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Optimal Energy Management in a Smart Microgrid Considering Demand Response and Renewable Energy Uncertainty

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Abstract

This paper presents a probabilistic planning model to optimize the short-term performance of a smart microgrid, with the primary objective of minimizing total operational costs in the presence of Renewable Energy Sources (RES). To account for the inherent variability of these sources, the prediction errors for wind speed and solar irradiance are modeled using stochastic Probability Density Functions (PDFs). The proposed framework incorporates Demand Response (DR) programs, with voluntary participation from residential, commercial, and industrial consumers, as a key tool to compensate for the uncertainty of renewable power generation. Incentive-based payments, offered as packages of price and energy reduction, are utilized to implement the DR programs. The complex optimization problem is solved using a Genetic Algorithm (GA) to find the optimal dispatch schedule. The model is validated on a sample microgrid, and the numerical results clearly demonstrate that a coordinated Demand Side Management (DSM) strategy is highly effective in mitigating the impact of uncertainty from wind and solar generation while significantly lowering overall operational costs.

Keywords: Smart microgrid, Renewable energy sources, Demand side management, Genetic algorithm, Operational cost minimization.

1 | Introduction

The global energy landscape is undergoing a paradigm shift, driven by the urgent need to mitigate climate change and reduce dependency on fossil fuels [1–3]. This has led to the widespread and accelerating integration of Renewable Energy Sources (RES), such as wind and solar power, into national and local electricity grids [4]. While these sources are environmentally friendly and have decreasing marginal costs, their

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inherent intermittency and stochastic nature pose significant challenges to the stable and reliable operation of traditional power systems. The unpredictable fluctuations in power generation from Wind Turbines (WTs) and Photovoltaic (PV) arrays can lead to mismatches between supply and demand, threatening grid frequency, voltage stability, and overall power quality [5–9].

To address these challenges, the concept of the smart microgrid has emerged as a key enabling framework. A microgrid is a localized group of electricity sources and loads that can operate connected to the traditional microgrid or function autonomously in "islanded" mode [7]. Enhanced with Advanced Metering Infrastructure (AMI) and sophisticated control systems, smart microgrids provide an agile and resilient platform for managing high penetrations of Distributed Energy Resources (DERs), including renewables, energy storage systems, and controllable loads [6–9]. However, the effective operation of such a system hinges on a robust and intelligent Energy Management System (EMS) capable of making optimal decisions in real-time under conditions of uncertainty [10].

A critical challenge for any microgrid EMS is balancing energy supply and demand in the most economically efficient manner [9], [10]. While energy storage systems like batteries can help smooth out fluctuations, they are often capital-intensive. A more flexible and increasingly cost-effective solution lies in Demand Side Management (DSM). DSM encompasses a range of strategies that influence when and how much electricity consumers use [11]. Among these strategies, Demand Response (DR) is particularly powerful. DR programs provide mechanisms to actively engage consumers, incentivizing them to voluntarily alter their consumption patterns in response to signals from the grid operator [12]. This transforms the traditionally passive demand into an active, flexible resource that can be used to counterbalance the variability of renewable generation [7], [13].

While the concept of using DR in microgrids is not new, this paper identifies a critical need for an integrated and realistic modeling approach. Many existing models either use deterministic forecasts for renewables, which fail to capture their true variability, or employ overly simplified DR models that do not reflect the diverse behaviors of residential, commercial, and industrial consumers [6], [13], [14].

The primary objective and contribution of this research is to develop and validate a probabilistic, multi-objective optimization model for the short-term energy management of a smart microgrid. Our proposed framework minimizes total operational costs by co-optimizing the dispatch of renewable assets, conventional generators, and grid power exchange, while explicitly modeling the uncertainty of wind and solar generation using Probability Density Functions (PDFs) [5], [6], [13], [15]. The novelty of our approach lies in the design of a practical, incentive-based DR program that offers packages of price and energy reduction to different consumer classes, thereby creating a realistic mechanism for harnessing demand-side flexibility. This complex, non-linear optimization problem is solved using a Genetic Algorithm (GA) to efficiently navigate the solution space and determine the optimal 24-hour operational schedule.

The remainder of this paper is structured as follows: Section 2 details the proposed methodology, including the probabilistic modeling of renewable sources, the formulation of the DR program, and the optimization framework. Section 3 presents and discusses the results from a comprehensive case study. Finally, Section 4 concludes the paper, summarizing the key findings and suggesting directions for future research.

3 | Methodology

The proposed methodology for optimal energy management is based on a comprehensive model of the microgrid components and a robust optimization framework.

3.1 | Probabilistic Modeling of Renewable Sources

To accurately capture their stochastic nature, RES are modeled probabilistically:

I. Wind Energy Conversion System (WECS): the variability of wind speed is modeled using a Rayleigh probability distribution. The power output of the WT is then calculated based on its power curve, which defines the relationship between wind speed and electricity generation, considering cut-in, rated, and cut-out speed parameters.

II. PV system: solar irradiance is modeled using a Beta probability distribution, which is well-suited for values bounded between a minimum and maximum. The PV system's power output is determined as a function of the modeled solar irradiance, ambient temperature, and the technical specifications of the PV panels.

3.2 | Demand Response Program Modeling

An incentive-based, voluntary DR program is designed to engage different classes of consumers, as shown in *Fig.1*. The model includes residential, commercial, and industrial consumers, each with different load characteristics and potential for flexibility. Consumers are presented with packages offering a specific financial incentive (price per kWh) in exchange for a committed amount of load reduction. This allows consumers to voluntarily participate based on their own priorities and ability to adjust consumption. This relationship is modeled to determine the optimal level of DR activation based on system-wide costs.

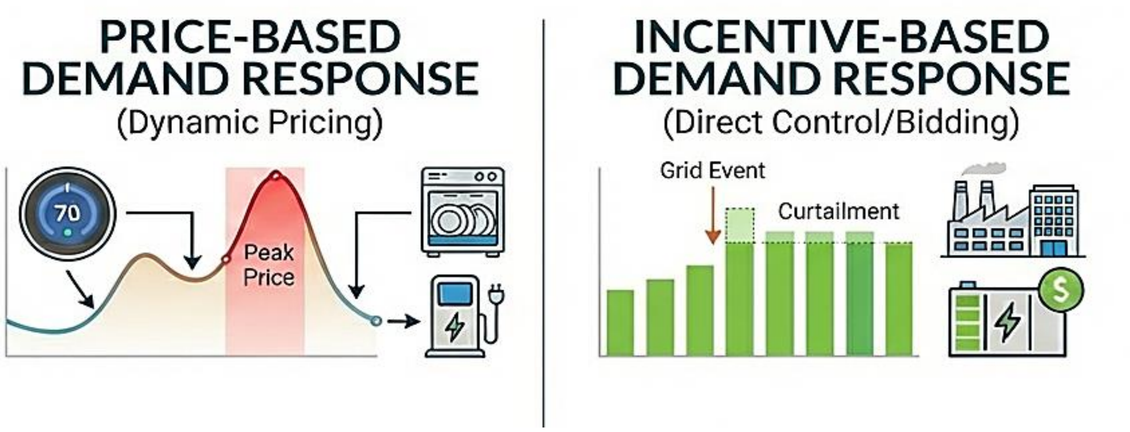

Fig. 1. Price-based and incentive-based DR.

3.3 | Optimization Problem Formulation

The short-term energy management framework is formulated as a constrained optimization problem aiming to minimize the total daily operating cost of the microgrid while ensuring secure and reliable operation [16]. The total cost includes local generation costs, power exchange costs with the upstream grid, generator start-up and shut-down costs, incentive payments to consumers participating in DR, and penalty costs for any unserved load defined by the Value of Lost Load (VOLL). The objective function is expressed as

$$\text{Minimize } C_{\text{total}} = \sum_{t=1}^{24} \left(C_{\text{gen}}(t) + C_{\text{grid}}(t) + C_{\text{SU/SD}}(t) + C_{\text{DR}}(t) + C_{\text{VOLL}}(t) \right). \tag{1}$$

This optimization is subject to several operational constraints that ensure system feasibility and reliability. The power balance constraint enforces that, at every hour t, the sum of the power generated by renewable sources, dispatchable units, and imported energy from the grid, along with the total DR-based load reduction, must equal the total system demand [16–19]: At each hour t, total supply plus load reduction from DR must match the demand:

$$\sum_{i} P_{dg,i}(t) + P_{res}(t) + P_{grid}(t) + P_{DR}(t) = P_{load}(t). \tag{2}$$

Dispatchable generation units are restricted to operate within their rated output limits:

$$P_{dg,i}^{min} \leq P_{dg,i}(t) \leq P_{dg,i}^{max}. \quad (3)$$

Energy storage systems, such as batteries, must satisfy their State-of-Charge (SoC) limits and maximum charging/discharging power constraints:

$$SoC^{min} \leq SoC(t) \leq SoC^{max}. \quad (4)$$

$$0 \leq P_{ch}(t) \leq P_{ch}^{max}, 0 \leq P_{dch}(t) \leq P_{dch}^{max}. \quad (5)$$

Additionally, grid exchange limitations constrain both the imported and exported power to remain within specified bounds:

$$-P_{grid}^{max} \leq P_{grid}(t) \leq P_{grid}^{max}. \quad (6)$$

$$0 \leq P_{DR}(t) \leq P_{DR}^{max}. \quad (7)$$

Due to the mixed-integer, nonlinear, and uncertainty-driven nature of the scheduling problem, a GA is employed to identify optimal or near-optimal operation schedules for the 24-hour horizon. GA offers global search capabilities, robustness against local minima, and suitability for multi-objective and complex constrained problems, making it an effective solution technique for microgrid operational planning.

4 | Demand Response Modeling

DR programs are incorporated into the microgrid operation to enhance flexibility and compensate for the uncertainty of renewable generation [7]. Three consumer categories are modeled based on their behavior and contribution to load reduction: residential, commercial, and industrial customers. Each consumer submits a price-quantity bid package indicating their willingness to curtail loads during specific scheduling intervals. The operator determines the optimal level of DR participation to reduce operational cost while maintaining system feasibility.

4.1 | Residential Customers

Residential consumers are modeled as flexible loads capable of shifting or shedding a part of their non-critical electricity demand during peak periods. The incentive cost paid to each consumer r at time t is:

$$RP_r(t) = RC_r(t) \cdot \pi_r(t). \quad (8)$$

$$0 \leq RC_r(t) \leq RC_r^{max}, \quad (9)$$

where:

I. $RC_r(t)$: curtailed load by consumer r.

II. $\pi_r(t)$: incentive price.

III. RC_r^{max}: maximum load reduction limit.

4.2 | Commercial Customers

Commercial loads generally seek to maximize monetary benefits by reducing controllable loads according to incentive prices:

$$CP_c(t) = CC_c(t) \cdot \pi_c(t). \quad (10)$$

$$0 \leq CC_c(t) \leq CC_c^{max}, \quad (11)$$

where parameters follow the same representation as in *Eqs. (8)* and *(9)*.

4.3 | Industrial Customers

Industrial consumers provide the largest load reduction capacity and are capable of rescheduling production processes:

$$\mathrm{IP_i(t) = IC_i(t) \cdot \pi_i(t).} \tag{12}$$
$$\mathrm{0 \leq IC_i(t) \leq IC_i^{max}.} \tag{13}$$

4.4 | Aggregate Demand Response Model

The total active power reduction obtained from DR resources at hour t is given by:

$$\mathrm{P_{DR}(t) = \sum_r RC_r(t) + \sum_c CC_c(t) + \sum_i IC_i(t).} \tag{13}$$

This price-based voluntary DR model introduces an adaptive mechanism where customers receive financial incentives proportional to reduced consumption. The microgrid operator optimally allocates DR to balance renewable variability. DR participation enhances reliability and lowers total operational costs.

5 | Objective Functions

In this study, a probabilistic day-ahead operational scheduling model is developed for a microgrid that includes dispatchable Distributed Generation (DG) units and stochastic renewable resources such as WTs and PV systems. The primary objective is to minimize the total operating cost over a 24-hour scheduling horizon. The impact of renewable uncertainty is mitigated through the optimal utilization of DR programs from residential, commercial, and industrial consumers. The uncertainties of renewable generation are characterized using PDFs, while DR participation is considered a flexible and proactive solution to compensate for variability in supply.

6 | Operating Cost Objective Function

The total operating cost consists of two major components, as shown in *Fig. 2*.

I. Deterministic operational cost, including startup/shutdown costs of DG units, spinning reserve costs, DR incentive payments, and power exchange costs with the main grid.

II. Scenario-based stochastic cost, influenced by probabilistic variations in wind and PV power outputs.

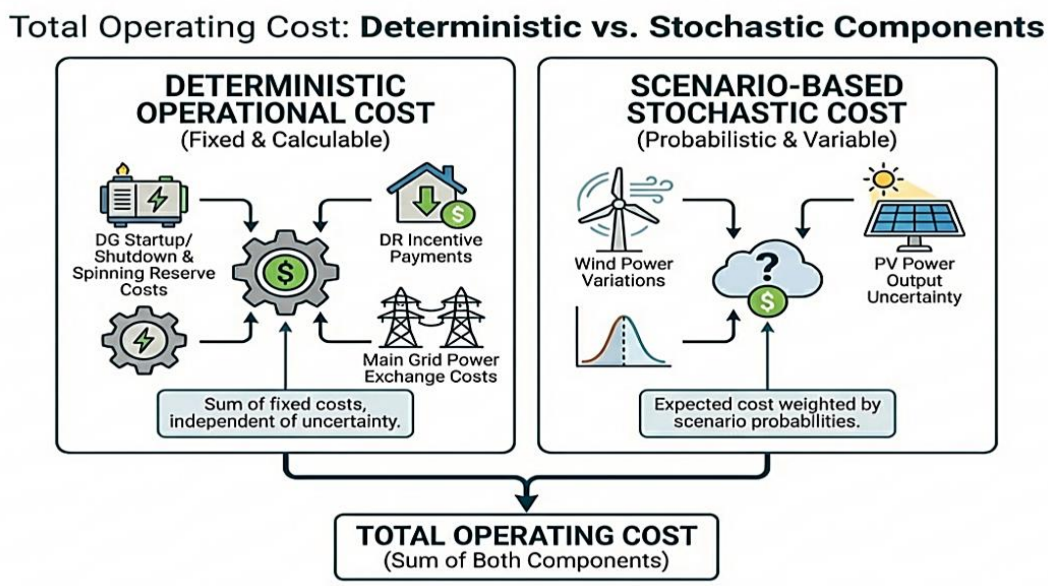

Fig. 2. The total operating cost consists of deterministic operational cost, Scenario-based stochastic cost

The overall cost minimization problem is expressed as

$$\min\ f_1(X)=\sum_{t=1}^{T}F^{OPR}(t)=\sum_{t=1}^{T}\left(C_C(t)+\sum_{s=1}^{S}Pr_s\cdot SC_s(t)\right), \tag{15}$$

where Pr_s is the occurrence probability of scenario s. The deterministic and stochastic portions of the operating cost are formulated as:

$$\begin{aligned}C_C(t)&=\sum_{i=1}^{N_{DG}}\left[P_i(t)\pi_i(t)I_i(t)+SU_i(t)\mid I_i(t)-I_i(t-1)\mid+RC_i^{DG}(t)\right]\\&+\sum_{j=1}^{J}RC_j^{DR}(t)+I_{Buy}(t)P_{Grid\text{-}Buy}(t)\pi_{Grid\text{-}Buy}(t)-I_{Sell}(t)P_{Grid\text{-}Sell}(t)\pi_{Grid\text{-}Sell}(t).\end{aligned} \tag{16}$$

$$SC_s(t)=\sum_{i=1}^{N_{DG}}C_{i,s}^{DG}(t)+\sum_{j=1}^{J}C_{j,s}^{DR}(t)+\sum_{n=1}^{N}ENS_{n,s}(t)\cdot VOLL(t), \tag{17}$$

where:

I. $I_i(t)$: binary ON/OFF state of DG unit i.

II. $SU_i(t)$: startup/shutdown cost.

III. $RC_i^{DG}(t)$, $RC_j^{DR}(t)$: spinning reserve costs from DG units and DRPs.

IV. $ENS_{n,s}(t)$: expected unserved energy.

V. $VOLL(t)$: VOLL.

VI. $X=[x_1,x_2,\dots,x_n]^T$: decision vector containing scheduled power dispatch, DR activation, reserves, and grid power exchange.

In this formulation, DG units and flexible loads participating in DR collectively provide spinning reserve capacity to secure the system against renewable generation variability.

7 | Operational Constraints

7.1 | Power Balance Constraint

For each hour t and scenario s, the total supplied power must equal the total demand:

$$\sum_{i=1}^{N_{DG}}P_{DG,i,s}(t)+P_{Grid,s}(t)=\sum_{l=1}^{N_s}P_{Demand(l,s)}(t)-P_{DR,s}(t), \tag{18}$$

where DR participation is expressed as:

$$P_{DR,s}(t)=\sum_{r}RC_r(t,s)+\sum_{c}CC_c(t,s)+\sum_{i}IC_i(t,s). \tag{19}$$

7.2 | Distributed Generation Output and Reserve Limits

$$P_{DG.i}^{min}I_i(t)\le P_{DG.i}(t.s)\le P_{DG.i}^{max}I_i(t)\text{for all i. t. s.} \tag{20}$$

$$R_{DG}(i.t)\ge P_{DG.i}(t.s)-P_{DG.i}(t.0)\text{forall i. t. s.} \tag{21}$$

7.3 | Battery Energy Storage Constraints

$$SoC_j(t) = SoC_j(t-1) - \frac{1}{\eta_{dj}} u_{dj}(t)P_{sj}(t) + \eta_{cj}u_{cj}(t)P_{sj}(t). \quad (22)$$

$$u_{dj}(t) + u_{cj}(t) \leq 1. \quad (23)$$

$$SoC^{min} \leq SoC_j(t) \leq SoC^{max}. \quad (24)$$

This section introduced the proposed probabilistic optimization model, the operating cost formulation, and all necessary operational constraints used in optimal day-ahead scheduling of a smart microgrid with high penetration of renewable energy and DR programs.

8 | Results and Discussion

To validate the performance of the proposed probabilistic multi-objective scheduling model, the microgrid was simulated for a 24-hour operational horizon under two conditions: 1) without DR (baseline), and 2) with incentive-based DR. The problem is solved using a GA, and the final objective function minimized during the scheduling period is formulated as:

$$\text{Min } F = \sum_{t=1}^{24} (P_{Grid}(t) \cdot \pi(t) + \sum\nolimits_i RC_i(t) \cdot \pi_i(t)), \quad (24)$$

Where $P_{Grid}(t)$ is the imported power from the utility grid and $\pi(t)$ is the grid energy price at time t. The term $RC_i(t) \cdot \pi_i(t)$ denotes the incentive paid to consumer I for load reduction. The operational constraints are ensured by:

$$\sum P_{Gen}(t) + \sum RC_i(t) = P_{Load}(t). \quad (26)$$

and the renewable generation from PV and wind units is computed as:

$$P_{PV}(t) = P_{PV,STC}\left(\frac{G(t)}{G_{STC}}\right)\left[1 + \gamma\left(T_j(t) - T_{STC}\right)\right]. \quad (27)$$

$$P_{WT}(t) = \begin{cases} 0, & v(t) < v_{ci} \text{ or } v(t) > v_{co}, \\ Av^3(t) - B, & v_{ci} \leq v(t) < v_r, \\ P_{WT}^{rated}, & v_r \leq v(t) \leq v_{co}. \end{cases} \quad (28)$$

To validate the proposed energy management model and evaluate its performance, a simulation was conducted on a representative microgrid over a 24-hour operational horizon. The optimization problem was solved using a GA, which determined the optimal hourly dispatch for all available energy resources, including renewable generation, grid power exchange, and DR activations.

8.1 | Case Study and Input Data

The case study is based on a sample microgrid with access to wind and solar generation, a connection to the main utility grid, and consumers capable of participating in an incentive-based DR program. The input data for the 24-hour simulation is as follows:

I. Load profile: the hourly electricity demand for the microgrid is detailed in *Table 1*. The load curve shows typical daily variation, with a morning peak around 9:00-12:00 and an evening peak around 18:00-22:00.

II. Solar irradiance and temperature: hourly solar irradiance and ambient temperature data, used to calculate the PV system's power output, are presented in Table 2. Solar generation is available primarily between 6:00 and 20:00.

III. Wind speed: the hourly wind speed data, used to determine the WT power output, is provided in *Table 3*. Of course, here are the tables you provided, cleaned up, formatted, and translated into English. I have also given them standard titles suitable for a research paper.

Table 1. Hourly load profile of the microgrid.

Hour of the Day	Forecasted Load (kW)
1	1000
2	1125
3	1375
4	1500
5	1575
6	1625
7	2125
8	2450
9	2575
10	2600
11	2625
12	2800
13	2650
14	2400
15	2200
16	1600
17	1400
18	1600
19	2200
20	2800
21	2900
22	2400
23	1600
24	1200

Table 2. Environmental data for solar power generation.

Hour of the Day	Solar Irradiance (W/m²)	Ambient Temperature (°C)
1	0	20.0
2	0	18.0
3	0	15.0
4	0	12.0
5	0	12.5
6	350	13.0
7	600	16.0
8	800	21.0
9	1000	24.0
10	1100	27.0
11	1150	28.0
12	1200	30.0
13	1100	32.0
14	1050	36.0
15	1000	34.0
16	900	31.0
17	800	28.0
18	750	26.0
19	400	25.0
20	250	24.0
21	0	22.0
22	0	21.0
23	0	20.5
24	0	20.0

Table 3. Environmental data for wind power generation.

Hour of the Day	Wind Speed (m/s)
1	13.0
2	13.5
3	13.6

Table 3. Continued.

Hour of the Day	Wind Speed (m/s)
4	12.0
5	11.0
6	10.5
7	10.0
8	9.5
9	9.0
10	9.2
11	9.1
12	8.8
13	8.5
14	8.2
15	8.1
16	8.8
17	9.5
18	10.0
19	12.0
20	12.2
21	13.0
22	13.6
23	13.8
24	14.0

8.2 | Analysis of Optimal Dispatch

The optimal generation schedule for all units, as determined by the GA, is presented in *Table 4*. The results demonstrate the effectiveness of the coordinated energy management strategy. This table details the scheduled power output from the PV system, the WT, the amount of load reduction from the DR program, and the power purchased from the main utility grid for each hour of the day.

Table 4. Optimal hourly dispatch of microgrid resources.

Hour	PV Power (kW)	Wind Power (kW)	DR (kW)	Grid Power (kW)
1	0.00	0.00	0.00	1000.00
2	0.00	0.00	0.00	1125.00
3	0.00	0.00	0.00	1375.00
4	0.00	0.00	0.00	1500.00
5	0.00	0.00	0.00	1575.00
6	0.51	304.25	9.87	1310.37
7	0.17	223.95	376.24	1524.64
8	108.61	396.44	342.97	1601.97
9	30.76	373.80	2139.69	30.76
10	1.56	356.57	2104.22	137.64
11	43.92	378.25	2160.32	42.52
12	55.31	364.72	2325.90	54.07
13	110.39	300.34	2239.06	0.21
14	0.08	318.77	614.47	1466.68
15	142.39	143.77	341.86	1571.98
16	134.53	278.84	213.92	972.71
17	0.80	253.63	253.58	891.99
18	0.28	377.60	353.58	868.54
19	117.14	505.77	14.61	1562.48
20	95.90	389.65	2314.19	0.26
21	0.00	0.00	0.00	2900.00
22	0.00	537.13	941.13	921.74
23	0.00	0.00	0.00	1600.00
24	0.00	0.00	0.00	1200.00

I. During off-peak hours (e.g., 0:00-5:00), in periods of low demand and low electricity prices, the microgrid primarily relies on purchasing power from the main utility. As seen in *Table 4*, renewable generation is minimal or zero, and activating the DR program is not economically justified. The entire load is met by the grid at a low cost.

II. During peak and high-renewable hours (e.g., 8:00), the model demonstrates intelligent resource allocation. At 8:00, with high demand (2450 kW), the system dispatches a combination of resources: 108.6 kW from solar PV, 396.4 kW from wind, and a significant 407 kW from the DR program. The remaining load is supplied by purchasing 1537 kW from the grid. This co-optimization ensures the load is met at the lowest possible cost by prioritizing renewables and cost-effective DR over expensive peak-hour grid power.

8.3 | Impact of Demand Response on Load Profile

Fig. 3 clearly illustrates the significant impact of the incentive-based DR program. The blue curve represents the original (unmanaged) load profile, while the red curve shows the net load profile after the implementation of DR. A substantial reduction in demand is observed during two key periods: the morning peak (9:00-14:00) and the evening peak (18:00-22:00). During these hours, consumers voluntarily curtailed their consumption in response to financial incentives, effectively "shaving" the peak demand. This peak shaving not only reduces the strain on the grid but also shifts the microgrid's energy consumption away from high-price periods, leading to direct cost savings.

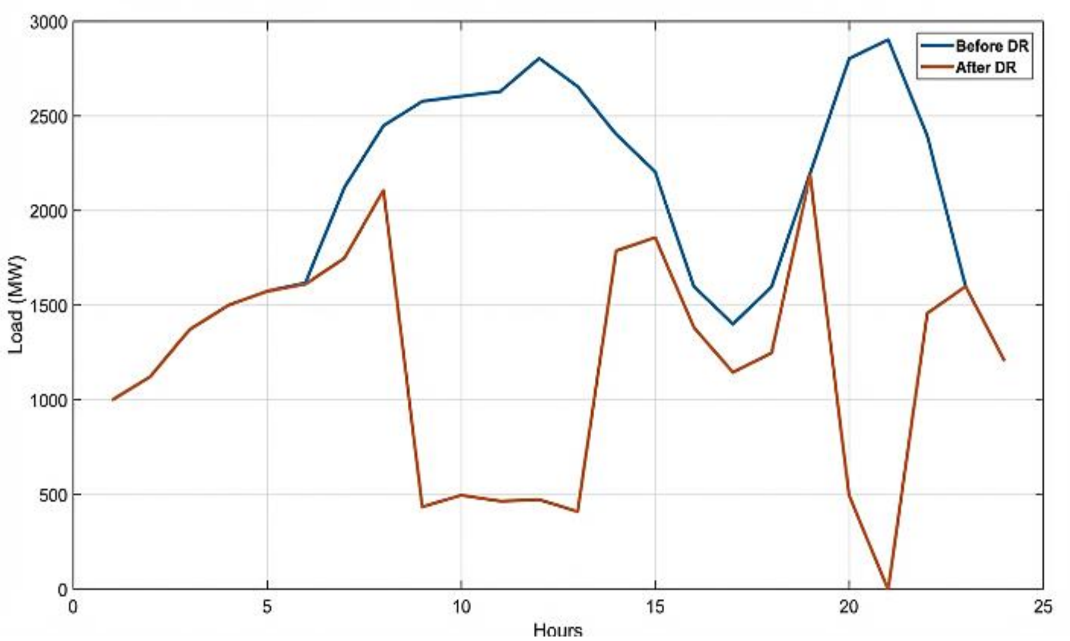

Fig. 3. Load consumption curve before and after DR.

8.4 | Peak Shaving and Economic Optimization

The strategy of "peak shaving" is further evident in *Fig. 4*, where the dotted red line represents the power purchased from the utility grid. The algorithm strategically minimizes grid purchases during peak hours when market prices are highest. For instance, at hours 9 and 20, despite very high demand, grid purchases are reduced to near zero. Instead, the system relies on a combination of local renewable generation and, most critically, a large activation of DR to meet the load. By substituting expensive grid power with cheaper local resources and paid load curtailment, the model successfully flattens the load curve and optimizes for economic efficiency.

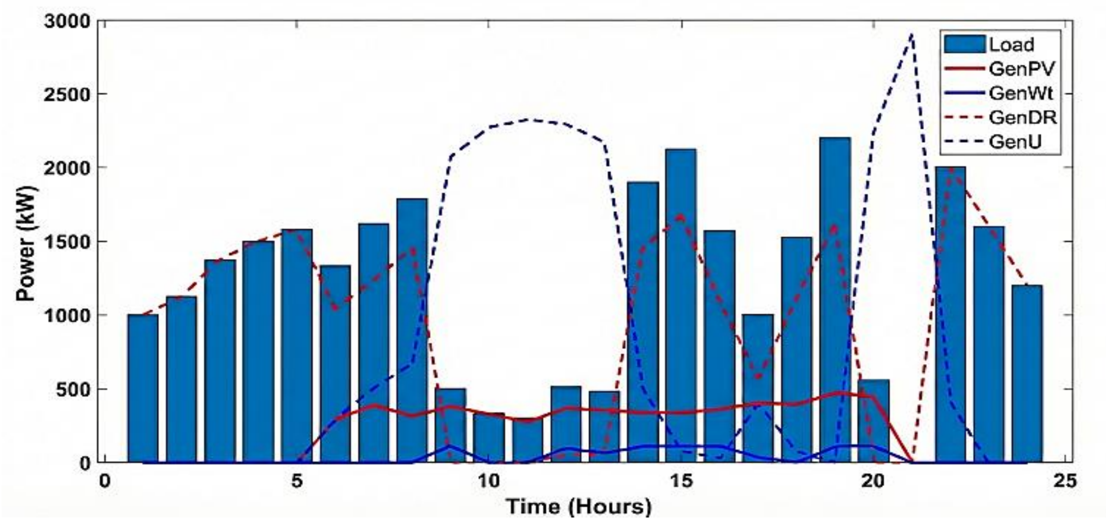

Fig. 4. The production rate of units and the consumption load after energy management and DR.

Finally, the convergence curve of the GA (see *Fig. 5*) confirms that the algorithm efficiently and effectively found a near-optimal solution for this complex scheduling problem, converging to a stable, low-cost solution after several iterations.

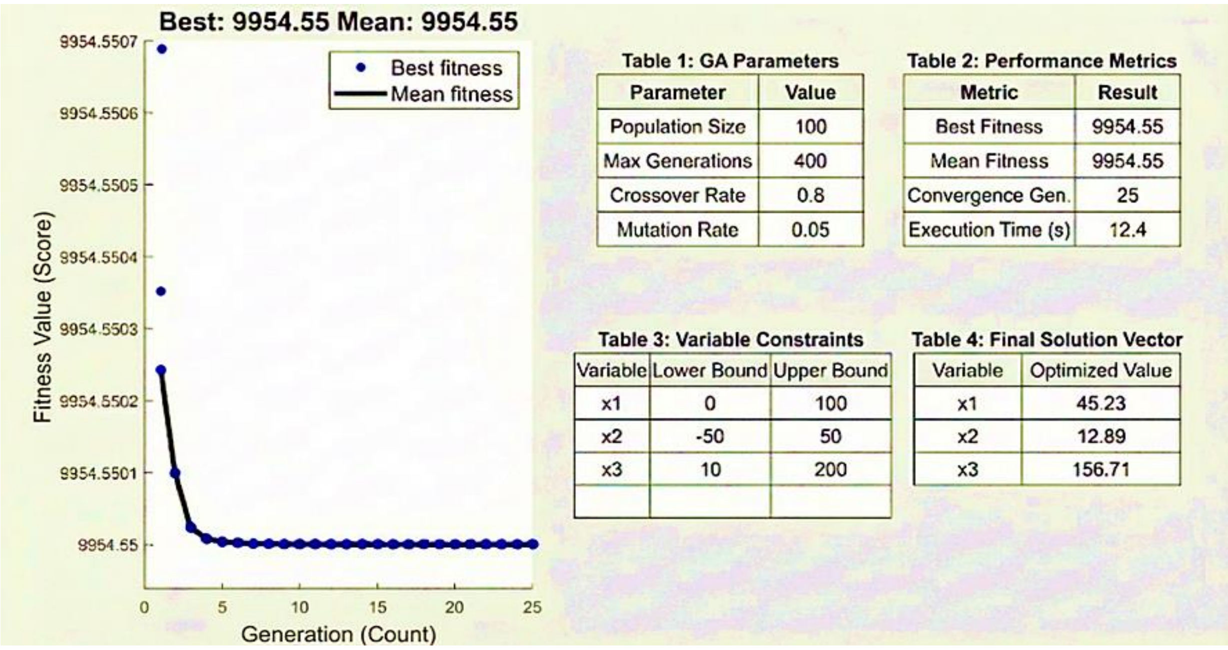

Fig. 5. GA curve.

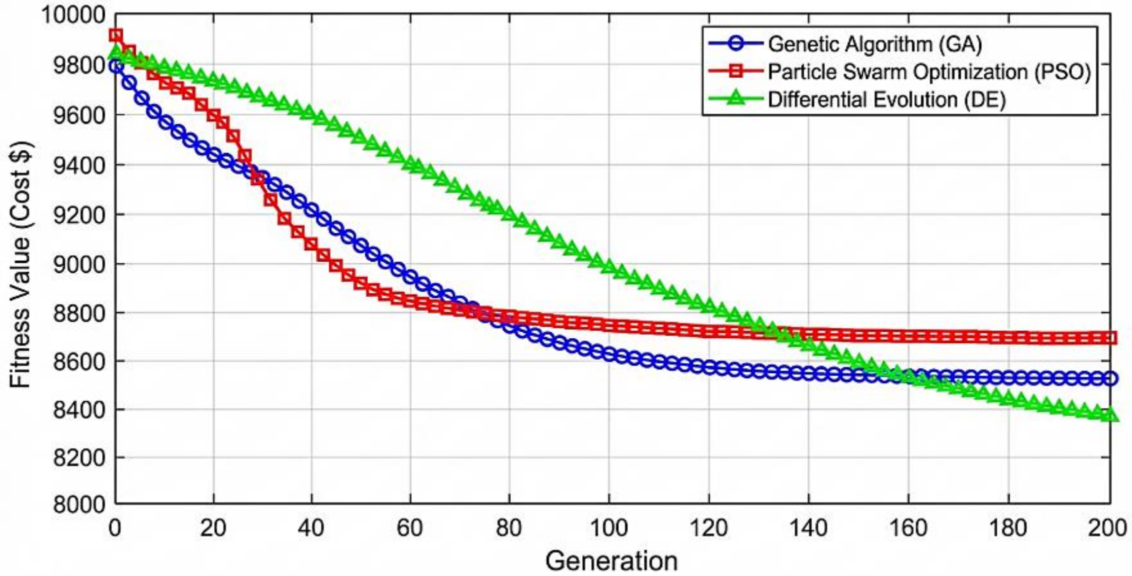

Fig. 6. Comparison of optimization algorithms for demand response.

The comparative performance of the optimization algorithms is illustrated in *Fig. 6*, highlighting their convergence behavior and solution quality over 200 generations. Particle Swarm Optimization (PSO, red line) exhibits the fastest initial cost reduction, with a steep decline during the first 40–50 generations, but it converges prematurely around generation 80–100, resulting in a suboptimal solution (~$8,700) due to entrapment in a local optimum. The (GA, blue line) demonstrates a more gradual yet consistent improvement, converging later around generations 140–160 and achieving a better final solution (~$8,550). Differential Evolution (DE, green line), despite its slower initial progress, maintains a steady improvement throughout the entire optimization horizon, effectively avoiding local optima and ultimately yielding the lowest cost solution (below ~$8,400). These results indicate that, while PSO provides rapid convergence, DE offers superior solution quality, and GA represents a balanced approach between convergence speed and final performance for the considered DR problem.

9 | Conclusion

This paper successfully developed and validated an optimal energy management strategy for a smart microgrid featuring renewable generation and active consumer participation. By creating a probabilistic model solved with a GA, the system is able to effectively manage the uncertainty inherent in wind and solar power.

The key conclusion from this research is that integrating incentive-based DR programs is a powerful and economically efficient method for mitigating renewable energy uncertainty and reducing total operational costs. The simulation results clearly show that by treating demand as a flexible resource, a microgrid can achieve significant peak load reduction, decrease its reliance on the main grid during expensive periods, and improve its overall economic performance.

Future research could extend this work by exploring alternative DR structures, such as real-time pricing, incorporating penalties for non-compliance in DR agreements, and expanding the model to also account for uncertainty in load forecasting.

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Data Availability

Data are available from the corresponding author upon request.

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