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Energy Management Optimization for an Island Microgrid with Renewable Energy, Storage, and Demand Response

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Abstract

This paper aims to optimize an energy management system for a microgrid that is powered by sustainable energy sources, integrating solar photovoltaic, wind turbines, diesel generators, battery storage, and demand response capabilities. The first goal is to reduce total operational expenses and maintain a dependable electricity supply. Technical and operational limits, as requirements, are met by the proposed energy management. The system is modeled as a linear optimization problem with hourly resolution for 24 h. The energy management system determines essential parameters such as diesel generator outputs, battery charge/discharge rates, and demand response adjustments. Battery storage helps balance fluctuations in renewable generation and load demand, reducing diesel generator utilization. Sequential quadratic programming (SQP) was used to solve the optimization problem, and linear programming (LP) was employed to verify the optimal objective value. The proposed method was tested using numerical simulations. The results show that battery storage reduces the 24-h operating cost from USD 313.35 to USD 187.17, corresponding to a 40.27% reduction. The simulations verify that the electricity generation always matches consumption, and the battery does not overcharge or over-discharge, which affects the overall cost of operating the system. However, demand response does not provide additional cost savings under the baseline operating conditions. This is particularly important for remote locations and islanded systems. The proposed approach supports cost-effective energy scheduling while satisfying power-balance and operational constraints under the evaluated conditions.

Keywords: demand response; energy management system; battery storage; optimization; renewable energy

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1. Introduction

Fossil fuels are finite and environmentally harmful. Also, climate change concerns are increasing because of this; countries are shifting toward renewable energy. Nowadays, microgrids are an important solution that allows local power generation to integrate renewable energy and maintain reliability [1,2]. Island microgrids operate independently, and they do not rely on the main grid. Due to this, they have some operational challenges and design opportunities. In grid-connected systems, the main grid absorbs the imbalance, and in island systems, supply must equal demand at every moment; therefore, no backup support exists. Some places cannot connect to the main grid because it is too expensive or is geographically difficult. As a result, island microgrids are ideal in these cases [3,4].

An island microgrid is not a single energy source. It includes multiple diverse resources such as renewable generation (PV, wind), conventional generation (diesel), storage

(battery), and flexible demand (DR). Intermittent generation sources such as PV and wind do not require fuel, and they have very low operating costs per unit of energy. Also, they do not release carbon dioxide during operational phases. Solar energy depends on sunlight, and wind energy depends on wind speed. These cannot be controlled; therefore, renewable output changes unpredictably, which affects the supply–demand balance [5,6]. Diesel generators can produce power whenever needed. They are controllable and predictable; however, fuel is expensive and produces emissions. Consequently, they should not be the main long-term solution.

Batteries solve the timing mismatch problem. When renewable output > demand → battery charges. When renewable output < demand → battery discharges [7]. Since power balance comprises two components, generation and load (demand), systems traditionally adjust generation to match demand. Demand response (DR) instead adjusts the load side. It provides flexibility by changing consumption patterns. Instead of increasing generation, some loads are postponed, or some loads are reduced. With DR, consumption is adapted to match renewable availability. This is especially useful when renewable output is low or high. Demand response provides several operational benefits, such as reducing peak demand pressure, allowing more renewable energy to be used instead of curtailed, and reducing the need to turn on diesel generators [8,9]. Island systems that have limited backup generation and cannot rely on the main grid often use expensive diesel. As a result, reducing demand during stress periods improves stability; DR helps avoid costly generation. Batteries provide supply-side flexibility, and demand response provides load-side flexibility. Combined, they give two levels of control and reduce diesel usage, which reduces the total cost.

EMS is the central intelligence of the microgrid that decides how much each source should generate, the battery charge/discharge cycles, and demand response activation events. It can operate in real-time or day-ahead optimization (24-h scheduling). The EMS must minimize total operating cost while always satisfying supply–demand balance, keep battery state of charge (SOC) within safe limits, and avoid too much load curtailment. Early systems used simple rules, which approach renewable energy first, charge the battery if there is excess, and start the diesel if there is a deficit. Despite their implementation simplicity and low computational burden, these methods lack mathematical optimality and cannot always adapt to changing conditions [10]. Researchers try to enhance EMS performance by employing optimization frameworks such as Linear Programming (LP), where all equations are linear, and Mixed-Integer Linear Programming (MILP), which is linear but includes binary decisions (on/off decisions for generators). These approaches offer advantages that provide guaranteed optimal solutions (if the problem is linear) and are widely used in microgrid scheduling applications [11,12]. In practice, battery physics introduces nonlinear behavior as charging and discharging efficiencies differ and may vary with power level losses depending on both current and SOC. Consequently, linear models approximate these complex relationships. However, for high accuracy, nonlinear relationships must be modeled. Therefore, nonlinear programming (NLP) is more appropriate [13].

Researchers have employed optimization techniques inspired by nature to solve EMS problems, such as Genetic Algorithm (GA), which emulates biological evolution, and Particle Swarm Optimization (PSO), which mimics swarm behavior. These are known as metaheuristics. They are popular due to their capability to handle nonlinear problems and multiple objectives (cost, emissions, battery health, etc.). They do not require gradient information or analytical derivatives [9,14]. These models enable the representation of complicated systems without simplifying too much. They perform well in simulations and benchmark evaluations while being adaptable to different system structures. However, metaheuristic methods do not guarantee the absolute best (global) solution and exhibit sensitivity to parameter tuning (population size, mutation rate, inertia weight, etc.).

They can give different results each time you run them and may lack reliability in critical real-time systems.

Model Predictive Control (MPC) solves an optimization problem repeatedly over a moving time window. At each control interval, it predicts future conditions, optimizes over a short horizon, applies only to the first control action, and subsequently repeats the process. MPC naturally handles prediction uncertainty, incorporates feedback from real-time measurements, and dynamically adapts to changing conditions. However, it requires accurate forecasting (load, solar, wind). Additionally, it solves optimization repeatedly in real time, which can be computationally expensive, and in large systems, this becomes challenging [7,15]. In microgrids, there is uncertainty in both renewable generation (solar and wind) and load demand forecasts. Since forecast errors affect scheduling decisions and economic outcomes, researchers have developed methods that explicitly consider uncertainty. Stochastic programming considers uncertainty by modeling uncertain variables (solar, load) as random variables, using probability distributions, and optimizing expected cost or risk. This approach offers probabilistic performance guarantees, improves reliability under uncertain conditions, and considers multiple possible future scenarios [16]. However, stochastic programming requires knowledge of probability distributions, which real data may not clearly define these distributions. Additionally, computational burden is intensive in many scenarios, potentially a large optimization problem.

Optimization does not assume probability distributions that define an uncertainty set (range of possible errors) and optimizes the worst-case scenario within that set. It eliminates the need for probabilistic information, ensures feasibility under worst-case conditions, and provides a strong reliability guarantee. However, it can be too conservative, may curtail renewable energy unnecessarily, and consequently use more diesel than needed, which increases operating costs [17]. Traditional day-ahead scheduling takes a deterministic approach: it uses a single point forecast for the next day and solves a standard optimization problem without modeling uncertainty. The implicit assumption is that forecasts will be sufficiently accurate. This method has several practical advantages. It is computationally lightweight, which matters for operational systems that need to run daily. The results are transparent and easy for operators to understand, and importantly, when the forecast quality is good, it delivers solid performance. Where it falls short is in handling forecast uncertainty. Because optimization does not account for the possibility of forecast errors, the resulting schedules can be suboptimal or even infeasible when actual generation or demand differs significantly from predictions.

In the present study, a deterministic energy management approach is adopted, in which renewable generation and load demand are represented by predefined hourly profiles. The optimization is performed independently at each hourly interval using the available generation and demand information. Consequently, forecast uncertainties are not explicitly incorporated into the optimization process. Although this approach provides a simplified framework for evaluating microgrid operation, deviations in renewable generation and load demand may affect the resulting operating cost and system feasibility.

Many studies have been published; however, the problem is not fully solved, and there are still limitations in current research. Some papers analyze battery storage optimization, while others optimize demand response. Few studies bring both together in one coordinated optimization model, especially in island microgrids. Some studies take a case study approach, focusing on a specific island, climate, and particular profile. Consequently, results may not apply well to other locations with different conditions. Researchers know batteries exhibit clear nonlinear behavior; efficiency varies with charging rate, and losses depend on operating conditions; however, most EMS optimization models still use linear approximations. The motivation is that linear models are easier to solve, though they sim-

plify reality, which may reduce solution accuracy. As a result, dispatch schedules may not reflect real battery performance.

Addressing these limitations requires an EMS framework that captures linear battery behavior, includes demand response flexibility, considers renewable uncertainty, remains computationally tractable, and applies to general island microgrids. In this paper, we develop a complete EMS optimization framework for an island microgrid that includes PV, wind, multiple diesel generators, battery storage, and demand response. The framework integrates all major resources into one unified model. We formulate the EMS as a linear program because battery efficiency is nonlinear. The model includes constraints (power balance, SOC limits, generator limits, etc.). We solve it using MATLAB R2021a fmincon solver with the Sequential quadratic programming (SQP) method, which is suitable for nonlinear constrained optimization. This approach allows linear modeling of battery operation while remaining computationally manageable for day-ahead scheduling. The problem is formulated as day-ahead scheduling with 24 decision intervals (1 h each). The optimization simultaneously determines diesel generator output, battery charging and discharging, and demand response activation schedules. The framework coordinates all decisions within a single optimization problem.

Three operational scenarios are evaluated to isolate and quantify the individual and combined contributions of battery storage and demand response to cost reduction and renewable energy utilization. The results demonstrate that coordinated deployment of both flexibility resources yields significantly greater economic and operational benefits than either resource deployed in isolation, with particular relevance to remote and islanded applications where reliability is paramount, and fuel supply logistics amplify the cost of diesel dependence [18].

The contribution of this study is a unified 24-h energy management formulation for an islanded microgrid incorporating photovoltaic and wind generation, diesel generators, battery storage, and demand response. Rather than proposing a new combination of technologies or optimization algorithm, the study provides a consistent comparative assessment of three operating configurations, evaluates the economic contribution of battery storage and demand response, verifies the solution against a linear programming benchmark, and examines the effects of predefined renewable generation and load variations. These results clarify the operational benefits and limitations of coordinated energy management under the considered conditions.

The remainder of this paper is organized as follows. Section 2 presents the microgrid system description and component models, formulates the optimization problem, and defines the EMS objective function and constraints. Section 3 describes the simulation case study and parameter settings. Section 4 presents and analyzes the simulation results across the three operational scenarios. Section 5 concludes the paper with a summary of findings and directions for future research.

2. System Description and Modeling

2.1. Microgrid Architecture

The studied system is an island renewable-based microgrid designed to supply local electrical loads without connection to the main utility grid. As illustrated conceptually, the microgrid consists of photovoltaic (PV) generation, wind turbine (WT) generation, multiple diesel generators (DGs), a battery storage system (BSS), and a demand response (DR) unit. The microgrid operates over a 24-h scheduling horizon with hourly resolution. Renewable energy sources are considered non-dispatchable and are utilized with priority whenever available. Diesel generators, battery storage, and demand response are

coordinated through an energy management system to ensure power balance, operational feasibility, and minimum operating cost.

2.2. Renewable Energy Generation Model

The islanded microgrid integrates photovoltaic (PV) and wind turbine (WT) generation as renewable energy sources. The total available renewable power at each scheduling interval is expressed as

$$P^{RG}(t) = P^{PV}(t) + P^{WT}(t) \tag{1}$$

where $P^{RG}(t)$ denotes the total renewable power, and $P^{PV}(t)$ and $P^{WT}(t)$ represent the photovoltaic and wind generation at time t respectively.

In the proposed optimization framework, renewable generation is represented by deterministic hourly profiles over a 24-h period. These profiles are assumed to be known at each hourly optimization interval. Therefore, uncertainties associated with solar and wind generation are not explicitly incorporated into the optimization model.

The renewable curtailment power is constrained by the available renewable generation at each scheduling interval, as expressed by

$$0 \le P^{Curt}(t) \le P^{RG}(t) \tag{2}$$

where the renewable curtailment power is constrained between zero and the available renewable generation at each scheduling interval. The renewable power utilized by the microgrid is therefore equal to the available renewable generation minus the curtailed power.

2.3. Diesel-Based Generation System

The microgrid includes DG diesel generators, each characterized by minimum and maximum power output limits. The diesel generator (DG) is constrained such as

$$P^{DG}_{i,\min} \le P^{DG}_{i}(t) \le P^{DG}_{i,\max};\ i = 1 \cdots N \tag{3}$$

In (3), the term P^{DG}_{i} refers to the electrical output of diesel generator i within the microgrid. $P^{DG}_{i,\ \min}$ is the lower limit and $P^{DG}_{i,\ max}$ is the upper limit, while N is the total number of diesel generators installed in the microgrid.

The operational limitation is captured by the permissible ramp-up and ramp-down rates for the diesel generator, which is expressed as

$$-P^{DG}_{i,dw} \le P^{DG}_{i}(t) - P^{DG}_{i}(t-1) \le P^{DG}_{i,up} \tag{4}$$

In (4), the terms $P^{DG}_{i,\ \mathrm{up}}$ and $P^{DG}_{i,\ \mathrm{dw}}$ denote the permissible ramp-up and ramp-down power limits.

2.4. Battery Storage System Model

The battery storage system is modeled using its state of charge (SOC), which represents the available stored energy as a percentage of the nominal battery energy capacity. The SOC dynamics are expressed as follows:

$$\mathrm{SOC}(t+1) = \mathrm{SOC}(t) + \frac{100\Delta t}{E}\left[\eta^{B} P^{B}_{ch}(t) - \frac{P^{B}_{dis}(t)}{\eta^{B}}\right] \tag{5}$$

The battery charging and discharging efficiencies are assumed to be constant in the present formulation. Consequently, the battery state-of-charge dynamics are linear with respect to the charging and discharging decision variables. The proposed formulation

does not represent nonlinear, power-dependent battery efficiency characteristics, and no improvement over nonlinear battery efficiency models is claimed.

In (5), SOC(t) denotes the battery state of charge expressed as a percentage, and the nonnegative charging and discharging powers, respectively, represent the battery charging and discharging efficiency; E is the nominal battery energy capacity, and is the scheduling time step.

The battery SOC is limited, such as

$$\mathrm{SOC}_{\min} \le \mathrm{SOC}(t) \le \mathrm{SOC}_{\max} \tag{6}$$

In (6), the terms $\mathrm{SOC}_{\min}$ and $\mathrm{SOC}_{\max}$ are the minimum and maximum values, respectively.

The battery charging and discharging powers are represented by separate nonnegative variables and are constrained by their maximum allowable values, as follows:

$$\begin{cases} 0 \le P_{ch}^{B}(t) \le P_{max}^{B} \\ 0 \le P_{dis}^{B}(t) \le P_{max}^{B} \end{cases} \tag{7}$$

2.5. Demand Response Model

Demand response (DR) is modeled as a controllable reduction in flexible load demand during each scheduling interval. The proposed formulation considers incentive-based load curtailment rather than load shifting. The curtailed demand is limited to a specified fraction of the original hourly load to restrict excessive demand reduction.

The load power in the microgrid is constrained within the limits such as

$$P_{\min}^{L} \le P^{L}(t) \le P_{\max}^{L} \tag{8}$$

In (8), the term P^L is the load power in the microgrid, and $P_{\min}^{L}$ and $P_{\max}^{L}$ are the lower and upper limits, respectively.

The hourly power balance in the microgrid is expressed as

$$\sum_{i=1}^{N} P_{i}^{DG}(t) + P^{RG}(t) + P_{dis}^{B}(t) - P_{ch}^{B}(t) + P^{DR}(t) - P^{curt}(t) = P^{L}(t) \tag{9}$$

In Equation (9), $P^{DR}(t)$ represents the nonnegative load reduction achieved through demand response, while $P^{Curt}(t)$ denotes renewable generation curtailment. The variables $P^{ch}(t)$ and $P^{dis}(t)$ represent battery charging and discharging power, respectively. Demand response is modeled as load curtailment only; load shifting and rebound effects are not considered.

The power of the demand response is limited, such as

$$0 \le P^{DR}(t) \le \alpha P^{L}(t) \tag{10}$$

In (10), α denotes the maximum allowable fraction of hourly load curtailment, which is set to 0.20 (20%) in this study. The demand-response cost is set to \$3/kWh and represents the assumed compensation or inconvenience cost associated with flexible-load curtailment.

2.6. Energy Management System with Optimization Capabilities

The optimization and energy management system (OEMS) is designed to operate an island renewable-based microgrid in a coordinated and cost-effective manner. The primary objective of the OEMS is to ensure a reliable supply of electrical energy to local loads while minimizing the total operating cost and satisfying all technical and operational constraints of the system components.

The OEMS coordinates the operation of photovoltaic and wind generation, diesel generators, battery storage, and demand response resources over a 24-h scheduling horizon. When solar or wind power is available, the system uses it first. Renewable energy is preferred over diesel or storage. This reduces fuel use and emissions. However, renewable generation is not always sufficient, so diesel generators provide backup power. Their operation is carefully scheduled, not continuous. Batteries help smooth differences between generation and demand, and they absorb short-term fluctuations. By doing this, batteries reduce how often diesel generators need to operate; loads can be adjusted when needed. Demand response helps during high demand, and when renewable output is low, this adds another layer of flexibility.

Through integrated coordination of generator outputs, battery storage operation, and demand response strategies, the OEMS maintains supply–demand balance at each hourly scheduling interval over the 24-h day-ahead optimization horizon, satisfies battery state-of-charge (SOC) constraints, and minimizes operating costs under the evaluated conditions.

2.7. Problem Formulation

The energy management problem of the island microgrid is formulated as a continuous linear optimization problem to minimize the total operating cost over a 24-h scheduling horizon. The optimization is performed with hourly resolution, considering diesel generator dispatch, battery charging and discharging, renewable generation curtailment, and demand-response load reduction. The formulation incorporates power-balance constraints, generator operating and ramp-rate limits, battery state-of-charge dynamics, and demand-response limits.

The mathematical form of the cost function is expressed as

$$\min F = \sum_{t=1}^{24} \Delta t \left[\sum_{i=1}^{N} c_i^{DG} P_i^{DG}(t) + c^B \left(P_{ch}^B(t) + P_{dis}^B(t) \right) + c^{DR} P^{DR}(t) \right] \tag{11}$$

In (11), F represents the total operating cost over the scheduling horizon, c_i^{DG} denotes the operating cost coefficient of diesel generator (i), c^B is the battery operating cost coefficient, and c^{DR} is the demand-response cost coefficient. The battery charging and discharging powers are represented by separate nonnegative variables. All cost coefficients are expressed in \$/kWh, and Δt is the scheduling interval in hours.

The decision variables include the dispatch levels of the N diesel generators, battery discharging and charging powers, demand-response load curtailment, and renewable generation curtailment. Accordingly, the decision-variable vector at each scheduling interval is defined as follows:

$$X(t) = \left[P_1^{DG}(t), \ldots, P_N^{DG}(t), P_{dis}^B(t), P_{ch}^B(t), P^{DR}(t), P^{curt}(t) \right]^T \tag{12}$$

The optimal solution consists of the optimized decision variables over the 24-h scheduling horizon and is expressed as:

$$X_{\text{opt}} = \left[X_{\text{opt}}(1)^T, \ldots, X_{\text{opt}}(24)^T \right]^T \tag{13}$$

The optimization procedure is detailed in Algorithm 1.

Although Sequential Quadratic Programming (SQP) is generally a local optimization method, the revised energy management formulation employs linear operating costs and linear equality and inequality constraints, including generator operating limits, ramp-rate constraints, battery state-of-charge dynamics, and demand-response bounds. Separate nonnegative variables are used to represent battery charging and discharging power. Therefore, the resulting continuous optimization problem is linear and convex.

Algorithm 1: Problem Formulation for Optimization

1: **Initialization**
Define DG, battery, and DR parameters, operating limits, and cost coefficients.
2: **Data Collection**
Obtain hourly load, PV, and wind generation profiles for 24 h.
3: **Optimization**
Decision variables: DG outputs, battery charging/discharging, DR, and renewable curtailment.
Objective: Minimize the total operating cost using Equation (11).
Constraints: Power balance (9), DG capacity and ramp-rate limits, battery SOC and power limits (5)–(7), DR limits (10), and renewable curtailment bounds.
4. **Solution**: Solve the 24-h optimization problem using SQP and verify the resulting optimal objective value using LP.
5: **Output**
Report optimal dispatch, battery SOC, demand response, renewable curtailment, and total operating cost.

To assess the optimality of the SQP solution, the same baseline scheduling problem was also evaluated using MATLAB's linear programming solver, linprog. Both methods produced an operating cost of approximately $187.17, indicating agreement between the SQP solution and the linear programming benchmark. For the continuous linear formulation, a successfully solved linear program provides a globally optimal solution.

The linear programming (LP) benchmark was selected because the revised optimization problem has a linear objective function and linear constraints with continuous decision variables. Therefore, LP provides a globally optimal solution when the problem is feasible. Mixed-integer linear programming (MILP) is not required because no binary or integer decision variables are included. Although genetic algorithms (GA) and particle swarm optimization (PSO) can be applied to energy management problems, they do not provide a stronger optimality guarantee for the present linear formulation. Accordingly, the comparison focuses on SQP and LP, while sensitivity analysis evaluates the effects of renewable generation reductions and load increases.

3. Case Study and Simulation Setup

Case Study Description

A representative island renewable-based microgrid is considered to evaluate the proposed optimization and energy management system. The microgrid consists of photovoltaic (PV) generation, wind turbines (WT), three diesel generators (DGs), a battery storage system (BSS), and a demand response (DR) unit. The system operates independently from the main utility grid and supplies local electrical loads typical of remote or isolated applications.

The study focuses on day-ahead operational scheduling with a 24-h horizon and hourly resolution. All simulations and numerical analyses were performed in MATLAB using the Optimization Toolbox. The optimization problem was solved using the fmincon function with the Sequential Quadratic Programming (SQP) algorithm, and the results were compared with those obtained using the linprog function for linear programming.

The objective is to determine the optimal coordination of dispatchable resources to minimize operating cost while maintaining power balance and satisfying all system constraints.

For renewable energy generation profiles, hourly solar irradiance and wind speed data are used to model renewable generation. Photovoltaic output is proportional to solar irradiance, while wind power output is derived from wind speed measurements. Renewable sources are treated as non-dispatchable and are fully utilized whenever available.

The electrical load is modeled using a normalized hourly demand profile scaled to a peak value of 150 kW. This profile represents typical consumption behavior in small island microgrids and is presented by

$$P_L(t) = 150 \times L(t) \tag{14}$$

In (14), the term P_L is the load demand at hour t, in kW, and L is the normalized load factor.

The operating cost coefficients are selected based on typical values reported in microgrid energy management literature. The model attributes the highest operating cost to diesel generators to capture fuel expenditure, while battery cycling and demand response actions are represented through degradation and penalty cost terms. All cost coefficients are held constant over the entire simulation horizon to maintain consistency between scenarios.

The main technical parameters of the microgrid components are provided in Tables 1–4. These parameters represent realistic operating conditions for islanded microgrids and are kept constant for all scenarios.

Table 1. Diesel Generators.

Value	Symbol	Parameter
3	N	Number of diesel generators
0 kW	$P^{DG}_{i,\min}$	Minimum power output
50 kW	$P^{DG}_{i,\max}$	Maximum power output
5 kW/h	$P^{DG}_{i,\mathrm{up}}$	Ramp-up limit
5 kW/h	$P^{DG}_{i,\mathrm{dw}}$	Ramp-down limit
0.20125, 0.20125, 0.20125 $/kWh	c^{DG}_i	Cost coefficient

Table 2. Battery Storage System.

Value	Symbol	Parameter
100 kW	$P^{B}_{\max}$	Battery power limit
1 MWh	E	Battery energy capacity
60%	$\mathrm{SOC}(0)$	Initial state of charge
30%	$\mathrm{SOC}_{\min}$	Minimum SOC
80%	$\mathrm{SOC}_{\max}$	Maximum SOC
95%	η^B	Charging/discharging efficiency
0.0273 $/kWh	c^B	Battery throughput degradation cost

Table 3. Demand Response Parameters.

Value	Symbol	Parameter
$3/kWh	c^{DR}	Demand response cost coefficient
20% of hourly load	$\alpha = 0.20$	Maximum DR participation fraction

Table 4. Load and Scheduling Horizon.

Value	Symbol	Parameter
24 h	T	Scheduling horizon
Variable hourly load (peak: 150 kW)	P_L	Load demand
1 h	Δt	Time resolution

The diesel generator ramp-up and ramp-down limits of 5 kW/h are treated as illustrative modeling assumptions, rather than manufacturer-validated operating specifications.

The operating cost coefficients in Tables 1–3 were selected using published technical and economic assumptions. For the three identical 50 kW diesel generators, a constant operating cost of USD 0.20125/kWh was estimated using a diesel price of USD 2.25/gallon, full-load fuel consumption of 4.25 gallons/hour, and variable maintenance cost of USD 0.01/kWh [19,20]. The battery throughput degradation cost was approximated as USD 0.0273/kWh using an assumed battery-pack replacement cost of USD 164/kWh [21] and a lifetime of 3000 equivalent full cycles, with the cost applied to both charging and discharging energy. A demand response compensation coefficient of USD 3/kWh was adopted as an illustrative assumption based on a published demand response study [22]. These coefficients are simplified economic assumptions rather than measured operating costs for a specific installation.

The optimization model was implemented in MATLAB using the fmincon solver with the sequential quadratic programming (SQP) algorithm. The linear programming benchmark was solved using linprog. Both methods used a 24-h scheduling horizon with a one-hour time step and identical system parameters and operational constraints.

4. Results and Discussion

This section details and examines the simulation results corresponding to the three operational scenarios defined in Section 3. Performance assessment focuses on diesel generator dispatch, battery cycling behavior, demand response participation, and aggregate operating cost.

4.1. Operational Scenarios

The subsequent scenarios, illustrated in Figure 1, are investigated to quantify the operational impacts of battery storage and demand response within the microgrid:

- **Scenario S1:** PV + WT + Diesel Generators
- **Scenario S2:** PV + WT + Diesel Generators + Battery Storage
- **Scenario S3:** PV + WT + Diesel Generators + Battery Storage + Demand Response (Proposed EMS)

Each scenario is evaluated using identical load, renewable generation inputs, and system parameters to guarantee an unbiased comparison.

4.2. Renewable Generation and Load Balance

Figure 2 presents the 24-h renewable generation and load demand curves. Due to changes in solar irradiance and wind speed, renewable output exhibits notable variability. High renewable production leads to reduced diesel generator operation, while low production requires dispatchable generators to meet the shortfall. These profiles indicate that renewable output is insufficient to meet demand at all times, thereby necessitating the support of dispatchable generators and battery storage in island operation.

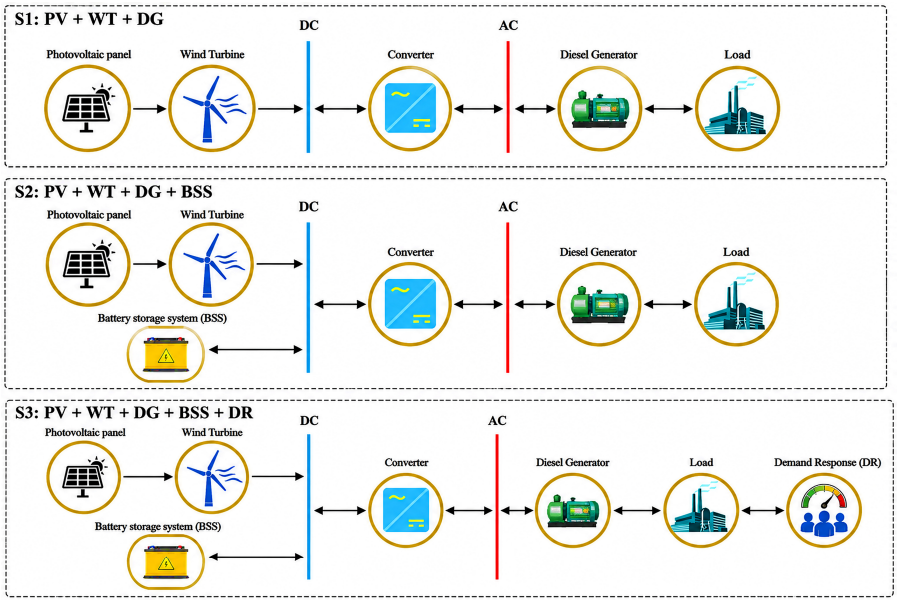


Figure 1. Three configurations of microgrid (scenarios).

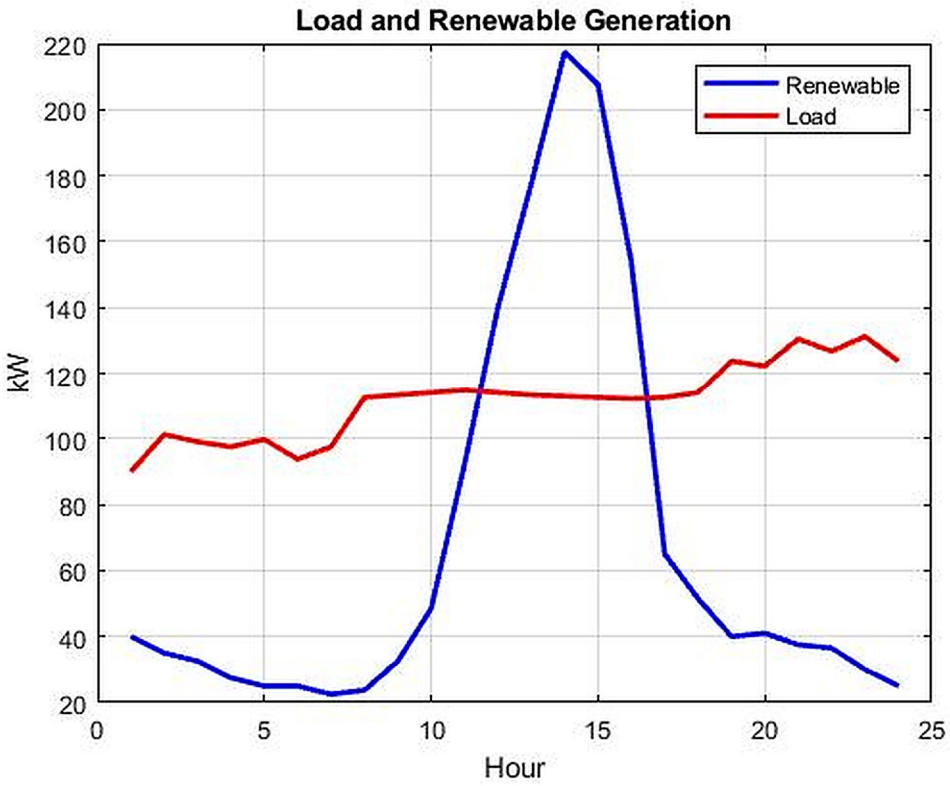


Figure 2. Load demand and renewable energy production over hourly intervals.

4.3. Diesel Generator Dispatch

Figure 3 depicts the optimal generation profiles of the three diesel units under Scenario S3. The units are scheduled in a coordinated fashion that adheres to both power capacity and ramp-rate restrictions.

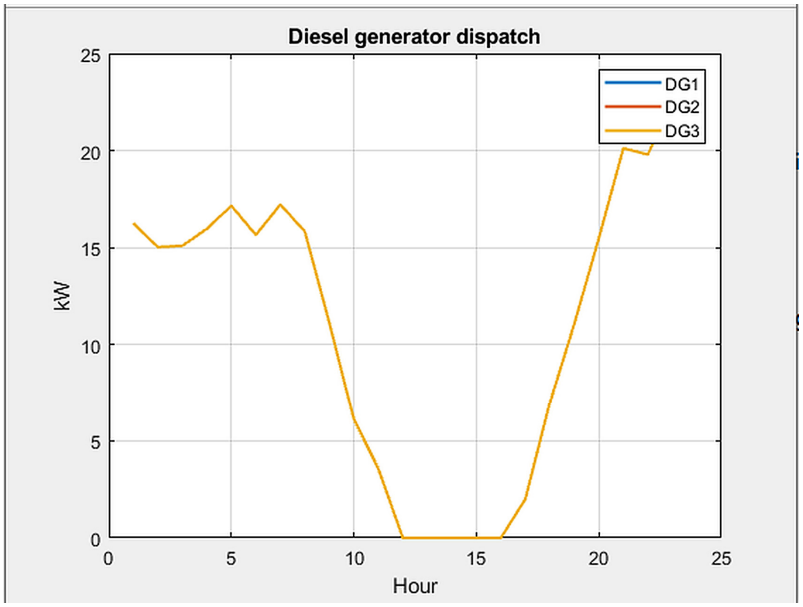


Figure 3. Diesel generator optimal output profiles (Scenario S3).

The revised results show that diesel generators and battery storage operate simultaneously during hours 5–10 to meet the remaining demand after renewable generation is utilized. Battery discharge reduces diesel generation requirements, while the dispatch is constrained by generator ramp-rate limits and battery operating limits. During periods of higher renewable generation, diesel generator outputs decrease and the battery is recharged. The battery starts with an assumed state of charge of 60%, rather than a measured initial value.

4.4. Battery Storage Operation

The charge and discharge schedules of the battery storage system for Scenarios S2 and S3 are displayed in Figure 4, with the resulting state-of-charge evolution shown in Figure 5.

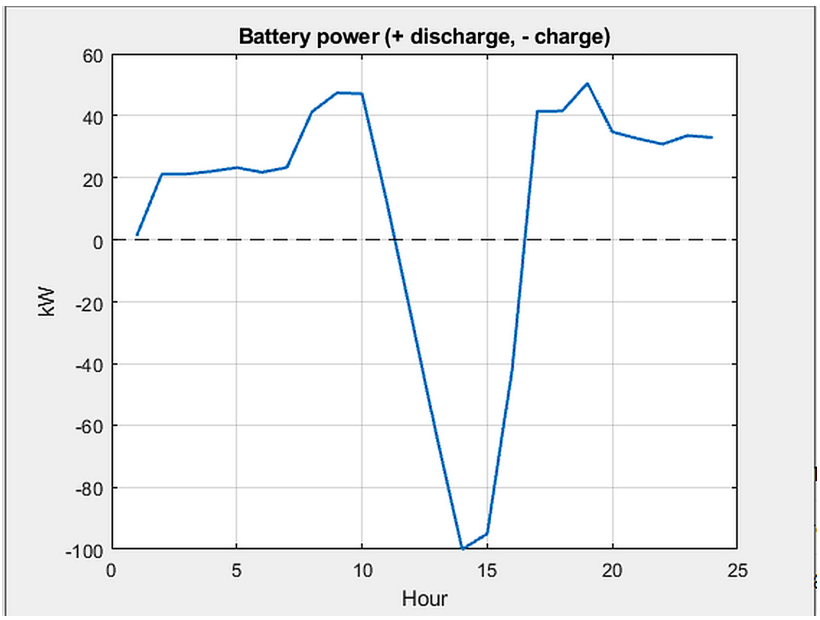


Figure 4. Battery charging and discharging power.

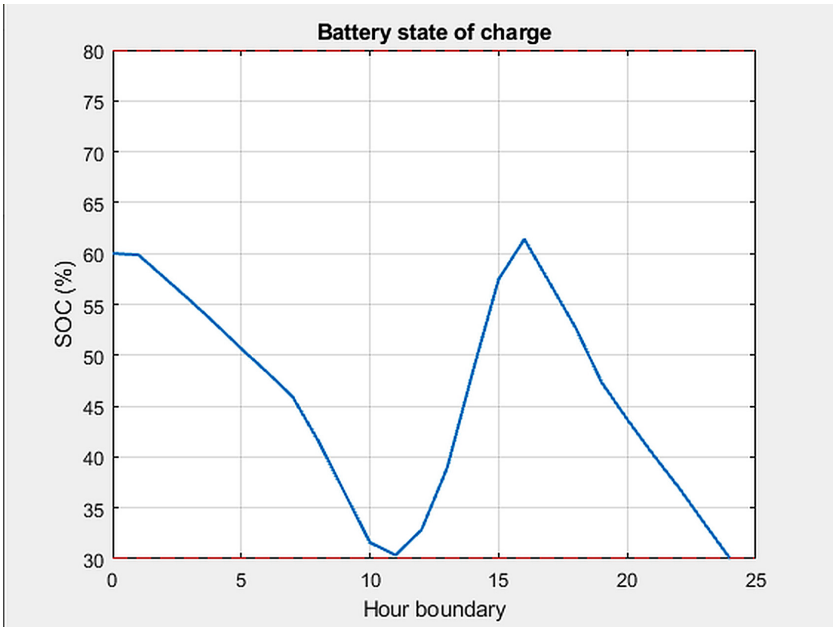


Figure 5. Battery SOC variation over time.

The battery state of charge (SOC) was calculated numerically using the optimized hourly charging and discharging power, the assumed initial SOC of 60%, the battery capacity of 1000 kWh, and the charging and discharging efficiency of 95%. The SOC was not obtained from experimental measurements. As shown in Figure 5, the SOC varies between 30% and approximately 61.4%, remaining within the prescribed operating limits of 30–80%. Battery charging occurs during periods of higher renewable generation, while discharging supports the system when additional power is required.

Figure 6 shows that renewable power curtailment occurs only around hour 14, reaching approximately 4.63 kW. The total curtailed renewable energy is approximately 4.63 kWh over the 24-h scheduling period. Renewable generation is otherwise fully utilized under the evaluated operating conditions.

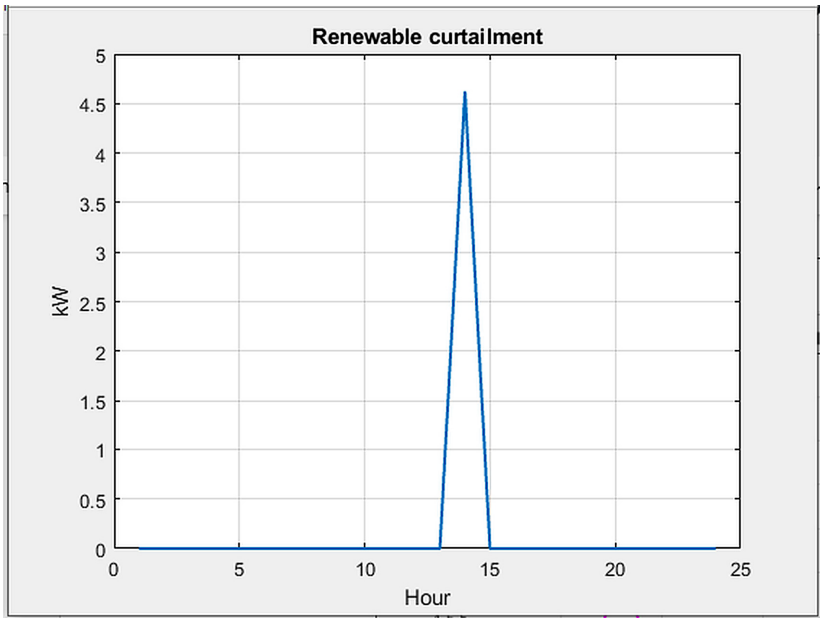


Figure 6. Renewable power curtailment during the 24-h scheduling period (Scenario S3).

4.5. Demand Response Activation

Figure 7 presents the demand response power trajectory under Scenario S3. The optimized demand response remains effectively zero throughout the 24-h scheduling period, indicating that load curtailment is not economically required under the considered operating conditions.

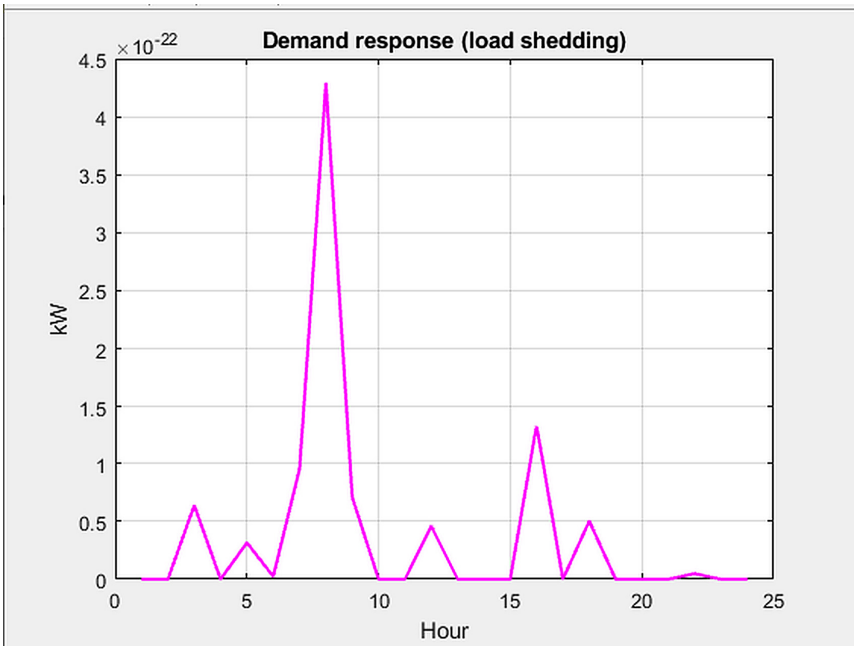


Figure 7. Demand response.

Although demand response is included as a controllable resource in the optimization framework, it is not activated in the baseline scenario because the available generation and battery storage can satisfy demand at a lower operating cost.

4.6. Cost Comparison Between Scenarios

Table 5 compares the total operating costs of the three scenarios illustrated in Figure 8. Scenario S2 reduces the operating cost from USD 313.35 to USD 187.17, representing a 40.27% reduction compared with Scenario S1. Scenario S3 achieves the same operating cost as S2, indicating that demand response does not provide additional cost savings under the evaluated baseline operating conditions.

Table 5. Cost Comparison Results.

Cost Reduction Relative to S1 (%)	Total Cost ($)	System Configuration	Scenario
–	313.35	PV + WT + DG	S1
40.27	187.17	PV + WT + DG + BSS	S2
40.27	187.17	PV + WT + DG + BSS + DR	S3

The battery capacity was corrected to 1 MWh, and all three operating scenarios were recalculated using consistent system parameters, revised cost coefficients, and an assumed initial output of 20 kW for each diesel generator. Battery integration reduced the operating cost by 40.27%. The addition of demand response did not produce further cost savings under the considered operating conditions because no load curtailment was economically required.

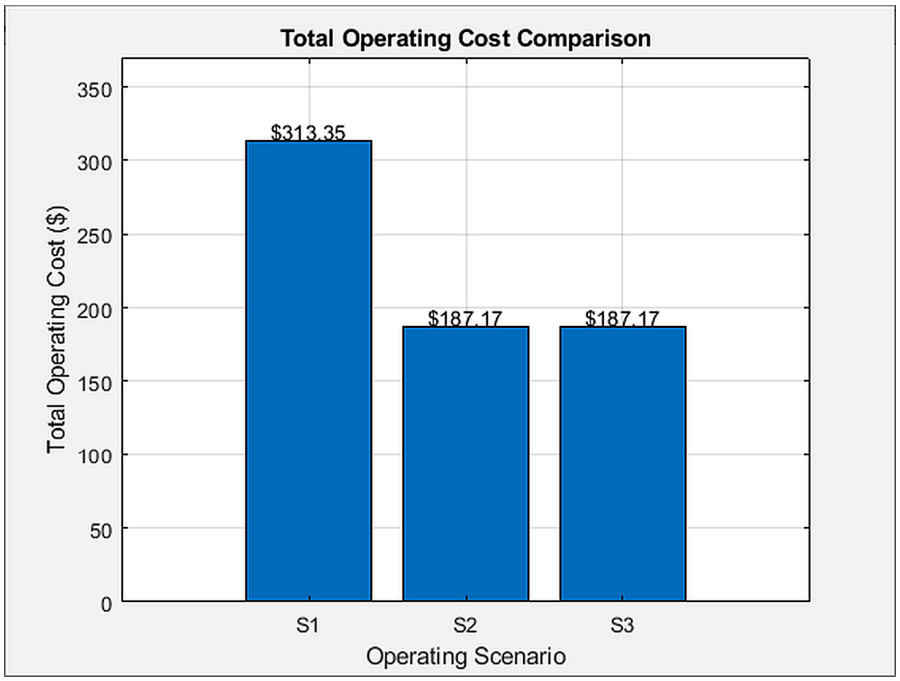


Figure 8. Total operating cost comparison.

Battery cycles are estimated from discharged energy divided by the 1000 kWh battery capacity. Diesel starts and stops are not reported because unit commitment is not explicitly modeled.

Table 6 compares the operational performance of the three scenarios. Battery integration increases renewable energy utilization from 69.18% in Scenario S1 to 99.72% in Scenarios S2 and S3. Total diesel generation decreases from 1557 kWh to 807 kWh. The battery completes approximately 0.58 equivalent full discharge cycles during the 24-h scheduling horizon. Scenarios S2 and S3 produce identical results under baseline conditions, with no demand response activation or additional cost savings from demand response.

Table 6. Comparison of operational performance indicators across three scenarios.

Indicator	S1	S2	S3
Renewable utilization (%)	69.18	99.72	99.72
Diesel generation (kWh)	1557	807	807
Battery equivalent full discharge cycles	0	0.58	0.58
Demand response (kWh)	0	0	0

Diesel generator start-up and shut-down events are not quantified because binary unit commitment decisions are not included in the optimization formulation.

4.7. SQP Convergence and Initial-Point Sensitivity Analysis

To evaluate the sensitivity of the SQP algorithm to initial conditions, five optimization runs were performed using different starting points and the results are shown in Table 7. The first run used a zero initial vector, while the remaining four runs randomly generated initial vectors within the decision-variable bounds. All five runs reached the same operating cost of USD 187.17, with iteration counts ranging from 41 to 89 and computation times ranging from 0.3351 to 0.7907 s. All runs terminated with exit flag 2, indicating that the step-size stopping criterion was satisfied while the constraints remained feasible. The resulting objective values also matched the globally optimal solution obtained using linear

programming. These findings indicate that the SQP results were insensitive to the tested initial points for the considered formulation, although SQP does not generally guarantee global optimality for nonlinear optimization problems.

Table 7. SQP convergence results for five different initial points.

Run	Cost ($)	Iterations	Time (s)	Exit Flag
1	187.17	41	0.3351	2
2	187.17	85	0.6439	2
3	187.17	89	0.6371	2
4	187.17	86	0.6530	2
5	187.17	78	0.7907	2

4.8. Sensitivity Analysis Under Renewable Generation and Load Variations

To evaluate the sensitivity of the proposed energy management model to variations in renewable generation and load demand, three adverse scenarios were investigated. The photovoltaic and wind generation profiles were reduced by 10%, 20%, and 30%, while the corresponding load demand was increased by the same percentages. For each scenario, the 24-h scheduling problem was re-optimized while respecting generator operating limits, battery state-of-charge constraints, and demand-response limits.

The baseline operating cost is USD 187.17. Under simultaneous renewable generation reductions and load demand increases of 10%, 20%, and 30%, the operating costs increase to USD 262.85, USD 343.41, and USD 427.44, respectively. These correspond to cost increases of 40.44%, 83.48%, and 128.37% relative to the baseline. Demand response utilization and unserved energy remain zero in all evaluated scenarios. These results demonstrate the sensitivity of operating costs to adverse renewable generation and load variations under deterministic scenario-based re-optimization.

The results demonstrate the sensitivity of operating costs and demand-response utilization to adverse variations in renewable generation and load demand. Because each scenario was optimized using its complete operating profiles, the analysis represents a perfect-information scenario sensitivity assessment rather than a validation of real-time forecast-error compensation or stochastic optimization.

Table 8 presents the sensitivity analysis results under simultaneous reductions in renewable generation and increases in load demand. The baseline operating cost is USD 187.17, increasing to USD 262.85, USD 343.41, and USD 427.44 under 10%, 20%, and 30% variations, respectively. These correspond to cost increases of 40.44%, 83.48%, and 128.37%. No demand response curtailment or unserved energy was recorded in the evaluated scenarios. The results indicate that higher net demand increases operating costs, while the optimization maintains feasible power balance under the considered conditions. These results represent deterministic scenario re-optimization with perfect information and do not establish robustness against real-time forecast errors.

Table 8. Operating performance under adverse renewable generation and load scenarios.

Scenario	Operating Cost ($)	Cost Increase (%)	DR (kWh)	Unserved Energy (kWh)
Baseline	187.17	—	0	0
10% variation	262.85	40.44	0	0
20% variation	343.41	83.48	0	0
30% variation	427.44	128.37	0	0

The load, solar irradiance, and wind-speed profiles used in this study are synthetic and are intended to evaluate the proposed energy management formulation under representative

operating conditions. The sensitivity analysis examines predefined deviations in renewable generation and load through scenario-based re-optimization. However, these results do not constitute validation using measured operational data or demonstrate robustness against real-time forecast errors. Future work will incorporate measured renewable generation and demand profiles, together with stochastic or robust optimization methods, to evaluate performance under forecast uncertainty.

To assess supply adequacy under the considered operating scenarios, unserved energy was included in the optimization model with a penalty of \$1000/kWh. The results in Table 8 show zero unserved energy for all evaluated scenarios, indicating that the scheduled generation, battery storage, and demand response were sufficient to satisfy demand within the modeled constraints under these specific conditions. However, this scenario-based assessment does not constitute a probabilistic reliability evaluation. Reliability indices such as Loss of Load Probability (LOLP) and Expected Energy Not Supplied (EENS) require additional probabilistic modeling of renewable generation, demand uncertainty, and component outages, which is beyond the scope of the present study.

4.9. Discussion of EMS Benefits

The simulation results indicate that the proposed energy management system enhances microgrid performance by:

1. Reducing total operating cost through battery integration.
2. Maintaining battery SOC within prescribed limits.
3. Satisfying hourly power-balance constraints.
4. Maintaining zero unserved energy under the evaluated scenarios.

The simulation results demonstrate that battery integration reduces operating costs while maintaining battery SOC and power-balance constraints. Demand response provides additional flexibility under adverse operating scenarios, although it does not reduce costs under baseline conditions. These findings are limited to the evaluated scenarios.

4.10. Limitations of the Study

This study has several limitations. First, synthetic load and renewable generation profiles were used rather than measured operational data. Second, the optimization model is deterministic, and the sensitivity analysis considers predefined changes in renewable generation and load with perfect-information re-optimization. Therefore, robustness against real-time forecast errors has not been demonstrated. Third, demand response is represented as aggregated curtailable load without detailed load-shifting or consumer behavior models. Finally, probabilistic component outages and reliability indices, such as Loss of Load Probability (LOLP) and Expected Energy Not Supplied (EENS), are not considered. Furthermore, the proposed energy management framework has been evaluated through numerical simulations only, without experimental or hardware-in-the-loop validation. Future work will investigate laboratory-scale or hardware-in-the-loop testing to assess the practical implementation of the scheduling approach, including its response to measurement errors, communication delays, and real-time operating constraints.

Future work will address these limitations using measured data, uncertainty-aware optimization, detailed demand response models, and probabilistic reliability analysis.

5. Conclusions

This paper presented a deterministic optimization framework for day-ahead energy management of an islanded microgrid integrating photovoltaic generation, wind turbines, diesel generators, battery storage, and demand response. The optimization problem was

formulated over a 24-h scheduling horizon with a one-hour time step and solved using MATLAB's fmincon solver with the Sequential Quadratic Programming (SQP) algorithm. A linear programming formulation was also solved using linprog to verify the optimal operating cost. Three operational scenarios were evaluated to assess the economic contributions of battery storage and demand response. The baseline scenario (S1), consisting of renewable and diesel generation, resulted in an operating cost of $313.35. Integrating battery storage in Scenario S2 reduced the operating cost to $187.17, representing a 40.27% reduction. Scenario S3, which additionally incorporated demand response, achieved the same operating cost as S2. Therefore, demand response did not provide additional cost savings under the baseline operating conditions. The simulation results showed that the optimization framework satisfied hourly power-balance constraints, maintained battery state of charge within its prescribed limits, and respected diesel generator operating constraints. The sensitivity analysis further demonstrated that operating costs increased under simultaneous reductions in renewable generation and increases in load. No demand response curtailment or unserved energy was recorded in any of the evaluated sensitivity scenarios. The main contribution of this study is the integrated formulation and comparative evaluation of different operating configurations, supported by a linear programming benchmark and scenario-based sensitivity analysis. The battery charging and discharging processes were represented using separate nonnegative variables, allowing the battery state-of-charge dynamics to be expressed through linear constraints. A positive aspect of the proposed framework is that it enables a consistent comparison of battery storage and demand response contributions under the same operating assumptions. The comparison with linear programming also provides a benchmark for assessing the SQP solution quality. The study is limited using synthetic input profiles, deterministic optimization, and simplified demand response modeling. Furthermore, the proposed framework has not been validated experimentally, and its practical performance under real-time operating conditions remains to be investigated. Although the evaluated scenarios satisfied the modeled supply–demand constraints, robustness against unknown real-time forecast errors and probabilistic reliability performance were not established. Future work will incorporate measured operational data, probabilistic renewable generation and load forecasts to account for prediction errors that are not represented in the current deterministic model. A rolling-horizon model predictive control (MPC) approach will be investigated to update generation and battery schedules as new forecasts and operating measurements become available, thereby correcting potential power imbalances caused by forecast deviations. Multi-day scheduling will also be considered to coordinate battery charging and discharging across consecutive days, including the transfer of stored energy between scheduling horizons through the battery's ending and initial state of charge. More detailed demand response models and probabilistic reliability assessments will be investigated to evaluate operational flexibility and supply adequacy under uncertain conditions. Laboratory-scale or hardware-in-the-loop validation will also be considered to evaluate the practical feasibility of the proposed energy management approach.

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