Optimal Robust Unit Commitment of Microgrid using Hybrid Particle Swarm Optimization with Sine Cosine Acceleration Coefficients

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Abstract- This paper introduces a Hybrid Particle Swarm Optimization with Sine Cosine Acceleration Coefficients (H-PSO-SCAC) for solving the Unit Commitment (UC) problem of grid connected Microgrid (MG). The optimal set point of MG's generation units is determined for a Day Ahead (DA) power market to supply the required demand. The studied MG consists of one Wind Turbine (WT) generator, one Photovoltaic (PV) panel and three Diesel Generators (DGs). The new algorithm is employed to minimize the fuel cost of DGs and the transaction costs of transferable power trade whilst taking into consideration load balance constraint and MG's generation units constraints. The performance of the new H-PSO-SCAC is examined by comparing with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The effectiveness of these methods is analyzed by using different criteria of the objective function. MATLAB environment is used to code H-PSO-SCAC, PSO, GA, and the system under study. The simulation results prove the robustness of the proposed method and approve its potential to get closer to the global optimum solution.

Keywords Hybrid particle swarm optimization with sine cosine acceleration coefficients, energy management system, unit commitment, microgrid, renewable energy.

1. Introduction

A Microgrid (MG) might be simply defined as : ''a distribution network that incorporates a variety of possible distributed energy resource that can be optimized and aggregated into single system that can balance loads and generation with or without energy storage and is capable of islanding whether connected or not connected to a traditional utility power grid." [1]. Therefore, a MG is an electrical network having local generation sources, located in the downstream of the grid through a point of common coupling. A MG can operate in two modes, Grid-Connected (GC) mode means that a MG is linked to the distribution grid, and can participate in the energy market by exchanging energy with the utility as buyer or seller. However, in Standalone (SA) mode, a MG operates as an autonomous component, which is disconnected from the grid, for different causes like brownout, geography position or economic issues.

An Energy Management System (EMS) has been defined as « a collection of control strategies and operational practices, together with the hardware and software to accomplish the objectives of energy management» [2]. Therefore, an EMS can optimally allocate the power output of the generating units, economically supply the Load Demand (LD), properly regulate the voltage and frequency of the MG systems, and automatically provide a smooth transition between GC operation mode and SA mode, according to real-time operating conditions and MG components. Boqtob et al. [3] have given a state of the art of MG-EMS based on recent works, discussing the used MG generation units and storage devices, the integration of electric vehicles and combined heat and power systems, and the Objective Functions (OFs) and constraints of MG-EMS as well as the applied optimization algorithms.

Unit Commitment (UC) is an important optimization problem applied in electric power systems. The UC is one of EMS solution based on Day Ahead (DA) scheduling of 24-h energy production and LD forecasting which aims to find the most cost-effective dispatch of production units while taking in consideration the satisfaction of LD and several equality and inequality constraints [4].

Given the attention of the UC problem, several studies have been made to resolve it using different techniques, deterministic and probabilistic.

Deterministic Methods (DMs) take advantage of the problem's analytical characteristics to make converge a set of points to the global optimal solution [5]. In literature, DMs are used to resolve a MG optimization problems by linear programming [6,7], mixed integer programming [8], mixed integer linear programming [9,10], and Non-Linear Programming (NLP) [11]. DMs are used for smooth and continuous OFs. Therefore, the Fuel Costs (FCs) make the UC problem discontinuous, this is a complication that DMs find difficult to deal with.

Probabilistic and Metaheuristic Methods (MMs) are widely used by dint of their ability to deal easily with these difficulties in the UC problem. MMs have stochastic elements in the data and the resultant solution is dependent on the set of random generated variables [12].

Swarm Intelligence (SI) techniques are one of MMs known also as nature-inspired methods inspired by the behaviour of agents like that of ant colonies, animal herding, bird flocking, bacterial growth, microbial intelligence, and fish schooling. In these methods, the agents belonging to the population interact locally with each other and their environment to attain the optimal solution.

Several SI algorithms have been studied and applied to resolve the MG optimization concepts, such as a Particle Swarm Optimization (PSO) [13], Genetic Algorithm (GA) [14, 15], Bat Algorithm (BA) [16], Cuckoo Search Algorithm (CSA) [17], Artificial Bee Colony Algorithm (ABC) [18], Whale Optimization Algorithm (WOA) [19] and Ant Lion Algorithm (ALA) [20].

Most of these algorithms have the drawback of premature convergence during the iteration process and so falling in a local optimal solution without the capacity to explore more areas of the search space. To circumvent this problem, improved SI algorithms have been proposed to resolve the UC problem and determine the optimal EMS of MG. To develop the performance of Fireworks Algorithm (FA), Wang et al. [21] have proposed a hybrid multi-objective based FA and Gravitational Search Operator (GSO) to resolve the multi-variable NLP problem subjected to multiple constraints. The proposed method used GSO to direct the sparks into the clustered region for exchanging location information with Pareto- optimal solutions at each generation process to reach the best results.

Advanced MMs have used chaotic sequences instead of random numbers to enhance their performance. Adarsh et al. [22] have applied the chaotic BA to optimize the economic dispatch of the used system. The proposed method incorporated chaotic sequences based sinusoidal sequence in the basic BA to improve its performance for reaching the global optimal result. Marzband et al. [23] have proposed a new Multi-Layer Ant Colony Optimization (MACO) for real time introduction of MG-EMS in SA mode. The MACO is developed from the basic ACO equalling the number of layers to the number of design variables and the number of nodes in each particular layer to the number of allowable values of each variable. Roy et al. [24] have proposed an Improved Artificial Bee Colony algorithm (IABC) to optimize a hybrid MG in GC operation mode. The author has improved the basic ABC by using the GSO to generate the scout bee and to upgrade searching accuracy, and hence improving the global optimal solution of the optimization problem. Naghdi et al. [25] have used Improved Bee Algorithm (IBA) to optimize the penetration level of Renewable Generators (RGs) in distribution networks. IBA differs from the ABC by the introduction of the elite bee location in the patch size of the next iteration, to increase the search accuracy in high dimensional problems and accelerate the IBA convergence.

In this paper, a new hybrid algorithm based on PSO is tested. Given that, the PSO is one of the most popular SI methods that has been widely applied to resolve complex optimization problems due to its implementation simplicity, fast convergence and high efficiency. Although, PSO is trapped easily in local optimum position due to its premature convergence. Therefore, the PSO finds difficult to balance exploration and exploitation.

To overcome these disadvantages, this paper presents the application of a new SI algorithm known as Hybrid PSO with Sine Cosine Acceleration Coefficients (H-PSO-SCAC) to the UC problem. A DA scheduling of a rural GC-MG has been resolved by the H-PSO-SCAC, and compared with other MMs to demonstrate its performance. The studied MG includes one Wind Turbine (WT), one Photovoltaic (PV) and three Diesel Generators (DGs). The H-PSO-SCAC has the ability to avoid premature convergence and shows promising results.

The rest of the paper is organized as follows. Section 2 describes UC problem formulation, Section 3 introduces the background of the PSO, Section 4 introduces the H-PSO-SCAC and Section 5 presents the methodology and simulation results, and Section 6 concludes the paper and gives an overview of the next work.

2. Unit Commitment Problem Formulation

In this paper, the MG consists of a hybrid energy system with PV panels, WT and DGs.

2.1. Photovoltaic Generator

All illustrations must be supplied at the correct resolution:

In a simple model, the hourly energy output of PV panels can be determined by Eq.(1) [26]:

$$E_{PV} = I_{PV} A_{PV} \eta_{PV} \tag{1}$$

Where I_{PV} is the hourly solar irradiation incident on the PV panels, A_{PV} is the PV panels area and η_{PV} is the PV panels efficiency.

2.2. Wind Turbine Generator

The hourly energy output of WT is mainly depended on the Wind Speed (WS) at the hub height, and can be mathematically described by Eq.(2) [26]:

$$E_{WT} = 0.5 \eta_{WT} \rho_{air} C_P A V^3 \tag{2}$$

Where η_{WT} is the WT's efficiency, ρ_{air} is the air density, C_P is the power coefficient of WT, A is swept area of WT rotor, V is The hourly WS at hub height, and it is modelled by Eq.(3) [27]:

$$V = V_{ref} \times (\frac{h_{hub}}{h_{ref}})^{\alpha} \tag{3}$$

Where V_{ref} is the hourly WS measured at the reference height h_{ref}, h_{hub} is the hub height and α is the power law exponent $\alpha \in \left[\frac{1}{7}, \frac{1}{4}\right]$.

2.3. Main Grid

The MG is assumed to operate in GC mode and a trading scheme is allowed between the MG and the grid. Therefore, the power can be sold or transferred to the MG from the grid and vice versa. The grid is used to cater the shortage of the RGs. If the MG generation units cannot satisfy the LD, then the MG has to purchase the power from the grid. Moreover, if the MG generation units exceed the LD, then the MG can sell the excess power to the grid.

2.4. Objective Function

From the selected MG energy sources, the production of PV and WT depend on the environmental conditions and generate energy with free cost. Therefore, the OF in this paper is minimizing the FC of DGs and the transaction costs of transferable power trade, and is described by Eq.(4) [28]:

$$\min \sum_{t=1}^{T} C_g(P_g(t)) + \sum_{t=1}^{T} \sum_{i=1}^{n} C_i(P_i(t)) \tag{4}$$

Where T is the horizon time, n is the total number of DGs, $C_g(P_g(t))$ is the transaction cost to trade transferable power $P_g(t)$ at t time and $C_i(P_i(t))$ is the FC of DG(i).

The transaction cost to trade transferable power can be modelled by Eq.(5):

$$C_g(P_g(t)) = \begin{cases} \gamma_g \times P_g(t) & P_g(t) \quad 0 \\ 0 & P_g(t) = 0 \\ -\gamma_g \times P_g(t) & P_g(t) \quad 0 \end{cases} \tag{5}$$

Where γ_g is the price to purchase power between the MG and the grid.

The fuel cost of DG can be modelled by a quadratic function of generator power output and is described by Eq.(6) [28]:

$$C_i(P_i(t)) = a_i P_i^2(t) + b_i P_i(t) \tag{6}$$

Where a_i and b_i are cost coefficients of DG(i), $P_i(t)$ is the power output of DG(i) at t time.

2.5. Problem Constraints

2.5.1. Power Flow Balance

The power generated from MG generation units should be equal to LD at time t as in Eq.(7):

$$\sum_{i=1}^{n} P_i(t) + P_w(t) + P_{PV}(t) + P_g(t) = P_{load}(t) \tag{7}$$

Where $P_i(t)$ is the power output of DG(i) at t time, $P_w(t)$ is the power generated by WT at time t, $P_{PV}(t)$ is the power generated by PV at time t, $P_g(t)$ is the transferable power between the MG and the grid at time t, and $P_{load}(t)$ is the power of LD at time t.

2.5.2. Renewable Generation Limits

The power generated by PV and WT at time t should be maintained within the minimum and maximum power limits as in Eq.(8) and Eq.(9) [29]:

$$P_{PV,\min} \le P_{PV}(t) \le P_{PV,\max} \tag{8}$$

$$P_{W,\min} \le P_W(t) \le P_{W,\max} \tag{9}$$

Where $P_{PV,\min}$ and $P_{PV,\max}$ are the minimum and maximum power limits generated by PV panels, respectively.

$P_{W,\min}$ and $P_{W,\max}$ are the minimum and maximum power limits generated by WT, respectively.

2.5.3. Diesel Generator Limits

The power generated by DG in period t should be maintained within minimum and maximum power limits as in Eq.(10) [28]:

$$P_{i,\min} \le P_i(t) \le P_{i,\max} \tag{10}$$

Where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum power limits generated by DG(i), respectively.

The power generated by DG is also limited by the physical constraints of starting up and shutting down, which are represented by ramp rate limits, and modelled by Eq.(11) [28]:

$$-DR_i \leq P_i(t+1) - P_i(t) \leq UR_i \tag{11}$$

Where DR_i and UR_i are the down-ramp and the up ramp limits of the DG(i), respectively.

3. The Backgrounds Of Particle Swarm Optimization Algorithm

The Particle Swarm Optimization (PSO) is nature inspired intelligence algorithm originally proposed by Kennedy and Eberhart in 1995 [30], inspired by social behaviour of the particles in schools of fishes or flocks of birds. A group of individuals are initially searching food in the search space in a random manner, and then look to follow the particle that is nearest to the food. In the PSO, each particle has a fitness value that is computed by the fitness function to be optimized, and has a velocity that direct the move of the particle. Based on the social behaviour of the particle described above, the PSO updates the particle position and velocity in every iteration as described by Eq.(12) and Eq.(13) [31] :

$$\begin{aligned} V^i(t+1) &= w \times V^i(t) + C_1 \times r_1 \times (pbest^i(t) - X^i(t)) \\ &+ C_2 \times r_2 \times (gbest(t) - X^i(t)) \end{aligned} \tag{12}$$

$$X^i(t+1) = X^i(t) + V^i(t+1) \tag{13}$$

Where w is the inertia weight, $r_1, r_2 \in [0,1]$ are two uniform distributed numbers, $C_1 = C_2 = 2$ are the acceleration parameters, $gbest$ is the global best position discovered by the full population, and $pbest^i$ is the personal best position of the particle(i).

The PSO updates the pbest and gbest as in Eq.(14) and Eq.(15) :

$$pbest^i(t) = X^i(t) \text{ if } f(X^i(t)) \geq f(pbest^i(t-1)) \tag{14}$$

$$gbest(t) = pbest^i(t) \text{ if } f(pbest^i(t)) \geq f(gbest(t-1)) \tag{15}$$

4. The Hybrid PSO With Sine Cosine Acceleration Coefficients

In PSO process, acceleration parameters C_1 and C_2 are also called the cognitive and the social components, respectively. These parameters modify the particle velocity. Therefore, they are responsible for obtaining an accurate optimal solution.

For an efficient evolutionary algorithm, it is desired that the particles wander through the whole search space. Therefore, during the early stage of the algorithm process, the global search ability should be improved in the search space. Otherwise, during the latter stage of the algorithm process, the ability to converge towards global optima should be enhanced throughout the search space.

To balance the global search of early stage and the global convergence of latter stage, the use of sine cosine acceleration coefficients into the PSO is proposed [32]. The sine map of acceleration coefficients can improve the population diversity into the search process and enhance the convergence ability to the global optimal. The proposed method is H-PSO-SCAC. In this paper, the H-PSO-SCAC is used to resolve the proposed UC problem. The flowchart of the proposed H-PSO-SCAC algorithm for the UC problem is shown in Fig.1.

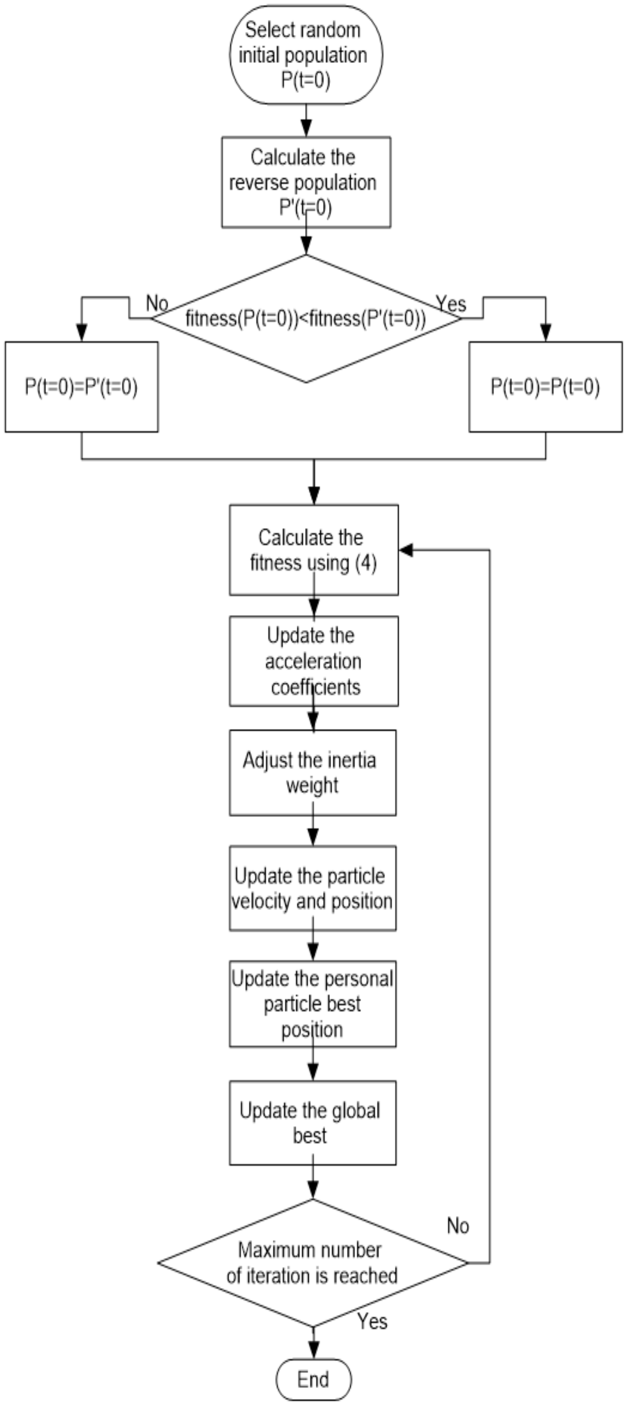


Fig. 1. Flowchart of H-PSO-SCAC algorithm.

5. Methodology And Simulation Results

5.1. Methodology

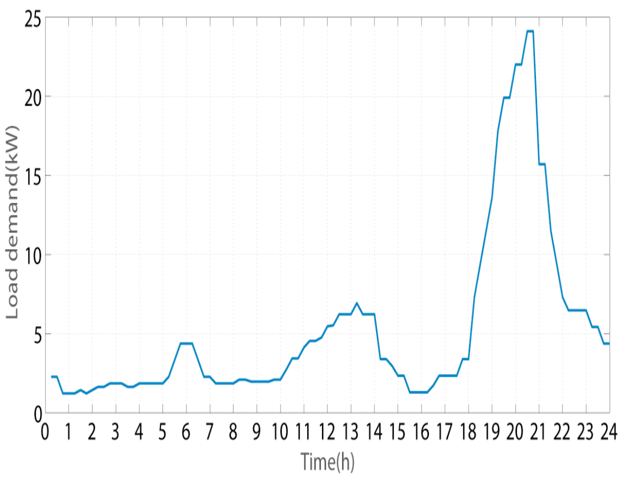
To validate the effectiveness of the H-PSO-SCAC to resolve a UC problem, a rural GC-MG is used with one WT, one PV solar and three DGs. Therefore, the decision variables are $P_w(t)$, $P_{PV}(t)$, $P_g(t)$ and $P_l(t)$. A DA is considered as a scheduling interval. Fig.2 shows the hourly LD. The LD has been ranged between 1 and 24 kW. The mean LD is 5 kW during the day. The LD required a higher power between 18h and 22h with a peak of 24 kW.

Fig.3 depicts the PV solar output power based on the solar radiation data for a site in Taza, Morocco (latitude 34,211°N) [33]. The PV solar has a maximum output power of 5 kW under the selected daily environmental conditions. The PV panel produces energy between 6h and 18h. Fig.4 gives the WT output power based on the WS data of Taza at 510 altitudes above sea level [33]. The WT has a maximum output power of 4,7kW. The WT generates energy between 10h and 18h. Values of the three DGs parameters are adapted from [28], including FC coefficients, power output limits and ramp rate limits, as shown in Table 1.

The UC problem optimization is carried out also by the GA and PSO for comparing the performance with that of the proposed H-PSO-SCAC. The number of particles (solutions) for all algorithms is assumed to be 50 and the maximum number of iterations is 100. A personal computer is used with a 2.59 GHz processor and 8 GB RAM, running on Windows 10, and the program is implemented into Matlab. The effectiveness of these methods is analyzed by using the Standard Deviation (SD), the Best Cost (BC), the max cost, and the Mean Cost (MC) of the OF [22], and the Cost Accuracy Percentage (CAP) [24], which can be calculated using Eq.(16):

$$CAP = \frac{(BC - WC)}{BC} * 100 \tag{16}$$

Where BC and WC are the best cost and worst cost respectively.



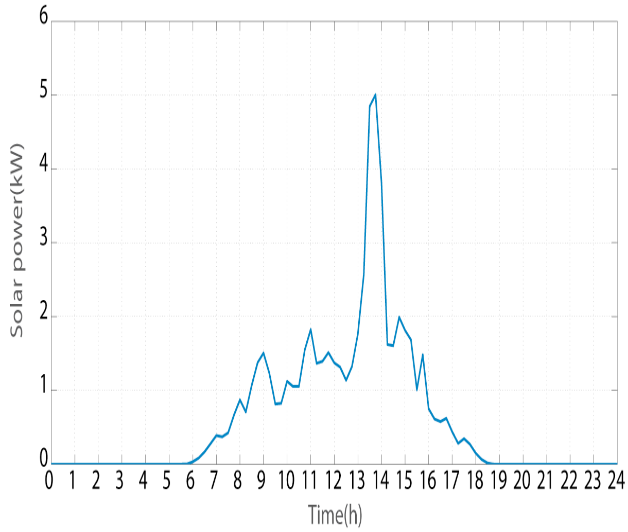
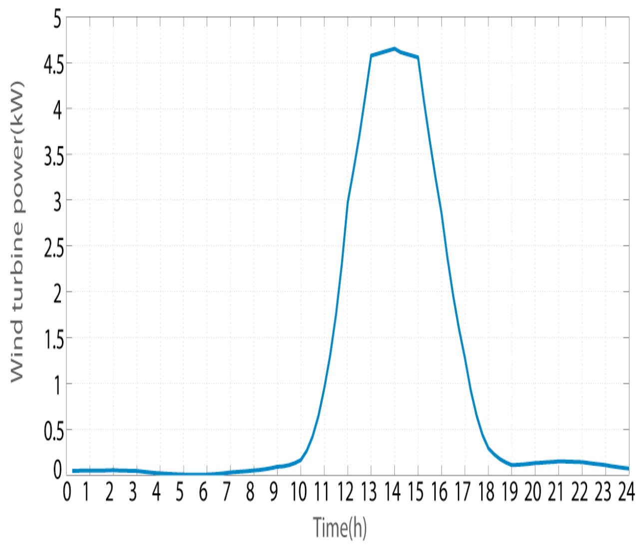


Fig. 2. Hourly load demand of a rural MG during a DA



time.

Fig. 3. Hourly PV output power during a DA time.

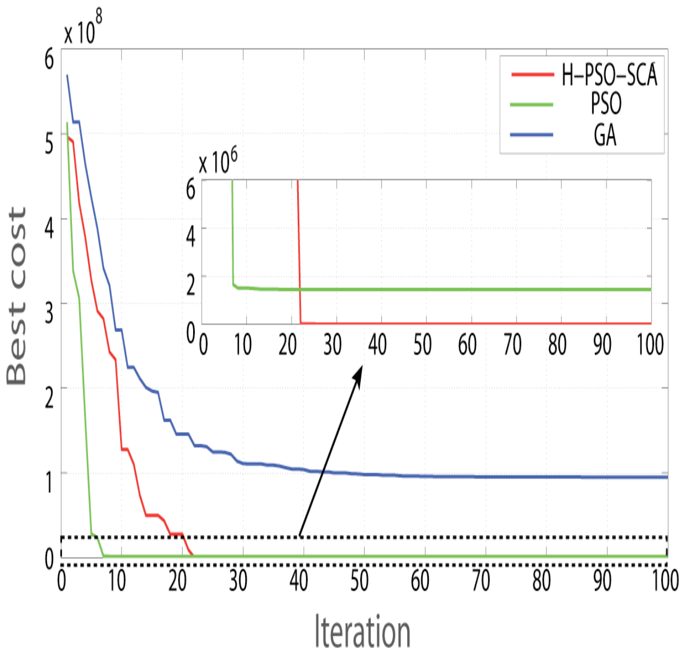
Fig. 4. Hourly WT output power during a DA time.

Table 1. Diesel generators parameters

DG_i	a_i	b_i	P_{min}	P_{max}	DR_i	UR_i
1	0.06	0.5	0 kW	4 kW	3 kW	3 kW
2	0.03	0.25	0 kW	6 kW	5 kW	5 kW
3	0.04	0.3	0 kW	9 kW	8 kW	8 kW

5.2. Results And Discussion

Fig.5 illustrates the comparison of the BC fitness function convergence attained from different algorithms against iterations. For the GA, the optimization process has required a large number of iterations to converge to a local optimum position, more than 40 trial runs. Based on the zoom screenshot in Fig.5, it clearly shows that the PSO is trapped easily in a local optimum position after 8 trial runs where the H-PSO-SCAC escape the local optimum solution and continue to search for the gbest solution. The proposed H-PSO-SCAC can get closer to the global optimum after 22



trial runs. The graph proves the ability of the proposed H-PSO-SCAC to avoid premature convergence and to enhance search accuracy.

Fig. 5. The best cost fitness function convergence using different algorithms.

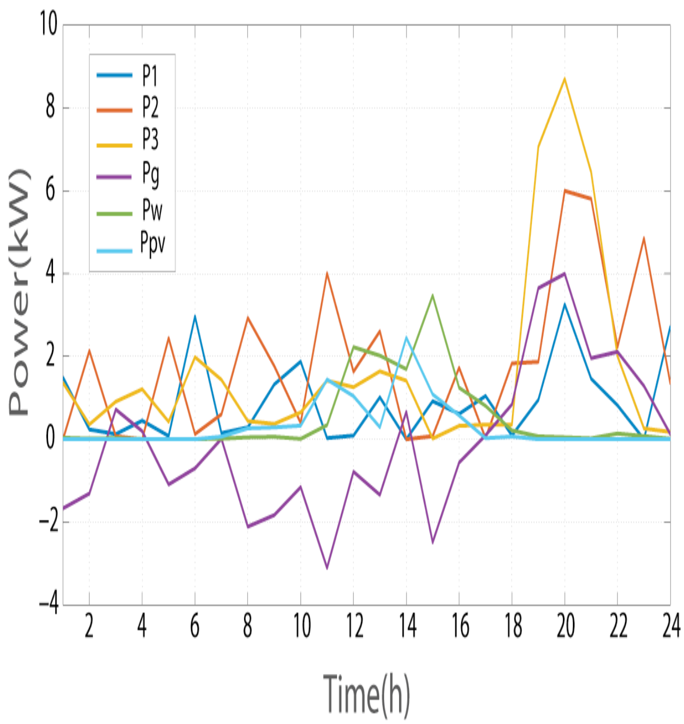
The optimization criteria of the UC problem using different techniques are described in Table 2. It can be concluded from the SD values that the PSO and the H-PSO-SCAC have both a larger population diversity that justify the capacity to explore more areas of the search space and then to yield better performance. The proposed H-PSO-SCAC is more cost effective, it provides the lowest BC, the lowest MC and WC in comparison with the GA and the PSO. From the CAP values, the results prove the effectiveness and accuracy of the H-PSO-SCAC to obtain the best solution in comparison with the PSO and GA.

Table 3 details the optimal power generated by the three DGs obtained by the H-PSO-SCAC. As the DGs are the main power source, it can be seen from Table 3 that the three DGs produce the energy all day long, with high production between 19h and 22h, and low value at the morning.

Table 4 gives the optimal power transferable between the MG and the grid $P_g(t)$ resulting from the H-PSO-SCAC. It can be observed that the power is often sold to the grid between 1h and 16h with a high value at the 11h; however, the power is purchased from the grid between 17h and 24h with a high at the 19h and 20h.

Moreover, Table 5 shows the optimal power generated by RGs $P_W(t)$ and $P_{PV}(t)$ obtained by H-PSO-SCAC. The RGs energy production can support the DGs production especially between 8h and 15h by PV generator and between 11h and 18h by the WT generator.

Fig.6 represents the plotting of the optimal power generated by MG units as in Table 3, Table 4 and Table 5. It can be shown that the LD is mainly supplied by the three DGs, and the RGs are used as auxiliary sources. When the PV and WT generators start producing energy, DGs 2 and 3 reduce their production. As observed from Fig.6, $P_g(t)$ can be positive or negative. $P_g(t)$ is positive means that the MG buy the power from the grid whilst if $P_g(t)$ is negative, the MG sell power to the grid. Therefore, the LD requires more power between 18h and 22h, when there is no renewable production. However, the DGs production cannot satisfy the LD, in this period the MG purchase the power from the grid to fill the need and support the DGs to satisfy the LD. Throughout the day between 1h and 16h, as it is a benefit to the MG, MG units can produce more power than LD, and the



excess power can be sold to the grid.

Fig. 6. The resulted UC solution of MG generation units.

Table 2. Performance comparison based on the mg total cost ($/day) calculated by different techniques for 100 trial runs

Algorithms	BC	MC	WC	CAP(%)	SD
GA	9.4972e+07	9.4999e+07	1.2367e+09	1,20E+03	7247.6
PSO	1.4501e+06	4.2121e+07	1.1625e+09	8,01E+04	4.8063e+07
H-PSO-SCAC	63.4000	5.7513e+06	9.3246e+08	1,47E+09	1.3281e+07

Table 3. Optimal power generated by diesel generators $P_i(t)$ by H-PSO-SCAC

Time(h)	P_1 (kW)	P_2 (kW)	P_3 (kW)
1	1,494695	0	1,362238
2	0,235273	2,135784	0,358993
3	0,12601	0,072348	0,910185
4	0,449523	0	1,207137
5	0,077147	2,444488	0,422936
6	2,966414	0,126718	1,981885
7	0,146752	0,603788	1,436219
8	0,286075	2,929532	0,440133
9	1,324898	1,770919	0,370595
10	1,875473	0,394907	0,649399
11	0,027281	4,008629	1,415716
12	0,087985	1,632865	1,25752
13	1,012369	2,606259	1,642515
14	0	0	1,416264
15	0,918105	0,074961	0,016211
16	0,611933	1,728849	0,32446
17	1,043591	0,025329	0,350446
18	0,090329	1,831834	0,354864
19	0,94948	1,8715	7,066197
20	3,256274	6	8,705664
21	1,461655	5,80957	6,451036
22	0,819013	2,230569	2,005586
23	0	4,853661	0,259287
24	2,730402	1,33694	0,176568

Table 4. Optimal power transferable between the MG and the grid $P_g(t)$ by H-PSO-SCAC

Time(h)	P_g (kW)	Time(h)	P_g (kW)
1	-1,66846	13	-1,3434
2	-1,31074	14	0,662547
3	0,718666	15	-2,48825
4	0,193574	16	-0,5643
5	-1,09306	17	0,093667
6	-0,70309	18	0,84073
7	0,01308	19	3,649455
8	-2,11118	20	3,995784
9	-1,83379	21	1,958866
10	-1,15921	22	2,111386

11	-3,10698	23	1,2857
12	-0,78343	24	0,120165

Table 5. Optimal power generated by renewable generators $P_W(t)$ and $P_{PV}(t)$ by H-PSO-SCAC

Time(h)	P_W (kW)	P_{PV} (kW)
1	0,036529	0
2	0,015689	0
3	0,027791	0
4	0,004765	0
5	0,003487	0
6	0,003075	0
7	0,011079	0,064082
8	0,047534	0,262902
9	0,059176	0,285703
10	0,010562	0,328865
11	0,343127	1,442226
12	2,224416	1,040645
13	2,021089	0,291171
14	1,695745	2,455444
15	3,471375	1,084559
16	1,246637	0,575387
17	0,80586	0,025691
18	0,212439	0,064404
19	0,067469	0
20	0,046378	0
21	0,022953	0
22	0,137547	0
23	0,076352	0
24	0,010925	0

6. Conclusion And Future Work

This paper has described H-PSO-SCAC to resolve UC problem of GC-MG. The proposed H-PSO-SCAC provided an optimal strategy for supplying the required LD in a GC-MG based on a hybrid energy system, including one WT generator, one PV and three DGs. The energy management focused on minimizing the FC of DGs and the transaction costs of transferable power trade for DA scheduling. The demand has been mainly supplied by the three DGs, and the RGs have been used as auxiliary sources. A trading scheme is allowed between the MG and the grid. The grid is used to cater the shortage of the RGs. The performance of the proposed H-PSO-SCAC is examined by comparing with PSO and GA. The effectiveness of these methods is demonstrated by using the SD, the BC, the max cost, and the MC of the OF, and the CAP. The simulation results have shown that the proposed H-PSO-SCAC is more robust than the PSO and GA. The H-PSO-SCAC has better performance with higher convergence accuracy, it has a larger population diversity that helps to yield better performance. The H-PSO-SCAC can be seen as a very efficient optimization algorithm, with the advantages of its efficiency, accuracy and reliability in searching.

As regards the environmental problem, future work aims to reduce the fuel consumption by saving the power excess generated by RGs. The use of storage devices becomes necessary to decrease the fuel dependence by charging the power at lower user demand with high renewable production, and then discharging the saved power at peak LD. The use of other RGs will be discussed in future work to maximize the clean energy contribution.

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