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Improved seeker optimization algorithm-based on artificial bee colony algorithm for solving optimal reactive power dispatch problem

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Abstract
This paper presents a seeker algorithm for solving the multi-objective reactive power dispatch problem. Swarm intelligence algorithms have been productively applied to hard optimization problems. Seeker optimization algorithm is one of the latest members of that class of metaheuristics and the primary type of this algorithm was less successful with multimodal functions. We propose hybridization of the seeker optimization algorithm with artificial bee colony (ABC) algorithm. At certain periods we modify seeker's location by search principles from the ABC algorithm and also adjust the inter-subpopulation learning phase by using the binomial crossover operator. In order to evaluate the efficiency of proposed algorithm, it has been tested in standard IEEE 30 bus system and compared to other specified algorithms.

1. Introduction

Optimal reactive power dispatch problem is one of the hard optimization problems in power systems. The reactive power dispatch problem comprises best employment of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to diminish the loss and to augment the voltage stability of the system. Various scientific methods have been implemented 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 trouble in handling inequality constraints. Recently Global Optimization methods such as genetic algorithms have been projected to solve the reactive power flow problem [8, 9]. In recent years, the problem of voltage stability and voltage collapse has become a major apprehension in power system planning and operation. To augment the voltage stability, voltage magnitudes alone will not be a dependable indicator of how far an operating point is from the collapse point [11]. This paper articulates 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. Genetic algorithm (GA) inspired by Darwin's theory of evolution [13], differential evolution (DE) [14] which is iteratively trying to progress a candidate solution with regard to a given measure of superiority, ant colony optimization (ACO) [15] based on ant colony foraging behaviour, particle swarm optimization (PSO) [16] inspired by the social behaviour of birds or fish, artificial bee colony (ABC) algorithm [17,18] based on honey bees foraging behaviour, and cuckoo search (CS) [19] based on cuckoo bird's

behaviour, are among the most popular metaheuristics which employ a population of individuals trying to solve the problem. Clean versions of these algorithms were later improved to progress the performance of the problems [20-25]. Sometimes they are united and efficaciously used for wide range of problems [26-29]. Karaboga has introduced an artificial bee colony (ABC) algorithm for arithmetical optimization problems [17]. The performance of the ABC algorithm was tested for optimization of multivariable unconstrained functions and the results were compared with GA, PSO and particle swarm inspired evolutionary algorithm (PS-EA) [30]. The results showed that ABC outclasses the other algorithms. Since that time, ABC has been altered by many researchers and has been applied to solve several arithmetical optimization problems [31-34].There are object-oriented software implementations [35], as well as parallelized varieties [36] for unconstrained optimization problems of the ABC. Seeker optimization algorithm (SOA), based on mimicking the act of human searching, is a fresh search algorithm for unconstrained optimization problems [37-42]. In this paper, we plan a hybrid algorithm named improved seeker optimization algorithm (ISOA), which incorporates seeker optimization algorithm (SOA) with artificial bee colony optimization (ABC) algorithm to solve optimal reactive power dispatch problem. The performance of ISOA has been appraised in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

2. Voltage Stability Evaluation

2.1. Modal Analysis for Voltage Stability Evaluation

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

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

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.

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

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

Where

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

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

$$J_R = \xi\wedge\eta \tag{5}$$

Where,
ξ = right eigenvector matrix of J_R
η = left eigenvector matrix of J_R
$\wedge$ = diagonal eigenvalue matrix of J_R and

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

From (3) and (6), we have

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

or

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

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,

$$\Delta Q_{mi} = K_i\xi_i \tag{9}$$

where,

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

Where
ξ_{ji} is the jth element of ξ_i
The corresponding ith modal voltage variation is

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

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

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

η_{1k} k th element of η_1
V –Q sensitivity at bus k

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

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.

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

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 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.

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

Where nl 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:

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

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

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:

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

4. Seeker optimization algorithm

Seeker optimization algorithm (SOA) models the deeds of human search population based on their memory, experience, uncertainty reasoning and communication with each other [37]. Therefore the individual of this population is called seeker or searcher. In the SOA, the total population is equally categorized into three subpopulations according to the directories of the seekers. All the seekers in the same subpopulation constitute a neighbourhood which symbolizes the social component for the social sharing of information.

Seeker *i* has the following attributes: the current Position $x_i = (x_{i1}, x_{i2}, .., x_{iD})$,the dimension of the problem D, the iteration number *t*, the personal best position $p_{i,best}$ so far, and the neighbourhood best position g_{best} so far. The algorithm uses exploration direction and step length to update the positions of seekers. In the SOA, the search direction is determined by seeker's egotistic behaviour, altruistic behaviour and pro-activeness behaviour, while step length is given by ambiguity reasoning behaviour. Search direction α_{ij} and step length d_{ij} are separately computed for each individual *i* on each dimension *j* at each iteration *t*, where $\alpha_{ij} \geq 0$ and $d_{ij} \in \{-1; 0; 1\}$. At each iteration the position of each seeker is modernized by:

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t).d_{ij} \quad (24)$$

Where i = 1,2,.., SN; j = 1,2,..,D (SN is the number of seekers). Also, at each iteration, the current positions of the poorest two individuals of each subpopulation are swapped with the best ones in each of the other two subpopulations, which are called inter-subpopulation learning.

The pseudo-code for the SOA is:

t = 0;

Create SN positions uniformly and arbitrarily in the exploration space;

Appraise all the seekers and save the historical best position;

repeat

Calculate search direction and step length for each seeker;

Modernize each seeker's position

Estimate all the seekers and save the historical best position;

Implement the inter-subpopulation learning operation;

t = t + 1 ;

until t = T_{max}

4.1. Design of the Search Direction

Seeker supportive behaviour types that are modelled are: egoistic, altruistic and pro-active behaviour. Seeker's

behaviour is considered egoistic if he believes that he should go toward his personal best position $p_{i;best}$ through intellectual learning. For reaching the desired goal, by altruistic behaviour, seekers want to communicate with each other and adjust their behaviours in response to other seekers in the same neighbourhood region. If a seeker wants to alter his exploration direction and exhibit goal-directed behaviour according to his previous behaviour, then it is considered that his behaviour is pro-active. The expression for exploration direction d_i, which models these types of behaviour, for the ith seeker is:

$$d_i = \omega.sign(p_{i,best} - x_i) + r_1.(g_{best} - x_i) + r_2.(x_i(t1)) - x_i(t2) \quad (25)$$

Where the function sign ( ) is a signum function on each dimension of the input vector, ω is the inertia weight, $t_1, t_2 \in \{t, t-1, t-2\}$, $x(t1)$ and $x(t2)$ are the best and the worst positions in the set $x(t)$, $x(t-1)$, $x(t-2)$ respectively, and r_1 and r_2 are real numbers chosen consistently and arbitrarily in the range [0,1]. The balance between global and local exploration and exploitation is provided by reducing the value of inertia weight. Here, inertia weight is linearly decreased from 0.9 to 0.1 during a run.

4.2. Design of the Step Size

Fuzzy reasoning is used to produce the step length because the uncertain reasoning of human searching. The ambiguity rule of intelligent search is described as "If {function value is small}, then {search radius is small}". The linear membership function was used for "step length". The vector μ_i which is the grade of membership from cloud model and fuzzy set theory needs to be planned in order to compute the step length. It is inverse proportional to the objective function value of x_i. Hence, the best position so far has the maximum $\mu_{max} = 1.0$,while other positions have a $\mu < 1.0$, and the worst position so far has the minimum μ_{min}The expression is presented as:

$$\mu_i = \mu_{max} - \frac{S-I_i}{S-1}.(\mu_{max} - \mu_{min}) \quad (26)$$

Where S denotes the size of the subpopulation to which the seekers belong, I_i is the sequence number of x_i after sorting the objective function values in ascending order. Besides the vector μ_i we need to calculate vector δ_i by:

$$\delta_i = \omega.abs(x_{max} - x_{min}) \quad (27)$$

Where the absolute value of the input vector as the corresponding output vector is represented by the symbol *abs* (), x_{max} and x_{min} are the positions of the best and the worst seeker in the subpopulation to which the ith seeker belongs, respectively. In order to introduce the arbitrariness in each variable and to progress the local search capability, the following equation is introduced to convert μ_i into a vector with elements as given by:

$$\mu_{ij} = rand(\mu_i, 1), j = 1,2,..,D \quad (28)$$

The equation used for creating the step length α_i for i^{th} seeker is :

$$\alpha_i = \delta_i.\sqrt{-1n(\mu_i)} \quad (29)$$

5. Artificial Bee Colony Algorithm

In ABC algorithm the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. All bees that are presently exploiting a food source are known as employed bees. The number of the employed bees is equal to the number of food sources and an employed bee is allocated to one of the sources. Each food source is a possible solution for the problem and the nectar amount of a food source signifies the quality of the solution represented by the fitness value. Onlookers are those bees that are waiting in the hive for the employed bees to share information about the food sources presently being exploited by them, while scouts are those bees that are penetrating for new food sources arbitrarily. The number of onlooker and employed bees is the same. Onlookers are assigned to a food source based on probability. Like the employed bees, onlookers compute a new solution from its food source. After certain number of cycles, if food source cannot be further developed, it is abandoned and swapped by arbitrarily generated food source. This is called exploration procedure and it is performed by the scout bees. Hence, employed and onlooker bees carry out exploitation procedure, while scout bees perform exploration. Short pseudo code of the ABC algorithm is given below:

Initialize the population of solutions
Calculate the population

$t = 0;$

Repeat
Employed bee phase
Compute probabilities for onlookers
Onlooker bee phase
Scout bee phase
Remember the best solution achieved so far

$t = t + 1;$

Until $t = T_{max}$

In employed bee phase an update procedure is performed for each solution in order to produce a new-fangled solution:

$$v_{ij} = x_{ij} + rand.(x_{ij} - x_{kj}) \quad (30)$$

Where k = 1,2,..,SN, j = 1,2,..,D are arbitrarily chosen indexes, k ≠ i, and rand is a random number between [-1,1] (SN is the number of solutions, D is the dimension of the problem). Then, a grasping selection is done between x_i and v_i, which completes the modernize process. The main dissimilarity between the employed bee phase and the onlooker bee phase is that every solution in the employed bee phase involves the update procedure, while only the selected solutions have the opportunity to update in the onlooker bee phase. An inactive solution refers to a solution that does not change over a certain number of generations. In scout bee

phase one of the most sluggish solutions is selected and swapped by a new arbitrarily created solution.

6. Improves Seeker Optimization Algorithm (ISOA)

Improved seeker optimization algorithm (ISOA) algorithm combines two different solution exploration equations of the ABC algorithm and solution exploration equation of the SOA in order to progress the performance of SOA and ABC algorithms. Also, algorithm implements the modified inter-subpopulation learning using the binomial crossover operator. Therefore, ISOA algorithm has changed the phase of updating seeker's positions and inter-subpopulation learning phase. The initialization phase remained the same as in SOA. Excluding common control parameters (solution number and maximum number of iterations), the ISOA algorithm keeps control parameter *SubpopN* (subpopulation number) from SOA, while it does not include any other control parameter from the ABC algorithm. The introduced modifications are described as follows.

6.1. Adjustment of Updating Seeker's Positions

In the first 55% of iterations the ISOA algorithm is searching for candidate solutions using exploration formula of ABC which is given by Eq. (30). After each candidate solution is formed and then appraised, its performance is compared with the old solution and a greedy selection mechanism is engaged as the selection operation between the old and the new candidate. If the new solution has better function value than the old candidate solution, it swaps the old one in the memory. In the continuing iterations, ISOA chooses between search equation Eq. (24) which is used in SOA and the variant of ABC search equation which can be described as:

$$v_{ij} = \begin{cases} x_{ij} + rand_i.(x_{ij} - x_{kj}), if R_j < 0.5 \\ x_{ij} \qquad , otherwise \end{cases} \tag{31}$$

Where R_j is a random number within [0, 1), *k* is randomly chosen index from the whole population and has to be different from i, and $rand_i$ is a random number between [-1, 1] and j = 1,2, ..,D. The similar search equation is used in the ABC algorithm extended for constrained optimization problems, but the main difference is that in the Eq. (31) the value $rand_i$ is kept fixed for every j = 1,2, ..,D. Also in [32], this modification is used in order to improve the ABC algorithm for the engineering optimization problems. The distinction between the Eq. (30) and the Eq. (31) is in the number of the optimization parameters which will be changed. In the basic ABC, while producing a new solution, v_i, changing only one parameter of the parent solution x_i results in a slow convergence rate. In order to overcome this disadvantage, we set the probability of changing the optimization parameter to 0.5. Also, in these iterations, the greedy selection mechanism is not used between the old and the new candidate solution. Hence, the diversity in the population is increased.

In the SOA search equation which is used in ISOA, the Eq. (27) for calculating vector δ_i is changed. In [38] it has been concluded that the vector δ is a sensitive parameter and that proposed calculation of its values was not suitable for optimization of multimodal functions. In order to overcome this obstacle, δ_i is calculated by:

$$\delta = \omega.abs(x_{max} - x_{rand}) \tag{32}$$

Where x_{rand} are the positions of the seekers in the same subpopulation where the solution *i* belongs. Also, in order to further increase the diversity of the solutions, and the population, in the ISOA algorithm the inertia weight parameter *w* is linearly decreased from 0.9 to 0.7 during a run.

The ISOA included a new control parameter which is called behavior rate (*BR*) in order to select the exploration equation in the following way: if an arbitrary number between [0,1] is less then *BR* the SOA search equation is used, otherwise the Eq. (31) is performed.

6.2. Modification of Inter-Subpopulation Learning

In the modified inter-subpopulation learning the positions of seekers with the lowest objective function values of each subpopulation *l* are united with the positions of seekers with the highest objective function values of (l+t) *mod SubpopN* subpopulations respectively, where t = 1,2,3,.., NSC. *NSC* denotes the number of the worst seekers of each population which are combined with the best seekers. The appropriate seekers are united using the following binomial crossover operator as expressed in:

$$xl_n j_{worst} = \begin{cases} x_{i_j}, best\ , if R_j < 0.5 \\ xl_n j, worst, otherwise \end{cases} \tag{33}$$

In Eq. (33) *Rj* is random number within [0,1],

$xl_n j_{worst}$ is denoted as the jth variable of the nth worst position in the lth subpopulation, $x_{i_j}, best$ is the jth variable of the best position in the ith subpopulation. It can be concluded that in the ISOA algorithm we have two new control parameters in comparison with the original SOA: the behavior rate (BR) and the number of seekers of each subpopulation for combination (NSC). Behavior rate parameter controls which of the exploration equations for producing new population will be used. In the inter-subpopulation learning of SOA it has been noticed that it may not always bring the benefits for multimodal functions since it may attract all agents towards a local optimal solution. Hence, in order to provide better equilibrium between exploitation and exploration capabilities of the algorithm, the described modifications are introduced.

7. Simulation Results

The accuracy of the proposed ISOA Algorithm method is

demonstrated by testing it in 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 ISOA – ORPD optimal control variables*

Control variables	Variable setting
V1	1.041
V2	1.042
V5	1.041
V8	1.030
V11	1.001
V13	1.043
T11	1.02
T12	1.01
T15	1.0
T36	1.0
Qc10	2
Qc12	3
Qc15	3
Qc17	0
Qc20	2
Qc23	3
Qc24	4
Qc29	2
Real power loss	4.2205
SVSM	0.2462

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 0.2462 to 0.2478, an advance in the system voltage stability. 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 ISOA -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	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	4
Qc12	4
Qc15	3
Qc17	4
Qc20	0
Qc23	3
Qc24	3
Qc29	4
Real power loss	4.9990
SVSM	0.2478

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

State variables	limits		ORPD	VSCRPD
	Lower	upper		
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[43]	5.0159
Genetic algorithm[44]	4.665
Real coded GA with Lindex as SVSM[45]	4.568
Real coded genetic algorithm[46]	4.5015
Proposed ISOA method	4.2205

8. Conclusion

In this paper a novel approach ISOA algorithm used to solve optimal reactive power dispatch problem.The effectiveness of the proposed method is validated succesfully by testing it in standard IEEE 30-bus system .The performance of the proposed ISOA algorithm demonstrated through its voltage stability assessment by modal analysis and is effective at various instants following system contingencies.This method given good performance in voltage stability Enhancement and real power loss has been considerably reduced.

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