Novelty Journals

International Journal of Novel Research in Electrical and Mechanical Engineering
Vol. 1, Issue 1, pp: (13-22), Month: September-December 2014, Available at: www.noveltyjournals.com

Reduction of real power loss by States of Matter Search

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***Abstract*: In this paper, a fresh nature-inspired algorithm called the States of Matter Search (SOMS) is introduced to solve optimal reactive power dispatch problem. The SOMS algorithm is based on the simulation of the states of matter occurrence. In SOMS, individuals follow molecules which interact to each other by using evolutionary operations which are based on the physical principles of the thermal-energy motion mechanism. The algorithm is developed by considering each state of matter atone different exploration–exploitation ratio. The evolutionary process is divided into three phases which emulate the three states of matter: gas, liquid and solid. This method can significantly progress the balance between exploration–exploitation, yet conserving the good search capabilities of an evolutionary approach. The proposed SOMS algorithm has been tested on standard IEEE 30 bus test system and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.**

Keywords: **Evolutionary Algorithm, optimal reactive power, Transmission loss.**

I. INTRODUCTION

Reactive power optimization places a significant role in optimal operation of power systems. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the intricacy in managing inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is projected to increase the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to elucidate the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes **S**tates of Matter Search (SOMS) algorithm to solve reactive power dispatch problem. This algorithm [21] is devised by considering each state of matter at one different exploration–exploitation ratio. Thus, the evolutionary process is divided into three stages which emulate the three states of matter: gas, liquid and solid. At each state, molecules (individuals) exhibit different behaviours. Commencing from the gas state (pure exploration), the algorithm amends the concentrations of exploration and exploitation until the solid state (pure exploitation) is reached. As a result, the method can substantially progress the balance between exploration–exploitation, yet conserving the good search capabilities of an evolutionary approach. The proposed SOMS algorithm has been evaluated on standard IEEE 57, bus test system. The simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

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II. PROBLEM FORMULATION

The OPF problem is considered as a common minimization problem with constraints, and can be written in the following form:

Minimize f(x, u) (1)

Subject to g(x,u)=0 (2)

and

$h(x, u) \leq 0$ (3)

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, .., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \ldots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

III. OBJECTIVE FUNCTION

A. Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be mathematically described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

Where g_k: is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

B. Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (9)$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (10)$$

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C. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L (11)$$

D. Inequality Constraints

The inequality constraints h(x,u) imitate the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (12)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \quad (16)$$

Where N is the total number of buses, N_T is the total number of Transformers; $N_c$is the total number of shunt reactive compensators.

IV. STATES OF MATTER

The matter can take different phases which are commonly known as states. Traditionally, three states of matter are known: solid, liquid, and gas. The differences among such states are based on forces which are exerted among particles composing a material [22].

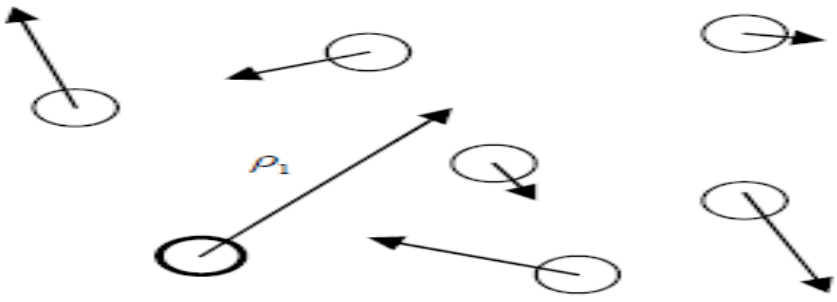

Fig 1(a)

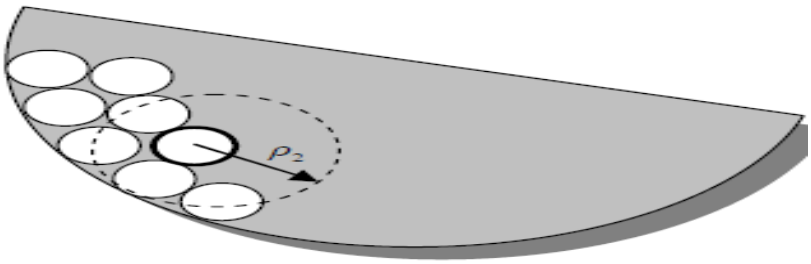

Fig1 (b)

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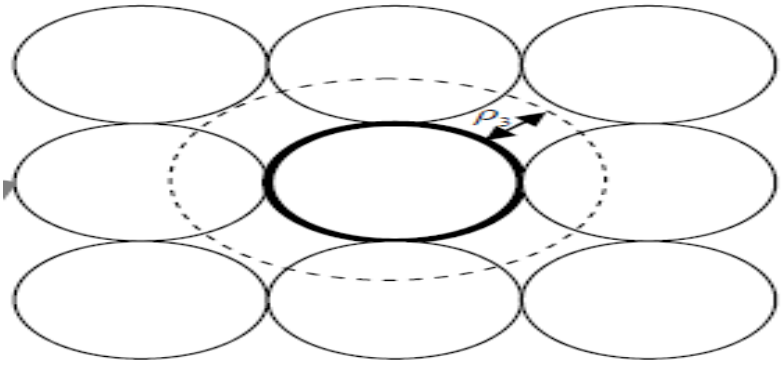

Fig1 (c)

Fig.1. Different states of matter: (a) gas, (b) liquid, and (c) solid.

In the gas phase, molecules present enough kinetic energy so that the effect of intermolecular forces is small (or zero for an ideal gas), while the typical distance between neighboring molecules is greater than the molecular size. A gas has no definite shape or volume, but occupies the entire container in which it is confined. Fig. 1(a)[21] shows the movements exerted by particles in a gas state. The movement experimented by the molecules represent the maximum permissible displacement $\rho 1$ among particles [23]. In a liquid state, intermolecular forces are more restrictive than those in the gas state. The molecules have enough energy to move relatively to each other still keeping a mobile structure. Therefore, the shape of a liquid is not definite but is determined by its container. Fig. 1(b) [21] presents a particle movement $\rho 2$ within a liquid state. Such movement is smaller than those considered by the gas state but larger than the solid state [24]. In the solid state, particles (or molecules) are packed together closely with forces among particles being strong enough so that the particles cannot move freely but only vibrate. As a result, a solid has a stable, definite shape and a definite volume. Solids can only change their shape by force, as when they are broken or cut. Fig. 1(c) [21] shows a molecule configuration in a solid state. Under such conditions, particles are able to vibrate considering a minimal $\rho 3$ distance [23].

V. STATES OF MATTER SEARCH (SOMS)

A. Description of Operators

In the approach, individuals are considered as molecules whose positions on a multidimensional space are modified as the algorithm progresses. The movement of such molecules is driven by the analogy to the motion of thermal-energy. The velocity and direction of each molecule's movement are determined by considering the collision, the attraction forces and the arbitrary phenomena experimented by the molecule set [25]. In our method, such behaviours have been applied by defining several operators such as the direction vector, the collision and the random positions operators, all of which emulate the behaviour of actual physics laws. The direction vector operator allocates a direction to each molecule in order to lead the particle movement as the evolution procedure takes place. On the other side, the collision operator mimics those collisions that are experimented by molecules as they interact to each other. A collision is considered when the distance between two molecules is shorter than a determined proximity distance. The collision operator is thus implemented by interchanging directions of the involved molecules. In order to simulate the arbitrary behaviour of molecules, the proposed algorithm produces arbitrary positions following a probabilistic condition that considers arbitrary locations within a feasible exploration space.

B. Direction vector

The direction vector operator mimics the way in which molecules change their positions as the evolution process develops. For each n-dimensional molecule P_i from the population **P**, it is assigned an n dimensional direction vector d_i which stores the vector that controls the particle movement. Initially, all the direction vectors $\left(D = \left\{d_1, d_2, .., d_{N_p}\right\}\right)$ are randomly chosen within the range of [-1, 1]. As the system evolves, molecules experiment several attraction forces. In

order to simulate such forces, the proposed algorithm implements the attraction phenomenon by moving each molecule towards the bestso-far particle. Therefore, the new direction vector for each molecule is iteratively computed considering the following model:

$$d_i^{k+1} = d_i^k \cdot \left(1 - \frac{k}{gen}\right) \cdot 0.5 + a_i \quad (17)$$

where a_i represents the attraction unitary vector calculated as $a_i = (P^{best} - P_i)/\|P^{best} - P_i\|$, being P^{best} thebest individual seen so-far, while P_i is the molecule i of population **P**. k represents the iteration number ,whereas *gen* involves the total iteration number that constitutes the complete evolution process. Under this operation, each particle is moved towards a new direction which combines the past direction, which was initially computed, with the attraction vector over the best individual seen so-far. It is important to point out that the relative importance of the past direction decreases as the evolving process advances.

In order to calculate the new molecule position, it is necessary to compute the velocity $V_i$of eachmolecule by using:

$$V_i = d_i \cdot v_{init} \quad (18)$$

Beingv_{init} the initial velocity magnitude which is calculated as follows:

$$v_{init} = \frac{\sum_{j=1}^{n}\left(b_j^{high} - b_j^{low}\right)}{n} \cdot \beta \quad (19)$$

whereb_j^{low} and $b_j^{high}$are the low j parameter bound and the upper j parameter bound respectively, whereas $\beta \in [0,1]$.

Then, the new position for each molecule is updated by:

$$P_{i,j}^{k+1} = P_{i,j}^k + v_{i,j} \cdot rand(0,1) \cdot \rho \cdot \left(b_j^{high} - b_j^{low}\right) \quad (20)$$

where $0.5 \leq \rho \leq 1$.

C. Collision

The collision operator mimics the collisions experimented by molecules while they interact to each other. Collisions are calculated if the distance between two molecules is shorter than a determined proximity value. Therefore, if$\|P_i - P_q\| < r$, a collision between molecules i and q is assumed; otherwise, there is no collision, considering $i, q \in \{1, .., N_P\}$such that $\neq q$. If a collision occurs, the direction vector for each particle is modified by interchanging their respective direction vectors as follows:

$$d_i = d_q \; and \; d_q = d_i \quad (21)$$

The collision radius is calculated by:

$$r = \frac{\sum_{j=1}^{n}\left(b_j^{high} - b_j^{low}\right)}{n} \cdot \alpha \quad (22)$$

Where $\alpha \in [0,1]$

Under this operator, a spatial region enclosed within the radius r is assigned to each particle. In case the particle regions collide to each other, the collision operator acts upon particles by forcing them out of the region. The radio r and the collision operator provide the ability to control diversity throughout the search process. In other words, the rate of increase or decrease of diversity is predetermined for each stage. The collision incorporation therefore enhances the exploratory behaviour in the proposed approach.

D. Random positions

In order to simulate the random behaviour of molecules, the proposed algorithm generates random positions following a probabilistic criterion within a feasible search space. For this operation, a uniform random number $r_m$is generated within

the range [0,1]. If $r_m$is smaller than others hold H, a random molecule´s position is generated; otherwise, the element remains with no change. Therefore such operation can be modelled as follows:

$$P_{i,j}^{k+1} = \begin{cases} b_j^{low} + rand(0,1) \cdot \left(b_j^{high} - b_j^{low}\right) with\ probability\ H \\ P_{i,j}^{k+1} with\ porbability\ 1 - H \end{cases} \quad (23)$$

Where $i \in \{1,..,N_P\}$ and $j \in \{1,,.,n\}$

E. Best Element Updating

Despite this updating operator does not belong to State of Matter metaphor, it is used to simply store thebest so-far solution. In order to update the best molecule $\mathbf{p}^{best}$ seen so-far, the best found individual fromthe current k population $\mathbf{p}^{best,k}$is compared to the best individual $\mathbf{p}^{best,k-1}$ of the last generation. If $\mathbf{p}^{best,k}$isbetter than $\mathbf{p}^{best,k-1}$ according to its fitness value, best $\mathbf{p}$ is updated with $\mathbf{p}^{best,k}$, otherwise $\mathbf{p}^{best}$remains withno change. Therefore, $\mathbf{p}^{best}$stores the best historical individual found so-far.

F. General procedure

At each stage, the same operations are implemented. However, depending on which state is referred, theyare employed considering a different parameter configuration. Such procedure is composed by five steps and maps the current population $\mathbf{P}^{k}$to a new population $\mathbf{P}^{k+1}$. The algorithm receives as input the current population $\mathbf{P}^{k}$andthe configuration parametersρ, β, α and H, whereas it yields the new population $\mathbf{P}^{k+1}$.

General procedure:

Step A: Find the best element of the population $P^{best} \in \{P\}$

Step B: Calculate $v_{init}$and r

Step C: Compute the new molecules by using the Direction vector operator.

Step D: Solve collisions by using the Collision operator

Step E: Generate new random positions by using the Random positions operator

G. The complete algorithm

The complete algorithm is divided into four different parts. The first corresponds to the initialization stage, whereas the last three represent the States of Matter. All the optimization process, which consists of a *gen* number of iterations, is organized into three different asymmetric phases, employing 50% of alliterations for the gas state (exploration), 40% for the liquid state (exploration-exploitation) and 10% for the solid state (exploitation).

Initialization

The algorithm begins by initializing a set $\mathbf{P}$ of N_p molecule $\left(P = \{P_1, P_2, .., P_{N_P}\}\right)$each molecule position $\mathbf{p}_i$is an-dimensional vector containing the parameter values to be optimized. Such values are randomly and uniformly distributed between the pre-specified lower initial parameter bound $b_j^{low}$and theupper initial parameter boundb_j^{high}, just as it is described by the following expressions:

$$P_{i,j}^{0} = b_j^{low} + rand(0,1) \cdot \left(b_j^{high} - b_j^{low}\right) \quad (24)$$

j=1,2,..,N , i=1,2,..,N_p

where j and i, are the parameter and molecule index respectively whereas zero indicates the initialpopulation. Hence, P_i^j is the j-th parameter of the i-thmolecule?

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Gas state

In the gas state, molecules experiment severe displacements and collisions. Such state is characterized by random movements produced by non-modelled molecule phenomena. Therefore, the ρ value fromthe direction vector operator is set to a value near to one so that the molecules can travel longer distances. Similarly, the H value representing the random positions operator is also configured to a value around one, in order to allow the random generation for other molecule positions. The gas state is the first phase and lasts for the 50% of all iterations which compose the complete optimization process. The computational procedure for the gas state can be summarized as follows:

Step 1: Set the parameters $\rho \in [0.8, 1]$,$\beta = 0.8$, $\alpha = 0.8$ and H=0.9 being consistent with the gas state.

Step 2: Apply the general procedure

Step 3: If the 50% of the total iteration number is completed ($1 \leq k \leq 0.5 \leq gen$) , then the process continues to the liquid state procedure; otherwise go back to step 2.

Liquid state

Although molecules currently at the liquid state exhibit restricted motion in comparison to the gas state, they still show a higher flexibility with respect to the solid state. Furthermore, the generation of random positions which are produced by non-modelled molecule phenomena is scarce. For this reason, theρ value from the direction vector operator is bounded to a value between 0.3 and 0.6. Similarly, therandom position operator H is configured to a value near to cero in order to allow the random generation of fewer molecule positions. In the liquid state, collisions are also less common than in gas state, so the collision radius that is controlled by is set to a smaller value in comparison to the gas state. The liquid state is the second phase and lasts the 40% of all iterations which compose the complete optimization process. The computational procedure for the liquid state can be summarized as follows:

Step 4: Set the parameters $\rho \in [0.3, 0.6]$, $\beta = 0.4$, $\alpha = 0.2$ and H=0.2 being consistent with the liquid state.

Step 5: Apply the general procedure.

Step 6: If the 90% (50% from the gas state and 40% from the liquid state) of the total iteration number is completed ($0.5 \cdot gen < k \leq 0.9 \cdot gen$), then the process continues to the solid state procedure; otherwise go back to step 5.

Solid state

In the solid state, forces among particles are stronger so that particles cannot move freely but only vibrate. As a result, effects such as collision and generation of random positions are not considered .Therefore the ρ value of the direction vector operator is set to a value near to zero indicating that themolecules can only vibrate around their original positions. The solid state is the third phase and lasts forthe 10% of all iterations which compose the complete optimization process. The computational procedure for the solid state can be summarized as follows:

Step 7: Set the parameters $\rho \in [0.0, 0.1]$ and $\beta = 0.1$,$\alpha = 0$ and H=0 being consistent with the solid state.

Step 8: Apply the general procedure that is defined in Algorithm 1.

Step 9: If the 100% of the total iteration number is completed ($0.9 \cdot gen < k \leq gen$), the process is finished; otherwise go back to step 8.

It is important to clarify that the use of this particular configuration ($\alpha = 0$ and H=0) disables the collision and generation of random positions operators which have been illustrated in the general procedure.

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VI. SIMULATION RESULTS

The validity of the proposed SOMS Algorithm technique has been demonstrated in standard IEEE-30 bus system. The test system has six generators at the buses 1, 2, 5, 8, 11and 13 and four transformers with off-nominal tap ratio at lines6-9, 6-10, 4-12, and 28-27 and the number of the optimized control variables is 10 for this reactive power dispatch problem. The minimum voltage magnitude limits at all buses are 0.95 pu. The maximum limit values for generator buses are 1.1pu &1.05 pu for the remaining buses .The minimum and maximum limits of the transformers tapping are 0.9 and 1.1 pu. The optimum control parameter settings of the proposed SOMS approach are given in Table 1. And table 2&3 shows the comparison of power loss and voltage deviations. Form the simulation, the most excellent value of active power loss is 4.422661. The voltage deviations obtained from proposed SOMS approach 0.103558 respectively.

Table I. Optimum control parameters values

Control Variables setting	Case 1: Power Loss	Case 2: Voltage Deviations
VG1	1.00	0.91
VG2	1.01	0.92
VG5	1.02	1.01
VG8	1.01	1.01
VG11	1.00	1.02
VG13	0.91	1.01
T6-9	1.00	0.90
T6-10	1.01	1.01
T4-12	1.01	1.02
T27-28	1.01	0.91
Power loss (MW)	4.422661	6.279079
Voltage deviations	0.721243	0.103558

Table II: Comparison of the Results for active Power Loss

Control Variables Setting	SOMS	GSA [27]	Individual Optimizations [28]	Multi Objective EA [28]	As Single Objective [28]
VG1	1.02	1.049998	1.050	1.050	1.045
VG2	1.03	1.024637	1.041	1.045	1.042
VG5	1.02	1.025120	1.018	1.024	1.020
VG8	1.01	1.026482	1.017	1.025	1.022
VG11	1.03	1.037116	1.084	1.073	1.057
VG13	0.91	0.985646	1.079	1.088	1.061
T6-9	1.01	1.063478	1.002	1.053	1.074
T6-10	1.02	1.083046	0.951	0.921	0.931
T4-12	1.03	1.100000	0.990	1.014	1.019
T27-28	1.03	1.039730	0.940	0.964	0.966
Power Loss (Mw)	4.422661	4.616657	5.1167	5.1168	5.1630
Voltage Deviations	0.721243	0.836338	0.7438	0.6291	0.3142

Table III: Comparison of the Results for voltage deviations

Control Variables Setting	SOMS	GSA [27]	Individual Optimizations [28]	Multi Objective EA [28]	As Single Objective [28]
VG1	0.90	0.995371	1.009	1.016	1.021
VG2	0.91	0.950069	1.006	1.012	1.021
VG5	1.00	1.043033	1.021	1.018	1.021
VG8	1.02	1.021292	0.998	1.003	1.002
VG11	1.01	1.100000	1.066	1.061	1.025
VG13	1.00	1.062669	1.051	1.034	1.030
T6-9	0.91	0.905907	1.093	1.090	1.045
T6-10	1.02	1.035611	0.904	0.907	0.909
T4-12	1.02	1.038107	1.002	0.970	0.964
T27-28	0.90	0.925607	0.941	0.943	0.941
Power Loss (Mw)	6.279079	6.371609	5.8889	5.6882	5.6474
Voltage Deviations	0.103558	0.106498	0.1435	0.1442	0.1446

VII. CONCLUSION

In this paper, the SOMS has been successfully implemented to solve Optimal Reactive Power Dispatch problem. The proposed algorithm has been tested on the standard IEEE 30-bus system. The results are compared with other heuristic methods and the proposed algorithm demonstrated its effectiveness and robustness in minimization of real power loss and various system control variables are well within the acceptable limits .

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