Research on Novel Whale Algorithm for Multi-objective Optimal Power Flow Problem

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Abstract. To solve the non-differentiable optimal power flow (OPF) problems while satisfying various operational constrains, a multi-objective novel whale optimization algorithm (MONWOA) is proposed. MONWOA algorithm can overcome the premature-convergence of standard whale optimization algorithm. A Pareto-dominant approach with constrains (PDA) is employed to guarantee no violations of various inequality constraints on state variables. MONWOA algorithm is applied to optimize fuel cost, emission, active power loss and fuel cost (with value-point loadings). The bi-objective and tri-objective trials are implemented on IEEE30-bus system and the IEEE57-bus system. A large number of experimental results obtained by MONWOA and MOPSO algorithms, demonstrate that MONWOA has the definite competitive advantages to obtain uniform distribution Pareto front set (PFs), high-quality Pareto optimal solution (POS) and search for the best compromise solution (BCS) in solving MOOPF problem.

1. Introduction

The optimal power flow (OPF), as a predominant method to ensure the safe and optimal operation of power system, has attracted the attention of scholars for years[1-3]. The OPF is very vital for achieving better operating statues and higher quality of power through the adjustments for continuous and discrete variables with zero violations of physical constraints.

The multi-objective optimal power flow (MOOPF) plays an increasingly significant role in optimizing multiple contradictory objectives simultaneously. The MOOPF problem is to seek a set of Pareto optimal solution and get a best compromise solution (BCS) ultimately. Theoretically speaking, the optimization of one objective may result in the degradation of another target[1]. Therefore, the MOOPF problem is much more difficult compared with single objective power flow optimization. Intelligent algorithms have been successfully applied on solving the non-convex and non-liner MOOPF problems. For instance, the firefly algorithm[5], the cuckoo search algorithm[4], the bat algorithm[5] and differential evolution[6] are capable to solve the complex problems effectively. In this paper, the novel algorithm has certain advantages over the multi-objective particle swarm optimization (MOPSO) method in seeking a better compromise solution undoubtedly.

Whale optimization algorithm (WOA) shows better competitive performance against several state-of-art metaheuristics for solving optimization problems[7]. In this paper, a multi-object novel WOA algorithm (MONWOA) is formed by the standard whale optimization algorithm with Lévy flight strategy. The Lévy flight behavior is applied to the process of individual location updating, which aim is to improve convergence rate of original WOA algorithm.
In order to verify the superiority of the MONWOA algorithm, simulation experiments are carried on IEEE30-bus and IEEE57-bus systems. Case1 aims to optimize power loss and fuel cost with value-point simultaneously on IEEE30-bus system. Case2 optimizes basic fuel cost, power loss and emission at the same time on IEEE30-bus system while Case3 optimizes emission and fuel cost concurrently on IEEE57-bus system.

2. Mathematical model of MOOPF

The mathematical model of multi-objective power flow problem is composed of two parts: objectives and constraints, which can be expressed as follows:

\[
\text{min } F(x, u) = [f_1(x, u), f_2(x, u), \cdots, f_M(x, u)]
\]

subject to:

\[
h_k(x, u) = 0, k = 1, 2, \cdots, H
\]

\[
g_j(x, u) \leq 0, k = 1, 2, \cdots, G
\]

In the formula, \(f_i(x,u)\) is the \(i_{th}\) objective and \(M(M \geq 2)\) represents the number of objectives to be optimized. \(h\) represents equality constraints (ECs) while \(g\) indicates inequality constraints (ICs), and \(H\) and \(G\) are the numbers of ECs and ICs respectively. \(x\) represents the sets of state variables. \(u\) is vector of control variables.

2.1. Objective functions

2.1.1. Active power losses minimization

\[
f_1(x, u) = \min P_{\text{loss}} = \sum_{k=1}^{N_k} g_k (V_i^2 + V_j^2 - 2V_iV_j \cos \delta_{kj}) \text{ MW}
\]

where \(P_{\text{loss}}\) is the total power loss of the power system. \(V_i\) is the voltage magnitude of \(i_{th}\) node. \(\delta_{kj}\) is the voltage phase between bus \(i_{th}\) node and \(j_{th}\) node. \(g_k\) is the conductance of the \(k_{th}\) branch which connect \(i_{th}\) node and \(j_{th}\) node. \(N_k\) is the number of branches.

2.1.2. Total emission minimization

\[
f_2(x, u) = \min E_m = \sum_{i=1}^{N_G} \left[ \alpha_i P_{G_i}^2 + \beta_i P_{G_i} + \gamma_i + \eta_i \exp(\lambda_i P_{G_i}) \right] \text{ ton / h}
\]

where \(E_m\) is the total emission of the power system. \(N_G\) indicates the amount of generator node. \(P_{G_i}\) represents the active power of the \(i_{th}\) generator node while the \(\alpha_i, \beta_i, \gamma_i, \eta_i\) and \(\lambda\) represent emission coefficients of the \(i_{th}\) generator node.

2.1.3. Basic fuel cost minimization

\[
f_3(x, u) = \min F_c = \sum_{i=1}^{N_G} (a_i + b_i P_{G_i} + c_i P_{G_i}^2) \text{ $ / h}$
\]

where \(F_c\) is the basic fuel cost of the power system. \(a_i, b_i\) and \(c_i\) represent the cost coefficients of the \(i_{th}\) generator node.

2.1.4. Fuel cost considering value-point effect minimization

\[
f_4(x, u) = \min F_v = \sum_{i=1}^{N_G} (a_i + b_i P_{G_i} + c_i P_{G_i}^2 + d_i \times \sin(e_i \times (P_{G_i}^\text{min} - P_{G_i}))) \text{ $ / h}$
\]

where \(F_v\) is the fuel cost of with value-point loading. \(d_i\) and \(e_i\) represent the value-point effect.

2.2. Constraints of MOOPF

The constraints of the power systems include equality constraints (ECs) and inequality constraints (ICs) as follows:
2.2.1. Equality constraints. The equality constraints are described by two power balanced equations, and the expression of them are formulated as following.

\[ \sum_{j \in N_i} V_j (G_{ij} \cos \delta_j + B_{ij} \sin \delta_j) = P_{Di} - P_{Di} \quad i \in N \]  

\[ \sum_{j \in N_i} V_j (G_{ij} \sin \delta_j - B_{ij} \cos \delta_j) = Q_{Di} - Q_{Di} \quad i \in N_{PQ} \]

where \( N \) represents the number of system nodes without the slack node. \( N_i \) represents the number of nodes linked to \( i \)th node. \( N_{PQ} \) is the number of \( PQ \) nodes. \( P_{Di} \) indicates the load active power at \( i \)th load node. \( Q_{Di} \) and \( Q_{Di} \) represent the load reactive power and load reactive power at \( i \)th load node. \( G_{ij} \) and \( B_{ij} \) respectively, indicate the real part and imaginary part of the \( i \)th component of the Y-bus matrix.

2.2.2. Inequality constraints. Eight inequality constraints consist of state variables and control ones, which are described as following.

- Active power \( P_{Gref} \) at slack bus.
  \[ P_{Gref,min} \leq P_{Gref} \leq P_{Gref,max} \]  

- Voltage limits at load bus.
  \[ V_{Li,min} \leq V_{Li} \leq V_{Li,max}, \quad i \in N_{PQ} \]  

- Reactive power limits at generator buses.
  \[ Q_{Gi,min} \leq Q_{Gi} \leq Q_{Gi,max}, \quad i \in N_G \]  

- Apparent power flow limits of all branches.
  \[ S_{ij} - S_{ij,max} \leq 0, \quad ij \in N_L \]  

- Active power \( P_G \) limits.
  \[ P_{Gi,min} \leq P_{Gi} \leq P_{Gi,max}, \quad i \in N_G \]  

- Voltage \( V_C \) limits.
  \[ V_{Ci,min} \leq V_{Ci} \leq V_{Ci,max}, \quad i \in N_C \]  

- Tap-setting \( T \) limits of transformers.
  \[ T_{i,min} \leq T_i \leq T_{i,max}, \quad i \in N_T \]  

- Reactive power sources \( Q_C \) limits.
  \[ Q_{Ci,min} \leq Q_{Ci} \leq Q_{Ci,max}, \quad i \in N_C \]

where \( N_{PQ}, N_G, N_L, N_T \) and \( N_C \) respectively, indicate the total number of \( PQ \) nodes, generators, transmission branches, transforms, and shut compensators.

2.3. Handling of constraints

In order to guarantee zero violations of various inequality constraints in the MOOPF problem, PDA approach is employed to deal with ICs on state variables. The principle of PDA is described as below. Initially, if any state variable of a whale \( i \) violates ICs, sum of constraint violations is calculated according to formula (18).

\[ Svio(u_i) = \sum_{j=1}^{N_i} \max(h_j(x,u_i),0) \]  

where \( N_i \) is the number of particular inequality constraints on state variables.

Secondly, the individuals \( u_1 \) and \( u_2 \) are selected from two different sets of control variables randomly, and then calculate \( Svio(u_1) \) and \( Svio(u_2) \). Next, the rules to determine the dominant relationship are as follows. If any of the formula (19) or (20) can be satisfied, \( u_1 \) will dominate \( u_2 \).

\[ Svio(u_1) < Svio(u_2) \]  

\[ Svio(u_1) = \sum_{j=1}^{N_i} \max(h_j(x,u_1),0) \]  

\[ Svio(u_2) = \sum_{j=1}^{N_i} \max(h_j(x,u_2),0) \]
Finally, $u_i$ is regarded as a POS based on PDA.

3. The multi-objective novel whale optimization algorithm
This section introduces the improved method of the WOA and the main steps of the novel algorithm in solving the MOOPF problem.

3.1. Basic whale optimization algorithm
The basic WOA algorithm is a novel nature-inspired meta-heuristic optimization algorithm, which mimics the social behavior of humpback whales, and it is mainly composed of three steps: encircling prey, bubble-net attacking and searching for prey[8]. This algorithm randomly generates an initial population $N_{\text{pop}}$ through the predation process of humpback whales. In the phase of encircling prey, WOA assumes that the current best candidate solution is the target prey, and all the other whale individuals update their positions towards the best individual as formula (21).

$$X(t + 1) = X^*(t) - A \cdot C \cdot X^*(t) - X(t)$$

$$A = 2a \cdot r - a$$

$$C = 2 \cdot r$$

$$a = 2 - 2 \times \frac{t}{t_{\text{max}}}$$

where $t$ is the current iteration, $X$ represents the current location, $X^*$ illustrates the best solution, $r$ is random number in [0,1], $A$, $C$ are the auxiliary coefficients of the updated position.

In the phase of bubble-net attacking, in order to simulate the bubble-net behavior of humpback whales, two approaches which include shrinking encircling mechanism and spiral updating position are proposed as formula (25).

$$X(t + 1) = \begin{cases} X^*(t) - A \cdot C \cdot X^*(t) - X(t), & \text{if } p < 0.5 \\ X^*(t) + \left| X^*(t) - X(t) \right| \cdot e^{bi \cdot \cos(2\pi l)}, & \text{if } p \geq 0.5 \end{cases}$$

where $l$ is random number in [-1,1], $b$ is a constant number, and $p$ is a random number in [0,1].

In the phase of searching for prey, humpback whales search for prey randomly according to the position of each other.

$$X(t + 1) = X_{\text{rand}} - A \cdot C \cdot X_{\text{rand}} - X$$

where $X_{\text{rand}}$ represents the position of a random whale from the current generation.

3.2. Novel whale optimization algorithm with Lévy flight
The WOA exhibits some shortcomings such as easily being trapped in local optima, and premature convergence[9], so the novel WOA is proposed to improve the performance of basic WOA. Lévy flight is incorporated into the all phases of WOA. The Lévy flight mechanism is applied to improve the global search efficiently[10]. Based on hybrid mechanisms, the updating of novel WOA can be expressed as:

$$\text{Levy}(\lambda) \sim \frac{\phi \mu}{|v|^\nu \rho}$$

$\mu \sim \text{N}(0, \sigma_\mu^2), \ \nu \sim \text{N}(0, \sigma_\nu^2)$
\[
\sigma_v = \left\{ \frac{\Gamma(1 + \beta) \times \sin\left(\pi \times \beta / 2\right)}{\Gamma\left[\left(1 + \beta\right) / 2\right] \times \beta \times 2^{\beta - 1} \times 2^{1/2}} \right\}^{1/\beta}, \sigma_v = 1
\]

\[X(t + 1) = X(t) + \alpha \times \frac{du}{\sqrt{\beta^2 \times 2^{\beta - 1} \times 2^{1/2}}} \times \left( X(t) - X^* (t) \right) \times r\]

where \(\Gamma\) is the standard Gamma function, \(\alpha\) is the step size scaling factor, \(\beta\) is a constant number.

### 3.3. The MONWOA Algorithm on MOOPF

The steps of solving MOOPF problem by the proposed MONWOA algorithm are as follows.

- Input the needed parameters of MONWOA algorithm and tested system data.
- Generate the initial whale population (WP) within the range of constrains randomly.
- Calculate individual (each whale) objective functions and constraint violations by Newton Raphson load flow calculation and choose the optimal whale \(X^*\).
- Consider the initial WP as the Pareto optional set to fill external alternative population (EAP), set the initial iteration as \(i = 1\) simultaneously.
- Increase the iterations by \(i = i + 1\), update the whale population by formulas (21) ~ (26).
- Form the hybrid population by integrating the initial population and the updated population, and then delete the same ones.
- Calculate individual ranks and crowding distance, and select the non-dominated solutions (whales) in hybrid population by PDA method to update the EAP and the optimal whale \(X^*\).
- Judge stopping condition. Go to next step if \(i = i_{max}\). If not, go to step 5.
- Stop the iterative of generation, the optional solution set (POS) and best compromise solution (BCS) in EAP will be output.

### 4. Trials and results

In order to verify comprehensive evaluation of the proposed novel algorithm for solving the MOOPF problem, three simulations trials are carried out on the IEEE 30-bus and IEEE57-bus system. The results of simulation provided by the proposed algorithm are compared with those of MOPSO.

The structure and typical parameters of the IEEE-30-bus system can be found in \([11, 12]\). The structure and typical parameters of the IEEE-57-bus system can be found in \([11, 13]\). The parameter-settings of two involved algorithms are shown in Table 1.

#### Table 1. Main parameters of algorithm.

| Parameters         | MONWOA | Parameters         | MOPSO |
|--------------------|--------|--------------------|-------|
| Population size: \(N_{pop}\) | 100    | Population size: \(N_{pop}\) | 100   |
| Max Iteration: \(k_{max}\)       | 300    | Max Iteration: \(k_{max}\)       | 300   |
| Constant number: \(b\)            | 1      | Learning factor: \(C_1\)      | 2     |
| Constant number: \(\alpha\)       | 1.5    | Learning factor: \(C_2\)      | 2     |
| Stepsize coefficient: \(\beta\)   | 0.01   | Weight coefficient: \(w\)     | 0.9   |

#### 4.1. Case1: optimizing power loss and fuel cost with value-point concurrently on IEEE 30-bus system

In Case 1, the proposed MONWOA and MOPSO algorithms are tested for optimizing the power loss and fuel cost with value-point simultaneously. Figure 1 shows the PFs of case1, it is clearly suggested that the proposed MONWOA method has the ability to gain well distributed PFs.
Figure 1. PFs obtained by MONWOA and MOPSO for Case1.

Table 2 gives the detailed control variables and the BCS obtained by the two algorithms. As seen in Table 2, the proposed MONWOA algorithm has the ability to find the smaller power loss and fuel cost with value-point correspondingly, which includes 5.7003 MW of power loss and 861.0878 \$/h of fuel cost with value-point. The BCS of MOPSO algorithm is composed by 5.7509 MW of power loss and 866.8241 \$/h of fuel cost with value-point, so the detailed results show that the proposed MONWOA is more advantageous in obtaining best BCS.

Table 2. Obtained BCS of case 1

| Control variables | MOPSO  | MONWOA | Control variables | MOPSO  | MONWOA |
|-------------------|--------|--------|-------------------|--------|--------|
| PG2(MW)           | 47.6902| 51.0201| T11(p.u.)         | 0.9090 | 0.9874 |
| PG5(MW)           | 28.5896| 29.8696| T12(p.u.)         | 0.9990 | 1.0429 |
| PG8(MW)           | 35.0000| 34.9851| Qc10(p.u.)        | 0.0500 | 0.0431 |
| PG11(MW)          | 30.0000| 21.1874| Qc12(p.u.)        | 0.0091 | 0.0189 |
| PG13(MW)          | 15.0994| 18.4918| Qc15(p.u.)        | 0.0191 | 0.0201 |
| VG1(p.u.)         | 1.1000 | 1.1000 | Qc17(p.u.)        | 0.0493 | 0.0484 |
| VG2(p.u.)         | 1.0924 | 1.0915 | Qc20(p.u.)        | 0.0411 | 0.0500 |
| VG5(p.u.)         | 1.0563 | 1.0716 | Qc21(p.u.)        | 0.0500 | 0.0500 |
| VG8(p.u.)         | 1.0811 | 1.0792 | Qc23(p.u.)        | 0.0500 | 0.0500 |
| VG11(p.u.)        | 1.1000 | 1.0980 | Qc24(p.u.)        | 0.0000 | 0.0437 |
| VG13(p.u.)        | 1.0880 | 1.1000 | Qc29(p.u.)        | 0.0500 | 0.0239 |
| T11(p.u.)         | 0.5520 | 1.0930 | Power loss (MW)   | 5.7509 | 5.7003 |
| T12(p.u.)         | 1.0996 | 0.9802 | Fuel cost vp (\$/h) | 866.8241 | 861.0878 |

4.2. Case2: optimizing basic fuel cost, power loss and emission concurrently on IEEE 30-bus system
In case 2, three objectives including basic fuel cost, power loss and emission are optimized on IEEE30-bus system simultaneously. Figure 2 shows the achieved PFs of case 2. The figure also shows MONWOA method has the ascendant ability to get higher quality Pareto solution set compared to MOPSO.
Figure 2. PFs obtained by MONWOA and MOPSO for Case2.

Table 3 gives the control variables and the BCS in PFs of MOPSO, MONWOA. The BCS of MONWOA algorithm includes 3.6573MW of power loss, 899.6939 $/h of basic fuel cost and 0.2103 ton/h total emission, and the BCS of MOPSO algorithm includes 3.6664MW of power loss, 893.5446 $/h of basic fuel cost and 0.2028 ton/h of total emission. The tri-objective function values of BCS and comparative curves clearly show that MONWOA obtain higher quality solutions compared to MOPSO.

Table 3. Obtained BCS of case 2

| Control variables | MOPSO | MONWOA | Control variables | MOPSO | MONWOA |
|-------------------|-------|--------|-------------------|-------|--------|
| PG2(MW)           | 63.5683 | 68.6271 | T3(p.u.)          | 1.0702 | 0.9907 |
| PG5(MW)           | 40.3386 | 40.8406 | QC10(p.u.)        | 0.0500 | 0.0086 |
| PG8(MW)           | 35.0000 | 35.0000 | QC12(p.u.)        | 0.0000 | 0.0494 |
| PG11(MW)          | 30.0000 | 30.0000 | QC15(p.u.)        | 0.0461 | 0.0445 |
| PG13(MW)          | 40.0000 | 32.9000 | QC17(p.u.)        | 0.0500 | 0.0497 |
| VG1(p.u.)         | 1.1000 | 1.0709 | QC20(p.u.)        | 0.0023 | 0.0121 |
| VG2(p.u.)         | 1.0967 | 1.0674 | QC21(p.u.)        | 0.0031 | 0.0367 |
| VG5(p.u.)         | 1.0891 | 1.0420 | QC23(p.u.)        | 0.0425 | 0.0495 |
| VG8(p.u.)         | 1.0932 | 1.0521 | QC24(p.u.)        | 0.0500 | 0.0399 |
| VG11(p.u.)        | 1.1000 | 1.0971 | QC29(p.u.)        | 0.0362 | 0.0206 |
| VG13(p.u.)        | 1.1000 | 1.0872 | Power loss (MW)   | 3.6664 | 3.6573 |
| T10(p.u.)         | 1.0072 | 1.0100 | Fuel cost ($/h)   | 899.6939 | 893.5446 |
| T15(p.u.)         | 0.9985 | 1.0344 | Emission (ton/h)  | 0.2103 | 0.2028 |
| T1(p.u.)          | 1.1000 | 1.0082 |

4.3. Case3: optimizing emission and basic fuel cost concurrently on IEEE 57-bus system

In Case 3, the proposed MONWOA and MOPSO have been applied to optimize emission and fuel cost simultaneously on IEEE57-bus system. Figure3 shows the achieved PFs of the two involved algorithms. It clearly shows that MONWOA can achieve the best PFs by seeking out smaller basic fuel cost and less emission simultaneously.
Figure 3. PFs obtained by MONWOA and MOPSO for Case3.

Table 4 gives the control variables and the BCS in PFs of MOPSO, MONWOA. Obviously, the BCS of MOPSO algorithm, which includes 43373.74 $/h of basic fuel cost and 1.2610 ton/h of total emission, the BCS of MONWOA algorithm, which includes 43171.24 $/h basic fuel cost and 1.2575 ton/h total emission. It clearly proves that the result obtained by MOPSO is inferior to MONWOA algorithm.

Table 4. Obtained BCS of case 3

| Control variables | MOPSO       | MONWOA      | Control variables | MOPSO       | MONWOA      |
|-------------------|-------------|-------------|-------------------|-------------|-------------|
| PG2 (MW)          | 99.9661     | 99.9994     | T17(p.u.)         | 1.0036      | 0.9788      |
| PG3 (MW)          | 89.8007     | 88.7133     | T41(p.u.)         | 1.0331      | 0.9570      |
| PG6 (MW)          | 100.0000    | 99.9980     | T46(p.u.)         | 0.9502      | 0.9741      |
| PG8 (MW)          | 376.3691    | 336.8285    | T54(p.u.)         | 1.0522      | 1.0310      |
| PG9 (MW)          | 99.9379     | 99.9753     | T58(p.u.)         | 0.9798      | 0.9523      |
| PG12 (MW)         | 291.0648    | 314.9246    | T59(p.u.)         | 0.9674      | 0.9452      |
| VG1(p.u.)         | 0.9433      | 1.0999      | T65(p.u.)         | 0.9520      | 1.0045      |
| VG2(p.u.)         | 0.9523      | 1.0952      | T66(p.u.)         | 1.0324      | 0.9344      |
| VG3(p.u.)         | 0.9862      | 1.0900      | T67(p.u.)         | 0.9293      | 0.9481      |
| VG6(p.u.)         | 1.0394      | 1.0991      | T71(p.u.)         | 0.9702      | 0.9621      |
| VG8(p.u.)         | 1.0686      | 1.0982      | T72(p.u.)         | 0.9945      | 0.9587      |
| VG9(p.u.)         | 1.0481      | 1.0882      | T73(p.u.)         | 1.0373      | 0.9703      |
| VG12(p.u.)        | 1.0199      | 1.0809      | Qc18(p.u.)        | 0.1479      | 0.0000      |
| T35(p.u.)         | 0.9550      | 0.9916      | Qc25(p.u.)        | 0.1383      | 0.1687      |
| T36(p.u.)         | 1.0113      | 0.9805      | Qc32(p.u.)        | 0.1945      | 0.1054      |
| T31(p.u.)         | 0.9351      | 0.9972      | Fuel cost ($/h)   | 43373.7400  | 43171.2400  |
| T30(p.u.)         | 0.9404      | 0.9693      | Emission (ton/h)  | 1.2610      | 1.2575      |

5. Conclusions
In this paper, a novel whale algorithm named as MONWOA has been proposed, which is successfully applied to solve nonlinear, non-convex MOOPF problem. Three multi-objective testing cases are
carried out, which include minimizing power loss and fuel cost with value-point simultaneously, basic fuel cost, power loss and emission concurrently for standard IEEE 30-bus system, optimizing emission and fuel cost simultaneously for standard IEEE 57-bus system respectively. The results show that the novel algorithm has absolute superiority in obtaining high-quality POS and BCS solutions simultaneously. MONWOA algorithm is a more effective method in solving MOOPF problems.

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