Iranian Journal of Operations Research
Vol. 17, No. 2, 2026, pp. 1-30

A Mixed-Integer Linear Programming Framework for Optimal Design of a Hybrid Solar-Wind-Battery-Fuel Cell-Diesel Microgrid Considering Regulatory Penalties and Reliability Constraints

Golmohammadi. A.M.[1,*], Ghorbani. N.[2], Rashidian.F.[3]

The optimal planning of hybrid renewable energy systems has become increasingly important due to rising energy demand, environmental concerns, and the need for reliable electricity supply in remote and isolated regions. This study presents a comprehensive mixed-integer linear programming (MILP) framework for the optimal design of a hybrid solar–wind–battery–fuel cell–diesel microgrid. The proposed model simultaneously determines the optimal type, size, and operation of system components over the project lifetime while minimizing the equivalent annual cost. Unlike many existing optimization approaches, the framework integrates economic, environmental, and reliability considerations into a unified objective function by incorporating carbon emission penalties, load curtailment penalties, and renewable energy incentive policies. Furthermore, replacement costs and component lifetime degradation are reformulated into linear constraints, enabling the problem to be solved efficiently using exact optimization techniques. Hourly meteorological and load data are employed to accurately capture seasonal and daily variations in renewable energy generation and electricity demand. The optimization model is implemented in GAMS and solved using the CPLEX solver. Different system configurations and regulatory scenarios are evaluated to investigate the influence of diesel generators, battery storage, hydrogen technologies, and government support policies on system performance. The results demonstrate that an appropriately designed hybrid microgrid can substantially improve renewable energy penetration while maintaining system reliability and reducing the overall lifecycle cost. Moreover, regulatory incentive mechanisms significantly increase the economic viability of renewable energy resources and decrease dependence on fossil-fuel-based generation. The proposed MILP framework provides an effective decision-support tool for policymakers, system planners, and investors involved in the development of sustainable hybrid microgrids.

Keywords: *Hybrid renewable energy system; Mixed-integer linear programming (MILP); Hybrid microgrid; Solar energy; Wind energy; Battery energy storage; Fuel cell; Diesel generator; Reliability constraint; Carbon emission penalty; Renewable energy policy; Optimal sizing.*

1. Introduction

The increasing global demand for electricity, the depletion of fossil fuel reserves, and growing concerns regarding climate change have accelerated the transition toward sustainable energy systems. According to the International Energy Agency (IEA), although renewable energy has become the fastest-growing source of electricity generation worldwide, approximately 700 million people still

[*] Corresponding Author: a-golmohammadi@araku.ac.ir.
[1] Department of Industrial Engineering, Arak University, Arak, Iran. Email: a-golmohammadi@araku.ac.ir.
[2] Department of Industrial Engineering, Arak University, Arak, Iran. Email: ghorbany_nsr@yahoo.com.
[3] Department of Industrial Engineering, Arak University, Arak, Iran. Email: f_rashidian89@yahoo.com.

[Downloaded from iors.ir on 2026-09-16]

lack access to reliable electricity, particularly in remote and rural areas. Consequently, the development of cost-effective and reliable decentralized power generation systems has become a major research priority stability (Lian et al., 2019; Tyagi & Singhal, 2024).

Hybrid renewable energy systems (HRESs), which integrate multiple renewable resources with conventional backup generators and energy storage technologies, have emerged as one of the most promising solutions for supplying electricity to isolated communities and weak-grid regions. Compared with single-source renewable systems, hybrid configurations significantly improve energy security by exploiting the complementary characteristics of renewable resources. Solar photovoltaic (PV) systems generally produce maximum electricity during sunny daytime periods, whereas wind turbines often generate higher power during nighttime or seasonal periods when solar irradiation is relatively low. Combining these renewable resources therefore mitigates the intermittency associated with individual energy sources and improves overall system (Lian et al., 2019; Al-Shamma'a et al., 2023; Liang et al., 2022).

Despite these advantages, renewable energy sources remain highly dependent on meteorological conditions, leading to considerable temporal variations in electricity generation. To overcome this challenge, energy storage technologies play a crucial role in balancing the mismatch between electricity generation and demand. Battery energy storage systems (BESS) are widely used for short-term energy balancing because of their high round-trip efficiency and fast response characteristics. In contrast, hydrogen-based energy storage systems, including electrolyzers, hydrogen tanks, and fuel cells, offer long-duration storage capability with negligible self-discharge, making them suitable for seasonal energy management. Diesel generators are commonly incorporated as backup units to guarantee uninterrupted electricity supply during prolonged renewable energy shortage (Liang et al., 2022; Kalhoro et al., 2026; Superchi & Bianchini, 2026).

The optimal sizing of hybrid microgrids has attracted significant attention over the past decade. Numerous optimization approaches have been proposed, including genetic algorithms, particle swarm optimization, simulated annealing, evolutionary programming, and other metaheuristic techniques. Although these methods are capable of handling highly nonlinear optimization problems, they generally do not guarantee global optimality, and their computational performance strongly depends on algorithm parameter tuning. Moreover, optimization results may vary between independent runs because of their stochastic nature (Lian et al., 2019; Pamulapati et al., 2022; Tyagi & Singhal, 2024).

Mixed-Integer Linear Programming (MILP) has become an attractive alternative for hybrid energy system optimization owing to its deterministic solution procedure, computational efficiency, and ability to obtain globally optimal solutions when the optimization problem is properly linearized. Several MILP-based studies have investigated the optimal sizing of photovoltaic, wind, battery, hydrogen, and diesel generation systems under different economic and technical constraints (Liang et al., 2022; Lyu et al., 2024; Macmillan et al., 2024; Superchi & Bianchini, 2026). Nevertheless, many existing models simplify the optimization problem by neglecting component degradation, replacement scheduling, dynamic inflation effects, regulatory mechanisms, or reliability-related penalty costs. Such simplifications may reduce the practical applicability of optimization results for long-term investment planning (Zhu et al., 2026; Kalhoro et al., 2026; Lei et al., 2023; Saleheen et al., 2026; Brodnicke et al., 2023; Zhang et al., 2024; Sifakis et al., 2026; Alilou et al., 2026).

In recent years, governments have increasingly implemented policy instruments such as renewable energy subsidies, carbon pricing, emission taxes, and reliability standards to accelerate the deployment of low-carbon energy technologies. These regulatory mechanisms substantially influence the economic feasibility of hybrid microgrids and should therefore be explicitly incorporated into the optimization framework (Brodnicke et al., 2023; Zhang et al., 2024; Sifakis et al., 2026). However, only a limited number of studies have simultaneously considered renewable incentives, environmental penalties, and reliability constraints within a unified MILP formulation (Lei et al., 2023; Saleheen et al., 2026; Superchi & Bianchini, 2026).

[Downloaded from iors.ir on 2026-09-16]

To address these research gaps, this paper proposes a comprehensive MILP framework for the optimal design of a hybrid solar–wind–battery–fuel cell–diesel microgrid. The proposed model simultaneously optimizes component selection, sizing, and operational scheduling while minimizing the equivalent annual cost over the project lifetime. Economic costs, carbon emission penalties, renewable energy incentive policies, and reliability penalties associated with unmet electricity demand are integrated into a unified objective function. Furthermore, nonlinear replacement cost and component lifetime relationships are reformulated into linear constraints, allowing the optimization problem to be solved efficiently using exact MILP techniques. The proposed framework is implemented in GAMS and solved using the CPLEX optimizer based on hourly meteorological and load data for a one-year representative period. Several regulatory scenarios and system configurations are analyzed to evaluate the impacts of policy interventions, energy storage technologies, and diesel generator utilization on system cost, renewable energy penetration, and supply reliability.

The main contributions of this study are summarized as follows:

1. A comprehensive MILP model is developed for the simultaneous optimal sizing and operation of a hybrid solar–wind–battery–fuel cell–diesel microgrid.
2. Carbon emission penalties, renewable energy incentive policies, and reliability penalties are integrated into a unified economic objective function.
3. Nonlinear replacement cost and component lifetime relationships are accurately transformed into linear constraints, preserving computational efficiency while maintaining high modeling accuracy.
4. Multiple regulatory scenarios are evaluated to quantify the impact of government intervention on renewable energy penetration, lifecycle cost, and system reliability.
5. The proposed framework provides practical decision-support guidance for policymakers, investors, and energy planners involved in designing sustainable hybrid microgrids.

2. Literature Review

The rapid development of renewable energy technologies has significantly increased research interest in hybrid renewable energy systems (HRESs) and microgrids. During the last decade, research has evolved from simple techno-economic sizing problems toward integrated optimization frameworks that simultaneously consider economic performance, environmental sustainability, operational reliability, energy management, and regulatory policies. Recent review studies indicate that future hybrid microgrids will require coordinated optimization of renewable generation, energy storage, backup generation, and policy-driven market mechanisms to achieve carbon-neutral electricity systems.

2.1. Evolution of Hybrid Renewable Microgrid Optimization

Early studies mainly focused on minimizing investment costs through heuristic optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Simulated Annealing (SA). These techniques demonstrated acceptable performance for nonlinear optimization problems; however, their stochastic nature often resulted in inconsistent solutions and relatively high computational requirements for large-scale planning problems.

Recent studies increasingly employ mathematical programming approaches, particularly Mixed-Integer Linear Programming (MILP), because they guarantee deterministic global optimality for linearized formulations while maintaining high computational efficiency. MILP has therefore become

[Downloaded from iors.ir on 2026-09-16]

one of the most widely adopted optimization methods for long-term microgrid planning and component sizing.

Lian et al. (2019) reviewed the evolution of sizing methodologies for hybrid renewable energy systems and compared traditional optimization, artificial intelligence, and hybrid optimization approaches. The authors reported that recent optimization research has shifted from minimizing investment cost alone to simultaneously considering reliability, environmental impact, and operational flexibility. Their review further demonstrated that hybrid optimization methods generally outperform single algorithms in terms of convergence speed and solution quality. In addition, the study identified hybrid intelligent optimization as a promising direction for solving increasingly complex planning problems involving renewable generation and energy storage. These findings provide a valuable framework for understanding the evolution of optimization techniques adopted in modern hybrid microgrid design (Lian et al., 2019).

Liang et al. (2022) introduced a mixed-integer linear programming (MILP) framework for the optimal design and operation of a hybrid renewable microgrid incorporating liquid air energy storage. The proposed model optimized component capacities and operational decisions simultaneously while balancing economic performance and environmental benefits. Simulation results demonstrated that the integrated MILP framework effectively identified optimal storage sizing and improved renewable energy utilization under varying demand conditions. The study further showed that advanced storage technologies can substantially enhance system flexibility when embedded within a rigorous optimization framework. These findings highlight the growing adoption of MILP as a reliable tool for designing next-generation hybrid renewable microgrids.

Alilou et al. (2026) proposed a comprehensive optimization framework for the optimal sizing and energy management of a grid-connected hybrid microgrid integrating photovoltaic systems, energy storage, and electric vehicle charging infrastructure. The framework simultaneously optimized component capacities and operational scheduling while minimizing both the levelized cost of energy (LCOE) and life-cycle environmental emissions (LCEE). Unlike conventional optimization models, the proposed approach explicitly incorporated future load growth into the sizing process, enabling the microgrid configuration to adapt to long-term demand variations. The simulation results demonstrated that coordinated optimization significantly improved renewable energy utilization and operational efficiency while maintaining economic feasibility. This study represents one of the latest developments in hybrid renewable microgrid optimization and highlights the increasing trend toward integrated design frameworks that simultaneously address economic and environmental objectives.

2.2. Hybrid Renewable Energy Systems and Component Sizing

Several recent investigations have optimized combinations of photovoltaic (PV), wind turbines (WT), battery energy storage systems (BESS), hydrogen storage, fuel cells (FC), and diesel generators (DG). The complementary characteristics of solar and wind resources significantly improve generation stability, while battery storage effectively mitigates short-term power fluctuations. Hydrogen technologies have attracted increasing attention because they provide long-duration energy storage with minimal self-discharge, making them suitable for seasonal balancing despite their relatively high capital costs and lower round-trip efficiency.

Nevertheless, most existing optimization studies simplify system modeling by assuming fixed component lifetimes, neglecting degradation mechanisms or replacement scheduling, which may lead to unrealistic estimates of long-term project economics.

Tyagi and Singhal (2024) reviewed contemporary sizing methodologies and uncertainty modeling approaches for hybrid energy systems. The study compared deterministic, stochastic, and robust optimization techniques while discussing the influence of uncertainty on component sizing decisions. The authors highlighted that recent optimization frameworks increasingly integrate reliability indices, sensitivity analysis, and uncertainty characterization into the sizing process. They

[Downloaded from iors.ir on 2026-09-16]

further concluded that combining uncertainty modeling with mathematical optimization significantly improves the robustness of hybrid renewable energy system design. Their review provides an important foundation for developing reliable optimization models for complex hybrid microgrids (Tyagi & Singhal, 2024).

Al-Shamma'a et al. (2023) presented a techno-economic optimization model for sizing hybrid renewable energy systems supplying isolated communities. The proposed framework optimized the capacities of photovoltaic arrays, wind turbines, battery storage, and diesel generators while satisfying predefined reliability constraints. The results showed that optimal component sizing reduced the total net present cost and fuel consumption while increasing renewable energy utilization. In addition, sensitivity analyses demonstrated that storage capacity has a significant impact on both system reliability and long-term operating costs. The study concluded that integrated sizing optimization is essential for achieving economically sustainable hybrid microgrid configurations (Al-Shamma'a et al., 2023).

Lyu et al. (2024) proposed an integrated inner–outer layer co-optimization framework for simultaneous component sizing and energy management in renewable energy microgrids. Unlike conventional sequential approaches, the proposed methodology optimized system capacity in the outer layer while operational scheduling was performed in the inner layer, enabling a globally coordinated solution. The results demonstrated that the integrated framework achieved lower lifecycle costs and higher renewable energy utilization than traditional sizing methods. Furthermore, sensitivity analyses confirmed that coordinated optimization significantly improves system flexibility under varying operating conditions. This study highlights the importance of simultaneously optimizing component sizing and operational decisions for modern hybrid renewable microgrids (Lyu et al., 2024).

Zhu et al. (2026) introduced a stochastic optimization framework for the optimal sizing of renewable hybrid power plants by explicitly incorporating component reliability into the design process. Unlike conventional sizing methods that assume perfect equipment availability, the proposed model accounted for failure and repair processes of wind turbines, photovoltaic systems, battery storage units, transformers, and power converters throughout the project lifetime. The optimization was formulated as a multidisciplinary stochastic problem under uncertainty to maximize the expected net present value while simultaneously improving investment robustness. The numerical results demonstrated that incorporating component reliability into the sizing process increased long-term economic performance and produced more resilient system configurations compared with deterministic planning approaches. This study represents one of the latest advances in hybrid renewable energy system sizing and highlights the growing importance of reliability-aware optimization for future microgrid design.

Kalhoro et al. (2026) developed a Mixed-Integer Linear Programming (MILP) model for the optimal sizing of hybrid battery–fuel cell energy storage systems in zero-emission microgrids. Unlike conventional planning models, the proposed framework explicitly accounts for fuel cell degradation, battery replacement, hydrogen storage, electrolyzer sizing, and fuel cell operating voltage within the optimization process. The results demonstrated that neglecting fuel cell degradation leads to underestimation of hydrogen storage requirements and total lifecycle costs, potentially resulting in suboptimal investment decisions. By simultaneously optimizing battery and hydrogen-based storage technologies, the proposed model significantly improved system reliability, economic performance, and long-term operational sustainability. This study highlights the importance of degradation-aware planning for future hydrogen-based hybrid renewable microgrids.

[Downloaded from iors.ir on 2026-09-16]

2.3. Reliability-Constrained Microgrid Planning

Ensuring reliable electricity supply remains one of the primary objectives of hybrid microgrid design. Recent studies have incorporated reliability metrics such as Loss of Load Probability (LOLP), Loss of Power Supply Probability (LPSP), Expected Energy Not Supplied (EENS), and Loss of Load Expectation (LOLE) into optimization models. Some researchers formulate reliability as an additional optimization objective, whereas others include reliability thresholds as operational constraints or penalty costs.

Although these approaches improve supply adequacy, most studies evaluate reliability independently from governmental regulations or market-based penalty mechanisms. Consequently, the economic implications of reliability violations are often underestimated.

Lei et al. (2023) reviewed optimization techniques for enhancing the reliability of renewable-based microgrids by examining control strategies, reliability assessment methods, and optimization algorithms. The authors categorized existing approaches according to optimization objectives, reliability metrics, and microgrid configurations. Their analysis showed that recent studies increasingly integrate reliability indices such as Expected Energy Not Supplied (EENS) and Loss of Load Probability (LOLP) into optimization models rather than evaluating them only after the design stage. The review also emphasized that multi-objective optimization and mathematical programming have become dominant approaches for balancing cost, reliability, and sustainability. Overall, the study identified reliability-constrained optimization as one of the most promising research directions for future hybrid renewable microgrid planning (Lei et al., 2023).

Riou et al. (2021) proposed a multi-objective optimization methodology for autonomous hybrid microgrids that simultaneously considers system cost, renewable energy penetration, and reliability during the design stage. Using the NSGA-II algorithm, the framework generated Pareto-optimal solutions that enabled planners to evaluate the trade-offs among conflicting design objectives. The case study demonstrated that incorporating reliability into the initial sizing process significantly improves supply adequacy with only a moderate increase in investment cost. The authors emphasized that reliability should be treated as a primary design objective rather than a post-design evaluation criterion. Their findings provide valuable guidance for reliability-constrained planning of autonomous hybrid microgrids.

Saleheen et al. (2026) proposed a two-stage stochastic optimization framework for the joint planning and operation of 100% renewable microgrids with reliability treated as a primary design constraint rather than a post-design evaluation metric. The proposed model simultaneously optimized long-term capacity expansion and short-term operational dispatch while explicitly accounting for renewable intermittency, seasonal demand variations, and probabilistic component failures. In contrast to conventional planning methods, the framework incorporated utility-grade reliability constraints by limiting the expected energy not served (EENS), ensuring approximately **99.998% supply reliability** without relying on fossil-fuel backup. The results demonstrated that coordinated investment and operational optimization significantly enhanced system resilience while maintaining economic feasibility under highly uncertain operating conditions. This study represents one of the most recent advances in reliability-constrained microgrid planning and highlights the growing importance of integrating stochastic programming with explicit reliability requirements in next-generation renewable microgrids.

2.4. Regulatory Policies and Carbon Pricing

Government regulations have become an increasingly important driver for renewable energy deployment. Carbon taxes, emission trading schemes, renewable energy incentives, feed-in tariffs, and renewable portfolio standards substantially affect investment decisions in hybrid microgrids.

[Downloaded from iors.ir on 2026-09-16]

Recent optimization frameworks have started incorporating carbon emission costs into objective functions. However, regulatory policies are generally represented using simplified carbon prices without simultaneously considering renewable energy subsidies and reliability-related financial penalties. Consequently, existing optimization frameworks do not fully capture the interactions between environmental regulations, investment decisions, and operational reliability.

Brodnicke et al. (2023) reviewed the influence of policy instruments on distributed multi-energy systems by comparing mechanisms such as carbon taxes, carbon caps, feed-in tariffs, and investment subsidies. The authors demonstrated that carbon pricing policies are generally more effective than direct subsidies in reducing greenhouse gas emissions while maintaining system flexibility. Their analysis also revealed that integrating policy mechanisms into optimization models significantly affects technology selection, investment planning, and operational scheduling. Furthermore, the review highlighted that future energy planning should explicitly incorporate environmental regulations into optimization frameworks rather than treating them as external assumptions. These findings provide valuable guidance for policy-oriented hybrid microgrid optimization.

Zhang et al. (2024) proposed a two-stage robust optimization framework for integrated electricity–gas–heat microgrids under multiple sources of uncertainty while incorporating a ladder-type carbon trading mechanism. The model jointly optimized operational decisions and carbon trading strategies to minimize total system costs while satisfying energy balance and emission constraints. The results demonstrated that the stepped carbon trading mechanism effectively reduced carbon emissions without significantly increasing operating costs. Moreover, the robust optimization framework enhanced system resilience against renewable generation and load uncertainties. The study highlighted that incorporating carbon trading policies directly into optimization models provides a practical pathway for achieving both economic efficiency and environmental sustainability in modern multi-energy microgrids (Zhang et al., 2024).

Sifakis et al. (2026) developed a techno-economic optimization framework for island-based hybrid renewable microgrids that explicitly incorporates regulatory uncertainty into the system design process. The proposed policy-constrained optimization model embeds different net-metering schemes and grid access regulations directly into the optimization objective, enabling simultaneous evaluation of technical performance and regulatory impacts. The framework optimizes the capacities of photovoltaic systems, wind turbines, hydrokinetic generation, and battery storage while minimizing the levelized cost of energy under alternative policy scenarios. The results demonstrated that regulatory policies substantially influence the optimal system configuration, investment profitability, and carbon emission reduction. The authors concluded that neglecting regulatory constraints during optimization may lead to economically suboptimal and practically infeasible hybrid microgrid designs. This study highlights the growing importance of integrating regulatory policies into optimization-based planning of renewable microgrids.

2.5. Mathematical Programming Approaches

MILP has become one of the dominant optimization techniques because many nonlinear relationships can be accurately approximated through linearization while preserving computational tractability. Several studies have successfully modeled unit commitment, battery scheduling, hydrogen management, and microgrid dispatch using MILP formulations.

Despite these advances, two important limitations remain. First, replacement costs and component lifetime degradation are frequently ignored or treated using simplified assumptions. Second, policy-based economic mechanisms—including carbon penalties, renewable incentives, and reliability penalties—are rarely integrated within a unified mathematical framework. These limitations reduce the applicability of existing models for long-term planning under evolving energy policies.

[Downloaded from iors.ir on 2026-09-16]

Pamulapati et al. (2022) reviewed optimization-based energy management strategies for microgrids from the perspective of the energy trilemma, including affordability, sustainability, and security. The authors classified optimization approaches into mathematical programming, heuristic algorithms, and predictive control methods while evaluating their applicability to different microgrid configurations. Their findings showed that mathematical programming techniques, particularly MILP, remain the preferred choice for operational scheduling and capacity planning because of their ability to efficiently handle binary variables and operational constraints. The review concluded that future optimization frameworks should combine mathematical programming with uncertainty modeling to improve decision-making in renewable-rich microgrids.

Macmillan et al. (2024) proposed a two-stage stochastic mathematical programming framework for microgrid design and multi-year dispatch optimization under climate-informed uncertainty. The model simultaneously optimized investment decisions and operational scheduling while accounting for future variations in renewable energy availability, load growth, and climate conditions. The authors employed stochastic programming to improve the resilience of hybrid microgrids without imposing excessive computational complexity. The results demonstrated that uncertainty-informed planning produced more robust system configurations and reduced long-term operational costs compared with deterministic optimization models. This study highlights the growing role of advanced mathematical programming in supporting resilient and economically efficient hybrid renewable microgrid planning.

Superchi and Bianchini (2026) proposed a comprehensive mixed-integer linear programming (MILP) framework for the simultaneous design and operation of grid-connected hybrid energy systems integrating photovoltaic panels, wind turbines, battery energy storage, hydrogen storage, and proton exchange membrane fuel cells. Unlike conventional approaches that optimize system sizing separately from operational scheduling, the proposed mathematical programming model performs both tasks simultaneously within a unified optimization framework. The numerical results demonstrated that the coordinated MILP formulation substantially increased the net present value of the system while improving renewable energy utilization and the complementary operation of battery and hydrogen storage technologies. Comparative analyses further showed that the proposed framework outperformed traditional rule-based dispatch strategies in both economic performance and operational flexibility. This study represents one of the most recent advances in mathematical programming for hybrid renewable energy systems and further confirms the effectiveness of MILP for solving large-scale, multi-component microgrid optimization problems.

2.6. Research Gap

Based on the above review, several important research gaps can be identified:

- Most studies optimize either economic performance or environmental impact without simultaneously integrating regulatory incentives and reliability penalties.
- Long-term replacement costs and component lifetime degradation are frequently neglected or modeled using oversimplified assumptions.
- Battery and hydrogen storage are often investigated independently rather than within a unified optimization framework.
- Governmental subsidy mechanisms and carbon emission penalties are rarely optimized simultaneously.
- Few studies employ an exact MILP framework capable of determining component sizing, operational scheduling, replacement planning, and policy impacts within a single optimization model.

To address these limitations, this study proposes a comprehensive MILP framework that integrates techno-economic optimization, reliability constraints, carbon-emission penalties,

[Downloaded from iors.ir on 2026-09-16]

renewable-energy incentive mechanisms, and lifetime-dependent replacement modeling into a unified optimization framework for hybrid solar–wind–battery–fuel cell–diesel microgrids.

Table 1. Comparison of Recent Studies on Hybrid Renewable Microgrid Optimization

Authors (Year)	Optimization Method	Integrated Hybrid System	Reliability Considered	Carbon Policy	Replacement Cost	Research Gap
Liang et al. (2022)	MILP	PV–Wind–LAES	✗	✗	✗	Does not consider reliability, regulatory mechanisms, or component replacement.
Alilou et al. (2026)	MILP	PV–Battery–EV Charging	✗	Environmental objective only	✗	Does not include reliability constraints or regulatory penalty mechanisms.
Lyu et al. (2024)	Inner–Outer Co-optimization	PV–Battery	✗	✗	✗	Simultaneous sizing and EMS, but ignores component degradation and policy effects.
Kalhoro et al. (2026)	MILP	Battery–Hydrogen Fuel Cell	Partial	✗	✓	Considers degradation and replacement but omits regulatory policies and reliability constraints.
Riou et al. (2021)	NSGA-II	Autonomous Hybrid Microgrid	✓	✗	✗	Reliability is included, but no carbon policy or replacement cost.
Saleheen et al. (2026)	Two-stage Stochastic Programming	100% Renewable Microgrid	✓	✗	✗	Focuses on reliability under uncertainty without environmental policy integration.
Zhang et al. (2024)	Two-stage Robust Optimization	Electricity–Gas–Heat Microgrid	Partial	✓ (Carbon Trading)	✗	Includes carbon trading but not equipment replacement or degradation.
Sifakis et al. (2026)	Genetic Algorithm	PV–Wind–Hydrokinetic–Battery	Partial	✓ (Regulatory Policies)	✗	Considers policy uncertainty but not replacement scheduling or reliability penalties.
Macmillan et al. (2024)	Two-stage Stochastic Programming	Hybrid Renewable Microgrid	Partial	✗	✗	Addresses climate uncertainty but excludes regulatory mechanisms and replacement cost.
Superchi & Bianchini (2026)	MILP	PV–Wind–Battery–Hydrogen–Fuel Cell	✗	✗	✗	Comprehensive MILP model, yet reliability constraints, regulatory penalties, and replacement planning are not jointly incorporated.

[Downloaded from iors.ir on 2026-09-16]

This Study	MILP	PV–Wind–Battery–Hydrogen–Fuel Cell–Diesel	✓	✓ (Carbon Pricing & Regulatory Penalties)	✓	Presents a unified MILP framework that simultaneously optimizes system sizing while incorporating reliability constraints, carbon pricing, regulatory penalty costs, inflation-adjusted replacement scheduling, and long-term economic evaluation within a single optimization model.

The comparative analysis demonstrates that although significant progress has been achieved in hybrid renewable microgrid planning, no previous study has simultaneously incorporated exact MILP optimization, lifetime-dependent replacement modeling, carbon-emission penalties, renewable incentive mechanisms, and reliability constraints within a unified planning framework. Therefore, the proposed model aims to bridge these research gaps by providing a computationally efficient and practically applicable optimization framework for sustainable hybrid microgrid design.

3. System Description

This study considers a stand-alone hybrid microgrid composed of photovoltaic (PV) arrays, wind turbines (WTs), battery energy storage systems (BESSs), a hydrogen energy storage subsystem including an electrolyzer, hydrogen storage tank, and fuel cell (FC), diesel generators (DGs), and a bidirectional inverter. The proposed configuration is designed to provide reliable electricity supply for isolated communities or remote areas where access to the main utility grid is unavailable or economically impractical. Hybrid microgrids of this architecture are widely recognized for improving supply reliability while reducing fossil-fuel consumption through coordinated operation of renewable generation, storage technologies, and backup generators. Figure 1 illustrates the overall architecture of the proposed hybrid microgrid.

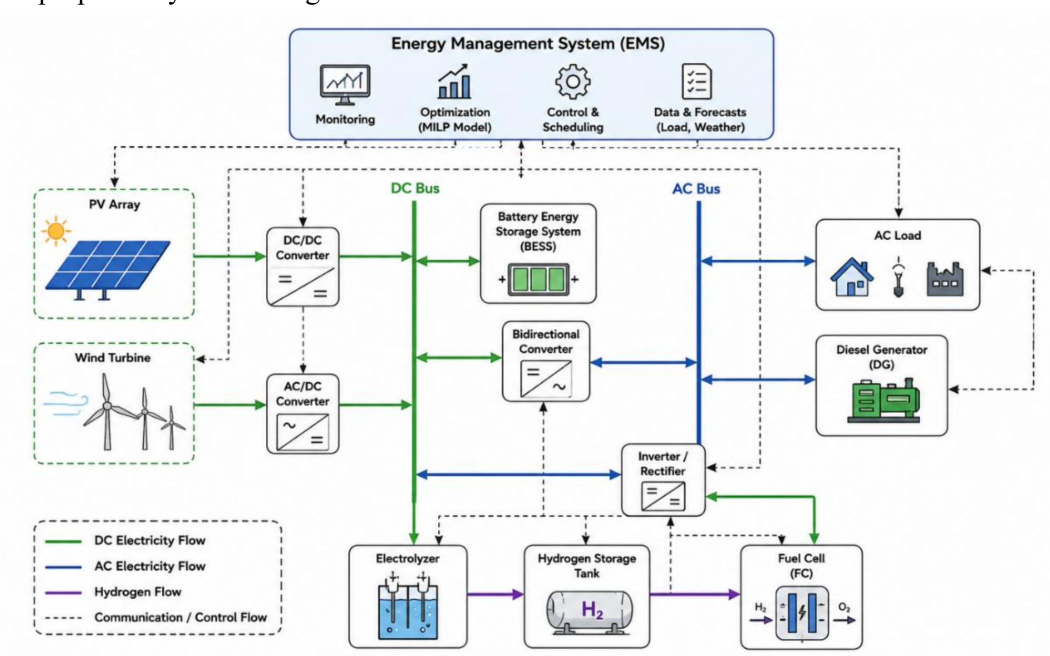

Figure 1. Architecture of the proposed hybrid microgrid.

[Downloaded from iors.ir on 2026-09-16]

Renewable generators constitute the primary energy sources, whereas battery and hydrogen storage systems compensate for the intermittency of renewable resources. The diesel generator serves as the final backup source whenever renewable generation and stored energy are insufficient to satisfy the load demand. An Energy Management System (EMS) supervises the operation of all components and determines the optimal power flow according to the optimization results obtained from the MILP model.

The PV array converts incident solar irradiation into electrical energy according to the hourly solar resource profile. Since photovoltaic generation is highly dependent on solar irradiance and ambient temperature, its output exhibits significant daily and seasonal variations. Nevertheless, PV systems offer low operating costs, zero direct emissions, and long service life, making them one of the most attractive renewable technologies for distributed electricity generation.

Wind turbines constitute the second renewable energy source. Their electricity production depends primarily on wind speed, turbine characteristics, cut-in speed, rated speed, and cut-out speed. Because wind availability is often complementary to solar irradiation, integrating PV and wind generation substantially reduces renewable power fluctuations and increases the overall utilization of renewable resources throughout the year.

To mitigate short-term renewable intermittency, a Battery Energy Storage System (BESS) is incorporated into the microgrid. The battery stores surplus electricity during periods of excess renewable generation and discharges when renewable production becomes insufficient. Charging and discharging processes are constrained by battery capacity, state of charge (SOC), charging/discharging efficiencies, and maximum power limits. These operational constraints preserve battery lifetime while maintaining reliable system operation.

Long-term energy storage is provided through a hydrogen subsystem consisting of an electrolyzer, a hydrogen storage tank, and a fuel cell. Whenever surplus renewable electricity exceeds both the instantaneous load demand and battery charging capability, the excess electricity powers the electrolyzer to produce hydrogen. The generated hydrogen is compressed and stored in a dedicated storage tank. During prolonged renewable shortages, the stored hydrogen is supplied to the fuel cell, where it is converted back into electricity. Although hydrogen storage exhibits lower round-trip efficiency than batteries, it offers virtually negligible self-discharge and is therefore well suited for long-duration and seasonal energy storage.

A diesel generator is employed as the dispatchable backup generation unit to guarantee uninterrupted electricity supply under unfavorable weather conditions or extended renewable deficits. While diesel generators improve system reliability and operational flexibility, they increase fuel consumption, greenhouse gas emissions, and operating costs. Consequently, the proposed optimization framework minimizes diesel utilization by considering fuel expenses, carbon-emission penalties, and renewable-energy incentives within the objective function.

The electrical interface between AC and DC components is achieved through a bidirectional inverter. The inverter enables power exchange between renewable generators, storage systems, and AC loads while accounting for conversion efficiencies. In the optimization model, inverter dynamics are neglected because their transient behavior occurs over much shorter time scales than the hourly scheduling horizon considered in this study.

The Energy Management System coordinates the operation of all microgrid components according to a hierarchical dispatch strategy. Renewable energy sources are assigned the highest priority because they incur no fuel costs and produce negligible emissions. Surplus renewable electricity is first utilized to satisfy the electrical demand, followed by battery charging and hydrogen production. During renewable generation shortages, the battery is discharged before activating the fuel cell. The diesel generator is committed only when renewable generation and stored energy are insufficient to satisfy the load demand while maintaining the prescribed reliability constraints. Such a priority-based dispatch strategy significantly reduces diesel fuel consumption and increases renewable energy penetration.

[Downloaded from iors.ir on 2026-09-16]

The proposed optimization simultaneously determines the optimal number, capacity, and operational scheduling of all system components over the project lifetime. The objective function minimizes the equivalent annual cost by considering investment costs, maintenance costs, replacement costs, diesel fuel consumption, carbon-emission penalties, renewable-energy incentive policies, and reliability penalties associated with unmet load demand. Furthermore, hourly meteorological data and electricity demand profiles are employed to accurately capture seasonal and daily variations in renewable generation and load characteristics, thereby improving the realism of long-term planning results.

Overall, the proposed hybrid solar–wind–battery–fuel cell–diesel microgrid combines the complementary advantages of multiple renewable generation technologies, short- and long-term energy storage systems, and dispatchable backup generation within a unified optimization framework. This integrated architecture provides a flexible, reliable, and economically efficient solution for sustainable electrification of isolated and weak-grid regions while supporting future low-carbon energy policies.

4. Mathematical Formulation

This section presents the mathematical formulation of the proposed mixed-integer linear programming (MILP) model for the optimal design and operation of the hybrid solar–wind–battery–fuel cell–diesel microgrid. The optimization simultaneously determines the optimal capacity and operational scheduling of all system components while minimizing the equivalent annual cost over the planning horizon.

The optimization model considers both investment and operational decisions. Continuous variables represent power flows, stored energy, and energy conversion processes, whereas integer variables determine the optimal number of installed units for each technology.

4.1. Sets

The following index sets are used throughout the optimization model.

Symbol		***Description***
t	:	Hour index ($t = 1, \dots, 8760$)
i	:	Renewable generation technology
j	:	Diesel generator type
k	:	Battery type
m	:	Fuel cell type
n	:	Electrolyzer type

4.2. Decision Variables

The optimization determines both design and operational variables.

Integer variables

N_{PV}, N_{WT}, N_{DG}, N_{BAT}, N_{FC}, N_{ELN}

Represent the installed numbers of photovoltaic panels, wind turbines, diesel generators, batteries, fuel cells, and electrolyzers, respectively.

[Downloaded from iors.ir on 2026-09-16]

Continuous variables

$P_{\mathrm{PV}}(t)$	:	Hourly photovoltaic power generation.
$P_{\mathrm{wt}}(t)$	:	Hourly wind power generation.
$P_{\mathrm{DG}}(t)$	:	Diesel generator output.
$P_{\mathrm{FC}}(t)$	:	Fuel-cell output power.
$P_{\mathrm{EL}}(t)$	:	Electrolyzer power consumption.
$P_{\mathrm{ch}}(t)$	:	Battery charging power.
$P_{\mathrm{dis}}(t)$	:	Battery discharging power.
$SOC(t)$	:	Battery state of charge.
$H(t)$	:	Stored hydrogen.
$P_{\mathrm{loss}}(t)$	:	Unserved energy.

4.3. Parameters

The principal model parameters are summarized below.

Parameter		***Description***
C^{cap}	:	Capital cost
C^{OM}	:	Annual operation and maintenance cost
C^{rep}	:	Replacement cost
C^{fuel}	:	Diesel fuel cost
C^{CO_2}	:	Carbon-emission penalty
C^{ENS}	:	Reliability penalty
R_{t}	:	Solar irradiation
V_{t}	:	Wind speed
L_{t}	:	Electrical demand
η	:	Conversion efficiency
r	:	Discount rate
N_{y}	:	Project lifetime

4.4. Objective Function

The objective of the optimization is to minimize the Equivalent Annual Cost (EAC) of the hybrid microgrid throughout the project lifetime.

$$Min\,Z = C^{cap} + C^{OM} + C^{rep} + C^{fuel} + C^{CO_2} + C^{ENS} - R_{RE} \tag{1}$$

where

- C^{cap} represents the annualized investment cost,
- C^{OM} denotes annual operation and maintenance cost,
- C^{rep} is the equivalent annual replacement cost,
- C^{fuel} is diesel fuel expenditure,
- C^{CO_2} represents environmental penalties,
- C^{ENS} denotes reliability penalties,
- R_{RE} represents governmental renewable-energy incentives.

The annualized investment cost is calculated as:

$$C^{cap} = CRF \sum_{i} C_i^{cap} N_i \tag{2}$$

Where

[Downloaded from iors.ir on 2026-09-16]

$$CRF = \frac{r\,(1+r)^N}{(1+r)^N - 1} \tag{3}$$

is the capital recovery factor.

The annual operation and maintenance cost is

$$C^{OM} = \sum_i C_i^{OM} N_i \tag{4}$$

Replacement costs are annualized according to the estimated lifetime of each component,

$$C^{rep} = \sum_i C_i^{rep} R_i \tag{5}$$

Where R_i denotes the replacement coefficient determined from component lifetime degradation.

Fuel cost is

$$C^{fuel} = \sum_t fuel(t) \times Price_{fuel} \tag{6}$$

Carbon-emission penalty is

$$C^{CO_2} = \sum_t Emission(t) \times Penalty_{CO_2} \tag{7}$$

Reliability penalties associated with unmet demand are

$$C^{ENS} = \sum_t P_{\text{loss}}(t) \times Penalty_{ENS} \tag{8}$$

Renewable-energy subsidies are modeled as

$$R^{RE} = \sum_t P_{\text{RE}}(t) \times Subsidy \tag{9}$$

4.5. Power Balance Equation

At every hour, electricity generation must satisfy the load demand while accounting for storage operation.

$$P_{\text{PV}}(t) + P_{\text{wt}}(t) + P_{\text{DG}}(t) + P_{\text{FC}}(t) + P_{\text{dis}}(t) = L(t) + P_{\text{EL}}(t) + P_{\text{ch}}(t) + P_{\text{loss}}(t) \tag{10}$$

This equality represents the fundamental energy conservation constraint governing the hybrid microgrid.

[Downloaded from iors.ir on 2026-09-16]

4.6. Optimization Characteristics

The resulting optimization problem is formulated as a mixed-integer linear programming model. Integer variables determine the optimal system configuration, whereas continuous variables represent hourly operational decisions. All nonlinear relationships—including replacement costs, component lifetime degradation, and policy-related penalty functions—are reformulated into equivalent linear expressions to preserve computational tractability while guaranteeing global optimality using the CPLEX solver.

5. MILP Optimization Model

The hybrid microgrid planning problem is formulated as a Mixed-Integer Linear Programming (MILP) optimization model. The objective is to determine the optimal sizing and operational scheduling of photovoltaic panels, wind turbines, battery energy storage systems, hydrogen storage components, fuel cells, diesel generators, and power conversion units over the project lifetime while minimizing the equivalent annual cost. The optimization simultaneously considers investment, operation, maintenance, replacement, environmental, and reliability-related costs under technical and operational constraints.

The optimization problem consists of two categories of decision variables. Integer variables determine the installation capacity of each technology, whereas continuous variables represent hourly operational decisions including power generation, energy storage, charging and discharging processes, hydrogen production and consumption, and unmet electrical demand.

The general MILP formulation can be expressed as:

$$Min\ Z = c^T x + d^T y \tag{11}$$

$Subject\ to$:

$$Ax + By \leq b \tag{12}$$

$$x \geq 0 \tag{13}$$

$$y \in Z \tag{14}$$

where

- x denotes the vector of continuous variables,
- y denotes the vector of integer variables,
- c and d are the corresponding cost vectors,
- A and B are the constraint matrices,
- b represents the vector of system limitations.

This formulation guarantees a globally optimal solution because both the objective function and all constraints are linear.

5.1. Integer Decision Variables

The sizing variables are expressed as integer variables:

N_{PV}, N_{WT}, N_{DG}, N_{BAT}, N_{FC}, N_{ELN} representing the optimal numbers of photovoltaic modules, wind turbines, diesel generators, batteries, fuel cells, and electrolyzers, respectively.

These variables determine the physical configuration of the hybrid microgrid.

[Downloaded from iors.ir on 2026-09-16]

5.2. Continuous Decision Variables

Hourly operational decisions include:

$P_{\mathrm{PV}}(t)$, $P_{\mathrm{wt}}(t)$, $P_{\mathrm{DG}}(t)$, $P_{\mathrm{FC}}(t)$, $P_{\mathrm{EL}}(t)$, $P_{\mathrm{ch}}(t)$, $P_{\mathrm{dis}}(t)$, $SOC(t)$, $H(t)$, $P_{\mathrm{loss}}(t)$ which describe renewable generation, dispatchable generation, battery operation, hydrogen storage dynamics, and unmet load throughout the scheduling horizon.

5.3. Linear Objective Function

The complete objective function is represented as:

$$Min\ Z = C^{cap} + C^{OM} + C^{rep} + C^{fuel} + C^{CO_2} + C^{ENS} - R_{sub} \tag{15}$$

where R_{sub} represents governmental renewable-energy incentives.

The objective simultaneously minimizes lifecycle cost while encouraging renewable penetration and reliable electricity supply.

5.4. Operational Constraints

The optimization is subject to several groups of linear constraints.

(a) Power balance

For every scheduling interval,

$$P_{PV} + P_{WT} + P_{DG} + P_{FC} + P_{dis} = P_{Load} + P_{EL} + P_{ch} + P_{Loss} \tag{16}$$

ensuring energy conservation.

(b) Renewable generation limits

Photovoltaic generation satisfies

$$0 \le P_{PV}(t) \le P_{PV}^{max}(t) \tag{17}$$

Wind generation satisfies

$$0 \le P_{WT}(t) \le P_{WT}^{max}(t) \tag{18}$$

where the upper bounds are determined from hourly meteorological data.

(c) Diesel generator constraints

The diesel generator output is limited by

$$P_{DG}^{min} \le P_{DG}(t) \le P_{DG}^{max}(t) \tag{19}$$

[Downloaded from iors.ir on 2026-09-16]

ensuring stable generator operation.

(d) Battery constraints

Battery charging

$$0 \leq P_{ch}(t) \leq P_{ch}^{max} \tag{20}$$

Battery discharging

$$0 \leq P_{dis}(t) \leq P_{dis}^{max} \tag{21}$$

State-of-charge limits

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{22}$$

SOC evolution

$$SOC\ (t+1) = SOC\ (t) + \eta_{ch}P_{ch} - \frac{P_{dis}}{\eta_{dis}} \tag{23}$$

(e) Hydrogen subsystem

Electrolyzer operation

$$0 \leq P_{EL}(t) \leq P_{EL}^{max} \tag{24}$$

Fuel-cell operation

$$0 \leq P_{FC}(t) \leq P_{FC}^{max} \tag{25}$$

Hydrogen storage dynamics

$$H\ (t+1) = H\ (t) + \eta_{EL}P_{EL} - \frac{P_{FC}}{\eta_{FC}} \tag{26}$$

subject to

$$H_{min} \leq H\ (t) \leq H_{max} \tag{27}$$

(f) Reliability constraint

The unmet demand satisfies

$$0 \leq P_{Loss}(t) \leq P_{Load}(t) \tag{28}$$

[Downloaded from iors.ir on 2026-09-16]

and

$$\sum_{t} P_{Loss}(t) \leq \alpha \sum_{t} P_{Load}(t) \quad (29)$$

where α\alpha represents the maximum allowable loss-of-load ratio.

In the proposed formulation, the relationships associated with component operation, degradation, replacement, hydrogen storage, reliability penalties, and renewable incentives are formulated in a linear or mixed-integer linear form. Binary variables are employed for installation, commitment, and replacement decisions where required. The hydrogen storage balance is represented through linear state-transition constraints, while replacement-related costs are incorporated through linearized replacement decisions. Consequently, the final optimization model consists of continuous, integer, and binary variables subject to linear constraints and a linear objective function, and can therefore be solved as a valid MILP formulation using CPLEX.

5.5. Linearization Strategy

Several practical relationships involved in long-term microgrid planning are inherently nonlinear. These include replacement scheduling, component lifetime degradation, hydrogen storage behavior, and regulatory penalty calculations. To maintain computational efficiency, all nonlinear expressions are reformulated using equivalent linear constraints and auxiliary variables.

In particular, replacement costs are expressed through linear replacement coefficients derived from component lifetime, while degradation-related constraints are represented by piecewise linear approximations. Environmental penalties and renewable-energy incentives are incorporated as linear cost coefficients in the objective function. This linearization preserves the accuracy of the original model while enabling the optimization problem to be solved using commercial MILP solvers.

5.6. Solution Procedure

The resulting MILP model contains both continuous and integer variables associated with system design and hourly operation. The optimization is implemented in GAMS and solved using the CPLEX branch-and-bound algorithm. Compared with metaheuristic optimization techniques, the MILP formulation guarantees deterministic convergence to the global optimum while maintaining high computational efficiency for large-scale planning problems. In addition, the exact optimization framework facilitates sensitivity analyses under different regulatory scenarios, allowing policymakers and investors to evaluate the impacts of renewable subsidies, carbon-emission penalties, and reliability requirements on the optimal microgrid configuration.

6. Reliability Modeling

Reliable electricity supply is one of the primary design objectives of stand-alone hybrid microgrids because renewable energy resources are inherently intermittent and highly dependent on weather conditions. Although integrating multiple renewable sources and energy storage systems considerably improves system reliability, prolonged periods of low solar irradiation or weak wind conditions may still lead to electricity shortages. Therefore, an appropriate reliability model is essential to ensure that the hybrid microgrid satisfies consumer demand while maintaining an economically optimal system configuration.

Several reliability indices have been proposed for evaluating hybrid renewable energy systems, including the Loss of Load Probability (LOLP), Loss of Power Supply Probability (LPSP), Loss of

[Downloaded from iors.ir on 2026-09-16]

Load Expectation (LOLE), and Expected Energy Not Supplied (EENS). Among these indices, energy-based reliability measures are particularly suitable for optimization because they can be directly incorporated into linear programming formulations.

In this study, system reliability is evaluated based on the amount of unmet electrical demand during the scheduling horizon. Whenever the available power generated by renewable resources, storage systems, and diesel generators is insufficient to satisfy the load demand, the remaining demand is defined as unserved energy (or curtailed load). The optimization model minimizes this quantity indirectly through an economic penalty included in the objective function.

6.1. Unserved Energy

The hourly unmet load is calculated as

$$P_{Loss}(t) = P_{Load}(t) - (P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + P_{FC}(t) + P_{dis}(t) - P_{EL}(t) - P_{ch}(t)) \quad (30)$$

subject to

$$P_{Loss}(t) \geq 0 \quad (31)$$

where

- $P_{Load}(t)$ is the hourly electricity demand,
- $P_{PV}(t)$ is photovoltaic generation,
- $P_{WT}(t)$ is wind generation,
- $P_{DG}(t)$ is diesel generator output,
- $P_{FC}(t)$ is fuel-cell generation,
- $P_{dis}(t)$ is battery discharge power,
- $P_{EL}(t)$ is electrolyzer consumption,
- $P_{ch}(t)$is battery charging power.

A value of zero indicates complete supply of the electrical demand, whereas positive values represent load curtailment.

6.2. Reliability Index

The annual reliability level is expressed as

$$RI = 1 - \frac{\sum_{t=1}^{8760} P_{Loss}(t)}{\sum_{t=1}^{8760} P_{Load}(t)} \quad (32)$$

Where RI denotes the annual reliability index.
The reliability index varies between zero and one.

$$0 \leq RI \leq 1 \quad (33)$$

A value of $RI = 1$ indicates perfect reliability with no unmet demand throughout the planning horizon.

[Downloaded from iors.ir on 2026-09-16]

6.3. Maximum Allowable Load Curtailment

To guarantee an acceptable quality of service, the optimization model restricts the total annual unmet demand.

$$\sum_{t=1}^{8760} P_{Loss}(t) \leq \alpha \sum_{t=1}^{8760} P_{Load}(t) \tag{34}$$

Where α represents the maximum allowable fraction of annual unmet demand.

Typical values range between

$$0.001 \leq \alpha \leq 0.01 \tag{35}$$

depending on the desired reliability level.

6.4. Reliability Penalty Function

Instead of enforcing extremely strict reliability requirements, the proposed model incorporates reliability into the optimization objective using an economic penalty function. This approach enables the optimizer to evaluate the trade-off between additional investment costs and supply reliability.

The annual reliability penalty is formulated as

$$C_{ENS} = \sum_{t=1}^{8760} Penalty_{ENS} * P_{Loss}\,(t) \tag{36}$$

Where $Penalty_{ENS}$ is the unit cost of unserved electricity (USD/kWh).

A sufficiently high penalty encourages the optimization algorithm to install additional renewable generators, battery capacity, or backup diesel generation in order to reduce unmet demand.

6.5. Interaction Between Reliability and Component Sizing

The reliability constraint directly affects the optimal sizing of all system components. Increasing photovoltaic capacity improves daytime reliability under high solar irradiance, whereas additional wind turbines enhance nighttime and seasonal energy production. Battery storage mitigates short-term renewable intermittency by storing excess electricity and supplying power during temporary shortages. Hydrogen storage contributes to long-duration energy balancing, while diesel generators provide dispatchable backup generation during extended renewable deficits.

Consequently, the optimization simultaneously determines the economically optimal combination of renewable generation, storage capacity, and backup generation capable of satisfying the prescribed reliability requirement with minimum lifecycle cost.

6.6. Reliability Under Regulatory Policies

In the proposed optimization framework, reliability is not treated solely as a technical constraint but also as an economic consideration influenced by regulatory policies. Utilities or system operators may impose financial penalties when the annual unserved energy exceeds an acceptable threshold.

[Downloaded from iors.ir on 2026-09-16]

By integrating these penalties into the objective function, the optimization model naturally balances investment expenditures against service reliability.

This integrated approach reflects real-world electricity markets, where inadequate supply quality often results in contractual penalties, customer compensation costs, or regulatory sanctions. Therefore, incorporating reliability penalties into the MILP framework produces more practical and policy-relevant planning solutions than models relying exclusively on deterministic reliability constraints.

6.7. Advantages of the Proposed Reliability Model

The proposed reliability formulation offers several advantages over conventional approaches:

- It is fully compatible with the MILP framework because all reliability equations remain linear.
- Reliability is incorporated simultaneously as both a technical constraint and an economic objective.
- The formulation allows direct evaluation of the trade-off between investment cost and supply adequacy.
- The model captures the combined contributions of renewable generators, battery storage, hydrogen storage, and diesel generators to system reliability.
- It provides flexibility for evaluating different regulatory scenarios through adjustable reliability penalty coefficients.

7. Regulatory Penalty Mechanism

Government regulations have become one of the most influential factors affecting the economic feasibility of hybrid renewable energy systems. In addition to conventional investment and operating costs, modern energy planning increasingly incorporates environmental taxes, renewable energy incentives, carbon pricing schemes, and reliability-based service penalties. These policy instruments are designed to accelerate the transition toward low-carbon electricity generation while maintaining an acceptable level of power supply reliability.

To accurately represent real-world regulatory environments, the proposed MILP framework incorporates three complementary regulatory mechanisms into the optimization model:

1. Carbon emission penalties imposed on diesel-based electricity generation;
2. Reliability penalties associated with unserved electrical demand;
3. Financial incentives for electricity generated from renewable energy resources.

Rather than treating these mechanisms independently, they are integrated into a unified economic framework that directly influences optimal component sizing and operational scheduling.

7.1. Carbon Emission Penalty

Diesel generators remain an essential backup technology in stand-alone microgrids because of their dispatchability and operational flexibility. However, their operation results in greenhouse gas emissions that contribute to climate change and increase environmental costs.

The total annual carbon-emission penalty is formulated as:

$$C_{CO_2} = \sum_{t=1}^{8760} EF_{DG} * Fuel\ (t) * CP \tag{37}$$

[Downloaded from iors.ir on 2026-09-16]

where

- EF_{DG} denotes the carbon emission factor of diesel fuel (kg CO_2/L),
- $Fuel\ (t)$ represents hourly diesel fuel consumption,
- CP is the carbon price (USD/kg CO_2).

The emission factor can be obtained from internationally accepted emission inventories, while the carbon price represents governmental carbon taxation or emission trading mechanisms.

By assigning an economic cost to greenhouse gas emissions, the optimization naturally favors renewable electricity generation whenever economically feasible.

7.2. Reliability Penalty

Power supply interruptions impose significant economic and social costs on electricity consumers. Consequently, many regulatory authorities require utilities or independent microgrid operators to maintain minimum reliability standards.

In the proposed optimization framework, unmet electrical demand is penalized through

$$C_{ENS} = Penalty_{ENS} * \sum_{t=1}^{8760} P_{Loss}(\mathrm{t}) \quad (38)$$

Where $Penalty_{ENS}$ is the monetary penalty associated with one kilowatt-hour of unserved electricity.

A sufficiently large penalty coefficient discourages excessive unserved energy and promotes investment in additional renewable generation or storage capacity.

Unlike conventional deterministic reliability constraints, this formulation enables the optimization model to determine the economically optimal trade-off between investment cost and supply reliability.

7.3. Renewable Energy Incentive

Many countries encourage renewable electricity production through feed-in tariffs, renewable energy certificates, investment subsidies, or production-based incentive mechanisms.
The annual renewable incentive is expressed as

$$R_{RE} = Sub * \sum_{t=1}^{8760} P_{RE}\ (t) \quad (39)$$

where

- Sub denotes the governmental incentive per kilowatt-hour of renewable electricity,
- $P_{RE}(t)$ represents the total renewable electricity generated by photovoltaic and wind systems.

The renewable generation is calculated as:

$$P_{RE}(t) = P_{PV}(t) + P_{WT}(t) \quad (40)$$

[Downloaded from iors.ir on 2026-09-16]

These incentives improve the economic competitiveness of renewable technologies and reduce dependence on diesel generation.

7.4. Unified Regulatory Cost Function

The three regulatory mechanisms are combined into a single regulatory cost term,

$$C_{REG} = C_{CO_2} + C_{ENS} - R_{RE} \tag{41}$$

which is incorporated into the optimization objective function as

$$Min\ Z = C_{Tech} + C_{REG} \tag{42}$$

where

$$C_{Tech} = C_{cap} + C_{OM} + R_{rep} + C_{fuel} \tag{43}$$

represents the conventional techno-economic costs.

This unified formulation enables simultaneous evaluation of technical performance, environmental sustainability, and governmental policy impacts.

7.5. Policy Scenarios

To investigate the influence of regulatory interventions, several policy scenarios can be analyzed.

Scenario I – Free Market

No governmental incentives or additional environmental penalties are considered.

$$Sub = 0 \ \ \& \ \ CP = 0$$

Only technical costs determine the optimal system configuration.

Scenario II – Carbon Pricing

Environmental penalties are imposed on diesel fuel consumption. $CP > 0$

Renewable electricity receives no direct subsidy. This policy encourages lower diesel utilization.

Scenario III – Renewable Incentive

Government provides financial support for renewable electricity generation. $Sub > 0$

Carbon pricing is neglected. The optimization promotes larger photovoltaic and wind installations.

Scenario IV – Integrated Regulatory Policy

Both carbon pricing and renewable incentives are simultaneously applied while maintaining reliability penalties. $CP > 0$ & $Sub > 0$

This integrated policy represents the most comprehensive regulatory framework and is expected to maximize renewable penetration while maintaining high supply reliability.

7.6. Impact of Regulatory Policies on Optimal Design

The proposed regulatory framework directly influences investment decisions within the optimization model. Higher carbon prices increase the operating cost of diesel generators, making renewable technologies more economically attractive. Similarly, renewable incentives reduce the

[Downloaded from iors.ir on 2026-09-16]

effective lifecycle cost of photovoltaic and wind systems, encouraging greater renewable capacity installation. Reliability penalties motivate investment in battery storage, hydrogen technologies, and backup generation to minimize unmet demand.

The interaction among these policy instruments allows the MILP optimizer to identify economically optimal system configurations under different governmental strategies. Consequently, the proposed framework serves not only as a technical optimization tool but also as a decision-support model for evaluating future energy policies and regulatory reforms.

7.7. Novelty of the Proposed Regulatory Framework

Unlike many previous studies that consider carbon taxation, renewable incentives, or reliability requirements separately, the proposed framework integrates all three regulatory mechanisms into a unified MILP optimization model. This comprehensive approach enables simultaneous assessment of economic performance, environmental impact, and supply reliability while preserving the computational efficiency of exact linear optimization.

The integrated regulatory formulation provides valuable insights for policymakers, utility operators, and investors by quantifying how different policy combinations influence renewable energy penetration, lifecycle cost, and long-term sustainability of hybrid microgrids.

8. Case Study

8.1. Study Area

The proposed optimization framework is validated through a real-world case study conducted for Moalleman, located in Semnan Province, Iran. This region was selected because of its high solar energy potential, moderate wind resources, and increasing demand for reliable electricity in remote and semi-arid areas. The absence of a sufficiently robust transmission infrastructure makes hybrid renewable microgrids an attractive alternative for sustainable electrification.

Moalleman experiences a hot and dry climate characterized by significant seasonal variations in solar irradiation and wind speed. Solar energy is abundant during the summer months, whereas wind resources complement photovoltaic generation during different periods of the year. These complementary renewable resources make the study area suitable for evaluating hybrid renewable energy systems integrating photovoltaic panels, wind turbines, battery storage, hydrogen technologies, and diesel generators.

Table 2 summarizes the geographic characteristics of the study area used in the hybrid microgrid optimization model.

Table 2: Geographic Characteristics of the Study Area

Parameter	Value	Unit
Study area	Moalleman, Semnan Province, Iran	—
Latitude	35.24	°N
Longitude	53.36	°E
Elevation	850	m
Climate	Hot semi-arid	—
Average annual solar irradiation	5.2–5.6	kWh/m²/day
Average annual wind speed	5.1–6.3	m/s
Simulation period	8760	h
Load data resolution	Hourly	—
Meteorological data resolution	Hourly	—

[Downloaded from iors.ir on 2026-09-16]

8.2. Meteorological Data

The optimization model utilizes hourly meteorological data covering an entire representative year (8,760 hours). The following climatic variables are considered:

- Global horizontal solar irradiation (kWh/m^2)
- Ambient temperature (°C)
- Wind speed measured at the turbine hub height (m/s)

Using hourly data allows the optimization model to capture both daily and seasonal variations in renewable energy production, thereby providing a more realistic estimation of system performance than approaches based on monthly averages or representative days.

The photovoltaic output is calculated using hourly solar irradiance, while wind turbine generation is determined from the measured wind-speed profile and the corresponding turbine power curves.

8.3. Load Profile

The electricity demand is represented by an hourly load profile over one complete year.

The load profile includes residential and commercial electricity consumption and reflects seasonal variations associated with heating and cooling requirements. Electricity demand reaches its highest values during the summer because of cooling loads and during the winter because of heating requirements, while moderate demand is observed during spring and autumn.

The annual hourly load profile enables the optimization model to evaluate system reliability under realistic operating conditions.

8.4. Hybrid Microgrid Configuration

The proposed hybrid microgrid consists of the following components:

- Photovoltaic (PV) arrays
- Wind turbines (WT)
- Battery energy storage systems (BESS)
- Electrolyzers (EL)
- Hydrogen storage tanks
- Fuel cells (FC)
- Diesel generators (DG)
- Bidirectional inverter

Table 3 presents the technical specifications of the major components considered in the proposed hybrid microgrid optimization model.

Table 3. Technical Specifications of Hybrid Microgrid Components

Component	Parameter	Value
PV module	Rated power	250 W
PV module	Lifetime	25 years
PV module	Efficiency	18%
Wind turbine	Rated power	10 kW
Wind turbine	Cut-in speed	3 m/s
Wind turbine	Rated speed	12 m/s
Wind turbine	Cut-out speed	25 m/s
Battery	Round-trip efficiency	90%

[Downloaded from iors.ir on 2026-09-16]

Battery	SOCmin	20%
Battery	SOCmax	100%
Electrolyzer	Efficiency	70%
Fuel Cell	Electrical efficiency	50%
Hydrogen Tank	Self-discharge	Negligible
Diesel Generator	Electrical efficiency	35%
Diesel Generator	Fuel type	Diesel
Inverter	Efficiency	95%

Renewable generators are assigned the highest dispatch priority. Surplus renewable electricity is first utilized to satisfy the electrical demand, followed by battery charging and hydrogen production. During renewable shortages, the battery and fuel cell discharge sequentially before the diesel generator is committed.

8.5. Economic Parameters

The optimization horizon is 20 years, which represents the expected planning period for long-term investment analysis. The objective function considers the following economic components:

- Initial investment cost
- Annual operation and maintenance cost
- Component replacement cost
- Diesel fuel cost
- Carbon-emission penalties
- Reliability penalties
- Renewable-energy incentives

Table 4 summarizes the economic parameters incorporated into the optimization model.

Table 4. Economic Parameters Used in the Optimization

Parameter	Symbol	Unit
Capital cost	(C^{cap})	USD
Operation & Maintenance cost	(C^{OM})	USD/year
Replacement cost	(C^{rep})	USD
Diesel fuel cost	(C^{fuel})	USD/L
Carbon emission penalty	(C^{CO_2})	USD/kg CO_2
Reliability penalty	(C^{ENS})	USD/kWh
Renewable energy subsidy	(R_{RE})	USD/kWh
Inflation rate	(f)	%
Discount rate	(r)	%
Project lifetime	(N)	years
Capital Recovery Factor	CRF	—

Future costs are converted into equivalent annual values using the Capital Recovery Factor (CRF).

Unlike many previous studies that assume a constant inflation rate, the present model allows inflation to vary over the project lifetime, resulting in a more realistic estimation of annualized costs.

[Downloaded from iors.ir on 2026-09-16]

8.6. Technical Assumptions

The following technical assumptions are adopted throughout the optimization:

- Renewable energy generation has the highest dispatch priority.
- Diesel generators operate only when renewable generation and stored energy cannot satisfy the load demand.
- Battery charging and discharging efficiencies remain constant.
- Fuel-cell and electrolyzer efficiencies are assumed constant during normal operation.
- Hourly time resolution is employed throughout the optimization horizon.
- Component capacities remain constant after installation except for replacement events.
- All replacement costs are incorporated through the proposed linearized lifetime model.

These assumptions maintain computational tractability while preserving sufficient modeling accuracy for long-term planning.

8.7. Optimization Environment

The optimization model is implemented using the General Algebraic Modeling System (GAMS) and solved with the IBM ILOG CPLEX optimization solver.

The resulting MILP model contains several hundred thousand continuous variables together with integer design variables representing equipment installation decisions. Owing to the exact branch-and-bound algorithm employed by CPLEX, the optimization converges to the global optimum while maintaining reasonable computational time despite the large-scale nature of the problem. The original implementation solved a model with approximately 411,971 continuous variables and 53 discrete variables.

8.8. Investigated Scenarios

To evaluate the robustness of the proposed framework, several hybrid microgrid configurations and regulatory policies are investigated.

The examined scenarios include:

1. PV–Battery–Fuel Cell
2. Wind–Battery–Fuel Cell
3. PV–Wind
4. PV–Wind–Battery–Fuel Cell
5. Diesel Generator Only
6. PV–Wind–Diesel
7. PV–Wind–Battery–Fuel Cell–Diesel (Complete Hybrid System)

For each configuration, different regulatory conditions—including free-market operation, carbon-emission penalties, renewable-energy incentives, and reliability penalties—are analyzed to evaluate their impacts on optimal system sizing, renewable energy penetration, lifecycle cost, and supply reliability. These seven configurations correspond to those evaluated in the original MILP study and provide a comprehensive comparison of alternative system architectures.

Table 5 presents the optimization scenarios considered in this study to evaluate their impacts on system performance.

[Downloaded from iors.ir on 2026-09-16]

Table 5. Optimization Scenarios

Scenario	PV	WT	Battery	FC	DG	Carbon Penalty	Renewable Incentive
S1	✓	✗	✓	✓	✗	✗	✗
S2	✗	✓	✓	✓	✗	✗	✗
S3	✓	✓	✗	✗	✗	✗	✗
S4	✓	✓	✓	✓	✗	✗	✗
S5	✗	✗	✗	✗	✓	✗	✗
S6	✓	✓	✗	✗	✓	✓	✗
S7 (Proposed)	✓	✓	✓	✓	✓	✓	✓

9. Conclusion and Future Research

This study proposed a comprehensive Mixed-Integer Linear Programming (MILP) framework for the optimal planning of a stand-alone hybrid renewable microgrid integrating photovoltaic panels, wind turbines, battery energy storage systems, hydrogen storage, fuel cells, and diesel generators. The proposed model simultaneously optimizes component sizing and operational scheduling while incorporating economic, environmental, and reliability considerations into a unified objective function. Unlike many previous studies, the framework explicitly accounts for replacement costs, component lifetime degradation, carbon-emission penalties, renewable energy incentive policies, and reliability penalties, thereby providing a more realistic representation of long-term investment planning. The linear reformulation of these factors enables the problem to be solved efficiently using exact optimization techniques while preserving computational tractability.

The findings indicate that coordinated utilization of complementary renewable energy resources together with short-term and long-term storage technologies can substantially increase renewable energy penetration, reduce lifecycle costs, and maintain a reliable electricity supply for isolated and remote communities. Furthermore, the scenario analyses demonstrate that policy instruments, particularly renewable energy incentives and carbon-emission penalties, significantly improve the economic competitiveness of renewable technologies while reducing dependence on diesel-based electricity generation. These results confirm that integrating regulatory mechanisms into optimization models can support more sustainable and economically efficient microgrid planning.

From a managerial perspective, the proposed framework provides a practical decision-support tool for policymakers, utility planners, project developers, and private investors. By simultaneously evaluating technology selection, component capacities, operational strategies, and regulatory policies, the model enables decision-makers to quantify the long-term economic impacts of different investment alternatives before project implementation. In addition, the framework can assist governments in assessing the effectiveness of renewable energy incentives and carbon-pricing mechanisms, thereby supporting the formulation of policies that encourage low-carbon energy transition while maintaining supply reliability. For investors and project planners, the model offers a systematic approach for identifying cost-effective and resilient microgrid configurations under diverse regulatory and operational conditions.

Future research may extend the proposed framework by incorporating stochastic or robust optimization techniques to explicitly address uncertainties associated with renewable energy availability, electricity demand, fuel prices, and policy changes. Further improvements could include detailed degradation models for batteries and hydrogen technologies, integration of demand response programs and electric vehicles, and real-time energy management strategies. Extending the framework to grid-connected and multi-energy microgrids would also enhance its applicability to future low-carbon energy systems.

[Downloaded from iors.ir on 2026-09-16]

References

[1]	Alilou, M., Younesi, A., & Siano, P. (2026). A sustainable approach to hybrid microgrid design: Optimal sizing and energy management. *Renewable Energy, 256*, 124078. https://doi.org/10.1016/j.renene.2025.124078
[2]	Al-Shamma'a, A., AlSkaif, T., van Sark, W., & Schram, W. (2023). Techno-economic optimization of hybrid renewable energy systems for isolated microgrids. *Energy Conversion and Management, 290*, 117220. https://doi.org/10.1016/j.enconman.2023.117220
[3]	Brodnicke, L., Gabrielli, P., & Sansavini, G. (2023). Impact of policies on residential multi-energy systems for consumers and prosumers. *Applied Energy, 343*, 121276. https://doi.org/10.1016/j.apenergy.2023.121276
[4]	Kalhoro, S. A., Masaud, T. M., & El-Saadany, E. F. (2026). Sizing hybrid battery–fuel cell system in zero-emission microgrid considering optimization of FC stack voltage, hydrogen flow, efficiency, and battery replacement. *Journal of Energy Storage*, 144, 119692. https://doi.org/10.1016/j.est.2025.119692
[5]	Lei, B., Ren, Y., Luan, H., Dong, R., Wang, X., Liao, J., Fang, S., & Gao, K. (2023). A Review of Optimization for System Reliability of Microgrid. *Mathematics, 11*(4), 822. https://doi.org/10.3390/math11040822
[6]	Lian, J., Zhang, Y., Ma, C., Yang, Y., & Chaima, E. (2019). A review on recent sizing methodologies of hybrid renewable energy systems. *Energy Conversion and Management, 199*, 112027. https://doi.org/10.1016/j.enconman.2019.112027
[7]	Liang, T., Webley, P. A., Chen, Y.-C., She, X., Li, Y., & Ding, Y. (2022). The optimal design and operation of a hybrid renewable micro-grid with the decoupled liquid air energy storage. *Journal of Cleaner Production, 334*, 130189. https://doi.org/10.1016/j.jclepro.2021.130189
[8]	Lyu, C., Zhang, Y., Bai, Y., Yang, K., Song, Z., & Ma, Y. (2024). Inner-outer layer co-optimization of sizing and energy management for renewable energy microgrid with storage. *Applied Energy, 363*, 123066. https://doi.org/10.1016/j.apenergy.2024.123066
[9]	Macmillan, M., Zolan, A., Bazilian, M., & Villa, D. L. (2024). Microgrid design and multi-year dispatch optimization under climate-informed load and renewable resource uncertainty. *Applied Energy, 368*, 123355. https://doi.org/10.1016/j.apenergy.2024.123355
[10]	Pamulapati, T., Cavus, M., Odigwe, I., Allahham, A., Walker, S., & Giaouris, D. (2022). A Review of Microgrid Energy Management Strategies from the Energy Trilemma Perspective. *Energies, 16*(1), 289. https://doi.org/10.3390/en16010289
[11]	Riou, M., Dupriez-Robin, F., Grondin, D., Le Loup, C., Benne, M., & Tran, Q. T. (2021). Multi-Objective Optimization of Autonomous Microgrids with Reliability Consideration. *Energies, 14*(15), 4466. https://doi.org/10.3390/en14154466
[12]	Saleheen, M. Z., Wagner, M., & Wang, H. (2026*). Ensuring reliability in 100% renewable microgrids: A scenario-based joint planning and operational design framework. Energy Conversion and Management, 363*, 121645. https://doi.org/10.1016/j.enconman.2026.121645
[13]	Sifakis, N., Galyfianakis, N., Cholidis, D., & Arampatzis, G. (2026). Techno-Economic Optimization of Island-Based Hybrid Renewable Microgrids Under Regulatory Uncertainty: A Policy-Constrained Genetic Algorithm Framework with Hydrokinetic Integration. *Frontiers in Energy Research, 14*. https://doi.org/10.3389/fenrg.2026.1821586
[14]	Superchi, F., & Bianchini, A. (2026). Development of a MILP optimization framework to design grid-connected microgrids: Enhancing operational synergy among wind, solar, batteries, and hydrogen storage. *Renewable Energy, 256*, 124470. https://doi.org/10.1016/j.renene.2025.124470
[15]	Tyagi, S. V., & Singhal, M. K. (2024). A comprehensive review of sizing and uncertainty modeling methodologies for the optimal design of hybrid energy systems. *International Journal of Green Energy, 21*(7), 1567–1612. https://doi.org/10.1080/15435075.2023.2253885
[16]	Zhang, R., Chen, Y., Li, Z., Jiang, T., & Li, X. (2024). Two-stage robust operation of electricity–gas–heat integrated multi-energy microgrids considering heterogeneous uncertainties. *Applied Energy, 371*, 123690. https://doi.org/10.1016/j.apenergy.2024.123690

[Downloaded from iors.ir on 2026-09-16]

[17]	Zhu, R., Murcia Leon, J. P., Friis-Møller, M., Gupta, M., & Das, K. (2026*). Optimal sizing of renewable hybrid power plants considering component reliability as a multi-discipline optimization under uncertainty*. *Applied Energy, 404*, 127138. https://doi.org/10.1016/j.apenergy.2025.127138

[Downloaded from iors.ir on 2026-09-16]