

Article

Multi-Objective Optimization Framework for Sustainable Operation of Grid-Connected Microgrids

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Abstract

This paper proposes an optimal operational framework for enhancing the economic, technical, and environmental performance of a renewable energy-based microgrid. The proposed system integrates photovoltaic (PV) generation, wind turbines (WTs), battery energy storage systems (BESSs), diesel generators (DGs), and utility grid interaction. Three multi-objective optimization algorithms, namely Multi-Objective Particle Swarm Optimization (MOPSO), Multi-Objective Genetic Algorithm (MOGA), and Multi-Objective Celestial Orbit Optimization (MOCOO), are employed to minimize the total operating cost and grid dependency. The obtained results demonstrate that MOPSO achieves the best techno-economic performance with a minimum operating microgrid cost of 2.2 M\$/year and a low grid dependency ratio of 0.0333. The operational analysis confirms that the proposed renewable-priority scheduling strategy significantly reduces operational emissions and reliance on the utility grid through coordinated BESS charging/discharging and efficiency-aware DG dispatch. The microgrid (MG) achieves zero-emission operation during operating periods dominated by renewable generation. Furthermore, the DG operates within an efficiency range of 36.8–39.3%, improving fuel utilization and reducing unnecessary emissions. The battery degradation analysis indicates high lifetime cycle capability under shallow depth-of-discharge operation, demonstrating improved long-term operational sustainability. Overall, the proposed framework provides a reliable and economically balanced solution for sustainable microgrid energy management.

Keywords: grid-connected microgrid; energy management system; multi-objective optimization; diesel generator efficiency; depth-of-discharge; battery degradation; grid dependency; renewable penetration; CO₂ emissions; social sustainability



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1. Introduction

The increasing penetration of renewable energy resources, including photovoltaic (PV) and wind energy systems, has significantly accelerated the development of modern microgrids (MGs) as sustainable and flexible energy infrastructures. Microgrids enable the coordinated integration of distributed energy resources, battery energy storage systems (BESSs), diesel generators (DGs), and utility grid interaction to improve system reliability, operational flexibility, and energy sustainability. Due to the intermittent nature of renewable energy generation and the stochastic variation of load demand, advanced

Energy Management Systems (EMSs) have become essential for achieving reliable and cost-effective microgrid operation [1,2].

Day-ahead EMS scheduling has recently received considerable attention because of its capability to optimally coordinate multiple energy resources while minimizing operational costs, reducing emissions, improving renewable utilization, and preserving storage system performance [3]. Various optimization techniques have been proposed in the literature, including the Modified Marine Predators Algorithm (MMPA) [4], Differential Evolution (DE) [5], the Multi-Objective Artificial Hummingbird Algorithm (MOAHA) [6], the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [7], the improved NSGA-II algorithm with Multi-stage Constraint-handling strategy (NSGA-II-MC) [8], the Improved Non-dominated Sorting Dung Beetle Optimization (INSDBO) algorithm [9], the Mixed-Integer Linear Programming (MILP) [10], the Chaotic Local Search with Sine Cosine Algorithm (CLSCA) [11], the Mountain Gazelle Optimizer (MGO) [12], and the Adaptive Genetic Particle Swarm Optimization (AGAPSO) [13].

1.1. Research Challenges

Despite the substantial progress achieved in microgrid EMS research, several technical and operational challenges remain unresolved. The improper coordination between DGs, BESSs, and utility grid interaction may lead to increased operational costs, excessive emissions, accelerated battery degradation, and inefficient DG operation [14,15].

One of the major operational challenges is associated with the realistic modeling of DG fuel efficiency. In practical operation, DG efficiency varies nonlinearly with loading conditions, and prolonged operation at low loading levels significantly reduces fuel efficiency and increases maintenance requirements. However, many existing EMS studies simplify DG operation using constant efficiency assumptions without considering minimum loading constraints or loading-dependent fuel consumption characteristics [4,5,8,11].

Battery degradation modeling also remains a critical challenge. Most available studies primarily rely on simplified state-of-charge (SOC) constraints while neglecting the nonlinear relationship between depth of discharge (DoD) and battery aging. Consequently, excessive cycling and deep discharge operation may accelerate battery degradation and reduce long-term system sustainability [7,8,10,12,13].

Additionally, the majority of existing studies focus mainly on economic and environmental objectives while social sustainability aspects, such as grid dependency reduction and local energy autonomy, remain insufficiently investigated [4–6,9–12]. Moreover, many studies evaluate EMS performance over short-term operational horizons without conducting comprehensive annual assessments capable of capturing seasonal variations and long-term operational behavior [4–13].

1.2. Literature Review and Existing Approaches

Several EMS frameworks have been developed to improve microgrid operational performance. In [4], MMPA was proposed to minimize operational costs while considering battery degradation using the Wöhler curve model. Similarly, the work presented in [6] incorporated degradation cost penalties based on DoD cycles using MOAHA. The study in [11] also integrated battery degradation cost into the EMS optimization problem using the CLSCA optimization technique.

Environmental and techno-economic objectives were addressed in [5], where an incentive-based demand response framework was proposed to reduce operating costs and emissions. Multi-objective optimization considering pumped storage systems and demand response was investigated in [9] using the INSDBO algorithm. In [12], MGO was introduced for multi-energy multi-microgrid scheduling under uncertain operating conditions.

Social sustainability aspects were partially addressed in [7,8,13] through the consideration of unmet load reduction or grid dependency minimization. Furthermore, the study presented in [10] investigated DG fuel efficiency improvement under varying loading conditions using MILP-based optimization.

Although these studies achieved significant improvements in operational scheduling, several limitations remain unresolved. Most existing works either neglect realistic DG efficiency behavior or employ simplified fixed-efficiency models [4,5,8,11]. In addition, many studies consider only SOC constraints without explicitly modeling DoD-dependent battery degradation [7,8,10,12,13]. Social sustainability metrics are also insufficiently integrated into current EMS frameworks, particularly regarding grid dependency reduction and energy autonomy enhancement [4–6,9–12].

Furthermore, long-term yearly analysis and representative-day operational assessment remain limited in many existing studies [4–13]. Therefore, there remains a need for a comprehensive EMS framework capable of simultaneously addressing economic, environmental, technical, and social sustainability objectives under realistic operational conditions, as shown in Table 1.

Table 1. Research gap matrix.

Ref.	Economic Objective	Environmental Objective	Social Sustainability	DG Efficiency Modeling	DoD-Based Battery Degradation	Long-Term/Yearly Assessment	Representative-Day Analysis
[4]	✓ ¹	✗ ²	✗	No Efficiency Specified	✓	✗	✗
[5]	✓	✓	✗	Fixed Efficiency	No BESS	✗	✗
[6]	✓	✓	✗	No DG	✓	✗	✗
[7]	✓	✓	✓	No DG	✗	✗	✗
[8]	✓	✗	✓	No Efficiency Specified	✗	✗	✗
[9]	✓	✓	✗	No DG	No BESS	✗	✗
[10]	✗	✗	✗	✓	✗	✗	✗
[11]	✓	✓	✗	No Efficiency Specified	✓	✗	✗
[12]	✓	✓	✗	No DG	✗	✗	✗
[13]	✓	✗	✓	No DG	✗	✗	✗
Proposed Study	✓	✓	✓	✓	✓	✓	✓

¹ ✓ indicates that the corresponding feature is considered or implemented in the referenced study. ² ✗ indicates that it is not considered or implemented.

1.3. Research Objectives and Contributions of the Proposed Study

Motivated by the aforementioned research gaps, this paper proposes a comprehensive day-ahead EMS framework for a grid-connected microgrid integrating renewable energy resources, BESSs, DGs, and utility grid interaction. The proposed framework simultaneously addresses economic, environmental, technical, and social sustainability objectives through coordinated multi-objective scheduling.

Unlike existing studies, the proposed framework explicitly incorporates the nonlinear relationship between DG loading and fuel efficiency to avoid inefficient low-loading operation and improve fuel utilization. In addition, DoD-dependent battery degradation modeling is integrated into the optimization framework to preserve battery lifetime and improve long-term storage sustainability.

Furthermore, the proposed study introduces grid dependency minimization as a social sustainability indicator to improve local energy autonomy and reduce excessive reliance on the utility grid. A continuous annual scheduling framework and representative-day analyses are also developed to evaluate long-term EMS performance under varying seasonal operating conditions.

The obtained results demonstrate the capability of the proposed EMS to effectively coordinate renewable generation, BESS operation, DG dispatch, and utility grid interaction while simultaneously minimizing operational costs, emissions, battery degradation, and grid dependency under varying operating conditions.

The main contributions of this work can be summarized as follows:

1. Development of a comprehensive multi-objective day-ahead EMS considering economic, environmental, technical, and social sustainability objectives.
2. Incorporation of DG loading-dependent fuel efficiency characteristics and minimum loading constraints for realistic DG operation.
3. Integration of DoD-dependent battery degradation modeling to preserve BESS lifetime.
4. Introduction of grid dependency minimization as a social sustainability metric.
5. Development of a continuous annual operational assessment framework.
6. Comprehensive representative-day analysis under varying operating scenarios.

The remainder of this paper is structured as follows. Section 2 presents the configuration and mathematical modeling of the proposed grid-connected microgrid system. Section 3 formulates the multi-objective optimization problem, including the objective functions and associated operational constraints. Section 4 briefly introduces the employed optimization techniques. Section 5 presents and analyzes the optimal operational results, including the evaluation of emission characteristics and battery degradation behavior. Section 6 provides a comprehensive discussion of the obtained techno-economic and environmental findings. Finally, Section 7 concludes the paper and outlines potential directions for future research.

2. Methodology

Figure 1 shows the structure of the proposed grid-connected MG. This MG integrates several energy sources: photovoltaic (PV) panels, wind turbines (WTs), battery storage units, and a diesel generator (DG). Additionally, a bidirectional converter links the AC and DC sides of the network. The proposed MG operates according to a renewable-priority energy management strategy. The PV system and WTs are utilized as the primary power sources to satisfy the load demand. During periods of surplus renewable generation, the excess energy is first stored in the BESS and then exported to the utility grid if the battery reaches its charging limits. Conversely, when the renewable generation is insufficient, the BESS is discharged to supply the remaining load demand. If the combined power from renewable sources and the BESS remains inadequate, the remaining demand is supplied by the DG, the utility grid, or both according to the optimal operating strategy, while satisfying all operational and technical constraints. The MG records a peak demand of 21,880 kW and an average daily energy consumption of 311,007.84 kWh/day on a certain day. The following sections describe the modeling of each component in more detail.

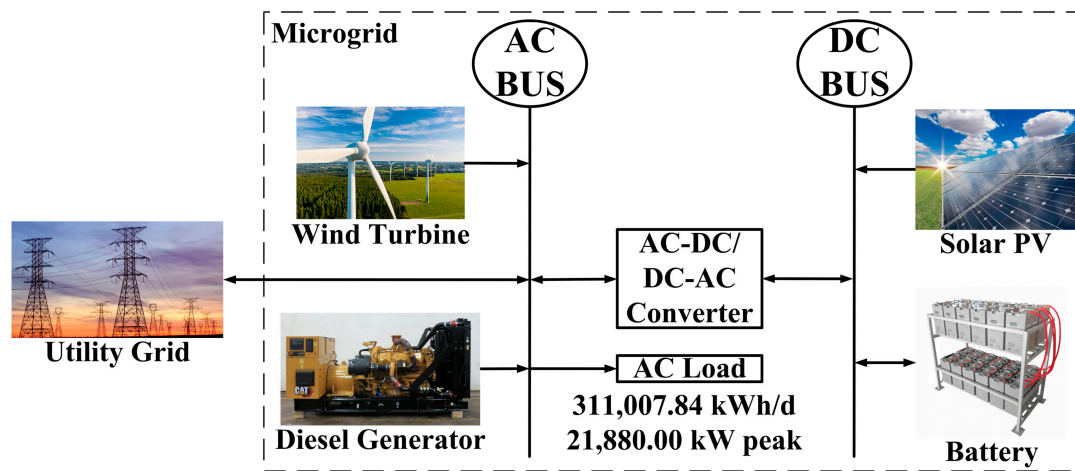


Figure 1. Configuration of the proposed grid-connected MG.

2.1. PV Modeling

The PV-generated power $P_S(t)$ can be computed using Equation (1) [16,17].

$$P_S(t) = N_S \times P_{STC} \times F_S \times \frac{I(t)}{1000} \quad (1)$$

where N_S is the number of PV modules, P_{STC} is the PV power rating at STC (kW), F_S is the PV module derating factor, and $I(t)$ is the global solar irradiance (W/m^2).

2.2. WT Modeling

WT output power $P_w(t)$ can be defined using Equation (2) [16,18].

$$P_w(t) = \begin{cases} 0 & 0 \leq v(t) \leq v_{ci} \\ N_w \times P_r \times \frac{v^2(t) - v_{ci}^2}{v_r^2 - v_{ci}^2} & v_{ci} \leq v(t) \leq v_r \\ N_w \times P_r & v_r \leq v(t) \leq v_{co} \\ 0 & v(t) \geq v_{co} \end{cases} \quad (2)$$

where P_r is the WT's rated power, and N_w is the number of WTs.

2.3. BESS Modeling

Recently, the utilization of lithium-ion batteries has become prevalent in MG applications due to their remarkable characteristics, including high power density, significant energy density, and prolonged lifespan. Battery Energy Storage Systems (BESSs) function through three distinct operational modes: charging, discharging, and idle mode.

2.3.1. Charging Mode

In instances where the power generated by MG sources exceeds load requirements, the excess power is directed toward charging the battery. Consequently, the methodology outlined below is employed to calculate the accumulated energy from this charging process [16,19,20]:

$$P_{CH}(t) = (P_S(t) + \eta_{CON} \times (P_{DG}(t) + P_W(t) - P_L(t))) \times \eta_{CH} \quad (3)$$

where $P_{CH}(t)$ is the power being charged at time t , $P_L(t)$ signifies the load power at time t , and $P_{DG}(t)$ is the power provided by DG at time t . The efficiencies of the converter and charging processes are denoted as η_{CON} and η_{CH} , respectively.

The battery State of Charge (SOC) is calculated as:

$$SOC(t) = SOC(t-1) + P_{CH}(t) \times \Delta t \quad (4)$$

where $SOC(t)$ and $SOC(t-1)$ are states of charge at two successive time instants of t and $t-1$, respectively.

When the calculated $P_{CH}(t)$ is greater than $(SOC_{max} - SOC(t-1))$, the power can be sold to the connected grid $P_{GS}(t)$ and calculated as:

$$P_{GS}(t) \times \Delta t = P_{CH}(t) \times \Delta t - SOC_{max} + SOC(t-1) \quad (5)$$

where SOC_{max} refers to the maximum SOC of the battery.

2.3.2. Discharging Mode

In cases where the energy demand of a load exceeds the output power of PV and WTs, the battery is discharged. The subsequent energy discharged and the corresponding SOC can be approximated using the following approach [16,19,20]:

$$P_{DIS}(t) = \frac{P_L(t) - P_{DG}(t) - P_W(t) - \eta_{CON} \times P_S(t)}{\eta_{CON} \times \eta_{DIS}} \quad (6)$$

$$SOC(t) = SOC(t-1) - P_{DIS}(t) \times \Delta t \quad (7)$$

where $P_{DIS}(t)$ is the battery discharging power at time t and η_{DIS} is the discharging efficiency.

In the event of a battery power shortage, the purchased grid power $P_{GP}(t)$ can be defined as:

$$P_{GP}(t) \times \Delta t = P_{DIS}(t) \times \Delta t - SOC(t-1) + SOC_{min} \quad (8)$$

where SOC_{min} is the battery's minimum permissible SOC.

2.3.3. Idle Mode

Upon reaching full charge, the surplus MG-generated power can be sold back to the grid. This situation is depicted as follows [16,21]:

$$P_{GS}(t) = P_{DG}(t) + P_W(t) - P_L(t) + P_S(t) \times \eta_{CON} \quad (9)$$

Once the battery's maximum discharge capacity is reached, any additional power needed will be procured from the grid. This scenario can be articulated as follows:

$$P_{GP}(t) = P_L(t) - P_{DG}(t) - P_W(t) - P_S(t) \times \eta_{CON} \quad (10)$$

3. Problem Formulation

This section outlines the technical constraints on the system as well as the optimization problem's objective functions.

3.1. The Objective Functions (OFs)

The study addresses the comprehensive OF inherent in the optimization challenge of microgrid (MG) operation. This OF includes two objectives: minimizing the operation cost of MG (OF₁) as presented in Equation (12) and minimizing MG dependence on the grid (OF₂) as defined in Equation (25). The optimization process considers operational constraints delineated in Equations (28)–(34). Consequently, the formulation of the OF is presented as follows:

$$\min_x(\text{OF}(x)) = \min_x(\text{OF}_1(x), \text{OF}_2(x)) \quad (11)$$

where x represents a vector containing optimization parameters: the power output of sources, storage, and converter.

3.1.1. MG Operation Cost Minimization

It can be calculated as follows [4,8,11]:

$$\text{OF}_1 = C_{PV} + C_{WIND} + C_{BESS} + C_{DG} + C_{GRID} + C_{EM} \quad (12)$$

where C_{PV} , C_{WIND} , C_{BESS} , C_{DG} , and C_{GRID} are Operating and Maintenance (O&M) costs of the PVs, wind turbines, batteries, DG, and grid, respectively. C_{EM} is the emissions cost.

PV Costs

The O&M costs of the PVs can be determined using Equation (13) [16,22]:

$$C_{PV} = N_{PV} \times P_{R_PV} \times C_{om_PV} \quad (13)$$

where N_{PV} indicates the number of PV units, P_{R_PV} is the PV capacity in kW, and C_{om_PV} is the PV O&M cost in (\$/kW).

WT Costs

The O&M costs of the WTs can be calculated using Equation (14) [16,23]:

$$C_{WIND} = N_{WIND} \times P_{R_WIND} \times C_{om_WIND} \quad (14)$$

where N_{WIND} indicates the number of WT units, P_{R_WIND} is the WT capacity in kW, and C_{om_WIND} is the WT O&M cost in (\$/kW).

BESS Cost

The processes of BESS charging and discharging can result in early replacements, impact BESS longevity, and increase BESS costs. The total cost of BESS includes the O&M cost and the degradation cost C_{BESS_deg} , as shown in Equation (15). The degradation cost rises at an exponential rate as the depth of discharge $DOD(t)$ value rises through the early degradation factor $\delta(t)$ at time t , as calculated using Equations (16)–(18). Increasing the $DOD(t)$ value decreases the BESS lifetime $B_{CYC}(t)$ (in cycles) at time t , as represented by Equation (19) [11,24,25].

$$C_{BESS} = N_{BESS} \times P_{R_BESS} \times C_{om_BESS} + C_{BESS_deg} \quad (15)$$

$$C_{BESS_deg} = \sum_{t=1}^{8760} \{K_B \times e^{2\delta(t)} \times SOC(t)\} \quad (16)$$

$$\delta(t) = 1 + DOD(t) \quad (17)$$

$$DOD(t) = 1 - \frac{SOC(t)}{SOC_{max}} \quad (18)$$

$$B_{CYC}(t) = \alpha \times DOD(t)^{-\beta} \times e^{-\gamma \times DOD(t)} \quad (19)$$

where α , β , and γ represent coefficients for LiFePO₄ battery curve fitting, N_{BESS} indicates the number of batteries, P_{R_BESS} is the BESS capacity in kWh, and C_{om_BESS} is the BESS O&M cost in (\$/kWh). K_B is the battery degradation cost coefficient (\$/kWh).

DG Cost

Unlike inverter-based sources, the DG behaves like a “heavy flywheel,” giving natural inertia but reacting slowly when conditions change. The DG does not maintain a linear efficiency curve; instead, its efficiency improves with load up to an optimal point, then declines at higher outputs. Therefore, in this MG, the optimization technique favors a larger contribution from the DG to operate it closer to its optimal efficiency point and to maintain economic justification. DG fuel consumption is influenced by how closely it operates to its rated capacity as well as by the characteristics of the fuel used. Accordingly, the total cost of DG is calculated using Equations (20)–(23) [25–27].

$$C_{DG} = H_{DG} \times P_{R_DG} \times C_{om_DG} + C_{fuel_DG} \quad (20)$$

$$C_{fuel_DG} = \sum_{t=1}^{8760} \left\{ K_{DG} \times \frac{P_{DG}(t)}{\eta_{DG}(t)} \right\} \quad (21)$$

$$\eta_{DG}(t) = \frac{3600 \times P_{DG}(t)}{q \times Fuel_{DG}(t) \times LHV} \quad (22)$$

$$Fuel_{DG}(t) = a \times P_{DG}(t) + b \times P_{R_DG} \times z(t) \quad (23)$$

where H_{DG} indicates the number of operating hours per year, P_{R_DG} is the DG capacity (kW), C_{om_DG} is the DG O&M cost (\$/kW), and C_{fuel_DG} is the DG fuel cost (\$). K_{DG} is the unit fuel cost coefficient (\$/kWh) and $\eta_{DG}(t)$ is the DG efficiency at time t . q is the diesel fuel density (kg/dm³), $Fuel_{DG}(t)$ is the fuel consumption rate at time t (dm³/h), and LHV is the diesel fuel lower heating value (MJ/kg). a and b denote the load-dependent fuel consumption coefficient (dm³/kWh) and no-load fuel consumption coefficient (dm³/kWh), respectively. $z(t)$ is the binary variable indicating the DG operating status at time t (1 = ON, 0 = OFF).

Grid Cost

The O&M cost of the grid can be represented as [16,17]:

$$C_{GRID} = \sum_{t=1}^{8760} \{ C_{gp}(t) \times P_{gp}(t) - C_{gs}(t) \times P_{gs}(t) \} \quad (24)$$

where $C_{gp}(t)$ is the per-unit buying grid power cost at the t^{th} hour in \$/kW, $P_{gp}(t)$ (kW) is the purchased power from the utility during the t^{th} hour, $C_{gs}(t)$ is the price of the grid sold power in \$/kW, and $P_{gs}(t)$ (kW) is the utility sold power.

The Emissions Cost

In the MG, both the grid and DG produce different emissions. The total emissions (EM) (kgCO₂-eq) are converted into an emission cost (C_{EM}) (\$) using a penalty factor (E_{pen}) (\$/tonCO₂-eq), as calculated in Equations (25) and (26) [16].

$$C_{EM} = \frac{E_{pen} \times EM}{1000} \quad (25)$$

$$EM = F_{GRID} \times E_{GRID} + F_{DG} \times E_{DG} \quad (26)$$

where F_{GRID} and F_{DG} are the CO₂ emissions (kgCO₂-eq/kWh) of the grid and DG, respectively. E_{GRID} and E_{DG} are the generated energy (kWh) of the grid and DG, respectively.

3.1.2. Grid Dependency Minimization

Grid dependency measures how much the MG relies on the purchased electricity from the grid. This metric helps assess the extent to which the MG depends on external electricity versus local generation sources like diesel generators, PV, WTs, and BESS. Minimizing grid dependency enhances the energy autonomy of the MG, increases the utilization of locally generated renewable energy, and improves system resilience against grid disturbances and electricity price fluctuations. The grid dependency index is therefore expressed as follows:

$$OF_2 = \frac{\sum_{t=1}^{8760} P_{gp}(t)}{\sum_{t=1}^{8760} P_L(t)} \quad (27)$$

3.2. The Technical Constraints

Operational parameters of MG components must adhere to established limits to ensure the integrity and dependability of the power supply infrastructure. Inequality and power balance constraints should be calculated and considered, as will be described in the following paragraphs.

3.2.1. The Inequality Constraints

Maximum and minimum boundaries of MG sources should be satisfied, as follows [21,28]:

$$0 \leq P_S(t) \leq P_{S_rated} \quad (28)$$

$$0 \leq P_w(t) \leq P_{w_rated} \quad (29)$$

$$-P_{CH_max} \leq P_b(t) \leq P_{DIS_max} \quad (30)$$

$$0 \leq |P_{INV}(t)| \leq P_{inv_max} \quad (31)$$

$$P_{DG_min} \leq P_{DG}(t) \leq P_{DG_max} \quad (32)$$

where $P_b(t)$ is storage power. P_{S_rated} , P_{w_rated} , P_{DG_max} and P_{inv_max} are RESs, DG, and converter capacities, respectively. P_{CH_max} and P_{DIS_max} represent the maximum battery charging and maximum battery discharging, respectively. P_{DG_min} is the minimum allowable operating power of the DG.

The SOC of the battery must be maintained within the acceptable range, as deep discharges and overcharging can both lead to a reduction in battery lifespan, as explained below [19,20]:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (33)$$

3.2.2. The Power Balance Constraints

Power equilibrium can be achieved through the utilization of the subsequent expression [21]:

$$P_L(t) = P_{GP}(t) - P_{GS}(t) + P_{DG}(t) + P_W(t) + \left(P_S(t) + P_{DIS}(t) \times \eta_{DIS} - \frac{P_{CH}(t)}{\eta_{CH}} \right) \times \eta_{CON} \quad (34)$$

The detailed financial and technical parameters of the components incorporated in the proposed MG are provided in Table A1 in Appendix A.

4. Optimization Algorithms

Three Multi-Objective Optimization (MOO) algorithms applied in this paper are mathematically modelled in this section.

4.1. Multi-Objective Particle Swarm Optimization (MOPSO) Algorithm

Since Kennedy and Eberhart's 1995 approach, PSO has been routinely used for optimization problems [29]. Coello et al. introduced MOPSO, an expanded version, in 2004 to overcome MOO challenges [30,31]. To save the nondominated solutions found during the search procedure, MOPSO integrates an external repository made up of an adaptable grid and an archive controller. Whether to add or remove a new solution from the archive is up to the archive controller.

By contrast, the adaptive grid divides the space of the objective function into areas to distribute it uniformly. Traditional approaches, on the other hand, combine several objectives into one. In particular, MOPSO produces more accurate outcomes for concave and disjointed Pareto fronts and handles MOO difficulties directly without requiring repeated runs.

The Pareto front of MOO problems has several global optima. MOPSO maintains a storage of non-dominated particles and employs an adaptive grid approach to assign a leader to each particle from the storage. Using this method, the Pareto front is accurately and diversely approximated.

The Pareto front optimum solutions generated by MOPSO represent the trade-off between cost and grid dependency for the studied microgrid optimization problem. The operator can select the best alternative from the suggested optimal solutions based on the data that is retrieved.

4.2. Multi-Objective Genetic Algorithm (MOGA)

MOGA is implemented in MATLAB R2021a using the “gamultiobj” solver [32]. This solver creates a set of Pareto-front points. It is based on an improved version of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and implements a controlled elitist genetic algorithm, which is well-suited for handling problems with multiple objectives and decision variables. Individuals who have better fitness values are always given preference by an elitist GA. Even those with a lesser fitness value are given preference in the controlled elitist GA if they can contribute to the population's increased diversity. The “gamultiobj” solver can perform several function evaluations to obtain impressive convergence, but it can quickly reach a region close to the optimal Pareto front. Each individual is given a non-dominated rank based on their relative fitness.

4.3. Multi-Objective Celestial Orbit Optimization (MOCOO) Algorithm

The inspiration behind the Celestial Orbit Optimization (COO) algorithm stems from the dynamic and regular behavior of celestial objects [33]. According to celestial mechanics, planets orbit stars in mostly circular or elliptical orbits. This rotation is the outcome of the balance between the planet's angular velocity and central gravitational force. This interaction of global attraction and local variation provides a natural metaphor for multi-objective search: the approach must converge to a Pareto set of solutions (a set of trade-off solutions) and ensure solution diversity so that the conflicting objectives are satisfied.

In the MOCOO algorithm, each candidate solution behaves like a planet moving under the influence of a central region representing the current set of non-dominated solutions (the Pareto front). The “orbital” motion towards the central region encourages the agents to explore different radii and directions (encouraging diversity), and a center-attracting acceleration guides the swarm towards the optimal trade-off region (encouraging convergence). Small random perturbations mimic external perturbations that avoid premature convergence and allow exploration of the Pareto front.

This nature-inspired geometric metaphor yields a multi-objective optimizer with the structured geometric intuition of COO but specifically generates a collection of non-dominated solutions rather than a single optimum solution.

The presented flowchart, Figure 2, illustrates the MOCOO's operational steps and shows the algorithm's systematic optimization strategy and computing operations.

The following is a summary of MOCOO based on Figure 2:

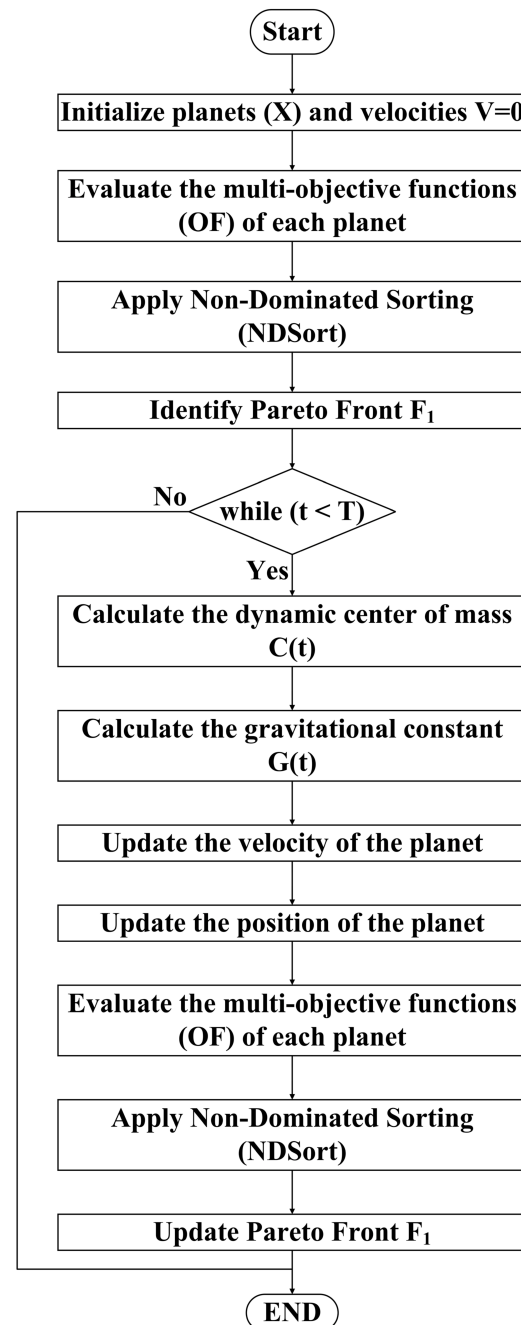


Figure 2. The flowchart of the MOCOO algorithm.

4.3.1. Initialization Process

The planets' initial population is created at random within the search space's specified bounds using Equation (35):

$$X_i = rand_{[0,1]} \times (X_{i,up} - X_{i,low}) + X_{i,low} \quad (35)$$

where X_i stands for the search space's i^{th} planet. $X_{i,up}$ indicates the maximum bound of the i^{th} planet, while $X_{i,low}$ indicates the minimum bound of the i^{th} planet.

Each planet is assigned an initial velocity vector $V_i = 0$. The fitness of each solution is evaluated using the two objective functions, and the population is classified into Pareto fronts using the Non-Dominated Sorting (NDSort) procedure.

4.3.2. Defining the Dynamic Center of Mass

In each iteration t , the gravitational influence of the best solutions (non-dominated front) is modeled through a dynamic center of mass $C(t)$, computed as the mean of the best front's positions using Equation (36):

$$C(t) = \frac{1}{|F_1|} \sum_{i \in F_1} x_i(t) \quad (36)$$

where F_1 denotes the first non-dominated front.

4.3.3. Defining the Gravitational Constant

The gravitational constant $G(t)$ decreases linearly with iterations to balance exploration and exploitation using Equation (37):

$$G(t) = 1 - \frac{t}{T} \quad (37)$$

where t is the current iteration, and T is the maximum number of iterations.

4.3.4. Updating Planets' Velocity

The planet's speed V_i is updated using Equation (38):

$$V_i(t+1) = 0.5 \times V_i(t) + G(t) \times (C(t) - X_i(t)) + \varepsilon \times \text{rand}_{[0,1]} \times (X_{i,up} - X_{i,low}) \quad (38)$$

where ε serves as a small perturbation factor.

4.3.5. Updating Planets' Positions

The position of each planet is updated using Equation (39):

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (39)$$

4.3.6. Non-Dominated Sorting and Pareto Update

After each position update, the fitness values are updated, and then the population is re-sorted using non-dominated sorting. Solutions receive dominance ranks based on Pareto dominance relations:

- A solution X_a dominates X_b if it is not worse in all objectives and better in at least one.
- The first non-dominated front F_1 denotes the approximation of the Pareto optimal set at the current iteration.

Therefore, the best front F_1 is stored as the current Pareto front, which evolves progressively through iterations as the search converges.

4.3.7. Termination and Output

The iterative process continues until the maximum iteration number T is reached. The final output of the algorithm is the non-dominated set of solutions, which provides the trade-off surface between the conflicting objectives.

The three selected algorithms represent different optimization philosophies and are therefore adopted to provide a comprehensive comparison framework for the proposed microgrid optimization problem. Their main strengths and limitations are summarized as follows. MOPSO is characterized by simple implementation, a limited number of control parameters, and effective approximation of the Pareto front. However, it may suffer from premature convergence and loss of diversity in highly complex search spaces. MOGA provides strong global search capability and preserves population diversity through evolutionary operators, although it generally requires a higher computational effort and longer optimization time. MOCOO is an emerging nature-inspired optimization algorithm that offers a good balance between exploration and exploitation and has demonstrated competitive performance across various optimization problems; however, its performance is sensitive to parameter tuning, and its application to microgrid optimization remains relatively limited.

Therefore, these three algorithms are selected because they represent well-established swarm intelligence, evolutionary, and emerging nature-inspired optimization approaches, enabling a balanced evaluation of the proposed microgrid energy management framework.

5. Results

The proposed microgrid model in this study is located in Benban city, within Aswan Governorate, Egypt, at geographic coordinates of 24.440° N latitude and 32.870° E longitude. Figure 3 indicates that solar irradiance remains high throughout the year, with a peak value of 1145.23 W/m^2 [34]. Higher median irradiance is observed during summer months (June to August), reflecting stronger solar availability. In contrast, Figure 4 shows that monthly wind speeds remain relatively consistent throughout the year, reaching a peak value of 12.997 m/s [35]. The highest wind activity is observed around May and June, where the median values are slightly elevated compared to the rest of the year. In this microgrid scenario, electricity purchase prices from the utility grid are set at $0.20 \text{ \$/kWh}$ from 12:00 a.m. to 8:00 a.m., $0.50 \text{ \$/kWh}$ from 8:00 a.m. to 4:00 p.m., and $0.30 \text{ \$/kWh}$ from 4:00 p.m. to 12:00 a.m., while the selling price of electricity to the utility grid is fixed at $0.06685 \text{ \$/kWh}$ [36]. Additionally, Figure 5 shows a clear seasonal variation in electricity demand, with lower loads in winter and higher median values in summer (from June to September). Peak demand reaches $21,880 \text{ kW}$, reflecting increased consumption and pronounced variability during the summer months [37].

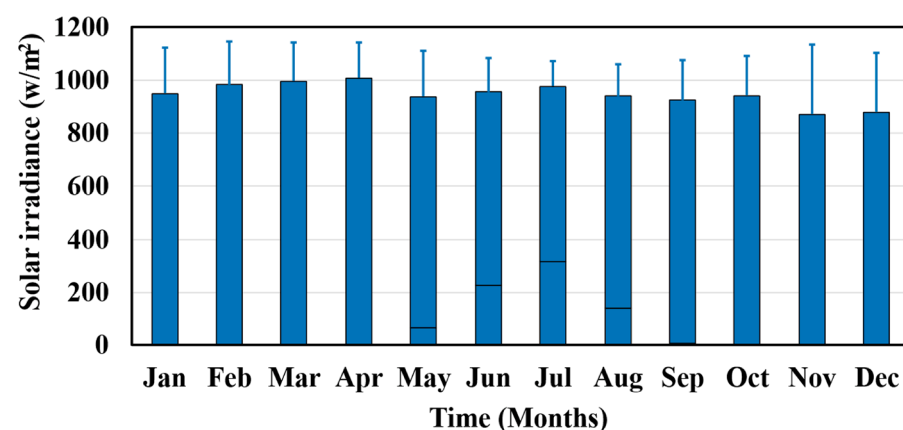


Figure 3. Monthly solar irradiance. The black horizontal lines represent the median monthly solar irradiance values.

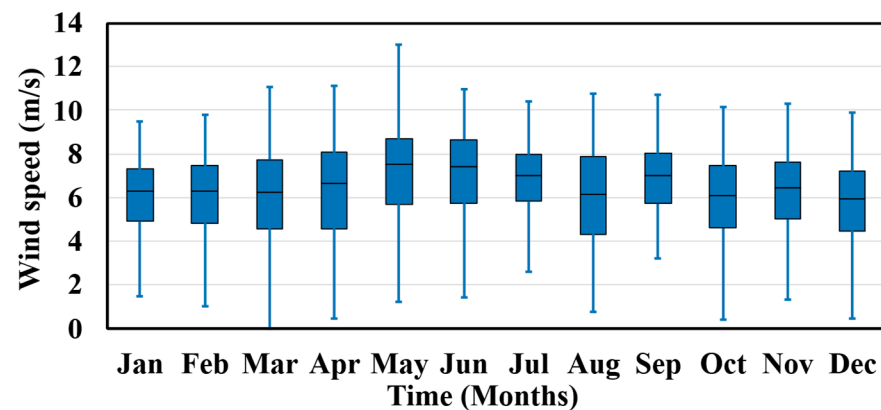


Figure 4. Monthly wind speed. The black horizontal lines represent the median monthly wind speed values.

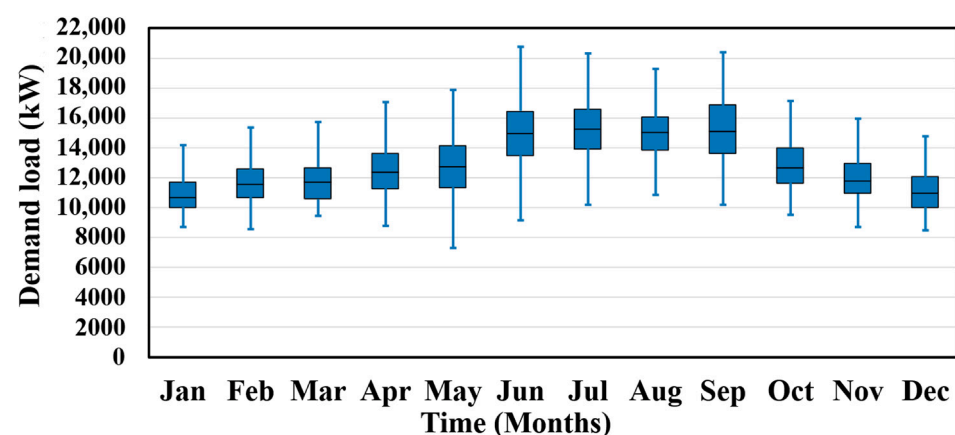


Figure 5. Monthly demand profile. The black horizontal lines represent the median monthly demand profile values.

In this section, the optimal sizing of the microgrid components is first performed using three multi-objective optimization techniques, namely MOPSO, MOGA, and MOCOO. A comparative assessment is then conducted based on key performance indicators, including total annual cost, grid dependency, and the optimal capacities of PV, wind, battery, and converter. Following the comparison, the algorithm that demonstrates the best overall performance is selected and subsequently employed to achieve the optimal operational scheduling of the microgrid using the optimally sized MG components. The detailed results of the optimal sizing and the optimal operation are presented in the following sub-sections:

5.1. Optimal Sizing

In this section, the optimal sizing of the MG components, including the PV system, wind turbine (WT), battery energy storage system (BESS), and converter, is performed using three multi-objective optimization algorithms: MOPSO, MOGA, and MOCOO. The sizing process is carried out based on the MG characteristics presented in [21]. The optimization process aims to minimize both the total annual microgrid cost and grid dependency while determining the most suitable component capacities. The optimal sizing results and computational times obtained by the three algorithms are summarized in Table 2.

As shown in Table 2, the computational time analysis indicates that MOPSO, MOGA, and MOCOO require 279.297 s, 589.822 s, and 241.693 s, respectively. From a computational efficiency perspective, MOCOO demonstrates the lowest computational time, whereas MOPSO achieves the best economic performance with the lowest total annual

cost of 11,620,148 \$/year while maintaining a relatively low grid dependency of 0.0333. MOGA produces a slightly higher annual cost of 11,629,803 \$/year with nearly identical grid dependency performance; however, it exhibits the highest computational burden among the three algorithms. In contrast, MOCOO achieves the minimum grid dependency value of 0.0278; however, this improvement is accompanied by the highest total annual cost of 11,709,992 \$/year due to its higher renewable generation and storage capacities, particularly the WT and BESS capacities. These results highlight the different resource allocation strategies adopted by the three optimization algorithms and demonstrate that MOPSO provides a balanced trade-off between computational efficiency, economic performance, and grid dependency, thereby justifying its use for practical microgrid energy management applications.

Table 2. Comparison of optimal sizing results and computational times obtained by the three algorithms.

	MOPSO	MOGA	MOCOO
Computational Time (s)	279.297	589.822	241.693
PV Capacity (kW)	28,353	28,022	27,803
Wind Capacity (kW)	29,852	30,450	32,441
Battery Capacity (kWh)	18,918	15,967	18,959
Converter Capacity (kW)	21,052	21,042	21,042
Grid Dependency	0.0333	0.0334	0.0278
Total Annual Cost of Microgrid (\$/year)	11,620,148	11,629,803	11,709,992

Figure 6 presents the Pareto front comparison obtained using the MOPSO, MOGA, and MOCOO algorithms for minimizing annual microgrid cost and grid dependency. The results demonstrate a clear trade-off between economic performance and energy autonomy, where lower grid dependency requires higher renewable and storage capacities, leading to increased annual cost.

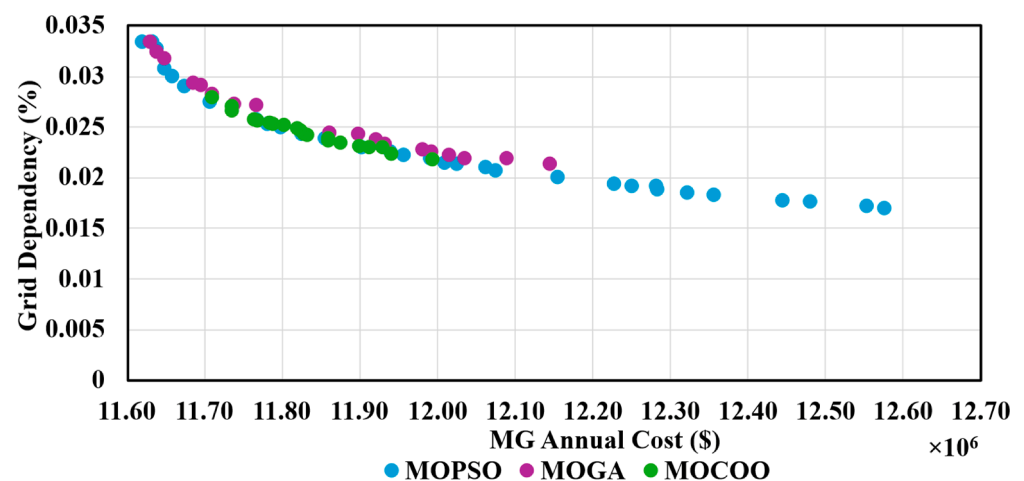


Figure 6. Pareto front comparison of annual microgrid cost and grid dependency.

The obtained results demonstrate that MOPSO provides the most economically balanced solution for the studied microgrid. Although MOCOO further reduces utility grid reliance, the additional reduction in grid dependency requires larger WT and BESS capacities, which increases both investment and operational costs. Consequently, the economic benefit associated with lower grid dependency gradually diminishes beyond a certain operational threshold.

From an operational perspective, the sizing results highlight the importance of coordinated hybrid renewable integration. The relatively high WT contribution compensates for reduced PV generation during nighttime and low-solar periods, while the BESS supports temporal energy shifting between high renewable generation intervals and peak demand periods. This coordinated sizing strategy improves renewable utilization, enhances operational flexibility, and reduces dependency on dispatchable fossil-fuel-based generation.

Based on the overall techno-economic performance, MOPSO is selected for the subsequent optimal operational scheduling stage due to its ability to minimize annual cost while maintaining acceptable energy autonomy and operational reliability.

5.2. Optimal Operation

Following the optimal sizing stage, the MOPSO algorithm—identified as the most effective technique—is employed to perform the optimal operation of the microgrid. The operation stage minimizes operational cost and grid dependency while satisfying load demand, respecting component constraints, and managing grid interaction. The obtained results demonstrate that the MOPSO algorithm achieves the minimum annual MG operating cost of 2.2 M\$/year along with a low grid dependency ratio of 0.0333. The optimal capacities obtained in the optimal sizing stage are used in the optimal operation stage for hourly operational scheduling. The results are presented in the following two subsections. Section 5.2.1 presents the yearly performance of the proposed microgrid, including key operational indicators. Section 5.2.2 provides a detailed comparative analysis of the microgrid operational behavior over three representative days (Days 27, 93, and 216).

5.2.1. Yearly Operational Performance

The yearly operational performance of the proposed microgrid is summarized in Table 3, which presents the minimum, average, and maximum values of key operational indicators, including emissions, MG operating cost, grid dependency, number of battery lifetime cycles, and DG efficiency.

Table 3. Yearly operational performance statistics of the proposed microgrid.

	Minimum	Average	Maximum
Emissions (kgCO ₂ -eq)	0	17,978	199,119
MG Operating Cost (\$)	−2656	6051	96,700
Grid Dependency	0	0.0327	0.2737
No. of Battery Lifetime Cycles	3918	31,251	33,981
DG Efficiency	0	0.3682	0.3929

As shown in Table 3, the microgrid achieves zero emissions during certain operating periods, indicating intervals of fully renewable operation without DG contribution or utility grid import. Conversely, the maximum emission level reaches 199,119 kgCO₂-eq during periods characterized by reduced renewable availability and increased dependency on dispatchable energy sources.

The MG operating cost exhibits a minimum negative value of −2656 \$, indicating periods in which surplus renewable energy is exported to the utility grid, thereby generating operational revenue. The average operating cost remains relatively moderate due to the effective coordination between renewable generation, BESS scheduling, and DG dispatch.

To evaluate the effectiveness of the DoD-dependent battery degradation model, a comparative analysis is conducted with and without considering the degradation model while maintaining the same microgrid configuration and operating conditions. The results show

that neglecting battery degradation reduces the annual MG operating cost from 2.2 M\$/year to 1.9 M\$/year, corresponding to an underestimation of 15.8%. This finding indicates that ignoring degradation costs leads to an underestimated economic assessment of the microgrid lifecycle. Notably, the remaining operational indicators, including emissions, grid dependency, DG efficiency, and battery lifetime cycles, remain unchanged under the investigated operating conditions. This behavior is attributed to the renewable-priority dispatch strategy, which inherently promotes shallow depth-of-discharge operation; therefore, the degradation cost primarily acts as an economic correction term rather than influencing the optimal short-term dispatch decisions. Nevertheless, incorporating the DoD-dependent degradation model is essential for realistic lifecycle cost evaluation, particularly in long-term planning and investment studies where battery replacement costs significantly affect the overall system economics.

The grid dependency remains relatively low, with an average value of 0.0327, demonstrating the capability of the proposed operational framework to maintain high energy autonomy through renewable-priority dispatch and coordinated energy storage utilization. Higher grid dependency values occur primarily during periods of low renewable generation and elevated load demand.

The estimated battery lifetime cycle capability reaches an average value of 31,251 cycles and a maximum value of 33,981 cycles. These high lifetime cycle values indicate that the BESS predominantly operates under shallow depth-of-discharge conditions, which reduces electrochemical degradation stress and improves long-term battery durability.

In addition, the DG operates within an efficiency range of approximately 36.8–39.3%, indicating that the proposed operational strategy successfully limits inefficient low-load operation. By maintaining DG operation near moderate-to-high loading conditions, the framework improves fuel utilization efficiency while reducing unnecessary fuel consumption and operational emissions.

5.2.2. Comparative Analysis of Daily Operational Performance

To gain deeper insight into the dynamic behavior of the microgrid under optimal operation, three representative days—Day 27, Day 93, and Day 216—are selected for detailed analysis. Their hourly operational characteristics, including emissions, MG operating cost, grid dependency, and battery lifetime cycles, are illustrated in Figures 7–10, respectively. The selection of Days 27, 93, and 216 is based on the annual operational results obtained from the proposed EMS while ensuring seasonal representation. Specifically, Day 27 is selected from the winter season because it achieves zero grid dependency and zero CO₂ emissions, as indicated by the simulation results, and it also exhibits the maximum battery cycling activity observed throughout the year due to intensive energy shifting under high renewable generation conditions. Day 93 is selected from the spring season because it corresponds to the highest grid dependency recorded during the annual simulation period. Day 216 is selected from the summer season because it results in the maximum operating cost and CO₂ emissions among all simulated days due to reduced renewable availability and increased reliance on grid power.

These pronounced differences are not determined by seasonal classification alone. Instead, they arise from the optimization-driven dispatch strategy of the EMS, which responds to variations in renewable generation, load demand profiles, and economic–environmental trade-offs across the year. Therefore, these representative days capture distinct and extreme operational states of the microgrid, enabling a comprehensive evaluation of the proposed EMS under environmentally optimal, grid-dependent, and economically challenging conditions. These days exhibit distinct patterns in renewable generation, load demand, and grid interaction. A comparative study is conducted across the three days with respect to key performance indicators—namely emissions, MG cost, grid dependency, number of battery lifetime cycles, and DG efficiency—as well as hourly power dispatch schedules including PV output, wind

power, grid exchange, DG contribution, battery charge/discharge, and load demand. The findings of this comparative analysis are presented in the following subsections.

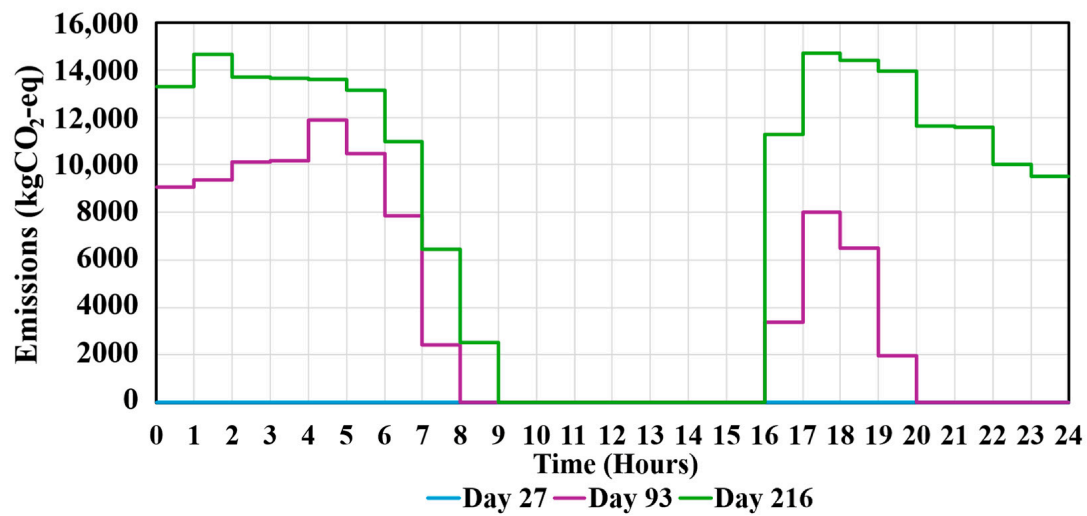


Figure 7. Hourly emissions profiles for Days 27, 93, and 216.

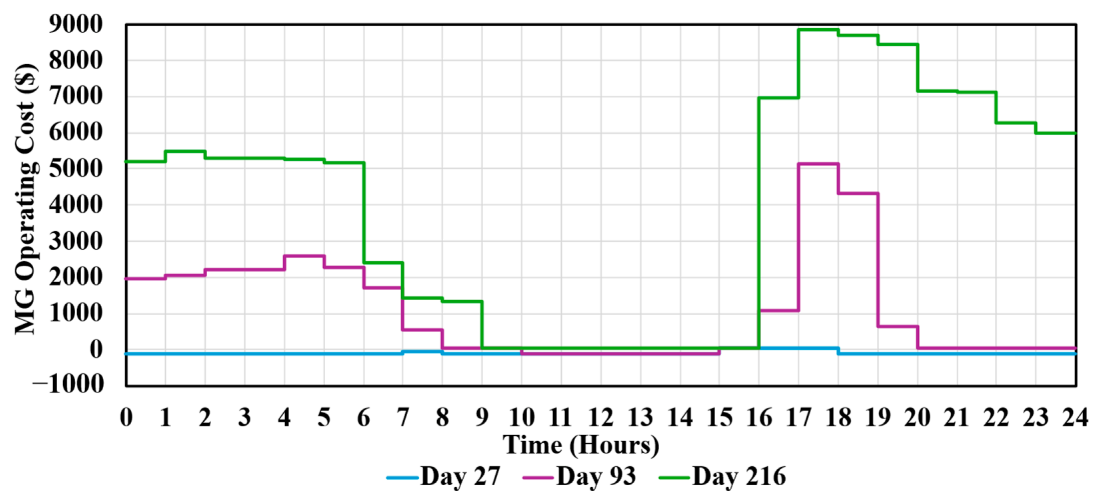


Figure 8. Hourly MG operating cost profiles for Days 27, 93, and 216.

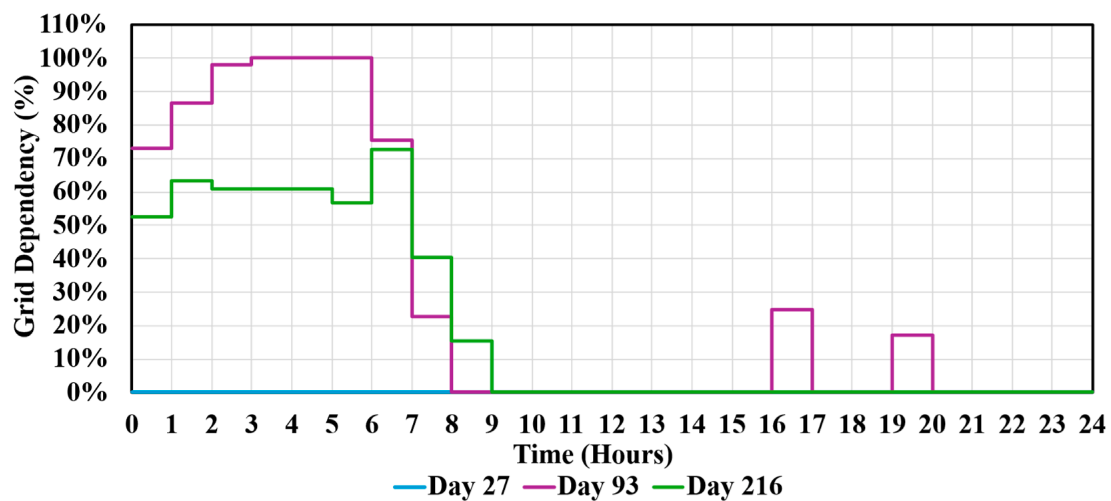


Figure 9. Hourly grid dependency profiles for Days 27, 93, and 216.

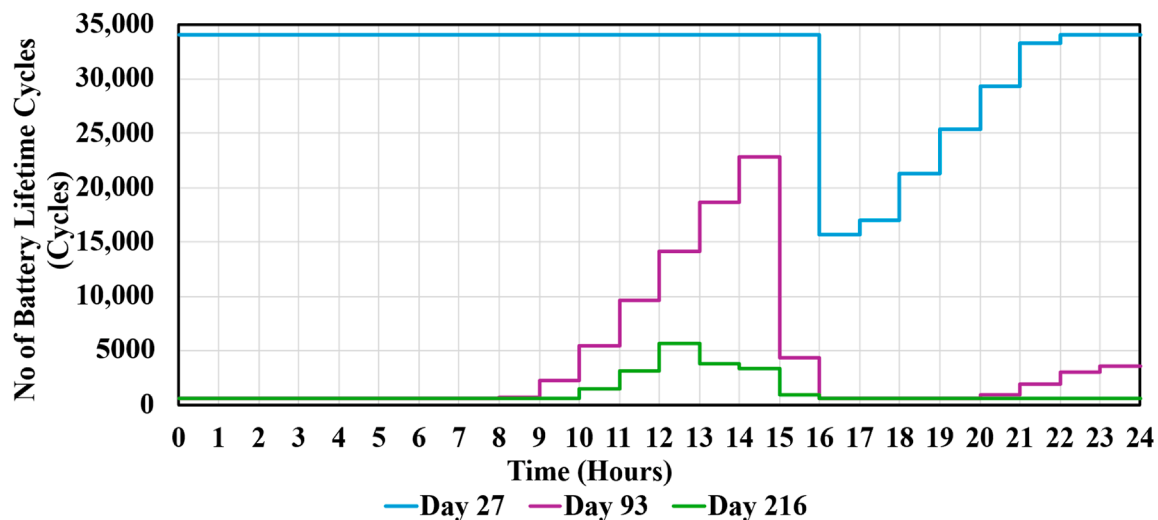


Figure 10. Hourly battery lifetime cycling profiles for Days 27, 93, and 216.

Key Performance Indicators

This subsection compares the hourly evolution of emissions, operational cost, grid dependency, number of battery lifetime cycles, and DG efficiency for the three days. Graphical illustrations of the data are provided below, followed by a corresponding textual description.

• Hourly Emissions Comparison

Figure 7 presents the hourly emissions profile for Days 27, 93, and 216 over a 24 h operating period. Day 27 exhibits nearly zero emissions throughout the entire day, indicating that the load demand is fully supplied by renewable energy resources without significant contribution from diesel generators or imported grid power.

For Day 93, the emissions are relatively high during the early operating hours, reaching 11,891 kgCO₂-eq/yr around Hour 5. The emissions gradually decrease from Hour 6 onward and become nearly zero between Hours 9 and 16 due to the increased contribution of renewable energy sources, particularly solar generation. During the evening period, emissions rise again between Hours 17 and 20 as conventional generation and grid support increase to satisfy the load demand after the reduction in renewable output.

Day 216 records the highest emission levels among the three days. Emissions remain high during the nighttime and early morning hours, reaching 14,710 kgCO₂-eq/yr around Hour 18. The emission level decreases gradually during the daytime period and becomes nearly zero between Hours 10 and 16 due to the peak contribution of renewable energy resources. However, emissions increase significantly again during the evening hours, particularly around Hours 17–18, indicating greater dependence on conventional generation sources and imported grid power during periods of reduced renewable availability.

• Hourly Operational Cost Comparison

Figure 8 illustrates the hourly MG operating cost for Days 27, 93, and 216 over 24 h. Day 27 exhibits the lowest operating cost throughout the day, with cost values ranging from −111\$ to 40 \$. This behavior indicates that the renewable generation is sufficient to satisfy the load demand and allows surplus energy to be exported to the utility grid, thereby reducing the overall operational cost of the microgrid.

For Day 93, the operating cost is moderate during the nighttime and early morning hours. The cost gradually decreases during the daytime period due to the increased penetration of renewable energy resources, particularly solar generation. During the evening hours, the operating cost rises significantly again, reaching a peak value of 5153 \$

around Hour 18, as the microgrid becomes more dependent on conventional generation sources and energy storage support to satisfy the increasing load demand.

Day 216 records the highest operating cost among the three days. The cost remains high during the early operating hours due to the larger dependence on diesel generation and imported grid power. Similar to the other cases, the operating cost decreases considerably during midday hours when renewable generation reaches its peak contribution. However, the cost increases sharply again during the evening period, reaching its maximum value of 8868 \$ around Hour 18, reflecting the reduced renewable contribution and increased reliance on conventional energy resources.

- Hourly Grid Dependency Comparison

Figure 9 presents the hourly grid dependency of the microgrid for Days 27, 93, and 216 over a 24 h operating period. Day 27 shows zero grid dependency throughout the entire day, indicating that the load demand is completely supplied by local renewable energy resources without requiring support from the utility grid. This reflects the high operational efficiency and renewable energy penetration of the microgrid on this day.

For Day 93, the grid dependency is significantly high during the early morning hours, reaching 100% between Hours 4 and 6. This indicates a strong reliance on imported grid power due to limited renewable generation during these hours. As solar generation increases during the daytime period, the grid dependency decreases rapidly and becomes zero after Hour 8. However, small increases in grid dependency appear again during the evening hours, particularly around Hours 17 and 20, due to the reduction in renewable generation and the increase in load demand.

Day 216 exhibits moderate grid dependency during the early operating hours, with values ranging between 53% and 73%. Similar to Day 93, the dependency decreases gradually during the daytime period and becomes zero after Hour 9 because of the increased contribution of renewable energy resources. Compared with Day 93, Day 216 demonstrates lower dependency on the utility grid during most operating hours, indicating improved utilization of local renewable generation and energy management resources within the microgrid.

- Hourly Battery Lifetime Cycles Comparison

Figure 10 presents the hourly battery cycling profile for Days 27, 93, and 216 over a 24 h operating period. Day 27 exhibits the highest number of battery lifetime cycles throughout the day, maintaining a constant value of 33,981 cycles from Hours 1 to 16. A significant reduction is observed at Hour 16, where the cycling level decreases to 15,700 cycles, followed by a gradual increase during the evening hours until the initial level is restored by the end of the day.

For Day 93, the battery cycling profile remains relatively low during the early operating hours and starts increasing noticeably after Hour 9. The number of lifetime cycles rises sharply between Hours 10 and 15, reaching a maximum value of 22,797 cycles at Hour 15. After this peak, the cycling level decreases abruptly and remains low for the rest of the operating period, with slight increases observed during the late evening hours.

In contrast, Day 216 demonstrates the lowest battery cycling activity among the studied days. The number of lifetime cycles remains low during most of the operating horizon, with moderate increases occurring between Hours 11 and 15. The maximum cycling level reaches 5703 cycles around Hour 13 before gradually decreasing again.

- Diesel Generator Efficiency Comparison

Figure 11 illustrates the hourly DG efficiency for Days 27, 93, and 216 over a 24 h operating period. Day 27 shows zero DG efficiency throughout the entire day, indicating that the diesel generator is not utilized during this operating condition.

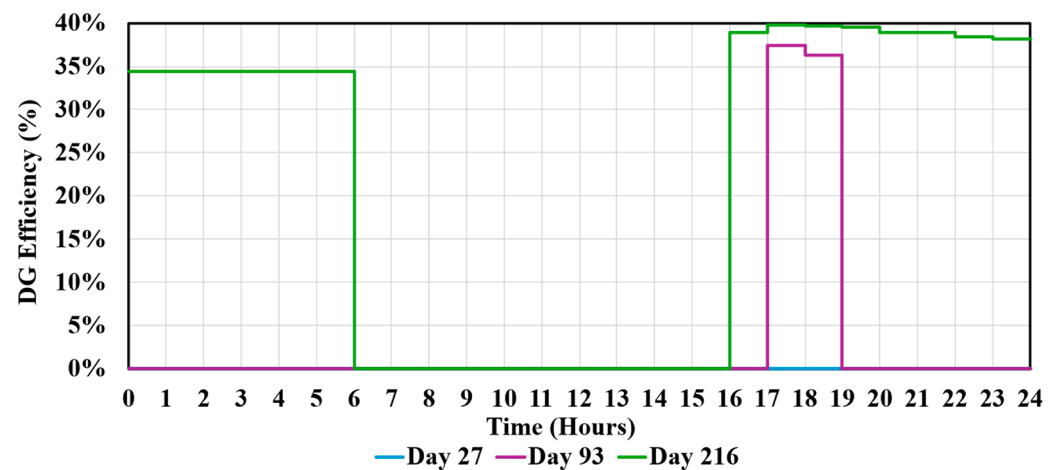


Figure 11. Hourly DG efficiency profiles for Days 27, 93, and 216.

For Day 93, the DG efficiency remains at zero during most of the day and becomes active only during the evening period between Hours 18 and 19. The efficiency reaches 37.4% at Hour 18 and decreases slightly to 36.3% at Hour 19 before returning to zero after Hour 20.

In contrast, Day 216 exhibits a longer DG operating duration compared with Day 93. The DG efficiency remains around 34.5% during the early operating hours between Hours 1 and 6, after which the diesel generator becomes inactive during the daytime period. The DG operation resumes again from Hour 16 onward, where the efficiency increases significantly to 38.9–39.6% between Hours 17 and 20. After Hour 20, a slight gradual reduction in efficiency is observed until the end of the operating horizon.

Overall, the results indicate that Day 216 experiences higher and more extended DG operation compared with Day 93, while Day 27 achieves complete operation without diesel generator utilization.

Hourly Power Dispatch Schedules

This subsection presents the hourly power dispatch from all sources—PV (Ps), wind (Pw), grid exchange (Pgp/Pgs), DG (Pdg), battery charge (Pch)/discharge (Pch), and the load (Pl)—for each of the three selected days. The data are presented graphically in the following figures, with a detailed description provided alongside each visualization.

- Day 27 Dispatch Schedule

Figure 12 presents the hourly power scheduling of the microgrid components for Day 27 over 24 h. Wind power represents the dominant renewable energy source throughout the day, maintaining relatively high output levels with moderate fluctuations.

The PV power begins contributing from Hour 7 and increases steadily to reach its peak generation at Hour 9. After the peak period, the solar contribution gradually declines toward the late afternoon and becomes negligible during nighttime hours. Compared with the wind generation, the solar output contributes for a shorter duration and mainly supports the system during daytime operation.

The exported power to the utility grid for most of the day indicates that the total generated renewable energy exceeds the local load demand during several operating hours. Meanwhile, the imported grid power and DG power are absent throughout the day, showing that the renewable generation is sufficient to satisfy the load demand without significant support from external or conventional sources.

The BESS charging power appears mainly around Hour 18 and during the evening peak period, indicating that part of the excess renewable energy is stored for later utilization.

In contrast, the BESS discharges during Hour 17, supporting the load demand during periods of reduced renewable generation and helping maintain the operational balance of the microgrid.

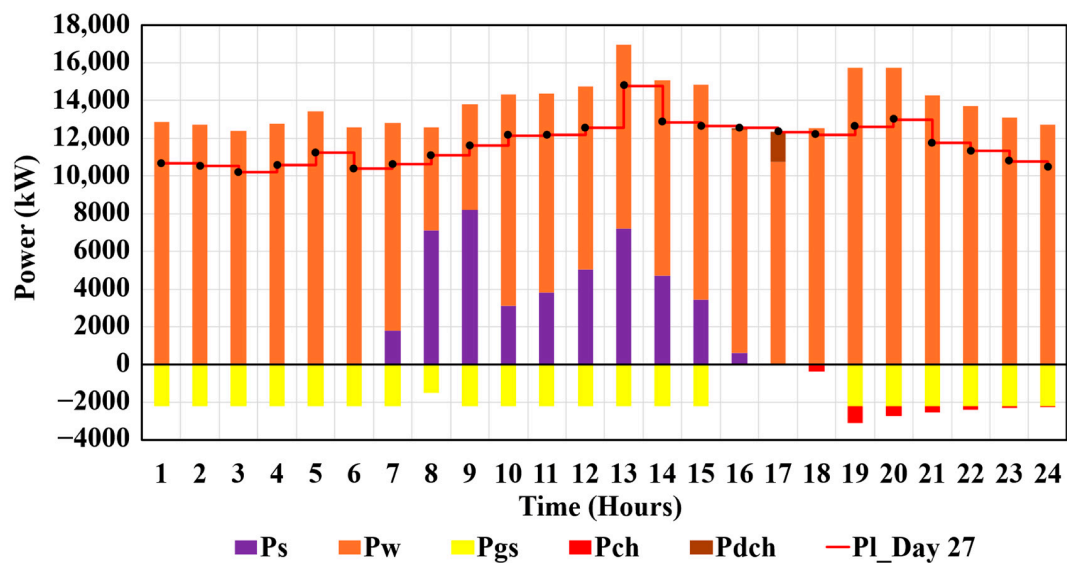


Figure 12. Hourly optimal power scheduling of microgrid components for Day 27. The red line represents the hourly load profile, while the black dots indicate the corresponding hourly load demand values.

- Day 93 Dispatch Schedule

Figure 13 illustrates the hourly power scheduling of the microgrid components for Day 93 over a 24 h operating horizon. The PV power starts increasing from Hour 7 and reaches its peak output of 17,610 kW around Hours 10–11. After this period, the solar contribution gradually decreases toward the afternoon and evening hours due to the reduction in solar irradiance.

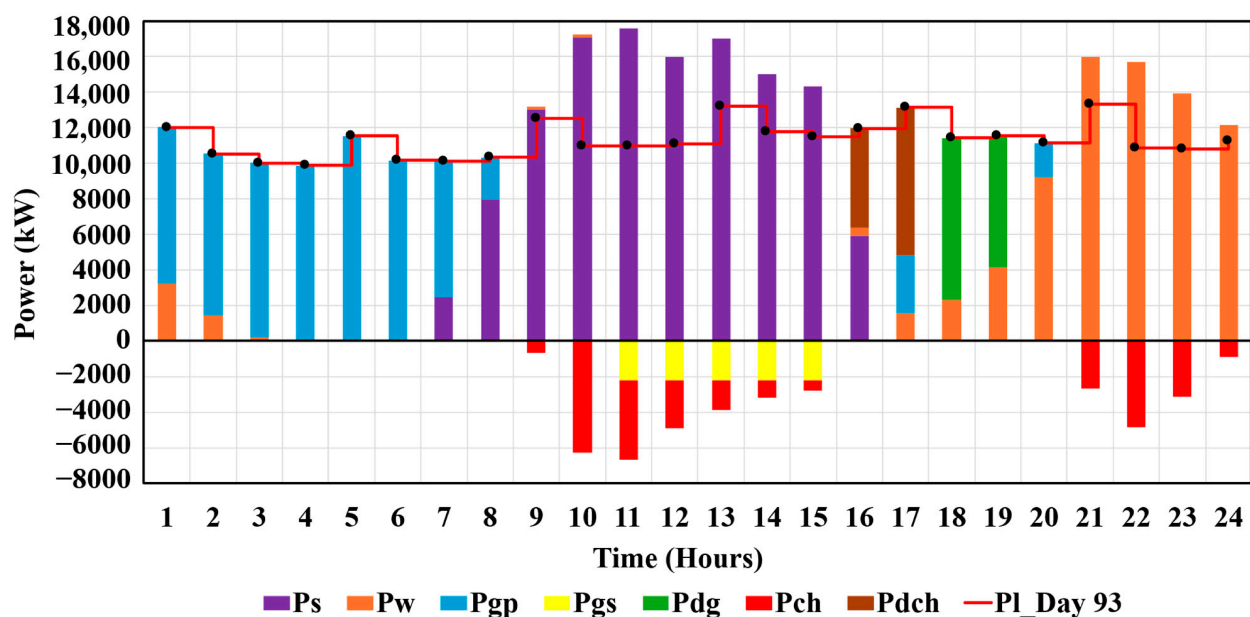


Figure 13. Hourly optimal power scheduling of microgrid components for Day 93. The red line represents the hourly load profile, while the black dots indicate the corresponding hourly load demand values.

The wind power becomes more significant during the evening and late-night hours (Hours 20–24). The utility grid power provides a major portion of the demand during the early operating hours (Hours 1–7). As solar generation increases during midday, the imported grid power decreases considerably, indicating reduced dependence on the main grid during periods of high renewable penetration.

The DG operates mainly during the evening hours (Hours 18–19) to support the load demand when the renewable contribution declines. In addition, the power exported to the utility grid appears during midday hours, indicating that surplus renewable energy is injected into the grid when local generation exceeds the load demand.

The BESS charges primarily between Hours 9 and 15, coinciding with the high solar generation period. Conversely, the BESS discharges during periods of higher demand and lower renewable generation (Hours 16–17).

- Day 216 Dispatch Schedule

Figure 14 illustrates the hourly power scheduling of the microgrid components over a 24 h operating period. The PV power begins to increase from Hour 7 and reaches its maximum output of about 21,561 kW during Hours 11–12, before gradually declining toward the evening period. The peak solar generation coincides with the charging interval of the BESS, indicating that excess renewable energy is stored during periods of high solar availability.

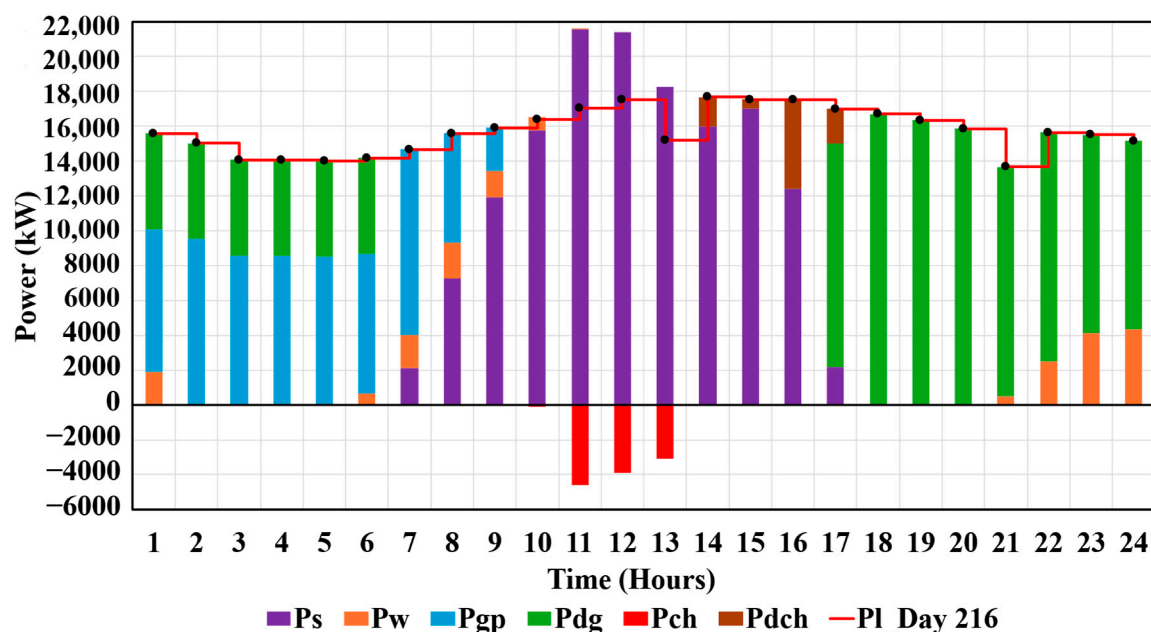


Figure 14. Hourly optimal power scheduling of microgrid components for Day 216. The red line represents the hourly load profile, while the black dots indicate the corresponding hourly load demand values.

The wind power remains relatively stable throughout the day with only minor fluctuations compared to the other generation sources. Meanwhile, the power imported from the utility grid is relatively high during the early operating hours (Hours 1–7) when renewable generation is limited. Its contribution decreases significantly during midday as solar generation reaches its peak output.

The DG power exhibits higher output during nighttime and early morning hours to support the load demand when renewable resources are insufficient. However, its contribution is noticeably reduced during midday due to the increased penetration of renewable energy sources.

The charging power of the BESS is mainly observed between Hours 11 and 13, confirming that surplus renewable energy is stored during high-generation intervals. In contrast, the BESS discharges during periods of increasing demand and reduced renewable generation (Hours 14–17).

6. Discussion

This section discusses the techno-economic, operational, and environmental implications of the obtained results for the proposed grid-connected microgrid framework. The analysis highlights the effectiveness of the renewable-priority operational strategy, the contribution of the battery energy storage system (BESS) to energy balancing and degradation mitigation, and the impact of the proposed framework on operational cost, grid dependency, diesel generator (DG) efficiency, and emission reduction under varying operating conditions.

6.1. Representative Daily Operational Analysis

To evaluate the operational robustness of the proposed framework under different renewable and demand conditions, three representative operating days are investigated:

6.1.1. Day 27 (Best-Case Scenario)

It is characterized by high renewable generation and favorable operating conditions. The microgrid achieves zero emissions, zero grid dependency, and negative operating cost due to revenue generated from surplus renewable energy export to the utility grid.

These results demonstrate the capability of the proposed framework to achieve near fully renewable and economically beneficial operation.

6.1.2. Day 93 (Typical Operating Scenario)

It represents moderate renewable availability and average load demand conditions. The results indicate high grid reliance during early morning periods (up to 100% between Hours 4 and 6), followed by near-zero emissions during midday intervals due to increased PV contribution.

This behavior confirms the effectiveness of solar-driven load coverage and coordinated BESS scheduling in reducing DG operation and utility grid import.

6.1.3. Day 216 (Worst-Case Scenario)

It represents high load demand combined with a reduced renewable contribution. Consequently, the highest emission level is recorded (14,710 kgCO₂-eq at Hour 18), the maximum operating cost reaches 8868 \$, while moderate grid dependency is maintained.

Despite these challenging conditions, the proposed framework successfully preserves operational reliability through coordinated DG, BESS, and utility grid support.

6.2. Battery Operational and Degradation Performance

The battery operational analysis demonstrates the critical role of the BESS in renewable energy balancing, peak shaving, load shifting, and operational flexibility enhancement.

The degradation analysis reveals that Day 216 experiences the lowest predicted battery lifetime capability (maximum of 5703 cycles) due to increased operational stress and deeper charging/discharging behavior. In contrast, Day 27 achieves significantly higher predicted lifetime cycle capability (33,981 cycles), indicating that shallow depth-of-discharge (DoD) operation substantially reduces electrochemical degradation stress and improves long-term battery durability.

These findings confirm that the proposed degradation-aware operational strategy effectively preserves battery lifetime while maintaining reliable microgrid operation.

6.3. Diesel Generator Operational Efficiency

The DG efficiency remains within approximately 38.9–39.6% during active operating periods, indicating efficient loading conditions and successful avoidance of prolonged low-load operation. Maintaining the DG within moderate-to-high loading regions improves fuel conversion efficiency, operational reliability, and emission reduction performance.

This behavior demonstrates the effectiveness of the proposed DG scheduling strategy compared with conventional fixed-efficiency operational approaches.

6.4. Key Contributions and Novelty of the Proposed Framework

The proposed energy management system (EMS) introduces several important contributions that collectively address major limitations in existing microgrid operational studies.

6.4.1. Loading-Dependent Diesel Generator Efficiency Modeling

Unlike several previous studies that assume constant DG efficiency [4,5,8,11], the proposed framework explicitly models nonlinear DG fuel consumption as a function of loading conditions using Equations (20)–(23). This approach avoids inefficient low-load operation, improves average DG efficiency, reduces unnecessary fuel consumption, and minimizes operational emissions.

6.4.2. Depth-of-Discharge (DoD)-Dependent Battery Degradation Cost

Most existing EMS frameworks only impose SOC operational constraints [7,8,10,12,13]. In contrast, the proposed model incorporates an exponential degradation cost function using Equations (15)–(18), enabling degradation-aware scheduling, reduced deep cycling behavior, lower degradation cost, and extended battery operational lifetime.

6.4.3. Grid Dependency as a Social Sustainability Objective

Existing microgrid studies have primarily focused on economic and environmental objectives, while social sustainability metrics such as grid dependency reduction and energy autonomy enhancement remain insufficiently integrated into EMS frameworks [4–6,9–12]. In contrast, the proposed framework explicitly minimizes grid dependency using Equation (27), thereby reducing utility grid reliance, improving energy independence, and enhancing the social sustainability of the microgrid operation.

6.4.4. Full-Year Operational Scheduling with Representative-Day Validation

Unlike many previous studies that evaluate EMS performance over limited scheduling horizons [4–13], the proposed framework performs continuous 8760 h annual optimization, followed by representative-day operational validation under best-case, typical, and worst-case scenarios.

This approach improves the realism of the operational assessment by capturing seasonal renewable variations, long-term operational behavior, and battery degradation characteristics.

6.5. Overall Framework Superiority

The superiority of the proposed framework is not merely incremental but structural due to its comprehensive operational formulation and realistic component modeling. This is demonstrated through:

6.5.1. Multi-Criteria Pareto Optimality

Previous studies generally focused on optimizing only two or three performance criteria, such as cost and emissions. In contrast, the proposed framework simultaneously

considers operational cost, emissions, battery degradation, and grid dependency within a unified optimization framework.

Furthermore, the MOPSO algorithm successfully converges to a diverse Pareto front, providing flexible trade-off solutions between economic, environmental, technical, and operational performance indicators.

6.5.2. Realistic Component Modeling

The incorporation of DG minimum loading constraints, loading-dependent efficiency, and DoD-dependent battery degradation significantly improves the practical applicability of the proposed framework compared with simplified linear or fixed-efficiency operational models commonly adopted in previous studies.

Overall, the obtained results confirm that the proposed framework effectively enhances renewable energy utilization, minimizes operational emissions, reduces utility grid dependency, and improves long-term operational sustainability while maintaining economically feasible and reliable microgrid operation.

7. Conclusions

The proposed day-ahead EMS successfully achieves coordinated economic, environmental, technical, and social sustainability objectives for the investigated microgrid. The obtained results confirmed the effectiveness of integrating DG loading-dependent efficiency modeling and DoD-based battery degradation assessment into the scheduling framework. The proposed strategy reduces operational cost, CO₂ emissions, excessive battery degradation, and utility grid dependency while maintaining reliable system operation under varying operating conditions. Furthermore, the annual and representative-day analyses validate the adaptability and robustness of the EMS during favorable and stressed scenarios. Overall, the proposed framework provides an effective and sustainable solution for intelligent microgrid operation with enhanced renewable energy utilization and improved long-term operational performance.

Future work may focus on integrating advanced uncertainty modeling and real-time adaptive control strategies to further enhance EMS robustness under forecasting errors and highly dynamic operating conditions. In addition, the incorporation of electric vehicles, hydrogen energy storage systems, and peer-to-peer energy trading mechanisms could further improve microgrid flexibility and sustainability. Machine learning and reinforcement learning techniques may also be investigated to enhance predictive scheduling and autonomous operational decision making.

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Appendix A

Table A1. Economic and technical specifications of the proposed MG components [21,24,26,38,39].

System	Parameter	Value
PV	Rated power	1 (kW)
	Derating factor	84%
	O&M cost	0.0074 (\$/kW)
Wind Turbine	Rated power	1 (kW)
	Cut-in speed	2.75 (m/s)
	Rated speed	10 (m/s)
	Cut-off speed	20 (m/s)
	Turbine hub height	50 (m)
	O&M cost	0.0074 (\$/kW)
BESS	Energy capacity	1.2 kWh (12 V, 100 Ah)
	SOC_{min}	20%
	SOC_{max}	100%
	Charging efficiency	90%
	Discharging efficiency	85%
	O&M cost	0.0044 (\$/kWh)
	Battery degradation cost coefficient	0.06 (\$/kWh)
	Battery curve fitting coefficients	$\alpha = 14,294$ (cycles), $\beta = 0.19676$, $\gamma = 4.0156$
Converter	Rated power	1 (kW)
	Efficiency	90%
DG	Rated power	22,000 (kW)
	Minimum power	5500 (kW)
	O&M cost	0.0015 (\$/kW)
	Fuel cost coefficient	0.2025 (\$/kWh)
	Diesel fuel density	0.82 (kg/dm ³)
	Diesel fuel lower heating value	43.2 (MJ/kg)
	Load-dependent fuel consumption coefficient	0.236 (dm ³ /kWh)
	No-load fuel consumption coefficient	0.0147 (dm ³ /kWh)
	CO ₂ emissions	0.88 (kgCO ₂ -eq/kWh)
Grid	CO ₂ emissions	1.03 (kgCO ₂ -eq/kWh)
	Penalty emission	20 (\$/tonCO ₂ -eq)

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