



# Demand-Side-Management-Based Bi-level Intelligent Optimal Approach for Cost-Centric Energy Management of a Microgrid System

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## Abstract

Demand side management (DSM) separates elastic and inelastic loads and reorganizes a distribution system's load demand model while reducing the overall cost of the operation. This is accomplished by shifting flexible loads to hours with lower utility costs per unit. In this study, a bi-level optimization technique is used to reduce the operating costs of a low voltage microgrid system that uses battery energy storage, renewable energy sources, and fossil fuel generators while running in grid-connected mode. The load model is reorganized at the first level of optimization according to the DSM involvement level. Thereafter, the restructured load demand models are taken into account, and distributed generator scheduling ideas are percolated for reducing the microgrid system's generating costs in the second level. The optimization tool for the study was a newly established hybrid swarm intelligence algorithm that has previously been utilized to solve a variety of power system optimization challenges. For various grid participation models and grid pricing schemes, both with and without taking into account DSM, the generating cost was reduced. When 10%, 20%, and 30% DSM involvement was taken into consideration, the numerical findings reveal 25%, 50%, and 70% reduction, respectively, in costs.

**Keywords** Grid-connected microgrid · Dynamic economic dispatch · Demand side management · Distributed energy resources, optimization · CSAJAYA

## 1 Introduction

### 1.1 Brief Overview

When all equality and inequality requirements are met, the economic load dispatch (ELD) approach distributes generation among the assessed generating units in order to reduce overall generation costs. Therefore, properly distributing a portion of the power demand might potentially result in lower fuel costs. The distribution of the power demand across several producing units has an influence on various processes, including estimating, invoicing, unit commitment, and others. The whole amount of electricity generated must equal the total amount of power demanded. Economic Dispatch may be separated into two categories depending on the type of load

demand. Static Economic Load Dispatch (SELD) is the first, while Dynamic Economic Load Dispatch (DELD) is the second one. Static Economic Load Dispatch is used when there is a single constant load demand, but dynamic Economic Load Dispatch requires a dynamic load demand. In order to provide large outputs, DELD predicts the power demand for the upcoming hours and distributes the electricity across numerous producing units. It appears that research is being done to incorporate renewable energy in ELD to address the problem of the depletion of fossil fuel reservoirs. Since traditional techniques like the Lagrange multiplier are unable to handle the practical limits involved, which cause the fitness function to be nonlinear and non-convex, the artificial intelligence and Metaheuristic swarm are essential for overcoming this difficulty. DSM, on the other hand, refers to the deliberate creation and implementation of plans to alter customers' dispatchable energy utilization.

### 1.2 Literature Review

The Enhanced exploratory whale optimization algorithm was developed in article [1], where the authors solved dynamic

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economic dispatch considering various effects and constraints. The authors of article [2] and [3] introduced Alternating biogeography-based optimization with brain storm optimization and a memory-based global differential evolution algorithm to address non-convex dynamic economic dispatch, respectively. Dey Bhattacharyya [4] considers a variety of costs, including installation, operation, maintenance, and depreciation, all of which has to dependent upon the lifespan of the resources of the distributed energy used, as well as fuel and emission costs, and the operating expenses is minimized using a neighbourhood-based differential algorithm. Ma et al. [5] proposed an ELD model for charging plug-in electric vehicles in order to reduce the cost of production and environmental pollutants. Authors of article [6], dealt with DELD in an islanded microgrid considering ramp rate constraints by novel alternating direction method of multipliers. A Modified self-organizing hierarchical particle swarm optimization with jumping time-varying acceleration coefficients algorithm was proposed in article [7] to deal with non-smooth DELD problem. Similarly, in article [8], Improved slap–swarm optimizer was introduced with accurate forecasting model for the DELD problem. Authors in article [9] introduced grasshopper optimization algorithm (GOA) for explaining dynamic economic load dispatch (DELD) problem with hybrid wind-based power system. In article [10], MABC-ANN (Hybrid Artificial Bees Colony (ABC) with Bat Search Algorithm (BAT) and Artificial Neural Network (ANN)) technique was proposed for the optimal scheduling of a microgrid system. Li [11] employed Multi-objective Pareto optimal solution to solve the optimization problem of space adaptive division for environmental economic dispatch. Demand side management with dynamic economic and emission dispatch was merged by Lokeshgupta and Sivasubramani [12]. One of the important parts of power system [13, 14] is cost-effective load dispatch or Economic Load Dispatch. The authors in article [15] created a DEED system that included high wind penetration, uncertainty, and intermittency, along with the energy storage system by utilizing the direct search method (DSM) using weighted sum methodology. Authors in article [16], proved the usefulness of the Interior search algorithm to cope with the CEED and ELD in an isolated microgrid scenario. ELD aids in finding the best and cost-effective schedule by balancing the electrical output in terms of power for multiple generators delivering the power demand [17, 18]. For four distinct load sharing situations, the authors [19] employed a neighbourhood-based differential algorithm to manage a sustainable integrated microgrid's economic dispatch. In the article [20], authors performed both static economic load dispatch and dynamic economic dispatch problems using Cuckoo Search Algorithm (CSA) and results compared to particle swarm optimization (PSO) and differential evolution (DE). In article [21], genetic algorithm (GA), whale

optimization-differential evolution (WODEGA) algorithm were used to solve optimal scheduling problem considering unit commitment. The authors in [22] employed the lambda iteration strategy to find the optimal scheduling for a 6-unit system considering transmission losses. For tackling the dynamic economic dispatch problem, authors [23] suggested an improvised genetic algorithm approach. The ELD were examined on 10 and 24 units considering valve point effects to establish the method's effectiveness. Linear, quadratic and cubic wind profiles were modelled to estimate wind power contribution from the dynamic wind velocity in the article [24], and thereafter, utilizing CSAJAYA, five different test systems were tested to perform dynamic economic dispatch. The authors of [25] used a demand side management with the novel CSAJAYA to lower the total generating expenses of a grid-connected microgrid system. Kumar and Dhillon [26] proposed a dynamically adjusted amalgamation of the simplex Search method (SSM) and artificial algae algorithm (AAA), AAA acting as a global optimizer and SSM providing local search. The created approach was tested on VPE on 13, 40, and 80 units including VPE effect, POZs and VPE on 140generators, and VPE including transmission losses on 40 generating units. The major objective in article [27] was to reduce total power generating costs while taking into consideration various constraints. Authors of [28], dealt with the power dispatch problem with demand side management using load profile management tool by a Newton-like particle swarm optimization. In reference [29], ISA not only outperformed the cuckoo search algorithm (CSA), but also outperformed the reduced gradient technique (RGM) and ant colony optimization while dealing the problem of the identical objective function. To handle out the uncertainty and system variability due to wind, the authors [30] employed a two-stage stochastic DELD model with a stochastic decomposition approach, which was performed and tested on PJM-5 and RTS-24 systems. To deal the ELD problem on a microgrid, the authors [31] employed lambda iteration, lambda logic, PSO, and DSM-optimization techniques. The reliable functioning of microgrids was also specified after the move from islanded mode to grid-connected mode and vice versa. An improved technique for Optimal Power Generation under the Energy Deficient Scenarios using Bagging Ensembles Algorithm was presented by the authors in article [32]. They also evaluated an IEEE 30-bus test system Bagging Ensembles Algorithm and artificial neural network (ANN) with feed-forward back-propagation model. The neural network-based ensemble classifier was utilized on the IEEE 30-bus test system to deal with the Short Term power dispatch model in article [33]. Authors in [34] did Combined Economic Emission Dispatch cost by Fully Informed Particle Swarm Optimization (FIPSO). By comparing the result with the PSO on IEEE 30 bus benchmark system it was shown that the FIPSO was superior. To deal with the Short Term

Load Forecasting for economic scheduling the authors of article [35] presented Bootstrap Aggregating Algorithm which is Based on Ensemble Artificial Neural Network. In article [36], authors optimized short term optimal scheduling problem like article [35] for a hydro-thermal unit by the Artificial Bee Colony Algorithm.

Demand side management (DSM) is an economic strategy which aims to restructure the load model by optimally shifting the elastic or dispatchable loads to hours when electricity market price is less. Apart from peak reduction, DSM also plays a crucial role in improving the load factor of the system. Numerous articles are published for minimizing the generation cost of a distributed system like microgrid but only a few of them incorporate an economic strategy like DSM. Authors in [37] implemented DSM to perform dynamic economic emission dispatch whereas the dispatchable residential loads were optimally scheduled using DSM by authors in [37] to minimize the generation cost of the system. Likewise DSM was implemented for solving dynamic optimal power flow algorithm by authors in [38] using a multi-objective harmony search algorithm. The primary factor for implementation of DSM is a dynamic time-of-usage-based electricity market pricing, which means DSM won't be economical if the electricity market price is fixed throughout the scheduling horizon. DSM is explained in much detail in Sect. 3.

### 1.3 Research Gap and Novel Contribution

Every day numerous new articles are being published in reputed journals which reports diverse range of fitness function evaluating economic energy management of microgrid systems. The complexity in these publications remain confined to the constraints of various DERs used including electric vehicles and combined heat and power systems but in some way or other ignore the most easy yet standard economization strategy such as demand side management. In this paper, different electricity market prices have been contrasted and examined to deal with optimal scheduling on low voltage microgrid system. Furthermore, the impact of the demand side management (DSM) has been thoroughly investigated while carrying out the bi-level optimal scheduling process. The novel contribution of this article is:

- i. Optimal restructuring of load demand model for various levels of DSM participation and thereafter analysing the peak reductions and load factor improvement.
- ii. Detailed technoeconomic analysis of the MG system for different cases.
- iii. Comparative analysis of the proposed algorithm with similar other algorithms.

### 1.4 Paper Orientation

The remaining sections of the paper are as follows: In Sect. 2, the problem formulation is structured. DSM scheme is described in Sect. 3; the case studies, results and the discussion have taken place in Sect. 4; and Sect. 5 concludes the entire work.

## 2 Problem Formulation

The prime objective of economic dispatch is to generate electrical energy at minimum cost while considering all equality and inequality constraints.

### 2.1 Cost-Based Fitness Function

The cost function viz. the objective function can be described as below.

$$C_T = \sum_{t=1}^{24} \sum_{i=1}^n (a_i P_{i,t}^2 + b_i P_{i,t} + c_i) + c_{grid}^t * P_{grid}^t \quad (1)$$

The entire expense for 24 h is  $C_T$  according to Eq. (1), where  $t$  is the hour indicator.  $a$ ,  $b$  and  $c$  are the cost coefficients of DG (Diesel Generator), MT (Micro-turbine) and FC (Fuel cell).  $c_{grid}^t$  is the electricity market price charged by the grid.

### 2.2 Inequality Constraint

The equation of the inequality constraint of the DERs can be written as below.

$$P_{i, \min} \leq P_i \leq P_{i, \max} \quad (2)$$

where  $P_{i, \min}$  and  $P_{i, \max}$  are the lower and upper limit of  $i$ th unit.

$$P_{Grid, \min} \leq P_{Grid} \leq P_{Grid, \max} \quad (3)$$

where  $P_{Grid, \min}$  and  $P_{Grid, \max}$  are the lower and upper limits of the associate grid.

### 2.3 Equality Constraint

The overall power generation should have to meet the demand as per Eq. (4) that do include RES and BES.

$$\sum_{i=1}^n P_{i,t} + P_{RES,t} + P_{Grid,t} + P_{BES,t} = P_{D,t} \quad (4)$$

The outputs of RES, grid, and battery energy storage in terms of power, at time interval  $t$ , can be denoted by,  $P_{RES,t}$ ,

$P_{Grid,t}$ , and  $P_{BES,t}$ , respectively.  $P_{D,t}$  is the power demand at hour  $t$ .

## 2.4 Energy Storage System Modelling

Let  $S_{i,t}^{st,ch}$  and  $S_{i,t}^{st,dch}$  be the charging and discharging powers, respectively, for the  $i$ th distributed storage at hour  $t$ . So the maximum charging rate and maximum discharging rate can be described by (5) and (6).

$$0 \leq S_{i,t}^{st,ch} \leq S_{i,max}^{st,ch} \quad (5)$$

$$0 \leq S_{i,t}^{st,dch} \leq S_{i,max}^{st,dch} \quad (6)$$

$$SoC_i^{\min} \leq SoC_{i,t} \leq SoC_i^{\max} \quad (7)$$

$$SoC_{i,t+1} \leq SoC_{i,t} + \eta_i S_{i,t}^{st,ch} \quad (8)$$

$$SoC_{i,t+1} \leq SoC_{i,t} - \eta_i S_{i,t}^{st,dch} \quad (9)$$

While charging, the distributed storage facility's state of charge (SoC) at hour  $t$  is given by (8), and when discharging, by (9). When analysing SoC, the charging and discharging efficiency are also taken into account. Each storage facility's upper and lower SoC values are limited by Eq. (7).

## 2.5 Uncertainty Modelling

Uncertainty modelling [24] is a probabilistic and futuristic predictive research that identifies the highest variation which can be obtained by expected data, while accounting for the unpredictable stochastic nature of renewable energy sources. The following diagram depicts the uncertainty modelling of solar and wind power in this article.

$$PV_{un}^t = dPV_{un} * n_1 + PV_{fc}^t \quad (10)$$

$$dPV_{un} = 0.7 * \sqrt{PV_{fc}^t} \quad (11)$$

where the deviation of PV output is denoted by  $PV_{un}^t$  and  $PV_{fc}^t$  is the day ahead forecasted PV output.

$$W_{un}^t = dP_W * n_2 + W_{fc}^t \quad (12)$$

$$dP_W = 0.8 * \sqrt{W_{fc}^t} \quad (13)$$

where  $W_{un}^t$  is uncertainty of wind,  $dP_W$  is the deviation of wind power and standard distribution function is denoted by  $n_2$ .

## 3 Demand Side Management

The management of microgrid energy with a focus on its economic operation has been and will continue to be a popular study area. However, if DSM strategy is not taken into account, the economic functioning of a microgrid system is essentially incomplete. If DSM had been taken into consideration, all the studies covered in the literature review section would become even more cost-effective. DSM specifically targets the subject network's elastic loads and optimally moves them to off-peak times. Even if the overall load demand at the end of the scheduling period (often a day) doesn't change, the peak demand is significantly decreased, which raises the load factor. Peak Clipping, Load shifting, Strategic growth, valley filling, strategic conversion, flexible load shape, etc. are some load shaping methods of DSM [25, 39–41].

The various load shaping methods are displayed in Fig. 1 for the DSM scheme. Authors in [25] employed the CSA-JAYA with DSM technique to reduce the overall cost of a grid-connected microgrid's generation. Following are the stages for implementing DSM:

*Step 1* Input the number of hours.

*Step 2* Input TOU grid price.

*Step 3* Input the DSM % according the elastic load share.

*Step 4* Calculate hourly elastic and inelastic load.

*Step 5* Calculate the minimum, maximum, and sum for the inelastic load. The control variables must be tuned for the elastic load requirement.

*Step 6* Using optimization technique,

$$\text{Minimize } [\cos t_{grid}^t * (\text{elastic\_load}^t + \text{inelastic\_load}^t)] \quad (14)$$

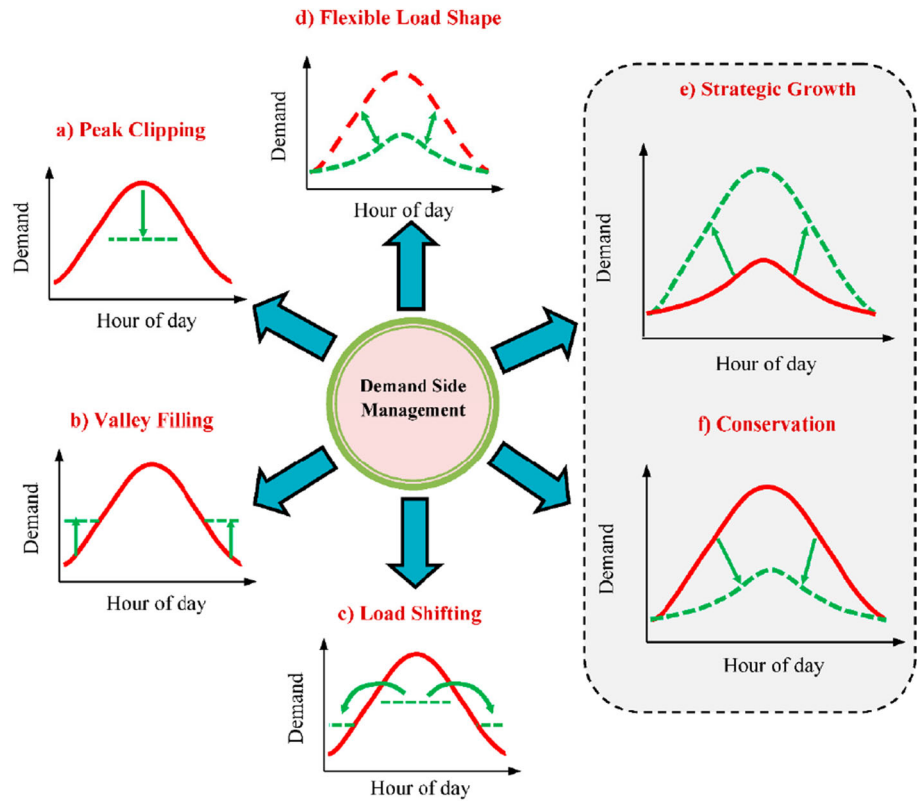
where

$$0 \leq \text{elastic\_load}^t \leq \text{elastic\_load}^{\max} \quad (15)$$

$$\text{Sum of load Demand} = \sum_{t=1}^T (\text{elastic\_load}^t + \text{inelastic\_load}^t) \quad (16)$$

*Step 7* The inelastic load demand for each hour is added to the newly restructured load demand model using the DSM approach, with the ideal elastic load values determined.

**Fig. 1** Various load shaping methods under DSM scheme [40]



**Table 1** Generator parameters [45]

Units	Max	Min	a (€/kW <sup>2</sup> )	b (€/kW)	c (€)
DG	600	30	0.0000073	0.0660	0.0045400
MT	300	0	0	0.0865	0
FC	300	0	0	0.1306	0
Grid	800	- 800	Refer to Fig. 3		

## 4 Descriptive Analysis of the Case Study

### 4.1 System Description

A low voltage grid-connected microgrid system with two PV systems, one wind farm, and a battery energy storage system was the primary test system taken into account for this study. A diesel generator, a micro-turbine, and a fuel cell were the additional fuel-consuming DGs. Table 1 shows the generating characteristics, and Fig. 2 displays a visual depiction of the microgrid system. The anticipated load demand and the market price for electricity based on time of consumption (TOU) are displayed in Fig. 3. Figure 4 depicts the expected hourly production of the wind farm and photovoltaic systems for the area where the microgrid was installed. The optimization tool for the study was a recently developed hybrid CSAJAYA algorithm, which has already demonstrated its superiority in solving a number of power system optimization problems, including reactive power problem [42], dynamic

economic emission dispatch [43, 44], and microgrid energy management problem [25]. In the appendix section, the details of the algorithm are tabulated. There were 10 populations in this study, and a maximum of 100 iterations were considered. An 8 GB RAM and Ryzen 5 5600 h processor HP laptop with the MATLAB R2021b environment was used to carry out the optimization process.

### 4.2 Case Study

A microgrid system’s DSM-based fuel cost reduction approach is essentially a bi-level optimization procedure. In the first level, the predicted load demand for each hour was divided into elastic and non-elastic loads depending on various DSM participation percentages. In order to create a revised load demand model for different percentages of DSM involvement, the elastic loads were then optimized in accordance with the TOU-based electricity market pricing. In Sect. 3, this topic is covered in detail. Figure 5 depicts

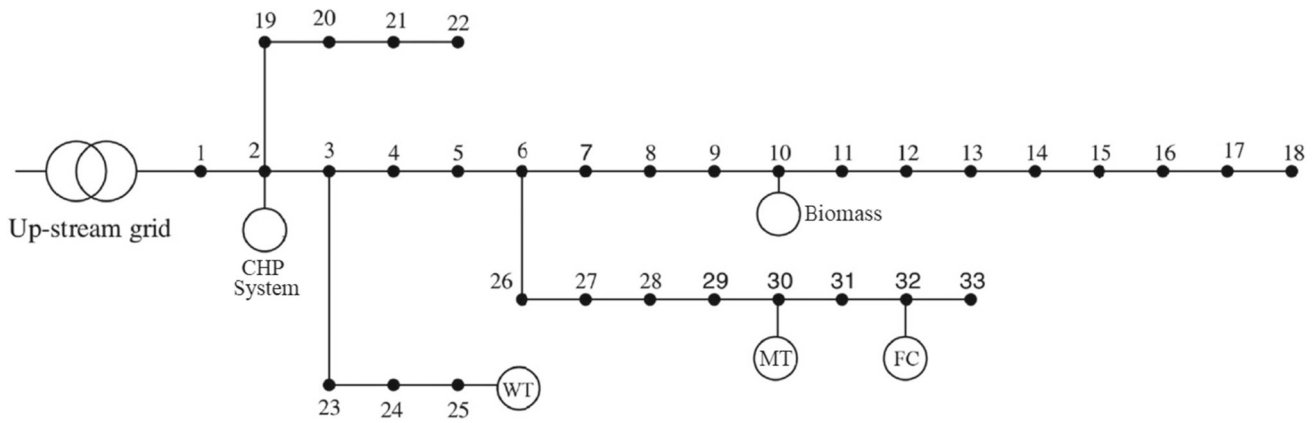


Fig. 2 Pictorial representation of the grid-connected microgrid model

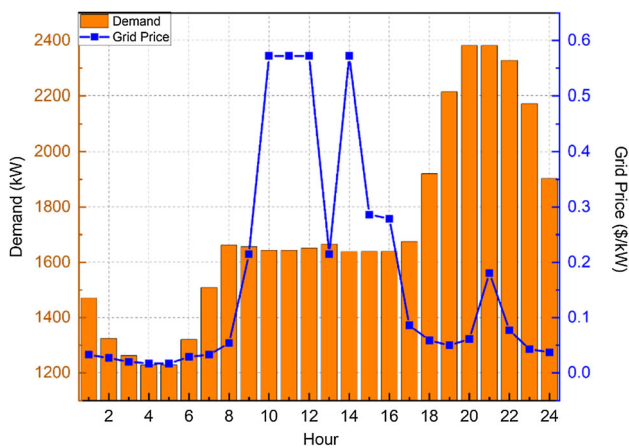


Fig. 3 Microgrid system load demand and electricity price [45]

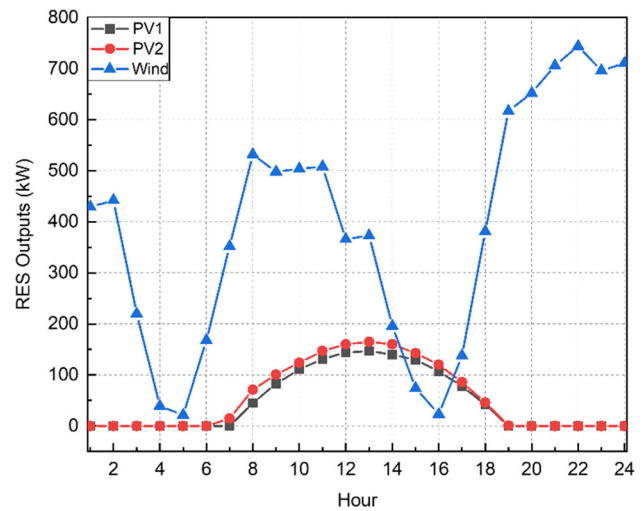


Fig. 4 Power output from PV1, PV2 and Wind [45]

the restructured electrical load demand model for both the levels and the electricity market price under the assumption that 10–30% of the total hourly load demand was elastic and took part in DSM modelling. Table 2 shows the benefits of this load demand restructuring with DSM participation. DSM lowers the peak of the demand curve without altering the distribution system’s average as well as total electrical demand. For 10, 20 and 30 per cent DSM involvement, the peak demand was decreased to 0.1202 per cent, 0.1854 per cent, and 2.06654 per cent, respectively.

For all load demand, the producing cost for the microgrid system is now decreased in four different situations. Four cases are investigated using this second level optimization technique to evaluate producing costs. For all cases and four different DSM schemes, generation costs are listed in Table 3.

- *Case 1, Active Grid:* In this scenario, it is considered that the grid actively engages in purchasing and selling electricity to and from the microgrid system. In this instance, the generation costs were determined to be \$1538.7466,

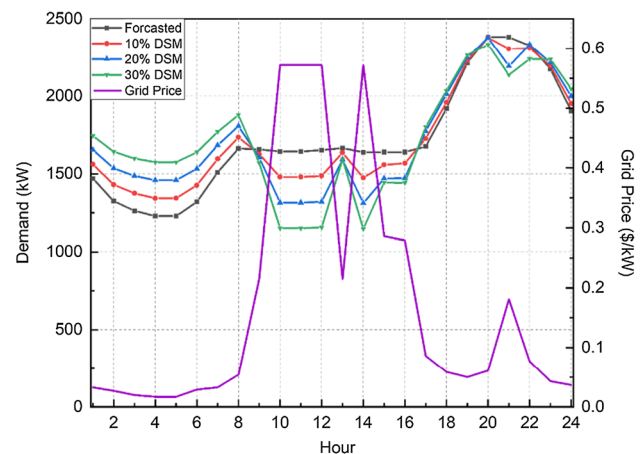


Fig. 5 Load demand curve without DSM, 10% DSM, 20% DSM, 30% DSM

**Table 2** Load demand (kW) characteristic with and without DSM

	Without DSM	With 10% DSM	With 20% DSM	With 30% DSM
Peak (kW)	2382	2379.1380	2377.5845	2332.78
Average (kW)	1715.4167	1715.4167	1715.4167	1715.42
Total (kW)	41,170	41,170.0006	41,170.0004	41,170.00
Peak Reduction (%)	Ref	0.1202	0.1854	2.06654
Load Factor (LF)	Ref	0.6641	0.6827	0.7005

**Table 3** Generation cost (\$) for various cases under different DSM schemes

DSM Schemes	With active grid CASE 1	With passive grid CASE 2	Without battery and active grid CASE 3	Active grid but fixed grid price CASE 4
Without DSM (Base Case)	1538.7466	1934.9457	1536.7861	2668.22
10% DSM	1159.9583	1866.3836	1158.4768	2668.22
20% DSM	774.9913	1827.6109	773.1922	2668.22
30% DSM	434.6957	1815.4967	440.2007	2677.12

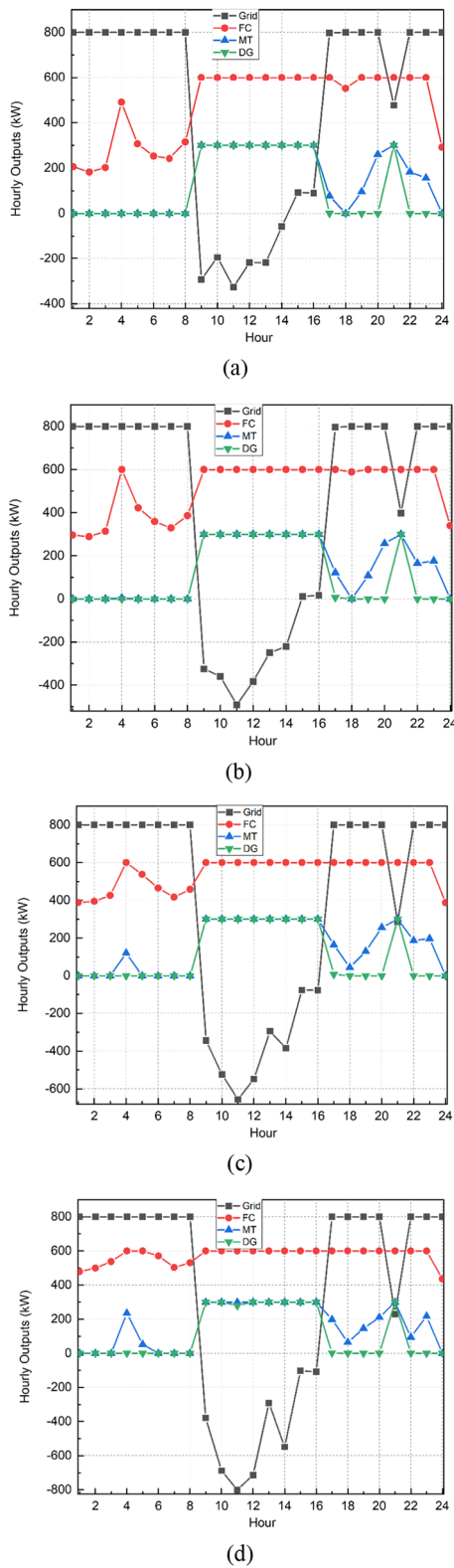
\$1159.9583, \$774.9913, and \$434.6957 for without DSM, 10% DSM, 20% DSM, and 30% DSM, respectively. That indicates that the 30% DSM plan had the largest reduction in generating costs, which is about a 72% reduction over the without DSM scheme. Figure 6a, b, c, and d shows the hourly output of the DERs when the minimum generation cost was evaluated without DSM, 10% DSM, 20% DSM, and 30% DSM scheme, respectively. It should be highlighted that the grid’s hourly production has a significant impact on the decrease in grid generating costs. The cost of production decreases when the grid purchases more electricity. Figure 7 displays the battery energy storage system’s hourly output and its SOC throughout the day when the minimal generating cost for case 1 was assessed.

- **Case 2, Passive Grid:** In this scenario, it is considered that the grid passively engages in selling electricity to the microgrid system. In this instance, the generation costs were determined to be \$1934.9457, \$1866.3836, \$1827.6109 and \$1815.4967 for without DSM, 10% DSM, 20% DSM, and 30% DSM schemes, respectively. It can be seen that the 30% DSM scheme is having the better cost than the others. During this hour the rest of the DERs suffices the total load demand of the microgrid system. Due to the grid’s passive participation, it was unable to purchase electricity, which increased the cost of generating compared to Case 1.
- **Case 3, Without Battery And Active Grid:** Without taking BES into account, the minimum generation cost was also assessed in order to analyse the impact of the storage system. Compared to Case 1, when the BES was not taken into account in the microgrid system, there was a significant increment in generating costs. Figure 8 displays the DERs’

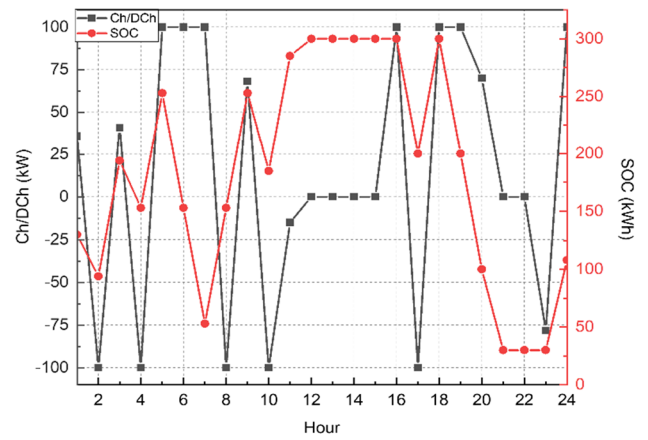
hourly output when BES was not taken into account. Like case 1 and case 2, generation costs were investigated under four different DSM schemes and the costs can be seen in the second last column of Table 3. Figure 9 shows the hourly output graph for the case, without battery and with 30% DSM.

- **Case 4, Active Grid But Fixed Grid Price:** Only the impact of electricity market price, as described by authors in [46, 47], was the purpose of this case study. DSM participation levels are not facilitated by fixed grid pricing. The grid’s best approach to charging microgrid consumers is to use a TOU-based power market pricing model. In this situation, the grid fixed the market price of electricity at 0.572\$ [45]. Compared to Case 1, the generating cost in Case 4 increased from 1538.7466 to 2668.22 \$. Afterwards, the generation cost did not change as a result of the DSM participation levels as shown in Table 3.

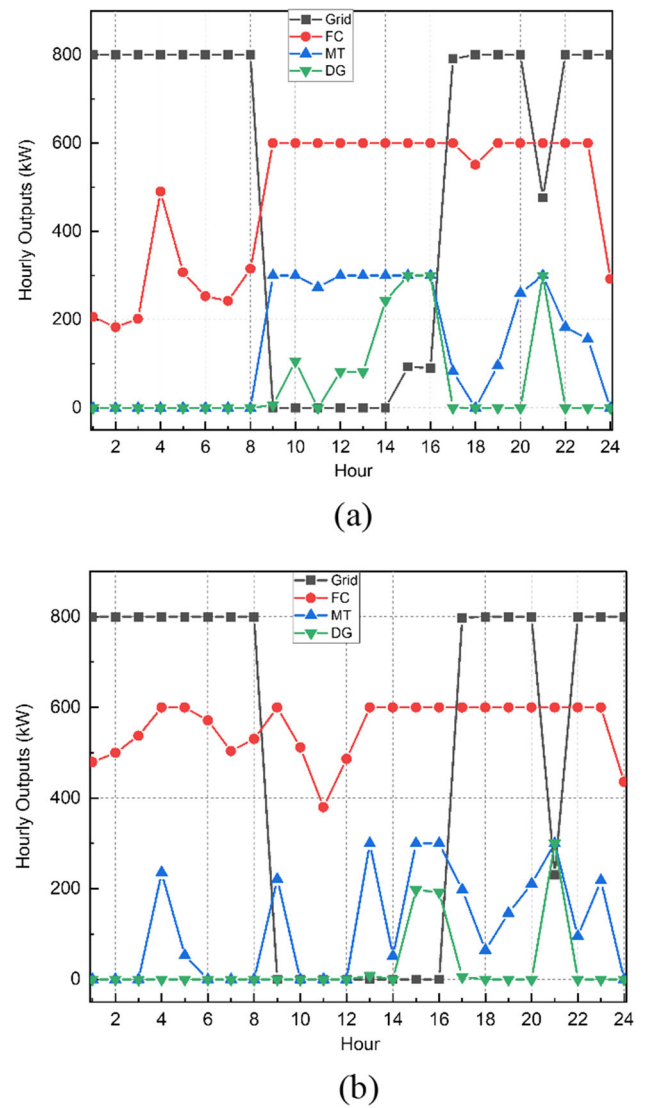
For a descriptive comparative analysis of the proposed algorithm, Case 1 was minimized using different algorithms like grey wolf optimizer (GWO) [48], whale optimization algorithm (WOA) [49], hybrid whale optimization algorithm sine cosine algorithm (WOASCA) [50] and hybrid modified GWO-SCA-crow search algorithm (MGWOSCACSA) [46, 47]. All of these algorithms were execute for 30 independent individual trials and the statistical results are displayed in Table 4. It can be seen that proposed CSAJAYA outperformed all the algorithms yielding least value of fitness function maximum number of times (28 out of 30). Furthermore minimum value of standard deviation and elapsed time points towards the robustness and efficiency of the proposed CSAJAYA algorithm.



**Fig. 6** Hourly output graph of active grid case: **a** without DSM, **b** 10% DSM, **c** 20% DSM, and **d** 30% DSM



**Fig. 7** Hourly output of the battery storage system and its state of charge (SOC) for case 1



**Fig. 8** Hourly output graph of passive grid case: **a** without DSM and **b** 30% DSM



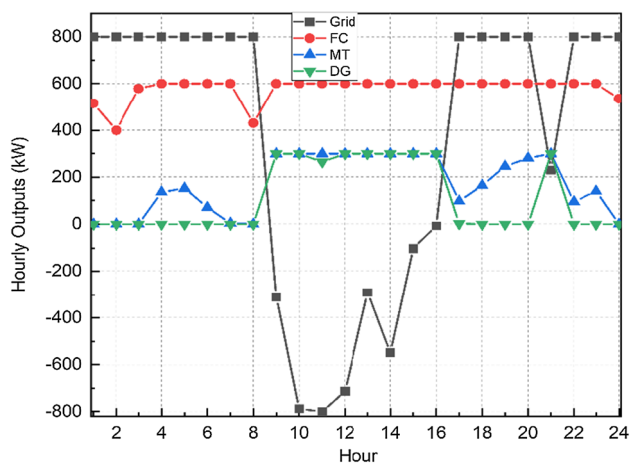


Fig. 9 Hourly output graph of without battery case with 30% DSM

Figure 10 shows Table 3 in visual form. This graph indicates the 25–72% reduction in generating costs with and without DSM. The generating costs of the microgrid system did not change when the grid imposed a fixed price electricity, as can also be seen in this figure. Figure 11 shows the convergence curve characteristics of various algorithms when Case 1 was evaluated without considering DSM. The minimum value of fitness function attained by CSAJAYA within 50–60 iterations can be seen from the figure.

### 5 Conclusion

An LV microgrid system performed a descriptive economic study. The benefits of DSM involvement, grid pricing as well as grid participation were highlighted in this study. The study’s concluding observations are stated below:

- Active grid involvements crucial for lowering the system’s generation costs. A comparison between the generation costs of Cases 1 and 2 portrays the same.
- Involvement of DSM minimizes the generation cost up to 25–72% w.r.t cost calculated without DSM. Furthermore, the added advantages of DSM also include reducing the peak demand and increasing the load factor without changing the total load and average load of the demand.

Table 4 Detailed statistical analysis among various algorithms for Case 1 (without DSM)

Algorithms	Min Cost (\$)	Max Cost (\$)	Mean Cost (\$)	SD	Time (sec)	Hits
WOA	1759.3605	1770.1450	1762.9553	5.1708	11.25	20
GWO	1671.1305	1685.6540	1675.0034	6.5323	12.36	22
WOASCA	1616.2334	1625.6578	1617.4900	3.2584	15.41	26
MGWOSCACSA	1593.4052	1601.2120	1594.1859	2.3821	9.47	27
CSAJAYA	1538.7466	1539.2340	1538.9801	0.1508	6.36	28

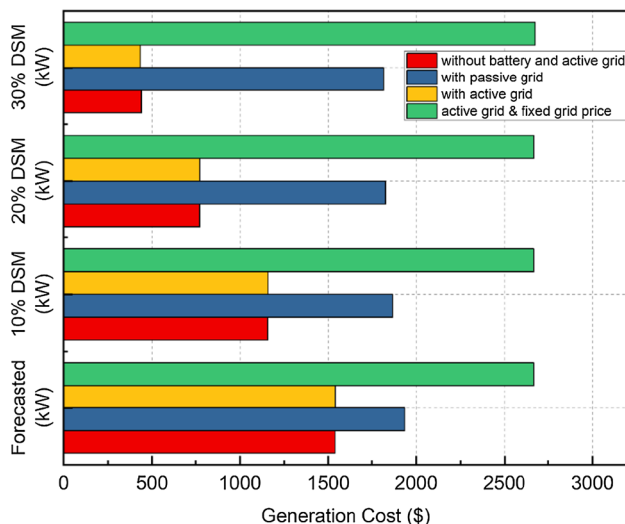


Fig. 10 Pictorial representation of costs for different cases studied with and without DSM

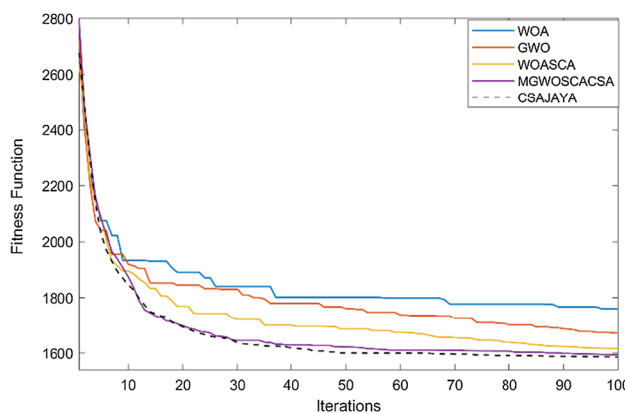
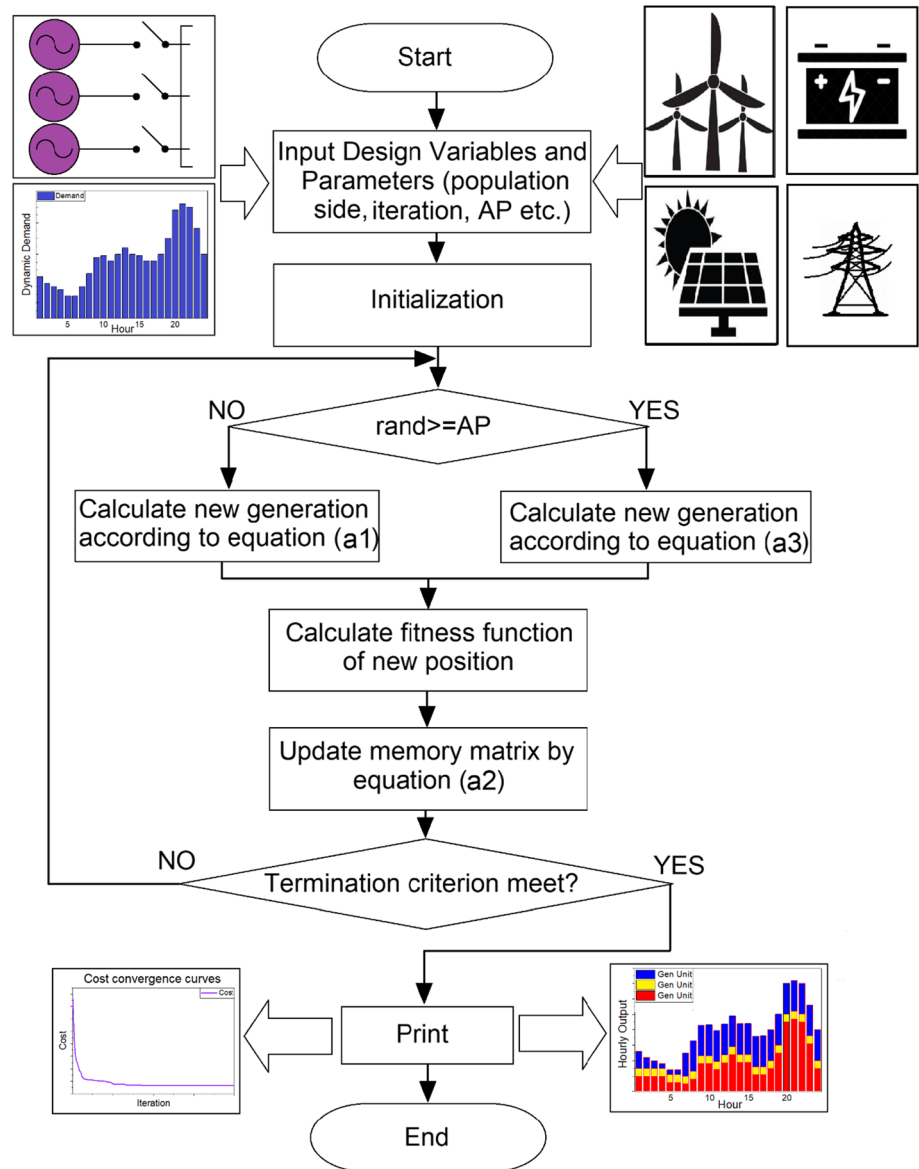


Fig. 11 Convergence curves for various algorithms

- The effectiveness of DSM completely depends on TOU-based power market pricing; hence, the price of electricity should change from hour to hour in response to demand. Electricity fixed prices have no bearing on DSM load modelling. On the other hand, when the grid price is set, the system’s generation costs increase. When comparing cases 1 and 4, the same behaviour can be seen.
- Detailed statistical analysis also portrays the robustness and efficiency of the proposed hybrid algorithm which have been used as the optimization tool for the study.

**Fig. 12** Flow chart of CSAJAYA for DED in grid-connected microgrid



Future scope of work: This issue may be resolved by incorporating unit commitment of the DERs, Incentive-based demand response, etc. in order to increase the complexity and comply with the recent trend of ongoing research related to microgrid energy management (see Fig. 12).

$$X^{u, iter+1} = \begin{cases} X^{u, iter} + rand_u \times fl^u \times (m^{v, iter} - X^{u, iter}), & \text{if } rand_v \geq AP^v \\ a \text{ random position,} & \text{otherwise} \end{cases} \tag{17}$$

$$m^{u, iter+1} = \begin{cases} X^{u, iter+1}, & \text{if } f(X^{u, iter+1}) < f(m^{u, iter}) \\ m^{u, iter}, & \text{otherwise} \end{cases} \tag{18}$$

### Appendix

The optimization tool used for minimization of generation cost for the microgrid system is a hybrid algorithm used by the amalgamation of crow search algorithm and JAYA algorithm. The mathematical modelling details of the algorithm are discussed below.

$$X_{k, q, iter+1} = X_{k, q, iter} + c' * (X_{k, best, iter} - |X_{k, q, iter}|) - c'' * (X_{k, worst, iter} - |X_{k, q, iter}|) \tag{19}$$

$$X^{u, iter+1} = \begin{cases} X^{u, iter} + rand_1 \times fl^u \times (m^{v, iter} - X^{u, iter}) & , \text{ when } rand_j \geq AP \ \& \ k = 1 : n \\ X^{u, iter, k} + rand_1 \times m_{best}^k \times |X^{u, iter, k}| - rand_2 \times m_{worst}^k \times |X^{u, iter, k}| & , \text{ when } rand_j \leq AP \ \& \ k = 1 : n \\ \text{end} \end{cases} \tag{20}$$

where X is solution of current iteration ‘iter’. AP, m, and fl are awareness probability, memory matrix, and flight length of the crow, respectively. X<sub>best</sub> and X<sub>worst</sub> are best and worst solution for iteration ‘iter’.

	CSA [51]	JAYA [52]	CSAJAYA [42–44]
Governing Equation	(17)	(19)	(20)
Memory Update	(18)	NA	(18)

### References

1. Yang, W.; Peng, Z.; Yang, Z.; Guo, Y.; Chen, Xu.: An enhanced exploratory whale optimization algorithm for dynamic economic dispatch. *Energy Rep.* **7**, 7015–7029 (2021)
2. Xiong, G.; Shi, D.: Hybrid biogeography-based optimization with brain storm optimization for non-convex dynamic economic dispatch with valve-point effects. *Energy* **157**, 424–435 (2018)
3. Zou, D.; Li, S.; Kong, X.; Ouyang, H.; Li, Z.: Solving the dynamic economic dispatch by a memory-based global differential evolution and a repair technique of constraint handling. *Energy* **147**, 59–80 (2018)
4. Dey, B.; Bhattacharyya, B.: Dynamic cost analysis of a grid connected microgrid using neighborhood based differential evolution technique. *Int. Trans. Electr. Energy Syst.* **29**, e2665 (2019)
5. Ma, H.; Yang, Z.; You, P.; Fei, M.: Multi-objective biogeography-based optimization for dynamic economic emission load dispatch considering plug-in electric vehicles charging. *Energy* **135**, 101–111 (2017)
6. He, X.; Zhao, Y.; Huang, T.: Optimizing the dynamic economic dispatch problem by the distributed consensus-based ADMM approach. *IEEE Trans. Industr. Inf.* **16**(5), 3210–3221 (2019)
7. Ghasemi, M.; Akbari, E.; Zand, M.; Hadipour, M.; Ghavidel, S.; Li, Li.: An efficient modified HPSO-TVAC-based dynamic economic dispatch of generating units. *Electr. Power Compon. Syst.* **47**(19–20), 1826–1840 (2019)
8. Karar, M.; Abdel-Nasser, M.; Mustafa, E.; Ali, Z.M.: Improved salp-swarm optimizer and accurate forecasting model for dynamic economic dispatch in sustainable power systems. *Sustainability* **12**(2), 576 (2020)
9. Barun, M.; Roy, P.K.: Dynamic economic dispatch problem in hybrid wind based power systems using oppositional based chaotic grasshopper optimization algorithm. *J. Renew. Sustain. Energy* **13**(1), 013306 (2021)
10. Roy, K.: An efficient MABC-ANN technique for optimal management and system modeling of micro grid. *Sustain. Comput. Inform. Syst.* **30**, 100552 (2021)

11. Li, C.: Multi-objective optimization of space adaptive division for environmental economic dispatch. *Sustain. Comput. Inform. Syst.* **30**, 100500 (2021)
12. Lokeshgupta, B.; Sivasubramani, S.: Multi-objective dynamic economic and emission dispatch with demand side management. *Int. J. Electr. Power Energy Syst.* **97**, 334–343 (2018)
13. Singh, D.; Dhillon, J.: Ameliorated grey wolf optimization for economic load dispatch problem. *Energy* **169**, 398–419 (2019)
14. Roy, S.: The maximum likelihood optima for an economic load dispatch in presence of demand and generation variability. *Energy* **147**, 915–923 (2018)
15. Alham, M.H.; Elshahed, M.; Ibrahim, D.K.; El Din, E.; El Zahab, A.: A dynamic economic emission dispatch considering wind power uncertainty incorporating energy storage system and demand side management. *Renew. Energy* **96**, 800–811 (2016)
16. Trivedi, I.N.; Jangir, P.; Bhoje, M.; Jangir, N.: An economic load dispatch and multiple environmental dispatch problem solution with microgrids using interior search algorithm. *Neural Comput. Appl.* **30**(7), 2173–2189 (2018)
17. Dai, W.; Yang, Z.; Yu, J.; Cui, W.; Li, W.; Li, J., et al.: Economic dispatch of interconnected networks considering hidden flexibility. *Energy* **223**, 120054 (2021)
18. Toopshakan, A.; Yousefi, H.; Astaraei, F.R.: Technical, economic, and performance analysis of a hybrid energy system using a novel dispatch strategy. *Energy* **213**, 118850 (2020)
19. Dey, B.; Roy, S. K.; Bhattacharyya, B.: Neighborhood based differential evolution technique to perform dynamic economic load dispatch on microgrid with renewables. in 2018 4th International Conference on Recent Advances in Information Technology (RAIT), 2018, pp. 1–6
20. Basu, M.; Chowdhury, A.: Cuckoo search algorithm for economic dispatch. *Energy* **60**, 99–108 (2013)
21. Amritpal, S.; Khamparia, A.: A hybrid whale optimization-differential evolution and genetic algorithm based approach to solve unit commitment scheduling problem: WODEGA. *Sustain. Comput. Inform. Syst.* **28**, 100442 (2020)
22. Chauhan, G.; Jain, A.; Verma, N.: Solving economic dispatch problem using MiPower by lambda iteration method. in 2017 1st International Conference on Intelligent Systems and Information Management (ICISIM), pp. 95–99. (2017)
23. Ganjefar, S.; Tofighi, M.: Dynamic economic dispatch solution using an improved genetic algorithm with non-stationary penalty functions. *Eur. Trans. Electr. Power* **21**(3), 1480–1492 (2011)
24. Basak, S.; Dey, B.; Bhattacharyya, B.: Uncertainty-based dynamic economic dispatch for diverse load and wind profiles using a novel hybrid algorithm. *Environ Dev Sustain* (2022). <https://doi.org/10.1007/s10668-022-02218-5>
25. Dey, B.; Basak, S.; Pal, A.: Demand-side management based optimal scheduling of distributed generators for clean and economic operation of a microgrid system. *Int. J. Energy Res.* (2022). <https://doi.org/10.1002/er.7758>
26. Kumar, M.; Dhillon, J.: Hybrid artificial algae algorithm for economic load dispatch. *Appl. Soft Comput.* **71**, 89–109 (2018)

27. Wu, K.; Li, Q.; Chen, Z.; Lin, J.; Yi, Y.; Chen, M.: Distributed optimization method with weighted gradients for economic dispatch problem of multi-microgrid systems. *Energy* **222**, 119898 (2021)
28. Caisheng, W.; Miller, C.J.; Hashem Nehrir, M.; Sheppard, J.W.; McElmurry, S.P.: A load profile management integrated power dispatch using a Newton-like particle swarm optimization method. *Sustain. Comput. Inform. Syst.* **8**, 8–17 (2015)
29. Trivedi, I.N.; Dhaval K.; Thesiya, A.E.; Pradeep J.: A multiple environment dispatch problem solution using ant colony optimization for micro-grids. In 2015 International Conference on Power and Advanced Control Engineering (ICPACE), pp. 109–115. IEEE, (2015)
30. Liu, Y.; Nair, N.-K.C.: A two-stage stochastic dynamic economic dispatch model considering wind uncertainty. *IEEE Trans. Sustain. Energy* **7**, 819–829 (2015)
31. Maulik, A.; Das, D.: Optimal operation of microgrid using four different optimization techniques. *Sustain. Energy Technol. Assess.* **21**, 100–120 (2017)
32. Mehmood, K.; Hassan, H.T.U.; Raza, A.; Altalbe, A.; Farooq, H.: Optimal power generation in energy-deficient scenarios using bagging ensembles. *IEEE Access* **7**, 155917–155929 (2019)
33. Kashif, M.; Cheema, K.M.; Tahir, M.F.; Tariq, A.R.; Milyani, A.H.; Elavarasan, R.M.; Shaheen, S.; Raju, K.: Short term power dispatch using neural network based ensemble classifier. *J. Energy Storage* **33**, 102101 (2021)
34. Tahir, M.F.; Mehmood, K.; Haoyong, C.; Iqbal, A.; Saleem, A.; Shaheen, S.: Multi-objective combined economic and emission dispatch by fully informed particle swarm optimization. *Int. J. Power Energy Syst.* **42**, 10 (2022)
35. Tahir, M.F.; Haoyong, C.; Mehmood, K.; Larik, N.A.; Khan, A.; Javed, M.S.: Short term load forecasting using bootstrap aggregating based ensemble artificial neural network. *Recent Adv. Electr. Electron. Eng. (Formerly Recent Patents Electr. Electron. Eng.)* **13**(7), 980–992 (2020)
36. Tehzeeb-ul-Hassan, T.A.; Butt, S.E.; Tahir, M.F.; Mehmood, K.: Short-term optimal scheduling of hydro-thermal power plants using artificial bee colony algorithm. *Energy Rep.* **6**, 984–992 (2020). <https://doi.org/10.1016/j.egypr.2020.04.003>
37. Lokeshgupta, B.; Sivasubramani, S.: Multi-objective dynamic economic and emission dispatch with demand side management. *Int. J. Electr Power Energy Syst.* **97**, 334–343 (2018)
38. Bhamidi, L.; Sivasubramani, S.: Optimal planning and operational strategy of a residential microgrid with demand side management. *IEEE Syst. J.* **14**(2), 2624–2632 (2019)
39. Bhamidi, L.; Shanmugavelu, S.: Multi-objective harmony search algorithm for dynamic optimal power flow with demand side management. *Electr Power Compon. Syst.* **47**(8), 692–702 (2019)
40. Abedinia, O.; Bagheri, M.: Power distribution optimization based on demand respond with improved multi-objective algorithm in power system planning. *Energies* **14**(10), 2961 (2021)
41. Basak, S.; Bishwajit D.; Biplab B.: Demand side management for solving environment constrained economic dispatch of a microgrid system using hybrid MGWOSCACSA algorithm. *CAAI Trans. Intell. Technol.* (2022)
42. Karmakar, N.; Bhattacharyya, B.: Optimal reactive power planning in power transmission system considering FACTS devices and implementing hybrid optimisation approach. *IET Gener. Transm. Distrib.* **14**(25), 6294–6305 (2020)
43. Bishwajit, D.; Basak, S.; Bhattacharyya, B.: A comparative analysis between price-penalty factor method and fractional programming method for combined economic emission dispatch problem using novel probabilistic CSA-JAYA algorithm. *IET Smart Grid* **4**, 136–141 (2021)
44. Sourav, B.; Bhattacharyya, B.; Dey, B.: Combined economic emission dispatch on dynamic systems using hybrid CSA-JAYA Algorithm. *Int. J. Syst. Assur. Eng. Manag.* **13**, 1–22 (2022)
45. Prakash, K.K.; Saravanan, B.: Day ahead scheduling of generation and storage in a microgrid considering demand Side management. *J. Energy Storage* **21**, 78–86 (2019)
46. Dey, B.; Bhattacharyya, B.; Devarapalli, R.: A novel hybrid algorithm for solving emerging electricity market pricing problem of microgrid. *Int. J. Intell. Syst.* **36**(2), 919–961 (2021)
47. Dey, B.; Raj, S.; Mahapatra, S.; Márquez, F.P.G.: Optimal scheduling of distributed energy resources in microgrid systems based on electricity market pricing strategies by a novel hybrid optimization technique. *Int. J. Electr. Power Energy Syst.* **134**, 107419 (2022)
48. Mirjalili, S.; Mirjalili, S.M.; Lewis, A.: Grey wolf optimizer. *Adv. Eng. Softw.* **69**, 46–61 (2014). <https://doi.org/10.1016/j.advengsoft.2013.12.007>
49. Mirjalili, S.; Lewis, A.: The whale optimization algorithm. *Adv. Eng. Softw.* **95**, 51–67 (2016)
50. Dey, B.; Márquez, F.P.G.; Panigrahi, P.K.; Bhattacharyya, B.: A novel metaheuristic approach to scale the economic impact of grid participation on a microgrid system. *Sustain. Energy Technol. Assess.* **53**, 102417 (2022). <https://doi.org/10.1016/j.seta.2022.102417>
51. Askarzadeh, A.: A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. *Comput. Struct.* **169**, 1–12 (2016)
52. Rao, R.: Jaya: a simple and new optimization algorithm for solving constrained and unconstrained optimization problems. *Int. J. Ind. Eng. Comput.* **7**(1), 19–34 (2016)

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