

League Championship Algorithm (LCA) 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. League championship algorithm (LCA) inspired from the competition of sport teams in a sport league, an algorithm is presented for solving constrained optimization problems. A number of individuals (solutions) as sport teams compete in an artificial league for several weeks (iterations). Based on the league schedule in each week, teams play in pairs and their game outcome is determined in terms of win or loss, given known the playing strength (fitness value) along with the teams' intended formations. Modeling an artificial match analysis, each team devises a new formation/ playing strategy (a new solution) for the next week contest and this process is repeated for a number of seasons (stopping condition). In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms reported those before in literature. Results show that HS is more efficient than others for solution of single-objective ORPD problem.

Keywords: Modal analysis, optimal reactive power, Transmission loss league championship, Meta heuristic, Optimization.



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]. 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 [11]. 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 [12] is used as the indicator of voltage stability.

There are several deterministic algorithms which are efficient to solve constraint optimization problems, such as recursive quadratic programming, projection method and the generalized reduced gradient method [17].

However, efficiency of these methods is under assumptions of differentiability and continuity of the objective functions which may rarely met in real world applications. Beside deterministic algorithms, meta heuristics, e.g., evolution strategies, particle swarm optimization, differential evolution, ant colony optimization etc, which are stochastic optimization techniques do not require any assumption on the objective function.

However, such methods lack a mechanism able to bias efficiently the search towards the feasible region in constrained search spaces. To cover this deficiency, a considerable amount of research has been devoted and a wide variety of approaches have been suggested in the last few

years to handle the constraints efficiently during the search [18], [19].

Inspired from the natural and social phenomena, meta-heuristic algorithms have attracted many researchers from various fields of science in recent years. This interest is by far in applying the existing meta-heuristics for solving real word optimization problems in many fields such as business, industry, engineering, etc.

However, beside all of these applications, occasionally a new meta-heuristic algorithm is introduced that uses a novel metaphor as guide for solving optimization problems.

The League Championship Algorithm (LCA) is a novel algorithm designed based on the metaphor of sporting competitions in sport leagues [20]. LCA can be metaphorically overviewed as follows: a number of individuals making role as sport teams compete in an artificial league for several weeks (iterations).

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.

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

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.

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

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

Where

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

J_R is called the reduced Jacobian matrix of the system.

2.2. Modes of Voltage Instability

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

Let

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

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of JR

Λ = diagonal eigenvalue matrix of JR and

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

From (3) and (6), we have

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

Or

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

Where ξ_i is the i^{th} column right eigenvector and

η the i^{th} row left eigenvector of JR .

The i^{th} 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 j^{th} element of ξ_i .

The corresponding i^{th} modal voltage variation is

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

It is seen that, when the reactive power variation is along the direction of ξ_i the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the i^{th} eigenvalue. In this sense, the magnitude of each eigenvalue λ_i determines the weakness of the corresponding modal voltage. The smaller the magnitude of λ_i , the weaker will be the corresponding modal voltage. If $|\lambda_i| = 0$ the i^{th} modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

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

$$\Delta V = \sum_i \frac{\eta_{ik} \xi_i}{\lambda_i} \quad (12)$$

η_{ik} , k^{th} element of η_1 , therefore, $V-Q$ sensitivity at bus k is:

$$\frac{\partial V_k}{\partial Q_k} = \sum_i \frac{\eta_{ik} \xi_i}{\lambda_i} = \sum_i \frac{P_{ki}}{\lambda_i} \quad (13)$$

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). This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude (V_g), reactive power generation of capacitor bank (Q_{ci}), and transformer tap setting (t_k). Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows.

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.

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

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 θ_{ij} 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.

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

Where n_l is the number of load busses and V_k 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:

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

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

where, n_b 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:

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

Where, n_c , n_g and n_t are numbers of the switchable reactive power sources, generators and transformers. During the simulation process, all constraints satisfied as explained below [15].

4. The League Championship Algorithm

Let us first have a look on the terminology related to team games, especially those terms which will be used metaphorically in LCA. A sports league is an organization that exists to provide a regulated competition for a number of people to compete in a specific sport. League is



generally used to refer to competitions involving team sports, not individual sports. A league championship may be contested in a number of ways. Each team may play every other team a certain number of times. In such a set-up, the team with the best record becomes champion, based on either a strict win-loss-tie system or on a points system where a certain number of points are awarded for a win, loss, or tie, while bonus points might also be added for teams meeting various criteria [21].

Generally each team has a playing style which is realized during the game via team formation. Formations are a method of positioning players on the pitch to allow a team to play according to their pre-set tactics. For example, the most common formations in soccer are variations of 4-4-2, 4-3-3, 3-2-3-2, 5-3-2 and 4-5-1 [22]. Usually each team has a best formation which is often related to the type of players available to the coach. It is vital for a sport team to devise suitable game plans and formations for every match. After each match, coaches analyze their

own game and their next opponent game to plan on how they can develop a style of play to improve on their weaknesses or afford more on their strengths. The analysis also includes the evaluation of opportunities and threats that comes along with the unique dynamics of the team. This kind of match analysis is typically known as strengths/weaknesses/opportunities/threats (SWOT) analysis, which explicitly links internal (strengths and weaknesses) and external factors (opportunities and threats). The SWOT analysis provides a structured approach to conduct the gap analysis. A gap is sometimes spoken of as “the space between where we are and where we want to be”. When the process of identifying gaps includes a deep analysis of the factors that have created the current state of the team, the groundwork has been laid for improvement planning. The gap analysis process can be used to ensure that the improvement process does not jump from identification of problem areas to proposed solutions without understanding the conditions that created the current state of the

team. We can match the above terms to the standard evolutionary terms as follows: “league” stands for the population of solutions; “team i ” stands for the i th solution in the population; “week” stands for “iteration”; “playing strength” stands for the “objective/fitness function value” and “a new formation” stands for “a new solution”. In the remainder of the paper we use both terminologies, alternately. As a pseudo-evolutionary algorithm, the selection in LCA is the greedy selection which consists of always replacing the legacy formation, recognized as the best formation, with a more productive team formation having better playing strength. The algorithm terminates after a certain number of “seasons” (S) in which each season comprises $L-I$ weeks, yielding $S \times (L-I)$ weeks of contests.

Before giving details of LCA, we first put forward several idealized rules which define the characteristics of artificial championship modelled by LCA.

1) It is more likely that a team with better playing strength wins the game. The term

“playing strength” refers to a team’s ability to beat another team.

2) The outcome of the game is not predictable given known playing strength of the teams perfectly.

3) The probability that team i beats team j is assumed equal from both teams point of view.

4) The outcome of the game is only win or loss; there is no tie.

5) When team i beats team j , any strength helped team i to win has a dual weakness caused team j to loss.

6) Teams focus only on their upcoming contest without regards of the other future matches. Formation settings are done just based on the previous week events.

Like many other evolutionary algorithms, LCA works with a population of solutions. Each member of the population is a potential solution that is related to one of teams and is interpreted as the team current formation. Given a function f of n variables, each solution such as i can be

represented with a vector of n real numbers. We can see each variable as one of players where changing in the value of the variables may reflect changing in the job of the relevant player. We use $X_i^t = (x_{i1}^t, x_{i2}^t, \dots, x_{in}^t)$ to address the formation of team i at week t . By $f(x_i^t)$ we address the function value relevant to x_i^t . This value is called the playing strength along with formation x_i^t . by $B_i^t = (b_{i1}^t, b_{i2}^t, \dots, b_{in}^t)$ we address the best formation for team i , experienced till week t . This is the best solution that has been obtained so far for the i th member. To determine B_i^t , a greedy selection is conducted at each iteration between X_i^t and b_i^{t-1} based on the objective values criterion.

4.1. Generating the league schedule

Since LCA mimics the championship in a sport league, it becomes required to schedule matches in the artificial league. A single round-robin schedule is utilized where each team plays every other participant once in each season. For a league of size L , single round robin tournament

requires $L(L-1)/2$ matches, because in each of $(L-1)$ rounds (weeks), $L/2$ matches will be run in parallel (if L is odd, there will be L rounds with $(L-1)/2$ matches, and one team have no game in that round). It is worth mentioning that the round-robin tournament can be modelled as an edge-colouring problem in a diagraph [23].

4.2. Winner/loser recognition

In a regular league system, teams compete on weekends and the outcome in terms of win, loss or tie is determined for each team. The degree of fit is proportional to the team's playing strength and is measured based on the distance with an ideal reference point.

Let us consider team i and j at week t , with formation strategies x_i^t and x_j^t and playing strengths $f(x_i^t)$ and $f(x_j^t)$ respectively. Let p_i^t be the chance of team i to beat team j at week t (can be defined accordingly). Let f^* be an ideal value (e.g., the optimal value or a lower bound on the optimal value). Based on the idealized rule I we can write,

$$\frac{f(x_i^t) - f}{f(x_j^t) - f} = \frac{p_i^t}{p_j^t} \quad (24)$$

In (24) we evaluate the teams based on their distance with a common reference point (the playing strength along with an ideal team formation), and thus the ratio of distances can determine the winning portion for each team. Based on the idealized rule 3 we can also write

$$p_i^t + p_j^t = 1 \quad (25)$$

From (24) and (25) we get

$$p_i^t = \frac{f(x_j^t) - f}{f(x_j^t) + f(x_i^t) - 2f} \quad (26)$$

To simulate the win or loss, a random number in $[0, 1]$ is generated and if it is less than or equal to p_i^t , team i wins and team j losses; otherwise team j wins and team i losses. This procedure is consistent with idealized rule 2 and 4.

4.3. Setting Up a New Team Formation

In LCA, the artificial analysis of the team's previous performance (at week t) is treated as internal evaluation (strengths/weaknesses) and analysis of the opponent's previous performance is accounted as external evaluation (opportunities/threats). In an artificial post match analysis of team i , if it has won (lost) the game from (to) team j at week t , then it is assumed that the prosper (loss) is the direct consequence of the team strengths (weaknesses) or based on the idealized rule 5, it is the direct consequence of the weaknesses (strengths) of team j . Now, based on the league schedule at week $t + 1$, assume that the next match of team i is with team l . If team l has won (lost) the game from (to) team k at week t , then this success (loss) and the team formation behind it might be a direct threat (opportunity) for team i . Apparently, this success (loss) is the result of some strengths (weaknesses). Focusing on the strengths (weaknesses) of team l , gives us an

intuitive way of avoiding the possible threats (affording the opportunities). Instead, based on idealized rule 5, we can focus on weaknesses (strengths) of team k . For example, if team i was winner and team l was loser, then it is reasonable that team i focuses on the strengths which enabled it to win. At the same time it should focus on the weaknesses that caused team l to lose. These weaknesses may open opportunities for team i .

Let us first introduce the following indices:

l = Index of the team that will play with team i based on the league schedule at week $t + 1$.

j = Index of the team that has played with team i based on the league schedule at week t .

k = Index of the team that has played with team l based on the league schedule at week t .

Table 1: Suitable Actions

	i:winner, l:winner Focussing on ..	i:winner, l:loser Focussing on ..	i:winner, l:loser Focussing on ..	i:winner, l:loser Focussing on ..
S	own strengths (or weaknesses of j)	own strengths (or weaknesses of j)	-	-
W	-	-	own weaknesses (or strengths of j)	own weaknesses (or strengths of j)
O	-	weaknesses of l (or strengths of k)	-	weaknesses of l (or strengths of k)
T	strengths of l (or weaknesses of k)	-	strengths of l (or weaknesses of k)	-

Table 1 shows suitable actions for team i when devising its formation for the next match (based on the win/loss states).

Given that normally teams play based on their current best formation (found it suitable over the times) while devising the required

changes recommended by match analysis, therefore we can setup the new formation

$$x_i^{t+1} = (x_{i1}^{t+1}, x_{i2}^{t+1}, \dots, x_{in}^{t+1}) \text{ for team } i \ (i$$

$= 1, \dots, L)$ at week $t+1$. It is rather unusual that coaches do changes in all or many dimensions of the team. Generally the number of changes is relatively low. To simulate the rate of changes (q_i^t) , we use a truncated geometric distribution [24]. Using a truncated geometric distribution, we can set the rate of changes dynamically, while putting more weights on the smaller rate of changes. The following formula gives the smaller rate of changes. The following formula gives the random number of changes made in B_i^t to get the new formation x_i^{t+1}

$$q_i^t = \left\lceil \frac{\ln(1 - (1 - (1 - p_c)^n)r)}{\ln(1 - p_c)} \right\rceil; q_i^t \in \{1, 2, 3, \dots, n\}. \quad (27)$$

Where r is a random number in $[0, 1]$ and $p_c \in (0, 1)$ is an input parameter. Typically p_c is known as the probability of success in the truncated geometric distribution. The larger

the value of p_c , the smaller the number of changes are recommended.

5. The League Championship Algorithm Adapted to Constrained Optimization

To adapt LCA to solve constrained optimization problems, the main idea is to preserve the main LCA structure while adding a mechanism to handle constraints. We use the notion of Deb's constraint handling method [25] in the body of our algorithm. Deb's method uses a tournament selection operator, where two solutions are compared at a time, and the following selection criteria are always enforced:

- (a) Between 2 feasible solutions, the one with better fitness value wins.
- (b) If one solution is feasible and the other one is infeasible, the feasible solution wins.
- (c) If both solutions are infeasible, the one with the

lowest sum of constraint violations is preferred.

In Deb's approach, feasible solutions are always considered better than infeasible ones. Therefore, this approach may have difficulties with problems in which the global optimum lies on the boundary between the feasible and the infeasible regions [26]. To remedy this deficiency, similar to the approach used in [27], we try to preserve diversity by allowing solutions having good value of objective functions remain in the population.

If x_i^t is feasible and x_j^t is infeasible then team i wins the game from j , that is $p_i^t = 0$

Else if x_i^t infeasible and x_j^t is feasible then team j wins the game from i , that is $p_i^t = 0$

Else if x_i^t is feasible and x_j^t is feasible too, then the probability that team i wins the game from j is calculated based on the objective function criterion as follows:

$$p_i^t = \frac{f(x_j^t) - \bar{f}}{f(x_j^t) + f(x_i^t) - 2\bar{f}} \quad (28)$$

Else if is infeasible x_i^t and x_j^t is infeasible too, then the probability that team i wins the game from j is calculated based on the total constraint violations criterion as follows:

$$p_i^t = \frac{cv(x_j^t) - \hat{c}v}{\hat{c}v(x_j^t) + \hat{c}v(x_i^t) - 2\hat{c}v} \quad (29)$$

In (29), $\hat{c}v$ is the lowest value among the total constraint violations values observed so far (similar to the definition of \bar{f}). As soon as the search approaches feasible regions we will have $\hat{c}v = 0$. In order to increase the probability to generate better solutions, each team is allowed to generate a number of alternative formations in each week (multiple offspring are generated) [12]. The number of generated formations (n_f) is a user defined parameter. Among the n_f alternative formations generated for each team, we select one of them based on the sequential using of Deb's criteria with a modification on the third criterion as follows:

If both solutions are infeasible then

If $r \leq T^t$ - The selection is based on conducting the greedy selection between them based on the objective value criterion.

Else

The selection is based on conducting the greedy selection between them based on the total constraint violations criterion.

End if

End if

We do not generate a predefined number of alternative formations (offspring) for each team as used in [12]. Instead we decrease the number of alternative formations systematically at certain milestones. Starting with $n_f = 5$. We decrease n_f by one every time that $\text{mod}(CE, NE/5) = 0$, where CE is the solution counter (CE is increased by one whenever a new solution is generated). Therefore, the algorithm performs its final searches with $n_f = 1$.

6. Simulation Results

The validity of the proposed Algorithm technique is demonstrated on 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 real power settings are taken from [1]. 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.

Table 2: Voltage Stability Under Contingency State

Sl.No	Contingency	ORPD Setting	VscrpD Setting
1	28-27	0.1400	0.1422
2	4-12	0.1658	0.1662
3	1-3	0.1784	0.1754
4	2-4	0.2012	0.2032

Table 3: 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 4: Comparison of Real Power Loss

Method	Minimum loss
Evolutionary programming[13]	5.0159
Genetic algorithm[14]	4.665
Real coded GA with Lindex as SVSM[15]	4.568
Real coded genetic algorithm[16]	4.5015
Proposed LCA method	4.2195

7. Conclusion

In this paper a novel approach LCA 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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