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# Solving Unit Commitment Problem for Microgrid Power Network Including Wind and Solar Sources Using Modified MVO Algorithm

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**Abstract:** The present paper represents an improved Multiverse Optimizer Algorithm (MVO) modified with Parallel Mirror based global learning opposition method to solve Unit Commitment problem in a Microgrid network including wind and solar sources. Unit Commitment (UC) is one of mathematical optimization problems that deal with the schedule of a given combination of generating units to achieve a minimum-cost production plan usually to satisfy the load demand. The mean objective of Unit Commitment problem is to achieve the optimal generation planning of the committed units while the overall generation cost is reduced, when subject to varying constraints at each time period. Hence, each (substantial) variation in the demand side must be matched by a corresponding amount of generation output. In fact, the minimum power generation scheduling is very difficult as UC problem encompasses a mix of variables as time varying unit constraints. The found results as the generation cost in the case without renewable sources (563977.0172$) show that the proposed method is capable to provide very competitive results and outperforms recent algorithms available in the literature which is above this result. The comparison shows clearly the effectiveness of the used technique.

**Keywords:** Unit commitment problem, MVO algorithm, Microgrid system, Startup cost, Renewable contribution.

## 1. Introduction

Power system utilities often encounter daily load patterns which present a significant variation between peak and off-peak hours corresponding to daily demand variation. The unit commitment problem is an important secure and economic option for system operator to meet the system energy demand at minimum fuel cost when subject to energy generation mix [1].

Generally, the problem facing the system operator is to determine which units should be on and the ones that should be off with their associated period. Several operating strategies or planning schedules are used to meet the demand changing through the time horizon. For this raison, it is necessary to use an optimum operating planning based on economic criteria to face this problem. The unit commitment (UC) problem deals with the on/off decisions and output power levels of generating units in a power system to achieve an appropriate scheduling of generation power output through the time horizon with the main objective of minimizing the total operating cost, while the economic dispatch issue (ED) aims to find the optimal operating point of the committed units. Thus, the (UC) problem is to decide which units will be online during the next period. Mathematically, the UC problem is expressed as a large scale, non-linear, mixed integer optimization problem [2].

In other words, unit commitment (UC) includes the computation of levels of generation relating to generating units and their commitment for a certain interval of time in the objective of minimizing the total generation cost [3].

Renewable sources are increasingly integrated in recent distributed generation systems regarding to their environmental as well as economic benefits, particularly in small size power systems or microgrid. Recent methods have been already used in the literature to deal with optimal generation planning.

In fact, several meta-heuristic techniques such as single or hybrid methods are used to deal with the unit commitment problem such as priority list (PL) [4], which is simple and fast but with not sufficient solution, dynamic programming (DP) [5] which is flexible but take more execution time, improved particle swarm method (IPSO) [6], more faster than the previous methods. A modified binary artificial bee colony (MBABC) [7], charged search system (CSS), (PSO) and ant colony search algorithm (ACS) artificial bee colony and cuckoo search algorithm (ABC-CSA) [8, 9] where CSS would not been affected by initial parameter setting as ant colony search, stochastic monte carlo optimization algorithm (SMCA) [10], intensify harris hawks optimizer (IHHO) [11], moth flame optimizer-based method (MFA) [12], particle swarm optimization (PSO) [13], parallel-series hybrid method (PSH) [14], ant colony optimization (ACO) [15, 16], binary moth-flame optimizer (BMFO) [17], hybrid PSO-GWO [18] and others that showed supported results in term of execution time and cost saving comparing with old methods that present a main drawback when subject to high dimensional power systems. These intelligent techniques attract more attention for researchers because of their ability to find a global optimal solution and can solve a variety of difficult nonlinear constraints problems. This paper proposes a new intelligent optimization technique called multiverse optimization MVO technique that has exhibited high efficiency across engineering and industry fields [19, 20] modified with new based learning opposition algorithm named parallel mirror technique PMT through application on a microgrid power system involving wind and solar power sources. Whereas the integration of these renewable sources is achieved by the insertion of a specified quantity of RES over the time horizon, in order to facilitate the computation. The MVO algorithm is an artificial intelligent optimization algorithm aims to mimic the creation of the universe from the first big-bang explosion that generating the universe and its different strange holes.

The rest of the paper is organized as follows; following the introduction, the unit commitment problem formulation is given in section two, then in section three a detail of the used algorithm is presented. Next, section four deals with the application case study and discussion of the found results and at last a conclusion is given in section five.

## 2. Unit commitment problem formulation

The first objective function of the unit commitment problem is the minimization of the total generating cost including the associated start-up and shut-down costs of the committed generator units and is expressedby: [21, 22].

$$F(U_i^t, P_i^t) = \sum_{i=1}^{T} \sum_{i=1}^{Ng} \left( C_i P_i^t + S_i^t (1 - U_i^{t-1}) \right) U_i^t \quad (1)$$

Where $C_i(P_i^t)$ represents the fuel cost of i[th] unit that supplies $P_i^t$ powerat time t, this cost is formulated using:

$$C_i(P_i^t) = \sum_{i=1}^{Ng} a_i (P_i^t)^2 + b_i P_i^t + c_i \ (\$) \quad (2)$$

The shut-down cost is usually ignored and assumed to be zero.

### 2.1 Power balance constraints

$$\begin{cases} \sum_{i=1}^{Ng} P_i^t U_i^t = P_d^t + R^t \\ P_d^t = P_{Dt}^t - P_{loss}^t - P_w^t - P_s^t \end{cases} \quad (3)$$

The unit commitment schedule is evaluated every hour only for the remaining ($N_g$-2) units to supply the new net demand Pd over time t.

### 2.2 Inequality constraints

Represent the outut power limits of generators unit, if an i[th] unit is commited, its generated output power must be bounded by the minimum and maximum limits, expressed by:

1-Generators limits:

$$P_{i,min} \leq P_i^t \leq P_{i,max} \quad (4)$$

2-Minimum generators on/off time constraints: which given by:

$$(U_i^{t-1} - U_i^t)(t_{i,(t-1)}^{on} - MU_i^t) \geq 0 \quad (5)$$

$$(U_i^t - U_i^{t-1})\left(t_{i,(t-1)}^{off} - MD_i^t\right) \geq 0 \quad (6)$$

where $t_{i,(t-1)}^{on}$ and $t_{i,(t-1)}^{off}$ are start-up and shut-downtimes of i[th] unit during the time (t-1) [23].

3-Start up/down time dependent constraints given by:

$$S_i^t = \begin{cases} HSC_i, & if\ TD_i \le T_{i,t}^{off} \le TD_i + T_{i,cold} \\ CSC_i, & if \qquad T_{i,t}^{off} > TD_i + T_{i,cold} \end{cases} \quad (7)$$

4-Ramp rate constraint: for i[th] unit during the timet and any increase or decrease in itsoutput power should not exceed the ramp rate bound,this given by:

$$\begin{cases} P_i^t - P_i^{t-1} \le RU_i \\ P_i^{t-1} - P_i^t \le RD_i \end{cases} \quad (8)$$

5-Minimum up and down time: if a unit (i) is turned off, it shouldremain offline for a specific period of time before it can be turned on again. Similarly, if a unit (i) is turned on, it remains online for a specific period of time before it can be turned off again , this status is given by:

$$D_i^t = \begin{cases} 1, & if\ T_{i,t}^{on} < MU_i \\ 0, & if\ T_{i,t}^{off} < MD_i \end{cases}, \quad \forall\, i, t \quad (9)$$

In this study, in order to calculate the cost of solar and wind, we used levelized cost of electricity (LCOE). The global average specifiedcost of solar energy is 0.09 $ per KWh and that of wind is 0.06 $ per KWh [43].

With the insertion of RES the objective function given by Eq. (1) which represent the total operating cost given above, is enhanced to become:

$$F(U_i^t, P_i^t) = \sum_{i=1}^{T} \sum_{i=1}^{Ng} \left( C_i P_i^t + S_i^t (1 - U_i^{t-1}) \right) U_i^t + 90 \times \sum_{t=1}^{T} P_s^t + 60 \times \sum_{t=1}^{T} P_w^t \quad (10)$$

Where; the numbers 90 and 60 represent the contribution amounts of wind and solar power sources in the mix of energy supply.

## 3. Proposed algorithm

### 3.1 MVO algorithm

The multiverse optimizer algorithm is an algorithm inspired by nature first found by Seyed-Ali Mirjalili [24], it is based on three notions of black hole, white hole and worm hole given in Fig. 1.

The white hole supposed to represent the original part of the universe as the first explosion which causes the birth of the universe, then the black hole attracting everything due to its enormous

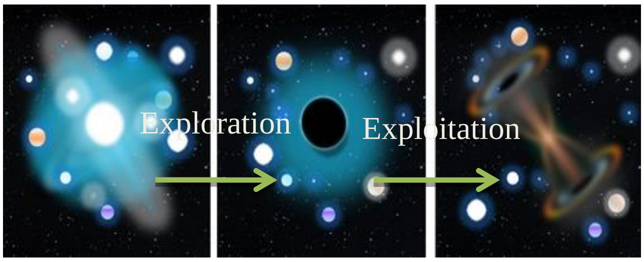

Figure. 1 The three concepts of MVO algorithm

force of gravity, therefore behaves completely unlike the first, the worm hole connects different parts of the universe together and acts like a time - space travel tunnel, where objects can easily travel between all sides of a universe. Each universe has an inflation rate, that causes its expansion through the space, and hence the inflation speed of a universe is very important to create the other universes, physical laws lead to a stable situation. These concepts are mathematically modeled to asses both exploitation and exploration, respectively [25]. Each solution is analogous to a universe and each variable of the solution is an object in this universe. Moreover we assign to each solution an inflation rate that corresponds to its fitness.

Rules of MVO algorithm:

The probability of having a white hole increases with the inflation rate.

The probability of having a black hole decreases when the inflation rate increases.

The universe that has increased inflation rate tends to send more objects through white holes.

The universe that has a lower inflation rate tends to receive more objects through black holes.

Objects from all universes can face random movement to create the best universe through wormhole universes

All these rules are showed in Fig. 2, different movements of objects between higher and lower inflation rate universes lead to improve the average

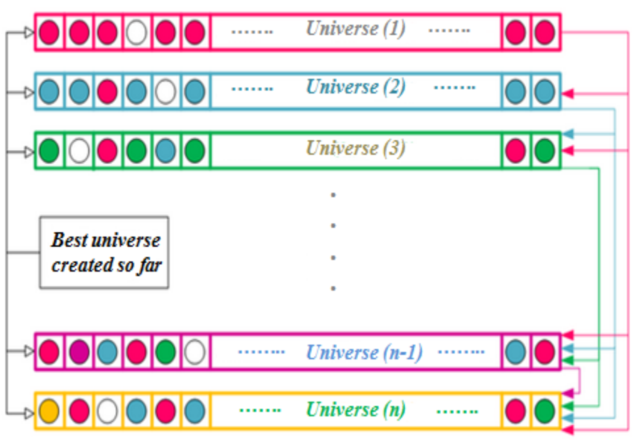

Figure. 2 Basic principal of MVO algorithm [24]

rate of inflation for the global universe over the iterations. At each moment, the universes are stored according to their inflation rates and one from them is selected as a white hole using the roulette wheel basic: [24]

The MVO algorithm is based on the set of following factors and rules:

1-number of runs, 2-number of universes as the candidate solutions, 3-roulette wheel principle, and 4-sorting mechanism.

$$U = \begin{bmatrix} x_1^1 x_1^2 \dots\dots\dots x_1^d \\ x_2^1 x_2^2 \dots\dots\dots x_2^d \\ \dots\dots\dots\dots\dots\dots\dots\dots \\ x_n^1 x_n^2 \dots\dots\dots x_n^d \end{bmatrix} \tag{11}$$

Where (d) represents the number of state variables and, (n) denotes the total number of solution candidates.

$$x_i^j = \begin{cases} x_i^j \quad r1 < NI(U_i) \\ x_k^j r1 < NI(U_i) \end{cases} \tag{12}$$

Where $x_{ij}$ represents the $i^{th}$ variable of the $i^{th}$ universe. $U_i$ is the $i^{th}$ universe, NI ($U_i$), is the normalized inflation rate of the $i^{th}$, universe, r1 is a random number in the range [0, 1], and $x_{kj}$, represents the $j^{th}$ variable of $k^{th}$ universe chosen by using the roulette wheel principle.

Updating the universe positions and giving the possibility of improving the inflation rate through the movement of worm holes. These particular worm hole tunnels are still established between the real universe and the best universe found so far and this can be described as:

$$x_i^j = \begin{cases} X_j + XTDR \times \begin{pmatrix} (ub_j - lb_j) \times r4 + lb_j \\ , r3 < 0.5 \;\; r2 < WEP \end{pmatrix} \\ \\ X_j - XTDR \times \begin{pmatrix} (ub_j - lb_j) \times r4 + lb_j \\ , r3 \geq 0.5 \;\; r2 < WEP \end{pmatrix} \\ x_i, \qquad\qquad\qquad\qquad r2 \geq WEP \end{cases} \tag{13}$$

where, $X_j$ represents $j^{th}$ variable of the fittest universe created until now, $Lb_j$, $Ub_j$ indicate the lower/upper bounds of $j^{th}$ variable of the $i^{th}$ universe and r1,…,r4 are random numbers in [0, 1]. The wormhole existence probability (WEP) and the ratio of distance traveled as chief coefficients defined as follows:

$$WEP = Min + t \times ((Max - Min)/t_{Max}) \tag{14}$$

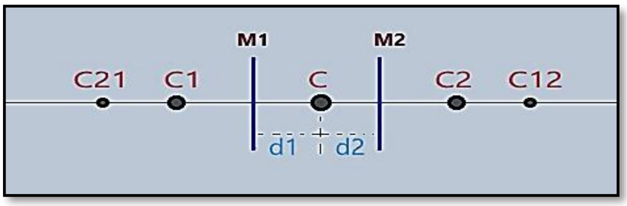


Figure. 3 Parallel mirror technique [44]

$$TDR = 1 - \left(l^{1/p} / L^{1/p}\right) \tag{15}$$

Where: t denotes the actual run, $t_{Max}$ is the maximum number of iterations, min denotes the minimum, max is the maximum, ($l$) indicates the current iteration, ($L$) is the maximum iterations number, ($p$) is the exploitation accuracy over iterations.

### 3.2 Parallel mirror technique

Parallel mirror technique is as a new opposition based learning method for improving the performance of existing met heuristics [43]. In PMT mechanism a candidate solution is positioned between two parallel mirrors as mentioned in Fig. 3. After the generation of the first images each image produces constantly another image into the opposite mirror by previous image, which lead to an infinite number of similar images in the virtual space. These images become new candidate solutions. The PMT permits the distribution of candidates through the searching space; this raises the probability of reaching the global optimum solution and avoiding local minima stagnation. In contrast to general opposition based learning techniques, the PMT uses more likelihood to explore enough in different opposite directions and generate more candidate solutions.

The parallel mirrors basic is given in Fig. 3 that shows the candidate solution bounded by two mirrors (M1, M2) and the distance c from each mirror to the candidate solution equals (d1, d2).

Primarily, the first image c1 is produced by mirror M1 from the initial value c, at the same time another image c2 is produced from the initial value c by M2 (c1, c2) and in turn will produce more new images in the virtual space.

Therefore, each image among the new produced images in opposite mirrors c12 and c21, respectively. Then each value of these created images (c12, c21) will generate an account less number of images into these two mirrors.

The c value is bounded with upper and lower limits in the search space.

The location of the mirrors M1 and M2 are defined using the following expressions:

Input: the population $X = \{X_1, X_2 .. X_n\}$
Output: $X_{Best}$ and the updated population $X' = \{X'_1, X'_2 .. X'_n\}$
**begin**
Set MI the maximum number of created images
Set MF the maximum failure images
Set initial $S_{best} = f(X)$
Set initial $X_{best} = 0$
Set initial mirror $d_1 = random()$
Set initial mirror $d_2 = random()$
**for** i=0; $i < MI$;
$X_i = generateImage(X)$
**if** $f(X_i) < f(X_{best}) then$
$S_{best} = f(X_i)$
$X_{best} = X_i$
**Else**
$Updated\ d_1 = random()$
$Updated\ d_2 = random()$
$MF = MF - 1$
**end If**
**iF MF==0**
Break //Stop the loop
EndIF
**end for**
Return the best population, $X$ and the best result

Figure. 4 Pseudo code for PMT [45]

$$position(M_1) = c - d_1;\ d_1 > 0 \quad (16)$$

$$position(M_2) = c - d_2;\ d_2 > 0 \quad (17)$$

Assuming the current candidate value as c0, then the next produced image c1, c2 …ci, is given by:

$$c_i = c_{i-1} \mp 2(i \times d_1 + (i-1)d_2) \quad (18)$$

Two stopping criteria are used in PMT to limit the number of images generation ; the maximum number of images (MI) and the maximum number of failure images (MF).

The MI is the maximum number of images that can be produced for each candidate and the MF is the maximum number of failure images (i.e., failed to reach a better solution).The procedure of applying PMT is shown as pseudo-code in Fig. 4.

### 3.3 PMT-MVO

As many other meta-heuristic algorithms, MVO suffers from a low convergence rate and local minima stagnation. Hence, engaging the PMT to improve MVO algorithm should give a chance for the MVO to overcome some of its weaknesses. The modified PMT-MVO algorithm pseudo-code is shown in Fig. 5.

Initialize random universes (U)
Set MI the maximum number of generated images
Set MF the maximum number of failed images
Initialize WER, TDR
Set initial Best universe inflation rate $S_{best}=f(U)$
Set initial Best universe $U_{best}=U_0$
SU=sorted universes
NI=Normalize the inflation rate (fitness) of universes
**while** the end criterion is not satisfied
Update WEP and TDR
**for** each universe indexed by i
**if** $f(U_i) < f(S_{best})$then
$S_{best} = f(U_i)$
$U_{best} = U_i$
**end if**
Black hole index=i;
Apply PMT steps as in fig. 2.
Update $U_{best}$
**end for**
**for** each object indexed by j
$r_1 = random([0, 1]);$
Update universes using equation (2)
$r_2 = random([0, 1])$
**if r2**< Wormhole existence probability
$r_3 = random([0, 1]);$
$r_4 = random([0, 1]);$
Update universes using equation (3)
**end if**
**end for**
**end while**

Figure. 5 PMT-MVO pseudo-cod

## 4. Results and discussion

The present study was performed on a practical microgrid system by solving the problem of unit commitment with and without renewable energy sources (RES).

In this section, simulations were performed using MATLAB version 2017a software; two case studies are investigated in this paper:

### 4.1 Case study 1

Without renewable energy sources:

In this case the UC problem was solved for 10 thermal generating units without any renewable energy source. The generating system data is taken

Table 1. UC schedule and generator output obtained for 10 generating units

| Hour | Load | Scheduled power output at each hour (MW) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | G9 | G10 |
| 1 | 700 | 455 | 245 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 750 | 455 | 295 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 850 | 455 | 370 | 0 | 0 | 25 | 0 | 0 | 0 | 0 | 0 |
| 4 | 950 | 455 | 455 | 0 | 0 | 39.9 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1000 | 455 | 390 | 0 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 6 | 1100 | 455 | 360.0 | 129.9 | 129.9 | 25 | 0 | 0 | 0 | 0 | 0 |
| 7 | 1150 | 455 | 410.0 | 129.9 | 129.9 | 25.0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 1200 | 455 | 454.9 | 129.9 | 129.9 | 30.0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 1300 | 455 | 455 | 130 | 130 | 85 | 20 | 25 | 0 | 0 | 0 |
| 10 | 1400 | 455 | 455 | 130 | 130 | 162 | 32.9 | 25 | 10 | 0 | 0 |
| 11 | 1450 | 455 | 455 | 130 | 130 | 162 | 73.0 | 25 | 10 | 10 | 0 |
| 12 | 1500 | 455 | 454.9 | 130 | 130 | 162 | 79.9 | 25 | 42.9 | 10 | 10 |
| 13 | 1400 | 455 | 455 | 130 | 130 | 162 | 32.9 | 25 | 10 | 0 | 0 |
| 14 | 1300 | 455 | 455 | 130 | 130 | 85 | 20 | 25 | 0 | 0 | 0 |
| 15 | 1200 | 455 | 454.9 | 129.9 | 129.9 | 30.0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 1050 | 455 | 310 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 17 | 1000 | 455 | 260 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 18 | 1100 | 455 | 360.0 | 129.9 | 129.9 | 25 | 0 | 0 | 0 | 0 | 0 |
| 19 | 1200 | 455 | 454.9 | 129.9 | 129.9 | 30.0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 1400 | 455 | 455 | 130 | 130 | 162 | 32.9 | 25 | 10 | 0 | 0 |
| 21 | 1300 | 455 | 455 | 130 | 130 | 85 | 20 | 25 | 0 | 0 | 0 |
| 22 | 1100 | 455 | 455 | 0 | 0 | 144.9 | 20.0 | 25 | 0 | 0 | 0 |
| 23 | 900 | 455 | 420 | 0 | 0 | 25.0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 800 | 455 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| start-up cost : **4070**$ | | Total Operating Cost : **563977.0172**$ | | | | | | | | | |

from ref [38]. The PMT-MVO algorithm was run for 500 iterations with a population size of 40. The generation hourly outputs as well as the total fuel cost are given in Table 1. Table 2 shows a comparison of total fuel cost through 24-hours period obtained by comparing PMT-MVO with the available methods in literature. As seen from these results, the total cost found by using Hybrid (PSO-GWO) in 18 was 56,5210 $, and the one found by using binary moth-flame optimizer (BMFO) in 17 was 564,809.9875 $ which mean the found total cost found by the used method that is 563977.0172 $ is better compared with them.

### 4.2 Case study 2

Micro grid with renewable DG sources.

This work is held on an islanded microgrid using wind farms and photovoltaic (PV) system an available RES for the minimization of the total fuel and emission costs, increase the efficiency and maintain an uninterrupted power supply.

UC problem for case 1 gives a startup cost of 4070 $ and operating cost of 563977.01 $. The operating cost achieved with PMT-MVO is considerably reduced as compared to that obtained by available algorithms. In this case study the UC problem was solved for 10 thermal generating units in presence of solar and wind renewable energy sources. The generating system data is adopted from [36].

The solar plant of 40 MW for which data is taken form [41] and 30MW wind farm as in [41] are considered. The PMT-MVO algorithm was run for 500 iterations with a population size of 40.

The thermal generator hourly output along with fuel cost is depicted in Table 3.

From, Table 3 of UC problem for case II, we can observe an increase in generators start-up cost. The renewable energy sources reduce the dependency on thermal generators and share the overall load demand to be supplied by others available sources. This can significantly reduce the emission level of thermal generators as an environmental benefit.

The operating cost of thermal generator reduces by 1.84 % (from 563977.01 $ to 553591.22 $) with inclusion of renewable energy sources. This reduction can further increase by increasing penetration level of renewable sources. The global

Table 2. Comparison with other algorithms in literature

| Method | Cost ($) |
|---|---|
| LSGA [26] | 609,023.69 |
| IBPSO [27] | 599,782 |
| PSO [29] | 581,450 |
| MPSO [30] | 574,905 |
| HPSO [31] | 574,153 |
| LCA–PSO [32] | 570,006 |
| TSGA [32] | 568,315 |
| PSO-SQP [34] | 568,032 |
| BCGA [25] | 567,367 |
| SM [35] | 566,686 |
| LR [35] | 566,107 |
| GA [35] | 565,866 |
| GA [36] | 565,852 |
| ESA [37] | 565,828 |
| LR [36] | 565,825 |
| DP [36] | 565,825 |
| IDP [38] | 565,823.23 |
| LRPSO [38] | 565,275.2 |
| NPSO [39] | 565,213.00 |
| Hybrid PSO–GWO [18] | 565,210.2564 |
| BMFO [17] | 564,809.98 |
| PMT_MVO [proposed] | 563,977.0172 |

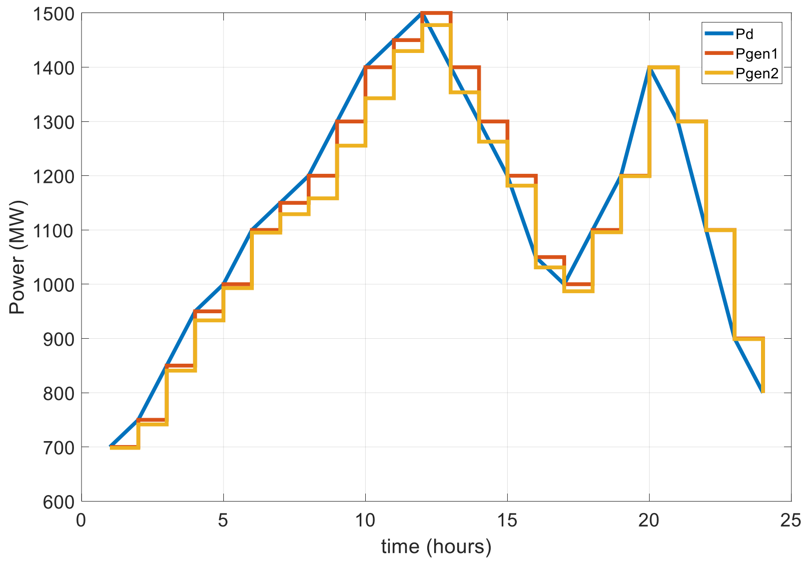


Figure. 4 Load demand, generating power with and without solar and wind

discounted average cost of wind and solar energy has also been calculated and given in Table 3.

Regarding to the found results with and without renewable power integration, we conclude an enhancement in the total generation cost by using PMT-MVO technique. Fig. 4 shows load demand as well as generating power production without wind and solar (curve in colour red) and with wind and solar (curve in golden colour), where it is evident

Table 3. UC schedule and generator output obtained for 10 generating units with solar and wind sources

| Hour | Load | PV (MW) | Wind (MW) | Optimized Power output at each hour (MW) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | G9 | G10 |
| 1 | 700 | 0 | 1.7 | 455 | 243.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 750 | 0 | 8.5 | 455 | 286.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 850 | 0 | 9.27 | 455 | 360.73 | 0 | 0 | 25 | 0 | 0 | 0 | 0 | 0 |
| 4 | 950 | 0 | 16.66 | 455 | 453.34 | 0 | 0 | 25 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1000 | 0 | 7.22 | 455 | 382.78 | 130 | 0 | 25 | 0 | 0 | 0 | 0 | 0 |
| 6 | 1100 | 0.03 | 4.91 | 455 | 355.06 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 7 | 1150 | 6.27 | 14.66 | 455 | 389.07 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 8 | 1200 | 16.18 | 25.56 | 455 | 418.26 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 9 | 1300 | 24.05 | 20.58 | 455 | 455 | 130 | 130 | 65.37 | 20 | 0 | 0 | 0 | 0 |
| 10 | 1400 | 39.37 | 17.85 | 455 | 455 | 130 | 130 | 127.78 | 20 | 25 | 0 | 0 | 0 |
| 11 | 1450 | 7.41 | 12.8 | 455 | 455 | 130 | 130 | 162 | 52.79 | 25 | 10 | 10 | 0 |
| 12 | 1500 | 3.65 | 18.65 | 455 | 455 | 130 | 130 | 162 | 80 | 25 | 20.7 | 10 | 10 |
| 13 | 1400 | 31.94 | 14.35 | 455 | 455 | 130 | 130 | 138.71 | 20 | 25 | 0 | 0 | 0 |
| 14 | 1300 | 26.81 | 10.35 | 455 | 455 | 130 | 130 | 72.84 | 20 | 0 | 0 | 0 | 0 |
| 15 | 1200 | 10.08 | 8.26 | 455 | 441.66 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 16 | 1050 | 5.3 | 13.71 | 455 | 290.99 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 17 | 1000 | 9.57 | 3.44 | 455 | 246.99 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 18 | 1100 | 2.31 | 1.87 | 455 | 355.82 | 130 | 130 | 25 | 0 | 0 | 0 | 0 | 0 |
| 19 | 1200 | 0 | 0.75 | 455 | 455 | 130 | 130 | 29.25 | 0 | 0 | 0 | 0 | 0 |
| 20 | 1400 | 0 | 0.17 | 455 | 455 | 130 | 130 | 162 | 32.83 | 25 | 10 | 0 | 0 |
| 21 | 1300 | 0 | 0.15 | 455 | 455 | 130 | 130 | 84.85 | 20 | 25 | 0 | 0 | 0 |
| 22 | 1100 | 0 | 0.31 | 455 | 455 | 0 | 0 | 144.69 | 20 | 25 | 0 | 0 | 0 |
| 23 | 900 | 0 | 1.07 | 455 | 418.93 | 0 | 0 | 25 | 0 | 0 | 0 | 0 | 0 |
| 24 | 800 | 0 | 0.58 | 455 | 344.42 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Cost of Wind power ( $) | | **12802.20** | Thermal generating startup cost ($) | | | **5340** | | Overall Cost of Microgrid (thermal +renewable energy) ($) | | | **582860.726$** | | |
| Cost of Solar power ( $) | | **16467.30** | Total generating cost of thermal generators ($) | | | **553,591.2262** | | | | | | | |

that the insertion of these sources enhance more the total generation and associated economic saving.

## 5. Conclusion

The UC and ED problems are chosen to decide when and which generator unit among the existing generation mix commit to be online and decommit to be offline. For the first problem the economic dispatch problem the paper proposes a new multiverse optimizer algorithm for in order to supply economic power to customers. The MVO algorithms modified with parallel mirror based opposition learning technique as a second solution for solving the problem of unit commitment (UC). The proposed technique is tested on a microgrid network with and without renewable energy resources. This study showed that, the integration of renewable energy resources impacts the startup and fuel cost of generators unit for UC problem. The results obtained by applying this strategy are finally compared with other algorithms found in the literature and depict the superiority of the proposed modified MVO in solving UC problem either in small micro power grid as well as in large scale power grid.

### Nomenclatures

$i$ Generator unit index, $i \in [1,...N]$

$t$ Time period index, $t \in [1,...T]$

$Ng$ Total number of generator units.

$T$ Total number of hours.

$F$ Total generation cost over the time horizon

$C_i^t$ Generation cost of i[th] unit($).

$U_i^t$ Status of i[th] unitat time t [0,1].

$U_{SU,i}^t$ Status of startup decision variable i[th] unit at time t

$U_{SD,i}^t$ Status of shutdown decision variable of i[th] unitat time t

$CSC_i$ Cold startup cost of i[th] unit ($)

$HSC_i$ Hot Startup Cost of i^th unit($)

$P_i^{\min}, P_i^{\max}$ Minimum and maximum real power of i^th unit(MW)

$a_i, b_i, c_i$ Coefficients of generating cost of generators.

$P_i^t$ Real power output of unit i at time t (MW)

$P_d^t$ Load demand at time t (MW)

$R^t$ Spinning reserve at time t (MW)

$SD_i^t$ Shut-down cost of i^th unitat time t ($)

$S_i^t$ Start-up cost of i^th unitat time t ($)

$MD_i$ Minimum time down of unit i (h)

$MU_i$ Maximum up time of unit i (h)

$T_i^{cold}$ Cold start time of i^th unit (h)

$T_i^{ON}$ Period during which unit i should kept "on"

$T_i^{OFF}$ Period during which i^th unit should kept "off"

$UR_i$ Ramp-up rate limit of i^th unit

$RD_i$ Ramp-down rate limit of i^th unit

$P_w^t$ Wind power generation at time t (MW)

$P_s^t$ Solar power output at time t (MW)

## Conflicts of interest

The authors declare no conflict of interest.

## Author contributions

The paper concepts and algorithm implementation, experimentation, validation, formal analysis, paper research, and original draft preparation of writing were developed by the first and third authors.

The project was supervised and managed by the second author.

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