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Sustainable Microgrid Operation: SNS Algorithm for Cost-Efficient Energy Management

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ABSTRACT

This paper proposes a social network search (SNS) algorithm for optimizing energy management systems (EMS) in microgrids. The EMS focuses on economic aspects, specifically addressing economic load dispatch (ELD) in both grid-connected and isolated operational modes, with a specific emphasis on integrating renewable energy resources (RES). The effectiveness and efficiency of the proposed SNS algorithm are evidenced through simulations using a microgrid model with five distinct cases, each featuring varying combinations of distributed energy resources (DERs). To ensure a comprehensive evaluation, the particle swarm optimization (PSO) algorithm is also utilized. The results show that the proposed SNS algorithm is effective in determining optimal dispatch strategies for DERs in all operational modes, as well as optimizing power transactions with the main grid to reduce operational costs in grid-connected configurations. Moreover, the proposed SNS algorithm outperforms the PSO algorithm in all cases studied. Furthermore, the findings highlight the positive impact of RES on total generation costs, demonstrating how increasing RES integration, particularly solar and wind power, contributes to lower microgrid costs and reduced dependence on external grid power procurement, thereby enhancing overall microgrid performance efficiency.

Keywords: *Microgrid; Renewable sources; Economic dispatch; Social network search; Grid-connected.*

1. Introduction

The rising electricity demand necessitates sustainable solutions to meet the growing population's energy requirements [1]. Microgrid presents a valuable solution to address these energy challenges due to their ability to enhance reliability, power quality, and energy efficiency and reduce interruption costs for customers [2]. The term microgrid refers to a small-scale system made up of distributed energy resources (DERs) and critical and non-critical loads [3–4]. The microgrid has two operational modes: islanded and grid-connected [5]. In normal conditions, the microgrid operates in a grid-connected mode where it exchanges power with the main grid based on generation and load demands, as well as market policies that enhance operational benefits [4, 6]. In cases of emergency, such as a fault occurring in the main grid, the microgrid isolates itself from the grid and continues to provide power to the critical loads, utilizing its DERs [7].

The microgrid is a hybrid system that enables efficient utilization of renewable energy sources (RES), such as wind turbines and solar photovoltaics, along with conventional generators and energy storage systems [8]. To ensure collaboration between these components and achieve stable and economical operation, a microgrid typically needs an energy management system (EMS) [7]. The EMS serves as the comprehensive framework responsible for monitoring, controlling, and optimizing energy generation, distribution, and consumption within the microgrid [8–9]. It continuously monitors the energy flow within the microgrid, integrating data from various energy sources, storage devices, loads, and the main grid [10]. It also optimizes the energy flow based on factors such as demand, availability of RES, energy storage levels, grid conditions, and cost considerations [11].

Furthermore, EMS manages energy distribution to loads, prioritizing critical loads, optimizing energy consumption profiles, and ensuring system stability [12]. Within the EMS domain, economic load dispatch (ELD) emerges as a pivotal component dedicated to optimizing power generation to meet load demands at minimum costs while considering system constraints [13]. By implementing ELD in a microgrid, operators can effectively manage the generation and consumption of electricity, reduce operational costs, and potentially integrate higher levels of RES, leading to more efficient and sustainable microgrid operation.

In recent literature, several methodologies and optimization techniques, such as harmony search algorithm (HS) [5], quadratic programming [14], mixed-integer linear programming [15], particle swarm optimization algorithm (PSO) [16–18], improved mayfly optimization algorithm (IMA) [19], genetic algorithm [20], etc., have been presented to solve the ELD problem in microgrid. These techniques consider the cost of generation, storage, and operation of DERs, as well as any technical constraints, to find the optimal dispatch schedule that minimizes the overall operating cost while ensuring a reliable and resilient power supply. However, most previous research has predominantly focused on addressing the ELD problem in isolated-mode microgrids, with limited attention given to grid-connected mode. This study aims to fill this gap by proposing an efficient approach to economic dispatch in grid-connected microgrids.

Handling ELD in a grid-connected mode poses additional challenges compared to managing ELD in an isolated mode. In a grid-connected mode, ELD must consider grid constraints imposed by the main grid, such as power quality requirements, voltage and frequency regulations, and grid stability criteria. Additionally, grid-connected microgrids often participate in electricity markets, where real-time pricing and market signals influence ELD decisions. Incorporating market dynamics, price volatility, and market participation strategies into ELD optimization adds complexity compared to isolated microgrid scenarios, where pricing dynamics are more straightforward or non-existent. The grid-connected microgrids also have bidirectional power flow requirements, where power can be imported from or exported to the grid. Managing bidirectional power flow during ELD optimization involves balancing power export/import decisions with cost considerations, grid constraints, and RES utilization. Furthermore, grid-connected microgrids are part of a larger electricity network, introducing additional complexity due to interactions with the main grid, multiple energy sources, and varying load profiles. Optimizing ELD in this interconnected system necessitates more sophisticated algorithms and control strategies to address the dynamic and interconnected nature of grid-connected microgrids.

This study presents the application of a new algorithm, known as social network search (SNS), to address the ELD problem in a grid-connected microgrid with diverse DERs, including wind, solar, and conventional generation units, under various operational scenarios. The primary objective is to minimize the operating cost of the microgrid, which includes grid operational costs, costs associated with RESs, and fuel costs of conventional units, while accounting for the microgrid's load profile over 24- hour period. The optimization process considers multiple constraints, such as grid limitations, electrical load balance requirements, power constraints of DERs, and grid tariffs. The microgrid can buy electricity from the main grid during peak demand periods or insufficiencies in its generation, as well as export excess power or sell electricity back to the grid during surplus production or off-peak hours. Furthermore, the microgrid can operate independently from the main grid in isolated mode, supplying power only to critical loads when necessary. The results show that the proposed SNS algorithm is effective in determining optimal dispatch strategies for DERs in all operational modes. It also outperforms PSO and other algorithms found in existing literature when applied to the same microgrid model.

The rest of the paper is structured as follows: Section 2 presents the problem formulation, Section 3 details the proposed SNS algorithm, Section 4 presents the implementation of the proposed algorithm to the ELD problem in microgrid, Section 5 presents the results and subsequent discussion, and Section 6 provides a summary and conclusions.

2. Problem formulation

The ELD problem in microgrids focuses on optimizing the scheduling and dispatch of DERs, such as solar photovoltaic systems, wind turbines, and small-scale generators, to minimize operating costs while meeting the electricity demand. This optimization considers various factors, including DER operating costs, renewable energy availability, demand forecasts, and grid connection constraints.

This section presents the mathematical formulation of the ELD problem in grid-connected mode, where the microgrid is connected to the main grid via a Point of Common Coupling (PCC). Figure 1 illustrates the schematic diagram of the microgrid under study [4]. The microgrid can purchase or sell power from/to the main grid based on load demand.

2.1 Objective Functions

2.1.1 Grid-connected operation

In this work, we focus on the grid-connected mode of operation. For proper system functionality, tariffs are implemented for power exchange between the microgrid and the main grid. These tariffs vary depending on peak and off-peak demand hours. During peak hours, the purchasing price is higher, while the selling price is lower, and vice versa. The cost of purchasing or selling power from the grid can be mathematically calculated as follows [21]:

$$C_G(P_G) = \mathrm{K} * P_G \qquad (1)$$

Where K is the microgrid's buying or selling price during scheduled time, as decided by the policy of tariffs in $/kWh, and P_G is the exchange power in kW. If $P_G > 0$, power is bought from the grid; if $P_G < 0$, power is sold to the grid.

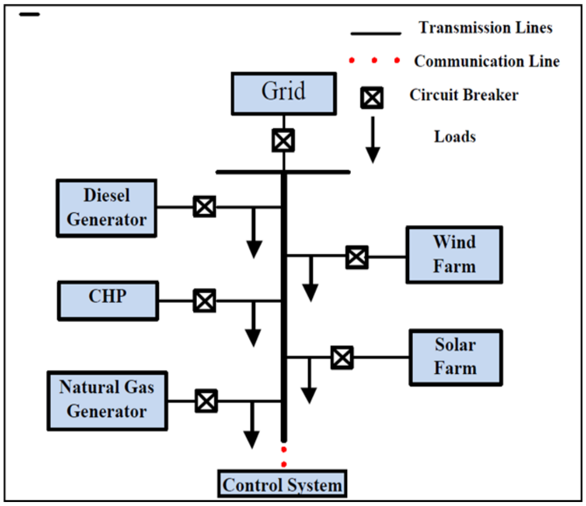


Figure 1- Schematic diagram of the microgrid.

2.1.2 Cost function of conventional generation units

The fuel cost function of conventional generating units such as diesel, natural gas, or combined heat and power generation units can be mathematically represented using the quadratic cost function as follows:

$$C_n(P_n) = r_n + s_n\, P_n + l_n P_n^2 \qquad (2)$$

Where P_n is the output power from the n^{th} unit in MW and r_n, s_n, and l_n are fuel cost coefficients of the n^{th} generation unit.

2.1.3 Cost function of wind generation units

The cost function of wind generation units can be mathematically formulated as follows:

$$C_W(P_W) = P_W(b\, l^P + O^E) \qquad (3)$$

$$b = \frac{r}{[1-(1+ri)^{-\beta}]} \qquad (4)$$

Where P_W is the wind power in kW; l^P is the investment cost to installed power ratio in $/h; O^E is the operation and maintenance cost to installed power ratio in $/h; b is the annuitization coefficient; ri is rate of interest; and β is investment lifetime. In this work, O^E is fixed at 0.016 $/kW invested over 20 years at a 9% interest rate [4-5]. Furthermore, l^P is set at 1400 $/kW. Therefore, the cost function of wind generation unit can be calculated as follows:

$$C_W(P_W) = 153.3810 * P_W \qquad (5)$$

2.1.4 Cost function of solar generation units

The cost function of solar generation units is similar to the cost function of wind, represented by Eqs. (3) and (4). However, the investment cost to installed power ratio (l^P) is set at 5000 $/kW [4-5]. Therefore, the cost function of solar generation unit can be calculated as follows:

$$C_S(P_S) = 547.7483 * P_S \qquad (6)$$

Where P_S is the solar power in kW.

2.1.5 Overall cost function of ELD problem

The overall total operational cost function (C_t) of the ELD problem in $/h can be mathematically expressed as:

$$\min C_t = \sum_{n=1}^{ng} C_n(P_n) + \sum_{W=1}^{nw} C_W(P_W) + \sum_{S=1}^{ns} C_S(P_S) + C_G(P_G) \qquad (7)$$

Where ng, nw, and ns are total number of conventional, wind, and solar units, respectively.

2.2 Constraints

The following constraints need to be considered when solving the ELD problem in a grid-connected microgrid:

2.2.1 Power balance constraint:

$$\sum_{n=1}^{ng} P_n + P_W + P_S + P_G = P_D \qquad (8)$$

Where P_D the load demand of microgrid.

2.2.2 Generation limits constraint:

$$P_n^{min} \le P_n \le P_n^{max} \qquad (9)$$

$$P_W^{min} \le P_W \le P_W^{max} \qquad (10)$$

$$P_S^{min} \le P_S \le P_S^{max} \qquad (11)$$

Where P^{min} and P^{max} are the minimum and maximum power of each generation source, respectively.

2.2.3 Transaction power limits between microgrid and main grid [22]:

$$P_G^{min} \leq P_G \leq P_G^{max} \tag{12}$$

Where P_G^{min} and P_G^{max} are the minimum and maximum transaction power between the microgrid and main grid, respectively. P_G has a positive value if the microgrid purchases power from the main grid. Otherwise, the microgrid sells power to the main grid.

3. Social network search algorithm

In 2021, H. Bayzidi et al. [23] introduced a social network search algorithm (SNS) that expresses people's distinctive viewpoints about a recent event by imitating their decision-making moods, such as imitation, conversation, disputation, and innovation.

1. Imitation: In this mode of thought, users try to imitate well-known individuals who share their thoughts by writing a discourse about a fascinating new event. This mood is mathematically represented by the following formula:

$$Y_{i,new} = Y_j + r1 \times r2 \times \left(Y_i - Y_j\right) \tag{13}$$

Where Y_i and Y_j are the i^{th} and j^{th} user's view vectors, randomly selected with $i \neq j$; $Y_{i,new}$ is the i^{th} user's new view; $r1$ and $r2$ are random vectors in the intervals [-1, 1] and [0, 1], respectively.

2. Conversation: When individuals are in a conversion mood, they can learn more about an event and develop new perspectives by exchanging information and considering it from various perspectives. This mood is mathematically represented by the following formula:

$$Y_{i,new} = Y_t + rand(0,1) \times [sign\left(f_i - f_j\right) \times \left(Y_i - Y_j\right)] \tag{14}$$

In Eq. (14), Y_t represents a randomly selected event vector that will be discussed; Y_i and Y_j represent the randomly selected views of users i and j, respectively, where $i \neq j \neq t$; f_i and f_j represent the objective functions of Y_i and Y_j, respectively; The sign function is represented by sign, and the expression $sign(f_i\text{-}f_j)$ establishes a comparison between f_i and f_j to explain the direction that Y_t is going.

3. Disputation: In this mode, individuals on social networks express and defend their opinions on a topic by commenting or participating in group discussions. They may come across different points of view and be influenced by the opinions of others. This mood is mathematically represented by the following formula:

$$Y_{i,new} = Y_i + rand(0,1) \times \frac{\sum_{r=1}^{N_u} Y_r}{N_u} - ((1 + Af) \times Y_i) \tag{15}$$

$$Af = round(rand(0,1)) \tag{16}$$

In this context, N_u refers to the randomly chosen group size for the disputation, selected from a range of 1 to N, Where N represents the number of network users. Af represents the admission factor, which signifies the impact of users on their views during discussions with others. This factor can take on a value of 1 or 2. Furthermore, the function round(.) is utilized to round real input to the nearest integer.

4. Innovation: In this mode, individuals have the opportunity to express their opinions and emotions regarding a specific event in innovative and imaginative ways, leading to the emergence of fresh ideas. The resulting shift in perspective can be mathematically represented as follows:

$$Y_{i,new} = [y_1, y_2, \dots \dots, y_{i,new}^d, \dots \dots, y_D]$$

$$y_{i,new}^d = r y_j^d + (1 - r) \times LB_d + rand(0,1) \times (UB_d - LB_d) \tag{17}$$

The above formula indicates that, in the innovation mode, a random number r is randomly selected from the range of 0 to 1. Another variable d is randomly chosen from the range of 0 to D, where D is the number of problem variables. The upper and lower boundaries of variable d are represented by UB_d and LB_d, respectively. The existing idea on the d^{th} variable created by user j is denoted by y_j^d, while $y_{i,new}^d$ represents the new vision of the event from the perspective of variable d, which replaces the current view of user i.

To implement the SNS algorithm, the maximum number of iterations (MaxIter), the number of users (N), and the limitations of the variables should be defined. Then, the starting population of users' views (Y_0) is initialized as follows:

$$Y_0 = LB + rand(0,1) \times (UB - LB) \tag{18}$$

where LB and UB stand for the variables' lower and upper bounds, respectively.

4. Implementation of SNS algorithm for ELD problem in grid-connected microgrids

This section applies the proposed SNS algorithm to solve the ELD problem in a grid-connected microgrid. The control variables for this optimization problem are the output power from DERs and the power exchange with the main grid. These control variables represent the population of users' views within the proposed SNS algorithm. The objective function then evaluates the fitness of each proposed solution based on these control variables. To satisfy the power balance constraint, one of the conventional generators is designated as a slack generator. Figure 2 illustrates the flowchart of the proposed SNS algorithm for solving the ELD problem. The detailed procedure for implementing the SNS algorithm in this context is as follows:

Step 1: Define the parameters of the proposed SNS algorithm, including the number of users and maximum number of iterations, as well as the test system data.

Step 2: Randomly initialize the control variables of the current problem within their predefined upper and lower limits, except for the slack generator. Each vector in the initial population represents a proposed solution to the problem.

Step 3: Compute the slack power (P_{slack}) utilizing Eq. (19) and check its feasibility utilizing Eq. (9). If the slack power violates its limits, penalize the corresponding solution.

$$P_{Slack} = P_D - \left(\sum_{n=1}^{ng-1} P_n + P_W + P_S + P_G\right) \tag{19}$$

Step 4: Using Eq. (20), calculate the fitness value of the proposed solutions and choose the best solution with the lowest cost.

$$Z_t = \sum_{n=1}^{ng} C_n(P_n) + \sum_{W=1}^{nw} C_W(P_W) + \sum_{S=1}^{ns} C_s(P_S) + C_G(P_G) + \lambda_s (P_{slack} - P_{slack}^{lim})^2 \tag{20}$$

Where λ_s a penalty factor for the slack unit; P_{slack}^{lim} is the output power limit of the slack unit, which can be set as follows:

$$P_{slack}^{lim} = \begin{cases} P_{slack}^{max} & if\ P_{slack} > P_{slack}^{max} \\ P_{slack}^{min} & if\ P_{slack} < P_{slack}^{min} \\ P_{slack} & if\ P_{slack}^{min} \le P_{slack} \le P_{slack}^{max} \end{cases} \tag{21}$$

Step 5: Begin the algorithm iteration process. Generate a random mood for each solution and obtain new solutions.

Step 6: Validate the feasibility of the new solutions, regenerating the violated ones.

Step 7: Compute the slack power, as described in step 3, and ensure it complies with specified limits.

Step 8: Calculate the fitness of the new solutions using Eq. (20).

Step 9: Compare the fitness of the new solutions with the existing solutions. If the new solution's fitness is better, replace the old solution with the new one, share it, and update the best solution. If not, retain the old solution and do not share the new solution.

Step 10: If the current iteration is less than the maximum iteration, return to Step 5. Otherwise, stop the algorithm and output the best solution.

5. Simulation results and discussions

The microgrid employed in this study consists of three conventional generators, a wind generation unit, and a solar generation unit. Table (1) displays data of conventional generators, power limits, cost coefficients, and grid limits. Table (2) shows the 24-hour critical and non-critical load demands as well as the 24-hour output power of solar and wind production units. The data in Tables (1) and (2) are obtained from [4]. In addition, the grid tariffs are sourced from [24]. To implement the SNS algorithm, the control parameters, including population size and maximum number of iterations, are selected utilizing empirical tests by running the algorithm several times with different parameter combinations. Performance evaluation using metrics like solution quality is carried out for each parameter set, and the results are compared to find the optimal parameter settings. To assess the effectiveness of the proposed SNS algorithm in solving the ELD for microgrids, five cases are carried out as follows:

1. Only conventional generation units are considered in grid-connected mode.
2. Conventional and solar units are considered in grid-connected mode.
3. Conventional and wind units are considered in grid-connected mode.
4. All sources are considered in grid-connected mode.
5. All sources are considered in isolated mode.

The findings of the SNS algorithm are compared with those of the particle swarm algorithm (PSO) for different cases to assess the efficacy of the proposed algorithm.

Table 1- Data of conventional generators and grid

Generators	Min Power (MW)	Max Power (MW)	l (\$/MW^{2}h)	s (\$/MWh)	r (\$/h)
G1	0.2	1.5	0.000240	0.210	15.3
G2	0.1	1	0.000435	0.300	14.88
G3	0.1	1	0.000315	0.306	9.00
Grid	-1.0	1.0	-	-	-

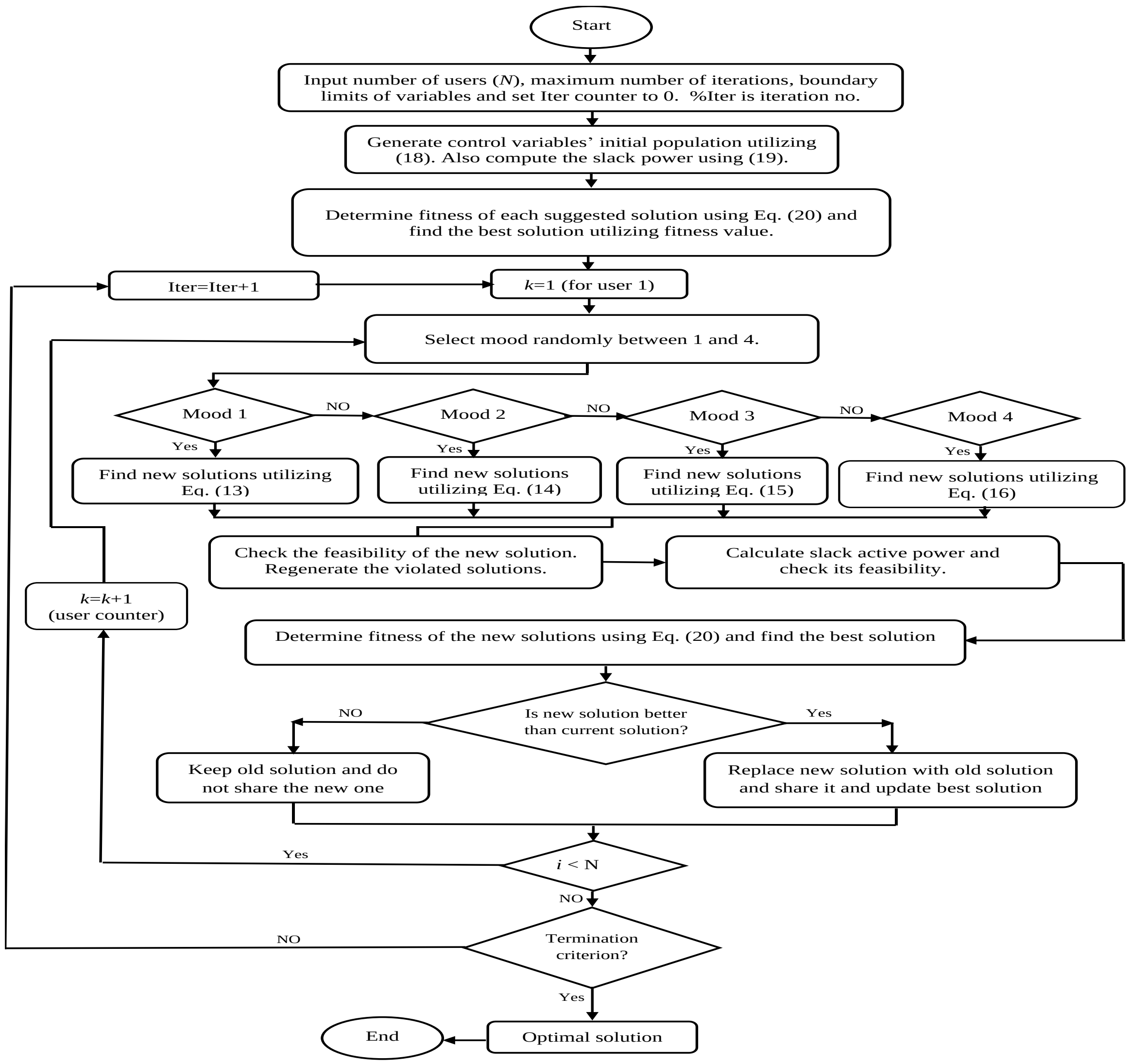


Figure 2-Flowchart of the proposed SNS algorithm for the ELD problem in grid-connected microgrid

Table 2- Critical load profile, non-critical load profile, wind and solar generation over 24 hours

Time (h)	Critical Load (MW)	Non-critical Load (MW)	Solar (MW)	Wind (MW)	Time (h)	Critical Load (MW)	Non-critical Load (MW)	Solar (MW)	Wind (MW)
1	3.3	2.3	0	0	13	2.824	2.225	.082	.375
2	3.3	2.3	0	0	14	2.949	2.250	.08	.4
3	3.2	2.2	0	.004	15	3.3	2.4	.073	.35
4	3.15	1.850	0	.009	16	3.5	2.3	.059	.267
5	3.625	2.025	0	.011	17	3.8	2.3	.04	.099
6	4.2	2.2	0	.056	18	4.3	2.450	.016	.03
7	4.35	2.350	.013	.094	19	4.4	2.4	.02	0
8	4.1991	2.4	.033	.0151	20	4.3	2.150	0	0
9	4.1	2.6	.053	.219	21	4.14	2.140	0	0
10	3.65	2.650	.07	.286	22	2.5	1.7	0	0
11	3.3	2.5	.077	.339	23	3.325	1.825	0	0
12	2.799	2.1	.083	.362	24	2.95	1.850	0	0

1. **Case 1: Only conventional generation units are considered in grid-connected mode**

In this case, the proposed SNS algorithm is applied to address the ELD problem within the context of the grid-connected microgrid, focusing on the operational cost of conventional units. Figure (3) depicts the dispatch results obtained by the SNS algorithm, illustrating the optimized power allocation results. In addition, Figure (4) displays the total power generated by conventional units, load demand, and power exchange with the main grid at each time interval. As observed, the proposed SNS algorithm can achieve the best solution by dispatching generation units so that the load demand is met at each period. Furthermore, the results show that the microgrid can trade power with the grid during off-peak and peak hours. Table (3) lists the hourly and total operating costs determined by the SNS and PSO algorithms. The total cost achieved by SNS is 2016.45669 $/h, which is better than that achieved by PSO (2361.86247 $/h). The results demonstrate that the operational costs are higher during peak hours (5-10 & 17-21) compared to off-peak, as the microgrid has to buy excess power from the main grid. The results also highlight the algorithm's capability to make decisions on power trading with the main grid, offering significant benefits to overall system efficiency.

Table 3-Operation costs obtained by SNS and PSO algorithms for Case 1

Time (h)	Proposed SNS	PSO	Time (h)	Proposed SNS	PSO
1	40.23648	45.92973	13	39.94465	45.78203
2	40.93751	45.93219	14	39.98450	45.81683
3	40.33376	45.89025	15	40.41147	45.96515
4	40.04829	45.89393	16	41.68321	51.11039
5	62.10829	63.74792	17	83.98308	91.02668
6	152.68506	180.08097	18	186.69383	205.40711
7	164.04035	203.68421	19	206.29493	215.13830
8	174.49397	179.51355	20	127.05615	203.58999
9	152.63823	166.41683	21	107.36859	170.15056
10	75.03109	81.54242	22	39.80339	45.68513
11	40.42573	46.01462	23	40.35137	45.93611
12	39.94694	45.78679	24	39.95582	45.82078
Total cost ($)				2016.45669	2361.86247

2. **Case 2: Conventional and solar units are considered in grid-connected mode**

In this case, the proposed SNS algorithm is employed to tackle the ELD problem within the framework of a grid-connected microgrid, taking into account the costs associated with the operation of conventional and solar units. The dispatch outcomes derived through the proposed SNS algorithm are presented in Figure (5). Additionally, Figure (6) displays the total power generation from conventional and solar units as well as the load demand and power exchange with the grid at each time interval. Notably, the accuracy of the algorithm outcomes is evidenced by the consistent matching of dispatched power with the prevailing load demands. Table (4) lists the hourly and total operating costs determined by the SNS and PSO algorithms. The findings reveal the superior performance of the proposed SNS algorithm, reflected in its ability to yield better cost results over 24 hours compared to the PSO algorithm. Furthermore, the utilization of solar energy as a form of negative load leads to a 1.84% savings in costs compared to Case 1, showcasing the beneficial impact of integrating solar power resources within the microgrid energy management framework.

Table 4-Operation costs obtained by SNS and PSO algorithms for Case 2

Time (h)	Proposed SNS	PSO	Time (h)	Proposed SNS	PSO
1	40.23648	45.92239	13	39.96421	45.79771
2	40.93751	45.93551	14	40.00358	45.83876
3	40.33376	45.89334	15	40.06992	45.95602
4	40.04829	45.88136	16	41.69727	46.12905
5	62.10829	60.90981	17	78.0167	88.89702
6	152.6851	183.61596	18	186.6976	196.99925
7	164.0434	201.35894	19	206.2997	213.58479
8	174.5018	179.32287	20	127.0562	199.87787
9	139.6041	146.09430	21	107.3686	172.07902
10	57.46472	69.25781	22	39.80339	45.67889
11	40.0835	45.94853	23	40.35137	45.93189
12	39.95256	45.78846	24	39.95582	45.81400
Total cost ($)				1979.28387	2308.5135

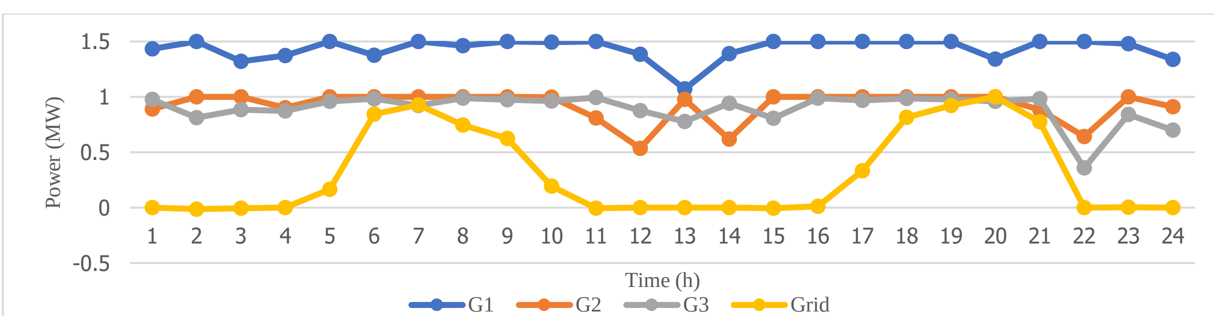


Figure 3- Dispatch results obtained by SNS algorithm for grid-connected mode for Case 1.

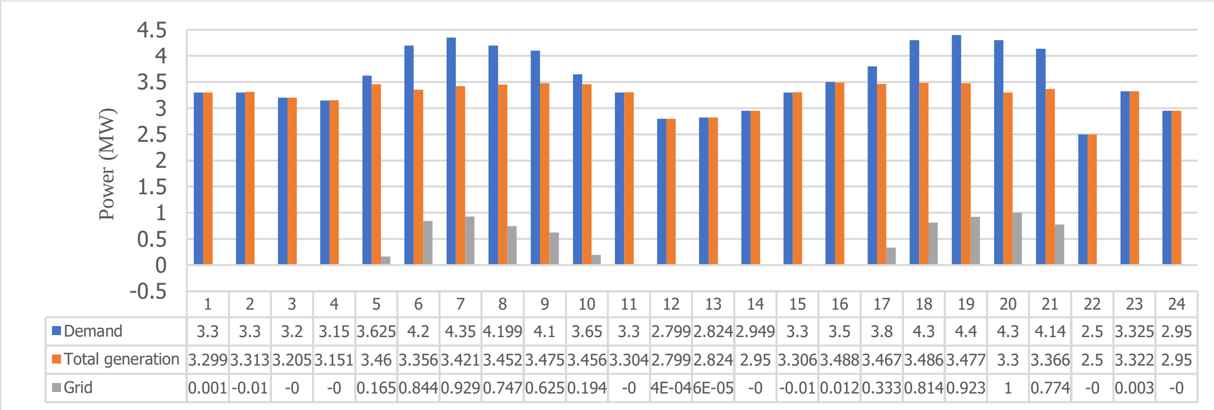


Figure 4- Load demand, total power generated and grid over 24-hour for Case 1.

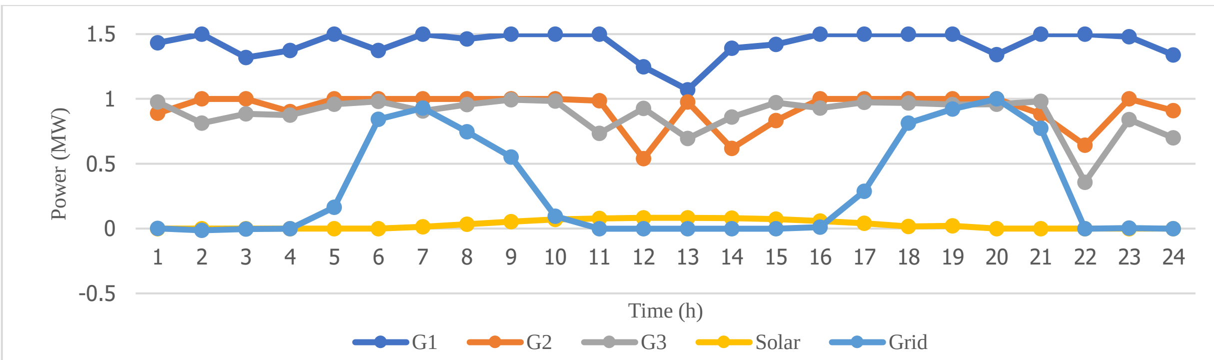


Figure 5- Dispatch results obtained by proposed SNS algorithm for grid-connected mode for Case 2.

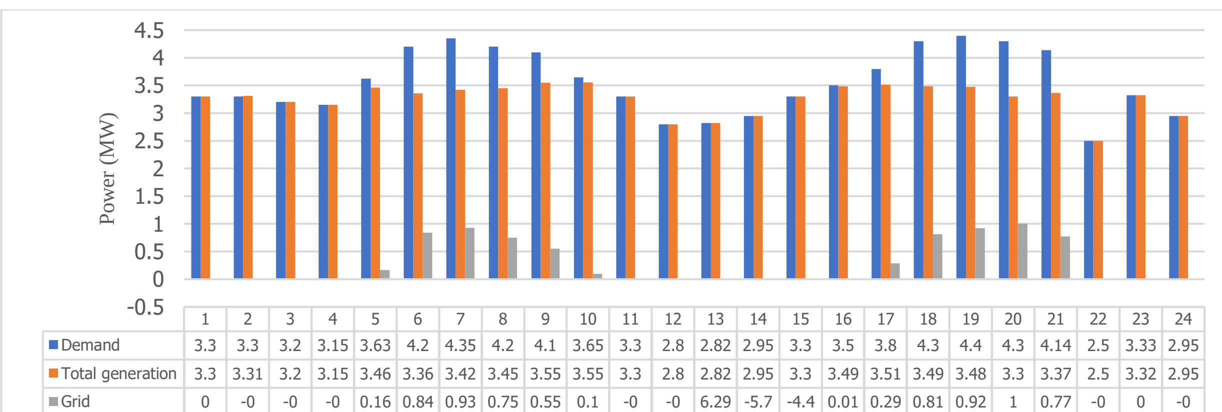


Figure 6- Load demand, total power generated and grid over 24-hour for Case 2.

3. Case 3: Conventional and wind units are considered in grid-connected mode

In this case, the proposed SNS algorithm is employed to tackle the ELD problem within the grid-connected microgrid, considering the operational costs associated with both conventional and wind units. The dispatch results derived through the proposed SNS algorithm are presented in Figure (7). Additionally, Figure (8) displays the total power generation from conventional and wind units as well as the load demand and power exchange with the grid at each time interval. Table (5) lists the hourly and total operating costs determined by the SNS and PSO algorithms. Similar to the previous cases, the proposed SNS satisfies the problem constraints and achieves an optimal cost surpassing that of the PSO algorithm. Noteworthy cost improvements are observed, with the incorporation of wind energy resulting in a cost reduction of 6.18% and 4.42% in comparison to Cases 1 and 2, respectively.

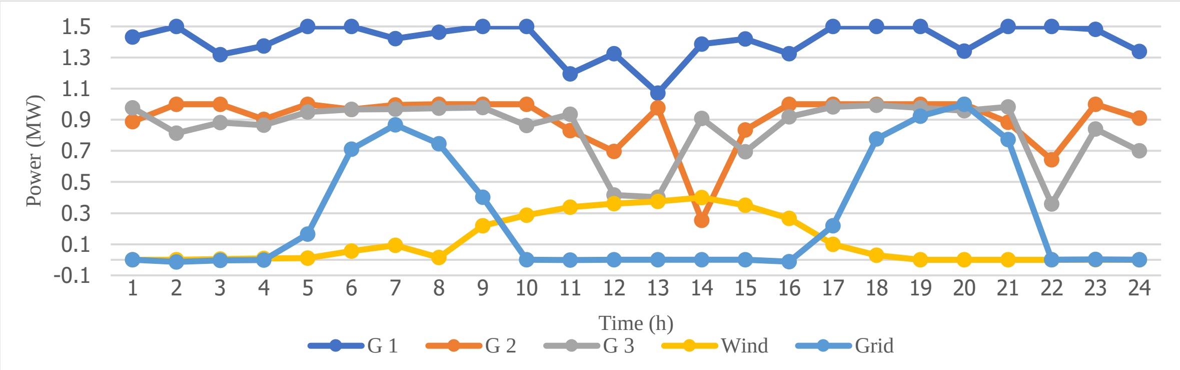
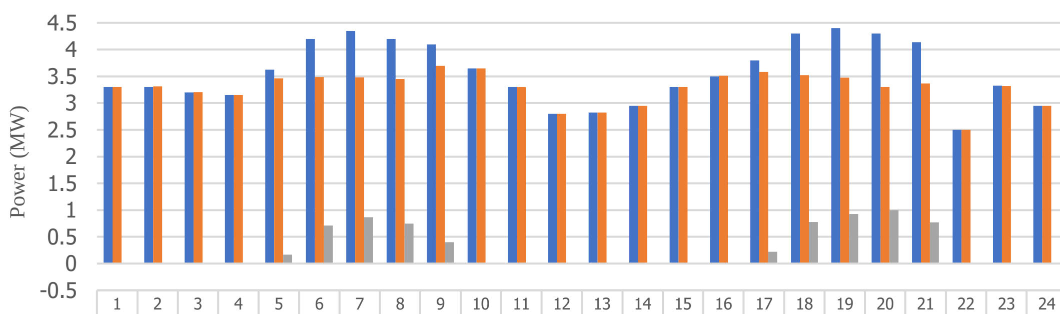


Figure 7- Dispatch results obtained by proposed SNS algorithm for grid-connected mode for Case 3.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Demand	3.3	3.3	3.2	3.15	3.63	4.2	4.35	4.2	4.1	3.65	3.3	2.8	2.82	2.95	3.3	3.5	3.8	4.3	4.4	4.3	4.14	2.5	3.33	2.95
Total generation	3.3	3.31	3.2	3.15	3.46	3.49	3.48	3.45	3.7	3.65	3.3	2.8	2.82	2.95	3.3	3.51	3.58	3.52	3.48	3.3	3.37	2.5	3.32	2.95
Grid	0	-0	-0	-0	0.16	0.71	0.87	0.75	0.4	0	-0	-0	6.29	1.13	-4.4	-0	0.22	0.78	0.92	1	0.77	-0	0	-0

Figure 8-Load demand, total power generated and grid over 24-hour for Case 3.

Table 5-Operation costs obtained by SNS and PSO algorithms for Case 3

Time (h)	Proposed SNS	PSO	Time (h)	Proposed SNS	PSO
1	40.23648	45.92973	13	39.88811	45.72735
2	40.93751	45.93219	14	39.88979	45.75586
3	40.33316	45.88966	15	39.99969	45.86804
4	40.04694	45.87941	16	40.82392	45.94546
5	62.10663	61.42909	17	68.88324	76.82386
6	134.9584	171.9446	18	179.7997	193.4445
7	155.9609	194.7891	19	206.2949	217.0469
8	174.4917	178.8926	20	127.0562	196.4234
9	112.4657	121.5802	21	107.3686	168.7585
10	40.14287	45.99753	22	39.80339	45.67811
11	40.0799	45.87327	23	40.35137	45.93032
12	39.87733	45.7191	24	39.95582	45.81457
Total cost ($)				1891.75225	2223.07335

4. Case 4: All sources are considered in grid-connected mode

In this case, the proposed SNS algorithm is employed to address the ELD problem within the context of a grid-connected microgrid, considering the operational costs associated with conventional, solar, and wind power units. The dispatch outcomes derived through the proposed SNS algorithm are represented in Figure (9). Additionally, Figure (10) displays the total power generation from conventional and RES units, as well as the load demand and power exchange with the grid at each time interval. These figures showcase the proficiency of the SNS algorithm in effectively dispatching diverse generation units to meet load demands throughout 24 hours, affirming its capability for grid power transactions. Table (6) lists the hourly and total operating costs determined by the SNS and PSO algorithms. Additionally, the results achieved by the proposed SNS algorithm are compared with those of the differential evolution (DE) [4] and PSO [4] algorithms in Table (7). The findings indicate the superior performance of the proposed SNS algorithm, as evidenced by its ability to achieve the most cost-efficient solutions in this case. Notable cost savings are observed with the integration of both wind and solar energy, resulting in cost reductions of 9.24%, 7.53%, and 3.25% compared to Cases 1, 2, and 3, respectively.

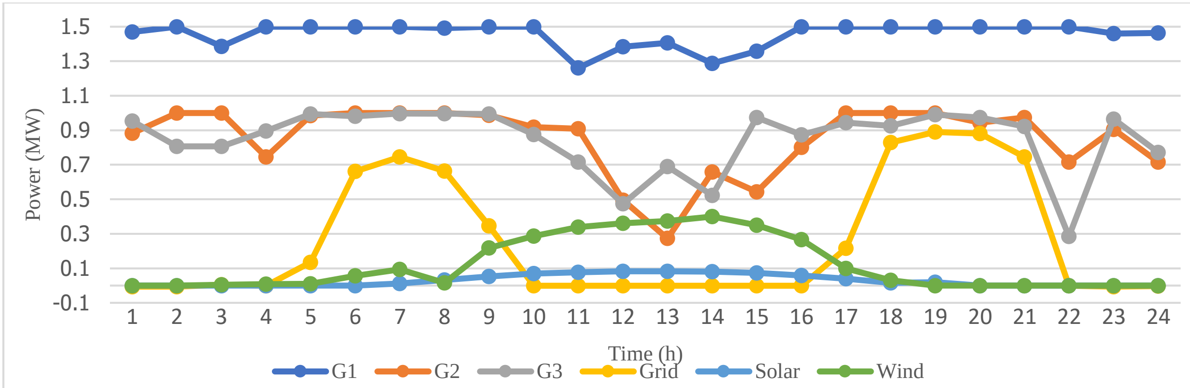


Figure 9- Dispatch results obtained by proposed SNS algorithm for grid-connected mode for Case 4.

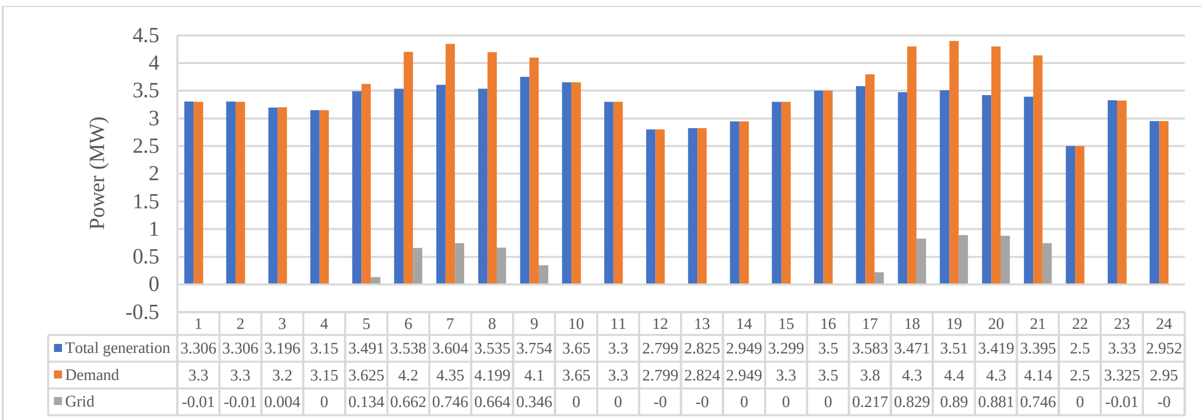


Figure 10- Load demand, total power generated and grid over 24-hour for Case 4.

Table 6-Operation costs obtained by SNS and PSO algorithms for Case 4

Time (h)	Proposed SNS	PSO	Time (h)	Proposed SNS	PSO
1	40.472	46.002	13	39.921	45.747
2	40.414	45.921	14	39.934	45.773
3	40.610	45.897	15	40.045	45.890
4	39.995	45.909	16	40.118	45.966
5	57.935	58.560	17	68.831	75.231
6	128.481	172.292	18	189.351	193.743
7	139.715	193.098	19	200.357	220.294
8	159.681	171.480	20	116.718	194.420
9	102.440	122.517	21	104.932	170.538
10	40.157	46.155	22	39.810	45.683
11	40.077	45.896	23	40.320	45.951
12	39.900	45.737	24	40.007	45.824
Total cost ($)				1830.221	2260.526

Table 7-Cost achieved by SNS algorithm compared to other algorithms for Case 4.

Algorithm	Cost ($)
Proposed SNS	1830.221
PSO	2260.526
DE [4]	2540.14
PSO [4]	2297.96

Figure (11) presents a comparison between total generation costs achieved utilizing proposed SNS algorithm for Cases 1-4 of grid-connected mode. It is evident that Case 1 exhibits the highest operational cost, whereas Case 4 demonstrates the lowest operational cost. This disparity can be attributed to the integration of RES in Case 4, which serves as a negative load, thereby reducing the reliance on conventional generation units and the main grid to meet energy demands. Additionally, Case 3 incurs lower costs compared to Case 2, primarily due to the higher expenses associated with solar energy as opposed to wind energy.

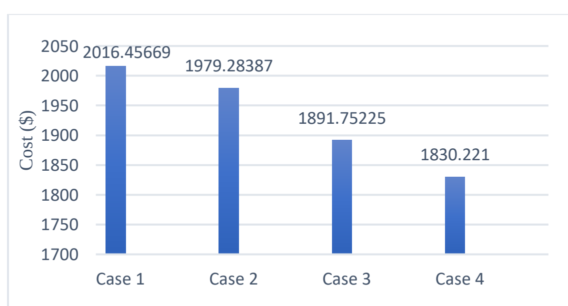


Figure 11-A comparative analysis of total generation costs in grid-connected mode

Figure (12) illustrates the comparative analysis of grid utilization across the four examined cases of grid-connected mode. As expected, the integration of RES results in a noticeable reduction in grid power procurement. Consequently, Case 1, devoid of RES utilization, exhibits the highest grid power purchases, while Case 4, benefiting from both solar and wind units, demonstrates the lowest grid power purchase levels.

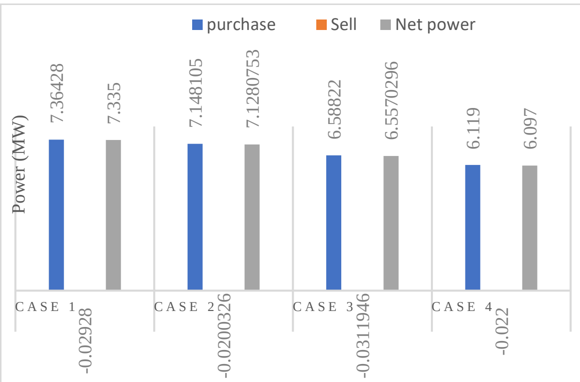


Figure 12-Utilization of the grid in the four cases of grid-connected mode

5. Case 5: All sources are considered in isolated mode

In this case, the proposed SNS algorithm is employed to address the ELD problem within the operational framework of an isolated-mode microgrid, considering the operational costs associated with conventional, solar, and wind power units. The microgrid is disconnected from the main grid and has to meet critical loads depending on its internal resources. The dispatch results derived through the proposed SNS algorithm are represented in Figure (13). Notably, Generator 1 is consistently operating at maximum capacity due to its lower fuel cost compared to the other generators, resulting in an overall system cost reduction. Furthermore, Figure (14) illustrates the total power generation from conventional and RES units, as well as the load demand at each time interval. As observed, the SNS algorithm demonstrates its efficiency in achieving the optimal solution by dispatching generation units so that the load demand is satisfied at each period. Table (8) lists the hourly and total operating costs determined by the SNS and PSO algorithms. The total cost achieved by SNS is 952.899 $/h, while that of PSO is 952.903 $/h. The cost difference between SNS and PSO is negligible, owing to the low load values. The results also show that the hourly operational costs are almost consistent throughout, as the system only supplies power to critical loads, and there are no load peak/off-peak demand changes.

Table 8-Operation costs obtained by SNS and PSO algorithms for Case 5

Time (h)	Proposed SNS	PSO	Time (h)	Proposed SNS	PSO
1	39.736	39.736	13	39.679	39.679
2	39.736	39.737	14	39.682	39.682
3	39.706	39.706	15	39.733	39.733
4	39.600	39.600	16	39.712	39.712
5	39.652	39.652	17	39.732	39.732
6	39.698	39.698	18	39.781	39.781
7	39.741	39.741	19	39.771	39.772
8	39.772	39.773	20	39.691	39.691
9	39.807	39.807	21	39.688	39.688
10	39.817	39.817	22	39.556	39.556
11	39.766	39.766	23	39.594	39.594
12	39.648	39.649	24	39.601	39.601
Total cost ($)				952.899	952.903

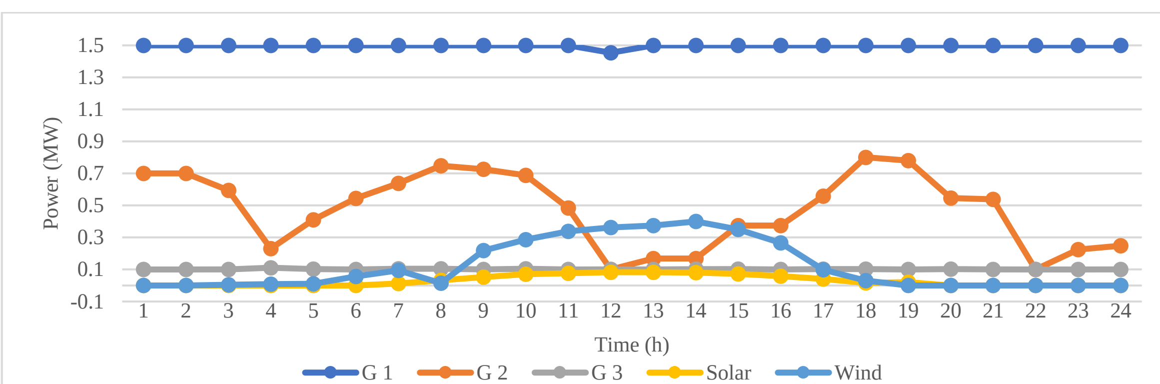
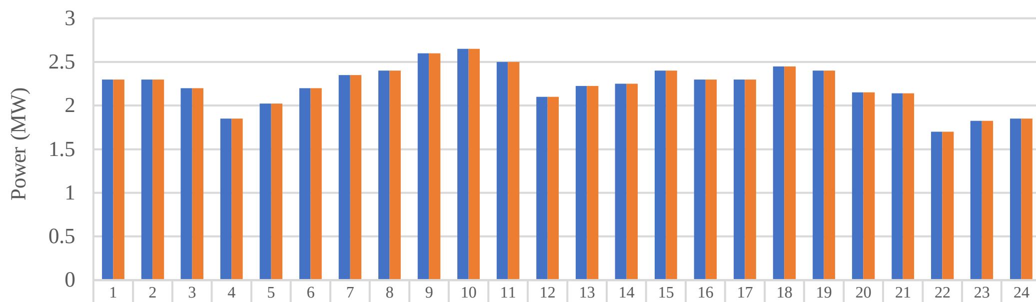


Figure 13- Dispatch results obtained by proposed SNS algorithm for isolated mode for Case 5.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Demand	2.3	2.3	2.2	1.85	2.025	2.2	2.35	2.4	2.6	2.65	2.5	2.1	2.225	2.25	2.4	2.3	2.3	2.45	2.4	2.15	2.14	1.7	1.825	1.85
Total generation	2.3	2.3	2.2	1.85	2.025	2.2	2.35	2.4	2.6	2.65	2.5	2.1	2.225	2.25	2.4	2.3	2.3	2.45	2.4	2.15	2.14	1.7	1.825	1.85

Figure 14-Load demand and total power generated over 24-hour for Case 5.

6. Conclusions

This paper proposes a social network search (SNS) algorithm implemented for optimizing the energy management system (EMS) of microgrids. The algorithm focuses on economic consideration, particularly addressing economic load dispatch (ELD) in grid-connected and isolated modes of operation while considering the presence of renewable energy resources (RES). The effectiveness of the proposed SNS algorithm has been demonstrated using a microgrid model with five test cases involving different combinations of distributed energy resources (DERs). To ensure a fair comparison, the particle swarm algorithm (PSO) has also been implemented. The results indicate that the proposed SNS algorithm successfully determines the optimal dispatching of DERs in both operational modes as well as for power trading with the main grid to minimize operational costs in grid-connected mode. Moreover, the proposed SNS algorithm outperforms PSO across all tested cases. Additionally, the results highlight the positive impact of RES integration on reducing total generation costs. Greater incorporation of RES, such as solar and wind power, leads to decreased generation costs for microgrids and reduced dependence on purchased power from the main grid, thereby enhancing overall microgrid efficiency. Future research could explore applying the proposed SNS algorithm to address combined economic and environmental dispatch challenges in grid-connected microgrids with energy storage systems.

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