MICRO-GRID EMC INCLUDING EV LOAD IN A RESIDENTIAL AREA

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ABSTRACT

This paper addresses the problem of Micro-Grid (MG) Energy Management Control (EMC) including Electric Vehicle (EV) scheduling with considering a reduction in the overall operating cost of MG in a residential grid. The main motivation for this study is the impact of the daily load profile combined with electric vehicles (EVs) on the grid. Unless the EV integration with load is monitored and controlled, the MG may experience an unexpectedly high or low load. So, EMS is a trend in recent years for optimal planning of MG. On the other hand, the available energy stored in the energy storage Battery can be utilized to free the distribution system from some of the congested load at certain times or to allow the grid to charge more EVs at any time of the day, including peak hours. This work was implemented by using four metaheuristic algorithms (Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Hybrid population-based algorithm (PSOGSA), and Capuchin Search Algorithm (CapSA) for optimal operation with minimum total daily cost without and with EVs included in MG by two different daily profile of EV. The MG used in this paper consisted of a diesel generator (DG), Battery storage device, photovoltaic (PV) system, and Wind turbine unit (WT). For a more dispatchable practical MG, Emissions from DG and deterioration of storage devices in addition to the cost of charging the EVs have been taken into account. The results demonstrate that CapSA is a suitable method for generating robust models for EMS. This means that the proposed CapSA approach can be applied in a wide range of complex nonlinear systems.

KEYWORDS: Electric Vehicles, Renewable energy sources, Microgrid, Capuchin search algorithm, Emission, Degradation.

التحكم في إدارة الطاقة لشبكة صغيرة تحتوي على أحمال مركبات كهربية في منطقة سكنية

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الملخص

يعتمد تأثير المركبات الكهربائية على الشبكة على شكل الحمل اليومي له. ما لم يتم التحكم في توقيت وكمية شحن المركبات الكهربائية ، فقد تواجه حملاً مرتفعاً أو منخفضًا غير متوقع. من ناحية أخرى ، يمكن استخدام الطاقة المتاحة المخزنة في بطارية تخزين الطاقة لتحرير نظام التوزيع من بعض الأحمال المزدحمة في أوقات معينة أو للسماح للشبكة بشحن المزيد

من المركبات الكهربائية في أي وقت من اليوم ، بما في ذلك ســـاعات الذروة. تتناول هذه الورقة مشـــكلة التحكم في إدارة الطاقة بالشـبكة الصـغيرة بما في ذلك جدولة المركبات الكهربائية مع مراعاة خفض تكلفة التشـغيل الإجمالية لشـبكة سـكنية صـغيرة. تم أخذ الانبعاثات من مولدات الديزل وتدهور أجهزة التخزين بالإضـافة إلى تكلفة شـحن المركبات الكهربائية في الاعتبار. تم تنفيذ هذا العمل باسـتخدام أربعة خوارزميات (تحسـين سـرب الجسـيمات، وخوارزمية البحث عن الجاذبية، وخوارزمية هجينة قائمة على الخوارزميتين السـابقتين ، وخوارزمية قرود الكابوشـي) للتشـغيل الأمثل بأقل تكلفة يومية إجمالية بدون ومع تضمين المركبات الكهربية كأحمال في الشبكة بواسطة ملفين مختلفين يوميًا لــــ شكل أحمال المركبات الكهربية.

الكلمات المفتاحية : شبكة سكنية, خوارزمية قرود الكابوشين, المركبات الكهربية, تكلفة الانبعاثات, تكلفة تدهور اجهزة التخزين

1. INTRODUCTION

Microgrid comprise low voltage distribution systems with energy storage devices (ESD), flexible loads and accommodate considerable amounts of distributed generation, such as PV and wind generation [1-3]. In recent years, there is a growing trend towards the use and adoption of EVs due to depleting fossil fuels and rising environmental concerns. The adoption of EVs as alternative means of transport requires development of charging infrastructure [4,5].

The development of MG's may help in creating efficient EV charging infrastructure without adversely affecting grid operation. An MG is an electricity distribution system comprising controllable loads and diverse distributed energy resources (DERs) which can be operated in a coordinated and controlled way [6]. An MG can either operate in parallel with a grid or work autonomously.

It can offer several benefits such as increasing reliability, flexibility, sustainability, and improvement of line losses [7]. However, electricity demand pattern will undergo significant changes due to variability associated with EVs charging pattern.

Such systems can be operated in islanded mode or connected to the main grid [8]. system performance, if managed and coordinated efficiently. The integration of many units of PV in networks can cause situations in which, in same periods, the available generation is higher than the demand. In such situations, the MG Operator (MGO) is able to manage the network [3] and its resources and sell electricity as scheduled by the resources management algorithm [9,10]. EMC problem with different uncertainty explained by Optimization algorithms like Simulated Annealing [11], Particle Swarm Optimization (PSO) [12], Crow Search Algorithm (CSA) [13], and Genetic Algorithm (GA) [14]. Artificial Bee Colony suggested [15] to address the day-ahead ERM in MG by taking into account uncertainties related to Renewable Generation (RG), EVs trip, market price and load demand. The Firefly Algorithm (FA) proposed in [16], for the Economical scheduling with optimized battery sizing. In [17] optimal scheduling is done by Imperialist Competitive Algorithm (ICA) in MG environment with uncertainty related to RG and load demand.

Finally, the main contribution of this paper can be summarized as follows:
- A new optimization algorithm called "Capuchin Search Algorithm (CapSA)" have been presented for minimizing the electricity costs for a MG.
- The robustness of the proposed CapSA optimization algorithm has been confirmed by comparing it with three other powerful algorithms "PSO, GSA, Hybrid PSOGSA".
- The optimal charging schemes for EV have been selected in order to achieve the lowest possible cost depending on the electricity price structure.
- Unlike other works, this paper presents a case study with the aim to minimize operating cost by considering 3-scenarios without and with EVs included in MG by two different daily profile of EV.

This paper is constructed as follows: Section 2 describes the problem formulation. In Section 3 the proposed algorithm is presented, and the simulation results are presented in Section 4. Finally, Section 5 summarizes the concluding remarks.

2. PROBLEM FORMULATION

The optimal resources management methodology proposed in this paper considers that it is possible to buy and sell electricity to energy suppliers. The solution aims to minimize the operation cost of the MG while satisfying various constraints [18].

The total cost of the MG contains the bids of EV charging, DG, PV, ESD, and WT. So, the objective function could be formulated as[19]:

$$\min\{f_1(x_t).f_2(x_t)....f_k(x_t)\} \tag{1}$$

$$g(x_t) = 0 \quad \& \quad h(x_t) \leq 0 \tag{2}$$

Where:$f_k(x_t)$ is the vector of k optimized objectives, t is the different dispatch period, $g(x_t)$ and $h(x_t)$ are the equality and the inequality constraints, respectively, and x_t can be presented as:

$$x_t = \{P_{x.t} . P_{utis.t} . P_{utim.t} . P_{EV.t} . P_{bt.t}^{ch} . P_{bt.t}^{dis} . P_{load.t}\} \tag{3}$$

Where:$P_{x,t} = (P_{wt}, P_{pv}P_{mt})$ are the active power of WT, PV and DG output in the MG, respectively, $P_{utis,t}$ is the drawing active power Purchased from main grid, $P_{utim,t}$ is the surplus energy of the MG selling to the main grid, $P_{EV,t}$ is the charging power of EV, $P_{bt,t}^{ch}$ and $P_{bt,t}^{dis}$ are the charge and discharge power of ESD and $P_{load,t}$ is the load demand.

2.1. Objective Function

The energy management system adjusts the output power setpoints of DGs to meet the load demand; the operating cost, the emission cost of pollutants and the degradation cost of ESD are minimized simultaneously while satisfying constraints [19]. The mathematical model of objective functions can be formulated as follows:

A. Operation cost function

During the operation of the MG, the total energy and operating cost is equal to the sum of the electricity bought from the grid and the generation cost of all units; the ESD cost subtracts the profit of selling excess energy to the main grid. Therefore, the operation cost function can be formulated by [19]:

$$f_1(x_t) = \sum_{t=1}^{H}\left[C_{uti}P_{uti.t} + F_{mt} + C_{pv}\sum_{n=1}^{N_{pv}}(P_{pv.t}^n) + C_{wt}\sum_{n=1}^{N_{wt}}P_{wt.t}^n\right] \tag{4}$$

Where: H, is total time taken, N_{pv}, N_{wt}, are the generator numbers of PV and WT respectively,C_{pv}, C_{wt} are the unit generation cost of PV and WT respectively (\$/Wh), C_{uti}, is the purchasing electricity price of the main grid (\$/Wh), and the F_{mt} is total operating cost of the diesel generator microturbine (MT) (\$) which can be expressed as:

$$\sum_{t=1}^{H} F_{mt} = \sum_{t=1}^{H}\left[C_{mt}\sum_{n=1}^{N_{mt}} P_{mt.t}^n + K_{oc}\sum_{n=1}^{N_{mt}} P_{mt.t}^n + SC_{mt.t}\right] \tag{5}$$

Where:C_{mt}, is the fuel cost of the MT unit (\$/Wh), K_{oc}, is operations and maintenance cost, $P_{mt,t}^n$, is the output power of the MT(W), and $SC_{mt,t}$ representing startup cost of the MT unit (\$), it can be calculated as:

$$\sum_{t=1}^{H} SC_{mt.t} = \sum_{t=1}^{H}\left[(\sigma_{mt} + \delta_{mt}(1 - e^{-\frac{\tau_{off.mt}}{\tau_{mt}}})),(1 - u_{(t-1).mt})\right] \tag{6}$$

Where:σ_{mt} andδ_{mt},are hot startup time and cold startup time of MT,$\tau_{off,mt}$ and τ_{mt}, are the time that MT is turned off, and cooling time of MT, and $u_{(t-1),mt}$, is MT status at step $t - 1$.

B. Emission cost function

The emission cost function includes the most pollutant gases: CO2, SO2 and NOx. The objective function of emission cost can be as [20]:

$$f_2(x_t) = \sum_{t=1}^{H}\left[\sum_{k=1}^{3} C_{emis.k}m_k(x_t)\right] = \sum_{t=1}^{H}\left[\sum_{k=1}^{3} C_{emis}u_k\sum_{n=1}^{N}(P_{mt.t}^n + P_{uti.t})\right] \tag{7}$$

Where:$k = (1, 2, 3)$ represent three pollutant gases: CO2, SO2 and NOx, &$m_k(x_t)$, is the mass of the emission pollutant gask&$C_{emis,k}$, is the cost coefficient of the pollutant gas k,&u_k, is the emission per unit wh in g/wh.

C. Degradation cost function

The third objective function (the ESD degradation cost) can be formulated as a linear function of the charged and discharged energy in addition to the bids of EV charging [21-22]:

$$f_3(x_t) = \sum_{t=1}^{H}\left[\sum_{B=1}^{N_B} C_{bt}\left(P_{bt.t}^{ch} + P_{bt.t}^{dis}\right) + C_{EV}\sum_{n=1}^{N_{EV}}(P_{EV.t}^n)\right] \qquad (8)$$

Where: N_B represent the ESD numbers, C_{bt} is the cost coefficient of the charging and discharging. The solution of Equation 1 finds the best optimal dispatch plan for MG running.

2.2. Constraints

The objective function is subjected to following constraints [20]:

$$P_{mt}^{min} \leq P_{mt.t} \leq P_{mt}^{max} \qquad (9)$$

$$0 \leq P_{wt.t} \leq P_{wt}^{max} \qquad (10)$$

$$0 \leq P_{pv.t} \leq P_{pv}^{max} \qquad (11)$$

$$\left\{\begin{matrix}0 \leq |P_{bt}^{ch}| \leq |P_{bt}^{ch.max}| \\ 0 \leq P_{bt}^{dis} \leq P_{bt}^{dis.max}\end{matrix}\right\} \qquad (12)$$

$$SOC_{min} \leq SOC_t \leq SOC_{max} \qquad (13)$$

Where: $P_{bt}^{ch,max}$, $P_{bt}^{dis,max}$ are the maximum power used to charge or offered to MG by the battery, and $SOC_{max} = 100\ \%$, $SOC_{min} = 50\ \%$ are the maximum and minimum state of charge of the battery.

$$P_{uti.t} = P_{load.t} + P_{EV.t} - [P_{mt.t} + P_{wt.t} + P_{pv.t} + P_{bt.t}] \qquad (14)$$

3. MATHEMATICLE MODEL OF OPTIMIZATION TECHNIQUES

Introduce for the first time in the energy management a devised approach called Capuchin Search Algorithm to augment search quality and shun an early convergence to a local minimum. CapSA is a recent meta-heuristic search algorithm inspired from the practices of capuchin monkeys during foraging activity in real life. Essentially, the facts of capuchins during foraging, was proposed by Braik [23], they use three ways in navigating around while searching for food sources: jumping, swinging and climbing. These behaviors of movements underlie the core assumptions of CapSA.

The population of capuchins in the CapSA, is divided into two main groups: (the leader) "Alpha" and "followers". The leader "Alpha" is responsible for finding food sources for capuchins' followers which update their positions by following the leaders in the group. While searching for food sources as presented in [23], the leaders in CapSA use the subsequent strategies: a. jumping on trees, b. jumping over riverbanks, c. swinging on trees, d. climbing on trees, and e. moving naturally and randomly on the ground. These strategies of motion are performed by the leaders continuously until they get a food source of (i.e., the desirable solution). To summarize, Braik et al. has developed CapSA as shown below:

The velocity of the ith capuchin in the jth dimension in CapSA was defined as:

$$v_j^i = \rho v_j^i + \tau a_1\left(X_{bestj}^i - x_j^i\right)r_1 + \tau a_2\left(F_j - x_j^i\right)r_2 \qquad (15)$$

Where v_j^i represents the current velocity of the ith capuchin in the jth dimension, x_j^i represents the current position of the ith alpha capuchin in the jth dimension, X_{bestj}^i identifies the position with the best fitness found so far for the ith capuchin in the ith dimension, F_j is the best position of the food found so far in the ith dimension, a_1 and a_2 are two acceleration constants that control the effects of X_{bestj}^i and F_j on the velocity, r_1 and r_2 are uniformly distributed random numbers independently created in the range from 0 to 1 and ρ is the inertia weight that controls the effect of the previous velocity on the current velocity and is defined as:

$$\rho = w_u - (w_u - w_l) * (k/K)^2 \qquad (16)$$

where w_l and w_u are the min and max coefficient values of the inertia weight, respectively. The optimization process is executed through an iterative loop practice, where the new positions of capuchins are appraised and updated. These procedures are repeated at each iteration loop until convergence, The search for the convergence is stopped when the criterion is satisfied. The CapSA could be briefly described by the pseudo code given in Algorithm 1 [23]. As CapSA has underlined its reliability and convergence behavior in adopting many tests benchmark functions [23]. Therefore, we concluded that the CapSA is appropriate alternative method to minimize the total cost of the MG.

Algorithm 1: A pseudo code describing the key steps of CapSA.

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1.   r1, r2, and ε are random numbers within [0, 1].
2.   Randomly initialize the positions x of the n capuchins.
3.   Evaluate the fitness of each capuchin's position
4.   Initialize the velocity of the capuchins
5.   Initialize the parameters: number of iterations (K), number of capuchins (n), dimension of the problem (m), elasticity probability (P_{ef}), balance probability of capuchins' tails (P_{bf}), acceleration due to gravity (g), upper bound dimension (u_j), lower bound dimension (l_j).
6.   **While** (termination condition is not satisfied "k < K") **do**
7.   Update τ .
8.   **For** k=1 to n (leaders and followers) **do**
9.   **if** (k < n/2) (n/2= the leader and the accompanying capuchins) **then**
10.   Update the velocity of the leaders.
11.   **if** (ε ≥ 0.1 AND ε ≤ 0.15) **then**
12.   Update the position of the leaders that leap on the trees.
13.   **else if** (ε > 0.15 AND ε ≤ 0.2) **then**
14.   Update the position of the leaders that over riverbanks.
15.   **else if** (ε > 0.2 AND ε ≤ 0.75) **then**
16.   Update the position of the leaders that walk on the ground.
17.   **else if** (ε > 0.75 AND ε ≤ 0.9) **then**
18.   Update the position of the leaders that swing on tree.
19.   **else if** (ε > 0.9 AND ε ≤ 1.0) **then**
20.   Update the position of the leaders that climb on trees.
21.   **else**
22.   Update the position of the leaders that relocate randomly.
23.   **end if**
24.   **else if** (k > n/2 and k ≤ n) **then**
25.   Update the position of the follower.
26.   **end if**
27.   **end for**
28.   Evaluate the new fitness value of each capuchin
29.   Evaluate and update the positions of the capuchins
30.   Update the global best solutions of the capuchins
31. k = k + 1
32. **end while**

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4. RESULTS and DISCUSSION

The MG structure as shown in **Fig. 1** consisting of the PV unit, WT, MT, ESD, EV unit, Residential loads, and conversion devices, which can operate in grid-connected or island modes. The operators use smart grid which including PV, WT, ESD, MT, EV, and conventional power sources to meet demand loads. The excess energy from the MG is stored in ESD system for future use or sell it to the utility [19].
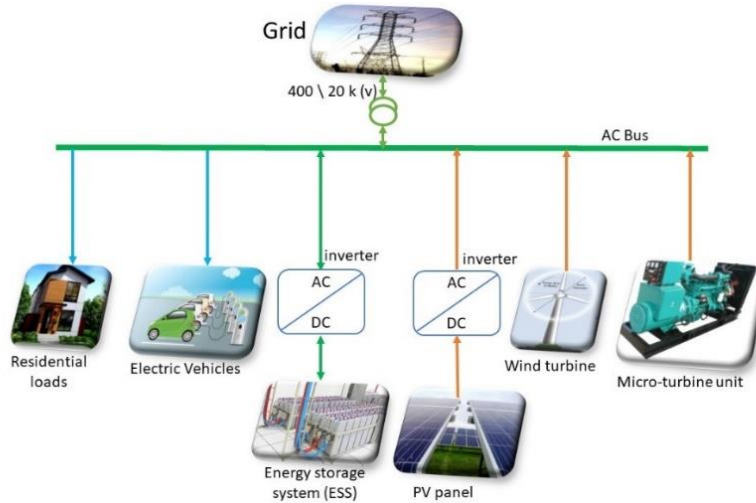
Fig. 1. Diagram of the microgrid system under study.

The load demand diagram is the same of that in [24], but its size is multiplied by 300 WH, as shown in **Fig. ٢. Table 1**. Shows the emission coefficients of different pollutants [25] and the limitation boundaries of the system have been mentioned in **Table 2**. The negative sign in the minimum power of the battery refers to the minimum discharge power.
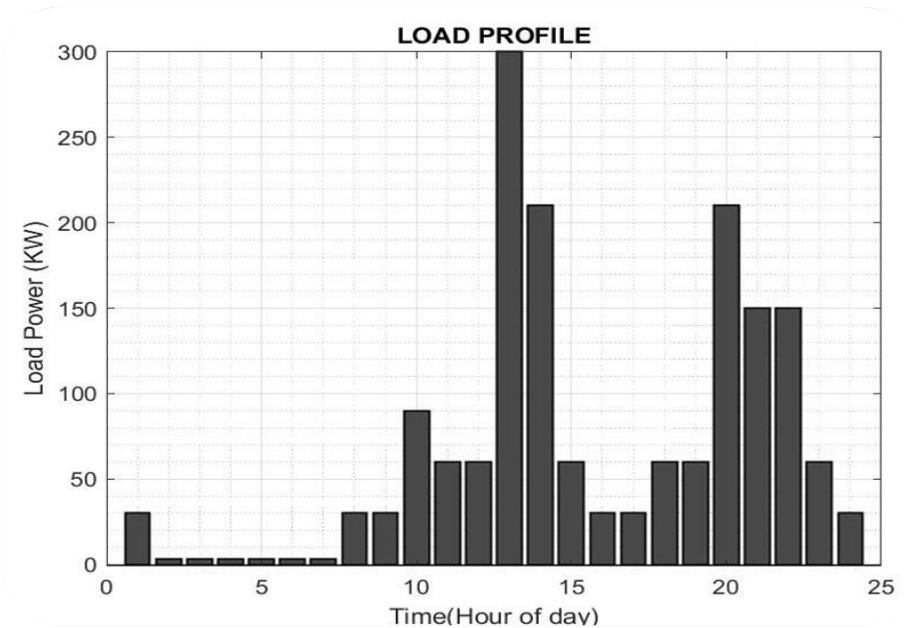

Fig. 2: Microgrid load power profile.

Table 1: Emission coefficient for micro-turbine

Type	Emission Factors for DEG (kg/kWh)
NOx	0.00052
SO2	3.63*10^-6
CO2	0.5025

Table 2: Data of DG units in the microgrid system.

| Unit	Max. Power (kW)	Min. Power (kW)
Wind turbine	100	0
Photovoltaic cell	100	0
Battery	60	-48
Diesel generator (MT)	60	12

The energy management process has been done by using PSO, GSA,PSOGSA and CapSA optimization techniques that discussed in Section 3. Suitable parameters for CapSA

optimization algorithm are given in **Table 3.** All the simulations are implemented in MatlabR2020a.

Figure. 3 presents the EVs trip demand in kWh. Maximum iteration number for any algorithm is set to 400. The results are average over 30 runs and the best results are indicated. **Figure. 4** shows the output power of the PV and Wind power as a percentage of its maximum output power and it is exactly the same for all case studies.

Table 3: Parameter settings of the capuchin search algorithm

Parameter	Value
Population size	50
Number of iterations	400 (max)
a_1, a_2	1.10, 1.25
w_l ,w_u	0.1, 0.9
P_{pf}	0.7
P_{ef}	19
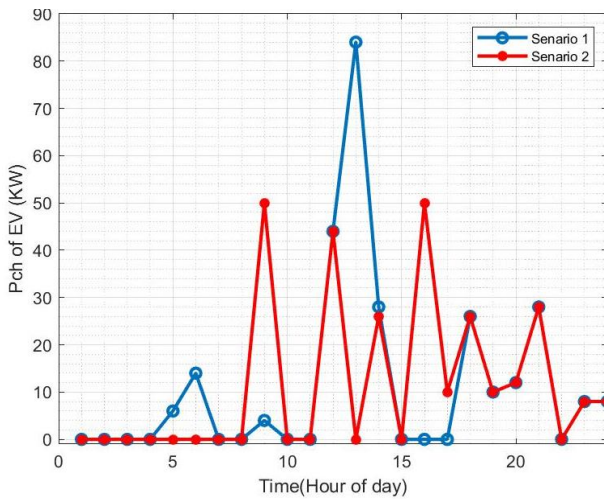
Fig. 3: The EVs trip demand (kWh)
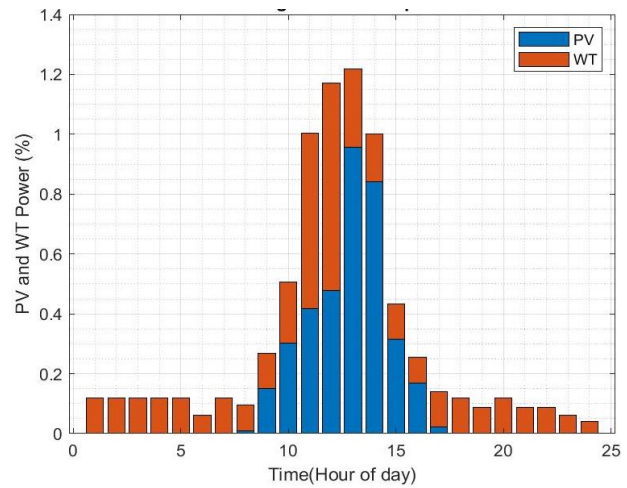
Fig. 4: The output power of the PV unit and Wind turbine

Scope of work:

The aim of the case study is to minimize operating cost in three scenarios: Scenario A is simulated without considering EVs, scenario B considers the random charging periods of the EVs, scenario C considers that the EVs charging by the same KWH of scenario B but during different periods.

i. *Scenario A: Without EVs*

Scenario A was simulated without considering EVs. The comparative convergence of the total cost (best solutions) of four different algorithms is shown in **Fig. 5**. It is shown clearly that all algorithms converged smoothly to the optimum value in the optimization process but the proposed CapSA optimization outperforms the PSO, GSA and PSOGSA methods as a whole; it has the advantage of reducing cost.

The hourly cost of all algorithms was mentioned in **Table 4.** And it can be seen that the best total Cost of scenario A was 124.8 \$. **Figure. 6** presents the resource energy scheduling without

EV's (scenario A) for the 24 periods under study using CapSA. As shown in **Fig. 6**, Some portion of the energy has been sold to the grid according to the resulting scheduling. The total selling energy to the Grid scheduled by the algorithm was 539 kWh.

Table 4: The Best hourly cost of all algorithms in three scenarios

Hours	cost/ hour ($/h)											
	Scenario A				Scenario B				Scenario C			
	PSO	GSA	PSOGSA	CapSA	PSO	GSA	PSOGSA	CapSA	PSO	GSA	PSOGSA	CapSA
1	4.77	3.09	2.58	1.39	3.22	2.03	0.55	1.49	3.94	0.10	0.17	-0.09
2	-0.06	-2.68	-3.67	2.34	1.42	4.61	0.24	-3.38	1.24	1.72	-1.37	-3.03
3	1.46	8.60	-0.55	-0.88	1.51	7.79	0.43	2.78	2.31	10.64	-2.71	-3.02
4	1.56	2.25	0.67	0.36	1.17	-2.68	1.29	0.84	1.97	7.69	2.12	0.86
5	4.60	-0.47	0.66	-1.36	5.14	-2.73	-3.08	-2.39	1.72	-3.02	3.17	-2.18
6	2.88	4.17	-0.04	1.50	4.56	7.46	7.27	0.80	2.29	7.61	1.98	-1.58
7	1.62	-0.83	0.49	-2.33	1.67	-5.36	-1.80	0.22	1.15	-2.86	-1.54	0.57
8	5.10	4.51	-0.08	7.05	5.07	8.14	1.72	1.01	6.41	1.26	-0.73	3.35
9	3.25	9.46	10.03	0.33	3.94	7.14	3.78	8.48	9.48	4.33	9.81	4.39
10	6.86	6.44	-1.61	4.89	8.14	9.21	4.75	1.53	6.39	2.09	1.64	6.72
11	-1.63	-3.92	0.01	-2.64	-1.35	-2.35	-0.44	-0.64	0.97	-1.82	-3.21	-4.40
12	-0.19	2.65	0.63	-3.12	2.71	2.33	-0.83	-0.38	1.48	7.69	-1.44	3.75
13	20.95	18.70	16.15	17.18	30.98	34.00	26.15	30.48	25.93	16.09	22.71	15.71
14	12.49	20.30	21.06	8.86	16.68	13.62	14.38	13.22	16.84	12.26	13.05	14.03
15	5.29	4.49	2.12	6.82	8.56	7.75	3.32	3.55	4.16	9.91	2.70	1.66
16	4.47	0.61	0.02	-0.23	1.16	-0.68	-1.51	0.89	9.54	9.54	8.16	11.55
17	4.54	3.28	7.17	2.22	5.47	-2.88	3.21	0.88	5.31	8.66	1.87	1.51
18	7.86	6.33	6.55	5.84	10.73	14.02	10.22	8.29	10.36	9.50	9.09	7.63
19	8.99	13.59	6.75	6.75	9.64	10.88	9.06	6.31	9.37	5.90	4.51	8.22
20	22.88	21.92	19.80	19.99	24.51	27.34	25.02	19.87	25.57	30.04	23.41	24.64
21	16.48	11.95	12.20	13.09	23.64	18.90	14.15	19.06	20.44	15.52	16.43	16.25
22	21.92	22.62	14.33	16.91	16.86	20.22	15.43	11.19	16.98	12.19	16.40	13.53
23	6.85	3.51	12.47	12.06	9.04	9.05	11.35	11.34	9.36	14.79	5.56	7.97
24	4.54	3.18	8.22	7.77	5.47	0.45	1.71	2.21	5.69	2.63	6.62	3.77
Total Cost/Day	167.49	163.77	135.96	**124.8**	199.93	188.27	146.37	**137.67**	198.90	182.48	138.39	**131.82**
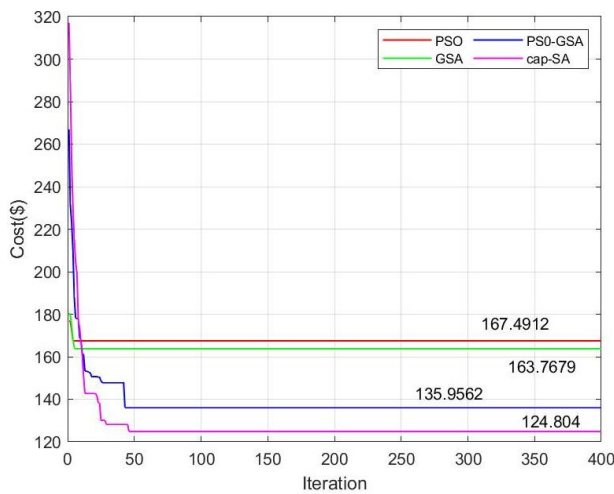
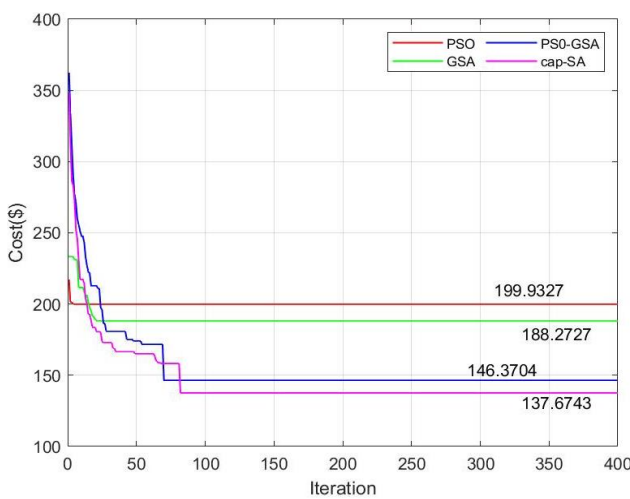**Fig. 5: Comparison between the convergence characteristics of the algorithms in scenario A.**
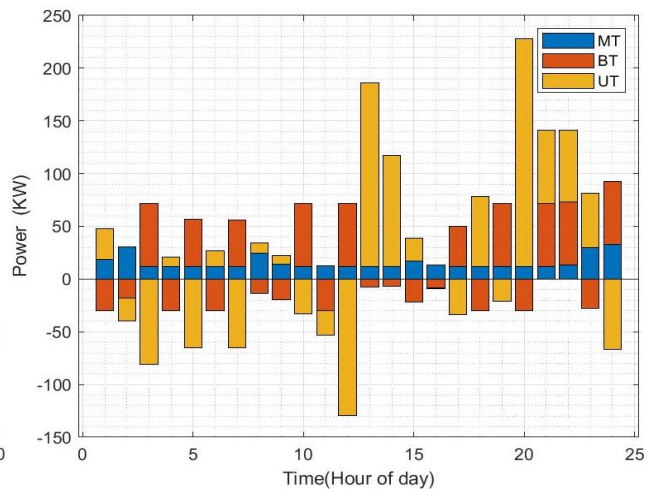
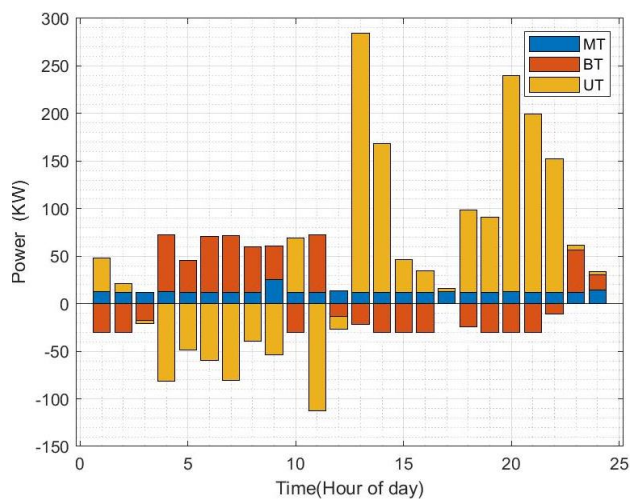**Fig. 6: Best solutions obtained EM problem using CapSA in scenario A.**

ii.   Scenario B: With EVs

This scenario considers the random charging periods of the EVs. The power production scheduling in this Scenario, is quite similar to scenario A with EV charging during any time of the day [22] as shown in **Fig. 3.** and **Fig. 7** show that the comparative convergence of the total cost of different algorithms. The total cost of scenario B was 137.7 $ related to the CapSA optimization as shown in **Table 4.** when compared with scenario A, the cost increased by 12.9 $. The increase seen in the cost was due to the presence of EVs, i.e the total load in the MG herein is greater by the load of EV's than the load of scenario A, which was inevitable.

In **Fig. 8** the power production of the resulting scheduling is illustrated. The total energy scheduled to charge the EVs was 272 kWh. The total selling energy to the Grid is 492 kWh while the energy purchased from main grid is 1319 kWh.

Fig.7: Comparison between the convergence characteristics of the algorithms in scenario B.
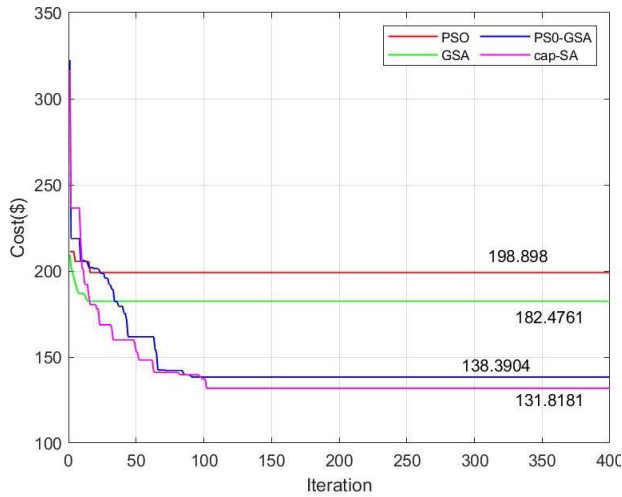

Fig. 8: Best solutions obtained EM problem using CapSA in scenario B.

iii.   Scenario C: With EVs

This scenario considers that the EVs charging by the same KWH but during the time that have maximum output power from PV and Wind units. i.e.: the MG operator can freely choose when to charge the vehicles. The convergence of the total cost of different algorithms shown in **Fig. 9.** The best Cost of this scenario was 131.8 $ related to the CapSA optimization as shown in **Table 4.**, **Fig. 10** depicts the power production for scenario C. In this case, the power consumption was similar to scenario B with different EV's charge schedules.

The total selling energy to the Grid is 397.5 kWh while the energy purchased from it is 1199 kWh. Although the energy sold to the network is less in this scenario than in scenario (B), the energy purchased from the network is also less in this scenario than in the scenario (B). Therefore, we can see that the total cost in this scenario is 5.9 less than in scenario (B). The reason for this is that the charging of electric vehicles is managed at times when power generation is greater than consumption.

Fig. 9: Comparison between the convergence characteristics of the algorithms in scenario C.
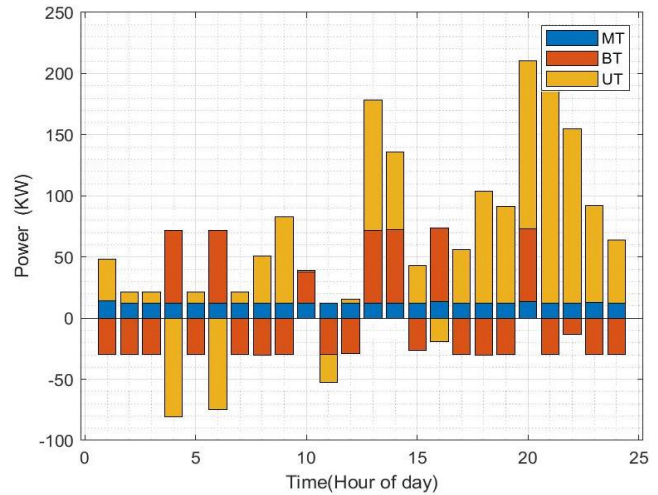
Fig. 10: Best solutions obtained EM problem using CapSA in scenario C.

5. CONCLUSIONS

This study proposes an optimal design methodology of an MG composed of PV arrays, WTs, EV, a battery, and a DGs, based on a novel computational intelligence algorithm called CapSA. The optimization approach is performed to completely satisfy the load requirements of an MG. The PSO, GSA, and PSOGSA algorithms were implemented to evaluate and compare the performance and effectiveness of the CapSA algorithm for the optimization problem to minimize the total cost with considering emission and degradation costs. Three scenarios were considered for the optimization: Scenario A was simulated without EVs, scenario B assume random charging periods of EVs, scenario C considers different periods of EVs charging with the same KWH of scenario B. The results indicate that the proposed Cap-SA optimization-based energy management for the under study Micro-grid, provided a better reduction in the objective function which proves the suitability and superiority of Cap-SA over other optimization algorithms in all scenarios. In addition, according to scenario C, the controlled charging of EVs has proven to be extremely important to reduce costs. This indicates that without any control, costs can be higher than those with more control.

Finally, in the future, CapSA optimization algorithm can be modified or mixed with other metaheuristic algorithms to tackle an extremely dynamic MG network with large integration of unpredictable energy sources and a broad range of scenarios.

NOMENCLATURE

$f_k(x_t)$	the vector of k optimized objectives	$C_{emis.k}$	cost coefficient of the pollutant gas k
t	dispatch period	u_k	the emission per unit wh in g/wh
$g(x_t). h(x_t)$	equality and the inequality constraints	N_B	numbers of ESD
$P_{x.t}$	active output power of WT, PV and MT	C_{bt}	the cost coefficient of the charging and discharging
$P_{utis.t}$	active power Purchased from main grid	$P_{bt}^{ch.max}$.	maximum power used to charge or offered to MG by the battery
$P_{utim.t}$	surplus energy of the MG selling to the main grid	$P_{bt}^{dis.max}$	
$P_{EV.t}$	charging power of EV	SOC_{max}.	maximum and minimum battery state of charge
$P_{bt.t}^{ch}, P_{bt.t}^{dis}$	charge and discharge power of ESS	SOC_{min}	
$P_{load.t}$	load demand	v_j^i	current velocity of the ith capuchin in the jth dimension
w_l , w_u	generator numbers of PV and WT		
N_{pv}, N_{wt}	unit generation cost of PV and WT in $/Wh	x_j^i	the current position of the ith alpha capuchin in the jth dimension
C_{pv}, C_{wt}	fuel cost of the MT in $/Wh		
C_{mt}	total operating cost of the MT in $	X_{bestj}^i	position with the best fitness found
F_{mt}	operations and maintenance cost	F_j	best position of the food found
K_{oc}	output power of the MT(W)	a_1 , a_2	two acceleration constants
$P_{mt.t}^n$	startup cost of the MT unit	r_1 , r_2	uniformly distributed random numbers independently created in the range from 0 to 1
$SC_{mt.t}$	hot startup time and cold startup time of MT,		
$\tau_{off.mt}$, τ_{mt}	time which MT is turned off, and cooling time of MT	ρ	the inertia weight
		w_l , w_u	minimum and maximum coefficient values of the inertia weight
$u_{(t-1).mt}$	MT status at time step $t-1$		
$m_k(x_t)$	mass of the emission pollutant gas k		

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