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Enriched Firefly Algorithm for Solving Reactive Power Problem

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Abstract

In this paper, Enriched Firefly Algorithm (EFA) is planned to solve optimal reactive power dispatch problem. This algorithm is a kind of swarm intelligence algorithm based on the response of a firefly to the light of other fireflies. In this paper, we plan an augmentation on the original firefly algorithm. The proposed algorithm extends the single population FA to the interacting multi-swarms by cooperative Models. The proposed EFA has been tested on standard IEEE 30 bus test system and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.

Keyword: *firefly algorithm, optimal reactive power, transmission loss*

1. Introduction

Various algorithms utilized to solve the reactive power problem. Various numerical methods like the gradient method [1]-[2], Newton method [3] and linear programming [4]-[7] have been utilized to solve the optimal reactive power dispatch problem. The problem of voltage stability and collapse play a key role in power system planning and operation [8].Evolutionary algorithms such as genetic algorithm have been already utilized to solve the reactive power flow problem [9]-[11]. In [12], Hybrid differential evolution algorithm is utilized to improve the voltage stability index. In [13] Biogeography Based algorithm have been used to solve the reactive power dispatch problem. In [14], a fuzzy based methodology is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads.This paper proposes Enriched Firefly Algorithm (EFA) to solve reactive power dispatch problem. Our proposed EFA approach is good in exploration and exploitation for searching the global near optimal solution, when compared to other literature surveyed algorithms. A firefly algorithm (FA) is a population-based algorithm enthused by the social behaviour of fireflies [21],[22]. Fireflies converse by flashing their light. Dimmer fireflies are attracted to brighter ones and move towards them to mate [23]. FA is extensively used to solve reliability and redundancy problems. A class of firefly called Lampyride also used pheromone to attract their mate [24]. The proposed Enriched Firefly Algorithm (EFA) extends the single population FA to the interacting multi-swarms by cooperative Models [25]. The proposed EFA algorithm has been evaluated on standard IEEE 30 bus test system. The simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

2. Objective function

The Optimal Power Flow problem is considered as a common minimization problem with constraints, and can be written in the following form:

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Minimize f(x, u) (1)

Subject to g(x,u)=0 (2)

And

$$h(x,u) \leq 0 \tag{3}$$

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \tag{4}$$

The control variables are the generator bus voltages, the shunt capacitors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \tag{5}$$

or

$$u = \left(V_{g1}, \ldots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \tag{6}$$

Where N_g, N_t and N_c are the number of generators, number of tap transformers and the number of shunt compensators respectively.

2.1. Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be mathematically described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_i V_j cos\theta_{ij}\right) \tag{7}$$

Or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \tag{8}$$

Where g_k: is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

2.2. Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \tag{9}$$

Where ω_v: is a weighting factor of voltage deviation.
VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \tag{10}$$

2.3. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \tag{11}$$

2.4. Inequality Constraints

The inequality constraints h(x,u) imitate the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{12}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{13}$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \tag{14}$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \tag{15}$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \tag{16}$$

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

3. Proposed Enriched Firefly Algorithm

There are three ideal rules amalgamated into the unique Firefly algorithm (FA), i) all fireflies are unisex so that a firefly is attracted to all other fireflies ii) a firefly's attractiveness is proportionate to its brightness seen by other fireflies. For any two fireflies, the dimmer firefly is attracted by the brighter one and moves towards it, but if there are no brighter fireflies nearby means then firefly moves arbitrarily iii) the brightness of a firefly is proportional to the value of its objective function. According to the above three rules, the degree of attractiveness of a firefly is planned by the following equation:

$$\beta = \beta_0 e^{-\gamma r^2} \tag{17}$$

where β is the degree of attractiveness of a firefly at a distance r, β_0 is the degree of attractiveness of the firefly at r= 0, r is the distance between any two fireflies, and γ is a light absorption coefficient.

The distance r between firefly i and firefly j located at x_i and x_j respectively is calculated as a Euclidean distance:

$$r = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{d}\left(X_i^k - X_j^k\right)^2} \tag{18}$$

The movement of the dimmer firefly i towards the brighter firefly j in terms of the dimmer one's updated location is determined by the following equation:

$$X_{i+1} = X_i + \beta_0 e^{-\gamma r^2}(X_i - X_j) + \alpha\left(rand - \frac{1}{2}\right) \quad (19)$$

The third term in (19) is included for the case where there is no brighter firefly than the one being considered and rand is a random number in the range of [0, 1].

3.1. Basic Firefly Algorithm

[Step 1] m fireflies are arbitrarily placed within the exploration range, supreme attractiveness is β_0, the light absorption is γ, randomization parameter is α, maximum number of iterations is T; the position of fireflies is arbitrary distributed.

[Step 2] Compute the fluorescence brightness of fireflies. Compute the objective function values of Firefly Algorithm that use the enriched Firefly Algorithm as the largest individual fluorescence brightness valueI_o.

[Step 3] Modernize the position of firefly. When the firefly i is no only attracted by a brighter firefly j but also prejudiced by the historical best position of group, the position formula is updating as function (20).The brightest fireflies will modernize their position as the following function:

$$x_{best}(t+1) = x_{best}(t) + \alpha \times (rand - 1/2) \quad (20)$$

Where$x_{best}(t+1)$ is the global optimal position at generation t.

[Step 4] Recalculate the fluorescence brightness value I_o by using the distance measure function $r_{tr}(S)$after updating the location and penetrating the local area for the toughest fluorescence brightness individual, modernizing the optimal solution when the target value is enriched, or else unchanged.

[Step 5] When reach the maximum iteration number T , record the optimal solution, otherwise repeat step (3), (4), (5) and start the next search. The optimal solution is also the global optimum valueH_{max} and the global optimum image threshold is the corresponding threshold value(S,T) at the position $x_{best}(t)$.

3.2. Enriched Firefly Algorithm

In order to overcome the early convergence of classical FA, Cooperative optimization model is amalgamated into FA to construct an Enriched FA in this paper. In order to progress the balance between the exploration and exploitation in EFA we suggest a modification of Eq. (21) used in traditional FA. The goal of the modification is to reinstate balance between exploration and exploitation affording increased possibility of escaping basin of attraction of local optima. In the suggested EFA ,the firefly i find a brighter firefly j when iterative search use Firefly Algorithm ,then move $i$towards j with a certain step, but the direction of movement will bounce under the influence of the historical best position of group. The direction that $i$towards j blend with the direction that towards the historical best position of group (x_{best}) is the deflect direction, in this way each search is affected by better solutions thereby improving the convergence rate. The principle of Firefly Algorithm with the influence of the historical best position of group .Suppose any firefly i in the probing range is attracted by a brighter firefly j and influenced by the historical best position of group, then the original direction of movement will change and move towards the optimal direction, thus speeding up the convergence rate.

$$x_i(t+1) = x_i(t) + \beta_o e^{-\gamma R_j^2} \times \left(x_j(t) - x_i(t)\right) + \beta_1 e^{-\gamma R_{best}^2} \times \left(x_{best}(t) - x_i(t)\right) + \lambda(rand - 1/2) \quad (21)$$

In the proposed EFA, Eq. (20) of old-style FA based on constants values of α and is modified by Eq. (21) Using new variables, λ and β_1 . In this case, the fireflies are adjusted by: Schematic procedure of Firefly Algorithm with the influence of the historical best position of group. The movement of a firefly is attracted to another more brighter firefly with the influence of the historical best position of group is determined by where is the updating position of firefly, $x_i(t)$ is the initial position of firefly which play an important role in balancing the global searching and the local searching, $\beta_o e^{-\gamma R_j^2} \times \left(x_j(t) - x_i(t)\right)$ represents the position of fireflies update under the attraction between fireflies, $\beta_1 e^{-\gamma R_{best}^2} \times \left(x_{best}(t) - x_i(t)\right)$represent the updating position of fireflies under the influence of the historical best position of group, $\lambda(rand - 1/2)$ is the arbitrary parameter that can avoid the result falling into local optimum.

Input:
Generate preliminary population of fireflies n within
d-dimensional search space x_{ik}, i = 1, 2, . . . , n and
k = 1, 2, . . . , d
Calculate the fitness of the population f (x_{ik}) which
is right proportional to light intensity I_{ik}
Algorithm's parameter— β_o, γ
Output:
Acquired least location: x_i min
start
reiteration
for i = 1 to n
for j = 1 to n
if $\left(I_j < I_i\right)$
Transport firefly i toward j in
d-dimension using Eq. (20)
end if
Attraction varies with distance r
Calculate new solutions and modernize light
intensity using Eq. (21)
end for j
end for i
Rank the fireflies and find the existing best
until stop condition true
end

4. Results and Discussion

EFA algorithm has been verified in IEEE 30-bus, 41 branch system. It has 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is slack bus and 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. Control variables limits are listed in Table 1.

Table 1. Preliminary Variable Limits (PU)

Variables	Min. Value	Max. Value	Type
Generator Bus	0.92	1.12	Continuous
Load Bus	0.94	1.04	Continuous
Transformer-Tap	0.94	1.04	Discrete
Shunt Reactive Compensator	-0.11	0.30	Discrete

The power limits generators buses are represented in Table 2. Generators buses (PV) 2,5,8,11,13 and slack bus is 1.

Table 2. Generators Power Limits

Bus	Pg	Pgmin	Pgmax	Qgmin
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

Table 3. Values of Control Variables After Optimization

Control Variables	EFA
V1	1.0621
V2	1.0522
V5	1.0317
V8	1.0422
V11	1.0821
V13	1.0641
T4,12	0.00
T6,9	0.02
T6,10	0.90
T28,27	0.91
Q10	0.11
Q24	0.11
Real power loss	4.3001
Voltage deviation	0.9070

Table 3 shows the proposed approach succeeds in keeping the control variables within limits. Table 4 summarizes the results of the optimal solution obtained by various methods.

Table 4. Comparison Results

Methods	Real power loss (MW)
SGA (26)	4.98
PSO (27)	4.9262
LP (28)	5.988
EP (28)	4.963
CGA (28)	4.980
AGA (28)	4.926
CLPSO (28)	4.7208
HSA (29)	4.7624
BB-BC (30)	4.690
EFA	4.3001

5. Conclusion

In this paper, the EFA has been effectively implemented to solve Optimal Reactive Power Dispatch problem. The proposed algorithm has been tested on the standard IEEE 30 bus system. Simulation results show the robustness of proposed EFA method for providing better optimal solution in decreasing the real power loss. The control variables obtained after the optimization by EFA is within the limits.

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