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Optimal Power Flow With Four Conflicting Objective Functions Using Multiobjective Ant Lion Algorithm: A Case Study of the Algerian Electrical Network

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Abstract: In this study, a multiobjective optimization is applied to Optimal Power Flow Problem (OPF). To effectively achieve this goal, a Multiobjective Ant Lion algorithm (MOALO) is proposed to find the Pareto optimal front for the multiobjective OPF. The aim of this work is to reach good solutions of Active and Reactive OPF problem by optimizing 4-conflicting objective functions simultaneously. Here are generation cost, environmental pollution emission, active power losses, and voltage deviation. The performance of the proposed MOALO algorithm has been tested on various electrical power systems with different sizes such as IEEE 30-bus, IEEE 57-bus, IEEE 118-bus, IEEE 300-bus systems and on practical Algerian DZ114-bus system. The results of the tests proved the versatility of the algorithm when applied to large systems. The effectiveness of the proposed method has been confirmed by comparing the results obtained with those obtained by other algorithms given in the literature for the same test systems.

Keywords: Optimal Power Flow, Multiobjective Ant Lion Algorithm, Algerian Electrical Network, Generation Cost, Environmental Pollution Emission, Active Power Losses, Voltage Deviation.

1 Introduction

OPTIMAL Power Flow (OPF) is one of the tasks in power system planning that helps the operators to run the system optimally under specific constraints. It has been extensively investigated since the pioneering work of Carpentier [1] in 1962. OPF can be applied periodically to minimize the total thermal unit fuel cost, emission of particulate and gaseous pollutants, real power loss, and to enhance voltage stability and to improve voltage profile as well. These can be achieved while satisfying certain constraints imposed by the network.

The OPF problem has been developed through the years from a single-objective optimization problem into a multiobjective optimization problem. Several methods have been developed to solve multiobjective optimization problems. For example, the method of the penalty function [2] and the weighted sum method [3] have been used to solve various multiobjective optimization problems. However, these methods have shortcomings and face difficulties. For example the penalty function method, choosing the appropriate penalty factors is a difficult task and it is too sensitive to the associated penalty parameters [4]. The weighted sum approach combines all the objectives with one goal using weighting factors. This formulation may lose the importance of the objective function and there is no a rational basis for determines the weighting factors of the non-commensurable objectives [5]. In order to overcome the drawbacks of these optimization methods, a wide variety of global optimization techniques have been developed to solve OPF in such complex power systems. These techniques are based on heuristic and stochastic aspects such as; Genetic algorithm (GA) [6-8], Particle Swarm Optimization (PSO) [9], Differential evolution (DE) [10], Artificial bee colony (ABC) [11], Biogeography based optimization method (BBO) [12, 13], Gravitational search algorithm (GSA)

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[14], Black hole algorithm (BH) [15],Cuckoo Optimization Algorithm (COA) [14], Grey Wolf Optimization (GWO) ,Ant Lion Optimization (ALO), Crow Search Algorithm (CSA), Dragonfly Algorithm (DA) [16].

Because of the nature of multiobjective problems, relational arithmetic operators cannot perform the comparison between different solutions. The concepts of Pareto optimal dominance allow us to compare multi-solutions in a multiobjective search space. There is no best solution, but a preferable solution. This means that several solutions are calculated, with different trade-offs between conflicting objectives and the engineer will select among them the most preferable for the problem at hand [17].

The OPF is an example of multiobjective optimization problems involving two, three objectives and in practically; the OPF can have more than three objectives [18-21].

In [18], authors proposed the use of multiobjective modified imperialist competitive algorithm (MOMICA) for the OPF problem which is applied to IEEE 30-bus and 57-bus test systems in order to solve four conflicting functions, generation cost, environmental pollution, voltage magnitude deviations and power losses.

In [19], Artificial bee colony algorithm with dynamic population (ABCDP) is proposed to solve multi-optimal power flow problems in power systems that consider the fuel cost, power losses, and emission impacts as objective functions.

Authors in [20] proposed two novel Jaya-based algorithms for solving different MOOPF problems; the modified Jaya algorithm (MJaya) and quasi-oppositional modified Jaya algorithm (QOMJaya). In this study the objectives functions were the fuel cost and the gas emission.

In [21], we proposed the use of multiobjective Dragonfly algorithm to solve single-objective, discrete, and multiobjective problems. The objectives were to reduce the total generation fuel cost, environmental pollution caused by fossil-based thermal generating units, active power losses and the voltage deviation.

In this paper a multiobjective optimization of optimal power flow (MOOPF) is carried out by using one of the latest meta-heuristic optimization techniques; the multiobjective ant lion algorithm (MOALO) using elitist non-dominating solution. MOALO technique is a new bio-inspired algorithm developed by Seyedali Mirjalili in 2016 [22], inspired from the behavior of ant lion to hunt a prey in nature.

The developed MOALO-based algorithm is applied and tested on the IEEE 30-bus, IEEE 57-bus, IEEE 118-bus systems and the Algerian electrical network DZ 114-bus for six cases of MOOPF problems. Fuel cost, total gas emission, total active losses and voltage deviation were considered to be the objective functions to be optimized. The Obtained results are compared with those of algorithms given in the literature for the same test systems to prove the effectiveness and the superiority of the proposed algorithm [21-23].

The remainder of this paper is organized as follows; in Section 2, the MOOPF problem is mathematically formulated. Then, the details of the proposed method are discussed. Next, we apply the proposed MOALO approach to solve the multiobjective OPF problem. Simulation results are presented and discussed in Section 5. Finally, Section 6 concludes the paper.

2 Problem Formulation

The task of multiobjective optimization is to find solutions to problems with several objective functions to optimize [25]. Multiobjective problem can be formulated as follows:

$$\text{Minimize} \quad F(\vec{x}) = \{f_1(\vec{x}), f_2(\vec{x}), f_3(\vec{x}), \ldots, f_{nobj}(\vec{x})\} \tag{1}$$

Subject to:

$$g_i(\vec{x}) \geq 0, \qquad i = 1,2,3,\ldots,m \tag{2}$$

$$h_i(\vec{x}) = 0, \qquad i = 1,2,3,\ldots,p \tag{3}$$

$$L_i \leq x_i \leq U_i, \quad i = 1,2,3,\ldots,n \tag{4}$$

where $f_1(\vec{x}), f_2(\vec{x}), f_3(\vec{x}), \ldots$ are the objective functions, x is the vector of control variables, g_i and h_i are the *i*-th inequality and equality constraints respectively, *n* is the number of variables, *nobj* is the number of objective functions, *m* and *p* are the numbers of equality and inequality constraints respectively and L_i, U_i are the limits of *i*-th variable.

The MOOPF is formulated as to minimize simultaneously different objective functions namely; the total fuel cost, the total emission, the active power losses and the voltage deviation.

2.1 Total Fuel Cost Function

The total fuel cost of production (F_1) of the real power of the interconnected generators is given by the quadratic function [26, 27].

$$F_1(x) = \sum_{i=1}^{ng}\left(A_i + B_i P_{gi} + C_i P_{gi}^2\right) \tag{5}$$

where A_i, B_i and C_i are the fuel cost coefficients of the generating unit *i*, P_{gi} is the generated active power at bus *i* and *ng* is number of generators including the slack bus.

2.2 Total Emission Function

The objective function (F_2) for emission minimization can be expressed as a combination of quadratic and exponential functions of the generated active power [28]:

$$F_2(x)=\sum_{i=1}^{ng}\left(a_i+b_iP_{gi}+c_iP_{gi}^2+d_i\exp\left(e_iP_{gi}\right)\right) \qquad (6)$$

where a_i, b_i, c_i, d_i and e_i are the total emission coefficients.

2.3 Function of Active Power Losses

The minimization of real power losses in the transmission network is one of the important objectives of the OPF problem. The function of active power transmission losses (F_3) is given by

$$F_3(x)=P_{loss}=\sum_{i=1}^{n}\left(G_K\left(V_i^2+V_j^2-2V_iV_j\cos\delta_{ij}\right)\right) \qquad (7)$$

where n is the branch number on the network, K is a branch with conductance G connecting the i-th bus to the j-th bus.

2.4 Voltage Magnitude Deviation Function

The objective is to minimize the voltage magnitude deviation at the load buses given by

$$F_4(x)=\Delta V=\sum_{i=1}^{Nbus}\left|V_M(i)-1\right| \qquad (8)$$

where V_M is the voltage in each bus of the network.

2.5 Minimization of the Voltage Stability Index (VSI)

The voltage stability index (VSI) is one of different indices for voltage stability and voltage collapse prediction. The voltage stability index can be defined as:

$$\begin{aligned}F_5(x)&=F_{L_{index}}(x)\\&=\min(VSI)\\&=Min\left(\max\left(L_j\right)\right)\end{aligned} \qquad (9)$$

with

$$L_j=\left|1-\sum_{i=1}^{N_w}\left(\left(-[Y_1]^{-1}\times[Y_2]\right)\times\frac{V_i}{V_j}\angle\left(\theta_{ij}+\left(\delta_i-\delta_j\right)\right)\right)\right|$$
$$,\ j=1,2,\ldots,N_{PQ} \qquad (10)$$

where Y_1 and Y_2 are the sub-matrices of the Y_{bus} and the operating range of L was set between [0-1].

2.6 Equality and Inequality Constraints

The multiobjective OPF constraints can be split into two parts: equality and inequality constraints. Equality constraints are the active and reactive power balance equations (Eq. (11)).

$$P_{g_i}-P_{d_i}=V_i\sum_{j=1}^{N}V_j\left(g_{ij}\cos\delta_{ij}+z_{ij}\sin\delta_{ij}\right)$$

$$Q_{g_i}-Q_{d_i}=V_i\sum_{j=1}^{N}V_j\left(g_{ij}\sin\delta_{ij}+z_{ij}\cos\delta_{ij}\right) \qquad (11)$$

The inequality constraints are presented as follows.

– Generators limits:

$$\begin{aligned}&P_{g_i}^{\min}\le P_{g_i}\le P_{g_i}^{\max}\\&Q_{g_i}^{\min}\le Q_{g_i}\le Q_{g_i}^{\max}\\&V_{g_i}^{\min}\le V_{g_i}\le V_{g_i}^{\max}\end{aligned} \qquad (12)$$

– Tap transformer limits:

$$T^{\min}\le T\le T^{\max} \qquad (13)$$

– Voltage magnitude for load buses limits:

$$V_{L_i}^{\min}\le V_{L_i}\le V_{L_i}^{\max} \qquad (14)$$

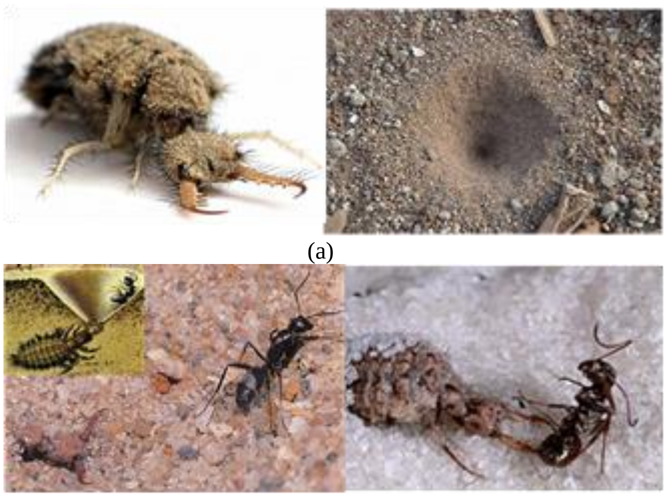
– Power flow of transmission lines limits:

$$S_{L_i}^{\min}\le S_{L_i}\le S_{L_i}^{\max} \qquad (15)$$

3 Multiobjective Antlion Optimizer (MOALO)

Antlion Optimizer (ALO) is a new nature-inspired algorithm proposed by Seyedali Mirjalili in 2016 [22] for solving constrained engineering optimization problems. ALO algorithm mimics the hunting mechanism of antlions in nature and the interaction of their favorite prey-ants- with them. The general steps of ALO which, describe the interaction between antlions and ants in the trap are as follows: Random walk of ants, building traps, entrapment of ants in traps, catching preys and rebuilding the traps and elitism.

Fig. 1(a) represent one of the cone-shapeds pits building by the antlions. In Fig. 1(b) the predator (antlion) hide in the bottom of the pit and waiting his prey (ant) to catch it. After catching the prey, the antlion



(a)

(b)

Fig. 1 Interaction the last between the antlions and ants in the trap.

rebuilding the traps for the next hunt. The main inspiration of ALO method is that the predators tend to dig a big trap when they is hungry.

The original random walk used in the ALO algorithm to simulate the random walk of ants is expressed as follows:

$$X(t)=\left[0, cumsum\left(2r\left(t_1\right)-1\right), cumsum\left(2r\left(t_2\right)-1\right), \ldots, cumsum\left(2r\left(t_n\right)-1\right)\right] \quad (16)$$

where, *cumsum* determines the cumulative sum, n shows the maximum number of iteration, t presents the step of random walk (iterations), and $r(t)$ *is* a stochastic function given as:

$$r(t)=\begin{cases}1 & \text{if } rand>0.5\\ 0 & \text{if } rand\le 0.5\end{cases} \quad (17)$$

where *rand* is a random number generated in the interval [0, 1].

To keep the random walk in the limits of the search space and prevent the ants from overshooting, the random walk is designated using the following expression:

$$X_i^t=\frac{\left(X_i^t-a_i\right)\left(d_i^t-c_i^t\right)}{\left(b_i-a_i\right)}+c_i^t \quad (18)$$

where d_i^t and c_i^t indicate the maximum and minimum of i-th variable at t-th iteration respectively, a_i and b_i are the minimum and maximum of random walks corresponding to the i-th variable, respectively.

The model of the trapping mechanism of antlions on ants is expressed by the Eqs. (19) and (20):

$$c_i^t=Antlion_j^t+c^t \quad (19)$$

$$d_i^t=Antlion_j^t+d^t \quad (20)$$

where c^t and d^t are the minimum and the maximum of all variables at t-th iteration, c^t and d^t are the minimum and the maximum of all variables for i-th ant, and $Antlion_j^t$ represents the position of the selected j-th antlion at t-th iteration.

In the nature, bigger pits are built by bigger antlions to increase their chance of survival. Mathematically this step is given below as:

$$c^t=\frac{c^t}{I} \quad (21)$$

$$d^t=\frac{d^t}{I} \quad (22)$$

where $I=10^w\ \dfrac{t}{\max iter}$ is the maximum number of iteration, t is the current iteration and w is a constant depends on t. w is defined as a follows:

$$w=\begin{cases}2 & \text{when} \quad t>0{,}1maxiter\\ 3 & \text{when} \quad t>0{,}5maxiter\\ 4 & \text{when} \quad t>0{,}75maxiter\\ 5 & \text{when} \quad t>0{,}9maxiter\\ 6 & \text{when} \quad t>0{,}95maxiter\end{cases}$$

In ALO, the following equation simulates the catching of the ant and rebuilding the pit:

$$Antlion_j^t=Ant_j^t \quad \text{if}: f\left(Ant_j^t\right)<f\left(Antlion_j^t\right) \quad (23)$$

where, t indicates the current iteration and Ant_j^t shows the position of i-th ant at t-th iteration.

The last step in ALO is elitism; where the best antlion obtained is selected and stored as an elite during the optimization process. Since the elite is the fittest antlion, it is able to affect the movements of the remaining ants along the iterations. Therefore, the position update of every ant is depending on the random walks around a selected antlion by the roulette wheel and the elite. The elitism mechanism is explained by this equation:

$$Ant_j^t=\frac{R_A^t+R_E^t}{2} \quad (24)$$

where, R_A^t is the random walks selected by the roulette wheel at t-th iteration around the antlion, and R_E^t is the random walk at t-th iteration around the elite.

- **Pareto Optimal Solution**

The pareto optimal approach is an effective method for the multiobjective optimization problem. This method includes a group of dominant answers that make compromise between objective functions. The Pareto-optimal solutions are illustrated as a diagram named "Pareto diagram". In the multiobjective optimization problem, any solution X_1 is dominant or none dominant the other solution X_2. Generally, X_1 is assumed to dominate X_2 only if two conditions are satisfied [29]:

$$\forall i\in\{1,2,\ldots,n\}: F_i\left(X_1\right)\le F_i\left(X_2\right)$$
$$\exists j\in\{1,2,\ldots,n\}: F_j\left(X_1\right)\le F_j\left(X_2\right) \quad (25)$$

- **Best Compromise Solution (BCS)**

In the MOALO approach, the non-dominated solutions are saved in a repository in all iterations. These solutions are stored by the decision maker function (power system operator). To select the best solution from the Pareto optimal solution, we apply the roulette wheel method at each iteration to obtain a membership function. The membership function $\boldsymbol{\mu}_i^h$ of the i-th objective function $\boldsymbol{F_i}$ is defined as [29]:

$$\mu_i^h = \begin{cases} 1 & F_i \le F_i^{min} \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} \le F_i \le F_i^{max} \\ 0 & F_i \ge F_i^{max} \end{cases} \tag{26}$$

where, F_i^{min} and F_i^{max} represent the minimum and the maximum value of the i-th objective function F_i.

When Eq. (26) is a maximum, the best non-dominated solution is defined as follows:

$$\mu^h = \frac{\sum_{i=1}^{N_{obj}} \mu_i^h}{\sum_{j=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^h} \tag{27}$$

where, M presents the number of the non-dominate solution.

- MOALO utilizes an archive to store and retrieve the best approximations of the non-dominated Pareto optimal set during optimization. Then, the solutions are chosen from this archive by the mechanism of the roulette wheel based on the coverage of solutions as antlions to lead ants towards promising regions of multiobjective search spaces.

The details of the MOALO method are represented in Fig. 2 as a follows:

4 MOALO for Multiobjective Optimal Power Flow (MOOPF)

The computational procedure for solving the MOOPF problems using MOALO method is described in the following steps:

Step 1: Initialize the parameters of system, and specify the boundaries of all variables.

Step 2: Generate the initial population ***Pop*** based on the upper and lower limits of the control variables Eq. (25). The vector of control variable can be generated using active and reactive powers, bus voltage magnitudes, and transformers tap values, etc.

While the end condition is not met
  For every ant
    Select a random antlion from the archive
    Select the elite using roulette wheel from the archive
    Update c^t and d^t using Eqs. (21) and (22)
    Create a random walk and normalize it using Eqs. (16) and (18)
    Update the position of the ant using Eq. (23)
  End for
  Calculate the objective values for all ants
  Update the archive
End while
Return archive

Fig. 2 Pseudo code of MOALO approach.

$$Pop = \begin{bmatrix} u_{1,1} & u_{1,2} & \cdots & u_{1,n} \\ u_{2,1} & u_{2,2} & \cdots & u_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{m,1} & u_{m,2} & \cdots & u_{m,n} \end{bmatrix} \tag{28}$$

The variable $u_{k,j}$ of the population can be described as follows:

$$u_{k,j} = u_j^{\min} + rand\left(Np, D\right) * \left(u_j^{\max} - u_j^{\min}\right) \tag{29}$$

where, N_p is the number of search agents, D is the dimension of the vector variable and $u_j^{\max}$ and $u_j^{\min}$ are the upper and lower limits of the j-th variable, respectively.

Step 3: Run the Newton Raphson load flow program to calculate the objective functions and evaluate the particles in the population.

Step 4: Apply Pareto optimal method and store the non-dominated solution.

Step 5: use the roulette wheel to choose a random solution from the archive and the elite, next, update parameters c^t and d^t by using Eqs. (21) and (22). After, create and normalize a random walk using Eqs. (12) and (18). Next, update the position of ant by Eq. (23).

Step 6: Calculate the objective values of each ant and update the archive.

Step 7: Determine the non-dominated solutions using the Pareto method.

Step 8: If the current iteration number reaches the maximum iteration number stop and go to step 5.

Step 9: Find the best compromise solution from the Pareto optimal solutions.

5 Case Studies

To verify the effectiveness of the proposed algorithm, different scales of power system cases have been considered: IEEE 30-bus, IEEE 57-bus, the IEEE 118-bus system and the Algerian transmission network DZ 114-bus (Fig. 3).

In these studies, six cases are discussed to demonstrate the usefulness of the proposed approach:

- **Case 1: Fuel cost**

$$\text{Minimize} F\left(\vec{x}\right) = \left\{F_1\left(\vec{x}\right)\right\} \tag{30}$$

- **Case 2: Fuel cost + Emission**

$$\text{Minimize } F\left(\vec{x}\right) = \left\{F_1\left(\vec{x}\right),\ F_2\left(\vec{x}\right)\right\} \tag{31}$$

- **Case 3: Fuel cost + Real power losses**

$$\text{Minimize } F\left(\vec{x}\right) = \left\{F_1\left(\vec{x}\right),\ F_3\left(\vec{x}\right)\right\} \tag{32}$$

- **Case 4: Fuel cost + Voltage magnitude deviation**

$$\text{Minimize } F\left(x\right) = \left\{F_1\left(x\right),\ F_4\left(x\right)\right\} \tag{33}$$

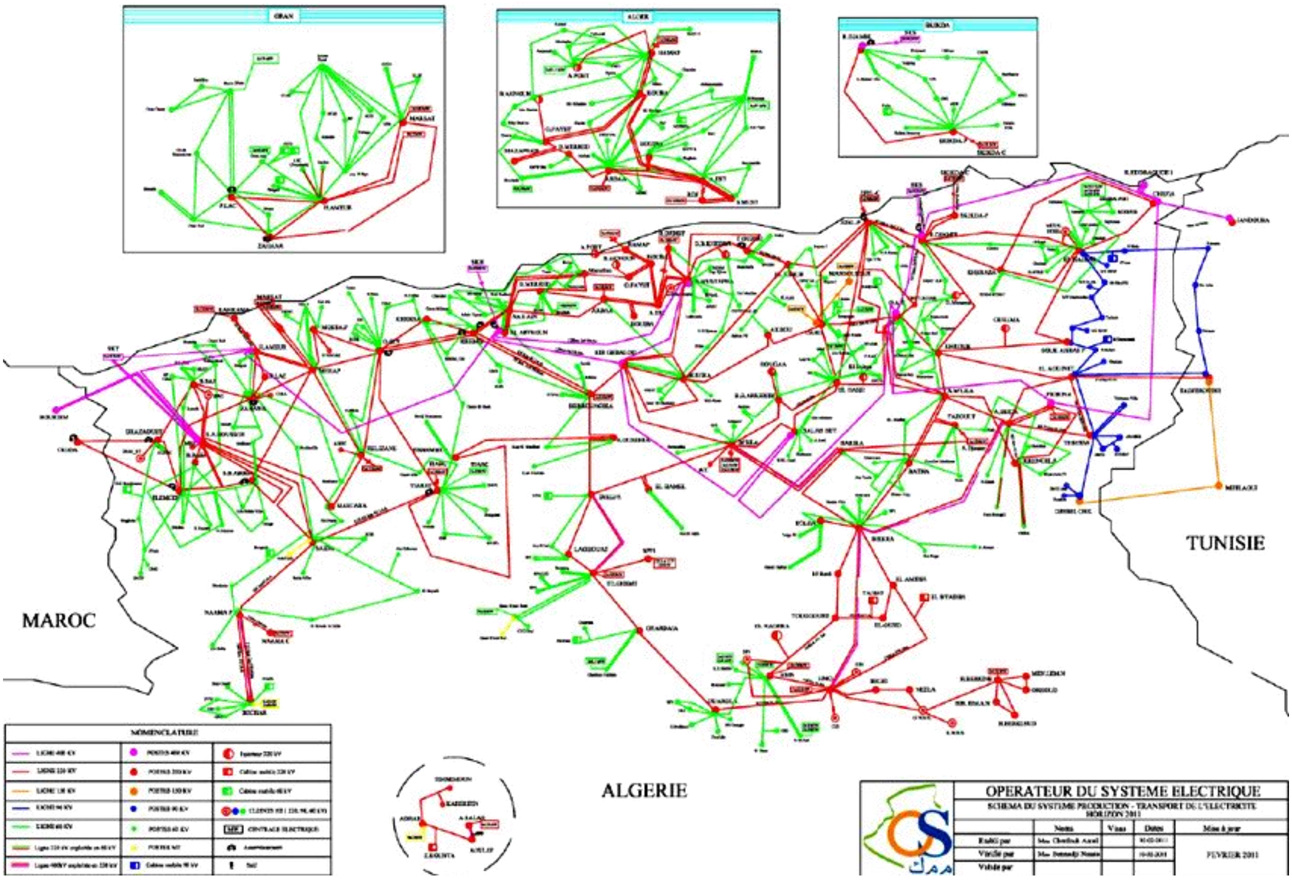


Fig. 3 Topology of the Algerian 114-bus power system [30].

- **Case 5: Fuel cost + Emission + Power losses**

$$\text{Minimize } F(x)=\{F_1(x), F_2(x), F_3(x)\} \tag{34}$$

- **Case 6: Fuel cost + Emission + Power losses + Voltage magnitude deviation**

$$\text{Minimize } F(x)=\{F_1(x), F_2(x), F_3(x), F_4(x)\} \tag{35}$$

The MOALO parameters utilized in this study is represented in Table.1.

5.1 IEEE 30-Bus Test System

The IEEE 30-bus test system [31, 32], comprises 6 generators installed at buses n° :1, 2, 5, 8, 11, and 13, forty one transmission lines including 4 transformers between buses (6-9), (6-10), (4-12), (28-27) and 9 compensators at the loads buses n° 10, 12, 15, 17, 20, 21, 23, 24, and 29 [33].The total load active power of this system is 2.834 pu at 100 MVA base.

The vector of control variables of IEEE 30-bus test system includes the generated active powers, magnitude voltages of generators, transformer tap settings and the capacitor banks.

$$\begin{aligned} x = [&P_{g_2}, P_{g_5}, P_{g_8}, P_{g_{11}}, P_{g_{13}}, V_1, V_2, V_5, V_8, V_{11}, V_{13}, T_{6\text{-}9}, \\ &T_{6\text{-}10}, T_{4\text{-}12}, T_{28\text{-}27}, Q_{c10}, Q_{c12}, Q_{c15}, Q_{c17}, Q_{c20}, Q_{c21}, \\ &Q_{c23}, Q_{c24}, Q_{c29}] \end{aligned} \tag{36}$$

Table.1 Control parameter settings of MOALO algorithm for test systems.

Parameter	Setting Value
Number of search agents (NSA)	100
Number of iterations	100 / 500
Archive maximum size	100
Search domain (*rand*)	[0 1]

In this simulation, 100 test runs were carried out for solving multiobjective optimal power flow problem using the proposed algorithm. Table 2 represents the best result of the simulation obtained from the MOALO algorithm for six cases, Tables 3 and 4 present the comparison between the results obtained by MOALO-MOOPF and other multiobjective techniques for All cases.

In the case 1, the only objective function is minimization of quadratic cost function. The BCS results in this case are presented in Table 2 and the convergence curve is exposed in Fig. 4. From Table 2 and Table 3; we can observe that the best compromise solutions obtained by MOALO as ($799.1436/h) is better than those obtained by the others methods.

The results obtained from case 2 trough case 6 are also presented in Table 2, and the set of dominant points of these results is illustrated in Fig 5. Table 3 presents the comparison of the proposed MOALO with other heuristic methods previously cited in the literature. It is

Table 2 Best results of multiobjective OPF problem for six cases using MOALO algorithm for IEEE 30-bus power system.

Cases	Min	Case 01	Case 02	Case 03	Case 04	Case 05	Case 06	Max
Pg_1	50	176.9100	121.9200	126.9200	178.7300	129.0300	130.9900	200
Pg_2	20	48.7224	56.1451	54.1799	47.1804	53.9095	62.0566	80
Pg_5	15	21.2700	33.4646	31.8519	20.6585	33.5281	26.6447	50
Pg_8	10	21.2925	31.2523	29.0306	19.5493	25.9640	20.8269	35
Pg_{11}	10	11.8465	23.6992	23.2661	13.5921	23.9419	24.5149	30
Pg_{13}	12	12.0000	22.5619	23.9276	14.9793	23.1179	25.5783	40
Vg_1	0.9	1.1000	1.0998	1.0995	1.0005	1.1000	1.0478	1.1
Vg_2	0.9	1.0881	1.0921	1.0950	1.0054	1.1000	1.0540	1.1
Vg_5	0.9	1.0620	1.0758	1.0801	1.0026	1.1000	1.0556	1.1
Vg_8	0.9	1.0700	1.0826	1.0870	1.0183	1.1000	1.0455	1.1
Vg_{11}	0.9	1.1000	1.0946	1.0884	1.0416	1.0936	1.0458	1.1
Vg_{13}	0.9	1.1000	1.0785	1.0764	1.0070	1.0907	1.0594	1.1
$T_{6\text{-}9}$	0.9	1.0066	1.0944	1.0865	0.9868	1.1000	1.0436	1.1
$T_{6\text{-}10}$	0.9	0.9444	1.0871	1.0892	0.9380	1.1000	1.0576	1.1
$T_{4\text{-}12}$	0.9	1.0095	1.0890	1.0855	0.9584	1.0896	1.0636	1.1
$T_{28\text{-}27}$	0.9	0.9702	1.0947	1.0675	0.9568	1.0894	1.0108	1.1
Qc_{10}	0	3.2615	2.4824	2.3749	2.4977	2.9352	3.3352	5
Qc_{12}	0	4.6706	3.4092	2.8808	3.9472	3.5515	1.5559	5
Qc_{15}	0	4.7018	2.6738	3.2391	3.2233	1.7035	2.1951	5
Qc_{17}	0	4.1172	2.0257	2.4554	3.0011	2.5251	3.4373	5
Qc_{20}	0	2.1428	1.1407	3.5667	2.3662	2.0506	3.5225	5
Qc_{21}	0	1.7861	1.3482	1.9240	2.0403	3.4073	2.6896	5
Qc_{23}	0	3.1086	2.7192	4.0104	1.8238	1.7189	3.2877	5
Qc_{24}	0	4.5001	2.2566	3.8068	2.1653	2.0920	1.8451	5
Qc_{29}	0	1.3933	1.3195	2.4957	3.1947	3.2858	2.9628	5
Fuel Cost [$/h]	-	799.1436	831.6764	826.4556	803,0611	828.3344	826.2676	-
Emission [ton/h]	-	0.3679	0.2576	0.2642	0.3718	0.2668	0.2730	-
Ploss [MW]	-	8.6400	5.639	5.7727	11.2870	6.0932	7.2073	-
DV [pu]	-	2.1930	1.2870	1.2560	0.0900	1.4080	0.7160	-

Table 3 Comparison of the BCS for cases 1 of IEEE 30-bus power system.

Fuel Cost [$/h]	Optimization Algorithm
799.1436	Multiobjective Ant Lion Optimizer (MOALO)
799.1821	League Championship Algorithm (LCA) [34]
799.1974	Differential Evolution (DE) [35]
799.2776	Interior search algorithm (ISA) [36]
799.2891	Simulated Annealing (SA) [37]
799.9217	Electromagnetism-Like Mechanism (EM) [38]
800.078	Genetic Evolving Ant Direction HDE (EADHDE) [34]
800.1579	Evolving Ant Direction Differential Evolution (EADDE) [39]
800.2041	Particle Swarm Optimization (PSO) [40]
800.41	Fuzzy Particle Swarm Optimization (FPSO) [41]
800.72	Improved Genetic Algorithms (IGA) [42]
800.805	Particle Swarm Optimization (PSO) [43]
800.8882	Black Hole Optimization Algorithm (BH) [15]

clear that the application of MOALO method to the multiobjective optimal power flow is giving better solutions than other algorithms and the Pareto optimal solutions are diverse and good distributed over the Pareto front. For example, in case 6 MOALO provides a minimum fuel cost and minimum voltage magnitude deviation compared with four recent algorithms ($826.2676/h and 0.0189 pu).

5.2 IEEE 57-Bus Test System

IEEE 57-bus test system constitutes of 7 generators, 80 transmission lines, 17 transformers and three capacitor banks [18]. The limits of voltage buses and transformer tap settings are between 0.9 and 1.1 pu [36].

The vector of control variables in this case also includes the generated active powers, magnitude voltages of generators, transformer tap settings and the capacitor banks' sizes.

Results of simulation obtained from the proposed method of all cases are presented in Table 5. A comparison for case 1 and for the rest of cases is cited in Table 6 and Table 7, respectively.

Table 4 Comparison of the BCS for case 2 through 6 of IEEE 30-bus power system.

Case 2: Fuel Cost +Emission				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	831.6764	0.2576	-	-
MOMICA[9]	865.0660	0.2221	-	-
BB-MPSO[9]	865.0985	0.2227	-	
Case 3 : Fuel Cost +Ploss				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	826.4556	-	5.7727	-
MJaya[20]	826.9651	-	5.7596	-
QOMJaya[20]	827.9124	-	5.7960	-
MOABC/D[44]	827.6360	-	5.2451	-
NKEA[20]	829.4911	-	5.8603	-
MOMICA[9]	848.0544	-	4.5603	-
MODA[10]	842.7550	-	5.2090	-
Case 4 : Fuel Cost +DV				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	803,0611	-	-	0,3787
MODA[10]	804.6862	-	-	0.0114
MOMICA[9]	804.9611	-	-	0.0952
BB-MPSO[9]	804.9639	-	-	0.1021
MINSGA-II[9]	805.0076	-	-	0.0989
ISA[36]	807.6408	-	-	0.1273
Case 5 : Fuel Cost +Emission +Ploss				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	828.3344	0.2668	6.0932	-
MODA[10]	867.9070	0.2640	5.9110	-
Case 6 : Fuel Cost +Emission +Ploss +DV				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	826.2676	0.2730	7.2073	0.0189
MODA[10]	828.4912	0.2648	5.9119	0.0585
MOMICA[9]	830.1884	0.2523	5.5851	0.2978
BB-MPSO[9]	833.0345	0.2479	5.6504	0.3945
NKEA[20]	834.6433	0.2491	5.8935	0.4448

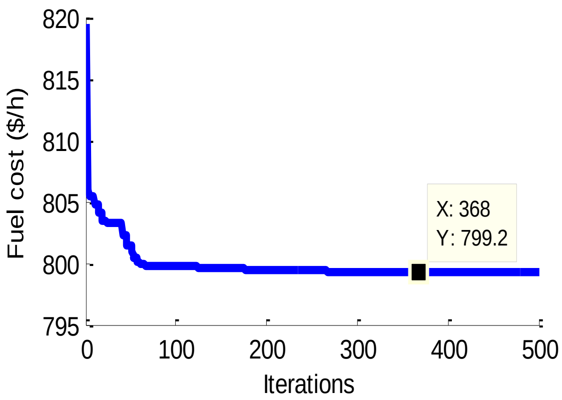
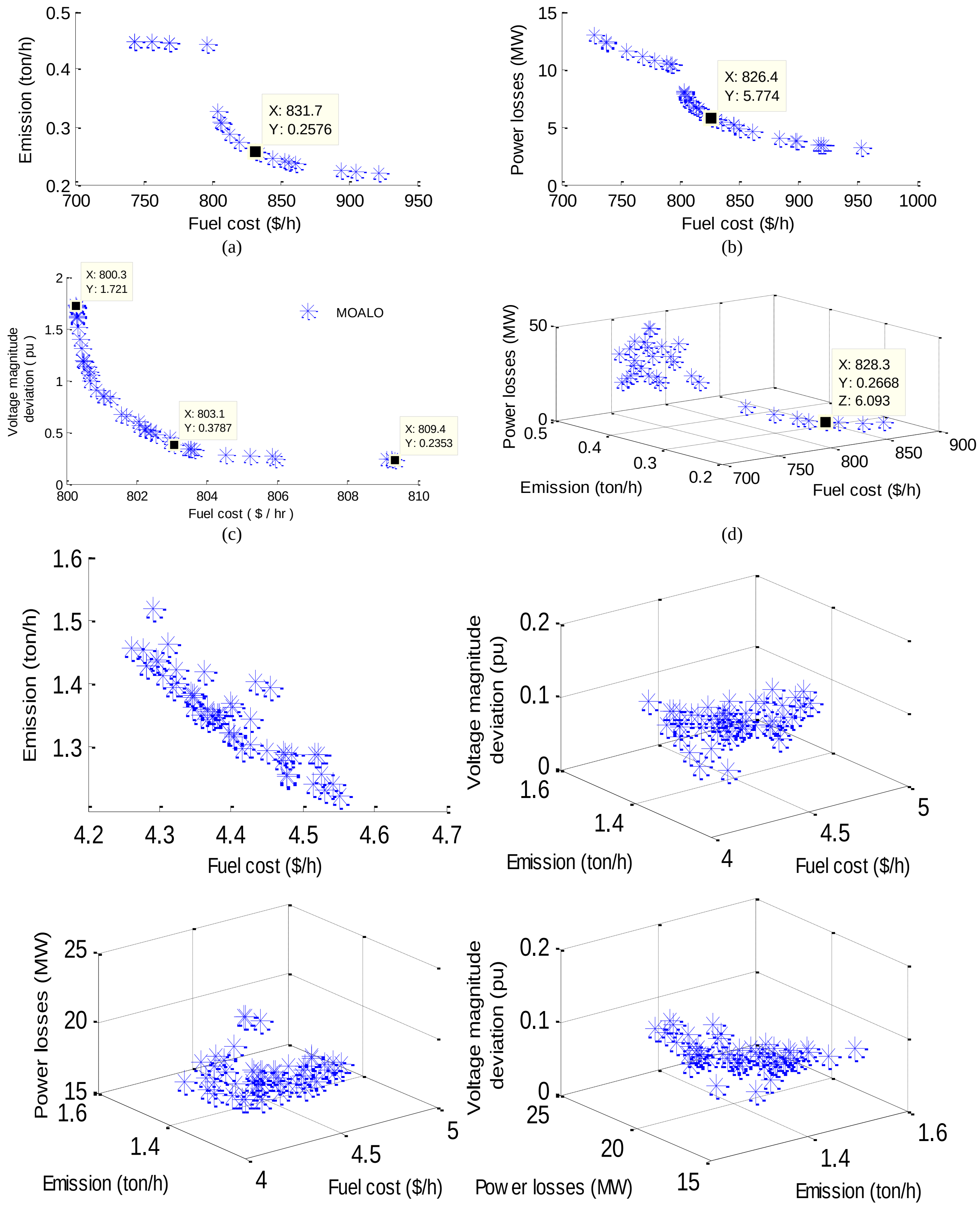


Fig. 4 The convergence of MOALO algorithm for IEEE 30-bus system in case 1.

In this simulation, Table 5 shows the best values of four competing objectives optimized by the MOALO. Convergence diagram of the fuel cost (case 1) is shown in Fig. 6 and the Pareto-optimal results from case 2 to case 6 are illustrated in Fig. 7. The comparison shown in Tables 6 and 7 prove that MOALO gives better results except in the last case where the power losses and the fuel cost are lower than those obtained by NKEA method by a percentage of -1.76% and -19.85%, respectively, but the emission and the voltage deviation are better by 5.84% and 92.04%, respectively. As a conclusion, MOALO is better than KNEA.



(e)

Fig. 5 Pareto-optimal solutions obtained in cases 2 through 6 for best solution for IEEE 30-bus power system; a) Case 02– Fuel cost + Emission, b) Case 03– Fuel cost +Ploss, c) Case 04– Fuel cost + DV, d) Case 05– Fuel cost +Emission +Ploss, and e) Case 06– Fuel cost + Emission +Ploss +DV.

Table 5 Results of MO-OPF problem for 6-cases using MOALO algorithm of 57-bus test system.

Cases	Case 01	Case 02	Case 03	Case 04	Case 05	Case 06
Pg_1	396.9100	214.3100	148.2700	156.3800	231.7600	207.7700
Pg_2	119.5583	98.7031	68.4795	97.5843	19.0593	68.1618
Pg_3	92.0553	98.5652	53.7031	49.4052	66.7253	80.1569
Pg_6	43.8150	84.0391	99.7128	36.2118	92.0849	96.8831
Pg_8	89.2414	383.0225	424.5749	479.7535	345.8168	337.1985
Pg_9	453.6108	100.0000	99.2418	92.5269	99.7837	98.8692
Pg_{12}	94.3669	292.6367	375.0308	365.9775	409.7688	377.2544
Vg_1	1.0973	1.0107	1.0988	1.0241	1.1000	1.0153
Vg_2	1.0999	0.9616	1.0971	1.0238	1.1000	1.0136
Vg_3	1.0901	0.9633	1.0893	1.0116	1.1000	1.0043
Vg_6	1.0986	0.9378	1.0899	1.0096	1.0913	0.9996
Vg_8	1.1000	1.1000	1.1000	1.0360	1.1000	1.0184
Vg_9	1.0962	0.9539	1.1000	1.0238	1.0910	1.0214
Vg_{12}	1.0849	0.9423	1.0957	1.0122	1.0999	1.0165
T_{4-18}	1.0865	0.9608	1.0987	1.0166	0.9940	1.0157
T_{4-18}	1.0799	0.9736	1.1000	1.0104	1.1000	0.9937
T_{21-20}	1.0942	0.9553	1.1000	0.9762	1.1000	1.0031
T_{24-25}	1.0489	1.0883	1.0963	1.0224	1.0000	1.0048
T_{24-25}	1.0661	0.9703	1.1000	0.9887	0.9912	1.0120
T_{24-26}	1.0535	0.9524	1.0921	1.0368	0.9928	1.0130
T_{7-29}	1.0428	1.0984	1.0958	0.9811	0.9999	0.9847
T_{34-32}	0.9861	1.0970	1.1000	0.9679	0.9963	1.0279
T_{11-41}	1.0400	1.0984	1.1000	0.9813	1.1000	1.0096
T_{15-45}	1.0160	1.1000	1.0971	0.9521	1.1000	0.9952
T_{14-46}	1.0108	1.0996	1.0969	0.9544	1.0959	0.9803
T_{10-51}	1.0261	1.1000	1.0867	0.9628	1.0972	0.9826
T_{13-49}	0.9867	0.9742	1.1000	0.9240	1.0984	0.9946
T_{11-43}	1.0661	1.0825	1.0917	0.9537	1.1000	0.9842
T_{40-56}	1.0459	1.1000	1.0980	1.0147	1.0736	0.9844
T_{39-57}	1.0547	0.9385	1.0911	0.9369	1.0981	0.9991
T_{9-55}	1.0495	0.9507	1.0915	0.9916	1.0000	1.0188
Q_{c18}	14.9026	10.8112	15.9580	13.0577	16.4537	16.4161
Q_{c25}	17.2390	0.5511	16.2033	16.4359	14.8909	15.3389
Q_{c53}	1.0045	0.2433	18.0000	11.5385	13.3389	14.3123
Fuel Cost [$/h]	41623.1352	41023.6757	41797.6457	41747.82233	42931.4007	42806.6894
Emission [ton/h]	-	1.3113	-	-	1,6349	1,4288
Ploss [MW]	-	-	14.8083	-	15,0270	16,7514
DV [pu]	-	-	-	0.9444	-	0,0830

Table 6 Comparison of the BCS obtained for the first case of 57-bus test system.

Fuel Cost [$/h]	Optimization Algorithm
41623.1352	Multiobjective Ant Lion Optimizer (MOALO)
41676.9466	Interior search algorithm (ISA) [36]
41693.9589	Artificial bee colony (ABC) [46]
41815.5035	Linearly decreasing inertia weight PSO (LDI-PSO) [46]
41866.8987	Black Hole Optimization Algorithm (BH) [14]
52819.7052	Gravitational search algorithm (GSA) [26]

5.3 IEEE 118-Bus Test System

The IEEE 118-bus test system consists of 54 generators, 9 transformers,14 capacitor banks, 186 transmission lines and 99 constant impedance loads, which consume total of 4242 MW and 1438 MVAr. The slack bus is the bus number 69 [25, 45].

For this system, the emission minimization is not a part of the optimization. Therefore, a new case study is discussed and explained by Eq. (37):

- **Case 7: Fuel cost + Power losses + Voltage magnitude deviation**

$$\text{Minimize } F(x)=\{F_1(x),\, F_3(x),\, F_4(x)\} \tag{37}$$

The control variable always contains the generated active powers P_{g_i}, generated magnitude voltages V_{g_i}, transformer tap settings T and the capacitor banks Q_{ci}. Best setting of control variables and BCS results of fuel cost, power losses and voltage magnitude deviation are presented in Table 8.

Table 7 BCS comparisons for cases 2, 3, 4, 5, 6 of IEEE 57-bus power system.

	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
Case 2: (Fuel +Emission)				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	41023.6757	1.3113	-	-
NKEA [20]	41928.8054	1.5256	-	-
BB-MPSO[9]	41947.3505	1.4957	-	-
Case 3: (Fuel +Ploss)				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	41797.6457	-	14.8083	-
MODA[10]	41903.0000	-	16.2646	-
Case 4: (Fuel +DV)				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	41747.82233	-	-	0.9444
ISA[36]	41939.7706	-	-	0.9931
Case 5: (Fuel +Emission +Ploss)				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	42931.4007	1,6349	15,0270	-
MODA[10]	43021.0000	1.5028	18.1103	-
Case 6: (Fuel +Emission +Ploss +DV)				
	Fuel Cost [$/h]	Emission [ton/h]	Ploss [MW]	DV [pu]
MOALO	42806.6894	1,4288	16,7514	0,0830
NKEA[20]	42065.9964	1.5174	13.9764	1.042
MODA[10]	43897.0000	1.6312	16.7039	0.0040

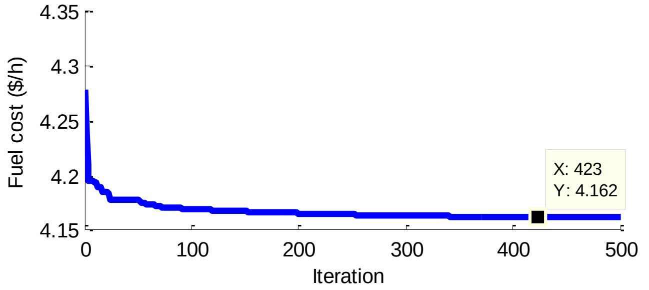
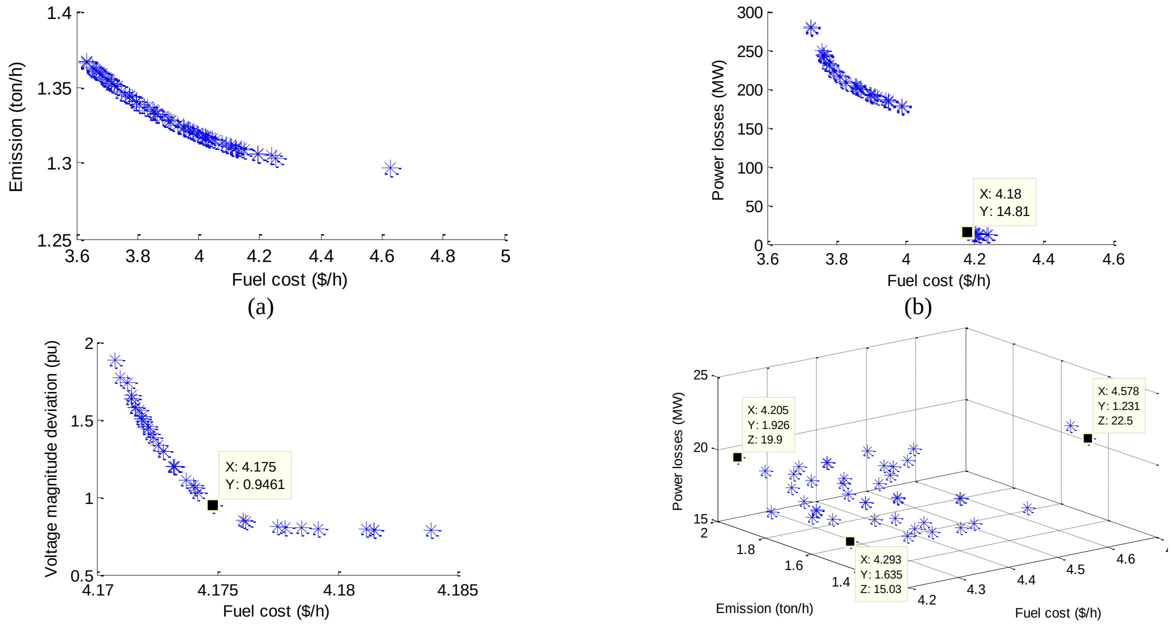
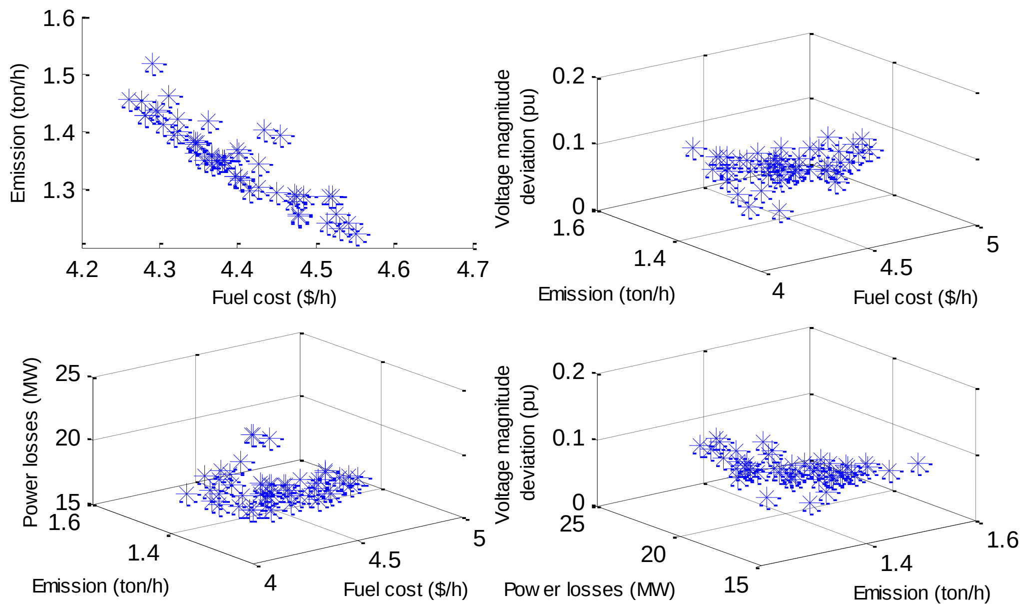


Fig. 6 The convergence of MOALO algorithm for IEEE 57-bus system in case 1.





(e)

Fig. 7 Pareto-optimal solutions obtained in cases 2 through 6 for best solution for IEEE 57-bus power system; a) Case 02– Fuel cost + Emission, b) Case 03– Fuel cost +Ploss, c) Case 04– Fuel cost + DV, d) Case 05– Fuel cost +Emission +Ploss, and e) Case 06– Fuel cost + Emission +Ploss +DV.

Table 8 Optimal results for Case 1, 3, 4 and 7 of IEEE 118-bus power system.

Cases	Case 01	Case 03	Case 04	Case 7
Pg_4	58.1168	69.8583	44.6068	63.9650
Pg_6	17.2000	73.4572	42.4465	19.5619
Pg_8	84.3508	28.0091	76.1095	89.7830
Pg_{10}	19.1079	30.4144	86.1295	86.3915
Pg_{12}	118.7846	498.6870	51.4846	155.5963
Pg_{15}	174.4868	2.4984	129.5705	149.4962
Pg_{18}	0.6334	37.1527	62.9925	2.6025
Pg_{19}	54.1591	12.2285	87.9390	8.6118
Pg_{24}	54.3537	14.0780	29.4575	2.9189
Pg_{25}	32.8639	54.3330	66.4895	98.7347
Pg_{26}	160.7403	1.1973	281.3176	312.2555
Pg_{27}	338.7957	314.7817	195.6322	184.0202
Pg_{31}	77.6353	2.8705	6.2279	1.0166
Pg_{32}	1.0385	14.4228	31.4108	79.4055
Pg_{34}	0.3106	7.9408	70.2945	12.0183
Pg_{36}	6.3241	56.4890	78.6520	65.8080
Pg_{40}	18.0225	39.2603	7.7960	31.9584
Pg_{42}	94.2710	5.9264	15.3099	61.9603
Pg_{46}	43.6254	7.6001	66.1496	64.1960
Pg_{49}	32.3166	110.9023	87.8088	28.6385
Pg_{54}	48.9984	138.6400	170.8760	140.7991
Pg_{55}	26.8054	32.4877	97.3909	27.4335
Pg_{56}	97.3955	21.2718	67.7258	97.4735
Pg_{59}	46.2018	70.8129	8.7094	87.4995
Pg_{61}	24.3733	1.1725	74.8891	229.7120
Pg_{62}	106.1739	208.1558	229.9273	25.9852
Pg_{65}	58.5854	7.1656	24.3411	26.8529
Pg_{66}	441.2616	268.8450	87.6940	294.3056
Pg_{69}	377.3800	336.0200	320.7800	31.1800
Pg_{70}	377.3800	336.0200	320.7800	31.1800
Pg_{72}	76.7580	51.7658	11.5616	41.8544
Pg_{73}	41.4256	61.9467	75.1968	2.3615
Pg_{74}	1.8683	3.4983	33.1718	3.0783
Pg_{76}	3.8279	44.3855	72.2557	98.8533
Pg_{77}	47.6012	15.0467	39.4746	36.2710

Table 8 (continued)

Cases	Case 01	Case 03	Case 04	Case 7
Pg 80	71.2533	32.8534	36.4830	88.5697
Pg 82	190.5333	480.8197	295.4521	136.3080
Pg 85	83.3912	19.7157	28.0725	43.9258
Pg 87	5.7173	65.2036	32.0903	4.0535
Pg 89	266.7971	124.7551	0.1264	14.1221
Pg 90	13.5108	46.6010	16.7436	62.7845
Pg 91	42.5798	45.0051	87.0267	83.6342
Pg 92	13.7082	52.8628	44.5061	99.7959
Pg 99	97.8962	65.9314	25.4837	52.8237
Pg 100	96.1863	2.0234	336.2604	340.5152
Pg 103	109.0864	61.8547	58.5041	2.3171
Pg 104	14.5428	72.8100	93.7458	28.1233
Pg 105	0.6748	35.0054	25.0862	89.5821
Pg 107	0.4153	26.4542	31.4203	47.8392
Pg 110	35.0067	76.9291	40.3314	50.8556
Pg 111	61.8038	4.0999	56.6691	73.4807
Pg 112	1.2605	20.6519	16.6129	79.9508
Pg 113	63.8670	32.8386	90.9933	72.0051
Pg116	99.1542	28.3386	29.9126	22.4616
Fuel Cost [$/h]	143023.6169	156745.8296	154570.9097	157453.3741
Ploss [MW]	-	90.6595	-	77,4969
DV [pu]	-	-	3.8870	2.5864

Table 9 Comparison between MOALO, PSO [45] and ABC [45] for case 1 of IEEE 118-bus power system.

	PSO[45]	ABC[45]	MOALO
Pg69 [MW]	206.0693	460 .5159	377.3800
Fuel Cost [$/h]	157731 .8400	148087.0000	143023.6170

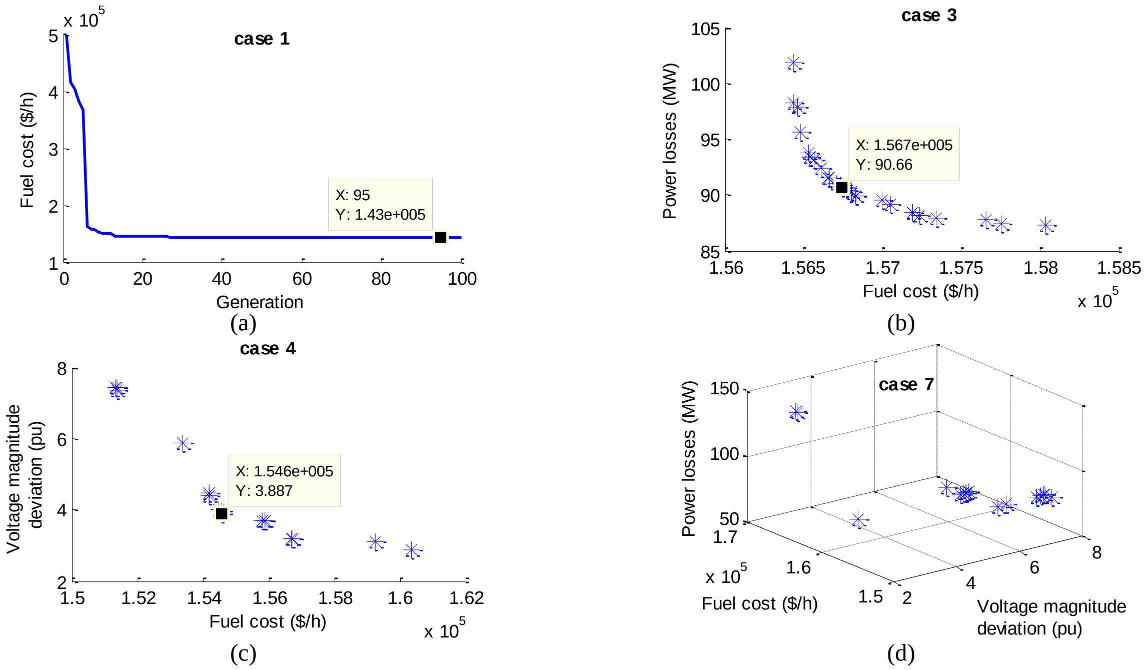


Fig. 8 Simulation results of IEEE 118-bus system for a) case 1, b) case 3, c) case 4, and d) case 7 using MOALO algorithm.

Table 8 and Fig. 8 present the simulation results of IEEE 118-bus system for case 1, 3, 4 and 7. A comparison between the obtained results with those given by other heuristic techniques is shown in Table 9. From the results illustrated in Tables 8 and 9, these results prove once again that the proposed MOALO is effective to solve the MOOPF problem. For case 1 the fuel cost obtained by MOALO is better than those obtained by ABC and PSO methods ($143023.6170/h compared to $148087.0000/h and $157731.8400/h respectively).

On the other hand, the pareto-optimal solutions for all cases except for case 1 (in case 1 there is one objective function: the fuel cost) converge to the near-optimal solution with the large-scale power system.

The Best generated magnitude voltages, transformer tap settings *T* and the capacitor banks obtained in the four cases are given in Figs. 9, 10 and 11. From this figures, we can see that all these results are between their minimum and maximum values.

5.4 DZ 114-Bus Power System

To demonstrate the applicability of the proposed MOALO algorithm in practical system; it has been examined and tested on the Algerian transmission network DZ 114-bus system [46]. This network is composed of 114 buses, 174 transmission lines, 15 generators, 16 transformers and 7 capacitor banks. It is worth mentioning that bus number 04 is the slack bus and the total load demand is 3727 MW. The minimum and maximum limits of the voltage generator buses and load buses in this system are 0.9 pu and 1.1 pu [30].

For Algerian transmission network, there are 53 control variables (15 generator power outputs, 15 generator voltages, 16 transformers and 7 capacitor banks), these variables are to be optimized. The optimal outputs of power generation are represented in Table 10, the total fuel cost, power losses and the voltage deviation are also represented in this table. The rest of the optimal values are shown in Figs. 12, 13 and 14.

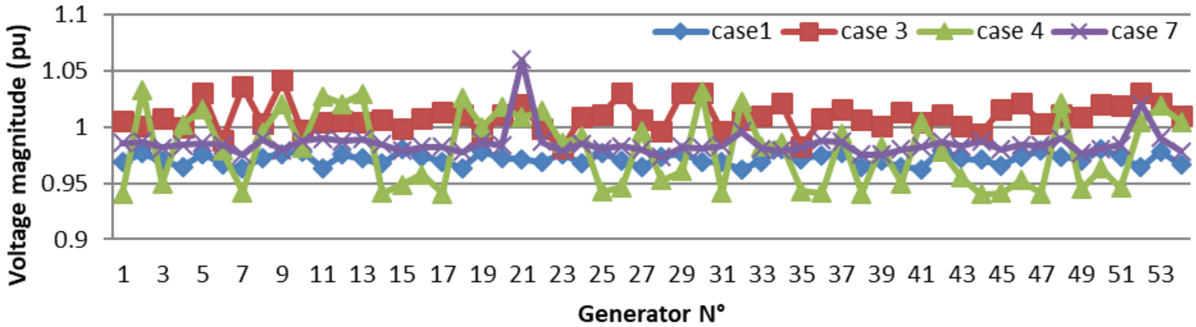


Fig. 9 Optimal voltage magnitude values of IEEE 118-bus system.

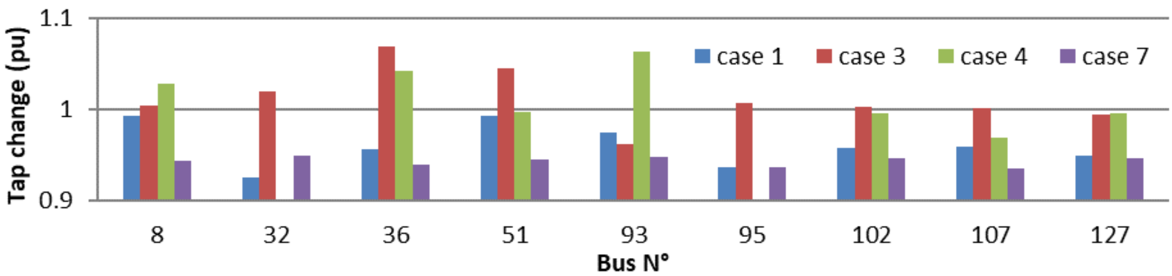


Fig. 10 Optimal tap change values of IEEE 118-bus system.

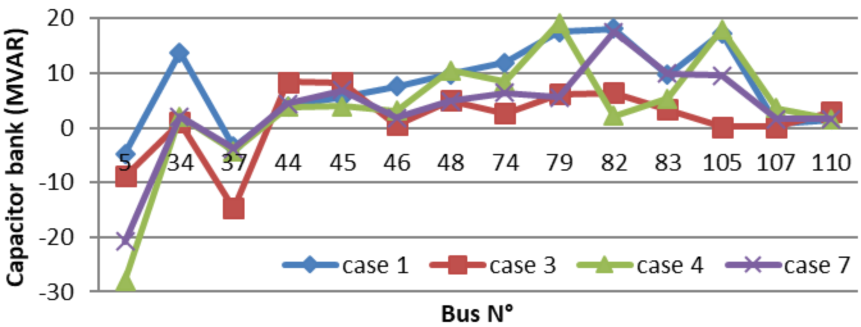


Fig. 11 Optimal capacitor bank values of IEEE 118-bus system.

Table 10 Optimal results for the Algerian network DZ 114-bus power system.

Cases	Min	Case 01	Case 03	Case 04	Case 7	Max
Pg_4	135.0000	458.0600	438.1300	427.64	420.9800	1350.0000
Pg_5	135.0000	451,1905	531.4987	484.6373	485.1794	1350.0000
Pg_{11}	10.0000	74,91904	86.3077	133.4379	173.8651	100.0000
Pg_{15}	30.0000	212,0149	176.6917	122.1698	150.4472	300.0000
Pg_{17}	135.0000	436,8922	430.6920	585.0619	575.4973	1350.0000
Pg_{19}	34.5000	236,6123	193.8471	255.4143	170.3209	345.0000
Pg_{22}	34.5000	197,7529	222.4540	229.9108	274.1317	345.0000
Pg_{52}	34.5000	246,6429	310.5442	150.3864	145.2838	345.0000
Pg_{80}	34.5000	171,7571	295.8228	279.1576	283.6721	345.0000
Pg_{83}	30.0000	163,4842	207.0043	206.3403	123.0331	300.0000
Pg_{98}	30.0000	214,0323	160.5078	223.5949	215.6620	300.0000
Pg_{100}	60.0000	599,9999	454.8742	489.0052	504.7741	600.0000
Pg_{101}	20.0000	199,9999	147.2013	101.6451	147.8956	200.0000
Pg_{109}	10.0000	67,19996	61.0977	55.0481	77.9005	100.0000
Pg_{111}	10.0000	81,96231	97.2401	73.6175	64.3927	100.0000
Fuel Cost [$/h]	-	19355.8595	20600.7073	20910.3473	20360.0830	-
Ploss [MW]	-	-	66.0278	-	70.216	-
DV [pu]	-	-	-	0.34066	0.6780	-

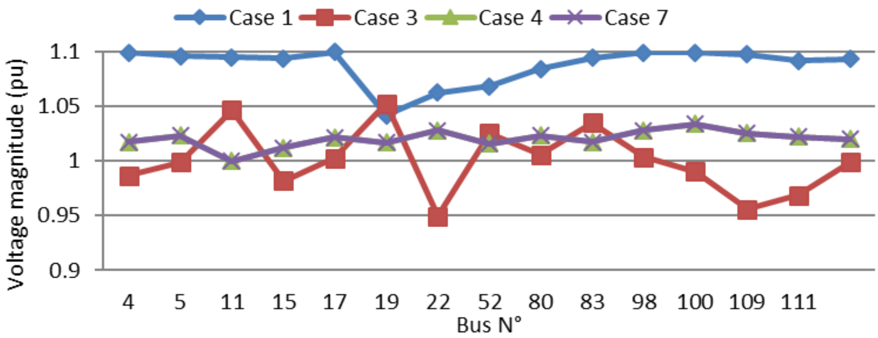


Fig. 12 The optimal voltage magnitude values of the Algerian network.

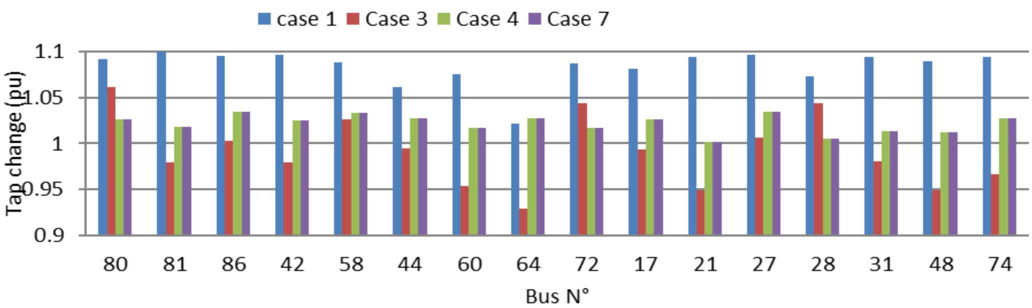


Fig. 13 The optimal tap change values of the Algerian network.

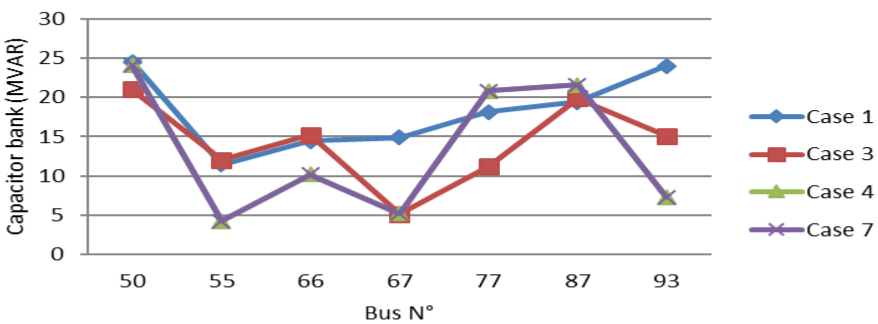


Fig. 14 The optimal capacitor bank values of the Algerian network.

We can see that all security constraints are checked for optimal voltage magnitudes, tap change values and capacitor bank (Figs. 12, 13 and 14).

Fig. 15 indicates that the proposed MOALO for DZ 114-bus system was successfully implemented the goal was to find the best different Pareto optimal front.

5.5 IEEE 300-Bus Test System

Finally, we have applied the MOALO to solve multiobjective optimal reactive power dispatch (MOORPD) problem considering large -scale power system IEEE 300 bus [44]. The MOORPD is an important issue in power system planning and operation. It is a well-known complex optimization problem with nonlinear characteristic. ORPD is formulated as multiobjective optimization problem, in which focuses to not only reduce transmission power losses, but also simultaneously minimizes the voltage stability index (*L*-index) or voltage deviation.

The objective of the voltage stability indices is to quantify how close a particular point is to the steady state voltage stability margin. These indices can be used on-line or offline to help operators in real time operation of power system.

The IEEE 300-bus test system, comprises 69 generators, 411 transmission lines including 107 transformers between and 14 compensators at the loads buses n° 96, 99, 133, 143, 145, 152, 158,169, 210, 217, 219, 227, 268 and 283.The total load active power of this system is (235.258 + j77.8797) pu at 100 MVA base.

The vector of control variables of IEEE 300-bus test system includes the magnitude voltages of generators, transformer tap settings and the capacitor banks.

Table 11 represents the best result of a part of the vector of control which represents 14 compensators obtained from the MOALO algorithm for different cases. The Pareto-optimal solutions are illustrated in Fig. 16.

Based on the simulation results of different case studies, it is observed that the results demonstrate the potential of the proposed approach and show clearly its effectiveness to solve practical OPF. All results obtained do not violate the generation capacity constraints. It is important to note that the security constraints are satisfied for voltage magnitudes and line flows. No load bus is under its lower limit of 0.90 pu.

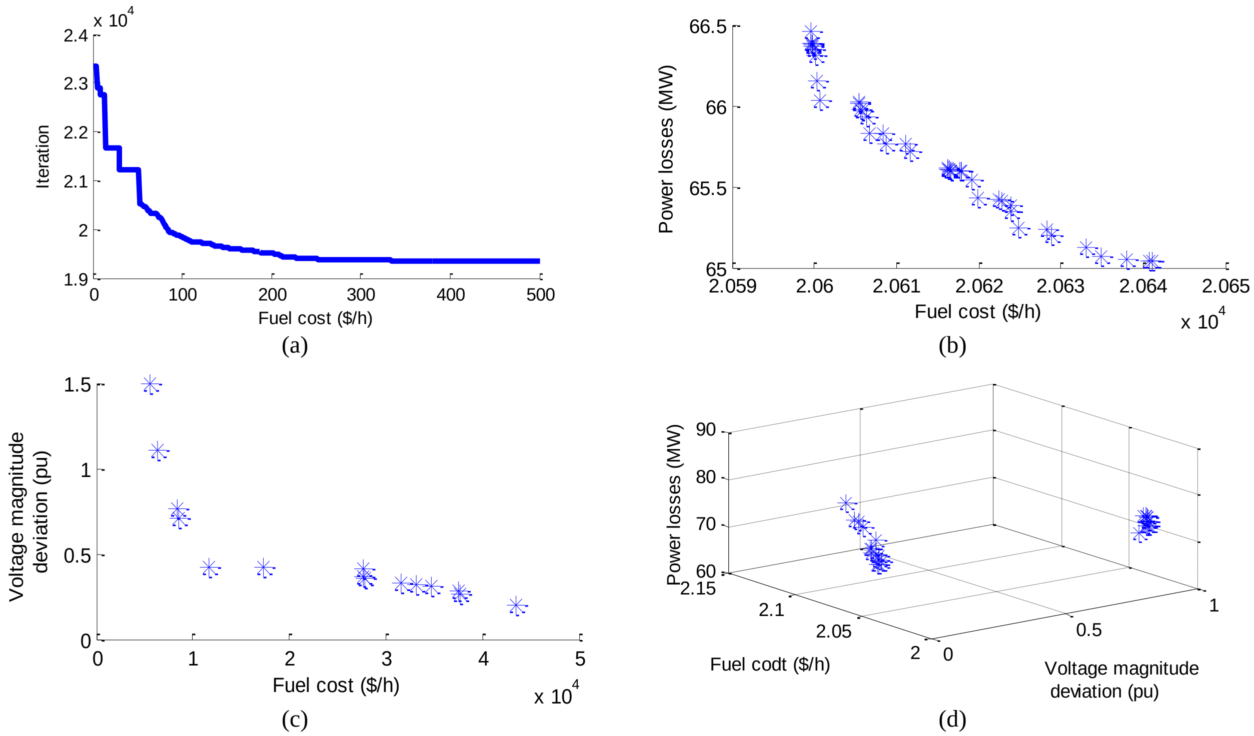


Fig. 15 Simulation results of the Algerian transmission network DZ 114-bus for (a) case 1 (b) case 3 (c) case 4 (d) case 7 using MOALO algorithm.

Table 11 Optimal results of IEEE 300-bus power system for different cases.

	Min	Case: Ploss	Case: L_index	Case: DV	Case: Ploss+L_index	Case: Ploss+L_index+DV	Max
Q_{96}	0	411.8360	274.9774	96.4914	270.0682	343.9224	450
Q_{99}	0	25.7816	27.7997	0.6444	41.7304	35.5968	59
Q_{133}	0	47.3180	16.4863	0.9891	56.3709	27.5005	59
Q_{143}	-450	-256.5247	-443.6522	-130.5488	-306.6606	-240.3758	0
Q_{145}	-450	-414.5873	-97.8828	-447.0338	-374.6129	-184.4596	0
Q_{152}	0	14.5335	45.0018	8.0079	58.0625	39.1839	59
Q_{158}	0	41.8650	55.1477	5.7232	51.4768	40.3758	59
Q_{169}	-250	-237.0456	-185.2194	-148.7700	-213.1328	-64.7152	0
Q_{210}	-450	-436.9324	-445.5752	-376.7078	-279.7349	-169.4061	0
Q_{217}	-450	-239.2131	-296.7490	-225.4550	-350.5397	-300.5593	0
Q_{219}	-150	-141.3918	-100.4646	-58.4613	-110.3498	-51.1462	0
Q_{227}	0	35.7928	44.9637	9.4773	43.7490	52.5504	59
Q_{268}	0	12.9098	3.2247	12.1349	14.3013	7.6123	15
Q_{283}	0	5.0810	9.4478	0.2379	12.1741	9.1863	15
Ploss(MW)	-	363,4262	-	-	384,3528	427,3942	-
L_index(pu)	-	-	0,14711	-	0,1564	0,1874	-
DV(pu)	-	-	--	1,3623	-	2,3780	-

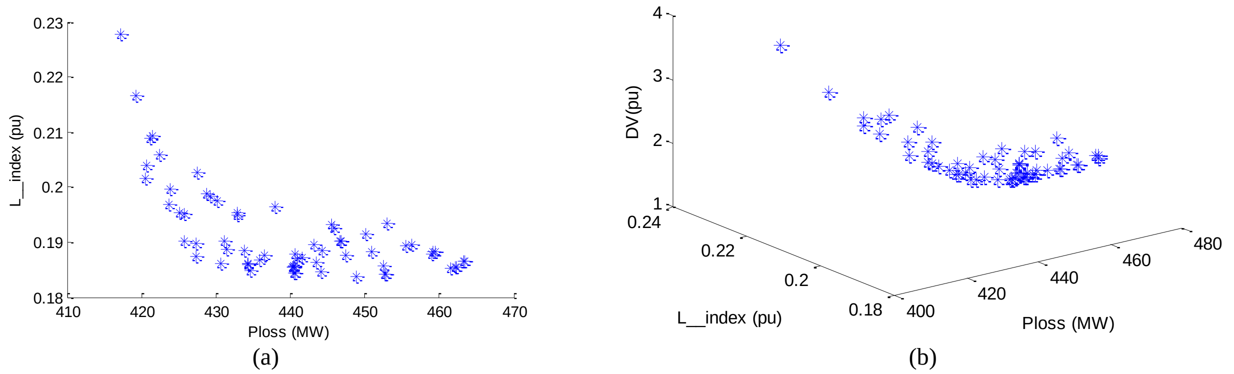


Fig. 16 Pareto-optimal solutions obtained for IEEE 300-bus power system; a) Case: Ploss+L_index and b) Case: Ploss+L_index+DV.

6 Conclusion

In this paper, a multiobjective optimal power flow problem (MOOPF) with four conflicting objectives; fuel cost, total emission, real power losses and magnitude voltage deviation under different constraints was solved using a recently developed MOALO algorithm. The proposed MOALO was applied to several cases studies in four power systems; namely IEEE 30-bus, IEEE 57-bus, IEEE 118-bus, IEEE 300-bus test systems and the Algerian network DZ 114-bus. The simulation results indicated that the proposed approach successfully achieved the goal of finding the best global settings of the control variables. The results obtained were compared with those obtained from two other algorithms namely MOMICA and MODA. The outcomes of the comparison confirm the effectiveness and the superiority of the proposed MOALO method in solving the optimal power flow (OPF) for small, medium and large scale electrical networks. Furthermore, MOALO has the ability more than the other algorithms (MOMICA, MODA) in solving the problems with more than two objective functions. Moreover, simulation results obviously demonstrate the capabilities of the proposed algorithm to generate a set of non-dominated feasible solutions.

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