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Whale optimization algorithm based optimal reactive power dispatch: A case study of the Algerian power system

Khaled ben oualid Medani ^{a,*}, Samir Sayah ^a, Abdelghani Bekrar ^b

^a *QUERE laboratory, Department of Electrical Engineering, Ferhat Abbas University of Setif 1, Setif 19000, Algeria*

^b *LAMIH, UMR CNRS 8201, University of Valenciennes and Hainaut-Cambrésis, UVHC, Le Mont Houy, 59313 Valenciennes Cedex, France*

A B S T R A C T

Optimal reactive power dispatch (ORPD) is a particular case of the optimal power flow. ORPD was usually considered as the minimization of an objective function representing the total active power losses in the electrical networks. The constraints involved are the generator voltages, tap regulating transformers ratios and the amount of reactive shunt compensators. The goal of this study is to find the best vector of control variables, so that the power loss decreasing can be realized. In this paper, a new metaheuristic technique inspired from the bubble-net hunting technique of humpback whales, namely whale optimization algorithm (WOA), has been applied to solve the ORPD problem. The WOA method has been examined and confirmed on the IEEE 14-bus, IEEE 30-bus, in addition to a practical and large scale Algerian electric 114-bus test system. The obtained outcomes have been compared with two own developed methods, namely, particle swarm optimization (PSO) and particle swarm optimization with time varying acceleration coefficients (PSO-TVAC). Afterwards, an analysis of variance (One-way ANOVA test) has been implemented in order to verify the performance of our proposed algorithm in solving the ORPD problem. In summary, the comparison study shows the potential of this recent optimization method, and proves its robustness and effectiveness in solving the ORPD problem.

Keywords:

Optimal reactive power dispatch (ORPD)

Metaheuristic techniques

Whale optimization algorithm (WOA)

Real power loss minimization

Algerian power system

Analysis of variance (One-way ANOVA test)

1. Introduction

Optimal reactive power dispatch (ORPD) problem can be classified as a part of the optimal power flow (OPF) problem. It is considered as nonlinear and non-convex constrained optimization problem with both discrete and continuous control variables. Moreover, it has both of equality and inequality constraints. To determine minimum loss, several main variables need to be controlled and set accordingly such as the voltage of generator buses, transformer tap setting, and the shunt capacitors value. In recent developments on power system research, ORPD is gaining much more attention than before because that reactive power has an important effect on system security and operation. From there, proper distribution and management of reactive power are the major worry for utilities in our days.

ORPD problems have been discussed and later been solved by applying numbers of classical algorithms. For instance, non-linear programming [1] mixed integer programming [2], quadratic programming [3]...etc. Unfortunately, these classical optimization

techniques have several drawbacks such as algorithmic complexity, convergence not guaranteed and sensitivity to initial search point. As alternative, metaheuristic algorithms have been the reasons of solving optimization problems by mimicking physical or biological phenomena. Several metaheuristic algorithms have been applied to solve numerous optimization problems. for example [4] used a multi-layer ant colony optimization to find energy management scheduling in microgrid, while [5] proposes an optimization method based on gravitational search algorithm to solve such problem in a microgrid. Metaheuristics can be classified in three categories which are cited as follow: physics-based, evolution-based, and swarm-based methods. Particle swarm optimization (PSO) [6] and artificial bee colony (ABC) [7] together with the variants of honey bee mating optimization (HBO) [8] are swarm-based methods. Furthermore, harmony search algorithm (HSA) [9] and improved HSA [10] as well as gravitational search algorithm (GSA) [11] are the techniques based on the physics approach. All those cited algorithms have been employed to solve ORPD problem. Some researchers tried to solve ORPD using hybrid techniques such as hybrid differential evolution with ant system [12] and hybrid of modified imperialist competitive algorithm with invasive weed optimization (MICA-IWO) [13]. Marzband et al. [14] used the mix-

* Corresponding author.

E-mail address: medani.khaled@univ-setif.dz (K.b.o. Medani).

Nomenclature

$f(X, U)$	Objective function
$h(X, U)$	Set of equality constraints
$g(X, U)$	Set of inequality constraints
P_{loss}	Active power loss
V_i, V_j	Voltage of i^{th} and j^{th} buses respectively
V_g, V_L	Generator voltages and load bus voltages respectively
P_{g1}	Real power generation of slack bus
P_{gi}, Q_{gi}	Active and reactive power of i^{th} generator bus
P_{di}, Q_{di}	Active and reactive power of i^{th} load bus
G_{ij}, B_{ij}	Conductance and admittance of ij^{th} element in the bus admittance matrix
T	Transformer tap settings
S_L	Transmission line loadings
N	Number of buses
NG	Number of generators
NT	Number of regulating transformers
NTL	Number of transmission lines
NC	Number of shunt VAR compensators
NPQ	Number of load buses
K_v, K_{Qgi}	Penalty factors
t	Current iteration
A, C	Coefficient vectors
X^*	Position vector of the best solution
X	Position vector
$ $	Absolute value
\cdot	Element-by-element multiplication
a	Vector linearly decreased from 2 to 0
r	Random vector within the range [0, 1]
b	Constant for defining the shape of the logarithmic spiral
l	Random number uniformly distributed in the range of [-1, 1]
p	Probability for each encircling way
X_{rand}	Randomly chosen position of whale agent

ture multiperiod artificial bee colony combined with markov chain based optimal energy management system for islanded microgrids.

Proposed in 2016 by Mirjalili and Lewis [15], whale Optimization algorithm WOA is a new metaheuristic search algorithm that mimics the bubble net hunting strategy of humpback whales. It has been reported in [15] that the imitation of the bubble-net hunting strategy of humpback whales used the randomness of the best search agents and the spiral encircling way which is the main advantage of WOA, and make it different from other similar approaches. On the other hand, the main drawbacks of WOA can be represented on its parameters which are dependent on the random distribution and it has a premature convergence like most of metaheuristic algorithms. Moreover, in [15], WOA has been tested over different benchmark functions and engineering design benchmark problems and compared with other heuristic algorithms. Due to its recently creation, only a limited number of research publications have been successfully verified in solving various optimization problems in the literature. In [16], WOA was used for optimizing connection weights in neural networks while [17] applied WOA to get the optimal size and location of capacitors in radial distribution power system. Oliva et al. [18], have developed an improved WOA to estimate the parameters of photovoltaic cells. Mafarja and Mirjalili [19] proposed a hybrid WOA and simulated annealing algorithms in a wrapper feature selection method.

The core contribution of this study is that a novel approach based on the WOA technique is applied for the ORPD problem.

Standard IEEE power systems (14 and 30 buses) and a large scale 114-buses Algerian electric test system are used in order to minimize the active power losses with satisfying the power system constraints. This paper also compares the proposed approach with other optimization techniques, such as PSO and PSO-TVAC and others reported from the literature. Additionally, a statistical analysis has been taken serious to test whether significant differences exist between the several algorithms presented in this study. Finally, the simulation results of WOA show acceptable and remarkable results in solving this optimization problem.

2. Problem formulation

2.1. Objective function

The basis of formulating ORPD problem is mainly concerned with minimization of real power loss. It can be formulated as follows [20]:

$$\text{Min} f(X, U) = P_{loss} = \sum_{k \in NTL} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \quad (1)$$

Subject to:

$$\begin{cases} h(X, U) = 0 \\ g(X, U) \leq 0 \end{cases} \quad (2)$$

where g_{ij} is the conductance of branch k and X is the vector of control variables. It can be written by:

$$X^T = [V_{L1} \dots V_{LNPQ}, S_{L1} \dots S_{LNTL}, Q_{G1} \dots Q_{GNG}] \quad (3)$$

where U is the vector of dependent variables. It can be expressed as:

$$U^T = [V_{G1} \dots V_{GNG}, T_1 \dots T_{NT}, Q_{C1} \dots Q_{CNC}] \quad (4)$$

2.2. Constraints

The problem is subject to both inequality and equality constraints.

2.2.1. Equality constraints

The equality constraints represent typical load flow equations, cited as follows:

$$P_{gi} - P_{di} - V_i \sum_{j=1}^N V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \quad (5)$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^N V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \quad (6)$$

2.2.2. Inequality constraints

The inequality constraints are mathematically expressed as follows:

- Generator constraints: real and reactive power outputs as well as generator voltages are bounded by their upper and lower limits, as follow:

$$\begin{aligned} V_{gi}^{\min} &< V_{gi} < V_{gi}^{\max} & i \in NG \\ P_{gi}^{\min} &< P_{gi} < P_{gi}^{\max} & i \in NG \\ Q_{gi}^{\min} &< Q_{gi} < Q_{gi}^{\max} & i \in NG \end{aligned} \quad (7)$$

- Transformer tap settings: are bounded by their lower and upper limits, as follows:

$$T_k^{\min} < T_k < T_k^{\max} \quad k \in NT \quad (8)$$

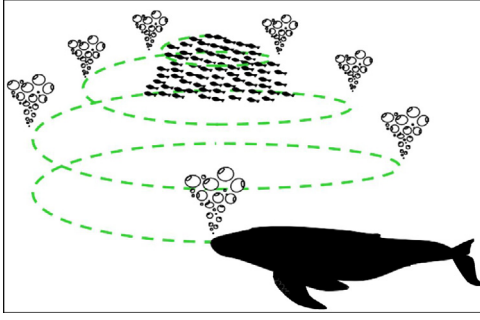


Fig. 1. Bubble-net hunting behavior of humpback whales.

- Reactive compensators (shunt VARs): are bounded by their minimum and maximum limits, as follows:

$$Q_{Ci}^{\min} < Q_{Ci} < Q_{Ci}^{\max} \quad i \in NC \quad (9)$$

The dependent variables constraints are included into the objective function as a penalty terms. Therefore, Eq. (1) is improved as presented in [21,22]. The penalty function terms would be zero, if all the control variables limits are not exceeded. Otherwise, its terms would be considered into the objective function.

$$F = P_{loss} + \sum K_V (V_i - V_i^{lim})^2 + \sum K_Q (Q_i - Q_i^{lim})^2 \quad (10)$$

where F represents the extended objective function. K_V and K_Q are penalty factors.

To make our research more reliable and efficient and to ensure accurate results of total transmission loss, MATPOWER 4.1 toolbox [23] is introduced to calculate the power flow and to fulfill the equality constraints.

3. The whale optimization algorithm

3.1. Brief review of whale optimization algorithm

Whale optimization algorithm (WOA) is one of the latest novel nature-inspired meta-heuristic optimization algorithms. Introduced by Mirjalili and Lewis in 2016 [15], WOA imitates the social behavior of humpback whales which have many interesting points in their social behaviors. They are considered to be the biggest mammals in the whole world, but the more impressive than the humpback whale size, is their intelligence and the sophisticated way on collective work.

According to [24], only half whale's brain sleeps, because they must breathe on the surface of oceans, such as the humpback social structure of whales. Typically, whales live by itself or in small groups. In summer, they may stay together longer to feed cooperatively. Their favorite preys are krill and small fish herds. Fig. 1 shows this mammal.

One of their most interesting behaviors is bubble-net feeding, a complex and coordinated tactic for catching many fish at once. The hunt begins as the whales dive beneath the school herring emitting high pitch calls. In a panic the fish flee to the surface, where the whales concentrate them by releasing columns of air bubbles along a circle or '9'-shaped path. The babbles act as a barrier where the fish will not swim through it and the whales coordinate their efforts so the bubbles around the herring. Finally, the whale leader emits a sound that ques all the whales to ascend with mouths open [25].

3.2. Whale optimization algorithm (WOA)

The mathematic model for WOA is designated as follows:

3.2.1. Shrinking encircling mechanism

When the whales began hunting, they tend to encircle their prey (the currently best candidate solution is assumed as the target prey) then update its position to the optimum solution. The following equations represent the encircling behavior [24]:

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \quad (11)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (12)$$

where t specifies the current iteration, A and C are coefficient vectors, X^* is the position vector of the best solution, X is the position vector, $| |$ is the absolute value and \cdot is the element-by-element multiplication.

It can be noted here that X^* has to be updated in each trial run if there is a better solution. The vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (13)$$

$$\vec{C} = 2\vec{r} \quad (14)$$

where a is linearly decreased from 2 to 0 (in both exploration and exploitation phases) and r is a random vector limited into $[0, 1]$.

3.2.2. Spiral updating position

Mathematical spiral equation for position update between humpback whale and prey is designed as follows:

$$\vec{D}' = |\vec{X}^*(t) - \vec{X}(t)| \quad (15)$$

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot (\cos 2\pi l) + \vec{X}^*(t) \quad (16)$$

where: b is a constant for defining the shape of the logarithmic spiral, and l is a random number uniformly distributed in the range of $[-1, 1]$.

In this part, we assume that there is 50% probability for each encircling way; either follows the shrinking encircling or logarithmic path during optimization. Mathematically it is modeled as follows:

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad \text{if } p < 0.5 \quad (a) \quad (17)$$

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot (\cos 2\pi l) + \vec{X}^*(t) \quad \text{if } p \geq 0.5 \quad (b)$$

where p is a probability for each encircling way.

To perform a global search, we update the position of a search agent by a randomly chosen search agent instead of relying on the best search agent found so far. This technique is employed when the random values of A is greater than 1. The mathematical model is as follows:

$$\vec{D} = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}(t)| \quad (18)$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \quad (19)$$

where X_{rand} is chosen randomly from whales in the current trial run.

3.3. Computational procedure of whale optimization algorithm

The computational procedure of WOA is illustrated in the following algorithm [15]:

Start

Initialize the whales population X_i ($i = 1, 2, \dots, n$)

Calculate the fitness of each whale agent

X^* is the best whale agent

While ($t < \text{maximum number of simulation run}$)

For each whale agent

Table 1
Description of test systems.

Description	IEEE 14-bus	IEEE 30-bus	Algerian 114 bus
Buses	14	30	114
Lines	20	41	175
Generators	5	6	15
Tap transformers	3	4	17
Shunt capacitors	2	9	7
Load buses	9	24	99
P load (MW)	259.00	283.40	3727.00
Q load (Mvar)	73.50	126.20	2070.00
P gen (MW)	272.39	289.211	3794.456
Q gen (Mvar)	82.44	108.922	2335.84
Initial P loss (MW)	13.393	5.811	67.456
Initial Q loss (Mvar)	54.54	32.417	265.84

Update a, A, C, l , and p (while $t <$ maximum number of iterations)
if1 ($p < 0.5$)
if2 $|A| < 1$
 Update the position of the current whale agent by Eq. (17).a
else if2 $|A| \geq 1$
 Select a random whale agent (X_{rand})
 Update the position of the current whale agent by Eq. (19)
End if2
else if1 ($p \geq 0.5$)
 Check if any search agent goes beyond the search space and amend it
 Calculate the fitness of each search update
 Update X^* if there is a better solution
 $t = t + 1$
End while
Return X^*
Update the position of the current search by Eq. (17).b
End if1

3.4. Implementation of WOA for ORPD problem

WOA based approach is used for solving the ORPD problem, which aims to find the near global optimum values of control variables in order to minimize the active power loss while satisfying all the constraints mentioned above. The steps considered in optimizing the function correlated to ORPD problem are enumerated in Fig. 2.

4. Simulation results and discussion

For the purpose of verifying the performance and efficiency of the proposed WOA algorithm, tests are carried out on IEEE 14 bus and IEEE 30 bus, in addition to the Algerian electric 114 bus test system. The description of these networks can be found in Table 1. All the simulations are carried out by using MATLAB 2008b, and computed on core (Tm) i7-3520M CPU a 2.90 GHz with 8 Go RAM. For establishing the superiority of the proposed WOA, 30 independent trial runs are performed for all the test cases with a comparative study reported in the following section.

4.1. Case study for IEEE 14 bus

The IEEE 14-bus test system includes five generators at the buses 1, 2, 3, 6 and 8 with 20 transmission lines and 3 tap-changing transformers [26]. The shunt reactive power sources are considered at buses 9 and 14. The load demand is 259.00 MW and 73.5 MVar on 100 MVA base. The variable limits are cited in Table 2. The upper and lower limits, as well as the near global optimum value of active and reactive power generations are shown in Table 3.

Table 2
The limits of the control variables for IEEE 14-bus test system.

Variables limits	Lower limit (pu)	Upper limit (pu)
Voltages for generator bus	0.9	1.1
Voltages for load bus	0.9	1.1
Tap setting	0.9	1.1
Shunt compensators Q_{C9}	0	0.18
Shunt compensators Q_{C14}	0	0.18

Table 3
Range, initial and obtained setting of generator active and reactive power output.

Buses	1	2	3	6	8
P_{min} (MW)	332.4	100	100	100	100
P_{max} (MW)	0	0	0	0	0
Initial value (MW)	232.4	40	0	0	0
Optimal value (MW)	231.39	40	0	0	0
Q_{min} (MVar)	0	-40	0	-6	-6
Q_{max} (MVar)	10	50	40	24	24
Initial value (MVar)	-16.9	42.4	23.4	12.2	17.4
Optimal value (MVar)	-5.49	29.26	20.79	7.24	21.98

The bold values represent the best results obtained by WOA algorithm.

Table 4
Comparison of results for IEEE 14-bus system.

Variables	Base case	MGBTLBO [27]	PSO	PSO-TVAC	WOA
V_1	1.06	1.1	1.1008	1.1013	1.1
V_2	1.045	1.0791	1.0804	1.0882	1.0859
V_3	1.01	1.0484	1.044	1.0585	1.0566
V_6	1.07	1.0553	1.0253	1.0418	1.0858
V_8	1.09	1.0326	1.077	1.044	1.1
T_{4-7}	0.9467	1.01	1.0357	1.042	0.95853
T_{4-9}	0.9524	1.01	1.0191	1.0176	1.0453
T_{5-6}	0.9091	1.03	1.0172	1.0747	1.0163
Q_{C9}	0.18	0.3	8.6926	17.100	12.497
Q_{C14}	0.18	0.07	7.0349	8.2049	8.0161
P_{loss}	13.393	12.3105	12.381	12.279	12.255
% reduction	-	8.082	7.556	8.311	8.497

The bold values represent the best results obtained by WOA algorithm.

Table 4 summarizes the results of the optimal settings obtained by WOA and shows the best results of ORPD obtained by several algorithms. From this table, the results indicate that applying WOA leads to **12.255 MW** active power loss, which is less compared with our developed algorithms: PSO and PSO-TVAC (12.381 MW and 12.279 MW respectively) and the other one from the literature (12.3105 MW) [27]. Furthermore, from the percentage reductions shown in Table 4, it can be seen that the proposed WOA gives 8.497% of loss reduction.

In case of ORPD problems, the reactive power generation has to be considered rather than active power generation. Furthermore, it is necessary to declare the active and reactive generation outputs. Table 3 shows the values of active and reactive power generation before and after optimization. It can be observed from this table that the active and reactive power generations are within their acceptable limits.

Fig. 3 shows the loss reduction process for WOA, PSO, and PSO-TVAC simultaneously. From this figure, it can be observed that satisfying results can be achieved after about conducting 28 iterations, which reflects the excellent searching ability of WOA algorithm against the two other techniques for solving in general nonlinear problems (ORPD in our case of study).

4.2. Case study for IEEE 30 bus

The IEEE 30-bus system involves 6 generators, 41 lines, 4 transformers that are located at lines 6-9, 4-12, 9-12 and 27-28 [28]. About this case study, 9 reactive compensators are installed at buses

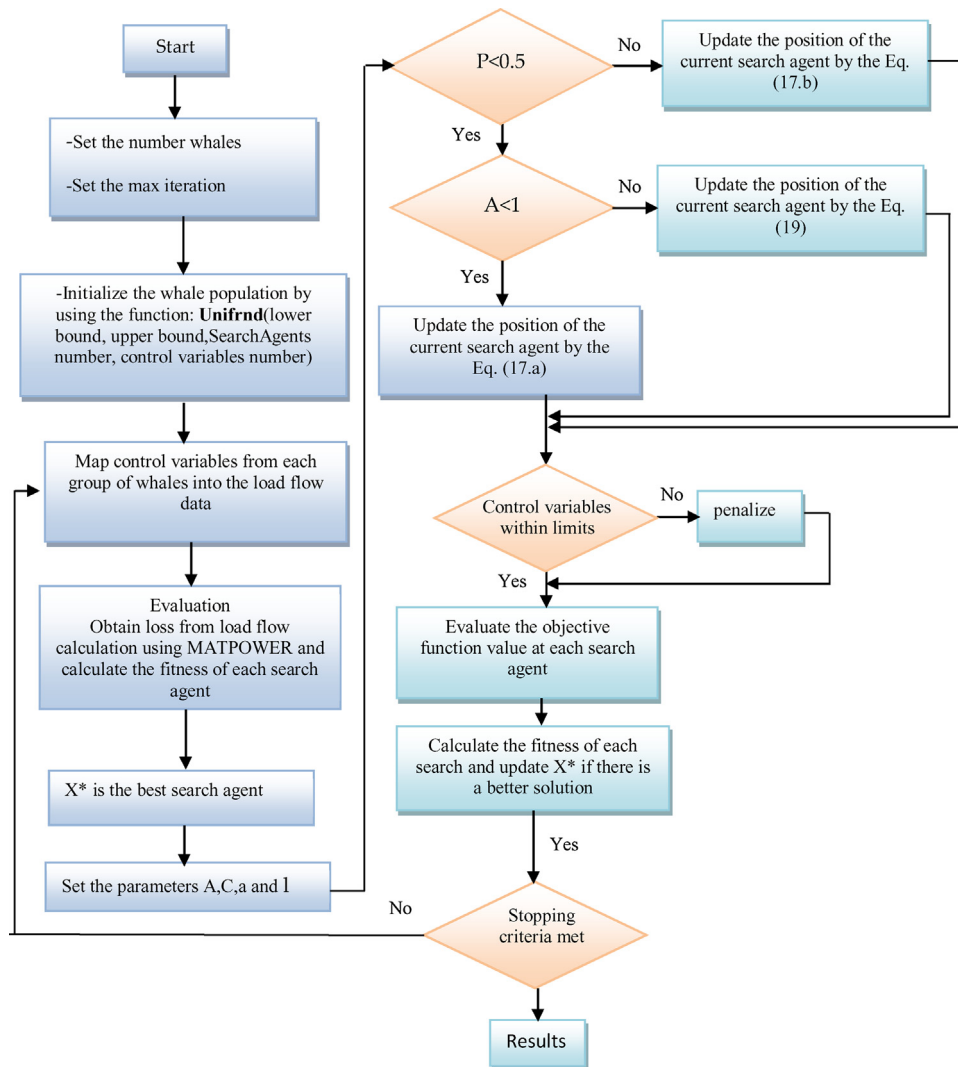


Fig. 2. Flowchart of the proposed WOA for solving ORPD.

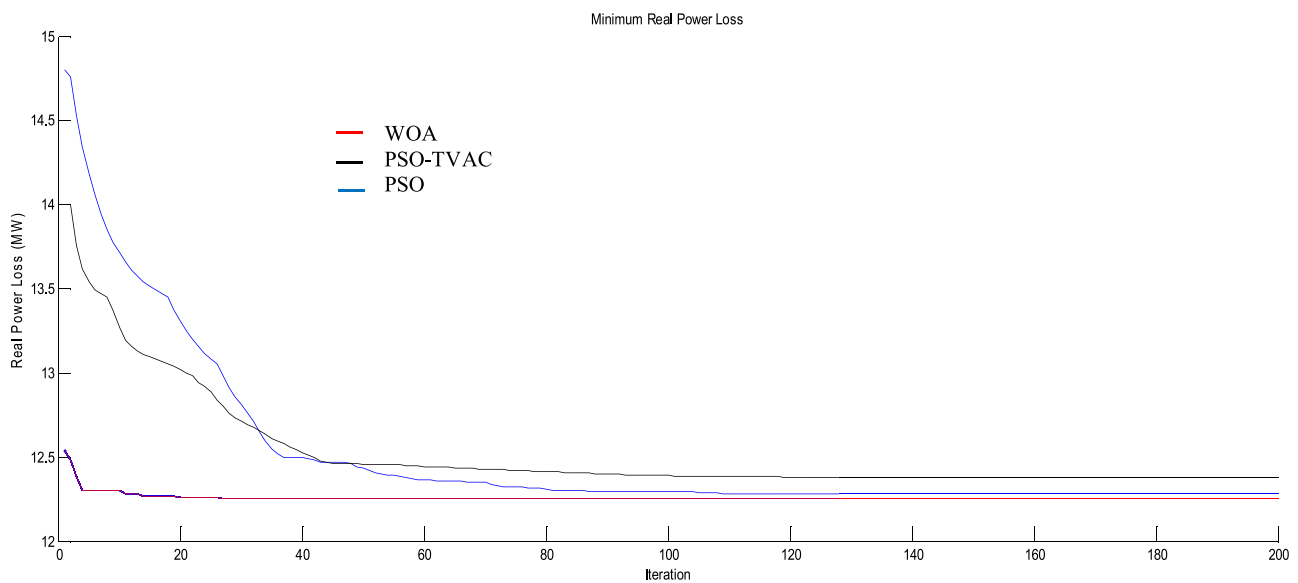


Fig. 3. Performance characteristics of algorithms for IEEE 14-bus test system.

Table 5
Limits of various variables for IEEE 30-bus test system.

Variables limits	Lower limit (pu)	Upper limit (pu)
Voltages for generator bus V_g	0.9	1.1
Voltages for load bus V_l	0.9	1.1
Tap setting T	0.9	1.1
Shunt compensators Q_c	0	0.05

Table 6
Range, initial and optimal setting of generator active and reactive power output.

Buses	1	2	5	8	11	13
P_{min} (MW)	20	20	15	10	10	12
P_{max} (MW)	200	80	50	35	30	40
Initial value (MW)	92.211	80	50	20	20	20
Optimal value (MW)	98	80	50	20	20	20
Q_{min} (MVar)	-20	-20	-15	-15	-10	-15
Q_{max} (MVar)	200	100	80	60	50	60
Initial value (MVar)	0	0	0	0	0	0
Optimal value (MVar)	-14.12	21.58	28.33	35.45	7.32	12.82

The bold values represent the best results obtained by WOA algorithm.

Table 7
Comparison of results for IEEE 30-bus system.

Variables	Initial	ABC [28]	GSA [29]	PSO	PSO-TVAC	WOA
V_1	1.05	1.1	1.0716	1.1	1.0971	1.1
V_2	1.04	1.0615	1.0221	1.093	1.0876	1.0963
V_5	1.01	1.0711	1.0400	1.0731	1.0658	1.0789
V_8	1.01	1.0849	1.0507	1.0743	1.07	1.0774
V_{11}	1.05	1.1	0.9771	1.0275	1.0669	1.0955
Q_{c13}	1.05	1.0665	0.9676	1.0335	1.0995	1.0929
T_{6-9}	1.078	0.97	1.0984	1.0161	0.97571	0.9936
T_{6-10}	1.069	1.05	0.9824	1.0008	0.92692	0.9867
T_{4-12}	1.032	0.99	1.0959	1.0089	0.99968	1.0214
T_{28-27}	1.068	0.99	1.0585	1.0245	0.96481	0.9867
Q_{c10}	0	5	1.6537	3.6433	1.0303	3.1695
Q_{c12}	0	5	4.3722	3.5418	3.2628	2.0477
Q_{c15}	0	5	0.1199	1.6649	4.4982	4.2956
Q_{c17}	0	5	2.0876	4.0095	4.6258	2.6782
Q_{c20}	0	4.1	0.3577	4.0649	1.4852	4.8116
Q_{c21}	0	3.3	0.2602	4.0831	4.548	4.8163
Q_{c23}	0	0.9	0.0000	4.1428	3.5751	3.5739
Q_{c24}	0	5	1.3839	3.9482	4.6527	4.1953
Q_{c29}	0	2.4	0.0003	2.2461	3.2407	2.0009
P_{loss} (MW)	5.812	4.6022	4.5143	4.7779	4.6469	4.5943
% reduction	-	20.81	22.32	17.79	20.04	20.95

The bold values represent the best results obtained by WOA algorithm.

10, 12, 15, 17, 20, 21, 23, 24 and 29. Minimum and maximum limit settings for tap setting transformers, reactive compensators and generators voltages are tabulated in Table 5.

Upper and lower limits, as well as the optimal value obtained of active and reactive power generations are cited in Table 6. From this table, it can be mentioned that the optimal values of active and reactive power generation are restricted by their upper and lower limits cited previously. From Table 7, it can be seen that the near global optimum result of active power loss obtained by WOA is **4.5943** MW, giving a remarkable value of power loss among all techniques examined and taken from the literature [28,29]. Comparison with PSO and PSO-TVAC give respectively about 17.79% and 20.04% reduction of total power loss.

The performance characteristics of WOA and other two techniques are shown in Fig. 4. It can be seen that the convergence of WOA algorithm has been obtained before the 40th iteration, in comparison to the 60th and the 80th iteration attained by PSO and PSO-TVAC, respectively.

Table 8
Limits of various variables for Algerian 114-bus test system.

Variables limits	Lower limit (pu)	Upper limit (pu)
Voltages for generator bus	0.9	1.1
Voltages for load bus	0.9	1.1
Tap setting	0.9	1.1
Shunt compensators Q_c	0	0.25

Table 9
Comparison of results for Algerian 114-bus system.

Variables	Base case	PSO	PSO-TVAC	WOA
V_4	1.07	1.0447	1.0351	1.0906
V_5	1.05	1.044	1.0363	1.0901
V_{11}	1.05	1.0454	1.0481	1.0906
V_{15}	1.04	1.0387	1.0198	1.091
V_{17}	1.08	1.0484	1.0437	1.0905
V_{19}	1.03	1.0182	1.0327	1.0892
V_{22}	1.04	1.0144	1.0311	1.09
V_{52}	1.05	1.0219	1.0364	1.0909
V_{80}	1.08	1.0514	1.0407	1.0824
V_{83}	1.05	1.0682	1.0552	1.0895
V_{98}	1.05	1.0577	1.0452	1.0895
V_{100}	1.08	1.0806	1.0719	1.0901
V_{101}	1.08	1.0646	1.0465	1.0908
V_{109}	1.05	1.0693	1.0643	1.0903
V_{111}	1.02	1.0573	1.0541	1.0903
T_{88-80}	1.03	1.0025	1.0021	1.0899
T_{90-81}	1.03	0.98926	0.99363	1.0061
T_{93-86}	1.03	0.98409	1.0004	1.0061
T_{41-42}	1.03	1.0035	1.0248	1.0661
T_{57-58}	1.03	0.9692	1.0176	1.0303
T_{43-44}	1.03	1.0035	0.9738	1.07
T_{59-60}	1.03	0.9979	1.0373	1.007
T_{63-64}	1.03	1.0331	1.0249	1.0303
T_{71-72}	1.03	1.0196	1.0059	1.0052
T_{18-17}	1.03	1.0259	1.0275	1.0053
T_{20-21}	1.03	0.97363	0.9804	0.97601
T_{26-27}	1.03	1.0217	0.98989	1.0067
T_{26-28}	1.03	0.9765	0.97195	1.0061
T_{30-31}	1.03	1.0494	0.98385	1.0049
T_{47-48}	1.03	0.96623	0.98857	1.0055
T_{76-74}	1.03	0.98411	1.0004	1.0777
Q_{c41}	0	10.469	23.703	10.488
Q_{c50}	0	15.697	19.369	24.876
Q_{c55}	0	23.66	13.59	22.935
Q_{c66}	0	22.568	16.317	24.876
Q_{c67}	0	19.672	20.867	24.876
Q_{c77}	0	19.308	10.484	24.876
Q_{c93}	0	18.24	16.915	13.949
P_{loss} (MW)	67.456	54.117	51.153	49.784
Reduction %	-	19.77	24.17	26.19

The bold values represent the best results obtained by WOA algorithm.

4.3. Practical Algerian electric power system

In order to verify the effectiveness of WOA in solving similar problems of larger dimensions, the ORPD is performed on practical and large-scale Algerian power test system with 114 bus. Fig. 5 shows the map of Algerian electric system. This network contains 15 generators, 175 lines, 99 load-bus, and 16 tap changer transformers from line 160 to line 175 [30]. The reactive compensation devices are installed at buses 41, 50, 55, 66, 67, 77, and 93. The total system real and reactive power demands are 3727 MW and 2070 MVar. The setting for minimum and maximum bounds for generators voltages, transformers tap setting, and reactive compensation devices are listed in Table 8. The optimal settings of control variables and reduction values for active power loss over 30 independent runs are represented in Table 9.

The near global optimum power loss obtained by WOA took a value of 49.784 MW. Compared to the base case, the three proposed techniques WOA, PSO and PSO-TVAC obtains respectively, 26.19%,

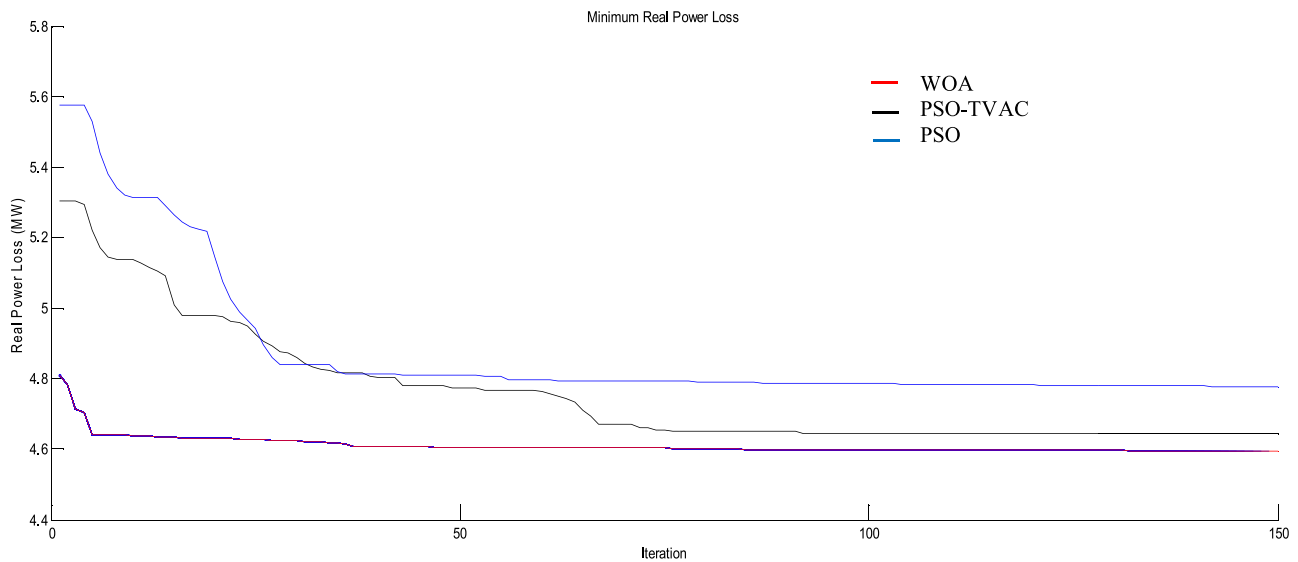


Fig. 4. Performance characteristics of algorithms for IEEE 30-bus test system.

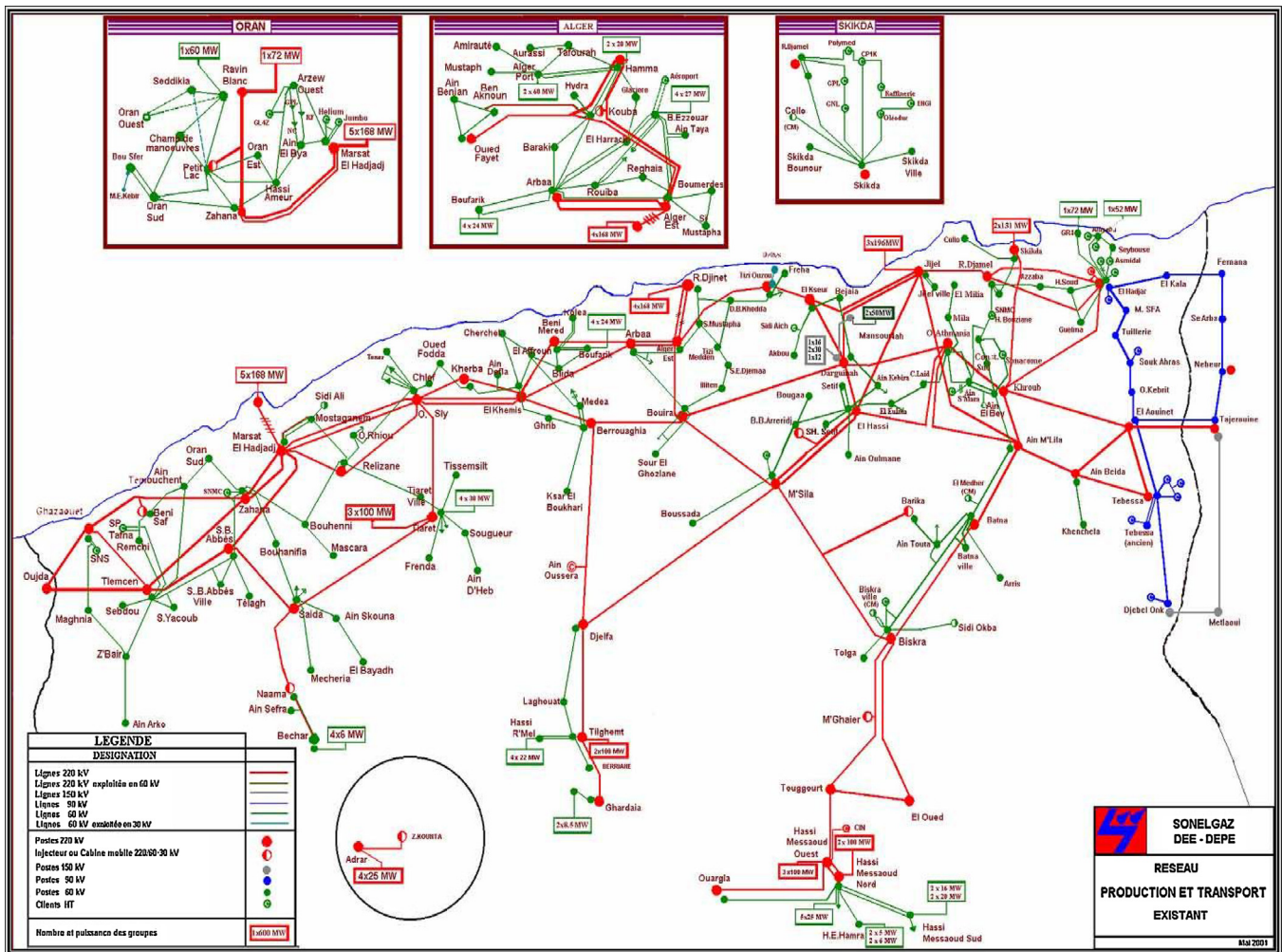


Fig. 5. The Algerian electric power system map.

24.17% and 19.77% of active power loss reduction. These results show the superiority of the WOA technique over the other considered methods, even for a large test power system. The convergence characteristics obtained by different methods are presented in

Fig. 6. It can be observed that the proposed WOA algorithm converges rapidly towards the near global optimum solution and gives better improvement of transmission loss compared to PSO and PSO-TVAC in solving the ORPD problem.

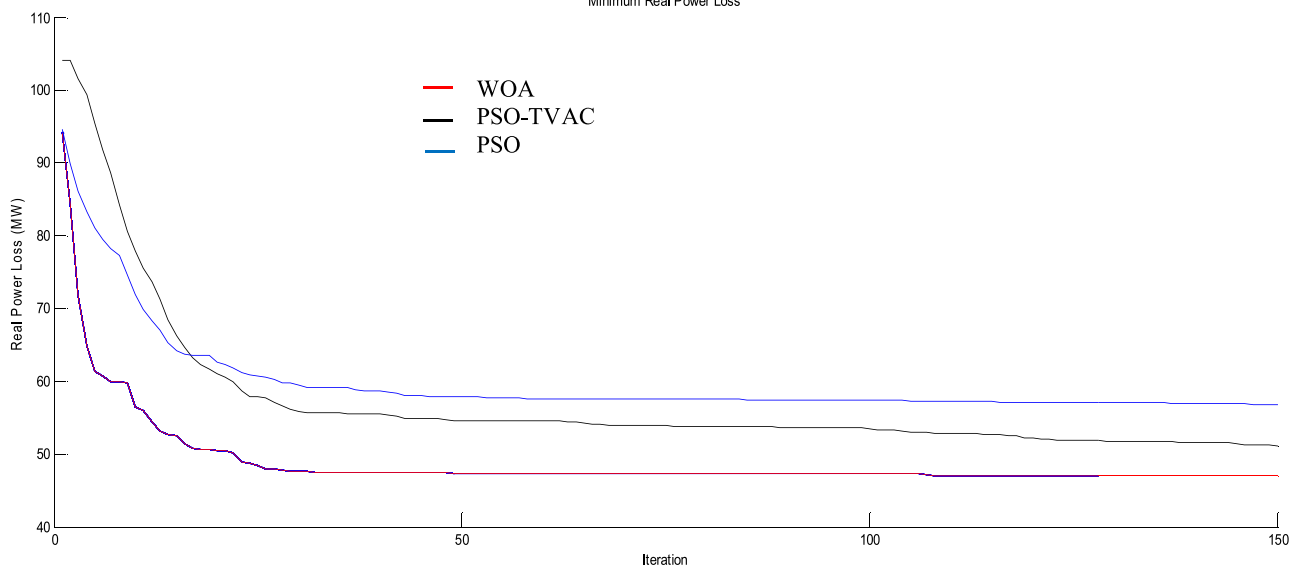


Fig. 6. Performance characteristics of WOA algorithm for equivalent Algerian test system.

Table 10

Analysis of variance for the results of the IEEE 14-bus system.

Source of variation	SS	df	MS	F	P-value	F crit
Between groups	0.152196376	2	0.076098	6.768	0.00185	4.8577
Within groups	0.97819039	87	0.011244			
Total	1.130386766	89				

Table 12

Analysis of variance for the results of the Algerian 114 bus system.

Source of variation	SS	df	MS	F	P-value	F crit
Between groups	43.114097	2	21.557	7.594	0.000911	4.8577
Within groups	246.9408712	87	2.8384			
Total	290.0549682	89				

4.4. Selection of the population size for different case study

To recognize the effect of population size (number of whales) on the performance of the proposed WOA algorithm, 30 trial runs have been executed for several population sizes (20, 30, 40 and 60) for all case studies. The results of different population size for each case study (IEEE 14 bus, IEEE 30 bus and equivalent Algerian power system 114 bus) are presented respectively in Figs. 7–9. From Fig. 7, it can be seen that 30 search agents is good enough to get the near global optimum value of real power loss and a higher consistency of the algorithm. From Fig. 8, it is observed that the best result is obtained for 40 search agents, which is adequate to get the best combination of control variables of ORPD. However, the consistency is fewer than obtained in 60 search agent. Also from Fig. 9, it is observed that best results have been reached for 20 search agents, however the consistency took its better place when considering a 30 search agents number.

5. Statistical study

Due to the nature of stochastic algorithms, it is imperative to run the algorithms several times on the same problem instance in order to get the result values, which could vary at every execution. Instead of relying on the statistics of the collected results (best, medium, worst and standard deviation), it is essential to perform an analysis of variance (One-way ANOVA) [31]. This test is required in order to

Table 11

Analysis of variance for the results of the IEEE 30-bus system.

Source of variation	SS	df	MS	F	P-value	F crit
Between groups	2.410599756	2	1.2053	28.958	0.00000000229	4.8577
Within groups	3.6210838	87	0.041622			
Total	6.031683556	89				

Table 13

One-way ANOVA test for the results obtained by PSO, PSO-TVAC and the proposed WOA method.

Case study	P-value	F-ratio
IEEE 14-bus	0.00000000229	28.978
IEEE 30-bus	0.00185	6.768
Algerian 114-bus	0.000911	7.594

give a certain level of confidence to our study and evaluate which algorithms are most suitable in solving the ORPD problem.

The one-way ANOVA test compares the means between the results obtained by our proposed WOA algorithm and the other own developed PSO and PSO-TVAC techniques. It is aimed to define whether data from the three algorithms have a common mean and find out whether the algorithms are actually different in the measured characteristic. In this study, a significance level of 1% is considered, i.e., if the P-value is less than 0.01, it means that there is a statistical significant difference between the performance of WOA method and other own developed methods.

Tables 10–12, represent respectively the one-way ANOVA results obtained from the experimented algorithms in three cases (IEEE 14 bus, IEEE 30 bus and Algerian 114 bus systems). Table 13 summarizes the F-ratio and the P-value of the ANOVA results obtained. As shown in this table, P-value is extremely less than 0.01 for all cases, which means that WOA is statistically different from PSO and PSO-TVAC.

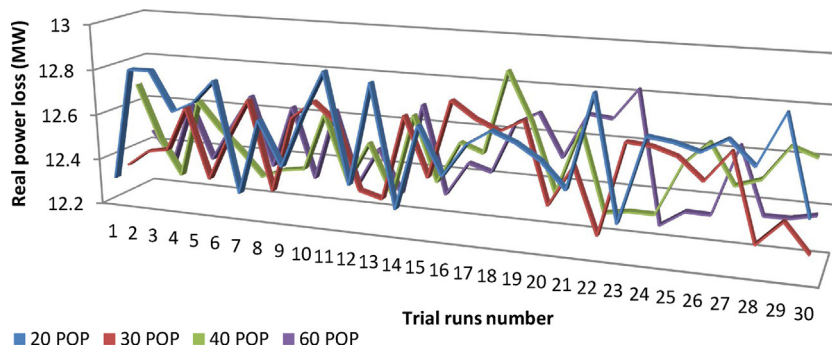


Fig. 7. Results of real power loss for different population size of whales, IEEE 14-bus.

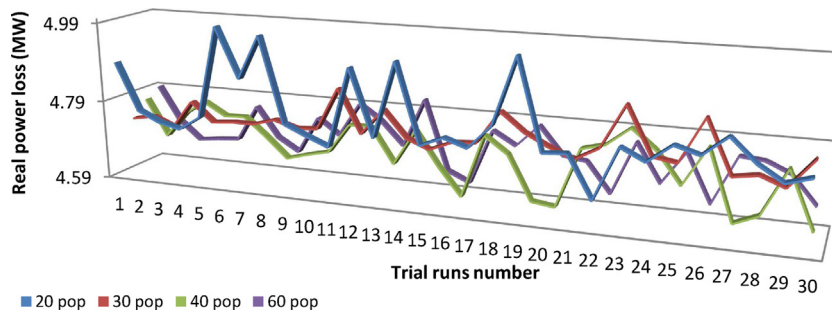


Fig. 8. Results of real power loss for different population size of whales, IEEE 30-bus.

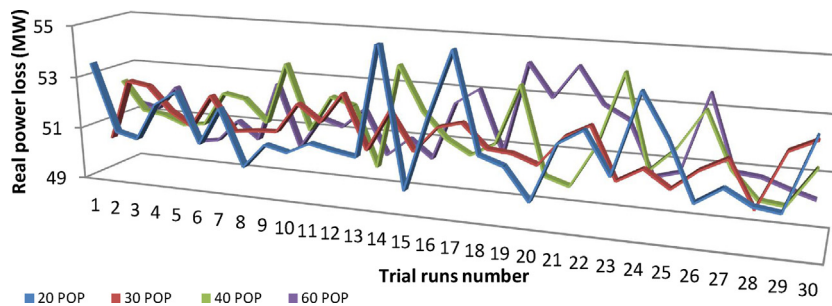


Fig. 9. Results of real power loss for different population size of whales, Algerian 114-bus.

6. Conclusions

In this paper, a recent metaheuristic technique namely whale optimization algorithm (WOA) was successfully applied to solve the optimal reactive power dispatch (ORPD) problem. The proposed WOA method has been examined and tested on the IEEE 14-bus system, IEEE 30-bus system and the practical and large-scale equivalent Algerian electric 114-bus power system. To validate the effectiveness of the proposed algorithm, the obtained results were compared with those obtained from two methods developed by us, namely, particle swarm optimization (PSO) and particle swarm optimization with time varying acceleration coefficients (PSO-TVAC) and others reported from the literature.

Considering the cases and comparative studies presented in this paper, WOA algorithm appears to be very effective in particular for its fast convergence to the global optimum as well as its significant active loss reduction. Based on one way ANOVA statistical test, the significance of its results against other methods (PSO and PSO-TVAC) has been confirmed which gives more confidence to our study.

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