Optimal Power Flow Solution using Ant Lion Optimizer Algorithm

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***Abstract*-- This paper presents an application of a new meta-heuristic optimization technique, namely Ant Lion Optimizer (ALO) for solving Optimal Power Flow (OPF) problem. The presented method is inspired from the hunting behaviors of antilions in the nature to catch pries. It is inspected and tested on the well known IEEE 30 bus test system considering various mono-objective optimization problems, where the objective functions are presented by smooth and non-smooth functions for fuel cost, non-quadratic total gas emission, and complex function of total active losses. The simulation results show that the proposed technique is qualified to achieve the best solution qualities overcoming other optimization techniques in the literature for the same test system.**

***Index Terms*—Ant Lion Optimizer, Fuel Cost, Gas Emission, Optimal Power Flow**

1. NOMENCLATURE

P_{gi} : Generated active power from unit *i*
Q_{gi} : Generated reactive power from unit *i*
V_{gi} : Voltage magnitude for unit *i*
T_i : Tap ratio of transformer *i*
Q_{Ci} : Reactive power from the *i-th* VAR compensator
V_{Li} : Voltage magnitude of *i-th* load bus
S_{Li} : Apparent loading power of *i-th* transmission line
N_g : number of generating units
N_t : number of tap changing transformers
N_{pq} : number of load buses
N_{tl} : number of transmission lines (branches)
N_C : number of VAR compensators
$Q_{gi,\ min}$, $Q_{gi,\ max}$ lower and upper limits of *i-th* reactive power generation unit
$P_{gi,\ min}$, $P_{gi,\ max}$ lower and upper limits of *i-th* active power generation unit
$T_{i,min}$, $T_{i,max}$ minimum and maximum of *i-th* transformer tap ratio
$V_{Li,min}$, $V_{Li,max}$ minimum and maximum voltage magnitude of *i-th* load bus
$Q_{Ci,\ min}$, $Q_{Ci,\ max}$ lower and upper limits of *i-th* VAR compensator
$S_{Li,\ min}$, $S_{Li,\ max}$ lower and upper power flow limits of *i-th* transmission line

2. INTRODUCTION

The Optimal power flow (OPF) is an important tool that can cover optimal analysis studies of the electrical power systems for both planners and operators. The main objective of the OPF is to specify the settings of the parameters related to the available equipments in the electrical network that optimize a specified objective function in the goal to get an economic and secure operation [1]. The objective function can be a total generation cost, total gas emission resulting from the burn of fuels, total active transmission losses or bus voltage deviation, etc. The OPF is a constrained optimization problem, where the power flow equations must be satisfied furthermore to power balance constraint (equality constraints), while the electrical network security and operating limits of equipments must be verified (inequality constraints).

In the literature, classical optimization methods have been employed for solving the OPF problem such as a Gradient based method [2], linear programming [3], Newton method [4] and quadratic programming [5].
However, these techniques fail to handle many optimization problems relying on the practical operating constraints where the objective function is non-convex, non-smooth and non-differentiable.
In the two last decades, important efforts have been focused on the application of evolutionary algorithms for solving OPF problems, trying to overcome the drawbacks of conventional techniques such as Genetic Algorithms (GA) [6], Particle Swarm Optimization (PSO) [7], Ant Colony Optimization (ACO) [8], Artificial Bee Colony (ABC) [9], Gravitational Search Algorithm (GSA) [10] and Grey Wolf Optimizer (GWO) [11] among other meta-heuristic optimization methods.

A new proposed bio-inspired algorithm called Ant Lion Optimizer (ALO) developed by S. Mirjalili in the year of 2015 [12], which is inspired from the behavior of antilion to hunt a prey (main pries are ants) in nature. The work in this paper is devoted to the resolution of the OPF problem using ALO algorithm. The proposed algorithm is examined and tested on the well known IEEE 30 bus test system for four cases of mono-objective optimization problems for smooth and non-smooth functions of fuel cost, non-quadratic total gas emission, and total active losses as objective functions. The simulation results are compared to those of other meta-heuristic methods in the literature for the same test system to evaluate the effectiveness of the proposed algorithm. In this paper, section 3 is devoted to the OPF formulation, while section 4 is reserved to the concept of ALO algorithm. The simulation and results are discussed in section 5. Conclusions are summarized in section 6.

3. OPTIMAL POWER FLOW FORMULATION

A. Mathematical formulation of the OPF problem

The goal of OPF is to determine the optimal settings of control variables in terms of one or more objective functions with the satisfaction of several equality and inequality constraints of electrical power system. In a general way, the conventional OPF problem can be mathematically formulated as below:

$$\begin{cases} \min f(x,u) \\ \text{subject to: } g(x,u)=0 \\ h(x,u)\le 0 \end{cases} \quad (1)$$

where f is the objective function to be optimized, g is the set of equality constraints represented by the non-linear power flow equations, h is the set of inequality constraints reflecting the operating limits of control equipments, u is the vector of control variables and x is the vector of state variables. The vector u can be expressed as:

$$u=[P_{g2}....P_{gN_g}, V_{g1}....V_{gN_g}, T_1...T_{N_t}, Q_{c1}....Q_{cNc}]^T \quad (2)$$

The vector x is given as below:

$$x=[P_{g1}, V_{L1},....V_{LN_{pq}}, Q_{g1},...Q_{gN_g}, S_{L1},....S_{LN_{tl}}]^T \quad (3)$$

The inequality constraints are mentioned as follow:
Limits of generators:

$$\begin{aligned} &P_{gi,min}\le P_{gi}\le P_{gi,max} \quad i=1,\dots,N_g \\ &Q_{gi,min}\le Q_{gi}\le Q_{gi,max} \quad i=1,\dots,N_g \\ &V_{gi,min}\le V_{gi}\le V_{gi,max} \quad i=1,\dots,N_g \end{aligned} \quad (4)$$

Limits of tap transformers:

$$T_{i,\min}\le T_i\le T_{i,\max} \quad i=1,\dots,N_t \quad (5)$$

Limits of reactive power compensators:

$$Q_{Ci,\min}\le Q_{Ci}\le Q_{Ci,\max} \quad i=1,\dots,N_C \quad (6)$$

Limits of voltage magnitude for load buses

$$V_{Li,min}\le V_{Li}\le V_{Li,max} \quad i=1,\dots,N_{pq} \quad (7)$$

Power flow limits of transmission lines:

$$S_{Li,\min}\le S_{Li}\le S_{Li,\max} \quad i=1,\dots,N_{tl} \quad (8)$$

To handle an inequality constraint of a state variable, a penalty function is introduced in the augmented objective function as below:

$$F_{aug}=f(x,u)+\sum_{k=1}^{Ns}\lambda_{Pk}.(x_k-x_k^{\lim})^2 \quad (9)$$

where x_k is the *k-th* violated state variable, $x^{lim}{}_k$ is the limit of the *k-th* violated state variable and λ_{Pk} is penalty factor for the penalty function of the *k-th* violated state variable.

B. Objective functions

Mono-objective optimization problem is considered for four cases of objective functions f in (1):

Case1: minimization of total fuel cost

The total generation cost of electrical power is expressed as a quadratic function [9] by:

$$f=\sum_{i=1}^{Ng}F_i(P_{gi})=\sum_{i=1}^{Ng}(a_i+b_iP_{gi}+c_iP_{gi}^2) \quad (10)$$

where a_i, b_i and c_i are the cost coefficients of the *i-th* generating unit.

Case2: minimization of total gas emission:
The emitted gasses from each generating unit can be expressed as a combination of quadratic and exponential functions of the generated active power [9]:

$$f=\sum_{i=1}^{Ng}(\alpha_i+\beta_iP_{gi}+\gamma_iP_{gi}^2+\delta_i\exp(\varepsilon_iP_{gi})) \ (Ton/h) \quad (11)$$

where f is the total gas emission (ton/h) and α_i, β_i, γ_i, δ_i, and ε_i are the emission coefficients of the *i-th* unit.

Case3: minimization of total fuel cost considering valve point effect
A sine component is added to the objective function expression in (11) for considering the valve point effect to evaluate the total fuel cost as [10]:

$$f=\sum_{i=1}^{Ng}F_i(P_{Gi})=\sum_{i=1}^{Ng}(a_i+b_iP_{gi}+c_iP_{gi}^2+f_{vpi}) \quad (12)$$

where $f_{vpi}=| d_i .sin[e_i(P_{gi,min}-P_{gi})]|$, while e_i and d_i are the fuel cost coefficients of the since component.

Case4: minimization of total active losses
The total active transmission losses for the power system can be expressed as [11]:

$$f=\sum_{k=1}^{Ntl}g_k[V_i^2+V_j^2-2V_iV_j\cos(\delta_i-\delta_j)] \quad (13)$$

where g_k is the conductance of *k-th* transmission line between buses i and j; V_i and V_j are the magnitude voltages at bus i and j respectively, δ_i and δ_j are voltage angles.

4. ANT LION OPTIMIZER ALGORITHM

Ant Lion Optimizer (ALO) is a novel nature inspired algorithm proposed by Seyedali Mirjalili in 2015 [12]. The ALO algorithm mimics the hunting mechanism of antlions in nature. The antlion has an attractive manner for hunting, it creates a small circular pit by digging backwards in the sand, then it is waiting at the bottom of the pit, and when an ant or other small insect falls into it, the hunter grabs it, pull it under the sand, and inject a special liquifying agent into its meal in order to consume it. The Fig. 1 represents the antlion, some types of pits and an ant in the jaws of antilion. Five main steps of hunting prey such as the random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building traps are implemented [13]. For mathematically model such hunting attitude, the both kinds of insects, ants and antlions are considered, where the ants inspect the search space to look for foods, and antlions try to catch them with traps well organized.

Fig. 1 Antilions and their various pits in order to catch ants

Assuming that ant population consists of Np ants in the search space with D dimensions, the position of *n-th* ant is $X_{At,n} =(X^1_{At,n}, X^2_{At,n}, ..., X^k_{At,n}, ... X^D_{At,n})$, where $X^k_{At,n}$ is the *k-th* variable position of *n-th* ant. The fitness function evaluation of all ants can be given in the fitness evaluation vector by $fit_{At}=(fit_{At,1}, fit_{At,2},..., fit_{At,n}, ..., fit_{At,Np})$, where $fit_{At,n}$ is the fitness value of *n-th* ant evaluated based on the objective function given by $f(X^1_{At,n}, X^2_{At,n}, ..., X^k_{At,n}, ... X^D_{At,n})$. In similar manner, Np antlions form the antilion population and hid somewhere in the search space of *D*-dimensions, assuming that the position of *n-th* antilion is $X_{AL,n} =(X^1_{AL,n}, X^2_{AL,n}, ..., X^k_{AL,n}, ... X^D_{AL,n})$, where $X^k_{AL,n}$ is the *k-th* variable position of *n-th* antlion. The fitness function evaluation of all antlions is stored in the vector $fit_{AL}=(fit_{AL,1}, fit_{AL,2},..., fit_{AL,n}, ..., fit_{AL,Np})$, where $fit_{AL,n}$ is the fitness value of *n-th* antlion evaluated based on the objective function given by $f(X^1_{AL,n}, X^2_{AL,n}, ..., X^k_{AL,n}, ... X^D_{AL,n})$.

A. Random walks of ants

In the natural life of ants, the movement of each ant is randomly created to look for food sources. A random walk is selected to model the ants' displacement as given by:

$$\begin{aligned} C(X^k_{At,n}(t)) = [0, cumsum(2r(t_1)-1), ...\\ ..cumsum(2r(t_2)-1), ..., cumsum(2r(t_{Ni\_\max})-1)] \end{aligned} \quad (14)$$

where $C(X^1_{At,n}\ (t))$ is the set of walks related to the *k-th* variable for the *n-th* ant in the *t-th* iteration, *cumsum* evaluates the cumulative sum, N_{i_max} is the maximum number of iterations, t is the step of random walk (iteration) and $r(t)$ is a stochastic function given as :

$$r(t) = \begin{cases} 0 & if \quad rand > 0.5 \\ 1 & otherwise \end{cases} \quad (15)$$

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

Referring to this attitude, the ants have three comportments of displacement, where the random walk fluctuates around the original position, increases its behavior or decreases its trend.

Nevertheless, the walks described by (14) are not introduced directly in the algorithm due to the violations of variables out of boundaries. Therefore, the normalization of the random walks is designated as given in the following equation:

$$X^k_{At,n}(t) = \frac{\left(X^k_{At,n}(t) - \min\left(C(X^k_{At,n}(t)\right)\right)(u^k_b(t) - l^k_b(t))}{\max\left(C(X^k_{At,n}(t)) - \min\left(C(X^k_{At,n}(t)\right)\right)} + l^k_b(t) \quad (16)$$

where $max(C(X^k_{At,n}\ (t)))$ and $min(C(X^k_{At,n}\ (t)))$ indicate the maximum and minimum of random walks for the *k-th* variable of the *n-th* ant, $l^k_b(t)$ and $u^k_b(t)$ are the lower and upper bounds of *k-th* variable at *t-th* iteration, respectively.

B. Slide of ants

When the antlion realizes that the ant is trapped in the pit, it throws the sand beyond the pit center in order to slide the prey down. To model mathematically such action, the radius of the random walks hypersphere is reduced in an adaptive manner, and therefore the lower and upper limits must decrease with the increase of the iterations as mentioned below:

$$\begin{aligned} l^k_b(t) &= \frac{l^k_b(t)}{I} \\ u^k_b(t) &= \frac{u^k_b(t)}{I} \end{aligned} \quad (17)$$

where I is a ratio given by $I=10^w \times t/N_{i\_max}$ and w is a constant adjusted based on the current iteration ($w=2$ when $t>0.1\times N_{i\_max}$, $w=3$ when $t>0.5\times N_{i\_max}$, $w=4$ when $t>0.75\times N_{i\_max}$, $w=5$ when $t>0.9\times N_{i\_max}$ and $w=6$ when $t>0.95\times N_{i\_max}$).

C. Trapping in antlion's pits

The random walks of ants are trapped by the pits of antilons, the modeling of such natural behavior in the mathematical environment is suggested by the following equations:

$$u^k_b(t) = \begin{cases} X^k_{AL}(t) + u^k_b(t) & if \quad rand > 0.5 \\ X^k_{AL}(t) - u^k_b(t) & otherwise \end{cases} \quad (18)$$

$$l^k_b(t) = \begin{cases} X^k_{AL}(t) + l^k_b(t) & if \quad rand > 0.5 \\ X^k_{AL}(t) - l^k_b(t) & otherwise \end{cases} \quad (19)$$

where $X^k_{AL}(t)$ is the *k-th* variable of an antilion at *t-th* iteration.

D. Antlions building traps

The stronger antilion is affected by a high probability for catching ants. The selection of an antilion P_{selec} in the current iteration t among the most fitted antilions is accomplished by the roulette wheel. Otherwise, the best antilion P_{elite} providing the best solution obtained so far should be taken into account, influencing on the displacements of all ants during the evolution of iterations. The traps defined by P_{selec} and P_{elite} are envisaged at the same time and their sizes are given in (17). The position of each ant randomly walks in the proximity of the traps defined by P_{selec} and P_{elite} is given by:

$$X_{At,n}^{k}(t)=\frac{R_S(t)+R_E(t)}{2} \qquad (20)$$

where $R_S(t)$ is the random walk in the vicinity of the selected antilion P_{selec}, while $R_E(t)$ is the random walk in the vicinity of the elite antilion P_{elite} using (14)-(16).

E. Catching ants and re-building traps

The hunting process is terminated when the ant becomes in the bottom of the antilion pit and the prey is pulled inside the sand by huge jaws of the antilion. This process can be imitated by assuming that the capture of prey is accomplished when the ant fitness is greater than that of corresponding antilion (sink into the sand).
Then the antlion updates its position to that of the hunted ant, as given by the following equation:

$$X_{AL,j}(t)=X_{At,i}(t) \quad if \quad f(X_{At,j}(t))>f(X_{AL,i}(t)) \qquad (21)$$

Where $X_{AL,\,j}(t)$ is the position of selected *j-th* antilion at *t-th* iteration, and $X_{At,\,i}(t)$ is the position of *i-th* ant at *t-th* iteration. The pseudo-code of ALO algorithm is detailed in the Appendix.

5. SIMULATION AND RESULTS

The IEEE-30 bus test system is used to investigate the aptitude of the proposed ALO algorithm to reach global OPF solutions for different cases of mono-objective optimization problems. The model has 6 generators, 41 branches (39 lines and 4 transformers with off-nominal tap ratios) and 24 load buses. Shunt VAR compensators are installed in buses 10, 12, 15, 17, 20, 21, 23, 24 and 29, where the reactive power injection is controlled between 0 and 5MVAR as lower and upper limits, respectively [10]. The system total demand was (2.834+j1.262) p.u for the apparent power at 100 MVA base. Bus 1 was taken as the slack bus. Upper and lower active power generating limits, reactive power limits, cost coefficients and emission characteristics of generators are taken from [14]. The ALO algorithm parameters are: Number of search agents is equal to the number of ants and antilions N_P=50, maximum number of iterations N_{i_max}=200 and the number of variables is $D=25$.
The software was written in Matlab 2009b using a personal computer running Windows XP professional, Pentium P-IV CPU 3 GHz processor and RAM of 1GB. Four objective functions are used to evaluate the performance of the proposed algorithm in order to reach the optimal solution. The optimal control settings of control variables and the corresponding objective function value are determined for 30 independent runs with different random seeds for different cases and with various objective functions (for the same test system IEEE 30 bus) using ALO algorithm. The average computation time of one independent run with N_P equal to 50, and N_{i_max} equal to 200 was 25.88 s. The same cases as in sub-section 3. B were considered:

Case1: Quadratic total fuel cost function
The objective function in (10) is evaluated for the optimal setting of control variables by running the ALO algorithm and the obtained optimal total fuel cost is 799.3264 $/h, which is reported in Table I and compared with that of other optimization techniques in the literature as ABC [9], PSO [7], GSA [10], GWO [15], Differential Evolution (DE) [15], Biogeography-Based Optimization BBO [16], Adaptive Real Coded (ARC) BBO [16], RCBBO [16], Teaching-Learning based Optimization (TLO) [17] and Modified TLO [17] algorithms. It is clearly seen that the proposed ALO algorithm gives a better result by comparison with other meta-heuristic methods in Table I. The evolution of the total fuel cost during the simulation is indicated in Fig. 2. Based on this Figure, it is noticed, in this case, that the convergence was very fast towards the optimal solution.

TABLE I Comparisons of the results obtained for case 1 of IEEE 30-bus system

Optimization technique	Optimal Cost ($/h)
ALO	**799.3264**
ABC [9]	800.6600
PSO [7]	800.41
GSA [10]	805.1752
GWO [15]	801.41
DE [15]	801.23
BBO [16]	801.0562
ARCBBO [16]	800.5159
RCBBO [16]	800.8703
TLO [17]	801.99
Modified TLO [17]	801.89

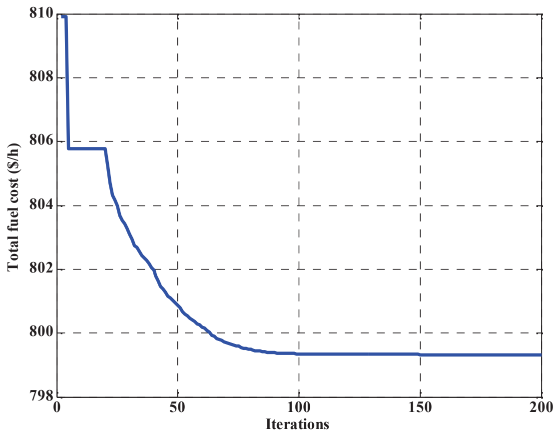

Fig. 2. Convergence of the ALO algorithm for case 1

Case2: total gas emission
The total gas emission selected as in (11) is minimized using the proposed ALO algorithm and the optimal value achieved is 0.20476 Ton/h, which is reported in the Table II and compared to the total gas emission evaluations of other methods applied for the same test system as hybrid Firefly Algorithm and GA (FFA-mGA) [18], GA [19], PSO [19], ABC [9], Shuffle Frog Leaping Algorithm (SFLA) [19] and Modified SFLA (MSFLA) [19]. By examining Table II, the minimum total gas emission obtained by the proposed ALO algorithm has been seen to be better than the results in the literature. The convergence of the total gas emission with the number of iterations is depicted in Fig. 3, showing that the proposed ALO algorithm gives faster convergence to the optimal solution.

TABLE II Comparisons of the results obtained for case 2 of IEEE 30-bus system

Optimization technique	Optimal Gas emission (Ton/h)
ALO	**0.20476**
FFA-mGA [18]	0.20677
GA [19]	0.21170
PSO [19]	0.20960
SFLA [19]	0.20630
ABC [9]	0.20482
MSFLA [19]	0.20560

Case3: total fuel cost considering valve point effect

The objective function given in (12) is provided for non-smooth curve of fuel cost function and that for the two generators in buses 1 and 2, where their cost coefficients are taken from [10]. The fuel cost curves of the remaining generators keep the same characteristics as in case1. The VAR compensators for this case are ignored, where the number of control variables is $D=16$. The minimum total fuel cost obtained using the proposed ALO algorithm and considering valve point effect was 921.3071 \$/h.

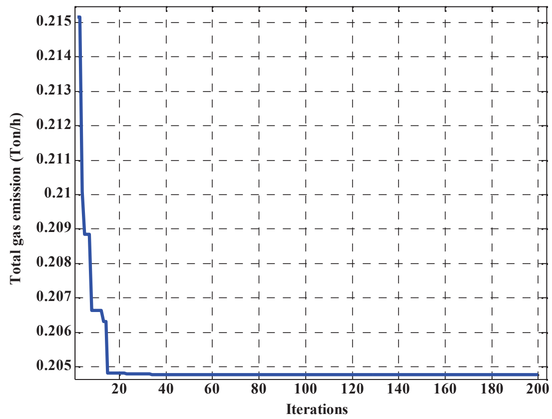

Fig. 3. Convergence of the ALO algorithm for case 2

The ALO algorithm shows a better solution than other methods displayed in Table III as ABC [9], Gbest guided ABC (GABC) [20], Multi-Agent based Differential Evolution (MADE) [21], GSA [10] and Modified DE (MDE) [22]. The progress of total fuel cost with iterations during the simulation is given in Fig. 4.

Case4: Total active losses

The transmission active losses in (13) adopted as objective function in this case is minimized by carrying out the proposed ALO algorithm. The optimal active total losses resulting from the simulation are given in Table IV.

TABLE III Comparisons of the results obtained for case 3 of IEEE 30-bus system

Optimization technique	Optimal Cost (\$/h)
ALO	**921.3071**
ABC [9]	945.4495
GABC [20]	931.7450
MADE [21]	929.6832
GSA [10]	929.7240
MDE [22]	930.793

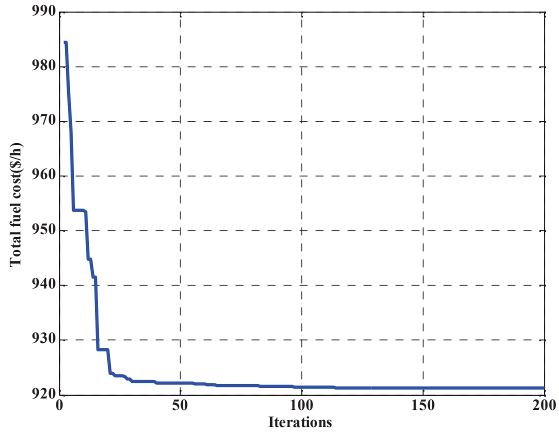

Fig. 4. Convergence of the ALO algorithm for case 3

The reported results of the optimization techniques revealed from the literature as ABC [9], GWO [15], DE [15], ARCBBO [16], and Modified Flower Pollination Algorithm (MFPA) [23] are compared with the result of ALO algorithm for the same test system. The best result is assigned to the proposed ALO algorithm. Fig. 5 shows the total losses variations with iteration progressions for the best result obtained by ALO.

TABLE IV Comparisons of the results obtained for case 4 of IEEE 30-bus system

Optimization technique	Optimal active total losses (MW)
ALO	**2.8820**
ABC[9]	3.1078
GWO [15]	3.4100
DE [15]	3.3800
ARCBBO [16]	3.1009
MFPA [23]	2.8877

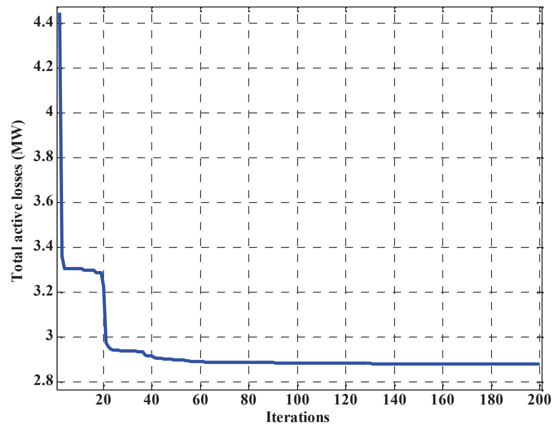

Fig. 5. Convergence of the ALO algorithm for case 4

As summarized in Tables I–IV, ALO algorithm method can obtain best quality solutions compared to all other methods listed in the tables, with moderately high speed of convergence based on Fig. 2-Fig. 4.

6. CONCLUSION

In this paper, the recently developed ALO algorithm has been applied to the OPF problem resolution, which is implemented for many cases of mono-objective optimization problems. The proposed algorithm has been tested and examined on the well known IEEE 30 bus test system. The performances of ALO algorithm were verified using four cases of study with various objective functions including convex and non-convex fuel costs. The simulation results obtained from the proposed approach were compared with those of the recent reported meta-heuristic methods in the literature. The comparison demonstrates the effectiveness and the superiority of the proposed ALO technique overcoming other optimization techniques in terms of solution quality. The ALO algorithm has a simple framework and successfully implementation characteristic and, therefore, could be used for the OPF problem in large-scale power systems.

APPENDIX

Pseudo-code of Ant Lion Optimizer

1.Initialize the search agent position of N_p ants and antilions randomly
2.Evaluate the fitness of all ants and antilions
3.Specified the antilion with the best fitness value representing the elite antilion P_{elite}
4.**while** ($t<N_{i\_max}$)
5. **for** each ant (i.e $i=1 \ldots. N_p$)
6. Select an antilion P_{selec} based on the fitness of all antilions using roulette wheel process
7. **for** each dimension (i.e $k=1 \ldots. D$)
8. update the lower and upper bounds using (17)
9. Evaluate the bounds around the selected antilion or the elite antilion by (18) and (19)
10. Determine $R_S(t)$ or $R_E(t)$ signifying the random walk around the selected antilion or the elite antilion respectively by (14)-(16)
11. Update the ant position using (20)
12. **end for**
13. **end for**
14. calculate the fitness values of all ants
15. All positions of ants and antilions are evaluated based on their fitness, these fitness values are sorted from the smallest to the largest
16. Replace an ant with its corresponding antilion if it becomes fitter based on (21)
17. Update elite if an antlion becomes fitter than the elite
18. **end while**.

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