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Voltage Stability Augmentation And Active Power Loss Reduction By Hybrid Evolutionary Firefly Optimization Algorithm

Mr.K.Lenin[1], Dr.B.RavindhranathReddy[2], Dr.M.Surya Kalavathi[3]

[1]Research Scholar, [2]Deputy Executive Engineer, [3]Professor of Electrical and Electronics Engineering, Jawaharlal Nehru Technological University Kukatpally, Hyderabad 500 085, India

Abstract: **This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in a power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. Global optimization methods play an important role to solve many real-world problems. However, the implementation of single methods is excessively preventive for high dimensionality and nonlinear problems, especially in term of the accuracy of finding best solutions and convergence speed performance. In recent years, hybrid optimization methods have shown potential achievements to overcome such challenges. In this paper, a new hybrid optimization method called Hybrid Evolutionary Firefly Algorithm (HEFA) is proposed. The method combines the standard Firefly Algorithm (FA) with the evolutionary operations of Differential Evolution (DE) method to improve the searching accuracy and information sharing among the fire flies. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other specified algorithms.**

Keywords: **Firefly Algorithm, Differential Evolution, hybrid optimization, optimal reactive power, Transmission loss.**

I. INTRODUCTION

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1,2], Newton method [3] and linear programming [4-7].The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently

Global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8,9]. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [10]. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis [10] is used as the indicator of voltage stability. Global optimization is an important task in most

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scientific and engineering problems. These problems include finding the minimal vehicle routing [15-16] and the optimal design in electronic systems [17]. For the past few years, many global optimization methods have been proposed to solve these problems. Most of these methods are metaheuristics methods such as Genetic Algorithm (GA) [18], Particle Swarm Optimization (PSO) [19] and Evolutionary Programming (EP) [20]. These methods have received remarkable attentions as they are known to be derivative free, robust and often involve a small number of parameter tunings. However, applying such single methods is sometimes too restrictive, especially for high dimensional and nonlinear problems [22]. This is because these methods usually require a substantially huge amount of computational times and are frequently trapped in one of the local optima. Recently, different methods have been combined to overcome these disadvantages. The hybrid optimization methods have proved their effectiveness in several high dimensional and nonlinear problems including in bioinformatics [21] and electrical engineering [22]. In this paper, a new hybrid optimization method is introduced. The proposed method, called Hybrid Evolutionary Firefly Algorithm (HEFA), combines the recently introduced Firefly Algorithm (FA) [23] with the evolutionary operations adopted from the Differential Evolution (DE) [24]. In this method, the population is firstly ranked according to the fitness value. Then, the sorted population is divided into two sub-populations. The first sub-population; which contains the solutions with potential fitness values, is subjected to undergo neighbourhood based optimization, whereas the other sub-population is subjected to perform the evolutionary operations.The performance of (HEFA) has been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

II. VOLTAGE STABILITY EVALUATION

A. Modal analysis for voltage stability evaluation

The linearized steady state system power flow equations are given by.

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

Where

ΔP=Incremental change in bus real power.

ΔQ = Incremental change in bus reactive

Power injection

$\Delta\theta$ = incremental change in bus voltage angle.

ΔV=Incremental change in bus voltage

Magnitude

$J_{p\theta}$, J_{PV} , $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let $\Delta P = 0$, then.

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

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

Where

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

$J_R$is called the reduced Jacobian matrix of the system.

B. Modes of Voltage instability:

Voltage Stability characteristics of the system can be identified by computing the eigen values and eigen vectors

Let

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

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R and

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

From (3) and (6), we have

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

or

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

Where ξ_i is the ith column right eigenvector and η the ith row left eigenvector of J_R.

λ_i is the ith eigen value of J_R.

The ith modal reactive power variation is,

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

where,

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

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

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

In (8), let $\Delta Q = e_k$ where e_k has all its elements zero except the kth one being 1. Then,

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

η_{1k} kth element of η_1

V –Q sensitivity at bus k

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

III. PROBLEM FORMULATION

The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

A. Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (Ploss) in transmission lines of a power system. This is mathematically stated as follows.

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

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

B. Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes (VD) at load buses. This is mathematically stated as follows.

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

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

C. System Constraints

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

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

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

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:

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

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:

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

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:

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

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

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

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

IV. HYBRID EVOLUTIONARY FIREFLY ALGORITHM (HEFA) METHOD

The proposed HEFA method is basically a combination of the FA [23] and DE [24] methods. In this method, each solution in a population represents a solution which is located randomly within a specified searching space. The *i*th solution,X_i, is represented as follows:

$$X_{i(t)} = \{X_{i1(t)}, X_{i2(t)}, \ldots, X_{id(t)}\} (24)$$

Where , $X_{i(t)}$is the vector with k = 1, 2, 3, ..., d, and *t* is the time step. Initially, the fitness value of each solution was evaluated. The solution that produced the best fitness value would be chosen as the current best solution in the population. Then, a sorting operation was performed. In this operation, the newly evaluated solutions were ranked based on the fitness values and divided into two sub-populations. The first sub-population contained solutions that produced potential fitness values. The fitness value of each *i*th solution in this sub-population was then compared with its *j*th neighbouring solution. If the fitness value of the neighbouring solution was better, the distance between every solution would then be calculated using the standard Euclidean distance measure. The distance was used to compute the attractiveness, β:

Where

$$\beta = \beta_0 e^{-\gamma r_i j^2} \quad (25)$$

Where β_0 , $\gamma$and $r_{ij}$are the predefined attractiveness, light absorption coefficient, and distance between *i*th solution and its *j*th neighbouring solution, respectively [9]. Later, this new attractiveness value was used to update the position of the solution, as follows:

$$x_{id} = x_{id} + \beta(x_{jd} - x_{id}) + \alpha\left(\delta - \frac{1}{2}\right) \qquad (26)$$

Where α and δ are uniformly distributed random values between 0 to 1. Thus, the updated attractiveness values assisted the population to move towards the solution that produced the current best fitness value [23, 25].

On the other hand, the second sub-population contained solutions that produced less significant fitness values. The solutions in this population were subjected to undergo the evolutionary operations of DE method. Firstly, the trivial solutions were produced by the mutation operation performed on the original counterparts. The ith trivial solution, V_i, was generated based on the following equation:

$V_{i(t)} = \{v_{i1(t)}, v_{i2(t)}, \ldots, v_{id(t)}\}$ (27)

$v_{i(t)} = x_{best(t)} + F.(x_{r1(t)} - x_{r2(t)})$ (28)

Where$x_{best(t)}$ is the vector of current best solution, F is the mutation factor, $x_{r1(t)}$ and $x_{r2(t)}$ are randomly chosen vectors from the neighbouring solutions [10]. Next, the offspring solution was produced by the crossover operation that involved the parent and the trivial solution. The vectors of the ith offspring solution, Y_i, were created as follows,

$Y_{i(t)} = \{y_{i1(t)}, y_{i2(t)}, \ldots, y_{id(t)}\}$ (29)

$$y_{i(t)} = \begin{cases} v_{i(t)} \; if \; R \; < CR \\ x_{i(t)} \; otherwise \end{cases} \quad (30)$$

Where R is a uniformly distributed random value between 0 to 1 and C R is the predefined crossover constant [24]. As the population of the offspring solution was produced, a selection operation was required to keep the population size constant. The operation was performed as follows:

$$X_{i(t+1)} = \begin{cases} Y_{i(t)} \; if \; f(Y_{i(t)}) \le f(X_{i(t)}) \\ X_{i(t)} \; if \; f(Y_{i(t)}) > f(X_{i(t)}) \end{cases} \quad (31)$$

This indicates that the original solution would be replaced by the offspring solution if the fitness value of the offspring solution was better than the original solution. Otherwise, the original solution would remain in the population for the next iteration. The whole procedure was repeated until the stopping criterion was met. Figure 1 shows the outline of the proposed HEFA method.

Hybrid Evolutionary Firefly Algorithm (HEFA) for optimal dispatch problem.

Input: Randomly initialized position of *d* dimension problem: X_i

Output: Position of the approximate global optima: X_G

Begin

Initialize population; Evaluate fitness value;

X_G ←Select current best solution;

For $\boldsymbol{t}$ ← **1**to *max*

Sort population based on the fitness value;

$X_{good} \leftarrow first_{half(X)}; X_{worst} \leftarrow second\_half(X)$;

For *i*←0 to number of X_{good}solutions

For *j* ←0 to number of X_{good}solutions

If $(f(X_i) > f(X_j))$ **then**

Calculate distance and attractiveness;

Update position;

End If

End For

End For

For *i*←0 to number of X_{worst} solutions

Create trivial solution, $V_{i(t)}$;

Perform crossover, $Y_{i(t)}$;

Perform selection, $X_{i(t)}$;

End For

$X \leftarrow combine(X_{good}, X_{worst})$;

X_G ← Select current best solution;

t← $t + 1$; 1;

End For

End Begin

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V. SIMULATION RESULTS

The accuracy of the proposed HEFA method is demonstrated by testing it on standard IEEE-30 bus system. The IEEE-30 bus system has 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. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus. The simulation results have been presented in Tables 1, 2, 3 &4. And in the Table 5 shows the proposed algorithm powerfully reduces the real power losses when compared to other given algorithms. The optimal values of the control variables along with the minimum loss obtained are given in Table 1. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table 1: Results of HEFA– ORPD optimal control variables

Control variables	Variable setting
V1	1.041
V2	1.042
V5	1.041
V8	1.03
V11	1.001
V13	1.043
T11	1.02
T12	1.01
T15	1
T36	1
Qc10	2
Qc12	3
Qc15	3
Qc17	0
Qc20	2
Qc23	3
Qc24	4
Qc29	2
Real power loss	4.1903
SVSM	0.248

ORPD together with voltage stability constraint problem was handled in this case as a multi-objective optimization problem where both power loss and maximum voltage stability margin of the system were optimized simultaneously. Table 2 indicates the optimal values of these control variables. Also it is found that there are no limit violations of the state variables. It indicates the voltage stability index has increased from 0.2480 to 0.2495, an advance in the system voltage stability. To determine the voltage security of the system, contingency analysis was conducted using the control variable setting obtained in case 1 and case 2. The Eigen values equivalents to the four critical contingencies are given in Table 3. From this result it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

Table 2: Results of HEFA -Voltage Stability Control Reactive Power Dispatch Optimal CONTROL VARIABLES

Control Variables	Variable Setting
V1	1.043
V2	1.044
V5	1.042
V8	1.031

V11	1.005
V13	1.035
T11	0.09
T12	0.09
T15	0.09
T36	0.09
Qc10	4
Qc12	4
Qc15	3
Qc17	4
Qc20	0
Qc23	3
Qc24	3
Qc29	4
Real power loss	4.9789
SVSM	0.2495

Table 3: Voltage Stability under Contingency State

Sl.No	Contigency	ORPD Setting	VSCRPD Setting
1	28-27	0.1410	0.1425
2	4-12	0.1658	0.1665
3	1-3	0.1774	0.1783
4	2-4	0.2032	0.2045

Table 4: Limit Violation Checking Of State Variables

State variables	limits		ORPD	VSCRPD
	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[11]	5.0159
Genetic algorithm[12]	4.665
Real coded GA with Lindex as SVSM[13]	4.568
Real coded genetic algorithm[14]	4.5015
Proposed HEFA method	4.1903

VI. CONCLUSION

In this paper a novel approach HEFA algorithm used to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied.The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a good performance for voltage stability Enhancement of large, complex power system networks. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system.

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