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Full Length Article

Ant lion optimizer for solving optimal reactive power dispatch problem in power systems

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ABSTRACT

This paper presents the use of a recent developed algorithm inspired by the hunting mechanism of antlions in nature, called ant lion optimizer (ALO) algorithm for solving optimal reactive power dispatch (ORPD) problem considering a large-scale power system. The ORPD is formulated as a complex combinatorial optimization problem with nonlinear characteristic. The ALO algorithm is inspired from the hunting mechanism of antlions. One of the most interesting things in antlions is that they have a unique hunting behaviour and exhibit high capability of escaping the local optima stagnation. The ALO is used to find the set of optimal control variables of ORPD problem, such as generators terminal voltage, position of tap changers of transformers, and number of switchable capacitor banks. The performance and feasibility of the proposed algorithm are demonstrated through several simulation cases on IEEE 30-bus, IEEE 118-bus power systems and large-scale power system IEEE 300-bus power system. Comparison of obtained results with those reported in the literature shows clearly the superiority of ALO algorithm over other recently published algorithms in regards to real power losses and computational time, and hence confirmation of the efficiency of ALO algorithm in providing near-optimal solution.

1. Introduction

At the present time, meticulous researchers on the Optimal Reactive Power Dispatch (ORPD) have been recorded due to the vital role of ORPD in the power system planning and operation. ORPD is considered as a complex combinatorial optimization problem with nonlinear characteristics. In the power system operation, every variations of load demand tend to change the applied reactive power generations, and hence load voltages variations. The adjustment of voltages can be accomplished locally by proper reactive power management. General objectives of ORPD are to minimize total real power losses and to improve the voltage stability index or voltage deviation. This is can be achieved through identification of optimal solution to the vector of control variables which consists of generator voltages as continuous variables, tap position of tap-changing transformers, and required number of shunt capacitors as discrete variables. This issue has undergone a growing interest over the last decade, to ensure safe and secure operation of an electric power system [1–5].

Over the past quarter of the previous century, a variety of classical optimization algorithms have been successfully applied for solving ORPD problem, among them the Newton Raphson methods' (NR) [3], quadratic programming (QP) [4], nonlinear programming (NLP) [5], and interior point methods (IP) [6]. However, from the use literature survey on the conventional optimization approaches (COA), appear that they are suffer from lack of flexibility with the practical systems and high computation time when dealing with complex objective functions (nonlinear handling characteristics). An additional problem is associated with these algorithms when dealing with discrete control variables since it sharply increases the complexity of the ORPD issue. This complexity grows exponentially as the number of discrete variables increases.

In recent years, numerous algorithms have been successfully introduced to deal the ORPD problem in an effort to alleviate the aforementioned drawbacks such as, genetic algorithms (GAs) [7], differential algorithm (DE) [2,8,9], simulated annealing (SA) [10], particle swarm optimization (PSO) [10,11], harmony search algorithm (HSA) [13], artificial bee colony algorithm (ABC) [14], gravitational search algorithm (GSA) [1] and Grey wolf optimizer (GWO)

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Nomenclature

ALO	ant lion optimizer
GWO	grey wolf optimizer
ABC	artificial bee colony algorithm
BA	bat algorithm
PSO	particle swarm optimization
P_{loss}	total power losses
g_k	conductance of kth branch connected between bus i and j
V_i, V_j	voltage magnitude of ith and jth bus
δ_{ij}	voltage angle difference between ith and bus jth
T_K	ratio of tap changing transformers
T_k^{max}	maximum tap ratio of kth tap changing transformer
T_k^{min}	minimum tap ratio of kth tap changing transformer
N_{PV}, N_{PQ}	number of PV and PQ buses respectively
P_g/Q_g	generator active/reactive power production
$P_{L,N_{PQ}}, Q_{L,N_{PQ}}$	active and reactive power at each PQ bus
NB	number of bus in the test system
NTL	number of transmission lines
NLB	number of load bus
NT	number of regulating transformer
NC	number of shunt capacitor banks
X^{max}	maximum limit of state variables
X^{min}	minimum limit of state variables
V_G	voltage magnitude for generator i
$V_{L,N_{PQ}}$	voltage magnitude for load bus i
V_i^{max}, V_i^{min}	maximum and minimum bus voltage magnitude at bus i
S_l	apparent power flow of branch
S_l^{max}	maximum apparent power flow limit of branch i
$\|Y_{ij}\|, \theta_{ij}$	elements of the bus admittance matrix
$P_{d,i}/Q_{d,i}$	active/reactive load consumption at bus i
$Q_{Ci}^{min}, Q_{Ci}^{max}$	minimum and maximum VAR injection limits of shunt capacitor banks

[15]. Extensive competitions between researchers have been done in last decade, in an effort to seek for a more suitable/reliable approach for handling different power system optimization problems [16–22]. In [16], the authors applied seeker optimization algorithm for solving optimal reactive power dispatch in larger power system with a detailed description of critical performance indices in which different objective functions are studied such as minimization of active power losses, improvement of voltage profile and minimization of voltage stability index. Also, in Xu et al. [17], an application of multi-agent based reinforcement learning for solving optimal reactive power dispatch problem is investigated. The objective is to minimize the active power loss. In another reported case, Ghasemi in [18], proposed an hybrid algorithm based on modified teaching learning algorithm and double differential evolution algorithm for solving ORPD problem, as a comparative study. In [19] Li *et al* proposed parallel PSO algorithm to deal the dynamic ORPD problem. In [20] the authors introduced the modified version of Gaussian bare-bones teaching-learning-based optimization (GBTLBO) algorithm to solve ORPD problem with both discrete and continuous optimisation variables in a medium-scale system. A firefly algorithm for real power loss minimization and voltage stability limit maximization as multi-objective optimization, has been offered by Balachennaiah in [21]. In [22] an novel hybrid particle swarm optimizer with multi verse optimizer (HPSO-MVO) is proposed for ORPD problem. However, these approaches already suffer from some disadvantages such as the susceptibility of falling into local optima, and difficulty tuning the main internal parameters such as mutation and crossover rate. In addition, there is no a global optimization algorithm for solving ORPD problem and on the basis of No-Free Lunch theorem, the seeking a more suitable approach for a such problem is remain necessary. The aforementioned reasons incite the present authors to highlight a simple, recently, and efficient optimization algorithm to solve the posed problem.

About one year ago, a new technique has been added to the meta-heuristic optimization approaches field, based on simulating of the hunting behaviour of antlions. This article proposes the use of ant lion optimization algorithm for solving the ORPD problem with an improved voltage stability index in power systems. The medium-scale, larger and large-scale test systems namely IEEE-30, IEEE-118 and IEEE 300-bus are selected to demonstrate the performance of the proposed approach. The obtained results by using ALO are compared with other results of recent published algorithms. Therefore, the results prove the consistency and robustness of ALO algorithm to find the optimal solution for each objective function.

The rest of the paper is structured as follows: the general formulations to the ORPD problem is introduced in Section 2 while Section 3 explains the proposed approach. Then, Section 4 is present the control variable treatment, and Section 5 of the paper is reserved to provide the experimental results along with a detailed comparison of ALO algorithm with some existing algorithms. Finally, Section 6 presents the conclusion of this paper.

2. Mathematical formulation

The mathematical formulation of ORPD problem is amply described in two parts as: objective functions and constraints, in which minimizes some objective functions while fulfilling equality and inequality constraints at the same time. Mathematically can be formulated as follows:

$$\text{Minimize } F(x,u) \tag{1}$$

$$\text{Subject to}: \begin{cases} g(x,u) = 0 \\ h(x,u) \leqslant 0 \end{cases} \tag{2}$$

where, F(x,u) is the objective function of transmission losses to be minimized, $g(x,u) = 0$ equality constraints, $h(x,u) = 0$ inequality constraints; x: is the vector of dependent variables or (control variables) consisting of load bus voltages, reactive power of generator, and transmission line loading.

Accordingly, vector x can be written mathematically as follow:

$$x^T = [V_L \ldots V_{L,N_{PQ}}, Q_{g,1} \ldots Q_{g,N_{PV}}, S_1 \ldots S_{NTL}] \tag{3}$$

u: is the vector of independent variables or (state variables) comprising: continuous and discrete control variables involving:

Voltages of PV bus as (continuous variables), transformer tap settings (discrete variables), and switching shunt capacitor banks (discrete variables). Hence, u can be illustrated mathematically as follow:

$$u^T = \left[\overbrace{V_{g,1} \ldots V_{g,N_{PV}}}^{\text{continuous}}, \overbrace{T_1 \ldots T_{NT}, Q_{C1} \ldots Q_{C,NC}}^{\text{Discrete}}\right] \tag{4}$$

In the present work, two different objective functions are separately studied:

- Minimization of total real power losses; and
- Minimization of voltage stability index (L-index).

2.1. Objective function

2.1.1. Minimization of power losses

In this objective we aim is to minimize the total active power loss through an optimal adjustment of power system control parameters [23]. Mathematically is described as follow:

$$f_1(x,u) = \min P_{loss} = \sum_{k=1}^{NTL} g_k \times (V_i^2 + V_j^2 - 2 \times V_i \times V_j \times \cos\delta_{ij}) \quad (5)$$

2.1.2. Objective 2: improvement of voltage stability index

The principal interest behind study of voltage stability index lies in the simplicity to provide the sufficient information's about the voltage instability or to quantify the vicinity of a power system to the voltage collapse. This is can be achieved by the minimization of the voltage stability indicator L-index (L_j) at every bus of the electrical network, and consequently the total power system (L-index), basing on information of normal load flow analysis of which the operating range of indicator L is set between 0 and 1 [24]. One widely used method in the literature is that proposed for the first time by *Kessel P* and *Glavitsch H* [25]. Therefore, the problem mentioned above mathematically defined as follows:

$$f_2(x,u) = VSI(x,u) = \min(\max(L_j)) \quad (6)$$

where L_j of the jth bus is formulated by the following equation:

$$L_j = \left|1.0 - \sum_{i=1}^{N_{PV}} F_{ji} \times \frac{V_i}{V_j}\angle\theta_{ji} + \delta_i - \delta_j\right| \quad j = 1,2,\ldots,N_{PQ} \quad (7)$$

with $F_{ji} = |F_{ji}|\angle\theta_{ji}$, $V_i = |V_i|\angle\delta_i$, $V_j = |V_j|\angle\delta_j$

$$F_{ji} = -[Y_1]^{-1} \times [Y_2] \quad (8)$$

Y_1, Y_2 : are the sub-matrices related to the system matrix Y_{bus} obtained after rearrangement the *PV* and *PQ* bus bars parameters as shown in Eq. (9):

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix}\begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \quad (9)$$

2.2. Constraints

2.2.1. Equality constraints: incequations which are given below

$$\begin{cases} P_{g,i} - P_{d,i} - \sum_{j=1}^{NB} |V_i| \times |V_j| \times |Y_{ij}| \times \cos\times(\theta_{ij} - \delta_i + \delta_j) = 0 \\ Q_{g,i} - Q_{d,i} - \sum_{j=1}^{NB} |V_i| \times |V_j| \times |Y_{ij}| \times \sin\times(\theta_{ij} - \delta_i + \delta_j) = 0 \end{cases} \quad (10)$$

2.2.2. Inequality constraints: include the power flow equation which are given below

i. Generator constraints

$$\begin{cases} V_{g,i}^{\min} \leqslant V_{g,i} \leqslant V_{g,i}^{\max}, \quad \text{and}, \\ Q_{g,i}^{\min} \leqslant Q_{g,i} \leqslant Q_{g,i}^{\max}, \quad i = 1,2\ldots Ng \end{cases} \quad (11)$$

ii. Voltage magnitudes at each bus in the system test and discrete transformer tap settings

$$\begin{cases} V_i^{\min} \leqslant V_i \leqslant V_i^{\max} & i \in NB \\ T_k^{\min} \leqslant T_k \leqslant T_k^{\max} & k \in NT \end{cases} \quad (12)$$

iii. The reactive power supplied by the capacitor banks is also limited by upper and lower values as follow:

$$\{Q_{Ci}^{\min} \leqslant Q_{Ci} \leqslant Q_{Ci}^{\max} \quad i \in NC \quad (13)$$

iv. The transmission lines loading are also restricted by upper values:

$$\{S_l \leqslant S_l^{\max} \quad l \in NTL \quad (14)$$

In this work, the control variables are self-constrained, while of stat variables are constrained by using the concept of penalty functions, of which only the violated variables of (V_i, Q_G, and S_l) are added to the objective function in order to discard any obtained unfeasible solution. Then, the modified objective function of the problem is expressed as follows:

$$P_{loss} = F_{obj}(x,u) + \lambda_V \times \sum_{i=1}^{N_{PQ}} \Delta V_i + \lambda_Q \times \sum_{i=1}^{NG} \Delta Q_i + \lambda_S \times \sum_{i=1}^{NTL} \Delta S_i \quad (15)$$

where $\lambda_V, \lambda_Q,$ and λ_l are the penalty factors; X_i^{limit} are the limit value of the dependent variables.

$$\Delta V_i = \begin{cases} (V_i^{\min} - V_i)^2 & \text{if } V_i < V_i^{\min} \\ (V_i - V_i^{\max})^2 & \text{if } V_i > V_i^{\max} \\ 0 & \text{if } V_i^{\min} \leqslant V_i < V_i^{\max} \end{cases} \quad (16)$$

$$\Delta Q_i = \begin{cases} (Q_i^{\min} - Q_i)^2 & \text{if } Q_i < Q_i^{\min} \\ (Q_i - Q_i^{\max})^2 & \text{if } Q_i > Q_i^{\max} \\ 0 & \text{if } Q_i^{\min} \leqslant Q_i < Q_i^{\max} \end{cases} \quad (17)$$

$$\Delta S_i = \begin{cases} (S_i - S_i^{\max})^2 & \text{if } S_i > S_i^{\max} \\ 0 & \text{if } S_i^{\min} \leqslant S_i < S_i^{\max} \end{cases} \quad (18)$$

3. The ant lion optimization (ALO) algorithm

The Ant lion optimizer is a new optimization algorithm which recently add to the *meta*-heuristics list, introduced by *Seydali Mirjalili* [26] for solving constrained engineering optimization problems. It is considered as a global optimizer, because it performs a good balance between exploration and exploitation ability and yields a high probability of avoiding stagnation into local optima and hence; guarantees the convergence. Another interesting point is that it has not any internal parameters to adjust (only external parameters such as number of agent and max iteration).

The ALO algorithm mimics the hunting behavior of ant lions, i.e., the interaction between predator (ant lions) and prey (ant). The different steps that describe the relationship between antlions and ants are depicted in Fig. 1. Like all other insects in nature, ants can easily detect the location of food by using a stochastic movement. This behavior is expressed mathematically by the following equations:

$$X(t) = [0, cumsu(2r(t_1) - 1), cumsu(2r(t_2) - 1), \ldots, cumsu(2r(t_n) - 1)] \quad (19)$$

where $X(t)$ is the random walks of ants, n is the max_iterations, t is the step of random walk, and $r(t)$ is a function defined as follows:

$$r(t) = \begin{Bmatrix} 1 & \text{if } rand > 0.5 \\ 0 & \text{if } rand < 0.5 \end{Bmatrix} \quad (20)$$

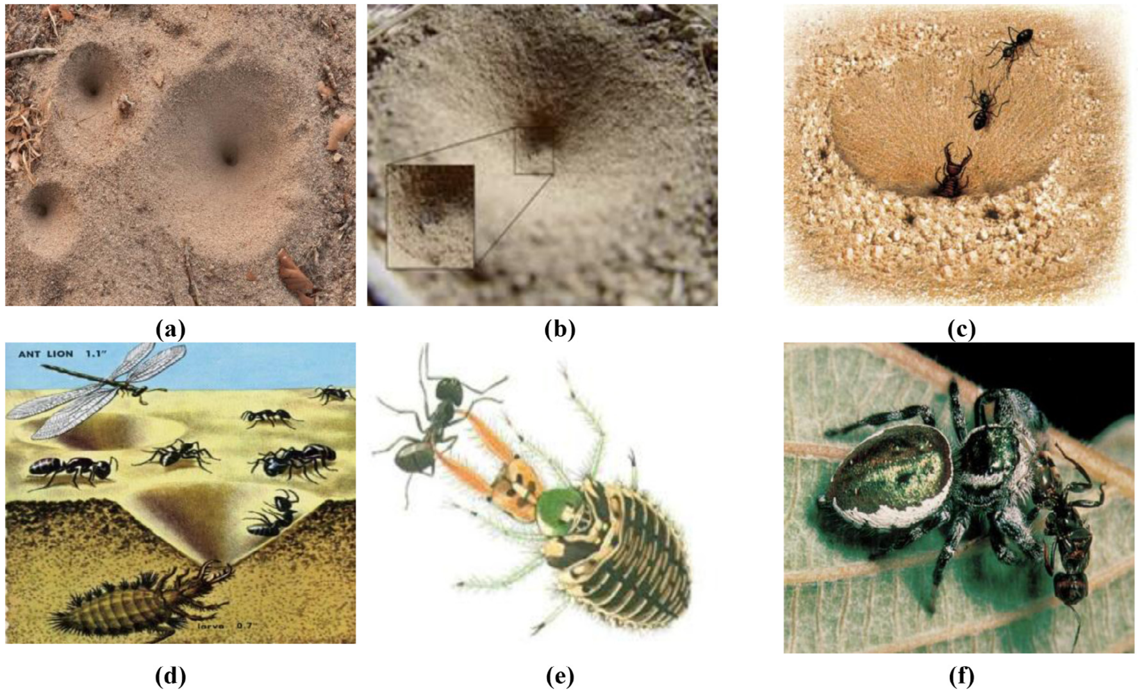

Fig. 1. (a–c) Making traps and entrapment of ants in pits; (d-f) Catching the prey and re-building.

where, rand is a randomly generated number uniformly distributed in the range of [0,1].

The following steps describe the five main phases in hunting technique of ant lions.

3.1. Random walk of ants

In every step of optimization, ants update their positions b to a random walk search Eq. (19) To ensure that all the positions of ants are inside the boundary of the search space, they are normalized by using the following expression:

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t \tag{21}$$

where the a_i, b_i are respectively the minimum and maximum of random walk corresponding of ith variable. c_i^t, d_i^t: are respectively indicated the minimum and maximum of ith variables at tth iteration.

3.2. Trapping in antlions traps

The following equations describes the effect of antlions traps on random walks of ants:

$$c_i^t = Antlion_j^t + c^t \tag{22}$$

$$d_i^t = Antlion_j^t + d^t \tag{23}$$

3.3. Building traps

During optimization, the ALO use the roulette wheel selection operator, to choose **antlions** based on their fitness. This strategy gives more chance for antlions to traps prey.

3.4. Sliding ants against toward antlion

According to the aforementioned mechanisms, antlions are able to construct traps proportional to their fitness and the ants move near of the center of pit. Once antlions catch an ant in trap, they will shoot the sand outward the middle of the trap**.** This mechanism mathematically modeled as follow, where I is the ratio.

$$c^t = \frac{c^t}{I} \tag{24}$$

$$d^t = \frac{d^t}{I} \tag{25}$$

3.5. Catching preys and rebuilding the traps

The catching the ants by predator and rebuilding the pit in order to catch new prey can be described with the following equations.

$$Antlion_j^t = Ant_i^t, \quad if\ f(Ant_i^t) > f(Antlion_j^t) \tag{26}$$

where $Antlion_j^t$ is jth the position of the selected antlion at iteration t and Ant_i^t is the position of the selected ant at iteration t.

3.6. Elitism

Elitism is one of the most important characteristic of evolutionary algorithms. In ALO algorithm, at any iteration the best antlion obtained (solution) is saved as an elite. Since the elite is the fittest antlion which is able to guide the movements of the remaining ants along the iterations. The elitism mechanism mathematically described as follows.

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{27}$$

where R_A^t is the random walk around the antlion is selected by using the roulette wheel at tth iteration, R_E^t is the random walk around the elite at tth iteration, and Ant_i^t denote the position of ith ant in tth iteration.

3.7. Flowchart for optimal reactive power dispatch using ALO

The utility of ALO in solving ORPD problem lies to find the set of optimal solution of control variables for minimizing the objective function while satisfying all constraints imposed by power systems.

The pseudo codes of ALO algorithm is defined by the following instructions:

1. Read system data, bus data, line data, and unit data;
2. Initialize the parameter for ALO, search agents, dimension, position, and maximum no of iterations;
3. Starts to initialize random walks of the ants and antlions like the first population using Eq. (19), and then calculate their values of fitness;
4. Map control variables from ants into power flow data, and evaluated it in order to obtain the power losses, L-index and voltage deviation from power flow calculation (MATPOWER) (each ant represents a solution).
5. Find the best antlions and affected it as the elite; *While* the end criterion is not reached *for* $i = 1 : nbr\ of\ ants$
6. Using roulette wheel to select the antlions and update parameters c and d using Eqs. (24) and (25);
7. Create a random walk and normalize it using Eqs. ((19) and (21))
8. Update the positions of ant obtained so far using Eq. (27) *End_for*
9. Checking the boundaries of the variables, and calculate the fitness value of all solutions(ants);
10. Outplace an antlion with its corresponding ant it if becomes fitter using Eq. (26);
11. Replace elite with antlion if an antlion is better than the elite.

Firstly, set the control parameters of ALO algorithm like the number of agents and maximum number of iteration. Construct the set of initial solution X_i^0 that comprises the variables of vector of control. The vector of initial solution can be expressed as follows:

$$M_{Antlion} = \begin{bmatrix} AL_{i1} & AL_{12} & \cdots AL_{1D} \\ AL_{21} & AL_{22} & \cdots AL_{2D} \\ \cdots & \cdots & \cdots \\ AL_{N,SA1} & AL_{N,SA2} & AL_{NSA\times D} \end{bmatrix}_{NSA\times D} \tag{28}$$

with $(i = 1, 2, \ldots, NSA$ and $j = 1, 2, \ldots, D)$, where the NSA is the number of search agents and D is the number of control variables to be optimized or position of antlions.

At this stage, each initial solution (position) mapped into the power flow data and then evaluated by using Newton-Raphson program to obtain the value of desired objective function (power losses Eq. (1), voltage deviation, or L-index value Eq. (5)). Once the evaluation process is accomplished, the best fitness such as minimum loss or L-index value with position is stored as elite antlion-fitness and elite antlion-position. Then, the same principle of evaluation process repeated by ALO using Eqs. (21)–(27) until the maximum number of iterations is reached.

4. Treatment of control variables

In our formulation, two distinct types of optimization variables are considered: discrete and continuous as mentioned in Eq. (4) that requires a special initialization. The continuous variables are initialized as follows, e.g., $P_{Gi} = \text{random}[P_{Gi}^{\min}, P_{Gi}^{\max}]$ and $U_{Gi} = \text{random}[U_{Gi}^{\min}, U_{Gi}^{\max}]$. But in the case of discrete variables, tap changers and the reactive power supplied by capacitor banks or shunt element are rounded off around their nearest decimal values. This operation is achieved by the introduction of the rounding operator in each step of ALO algorithm. Mathematically, the rounding can be written as follows: $\text{round}(\text{random}[T_i^{\min}, T_i^{\max}], 0.01)$ $\text{round}(\text{random}[Q_{Ci}^{\min}, Q_{Ci}^{\max}], 1)$.

After initialization phase, the solution vector is then subjected to update in changing the previous solution in order to find a new better vicinity solution vector using the Eq. (21), yielding a vector uniformly distributed random due from the addition of two different nature of vectors. The rounding operator is solicited again just after every update for acting only on the discrete control variables. Once the rounding process is over, all solution elements go through a feasibility check [14]. This simple rounding technique guarantees that load flow calculation along with fitness function are obtained only when all problem variables are correctly assigned to their corresponding types.

5. Numerical results and discussions

In order to verify the capability and robustness of the proposed algorithm, the IEEE 30-bus, IEEE 118-bus and large-scale power system IEEE 300-bus are considered under different simulation cases. In all cases of each power system, 50 independent runs were executed to report the optimal solution. The proposed approach was implemented in MATLAB Platform 7.10 and the simulation conducted on a personal computer "Core (TM i3; CPU 1.80 GHz-4Go RAM)." The number of control variables and real power losses value in the initial conditions are respectively listed in Table 1. Table 2 presents the limits on control variables and state variables for each test systems.

Table 1
Description of test power systems.

	30-Bus	118-Bus	300-Bus
Number of control variables	19	77	190
Number of Generator	6	54	69
Number of Taps	4	9	107
Number of $Q_{\text{-shunt}}$	9	14	14
Equality constraints	60	236	530
Inequality constraints	125	572	706
Discrete variable	13	21	107
P_{Loss}^0 (MW)	5.81	132.863	408.316

Table 2
Control variables settings for all power systems.

Test system	Variables	Min	Max	Step
IEEE 30-bus [13,28]	V_{PV} and V_{PQ}	0.95	1.1	Continuous
	T	0.9	1.1	0.01
	$Q_{\text{-shunt}}$ (9)	0	5	1
IEEE 118-bus [28]	V_{PV} and V_{PQ}	0.94	1.06	Continuous
	T	0.9	1.1	0.01
	$Q_{\text{-shunt}}$	See in [29]		1
IEEE 300-bus [28]	V_{PV} and V_{PQ}	0.9	1.1	Continuous
	T	0.9	1.1	0.01
	$Q_{\text{-shunt}}$	See in [30]		1

Table 3
Comparison of simulation results of different algorithms for IEEE 30-bus power system.

Cont. varia	PSO [12]	CLPSO [12]	BA	GWO	ABC	ALO
V_{G1}	1.1000	1.1000	1.100	1.1000	1.1000	1.1000
V_{G2}	1.1000	1.1000	1.094	1.0938	1.0971	1.0953
V_{G5}	1.0832	1.0795	1.074	1.0737	1.0866	1.0767
V_{G8}	1.1000	1.1000	1.076	1.0797	1.0800	1.0788
V_{G11}	0.9500	1.1000	1.100	1.1000	1.0850	1.1000
V_{G13}	1.1000	1.1000	1.100	1.0944	1.1000	1.1000
T_{6-9}	1.1000	0.9154	0.95	0.98	1.07	1.01
T_{6-10}	1.0953	0.9000	1.03	0.97	0.95	0.99
T_{4-12}	0.9000	0.9000	0.99	1.02	1.02	1.02
T_{28-27}	1.0137	0.9397	0.97	0.99	1.01	1.000
Q_{C10}	5	4.9265	5	2	5	4
Q_{C12}	5	5	0	5	0	2
Q_{C15}	0	5	5	4	2	4
Q_{C17}	5	5	5	4	5	3
Q_{C20}	5	5	0	4	4	2
Q_{C21}	5	5	0	0	5	4
Q_{C23}	5	5	0	5	4	3
Q_{C24}	5	5	5	3	5	5
Q_{C29}	5	5	0	3	4	5
Min P_{Loss}	4.6862	4.5615	4.628	4.6119	4.61100	4.5900
Max L_{index} (p.u)	NA	NA	0.1247	0.1303	0.1326	0.1307
CPU (s)	NA	138	129.4	127.2	130.6	119.3
% P_{save}	19.37	21.51583	20.344	20.759	20.636	21.292
$\sum PG$	NA	2.87961	2.880	2.8800	2.8801	2.8799

5.1. Results of IEEE 30-bus test power system

5.1.1. Minimization of total real power losses

Firstly, the ALO algorithm is applied on the IEEE 30-bus test power system, which consists of six generators placed at the buses 1, 2, 5, 8, 11, and 13 while the remaining ones are the PQ buses. 4 transformers, between the branches 6–9, 6–10, 4–10, and 27–28, equipped on-load tap-changers (OLTC). In addition, nine capacitor banks installed at the buses 10, 12, 15, 17, 20, 21, 23, 24, and 29 as given in [23].

Case 1: IEEE-30 bus test power system used in [24,1,2].

The set of optimal solutions of control variables obtained are summarized in Table 3. The obtained results from ALO algorithm are compared with other existing algorithms (PSO) and (CLPSO) [27], including our implementation of the three approaches, namely bat algorithm (BA), grey wolf optimizer (GWO), ant lion optimizer (ALO), and artificial bee colony algorithm (ABC). The corresponding convergence curves are shown in Fig. 2. From Table 3 and Fig. 2, it can be observed that proposed algorithm converges in 30th iteration achieving the least real power loss of 4.5900 in less execution time for simulation than all the other presented algorithms, but the real power loss reported by the CLPSO algorithm is a little bit better than our result. However, the ALO algorithm has a small value of CPU time compared to that obtained by of CLPSO algorithm. Hence, it clearly appears that the ALO algorithm has a great ability to locate the optimal or the near-optimal solutions and efficiently handle the constraints of the optimization problem at hand.

Case 2: Improvement of Voltage Stability Index for IEEE 30-bus power system

The improvement of voltage stability index is the second objective function. The limit on control variables and dependent variables are similar to the first case as indicated in Table 2. The optimal results by using the proposed algorithm and those of the other approaches are exhibited in Table 4. Likewise, the obtained maximum real power loss, minimum L-index, and average execution time for simulation are compared to those of the honey bee mating optimization (HBMO), and Chaotic Parallel Vector Evaluated HBMO (CPVEIHB). This comparison shows that the ALO algorithm has better performance in both convergence speed and global best solution. The consumed CPU time is equal at 97.9243 second for reaching optimal solution. Likewise, we can also remark that all the taps positions transformers converge to a steady state value after the 30th iteration. The convergence curves of four implemented algorithms are depicted in Fig. 3.

5.2. Results of IEEE 118-bus test power system

5.2.1. Minimization of total real power losses

In order to illustrate the effectiveness and the robustness of the proposed algorithm in a large-scale power system, the standard IEEE 118-bus test power system is considered to solve the ORPD problem. The bus data, the line data, the upper and lower limits of reactive power sources for this test system are available in the reference [28,29]. The set of optimal control variables achieved by using the ALO and other approaches are given in Table 5. Table 5, also depicts the comparison of minimum real power loss, average saving percent of real power loss, maximum voltage stability index, and average execution time for simulation with existing results from the literature along with other meta-heuristics implementing by us.

In the Table 6, the left column summarizes the reported results from literature articles and the third column lists the calculated power losses using the reported optimal control variables as input parameters to the power flow. Again, it appears that the uncertainty between reported and recalculated results marked with "(a)" are too large rather than the remaining approaches have an error around to 10^{-3}.

From this analysis, it can be seen that the results of ALO are much better than all the listed other algorithms, in which the biggest reduction of total real power loss and stability index value are accomplished by using ALO along with least amount of execution time for simulation without any violation of system constraints. The convergence curves of the ALO algorithm and ABC algorithm are presented in Fig. 4 in which the proposed algorithm converges to the steady value after 60th iteration. According to the comparison presented in Tables 5 and 6, it appears that ALO algorithm has the best performance along with lower computation time among all presented algorithms. In addition, it is noteworthy to mention that the ALO algorithm has an excellent convergence rate in comparison with ABC Fig. 5.

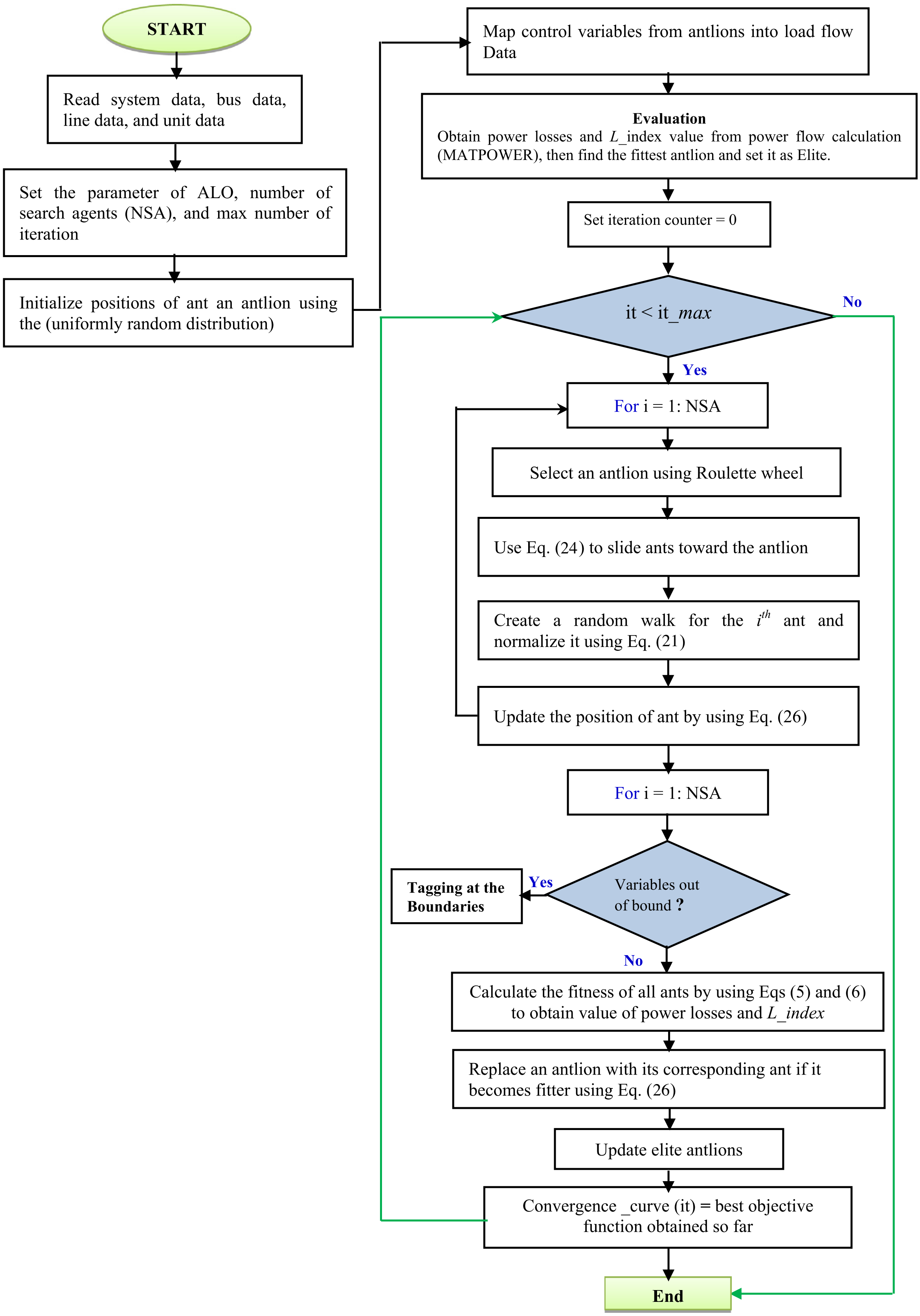

Fig. 2. Flowchart of proposed ALO algorithm.

Table 4
Comparison of simulation results of case 2 for IEEE 30-bus test power system.

Control variables	CPVEIHB-MO[a] [34]	HBMO[a] [34]	BA	GWO	ABC	ALO
V_{G1}	1.1	1.1	1.097	1.0965	1.0829	1.0992
V_{G2}	1.1	1.1	1.093	1.0807	1.0730	1.0948
V_{G5}	1.1	1.1	1.049	1.0693	1.0759	1.0975
V_{G8}	1.1	1.1	1.071	1.0624	1.0744	1.0997
V_{G11}	1.1	1.1	1.060	1.0977	1.1000	1.0979
V_{G13}	1.1	1.1	1.097	1.0927	1.0804	1.1000
T_{6-9}	0.900000	0.900	1.09	0.96	1.03	1.04
T_{6-10}	0.839363	0.900	0.90	1.01	0.92	0.95
T_{4-12}	0.895746	0.900	1.10	0.97	0.92	0.98
T_{28-27}	1.023412	1.03241	0.93	0.94	0.97	0.97
Q_{C10}	5	5	3	2	5	5
Q_{C12}	5	5	4	1	5	3
Q_{C15}	5	5	3	1	5	3
Q_{C17}	5	5	5	2	4	4
Q_{C20}	5	5	5	2	5	3
Q_{C21}	5	5	0	1	3	2
Q_{C23}	5	5	0	4	4	1
Q_{C24}	5	5	0	4	4	2
Q_{C29}	5	5	3	4	5	4
Max P_{Loss} (MW)	6.650192	6.6600	5.0748	4.8269	4.9688	4.8693
Min L_{index} (p.u)	0.111029	0.11473	0.1191	0.1180	0.1161	0.1161
CPU (s)	NA	NA	94.65	104.29	105.04	97.92

V in [p.u]; ***Q*** in [MVAR].

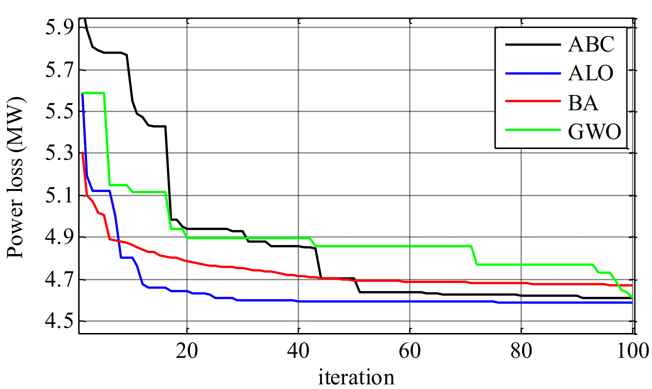

Fig. 3. Convergence curve for P_{Loss} minimization, IEEE-30 bus.

5.3. Results of IEEE 300-bus power system (large-scale power System)

5.3.1. Minimization of total real power losses

In order to show the applicability of the proposed algorithm on the large-scale power system, the IEEE 300-bus test system is considered. This system consists of 69 generators, 411 transmission lines loads, in which 107 branches with off-nominal tap ratio discretized into 21 levels as [0.9 0.91 0.92. . .until, 1.1]. In addition, 14 reactive power sources as given in [30]. The total load demand is (235.258 + j77.8797) p.u. at 100 MVA base MVA. Bus 258 is selected as the slack bus. The data for this test system can be found in [28,31]. The lower and upper limits of all control variables are given in Table. 2.

The minimum real power losses, L-index value and computation time consumed obtained from proposed ALO algorithm are summarized in Table 7. The corresponding convergence curve is shown in Fig. 6. Likewise, the obtained results RE compared with differential evolutionary particle swarm optimization (DEEPSO) and mean variance mapping optimization (MVMO). The set of optimal control variables corresponding of generator terminal voltage are drawn under graphical in Fig. 7. The obtained easily found the near-optimal solutions, even with a large-scale power system. In addition, it is noteworthy to mention that all optimal control variables are in the admissible limits.

6. Performance vs. computation efficiency

Extensive stochastic optimisation algorithms in the literature have been addressed for handling the ORPD problems, in reason to achieve both characteristics at same time, the good performance along with lower computation time. However, these algorithms are still favouring only one characteristic (performance or computation time), because the performances of stochastic search algorithms are based on number of trials, i.e., it should be mandatory to run many trials with different control parameter settings of such algorithm in selecting the suitable control parameters to achieve the best solution. Therefore, the ALO algorithm has only two parameters to adjust, the maximum number of iterations and the population size. In other hand, these two parameter are conflicting to each other, i.e., when the population size increases, the algorithm produces better results. However, after a sufficient value for search agent, any increment in the value does not improve the performance of the ALO algorithm significantly, and just contribute only a wasting time of calculating during the converging process. So, for best performance of any optimisation method, an empirical study is required.

7. Conclusion

In this paper, a recently developed algorithm was successfully implemented aimed to solve the ORPD problem. This algorithm can overcome some already aforementioned problems with other algorithms. Three different test systems including medium-scale IEEE 30-bus and larger IEEE 118-bus and Large-scale power system IEEE 300-bus are utilized to demonstrate the consistency of proposed algorithm to reach the near optimal solutions to self-posed problem. Therefore, the superiority of ALO algorithm in term of solution quality and computation cost over recently published algorithms is demonstrated through a detailed comparison in numerous simulation cases. The obtained results prove the capability of ALO to locate the near-optimal solution compared to the other well-known algorithms, and hence confirm the effectiveness of the ALO approach to solve the discrete optimal reactive power dispatch problem.

Table 5
Comparison of simulation results for IEEE 118-bus power system.

Control variables	OGSA [27]	ABC	GWO	ALO
Generator Voltage (p.u)				
V_1	1.035	1.0250	0.9960	1.0164
V_4	1.0554	1.0440	1.0510	1.0299
V_6	1.0301	1.0320	1.0480	1.0355
V_8	1.0175	1.0240	0.9880	1.0247
V_{10}	1.025	1.0600	1.0250	1.0469
V_{12}	1.041	1.0320	1.0210	1.0259
V_{15}	0.9973	0.9950	0.9860	1.0526
V_{18}	1.0047	0.9710	0.9720	1.0580
V_{19}	0.9899	0.9830	0.9820	1.0565
V_{24}	1.0287	1.0050	1.0310	1.0549
V_{25}	1.06	1.0300	1.0600	1.0600
V_{26}	1.0855	0.9770	1.0140	1.0457
V_{27}	1.0081	1.0060	1.0240	1.0583
V_{31}	0.9948	0.9920	0.9980	1.0573
V_{32}	0.9993	1.0030	1.0190	1.0455
V_{34}	0.9958	1.0310	1.0200	1.0322
V_{36}	0.9835	1.0270	1.0130	1.0264
V_{40}	0.9981	0.9850	1.0390	1.0124
V_{42}	1.0068	0.9770	1.0210	1.0321
V_{46}	1.0355	1.0230	0.9930	1.0446
V_{49}	1.0333	1.0350	1.0420	1.0572
V_{54}	0.9911	1.0080	1.0490	1.0313
V_{55}	0.9914	0.9980	1.0340	1.0305
V_{56}	0.992	1.0040	1.0430	1.0292
V_{59}	0.9909	1.0350	1.0450	1.0269
V_{61}	1.0747	1.0360	0.9870	1.0373
V_{62}	1.0753	1.0370	0.9910	1.0217
V_{65}	0.9814	1.0410	1.0230	1.0582
V_{66}	1.0487	1.0600	1.0540	1.0591
V_{69}	1.049	1.0120	1.0060	1.0600
V_{70}	1.0395	1.0520	0.9780	1.0577
V_{72}	0.99	1.0150	1.0070	1.0592
V_{73}	1.0547	1.0390	1.0360	1.0348
V_{74}	1.0167	1.0140	0.9730	1.0533
V_{76}	0.9972	1.0360	0.9980	1.0382
V_{77}	1.0071	1.0230	0.9830	1.0395
V_{80}	1.0066	1.0280	1.0090	1.0508
V_{85}	0.9893	1.0180	0.9930	1.0529
V_{87}	0.9693	1.0240	1.0540	1.0510
V_{89}	1.0527	1.0250	1.0380	1.0600
V_{60}	1.029	0.9960	1.0070	1.0382
V_{91}	1.0297	1.0380	1.0060	1.0223
V_{92}	1.0353	1.0130	1.0130	1.0532
V_{99}	1.0395	1.0160	1.0170	1.0447
V_{100}	1.0275	1.0300	1.0020	1.0445
V_{103}	1.0158	1.0530	1.0050	1.0385
V_{104}	1.0165	1.0210	1.0000	1.0218
V_{105}	1.0197	1.0080	1.0000	1.0376
V_{107}	1.0408	1.0240	0.9750	1.0285
V_{110}	1.0288	0.9800	1.0120	1.0458
V_{111}	1.0194	0.9980	0.9990	1.0254
V_{112}	1.0132	1.0050	1.0020	1.0275
V_{113}	1.0386	1.0010	0.9780	1.0567
V_{116}	0.9724	1.0190	1.0190	1.0577
Transformer tap ratio				
T_{8-5}	0.9568	0.97	0.96	1.00
T_{26-25}	1.0409	0.95	1.01	0.99
T_{30-17}	0.9963	1.00	0.92	1.00
T_{38-37}	0.9775	1.02	1.02	1.01
T_{63-59}	0.956	1.02	0.98	1.03
T_{64-61}	0.9956	0.93	1.02	1.02
T_{65-66}	0.9882	0.94	0.96	0.97
T_{68-69}	0.9251	0.95	1.01	0.94
T_{81-80}	1.0661	0.99	0.94	1.00
Capacitor banks (MVAR)				
Q_{C-5}	−33.19	32	−9	−19
Q_{C-34}	4.8	8	10	6
Q_{C-37}	−24.9	0	−13	−19
Q_{C-44}	3.28	7	6	3
Q_{C-45}	3.83	7	7	6
Q_{C-64}	5.45	4	6	5
Q_{C-48}	1.81	9	6	9
Q_{C-74}	5.09	10	6	7
Q_{C-79}	11.04	12	6	6

Table 5 (*continued*)

Control variables	OGSA [27]	ABC	GWO	ALO
Q_{C-82}	9.65	11	13	12
Q_{C-83}	2.63	8	4	6
Q_{C-105}	4.42	4	7	4
Q_{C-107}	0.85	2	4	3
Q_{C-110}	1.44	3	2	3
Min P_{Loss} (MW)	126.99	120.4288	131.2620	119.7792
Max *L-index* (p.u)	0.14	0.0677	0.0668	0.0642
Pg_{slack} (MW)	NA	501.43	512.26	500.78
P_{save} (%)	4.4203	9.35	1.205	9.847
CPU (s)	1152	730.4	722.45	716.7

Table 6
Statistics of trial result to ALO algorithm and other algorithms for IEEE 118-bus.

Algorithms	P_{Loss} (reported) MW	P_{Loss} (calculated) MW	CPU (s)
GSA[a] [1]	127.7603	152.886	1198.6583
OGSA[a] [27]	126.99	130.351	1152.32
ICA [32]	123.0825	123.0825	1263
GSA [32]	122.6139	122.614	936.43
PSO[a] [12]	131.99	274.160	1215
CLPSO[a] [12]	130.96	236.174	1472
CPVEIHBMO[a] [15]	124.098	139.743	1053.37
HFA[a] [33]	134.24	135.381	NA
ABC	120.4288	120.41	730.4
GWO	131.2620	131.269	722.45
ALO	119.7792	119.785	716.7565

[a] Are the infeasible solutions.

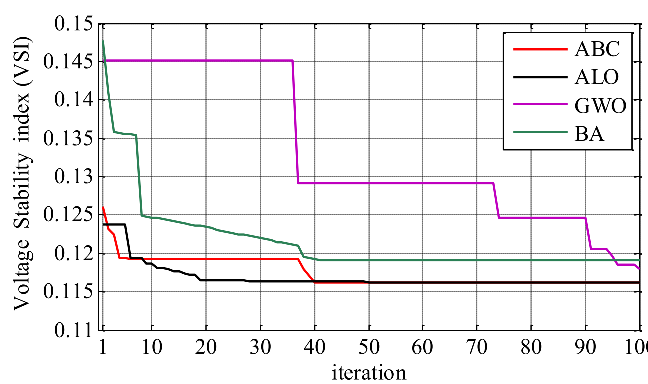

Fig. 4. Convergence curves for *L_index* minimization in case 2 of IEEE 30-bus power system.

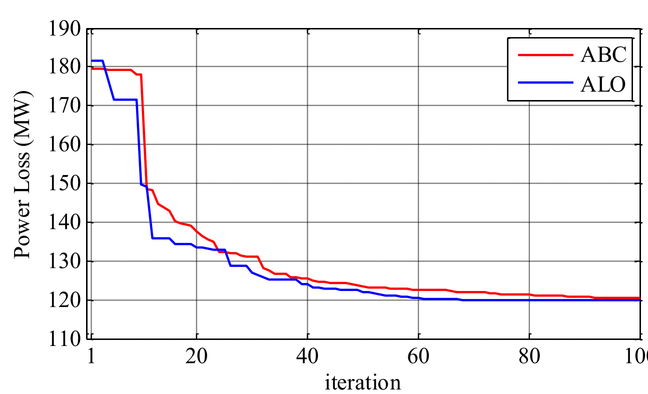

Fig. 5. Convergence curves for P_{Loss} minimization of IEEE-118 bus power system.

Table 7
Comparison of results of ALO algorithm and other algorithms for IEEE 300-bus.

Algorithms	MVMO [31]	DEEPSO [31]	ALO
Min P_{Loss} (MW)	385.6284	394.4343	384.9224
Max *L-index* (p.u)	NA	NA	0.3663
CPU (s)	NA	NA	4022.9

NA: not a number.

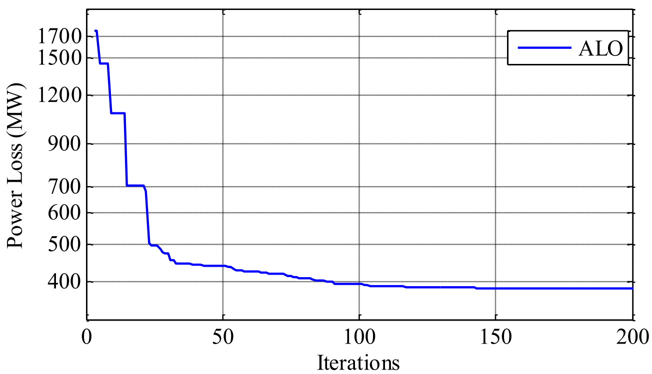

Fig. 6. Convergence curves for P_{Loss} minimization of IEEE-300 bus power system.

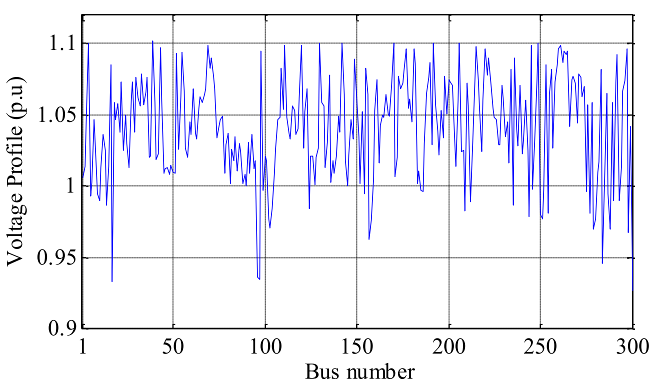

Fig. 7. Bus voltage profile for IEEE-300 Bus power system.

8. Disclosure of potential conflicts of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Appendix A.

See Table A.1.

Table A.1
Control parameter settings of ALO algorithm for test power systems.

Parameter	Setting Value		
	IEEE 30-bus	IEEE 118-bus	IEEE 300-bus
No of search agents (NSA)	40	40	40
No of iterations	100	100	200
Search domain (*rand*)	[0 1]		
Dimension	Same as number of features in any given database		
Penalty factor of voltage λ_V	50	50	10^{-5}
Penalty factor of reactive power λ_Q	100	1000	10^{-6}
Penalty factor of transmission line λ_S	100	100	10^{-6}

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