Combined FC, RPL, Net VSI and Max VSI in Power System by using Self Adaptive Firefly Algorithm

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Abstract

Economic load dispatch (ELD) is an important operational problem of the power system, aiming to combined FC,RPL,NetVSI and MaxVSI in Power System .The firefly algorithm (FA), a heuristic numeric optimization algorithm inspired by the behavior of fireflies, appears to be a robust and reliable technique. This paper presents a self adaptive FA for the solution of the ELD problem. The proposed algorithm (PA) is applied to the standard IEEE57bus test system and the result are presented to demonstrate its effectiveness.

Keywords

Economic Load Dispatch, Load flow, Firefly algorithm.

NOMENCLATURE

a_i b_i c_i	Fuel cost coefficients
d_i e_i	Coefficients of valve point effects of the generator
ELD	Economic load dispatch
FA	Firefly algorithm
F_C	Net fuel cost
I_i	Light intensity of the i -th firefly
$Iter^{max}$	Maximum number of iterations for convergence check.
nd	Number of decision variables
nf	Number of fireflies in the populations
ng	Number of generators
PA	Proposed algorithm
$p(V,\delta)$	Real power at bus as a function of voltage magnitude and voltage angle
$q(V,\delta)$	Reactive power at bus as a function of voltage magnitude and voltage angle
P_{Gi} and Q_{Gi}	Real and Reactive power generation at i -th bus respectively
P_{Di} and Q_{Di}	Real and Reactive power demand at i -th bus respectively

P_D	Total load demand
P_L	Total Transmission losses
P_{Gi}^{min} and P_{Gi}^{max}	lower and upper limits of P_{Gi}
Q_{Gi}^{min} and Q_{Gi}^{max}	lower and upper limits of Q_{Gi}
r_{ij}	Cartesian distance between the i -th and j -th firefly
SAFA	Self adaptive FA
t	iteration counter
x_i	i -th firefly
$\beta_{i,j}$	Attractiveness between the i -th and j -th firefly
β_o and γ	Maximum attractiveness and light intensity absorption coefficient respectively

I. INTRODUCTION

Present day power systems have the problem of deciding how best to meet the varying power demand that has a daily , weekly and yearly cycle in order to maintain a high degree of economy and reliability. Among the options that are available for an engineer in choosing how to operate the system, economic load dispatch (ELD) is the most significant.ELD is a computational process whereby the total required generation is distributed among the generating units in operation also calculate total line losses subject to load and operational constraints. The objective of proposed algorithm to reduce power losses while satisfying various constraints [1].

Over the years numerous methods with various degrees of near-optimality, efficiency, ability to handle difficult constraints and heuristics, are suggested in the literature for solving the dispatch problems. These problems are traditionally solved using mathematical programming techniques such as lambda iteration method, gradient method, linear programming, dynamic programming method and so on. The additional constraints such as line flow limits cannot be included in the lambda iteration approach

and the convergence of the iterations is dependent on the initial choice of lambda. In large power systems, this method has oscillatory problems that increase the computation time [1,2].

Apart from the above methods, there is another class of numerical techniques called evolutionary search algorithms such as simulated annealing, genetic algorithms, evolutionary programming, ant colony, artificial bee colony and particle swarm optimization have been applied in solving ELD [3-8].The main difficulty is their sensitivity to the choice of the parameters, such as temperature in SA, the crossover and mutation probabilities in GA and the inertia weight, acceleration coefficients and velocity limits in PSO.

Recently, firefly algorithm (FA) has been suggested for solving optimization problems [9-13]. 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 ELD problems [14-18] and found to yield satisfactory results. However, the choice of FA parameters is important in obtaining good convergence and global optimal solution.

A self adaptive FA (SAFA) for obtaining the global best solution has been suggested in this paper. The proposed algorithm (PA) has been tested on the IEEE 57 bus test systems to illustrate the performance.

II. PROBLEM FORMULATION

The ELD problem is formulated as an optimization problem of minimizing the fuel cost while satisfying several equality and inequality constraints.More accurate solution can be obtained, if network loss is calculated from load flow. In this paper, Newton-Raphson load flow technique [18] is used to calculate the loss. The constrained optimization problem involving load flow is formulated as follows.

Minimize

$$F_C = \sum_{i=1}^{ng} a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left| d_i \sin(e_i (P_{Gi}^{min} - P_{Gi})) \right| \quad (1)$$

Subject to:

Real Power balance Constraints

$$\sum_{i=1}^{ng} P_{Gi} - (P_D + P_L) = 0 \quad (2)$$

Real and Reactive power generation limits

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (3)$$

$$\iota = 1, 2, 3 \cdots , ng$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad (4)$$

$$\iota = 1, 2, 3 \cdots , ng$$

Load flow equations

$$P_{Gi} - P_{Di} - p(V, \delta) = 0 \quad (5)$$

$$Q_{Gi} - Q_{Di} - q(V, \delta) = 0 \quad (6)$$

III. SELF ADAPTIVE FIREFLY ALGORITHM

The FA is a Meta heuristic, nature-inspired, optimization algorithm which is based on the social flashing behavior of fireflies, or lighting bugs, in the summer sky in the tropical temperature regions. It was developed by Dr. Xin-She Yang at Cambridge University in 2007, and it is based on the swarm behavior such as fish, insects, or bird schooling in nature. It is similar to other optimization algorithms employing swarm intelligence such as PSO and ABC. But FA is found to have superior performance in many cases [9-13]. The brightness of each firefly depends on the fitness value of that firefly. Each firefly is attracted by the brightness of other fire-flies and tries to move towards them. The velocity or the pull a firefly towards another firefly depends on the attractiveness. The attractiveness depends on the relative distance between the fireflies. It can be a function of the brightness of the fireflies as well. The number of fireflies in the swarm is known as the population size, nf . The selection of population size depends on the specific optimization problem. However, typically a population size of 20 to 40 is used for PSO and FA for most applications [9-13]. Each i -th firefly is denoted by a vector x_i as

$$x_i = \left[x_i^1, x_i^2 \cdots , x_i^{nd} \right] \quad (7)$$

The search space is limited by the following inequality

$$x^k (min) \leq x^k \leq x^k (max) \quad : \quad k = 1, 2, \cdots , nd \quad (8)$$

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

$$x_i^k = x^k (min) + \left(x^k (max) - x^k (min) \right) \times rand \quad (9)$$

Here, $rand$ is a random number between 0 and 1, taken from a uniform distribution. Eq. (9) generates random values from a uniform distribution within the prescribed range defined by Eq. (8).

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

$$I_i = Fitness \quad (x_i) \tag{10}$$

The attractiveness between the i -th and j -th firefly, $\beta_{i,j}$ is given by

$$\beta_{i,j} = \beta_o \exp\left(-\gamma \, r_{i,j}^2\right) \tag{11}$$

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

$$r_{i,j} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{nd} \left(x_i^k - x_j^k\right)^2} \tag{12}$$

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:

$$x_i(t) = x_i(t-1) + \beta_{i,j}\left(x_j(t-1) - x_i(t-1)\right) + \alpha\left(rand \; -0.5\right)$$
$$(13)$$

α is a constant 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 (12). The influence of other solutions is controlled by the value of attractiveness of Eq. (11), which can be adjusted by modifying two parameters β_o and γ. The first parameter describes attractiveness at $r_{i,j} = 0$ i.e. when two fireflies are found at the same point of solution space. In general $\beta_o \in [0,1]$ should be used and two limiting cases can be defined.

The self-adaptive control of these two parameters during the search process effectively leads the algorithm to land at the global best solution with minimum computational effort. Each firefly with nd decision variables in the FA will be defined to encompass $nd +2$ FA variables in a self-adaptive method, where the last two variables represent β_o and γ. A firefly can be represented as

$$x_i = \left[x_i^1, x_i^2 \cdots, x_i^{nd}, \beta_{o,i}, \gamma_i\right] \tag{14}$$

Each firefly possessing the solution vector, $\beta_{o,i}$ and γ_i undergo the whole search process of the FA, thereby resulting in better off-springs during the search with lower computational effort. Eq. (11) is accordingly modified as

$$\beta_{i,j} = \beta_{o,i} \exp\left(-\gamma_i \, r_{i,j}^2\right) \tag{15}$$

The self adaptive scheme attempts to prevent sub-optimal solution and enhance the convergence of the algorithm.

IV. PROPOSED ALGORITHM

The proposed SAFA based solution process involves representation of problem variables β_o and γ; and formation of a light intensity function.

A. Representation of decision variables

The decision variables in the PA are real power generation at generator buses except slack bus, β_o and γ. Each firefly in the PA is defined to denote these decision variables in vector form as

$$x = [\,P_{G2}, \cdots, P_{Gng}, \beta_o, \gamma\,] \tag{16}$$

B. Intensity Function

The SAFA searches for optimal solution by maximizing an intensity function, denoted by I_i, which is formulated from the objective function, Eq. (1).

$$Max \quad I_i = \frac{1}{1 + F_C} \tag{17}$$

It is to be noted that the real power generation, which includes network loss, at slack bus is obtained from the load flow.

C. Stopping Criterion

The process of generating new swarm can be terminated either after a fixed number of iterations or if there is no further significant improvement in the global best solution.

D. Solution Process

An initial swarm of fireflies is obtained by generating random values within their respective limits to every individual in the swarm through Eq. (3). The iterative process is continued till convergence. The pseudo code of the PA is as follows.

Read the Power System Data

Choose the number of fireflies in the population, nf and $Iter^{max}$ for convergence check.

Generate the initial population of fireflies
Set the iteration counter
   $t = 0$
while (termination requirements are not met) do
   for $i = 1 : nf$

Alter the system data and $\beta_o \; \gamma$ according to i -th firefly values
  Run load flow and obtain slack bus power

Evaluate F_C and I_i using Eqs. 1 and 17 respectively
   for $j = 1 : nf$

Alter the system data according to j -th firefly values
  Run load flow and obtain slack bus power

Evaluate F_C and I_j using Eqs. 1 and 17 respectively
  if $I_i > I_j$

      Compute r_{ij} using Eq. (12)

      Evaluate β_{ij} using Eq. (15)

Move j -th firefly towards i -th firefly through Eq. (13)
  end-(if)
  end-(j)
  end-(i)
  Rank the fireflies
end-(while)

V. SIMULATION

The PA is tested on IEEE 57 bus test system, whose data have been taken from Ref. [19]. The fuel cost coefficients, lower and upper limits for real power generations for IEEE 57 bus test system are given in Table 8.1 of the appendix. Programs are developed in Matlab 7.5 and executed on a 2.3 GHz Pentium-IV personal computer. Newton Raphson technique [18] is used to carry out the load flow during the optimization process. The parameters chosen for the PA are given in Table 5.1.

Table 5.1 FA parameters

Parameter	Value
nf	30
$Iter^{max}$	300

Table 5.2 Results of IEEE 57 bus test system

Control Variables (p.u)	Before Optimization	PA
P^G	351.367 35.000 40.000 50.000 450.000 35.000 310.000	265.971982 10.623121 78.561993 48.039397 409.650750 42.324655 410.000000
β_o	---	0.604470
γ	---	0.328375
Load Demand(MW)	1250.8	1250.8
Net VSI	5.7922	5.7577
Max VSI	0.2888	0.2868
RPL	20.5668	14.3719
FC	4532.3340	4686.0562

The solution obtained by the PA for IEEE 57 bus test system are given along with the initial solution before optimization in Tables 5.2 respectively. While analyzing in performances, it can be observed that if one performance among the chosen objectives decreases , the other increases due to the conflicting nature of the objectives and vice- versa. The quality of the compromised solutions cannot be estimated as it depends on the weight values assigned to the individual objectives and the range of the each objectives function values.

VI. SUMMARY

Indeed the FA is a powerful novel population based method for solving complex optimization problems. The convergence and searching capability can be improved with a view to prevent sub-optimal solution through self-adaptive control of FA parameters. In this paper, SAFA solution technique for ELD problem is developed and tested on IEEE57 bus test system. The algorithm uses NR load flow technique for computing the slack bus power that includes network loss and is able to offer the global best solution at lower computational burden.

VII. ACKNOWLEDGEMENT

VIII .APPENDIX

Table 8.1 Generator Data for IEEE 57 bus test system

Bus No	a	b	c	d	e	P_{Gi}^{min}	P_{Gi}^{max}
1	0.0017	1.7365	0.0	0.0	0.0	50	576
2	0.0100	10.000	0.0	0.0	0.0	10	100
3	0.0071	7.1429	0.0	0.0	0.0	20	140
6	0.0100	10.000	0.0	0.0	0.0	10	100
8	0.0018	1.8100	0.0	0.0	0.0	40	550
9	0.0100	10.000	0.0	0.0	0.0	10	100
12	0.0024	2.4390	0.0	0.0	0.0	30	410

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