IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-6, June 2018 E-ISSN: 2347-2693

Advanced Fireworks Algorithm for Solving Optimal Reactive Power Dispatch Problem

K. Lenin

Department of EEE, Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh -520007.

Available online at: www.ijcseonline.org

Accepted: 07/Jun/2018, Published: 30/Jun/2018

Abstract: This paper presents an Advanced Fireworks Algorithm (AFA) for solving optimal reactive power dispatch problem. Fireworks algorithm (FWA) is inspired by the fireworks explosion in the sky at night. When a firework bursts, a shower of sparks appears around it. In this way, the neighboring area of the firework is explored. By directing the amplitude of the explosion, the capability of confined exploration for Advanced Fireworks Algorithm (AFA) is guaranteed. The way of fireworks algorithm probing the neighboring area can be further enriched by differential mutation operator. In order to assess the efficiency of proposed algorithm, it has been tested on IEEE 30 system and compared to other standard algorithms. The simulation results demonstrate worthy performance of the Advanced Fireworks Algorithm (AFA) in solving optimal reactive power dispatch problem.

Key words: optimal reactive power, Transmission loss, Fireworks algorithm, differential mutation operator.

1. Introduction

In recent years the optimal reactive power dispatch (ORPD) problem has received great attention as a result of the improvement on economy and security of power system operation. Gradient method [1, 2] Newton method [3] and linear programming [4-6] like various mathematical techniques have been adopted to solve the optimal reactive power dispatch problem. But they have difficulty in handling inequality constraints. Many Evolutionary algorithms such as have been proposed to solve the reactive power dispatch problem [7-10]. This paper presents an Advanced Fireworks Algorithm (AFA) for solving optimal reactive power dispatch problem. Fireworks algorithm (FWA) is explored by Tan and Zhu in 2010 [11]. As a firework bursts, a shower of sparks appears around the firework while the neighbouring area is illuminated. The explosion operator in FWA is to find global minimum values by penetrating the encircled area of an individual. Janacek et al. smeared FWA to non-negative matrix factorization [12-14]. Gao et al. used FWA to design digital filters [15]. He W. et al. applied FWA to the fields of spam detection [16].Differential evolution (DE) algorithm was projected by Storn and Price [17]. Brest et al. studied the self-adaptive limitations in DE algorithm on numeric benchmark problems [18]. Das and Suganthan presented the information of DE and investigated the major variations, application and theory [19]. Millipede et al. smeared ensemble of parameters and mutation approaches to DE algorithm [20]. Still, there are many researches concentrating on DE algorithm [21-25]. In this paper, DE mutation operator is integrated to fireworks algorithm (FWA) so as to form a new Advanced Fireworks Algorithm (AFA). In order to assess the efficiency of proposed algorithm, it has been tested on IEEE 30 system and compared to other standard algorithms. The simulation results demonstrate worthy performance of the Advanced Fireworks Algorithm (AFA) in solving optimal reactive power dispatch problem.

2. Voltage Stability Evaluation

2.1.Modal analysis for voltage stability evaluation

Power flow equations of the steady state system is given by,

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = \begin{bmatrix}J_{p\theta} & J_{pv}\\ J_{q\theta} & J_{QV}\end{bmatrix}\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \quad (1)$$

Where

ΔP = bus real power change incrementally.

ΔQ = bus reactive Power injection change incrementally.

$\Delta\theta$ = bus voltage angle change incrementally.

ΔV = bus voltage Magnitude change incrementally.

$J_{p\theta}$, JPV , JQθ , JQV are sub-matrixes of the System voltage stability in jacobian matrix and both P and Q get affected by this.

Presume $\Delta P = 0$, then equation (1) can be written as,

$$\Delta Q = \left[J_{QV} - J_{Q\theta}J_{P\theta^{-1}}J_{PV}\right]\Delta V = J_R\Delta V \quad (2)$$

$\Delta V = J^{-1} - \Delta Q$ (3)

Where

$J_R = \left(J_{QV} - J_{Q\theta} J_{P\theta^{-1}} JPV\right)$ (4)

J_R denote the reduced Jacobian matrix of the system.

2.2. Modes of Voltage instability:
Voltage Stability characteristics of the system have been identified through computation of the Eigen values and Eigen vectors.

$J_R = \xi \wedge \eta$ (5)

Where,

ξ denote the right eigenvector matrix of JR, η denote the left eigenvector matrix of JR, $\wedge$ denote the diagonal eigenvalue matrix of JR.

$J_{R^{-1}} = \xi \wedge^{-1} \eta$ (6)

From the equations (5) and (6),

$\Delta V = \xi \wedge^{-1} \eta \Delta Q$ (7)

or

$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q$ (8)

ξi denote the ith column right eigenvector & η is the ith row left eigenvector of JR.

λi indicate the ith Eigen value of JR.

reactive power variation of the ith modal is given by,

$\Delta Q_{mi} = K_i \xi_i$ (9)

where,

$K_i = \sum_j \xi_{ij^2} - 1$ (10)

Where ξji is the jth element of ξi

ith modal voltage variation is mathematically given by,

$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi}$ (11)

When the value of | λi | =0 then the ith modal voltage will get collapsed.

In equation (8), when ΔQ = ek is assumed , then ek has all its elements zero except the kth one being 1. Then ΔV can be formulated as follows,

$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1}$ (12)

η_{1k} is k th element of η_1

At bus k V –Q sensitivity is given by,

$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1}$ (13)

3. Problem Formulation

To minimize the real power loss and also to maximize the static voltage stability margin (SVSM) is the key objectives of the reactive power dispatch problem.

3.1. Minimization of Real Power Loss
Real power loss (Ploss) minimization in transmission lines is mathematically given as,

$P_{loss} = \sum_{\substack{k=1 \\ k=(i,j)}}^{n} g_{k(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij})}$ (14)

Where n is the number of transmission lines, gk is the conductance of branch k, Vi and Vj are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

3.2. Minimization of Voltage Deviation
At load buses minimization of the voltage deviation magnitudes (VD) is stated as follows,

Minimize VD = $\sum_{k=1}^{nl} |V_k - 1.0|$ (15)

Where nl is the number of load busses and Vk is the voltage magnitude at bus k.

3.3. System Constraints
These are the following constraints subjected to objective function as given below,

Load flow equality constraints:

$P_{Gi} - P_{Di} - V_{i \sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb$
(16)

$Q_{Gi} - Q_{Di} - V_{i \sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \sin\theta_{ij} \\ +B_{ij} & \cos\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb$
(17)

where, nb is the number of buses, P_G and Q_G are the real and reactive power of the generator, P_D and Q_D are the real and reactive load of the generator, and G_{ij} and B_{ij} are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (V_{Gi}) inequality constraint:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i \in ng \quad (18)$$

Load bus voltage (V_{Li}) inequality constraint:

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i \in nl \quad (19)$$

Switchable reactive power compensations (Q_{Ci}) inequality constraint:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i \in nc \quad (20)$$

Reactive power generation (Q_{Gi}) inequality constraint:

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i \in ng \quad (21)$$

Transformers tap setting (T_i) inequality constraint:

$$T_{i}^{min} \le T_{i} \le T_{i}^{max}, i \in nt \quad (22)$$

Transmission line flow (S_{Li}) inequality constraint:

$$S_{Li}^{min} \le S_{Li}^{max}, i \in nl \quad (23)$$

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

4. Differential Evolution

Differential evolution (DE) algorithm is simple and easy to implement. The primary operator in DE is mutation operator. This operator balances the difference of two individuals in the similar population, creating a mutant by adding the scaled difference to a third individual. The created mutant is then smeared to its parent individual and a trial vector is created. Last, the trial vector is compared with the parent individual and the better one is kept for subsequent generation. The process of DE is similar to other evolutionary algorithms, including population initialization, fitness function evaluation and population iteration. Algorithm 1 displays DE with DE/rand/1/bin strategy. InThe procedure of DE/rand/1/bin algorithm, the basic of the strategy lies in line 9, while lines 14 to 19 shows the selection process. Parameter NP stands for the number of individuals in a population and parameter D is the dimension of the problem. Other parameters are CR and F, which represent crossover possibility and scale factor, respectively. rand(0; 1) produces random numbers from the region (0; 1) with uniform distribution.

a) Mutation Operator: As the main operator of DE algorithm, differential evolution operator plays a significant role in DE algorithm. DE/rand/1 is one of the differential evolution operators. In fact, there are more mutation operators in DE algorithm. The operators are stated in a form of DE/a/b, where DE represents the DE algorithm, 'a' stands for the way to select basic vectors and 'b' designates the number of vectors that involved in the mutation operation.

b) Crossover Operator: There are two methods of crossover operator in DE algorithm, including binomial crossover operator and exponential crossover operator. The crossover operator creates the trial vector U_i by dealing with the mutant vector V_i and the parent vector X_i. The crossover operation can be stated as follows.

$$U_i(j) = \begin{cases} V_j(j), if\ rand\ (0,1) \le CR\ or\ j == j_{rand} \\ X_i(j), otherwsie \end{cases}$$
(24)

In Eq. 24, rand(0; 1) produces random numbers between 0 and 1 with uniform distribution. Parameter CR is the crossover possibility and parameter j_{rand} is a randomly selected dimension number, which varies from 1 to D.

c) Selection Operator: After creating a children population with a differential mutate operator and a crossover operator, the individuals in the children population are compared with their corresponding parent individuals by selection operation. The ones with superior fitness values are then selected for next generation. The selection operation can be described as follows.

$$X_i = \begin{cases} U_i\ , if\ \left(f(U_i) < f(X_i)\right) \\ X_i\ , otherwise \end{cases} \quad (25)$$

In Eq. 25, $f(X_i)$ stands for the fitness value of an individual X_i. It can be seen from Eq. 12 that the superior one is always kept for next generation.

Theprocedure of DE/rand/1/bin algorithm

Arbitrarily produce the initial population with NP individuals
Calculate the fitness values for all individuals
While terminal condition not met do
For i= 1 →NP do
Arbitrarily selects r1 ≠r2 ≠r3≠i
Arbitrarily selects j_{rand} from [1, D] =/∗D stands for dimension∗/
For j = 1 →D do
If rand (0; 1) ≤ CR or j == j_{rand} then
$U_i(j) = X_{r1}(j) + F \times (X_{r2}(j) - X_{r3}(j))$
Else
$U_i(j) = X_i(j)$
End if
End for
End for
For j = 1→D do
Calculate the fitness values for U_i

If U_i is superior than X_i then; $X_i = U_i$
End if
End for
End while

5. Fireworks Algorithm

The knowledge of Fire works algorithm (FWA) was enthused by the fireworks explosion in the night sky. When a firework burst out, a shower of sparks appears around it. In this way, the neighbouring area of the spark is illuminated. The procedure of fireworks explosion can be treated as a worthy way to exploration the area around a specific point. Hence, when FWA explores the area, there are two parameters that have to be determined. The first parameter is the number of explosion sparks and the second parameter is the amplitude of the explosion. S_i denotes the number of sparks for a firework X_i.

$$S_i = S * \frac{Y_{max} - f(x_i) + \varepsilon}{\sum_{i=1}^{N} (Y_{max} - f(x_i)) + \varepsilon} \quad (26)$$

In Eq. 26, $\hat{S}$ is a constant that stands for the total number of sparks. Parameter Y_{max} means the fitness value of the worst individual in the population. $f(x_i)$ is the fitness value for an individual x_i, while the last parameter ε is used to avoid the denominator from becoming zero.A_i denotes the amplitude for the ith individual.

$$A_i = \hat{A} \ * \frac{f(x_i) - Y_{min} + \varepsilon}{\sum_{i=1}^{N} (f(x_i) - Y_{min}) + \varepsilon} \quad (27)$$

In Eq. 27, $\hat{A}$ is a constant representing the sum of all the amplitudes. Parameter Y_{min} means the fitness value of the best individual in the population. The meaning of $f(x_i)$ and parameter ε are the same as a forementioned. As pointed in [26], when an amplitude is too small, it leads to inadequate explosion since the new created sparks are close and similar. Therefore, a new parameter is projected to avert the amplitudes from being too small. A_{min} denotes the minimum of the amplitude. There are two ways to set the parameter A_{min}, as linear and non-linear decreasing method, respectively. The value of A_{min} decreasing while the number of iteration increasing.

$$(Linear) A_{min} = A_{init} - \left(A_{init} - A_{final}\right) * iter/maxeval$$

$$\overbrace{{}^{*}\sqrt{(2 * maxeval - iter)}}^{(nin-linear) A_{min} = A_{min} - (A_{init} - A_{final})} * iter/maxeval \quad (28)$$

6. Advanced Fireworks Algorithm

At first, NP individuals are initialized arbitrarily with uniform distribution. This population with NP individuals is marked as POP1. Furthermore, a spark is produced around each individual within a certain amplitude. The amplitude is determined by FWA and greater than A_{min} at the same time. The explosion sparks form a population POP2. Thirdly, the individuals in POP1 are compared with the corresponding individuals in POP2 in pairs. The ones with superior fitness values are kept and used to form a new population marked as POP3. Fourthly, the mutation and crossover operators in DE algorithm are smeared to POP3 and a new population is generated as POP4. Finally, the selection operator is applied to POP4 and the designated individuals are used to form a new population POP1. The iteration continues until the maximum times of function calculations are achieved. In this way, DE mutation operator is smeared to FWA.

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arbitrarily create the initial population with NP individuals as POP1
calculate the fitness values for all individuals
while terminal condition not met do
for i = 1 → NP do
smear FWA to POP1 and procedures POP2
select the superior ones from POP1 and POP2 and forms POP3
arbitrarily select r1 ≠ r2 ≠ r3 ≠ i
arbitrarily select j_{rand} from [1, D]
for j = 1 → D do
if rand(0; 1) ≤ CR or j == jrand then
$U_i(j) = X_{r1}(j) + F \times (X_{r2}(j) - X_{r3}(j))$
else
$U_i(j) = X_i(j)$ =/∗U_i forms POP4 ∗/
end if
end for
end for
for j = 1 → D do
calculate the fitness values for U_i
if U_i is superior than X_i then
$X_i = U_i$ =/∗ X_i return to POP1 ∗/
end if
end for
end while

7. Simulation Results

The efficiency of the proposed Advanced Fireworks Algorithm (AFA) is demonstrated by testing it on standard IEEE-30 bus system. 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers in standard IEEE-30 bus system. Lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses, for PQ buses & reference bus it is 1.05 p.u.. Comparisons of results are shown in Table 5. In Table 1 optimal values of the control variables are given.

Table 1.Results of AFA – ORPD optimal control variables

Control variables	Values of Variable setting
V1	1.0404
V2	1.0416
V5	1.0425
V8	1.0300
V11	1.0028
V13	1.0300
T11	1.000
T12	1.000
T15	1.010
T36	1.010
Qc10	2
Qc12	3
Qc15	2
Qc17	0
Qc20	2
Qc23	2
Qc24	3
Qc29	2
Real power loss	4.2108
SVSM	0.2480

Table 2 indicates the optimal values of the control variables & there is no limit violations in state variables. Mainly static voltage stability margin (SVSM) has increased from 0.2480 to 0.2492. contingency analysis was conducted using the control variable setting obtained in case 1 and case 2 to determine the voltage security of the system. In Table 3 the Eigen values equivalents to the four critical contingencies are given. Result reveal about the Eigen value has been improved considerably for all contingencies in the second case.

Table 2.Results of AFA -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	Values of Variable Setting
V1	1.0454
V2	1.0472
V5	1.0481
V8	1.0301
V11	1.0036
V13	1.0325
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	2
Qc15	2
Qc17	3
Qc20	0
Qc23	2

Qc24	2
Qc29	3
Real power loss	4.9884
SVSM	0.2492

Table 3. Voltage Stability under Contingency State

Sl.No	Contingency	Optimal Reactive Power Dispatch Setting	Voltage Stability Control Reactive Power Dispatch Setting
1	28-27	0.1419	0.1424
2	4-12	0.1642	0.1651
3	1-3	0.1761	0.1764
4	2-4	0.2022	0.2052

Table 4. Limit Violation Checking Of State Variables

State variables	limits		Optimal Reactive Power Dispatch Setting	Voltage Stability Control Reactive Power Dispatch Setting
	Lower	upper		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400
V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

Table 5. Comparison of Real Power Loss

Method	Minimum loss
Evolutionary programming [27]	5.0159
Genetic algorithm [28]	4.665
Real coded GA with Lindex as SVSM[29]	4.568
Real coded genetic algorithm [30]	4.5015
Proposed AFA method	4.2108

8. Conclusion

In this paper a novel approach Advanced Fireworks Algorithm (AFA) succesfully solved the optimal reactive power dispatch problem. Fireworks algorithm (FWA) is inspired by the fireworks explosion in the sky at night. When a firework bursts, a shower of sparks appears around it. In this way, the neighboring area of the firework is explored. By directing the amplitude of the explosion, the capability of confined exploration for Advanced Fireworks Algorithm (AFA) is guaranteed. The way of fireworks algorithm probing the neighboring area can be further enriched by differential mutation operator. In order to assess the efficiency of proposed algorithm, it has been tested on IEEE 30 system and compared to other standard algorithms. The simulation results demonstrate worthy performance of the Advanced Fireworks Algorithm (AFA) in solving optimal reactive power dispatch problem.

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Authors Profile

Dr.K.Lenin, working as professor in the Department of Electrical & Electronics Engineering in Prasad V. Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh. Published more than 200 intrenational journal papers in the area of nature inspired algorithms to power system optimization probem.

