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A New charged system Search for Solving Optimal Reactive Power Dispatch Problem

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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. This paper presents a new optimization algorithm based on some principles from physics and mechanics, which will be called Charged System Search (CSS). We utilize the governing Coulomb law from electrostatics and the Newtonian laws of mechanics. CSS is a multi-agent approach in which each agent is a Charged Particle (CP). CPs can affect each other based on their fitness values and their separation distances. The quantity of the resultant force is determined by using the electrostatics laws and the quality of the movement is determined using Newtonian mechanics laws. CSS can be utilized in all optimization fields; especially it is suitable for non-smooth or non-convex domains. CSS needs neither the gradient information nor the continuity of the search space. Proposed algorithm has been tested in standard IEEE 30 bus test system.

Keywords: Modal analysis; optimal reactive power; Transmission loss, Charged System Search (CSS);charged particle .

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1. 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].

There are two general methods to optimize a function, namely, mathematical programming and Meta heuristic methods. Various mathematical programming methods such as linear programming, homogenous linear programming, integer programming, dynamic programming, and nonlinear programming have been applied for solving optimization problems. These methods use gradient information to search the solution space near an initial starting point. In general, gradient-based methods converge faster and can obtain solutions with higher accuracy compared to stochastic approaches in fulfilling the local search task. However, for effective implementation of these methods, the variables and cost function of the generators need to be continuous. Furthermore, a good starting point is vital for these methods to be executed successfully. In many optimization problems, prohibited zones, side limits, and non-smooth or non-convex cost functions need to be considered. As a result, these non-convex optimization problems cannot be solved by the traditional mathematical programming methods. Although dynamic programming or mixed integer nonlinear programming and their modifications offer some facility in solving non-convex problems, these methods, in general, require considerable computational effort. As an alternative to the conventional mathematical approaches, the meta-heuristic optimization techniques have been used to obtain global or near-global optimum solutions. Due to their capability of exploring and finding promising regions in the search space in an affordable time, these methods are quite suitable for global searches and furthermore alleviate the need for continuous cost functions and variables used for mathematical optimization methods. Though these are approximate methods, i.e., their solution are good, but not necessarily optimal, they do not require the derivatives of the objective function and constraints and employ probabilistic transition rules instead of deterministic ones [14]. Nature has always been a major source of inspiration to engineers and natural philosophers and many meta-heuristic approaches are inspired by solutions that nature herself seems to have chosen for hard problems. The Evolutionary Algorithm (EA) proposed by Fogel et al. [15], De Jong [16] and Koza [17], and the Genetic Algorithm (GA) proposed by Holland [18] and Goldberg [19] are inspired from the biological evolutionary process. Studies on animal behavior led to the method of Tabu Search (TS) presented by Glover [20], Ant Colony Optimization (ACO) proposed by Dorigo et al. [21] and Particle Swarm Optimizer (PSO) formulated by Eberhart and Kennedy [22]. Also, Simulated Annealing proposed by Kirkpatrick et al. [23], the Big Bang–Big Crunch algorithm (BB–BC)

proposed by Erol and Eksin [24] and improved by Kaveh and Talatahari [25], and the Gravitational Search Algorithm (GSA) presented by Rashedi et al. [26] are introduced using physical phenomena. The objective of this paper is to present a new optimization algorithm based on principles from physics and mechanics, which will be called Charged System Search (CSS). We utilize the governing Coulomb law from physics and the governing motion from Newtonian mechanics.

2. Voltage Stability Evaluation

2.1 Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing eigen values and right and left eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by.

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

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.

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

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

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.

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 JR

η = left eigenvector matrix of JR

$\wedge$ = diagonal eigenvalue matrix of JR and

$$J_R^{-1} = \xi \wedge^{-1} \eta \quad (6)$$

From (3) and (6), we have

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

or

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

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

λ_i is the ith eigen value of JR.

The ith modal reactive power variation is,

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

where,

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

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

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

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

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

η_{1k} k th element of η_1

V –Q sensitivity at bus k

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

3. 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).

3.1 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.

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

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

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

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

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

3.3 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:

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

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

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

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

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

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

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

Transformers tap setting (T_i) inequality constraint:

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

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

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

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

4. Charged Search System (CSS)

In this section, a new efficient optimization algorithm is established utilizing the aforementioned physics laws, which is called Charged System Search (CSS). In the CSS, each solution candidate X i containing a number of decision variables i.e ($X_i = \{x_{i,j}\}$) is considered as a charged particle. The charged particle is affected by the electrical fields of the other agents. The quantity of the resultant force is determined by using the electrostatics laws and the quality of the movement is determined using the Newtonian mechanics laws. It seems that an agent with good results must exert a stronger force than the bad ones, so the amount of the charge will be defined considering the objective function value, fit (i). In order to introduce CSS, the following rules are developed:

Rule 1 Many of the natural evolution algorithms maintain a population of solutions which are evolved through random alterations and selection [28]–[29]. Similarly, CSS considers a number of Charged Particles (CP). Each CP has a magnitude of charge (qi) and as a result creates an electrical field around its space. The magnitude of the charge is defined considering the quality of its solution, as follows:

$$qi = \frac{\text{fit (i)} - \text{fitworst}}{\text{fitbest} - \text{fitworst}},\ i = 1,2,\dots,N, \qquad (24)$$

where fitbest and fitworst are the so far best and the worst fitness of all particles; fit (i) represents the objective function value or the fitness of the agent i; and N is the total number of CPs. The separation distance rij between two charged particles is defined as follows:

$$r_{ij} = \frac{\|X_i - X_j\|}{\left\|\frac{(X_i + X_j)}{2} - X_{best}\right\| + \varepsilon}, \qquad (25)$$

where Xi and Xj are the positions of the i th and j th CPs, Xbest is the position of the best current CP, and ε is a small positive number to avoid singularities.

Rule 2 The initial positions of CPs are determined randomly in the search space

$$x_{i,j}^{(0)} = x_{i,min} + rand \cdot (x_{i,max} - x_{i,min}), i = 1,2,..,n \qquad (26)$$

where $x_{i,j}^{(0)}$ determines the initial value of the i th variable for the j th CP; $x_{i,min}$ and$x_{i,max}$ are the minimum and the maximum allowable values for the i th variable; rand is a random number in the interval [0,1]; and n is the number of variables. The initial velocities of charged particles are zero

$$v_{i,j}^{(0)} = 0, i = 1,2,..,n. \qquad (27)$$

Rule 3 Three conditions could be considered related to the kind of the attractive forces: Any CP can affect another one; i.e., a bad CP can affect a good one and vice versa ($p_{ij} = 1$). A CP can attract another if its electric charge amount (fitness with revise relation in minimizing problems) is better than other. In other words, a good CP attracts a bad CP:

$$p_{ij} = \begin{cases} 1 & \text{fit(j)} > fit\text{(i)}, \\ 0 & \text{else} \end{cases} \quad (28)$$

All good CPs can attract bad CPs and only some of bad agents attract good agents, considering following probability function:

$$p_{ij} = \begin{cases} 1 & \frac{\text{fit(i)}-\text{fitbest}}{\text{fit(j)}-\text{fit(i)}} > \text{rand} \vee \text{fit(j)} > \text{fit(i)} \\ 0 & \text{else} \end{cases} \quad (29)$$

According to the above conditions, when a good agent attracts a bad one, the exploitation ability for the algorithm is provided, and vice versa if a bad CP attracts a good CP, the exploration is provided. When a CP moves toward a good agent it improves its performance, and so the self-adaptation principle is guaranteed. Moving a good CP toward a bad one may cause losing the previous good solution or at least increasing the computational cost to find a good solution. To resolve this problem, a memory which saves the best-so-far solution can be considered. Therefore, it seems that the third kind of the above conditions is the best rule because of providing strong exploration ability and an efficient exploitation.

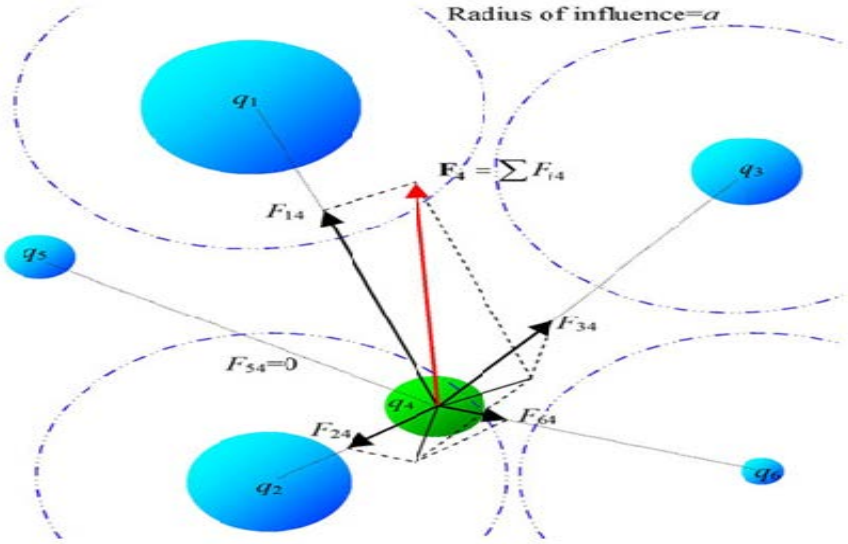

Fig.1 Determining the resultant electrical force acting on a CP

Rule 4 The value of the resultant electrical force acting on a CP is

$$F_j = q_j \sum_{i,i\neq j} \left(\frac{qi}{a^3} r_{ij} \cdot i_1 + \frac{qi}{r_{ij}^2} \cdot i_2\right) p_{ij}(X_i - X_j), \begin{cases} j = 1,2,..,N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq a \end{cases} \quad (30)$$

where Fj is the resultant force acting on the j th CP, as illustrated in Fig. 1.

In this algorithm, each CP is considered as a charged sphere with radius a, which has a uniform volume charge density. In this paper, the magnitude of a is set to unity; however, for more complex examples, the appropriate value for a must be defined considering the size of the search space. One can utilize the following equation as a general formula:

$$a=0.10x\max(\{x_{i,max} - x_{i,min} \mid i = 1,2,..,n\}). \quad (31)$$

According to this rule, in the first iteration where the agents are far from each other the magnitude of the resultant force acting on a CP is inversely proportional to the square of the separation between the particles. Thus the exploration power in this condition is high because of performing more searches in the early iterations. It is necessary to increase the exploitation of the algorithm and to decrease the exploration gradually. After a number of searches where CPs are collected in a small space and the separation between the CPs becomes small, say 0.1, then the resultant force becomes proportional to the separation distance of the particles instead of being inversely proportional to the square of the separation distance. Therefore, the parameter a separates the global search phase and the local search phase, i.e., when majority of the agents are collected in a space with radius a, the global search is finished and the optimizing process is continued by improving the previous results, and thus the local search starts. Besides, using these principles controls the balance between the exploration and the exploitation. It should be noted that this rule considers the competition step of the algorithm. Since the resultant force is proportional to the magnitude of the charge, a better fitness (great qi) can create a stronger attracting force, so the tendency to move toward a good CP becomes more than toward a bad particle.

Rule 5 The new position and velocity of each CP is

$$X_{j,new} = rand_{j1} \cdot k_a \cdot \frac{F_j}{m_j} \cdot \Delta t^2 + rand_{j2} \cdot k_v \cdot V_{j,old} \cdot \Delta t + X_{j,old},$$

(32)

$$V_{j,new} = \frac{X_{j,new} - X_{j,old}}{\Delta t}, \quad (33)$$

Where ka is the acceleration coefficient; kv is the velocity coefficient to control the influence of the previous velocity; and rand j1 and rand j2 are two random numbers uniformly distributed in the range of (0,1). Here, m j is the mass of the jth CP which is equal to $qj \cdot \Delta t$is the time step and is set to unity. The effect of the pervious velocity and the resultant force acting on a CP can be decreased or increased based on the values of the kv and

ka, respectively. Excessive search in the early iterations may improve the exploration ability; however, it must be decreased gradually, as described before. Since ka is the parameter related to the attracting forces, selecting a large value for this parameter may cause a fast convergence and vice versa a small value can increase the computational time. In fact ka t is a control parameter of the exploitation. Therefore, choosing an incremental function can improve the performance of the algorithm. Also, the direction of the pervious velocity of a CP is not necessarily the same as the resultant force. Thus, it can be concluded that the velocity coefficient kv controls the exploration process and therefore a decreasing function can be selected. Thus, kv and ka are defined as,

$$k_v=0.5(1-\text{iter}/\text{iter}_{max}), k_a=0.5(1+\text{iter}/\text{iter}_{max}) \quad (34)$$

Where iter is the actual iteration number and itermax is the maximum number of iterations. With this equation, kv decreases linearly to zero while ka increases to one when the number of iterations rises. In this way, the balance between the exploration and the fast rate of convergence is saved. Considering the values of these parameters, Eqs. (35) and (36) can be rewritten as

$$X_{j,new} = 0.5rand_{j1}\cdot(1+\text{iter}/\text{iter}_{max})\cdot\sum_{i,i\neq j}\left(\frac{qi}{a^3}r_{ij}\cdot i_1+\frac{qi}{r_{ij}^2}\cdot i_2\right)p_{ij}(X_i-x_j)+0.5rand_{j2}\cdot(1+\text{iter}/\text{iter}_{max})\cdot V_{j,old}+X_{j,old} \quad (35)$$

$$V_{j,new}=X_{j,new}-X_{j,old}, \quad (36)$$

Figure 5 illustrates the motion of a CP to its new position using this rule. The rules 5 and 6 provide the cooperation step of the CPs, where agents collaborate with each other by information transferring.

Rule 6 Considering a memory which saves the best CP vectors and their related objective function values can improve the algorithm performance without increasing the computational cost. To fulfill this aim, Charged Memory (CM) is utilized to save a number of the best so far solutions. In this paper, the size of the CM (i.e. CMS) is taken as N/4. Another benefit of the CM consists of utilizing this memory to guide the current CPs. In other words, the vectors stored in the CM can attract current CPs according to Eq. (30). Instead, it is assumed that the same number of the current worst particles cannot attract the others.

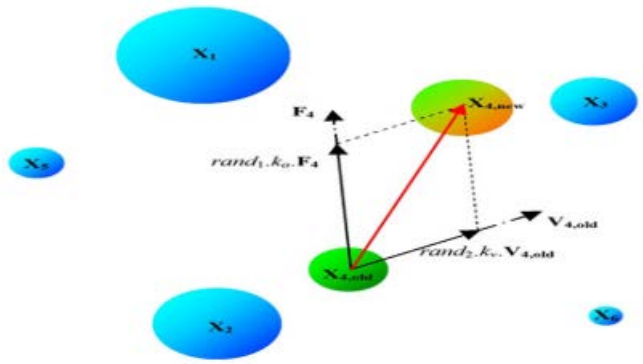

Fig. 2 The movement of a CP to the new position

Rule 7 There are two major problems in relation to many meta-heuristic algorithms; the first problem is the balance between exploration and exploitation in the beginning, during, and at the end of the search, and the second is how to deal with an agent violating the limits of the variables. The first problem is solved naturally through the application of above-stated rules; however, in order to solve the second problem, one of the simplest approaches is utilizing the nearest limit values for the violated variable. Alternatively, one can force the violating particle to return to its previous position, or one can reduce the maximum value of the velocity to allow fewer particles to violate the variable boundaries. Although these approaches are simple, they are not sufficiently efficient and may lead to reduce the exploration of the search space. This problem has previously been addressed and solved using the harmony search-based handling approach [28, 30]. According to this mechanism, any component of the solution vector violating the variable boundaries can be regenerated from the CM as

$$x_{i,j} = \begin{cases} \text{w. p. CMCR} \\ \text{w. p. } (1 - \text{CMCR}) \end{cases} \quad (37)$$

Subject to

⇒Select a new value for a variable from CM

⇒w.p (1-PAR) do nothing

⇒w.p.PAR choose a neighbouring value

⇒select a new value

where “w.p.” is the abbreviation for “with the probability”; xij is the i th component of the CP j ; The CMCR (the Charged Memory Considering Rate) varying between 0 and 1 sets the rate of choosing a value in the new vector from the historic values stored in the CM, and (1 – CMCR)sets the rate of randomly choosing one value from the possible range of values. The pitch adjusting process is performed only after a value is chosen from CM. The value (1−PAR) sets the rate of doing nothing, and PAR sets the rate of choosing a value from neighbouring the best CP.

Rule 8 The terminating criterion is one of the following:

Maximum number of iterations: the optimization process is terminated after a fixed number of iterations, for example, 1,000 iterations. Number of iterations without improvement: the optimization process is terminated after some fixed number of iterations without any improvement. Minimum objective function error: the difference between the values of the best objective function and the global optimum is less than a pre-fixed anticipated threshold. Difference between the best and the worst CPs: the optimization process is stopped if the difference between the objective values of the best and the worst CPs becomes less than a specified accuracy. Maximum distance of CPs: the maximum distance between CPs is less than a pre-fixed value. Now we can

establish a new optimization algorithm utilizing the above rules. The following steps summarize the CSS algorithm:

Level 1: Initialization

Step 1: Initialization. Initialize CSS algorithm parameters; Initialize an array of Charged Particles with random positions and their associated velocities (Rules 1 and 2).

Step 2: CP ranking. Evaluate the values of the fitness function for the CPs, compare with each other and sort increasingly.

Step 3: CM creation. Store CMS number of the first CPs and their related values of the objective function in the CM.

Level 2: Search

Step 1: Attracting force determination.Determine the probability of moving each CP toward others (Rule 3), and calculate the attracting force vector for each CP (Rule 4).

Step 2: Solution construction. Move each CP to the new position and find the velocities (Rule 5).

Step 3: CP position correction. If each CP exits from the allowable search space, correct its position using Rule 7.

Step 4: CP ranking. Evaluate and compare the values of the objective function for the new CPs, and sort them increasingly.

Step 5: CM updating. If some new CP vectors are better than the worst ones in the CM, include the better vectors in the CM and exclude the worst ones from the CM (Rule 6)

Level 3: Terminating criterion controlling

Repeat search level steps until a terminating criterion is satisfied (Rule 8).

5. Simulation Results

The accuracy of the proposed CSS 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 I. TABLE I. RESULTS OF CSS – ORPD OPTIMAL CONTROL VARIABLES

Control variables	Variable setting
V1	1.042
V2	1.043
V5	1.042
V8	1.031
V11	1.002
V13	1.040
T11	1.03
T12	1.01
T15	1.0
T36	1.0
Qc10	4
Qc12	3
Qc15	3
Qc17	0
Qc20	4
Qc23	4
Qc24	2
Qc29	4
Real power loss	4.3058
SVSM	0.2471

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 0.2471 to 0.2483, 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 II. RESULTS OF CSS -VOLTAGE STABILITY CONTROL REACTIVE POWER DISPATCH OPTIMAL CONTROL VARIABLES

Control Variables	Variable Setting
V1	1.044
V2	1.043
V5	1.042
V8	1.032
V11	1.006
V13	1.033
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	4
Qc15	3
Qc17	3
Qc20	0
Qc23	3
Qc24	4
Qc29	4
Real power loss	4.9889
SVSM	0.2483

TABLE III. VOLTAGE STABILITY UNDER CONTINGENCY STATE

Sl.No	Contigency	ORPD Setting	VSCRPD Setting
1	28-27	0.1410	0.1432
2	4-12	0.1658	0.1663
3	1-3	0.1774	0.1772
4	2-4	0.2032	0.2043

TABLE IV. 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 V. COMPARISON OF REAL POWER LOSS

Method	Minimum loss
Evolutionary programming[10]	5.0159
Genetic algorithm[11]	4.665
Real coded GA with Lindex as SVSM[12]	4.568
Real coded genetic algorithm[13]	4.5015
Proposed CSS method	4.3058

6. Conclusion

In this paper a novel approach CSS algorithm used to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied. To handle the mixed variables a flexible representation scheme was proposed. 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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