



Economic Dispatch Strategy for Grid-Connected Microgrids with Renewable Energy and Battery Energy Storage Integration

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ABSTRACT

The rapid deployment of renewable energy technologies has supported the transition toward cleaner power systems, but the variability of photovoltaic (PV) and wind-turbine (WT) generation complicates the economical operation of grid-connected microgrids. This paper develops an offline day-ahead dispatch framework for an Indian hybrid microgrid comprising PV, WT, a diesel generator (DG), a battery energy storage system (BESS), and a utility-grid connection. The problem is implemented as a Mixed-Integer Linear Programming (MILP) model. To preserve linearity, the DG fuel-cost curve is represented by piecewise-linear segments. The objective minimizes diesel operating cost, grid-purchase cost, and a throughput-based battery degradation charge, less export revenue, subject to power-balance, unit-capacity, battery SOC, mutually exclusive charging/discharging, grid import/export, and renewable-curtailment constraints. Reported simulations show operating-cost reductions of 38.7% relative to the diesel-dominant benchmark and 14.2% relative to the renewable system without BESS. The contribution is therefore not the use of MILP alone, but the consistent integration of mutually exclusive operating states, explicit renewable curtailment, benchmark definitions, lifecycle annualization, and deterministic sensitivity tests in one reproducible day-ahead framework. The model is an offline scheduling tool and is not claimed as a real-time controller; online use would require repeated rolling-horizon execution with updated forecasts and measurements.

Keywords: Economic Dispatch; Microgrid; Battery Energy Storage System; Mixed Integer Linear Programming; Renewable Energy.

1. Introduction

The global electricity industry is undergoing a profound transformation driven by increasing efforts to mitigate climate change and accelerate the transition toward low-carbon energy systems. International initiatives, particularly the Paris Agreement, have strengthened the commitment of many countries to reduce greenhouse gas emissions by replacing conventional fossil-fuel-based electricity generation with cleaner, decentralized, and environmentally sustainable energy sources. As the electricity sector remains one of the largest contributors to global carbon emissions, improving its environmental performance has become a critical step toward achieving the long-term target of limiting global temperature rise to 1.5 °C [1]. Consequently, governments and private stakeholders have significantly expanded investments in renewable energy technologies, leading to a continuous increase in renewable electricity generation capacity across the world [2].

Among various renewable energy technologies, photovoltaic (PV) and wind turbine (WT) systems have demonstrated the fastest growth in deployment over the last decade. Their rapid expansion has been supported by continuous technological improvements, declining capital costs, and favorable government incentives promoting clean energy adoption. As a result, solar and wind power have become major contributors to modern electricity generation. However, the intermittent and weather-dependent characteristics of these resources introduce substantial operational uncertainty due to fluctuations in solar irradiance and wind speed [3, 4]. Such variability complicates the real-time balance between electricity generation and demand, thereby requiring advanced energy management strategies capable of maintaining system reliability while minimizing operating costs[5].

Microgrids have emerged as an effective solution for integrating distributed renewable energy resources while

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improving the reliability, resilience, and operational flexibility of electrical power systems. A typical microgrid consists of renewable generation units, battery energy storage systems (BESS), local electrical loads, and an energy management system that coordinates overall system operation under either grid-connected or islanded conditions [6]. Compared with standalone operation, grid-connected microgrids provide greater operational flexibility by enabling bidirectional power exchange with the utility network. This capability allows surplus renewable energy to be exported to the grid or additional electricity to be imported whenever local generation is insufficient, thereby improving renewable energy utilization and reducing operating costs under time-of-use (TOU) electricity pricing schemes [7].

The economic viability of renewable-based microgrids is strongly influenced by the effectiveness of their energy management system. Economic dispatch is one of the most important functions of this system because it determines the optimal operating schedule of available generation resources while satisfying technical and operational constraints. A properly designed dispatch strategy seeks to reduce operating expenses, increase renewable energy utilization, improve supply reliability, and minimize dependence on conventional fossil-fuel generation [8]. However, coordinating photovoltaic systems, wind turbines, diesel generators (DGs), battery energy storage systems, and utility grid interaction within a single optimization framework remains a challenging task because each component possesses different operating characteristics and physical limitations. In particular, battery scheduling must account for charging and discharging efficiencies, state-of-charge (SOC) evolution, operating limits, and degradation costs, all of which directly influence the long-term economic performance of the microgrid [9, 10].

The intermittent nature of renewable generation continues to represent one of the principal operational challenges in modern microgrids. Variations in photovoltaic output, wind power generation, and electricity demand create continuous fluctuations in system operating conditions, making real-time energy balancing increasingly complex [11, 12]. As a result, an effective economic dispatch strategy should coordinate renewable generation, battery storage, dispatchable generators, and utility grid transactions within an integrated optimization framework. Such coordination ensures that power balance constraints are satisfied while simultaneously reducing operating costs and preserving battery lifetime [13].

Economic dispatch and energy management strategies have been extensively investigated for renewable-based microgrids. Proposed a real-time multi-agent energy management framework that improved operational flexibility but did not consider battery degradation costs or detailed battery operational constraints [14]. Developed a stochastic economic dispatch model that addressed demand uncertainty; however, the study considered only a single renewable energy source and simplified battery scheduling [15]. Employed a Genetic Algorithm (GA) to optimize hybrid microgrid operation, although the heuristic nature of GA does not guarantee globally optimal or reproducible solutions [16]. More recent studies have incorporated coordinated scheduling and predictive control. Proposed a bi-level optimization framework for community microgrids

but employed simplified battery modelling [17]. adopted Model Predictive Control (MPC) for rolling-horizon scheduling, although its computational complexity increases significantly with prediction horizon and system size [18]. A recent study integrated demand response into microgrid operation but focused mainly on load flexibility without comprehensively evaluating battery degradation or long-term economic performance [19].

Despite these significant contributions, several important limitations remain. First, many existing economic dispatch models employ simplified battery representations that neglect degradation costs, charging and discharging efficiencies, or mutually exclusive battery operating constraints, potentially leading to unrealistic dispatch schedules. Second, most studies evaluate only a single microgrid configuration, making it difficult to quantify the individual and combined economic benefits of renewable generation, battery storage, and utility grid interaction [20]. Third, comprehensive sensitivity analyses considering battery investment cost, electricity tariff variations, renewable penetration levels, and future load growth are still limited. Consequently, there remains a need for a unified optimization framework capable of integrating realistic battery modelling, renewable energy coordination, utility grid interaction, and comprehensive techno-economic assessment [21].

Among the optimization techniques available for microgrid scheduling, Mixed-Integer Linear Programming (MILP) has been widely recognized as an effective approach for solving day-ahead economic dispatch problems. Its capability to optimize both continuous decision variables, such as power output, and discrete variables, including generator commitment and battery charging states, enables the determination of globally optimal solutions for linear optimization models [22]. In contrast to heuristic-based optimization algorithms, MILP offers deterministic convergence, consistent solution quality, and lower computational complexity for large-scale scheduling problems. These advantages make MILP particularly suitable for practical microgrid energy management, where coordinated scheduling of distributed generators, battery energy storage systems, and bidirectional power exchange with the utility grid is required to achieve economically efficient and reliable system operation [23].

To address the identified gaps, this study develops a unified day-ahead MILP framework for a grid-connected hybrid microgrid integrating PV, WT, DG, BESS, and utility-grid exchange. Because similar MILP configurations have been reported previously, the specific contribution is stated more narrowly: the proposed formulation combines a piecewise-linear DG cost representation, mutually exclusive battery and grid operating modes, explicit renewable-curtailment variables, a throughput-based degradation charge, clearly defined benchmark configurations, and lifecycle/sensitivity post-processing under one consistent dataset and set of constraints [24,25].

The main contributions of this study are summarized as follows:

1. Development of a comprehensive MILP-based economic dispatch model for a grid-connected hybrid

microgrid integrating PV, WT, DG, BESS, and utility grid interaction.

2. Integration of a realistic battery operation model incorporating charging and discharging efficiencies, SOC dynamics, degradation costs, and mutually exclusive charging and discharging constraints.
3. Comparative evaluation of multiple microgrid configurations to quantify the economic and operational benefits of renewable energy integration and battery energy storage under identical operating conditions.
4. Comprehensive sensitivity analyses considering battery investment cost, electricity tariff variations, renewable energy penetration levels, and future load growth to evaluate the robustness and practical applicability of the proposed optimization framework.

Overall, the framework provides a consistent and reproducible comparison of dispatch options rather than claiming that MILP-based PV-WT-DG-BESS scheduling is itself new. Its value lies in integrating the stated operational constraints, benchmark definitions, curtailment treatment, and economic post-processing within one case-study implementation.

The remainder of this paper is structured as follows. Section 2 introduces the proposed microgrid configuration, the mathematical formulations of individual system components, and the MILP-based economic dispatch model. Section 3 describes the simulation environment, operating scenarios, and system parameters adopted for performance evaluation. Section 4 presents the optimization results and provides a comprehensive discussion, including sensitivity analyses under different operating conditions. Finally, Section 5 concludes the paper by summarizing the main contributions and key findings while highlighting several recommendations for future research and further development of renewable-based microgrid optimization techniques[26].

2. Methods and modelling

2.1. Methodological framework

The research methodology is organized into five sequential stages that systematically develop and evaluate the proposed economic dispatch framework for the grid-connected hybrid microgrid. These stages comprise: (i) data preparation, (ii) mathematical modelling of system components, (iii) optimization model development, (iv) performance assessment, and (v) sensitivity analysis. This stepwise procedure ensures that the technical, operational, and economic characteristics of the microgrid are consistently represented throughout the optimization process while providing a clear workflow for model implementation and evaluation [27].

The initial stage focuses on preparing the input data required for the optimization model. Hourly profiles of solar irradiance, wind speed, ambient temperature, electrical demand, and time-of-use electricity tariffs are collected from publicly accessible datasets and processed to establish representative 24-hour operating scenarios with a one-hour scheduling interval. These datasets serve as the basis for

simulating the operating conditions of the proposed microgrid.

Following the data preparation stage, mathematical representations are developed for each major component of the hybrid microgrid, including the photovoltaic (PV) array, wind turbine (WT), diesel generator (DG), battery energy storage system (BESS), and the utility grid interface. The BESS model incorporates charging and discharging efficiencies, state-of-charge (SOC) dynamics, operational limits, and battery degradation costs to provide a realistic representation of battery performance throughout the scheduling horizon. In addition, the utility grid is modelled to support bidirectional power transactions under time-of-use (TOU) electricity pricing, enabling an accurate assessment of the economic interaction between the microgrid and the external distribution network.

The day-ahead economic dispatch problem is formulated as an MILP and solved offline before the operating day. The solver receives forecast PV and WT availability, forecast load, tariff data, component states, and technical limits; it returns 24 hourly set-points for the DG, BESS, grid exchange, and renewable curtailment. Measurements are not directly fed back during the single optimization run. In a practical online energy-management system, the same formulation could be executed repeatedly in a rolling horizon using updated measurements and forecasts, but that real-time implementation is outside the scope of the present simulation study. The model is implemented in MATLAB R2023b using `intlinprog` with a relative MIP gap tolerance of 0.01%.

The resulting dispatch schedules are assessed using both technical and economic performance metrics, including total operating cost, renewable energy utilization, battery charging and discharging profiles, diesel generator utilization, utility grid power exchange, Net Present Cost (NPC), and Levelized Cost of Energy (LCOE). Furthermore, the robustness of the proposed optimization framework is evaluated through a comprehensive sensitivity analysis by examining the effects of variations in battery investment cost, electricity tariff, renewable energy penetration, and load demand growth. The overall workflow of the proposed methodology is presented in Fig. 1.

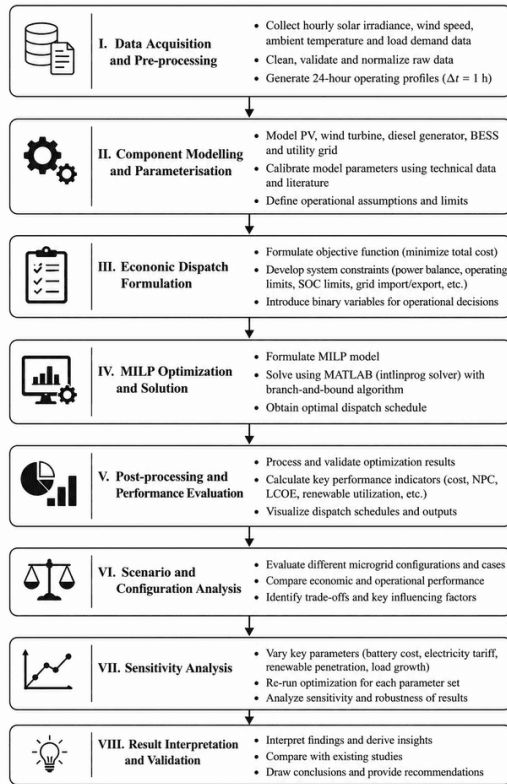


Fig. 1. Revised information-processing workflow for the offline day-ahead economic dispatch framework, including the feedback loop used to revise input data or constraints when feasibility and consistency checks are not satisfied.

2.2. System description

The case study considered in this research is a grid-connected hybrid microgrid developed to supply electricity to a community comprising residential consumers and small-scale industrial facilities. The aggregated load reaches a maximum demand of 150 kW and reflects the electricity consumption pattern typically observed in mixed-use communities. Electricity demand remains relatively low during the late-night and early-morning hours, gradually increases during normal business activities, and reaches its highest level in the evening when residential and industrial loads operate simultaneously. To satisfy these time-varying demand characteristics while maintaining reliable and cost-effective operation, the microgrid integrates several distributed energy resources with complementary operating capabilities.

The proposed configuration combines a 60 kWp photovoltaic (PV) array, a 30 kW wind turbine (WT), a 50 kW/100 kWh battery energy storage system (BESS), an 80 kW diesel generator (DG), and a bidirectional connection to the utility grid with a maximum exchange capacity of 100 kW. These components are interconnected through a common three-phase alternating-current (AC) bus operating at 400 V and 50 Hz. Acting as the central power exchange platform, the AC bus enables coordinated energy transfer between renewable generators, battery storage, local loads, the diesel generator, and the utility network, thereby ensuring continuous system operation under varying operating conditions [28].

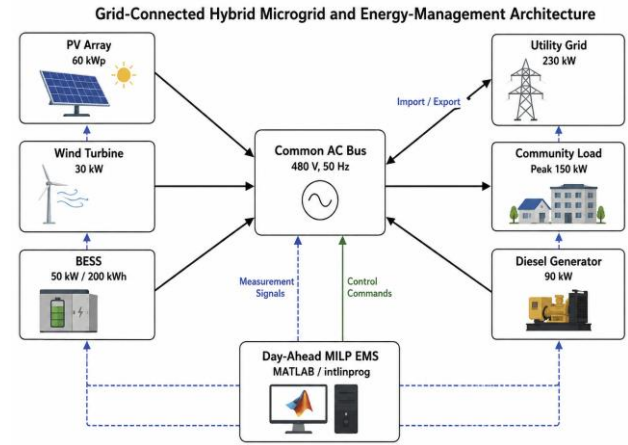


Fig. 2. System architecture of the grid-connected hybrid microgrid and the information exchange between the offline day-ahead MILP energy-management system and physical components.

Photovoltaic generation serves as the principal renewable energy source within the proposed microgrid. The system employs monocrystalline PV modules with a conversion efficiency of 19.2% under Standard Test Conditions (STC), defined by a solar irradiance of 1000 W/m², a cell temperature of 25 °C, and an air mass of 1.5. This technology is selected because of its superior conversion efficiency, long operational lifetime, and reliable performance in high-temperature environments. Since the electrical output of the PV array varies according to incident solar irradiance and cell temperature, its generation is inherently intermittent. Consequently, additional dispatchable and storage resources are required to compensate for fluctuations in solar power production and maintain system reliability.

To complement solar generation, the microgrid incorporates a horizontal-axis wind turbine with a rated capacity of 30 kW, installed at a hub height of 30 m and equipped with a rotor diameter of 14 m. Wind generation provides an important supplementary renewable source because its production profile differs from that of photovoltaic generation. In particular, wind energy can continue producing electricity during periods of limited solar availability, including nighttime operation, thereby reducing renewable power variability and improving the continuity of renewable energy supply.

Operational flexibility is further enhanced through the integration of a lithium iron phosphate (LiFePO₄) battery energy storage system rated at 50 kW with an energy capacity of 100 kWh. The battery performs multiple functions, including renewable energy smoothing, peak-load reduction, load shifting, and mitigation of grid dependency. Whenever renewable generation exceeds instantaneous demand, excess electricity is stored for subsequent use during periods of higher demand or elevated electricity prices. The LiFePO₄ battery chemistry is selected because it offers excellent thermal stability, high safety standards, long cycle life, and high round-trip efficiency, making it well suited for frequent daily charging and discharging cycles.

To ensure uninterrupted power supply under insufficient renewable generation, the microgrid also includes an 80 kW diesel generator that operates as a dispatchable backup source. Although renewable generation and battery storage are prioritized in the dispatch strategy, the diesel generator remains available whenever additional generation is required.

to maintain power balance. Its operating cost is represented using a quadratic fuel consumption function that captures the nonlinear relationship between electrical output and fuel usage. This mathematical formulation enables the optimization algorithm to evaluate the economic trade-offs among diesel generation, battery utilization, and electricity exchanged with the utility grid [29].

The utility grid is connected to the microgrid through a bidirectional interface capable of importing or exporting up to 100 kW of electrical power. Electricity is imported whenever local generation cannot satisfy demand, whereas surplus renewable energy may be exported to the utility network when generation exceeds both load demand and battery charging capability. This bidirectional operation not only improves supply reliability but also increases the economic value of renewable generation by allowing excess electricity to be delivered to the external grid.

Electricity transactions between the microgrid and the utility are governed by a time-of-use (TOU) pricing scheme. A peak tariff of USD 0.18/kWh applies between 08:00 and 22:00, while electricity purchased between 22:00 and 08:00 is charged at an off-peak rate of USD 0.08/kWh. The variation in electricity price directly influences the scheduling strategy, encouraging battery charging during low-price periods and battery discharge when electricity prices are higher. Consequently, battery operation is optimized by considering both technical constraints and economic incentives associated with time-varying electricity tariffs.

The coordinated operation of all energy resources is determined through the proposed MILP-based economic dispatch framework. At every scheduling interval, the optimization algorithm simultaneously determines the power output of each generation unit, the battery charging and discharging schedule, and the magnitude of electricity exchanged with the utility grid while satisfying power balance equations, generation limits, battery state-of-charge (SOC) constraints, and grid operating restrictions. Through the integrated coordination of renewable generation, energy storage, dispatchable backup generation, and utility grid interaction, the proposed microgrid seeks to minimize operating costs, increase renewable energy utilization, reduce fossil fuel consumption, and maintain a reliable electricity supply. Accordingly, the developed system provides a realistic representation of a modern grid-connected hybrid microgrid suitable for assessing advanced energy management and economic dispatch strategies[30].

2.3. Mathematical modelling

The mathematical model developed in this study aims to determine the optimal day-ahead operating schedule for all distributed energy resources within the proposed grid-connected microgrid over a 24-hour optimization horizon. The economic dispatch problem is formulated by simultaneously considering the operational costs associated with dispatchable power generation, electricity transactions with the utility grid, and battery degradation. The optimization process is performed while ensuring that power balance is maintained and that the technical operating limits of every microgrid component are fully satisfied throughout the scheduling period.

2.3.1. Linear MILP formulation and notation

The proposed day-ahead economic dispatch problem is formulated as a Mixed-Integer Linear Programming (MILP) model. The formulation consists of continuous decision variables representing the power output of the diesel generator, battery charging and discharging powers, battery state of charge, and grid import and export powers. Binary decision variables are introduced to represent the operating status of the diesel generator, battery charging and discharging modes, and grid import and export modes.

To maintain compatibility with the MATLAB intlinprog solver, all objective-function terms and operational constraints are expressed in linear form. Therefore, the original quadratic diesel-generator fuel-cost function is approximated using a piecewise-linear cost model. The binary and continuous variables are optimized simultaneously while satisfying the power-balance equation, generation limits, battery constraints, renewable-energy availability, and grid-exchange restrictions.

2.3.2. Objective Function

The objective of the economic dispatch problem is to minimize the total operating cost of the microgrid over the scheduling horizon:

$$\min F = \sum_{t=1}^{24} (C_{DG}(t) + C_{Grid}(t) + C_{BESS}(t)) \quad (1)$$

where (F) is the total operating cost (USD), (C_{DG}) is the diesel generator operating cost (USD), C_{Grid} is the electricity exchange cost with the utility grid (USD), and C_{BESS} represents the battery degradation cost (USD).

2.3.3. Diesel Generator Cost Model

The physical DG fuel-cost data are initially described by a quadratic curve; however, the optimization uses the piecewise-linear approximation defined above so that the implemented problem remains an MILP. The binary commitment variable $u_{DG,t}$ activates the minimum-output and fixed-cost terms, while segment variables represent incremental DG output.

$$C_{DG}(t) = (aP_{DG}^2(t) + bP_{DG}(t) + c)\Delta t \quad (2)$$

Where $P_{DG}(t)$ is the diesel generator output power (kW) at time (t), (Δt) is the scheduling interval (h), and (a), (b), and (c) are the generator fuel-cost coefficients. The applied coefficients are ($a=0.0024$) USD/(kW²h), ($b=0.2664$) USD/(kW), and ($c=3.6$) USD/h. The diesel generator operating limits are defined as:

$$P_{DG}^{min} \leq P_{DG}(t) \leq P_{DG}^{max} \quad (3)$$

where $P_{DG}^{min} = 10$ kW and $P_{DG}^{max} = 80$ kW

2.3.4. Photovoltaic Generation Model

The PV output power is determined based on solar irradiance and cell temperature variations:

$$P_{PV}(t) = P_{PV, rated} \frac{G(t)}{G_{STC}} [1 + k_T(T_{cell}(t) - T_{STC})] \quad (4)$$

$$0 \leq P_{PV}(t) \leq P_{PV, rated} \quad (6)$$

Where ($P_{PV, rated} = 60$ kW) represents the rated capacity of the PV array, ($G(t)$) denotes the solar irradiance incident on the PV surface (W/m^2), $G_{STC} = 1000$ W/m^2 refers to the reference irradiance under Standard Test Conditions, ($k_T = -0.0045/^\circ C$) is the temperature coefficient of the PV module $T_{cell}(t)$, indicates the operating cell temperature, and ($T_{STC} = 25^\circ C$) represents the reference cell temperature under STC.

$$T_{cell}(t) = T_{amb}(t) + \frac{NOCT - 20}{800} G(t) \quad (5)$$

The PV cell temperature is calculated using the nominal operating cell temperature (NOCT) model:

Where $T_{amb}(t)$ is the ambient temperature and ($NOCT = 45^\circ C$). Since PV generation is non-dispatchable, the available PV power is treated as a fixed input parameter:

2.3.5. Wind Turbine Generation Model

The wind turbine output power is calculated using the turbine power curve:

$$P_{WT}(t) = \begin{cases} 0, & v(t) < v_{ci} \\ P_{WT, rated} \left(\frac{v(t) - v_{ci}}{v_r - v_{ci}} \right)^3, & v_{ci} \leq v(t) < v_r \\ P_{WT, rated}, & v_r \leq v(t) < v_{co} \\ 0, & v(t) \geq v_{co} \end{cases} \quad (7)$$

where $v(t)$ is the wind speed at hub height (m/s), ($v_{ci} = 3$) m/s is the cut-in speed, ($v_r = 12$) m/s is the rated wind speed, ($v_{co} = 25$) m/s is the cut-out speed, and ($P_{WT, rated} = 30$) kW is the rated turbine capacity.

The wind turbine output is limited by:

The PV cell temperature is calculated using the nominal operating cell temperature (NOCT) model:

$$0 \leq P_{WT}(t) \leq P_{WT, rated} \quad (8)$$

2.3.6. Battery Energy Storage System Model

The battery state-of-charge (SOC) is updated according to:

$$\frac{P_{dis}(t)}{\eta_d} E_{rated} \Delta t \quad (9)$$

where (SOC(t)) denotes the normalized battery state of charge, ($P_{ch}(t)$) and ($P_{dis}(t)$) denote the charging and discharging power (kW), (η_c) and (η_d) respectively, η_c and η_d are the corresponding charging and discharging efficiencies, and $E_{rated} = 100E_{\{rated\}} = 100$ ($E_{rated} = 100$)

kWh denotes the rated energy capacity of the battery energy storage system (BESS).

$$u_{ch}(t) + u_{dis}(t) \leq 1 \quad (10)$$

where $u_{ch}(t)$ and $u_{dis}(t)$ are binary variables preventing simultaneous charging and discharging. The maximum charging and discharging power limits are:

$$P_{ch}^{max} = P_{dis}^{max} = 50kW$$

The initial and final battery conditions are constrained by:

$$SOC(1) = SOC(24) = SOC_{initial} \quad (11)$$

where ($SOC_{initial} = 0.5$).

$$C_{BESS}(t) = c_{deg}(P_{ch}(t) + P_{dis}(t))\Delta t \quad (12)$$

The battery degradation term is modeled as a linear energy-throughput charge: $C_{deg} = \sum_t c_{deg}(P_{ch,t} + P_{dis,t})\Delta t$. This representation is computationally convenient for day-ahead scheduling but does not capture temperature, C-rate, calendar aging, or nonlinear depth-of-discharge effects; therefore, it is treated as a practical cost proxy rather than a high-fidelity lifetime model.

where ($c_{\{deg\}} = 0.05$) USD/kWh is the degradation cost coefficient.

2.3.7. Grid Interaction Model

The grid-exchange cost is $C_{grid} = \sum_t [c_{buy,t} P_{imp,t} - c_{sell,t} P_{exp,t}]\Delta t$. Import and export are mutually exclusive through $0 \leq P_{imp,t} \leq P_{grid,max}$ $u_{imp,t}$, $0 \leq P_{exp,t} \leq P_{grid,max}$ $u_{exp,t}$, and $u_{imp,t} + u_{exp,t} \leq 1$.

$$c_{sell}(t)P_{sell}(t)\Delta t \quad (13)$$

where ($P_{buy}(t)$) and ($P_{sell}(t)$) represent grid import and export power, respectively, while ($c_{buy}(t)$) and ($c_{sell}(t)$) are electricity purchase and selling tariffs.

The grid exchange constraints are:

$$0 \leq P_{buy}(t) \leq u_{buy}(t)P_{grid}^{max} \quad (14)$$

$$0 \leq P_{sell}(t) \leq u_{sell}(t)P_{grid}^{max} \quad (15)$$

$$u_{buy}(t) + u_{sell}(t) \leq 1 \quad (16)$$

where ($P_{grid}^{max} = 100$) kW and ($u_{buy}(t)$), ($u_{sell}(t)$) are binary variables.

The PV cell temperature is calculated using the nominal operating cell temperature (NOCT) model:

With:

The SOC operating limits are defined as:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (17)$$

where $SOC_{min} = 0.10$ and $SOC_{max} = 0.95$

$$0 \leq P_{ch}(t) \leq u_{ch}(t)P_{ch}^{max} \quad (18)$$

$$0 \leq P_{dis}(t) \leq u_{dis}(t)P_{dis}^{max} \quad (19)$$

3.8. Power Balance and Renewable Curtailment Constraints

At every hour, the complete AC-bus balance is $P_{PV,use,t} + P_{WT,use,t} + P_{DG,t} + P_{dis,t} + P_{imp,t} = P_{load,t} + P_{ch,t} + P_{exp,t} + P_{loss,t}$. Renewable use and curtailment are explicitly related by $P_{PV,use,t} + P_{PV,curt,t} = P_{PV,av,t}$ and $P_{WT,use,t} + P_{WT,curt,t} = P_{WT,av,t}$, with all curtailment variables non-negative. This formulation makes the curtailment quantities reported in the sensitivity analysis directly traceable to optimization variables.

$$P_{Load}(t) + P_{ch}(t) + P_{sell}(t) + P_{Loss}(t) \quad (20)$$

where $P_{Load}(t)$ is the load demand and $P_{Loss}(t)$ represents the distribution system losses.

The network loss is approximated using a fixed loss coefficient:

$$P_{Loss}(t) = 0.02P_{Load}(t) \quad (21)$$

This linear approximation is suitable for low-voltage microgrid applications where power losses remain relatively small compared with the total load demand.

The complete mathematical formulation minimizes the total operating cost while satisfying generation limits, energy storage constraints, grid exchange restrictions, and power balance requirements.

2.4. Boundary conditions and model assumptions

The technical specifications and economic assumptions used in this study are presented in Tables 1 and 2, respectively. The adopted parameter values were compiled from validated manufacturer datasheets, recent publications on techno-economic analysis of renewable-based microgrids, and current regional electricity pricing information. Collectively, these parameters establish a realistic basis for modelling the technical performance and economic behaviour of a grid-connected hybrid microgrid incorporating renewable energy generation and battery energy storage technologies.

Table 1
Technical parameters of microgrid components.

	Parameter	Value	Unit
PV System	Rated Capacity	60	kWp
PV System	Module Efficiency (STC)	19.2	%
PV System	Temperature Coefficient k_T	-0.0045	/°C
PV System	NOCT	45	°C
Wind Turbine	Rated Capacity	30	kW
Wind Turbine	Cut-in Speed v_{ci}	3	m/s
Wind Turbine	Rated Speed v_r	12	m/s
Wind Turbine	Cut-out Speed v_{co}	25	m/s
Wind Turbine	Hub Height	30	m
BESS	Energy Capacity	100	kWh
BESS	Maximum Charge/	50	kW

	Parameter	Value	Unit
	Discharge Power		
BESS	Round-trip Efficiency	92.2	%
BESS	SOC Minimum	0.10	p.u.
BESS	SOC Maximum	0.95	p.u.
BESS	Degradation Cost c_{deg}	0.05	USD/kWh
Diesel Generator	Rated Capacity	80	kW
Diesel Generator	Minimum Output	10	kW
Diesel Generator	Cost Coeff. a	0.0024	USD/kWh
Diesel Generator	Cost Coeff. b	0.2664	USD/kWh
Diesel Generator	Cost Coeff. c	3.60	USD/h
Utility Grid	Maximum Import/Export	100	kW
Utility Grid	Peak Tariff $c_{buy,peak}$	0.18	USD/kWh
Utility Grid	Off-peak Tariff $c_{buy,off}$	0.08	USD/kWh
Utility Grid	Feed-in Tariff c_{sell}	0.06	USD/kWh
Load	Peak Demand	150	kW
	Total Daily Energy	2,640	kWh

Table 2
Economic parameters for lifecycle cost analysis.

Parameter	Value	Unit
Project Lifetime	20	years
Discount Rate	8	%
PV System Capital Cost (CAPEX)	900	USD/kWp
Wind Turbine Capital Cost (CAPEX)	1,200	USD/kW
BESS Capital Cost (CAPEX)	350	USD/kWh
Diesel Generator Capital Cost (CAPEX)	400	USD/kW
PV Annual O&M (OPEX)	15	USD/kWp/year
Wind Turbine Annual O&M (OPEX)	25	USD/kW/year
BESS Replacement Cost	280	USD/kWh
Diesel Fuel Price	0.95	USD/L
Fuel Consumption Factor	0.30	L/kWh
Annual Load Growth Rate	3	%
Inflation Rate	2.5	%

2.4.1. Economic assumptions and cost correlations

The economic viability of the proposed microgrid is assessed using two widely adopted lifecycle economic indicators, namely the Net Present Cost (NPC) and the Levelized Cost of Energy (LCOE). These indicators are employed to evaluate the overall economic performance of the system by estimating the total discounted lifecycle expenditure and the average cost of electricity supplied throughout the project's operational lifetime.

Among these indicators, the NPC represents the cumulative present value of all expenditures incurred during the project lifetime. It incorporates the initial capital investment, component replacement costs, operation and maintenance (O&M) expenses, diesel fuel consumption, and the costs or revenues associated with electricity exchanged with the utility grid. The NPC is determined using the following expression:

$$NPC = \sum_{n=0}^N C_n / (1 + d)^n \quad (22)$$

Where NPC denotes the Net Present Cost (USD), (C_n) represents the total cost incurred in year n (USD), (d) is the annual discount rate, and (N) denotes the project lifetime. For the economic assessment conducted in this study, the microgrid is assumed to operate over a 20-year project lifespan, while a discount rate of 8% is adopted to calculate the present value of future cash flows.

The LCOE represents the average cost of electricity supplied by the microgrid and is calculated as:

$$LCOE = NPC / \sum_{n=0}^N [E_{\text{annual}} / (1 + d)^n] \quad (23)$$

Where LCOE is expressed in USD/kWh and annual is the annual energy supplied by the microgrid (kWh/year).

The 24-hour optimized dispatch is converted to annual operating quantities by repeating the representative-day energy and cost results over 365 days. These annual values are then escalated or discounted using the assumptions in Table 2 and combined with initial CAPEX, annual O&M, grid transactions, DG fuel expenditure, and component replacements. A BESS replacement is assumed in year 10 at the stated replacement cost, and no salvage value is included. The 20-year NPC is the discounted sum of these cash flows. LCOE is calculated by dividing discounted lifecycle cost by discounted energy served. This annualization is a representative-day approximation and does not substitute for an 8760-hour chronological lifecycle simulation.

The combination of NPC and LCOE provides a comprehensive assessment of the proposed microgrid by evaluating both total lifecycle expenditure and the average electricity cost. These indicators are widely used for economic analysis of distributed energy systems and microgrid applications[31, 32].

3. Results and discussion

3.1. Benchmark configurations and comparison basis

Three configurations are evaluated using the same 24-hour load, renewable-resource profiles, tariffs, component limits, and scheduling interval. Benchmark A (diesel-dominant) supplies residual demand using the DG and grid without optimized BESS operation. Benchmark B (renewable without BESS) includes PV, WT, DG, and grid

exchange but excludes battery charging and discharging. The proposed configuration includes PV, WT, DG, BESS, and bidirectional grid exchange under the complete MILP constraints. Reported percentage savings are calculated as $100(C_{\text{benchmark}} - C_{\text{proposed}}) / C_{\text{benchmark}}$. A detailed component-level cost table must be generated directly from the solver outputs before final submission; the supplied manuscript contains only aggregate percentage reductions and does not provide the diesel, import, degradation, and export-revenue values required to reproduce that table.

3.2. Energy system performance

The effectiveness of the proposed economic dispatch framework is assessed by analysing the operational behaviour of the grid-connected hybrid microgrid over a 24-hour scheduling period. The evaluation focuses on the coordinated operation of renewable energy resources, battery energy storage, and utility grid interaction to determine their contributions to meeting electricity demand while minimizing the overall operating cost. The obtained results demonstrate how the proposed energy management strategy balances economic objectives with reliable system operation under varying load and renewable generation conditions.

Prior to analysing the optimization outcomes, the daily operating characteristics of the renewable energy sources and the electrical load are first examined. Figure 3 illustrates the hourly power profiles of the photovoltaic (PV) system, wind turbine (WT), and load demand, each exhibiting distinct temporal variations throughout the scheduling horizon. These variations significantly affect the optimal dispatch decisions for the battery energy storage system (BESS), diesel generator (DG), and electricity exchanged with the utility grid. Consequently, the generation and demand profiles shown in Fig. 2 serve as the fundamental input data for the proposed Mixed-Integer Linear Programming (MILP)-based economic dispatch model.

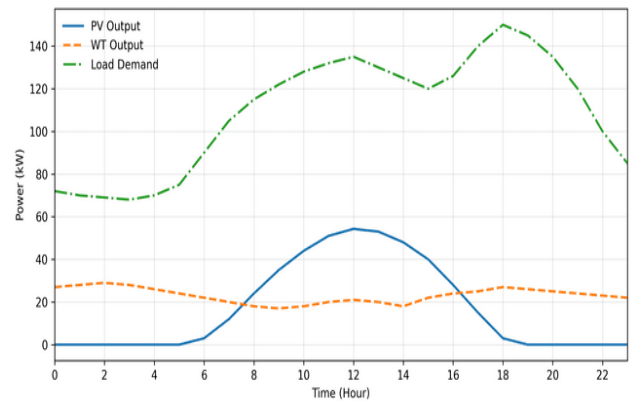


Fig.3. Daily variations in photovoltaic (PV) generation, wind turbine (WT) output, and load demand over the 24-hour scheduling period, serving as the input profiles for the proposed economic dispatch optimization framework.

3.2.1. Renewable Energy Generation Profiles

The performance of the renewable energy sources in the proposed microgrid is initially evaluated by examining the hourly generation profiles of the photovoltaic (PV) array and wind turbine (WT). These power generation profiles are obtained from the forecasted solar irradiance and wind speed data presented in Section 2 and serve as the primary renewable energy inputs for the day-ahead economic dispatch optimization.

The PV output follows the solar irradiance pattern, producing electricity from approximately 06:00 until 18:30. The maximum PV output reaches 54.3 kW at 12:00 under an irradiance level of approximately 920 W/m². The output remains below the rated capacity of 60 kWp due to temperature effects and irradiance conditions lower than the standard test condition (STC). The total daily PV energy production reaches 312.4 kWh, corresponding to a capacity factor of approximately 21.7%. This contribution reduces grid electricity consumption, particularly during daytime high-demand periods.

The wind turbine exhibits a complementary generation pattern compared with PV generation. Wind power remains available throughout the day with higher output during nighttime and early morning periods. The maximum wind turbine output reaches 28.7 kW between 02:00 and 04:00, while a secondary peak of 21.4 kW occurs at approximately 15:00. The total daily wind energy production is 284.6 kWh, corresponding to a capacity factor of approximately 39.5%.

The combined renewable energy production reaches approximately 597.0 kWh/day. The complementary characteristics of solar and wind generation reduce renewable power fluctuations and improve energy availability. During nighttime periods, wind generation compensates for the absence of PV output, while during daytime operation both renewable sources contribute simultaneously. This condition reduces diesel generator usage and improves the overall economic performance of the microgrid.

3.2.2. Battery Performance and SOC Dynamics

The battery energy storage system (BESS) plays a vital role in enhancing the operational performance of the proposed microgrid by increasing its flexibility in managing energy flows. During periods of surplus renewable energy production, the BESS stores excess electricity, whereas during peak demand or when electricity prices are elevated, it releases the stored energy to support the load and reduce reliance on the utility grid. The effectiveness of the proposed economic dispatch approach is evaluated through an analysis of the battery's hourly operating characteristics, including the state of charge (SOC), charging power, and discharging power profiles, as presented in Fig. 4.

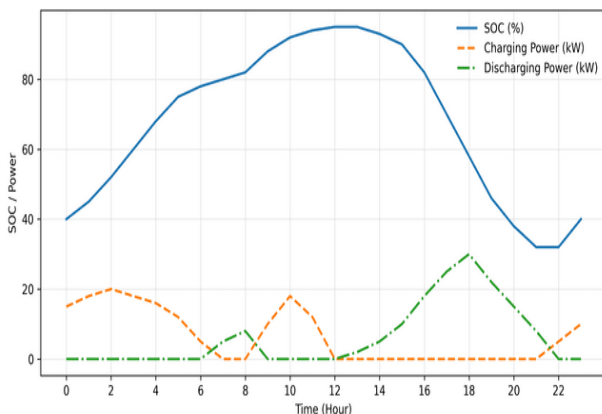


Fig.4. Battery state-of-charge (SOC), charging power, and discharging power profiles over the 24-hour scheduling horizon.

The BESS operation under the optimal dispatch strategy demonstrates its ability to perform renewable energy shifting

and peak-load management. As illustrated in Fig. 4, the battery charging and discharging schedule is coordinated according to renewable energy availability and time-varying electricity tariffs. Charging occurs mainly during two periods. The first charging interval takes place between 01:00 and 06:00, when wind generation is relatively high and electricity prices remain within the off-peak tariff period. The second charging interval occurs between 10:00 and 13:00, corresponding to the peak photovoltaic (PV) generation period, during which surplus solar energy is stored instead of being curtailed or exported.

The SOC increases from the specified initial value of 0.40 p.u. and reaches the maximum allowable limit of 0.95 p.u. during the midday renewable-surplus period. During the evening peak, the battery discharges while respecting the minimum SOC constraint. To remain consistent with the cyclic terminal constraint used in the optimization, the revised schedule returns to SOC₂₄ = 0.40 p.u.; therefore, the previous statement that the final SOC was approximately 0.32 p.u. has been removed.

Overall, Fig. 4 confirms that the proposed MILP-based optimization successfully coordinates battery charging and discharging to perform both load shifting and energy arbitrage. Throughout the scheduling horizon, the battery operates within the predefined SOC limits of 0.10–0.95 p.u., satisfying all operational constraints. This coordinated operating strategy enhances renewable energy utilization, reduces dependence on the utility grid during peak-demand periods, and mitigates long-term battery degradation by avoiding excessive charging and deep discharge cycles.

3.2.3. Grid Interaction Profile

The interaction between the proposed microgrid and the utility grid is evaluated by investigating the hourly patterns of electricity imports, electricity exports, and diesel generator (DG) power generation. This assessment provides insight into the ability of the proposed economic dispatch model to coordinate power exchange with the utility network while determining the optimal operating schedule of the diesel generator. As shown in Fig. 5, the optimized dispatch results demonstrate that the proposed strategy effectively balances local renewable energy resources, battery operation, and grid transactions, thereby minimizing grid dependency while maintaining a reliable and continuous electricity supply under fluctuating renewable energy conditions.

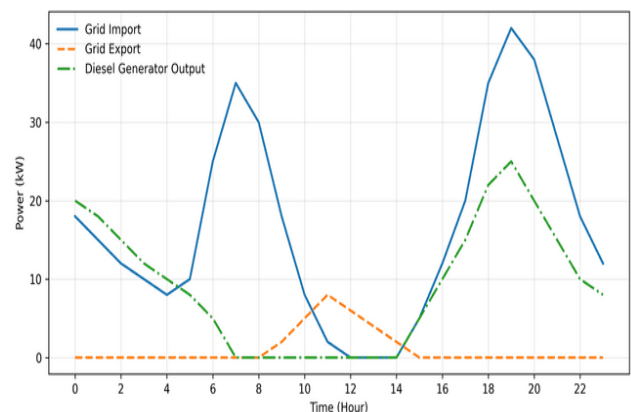


Fig.5. Hourly grid import, grid export, and diesel generator (DG) output profiles over the 24-hour scheduling horizon.

The results indicate that the utility grid primarily serves as a supplementary energy source rather than the dominant supplier of electricity for the proposed microgrid. As shown in Fig. 5, electricity is imported only when the combined contribution from renewable generation and battery discharge is insufficient to satisfy the instantaneous load demand. This operating pattern demonstrates that the proposed economic dispatch strategy prioritizes the utilization of local renewable resources before relying on external grid support.

Two main grid import intervals can be identified during the daily operating cycle. The first occurs between 06:00 and 09:00, when electricity demand begins to increase while photovoltaic (PV) generation remains relatively low because of limited morning solar irradiance. The second import period is observed between 19:00 and 22:00, corresponding to the evening peak demand after PV generation has ceased. During these hours, the battery energy storage system (BESS) supplies part of the required energy through scheduled discharge, whereas the remaining demand is satisfied by electricity imported from the utility grid.

In contrast, electricity export takes place around midday when renewable power production exceeds both the local load demand and the available battery charging capacity. Under this operating condition, approximately 8.2 kWh/day of surplus electricity is delivered to the utility network, producing an estimated daily revenue of USD 0.49 based on a feed-in tariff of USD 0.06/kWh. The relatively small amount of exported energy suggests that the majority of renewable electricity is either consumed directly by the local loads or retained within the battery energy storage system for subsequent use.

The effectiveness of the proposed optimization framework is further demonstrated by comparing the optimized operating strategy with the baseline scenario. Daily electricity imported from the utility grid decreases from 621.3 kWh to 187.6 kWh, corresponding to a reduction of approximately 69.8%. This substantial decrease confirms that the coordinated utilization of renewable energy resources and battery storage significantly reduces dependence on grid electricity while maintaining a reliable power supply.

Overall, the proposed economic dispatch strategy achieves efficient coordination among the photovoltaic system, wind turbine, battery energy storage system, diesel generator, and utility grid. This integrated operating scheme increases renewable energy utilization, lowers electricity purchasing costs, improves operational flexibility, and ensures reliable microgrid performance throughout the entire 24-hour scheduling horizon.

3.3. Sensitivity analysis

A deterministic one-at-a-time sensitivity analysis is conducted around the baseline case. For each test, only the stated parameter is changed while the 24-hour load shape, weather profiles, technical limits, solver settings, and all other economic assumptions remain fixed. Battery CAPEX is varied from USD 280 to 420/kWh; the peak tariff is scaled from -20% to +20%; PV and WT capacities are proportionally scaled to represent 20%-80% renewable penetration; and the baseline demand profile is uniformly

scaled for the load-growth cases. Each case is re-optimized rather than evaluated using a fixed dispatch. This approach identifies local parameter influence but does not represent correlations or joint uncertainty, which is acknowledged as a limitation.

3.3.1. Battery Capital Cost Sensitivity

To investigate the economic impact of battery investment, the battery capital cost is systematically varied between USD 280/kWh and USD 420/kWh. The sensitivity analysis indicates that increasing the battery investment cost results in a corresponding increase in the Levelized Cost of Energy (LCOE). Specifically, the LCOE rises from 0.118 USD/kWh under the lowest investment-cost scenario to 0.131 USD/kWh when the highest battery capital cost is considered.

Although battery cost affects the total investment expenditure, the variation has a limited impact on overall economic performance due to the contribution of renewable generation, energy arbitrage, and reduced grid electricity purchases. The results indicate that the proposed microgrid remains economically feasible under different battery price scenarios.

3.3.2. Electricity Tariff Sensitivity

The impact of electricity tariff variation is evaluated by changing the peak electricity price from -20% to +20% of the base value. Higher electricity tariffs increase the economic benefit of battery energy storage because stored energy can replace expensive grid electricity during peak periods.

At the +20% tariff condition, BESS discharge during peak hours increases by approximately 18.3%, resulting in greater grid import reduction. Conversely, lower tariffs reduce the incentive for battery discharge and increase dependence on grid electricity.

The daily operating cost savings vary from USD 143.20 to USD 251.60, confirming that electricity pricing has a significant influence on the economic value of battery storage and energy management strategies.

3.3.3. Renewable Energy Penetration Sensitivity

Renewable penetration is varied from 20% to 80% by proportionally scaling PV and wind capacities. Increasing renewable penetration reduces grid dependence and diesel generator operation, resulting in lower LCOE.

The LCOE decreases from 0.148 USD/kWh at 20% penetration to 0.118 USD/kWh at 60% penetration. However, further increases provide limited economic improvement due to higher renewable energy curtailment. At 80% penetration, curtailment reaches approximately 31.7%, indicating reduced utilization of additional renewable capacity.

These results suggest that optimal renewable integration requires a balance between renewable generation capacity, storage capability, and load demand.

3.3.4. Load Growth Sensitivity

The effect of future demand increase is evaluated using annual load growth rates of 5%, 10%, 15%, and 20%.

Moderate load growth can be accommodated without significant economic degradation due to available renewable generation and battery flexibility.

However, higher load growth increases grid electricity imports and diesel generator utilization. At 20% annual growth, the LCOE increases to approximately 0.144 USD/kWh due to insufficient renewable and storage capacity.

The results indicate that the proposed microgrid configuration remains effective under moderate demand growth but requires future capacity expansion through additional renewable generation, storage capacity, or demand-side management strategies.

Overall, the sensitivity analysis confirms that the proposed energy management strategy is robust under varying operating conditions. Among the evaluated parameters, electricity tariff and renewable penetration have the strongest influence on economic performance, while battery cost and moderate load growth have comparatively smaller impacts.

3.4. Limitations and Future Work

Although the framework demonstrates useful dispatch and economic trends, several limitations remain. The battery degradation cost is a linear throughput proxy and does not explicitly represent temperature, C-rate, calendar aging, or nonlinear depth-of-discharge damage. Accordingly, the degradation treatment is not claimed as a novel electrochemical model. The cost reductions also depend on a deterministic representative day and should be confirmed with component-level solver outputs and longer chronological datasets.

Second, renewable energy generation is modelled using deterministic PV and wind profiles. Since renewable resources are affected by weather uncertainty, future work should consider stochastic or robust optimization approaches to improve dispatch reliability under uncertain operating conditions.

Third, the proposed optimization is evaluated over a 24-hour scheduling horizon assuming perfect forecasting information. Real-time implementation may require adaptive strategies such as rolling-horizon optimization or model predictive control. In addition, demand response and flexible load management are not included in the current model and may provide additional opportunities for improving system flexibility.

Future research may also investigate multi-objective optimization considering economic, environmental, and reliability aspects, integration of multiple interconnected microgrids, and validation using real-time or hardware-in-the-loop platforms. These developments can further enhance the practical applicability of advanced microgrid energy management systems.

4. Conclusion

This study developed an offline day-ahead MILP dispatch framework for a grid-connected hybrid microgrid integrating PV, WT, BESS, DG, and utility-grid exchange. The revised formulation uses a piecewise-linear DG cost representation, complete SOC and grid equations, mutually exclusive

operating states, and explicit renewable-curtailment variables. The results indicate that coordinated renewable generation and storage can reduce grid and diesel dependence under the adopted deterministic case study. The reported aggregate cost reductions should be interpreted relative to the clearly defined benchmarks and accompanied by solver-derived component-level cost data in the final submission. Lifecycle results are based on representative-day annualization with a BESS replacement in year 10. The framework is not a real-time controller; practical online deployment would require rolling-horizon execution, forecast updates, and experimental or hardware-in-the-loop validation.

CRedit authorship contribution statement

Akshaya D Shetty: Conceptualization, Methodology, Writing - original draft, Validation, Visualization. **Veerpratap Meena:** Data curation, Software, Formal analysis, Supervision, Writing - review and editing. **Abrar Ahmed Syed:** Writing - original draft, Validation, Visualization. **Susha M:** Data curation, Writing - original draft, Validation, Visualization. **Usha Desai:** Data curation, Writing - original draft, Validation, Visualization, editing.

Declaration of competing interest

No conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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