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Cost-Optimal Solar Microgrid Management : Exact versus Metaheuristic Optimization

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ABSTRACT:

Efficient energy management in solar microgrids is essential for ensuring reliable, cost-effective, and sustainable electricity supply, particularly in rural and off-grid environments. This study develops and evaluates a hybrid optimization framework combining an exact Mixed-Integer Linear Programming (MILP) model solved with IBM ILOG CPLEX and a tailored Genetic Algorithm (GA) to minimize daily operational costs while satisfying all technical and operational constraints. Ten real-inspired benchmark instances were constructed, each representing different hourly profiles of solar availability, electricity demand, and grid prices. Results show that CPLEX consistently obtained globally optimal schedules, achieving the lowest possible operational cost with full constraint satisfaction. The GA demonstrated strong convergence behavior, producing fully feasible solutions with zero violations and maintaining a cost deviation of only **11–16%** from the optimal CPLEX benchmark. The analysis further reveals consistent energy-use patterns across instances, where both CPLEX and GA prioritize solar PV utilization and strategically coordinate battery charging and discharging to reduce grid dependency. These findings confirm the effectiveness of exact optimization for small- to medium-scale systems and highlight the GA as a scalable and computationally efficient alternative for larger microgrids where exact methods become intractable. The proposed dual-method framework provides practical insights for microgrid operators, policymakers, and energy planners seeking to optimize renewable-based systems under uncertainty. Future extensions will integrate multi-day horizons, stochastic weather forecasts, battery aging, and advanced hybrid metaheuristics.

Keywords:
Solar microgrid; Energy management optimization; Mixed-Integer Linear Programming (MILP); Renewable energy scheduling; Battery storage optimization; Metaheuristic optimization.

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الملخص:

تُعدّ الإدارة القديرة للطاقة في الشبكات الكهربائية المصغّرة المعتمدة على الطاقة الشمسية أمرًا ضروريًا لضمان إمداد كهربائي موثوق واقتصادي ومستدام، ولا سيما في المناطق الريفية والمناطق غير المتصلة بالشبكة العامة. تطوّر هذه الدراسة إطارًا هجينًا للتحسين وتقيّمه، يجمع بين نموذج دقيق للبرمجة الخطية المختلطة بالأعداد الصحيحة (MILP)، تمت المعالجة باستخدام برنامج IBM ILOG CPLEX، وخوارزمية جينية (GA) مصممة خصيصًا، بهدف تقليل تكاليف التشغيل اليومية مع الالتزام بجميع القيود الفنية والتشغيلية.

تم إعداد عشر حالات اختبار معيارية مستوحاة من بيانات واقعية، تمثّل كل منها أنماطًا مختلفة على مدار الساعة لتوافر الطاقة الشمسية، والطلب على الكهرباء، وأسعار الكهرباء من الشبكة العامة. أظهرت النتائج أن برنامج CPLEX توصّل بصورة متسقة إلى جداول تشغيل جيدة عالميًا، محققًا أدنى تكلفة تشغيلية ممكنة مع استيفاء جميع القيود بالكامل. كما أظهرت الخوارزمية الجينية سلوكًا قويًا في التقارب، إذ أنتجت حلولًا قابلة للتنفيذ بالكامل من دون أي إخلال للقيود، مع الحفاظ على انحراف في التكلفة تراوح بين 11% و16% مقارنةً بالحل الأمثل الناتج عن برنامج CPLEX.

وكشف التحليل كذلك عن وجود أنماط متسقة لاستخدام الطاقة عبر مختلف حالات الاختبار، حيث أعطت كل من طريقة CPLEX والخوارزمية الجينية الأولوية للاستفادة من الطاقة الشمسية الكهروضوئية، مع التنسيق الاستراتيجي لعمليات شحن البطارية وتفريغها من أجل تقليل الاعتماد على الشبكة الكهربائية العامة.

تؤكد هذه النتائج فعالية أساليب التحسين الدقيقة في الأنظمة الصغيرة والمتوسطة الحجم، كما تبرز الخوارزمية الجينية بوصفها بديلًا قابلًا للتوسع وفعّالًا من الناحية الحاسوبية في الشبكات المصغّرة الأكبر حجمًا، التي قد تصبح فيها الطرق الدقيقة غير قابلة للمعالجة حسابيًا. ويوفر الإطار المقترح القائم على الطريقتين رؤى عملية لمشغلي الشبكات المصغّرة، وصنّاع السياسات، ومخططي الطاقة الذين يسعون إلى تحسين الأنظمة المعتمدة على مصادر الطاقة المتجددة في ظل ظروف عدم اليقين. وستشمل التطويرات المستقبلية دمج آفاق تشغيل تمتد لعدة أيام، وتنبؤات جوية احتمالية، وتأثير تقادم البطاريات، وأساليب هجينة متقدمة للتحسين فوق الاستدلالي.

الكلمات المفتاحية: الشبكات الكهربائية المصغّرة الشمسية؛ تحسين إدارة الطاقة؛ البرمجة الخطية المختلطة بالأعداد الصحيحة (MILP)؛ جدولة الطاقة المتجددة؛ تحسين أنظمة تخزين الطاقة بالبطاريات؛ التحسين باستخدام الخوارزميات فوق الاستدلالية.

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1. INTRODUCTION

The response to climate-change mitigation efforts in transitioning from fossil-fuel–based energy systems toward renewable energy has accelerated in the strategic pursuit of the United Nations' Sustainable Development Goal 7 — Affordable and Clean Energy. Among renewable resources, solar photovoltaic (PV) energy has emerged as a particularly suitable solution for the abundant world-wide and sun-rich regions where solar irradiance offers substantial potential for decentralized and autonomous energy production. Numerous recent reviews confirm the growing relevance of hybrid renewable microgrids in this transition, highlighting their design parameters, operational challenges, and optimisation requirements [1–4].

Nevertheless, the intermittent nature of solar generation and the variability of rural electricity demand create significant operational challenges for ensuring stable, reliable, and cost-efficient microgrid performance. These challenges become even more prominent in isolated or resource-constrained regions, where accurate forecasting, efficient scheduling, and optimal storage utilisation are essential to guarantee continuous supply at minimal cost. Reviews on hybrid renewable energy systems emphasise that integrating solar and storage resources requires robust optimisation and control strategies capable of addressing uncertainty and system variability [2–4].

To address these complexities, approaches such as Mixed-Integer Linear Programming (MILP), stochastic formulations, and multi-period optimisation provide a rigorous mathematical foundation for the optimal scheduling of production, storage, and grid exchanges in Hybrid Renewable Energy Systems (HRES). Parallel to these optimisation techniques, Artificial Intelligence (AI) methods — including Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks — have demonstrated strong capabilities in forecasting solar irradiance and load profiles by capturing nonlinear temporal relationships from historical and meteorological data. Recent studies further underline the importance of combining forecasting with optimisation to enhance energy management performance in microgrids [1,3,4].

Metaheuristic optimisation — particularly Genetic Algorithms (GA) — has gained increased attention due to its adaptability, robustness, and capacity to handle nonlinear

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and multi-modal optimisation landscapes. Several works have demonstrated the effectiveness of GA in microgrid scheduling, optimal sizing, and smart energy management, including advanced versions that integrate battery degradation, demand-response dynamics, and forecasting-aided scheduling [5–7]. Additionally, recent research confirms the importance of capacity configuration optimisation and system reliability assessment in renewable-energy-dominated networks, further motivating the integration of GA-based optimisation into modern microgrid design frameworks [8].

The combination of ML-based forecasting and OR-based optimisation has thus led to the development of hybrid frameworks capable of enhancing decision-making under uncertainty and dynamically adapting to variable supply–demand conditions. In line with this paradigm, the presented study proposes a hybrid, data-driven optimisation structure for solar microgrid energy management, centred on the comparative evaluation of two optimisation strategies. The study makes use of a combined MILP solver using IBM ILOG CPLEX and AI-based machine learning and metaheuristic algorithms, specifically the Genetic Algorithm (GA), following the recent methodological directions highlighted in the literature [5–7].

Both approaches are tested on several benchmark instances constructed from real solar and load profiles, enabling a reproducible and rigorous experimental comparison. The objective of the study is to validate the utility of this combined approach and to assess cost-minimisation performance, algorithmic robustness, and computational trade-offs for practical deployment in sun-rich but data-limited regions.

In line with this paradigm, the present study proposes a hybrid, data-driven optimisation structure for solar microgrid energy management, centred on the comparative evaluation of two optimisation strategies:

- an exact MILP solver using IBM ILOG CPLEX,
- and a metaheuristic Genetic Algorithm (GA).

Both approaches are tested on benchmark instances constructed from real solar and load profiles, enabling a reproducible and rigorous experimental comparison. The objective is to assess cost minimisation performance, algorithmic robustness, and computational trade-offs for practical deployment in Libya, Tunisia, and other sun-rich but data-limited regions.

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2. LITTERATURE REVIEW

Hybrid Renewable Energy Systems (HRES), which integrate renewable sources such as solar PV with storage units and possibly backup generators or grid interconnections, are widely recognised as effective solutions for achieving sustainable, reliable, and economically viable energy supply in remote and developing areas [9]. Energy-storage technologies — particularly lithium-ion batteries — play a crucial role in mitigating the intermittency of renewable sources and maintaining system reliability [10].

Optimising the operation of such systems remains a complex task due to the multi-period, multi-constraint nature of energy flows, battery efficiencies, degradation effects, and fluctuating load patterns. Mathematical optimisation techniques, especially MILP and stochastic programming, have been extensively used to structure these operational challenges, allowing for the representation of technical constraints and economic objectives such as cost minimisation and energy-loss reduction [4,11].

However, the effectiveness of optimisation heavily depends on the accuracy of demand and solar-generation forecasts. Machine-learning techniques — including ANNs and LSTMs — have been shown to significantly enhance forecasting accuracy by capturing nonlinear and temporal dependencies in historical time-series data [5,12]. The integration of such ML-based forecasting into optimisation models yields hybrid frameworks that dynamically adapt operational decisions to anticipated variability [7,13].

Despite these advances, several research gaps persist.
Notably:

- limited comparative studies between exact MILP solvers and metaheuristic algorithms using identical benchmark datasets;
- challenges in integrating real-time IoT data streams;
- difficulties in modelling full stochastic uncertainty;
- limited consideration of battery-aging mechanisms;
- and insufficient applications in data-scarce regions such as North Africa or the Middle East [2,14].

Furthermore, Energy Management Systems (EMS) employing Model Predictive Control (MPC) have demonstrated promising capabilities for dynamically optimising system operations and improving resilience [15]. Yet, MPC effectiveness relies heavily on accurate underlying optimisation models and reliable forecasts.

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Recent literature emphasises the need for robust techno-economic–environmental frameworks, improved stochastic and robust optimisation techniques, and scalable control strategies for real-world HRES applications [8,14]. This study contributes to this research stream by providing a rigorous comparison between an exact solver (CPLEX) and a Genetic Algorithm, using ten realistic and reproducible benchmark instances to assess performance in solar microgrid cost optimisation.

3. RESEARCH PROBLEM

The growing integration of renewable energy sources—particularly solar photovoltaics—into microgrid systems has introduced new operational challenges related to variability, intermittency, and real-time balancing between supply, storage, and demand. Ensuring cost-efficient and reliable energy management requires solving complex optimization problems that involve nonlinear interactions among generation, battery storage, grid exchange, and consumption profiles.

While exact optimization methods such as Mixed-Integer Linear Programming (MILP) solved with IBM ILOG CPLEX provide mathematically optimal solutions, their scalability and computational burden limit their applicability when the system size increases or when high-resolution time steps are required. Conversely, metaheuristic approaches, particularly the Genetic Algorithm (GA), offer flexibility and reduced computational effort but may converge to near-optimal instead of strictly optimal solutions.

However, few studies have conducted a systematic and controlled comparison between exact MILP solvers and metaheuristic GA approaches using identical benchmark microgrid instances constructed from real solar and load profiles. The absence of such comparative studies limits our ability to assess:

- How close GA solutions are to the CPLEX global optimum,
- Whether GA provides consistent performance across varying demand–solar scenarios,
- The trade-offs between computational cost and solution accuracy,
- The practical implications for real microgrid control systems, especially in developing regions where computational resources are limited.

Therefore, the central research problem addressed in this study is:

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How can we evaluate, quantify, and compare the performance of an exact MILP solver (CPLEX) and a Genetic Algorithm for optimal energy management in a solar microgrid, in terms of cost minimization, solution quality, computational efficiency, and robustness across multiple benchmark instances?

This research fills an existing gap by providing a rigorous mathematical formulation, a reproducible benchmark set, and an experimental comparison between exact and metaheuristic optimization approaches.

4. METHODOLOGY

The methodological framework adopted in this study integrates an exact optimization approach based on Mixed-Integer Linear Programming (MILP) with a metaheuristic Genetic Algorithm (GA) to evaluate the performance, robustness, and efficiency of different optimization paradigms for microgrid energy management. Figure X illustrates the global workflow, which comprises four main stages: data preparation, mathematical modeling, exact optimization using CPLEX, and heuristic optimization using GA.

4.1. DATA PREPARATION AND BENCHMARK DESIGN

A benchmark composed of ten real-world inspired 24-hour solar microgrid instances was developed. Each instance includes:

- Hourly electricity demand (kW)
- Available solar generation potential (kW)
- Market buying price
- Technical specifications of storage and energy sources

All data files were standardized in CSV format to guarantee compatibility with both optimization engines. The benchmark was executed in a controlled Python environment using Pyomo for MILP modeling and custom GA implementation for evolutionary optimization.

A preprocessing step verifies data consistency, normalizes the numerical scales, assigns time index sets, and ensures the absence of missing values. The same datasets are used for both CPLEX and GA to guarantee objective comparability

4.2. EXACT OPTIMIZATION WITH CPLEX

CPLEX is used as the reference exact solver due to its proven numerical stability and superior performance for linear energy dispatch problems [17]. For each instance:

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- The MILP model is compiled and provided to CPLEX.
- Optimal solutions are identified using branch-and-bound and presolve techniques.
- A tolerance of 10^{-6} and a deterministic single-thread mode were enforced to guarantee reproducibility.

The outputs include:

- Hourly energy flows
- Battery operational schedule
- Optimal total cost
- Dual information (for further sensitivity analysis)

The optimal cost from CPLEX serves as the lower bound for benchmarking heuristic performance.

4.3. GENETIC ALGORITHM DESIGN

To evaluate the performance of evolutionary search, a custom-coded Genetic Algorithm (GA) was developed (table1). The GA encodes each 24-hour schedule as a continuous chromosome vector representing:

- Grid power
- Battery charging power
- Battery discharging power
- Solar utilization share

Table 1 : GA Components

Component	Method used	Rationale
Representation	Real-coded vector	Improved precision for energy variables
Initialization	Random feasible solutions	Ensures operational validity
Selection	Tournament selection	Robust pressure and diversity maintenance
Crossover	Blend Crossover (BLX-α)	Suitable for continuous microgrid decisions
Mutation	Gaussian mutation	Local refinement and exploration
Repair operator	Constraint projection	Guarantees feasibility (no violation allowed)
Fitness function	Cost + penalty	Penalty = 0 when all constraints satisfied

A penalty-based feasibility check ensures that all microgrid physical limits are always respected. Mutation and crossover probabilities were tuned empirically (0.1 and 0.8 respectively), while population size and number of generations were chosen to balance precision and computation time.

Each instance was executed with:

- Population size = 50

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- Generations = 200
- Random seed set for reproducibility

4.4. PERFORMANCE METRICS

To compare both optimization paradigms, three evaluation metrics were computed:

1. Optimality Gap (%)

GAP= $\frac{GA-CPLEX}{CPLEX} * 100$

2. Feasibility Indicator

Ensures whether the GA solution violates any physical constraint (all penalties were 0).

3. Convergence Profile

Tracks best fitness evolution across generations.

These metrics allow a rigorous comparison between exact and heuristic optimization.

4.5. EXPERIMENTAL ENVIRONMENT

All tests were executed under:

- Python 3.10
- Pyomo 6.7.1
- CPLEX 22.1
- Intel Core i5, 8 GB RAM
- Windows 10 (64-bit)

This environment ensures computational consistency across all optimization runs.

5. MATHEMATICAL FORMULATION

- **SETS AND INDICES**

$t\epsilon T$: Set of Time periods (hours of the day)

$i\epsilon I$: Set of Energy sources (solar, battery, grid, diesel, etc)

$s\epsilon S$: Set of uncertainty scenarios (forecast variations).

- **PARAMETERS**

C_i: Operational cost of source i $/kWh

P_i^{max}: Maximum capacity of source I (kW)

D_t^s: Forecasted demand at time t under scenario s [kW]

W_t^s: Forecasted solar irradiance at time t under scenario s [0–1]

SC : Installed Solar panel capacity (kW)

η : Solar panel efficiency

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S^{max}: $Maximum$ Battery capacity (kWh)

η_{ch} η_{dis}: Battery charge and discharge efficiencies

γ : Cost of energy loss or curtailment $

SOC^{init}: Initial state of charge of battery (kWh)

p_s: Probability of occurrence of scenario s

- **DECISION VARIABLES**

$P_{i,t}^{s}$: Power generated by source i at time t under scenario (kW)

P_{bat}^{ch}(t, s) : Power charged into battery at time t (kW)

P_{bat}^{dis}(t, s) : Power discharged from battery at time t (kW)

SOC_t^s: Battery state of charge at time t (kWh)

$Loss_t^s$: Unused or wasted energy at time t (kWh)

- **OBJECTIVE FUNCTION**

Minimize total expected operational and curtailment costs.

$$\min Z = \sum_{s \in S} p_s \sum_{t \in T} \Delta t \left(\sum_{i \in I} C_i * P_{i,t}^{s} + \gamma Loss_t^s\right)$$

- **CONSTRAINTS**

a) Energy balance

$$\sum_{i \in I} P_{i,t}^{s} + P_{bat}^{dis}(t,s) + Loss_t^s = D_t^s + P_{bat}^{ch}(t,s) \qquad \forall t,s \qquad (1)$$

b) Battery dynamics

$$SOC_t^s = SOC_{t-1}^s + \eta_{ch} * P_{bat}^{ch}(t,s) - \frac{1}{\eta_{dis}} * P_{bat}^{dis}(t,s) \qquad \forall t,s \qquad (2)$$

c) Battery Capacity Limits:

$$0 \le SOC_t^s \le S^{max} \qquad \forall t,s \qquad (3)$$

d) Charging and Discharging Limits:

$$P_{bat}^{ch}(t,s) \ge 0 \qquad P_{bat}^{dis}(t,s)) \ge 0 \qquad \forall t,s \qquad (4)$$

e) Source Capacity Limits:

$$0 \le P_{i,t}^{s} \le P_i^{max} \qquad \forall i,t,s \qquad (5)$$

f) Source Generation Limit:

$$P_{solar,t}^{s} \le \eta * W_t^s * SC \qquad \forall t,s \qquad (6)$$

g) Initial Battery State of Charge:

$$SOC_0^s = SOC^{init} \qquad \forall s \qquad (7)$$

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This hybrid optimization model seeks to minimize the expected total operational and curtailment costs over a given planning horizon by optimally allocating energy among multiple sources, including solar panels, batteries, and the main grid, under different uncertainty scenarios. The formulation incorporates several key constraints: (1) an energy balance constraint, ensuring that total generation and battery discharge satisfy the predicted demand while accounting for charging and possible energy losses; (2) a battery state-of-charge (SOC) update equation, which dynamically models the evolution of stored energy based on charging and discharging efficiencies; (3) battery capacity limits, preventing overcharging or excessive discharge; (4) non-negativity constraints on charging and discharging power; (5) generation capacity limits for all energy sources; (6) a solar power generation constraint linking photovoltaic output to forecasted irradiance and installed panel capacity; and (7) an initial SOC condition defining the starting level of stored energy. By integrating machine learning-based forecasts for solar irradiance and demand into the optimization process, the framework achieves a balanced, reliable, and cost-efficient energy management strategy for rural smart grids operating under uncertainty.

6. RESULTS AND COMPARATIVE ANALYSIS

The comparative results reveal a clear distinction between the performance of the exact Mixed-Integer Linear Programming (MILP) solver CPLEX and the evolutionary Genetic Algorithm (GA) (table 2). CPLEX systematically reaches the optimal solution across all ten test instances, confirming its efficiency for linear energy management problems with moderate dimensionality. This behavior is consistent with prior studies that utilize MILP for optimal microgrid scheduling [16][17].

The GA produces feasible solutions with zero constraint violation, indicating that the evolutionary operators successfully preserve feasibility regarding power balance, battery charge/discharge limits, and resource capacity constraints. However, GA results present a consistent 13–15% deviation from the optimal values. Such deviations are standard for non-hybrid evolutionary techniques in energy optimization [18][19].

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Table 2: Comparison of CPLEX optimal solutions and GA best solutions across the 10 benchmark instances

Dataset	Inst 01	Inst 02	Inst 03	Inst 04	Inst 05	Inst 06	Inst 07	Inst 08	Inst 09	Inst 10
CPLEX	31.689	31.166	32.202	31.259	31.855	32.472	30.726	30.872	31.295	31.72
GA (Best	35.913	35.338	36.803	35.713	36.252	37.152	34.727	35.523	35.366	35.964
GAP (%)	13.3	13.4	14.3	14.2	13.8	14.4	13	15.1	13	13.4

Average GAP = 13.89%

Convergence curves show two classical phases:

- Rapid exploration, with steep improvements during early generations,
- Local exploitation, where the fitness plateau stabilizes progressively.

This behavior is aligned with the canonical description of evolutionary search patterns by [20] and [21]. Although the GA does not reach optimality, it exhibits stable convergence and robustness, producing operationally acceptable solutions with no constraint violation.

❖ **Energy Behavior Analysis**

The energy flow patterns derived from the optimization results highlight consistent operational strategies:

Under CPLEX (optimal scheduling):

- Solar generation is exploited at maximum during daylight hours, minimizing reliance on grid power.
- The battery is strategically charged and discharged to smooth demand peaks.
- Grid power is used only when solar and storage resources are insufficient.

Under GA (near-optimal scheduling):

The algorithm generally replicates the same operational structure, but with slight inefficiencies:

- Some battery discharge periods are not perfectly timed,

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- Occasional suboptimal charge/discharge transitions,
- Slightly higher grid usage during specific hours.

These differences explain the average cost deviation (~14%). Similar behavior has been documented in studies applying GA to energy scheduling in microgrids [22].

❖ **Practical Implications**

The comparative results have several practical implications for microgrid operators and energy planners:

Suitability of CPLEX

- Ideal for systems with linear or linearized models,
- Guarantees minimal operational cost,
- Best suited for offline planning with sufficient computational resources.

Suitability of GA

- Highly relevant for large-scale, nonlinear, or stochastic microgrid models,
- Capable of producing feasible solutions rapidly,
- Works well in real-time or near real-time applications where optimality is less critical.

Robust Decision Making

Despite not achieving optimality, GA always yields feasible schedules (penalty = 0), ensuring operational safety.

Flexibility

GA can easily integrate additional objectives (emissions, battery degradation, uncertainty), making it attractive for multi-objective or multi-energy microgrids.

7. CONCLUSIONS

This study proposed and evaluated a hybrid optimization framework for solar microgrid energy management in rural contexts, combining an exact Mixed-Integer Linear Programming (MILP) model solved with IBM ILOG CPLEX and a tailored Genetic Algorithm (GA). The objective was to assess the capability of both approaches to minimize the daily operational cost of a microgrid while satisfying all technical, operational, and environmental constraints.

Across ten benchmark instances representing diverse solar availability and demand profiles, the MILP model systematically produced globally optimal solutions, with total

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costs ranging from 30.72 to 32.47 units. These results confirm the effectiveness of deterministic linear optimization for microgrid scheduling problems, consistent with observations in the literature that MILP offers strong guarantees for convex or linearized energy systems [17].

The GA, designed with real-coded chromosomes, blended crossover, Gaussian mutation, and a feasibility-preserving repair operator, demonstrated strong convergence properties and robustness. All GA runs converged to feasible schedules with zero constraint violations, and the final cost exceeded the CPLEX optimum by only 11% to 16%, depending on the instance. This level of accuracy aligns with prior research showing that evolutionary algorithms can approach optimal dispatch solutions with relatively low computational overhead. The convergence curves further revealed two distinct phases—an initial rapid descent followed by stable exploitation—indicating that the GA maintains a balanced exploration–exploitation dynamic.

Beyond numerical comparison, the analysis highlighted consistent operational patterns. CPLEX systematically prioritizes solar energy during peak irradiance hours and strategically manages battery discharge to minimize grid purchases. The GA reproduces similar qualitative behaviors, confirming its ability to capture the physical logic of microgrid operation even without full knowledge of the mathematical structure.

Overall, the findings show that CPLEX is ideal for instances of small to medium scale, where optimal solutions are essential for system design, calibration, or policy evaluation. In contrast, the GA provides a scalable and flexible alternative for larger systems where exact optimization becomes computationally prohibitive. These complementary strengths position the hybrid framework as a powerful analytical tool for rural electrification planning, decentralized renewable systems, and resilient smart-grid operation under uncertainty.

Future research will extend the model to incorporate multi-day horizons, stochastic weather uncertainty, battery degradation, and demand response mechanisms. Additional metaheuristics—such as Particle Swarm Optimization, Differential Evolution, and hybrid GA–LNS approaches—will also be explored to enhance scalability and solution quality. Integration with predictive machine learning models for solar and demand forecasting represents another promising avenue toward fully autonomous and intelligent microgrid management.

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