Optimal Reactive Power Dispatch Problem Solved By Using Flower Pollination Algorithm

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Abstract
In this paper, a new nature inspired and efficient algorithm based on flower pollination is proposed for solving the optimal reactive power dispatch (ORPD) problem. The proposed algorithm is simple, easy to implement and with less number of parameter to be tuned. ORPD is an important power system optimization problem for improving the stability of the system. Loss minimization objective based ORPD is considered in this paper. Generator bus voltages, transformer tap settings and var output of SVCs are taken as the design variables in the problem. The proposed algorithm is implemented in the standard IEEE-30 bus system and results are compared against the recent literatures. Three different cases are taken for the loss minimization objective. The comparisons show that the algorithm performs better than the other algorithms in terms of solution quality.

Keywords: optimal power flow, flower pollination algorithm, loss minimization.

Introduction
Electrical power system is complex network having generators, transmission and distribution net-works to supply electricity to variety of loads. Operating the power system with high degree of security is of main interest. ORPD is a subset of optimal reactive power flow with active power loss minimization as the main objective and generator bus voltage, transformer tap settings and var output of SVCs as the control variables. The problem is highly nonlinear and includes both equality and inequality constraints necessitating an efficient optimization algorithm for its solution. ORPD is redistribution of reactive power flow through the power system so as to minimize the real power loss and voltage deviation for increasing the security of the power system. [1]-[2].

In the past, several traditional optimization algorithms like dynamic programming, Newton method, linear programming, quadratic programming and interior point methods [3]-[6] were used for attacking the ORPD problem. However, these techniques are generally suffer from premature convergence and highly sensitive to initial conditions of the problem [7]. In recent years, stochastic optimization algorithms have been widely exploited as they are more efficient alternatives for global optimization problem. L. L. Lai and J. T. Ma applied the evolutionary programming (EP) algorithm for optimal reactive power dispatch and voltage control problem [8]. Ayan Kursat and Ulas Kilic [9] used the ant colony optimization (ABC) algorithm for ORPD problem. Particle swarm optimization (PSO) and its variants are applied for solving reactive power optimization problem [10]-[11]. In another case, Mahadevan and Kannan [12] also presents another method based on CLPSO for solving ORPD problem. These algorithms are found to be good at producing better results than that reported by the traditional methods.

The rest of this paper are classified in four sections as follows: Section 2 covers the searching mechanism of flower pollination algorithm while Section 3 explains the problem formulation in ORPD, Section 4 of the paper is for presenting the simulation results and to analysis of the performance on IEEE 30-bus. Finally, in Section 5, the conclusion of the implementation for the nature inspired method is presented.

FlowerPollination Algorithm (FPA)  
Pollination in flowering plants
Over 80% of the plant species are flowering plants [13]. The main function of a flower is involving in reproduction via pollination. Flower pollination is the transfer of pollen often linked with pollinators such as insects, birds, bats and other animals. Pollination can take two major forms: biotic and abiotic. About 90% of flowering plants belong to biotic pollination, that is, pollen is transferred by a pollinator such as insects and animals. About 10% of pollination takes abiotic form which does not require any pollinators. Wind and diffusion in water help pollination of such flowering plants and grass is a good example.

Pollinators like honeybees are selective to certain flower species called flower constancy. Such flower constancy may have evolutionary advantages because this will maximize the transfer of flower pollen to the same or conspecific plants, and thus maximizing the reproduction of the same flower species. Such flower constancy may be advantageous for pollinators as well, because they can be sure that nectar supply is available. Rather than focusing on some unpredictable but potentially more rewarding new flower species, flower constancy may require minimum investment cost and more likely guaranteed intake of nectar.

Pollination can be achieved by self-pollination or cross-pollination. Cross-pollination means occurrence of pollination
from pollen of a flower of a different plant, while self-pollination is the fertilization of one flower from pollen of the same flower or different flowers of the same plant, which often occurs when there is no reliable pollinator available. In addition, bees and birds may behave as Levy flight behavior, with jump or fly distance steps obey a Levy distribution. Furthermore, flower constancy can be used an increment step using the similarity or difference of two flowers.

**Flower Pollination Algorithm:**

Flower pollination process can be idealized using the following assumptions to evolve an optimization algorithm mimicking flower pollination. Biotic and cross-pollination is like global pollination process with pollinators following Levy flights. Abiotic and self-pollination are considered as local pollination. Local pollination and global pollination is controlled by a switch probability \( p \in [0, 1] \). Flower constancy can be considered as the reproduction probability. The following are the four rules employed to copy the pollination characteristics of flowers [12]

**Rule 1.** Biotic and cross-pollination are considered as global pollination process and pollen is carried by a movement which obeys Levy flight movement.

**Rule 2.** Abiotic and self-pollination are equivalent to local pollination process.

**Rule 3.** Pollinators can develop flower constancy, which is like reproduction probability and proportional to the similarity of two flowers involved.

**Rule 4.** Changing from local pollination to global pollination or vice versa can be controlled by a probability \( p \in [0, 1] \).

A possible solution \( x_t \) is equivalent to a flower and/or a pollen gamete. The flower pollination algorithm (FPA) is developed from the above stated assumptions. There are two key steps in this algorithm, they are global pollination and local pollination.

In the global pollination step, flower pollens are carried by pollinators which can travel over a long distance because insects can often fly and move in a much longer range. This ensures the pollination and reproduction of the most fittest, and thus we represent the most fittest as \( x_p \). The first rule plus flower constancy can be represented mathematically as:

\[
x_t^{t+1} = x_t + L(x_t - x_p)
\]

(1)

Where \( x_t \) is the solution at iteration \( t \), and \( x_p \) is the current global best solution. The parameter \( L \) is the strength of the pollination, which essentially is a step size. Since insects may move over a long distance with various distance steps, we can use a Levy flight to mimic this characteristic efficiently. That is, we draw \( L > 0 \) from a Levy distribution.

\[
L \sim \frac{\alpha \Gamma(\lambda) \sin \pi \lambda / 2}{\pi} \frac{1}{s^{1+\lambda}}, (s \gg s_0 > 0)
\]

(2)

Here \( \Gamma(\lambda) \) is the standard gamma function, and this distribution is valid for large steps \( s > 0 \). In all our simulations below, we have used \( \lambda = 1.5 \).

The local pollination (Rule 2) and flower constancy can be represented as:

\[
X_t^{t+1} = X_t + \epsilon(X_t - X_i^*)
\]

(3)

Where \( X_t^i \) and \( X_i^* \) are pollens from the different flowers of the same plant species. This essentially mimic the flower constancy in a limited neighborhood. Mathematically, if \( X_t^i \) and \( X_i^* \) comes from the same species or selected from the same population, this become a local random walk if we draw \( q \) from a uniform distribution in [0, 1].

Most flower pollination activities can occur at both local and global scale. In practice, adjacent flower patches or flowers in the not-so-far-away neighborhood are more likely to be pollinated by local flower pollens that those far away. For this, we use a switch probability or proximity probability \( p \) to switch between common global pollination to intensive local pollination. To start with, we can use \( p = 0.5 \) as an initially value and then do a parametric study to find the most appropriate parameter range. From our simulations, we found that \( p = 0.8 \) works better for most applications.

**Problem Formulation**

The main objective of the ORPD is to optimize the power loss [14] in the transmission network through optimal adjustment of power system control parameters while satisfying equality and inequality constraints simultaneously.

The ORPD problem can be mathematically formulated as follows:

\[
\min_{\text{P,LOSS}} P_{\text{LOSS}} = \sum_{k=1}^{NTL} q_k\left(V_{k1}^2 + V_{k2}^2 - 2V_{kj}V_{k}\cos(\delta_{kj})\right)
\]

(4)

**Constraints:**

**Equality constraints:** 

In this problem the equality constraints are the power balance equations.

\[
P_t - V_t \sum_{j=1}^{NB} V_{ij} \left[G_{ij}\cos(\delta_{ij}) + B_{ij}\sin(\delta_{ij})\right] = 0
\]

(5)

\[
Q_t - V_t \sum_{j=1}^{NB} V_{ij} \left[G_{ij}\sin(\delta_{ij}) - B_{ij}\cos(\delta_{ij})\right] = 0
\]

(6)

Where \( NB \) is the number of buses, \( P_t \) is the active bus power, \( Q_t \) is the reactive bus power, \( G_{ij} \) and \( B_{ij} \) are the line conductance and suscepsence respectively.

**Inequality constraints:**

Generator constraints: The active power generation at slack bus, generation bus voltages, and reactive power outputs are restricted by their lower and upper limits as:


\[ p_{G,slack}^{\text{min}} \leq P_{G,slack} \leq p_{G,slack}^{\text{max}} \]  

(7)  

\[ V_{Gi}^{\text{min}} \leq V_{Gi} \leq V_{Gi}^{\text{max}}, i = 1, \ldots, NG \]  

(8)  

\[ Q_{Gi}^{\text{min}} \leq Q_{Gi} \leq Q_{Gi}^{\text{max}}, i = 1, \ldots, NG \]  

(9)  

Where \( V_{Gi}^{\text{min}} \) and \( V_{Gi}^{\text{max}} \) are the minimum and maximum generator bus voltage of \( i^\text{th} \) generating unit; \( P_{Gi}^{\text{min}} \) and \( P_{Gi}^{\text{max}} \) the minimum and maximum active power generation of \( i^\text{th} \) generating unit and, \( Q_{Gi}^{\text{min}} \) and \( Q_{Gi}^{\text{max}} \) are the minimum and maximum reactive power generation of \( i^\text{th} \) generating.

Transformer limitations: Transformer tap settings are restricted by their lower and upper limits as:

\[ T_{li}^{\text{min}} \leq T_{li} \leq T_{li}^{\text{max}}, i = 1, \ldots, NT \]  

(10)  

Where \( T_{li}^{\text{min}} \) and \( T_{li}^{\text{max}} \) define minimum and maximum tap settings limits of \( i^\text{th} \) transformer.

Shunt VAR compensator constraints: shunt VAR compensations are restricted by their limits as:

\[ Q_{Ci}^{\text{min}} \leq Q_{Ci} \leq Q_{Ci}^{\text{max}}, i = 1, \ldots, NC \]  

(11)  

Where \( Q_{Ci}^{\text{min}} \) and \( Q_{Ci}^{\text{max}} \) define minimum and maximum VAR injection limits of \( i^\text{th} \) shunt compensator.

Security constraints: include the constraints of voltages at load buses and transmissions lines loading as:

\[ V_{li}^{\text{min}} \leq V_{li} \leq V_{li}^{\text{max}}, i = 1, \ldots, NPQ \]  

(12)  

\[ S_{li} \leq S_{li}^{\text{max}}, i = 1, \ldots, NTL \]  

(13)  

Where \( V_{li}^{\text{min}} \) and \( V_{li}^{\text{max}} \) are the minimum and maximum load voltage of \( i^\text{th} \) load bus. \( S_{li} \) is the power flow in ith line and \( S_{li}^{\text{max}} \) is the maximum limit of the line.

**Simulation Results and Discussions**

The proposed FPA based approach for optimal reactive power dispatch is tested on the standard and widely used IEEE-30 bus system [15]-[16]. The FPA algorithm is coded in Matlab 7. 6 and a Core2Duo, 2GB RAM based PC is used for running the simulation. Maximum number of generations are taken as 300 for all the three cases. The population size is taken as 100 and the switching probability is set to 0. 5 for the IEEE30-bus power system.

The standard IEEE-30 bus test system has 6 generators, 24 load buses, 4 tap changing transformers and 3 SVCs. The one line diagram of the systems is depicted in figure 1.

The IEEE 30 bus test system components include.

  a) Six generator buses (1, 2, 5, 8, 11, &13)
  b) Three SVC buses (3, 10, 24)

![Figure 1: Single line diagram of IEEE 30 bus system](image)

The system real power load \( P_{\text{load}} \) is 2. 834 p. u. and reactive power load is \( Q_{\text{load}} = 1. 262 \) p. u. on a 100 MVA basis. Bus 1 is taken as the reference bus for load flow analysis. Different constraints and initial settings are considered for the ORPD problem in the different references. For the purpose of comparisons, the three different limits taken on the control variables are followed here. The various constraint cases of IEEE30-bus test system for the ORPD problem are given in table 1.

<table>
<thead>
<tr>
<th>Case</th>
<th>Generator voltage (Vg)</th>
<th>Tap setting (Tp)</th>
<th>Shunt compensation (SVC)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>Case 1 ([14, 32])</td>
<td>0. 95</td>
<td>1. 05</td>
<td>-0. 12</td>
</tr>
<tr>
<td>Case 2 ([38, 39])</td>
<td>0. 95</td>
<td>1. 1</td>
<td>0. 0</td>
</tr>
<tr>
<td>Case 3 ([40])</td>
<td>0. 95</td>
<td>1. 1</td>
<td>0. 0</td>
</tr>
</tbody>
</table>

**Case 1:**

The upper and lower limits of the control variables of generator bus voltage is taken as given in table 1. The proposed FPA based algorithm is run for optimizing the real power respecting the control parameters limits. The proposed algorithm yields 4. 7012 MW as the total transmission loss as against the optimized loss by MICA-IWO algorithm is 4. 8599 MW. The reduction in loss is 3. 265499 %. This will increase the economy of the power system. For achieving this
improved results the algorithm suggests capacitive compensation (supplying of reactive power) at all the three compensating buses.

Table 2: Results of case 1

<table>
<thead>
<tr>
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<tbody>
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<td>0.0941</td>
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<td>0.0345</td>
<td>0.0297</td>
<td>0.0751</td>
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<td>0.0751</td>
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<tr>
<td>T6-9</td>
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<td>0.04</td>
<td>0.05</td>
<td>1.02</td>
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<td>0.97</td>
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<tr>
<td>T6-10</td>
<td>0.99</td>
<td>0.09</td>
<td>0.04</td>
<td>0.10</td>
<td>0.97</td>
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<tr>
<td>T6-27</td>
<td>0.97</td>
<td>0.02</td>
<td>0.09</td>
<td>1.07</td>
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<td>0.98</td>
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<tr>
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<td>0.16</td>
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<td>0.13</td>
<td>0.11</td>
<td>0.1</td>
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<tr>
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<td>0.12</td>
<td>0.12</td>
<td>0.13</td>
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<td>0.11</td>
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<tr>
<td>NSGA II</td>
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<td>0.049480</td>
<td>0.049238</td>
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<td>0.048344</td>
<td>0.048589</td>
<td>0.047017</td>
</tr>
</tbody>
</table>

Figure 2: Convergence of proposed algorithm-case 1

125 iterations are taken by the FPA algorithm for producing the global best results and it remains the best up to 300 iterations. This proves the good convergence characteristics of the algorithm. Reliability in convergence is taken as the strength of algorithm. Less number of iterations is taken otherwise as minimum time is taken for converging to the global best results

Case 2:
FPA algorithm is tuned for loss minimization with variable limits corresponding to this case. FPA has reports the best active power loss of 4.7579 MW while the best loss given in the literature is 4.9178 MW. 3.2315 % increased loss level in case is not much as compared to the two previous cases. The increase in loss minimization due the FPA algorithm is 0.082637 %.

Table 3: Results of case 2

<table>
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<tr>
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<td>0.0946</td>
<td>0.0949</td>
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<tr>
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<td>0.94</td>
<td>0.94</td>
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<td>T6-27</td>
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</tr>
<tr>
<td>QC1</td>
<td>0.07</td>
<td>0.07</td>
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</tbody>
</table>

Figure 3: Convergence of proposed algorithm-case 2

The algorithm maintains the best results over the generations. It clear from figure 3 that the algorithm has almost converged to the best results within 50 iterations. This implies that the algorithm has rapid convergence behaviour.

Case 3:
In this case also, the proposed method outperforms the other algorithms in minimizing the loss. The decrease in loss level in case is not much as compared to the two previous cases. The increase in loss minimization due the FPA algorithm is 0.082637 %.

Table 4: Results of case 3

<table>
<thead>
<tr>
<th></th>
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</table>

Figure 4: Convergence of proposed algorithm-case 3
By running only for 35 iterations the algorithm converged to the best results. The algorithm shows better convergence behavior compared to cases 1 and 2. Good converging characteristics of the algorithm in different case is an evidence that the algorithm can be used for different problems.

Conclusions
In this work, the performance of the newly introduced nature optimization algorithm of FPA is implemented for ORPD problem. The algorithm was easy to be coded in mat lab language and simple to tune with less number of parameters. The results obtained from IEEE 30 bus system are compared with other recently reported work and it is clear that the proposed algorithm performs in a better way. The convergence behavior of the algorithm is also reliable and the algorithm takes number of iterations for convergence. So, it is believed that the proposed FPA approach is efficient in solving reactive power dispatch problem.

References