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Multi-objective energy management and environmental index optimization of a microgrid using swarm intelligence algorithm

Ahmed Bahri[1], Nabil Mezhoud[2], Bilel Ayachi[2], Farouk Boukhenoufa[2], Lakhdar Bouras[2]
[1]Department of Automatics and Electromechanics, Faculty of Science and Technology, Materials, Energy Systems Technology and Environment Laboratory (MESTE), Université de Ghardaia, Ghardaia, Algeria
[2]Electrical Engineering Department, Faculty of Technology, LES Laboratory, Université 20 Août 1955, Skikda, Algeria

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ABSTRACT

Due to the need for better reliability, high energy quality, lower losses and cost, and clean environment, the application of renewable energy sources such as wind energy and solar energy in recent years has become more widespread mainly. In this work, one of the most general of all swarm intelligence algorithms, called particle swarm optimization (PSO) is applied to solve the optimal energy management (OEM) and environmental index optimization (EIO) problems of micro-grid (MG) operating by renewable and sustainable generation systems (RSGS). The PSO approach was examined and tested on standard MG composed of different types of RSGS, such as wind turbines (WT), photovoltaic systems (PV), fuel cells (FC), micro turbine (MT), and diesel electric generator (DEG) with energy storage systems (ESS). The results are promising and show the effectiveness and robustness of proposed approach to solve the OEM and the EIO. The results obtained were compared with some well-known references. The results show that the optimization process reduced the energy generation costs from 257283 ($/h), 263929 ($/h), and 263526 ($/h), respectively. While the environmental index further improved to 0.1548 (ton/h).

Corresponding Author:

Ahmed Bahri
Department of Automatics and Electromechanics, Faculty of Science and Technology
Materials, Energy Systems Technology and Environment Laboratory (MESTE), Université de Ghardaia
Ghardaia, Algeria
Email: bahri.ahmed@univ-ghardaia.edu.dz

1. INTRODUCTION

The rise in electricity demand is related by population growth, digitization, and industrial development. Renewable energy research and adoption have increased significantly, especially wind energy [1]. However, the fluctuations of this energy due to fluctuating wind speeds can affect the quality of voltage and current in the grid [2].

Esoteric-fuel power plants are major air pollution sources, emitting harmful gases from burning coal, gas, and oil [3]. Coal combustion releases high levels of CO_2, SOx, and NOx, with emissions varying by fuel type and quality [4], [5]. Environmental concerns like pollution and greenhouse gases have driven efforts to enhance energy system efficiency, leading to various emission reduction strategies [6]. Following the 1990 Clean Air Act amendment and rising environmental awareness, electricity producers were required to modify their designs and strategies to reduce power plant emissions [4].

Distributed generation (DG) has steadily grown over the past two decades. Geographical and meteorological factors influence how renewable DG sources such as PV and WT are integrated in main grid. While non-renewable sources like fuel cells (FC), micro turbine (MT), and diesel electric generator (DEG) provide stable power and can be attached to any point within the grid [6].

Effective DG management improves power quality, reliability, and efficiency while reducing losses and emissions. The concept of microgrids (MGs) [2], [7] is the coordinated operation and control of storage devices and controllable loads. The latter can operate independently or with the main grid [8]. Ensuring MG stability with varying loads prevents voltage disturbances at the point of common coupling (PCC) [9]. As a resilient and intelligent energy solution, MGs are key to modern power systems [10].

Microgrids are central to modern power distribution networks. Integrating RES in MGs and the main grid optimizes system performance, enhancing profitability and reducing dependence on the main network [11], [12]. Energy management aims to maximize efficiency and minimize losses, making it a complex optimization challenge with constraints. Numerous mathematical and artificial intelligence-based methods have been used to address EMO and environmental index optimization (EIO) challenges.

Recently, population-based methods and evolutionary algorithms have been widely used for optimal energy management (OEM) optimization. Genetic algorithms (GA) are frequently employed, as highlighted in [13], while evolutionary programming and differential evolution (DE) proposed in [14] and [15] are developed to improve the performance of OEM. Similarly, backtracking search optimization (BTA) was applied in [16] for the same purpose. Swarm intelligence methods have been applied to optimal energy management. Particle swarm optimization (PSO) [10], [17], artificial bee colony (ABC) [18], and ant colony optimization (ACO) [19] aim to minimize the energy management in MG and distributed networks.

Physical algorithms such as gravitational search algorithms (GSA) [20], [21], black hole optimization (BHO) [22], and wind-driven optimization (WDO) [23] also target OEM in electrical micro-grid. Nature-inspired and bio-inspired methods, including firefly algorithm (FFA) [24], [25], grey wolf optimization [26], [27], bacterial foraging [28], cuckoo search [29], shuffled frog-leaping algorithm [30], and moth-swarm algorithm [31], are used for optimal energy management. In this work, the PSO approach is used to solve the OEM and EIO problems.

2. PROBLEM FORMULATION

The OEM and the EIO problems, generally expressed as (1)-(4) [27]. These formulations represent the standard expressions for both problems.

$$Min f(x,u) \tag{1}$$

Subject to (2)-(4).

$$h(x,u) = 0 \tag{2}$$

$$g(x,u) \leq 0 \tag{3}$$

$$x_{min} \leq \text{x} \leq x_{max} \text{ and}$$
$$u_{min} \leq \text{u} \leq u_{max} \tag{4}$$

$f(x,u)$ is the objective function. The constraints are denoted as $h(x,u)$ for equality and $g(x,u)$ for inequality. The state and control variables are respectively, x and u.

2.1. Objective functions

2.1.1. Environmental index optimization

Generally, the EIO problem can be expressed as (5). It shows the general formulation used in the literature.

$$min\, f(x,u) = min \sum_{k=1}^{ni} 10^{-2}(\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2) + \xi_i \exp\,(\lambda_i P_{gi}) \tag{5}$$

α_i, β_i, γ_i, ζ_i, and λ_i are the emission coefficients of generator i. Hence, x and u can be expressed as given in (6) and (7), respectively.

$$x^t = \left\{P_{g_1}, |V_{L_i}|, \ldots |V_{L_{nl}}|, +Q_{g_1}, \ldots Q_{g_{ng}}, S_1, \ldots S_{n_{br}}\right\} \tag{6}$$

The scheduled active power at slack bus, the reactive power scheduled by all generators, the magnitude voltage of all load buses, and the apparent power flow in all lines are represented, respectively, by P_g, Q_g, V_L, and S_i. The total number of generators, of load buses, and branches are, respectively, denoted by n_g, n_L, and n_{br}. The control variable vector is presented as (7) [25], [27].

$$u^t = \left\{P_{g_2}, \dots P_{g_{ng}}, \left|V_{g_1}\right|, \dots \left|V_{g_{ng}}\right|, Q_{1_{com}}, \dots Q_{n_{com}}, T_1, \dots T_{n_T}\right\} \tag{7}$$

The active power generation excluding slack bus, the magnitudes voltages of generators, the ration of transformers, and the compensated reactive power are denoted, respectively, by P_g, V_g, T, and Q_{com}. The transformers and compensators numbers are noted, respectively by n_{com} and n_T.

– Equality constraints

The nonlinear load flow equations are presented as equality constraints as given in (8). The active and reactive power generations, the active and reactive power injections, and the active and reactive power loads are presented, respectively, by P_{gi} and Q_{gi} P_i, Q_i, P_{di}, and Q_{di}.

$$\begin{cases} P_{g_i=} P_i + P_{di} \\ Q_{g_i} - Q_{comi} = Q_i + Q_{di} \end{cases} \tag{8}$$

– Equality constraints

The inequality constraints are presented by (9)-(13) [25]. Here, S_{kj}^{max} is the maximum apparent power exchange between buses *i* and *j*.

$$P_{gi}^{min} \le P_{g_i} \le P_{gi}^{max} \; and \; Q_{gi}^{min} \le Q_{g_i} \le Q_{gi}^{max} \text{ where } i = 1, \dots, n_g \tag{9}$$

$$V_i^{min} \le V_i \le V_i^{max} \text{ and } \theta_i^{min} \le \theta_i \le \theta_i^{max} \text{ where } i = 1, \dots, n_b \tag{10}$$

$$T_i^{min} \le T_i \le T_i^{max} \text{ where } i = 1, \dots, n_T \tag{11}$$

$$Q_{comi}^{min} \le Q_{com_i} \le Q_{comi}^{max} \text{ where } i = 1, \dots, n_{com} \tag{12}$$

$$S_{ij} \le S_{ij}^{max} \text{ where } i = j = 1, \dots, n_{br} \tag{13}$$

2.1.2. Energy management optimization

The OEM problem is defined in this study based on the first market policy, and the primary goal of OEM is to reduce the MG's operational expenses, though additional goals can be included. The OEM problem generally can be expressed as given in (14).

$$\min f(x,u) = min \sum_{i=1}^{NT} cost^t(x^t, u^t) = min \sum_{i=1}^{NT} \sum_{i=1}^{NG} [B_{Gi}(P_{Gi}^t) + MP^t P_{Grid}^t] \tag{14}$$

Where $f(x,u)$ is the cost function throughout the planning horizon. The active power exchanged with the grid at time *t* is denoted by P_{Grid}^t. *NT* and *NG* are the total count of time and DGs, including storage; P_{Gi}^t, $B_{Gi}(P_{Gi}^t)$, and MP^t are, respectively, the active power output, the bid of *i*[th] DG, and the electricity exchange price between the MG and grid at time *t* [32], [33]. The state and control variables, *x* and *u*, are defined as (15) and (16).

$$x^t =\le P_{Grid}^t \tag{15}$$

$$u^t = \left[P_{G_1}^t, P_{G_2}^t, \dots, P_{G_{NG}}^t\right]_{g_i} \tag{16}$$

– Constraints

i) Constraint of balance power (CBP)

The power balance constraint, when the active loss in the MG is ignored, is represented as (17). Here, *ND* represents the total load levels and P_{L_D} is the tenth load level's quantity.

$$\sum_{i=1}^{NG} P_{Gi}^t + P_{Grid}^t = \sum_{D=1}^{ND} P_{L_D}^t \tag{17}$$

ii) Constraints of power generation capacity (CPGC)

The active power output limits for every DG in the MG are presented as (18) and (19). P_{Gi-min}^t, $P_{Grid-min}^t$, P_{Gi-max}^t, and $P_{Grid-max}^t$ are, respectively, the DG and utility active power limits at time *t*.

$$P_{Gi-min}^t \le P_{Gi}^t \le P_{Gi-max}^t \tag{18}$$

$$P_{Grid-min}^{t} \leq P_{Grid}^{t} \leq P_{Grid-max}^{t} \quad (19)$$

iii) Constraints of spinning reserve (CSR)

Due to load and renewable energy fluctuations, SC is important to maintain system reliability. For this, the constraint listed in (20) must be satisfied [33]. R^t is the reserve spinning at time *t*.

$$P_{Gi-min}^{t} - P_{Gi-max}^{t} = \sum_{D=1}^{ND} P_{L_D}^{t} + R^t \quad (20)$$

iv) Limits of energy storage (LES)

The (21) represents the constraints for a typical battery during each time period t [32]. W_{ess_t} and W_{ess_t-1} denote battery capacity. The permitted charge/discharge rate for Δt is $P_{ch\,arg\,e}(P_{dech\,arg\,e})$, W_{ess_min}, and W_{ess_max} are the storage limits. The charge/discharge rate per Δt and battery efficiency are denoted by $Pdich\,arg\,e - \_max_{ch\,arg\,e\_max}$ and $\eta_{ch\,arg\,e}(\eta_{dech\,arg\,e})$.

$$W_{ess\_t} = W_{ess_{t}-1} + \eta_{charge} P_{charge} \Delta t - \frac{P_{charge}}{\eta_{charge}} \Delta t \quad (21)$$

$$where \quad \begin{cases} W_{ess_t} = W_{ess_t-1} \\ P_{charge\_t} \leq P_{charge\_max} \quad and \quad P_{decharge\_t} \leq P_{decharge\_max} \end{cases}$$

v) Active power calculation for grid exchange

Active power exchange is treated as a dependent variable, with grid power determined by (22). P_{Grid}^{t} is checked whether it satisfies constraint (19) or not. Thus, the variable $P_{Grid\_lim}^{t}$ is defined as (23).

$$P_{Grid}^{t} = \sum_{D=1}^{ND} P_{L_D}^{t} - \sum_{D=1}^{NG} P_{Gi}^{t} \quad (22)$$

$$P_{Grid\_lim}^{t} = \begin{cases} P_{Grid\_max}^{t} & if \;\; P_{Grid}^{t} > P_{Grid\_max}^{t} \\ P_{Grid\_min}^{t} & if \;\; P_{Grid}^{t} < P_{Grid\_min}^{t} \\ P_{Grid}^{t} & if \;\; P_{Grid\_min}^{t} \leq P_{Grid}^{t} < P_{Grid\_max}^{t} \end{cases} \quad (23)$$

The new objective function to be optimized after added the dependent variable, i.e., P_{Grid}^{t} as a quadratic penalty term is defined as (24). Here, λ_p represent the penalty factor.

$$\min_{u} F_p = \min_{u} \sum_{t=1}^{NT} cos^t(x^t, u^t) + \lambda_p \,(P_{Grid}^{t} - P_{Grid\_lim}^{t})^2 \quad (24)$$

– Distributed generation bid calculation

As per (25), DG bids are quadratic. They can be expressed as:

$$B_{Gi} = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad (25)$$

i) Fuel cell and micro-turbine

The bids of FC and MT in (\$/h) are determined as (26) [34]. It represents their bidding formulation.

$$B_G = C_{fuel} \frac{P_G}{\eta_G} + C_{inv} \quad (26)$$

P_g is the electrical power supplied by DGs (MT or FC) in (kW), η_g and C_{fuel} are the efficiency and the DG fuel (gas) price (\$/kWh). C_{inv} represents the hourly rate (\$/h).

$$C_{inv} = AC \frac{P_{G\_nom}}{AP} \;\; and \;\; AC = \frac{i(i+1)^n}{(i+1)^n - 1} IC \quad (27)$$

The installation cost of *DG is* represented by *IC*, *n* and *i* are the amortization period (years), and the interest rate, respectively.

ii) Photovoltaic and wind turbines

WT and PV bids consider AP (kWh/kW) and AC (\$/kW) represented by (27). These sources are uncontrollable, relying on primary source availability. The PV output power depends on solar irradiation, ambient temperature, and characteristics of module. The (28) is used to calculate the PV output power [34]-[37].

$$P_{PV} = P_{STC}\frac{I_S}{1000}[1 + \gamma(T_C - 25)] \tag{28}$$

P_{STC} is the PV maximum power under STC in (W); I_S is the solar irradiation of PV in (W/m^2); and γ is the PV module temperature coefficient for power in (°C^{-1}). The temperature of PV cell in (C), is denoted by T_C and determined by the module's nominal operating cell temperature (NOCT) [32], [34] given by (29).

$$T_C = T_a + \frac{I_S}{800}(T_{NOCT} - 20) \tag{29}$$

T_a and T_{NOCT} are, respectively, the ambient temperature and the module's NOCT (°C). As per [33], [34], the WT power curve is presented by (30).

$$P_{WT} = \begin{cases} 0 \quad if \;\; v \le v_{ci} \quad and \quad v \ge v_{co} \\ \frac{v^2 - v_{ci}^2}{v_{nom}^2 - v_{ci}^2} P_{WT\_nom} \quad if \;\; v_{ci} < v \le v_{nom} \\ P_{nom} \quad if \;\; v_{nom} < v \le v_{co} \end{cases} \tag{30}$$

P_{WT_nom} and P_{WT} are the output power and rated power of WT. v ,v_{nom}, v_{ci} and v_{co} are, respectively, the rated wind speed, switch-in wind speed, and switch-on wind speed of WT [33].

iii) Diesel electric generators (DEG)

The DEG fuel consumption can be modeled as a quadratic function in (31). $Fuel_{DEG}$ is fuel consumption (L/h); P_{DEG} is DEG output power (kW); and α_f, b_f, and c_f are fuel consumption coefficients. DEG bids ($/h) are calculated as (32).

$$Fuel_{DEG} = a_f P_{DEG}^2 + b_f P_{DEG} + c_f \tag{31}$$

$$B_G = Fuel_{DEG} + C_{inv} \tag{32}$$

Where, C_{fuel} is the diesel fuel price in ($/L). C_{inv} is the investment cost determined by (27).

iv) Electric grid

The energy market costs ($/h) are represented by the following quadratic function. f_{gr} represent the electric power (kW), while *a*, *b*, and *c* are cost coefficients.

$$f_{gr} = a + bP_{gr} + cP_{gr}^2 \tag{33}$$

3. PARTICLE SWARM OPTIMIZATION

PSO, developed by Kennedy and Eberhart [38], is an evolutionary optimization method inspired by the movement of bird flocks and fish schools. It uses a swarm of particles that explore a search space, adjusting positions based on personal and neighbor experiences to find the optimal solution in nonlinear systems [39].

In PSO, particles navigate a multidimensional space, and the movement optimization is influenced by past best positions and the swarm's collective history [40], [41]. Each particle's best past position is recorded and denoted as $pbest$, while among all the particles, the best particle position is represented as $gbest$. The velocity and position are updated accordingly using (34) and (35), respectively.

$$v_j^{(i+1)} = k\left(w.v_j^{(i)} + c_i rand_1.\left(pbest_j - x_j^{(i)}\right) + c_2 rand_2.\left(gbest_j - x_j^{(i)}\right)\right) \tag{34}$$

$$x_j^{(i+1)} = x_j^{(i)} + v_j^{(i+1)} \qquad \forall\; j = 1,2,3,\dots,n_S \tag{35}$$

The current position and particle velocity of at the j^{th} generation are represented, respectively, by x_j and v_j. *w*, c_1 and c_2 are inertia weight factor and the acceleration constants, while, n_S and $rand$ are the number of swarms, and random numbers between 0 and 1. Generally, *ww* is expressed as (36) [41]-[43].

$$w = w_{max} - \frac{w_{max} - w_{min}}{i_{max}} . i \qquad (36)$$

Here, i and i_{max} represent the current and maximum iterations, while w_{max} and w_{min} define the weight limits [41]-[43]. K is a constriction factor ensuring convergence without premature stability loss and is expressed as (37).

$$k = \frac{2}{\left|2 - c - \sqrt{c^2 - 4c}\right|} \text{ where } c = c_1 + c_2 \ \ and \ c > 4 \qquad (37)$$

The particle velocity is capped by v_{max}, typically set from 10–20% of the variable's dynamic range per dimension in PSO.

3.1. Implementation of PSO for EMO

The PSO algorithm for solving the OEM problem follows these steps:

Step 1 : The MG system, including DG, storage, and load data;
Step 2 : Set the objective function (14) and variable limits (17)-(18);
Step 3 : Initialize PSO parameters, including population size, inertia weight, and constants;
Step 4 : Generate a random particle population;
Step 5 : Compute power exchange (22) and verify constraints (17)-(18);
Step 6 : Evaluate fitness for each particle using (14) and (24);
Step 7 : Personal and global best values.
Step 8 : Update velocity (34) and position (35) of each particle;
Step 10 : Until the it_{max} stop criteria is reached, repeat steps 5–8;
Step 11 : Return the best option found; Stop.

4. RESULTS AND DISCUSSION

To demonstrate how to ascertain the offers of the various DG units, the modified IEEE-34 bus system as shown in Figure 1 is used. This system comprises of 26 buses, and 25 branches, with 23 of them serving as transmission lines, 2 are the voltage regulators, and 1 as the tap changer transformer. Five distinct DG units with one SSEs and electrical loads represent the MG systems. The WT connected to bus 4, an MT connected to bus 7, a PV connected to bus 11, a DEG attached to bus 19, and an FC connected to bus 23. In addition, the MG has 2 compensation capacitors placed at buses 21 and 24, respectively.

The relevant data, including the cost and emission coefficients of 5 DG units, were taken from [32]. Each DG is assumed to produce active power with a uniform power factor. The main grid and MG exchange power through the PCC over a one-day period, regulated by the MG central controller (MGCC) [44], as illustrated in Figure 1. For safe operation mode of microgrid and ensure a harmony, and reliability, if exist more than one microgrid, MGCCs communicate with distribution management system (DMS).

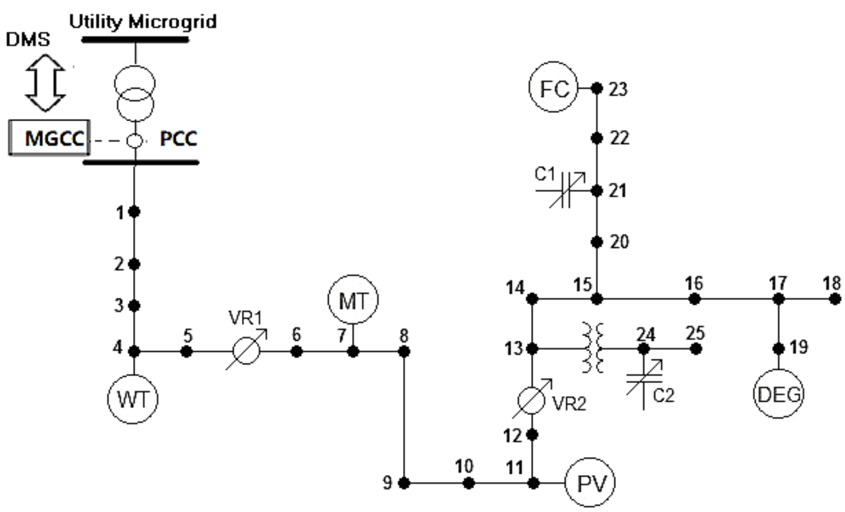


Figure 1. One-line diagram of test system

The proposed algorithm implemented and the computations were performed using MATLAB software, R2021a and all cases were run on a desktop computer Windows-10, 64-bit, Intel(R) Core(TM) i5-6500 CPU, 3.20 GHz processing frequency and 8.0 GB RAM. The PSO approach is used to identify the best solutions of OEM and EIO problems in MG. For establishing the superiority of the proposed PSO, 10 independent trial runs are performed for all the test cases.

In the MG, all eligible DGs generate electricity, with excess or additional demand managed through the PCC to the main grid [8]. The exchange energy with the MG without any restrictions. In this scenario, the impact of energy market price is investigated in three cases as shown as:
Case 1: Low energy market price;
Case 2: Average energy market price;
Case 3: Genuine value of energy market price.

Figure 2(a) display, respectively, forecast data for wind speed, energy market price, ambient temperature, and daily load diagram. It was assumed that, in comparison to nominal values, the active and reactive power loads varies in accordance with daily load diagram. Figure 2 is scaled for a 24-hour period. The convergence characteristics of EIO are shown in Figure 2(b). Table 1 shows the output active and reactive power and control variables of EIO problem. The convergence characteristics of total cost corresponding to OEM for cases 1, 2, and 3, respectively, are shown in Figure 3(a). For all cases, the obtained results of the provided DG's powers, utility power, and daily cost are shown in Figure 3(b) and Figure 4, respectively.

Due to the low market price for case 1, especially during times of low and medium load levels, in the first case the utility supplies the load inside the MG on its own. In this case, the optimal operating cost found is 257,283 ($/h). In the second case, while the market price is middle range, the majority of the loads power are provided by the MT and FC. During periods of average load, corresponding to the average market price (5.6 $/kWh), excess energy is exported from the MG to the utility. The best operation cost in this case is 263,929 ($/h).

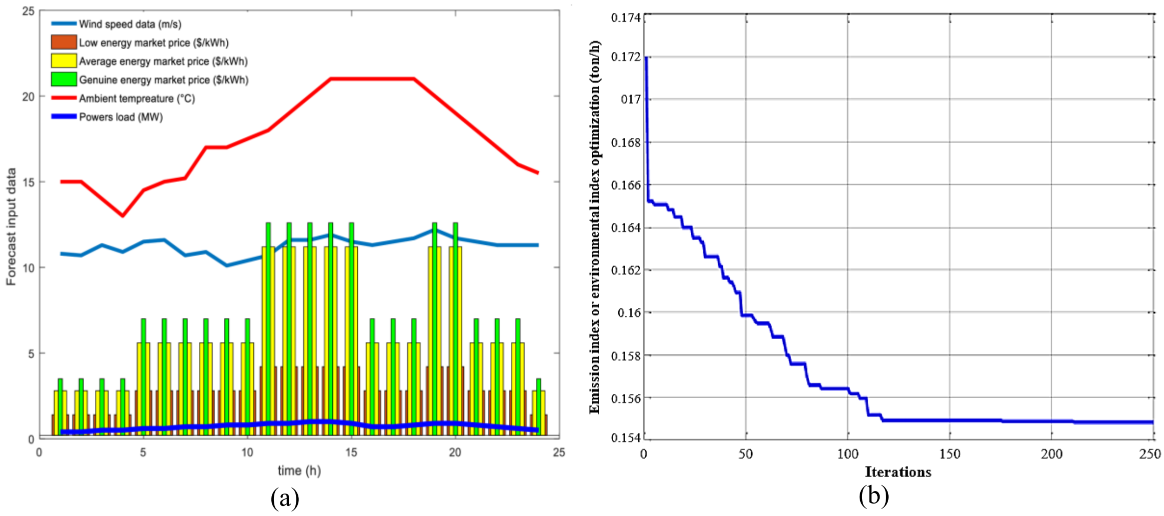
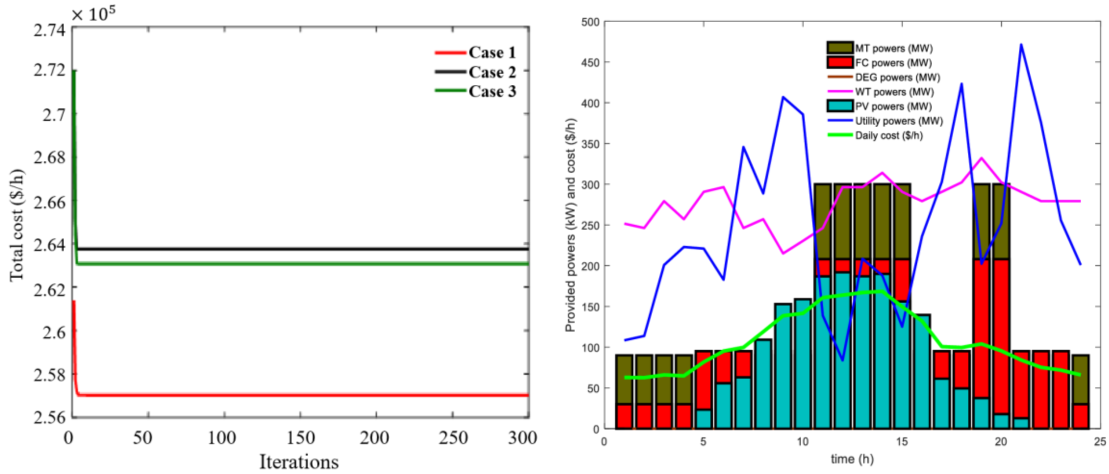


Figure 2. Forecast input data, demand profile and environmental index optimization results: (a) forecast input data, demand profile and (b) emission index or environmental index optimization

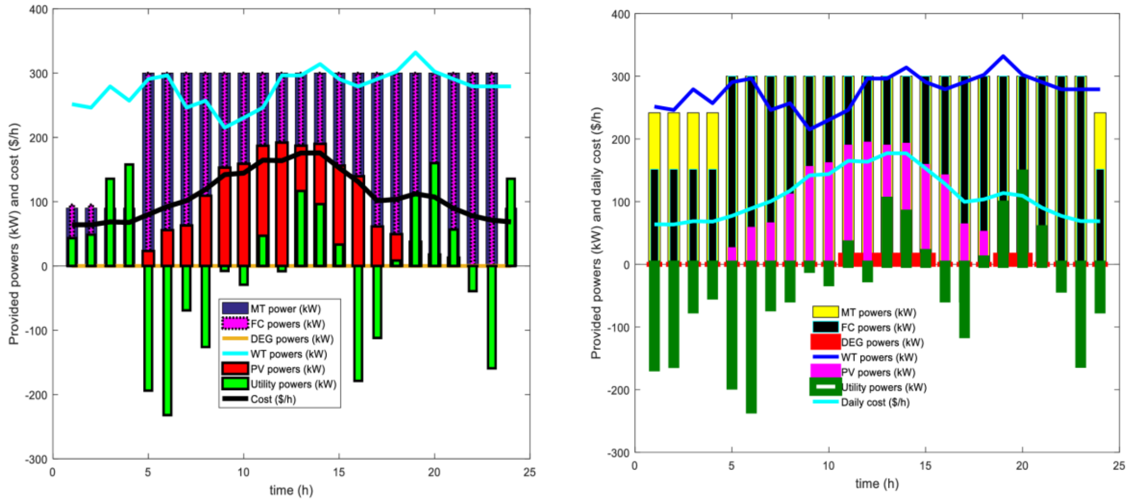
Table 1. Control variables for EIO

Control variables			
Variable	Quantity	Variable	Quantity
P_{G7} (MW)	0.300	Q_{com21} (MVAr)	0.143
P_{G19} (MW)	0.144	Q_{com24} (MVAr)	0.165
P_{G23} (MW)	0.300	T_{5-6} (p.u.)	0.925
P_{G11} (MW)	0.158	T_{12-13} (p.u.)	0.964
P_{G4} (MW)	0.230	Cost ($/h)	144.32
$P_{Utility}$ (MW)	0.384	Loss (MW)	6.46
V_0 (pu)	0.993	EIO (ton/h)	0.1548
V_{23} (pu)	0.993	CPU (s)	204.30



(a) (b)

Figure 3. Total cost and results of case 1: (a) total cost and (b) results of case 1



(a) (b)

Figure 4. Results of cases 2 and 3: (a) results of case 2 and (b) results of case 3

When the price reaches its genuine value in the third case, the MT and FC units operate at maximum power during periods of medium and high loads. In addition, for majority of the day, excess energy is exported from the MG to the utility. In this case, the optimal operation cost was achieved at 263526 ($/h). The simulation results highlight the effectiveness of the PSO approach in solving the OEM in MG. By comparison between the acquired results and literature results, the simulation results in this study show how effective the PSO strategy is at addressing MG's OEM and EIO. As a result, the findings above show that the PSO algorithm is capable of producing higher-quality solutions while maintaining computational efficiency and robustness.

5. CONCLUSION

This paper presents a successful way to solving an MG's problems that is based on the PSO method. The proposed approach has been studied and validated on an MG connected to multiple DG units and ESS. The simulation's results show how successfully the proposed approach to resolving the OEM and EIO performed in a variety of operational scenario (case studies). Moreover, the results achieved by proposed method are either better than or on par with those produced by other methods that have been reported in the literature.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ahmed Bahri		✓	✓	✓	✓	✓		✓	✓	✓		✓		
Nabil Mezhoud	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		
Bilel Ayachi	✓		✓		✓			✓	✓	✓	✓			
Farouk Boukhenoufa				✓		✓		✓		✓				
Lakhdar Bouras				✓		✓		✓		✓				

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Dr. Ahmed Bahri is a lecturer professor at the University of Ghardaia, Algeria. He received the diploma of Ph.D. in electrical engineering in 2022. He has published several research papers in conferences, journals, and reviews. Currently, he is responsible for renewable energies specialty. His areas of interest are optimization of the electrical energy produced by multi-source systems (renewable systems), subsequently injected into the electricity grid, power system stability, and control. He can be contacted at email: bahri.ahmed@univ-ghardaia.edu.dz.

Dr. Nabil Mezhoud is a lecturer professor in Electrical Engineering Department at Université 20 Août 1955-Skikda, Algeria. He received the Diploma of Ph.D. in electrical engineering in 2017. He has published several research papers in journals, reviews, and conferences. Currently, he is responsible for the electric control specialty for master degree students. He is also a member of LES Laboratory. His areas of interest are: modeling, simulation, and application of FACTS and HVDC systems, application of intelligent approaches to optimal power flow (OPF) problem, hybrid and multi-objective OPF, power system stability and control, integration of renewable energy into electrical networks, microgrid, electric vehicles, and smart grid systems. He can be contacted at email: n.mezhoud@univ-skikda.dz.

Dr. Bilel Ayachi is a lecturer professor in the Electrical Engineering Department at Université 20 Août 1955-Skikda, Algeria. He received the engineer degree in electrical engineering (electrical networks) from the Université 20 Août 1955-Skikda, Algeria, in 2004, M.Sc. degree in electrical engineering (modeling and simulation of electrical power networks) from the same University in 2008, and Ph.D. in 2020. He is also a member of LES Laboratory in the Electrical Engineering Department. His areas of interest are: FACTS, HVDC modeling and simulation in electrical power systems, power systems stability, and optimal power flow (OPF) problems. He can be contacted at email: b.ayachi@univ-skikda.dz.

Farouk Boukhenoufa is an assistant professor in Electrical Engineering Department at Université 20 Août 1955-Skikda, Algeria. He received the engineer degree in electrical engineering (electrical networks) from the Université 20 Août 1955-Skikda, Algeria, in 2004, M.Sc. degree in electrical engineering (modeling and simulation of electrical power networks) from the same University in 2008. Currently, preparing of Ph.D. degree. His areas of interest are: optimal design of electrical machines and transformers, magneto-thermal and aerodynamic study and modelling, electromagnetics, and electrical power systems. He can be contacted at email: f.boukhenoufa@univ-skikda.dz.

Lakhdar Bouras is an assistant professor in the Electrical Engineering Department at Université 20 Août 1955-Skikda, Algeria. He received the engineer degree in electrical engineering (electrical networks) from the Université of Batna, Algeria, in 1993, MSc degree in electrical engineering from the University of Oum Bouaghi, Algeria, in 2005. Currently, head of the Electrical Engineering Department, University 20 Août 1955-Skikda. His areas of interest are: modeling and control of electrical machines, diagnosis and fault detection in electrical machines and transformers, renewable energy, and smart grid. He can be contacted at email: l.bouras@univ-skikda.dz.