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Firefly Algorithm based Optimal Reactive Power Flow

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Abstract

The optimal reactive power flow (ORPF) helps to effectively utilize the existing reactive power sources for minimizing the network loss. Firefly Algorithm (FA), inspired by social flashing behavior of fireflies, is one of the evolutionary computing models for solving multimodal optimization problems. This paper attempts to obtain global best solution of ORPF using FA. The results of IEEE 57 bus system are presented to demonstrate its performance.

Keywords: *optimal reactive power flow, firefly algorithm*

Nomenclature

FA	firefly algorithm
f_i	i -th firefly
f_i^j	j -th design variable of i -th firefly
$G_{ij} + jBij$	real and imaginary terms of bus admittance matrix corresponding to k -th row and - j -th column
g_{ij}	conductance of the transmission line connected between buses - i and j
$g(x,u)$	equality constraint
$h(x,u)$	inequality constraint
$J(x,u)$	objective function
LI_i	light intensity of i -th firefly
nc	number of shunt reactive power compensators
n	number of decision variables
$nobj$	number of objectives
ng	number of generators
nt	number of transformers
nf	number of fireflies in the population
ORPF	optimal reactive power flow
PFAM	proposed FA based method
Q_{Gi}	reactive power generation at bus- i
Q_{Ci}	reactive power injection by i -th shunt compensator
RPL	real power loss
r_{ij}	Cartesian distance between i -th and j -th fireflies
T_i	tap settings of i -th transformer
VP	voltage profile
V_i	voltage at i -th bus
$V_{Li}^{\lim it}$	limit violated voltage magnitude at i -th load bus

$Q_{Gi}^{\lim it}$	limit violated reactive power generation at i -th PV bus
V_{Gi}	voltage magnitude at i -th generator bus
V_{Li}	voltage magnitude at i -th load bus
x	vector of dependant variables
u	vector of control or independent variables
α	random movement factor
β_o	attractiveness parameter
β_{ij}	attractiveness between i -th and j -th fireflies
γ	absorption factor
λ_V and λ_Q	penalty factors
ω_i	structure of i -th molecule
$\Im$	a set of transmission lines
Φ	a set of load buses
Ω	a set of generator buses
superscript $\min$ and $\max$	lower and upper limits respectively

I. Introduction

The Optimal Reactive Power Flow (ORPF) attempts to minimize the real power loss (RPL) via the optimal adjustment of the power system control variables, while at the same time satisfying various equality and inequality constraints. The ORPF problem is a large scale highly constrained nonconvex and multimodal optimization problem [1,2]. Several traditional optimization techniques such as gradient method [1,2], Newton method [3], linear programming [4-7], interior point method [8] and non linear programming [9] have been applied to solve the ORPF problem. These methods have severe limitations in handling non-linear and discontinuous objectives and constraints. Besides, these classical optimization techniques involving derivatives and gradients may not be able to determine the global optimum. In order to overcome these drawbacks, nature inspired optimization methods such as genetic algorithm (GA) [10-12], evolutionary programming [13], particle swarm optimization (PSO) [14], differential evolution (DE) [15-17], seeker optimization algorithm [18] and biogeography based optimization (BBO) [19] have been recently applied in solving the ORPF problems.

Recently, firefly optimization (FFO) has been suggested for solving optimization problems [20,21]. It is inspired by the light attenuation over the distance and fireflies' mutual attraction rather than the phenomenon of the fireflies' light flashing. In this approach, each problem solution is represented by a firefly, which tries to move to a greater light source, than its own. It has been applied to a variety of power system problems [22-24] and found to yield satisfactory results. This paper attempts to develop FA based method for obtaining the solution of ORPF. The results on IEEE 57 bus system are presented to demonstrate the effectiveness of the developed strategy.

II. Firefly Algorithm

The FFO, a nature-inspired optimization algorithm, is based on the social flashing behavior of fireflies and similar to other optimization algorithms employing swarm intelligence such as particle swarm optimization. FFO initially produces a swarm of fireflies located randomly in the problem space. The position of each firefly in the problem space represents a potential solution of the optimization problem. The fitness function takes the position of a firefly as input and produces a single numerical output value denoting how good the potential solution is. The brightness of each firefly depends on the fitness value of that firefly. Each firefly is attracted by the brightness of other fireflies and tries to move towards them. The velocity or the pull of a firefly towards another firefly depends on the attractiveness. The attractiveness depends on the relative distance between the fireflies and is a function of the brightness of the fireflies as well. A brighter firefly far away may not be as attractive as a less bright firefly that is closer. In each iterative step, FFO computes the brightness and the relative attractiveness of each firefly. Depending on these values, the positions of the fireflies are updated. After sufficient amount of iterations, all fireflies converge to the best possible position in the search space. Each i -th firefly is denoted by a vector f_i as [20,21]

$$f_i = \left[f_i^1,\ f_i^2 \cdots ,\ f_i^{nd} \right] \qquad (1)$$

The search space is limited by the following inequality

$$f^{k}(min) \le f^{k} \le f^{k}(max) \ : \ k = 1, 2, \cdots, nd \qquad (2)$$

Initially, the positions of the fireflies are generated from a uniform distribution using the following equation

$$f_i^{\,k} = f^{k}(min) + \left(f^{k}(max) - f^{k}(min)\right) \times rand \qquad (3)$$

Here, $rand$ is a random number between 0 and 1, taken from a uniform distribution. Eq. (3) generates random values from a uniform distribution within the prescribed range defined by Eq. (2). The initial distribution does not significantly affect the performance of the algorithm. Each time the algorithm is executed, the optimization process starts with a different set of initial points. However, in each case, the algorithm searches for the optimum solution. In case of multiple possible sets of solutions, the algorithm may converge on different solutions each time. But each of those solutions will be valid as they all will satisfy the requirements.

The light intensity of the i -th firefly, LI_i is given by

$$LI_i = Fitness \ (f_i) \qquad (4)$$

The attractiveness between the i -th and j -th firefly, β_{ij} is given by

$$\beta_{ij} = \beta_o \exp\left(-\gamma\, r_{ij}^2\right) \qquad (5)$$

Where r_{ij} is Cartesian distance between i -th and j -th firefly

$$r_{ij} = \left\| f_i - f_j \right\| = \sqrt{\sum_{k=1}^{nd} \left(f_i^{\,k} - f_j^{\,k}\right)^2} \qquad (6)$$

β_o is a constant taken to be 1. γ is another constant whose value is related to the dynamic range of the solution space. The position of firefly is updated in each iterative step. If the light intensity of j -th firefly is larger than the intensity of the i -th firefly, then the i -th firefly moves towards the j -th firefly and its motion at t -th iteration is denoted by the following equation:

$$f_i(t) = f_i(t-1) + \beta_{ij}\left(f_j(t-1) - f_i(t-1)\right) + \alpha\left(rand - 0.5\right) \qquad (7)$$

α is a random movement factor, whose value depends on the dynamic range of the solution space. At each iterative step, the intensity and the attractiveness of each firefly is calculated. The intensity of each firefly is compared with all other fireflies and the positions of the fireflies are updated using Eq. (7). After a sufficient number of iterations, all the fireflies converge to the same position in the search space and the global optimum is achieved.

III. Problem Formulation

The ORPF problem is formulated as an optimization problem with several equality and inequality constraints as

$$\text{Minimize} \quad J(x,u) = RPL = \sum_{k \in \Im} g_{ij} \left(\left|V_i\right|^2 + \left|V_j\right|^2 - 2\left|V_i\right|\left|V_j\right| \cos\delta_{ij} \right) \qquad (8)$$

Subject to

$$g(x,u) = 0 \qquad (9)$$

$$h(x,u) \le 0 \qquad (10)$$

Where x is the vector of dependant variables consisting of load bus voltage magnitudes, reactive power generation at generator buses and real power generation at slack bus. u is the vector of control or independent variables comprising of generator bus voltage magnitudes, transformer tap settings and output of reactive shunt compensators. RPL can be calculated from the load flow solution. The equality constraints $g(x,u)$ are the sets of non-linear power flow equations that govern the power system

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} V_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij}\right) = 0 \qquad (11)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} V_j \left(G_{ij} \sin\delta_{ij} - B_{ij} \cos\delta_{ij}\right) = 0 \qquad (12)$$

The equality constraints $h(x,u)$ represent the operating limits on reactive power generations, transformer tap settings and voltage magnitudes.

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \tag{13}$$

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \tag{14}$$

$$T_{i}^{\min} \le T_{i} \le T_{i}^{\max} \tag{15}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \tag{16}$$

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max} \tag{17}$$

IV. Proposed Method

The proposed FA based method (PFAM) involves representation of problem variables and the formation of appropriate LI function.

Representation of Control Variables: In FA, a solution is represented by a firefly- f_i. In the PFAM, each firefly f_i is defined to denote the control variables of voltage magnitude at generator buses, transformer tap positions and reactive power of shunt compensators in vector form as

$$f_i = \left[f_i^1, f_i^2 \cdots, f_i^{nd} \right] = [V_{G1}, V_{G2}, \cdots, V_{Gng}, T_1, T_2, \cdots, T_{nt}, Q_{C1}, Q_{C2}, \cdots, Q_{Cnc}] \tag{18}$$

Formation of LI function: The proposed method searches for optimal solution by minimizing a LI function, which is formulated from the objective function and the penalty terms representing the limit violation of the dependant variables such as reactive power generation at PV buses and voltage magnitude at load buses. The LI function is built as

$$LI = J(x,u) + \lambda_V \sum_{i \in \Phi} \left(V_{Li} - V_{Li}^{\lim it} \right)^2 + \lambda_Q \sum_{i \in \Omega} \left(Q_{Gi} - Q_{Gi}^{\lim it} \right)^2 \tag{19}$$

Where

$$V_{Li}^{\lim it} = \begin{cases} V_{Li}^{\min} & if \;\; V_{Li} < V_{Li}^{\min} \\ V_{Li}^{\max} & if \;\; V_{Li} > V_{Li}^{\max} \\ V_{Li} & else \end{cases} \tag{20}$$

$$Q_{Gi}^{\lim it} = \begin{cases} Q_{Gi}^{\min} & if \;\; Q_{Gi} < Q_{Gi}^{\min} \\ Q_{Gi}^{\max} & if \;\; Q_{Gi} > Q_{Gi}^{\max} \\ Q_{Gi} & else \end{cases} \tag{21}$$

Solution Process: An initial population of fireflies is obtained by generating random values within their respective limits. The LI is calculated by considering the values of each firefly and the movements of all fireflies are performed with a view of maximizing the LI till the number of iterations reaches a specified maximum number of iterations. The pseudo code of the PFAM is as follows.

Read the ORPF Data
Choose the parameters, nf , $Iter^{\max}$, α , β_o *and* γ .
Generate the initial swarm of fireflies
Set the iteration counter $t = 0$
while (termination requirements are not met) do
for $i = 1 : nf$
    Obtain the control parameters from i *-th firefly.*
    Perform load flow.
    Evaluate RPL and then compute LI_i *using Eqs. 8 and 19 respectively*
    for $j = 1 : nf$
        Obtain the control parameters from j *-th firefly.*
        Perform load flow.
        Evaluate RPL and then compute LI_j *using Eqs. 8 and 19 respectively*
        if $LI_i < LI_j$
            Compute r_{ij} *using Eq. (6)*
            Evaluate β_{ij} *using Eq. (5)*

Move i -th firefly towards j -th firefly through Eq. (7)
end-(if)
end-(j)

end-(i)
Rank the fireflies and find the current best.
end-(while)
Choose the best firefly possessing the largest LI_i in the population as the optimal solution
Stop

V. Simulations

The PFAM is tested on IEEE 57 bus test system, whose data have been taken from Ref. [25]. The system possesses seven generators at buses 1, 2, 3, 6, 8, 9 and 12 and fifteen tap changing transformers. The controllable shunt reactive power sources with a capacity of 0.1, 0.06 and 0.063 per units are connected at buses 18, 25 and 53 respectively. The total system active and reactive power demand are 12.508 per unit and 3.364 per unit on 100 MVA base. The lower and upper voltages for all buses are taken as 0.95 and 1.1 respectively. NR technique [26] is used to carry out the load flow during the optimization process. The optimal solution obtained by the PFAM is presented along with base-case solution in Table 1. It is very clear from the table that the PFAM is able to reduce the loss to the lowest value of **23.484 MW**, which leads to 13.72% loss savings with respect to base case. The voltage magnitudes of all load buses of the PFAM are graphically compared with that of the base-case voltages in Fig.1. It clearly indicates that the PFAM offer better voltage profile and they lie between the lower and upper limits.

Table 1 Results of the PFAM

ControlVariables	Base Case	PFAM
V_{G1}	1.04	1.07698
V_{G2}	1.01	1.06324
V_{G3}	0.985	1.04317
V_{G6}	0.980	1.02890
V_{G8}	1.005	1.04960
V_{G9}	0.980	1.03046
V_{G12}	1.015	1.05485
T_{4-18}	0.97	0.91757
T_{4-18}	0.978	0.97055
T_{21-20}	1.043	1.01312
T_{24-26}	1.043	0.99879
T_{7-29}	0.967	0.92387
T_{34-32}	0.975	0.97378
T_{11-41}	0.955	0.90395
T_{15-45}	0.955	0.94037
T_{14-46}	0.900	0.92395
T_{10-51}	0.93	0.93090
T_{13-49}	0.895	0.90101
T_{11-43}	0.958	0.92190
T_{40-56}	0.958	1.01193
T_{39-57}	0.98	0.97473
T_{9-55}	0.94	0.93177
Q_{C18}	0.010	0.09938
Q_{C25}	0.059	0.05961

$Q_{C\,53}$	0.063	0.06279
RPL	**27.22**	**23.484**

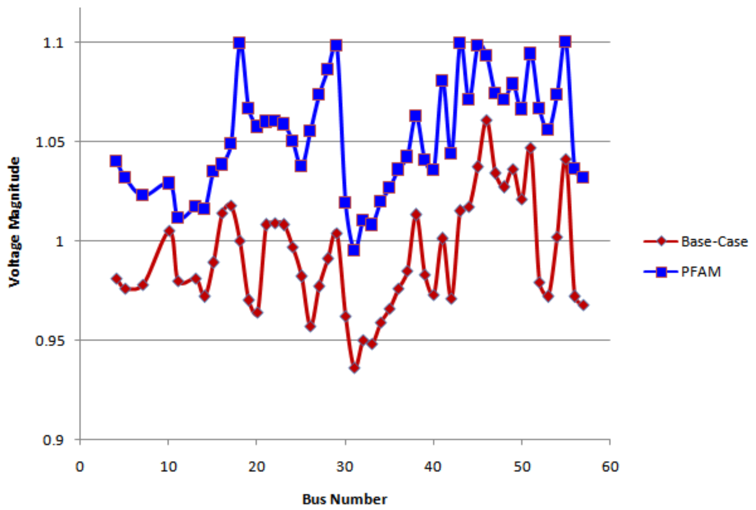

Fig. 1 Plot of voltage profile

VI. Conclusion

Indeed the FFO is a powerful population based method for solving complex optimization problems. ORPF is a complex optimization problem determines the values for system control variables that minimize the RPL, while at the same time satisfying various equality and inequality constraints. The FA is applied to solve ORPF problem. The PFAM attempts to efficiently search the solution space, and find the global best solution. The results of IEEE 57 bus test system project the ability of the PFAM in obtaining the global best solution. Besides the PFAM offers a better VP that lies in between the lower and upper limits. The PFAM for solving ORPF will go a long way in serving as a constructive tool in load dispatch centre.

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