Optimal Scheduling of Grid-Connected Microgrids Using an Enhanced Generalized Normal Distribution Optimization

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ABSTRACT

The increasing penetration of microgrids in modern power systems has heightened the need for advanced operational strategies that can effectively manage the intermittency of renewable energy sources, load uncertainty, and complex operational constraints. Existing studies have extensively explored mathematical and metaheuristic optimization techniques for microgrid operation; however, many approaches still suffer from premature convergence and reduced effectiveness when applied to highly constrained, nonconvex scheduling problems. Hence, this research proposes an Enhanced Generalized Normal Distribution Optimization (EGNDO) for optimal microgrid scheduling, which comprises dispatchable Distributed Energy Resources (DERs), renewable generation units, and a Battery Energy Storage System (BESS). The scheduling problem was formulated to minimize the total operating cost, including the generation, start-up, electricity trading, and BESS degradation costs, while satisfying the technical and operational constraints. Three operational scenarios with varying grid pricing and power exchange policies were examined over a 24-h period. Simulation results on a modified IEEE 13-bus test system demonstrated that active and bidirectional grid participation can significantly reduce operating costs. Furthermore,

comparative studies confirm that the proposed EGNDO consistently outperforms benchmark metaheuristic algorithms in terms of solution quality and robustness, highlighting its effectiveness for complex microgrid scheduling problems.

Keywords-battery energy storage system; distributed energy resources; generalized normal distribution optimization; microgrid

I. INTRODUCTION

A. Background and Literature Review

Microgrids constitute a significant building block of future smart power systems due to their ability to integrate DERs, enhance supply reliability, and support the transition toward low-carbon energy systems [1]. The former can operate independently of the main power grid and seamlessly transition to islanded mode [2]. By coordinating local generation, energy storage, and controllable loads, microgrids can reduce transmission losses, improve power quality, and increase the penetration of renewable energy sources [3]. Typical DERs include dispatchable units, such as microturbines, diesel engines, and fuel cells, as well as non-dispatchable renewable sources such as Photo-Voltaic (PV) systems and Wind Generators (WG) [4]. Among these components, BESS plays a critical role in enabling energy arbitrage, peak shaving, and mitigation of renewable intermittency [5]. As a result, the optimal scheduling of microgrids has become a main research topic in modern power and energy systems.

However, the efficient operation of microgrids remains a challenging task. The stochastic nature of renewable generation, time-varying electricity prices, and diverse operational constraints lead to a highly nonlinear and non-convex optimization problem [6]. Mathematical optimization methods, which typically rely on accurate statistical information for uncertainty modeling and involve high computational complexity, often struggle to cope with such challenges, especially in the presence of discrete decision variables, non-smooth cost functions, and tightly coupled operational constraints [7]. Thus, metaheuristic algorithms have gained increasing attention for microgrid scheduling applications due to their flexibility and problem-independent nature [8]. Representative approaches include the genetic algorithm [9], Grey Wolf Optimization (GWO) [10], improved GWO [11], circle search algorithm [12], whale optimizer algorithm [13], differential evolution [14], crow search algorithm [15], and moth-flame optimizer [16].

B. Research Gap

Although these methods have demonstrated promising performance, many of them still suffer from premature convergence and insufficient exploration capability when addressing large-scale, highly constrained, or strongly nonlinear microgrid scheduling problems. Moreover, many studies evaluate scheduling strategies using simplified microgrid models that neglect network constraints (e.g., bus voltage limits, line thermal limits, and power flow feasibility). These limitations collectively motivate the development of more robust optimization strategies and network-aware frameworks to ensure both solution quality and engineering applicability.

C. Research Contributions

This study proposes an Enhanced Generalized Normal Distribution Optimizer (EGNDO) for optimal microgrid scheduling. The proposed approach extends the original GNDO by incorporating a Chaotic Local Search (CLS) mechanism, which improves population diversity and enhances convergence toward high-quality solutions. The optimization framework explicitly accounts for BESS degradation costs, dispatchable and non-dispatchable DERs, and dynamic interactions with the main grid. To evaluate the proposed method, three operating scenarios with different grid pricing schemes and power exchange policies were examined. Comparative evaluation against metaheuristic algorithms was conducted to demonstrate the effectiveness of the proposed method.

II. PROBLEM FORMULATION

Figure 1 presents the configuration of the grid-connected microgrid based on a modified IEEE 13-bus test network, comprising a WG, PV, and dispatchable units including a Micro-Turbine (MT), Diesel Engine (DE), Fuel Cell (FC), and a BESS.

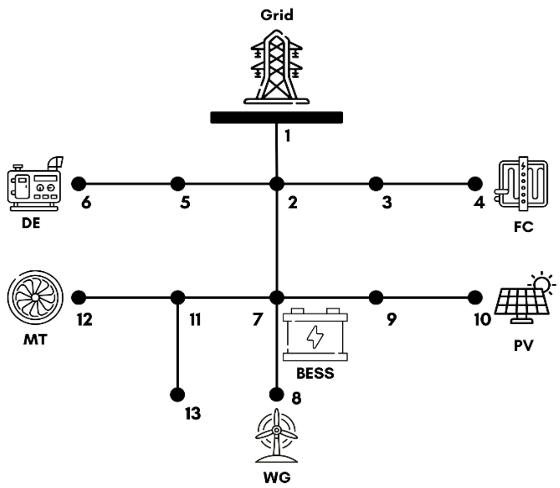

Fig. 1. Grid-connected microgrid system.

The main aim is to optimize the total operational cost of the microgrid:

$$\sum_t \sum_i u_i(t)c_i(t) + c_i^{st}v_i(t) + c_b(t) + P_{ss}(t)d(t) \quad (1)$$

where $d(t)$ denotes the electricity price, $P_{ss}(t)$ is the power exchanged with the grid at time t, $c_i(t)$ and c_i^{st} denote the generation and start-up costs of the DER unit, respectively, i, $u_i(t)$ and $v_i(t)$ represent the on/off operating status and start-up indicator of the DER unit i, respectively, and $c_b(t)$ is the BESS degradation cost.

The generation cost of the DER unit i is expressed as:

$$c_i(t) = \alpha_i u_{i(t)} + \beta_i P_{DER,i}(t) + \gamma_i P_{DER,i}^2(t);\ \forall t \quad (2)$$

where $P_i(t)$ is the power output of the DER unit i at time t, and α_i, β_i, and γ_i are cost coefficients. The BESS degradation cost is defined as:

$$c_b(t) = \left(P_{b,ch}(t) + P_{b,dch}(t)\right) \cdot c_{b,deg} \cdot \Delta t\ ;\ \forall t \quad (3)$$

where $P_{b,ch}(t)/P_{b,dch}(t)$ represents the charging/discharging power of the BESS at time t, $c_{b,deg}$ is the degradation cost coefficient, and Δt is the scheduling time interval.

The vector of decision variables represents the 24-h operating schedule of the microgrid:

$$X = [P_{DER,1}(1), \dots, P_{DER,1}(24), P_{DER,2}(1), \dots, P_{DER,2}(24),$$

$$P_{DER,NG}(1), \dots, P_{DER,NG}(24), P_b(1), \dots, P_b(24)] \quad (4)$$

where $P_{DER,i}$ is the scheduled output power of the dispatchable DER unit i at time t, and $P_b(t) = P_{b,ch}(t) - P_{b,dch}(t)$ is the net charging/discharging power of the BESS at time t. In this study, the dispatchable DERs consisted of an MT, DE, and FC. The optimization problem is subject to the operational and technical constraints described below.

A. Power Balance

The microgrid must satisfy the power balance constraint:

$$P_{ss}(t) + P_{pv}(t) + P_{wg}(t) + \sum_{i=1}^{NG} P_{DER,i}(t) + P_{b,dch}(t) = P_{b,ch}(t) + P_d(t) + \sum_{i=1}^{NL} P_{L,l}(t) \quad (5)$$

where $P_d(t)$ represents the electrical load demand at time t, $P_{pv}(t)$ and $P_{wg}(t)$ are power generated by the PV and WG, respectively, $P_{L,l}(t)$ is the power losses in the lth branch at time t, and NG is the total number of DER units. In this work, power flow analysis was carried out with MATPOWER 6.0 [17].

B. Power Generation Constraints

The operating limits of power generation and exchange for each component of the microgrid are constrained as:

$$P_{ss}^{min} \le P_{ss}(t) \le P_{ss}^{max} \quad (6)$$

$$P_{DER,i}^{min} \le P_{DER,i}(t) \le P_{DER,i}^{max} \quad (7)$$

$$P_b^{min} \le P_b(t) \le P_b^{max} \quad (8)$$

where P_{ss}^{max} and P_{ss}^{min} represent the maximum and minimum exchanged power of the microgrid, respectively, $P_{DER,i}^{max}$ and $P_{DER,i}^{min}$ represent the maximum and minimum power output of dispatchable unit i, respectively, P P_b^{min} and P_b^{max} are the minimum and maximum power limits of the BESS.

C. BESS Constraints

The energy dynamics of the BESS were modeled as:

$$\varepsilon_b(t) = \varepsilon_b(t-1) + \left(\eta_{b,ch} P_{b,ch} - \frac{P_{b,dch}}{\eta_{b,dch}}\right)\Delta t;\ \forall t \quad (9)$$

$$\varepsilon_b^{min} \le \varepsilon_b(t) \le \varepsilon_b^{max} \quad (10)$$

where $\varepsilon_b(t)$ denotes the stored energy of the BESS at time t, $\eta_{b,ch}$ and $\eta_{b,dch}$ represent the charging and discharging efficiencies, respectively, and ε_b^{min} and ε_b^{max} denote the minimum and maximum allowable energy capacities of the BESS.

D. Voltage and Thermal Constraints

The voltage magnitude and line current are restricted by:

$$V_i^{min} \le V_i(t) \le V_i^{max} \quad (11)$$

$$I_l(t) \le |I_l^{max}| \quad (12)$$

where V_i^{min} and V_i^{max} are the lower and upper voltage limits at the bus i, respectively, and $I_l^{\max}$ is the maximum allowable current of the branch l.

III. GNDO

GNDO is developed based on a normal distribution framework, in which the positions of all individuals are treated as random variables [18]. GNDO operates through two main phases: local exploitation and global exploration.

A. Local Exploration

This stage focuses on enhancing the current solution by examining the vicinity of the better solutions as:

$$v_i^k = \mu_i + \delta_i \times \eta \quad (13)$$

where η is the penalty factor μ_i, δ_i and v_i^k are the generalized mean position, standard deviation, and new position of the ith individual at iteration k, respectively, which is given by:

$$\mu_i = \frac{1}{3}(x_i^t + x_{best}^t + M) \quad (14)$$

$$\delta_i = \sqrt{\frac{1}{3}\left[\left(x_i^t - \mu\right)^2 + (x_{best}^t - \mu)^2 + (M - \mu)^2\right]} \quad (15)$$

$$\eta = \begin{cases} \sqrt{-\log(\lambda_1) \times \cos(2\pi\lambda_2)} & \text{if } a \le b \\ \sqrt{-\log(\lambda_1) \times \cos(2\pi\lambda_2 + \pi)} & \text{otherwise} \end{cases} \quad (16)$$

$$\mu_i = \frac{\sum_{i=1}^{N} x_i^t}{N} \quad (17)$$

where N denotes the population size, x_{best}^t and M represent the best position and mean position of the current population, a, b, λ_1, and λ_2 are random numbers.

B. Global Exploration

This stage aims to identify new areas and discover potential solutions using three randomly selected individuals:

$$v_i^t = x_i^t + \beta \times |\lambda_3| \times v_1 + (1 - \beta) \times |\lambda_4| \times v_2 \quad (18)$$

where x_i^t and v_i^t are current and updated positions, β denotes a tuning factor that controls the exchange of information between local and global operators, λ_3 and λ_4 denote two random numbers, and v_1 and v_2 are defined as:

$$v_1 = \begin{cases} x_i^t - x_{p1}^t & \text{if } f(x_i^t) \le f\left(x_{p1}^t\right) \\ x_{p1}^t - x_i^t & \text{otherwise} \end{cases} \quad (19)$$

$$v_2 = \begin{cases} x_{p2}^t - x_{p3}^t & \text{if } f\left(x_{p2}^t\right) \le f\left(x_{p3}^t\right) \\ x_{p3}^t - x_{p2}^t & \text{otherwise} \end{cases} \quad (20)$$

where x_{p1}^t, x_{p2}^t, and x_{p3}^t denote three individuals, which are chosen at random from the current population.

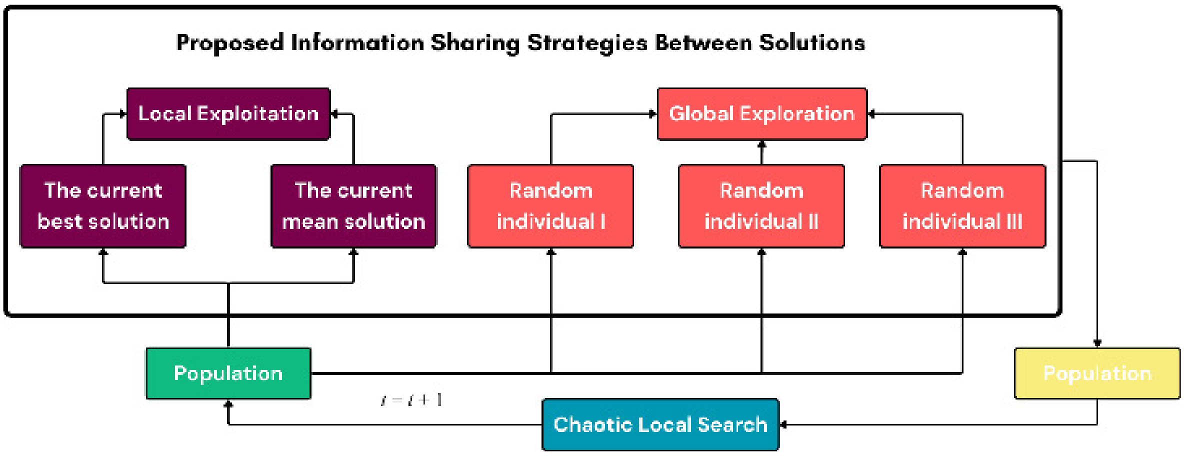

Fig. 2. Flowchart of the GNDO.

C. Enhanced GNDO

GNDO may deteriorate when the search becomes trapped in local optima due to an imbalanced exploration–exploitation trade-off, leading to premature convergence. To enhance the search efficiency and diversification, the GNDO was hybridized with a chaotic strategy to form an EGNDO, which operates in two stages: GNDO performs global and local search, followed by a CLS to refine the current best solution and improve convergence accuracy, which can be formulated as:

$$X_{best,m}^{new} = X_{best,m} + \left(X_{a,m} - X_{b,m}\right)Z_m \qquad (21)$$

where $X_{best,m}^{new}$ and $X_{best,m}$ denote the newly generated candidate solution and the current best solution, respectively, $X_{a,m}$ and $X_{b,m}$ are two random solutions, and Z_k is a chaotic sequence variable generated using the logistic map, defined as:

$$Z_{k+1} = \mu(1 - Z_k)Z_k \qquad (22)$$

where $Z_k \in (0,1)$ for all k and $\mu \in (0,4]$ is the control parameter governing the chaotic behavior. The newly generated solution replaces the current best solution if it yields a lower objective function value. Figure 2 displays the EGNDO flowchart.

IV. RESULTS

The EGNDO was applied to a microgrid system modeled on a modified IEEE 13-bus test network, integrating an FC, DE, MT, WG, PV, and BESS (Figure 1). The microgrid parameters are summarized in Tables I and II. In addition, Figures 3(a) and 3(b) illustrate the 24-h forecasts of electricity prices, load demand, and WG and PV power outputs. Three scenarios were considered to evaluate different levels of grid interaction and operational flexibility: (i) static pricing with export allowed, (ii) real-time pricing with grid export prohibited, and (iii) real-time pricing with bidirectional power exchange.

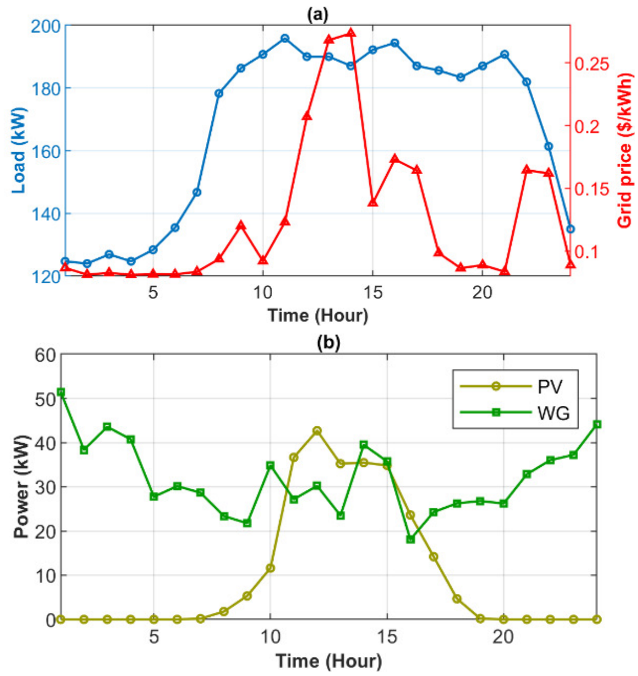

Fig. 3. PV and WG output power.

TABLE I. DER PARAMETERS

Type	Cost coefficients			Max (kW)	Min (kW)	Start-up cost ($)
	α	*β*	*γ*			
MT	0.40	0.0397	0.00051	10	30	2
DE	1.30	0.0304	0.00104	20	60	3
FC	0.38	0.0267	0.00024	10	30	1.5

TABLE II. BESS PARAMETERS

Parameter	$\varepsilon_b^{max}/\varepsilon_b^{min}$ (kWh)	P_b^{min}/P_b^{max} (kW)	$\eta_{b,ch}/\eta_{b,dch}$	$c_{b,deg}$ ($/kWh)
Value	90 / 25	-50/50	0.9/0.9	0.02

1) Case 1

In the first case, the microgrid adopts a static pricing scheme based on the average day-ahead electricity price. The total generation cost reached $267.28, the highest among all evaluated scenarios. From Figure 4, FC, DE, and MT operate close to their upper power limits for most hours of the day. This behavior indicates that the microgrid prioritizes the full utilization of local dispatchable DERs to meet demand. Meanwhile, WG contributes a moderate and fluctuating share depending on resource availability, whereas PV generation is concentrated around midday hours, consistent with solar irradiance patterns. The BESS exhibited only marginal charging and discharging activities. This limited utilization reflects the lack of economic incentives for energy arbitrage under static pricing, as storing or shifting energy in time does not yield cost benefits. Consequently, the grid power profile indicates that electricity is primarily imported during periods when local generation and renewable sources are insufficient, whereas exports remain minimal and sporadic. Overall, the static pricing mechanism constrains the microgrid operational flexibility. The microgrid cannot exploit lower-cost grid energy during off-peak periods or strategically export surplus power during high-demand intervals. Hence, the microgrid relies heavily on dispatchable generators, leading to high operating costs.

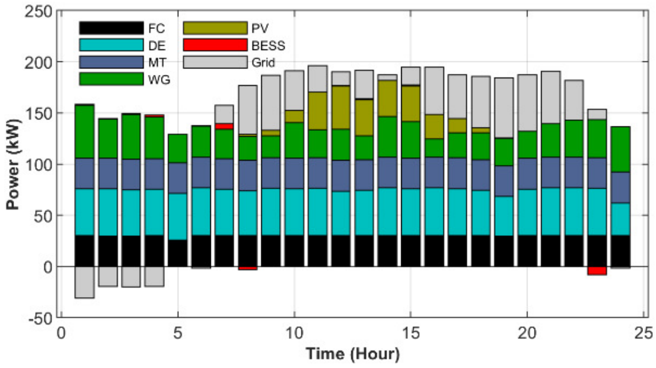

Fig. 4. Optimal operations of the microgrid in case 1.

2) Case 2

In the second case, the microgrid operates under a real-time pricing mechanism; however, exporting excess energy is prohibited. As shown in Figure 5, the DERs display more variable output patterns compared to case 1. While these units still operate close to their rated capacities for several hours, noticeable reductions occur when renewable energy source generation is high or when the BESS actively supports the load. Notably, the BESS demonstrated significantly higher charging and discharging activity in this case, indicating active energy shifting across hours and allowing excess renewable generation to be stored and later used to meet the demand. This storage operation reduces the need for expensive grid imports during peak demand periods. Thus, the combined effect of enhanced BESS utilization and improved coordination among DERs leads to a reduced total generation cost of $264.79 when using the EGNDO, which is slightly lower than that of the static-pricing scenario. Nevertheless, the overall cost reduction remains limited because the microgrid cannot generate additional revenue by exporting excess power during periods of high renewable energy production.

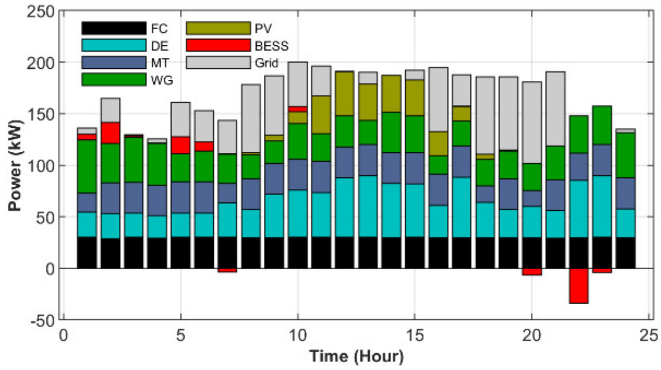

Fig. 5. Optimal operations of the microgrid in case 2.

3) Case 3

In the third case, the microgrid operated under a bidirectional power exchange with real-time pricing. This configuration enables the system to fully exploit the operational flexibility of DERs and represents the most economically and operationally efficient case. As illustrated in Figure 6, although the FC, DE, and MT units still contribute significantly to meeting demand, their outputs are no longer persistently driven toward the maximum capacity. Instead, their generation levels adjust dynamically in response to price signals and grid interactions, indicating reduced reliance on high-cost local generation when more economical alternatives are available. Periods of high renewable output are actively leveraged through both BESS operation and grid export. The BESS shows pronounced charging and discharging behavior. Specifically, it stores energy during periods of low prices or excess generation and releases it during periods of high prices or peak demand, thereby improving system flexibility. Most notably, the microgrid actively participated in both electricity imports and exports throughout the planning period. During off-peak periods, when electricity prices are lower, the microgrid purchases power from the grid. Conversely, during peak-price periods or periods of high renewable energy availability, surplus energy is exported. This bidirectional interaction substantially reduces dependence on expensive dispatchable units, such as MT, DE, and FC, directly contributing to cost minimization. As a result of this coordinated operation, the microgrid achieved the lowest total generation cost of $259.02 among all scenarios. Beyond economic benefits, this operating mode enhances system efficiency and sustainability by prioritizing renewable utilization, reducing fossil-based generation, and enabling effective demand–supply balancing. Overall, the comparison of the three scenarios demonstrates that higher levels of grid interaction progressively enhance operational performance. Case 3 allows the microgrid to fully leverage DERs and emerges as the most efficient scenario from both economic and operational perspectives. Figure 7 shows that the bus voltages in case 3 remain within the permissible range (0.95–1.05 p.u.), confirming that the EGNDO-based schedules satisfy network constraints and are operationally feasible.

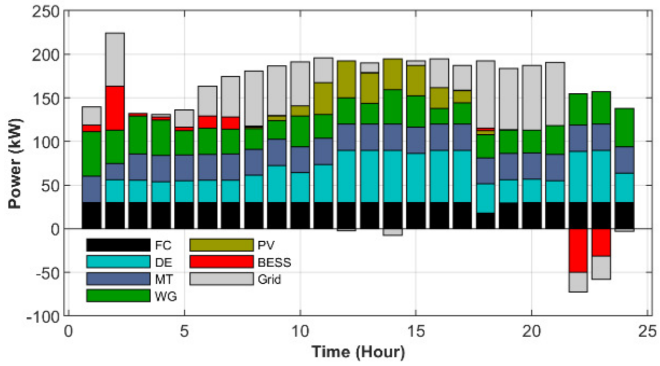

Fig. 6. Optimal operations of the microgrid in case 3.

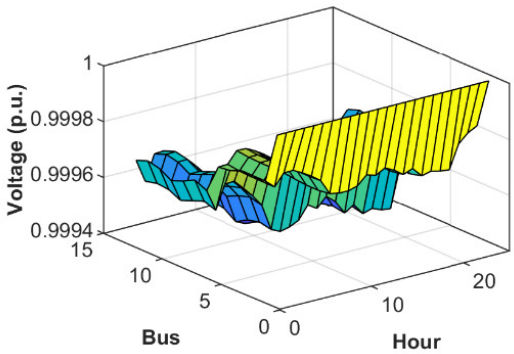

Fig. 7. Voltage profiles of the microgrid system for case 3.

B. Comparison With Other Methods

To assess the performance and robustness of the proposed approach, the EGNDO, GNDO, Grasshopper Optimization Algorithm (GOA), Whale Optimization Algorithm (WOA), and Grey Wolf Optimization (GWO) were executed over 10 independent runs for the optimal microgrid scheduling problem. Table III summarizes the statistical performance of the proposed EGNDO method in comparison with the benchmark metaheuristic algorithms, reporting the best, mean, worst, and standard deviation values across all test cases.

TABLE III. COMPARATIVE ANALYSIS OF THE PROPOSED AND EXISTING ALGORITHMS

Cases	Algorithms	Daily operation cost ($)			
		Best	Mean	Worst	Standard deviation
Case 1	EGNDO	267.28	269.30	271.73	1.1104
	GNDO	273.64	279.57	286.07	3.8924
	GWO	283.46	296.61	309.35	7.3134
	WOA	317.01	332.01	340.33	6.3078
	GOA	298.97	308.90	318.96	6.6736
Case 2	EGNDO	264.79	268.65	277.62	3.8962
	GNDO	267.81	273.67	279.52	3.7967
	GWO	281.17	295.70	316.25	11.2545
	WOA	320.93	350.82	375.87	15.7150
	GOA	307.50	320.19	330.91	8.2801
Case 3	EGNDO	259.02	261.69	266.35	2.6276
	GNDO	262.63	269.63	278.03	3.8742
	GWO	284.67	301.59	322.60	8.8872
	WOA	332.96	351.93	363.80	10.31
	GOA	301.86	313.23	327.95	8.9395

The results show that EGNDO consistently achieves the best generation cost in all cases. Specifically, EGNDO attains costs of $267.28, $264.79, and $259.02 in cases 1, 2, and 3, respectively, outperforming all competing methods by a noticeable margin. Moreover, EGNDO achieved very low standard deviation values across all cases, indicating a high level of robustness and consistent performance. This superior performance highlights its enhanced exploration–exploitation balance and robustness, enabling it to generate higher-quality scheduling solutions.

V. CONCLUSIONS

This work presents an Enhanced Generalized Normal Distribution Optimizer (EGNDO) for the optimal microgrid scheduling on a modified IEEE 13-bus test network, considering dispatchable Distributed Energy Resources (DERs), Renewable Energy Sources (RESs), and a Battery Energy Storage System (BESS). Three operating cases with different electricity pricing mechanisms and grid power exchange policies were examined. The results indicate that increasing the level of grid interaction enhances the economic performance of microgrids. Specifically, the bidirectional trading case under real-time pricing yielded the minimum operating cost by enabling effective energy arbitrage, increasing RES utilization through coordinated BESS operation, and reducing reliance on comparatively expensive DER generation. Comparisons against other methods verified that EGNDO consistently achieves superior solution quality and improved robustness, as evidenced by lower costs and smaller standard deviations across multiple independent runs. These findings confirm that the proposed enhancement strategy strengthens the exploration–exploitation balance and provides a reliable optimization tool for practical microgrid scheduling. Future work will focus on extending the proposed framework to stochastic and multi-objective formulations and applying the method to larger-scale and multi-microgrid systems.

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