutation operators, and diversity preservation mechanisms. The performance of the PGA is rigorously compared against other metaheuristic optimizers (PSO, JAYA, GNDO) through solid statistical analysis (ANOVA, Tukey HSD), contributing to the literature with a standardized methodology for benchmarking optimization algorithms in energy systems.

From the power sector perspective, this work provides practical tools for more flexible, efficient, and sustainable energy management in MGs. The results obtained on a 33-bus and a 69-bus test networks with real demand and wind generation profiles from Colombia demonstrate the applicability of the proposed approach in real-world operational contexts, particularly in rural or peri-urban areas with limited infrastructure or intermittent grid connectivity. By validating the model under both grid-connected and islanded modes, the study highlights its robustness and relevance for distribution system operators (DSOs) who must manage variable renewable resources without compromising reliability. The proposed framework enables decision-makers to dynamically prioritize between loss reduction and CO_2 emission minimization according to system needs, policy targets, or economic incentives, thereby aligning technical operation with regulatory and environmental objectives. Additionally, the comparative analysis of metaheuristic algorithms provides actionable insights for selecting and deploying optimization tools in complex energy dispatch problems, contributing to more informed planning and real-time operational strategies in distributed power systems.

This paper is organized as follows: Section 2 introduces the mathematical formulation of the optimization problem, detailing the objective functions and constraints related to energy losses and CO_2 emissions. Section 3 explains the proposed methodology and provides an overview of the metaheuristic algorithms used for comparison, and describes the tunning optimization process. Section 4 describes the electrical configuration and parameter data of the test systems employed. Section 5 presents a detailed analysis of the results, including comparative performance metrics for each algorithm. Finally, Section 6 discusses the key contributions of the study, its practical implications, and suggestions for future research aimed at advancing environmental performance objectives within MGs.

2. Mathematical Formulation of the Problem

This section provides the mathematical formulation for the optimization problem focusing on minimizing both active power losses and CO_2 emissions in a MG equipped with distributed WGs. The formulation considers the unique operational characteristics of MGs, including grid-connected and islanded modes, while addressing constraints specific to power generation, load demand, and technical limitations of the network.

2.1. Objective Functions

The optimization problem in this study is designed to achieve two primary objectives: minimizing active power losses (FO_1) and minimizing CO_2 emissions (FO_1).

The first objective function, FO_1, aims to minimize the total active power losses across the MG network, which directly impacts the efficiency of power delivery. The function is defined as follows:

$$FO_1 = \min E_{loss} = \min \left(\sum_{h \in \Omega_{\mathcal{H}}} \sum_{i \in \Omega_L} R_l |I_{l,h}|^2 \Delta h \right) \tag{1}$$

In Equation (1), E_{loss} represents the cumulative power losses over a specified time horizon, $\Omega_{\mathcal{H}}$. The term R_l denotes the resistance of line l, while $I_{l,h}$ represents the current flowing through line l at time h. The power losses are integrated over each period Δh, ensuring that losses are minimized for the entire day.

The second objective function, FO_2, seeks to minimize CO_2 emissions associated with conventional power generation within the MG (grid and Fossil generation). This objective is crucial for aligning the MG's operation with environmental sustainability goals. The emission minimization function is expressed as:

$$FO_2 = \min E_{CO_2} = \min \left(\sum_{h\in\Omega_{\mathcal{H}}} \sum_{i\in\Omega_{\mathcal{N}}} CE_i P^s_{i,h} \Delta h \right) \tag{2}$$

In Equation (2), E_{CO_2} represents the total CO_2 emissions over the time horizon $\Omega_{\mathcal{H}}$. The term CE_i corresponds to the emission factor associated with the conventional generator at node i, which may vary depending on the type of conventional generation supplying energy to the grid, such as grid connection, diesel generation, gas generation, or other sources [6]. While $P^s_{i,h}$ is the active power generated by conventional sources at node i during hour h. The summation over h and i captures the cumulative emissions over the operational day, and Δh represents the duration of each hourly interval.

2.2. Constraints

The optimization model incorporates all the constraints necessary to reflect the technical and operational limitations of the MG system. These constraints ensure that the solutions obtained are not only optimal in terms of the defined objectives but also feasible for real-world application.

$$P^s_{i,h} - P^d_{i,h} + P^{ag}_{i,h} = V_{i,h} \sum_{j\in\mathcal{N}} Y_{i,j} V_{j,h} \cos(\theta_{i,h} - \theta_{j,h} - \varphi_{i,j}), \quad \forall i \in \mathcal{N}, \forall h \in \mathcal{H} \tag{3}$$

The first set of constraints, in Equation 3, addresses the power balance within the MG, ensuring that active and reactive power demand is met at every node. The active power balance is given in 3. In this equation, $P^s_{i,h}$ is the active power supplied by conventional sources at node i at time h, $P^d_{i,h}$ denotes the active power demand at node i, and $P^{ag}_{i,h}$ is the active power contributed by the wind generator at node i. The terms $V_{i,h}$ and $V_{j,h}$ represent the voltage magnitudes at nodes i and j, respectively, while $Y_{i,j}$ is the admittance magnitude between nodes i and j, and $\varphi_{i,j}$ is the admittance angle.

$$Q^s_{i,h} - Q^d_{i,h} = V_{i,h} \sum_{j\in\mathcal{N}} Y_{i,j} V_{j,h} \sin(\theta_{i,h} - \theta_{j,h} - \varphi_{i,j}), \quad \forall i \in \mathcal{N}, \forall h \in \mathcal{H} \tag{4}$$

The reactive power balance constraint, in Equation 4, is similarly defined in 4. Where, $Q^s_{i,h}$ is the reactive power supplied by conventional generators at node i, and $Q^d_{i,h}$ represents the reactive power demand at node i.

$$P^{gc,\min}_i \le P^{gc}_{i,h} \le P^{gc,\max}_i, \quad \forall i \in \mathcal{N}, \forall h \in \mathcal{H} \tag{5}$$

$$Q^{gc,\min}_i \le Q^{gc}_{i,h} \le Q^{gc,\max}_i, \quad \forall i \in \mathcal{N}, \forall h \in \mathcal{H} \tag{6}$$

Additionally, the generation limits of conventional generators are constrained by Equations 5 and 6. Specifically, $P^{gc,\min}_i$ and $P^{gc,\max}_i$ represent the minimum and maximum active power limits, respectively, for the conventional generator at node i, while $Q^{gc,\min}_i$ and $Q^{gc,\max}_i$ define the corresponding reactive power limits. In the connected mode of the MG, these limits depend on the grid's capacity during each operational hour. Conversely, in the isolated mode, they are determined by the power limits specified in the datasheet of the generator installed within the MG.

$$P^{ag,\min}_i \le P^{ag}_{i,h} \le P^{ag}_i G^{ag}_h, \quad \forall i \in \mathcal{N}, \forall h \in \mathcal{H} \tag{7}$$

The power output from WGs, $P^{ag}_{i,h}$, is also limited by the available wind energy at each hour h, as can be appreciated in Equation 7. Where $P^{ag,\min}_i$ represents the minimum power that can be generated by the WGs at node i, and G^{ag}_h denotes the wind generation curve based on wind speed and turbine characteristics.

$$V^{\min}_i \le V_{i,h} \le V^{\max}_i, \quad \forall i \in \mathcal{N}, \forall h \in \mathcal{H} \tag{8}$$

Voltage limits across all nodes are enforced by using Equation 8. Being $V^{\min}_i$ and $V^{\max}_i$ the minimum and maximum allowable voltages at node i.

$$|I_{ij,h}| \leq I_{ij}^{\max}, \quad \forall ij \in \mathcal{N}, \forall h \in \mathcal{H} \tag{9}$$

Lastly, line current constraints are imposed to prevent overloading by using Equation 9. In this Equation, $I_{ij,h}$ denotes the current through line ij at hour h, and $I_{ij}^{\max}$ is the maximum permissible current.

$$0 \leq P_{i,h}^{gc}, \quad \forall i \in \mathcal{N}, \forall h \in \mathcal{H} \tag{10}$$

Both objectives, minimizing power losses and CO_2 emissions, are achieved while adhering to the technical and operational constraints required for the safe and efficient operation of the MG in both grid-connected and isolated modes. In the islanded operation mode, an additional constraint must be introduced to reflect the operational limits of the conventional diesel generator, which becomes the sole dispatchable resource. Unlike the grid-connected mode, the islanded mode lacks energy storage systems that would allow the MG to absorb excess power. Therefore, it is essential to ensure that the diesel generator does not operate with negative output power. This requirement is explicitly addressed in the mathematical formulation through Equation 10, which sets a minimum power output of zero. Furthermore, to ensure realistic and reliable operation, a typical nominal operating range of 40% to 80% of the generator's rated power is considered [26]. Although the model is formulated in terms of power variables using power flow analysis, current-based constraints can be readily derived from voltage and power values when needed for compatibility with protection or control systems.

2.3 Interpretative Overview of the Mathematical Model

To enhance interpretability, this section provides a simplified explanation of how the mathematical formulation applies to practical microgrid operations.

The two objective functions, minimization of energy losses and CO_2 emissions, can be viewed as performance indicators that grid operators seek to improve through optimized scheduling and dispatch of available generation sources. Equation (1), for instance, models how energy is dissipated in transmission lines due to their resistance and current levels over time. Minimizing this quantity means operating the MG in a way that reduces unnecessary power flow, which directly translates to improved efficiency.

Similarly, Equation (2) quantifies total CO_2 emissions by multiplying the power generated by conventional sources at each time step with their associated emission factors. In a practical setting, this encourages the MG controller to prioritize clean wind energy over grid or diesel power, particularly during hours when demand and generation patterns are aligned.

The constraint equations represent the physical and operational boundaries of the MG. For example, Equation (3) ensures that the total power injected at each bus equals the sum of power demands and line flows, which reflects Kirchhoff's current law in power systems. Voltage and current constraints (Equations (8) and (9)) prevent damage to equipment and ensure stable operation.

To visualize, one might think of the optimization algorithm as a control assistant that tests thousands of possible daily dispatch schedules, each conforming to the system constraints, and selects the one that results in the least amount of energy waste and environmental impact.

3. Solution Methodology

The optimization problem defined in this study is solved using the PGA combined with an hourly power flow method based on the SA method to evaluate the objective function and constraints representing the problem. The hourly power flow methodology, as described in [27], is applied consistently across all solution methodologies used in this study. For comparison, three widely employed metaheuristic algorithms in energy management systems for MG and distribution systems are also implemented: PSO, JAYA, and GNDO. Each one of these methods brings distinct approaches to exploring the solution space for minimizing power losses and CO_2 emissions within a MG system, operating in both grid-connected and isolated modes. A comparative analysis is conducted to evaluate the effectiveness of each algorithm in obtaining optimal solutions for the defined objective functions.

The selection of the four metaheuristic algorithms (PGA, PSO, JAYA, and GNDO) was guided by a balance between exploration-exploitation capabilities, relevance in recent power system literature, and algorithmic diversity. PGA was selected as the primary method due to its robust evolutionary dynamics and low susceptibility to premature convergence, particularly suitable for constrained nonlinear problems with multiple local minima, such as microgrid energy management. PSO and JAYA were included due to their widespread use in energy optimization problems and their complementary characteristics: PSO emphasizes swarm intelligence with tunable convergence behavior, while JAYA requires no control parameters, reducing the burden of configuration. GNDO was chosen to evaluate a probabilistic population model based on normal distribution, offering a contrasting search behavior and higher randomness. Regarding parameter tuning, each algorithm's hyperparameters were optimized using an external PSO-based tuning procedure, following the approach in [28]. This ensures fairness in comparison and improves each algorithm's ability to exploit the search space effectively. The tuning process considered both solution quality and computational efficiency.

The PGA, proposed as the solution methodology for the problem addressed in this paper, is an optimization technique inspired by natural selection, recombination, and mutation, designed to effectively explore complex and non-linear solution spaces [29]. The PGA balances exploration and exploitation by maintaining diversity within a population of solutions. It is particularly effective at avoiding local optima in constrained and dynamic problems, such as energy management in MGs. Its capability to handle multi-objective optimization tasks and integrate specific problem constraints enhances its versatility, offering robust performance in scenarios where identifying global optima is challenging. Additionally, implementing a descendant population reduces convergence time. It improves solution quality in terms of the best and average results and the repeatability of high-performance outcomes across executions. To the best of our knowledge, there is no evidence in the literature of this method being applied to optimize the operation WGs in MGs, considering both isolated and connected modes.

The PSO is inspired by the social behavior observed in swarms and flocks in nature [30]. In PSO, each particle, representing a candidate solution, adjusts its position within the solution space based on its own best-known position and the best-known position discovered by the swarm. This adjustment process is guided by velocity updates that incorporate both cognitive and social components, enabling particles to balance exploration and exploitation of the search space effectively [31], which makes it suitable for comparing their results with other methods. The algorithm's strength lies in its simplicity and ability to converge to high-quality solutions with relatively few parameters to configure, making it well-suited for solving complex multi-objective optimization problems [24].

The JAYA algorithm is a parameter-free optimization method designed to minimize or maximize a given objective function by iteratively adjusting solutions within a population to move closer to the best solution and away from the worst solution . Each candidate solution is influenced by the best and worst solutions in the population at each iteration, resulting in an efficient exploration of the search space without requiring additional control parameters. This feature distinguishes JAYA from other algorithms, as it reduces the risk of suboptimal parameter tuning and enhances robustness across different optimization scenarios [32]. JAYA's parameter-free design also simplifies its implementation, making it a practical choice for operational optimization tasks such as those presented in this MG study.

The GNDO is based on statistical modeling of populations using normal distribution properties. GNDO alternates between global and local search phases by adjusting the population mean and standard deviation, ensuring diversity in the search process. During the local search, GNDO narrows down the search space by aligning individuals closer to the best-performing solution, while the global search uses random perturbations within the normal distribution to explore broader areas of the solution space. This dual-phase approach provides a robust mechanism for escaping local optima, which is particularly advantageous in complex optimization landscapes like those encountered in MG operational problems [25].

The proposed methodology uses the PGA for solving the problem of optimal operation of WGs in the AC MG for reducing the energy losses and CO_2 emissions, by using an hourly power flow method based on SA method for evaluating the objective function and set of constraints related to each solution proposed by the PGA.

The PGA is an evolutionary optimization technique inspired by natural selection and genetic evolution, processes that shape the adaptive capabilities of biological organisms [3]. PGA utilizes genetic operators—selection, recombination, and mutation—to iteratively improve a population of candidate solutions. Each candidate solution, or individual, represents a possible configuration for the MG operation. Distinct from the traditional GA proposed by Chu and Beasley, PGA performs population-wide evolution by updating an entire generation of parents with offspring that encode the best genetic information, thereby accelerating convergence and enhancing solution quality. This characteristic allows PGA to maintain diversity within the population and prevents premature convergence.

Algorithm 1: Iterative Process of the PGA

```
Data: Initialize MG parameters and PGA parameters
for t = 1 : iter_max do
    if iter == 1 then
        1. Generate the initial population randomly;
        2. Evaluate the fitness function for each individual using the using the hourly power flow based on
           SA;
        3. Select the best solution as the incumbent;
    else
        4. Generate a population of offspring using selection, recombination, and mutation processes;
        5. Evaluate the fitness function for the offspring population using the hourly power flow based on
           SA;
        6. Replace parents with offspring that yield improved fitness values;
        7. Update the incumbent with the best solution;
        8. if convergence criterion met then
            8.1 End the iterative process and select the incumbent as the solution to the problem;
            Break;
        else
            8.2 Return to Step 4;
```

The core processes of PGA involve selection, recombination, and mutation, each contributing to the progressive improvement of the population. Initially, an entire population of individuals is randomly generated, with each individual representing a set of power outputs for the distributed WGs within the MG. The selection process involves choosing parent individuals based on their fitness values, allowing those with higher performance to pass on their traits to the next generation. Recombination creates offspring by combining traits from pairs of parents, often using averaging techniques that are suitable for continuous optimization problems. Mutation introduces random alterations to offspring, generating values within the permissible limits of active power for each time period.

The proposed PGA introduces key modifications compared to traditional Genetic Algorithms. Specifically, it applies a generational replacement strategy, where the entire parent population can be replaced if all offspring exhibit superior fitness, promoting faster convergence. Moreover, the algorithm utilizes real-valued recombination through averaging and bounded mutation within operational limits, both tailored to the continuous nature of the microgrid dispatch problem. These adaptations help preserve population diversity and improve solution quality, addressing common limitations of conventional GAs [33].

To maintain the readability of the main text, a summary of the pseudocode and key steps for the PSO, JAYA, and GNDO algorithms is provided in Appendix A. Each algorithm follows its standard population-based iterative structure, adapted to the specific requirements of the power flow model and the constraint-handling penalty function.

The selection of the four metaheuristic algorithms (PGA, PSO, JAYA, and GNDO) was guided by their prominence in recent power system optimization literature, algorithmic diversity, and demonstrated effectiveness in solving non-linear and constrained problems characteristic of microgrid energy management [34, 23, 25]. The

PGA was chosen as the primary method due to its strong global search capabilities, resilience against premature convergence, and flexibility in evolutionary adaptation.

PSO and JAYA were included as benchmark algorithms because of their extensive use in energy-related applications and their complementary features: PSO relies on swarm-based search dynamics with tunable convergence behavior, while JAYA employs a parameter-free mechanism that reduces the complexity of algorithm configuration. GNDO was selected for its probabilistic exploration strategy based on normal distribution learning, offering a contrasting search behavior that enriches the comparative analysis.

This selection enables a comprehensive and balanced evaluation across diverse heuristic paradigms. Furthermore, to ensure fairness and reproducibility in performance assessment, all algorithms were consistently tuned using a PSO-based parameter optimization procedure.

The evaluation of fitness values occurs at each generation, measuring the effectiveness of each individual in achieving the objective of minimizing either power losses or CO_2 emissions, depending on the context of the function used, while penalizing the fitness value whenever a constraint is violated. Offspring with superior fitness values replace less fit parents, thereby improving the population's average performance.

An hourly power flow method based on the SA technique is employed to evaluate the proposed power injections for WGs installed in the MG. This approach ensures efficient load flow analysis with low computational demand and reliable convergence [35]. The method performs an hourly power flow calculations, 24 hours in this particular case, adjusting system generation and demand according to the provided data for each time period. During this process, the hourly impact on the objective function and system constraints is assessed using nodal voltage values obtained from each power flow and other system parameters. Constraint violations are penalized through an adaptation function, which adjusts the objective function accordingly. After analyzing all 24 hours, the total daily impact on the objective function is calculated by summing the hourly results, representing the MG's operational performance over the day.

To perform this task, PGA supplies essential input data for the hourly power flow, including system parameters, hourly wind generation power (variables of the problem), and power demand. Subsequently, for each hour h, the following steps are executed:

- Load user demand for hour h.
- Load the wind generation power for each distributed generator at hour h.
- Solve the power flow for hour h using the SA method [36]. This iterative approach calculates nodal voltages, as expressed in Equation 11, where voltage convergence is achieved when the tolerance criterion ($\varepsilon = 1 \times 10^{-10}$) is met.

$$V_{d,h}^{t+1} = -Y_{dd}^{-1}[diag^{-1}(V_d^t)S_{d,h} + Y_{dg}V_{g,h}] \tag{11}$$

- Evaluate the objective function (e.g., energy losses or CO_2 emissions), and identify constraint violations for hour h.
- Apply penalties for violations using the adaptation function (Equation 12), which adjusts the objective function by incorporating penalties based on the severity of the violations.

$$FA = FO + Pen \tag{12}$$

For grid-connected operation, penalties are defined as:

$$Pen = fp_1 \cdot Vl_{\text{load}} + fp_2 \cdot Vl_{\text{voltage}} \tag{13}$$

Where Vl_{load} and Vl_{voltage} denote violations of loading and voltage limits, and fp_1 and fp_2 are heuristic penalty factors (set at 1000). This fixed-penalty approach follows common practices in the literature and offers a good trade-off between computational simplicity and effective constraint handling [34, 37].

For isolated operation, additional constraints are incorporated:

$$Pen = fp_1 \cdot Vl_{\text{load}} + fp_2 \cdot Vl_{\text{voltage}} + fp_3 \cdot Vl_{Pslack} + fp_4 \cdot Vl_{\text{diesel}} \tag{14}$$

Here, Vl_{Pslack} and Vl_{diesel} correspond to violations related to energy sales at the slack bus and diesel generator outputs exceeding their defined limits, respectively.
- Accumulate hourly adaptation functions into a single daily value.
- Send the computed adaptation function back to the PGA for the next iteration.

After to evaluate the fitness functions of all individuals, the best solution within the current population is stored as the incumbent and is updated whenever a new superior solution is found in subsequent iterations. This iterative process continues until a specified convergence criterion, typically the maximum number of generations, is met.

PGA's approach to replacement and population evolution allows it to maintain a high diversity in solution configurations while achieving rapid convergence toward optimal solutions. By adapting the power outputs based on selection pressures, the algorithm continuously refines the MG's operational parameters, offering a robust solution for minimizing operational objectives within the given constraints.

3.1. Tuning of Optimization Parameters

To ensure a fair and effective comparison between optimization methods, each algorithm was systematically tuned using a dedicated PSO algorithm, referred to here as the PSO-tuner. The objective of the PSO-tuner was to identify the optimal set of hyperparameters for each metaheuristic algorithm (PGA, PSO, JAYA, GNDO) that minimized the primary objective functions (FO_1 and FO_2) in both grid-connected and isolated modes.

This tuning process was performed independently for each optimization method, following the methodology reported in [28]. For each candidate hyperparameter set, the corresponding metaheuristic algorithm was executed three times and the average objective function value was used as the fitness value. The convergence criterion of the PSO-tuner was defined as either a maximum of 300 generations or no improvement in the global best solution over 30 consecutive iterations. The PSO-tuner parameters are detailed in Table 2.

Table 2. Configuration of the PSO-Tuner for Metaheuristic Parameter Optimization

Parameter	Value	Description
Swarm Size	8 particles	Number of hyperparameter candidates per generation
Max Generations	300	Maximum number of iterations
Cognitive Factor (c_1)	1.494	Self-learning influence
Social Factor (c_2)	1.494	Group-learning influence
Inertia Weight (w)	Linearly decreasing from 0.7 to 0.001	Balance between exploration and exploitation
Velocity Clamping	Dynamic, based on parameter bounds	Prevents divergence
Fitness Evaluation	Mean of algorithm executions	Reduces stochastic variability
Convergence Criterion	Max generation or stagnation in 30 iterations	Stopping rule

A sensitivity analysis of the PSO-tuner results showed stable convergence behavior across all methods. The best parameter configurations were found to be consistent within small deviations ($< 5\%$) when the PSO-tuner was run multiple times under different seeds. This confirms the robustness and repeatability of the tuning process.

The final tuned parameter values for each algorithm in both microgrid configurations are reported in Table 3.

4. Test Systems

To verify the scalability of both the proposed model and optimization strategy, two standardized test systems of 33 and 69 buses are employed [38, 39]. The 33-bus MG is used to assess the performance of the proposed strategy alongside the other comparison techniques. Once the superiority of the proposed approach is established, its flexibility and ability to adapt to more complex networks are further evaluated through its application to a 69-bus MG.

4.1. Test System: 33-nodes AC MG

This work employs an adapted version of the 33-node AC MG reported in [38] as the test system. The adapted system preserves the original configuration of 33 nodes and 32 lines while enabling operation in both connected

Table 3. Parameters of Optimization Methodologies for the 33-node MG in Grid-Connected and Standalone Modes

Methodology	Parameter	Grid-Connected Mode	Isolated Mode
PGA	Number of Individuals	32	35
	Number of Iterations	6000	6000
	Number of Mutations	1	1
PSO	Number of Individuals	168	462
	Number of Iterations	1987	648
	Minimum Inertia	0.5515	0.7522
	Maximum Inertia	0.6333	0.8136
	Cognitive Factor	1.9861	0.6259
	Social Factor	1.4330	1.2795
	Velocity Limit Factor	0.0814	0.0271
JAYA	Number of Individuals	17	21
	Number of Iterations	12000	9863
GNDO	Number of Individuals	500	500
	Number of Iterations	500	500

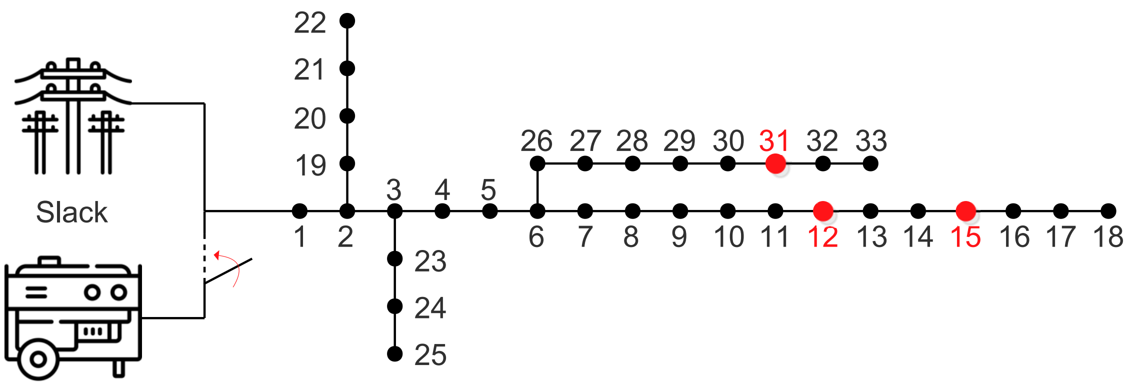

Figure 1. Electrical diagram of the 33 nodes MG by considering connected and isolated operating modes.

and isolated modes. Node 1 is the slack bus, integrating a diesel generator and the electrical grid to facilitate these operational modes. Additionally, three distributed WGs with a nominal capacity of 1200 kW are installed at buses 12, 15, and 31 to enhance renewable energy integration. The diesel generator has a nominal capacity of 4000 kW, with a power output range of 40% to 80% of its nominal capacity. For emission factors, this work considers values of 0.1644 kg of CO_2 per kWh for grid electricity emissions and 0.2671 kg of CO_2 per kWh for diesel emissions.

The technical parameters of the MG, summarized in Table 4, include detailed information for each line, such as the line number, sending and receiving buses, resistance and reactance line, active and reactive power demands at the receiving bus, and the maximum current capacity of the line. Finally, this test system considers a maximum voltage profile variation of ±8% of the nominal grid voltage. This configuration provides a robust framework for analyzing energy management and operational strategies under diverse scenarios.

To incorporate the effects of variable power generation and demand in the MG, this work utilizes wind generation and power demand data reported for a region in Colombia, as illustrated in Figure 2. The wind generation profiles were derived using NASA-reported data and the parameters of the wind turbines, following the methodology outlined in [40]. Meanwhile, the power demand behavior was obtained from data provided by the local utility, ensuring a realistic representation of energy consumption patterns in the region.

Table 4. Technical parameters of the 33-node MG.

Line l	Sending Node i	Receiving 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
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	14	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	2	19	0.1640	0.1565	90	40	40
19	19	20	1.5042	1.3554	90	40	25
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

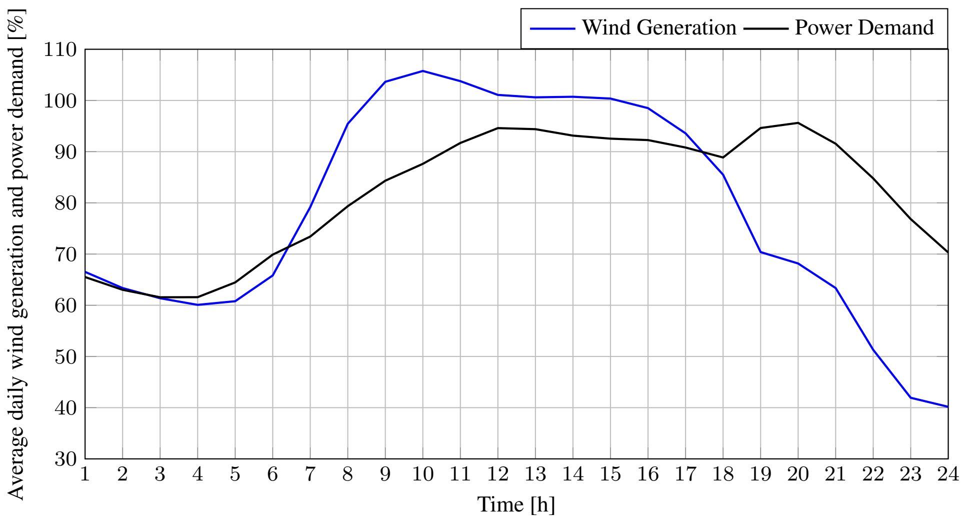

Figure 2. *Average daily generation of WGs and power demand.*

4.2. Test System: 69-nodes AC MG

After validating the proposed strategy and the comparison techniques on the 33-bus test system, the methodology is subsequently applied to a 69-bus test system, as reported in [39]. The technical specifications of this system are provided in Appendix B to avoid interrupting the flow of the main text, given the extensive size of the corresponding table.

As in the 33-bus network, Node 1 can operate either connected to the main grid or in isolated mode, supported by a diesel generator. Although the same emission factors are used, some modifications were necessary to adapt the methodology to the characteristics of this MG. First, WGs are installed at Buses 15, 33, and 62. Additionally, in islanded mode, the diesel generator has a rated power of 3000 kW. Finally, to introduce greater variability in both demand and generation, the profiles shown in Figures 3 and 4 are employed.

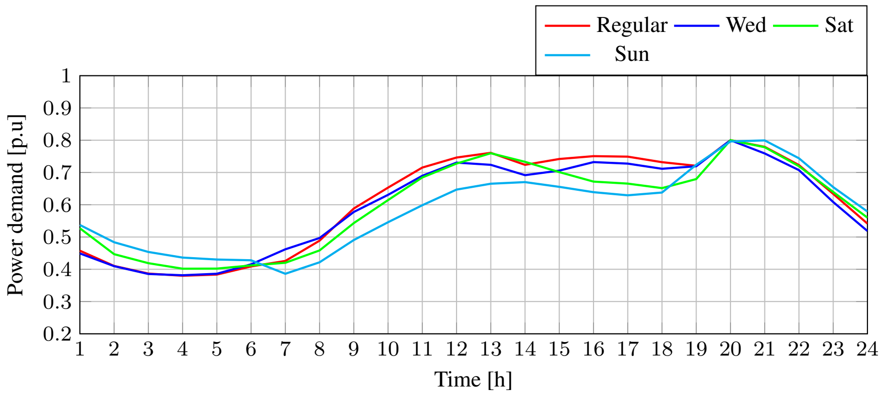

Figure 3. Hourly power demand.

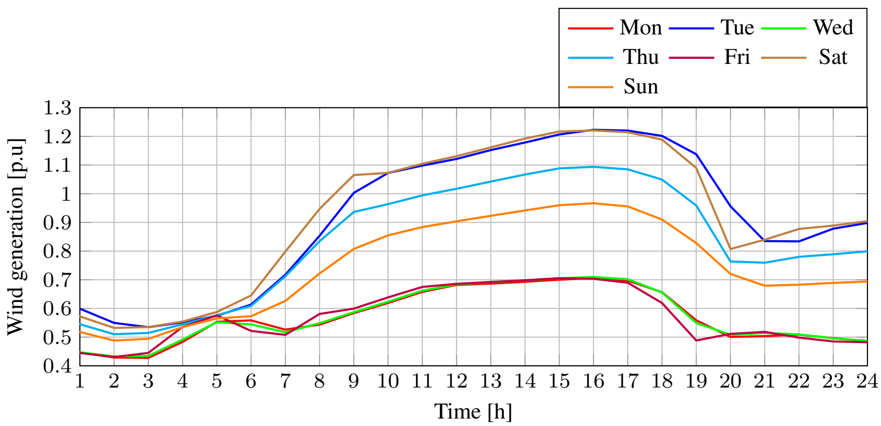

Figure 4. Hourly power generation by WGs

The demand profile was provided by a distribution company in Colombia, while the generation profile was obtained using artificial neural networks (ANNs), based on the climatic behavior of a specific region in the country [38]. Figure 3 illustrates the weekly demand profile. The curve labeled ”regular” corresponds to the typical behavior observed on Mondays, Tuesdays, Thursdays, and Fridays, while the remaining curves represent the specific demand patterns for the other days of the week. Conversely, Figure 4 depicts the wind turbine generation patterns for each of the seven days.

5. Results and Discussion

Each algorithm was independently executed 100 times for each objective function to obtain statistical data for a robust performance comparison. As discussed below, the evaluation of each algorithm's effectiveness considers several parameters, such as the best solution achieved, consistency across multiple runs, and other statistical metrics [41].

The simulations were executed using the MATLAB software on a personal computer with an Intel(R) Core(TM) i7-11800H processor running at 2.30GHz, 16 GB of RAM, and a 64-bit Windows 11 OS. To evaluate the performance of each algorithm, each method was run 100 times. All algorithms were custom-implemented in MATLAB R2023a. To ensure transparency, pseudocode for the PGA is presented in Section 3, and additional pseudocode for PSO, JAYA, and GNDO is available in Appendix A. Additionally, the PGA is compared with two other optimization techniques, Gray Wolf Optimizer (GWO) [42] and Harris Hawks Optimizer (HHO) [43], in order to evaluate the performance of the proposed strategy against more recent methods reported in the literature. These two techniques did not achieve sufficiently strong performance to warrant prioritization in the main body of the document. Therefore, their results are presented in Appendix C, in order to avoid disrupting the flow and clarity of the analysis provided for the other comparison techniques. Subsequently, the functionality and flexibility of the PGA are validated in a larger MG, considering both grid-connected and islanded operating modes.

5.1. Statistical Results for Objective Function FO_1: Energy Losses

Table 5 presents the statistical results for FO_1 (energy losses in kWh) for both the connected and isolated MG configurations. The metrics include minimum values, mean values, and standard deviations for each algorithm. These results demonstrate the performance of the optimization methods in reducing energy losses.

The connected configuration shows that the PGA algorithm achieved the lowest average energy losses (1399.47 kWh) with a minimal standard deviation (0.019 kWh). This highlights its high consistency and effectiveness. Similarly, the PSO and JAYA algorithms also performed well, achieving losses close to PGA but with slightly higher variations. On the other hand, GNDO exhibited higher average energy losses (1457.27 kWh) and a more substantial standard deviation (10.38 kWh), indicating lower performance and stability than the other algorithms.

In the isolated configuration, the results maintain a similar trend, with PGA achieving the lowest average losses (1443.54 kWh) and a standard deviation of 1.90 kWh. PSO and JAYA produced competitive results, but their higher standard deviations indicate less stability in this configuration. GNDO again recorded the highest losses on average (1512.62 kWh), reinforcing its inferior performance in minimizing energy losses.

Another analysis can be conducted by comparing the different metaheuristic techniques with their corresponding base cases. For the base case of the MG in connected mode, energy losses amount to 3378.92 kWh. All algorithms demonstrated significant improvements over this baseline in both configurations. For example, the PGA algorithm reduced energy losses by an average of 58.6%. Even the least efficient algorithm, GNDO, achieved an average reduction of 56.9%. These results highlight the effectiveness of all algorithms in reducing energy losses relative to the base case, with PGA emerging as the most efficient and consistent.

However, no base case is provided for the MG operating in isolated mode. This is due to the fact that to meet demand, the diesel generators operate during hours that exceed their technical and physical limitations, as outlined in the constraints of Equations 5, 6, and 10. As a result, this analysis for the isolated mode is not feasible.

5.2. Statistical Results for Objective Function FO_2: CO_2 Emissions

Table 6 presents the results for the objective function FO_2, which evaluates the ability of each algorithm to minimize CO_2 emissions in both the connected and isolated MG configurations. The analysis focuses on the minimum values, mean values, and standard deviations of emissions, providing insights into the performance and consistency of each method.

In the connected configuration, the PGA algorithm achieved the lowest average CO_2 emissions at 4564.63 kg, with a low standard deviation of 1.03 kg, highlighting its consistent and superior performance. The PSO and JAYA algorithms produced slightly higher average emissions at 4616.32 kg and 4620.64 kg, respectively, with considerably more significant standard deviations (81.40 kg for PSO and 115.56 kg for JAYA). The GNDO

Table 5. Statistical Results for Objective Function FO_1 (Energy Losses kWh)

MG Configuration	Algorithm	Min	Average	Std. Deviation	Confidence Interval (95%)
Connected	PGA	1399.415121	1399.466560	0.019275	[1399.46, 1399.47]
	PSO	1399.322343	1404.610195	8.490610	[1402.94, 1406.28]
	JAYA	1399.322343	1402.689994	7.101619	[1401.30, 1404.08]
	GNDO	1435.638261	1457.270673	10.382137	[1455.24, 1459.30]
Isolated	PGA	1439.652477	1443.538385	1.900417	[1443.16, 1443.92]
	PSO	1437.395317	1447.720331	11.582392	[1445.42, 1450.02]
	JAYA	1437.302769	1459.141396	20.771458	[1454.99, 1463.29]
	GNDO	1476.241751	1512.618975	14.043032	[1509.86, 1515.38]

algorithm exhibits higher average CO_2 emissions than the other methodologies (5892.02 kg) and a considerable standard deviation (96.7911 kg), positioning it as the poorest performance algorithm.

In the isolated configuration, the PGA algorithm again achieved the lowest average emissions at 10295.68 kg, with a standard deviation of 0.57 kg, confirming its effectiveness and stability across configurations. The PSO and JAYA algorithms produced higher average emissions at 10343.31 kg and 10423.74 kg, with significantly larger deviations (83.94 kg for PSO and 171.95 kg for JAYA). The GNDO algorithm recorded the highest average emissions at 11478.59 kg with the largest deviation (201.99 kg), indicating its poor performance in minimizing CO_2 emissions under isolated conditions.

The base case for CO_2 emissions in the MG operating in connected mode is 12,541.20 kg. Following the same procedure used for energy loss reduction, an analysis can be conducted to compare the performance of different metaheuristic techniques against the base case in connected mode. For example, the PGA algorithm reduced emissions by an average of 63.6%, while PSO and JAYA achieved reductions of 63.2% and 63.1%, respectively. GNDO also outperformed the base case, achieving a reduction of 53.02%. These results demonstrate that all algorithms significantly improve upon the base case, with PGA achieving the best overall balance of consistency, robustness, and emissions reduction.

Table 6. Statistical Results for Objective Function FO_2 (kg of CO_2 Emissions)

MG Configuration	Algorithm	Min	Average	Std. Deviation	Confidence Interval (95%)
Connected	PGA	4562.390072	4564.626150	1.027337	[4564.43, 4564.82]
	PSO	4555.664572	4616.322794	81.401744	[4599.36, 4633.29]
	JAYA	4555.757447	4620.642668	115.556099	[4597.68, 4643.60]
	GNDO	5647.699742	5892.018031	96.791183	[5872.70, 5911.33]
Isolated	PGA	10293.893570	10295.677661	0.565508	[10295.56, 10295.80]
	PSO	10282.780898	10343.312645	83.936778	[10326.80, 10359.82]
	JAYA	10282.642841	10423.743669	171.951890	[10390.56, 10456.92]
	GNDO	11020.397672	11478.588214	201.987411	[11438.47, 11518.70]

The findings highlight the superior performance of the PGA algorithm in minimizing CO_2 emissions, maintaining consistent results with low variability across configurations. Although PSO and JAYA also performed well, their higher deviations indicate less stability than PGA. GNDO exhibited the highest emissions in the isolated configuration and a higher standard deviation on both configurations of the MG, making it a less reliable option for emissions optimization.

Figures 5 and 6 visually compare the performance of the algorithms using boxplots and violin plots. These visualizations provide a comprehensive overview of each algorithm's distribution and consistency in both connected and isolated configurations, supporting the statistical findings.

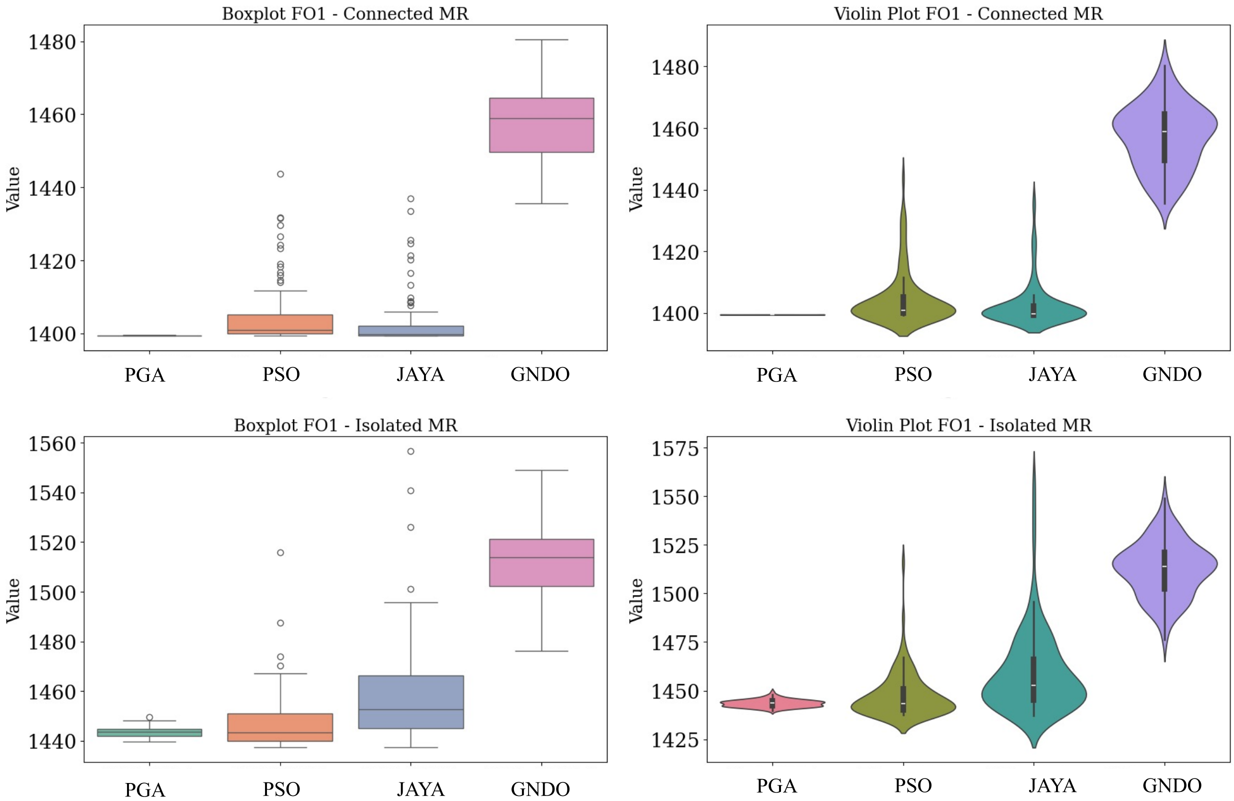

Figure 5. Boxplot and Violin Plot Analysis of FO_1 (Energy Losses) for Connected and Isolated MG Configurations

5.3. Analysis of FO_1 - Energy Losses

For the objective FO_1, which targets the minimization of energy losses, the results across the connected and isolated configurations reveal significant insights. In the connected configuration (top left plots in Figure 5), the boxplot indicates that the PGA algorithm consistently achieves the lowest median energy loss values, with minimal variance, as evidenced by a nearly imperceptible interquartile range and a small number of outliers. This suggests that PGA provides a highly robust and stable solution for minimizing energy losses in a connected setup, where variations in solution quality are virtually negligible.

In contrast, PSO and JAYA exhibit greater variability in their results, as shown by the wider spread of data points in the violin plots. Specifically, PSO displays a notable range in solution quality, likely due to its particle-based search strategy that explores a broader solution space. JAYA also shows a moderate level of dispersion, indicating that it occasionally approaches optimal values but lacks the precision of PGA. The GNDO algorithm, however, demonstrates the highest energy losses and the largest variability, suggesting it is less suitable for this objective within a connected MG scenario.

For the isolated configuration (bottom left plots in Figure 5), PGA again proves to be the most effective algorithm. The results are tightly clustered around a low mean energy loss, reinforcing PGA's reliability in providing consistently low-loss solutions even when the MG operates independently. Similar to the connected case, PSO and JAYA show larger spreads and higher mean values, while GNDO once more yields the highest loss values, indicating it is less effective for minimizing energy losses in isolated settings.

5.4. Analysis of FO_2 - CO_2 Emissions

The objective FO_2 focuses on minimizing CO_2 emissions, with results presented in Figure 6. In the connected MG configuration (top plots), PGA emerges as the most effective method, as it consistently achieves the lowest CO_2 emissions with minimal dispersion, as seen in the compactness of the violin plot. PSO and JAYA, although capable of attaining competitive solutions, show greater variability and higher mean emissions than PGA, underscoring the superior stability of PGA in emission reduction. GNDO, however, produces significantly higher emissions, still, its results appear inconsistent and may be less reliable due to the span of the boxplot, suggesting a lack of robustness in maintaining stable low-emission outcomes.

In the isolated configuration (bottom plots), PGA demonstrates superior performance, achieving consistently low emissions with a narrow distribution of results. PSO and JAYA present moderate variability, indicating that their performance is more sensitive to initial conditions and algorithmic parameters in isolated setups. GNDO, while achieving a range of values, generally produces higher CO_2 emissions, reinforcing its unsuitability for stringent emission reduction goals in this context.

The boxplot and violin plot analyses collectively highlight PGA as the most reliable and robust algorithm across both objectives and MG configurations. Its minimal variance and superior performance in achieving low energy losses and CO_2 emissions indicate that PGA is particularly well-suited for this optimization problem. The consistency observed in PGA's results contrasts with the performance of PSO and JAYA, which, although sometimes competitive, show greater variability and are more prone to suboptimal outcomes. GNDO is regarded as the least effective method, achieving high-emission values in connected and isolated cases, and it also lacks the stability necessary for practical implementation.

The findings suggest that implementing PGA can effectively meet both energy and environmental objectives in MG operations. Its robustness and efficiency make it a highly advantageous choice for both connected and isolated scenarios, particularly when precise, low-variance solutions are essential.

5.5. ANOVA Analysis of Algorithm Performance

To statistically validate the differences in performance among the algorithms for the objectives FO_1 (energy losses) and FO_2 (CO_2 emissions), an ANOVA analysis was conducted. This test compares the mean values achieved by each algorithm across 100 independent runs, determining if the observed differences in results are statistically significant. The analysis was carried out for both the connected and isolated configurations of the MG, and includes assessments of normality and homoscedasticity via Shapiro-Wilk and Levene's tests, respectively.

5.5.1. ANOVA Results for FO_1 - Energy Losses For the connected MG configuration with FO_1 as the objective, the ANOVA results indicate a highly significant difference between the algorithms, with a p-value of 7.39×10^{-206}. The high F-statistic of 1321.98 (see Table 7) suggests that at least one algorithm performs statistically differently in minimizing energy losses. The Shapiro-Wilk test yielded a statistic of 0.846, with a p-value of 2.58×10^{-19}, suggesting a deviation from normality in the residuals. Furthermore, Levene's test for equality of variances returned a statistic of 32.40 with a p-value of 9.49×10^{-19}, indicating heteroscedasticity, which implies that variances across the algorithms are not homogeneous.

For the isolated MG configuration, ANOVA results reveal similar trends, with a significant F-statistic of 532.13 and a p-value of 1.66×10^{-138}, as shown in Table 7. The Shapiro-Wilk and Levene's tests indicate non-normality and heteroscedasticity, with p-values of 3.28×10^{-19} and 3.41×10^{-15}, respectively. These findings imply that, despite variability in the data, there are statistically significant differences in energy loss minimization across the algorithms in both MG configurations.

5.5.2. ANOVA Results for FO_2 - CO_2 Emissions ANOVA analysis indicates statistically significant differences among the algorithms for objective FO_2, which focuses on minimizing CO_2 emissions, in both connected and isolated microgrid configurations.

In the connected configuration, the F-statistic is extremely high at 5691.94, with a p-value of effectively 0 (Table 8). These results confirm that the algorithms exhibit significant variation in their ability to minimize emissions.

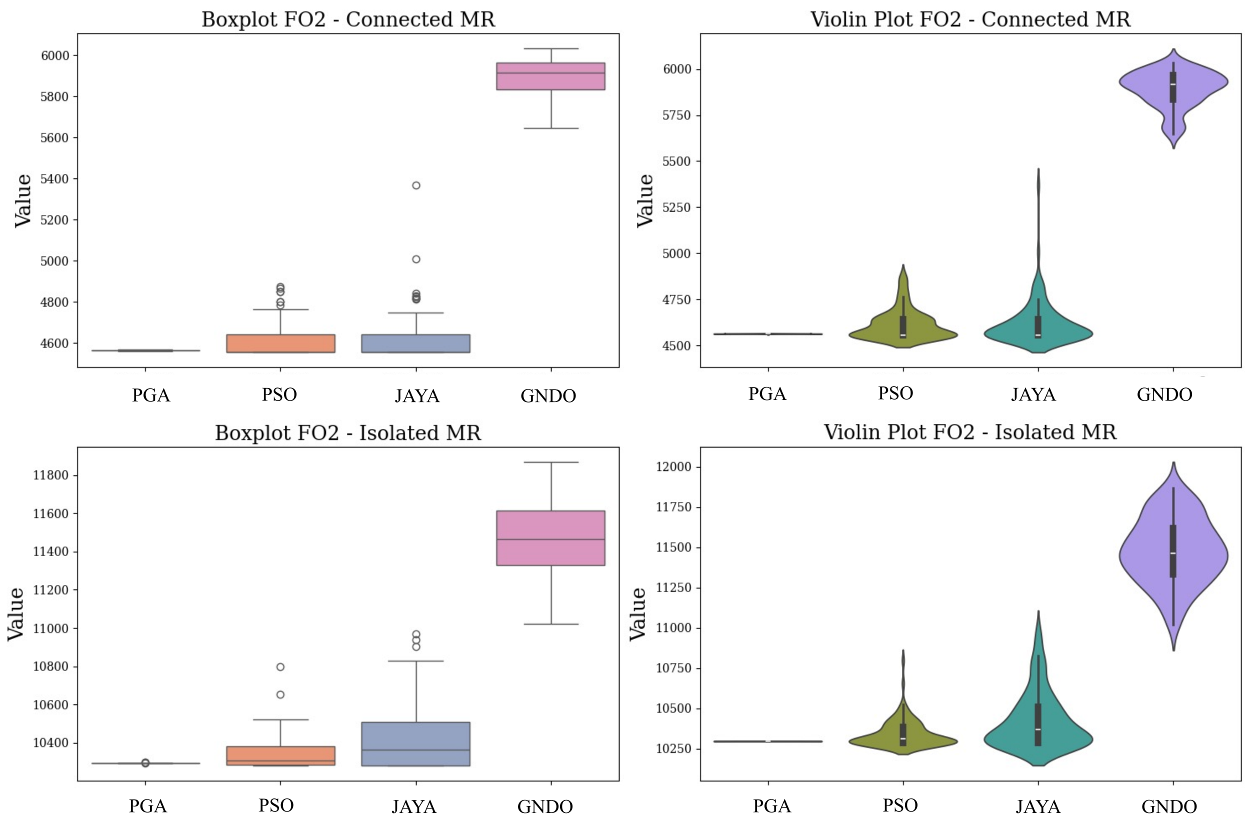

Figure 6. Boxplot and Violin Plot Analysis of FO_2 (CO_2 Emissions) for Connected and Isolated MG Configurations

Table 7. ANOVA Results for FO_1 (Energy Losses) in Connected and Isolated MG Configurations

Configuration	**Sum of Squares**	**df**	**F**	***p*-value**
Connected (Algorithm)	228350.67	3	1321.98	7.39×10^{-206}
Connected (Residual)	22800.95	396	-	-
Isolated (Algorithm)	305879.92	3	532.13	1.66×10^{-138}
Isolated (Residual)	75875.94	396	-	-

The Shapiro-Wilk test for normality yields a statistic of 0.828 and a p-value of 2.16×10^{-20}, indicating non-normal residuals. Furthermore, Levene's test reveals heteroscedasticity, with a statistic of 18.00 and a p-value of 5.73×10^{-11}, suggesting that variances among the algorithms are unequal.

In the isolated configuration, ANOVA results remain highly significant, with an F-statistic of 1647.45 and a p-value of 3.18×10^{-223}. The Shapiro-Wilk test produces a statistic of 0.915 and a p-value of 2.97×10^{-14}, again confirming the non-normality of residuals. Levene's test (p-value of 3.40×10^{-32}) further corroborates the presence of unequal variances across the algorithms.

These findings highlight substantial differences in the algorithms' performances in minimizing CO_2 emissions across configurations. While all methods provide improvements over the base case, the variability observed in some algorithms, such as GNDO and JAYA, underscores the need for careful algorithm selection based on the desired balance between robustness and emission reduction.

The statistical analysis reinforces that the PGA algorithm consistently achieves superior performance in minimizing CO_2 emissions in both configurations, with significantly lower mean emissions and reduced variability

Table 8. ANOVA Results for FO_2 (CO_2 Emissions) in Connected and Isolated MG Configurations

Configuration	Sum of Squares	df	F	p-value
Connected (Algorithm)	1.2529e+08	3	5691.94	0.0
Connected (Residual)	2.9056e+06	396	-	-
Isolated (Algorithm)	9.5649e+07	3	1647.45	3.18×10^{-223}
Isolated (Residual)	7.6638e+06	396	-	-

compared to the other algorithms. The non-normality and heteroscedasticity observed in the residuals suggest that while PGA demonstrates robustness and reliability, other methods, such as GNDO and JAYA, exhibit greater variability, potentially limiting their applicability in scenarios requiring consistent performance. These results further validate PGA as a reliable choice for optimization in microgrid systems where emission minimization is a critical objective.

5.6. Tukey HSD Test Analysis

To further analyze the effectiveness of each optimization algorithm, a Tukey HSD (Honestly Significant Difference) test was conducted for the objective functions FO_1 (energy losses) and FO_2 (CO_2 emissions). This test assesses pairwise differences between algorithmic means, identifying which pairs exhibit statistically significant differences. The results provide insights into whether the PGA consistently outperforms other methods across connected and isolated MG configurations.

5.6.1. Tukey HSD Results for FO_1 - Energy Losses For the connected microgrid configuration, the Tukey test results for FO_1 demonstrate statistically significant differences between most algorithm pairs at a confidence level of 95%. The algorithm GNDO exhibited significantly higher energy losses than the other algorithms, with mean differences of -54.58, -57.80, and -52.66 compared to JAYA, PGA, and PSO, respectively. These results, with corresponding p-values of 0.0, strongly suggest that GNDO is suboptimal for minimizing energy losses.

The comparison between JAYA and PGA yielded a mean difference of -3.22 with a p-value of 0.015, indicating a statistically significant advantage for PGA. Additionally, the difference between PGA and PSO was found to be 5.14 with a p-value of 0.0, reinforcing the superior performance of PGA in this configuration. However, the comparison between JAYA and PSO did not reach statistical significance (p-value = 0.2799), suggesting similar performance between these two algorithms for FO_1 in the connected setup.

In the isolated configuration, the Tukey test results also highlighted GNDO as the least effective algorithm, with substantial and statistically significant mean differences compared to JAYA, PGA, and PSO, all with p-values of 0.0. The mean difference between JAYA and PGA was -15.60 (p-value = 0.0), further confirming the superior efficiency of PGA in reducing energy losses. The comparison between PGA and PSO did not reach significance in this setup (p-value = 0.1435), indicating similar performance between these two algorithms in the isolated configuration.

5.6.2. Tukey HSD Results for FO_2 - CO_2 Emissions The Tukey HSD test for FO_2 (CO_2 emissions) reveals significant differences among the algorithms in the connected configuration. GNDO consistently underperforms, with significantly higher emissions compared to JAYA, PGA, and PSO. The mean differences between GNDO and the other algorithms are -1271.38, -1327.39, and -1275.70, respectively, all with p-values of 0.0. This indicates that GNDO's performance in minimizing emissions is statistically inferior in the connected configuration.

In terms of pairwise comparisons among the other algorithms, JAYA and PGA show a statistically significant mean difference of -56.02 (p-value = 0.0), confirming PGA's superior performance in emission reduction. Similarly, the comparison between PGA and PSO yields a mean difference of 51.70 (p-value = 0.0001), favoring PGA. On the other hand, the comparison between JAYA and PSO is not statistically significant, with a mean difference of -4.32 (p-value = 0.9844), suggesting comparable effectiveness between these two algorithms for emissions reduction.

In the isolated configuration, the Tukey test results further confirm GNDO's poor performance, with significant differences compared to the other algorithms, all with p-values of 0.0. The mean difference between JAYA and

PGA is -128.07 (p-value = 0.0), indicating that PGA significantly outperforms JAYA in minimizing emissions. However, the comparison between PGA and PSO in this configuration is marginal, with a mean difference of 47.64 and a p-value of 0.0747, suggesting similar performance between these two algorithms under isolated conditions.

Table 9. Tukey HSD Test Summary for FO_1 (Energy Losses) and FO_2 (CO_2 Emissions) in Connected and Isolated MG Configurations

Objective	Configuration	Algorithm Comparison	Mean Difference	p-value
FO1	Connected	GNDO - PGA	-57.80	0.0
FO1	Connected	JAYA - PGA	-3.22	0.015
FO1	Connected	PGA - PSO	5.14	0.0
FO1	Isolated	GNDO - PGA	-69.08	0.0
FO1	Isolated	JAYA - PGA	-15.60	0.0
FO1	Isolated	PGA - PSO	4.18	0.1435
FO2	Connected	GNDO - JAYA	-1271.38	0.0
FO2	Connected	GNDO - PGA	-1327.39	0.0
FO2	Connected	GNDO - PSO	-1275.70	0.0
FO2	Connected	JAYA - PGA	-56.02	0.0
FO2	Connected	JAYA - PSO	-4.32	0.9844
FO2	Connected	PGA - PSO	51.70	0.0001
FO2	Isolated	GNDO - PGA	-1182.91	0.0
FO2	Isolated	JAYA - PGA	-128.07	0.0
FO2	Isolated	PGA - PSO	47.64	0.0747

The Tukey HSD analysis reaffirms that PGA is the most effective algorithm for minimizing both energy losses and CO_2 emissions across different configurations, with statistically significant improvements over other methods in most pairwise comparisons. GNDO consistently performs poorly, and JAYA is outperformed by PGA in nearly all significant comparisons. Although PSO sometimes achieves results similar to PGA, particularly in the isolated configuration, PGA's consistent superiority across different setups supports its selection as the optimal method for this specific problem.

5.7. Application and results of the proposed methodology on a 69-bus system.

Finally, in order to validate the capability and flexibility of the proposed strategy to operate on larger systems, additional tests were conducted considering variations in demand and generation over a one-week operational horizon. This is presented in Tables 10 and 11.

Table 10. Statistical Results for Objective Function FO_1 (Energy Losses kWh) in 69-node MG.

Operation Mode	Case	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Connected	Base Case	2030.622553	2030.622553	1936.407934	2030.622553	2030.622553	1922.856209	1810.562951
	PGA	760.6296204	750.6348379	721.9494392	755.1520891	760.5338122	705.7271153	689.206721
Isolated	PGA	830.6388696	840.5781539	790.2559191	831.8810829	828.9988515	790.5427154	773.5415531

Table 10 shows the 69-node MG in both grid-connected and isolated modes, with the implementation of the PGA algorithm, in accordance with the proposed methodology to reduce energy losses. First, in the grid-connected mode, a weekly average value of 734.8334 kWh is obtained after comparing with the base case, corresponding to an average weekly reduction of 62.6977%. In the islanded mode, although no base case is available, due to the same reasons stated for the 33-node MG, a weekly average energy value of 812.3482 kWh is achieved, complying with the system's technical constraints.

Table 11 presents the implementation of the PGA algorithm for reducing CO_2 emissions in the 69-node MG. In grid-connected mode, the PGA achieves an average emission value of -1226.7908 $KgCO_2$. It is important to clarify that this negative value does not indicate a computational error; rather, it reflects that the MG supplies more

Table 11. Statistical Results for Objective Function FO_2 (kg of CO_2 Emissions) in 69-node MG.

Operation Mode	**Case**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Connected	Base Case	9735.63236	9735.63236	9540.216466	9735.63236	9735.63236	9536.162274	9284.906718
	PGA	-915.6485283	-1575.008902	-1101.380518	-1199.101298	-917.7383889	-1469.271553	-1409.437365
Isolated	PGA	7701.459191	7703.637442	7702.150508	7702.479587	7702.653622	7702.204556	7702.670412

energy to the main grid than it consumes. As a result, a net emission reduction is achieved not only within the MG itself but also across the wider electrical system. In contrast, under isolated operation, an average emission value of 7702.4650 $KgCO_2$ is recorded. This value cannot be negative due to the generation constraints of diesel generators and complies with the system's technical limitations.

6. Conclusions

This study evaluated the performance of four metaheuristic algorithms, PGA, PSO, JAYA, and GNDO, in optimizing two key objectives in MG operation: energy losses and CO_2 emissions. This research provides robust evidence of PGA's consistent superiority in minimizing both objectives across different MG configurations (connected and isolated) by conducting a comprehensive statistical analysis, including box plots, violin plots, ANOVA, and Tukey HSD tests. The results showed that PGA achieved statistically significantly lower values for both objective functions compared to the other methods, especially GNDO, which consistently underperformed in all configurations. Additionally, while PSO occasionally achieved results comparable to PGA, particularly in isolated settings, the consistent efficacy of PGA across all scenarios validates its suitability as the optimal algorithm for these objectives in MG optimization.

Numerically, the PGA algorithm achieved a 58.6% reduction in energy losses in the connected configuration of the MG, compared to the base case of 3378.92 kWh. Similarly, for CO_2 emissions, PGA reduced emissions in the connected configuration by 63.6%, relative to the base case of 12,541.20 kg. While PSO and JAYA also provided competitive reductions, particularly in isolated conditions, PGA's stability and low deviation across scenarios further solidify its position as the most reliable choice for optimizing energy and environmental performance in MGs.

The strong performance of the proposed PGA was subsequently validated in a 69-bus MG under both grid-connected and isolated operating modes. In the grid-connected configuration, the PGA achieved an average reduction of 62.6977% in energy losses. For emissions reduction, it yielded an average value of -1226.7908 $kgCO_2$, demonstrating that the strategy enables an intelligent dispatch of WGs that contributes to a system-wide reduction in emissions, including those from the main power grid. In the isolated mode, the PGA achieved average values of 812.3482 kWh and 7702.4650 $kgCO_2$ for the optimization of energy losses and emissions, respectively, while satisfying the technical constraints of the MG in this configuration.

The primary contribution of this research lies in its rigorous statistical evaluation of metaheuristic algorithms for minimizing energy losses and CO_2 emissions in MGs. By addressing the gaps in existing literature regarding the comparative performance of these algorithms by considering multiple objective functions related to technical and environmental aspects, this study provides valuable insights into algorithm selection for similar energy systems. The findings support the notion that PGA's evolutionary mechanisms provide a robust solution for problems where both energy efficiency and environmental impact are critical, thereby advancing the understanding of effective optimization in renewable energy applications.

Future research could extend this analysis by incorporating additional objective functions, such as total operating cost and system reliability, to develop a more holistic optimization framework. Furthermore, the impact of dynamic constraints related to renewable energy variability and power demand could be examined: generator ramp rates, demand-side management strategies, as well as the optimal operation of batteries in conjunction with wind generators, by considering degradation effects and cycling costs to enhance the realism and flexibility of the microgrid model. Furthermore, it could be considered the integration of advanced hybrid metaheuristics that combine the strengths of multiple algorithms. A specific focus on minimizing power losses (P_{loss}) and CO_2 emissions could provide further insights into sustainable MG operation, particularly under different environmental conditions and grid configurations. Furthermore, it can be considered as future work to extend the optimization framework to incorporate economic objectives, such as the minimization of the Levelized Cost of Energy (LCOE), alongside technical and environmental goals. Finally, the application of machine learning techniques for predictive analysis and adaptive algorithm tuning could enhance real-time optimization, contributing to more responsive and resilient MG systems. Although the proposed approach demonstrated robust performance using fixed heuristic penalty factors, we recognize that this strategy may face limitations as the dimensionality and complexity of the optimization problem increase.

Appendix A. Pseudocode of Comparative Algorithms

This appendix presents the pseudocode for the PSO, JAYA, and GNDO algorithms used in this study.

A.1 Particle Swarm Optimization (PSO)

Algorithm 2: PSO Pseudocode

```
Data: Initialize system data, PSO parameters (e.g., w, c_1, c_2)
Generate initial population of particles with random positions and velocities;
Evaluate fitness of each particle using SA-based power flow;
Set personal best (pbest) and global best (gbest);
for each iteration do
    for each particle do
        Update velocity: v_i^{t+1} = w v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t);
        Update position: x_i^{t+1} = x_i^t + v_i^{t+1};
        Evaluate new fitness and apply penalties;
        Update pbest and gbest if necessary;
    if stopping criterion met then
        break;
Result: Best particle position (solution)
```

A.2 JAYA Algorithm

Algorithm 3: JAYA Pseudocode

```
Data: Initialize system data and JAYA parameters
Generate initial population of candidate solutions;
Evaluate fitness of each individual using SA-based power flow;
for each iteration do
    Identify best and worst solutions in the population;
    for each candidate do
        Update solution using: X_new = X + r_1 · (X_best - |X|) - r_2 · (X_worst - |X|);
        Apply boundary limits and evaluate new fitness;
        Replace if X_new is better;
    if stopping criterion met then
        break;
Result: Best solution found
```

A.3 Generalized Normal Distribution Optimizer (GNDO)

Algorithm 4: GNDO Pseudocode

Data: Initialize system data and GNDO parameters
Generate initial population from normal distribution;
Evaluate fitness of each individual using SA-based power flow;
for *each iteration* **do**
    Compute population mean μ and standard deviation σ;
    for *each individual* **do**
        Generate local and global search candidate solutions using $\mathcal{N}(\mu, \sigma)$;
        Evaluate candidates and choose the better one;
        Replace individual if new solution is superior;
    if *stopping criterion met* **then**
        break;
Result: Best solution in final population

Appendix B. Technical parameters of the 69-node MG

This appendix provides the parameters of the 69-bus MG used in this study, including the technical specifications of the lines and the nodal load demands, see details in the Table 12.

Appendix C. Validation with additional Recent Methodologies.

In this appendix, to assess the effectiveness of the proposed methodology against other recent metaheuristic techniques, Tables 13 and 14 are presented. These tables show the results obtained using the GWO and HHO, which are compared to the PGA for both objective functions. The corresponding parameter settings for these algorithms are provided in Table 15.

Upon analyzing the results obtained by these techniques, as presented in Tables 13 and 14, it can be observed that the HHO exhibits very high standard deviations, exceeding those of all other techniques studied in this work, with a maximum reaching 357.4346 $kgCO_2$. In the case of the GWO, although it achieved satisfactory results, it did not outperform the PGA in any of the evaluated performance metrics. This is particularly evident in the standard deviation, where GWO presents a value approximately 15 times higher than that of the PGA. For these reasons, the latter two techniques are not examined in as much depth as the other comparison methods; however, they still provide insight into the performance of newer algorithms in the proposed system.

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Data availability Satatement

The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Table 12. Technical parameters of the 69-node MG

Line l	Sending Node i	Receiving Node j	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kvar)	$I_{ij}^{\max}$ (A)
1	1	2	0.0005	0.0012	0	0	410
2	2	3	0.0005	0.0012	0	0	410
3	3	4	0.0015	0.0036	0	0	410
4	4	5	0.0251	0.0294	0	0	266
5	5	6	0.366	0.1864	2.6	2.2	266
6	6	7	0.3811	0.1941	40.4	30	266
7	7	8	0.0922	0.047	75	54	266
8	8	9	0.0493	0.0251	30	22	266
9	9	10	0.819	0.2707	28	19	99
10	10	11	0.1872	0.0619	145	104	99
11	11	12	0.7114	0.2351	145	104	99
12	12	13	1.03	0.34	8	5	99
13	13	14	1.044	0.345	8	5	99
14	14	15	1.058	0.3496	0	0	99
15	15	16	0.1966	0.065	45	30	99
16	16	17	0.3744	0.1238	60	35	99
17	17	18	0.0047	0.0016	60	35	99
18	18	19	0.3276	0.1083	0	0	99
19	19	20	0.2106	0.069	1	0.6	99
20	20	21	0.3416	0.1129	114	81	99
21	21	22	0.014	0.0046	5	3.5	99
22	22	23	0.1591	0.0526	0	0	99
23	23	24	0.3463	0.1145	28	20	99
24	24	25	0.7488	0.2475	0	0	99
25	25	26	0.3089	0.1021	14	10	99
26	26	27	0.1732	0.0572	14	10	99
27	3	28	0.0044	0.0108	26	18.6	99
28	28	29	0.064	0.1565	26	18.6	99
29	29	30	0.3978	0.1315	0	0	99
30	30	31	0.0702	0.0232	0	0	99
31	31	32	0.351	0.116	0	0	99
32	32	33	0.839	0.2816	10	10	99
33	33	34	1.708	0.5646	14	14	99
34	34	35	1.474	0.4873	4	4	99
35	3	36	0.0044	0.0108	26	18.55	99
36	36	37	0.064	0.1565	26	18.55	99
37	37	38	0.1053	0.123	0	0	99
38	38	39	0.0304	0.0355	24	17	99
39	39	40	0.0018	0.0021	24	17	99
40	40	41	0.7283	0.8509	102	1	99
41	41	42	0.31	0.3623	0	0	99
42	42	43	0.041	0.0478	6	4.3	99
43	43	44	0.0092	0.0116	0	0	99
44	44	45	0.1089	0.1373	39.22	26.3	99
45	45	46	0.0009	0.0012	39.22	26.3	99
46	4	47	0.0034	0.0084	0	0	99
47	47	48	0.0851	0.2083	79	56.4	99
48	48	49	0.2898	0.7091	384.7	274.5	99
49	49	50	0.0822	0.2011	384.7	274.5	99
50	8	51	0.0928	0.0473	40.5	28.3	99
51	51	52	0.3319	0.114	3.6	2.7	99
52	9	53	0.174	0.0886	4.35	3.5	195
53	53	54	0.203	0.1034	26.4	19	195
54	54	55	0.2842	0.1447	24	17.2	195
55	55	56	0.2813	0.1433	0	0	195
56	56	57	1.59	0.5337	0	0	195
57	57	58	0.7837	0.263	0	0	195
58	58	59	0.3042	0.1006	100	72	195
59	59	60	0.3861	0.1172	0	0	195
60	60	61	0.5075	0.2585	1244	888	195
61	61	62	0.0974	0.0496	32	23	99
62	62	63	0.145	0.0738	0	0	99
63	63	64	0.7105	0.3619	227	162	99
64	64	65	1.041	0.5302	59	42	99
65	11	66	0.2012	0.0611	18	13	99
66	66	67	0.0047	0.0014	18	13	99
67	12	68	0.7394	0.2444	28	20	99
68	68	69	0.0047	0.0016	28	20	99

Table 13. Additional Statistical Results for Objective Function FO_1 (Energy Losses kWh) for GWO and HHO

MG Configuration	Algorithm	Min	Average	Std. Deviation	Confidence Interval (95%)
Connected	PGA	1399.415121	1399.466560	0.019275	[1399.46, 1399.47]
	GWO	1399.593203	1399.765229	0.118485	[1399.74, 1399.79]
	HHO	1510.055314	1519.779417	7.492373	[1518.31, 1521.25]
Isolated	PGA	1439.652477	1443.538385	1.900417	[1443.16, 1443.92]
	GWO	1442.677862	1449.267999	3.619485	[1448.56, 1449.98]
	HHO	1863.481322	1926.153201	36.471287	[1919.00, 1933.30]

Table 14. Additional Statistical Results for Objective Function FO_2 (kg of CO_2 Emissions) for GWO and HHO

MG Configuration	Algorithm	Min	Average	Std. Deviation	Confidence Interval (95%)
Connected	PGA	4562.390072	4564.626150	1.027337	[4564.43, 4564.82]
	GWO	4614.116806	4633.752997	16.251334	[4630.57, 4636.94]
	HHO	6459.417996	6507.939523	31.417839	[6501.78, 6514.10]
Isolated	PGA	10293.893570	10295.677661	0.565508	[10295.56, 10295.80]
	GWO	10390.152009	10431.623638	52.713135	[10421.29, 10441.96]
	HHO	14182.850004	14878.538489	357.434610	[14808.48, 14948.60]

Table 15. Additional Parameters of Optimization Methodologies for the 33-node MG in Grid-Connected and Standalone Modes (GWO and HHO)

Methodology	Parameter	Grid-Connected Mode	Isolated Mode
GWO	Number of Individuals	195	200
	Number of Iterations	1100	1000
	Control coefficient	0.1166	0.1355
GNDO	Number of Individuals	50	46
	Number of Iterations	5000	5200

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