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Energy Management of Microgrid Considering Demand Response Using Honey Badger Optimizer

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Abstract Recently, Microgrids (MGs) have received great attention for solving power system problems, due to their low environmental effects and their economic benefits. This paper proposes a new application of an effective metaheuristic optimization method, namely, Honey Badger Algorithm (HBA), to solve energy management for optimal dispatch of the grid-connected MG incorporating Demand Response programs (DRP). Honey badger algorithm is used to solve an incentive DRP, with the aim of minimizing the total cost, which includes conventional generators fuel cost and the cost of power transaction with the main grid considering the load demand. In this paper, two case studies are conducted using HBA and simulation results are compared with those obtained by other algorithms (particle swarm optimization and JAYA algorithm). First case consists of three diesel generators, a PV generator and a wind generator. To prove the scalability of the HBA, the second case, which is much larger, is tested. Simulation results for both case studies obtained by PSO, JAYA, and HBA are deeply discussed. The results show the HBA's effectiveness in solving the energy management with DR problem for MG compared with other well-known optimization techniques.

Key words: Demand Response, Energy Management, Microgrid, Incentive, optimization, Honey badger algorithm)

1. Introduction

Microgrids (MGs) consist of different types of Distributed Generation (DG), controllable loads, and Energy Storage Systems (ESS) sited near the places of consumption [1]. The generation units in MGs can be either renewable energy sources (RES) such as wind power and solar PV power; or conventional generation sources as diesel generation or thermal generation.

Nowadays, generation from RES has become preferable in MGs due to cost and environmental benefits over the generation from conventional sources [2]. Microgrid Energy Management (EM) has received great attention in research for optimal operation of MGs. EM involves maximization or minimization of one or more objective functions such as maximization of the profit or minimization of the total cost.

However, the peak load hours are only a couple of hours daily, the peak to average ratio (PAR) of demand in electric power systems is high[3]; in order to supply the peak loads, a high increase in the investment should be made, which results in an increase in the electricity cost. To solve this challenge, demand-side management (DSM) should be considered [4].

DR can be further classified mainly into two types: first price-based DR (PDR), the consumers where the electricity prices are changed at different times; for example, high prices at peak, medium for off-peaks, and low prices for low-peak periods; and second incentive-based DR (IDR) get an incentive awards for the change in their consumption [5].

In [6], DR and Optimal power flow in combined heat and power (CHP) system have been introduced in Microgrid with energy storage system, using a combination of hybrid augmented weighted ε-constraint technique and lexicographic optimization. In [7], a PDR has been discussed to maximize the MG profit for fixed and dynamic pricing strategies, while the optimization problem has been solved using PSO. An IDR program has been proposed to solve a multi-objective problem to reduce the cost and environmental effect using an advanced interactive multi-dimensional modelling method in [8].

In [9], a multi-agent algorithm with Distributed Constraint Optimization Problems has been introduced to solve the economic dispatch and demand response to maximize the customer benefits and minimize generation cost. In addition, an IDR program has been used to minimize energy cost and ensure customer benefits using the technique of weighted sum and the fuzzy satisfying method. In [10], the dynamic economic dispatch using Model Predictive control, considering the DR and environmental emission, has been addressed. In [11] PSO technique has been applied to manage the MG resources and DR to minimize the operation cost for the MG operator.

The objective of this paper is to solve energy management problem for Microgrid with an incentive Demand response program using a recently developed optimization algorithm, called Honey badger algorithm. To show the robustness of the proposed energy management algorithm, HBA results are compared with those obtained by other well-known algorithms; PSO and JAYA.

2. Mathematical Model for Grid-connected Microgrid

The structure of grid-connected MG in this paper is shown in Fig. 1. It consists of renewable sources such as

Solar PV Power generators and Wind Turbine (WT) generators, conventional generators, and customers with DR.

A. Modelling of WT

Wind turbine output power depends on the wind speed, air density, rotor swept area and converter efficiency, where the wind speed for a specific height of tower is calculated as[12] :

$$v_{hub_t} = v_{ref_t}\left(\frac{h_{hub}}{h_{ref}}\right)^{\beta} \quad (1)$$

Where, v_{hub_t} is the hourly speed of the wind at the desired height h_{hub}; v_{ref_t} is the wind speed (hourly) at the reference height h_{ref} and β is the power law exponent ,which usually is in the range between $\frac{1}{4}$ and $\frac{1}{7}$. In this work it is used as $\frac{1}{7}$.

The hourly wind power is calculated as :

$$P_{w_t} = 0.5 n_w p_{air} C_p A v_{hub_t} \quad (2)$$

where, n_w is the wind generator efficiency, p_{air} air density, C_p is the power coefficient of the turbine, A swept area by the rotor.

B. Solar power modeling

For a given area, the hourly output power from the solar PV generator is given as:

$$P_{s_t} = \eta_{pv} A_c I_{Pv_t} \quad (3)$$

where, η_{pv} is the efficiency of the solar PV generator, which is a function of the incident solar irradiation on the PV array I_{Pv_t} (kW h/m2), and the ambient temperature and A_c is the PV array area [13].

C. Grid-connected Microgrid

In this work, it is assumed that there is a power transaction between the MG and the main grid; hence power can either be sold from the main grid or transferred to it. Let power transferred at any time between MG and main grid as $\mathbf{P_{r_t}}$, Locational Marginal Prices (LMP's) (given as $\boldsymbol{\gamma_t}$)[14] are used for purchasing the power between MG and the main grid. Hence, the cost for power transaction ($\mathbf{C_r}(\mathbf{P_{r_t}})$) is expressed as in Eq. (4).

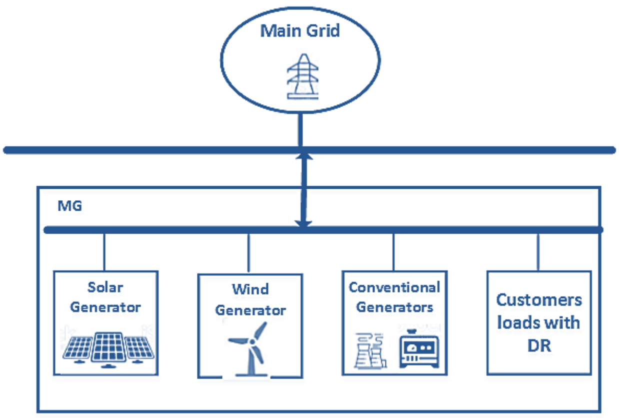

Fig. 1 Microgrid Structure with demand response model

$$C_r(P_{r_t}) = \begin{cases} \gamma_t \times P_{r_t} & P_{r_t} > 0 \\ 0 & P_{r_t} = 0 \\ -\gamma_t \times P_{r_t} & P_{r_t} < 0 \end{cases} \quad (4)$$

D. Demand response model:

If we donate the cost that customer incurred as $C(\theta, x)$; where θ is customer type and x is the reduction of customer consumption (MW), the customer benefit can be expressed as:

$$F_1(\theta, y, x) = y - C(\theta, x) \quad (5)$$

Where y is the incentive that customers receive for their reduction. Hence, the customer will participate in DR program only in the case of $F_1 \geq 0$. Also, the benefit of the MG is given as:

$$F_2(\theta, \lambda) = \lambda x - y \quad (6)$$

Where λ is the cost of power interruption from a particular customer, it is known as power interruptibility, and it can be calculated from optimal power flow analysis [15].

E. Customer cost function:

The mathematical formulation for the cost function ($C(\theta, x)$) for the customer who participated in DRP can be calculated as:

$$C(\theta, x) = k_1 x^2 + k_2 x - k_2 x \theta \quad (7)$$

where:

- θ is customer type; its value varies between 0 and 1 that the customer with a lower willing has this value as 0 and the higher willing customer has a value of 1.
- k_1 , and k_2 are cost coefficients.

Contract formulation for all customers is given in [15]: thus, if we donate the customer (j) payment as y_j so that customer benefit can be expressed as:

$$U_j = y_j - (k_1 x_j{}^2 + k_2 x_j - k_2 x_j \theta), \text{for } j = 1,2,\dots J \quad (8)$$

Moreover, MG benefit is calculated as:

$$U_0 = \sum_{j=1}^{J} \lambda_j x_j - y_j \quad (9)$$

F. Objective function:

1. First objective function

First objective function in the studied optimization procedure for energy management in MG connected to the main grid is the minimization of conventional generators' fuel cost and the reduction of the cost for power transaction between MG and the main grid and is given as:

$$\min f_1(x) = \min \sum_{t=1}^{T} \sum_{i=1}^{I} C_i(P_{i_t}) + \sum_{t=1}^{T} C_r(P_{r_t}) \quad (10)$$

2. Second objective function

As aforementioned, the MG benefit is calculated by (9). The objective is the maximizing the expected MG benefits as follows:

$$\max f_2(x) = \max \sum_{t=1}^{T} \sum_{i=1}^{I} \lambda_j x_j - y_j \quad (11)$$

Therefore, the MG operator can get a profit in the case of selecting not to supply power to certain customers or paying incentive payments for the customer as in (11).

Constraints:

$$\sum_{i=1}^{I} P_{i_t} + P_{w_t} + P_{s_t} + P_{r_t} = D_t - \sum_{j=1}^{J} x_{j,t}. \quad (12)$$

$$P_{i_{min}} \le P_{i_t} \le P_{i_{max}} \quad (13)$$

$$-DR_i \le P_{i_{t+1}} - P_{i_t} \le UR_i \quad (14)$$

$$0 \le P_{s_t} \le P_{st_{max}} \quad (15)$$

$$0 \le P_{w_t} \le P_{wt_{max}} \quad (16)$$

$$-P_{r_{max}} \le P_{i_t} \le P_{r_{max}} \quad (17)$$

where:
D_t (MW) is the total demand at any time t.
$x_{j,t}$ is the value of power curtailed for customer j at time t.
$P_{i_{min}}$ and $P_{i_{max}}$ are the minimum and maximum power generated from ant generator I, respectively.
$P_{st_{max}}$ is the forecasted maximum power from Solar PV generator at any time t
$P_{wt_{max}}$ is the maximum forecasted wind generator power at any time t.
$P_{r_{max}}$ is the maximum permissible power to be transferred between main grid and MG.
UR_i and DR_i are the maximum ramp up and ramp down rates for generator I.
T and I are the dispatch interval and the number of conventional generators, respectively.

Eq. (12) describes the power balance constraint to ensure that the total production and power transferred from or to the main grid at any time t will equal the total demand.

Constraint (13) is the limits of any conventional generator I to ensure the generation limits are not exceeded, while constraint (14) is ramping up and down rate limits to ensure not to violate those rates.

Eqs. (15) and (16) represent the constraints of the maximum and minimum generation limits of WT generator and solar PV generation, respectively. Eq.(17) represents the transacted power constraint, which limits the power transacted between the MG and the utility grid not to exceed the maximum limit $P_{r_{max}}$.

The fuel cost for conventional generators ($C_i(P_{i_t})$)is represented by quadratic Model as follows:

$$C_i(P_{i_t}) = a_i p^2{}_{i_t} + b_i P_{i_t} \quad (18)$$

Where a_i and b_i are the cost coefficients of fuel for conventional generator i.

Demand response constraints:

$$\sum_{t=1}^{T} y_{j,t} - (k_1 x_{j,t}{}^2 + k_2 x_{j,t} - k_2 x_{j,t}\theta) \ge 0 \quad (19)$$

$$\sum_{t=1}^{T} y_{j,t} - (k_1 x_{j,t}{}^2 + k_2 x_{j,t} - k_2 x_{j,t}\theta) \ge \sum_{t=1}^{T} y_{j-1,t} - (k_1 x_{j-1,t}{}^2 + k_2 x_{j-1,t} - k_2 x_{j-1,t}\theta) \quad (20)$$

For j=2,3,…., J

$$\sum_{t=1}^{T}\sum_{j=1}^{J} y_{j,t} \le UB \quad (21)$$

$$\sum_{t=1}^{J} x_{j,t} \le CM_j \quad (22)$$

Where UB is the upper limit for MG budget limit and CM_j is the maximum permissible daily power curtailment for customer j.

The demand management contract formulations in (8) are extended for the whole interval 24 hours (one day) instead of only one hour, which means more practical economical. Constraint in (19) is to ensure that the customer gets a total incentive for all power curtailed to exceed the cost of interruption. Also, the customer should get a greater incentive if he/she increases his/her curtailment (constraint in (20)). The total MG budget limit constraint is described in (21) to ensure the daily budget is lower than the limit. Eq (**22**) is to ensure the total curtailment of any customer j is within the permissible limits.

The mathematical model of the objective function is given as:

$$\min w\left[\sum_{t=1}^{T}\sum_{i=1}^{I} C_i(P_{i_t}) + \sum_{t=1}^{T} C_r(P_{r_t})\right] + (1 - w)\left[\sum_{t=1}^{T}\sum_{i=1}^{I} \lambda_j x_j - y_j\right] \quad (23)$$

where w is the weighting factor and the following equation must be satisfied:

$$w + (1 - w) = 1 \quad (24)$$

3. Honey Badger Algorithm

This algorithm is one of the recent population-based metaheuristic optimization techniques that have better ability in exploration and exploitation for global optima in search space[16]. HBA is proposed in 2021 in [17]. It is inspired by the foraging behaviour of honey badger. Honey badger either uses smelling to approximate prey location and then start the digging or follows a guide bird to directly locate their food sources.

In the first step, like several recent optimization algorithms, the optimization process of HBA is started by generating a random population in the dimensional of search space for the optimization problem; according to the number of variables and population size random initialization for solutions, they are described as:

$$X_i = lb_i + r_1(ub_i - lb_i) \quad (25)$$

Where, X_i is the ith position (or candidate solution) for a honey badger in a population N; ub_i and lb_i are the upper and lower bands for the variables in the search domain; and r_1 is a random number between 0 and 1.

The second step includes defining the intensity (I), and it is related to the concentration and the distance between ith solution (prey) and the honey badger; the motion will be fast if I_i smell intensity is high; the intensity (I) is defined by (26) based on the inverse square low.

$$I_i = r_2 \times \frac{S_i}{4\pi d_i{}^2} \quad (26)$$
$$S_i = (x_i - x_{i+1})^2$$
$$d_i = (x_{prey} - x_i)$$

where, r_2 is a random generated number in a range of [0,1]; S is the concentration strength(location of prey); d is the distance between i^{th} badger and prey.
For each iteration, the density factor (α) is updated, and its value is decreased with iterations to decrease the randomization. Eq.(27) describes the updating of α.

$$\alpha = C \times \exp\left(\frac{-t}{T}\right) \quad (27)$$

Where C is a constant ≥ 1; t is the current iteration number; T is the maximum number of iterations. This is followed by updating the agent's position, which consists of two parts named digging phase or honey phase, as described in the following steps:

- Digging phase: in this phase, for each iteration, the position is updated similar to the motion of Cardioid shape as :

$$X_{i\_new}(k) = X_{prey} + F \times \beta \times I \times X_{prey} + F \times r_3 \times \alpha \times d_i(k) \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \quad (28)$$

where, X_{prey} is the pest position (global best) founded over the search process; β is constant ≥ 1, which describe the ability for a badger to get its prey; r_3, r_4, and r_5 are three randomly generated numbers in the range [0, 1]. F is a flag to control the direction of the search and it is determined as in
(29).

$$F = \begin{cases} 1 & \text{if } r_6 \leq 0.5 \\ -1 & \text{else} \end{cases} \quad (29)$$

And r_6 is a random generated number between 0 and 1.

- Honey phase: in this phase, the badger follows a bird as a guide to reach his food source; this is simulated as in (30).

$$X_{i\_new}(k) = X_{prey} + F \times r_7 \times \alpha \times d_i \quad (30)$$

It is obvious that the honey badger starts to search near the prey X_{prey} or the best solution founded so far and based on the distance between the prey and the badger.

4. Results and discussion

Two different cases are used to validate the effectiveness of the HBA for solving DR problem in grid-connected MG. The first case study (Case study 1) consists of one wind generator, one Solar PV generator, three conventional generation units (diesel), and three residential customers with DRP and to validate the scalability of the algorithm, it is tested for larger MG; case study 2 which consists of aggregated Model for solar PV and wind and generators This study is considered for one day (24 h). Conventional generators parameters (cost-coefficients, maximum and minimum generation limits, ramp up and down rates) are given in Table I and Table II for the two cases. values of power interruptibility for each hour ($\lambda i,t$) and hourly total initial MG demand for case 1 are used in [8]; while initial load data and values of power interruptibility for case 2 have been used in [8]. It is assumed that all customers have the same hourly power interruptibility. The solar PV, wind hourly data for two cases are given in Table III,
Table IV detailes Customer data (customer type, cost function coefficients, and daily power curtailment maximum limit). The MG daily budget (UB) equals to $ 500 and $ 15000 for the first and second case respectively.Initial load data and values of power interruptibility for case 2 have been used in [8].
The results of the studied two cases obtained by different optimization techniques, PSO, JAYA and HBA, are explained in the following section.

Table I Conventional generators data (Case study 1).

i	a_i($/kW^{2}h)	b_i($/kWh)	$P_{i,min}$ (kW)	$P_{i,max}$(KW)	DR_i (KW/h)	UR_i (KW/h)
1	0.06	0.5	0	4	3	3
2	0.03	0.25	0	6	5	5
3	0.04	0.3	0	9	8	8

Table II seven conventional generators units data (Case study 2).

i	a_i ($/MW^{2}h)	b_i ($/MWh)	$P_{i,min}$ (MW)	$P_{i,max}$ (MW)	DR_i (MW/h)	UR_i (MW/h)
1	0.00043	21.6	30	370	200	200
2	0.00063	21.05	35	360	200	200
3	0.000394	20.81	33	240	150	150
4	0.0007	23.9	30	200	100	100
5	0.00079	21.62	33	143	80	80
6	0.00056	17.87	37	60	30	30
7	0.00211	16.51	20	30	30	30
8	0.0048	23.23	27	120	60	60
9	0.10908	19.58	20	80	40	40
10	0.00951	22.54	25	55	30	30

Table III Solar and wind power data (case study 1 and 2)

Time (h)	Solar (Case1) (KW)	Wind (case1) (KW)	Solar (Case1) (KW)	Wind (Case2) (MW)
t=1	0	7.56	113.44	0
t=2	0	7.5	112.55	0
t=3	0	8.25	123.76	0
t=4	0	8.48	127.21	0
t=5	0	8.48	127.33	0
t=6	0	9.42	141.44	0
t=7	0	9.82	147.39	0
t=8	7.99	10.35	155.38	79.94
t=9	10.56	10.88	168.33	105.69
t=10	13.61	11.01	165.28	136.18
t=11	14.97	10.94	164.23	149.75
t=12	15	10.68	160.32	150
t=13	14.78	10.42	156.31	147.89
t=14	14.59	10.15	152.3	145.92
t=15	13.56	9.67	145.05	135.65
t=16	11.83	8.98	134.8	118.36
t=17	10.17	8.37	125.64	101.71
t=18	7.66	7.61	114.2	77.68
t=19	0	6.7	100.63	0
t=20	0	5.72	85.95	0
t=21	0	7.21	108.26	0
t=22	0	7.75	116.38	0
t=23	0	7.88	118.33	0
t=24	0	7.69	115.38	0

Table IV customer type coefficient, Customers' cost function coefficients, and daily curtailment limit

Case 1				
j	θ	$K_{1,j}$	$K_{2,j}$	CM_j(KW)
1	0	1.079	1.32	30
2	0.45	1.378	1.36	35
3	0.9	1.847	1.64	40
Case2				
J	$\boldsymbol{\theta}$	$K_{1,j}$	$K_{2,j}$	CM_j(MW)
1	0	1.847	11.64	180
2	0.14	1.378	11.63	230

3	0.26	1.079	11.32	310
4	0.37	0.9124	11.5	390
5	0.55	0.8794	11.21	440
6	0.84	1.378	11.63	530
7	1	1.5231	11.5	600

Furthermore, 20 independent trial runs were performed for each algorithm; using HBA technique the convergence characteristic curve of objective function is shown in Fig. 2. the simulation results for all studied technique are shown in Table V, the results demonstrate the efficacy of the HBA technique with the best of the objective function cost value when compared to other techniques; Using HBA, the optimal power generated from the three conventional generators (case1) is shown in, Fig. 3. The optimal power generated from: Solar PV generator, wind generator, and power transacted between main grid and MG is shown in Fig. 4. The optimal power curtailed from the three customers, and the incentive they get is shown in Fig. 5.

Total power curtailed over the day for each customer for the best case using PSO, JAYA, and HBA are detailed in Table VI for case 1 and Table VII for case 2. A comparison between the total cost for the three optimization techniques is shown in Table VIII and Table IX.

Table V Comparison of the EM problem for Case 1

	Total operating cost ($)			
Technique	Worst	Best	Mean	SD
PSO [18]	807.35	477.4	658.49	90.47
JAYA [19]	790.67	647.49	711.32	41.57
HBA	672.81	460.39	545.31	40.11

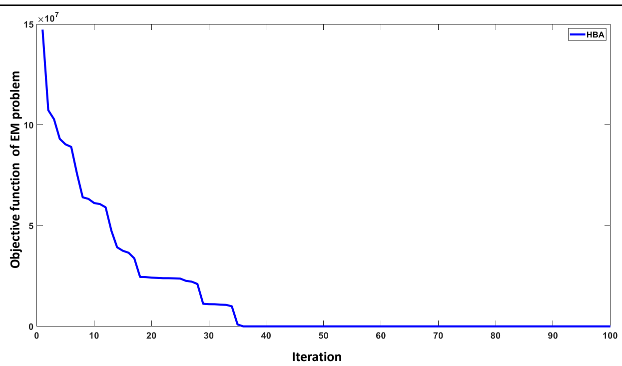

Fig. 2 Convergence characteristic curve of HBA for Case 1.

Looking closely at the simulation results for case study 1, the results in Table VI shows that however the total power curtailment is slightly lower in the case of HBA than other techniques, the total incentive payment is much lower. Also, from Table VIII, it is shown that the total power transferred from the grid is much lower in the case of HBA. Also, the total cost is the lowest in this case. For case study 2, the results in Table VII indicates that the total power curtailment for all customers is higher in case of HBA with total incentive much lower than the PSO and JAYA cases. Also, it is clear from Table IX that using HBA technique gives the lower total cost over the other techniques.

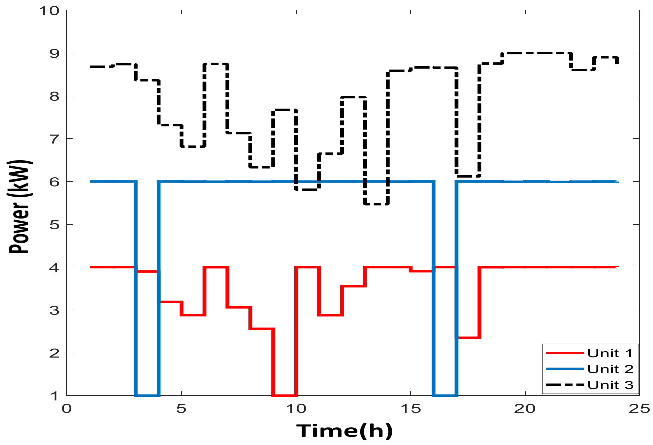

Fig. 3 Optimal output power for conventional generation units obtained by the studied optimization technique(case1).

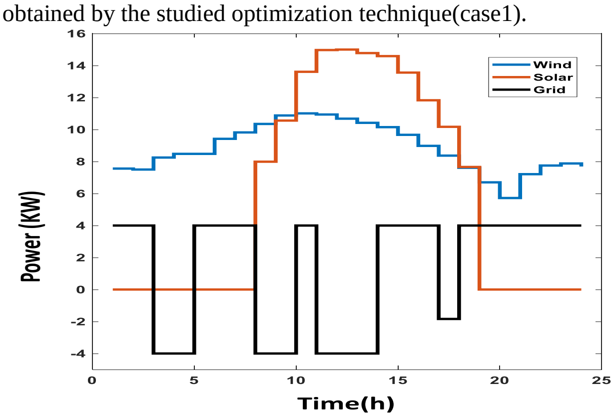

Fig. 4 Optimal output power for solar, wind and grid power transaction (case study 1).

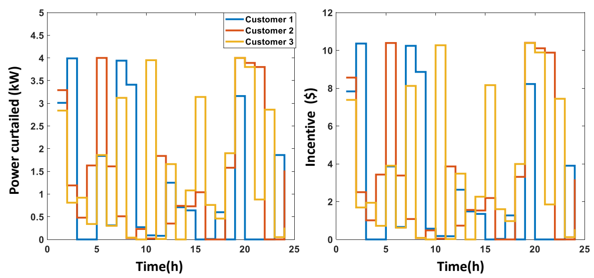

Fig. 5 Optimal power curtailed and incentive paid to customers obtained by the studied optimization techniques.

Table VI Total energy curtailed and total incentive received (Case 1)

No	PSO		JAYA		HBA	
j	saving (kWh)	Incentive ($)	saving (kWh)	Incentive ($)	saving (kWh)	Incentive ($)
1	25.02	69.18	27.21	77.78	25.18	61.62
2	33.20	82.23	32.599	88.05	32.49	77.71
3	35.38	84.56	39.15	111.72	35.03	85.42
Tot	93.6	235.97	98.96	277.56	92.70	224.77

Table VII Total energy curtailed and total incentive received(Case2)

No	PSO		JAYA		HBA	
j	saving (MWh)	Incentive ($)	saving (MWh	Incentive ($)	saving (MWh)	Incentive ($)
1	179.24	8961.90	179.9	8994.90	179.92	8683.9
2	229.24	11461.8	226	11333.90	229.87	12300.5
3	307.52	15376.0	307.52	15439.70	309.34	13323.7
4	389.21	19460.70	389.21	19438.90	389.9	19328.05
5	439.55	21977.70	439.55	21888.80	439.97	20927.8
6	529.48	26474.10	529.48	26470.80	528.93	21882.8
7	599.94	29996.90	599.94	29964.40	598.57	29352.4
Total	2674.2	133709.0	2670.6	133531.3	2676.5	125799.2

Table VIII cost breakdown for the three optimization techniques (case study 1)

	PSO	JAYA	HBA
Total Conventional Power (KW)	421.7591	390.0616	429.557
Total Conventional Power Cost ($)	246.52	224.2431	254.1028
Total Transferred Power (KW)	-0.83	28.86	-3.36078
Total transferred power Cost ($)	-4.56305	140.2848	-18.4843
Total Customer Incentive ($)	235.439	282.9575	224.7758
Total Cost ($)	477.40	647.4854	460.3943

Table IX cost breakdown for the three optimization techniques (case study2)

	PSO	JAYA	HBA
Total Conventional Power (MW)	33257.42	30330.53	30032.43
Total Conventional Power Cost ($)	674639.9	665480	658960
Total Transferred Power (MW)	419	3229.667	3642.39
Total Transferred Power Cost ($)	3142.5	23899.536	26317.925
Total Customer Incentive ($)	133709.00	133531.30	125799.2
Total Cost ($)	812491.4	822910.84	811077.1

5. Conclusion

In this work, the energy management problem for grid-connected mode MG with DRP has been investigated. The main objective of this paper is to get the minimum conventional generation cost, minimize the transaction cost, and maximize the MG operator benefit. For an interval of 24h (one day), different optimization techniques (PSO, JAYA and HBA) have been applied to solve the energy management problem in MG to get an optimal operation at both sides, generation and demand side. Based on the results obtained by HBA showed best performance in reduction of operating cost, with a reduction in energy consumption about 93 KWh for the first case and 2676 MWh for the second case. The results for two case studies have been discussed for the three studied optimization techniques, which prove that the HBA gives the lowest total cost.

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