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Improved Spider Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract: **In this paper improved spider algorithm (ISA) is projected to solve the optimal reactive power dispatch (ORPD) Problem. Stimulated by the societal spiders, we suggest a new Improved Spider Algorithm (ISA) to solve ORPD problem. The structure is chiefly based on the foraging approach of social spiders, which make use of the vibrations spread over the spider web to decide the position of preys. The simulation results demonstrate high-quality performance of ISA in solving an optimal reactive power dispatch problem. The projected algorithm has been tested on IEEE 30 bus system and compared to other specified algorithms. Results show that ISA is more efficient than other algorithms to reduce the real power loss and to enhance the voltage profile index.**

Keywords: **spider algorithm, swarm intelligence, evolutionary computation, optimal reactive power, Transmission loss.**

1. INTRODUCTION

In recent years the optimal reactive power dispatch (ORPD) problem has received huge attention as a result of the enhancement on economy and security of power system operation. Solutions of ORPD problem intend to minimize object functions such as fuel cost, power system loses, etc. while satisfying a number of constraints like limits of bus voltages, tap settings of transformers, reactive and active power of power resources and transmission lines and a number of controllable Variables [1, 2]. In the literature, many methods for solving the ORPD problem have been done up to now. At the beginning, several classical methods such as gradient based [3], interior point [4], linear programming [5] and quadratic programming [6] have been effectively used in order to solve the ORPD problem. However, these methods have some disadvantages in the procedure of solving the complex ORPD problem. Drawbacks of these algorithms can be declared insecure convergence properties, extended execution time, and algorithmic intricacy. In addition, the solution can be trapped in local minima [1, 7]. In order to triumph over these disadvantages, researches have been effectively applied evolutionary and heuristic algorithms such as Genetic Algorithm (GA) [2], Differential Evolution (DE) [8] and Particle Swarm Optimization (PSO) [9]. Voltage stability evaluation using modal analysis [10] is used as the indicator of voltage stability. At present several types of Evolutionary algorithm (EA) have been extensively employed to solve real world combinatorial problems. These algorithms reveal reasonable performance compared with conventional optimization techniques, particularly when applied to solve non-convex optimization problems [11]. In the past decade, swarm intelligence, a fresh kind of evolutionary computing technique, has fascinated much research interest [12]. Swarm intelligence is chiefly concerned with the methodology to model the behaviour of social animals and insects for problem solving. Researchers develop optimization algorithms by mimicking the behaviour of ants, bees, bacteria, fireflies and other organisms. The thrust of creating such algorithms was provided by the rising needs to solve optimization problems that were very complicated or even considered as obdurate. Among all spiders has been a chief research subject in bionic engineering for several years. Conversely, the majority of research interrelated to spiders focused on the simulation of its walking pattern to design robots [13]. A probable motive for this is that a majority of the spiders observed are lonely [14], which means that they spend most of their lives without intermingle with others of their species. Conversely, among the 35 000 spider species observed and described by scientists, some species are societal. These spiders live in groups, e.g. Mallos gregalis and Oecobius civitas. Based on these social spiders, this paper formulates a new global optimization method to solve the ORPD problem. Spiders are air-breathing arthropods. They have eight legs and chelicerae with fangs.

They use an extensive range of different strategies for foraging, and most of them sense prey by sensing vibrations. Spiders have long been known to be very responsive to vibratory stimulation, as vibrations on their webs notify them of the capture of prey. If the vibrations are in a defined range of frequency, spiders attack the vibration source. The social spiders can also distinguish vibrations generated by the prey with ones generated by other spiders [15]. The social spiders submissively receive the vibrations produced by other spiders on the same web to have an apparent view of the web. This is one of the exclusive characteristics which differentiates the social spiders from other organisms as the latter habitually exchange information actively, which decreases the information loss to some degree but augments the energy used for contact [16]. In this paper, enthused by the social behaviour of the social spiders, particularly their foraging behavior, we put forward a new Improved Spider Algorithm (ISA) to solve ORPD problem. The foraging behaviour of the social spider can be explained as the mutual movement of the spiders towards the food source location. The spiders receive and analyses the vibrations proliferated on the web to decide the potential direction of a food source [17]. In this procedure, the spiders help each other to move towards the prey. We exploit this natural behaviour to perform optimization over the search space in ISA. The crowd living phenomenon has been studied intensively in animal behaviour ecology. One of the causes that animals congregate and live together are to augment the possibility of successful foraging and diminish the energy cost in this process [18]. In order to smooth the progress of the analysis of social foraging behaviour, researchers projected two foraging models: information sharing (IS) model [19] and producer-scrounger (PS) model [20]. The individuals below the IS model execute individual searching and look for for opportunity to join other individuals concurrently. In the PS model, the individuals are alienated into leaders and followers. Since there is no leader in social spiders [21], it seems the IS model is more appropriate, and we use this model to manage the searching pattern of ISA. Swarm intelligence algorithms imitate the methods in nature to drive a search for the optimal solution. The performance of ISA 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.

2. VOLTAGE STABILITY EVALUATION

2.1. Modal analysis for voltage stability evaluation

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

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

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

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

J_R is called the reduced Jacobian matrix of the system.

A. Modes of Voltage instability:

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

Let

$J_R = \xi \wedge \eta$ (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 i_{th} column right eigenvector and η the i_{th} row left eigenvector of J_R.

λ_i is the i_{th} eigen value of J_R.

The i_{th} 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 j_{th} 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 k_{th} one being 1. Then,

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

η_{1k} k th element of η_1

V –Q sensitivity at bus k

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

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).

3.1Minimization of Real Power Loss

Minimization of the real power loss (Ploss) in transmission lines of a power system 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, gk 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.

3.2Minimization of Voltage Deviation

Minimization of the Deviations in voltage magnitudes (VD) at load buses 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 Vk is the voltage magnitude at bus k.

3.3System 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, PD and QD 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. IMPROVED SPIDER ALGORITHM

In ISA, we formulate the explore space of the optimization problem as a hyper-dimensional spider web. Every position on the web symbolizes a feasible solution to the optimization problem and all feasible solutions to the problem have equivalent positions on this web. The web as well serves the transmission media of the vibrations created by the spiders. Each spider on the web grasp a position and the quality of the solution is based on the objective function, and characterized by the potential of finding a food source at the position. The spiders can move liberally on the web.

However, they cannot go away from the web as the positions off the web represent infeasible solutions to the optimization problem. When a spider shifts to a new position, it creates a vibration which is propagated over the web. Each vibration holds the information of one spider and other spiders can get the information upon receiving the vibration.

A. Spider

The spiders are the agent of ISA to execute optimization. At the beginning of the algorithm, a pre-defined number of spiders are placed on the web. Each spider (s) holds a memory, storing the following individual information:

1) The location of (s) on the web.

2) The fitness of the present position of (s).

3) The goal vibration of (s) in the previous iteration.

The first two types of information explain the individual situation of (s), while the third type of information is concerned in directing (s) to new-fangled positions.

Based on observations, spiders are found to have very precise senses of vibration. In addition, they can divide different vibrations promulgated on the same web and sense their relevant intensities [21]. In ISA, a spider will create a vibration when it reaches a new-fangled position different from the previous one. The concentration of the vibration is connected with the fitness of the position. The vibration will propagate over the web and other spiders can sense it. In such a way, the spiders on the same web distribute their personal information with others to form a combined social knowledge.

B. Vibration

Vibration is a very significant concept in ISA. It is one of the key characteristics that distinguish ISA from other algorithms. In ISA, we use two properties to describe a vibration, namely the source position and the source concentration of the vibration. The source position is defined by the explore space of the optimization problem, and we define the concentration of a vibration in the range [0, +∞]. Every time a spider moves to a new position, it produces a vibration at its present position. We define the position of spider a at time t as P_a (t), or simply as P_a if the argument is t. We further use I (P_a, P_b , t) to represent the vibration concentration sensed by a spider at position P_b at time t and the source of the vibration is at position P_a. Thus I (P_s, P_s, t) defines the concentration of the vibration created by spider s at the source position. This vibration concentration at the source position is associated with the fitness of this position f (P_s), and we define the concentration value as follows:

$$I(P_s, P_s, t) = \begin{cases} 1/\left(C_{max} - f(P_s)\right) \text{for maximization} \\ 1/(f(P_s) - C_{min}) \text{ for minimization} \end{cases} \qquad (24)$$

Where C_{max} is a confidently large constant selected such that all possible fitness values of the maximization problem are smaller than C_{max}, and C_{min} is a assertively small constant such that all possible fitness values of the minimization problem is larger than C_{min}. Equation (24) guarantees that the probable vibration intensities of any optimization problem are all positive values. It further assurance that a better fitness value, i.e. larger for maximization or smaller for minimization problem, corresponds to larger vibration concentration.

C. Intensity Attenuation

As a form of energy, vibration attenuates over time and distance. This physical occurrence is accounted for in the design of ISA by two equations.

1) Attenuation over Distance: We define the vibration attenuation over distance as follows. We describe the distance between spider a and b as D (P_a,P_b), and the maximum distance between two points in the search space as D_{max}. The description of D_{max} can be problem dependent, and we use the following equation for simplicity:

$$D_{max} = \left\|\bar{x} - \underline{x}\right\|_p, \qquad (25)$$

Where $\bar{x}$ is the upper bound of the search space and $\underline{x}$ is the lower bound of the search space. p indicates that we use p-norm as the technique to compute the distance between spiders, i.e.,

$$D(P_a, P_b) = \|P_a - P_b\|_p \qquad (26)$$

In this paper we use 1-norm or Manhattan norm in distance calculation. If the search space is not constrained, $\bar{x}$ and $\underline{x}$ in Eqn. (25) stand for the upper and lower bound of the initial solution generation space, respectively. With the above definitions, we define the vibration attenuation over distance as follows:

$$I(P_a, P_b, t) = I(P_a, P_a, t) \times \exp\left(-\frac{D(P_a,P_b)}{D_{max} \times r_a}\right), \qquad (27)$$

In the above formula we introduce a user-controlled parameter $r_a \in (0, 1)$. This parameter controls the attenuation rate of the vibration concentration over distance. The larger r_a is, the weaker the attenuation forced on the vibration.

2) Attenuation over Time: We also bring in an equation to model vibration attenuation over time. As the vibration biases other spiders to move, a non-decaying vibration may potentially draw other spiders incessantly, causing the algorithm to converge pre-maturely. So the power of previous vibrations shall be properly attenuated to prevent pre-mature convergence. The vibration attenuation over time is defined as follows:

$$I(P_a(t), P_a(t), t+1) = I(P_a, P_a, t) \times r_a \qquad (28)$$

In each iteration, all vibrations created in the previous iteration are attenuated by the factor r_a. We utilize the same parameter r_a introduced in the vibration attenuation over distance formula for ease of parameter tuning. At time t + 1, the location of spider a may change to $P_a(t + 1)$, but the source position of the vibration remains at $P_a(t)$.

D. Search Pattern

Here we express the above thoughts in terms of an algorithm. There are three phases in ISA: initialize, iteration, and conclusion. These three phases are executed successively. In every run of ISA, we begin with the initialize stage, then execute searching in an iterative manner, and lastly stop the algorithm and output the solutions found. In the initialize stage, the algorithm describes the objective function and its solution space. As the number of spiders remains unchanged during the simulation of ISA, a fixed size memory is allocated to accumulate their information. The location of spiders is arbitrarily created in the explore space, with their fitness values calculated and stored. The target vibration of each spider in the population is set at its current position, and the vibration concentration is zero. This ends the initialize stage and the algorithm starts the iteration stage, which execute the search with the artificial spiders produced. In the iteration phase, a number of iterations are executed by the algorithm. In each iteration, all spiders on the web shift to a new position and calculate their fitness values. The algorithm first computes the fitness values of all the artificial spiders on different positions on the web. Then these spiders generate vibrations at their locations using Equation (24). After all the vibrations are created, the algorithm simulates the propagation method of these vibrations using Equation (27). In this procedure, each spider s will accept pop Size – 1 different vibrations created by other spiders. The received information of these vibrations includes the source position of the vibration and its attenuated concentration. We use V to symbolize these pop Size − 1 vibrations. Upon the receipt of V, s will select the strongest vibration v_{best} from V and compare its strength with the concentration of the target vibration v_{tar} stored in its memory. s will store v_{best} as v_{tar} if the intensity of v_{best} is larger, otherwise the original v_{tar} is preserved.

$$P_s(t+1) = P_s + (P_{tar} - P_s) \odot (1 - R \odot R), \qquad (29)$$

Where ʘ denotes element-wise multiplication. P_{tar} is the vibration source location of the target vibration v_{tar}. R is a vector of arbitrary numbers generated from zero to one uniformly, whose length is weak, and 1 is a vector of one's of length weak. The algorithm repeats this process for all the spiders in pop. To avoid ISA getting stuck in a local optimum, we initiate an artificial spider jump away process. Each spider in pop, right after the arbitrary walk step, has a small probability to decide not to follow its present target and jump away from its current position. The probability is defined using the following equation:

$$P_j = \frac{r_j}{\exp(D(P_s, P_{tar})/D_{max})}, \qquad (30)$$

Where r_j is a user-defined jump away rate parameter. If spider s is chosen to jump away, a new arbitrary position in the explore space is generated and assigned as the new position of s. The last step of the algorithm is to attenuate the concentration of the stored target vibration using Equation (28) and this end the iteration phase. The iteration phase loops until the end criteria are matched. The stop criteria can be defined as the maximum iteration number reached, the maximum CPU time used, the error rate reached, the maximum number of iterations with no development on the best fitness value. After the iteration phase, the algorithm outputs the best solution with the best fitness established.

The above three phases comprise the complete algorithm of ISA.

Algorithm - Improved Spider Algorithm for ORPD problem

1: Assign values to the parameters of ISA.

2: Create the population of spiders pop and allocate memory for them.

3: Initialize v_{tar} for every spider.

4: while stopping criteria not met do

5: for every spider s in pop do

6: compute the fitness value of s.

7: create a vibration at the position of s.

8: end for

9: For every spider s in pop do

10: Compute the concentration of the vibrations V created by other spiders.

11: pick the strongest vibration v_{best} from V .

12: if the concentration of v_{best} is larger than v_{tar} then

13: Gather v_{best} as v_{tar}.

14: end if

15: Carry out a arbitrary walk towards v_{tar}.

16: create a arbitrary number r from [0,1].

17: if $r < p_j$ then

18: allot an arbitrary position to s.

19: end if

20: alleviate the concentration of v_{tar}.

21: end for

22: end while

23: Display Output – when best solution found.

5. SIMULATION RESULTS

The accurateness of the projected ISA 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 ISA – ORPD optimal control variables

Control variables	Variable setting
V1	1.042
V2	1.040
V5	1.040
V8	1.030
V11	1.004
V13	1.040
T11	1.01
T12	1.00
T15	1.01
T36	1.02
Qc10	4
Qc12	2
Qc15	4
Qc17	0
Qc20	4
Qc23	3
Qc24	3
Qc29	3
Real power loss	4.3799
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 concurrently. 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 0.2472, 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 ISA -Voltage Stability Control Reactive Power Dispatch Optimal CONTROL VARIABLES

Control Variables	Variable Setting
V1	1.044
V2	1.043
V5	1.041
V8	1.030
V11	1.004
V13	1.033
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	4
Qc15	4
Qc17	2
Qc20	0
Qc23	4
Qc24	2
Qc29	4
Real power loss	4.9970
SVSM	0.2472

Table 3. Voltage Stability under Contingency State

Sl.No	Contigency	ORPD Setting	VSCRPD Setting
1	28-27	0.1410	0.1427
2	4-12	0.1658	0.1668
3	1-3	0.1774	0.1784
4	2-4	0.2032	0.2047

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[22]	5.0159
Genetic algorithm[23]	4.665
Real coded GA with Lindex as SVSM[24]	4.568
Real coded genetic algorithm[25]	4.5015
Proposed ISA method	4.3799

6. CONCLUSION

In this paper, one of the recently developed stochastic algorithms ISA has been demonstrated and applied to solve optimal reactive power dispatch problem. The problem has been formulated as a constrained optimization problem. Different objective functions have been utilized to minimize real power loss and the voltage profile has been enhanced within the limits. The proposed approach has been tested on the IEEE 30-bus power system and the simulation results indicate the effectiveness and robustness of the proposed algorithm to solve optimal reactive power dispatch problem.

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