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CONDITION OF SUBSTANCE SEARCH ALGORITHM FOR SOLVING REACTIVE POWER PROBLEM

Dr.K.Lenin [*1]

[*1] Professor, Department of EEE, Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh -520007, India

Abstract

In this paper, Condition of Substance Search (COS) algorithm is introduced to solve optimal reactive power dispatch problem. The Condition of Substance Search (COS) algorithm is based on the simulation of the shape of substance incidence. In Condition of Substance Search (COS) algorithm, individuals follow molecules which interrelate to each other by using evolutionary operations which are based on the corporal principles of the thermal-energy motion mechanism. The algorithm is developed by considering each condition of substance in harmony with different exploration–exploitation ratio. The evolutionary progression is alienated into three phases which emulate the three condition of substance: solid, liquid & gas. This technique can considerably improve the equilibrium between exploration–exploitation, however preserving the high-quality search ability of an evolutionary approach. The proposed Condition of Substance Search (COS) algorithm has been tested on standard IEEE 30 bus test system and simulation results show clearly the improved performance of the projected Condition of Substance Search (COS) algorithm in reducing the real power loss and voltage stability also enhanced.

Keywords: Condition of Substance Search; Exploration & Exploitation; Optimal Reactive Power; Transmission Loss.

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1. Introduction

In recent years the optimal reactive power dispatch (ORPD) problem has received great attention as a result of the improvement on economy and security of power system operation. Solutions of ORPD problem aim 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. 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

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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 put forward Condition of Substance Search (COS) algorithm to solve reactive power dispatch problem. This algorithm is developed by considering each condition of substance at different exploration–exploitation ratio. Consequently, the evolutionary progression is divided into three phases which imitate the three conditions of matter: gas, liquid and solid. At every condition, molecules (individuals) reveal dissimilar behaviours [21]. Beginning from the gas state (wholesome exploration), the algorithm modify the deliberation of exploration and exploitation until the solid state (wholesome exploitation) is reached. As a result, the process can significantly step forward to balance between exploration–exploitation, however preserving the high-quality exploration ability of an evolutionary approach. Proposed Condition of Substance Search (COS) algorithm has been evaluated on standard IEEE 30 bus test system. The simulation results show that our proposed approach outperforms all the reported standard algorithms in minimization of real power loss & voltage stability enhanced.

2. Voltage Stability Evaluation

2.1. Modal analysis for Voltage Stability Evaluation

Modal analysis is one among best methods for voltage stability enhancement in power systems. The steady state system power flow equations are given by.

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

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.

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To reduce (1), let $\Delta P = 0$, then.

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

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

Where

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

J_R is called the reduced Jacobian matrix of the system.

2.2. Modes of Voltage Instability

Voltage Stability characteristics of the system have been identified by computing the Eigen values and Eigen vectors.

Let

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

Where,

ξ = right eigenvector matrix of JR

η = left eigenvector matrix of JR

$\wedge$ = diagonal eigenvalue matrix of JR and

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

From (5) and (8), we have

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

or

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

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

λi is the ith Eigen value of JR.

The ith modal reactive power variation is,

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

where,

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

Where

ξji is the jth element of ξi

The corresponding ith modal voltage variation is

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

If $|\ \lambda i\ | = 0$ then the ith modal voltage will collapse .

In (10), let $\Delta Q = ek$ where ek has all its elements zero except the kth 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

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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 is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

3.1. Minimization of Real Power Loss

Minimization of the real power loss (Ploss) in transmission lines 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, Vi and Vj are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

3.2. Minimization of Voltage Deviation

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

3.3. System Constraints

Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

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

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

where, nb is the number of buses, PG and QG are the real and reactive power of the generator, PD and QD are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (VGi) inequality constraint:

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

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Load bus voltage (VLi) inequality constraint:

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

Switchable reactive power compensations (QCi) inequality constraint:

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

Reactive power generation (QGi) inequality constraint:

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

Transformers tap setting (Ti) inequality constraint:

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

Transmission line flow (SLi) 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. Condition of Substance

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

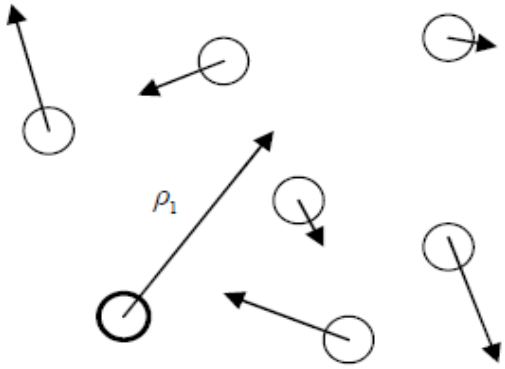

Figure 1(a):

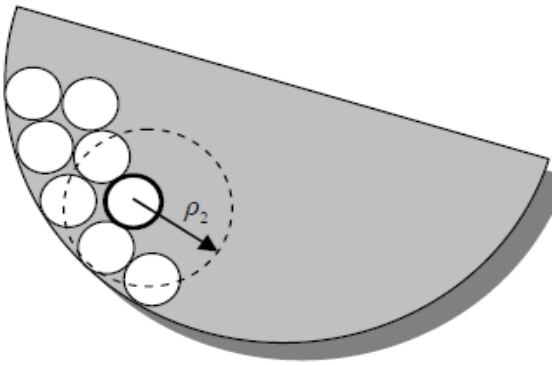

Figure 1(b):

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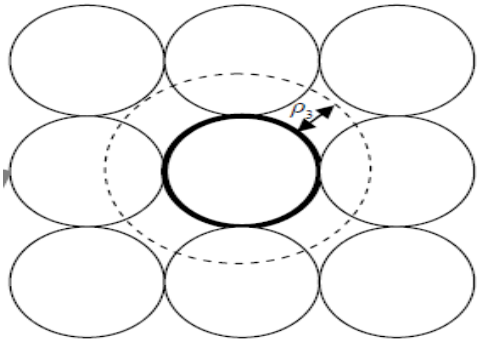

Figure 1(c):
Figure 1: Different condition of substance: (a) gas, (b) liquid, and (c) solid.

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 neighbouring 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].

5. Condition of Substance Search (COS) algorithm

A. Explanation of Functioning

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

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produces arbitrary positions following a probabilistic condition that considers arbitrary locations within a feasible exploration space.

B. Path 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, allthe 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 best so-far particle. Therefore, the new direction vector for each molecule is iteratively computed considering the following model:

$$d_i^{k+1} = d_i^k \cdot \left(1 - \frac{k}{gen}\right) \cdot 0.5 + a_i \quad (24)$$

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:

$$V_i = d_i \cdot v_{init} \quad (25)$$

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

$$v_{init} = \frac{\sum_{j=1}^{n}\left(b_j^{high} - b_j^{low}\right)}{n} \cdot \beta \quad (26)$$

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:

$$P_{i,j}^{k+1} = P_{i,j}^k + v_{i,j} \cdot rand(0,1) \cdot \rho \cdot \left(b_j^{high} - b_j^{low}\right) \quad (27)$$

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$\left\|P_i - P_q\right\| < r$, 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

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collision occurs, the direction vector for each particle is modified by interchanging their respective direction vectors as follows:

$$d_i = d_q \; and \; d_q = d_i \tag{28}$$

The collision radius is calculated by:

$$r = \frac{\sum_{j=1}^{n}\left(b_j^{high} - b_j^{low}\right)}{n} \cdot \alpha \tag{29}$$

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. Arbitrary Location

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 a threshold H, a random molecule´s position is generated; otherwise, the element remains with no change. Therefore such operation can be modelled as follows:

$$P_{i,j}^{k+1} = \begin{cases} b_j^{low} + rand(0,1) \cdot \left(b_j^{high} - b_j^{low}\right) with\ probability\ H \\ P_{i,j}^{k+1} with\ porbability\ 1 - H \end{cases} \tag{30}$$

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

E. Most Excellent Component Modernizing

Despite this updating operator does not belong to condition of substance metaphor, it is used to simply store the best so-far solution. In order to update the best molecule $\mathbf{p}^{\mathbf{best}}$ seen so-far, the best found individual from the current k population $\mathbf{p}^{\mathbf{best,k}}$ is compared to the best individual $\mathbf{p}^{\mathbf{best,k-1}}$ of the last generation. If $\mathbf{p}^{\mathbf{best,k}}$ is better than $\mathbf{p}^{\mathbf{best,k-1}}$ according to its fitness value, best $\mathbf{p}$ is updated with $\mathbf{p}^{\mathbf{best,k}}$, otherwise $\mathbf{p}^{\mathbf{best}}$ remains with no change. Therefore, $\mathbf{p}^{\mathbf{best}}$ stores the best historical individual found so-far.

F. Common Process

At each stage, the same operations are implemented. However, depending on which state is referred, they are 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 $\mathbf{P}^{k}$ and the configuration parameters ρ, β, α and H, where as it yields the new population $\mathbf{P}^{k+1}$**.**

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.

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Step d: Solve collisions by using the Collision operator
Step e: Generate new random positions by using the Random positions operator

G. The Comprehensive Algorithm

The comprehensive algorithm is divided into four different parts. The first corresponds to the initialization stage, whereas the last three represent the condition of substance. 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 **P** of N_p molecule$\left(P = \{P_1, P_2, .., P_{N_P}\}\right)$each moleculeposition $\mathbf{p}_i$is a*n*-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:

$$P_{i,j}^0 = b_j^{low} + rand(0,1) \cdot \left(b_j^{high} - b_j^{low}\right) \quad (31)$$

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

Where j and i, are the parameter and molecule index respectively whereas zero indicates the initial population. Hence, P_i^j is the j-th parameter of the i-th molecule.

Gas Condition

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 from the 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 a: 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 b: Apply the general procedure
Step c: 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 b.

Liquid Condition

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, the ρ value from the direction vector operator is bounded to a value between 0.30 and 0.60. Similarly, the random 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, which is controlled by,

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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 d: 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 e: Apply the general procedure.
Step f: 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 e.

Solid Condition
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 the molecules can only vibrate around their original positions. The solid state is the third phase and lasts for the 10% of all iterations which compose the complete optimization process. The computational procedure for the solid state can be summarized as follows:
Step g: 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 h: Apply common process
Step i: 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 h.
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.

6. Simulation Results

The efficiency of the proposed Condition of Substance Search (COS) algorithm 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 COS – ORPD optimal control variables

Control Variables	Variable Setting
V1	1.047
V2	1.044
V5	1.046
V8	1.033
V11	1.002

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V13	1.036
T11	1.00
T12	1.00
T15	1.01
T36	1.01
Qc10	2
Qc12	3
Qc15	2
Qc17	0
Qc20	2
Qc23	2
Qc24	3
Qc29	2
Real power loss	4.2796
SVSM	0.2486

Optimal Reactive Power Dispatch problem 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 0.2486 to 0.2498, 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 COS -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	**Variable Setting**
V1	1.048
V2	1.047
V5	1.049
V8	1.034
V11	1.005
V13	1.038
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	2
Qc15	2
Qc17	3
Qc20	0
Qc23	2

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Qc24	2
Qc29	3
Real power loss	4.9896
SVSM	0.2498

Table 3: Voltage Stability under Contingency State

Sl.No	Contingency	ORPD Setting	VSCRPD Setting
1	28-27	0.1419	0.1434
2	4-12	0.1642	0.1650
3	1-3	0.1761	0.1772
4	2-4	0.2022	0.2043

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

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Table 5: Comparison of Real Power Loss

Method	Minimum loss
Evolutionary programming [26]	5.0159
Genetic algorithm [27]	4.665
Real coded GA with Lindex as SVSM [28]	4.568
Real coded genetic algorithm [29]	4.5015
Proposed COS method	4.2796

7. Conclusion

In this paper, the Condition of Substance Search (COS) algorithm has been successfully implemented to solve Optimal Reactive Power Dispatch problem. The proposed algorithm has been tested in standard IEEE 30-bus system. The results are compared with other heuristic methods and the proposed Condition of Substance Search (COS) algorithm demonstrated its effectiveness in minimization of real power loss & voltage stability also enhanced. Simulation Results clearly shows various system control variables are well within the acceptable limits.

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*Corresponding author.
E-mail address: gklenin@ gmail.com