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Optimal Active and Reactive Power Dispatch Problem Solution using Whale Optimization Algorithm

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Abstract

Background/Objectives: Optimal Power Flow (OPF) problem is very common and important problem for effective power system operation and planning. OPF is previously solved by many optimization techniques. **Methods/Statistical analysis:** To solve the OPF problem, the Whale Optimization Algorithm (WOA) is employed on the IEEE-30 bus test system. It is a population-based algorithm.WOA is inspired from the bubble-net hunting strategy of humpback whales. WOA has a fast convergence rate due to the use of roulette wheel selection method. Various mathematical steps are used in the algorithm. **Findings:** The problems con-sidered in the OPF problem are Fuel Cost Reduction, Active Power Loss Minimization, and Reactive Power Loss Minimization. These problems are solved by adjusting the control parameters of the system. The results obtained by WOA are compared with other techniques such as Flower Pollination Algorithm (FPA) and Particle Swarm Optimizer (PSO). **Application/Improvements:** Results shows that WOA gives better optimisation values for the particular case as compared with FPA, PSO and other well-known techniques that confirm the effectiveness of the suggested algorithm.

Keywords: Active Power Loss Minimization, Optimal Power Flow, Reactive Power Loss Minimization, Whale Optimization Algorithm

1. Introduction

At the present time, The Optimal Power Flow (OPF) is a very significant problem and most focused objective for power system scheduling as well as operation[1]. The OPF is the elementary tool which permits the utilities to identify the economic operational and considerable secure states in the system[2,3]. The prior aim of the OPF is to evaluate the optimum operational state of an electric network by minimizing a specific objective function within the limits of the operational constraints like equality constraints and inequality constraints[4,5]. Hence, the OPF problem can be defined as a highly non-linear and non-convex multimodal optimization problem[6]. From the past few years too many optimization techniques were used to solve the OPF problem[7,8]. Some traditional methods are used to solve the proposed problem have been suffered from some limitations like converging at local optima, not suitable for binary or integer problems and also have the assumptions like the convexity, differentiability, and continuity[9,10]. Hence, these techniques are not suitable for the actual OPF situation[11,12]. All these limitations are overcome by meta-heuristic optimization methods like BHBO, TLBO, LCA, etc.

In the present work, a newly introduced meta-heuristic optimization approach named Whale Optimization Algorithm (WOA) is used to solve the problem of Optimal Power Flow. The WOA technique is a biological and sociological inspired algorithm. This technique is inspired by the bubble-net hunting strategy

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of the Whale[13]. The capabilities of WOA are finding the global solution, fast convergence rate due to the use of roulette wheel selection, can evaluate continuous and discrete optimization problems. In the present work, the WOA is implemented for standard IEEE-30 bus test system to solve the OPF problem. There are three objective cases considered in this paper that have to be optimize using WOA technique are Fuel Cost Reduction, Active Power Loss Minimization and Reactive Power Loss Minimization. The result shows the optimal adjustments of control variables in accordance with their limits. The results obtained using WOA technique has been compared with Flower Pollination Algorithm (FPA) and Particle Swarm Optimization (PSO) techniques. The results show that WOA gives better optimization values as compared to different methods which prove the strength of the suggested method.

1.1 Whale Optimization Algorithm

In the meta-heuristic algorithm, a newly purposed optimization algorithm called WOA, which inspired from the bubble-net hunting strategy. Algorithm describes the special hunting behavior of humpback whales, the whales follows the typical bubbles causes the creation of circular or '9-shaped path' while encircling prey during hunting. Simply bubble-net feeding/hunting behavior could understand such that humpback whale went down in water approximate 10-15 meter and then after the start to produce bubbles in a spiral shape encircles prey and then follows the bubbles and moves upward the surface. Mathematic model for WOA is given as follows[13]:

1.2 Encircling Prey Equation

Humpback whale encircles the prey (small fishes) then updates its position towards the optimum solution over the course of increasing number of iteration from start to a maximum number of iteration[13].

$$\vec{D} = \left| C.\vec{X}^*(t) - X(t) \right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}.\vec{D} \quad (2)$$

Where: $\vec{A}$, $\vec{D}$ are coefficient vectors, t is a current iteration, $\vec{X}^*(t)$ is position vector of the optimum solution so far and $X(t)$ is position vector.

Coefficient vectors $\vec{A}$, $\vec{D}$ are calculated as follows:

$$\vec{A} = 2\vec{a} * r - \vec{a} \quad (3)$$

$$\vec{C} = 2 * r \quad (4)$$

Where: $\vec{a}$ is a variable linearly decrease from 2 to 0 over the course of iteration and *r* is a random number [0, 1].

1.3 Bubble-Net Attacking Method

In order to mathematical equation for bubble-net behavior of humpback whales, two methods are modeled as[13]:

1.3.1 Shrinking Encircling Mechanism

This technique is employed by decreasing linearly the value of $\vec{a}$ from 2 to 0. Random value for a vector $\vec{A}$ in range between [-1, 1].

1.3.2 Spiral Updating Position

Mathematical spiral equation for position update between humpback whale and prey that was helix-shaped movement given as follows[13]:

$$\vec{X}(t+1) = \vec{D}' * e^{bt} * \cos(2\pi l) + \vec{X}^*(t) \quad (5)$$

Where: *l* is a random number [-1, 1], *b* is constant defines the logarithmic shape, $\vec{D}' = \left| \vec{X}^*(t) - X(t) \right|$ expresses the distance between i^{th} whale to the prey mean the best solution so far.

Note: We assume that there is 50-50% probability that whale either follow the shrinking encircling or logarithmic path during optimization. Mathematically we modeled as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D} & if \quad p < 0.5 \\ \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}^*(t) & if \quad p \geq 0.5 \end{cases} \quad (6)$$

Where: p expresses random number between [0, 1].

1.3.3 Search for Prey

The vector $\vec{A}$ can be used for exploration to search for prey; vector $\vec{A}$ also takes the values greater than one or less than -1. Exploration follows two conditions

$$\vec{D} = \left| \vec{C}\,\vec{X}_{rand} - \vec{X} \right| \quad (7)$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \quad (8)$$

Finally follows these conditions:

- $\left|\vec{A}\right| > 1$ enforces exploration to WOA algorithm to find out global optimum avoids local optima

- $|\vec{A}| < 1$ For updating the position of current search agent/best solution is selected.

The control parameters used in the WOA are given in Table 1.

Table 1. Control parameters of WOA

Control Parameter	Value
Population Size	40
Maximum Iteration (N)	500
Number of variable (d)	6
Random number (r)	[0,1]

1.4 OPF Problem Solution

As specified before, OPF is a common power flow problem that provides the optimal values of control variables by minimizing a predefined objective function with respect to the operating bounds of the system. The OPF can be mathematically calculated as:

$$Minimize[f(a,b)] \tag{9}$$

$$\text{subject to } s(a,b)=0 \tag{10}$$

$$\text{And } \quad h(a,b) \le 0 \tag{11}$$

Where, b=vector of control variables, a=vector of state variables, f (a,b) = objective function, s (a,b) = set of equality constraints, h (a,b) =set of inequality constraints.

2. Variables

2.1 Control Variables

These are the variables that may be adjusted to fulfill the power flow equations. The control variables can be represented as:

$$b^T = [P_{G_2} \dots P_{G_{NGen}}, V_{G_1} \dots V_{G_{NGen}}, Q_{C_1} \dots Q_{C_{NCom}}, T_1 \dots T_{NTr}] \tag{12}$$

Where: P_G= real power output at the generator buses not including the slack bus.V_G=Voltage magnitude at generator buses. Q_C=Shunt VAR compensation. T= tap settings of the transformer. NGen, NTr, NCom= no. of generator units, the no. of transformers and the no. of shunt reactive power compensators, respectively.

2.2 State Variables

The variables that need to characterize the operating state of the network. The set of state variables can be represented as:

$$a^T = [P_{G_1}, V_{L_1} \dots V_{L_{NLB}}, Q_{G_1} \dots Q_{G_{NGen}}, S_{l_1} \dots S_{l_{Nline}}] \tag{13}$$

Where: P_G= the real power generation at reference bus. V_L= the voltage at load buses; Q_G= =the output of reactive power of all generators. S_l= the line flows. NLB, Nline= no. of PQ buses, and the no. of lines, respectively.

3. Constraints

Power system constraints may be categorized into equality constraints and inequality constraints.

3.1 Equality Constraints

The equality constraints reveal the physical behavior of the system. These constraints are:

3.2 Real Power Constraints

$$P_{Gi} - P_{Di} - V_i \sum_{J=i}^{NB} V_j [G_{ij} Cos(\delta_{ij}) + B_{ij} Sin(\delta_{ij})] = 0 \tag{14}$$

3.3 Reactive Power Constraints

$$Q_{Gi} - Q_{Di} - V_i \sum_{J=i}^{NB} V_j [G_{ij} Cos(\delta_{ij}) + B_{ij} Sin(\delta_{ij})] = 0 \tag{15}$$

Where, $\delta_{ij} = \delta_i - \delta_j$

Where, NB= No. of buses, P_G= the output of active power, Q_G= the output of reactive power, P_D= real power load demand, Q_D= reactive power load demand, G_{ij} and B_{ij}= elements of the admittance matrix $Y_{ij} = (G_{ij} + jB_{ij})$ showing the conductance and susceptance among bus i and bus j, respectively.

3.4 Inequality Constraints

The inequality constraints show the bounds on electrical devices existing in the power system plus the bounds formed to surety system safety.

3.5 Generator Constraints

For every generator together with the reference bus: voltage, real and reactive outputs should be constrained by the minimum and maximum bounds as follows:

$$V_{G_i}^{lower} \le V_{G_i} \le V_{G_i}^{upper}, \; i = 1, \dots, NGen \tag{16}$$

$$P_{G_i}^{lower} \le P_{G_i} \le P_{G_i}^{upper}, \; i = 1, \dots, NGen \tag{17}$$

$$Q_{G_i}^{lower} \le Q_{G_i} \le Q_{G_i}^{upper}, \; i = 1, \dots, NGen \tag{18}$$

3.6 Transformer Constraints

Transformer tap positions should be constrained inside their stated minimum and maximum bounds as follows:

$$T_{G_i}^{lower} \le T_{G_i} \le T_{G_i}^{upper},\ i = 1,....,NTr \qquad (19)$$

3.7 Shunt VAR Compensator Constraints

Shunt reactive compensators need to be constrained by their minimum and maximum bounds as follows:

$$Q_{C_i}^{lower} \le Q_{GC_i} \le Q_{C_i}^{upper},\ i = 1,....,NGen \qquad (20)$$

3.8 Security Constraints

These comprise the bounds of a voltage at PQ buses and line flows. Each load bus Voltage should not violate from its minimum and maximum operational bounds. Line loading over each line should not exceed to its maximum bounds. These limitations can be expressed as:

$$V_{L_i}^{lower} \le V_{L_i} \le V_{L_i}^{upper},\ i = 1,....,NLB \qquad (21)$$

$$S_{l_i} \le S_{l_i}^{upper},\ i = 1,....,Nline \qquad (22)$$

The inequality constraints comprise load bus voltage, the output of real power at reference bus, the output of reactive power and line flow may be encompassed as quadratic penalty functions.

Penalty function can be formulated as:

$$J_{aug} = J + \partial_P \left(P_{G_1} - P_{G_1}^{lim}\right)^2 + \partial_V \sum_{i=1}^{NLB} (V_{L_i} - V_{L_i}^{lim})^2 + \partial_Q \sum_{i=1}^{NGen} + \partial_S \sum_{i=0}^{Nline} (S_{l_i} - S_{l_i}^{max})^2 \qquad (23)$$

Where, $\partial_P, \partial_V, \partial_Q, \partial_S$ = penalty factors

U_{lim}= Boundary value of the state variable U.

If U is greater than the maximum bound, U_{lim} takings the value of that one, if U is lesser than the minimum bound U_{lim} takings the value of that bound so:

$$U^{lim} = \begin{cases} U^{upper} & ;U > U^{upper} \\ U^{lower} & ;U < U^{lower} \end{cases} \qquad (24)$$

4. Application and Results

The WOA technique is implemented to resolve the OPF problem for standard IEEE 30-bus test system and for a number of cases with dissimilar objective functions. The software program is inscribed in MATLAB 2013a and applied on a 2.60 GHz i5 PC having 4 GB RAM. In the present work the WOA population size is selected to be 40.

4.1 IEEE 30-Bus Test System

With the purpose of elucidating the effectiveness of the suggested WOA technique, it is examined for the standard IEEE 30-bus system. The IEEE 30-bus test system selected in this work has comprises: 6 generating units at buses 1,2,5,8,11 and 13, four tap changing transformers between buses 6-9, 6-10, 4-12, and 28-27, nine shunt reactive compensators at buses 10,12,15,17,20,21,23,24 and 29.

Table 2 shows the min-max limits for different control variables. P_G is the power limit for 6 generators, V_G is the voltage limits for 6 generators, T_{nn} is the tap settings limits for 4 transformers, and Q_c is the limits for 9 shunt compensators.

Table 2. Limits for different control variables

Variables	Min	Max	Variables	Min	Max
P_{G1}	50	200	P_{G8}	10	35
P_{G2}	20	80	P_{G11}	10	30
P_{G5}	15	50	P_{G13}	12	40
T_{nn}	0.9	1.1	Q_c	0	5
V_G	0.95	1.1	-	-	-

In addition, the line data, bus data, generator data and the upper and lower bounds for the control variables are specified in [4], [9]. Further, fuel cost ($/h), Ploss (MW) and Qloss (MVAR) represent the total fuel cost, the active power losses and the reactive power losses, respectively.

4.1.1 Case 1: Minimization of Generation Fuel Cost

The fuel cost reduction is the fundamental OPF objective. Hence, Y gives the total fuel cost of each generator and it is describing as:

$$Y = \sum_{i=1}^{NGen} f_i(\$/h) \qquad (25)$$

Where, f_i is the fuel cost of the i^{th} generator.

f_i, may be formulated as:

$$f_i = u_i + v_i P_{Gi} + w_i P_{Gi}^2 (\$/h) \qquad (26)$$

Where, u_i, v_i and w_i are the cost coefficients of the i^{th} generator. The coefficients values are specified in[9].

The fuel cost variations with the different algorithm can be shown in Figure 1. The optimal value of a fuel cost obtained with WOA is compared with FPA and PSO as shown in Table 3. Comparison displays that WOA give better result as compared to FPA and PSO. The optimization is done by setting the values of control variables in accordance with their limits. The control variables which are to be optimized are active power and voltage magnitudes at six generating units along with tap settings of four transformers and nine compensation devices.

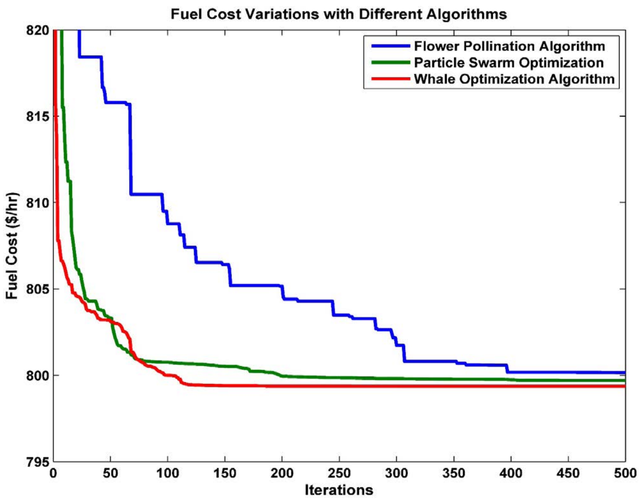

Figure 1. Fuel cost variations with different algorithms.

Table 3. Optimal values of fuel costs for different methods

Method	Fuel Cost ($/hr)	Method description
WOA	799.367	Whale Optimization Algorithm
FPA	800.161	Flower Pollination Algorithm
PSO	799.704	Particle Swarm Optimizer
BHBO	799.921	Black Hole- Based Optimization

4.1.2 Case 2: Minimization of Active Power Losses

In the case 2 the OPF objective is to reduce the active power transmission losses, which can be represented by power balance equation as follows:

$$J = \sum_{i=1}^{NGen} P_i = \sum_{i=1}^{NGen} P_{Gi} - \sum_{i=1}^{NGen} P_{Di} \quad (27)$$

Figure 2 shows the tendency for reducing the total real power losses objective function using the different techniques.

The active power losses obtained with different techniques are shown in Table 4 which made sense that the results obtained by WOA give better values than the other methods. By means of the same settings the results achieved in case 2 with the WOA technique are compared to some other methods and it displays that the real power transmission losses are greatly reduced compared to FPA and PSO.

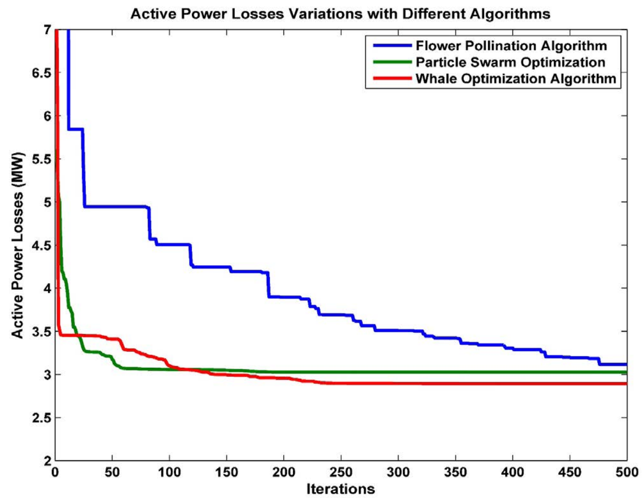

Figure 2. Active power losses variations with different algorithms.

Table 4. Optimal values of PLosses for different methods

Method	P_{losses} (MW)	Method description
WOA	2.892	Whale Optimization Algorithm
FPA	3.115	Flower Pollination Algorithm
PSO	3.026	Particle Swarm Optimizer
BHBO	3.503	Black Hole- Based Optimization

4.1.3 Case 3: Minimization of Reactive Power Losses

The accessibility of reactive power is the main point for static system voltage stability margin to support the transmission of active power from the source to sinks.

Thus, the minimization of *VAR* losses is given by the following expression:

$$J = \sum_{i=1}^{NGen} Q_i = \sum_{i=1}^{NGen} Q_{Gi} - \sum_{i=1}^{NGen} Q_{Di} \quad (28)$$

It is notable that the reactive power losses are not essentially positive. The variation of reactive power losses with different methods shown in Figure 3. It demonstrates that the suggested method has good convergence characteristics. The statistical values of reactive power losses obtained with different methods are shown in Table 5 which displays that the results obtained by WOA are better than the other methods. It is clear from the results that the reactive power losses are greatly reduced compared to FPA and PSO.

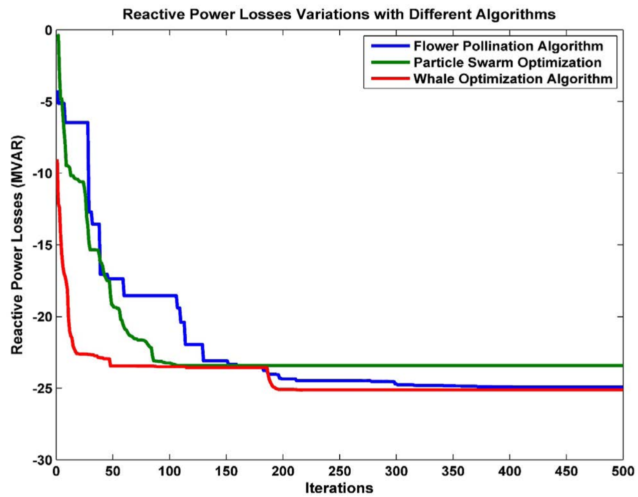

Figure 3. Reactive power losses variations with different algorithms.

Table 5. Optimal values of QLosses for different methods

Method	Q_{losses} (MVAR)	Method Description
WOA	-25.1124	Whale Optimization Algorithm
FPA	-25.056	Flower Pollination Algorithm
PSO	-23.407	Particle Swarm Optimizer
BHBO	-20.152	Black Hole- Based Optimization

5. Conclusion

In the present work, OPF problem is optimized on the IEEE 30 bus system using WOA technique. The results achieved by WOA method are compared with FPA and PSO techniques. The results obtained by WOA method give better optimization values, fast convergence and less computational time compared to other two methods which confirms the strength of recommended algorithm.

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7. References

1. Duman S, Güvenç U, Sönmez Y, Yörükeren N. Optimal power flow using gravitational search algorithm. Energy Conversion and Management. 2012 Jul; 59:86–95.
2. Bouchekara HREH, Abido MA, Chaib AE, Mehasni R. Optimal power flow using the league championship algorithm: a case study of the Algerian power system. Energy Conversion and Management. 2014 Nov; 87:58–70.
3. Bouchekara HREH, Abido MA, Boucherma M. Optimal power flow using teaching-learning-based optimization technique. Electric Power Systems Research. 2014 Sep; 114:49–59.
4. Ela AAAE, Abido MA. Optimal power flow using differential evolution algorithm. Electric Power Systems Research. 2010 Jul; 80(7):878–85.
5. Bouchekara HREH. Optimal power flow using black-hole-based optimization approach. Applied Soft Computing. 2014 Nov; 24:879–88.
6. Frank S, Steponavice I, Rebennack S. Optimal power flow: a bibliographic survey I. Formulations and deterministic methods. Energy Systems. 2012 Sep; 3(3):221–58.
7. AlRashidi MR, El-Hawary ME. Applications of computational intelligence techniques for solving the revived optimal power flow problem. Electric Power Systems Research. 2009 Apr; 79(4):694–702.
8. Abido MA. Optimal power flow using particle swarm optimization. International Journal of Electrical Power and Energy Systems. 2002 Oct; 24(7):563–71.
9. Lee K, Park Y, Ortiz J. A united approach to optimal real and reactive power dispatch. Institute of Electrical and Electronics Engineers (IEEE) Transactions on Power Apparatus and Systems. 1985 May; PAS-104(5):1147–53.
10. Alsac O, Stot B. Optimal load flow with steady-state security. Institute of Electrical and Electronics Engineers (IEEE) Transactions on Power Apparatus and Systems. 1974 May; PAS-93(3):745–51.
11. Hariharan T, Sundaram KM. Optimal power flow using hybrid intelligent algorithm. Indian Journal of Science and Technology. 2015 Sep; 8(23):1–9.
12. Rahmati M, Effatnejad R, Safari A. Comprehensive Learning Particle Swarm Optimization (CLPSO) for multi-objective optimal power flow. Indian Journal of Science and Technology. 2014 Mar; 7(3):262–70.
13. Mirjalili S, Lewis A. The Whale Optimization Algorithm (WOA). Journal Advance in Engineering Software. 2016 May; 95(C):51–67.