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Highlights

- Modified Grey Wolf Optimization (MGWO) algorithm optimizes microgrid energy management.
- MGWO beats Particle Swarm Optimization (PSO) in two scenarios, reducing costs and improving efficiency.
- Negative energy costs indicate economic gains from electricity sales, especially with renewables.

Graphical Abstract

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Optimal Operation and Management of Energy Resources in Microgrids in the Presence of Renewable Resources and Energy Storage by Modified Grey Wolf Optimization Algorithm

Javad Nikoukar [1], Shokoofeh Mohammadi [1,2], Hamid Reza Hanif [3,*], Reza Aminpour Gogani [4], Masoumeh Ghafari [5], Abdolreza Behvandi [6]

[1] *Department of Electrical Engineering, Saveh Branch, Islamic Azad University, Saveh, Iran.*
[2] *Department of Electrical Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran.*
[3] *Iran University of Science and Technology (IUST), Tehran, Iran.*
[4] *Resilient Smart Grid Research Lab, Department of Electrical Engineering, Azarbaijan Shahid Madani University, Tabriz, Iran.*
[5] *Electrical and Computer Engineering Department, Babol Noshirvani University of Technology, Babol, Iran.*
[6] *Department of Electrical Engineering, Ramhormoz Branch, Islamic Azad University, Ramhormoz, Iran.*

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* ***Corresponding author***
E-mail address:
h.hanif.iustz@gmail.com (H. R. Hanif)

ABSTRACT

This paper delves into the meticulous optimization of distributed energy resources and their storage within a conventional microgrid framework. The optimization endeavor leverages an array of cutting-edge technologies including photovoltaic, wind, fuel cells, micro-turbines, and batteries, with the dual objectives of curtailing operational expenses and fortifying system reliability. To attain these objectives, the article employs a refined algorithm derived from the Grey Wolf Optimization technique. Furthermore, simulations are executed under two distinct scenarios. In the first scenario, the presumption is that all distributed energy resources within the microgrid are exploitable, whereas in the second scenario, spatial constraints necessitate the exclusion of photovoltaic and wind turbine resources. Simulation outcomes evince that post-implementation of energy management via metaheuristic algorithms, there is a discernible reduction in the operational costs of the microgrid alongside an enhancement in system reliability. Additionally, the elimination of photovoltaic and wind resources results in escalated costs and grid blackout within the microgrid. In summary, the simulation findings affirm the superior efficacy of the proposed modified Grey Wolf algorithm in addressing energy management quandaries in comparison to the Particle Swarm Optimization algorithm.

1. Introduction

The energy sector is witnessing a crucial shift towards decentralized renewable sources [1] due to the environmental and economic challenges posed by diminishing fossil fuels. This shift aims to combat rising global temperatures and environmental degradation. Recent research has focused on developing efficient energy systems, reducing power losses by utilizing decentralized generation resources, also known as Distributed Energy Resources (DERs) [2]. DERs, equipped with power electronics, can actively manage grid parameters when integrated.

Microgrids represent a significant advancement in aggregating these DERs [3]. They are self-contained networks comprising various renewable sources, storage, and controllable loads, with the capability to operate independently. Microgrids are designed with power electronic converters to ensure flexibility and seamless operation. Engineers advocate for decentralized generation within microgrids to reduce energy costs, especially in remote areas, where they can harness wind, solar, and other renewable sources. This approach offers multiple benefits, including cost savings, load optimization, and improved system stability [4], while also reducing environmental impacts. The successful integration of DERs into microgrids is a key strategy for a sustainable energy future, addressing both economic and environmental concerns. A variety of solutions has been developed for optimal microgrid operation management, predominantly falling under the following categories delineated in research spanning the last two decades:

A variety of solutions has been developed for optimal microgrid operation management, predominantly falling under the following categories delineated in research spanning the last two decades:

A) Traditional Optimization Methods:

• Nonlinear programming [5,6]
• Linear programming [7]
• Mixed-integer programming [8]
• Modified interior point method [9]

B) Intelligent Optimization Methods:

• Genetic algorithm [10]
• Particle swarm optimization algorithm [11]
• Artificial neural network [12]

Conventional optimization algorithms employed for microgrid operation planning typically employ diverse search techniques, capable of addressing second-degree objective optimization problems with singular minima. In recent years, sophisticated optimization methodologies grounded in artificial intelligence have gained traction in optimal microgrid management, aimed at ameliorating the local optimum conundrum and addressing uncertainties inherent in the problem [13-16].

This paper focuses on the optimal management of renewable energy and electrical energy storage within standard microgrids to reduce operational costs while upholding reliability metrics. A refined and enhanced iteration of the Grey Wolf Optimization (GWO) technique, dubbed the Modified Grey Wolf Optimization (MGWO) algorithm, is proposed herein for this purpose. The subsequent sections delineate the mathematical formulation of the problem, elucidate the proposed algorithm, and present simulation results derived from the implementation of the algorithm under two scenarios, with and without renewable resources.

2. Microgrid

Microgrids constitute an integral component of the power distribution framework, encompassing diverse arrays of distributed energy resources and consumers of both electricity and thermal energy. Outfitted with switchgear and transformers, these grids possess the capability to seamlessly connect to or disconnect from the primary network, catering to a spectrum of subscribers spanning residential, commercial, and industrial domains. Illustrated in Figure 1, a microgrid interfaces with the upstream network while offering not only energy provision for local demands but also ancillary services and thermal energy, exemplifying its multifunctionality. The foundational configuration of a microgrid, as depicted in Figure 1, features a pivotal node, facilitated by a switch, establishing connection with the upstream network.

In contrast to traditional power systems reliant on centralized operation of large-scale thermal power plants, microgrids exert significantly lesser environmental strain. Leveraging non-fossil energy sources, microgrids play a pivotal role in curbing greenhouse gas emissions, constituting one of their most notable advantages. Moreover, the proximity of consumers to energy sources fosters heightened awareness regarding optimal energy utilization, thereby augmenting overall efficiency.

In the market milieu, two overarching policies govern the integration of microgrids. Firstly, the microgrid's entire energy demand is met through local resources, disregarding interactions with the upstream network. Under this paradigm, the microgrid operator endeavors to minimize operational costs on an hourly basis. Secondly, the operator retains the option to engage in power exchange within the market, striving to optimize cost efficiency and production output for sale to the upstream network, thereby maximizing revenue.

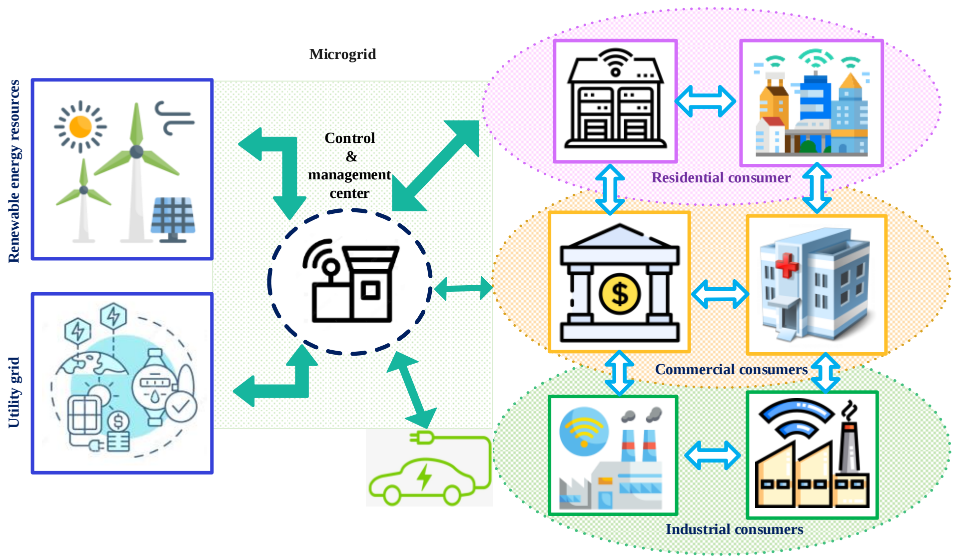

Figure 1. A model of a sample microgrid.

Effective planning and operation of microgrids necessitate consideration of both short-term exigencies and long-term imperatives. Short-term operational constraints encompass load shedding protocols, transient voltage and frequency modulation, dynamic response adequacy, and power quality standards for sensitive loads. Control architecture within microgrids is dichotomized into centralized and decentralized frameworks, each comprising three hierarchical tiers: Distribution Network Operator (DNO), potentially accompanied by a Market Operator (MO), Microgrid Central Controller (MGCC) incorporating the microgrid operator, and local controllers affiliated with individual distributed generation units or loads.

Seamless bidirectional communication between local controllers and the microgrid's central controller constitutes a fundamental requisite, feasibly facilitated through telecommunications infrastructure, power transmission channels, or wireless mediums. The central controller of the microgrid is vested with the responsibility of optimizing power interchange with the primary network and maximizing production, informed by prevailing market dynamics and security constraints. Planning activities undertaken by the central controller occur at predefined intervals, such as every 15 minutes for forthcoming hours.

In alignment with market-oriented strategies, the microgrid operator orchestrates planning and execution processes based on a plethora of inputs, encompassing market prices, proposed pricing structures, and priority delineations for local supply, iteratively coordinated with local controllers. Additionally, the operator devises strategies and implements proposed pricing mechanisms alongside production levels stipulated by controllers of dispersed generation resources, while adhering to network security imperatives and leveraging predictive analytics for renewable energy sources.

3. Model of Cascading Networks Under Study

This article delves into the intricacies of managing microgrid energy, as depicted by the schematic in Figure 2. The microgrid under examination harnesses a blend of photovoltaic panels, wind turbines, and microturbines as its distributed generation sources. To store the electrical bounty, it relies on fuel cells and batteries. Seamless integration with the main power grid is enabled through a distribution transformer, ensuring fluid power exchange. Noteworthy is the microgrid's ability to monetize surplus energy by vending it to the grid, thus providing economic dividends for its operator. Operating at a voltage of 400 volts, it engages in power transactions with the upper grid through a 20/0.4 kilovolt distribution transformer, maintaining a frequency of 50 hertz. The microgrid's load peaks at approximately 1695 kilowatts, with a zenith of 90 kilowatts around hour 19.

Within the microgrid, loads are presumed to be temporally distributed and variable. Energy procurement costs from the grid are judiciously managed on a time-of-use (TOU) framework. Figure 3 meticulously outlines consumer energy demands juxtaposed against hourly electricity prices. The microgrid's energy tariff fluctuates between \$0.14 and \$0.4 per kilowatt-hour, aligning with grid loads ranging from 50 kilowatts to 90 kilowatts. The calculation of consumed energy costs involves a simple multiplication of hourly consumption with the corresponding electricity price, elegantly visualized in Figure 4.

Consequently, the total system cost, bereft of distributed generation sources, tallies up to \$2164. Solar and wind generation capacities within the microgrid are intricately tied to solar irradiance, local wind speeds, and the installation density of solar panels and wind turbines. Consequently, the maximum generation capacities from these sources are meticulously derived and showcased in Figure 5. The microgrid's distributed generation and battery storage capabilities are bound by power constraints, meticulously laid out in Table 1. Negative power values for the battery denote storage operations. Moreover, accounting for startup costs in fuel cell and microturbine generation, power exchange with the main grid, capped at a maximum of 30 kilowatts, remains a viable option.

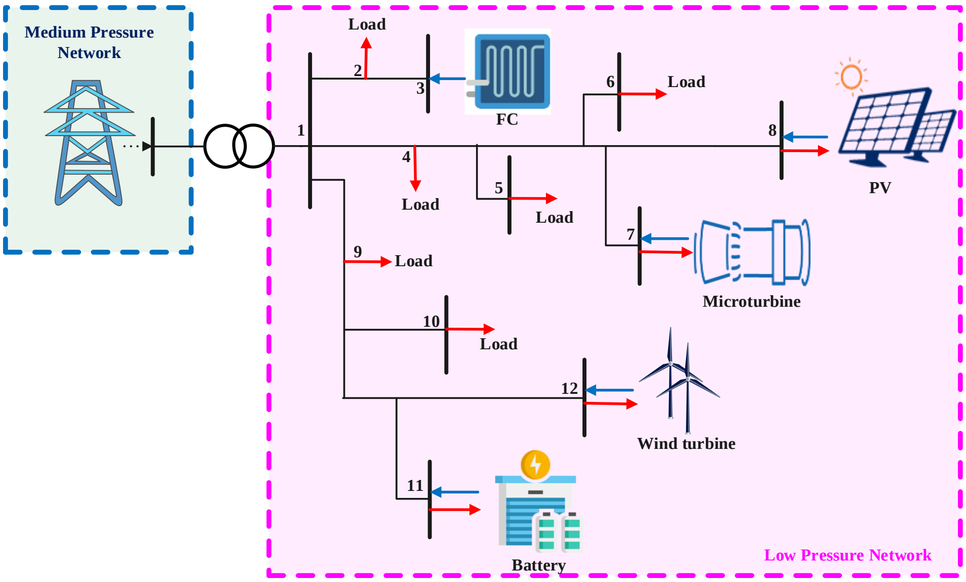

Figure 2. The studied microgrid model.

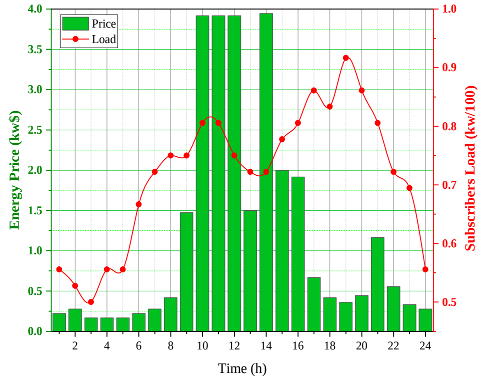

Figure 3. The amount of load and the price of electricity [17].

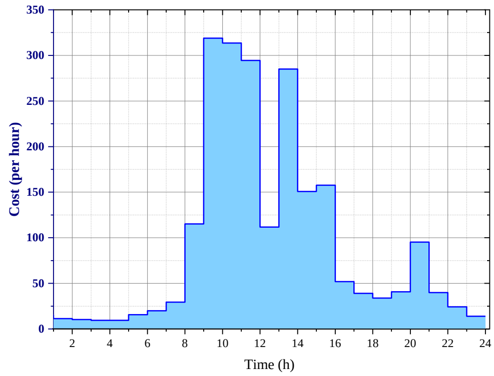

Figure 4. Cost of energy supply per hour in case of non-use of scattered products.

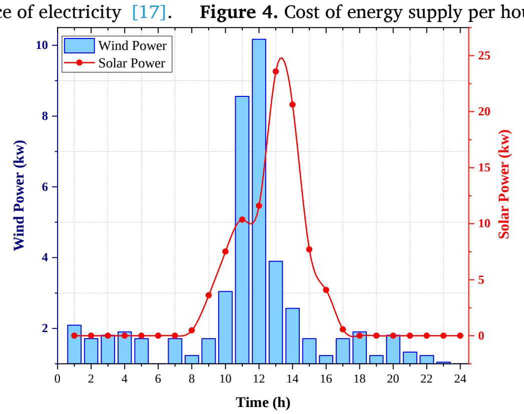

Figure 5. Maximum wind and photovoltaic power [17].

Table 1. The cost of generating power resources [17].

Sources Cost	Solar Cells	Wind Turbine	Micro Turbine	Fuel Cell	Battery
Setup Fee ($)	0	0	0.96	1.65	0
Power Generation Cost ($/KWh)	2.584	1.073	0.475	0.294	0.38
Minimum Power (kwh)	0	0	6	3	-30
Maximum Power (kwh)	Variable Every Hour	Variable Every Hour	30	30	30

3.1. Operating Constraints

To enhance microgrid efficiency, it is imperative to address crucial requisites. Within a microgrid, equilibrium between generated power and incoming power from the primary grid is paramount. This amalgamated power, comprising consumers' demand and losses, must align with the microgrid's generation input. To achieve this, we establish Equation (1):

$$\sum_{i=1}^{Ng} P_{Gi}(t) + \sum_{j=1}^{Ns} P_{Sj}(t) + P_{Grid}(t) = \sum_{k=1}^{Nk} P_{Lk}(t) - ENS(t) \tag{1}$$

Here, P_{Lk} denotes the load for load K, and N_k signifies the number of loads linked to the microgrid. During microgrid operation, it is essential to consider approximate power generation limits for each distributed generation. Imposing these constraints prevents unauthorized distributed generation activities during unauthorized intervals. Equation (2) outlines power generation capacity constraints, encompassing lower and upper limits for generator and energy storage capacities. Furthermore, it delineates constraints on battery charging and discharging within each time interval:

$$\begin{aligned} &P_{min}^{gn}(t) \le P^{gn}(T) \le P_{max}^{gn}(t) \\ &P_{min}^{sm}(t) \le P^{sm}(T) \le P_{max}^{sm}(t) \\ &P_{min}^{grid}(t) \le P^{grid}(T) \le P_{max}^{grid}(t) \end{aligned} \tag{2}$$

In Equation (3), V_{tess} signifies the battery's stored energy at hour t, while P^{charge} and $P^{discharge}$ denote permissible rates of battery charging and discharging over specific periods. Vmaxess and Vminess represent the maximum and minimum allowable energy storage values in batteries, and P_{max} charge and P_{min} charge denote the maximum and minimum limits of battery charging and discharging:

$$\begin{aligned} & V_{min}^{ess} \le V_t^{ess} \le V_{max}^{ess} \\ & P_t^{charge} \le P_{max}^{charge} \\ & P_t^{discharge} \le P_{max}^{discharge} \end{aligned} \tag{3}$$

3.2. Grey Wolf Algorithm

Grey wolves (Canis lupus), revered apex predators within the Canidae family, command a pivotal role in their ecosystem's intricate web of life. Occupying the zenith of the food chain, they wield dominance with grace. Group-oriented by nature, their packs, typically comprising 5 to 12 individuals, boast a sophisticated social fabric, crucial for decision-making and cohesion, vividly depicted in Figure 6.

At the helm of these packs stand alpha pairs, orchestrating the hunt, determining resting grounds, and dictating the rhythm of pack life. Despite their authoritative stance, glimpses of democracy surface, with alphas occasionally yielding to the collective wisdom. The pack, in turn, executes commands under alpha tutelage, underscoring their mastery in leadership and organizational finesse.

Nestled beneath the alphas lie the beta wolves, dutiful aides entrusted with executing decisions and upholding pack unity. Gender-neutral in their role, betas seamlessly transition to leadership in the absence or incapacity of alphas, deftly balancing deference with authority, providing invaluable counsel and feedback. In the depths of the hierarchy reside the omegas, bearing the weight of submission within the pack's dynamics. Often overlooked, they serve as the unassuming linchpin, their absence capable of unleashing turmoil within the pack's delicate equilibrium, a testament to their silent but profound influence. Beyond the intricacies of social order, Grey wolves exhibit a mesmerizing tapestry of group hunting tactics, weaving together search, pursuit, and ambush strategies, meticulously illustrated in Figure 7. This article delves into the quantitative modeling of these behaviors and hierarchical dynamics, culminating in the refinement and optimization of the groundbreaking GWO algorithm.

3.3. Algorithm and Mathematical Model

In this segment, we delve into mathematical models concerning social hierarchy, pursuit, entrapment, and prey attack, followed by an exposition on the GWO algorithm [18].

The objective of microgrid energy management lies in determining the hourly generation capacity of each resource to curtail costs. This article presents studies conducted under two scenarios. In the initial scenario, where the utilization of all dispersed generation resources is assumed, energy management is executed. Conversely, the second scenario explores spatial constraints for wind turbine and solar panel installation. To regulate energy resources in the microgrid, we employ the MGWO for optimization. Its operation ensures compliance with constraints pertinent to power generation from each resource. To validate algorithmic outcomes, results from the MGWO are juxtaposed with those derived from the Particle Swarm Optimization (PSO) algorithm. Parameter values for both algorithms are outlined in Table 2. Consistency in population size and iterations is maintained across both algorithms. The process of optimal management of dispersed generation resources in the microgrid, facilitated by intelligent algorithms, is depicted in Figure 8.

For intelligent management of dispersed generation resources in the microgrid, initial input entails monthly average load, geographical coordinates, and specific dates into the Homer software. The software outputs daily average load alongside wind and solar irradiation conditions. Leveraging this data, management is executed through the MGWO and PSO algorithms, aiming to achieve minimum costs with a high level of confidence [1].

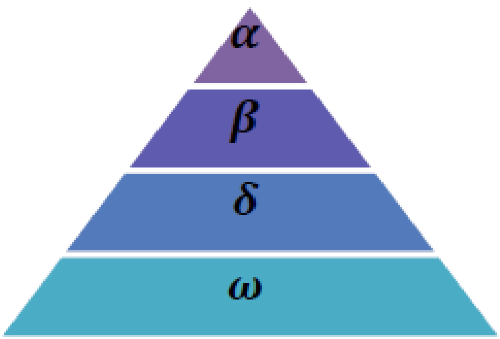

Figure 6. Grey wolf hierarchy [18].

Figure 7. Hunting behavior of Grey wolves: (A) tracking, chasing and approaching prey (B-D) chasing, boring and encirclement (E) standing position and attacking.

Table 2. Parameter of Grey wolf and particle swarm.

Solution Method	Best Answer ($)	Worst Answer ($)	Average Responses ($)	Standard Deviation	Solution Method
Modified Grey Wolf	163.8	172.9	166.9	4.14	Modified Grey Wolf
Particle Swarm Optimization	168.4	182.1	175.4	6.89	Particle Swarm Optimization
Solution Method	Best Answer ($)	Worst Answer ($)	Average Responses ($)	Standard Deviation	Solution Method
Modified Grey Wolf	163.8	172.9	166.9	4.14	Modified Grey Wolf

4. The Results Obtained from The Simulation

4.1. Analysis of the Results of Scenario One

In the initial scenario, under the assumption of sufficient space for accommodating all distributed generation resources within the microgrid, the intricate task of supplying loads is delegated to a composite of distributed generation resources, battery storage, and the primary electricity grid. To finely tune energy supply costs, sophisticated algorithms such as MGWO and PSO have been harnessed for the astute management of distributed generation resources.

Through a rigorous regimen of thirty executions, the outcomes of these algorithms are laid bare in Figure 9. Impressively, across a majority of iterations, the GWO algorithm consistently outperforms its counterpart by yielding lower final objective function values. The minimum values achieved by the MGWO and PSO algorithms were $163.8 and $168.4 respectively, with the maximum values oscillating between $172.9 and $182.1 respectively over thirty executions.

Delving deeper, Table 3 unveils a comprehensive analysis encompassing the best and worst responses, average responses, and standard deviations across thirty optimization runs. Notably, the GWO algorithm's average responses and standard deviations exhibit superior performance over the PSO algorithm, affirming the efficacy of the proposed methodology. A diminutive standard deviation connotes a tighter convergence amongst responses across diverse iterations. Illustrated in Figure 10, the convergence trajectories of both algorithms depict the PSO algorithm reaching $168.4 after 137 iterations, while the GWO algorithm attains $163.8 after 146 iterations, emblematic of a lower final cost.

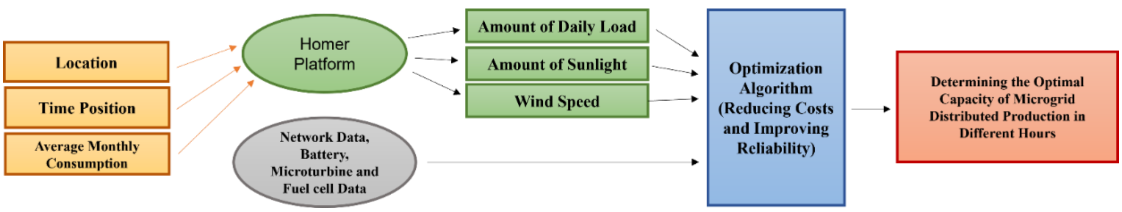

Figure 8. The trend of optimal resource management in microgrid.

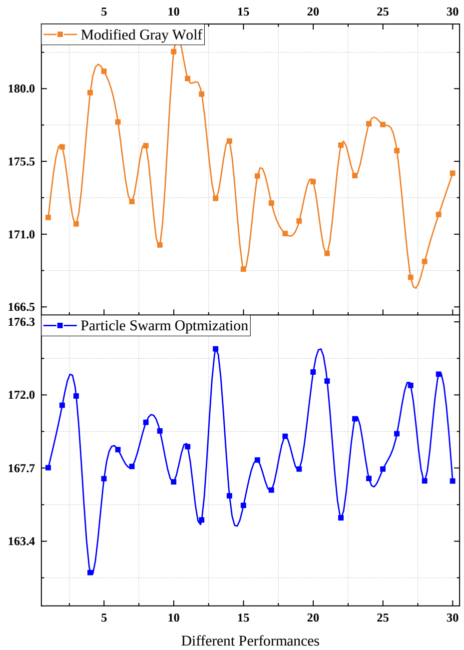

Figure 9. The final optimization values by Modified Grey Wolf Optimizer and Particle swarm optimizer in the first scenario in 30 different executions.

Table 3. Optimization results in 30 times of running the algorithms in the first scenario.

Gray Wolf Algorithm				
Number of Population	Algorithm Iterations	β	α	γ
50	200	0.85	0.6	0.04
Particle Swarm Algorithm				
Number of Population	Algorithm Iterations	C1 = C2	w_{min}	w_{max}
50	200	2	0.6	0.9

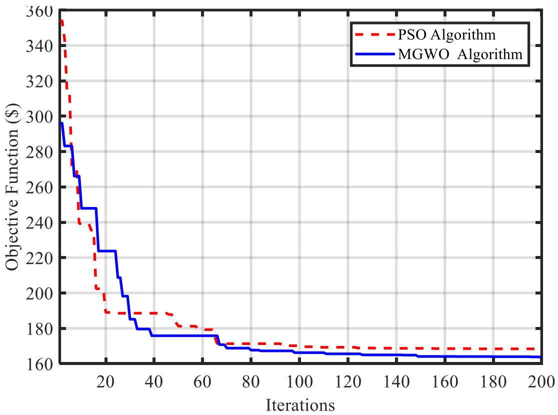

Figure 10. The process of convergence of Modified GWO and Particle swarm optimization algorithms in the first scenario.

Additionally, Figure 11 delineates the nuanced contribution of each distributed generation resource towards fulfilling the microgrid's electrical energy demands over a 24-hour timeframe post-optimization by MGWO and PSO algorithms. Strategically managing energy during specified hours significantly mitigates electricity costs by capitalizing on the upstream network and judiciously charging the battery during off-peak periods.

During peak hours characterized by escalated electricity prices, the microgrid's power requisites lean heavily on distributed generation and storage resources, with surplus energy judiciously sold back to the main grid. Consequently, hours 10 to 17 witness not only a cessation in energy procurement from the main grid but also a surplus sold back, as elucidated in Table 4.

Further dissected in Figure 12, the cost breakdown underscores negative costs for procuring energy from the main grid, indicative of a surplus income derived from electricity sales compared to procurement expenditures. Optimized energy management by the PSO algorithm yields an estimated income of $459.15 from exchanging electrical energy with the upstream network, while the proposed GWO algorithm amplifies this to $494.3. The penalty for unmet energy supply incurred by the MGWO algorithm towers at $74.23, surpassing that of the PSO algorithm standing at $68.45

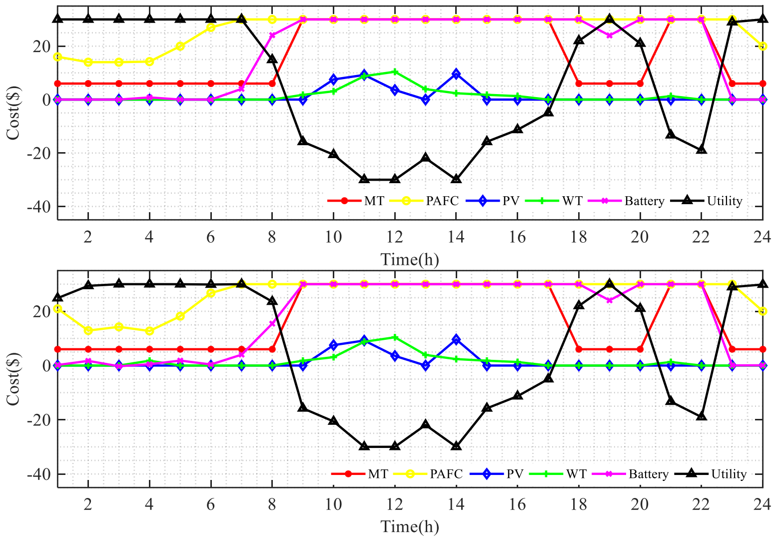

Figure 11. The contribution of each of the distributed production sources in the energy supply in the microgrid

a) Modified Grey Wolf Optimizer b) Particle swarm optimizer.

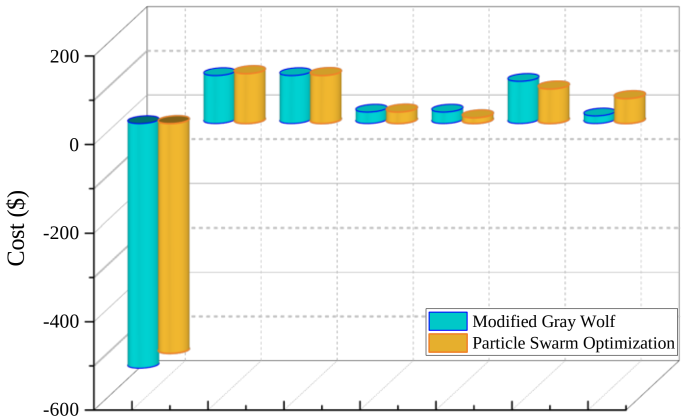

Figure 12. Disaggregated cost in the first scenario.

Table 4. Power resources and energy exchanged with the national electricity grid in the first scenario.

Hour	1	2	3	4	5	6	7	8	9	10	11	12
NET	25	29	30	30	30	30	30	24	-15	-20	-30	-30
FC	21	13	15	13	18	27	30	30	30	30	29	30
MT	6	6	6	6	6	6	6	6	30	30	30	30
PV	0	0	0	0	0	0	0	0	0	7	9	3
WT	0	0	0	0	2	0	0	0	0	1	3	9
BAT	0	2	0	0	1	0	4	15	30	30	30	30
Hour	13	14	15	16	17	18	19	20	21	22	23	24
NET	-22	-30	-15	-11	-5	22	30	21	-13	-19	28	30
FC	30	30	30	30	30	30	30	30	30	30	30	20
MT	30	30	30	30	30	6	6	6	29	30	6	6
PV	0	9	0	0	0	0	0	0	0	0	0	0
WT	11	4	2	1	1	0	0	0	-1	1	0	0
BAT	30	29	30	30	30	29	24	29	30	29	0	0

4.2. Analysis of the Results of Scenario Two

In the subsequent phase of simulations, the microgrid's spatial limitations precluded the installation of wind turbines and solar panels, compelling reliance on fuel cells, micro-turbines, batteries, and the main grid to meet subscribers' energy needs. To optimize the management of distributed generation resources, we employed two enhanced GWO algorithms alongside the PSO algorithm, with the primary objectives of cost reduction and system reliability enhancement.

Figure 13 vividly portrays the results of 30 iterations for both algorithms. It's noteworthy that throughout most iterations, the GWO algorithm consistently outperformed the PSO algorithm in achieving the final optimized objective function value. Post-optimization, the lowest attained value with MGWO and PSO algorithms in the second scenario stood at $9,276 and $4,282, respectively, marking a significant increase compared to analogous values in the first scenario. Conversely, the highest objective function value among the 30 different runs for both MGWO and PSO algorithms amounted to $9,285 and $3,294, respectively.

Table 5 succinctly summarizes the simulation outcomes of 30 optimization algorithm runs in the second scenario. The results indicate that the average responses and standard deviations from 30 runs of the proposed GWO algorithm were $6,280 and $45.4, respectively, demonstrating superior performance compared to the PSO algorithm.

Further insights into convergence patterns are provided in Figure 14, illustrating the optimization process's trajectory in the second scenario. Notably, the PSO algorithm converged to $4,282 after 143 iterations, while the modified GWO algorithm reached $9,276 after 137 iterations, reaffirming the former's superior efficiency.

Additionally, Figure 15 offers a detailed depiction of simulation trends, illustrating the respective contributions of distributed generation resources to supplying electrical energy to microgrid subscribers over a 24-hour study period post-optimization by MGWO and PSO algorithms. Notably, during peak consumption hours, the shortfall in generated energy results in an excess of over 20 kilowatts of electrical energy, impacting profitability from electricity sales. The stability of the energy supply pattern is evident, with procurement from the main power grid timed during cheaper hours and sales deferred to more expensive ones. The heightened operation of distributed generation capacities from 9 a.m. to 5 p.m. is primarily driven by the high electricity prices during those hours, albeit with reduced profitability compared to the first scenario.

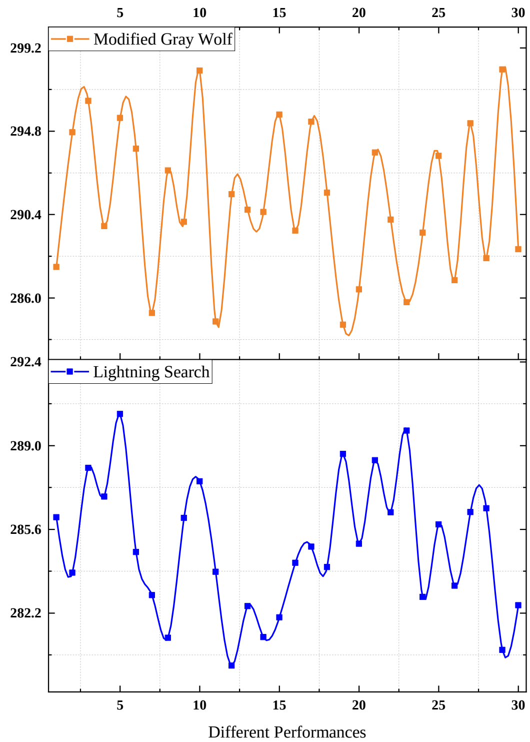

Figure 13. The final optimization values by Modified Grey Wolf Optimizer and PSO in the second scenario in 30 different executions.

Table 5. Optimization results in 30 executions of algorithms in the second scenario.

Solution Method	Best Answer($)	Worst Answer($)	Average Responses($)	Standard Deviation
Gray Wolf Algorithm	276.9	285.9	280.6	4.45
Particle Swarm Algorithm	282.4	294.3	289.8	6.11

Table 6 provides further insights into the production quantities of distributed generation sources and the exchanged power with the main power grid in the first scenario.

Moreover, Figure 16 delineates the individual component costs, underscoring the diminished profitability from selling electricity to the main grid compared to the first scenario. Post-optimization by the GWO algorithm, estimated profitability stands at approximately \$6,362, while after optimization by the PSO algorithm, it amounts to \$4,353. Conversely, optimal energy management by the proposed MGWO algorithm determines a penalty for unsupplied energy at \$3,123, compared to approximately \$2,156 after optimization by the PSO algorithm, reflecting the latter's enhanced microgrid reliability.

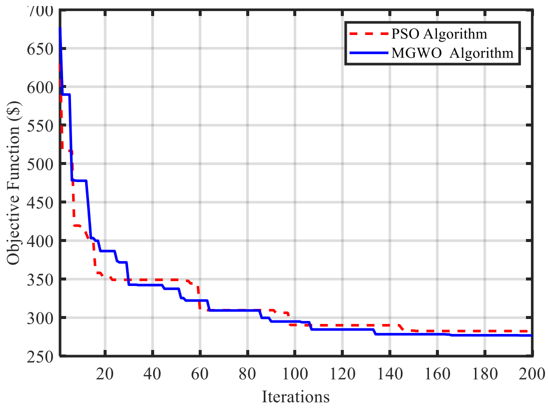

Figure 14. The process of convergence of MGWO and PSO optimization algorithms in the second scenario.

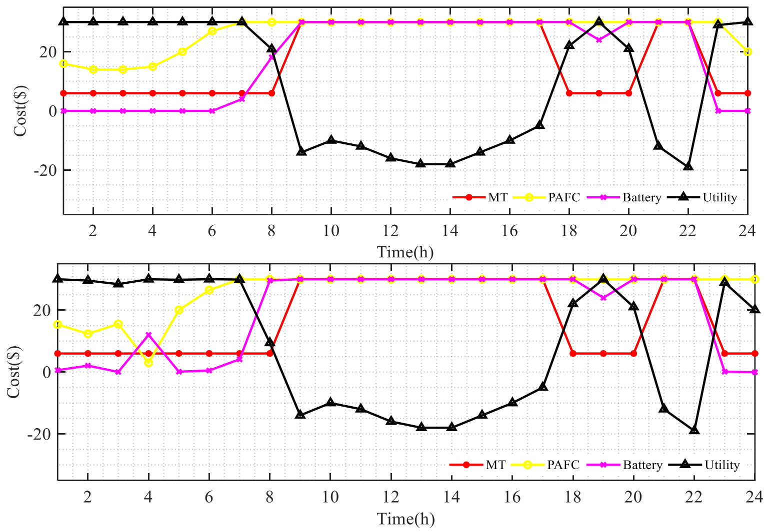

Figure 15. The contribution of each of the distributed production sources in the energy supply in the microgrid a) Modified Grey Wolf Optimization

b) Particle swarm optimization.

Table 6. Power resources and energy exchanged with the national electricity grid in the second scenario.

Hour	1	2	3	4	5	6	7	8	9	10	11	12
NET	30	29	28	30	29	30	30	9	-14	-10	-12	-16
FC	15	12	15	3	20	27	30	30	30	30	30	30
MT	6	6	6	6	6	5	6	6	30	30	30	30
BAT	1	1	0	12	0	0	4	30	30	30	31	30
Hour	13	14	15	16	17	18	19	20	21	22	23	24
NET	-18	-18	-14	-9	-5	23	30	21	-11	-18	29	21
FC	30	30	30	30	30	30	30	30	30	30	30	30
MT	30	30	30	30	30	6	6	6	30	30	6	6
BAT	30	30	31	30	30	30	24	30	30	30	0	1

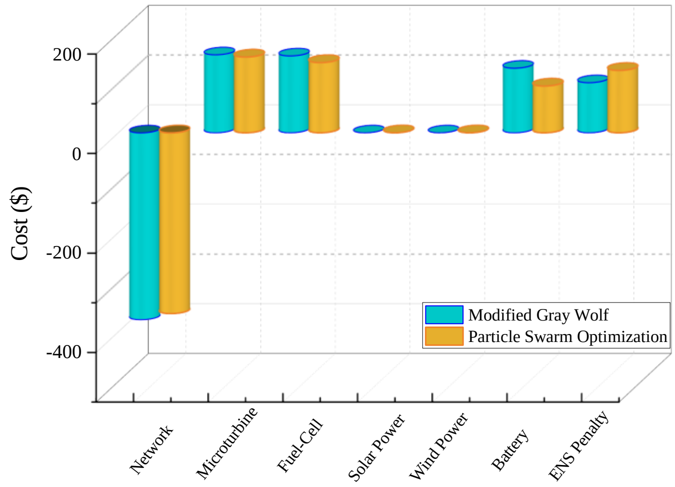

Figure 16. Separated cost in the second scenario.

4.3. Comparison of Two Scenarios

The quantification of power exchange through the national electricity grid has been meticulously calculated under two distinct scenarios, with their outcomes meticulously summarized in Table 7.

While the second scenario witnessed a decrease in profitability compared to the first, the reduction in exchanged power can be attributed to the exclusion of photovoltaic and wind renewable sources.

In the initial scenario, procurement from the national grid amounted to 357 kilowatt-hours, with 210 kilowatt-hours being sold. Conversely, the second scenario saw a decrease in exchanged power, with only 97 kilowatt-hours sold back to the national grid.

5. Conclusions

In this study, we meticulously orchestrated the energy management of a microgrid, utilizing advanced optimization algorithms—PSO and MGWO—to strategically mitigate costs. Our analysis encompassed a spectrum of distributed generation resources: solar panels, wind turbines, diesel generators, fuel cells, and battery storage systems.

Our investigation unfolded across two distinct scenarios: initially, a comprehensive exploration where all distributed generation resources were presumed operable, and subsequently, a more constrained scenario where spatial limitations precluded the installation of wind turbines and solar panels.

In the former scenario, we meticulously optimized energy distribution utilizing MGWO and PSO algorithms, with each algorithm subjected to 30 iterations. Impressively, the MGWO algorithm yielded a minimum optimized value of $163.8, outperforming the PSO algorithm, which yielded $168.4. Notably, the GWO Algorithm exhibited heightened efficiency and accuracy, evidenced by lower average and standard deviation values compared to PSO. The negative energy purchase cost from the main grid underscored a surplus in revenue from electricity sales—a promising indicator of economic viability.

Transitioning to the latter scenario, constrained by spatial limitations, we ingeniously leveraged a combination of fuel cells, microturbines, batteries, and the main grid to meet consumer energy demands. Despite the absence of wind turbines and solar panels, our optimization efforts persisted. Once again, both the GWO Algorithm and PSO were employed 30 times each, yielding minimum optimized values of $276.9 and $282.4, respectively—a marginally higher expenditure compared to the previous scenario. Demonstrating continued superiority, the GWO Algorithm maintained higher efficiency, as evidenced by lower average and standard deviation values. However, it's worth noting that profit from electricity sales to the main grid witnessed a decline compared to the first scenario, showcasing the nuanced impact of spatial constraints on economic outcomes.

Furthermore, our assessment encompassed penalties for unmet energy demands post-optimization, revealing the robustness of our approach. Specifically, penalties for unmet energy stood at $123.3 and $156.2 for MGWO and PSO algorithms, respectively, reaffirming the efficacy of our optimization strategies in addressing energy shortfalls.

Table 7. Power exchanged with the national electricity grid in two scenarios.

Hour	1	2	3	4	5	6	7	8	9	10	11	12
First scenario	30	30	29	30	30	30	30	15	-15	-21	-30	-30
Second scenario	30	30	30	30	30	29	29	20	-14	-11	-13	-17
Hour	13	14	15	16	17	18	19	20	21	22	23	24
First scenario	-21	-30	-15	-11	-5	22	31	21	-13	-19	30	30
Second scenario	-19	-18	-14	-10	-6	22	29	21	-12	-20	28	2

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

Bibliography

Javad Nikoukar was born in Mashhad, Iran, in 1983. He received the B.S. degree in electrical power engineering from Ferdowsi University, Mashhad, Iran, in 2006 and the M.S. degree in electrical power engineering from the University of Tehran, Tehran, Iran, in 2008. He earned his Ph.D. degree in electrical power engineering from Sharif University of Technology, Tehran, Iran in 2013. Since 2015 he has been an assistant professor in Mashhad branch, Islamic Azad University, Mashhad, Iran. His primary research interests are electric machine analysis, modelling, and simulation, innovative electrical drive control approaches, and renewable energy systems.
Email: Javad.Nikoukar@iau.ac.ir
ORCID: 0000-0002-5142-0924
Contribution Statement: Conceptualization, Project administration, Visualization, Methodology.

Shokoofeh Mohammadi was born in Saveh, Iran, in 1988. She received the B.Sc., M.Sc., degrees in 2015, 2018, respectively, in Chemist and Energy systems engineering, energy systems modeling engineering, respectively. She is currently an, TA with the Department of mechanical engineering, Islamic Azad University, Saveh, Iran. And Ph.D. student at Science and Research Branch, Islamic Azad University, Tehran, Iran. Her main research interests are energy system analysis and reliability, Exergy Analysis, Modeling and Simulation. She has Active as a researcher/ QA manager in different Industrial Companies**.**
Email: Sh.mohammadi8959@gmail.com
ORCID: 0009-0004-0435-7426
Contribution Statement: Data curation, Formal analysis, Investigation, Resources, Writing-review & editing.

Hamid Reza Hanif received his B.Sc. and M.Sc. in Mathematics and PHD degrees in Electrical Power Engineering from Iran University of Science and Technology, Iran Tehran in 2014 and 2019 and 2023 respectively. He has authored and co-authored more than 75 papers in international journals and conferences. He has also published a book and co-authored some book chapters. His main research interests include renewable energy, technologies, Microgrids, Power System Planning, Power Systems, Smart grids, Electric vehicles, and fault location. Since 2018 he has been a reviewer and Editorial Board Member of several high-quality journals.
Email: h.hanif.iustz@gmail.com
ORCID: 0000-0001-9289-2947
Contribution Statement: Data curation, Funding acquisition, Visualization, Writing-review & editing.

Reza Aminpour gogani received his B.Sc. and M.Sc. and Ph.D. in Electrical Power Engineering from Azarbaijan Shahid Madani University. He has authored and co-authored more than 10 papers in international journals and conferences. He has also published a book and co-authored some book chapters. His main research interests include renewable energy, technologies, Microgrids, Power system Planning, Power Systems, Smart grids, Electric vehicles, and fault location. Since 2018 he has been a reviewer of several high-quality journals.
Email: Reza.aminpour@azaruniv.ac.ir
ORCID: 0009-0007-7013-6965
Contribution Statement: Methodology, Resources, Validation, Roles/Writing-original draft.

Masoumeh Ghafari was born in 2000 in Ilam, Iran. She received the bachelor's degree in Electrical Engineering from Malayer University, Malayer, Iran, in 2023. With a keen interest in advancing the field of Electrical Engineering, she is currently pursuing the master's degree at Babol Noshirvani University of Technology, Babol, Iran, Specializing in Electrical Engineering with a focus on Control Systems. her research interests include Smart Grids, Energy Optimization, and Application of Neural Networks in Renewable Energy Systems.
Email: ma.ghafari1379@gmail.com
ORCID: 0009-0000-4909-4616
Contribution Statement: Software, Resources, Software, Roles/Writing-original draft, Writing-review & editing.

Abdolreza Behvandi was born in 1987 in Iran. He received his B.Sc., M.Sc., and Ph.D. degrees all in Electrical Engineering (Power Systems) in 2010, 2012, and 2019 from Isfahan University of Technology, Isfahan University, and Shahid Chamran University of Ahvaz, respectively. Currently, he is an Assistant Professor at Department of Electrical Engineering, Ramhormoz Branch, Islamic Azad University, Ramhormoz, Iran. His special interests are power system studies, power system protection, renewable energy, and microgrids.
Email: rezabehvandi@gmail.com
ORCID: 0000-0002-4879-1994
Contribution Statement: Data curation, Formal analysis, Investigation, Resources, Validation.