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An Improved Transient Search Optimizer for Microgrid Energy Management and Optimization Incorporating Multi-energy and Storage System and Demand Response

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ABSTRACT
In this paper, the energy management (EM), and optimization of a microgrid including photovoltaic, wind turbine, micro-turbine, fuel cell, and battery energy storage is implemented considering demand response (DR). The optimization of the microgrid is performed with the presentation of a three-dimensional objective function including minimizing the costs of energy loss (ELC), operation (OC), and emission (EC) satisfying the operational and components constraints. In this research, an improved transient search optimizer based on golden sine strategy (MOTSOGS) via fuzzy decision-making is used to optimize the position and size of the microgrid components. The outcomes cleared that the energy resources integrated with the energy storage using the proposed optimizer are capable of supplying the microgrid load in conditions without and with DR. Also, the obtained results demonstrated that considering DR, reduced ELC, OM, and EC by 10.80%, 9.68%, and 8.01%, respectively compared to the case without DR. Moreover, the superiority of the MOTSOGS is confirmed to solve the problem compared with MOPSO.

Keywords: Microgrid, Energy Management, Operation and Emission Cost, Golden Sine Strategy, Multi-objective Improved Transient Search Optimizer, Fuzzy Decision-making

1. INTRODUCTION

Microgrids are small-scale energy systems that can operate in two modes: on-grid or off-grid [1].These systems often combine a number of energy sources, such as solar photovoltaics (PV), wind turbines, and biomass, with modern technology including energy storages and demand response mechanisms [2].

The use of renewable energy in microgrids provides various benefits while also posing multiple issues. The production of renewable energy is frequently characterized by intermittency and variability due to weather conditions and daily cycles [3]. Furthermore, the variable nature of electrical demand makes the supply-demand balance difficult to maintain. To address these difficulties, complex energy management (EM) strategies must be developed and implemented to improve the functioning and optimization of the microgrid [4]. Numerous research have investigated microgrid energy management, with an emphasis on different factors of microgrid management and optimization. Researchers have suggested a variety of tactics and methodologies for managing energy flow, balancing supply and load, and increasing the use of energy sources inside microgrids. In [5], a grasshopper optimization algorithm (GOA) is integrated with an EM strategy to reduce operational costs. In [6,] a fuzzy grey wolf optimizer (FGWO) is used for both EM and storage sizing in a microgrid with the goal of minimizing production costs. The boosted beluga whale optimizer (BBWO) is suggested for EM in order to optimize battery energy in a microgrid and reduce operating expenses [7]. In [8], a method of management aiming at determining the most effective operation of a microgrid is described as an optimization approach to reduce operating expenses based on a distribution system management method. The barnacles mating optimizer (BMO) is used in [10] for optimization of a microgrid employing energy sources and battery energy storage.

The contributions to this publication are presented as follows:

-Optimizing a microgrid to reduce energy loss, operational costs, and emissions while considering demand responsiveness.

-Developing a three-dimensional objective function to optimize the microgrid.

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-Using of a multi-objective transient search optimization method based on Golden sine strategy (MOTSOGS), to optimize energy management in microgrids with fuzzy decision-making.

2. METHODOLOGY

In this paper, a multi-objective optimization model for microgrid EM and optimization is proposed, taking into account the DR and MOTSOGS, with the goal of minimizing energy loss, operational costs, and emission costs. The microgrid is made up of photovoltaic (PV), wind turbine (WT), microturbine (MT), fuel cell (FC), and battery energy storage.

2.1 Modeling of the DR

The DR is considered an incentive-based scheme. The formulas listed below show that their behaviors can be represented. This study categorizes consumers of electricity under three groups: residential, commercial, and industrial. Limitations necessitate that each user's overall amount of energy saved per hour be below or equal to the maximum quantity of its offerings [3].

$$RP(r,t) = RC(r,t).\xi_{r,t} \qquad ,RC(r,t) \le RC_t^{max} \tag{1}$$

$$CP(c,t) = CC(c,t).\xi_{c,t} \qquad ,CC(c,t) \le CC_t^{max} \tag{2}$$

$$IP(i,t) = IC(i,t).\xi_{i,t} \qquad ,IC(i,t) \le IC_t^{max} \tag{3}$$

Where, r, c, and i refer to the residential (RC), commercial (CC), and industrial (IC) customers number; $RC(r,t)$, $CC(c,t)$, and $IC(i,t)$ are demand reduction value by each RC, CC, and IC customer at time t; RC_t^{max}, CC_t^{max}, and IC_t^{max} denote the maximum suggested demand reduction via each customer at time t; $\xi_{r,t}$,, $\xi_{c,t}$, and $\xi_{i,t}$ are payment value of incentive to each customer at time t; and $RP(r,t)$, $CP(c,t)$, and $IP(i,t)$ refer to the cost of demand decreasing by RC, CC, and IC consumers at time t for the suggested demand decreasing, respectively.

2.2 Modeling of the OF

The microgrid [3] is optimized using a three-dimensional objective function that includes lowering the costs of energy loss (ELC), operation (OC), and emissions (EC) while meeting operational and component restrictions.

Energy loss cost (ELC): The power loss of the microgrid is calculated by

$$ELC = \sum_{t=1}^{T} P_{Loss}(t) \times C_{Loss} \tag{4}$$

Where, P_{Loss} is power loss, C_{Loss} ($0.06) denotes cost of per kW of power loss, and T is simulation period (24 hours).

Operating cost (OC): The OC includes the cost of grid-purchased power, the cost of microgrid components for energy generation and storage, as well as the cost of demand response, as follows [3, 12]:

$$OC = \sum_{t=1}^{T} P_{Grid}(t) \,.\, C_{Grid} + \sum_{i=1}^{N_{Com}} \sum_{t=1}^{T} P_{Com}(t) \,.\, C_{com} \tag{5}$$

Where, P_{Grid} is purchased power from the main grid, C_{Grid} is grid price for per Kw, N_{Com} is the OC of the components for energy production (PV, WT, MT, and FC) , storage (Battery) and also DR. C_{com} is price of per unit capacity of per components.

Emission cost (EC): The emission cost determines the pollution created by DG devices and the main grid at the time of purchase. Pollutants include CO_2, SO_2, and NO_x, and the outcome of the emission cost can be calculated as follow.

$$EC = \sum_{t=1}^{T} C_{Emiss-DG}(t) + \sum_{t=1}^{T} C_{Emiss-Grid}(t) \tag{6}$$

Where, $C_{Emiss-DG}(t)$ and $C_{Emiss-Grid}(t)$ are the pollution cost of energy units and the pollution cost of grid-purchased power, respectively.

2.4 Modeling of the CNSs

- *Power balance*

$$\sum_{i=1}^{N_{DG}} P_{DG,i} + P_{Grid} = P_d - P_{DR} \tag{7}$$

Where, P_{Demand} and P_{DR} represent the power required through the load and the not-met power according to the DR at time t, respectively.

- *DR*

P_{DR} is the amount of interested involvement in DR taking into account residential demand cost (RC), commercial demand cost (CC), and industrial demand cost (IC) and defined by

$$P_{DR} = \sum_{r} RC(r,t) + \sum_{c} CC(c,t) + \sum_{i} IC(i,t) \tag{8}$$

- *DGs power*

$$P_{DGi-min}(t) \le P_{DGi} \le P_{DGi-max} \tag{9}$$

Where, $P_{DGi-min}$ and $P_{DGi-max}$ denote maximum and minimum size of DG.

- *Battery size*

Because there are constraints to charging and discharging in storage throughout each time period, the stored energy value with the charge/discharge amount of the battery are restricted [3, 12] by

$$E(W_b(t)) = E(W_b(t-1)) + \eta_{ch} \times E(P_{ch}(t)) \times \Delta t - \frac{1}{\eta_{dch}} E(P_{dch}(t)) \times \Delta t \qquad (10)$$

$$\begin{cases} W_{bmin} \le E(W_b(t)) \le W_{bmax} \\ E(P_{ch}(t)) \le P_{chmax} \\ E(P_{dch}(t)) \le P_{dchmax} \end{cases}$$

Where, $W_b(t)$ and $W_b(t-1)$ represent the energy stored in the battery at time t and t-1, respectively. $P_{ch}(t)$ and $P_{dch}(t)$ represent the charge and discharge capacity of the battery bank at time t, while η_{ch} and η_{dch} represent the battery's charge and discharge efficiency, respectively. P_{chmax} and P_{dchmax} represent the battery's highest charge and discharge capacities, respectively.

2.3 Proposed optimizer and implementation

2.3.1 TSOGS

In this study, TSO [13] is employed to improve the EM and optimization of the microgrid under consideration. The concept is inspired by the transitory properties of electrical circuits that include energy storage components like capacitors and inductors [13]. Also, a golden sine technique [14] is used in TSO to aid Individuals enter the exploratory stage in changing their places, and the improved TSO is called (TSOGS). This technique uses the sine function and the golden average factor to enhance the search process's efficiency. In accordance with the findings in Ref. [14], the expansion steps associated with the golden mean factor are constant, needing Just a single iteration per step. Integrating the golden average with the sine function, optimal amounts can be determined more quickly while also reducing the chance of becoming caught in local optima.

2.3.2 Multi-objective TSOGS (MOTSOGS)

A multi-objective issue entails optimizing numerous contradicting objectives simultaneously while adhering to a number of constraints. As a result, the main objective of tackling the problem through optimization with various objectives is to determine the Pareto front [8] of the ideal solution so as to create a feasible compromise within each goal. The Pareto front contains numerous solutions. Planners utilize instinct as a primary tool to select the best answer from a set of Pareto options using fuzzy decision-making. The membership function of the zth function that links the kth optimal Pareto solution (μ_Z^k) is stated as follow.

$$\mu_z^k = \begin{cases} 1, & f_Z(X) \le f_Z^{\min} \\ \dfrac{f_Z^{\max} - f_Z}{f_Z^{\max} - f_Z^{\min}}, & f_Z^{\min} < f_Z(X) < f_Z^{\max} \\ 0, & f_Z(X) \ge f_Z^{\max} \end{cases} \qquad (11)$$

Consequently, the compromised answer is computed as

$$max\{\mu^k(X)\} \qquad (12)$$

The greatest value represents the finest compromise answer.

2.3.3 Implementation

This section describes the MOTSOGS implementation process for optimizing the microgrid EM.

Step 1: Establish technical and economic components for microgrid data and main grid.

Step 2: Determine the optimization variables.

Step 3: Determine the target function amount (Eq. (12)) for every set of random variables that meets the restrictions.

Step 4: Identify the non-dominant answers.

Step 5: Archive the non-dominated solutions.

Step 6: Identify the most desirable non-dominant options.

Step 7: Update the algorithm population.

Step 8: Archive the new dominated answers.

Step 9: Eliminate the dominating answers from the archive.

Step 10: Update the optimizer population using the golden sine strategy.

Step 11: Archive the new dominated answers and eliminate the dominated answers into the archive.

Step 12: Are the convergence requirements fulfilled? If the answer is yes, proceed to Step 13, otherwise to Step 2.

Step 13: Stop the optimizer and save the final answer.

3. SIMULATION RESULTS AND DISCUSSION

3.1 Data

Fig. 1 depicts a 33-bus distribution microgrid consisting of MT, WT, PV, FC, and battery without and with DR. The microgrid line data is obtained via Ref. [3, 16].

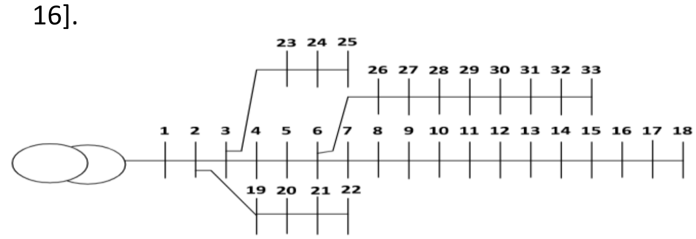


Fig. 1. The studied 33-bus distribution microgrid

Figures 2-5 [3] show the predicted hourly power of the PV and WT units, the network's peak load % over 24 hours, and the grid pricing. Tables 1 and 2 show the grid pricing and emission coefficients for various ERs, as well as the recommended DR program.

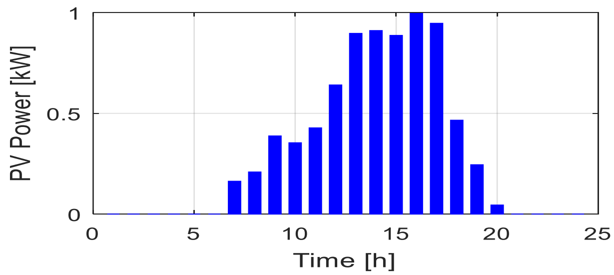


Fig. 2. Predicted PV power for 24 hours [3]

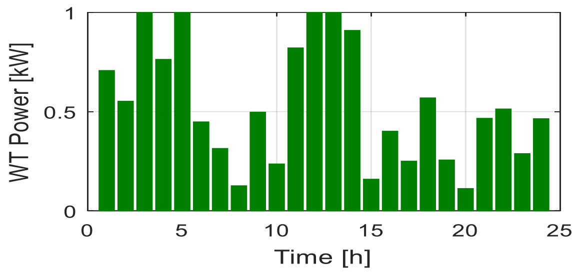


Fig. 3. Predicted WT power for 24 hours [3]

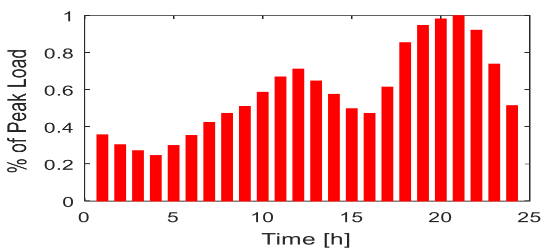


Fig. 4. % of network peak load for 24 hours [3]

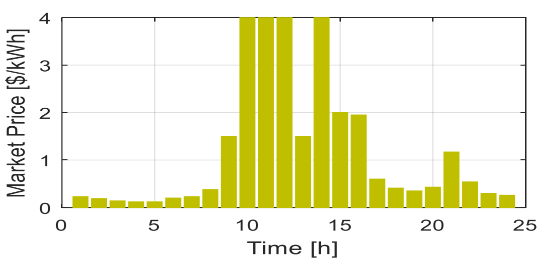


Fig. 5. The market price of the grid power [3]

Table 1. Power cost and emission coefficients of DGs [3, 16]

Unit	Type	Bid ($/kWh)	CO_2 (kg/MWh)	SO_2 (kg/MWh)	NO_2 (kg/MWh)	P_{min} (kW)	P_{max} (kW)
1	MT	0.457	720	0.0036	0.1	0	300
2	PAFC	0.294	460	0.003	0.0075	0	300
3	PV	2.584	0	0	0	0	300
4	WT	1.073	0	0	0	0	300
5	BA	0.38	10	0.0002	0.001	-300	300
6	Grid	-	950	0.5	2.1	-300	300

Table 2. The details of DR package [12]

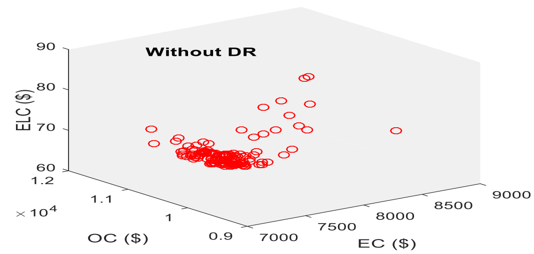
Quantity (kW)	0-5	5-20	20-30	30-60
Price ($/kWh)	0.04	0.07	0.28	0.43

The efficiency of the recommended framework is simulated and tested in the following cases:

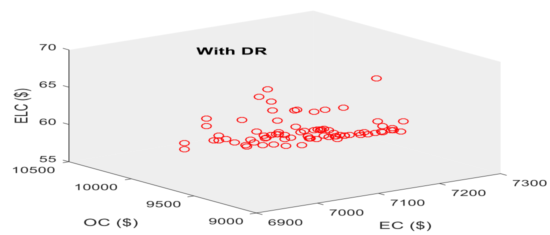
- Case I) EM and optimization of microgrid with MOGSTSO without DR using MOTSOGS
- Case II) EM and optimization of microgrid with MOGSTSO with DR using MOTSOGS

3.2 Results without and with DR

Case I presents the results of EM and optimization of a microgrid using MOGSTSO without DR to minimize the ELC, OC, and EC costs. In these scenarios, the effect of including DR is compared to EM and microgrid optimization without DR. Figures 6 (a) and 6 (b) demonstrate the Pareto optimal solution sets achieved for examples 1 and 2 via the MOGSTSO. According to the Pareto solution set, case 2 has higher dispersion than case I, as shown in Figs. 6 (a) and (b), respectively.



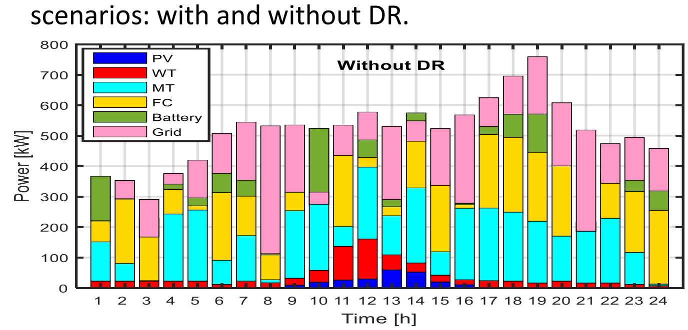
(a)



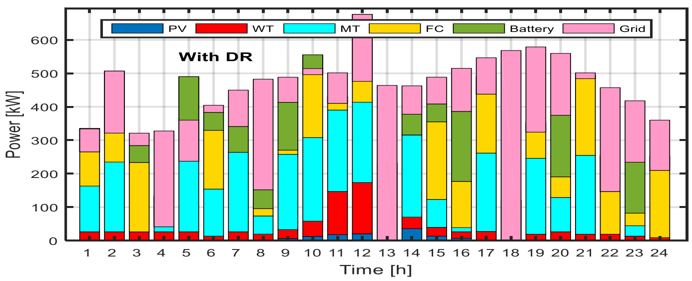
(b)

Fig. 6. Pareto solution set for a) without DR and b) with DR

Figure 7 displays the final answer, incorporating the optimal capacity of microgrid equipment among the non-dominated possibilities, as determined according to the decision-making approach in examples I and II. Furthermore, Figure 8 depicts battery power in two scenarios: with and without DR.

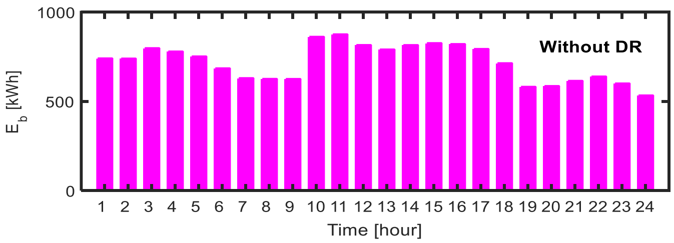


(a)

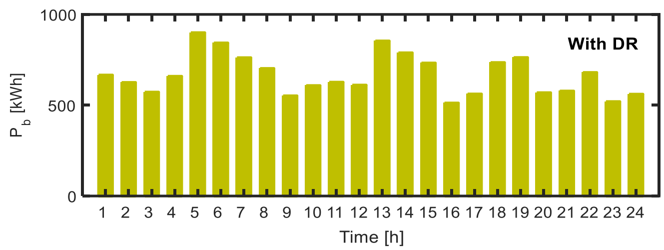


(b)

Fig. 7. The best solution obtained for optimization a) without DR and b) with DR



(a)



(b)

Fig. 8. a) Battery power for optimization a) without DR and b) with DR

According to Tables 3-4, the results show that 62 kW PV power, 189 kW wind power, 874 kW battery power, 246 kW MT power, and 248 kW FC power in scenario I, and 42 kW PV power, 221 kW wind power, 900 kW battery power, 250 kW MT power, and 247 kW FC power in case I. In case I, the ELC, OC, and EC are calculated at 67.96, 10400.30, and 7754.51, respectively, and these values are obtained at 60.62, 9392.53, and 7132.62, respectively for case II. Therefore, the utilization of DR results in more reduction of ELC, OC, and EC compared to the case without considering the DR (Case I). The obtained results of the different cases demonstrated that considering DR, reduced ELC, OM, and EC by 10.80%, 9.68%, and 8.01% compared to the case without DR (Case I).

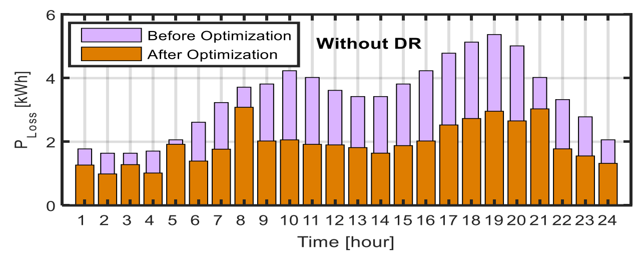
Table 3. The best solution for a) without DR and b) with DR

Device	PV	WT	Battery	MT	FC
Case I					
Size (kW)	62	189	874	246	248
Location (Bus)	28	32	33	6	12
Cost ($)	1216	2605	435	1667	1115
Case II					
Size (kW)	42	218	900	244	247
Location (Bus)	21	32	23	8	3
Cost ($)	826	3042	482	1436	980

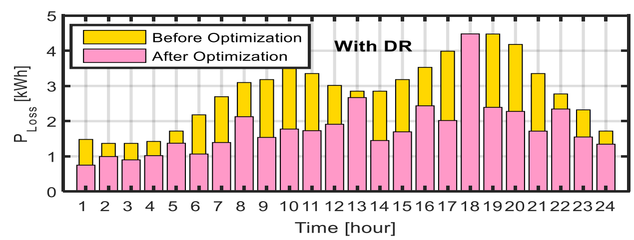
Table 4. Value of cost functions a) without DR and b) with DR

Item/Scenario	Case I	Case II
Cost of Energy Loss, CEL ($)	67.96	60.62
Cost of Operation, CO ($)	10400.30	9392.53
Cost of Emission, CE ($)	7754.51	7132.62

The changes of microgrid active power loss before and after optimization are shown in Fig. 9, for two cases without and with DR. As can be seen, by optimizing the microgrid, its losses have been reduced significantly in all hours of the study. Also, considering the DR will reduce the cost of energy losses more compared to not considering it.



(a)



(b)

Fig. 9. Power loss of microgrid for a) without DR and b) with DR

3.3 Evaluation of the MOTSOGS superiority

Using 20 different runs of Case II, the numerical results from the MOTSOGS, MOTSO, and MOPSO algorithms are compared. The results of the previously stated optimizers were compared using the C index (CI). The CI clears the percentage of dominant solutions of a multi-objective optimizer compared with another one. In Table 5, the results of ELC, OC, and EC for each algorithm are presented. As given in Table 5, the MOTSOGS has obtained the lowest ELC, OC, and EC compared to the MOTSO, and MOPSO. Also, in Table 6, C index analysis is presented for different multi-objective optimizers. The results demonstrated that the MOTSOGS has higher dominant solutions by 74.28 %, and 68.28 % compared with the MOTSO, and MOPSO. These findings confirmed the superiority of the MOTSOGS integrated with gold sine strategy in comparison with the MOTSO, and MOPSO optimizers.

Table 5. Value of cost functions for MOTSOGS, MOTSO, and MOPSO

Item/Scenario	MOTSOGS	MOTSO	MOPSO
Cost of Energy Loss, CEL ($)	60.62	65.04	62.14
Cost of Operation, CO ($)	9392.53	9638.26	9424.18
Cost of Emission, CE ($)	7132.62	7250.33	7185.02

Table 6. CI analysis for MOTSOGS, MOTSO, and MOPSO

C Index	Mean	Std	Maximum	Minimum
C(MOTSO, MOTSOGS)	74.28	28.63	100.00	0
C(MOTSOGS, MOTSO)	24.05	18.56	36.27	11.74
C(MOPSO, MOTSOGS)	68.28	24.66	87.30	8.21
C(MOTSOGS, MOPSO)	23.54	29.02	46.91	19.45

4. CONCLUSION

This study presents optimization of a microgrid with different energy resources and storage system incorporating DR. The findings in two cases without and with considering the DR, respectively cases I, and II under a three-dimensional optimization framework based on fuzzy decision-making are presented as follows:

-In case I, the ELC, OC, and EC are calculated at 67.96, 10400.30, and 7754.51, respectively and these values are obtained at 60.62, 9392.53, and 7132.62, respectively for case II.

-The utilization of DR in EM and optimization of microgrid has resulted in decreasing the capacity of power production in the microgrid and increasing the storage level compared to the optimization without DR.

-The results demonstrated that the MOTSOGS has higher dominant solutions by 74.28 %, and 68.28 % (Mean value) compared with the MOTSO, and MOPSO. These findings confirmed the superiority of the MOTSOGS integrated with gold sine strategy in comparison with the MOTSO, and MOPSO optimizers.

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