Voltage Enhancement and Reduction of Real Power Loss by Particle Swarm Optimization Algorithm Based on Membrane Computing

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***Abstract*—This paper proposes Particle Swarm optimization algorithm based on Membrane Computing (PSOMC) for solving optimal reactive power dispatch problem. PSOMC is designed with the framework and rules of a cell-like P systems, and particle swarm optimization with the neighbourhood search. In order to evaluate the efficiency of the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other specified algorithms. Simulation results show that PSOMC is superior to other algorithms in reducing the real power loss and improving the voltage stability.**

***Index Terms*—membrane computing, particle swarm optimization, optimal reactive power, transmission loss.**

I. Introduction

Power system reliability is related through security, and it refers to stability of service, trustworthiness in frequency and specified voltage limitations. Key assignment is to maintain the voltage profiles within the limits by increase or decrease in reactive power. Choose the ideal parameter of reactive power resources and it is one of the centre ways for the protected function of transmission system. The inadequate regulation of reactive power sources limits the active power transmission, which can be foundation for uncontrolled declined in voltage and tension fall down in the load buses. Optimal reactive power dispatch is one among the key focus for best operation and control of power systems, and it should be carried out appropriately, such that system reliability should not get affected.The gradient method [1], [2], Newton method [3] and linear programming [4]-[7] experience from the difficulty of managing the inequality constraints. In recent times widespread Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8], [9]. This paper presents the reactive power dispatch problem as multi-objective optimization problem with real power loss minimization and maximization of static voltage stability margin (SVSM) .Voltage stability evaluation is done by using modal analysis [10] and it is used as the pointer of voltage stability. Various evolutionary algorithms like evolutionary programming [11], PSO using multiagent [12], cooperative co-evolutionary differential evolution [13], differential evolution [14], learning particle swarm optimization [15], self-adaptive real coded genetic algorithm [16], were developed to solve the ORPD problem. In this paper, Particle Swarm optimization algorithm based on Membrane Computing (PSOMC) for solving optimal reactive power dispatch problem. Membrane computing (P systems) was initiated by Paun [17] in 1998, which is a category of new-fangled computing replica abstracted from the structure and functioning of living cells, as well as from the interactions of living cells in tissues. In recent years, many variant of membrane computing models have been developed rapidly, and also have turned out that membrane computing has an important probable to be applied for variety of computationally hard problems. The performance of PSOMC algorithm has been evaluated in standard IEEE 30 bus test system and the simulation results shows that our proposed method outperforms all approaches investigated in this paper.

II. Voltage Stability Evaluation

A. 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 operational 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.

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

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

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.

B. Modes of Voltage Instability:

Voltage Stability characteristics are computed by the Eigen values and Eigen vectors.
Let

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

where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal Eigen value matrix of J_R and

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

From (3) and (6), 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 ξ_i is the ith column right Eigen vector 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,

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

where,

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

where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

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

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

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

η_{1k} k th element of η_1

V –Q sensitivity at bus k

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

III. Problem Formulation

The objective of the reactive power dispatch problem is to control the real power loss and maximize the static voltage stability margins (SVSM) index.

A. Minimization of Real Power Loss

Minimization of 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, g_k is the conductance of branch k, V_i and V_j are voltage magnitude at bus i and bus j, and θ_{ij} is the voltage angle difference between bus i and bus j.

B. Minimization of Voltage Deviation

Minimization of Deviations in voltage 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 V_k is the voltage magnitude at bus k.

C. System Constraints

Objective functions are subjected to the following constraints ,

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:

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

Load bus voltage (V_{Li}) inequality constraint:

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

Switchable reactive power compensations (Q_{Ci}) inequality constraint:

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

Reactive power generation (Q_{Gi}) inequality constraint:

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

Transformers tap setting (T_i) inequality constraint:

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

Transmission line flow (S_{Li}) inequality constraint:

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

where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

IV. Particle Swarm Optimization Algorithm Based on Membrane Computing

A. Cell-Like P Systems

P systems can be classified into the cell-like P systems, the tissue-like P systems and neural-like P systems [18]. In cell-like P systems, the covering structure is a hierarchical arrangement of membranes embedded in the skin membrane. A membrane without any other membranes within is assumed to be an elementary membrane. Every membrane has an area containing a multi-set of objects and a set of evolutionary rules. The multi-sets of objects progress in each region and move from a region to a neighbouring one by applying the rules in a nondeterministic and maximally similar way.

The membrane structure of a cell-like P system can be formally defined as follows [19].

$$\Pi = (o.T, u, s_1, .., s_n, R_1, ., R_n, i_0) \quad (24)$$

where:

(i) O is the alphabet of objects;

(ii) T is the output alphabet, $T \subseteq O$;

(iii) μ is a membrane structure consisting of n membranes, and the membranes labeled with

1, 2,.., n ; n is called the degree of the system Π ;

(iv) $s_i (1 \leq i \leq n)$ are strings which represent multi-sets over O associated with the region 1, 2,.., n of μ .

(v) $R_i (1 \leq i \leq n)$ are the evolution rules over O^* , R_i is associated with region i of μ , and it is of the following forms.

(a) $[i\ s_1 \rightarrow s_2]$, where $i \in \{1, 2,.., n\}$, and $s_1, s_2 \in o^*$

(Evolution rules: a rule of this type works on a string objects by the local search algorithm or various evolutionary operator, and the new strings object are created in region i .)

(b) $s_1[i] \rightarrow [i\ s_2]_i$,where $i \in \{1, 2,.., n\}$, and $s_1, s_2 \in o^*$.

(Send-in communication rules; a string object is send in the region i .)

(c) $[i\ s_1]_i \rightarrow [i]_i\ s_2$, where $i \in \{1, 2,.., n\}$, and $s_1, s_2 \in o^*$.

(Send-out communication rules; a string object is sent out of the region i .)

(vi) i_o is the output membrane.

A P system, regarded as a model of computation, and is called as membrane algorithm, which is poised of a series of computing steps between configurations. Each calculation starts from the primary configuration, and halts when there are no more rules applicable in any region. In the computing procedure, the system will go from one configuration to a new one by applying the regulations related to regions in a non-deterministic and maximally equivalent manner. The result of the calculation is obtained in region i_o.

The membrane algorithm

Start
Initialize the membrane structure and parameters,
gen=0;
While (Not termination condition) **do**
Evaluate the evolution rules in all elementary membranes;
Determine the fitness by the fitness function;
Perform the communication rules;
Record the current best solution;
gen=*gen*+1;
end while
End start

B. Standard PSO

PSO is a population-based, co-operative search meta-heuristic introduced by Kennedy and Eberhart. The fundament for the development of PSO is hypothesis that a potential solution to an optimization problem is treated as a bird without quality and volume, which is called a particle, coexisting and evolving simultaneously based on knowledge sharing with neighbouring particles. While flying through the problem search space, each particle modifies its velocity to find a better solution (position) by applying its own flying experience (i.e. memory having best position found in the earlier flights) and experience of neighbouring particles (i.e. best-found solution of the population). Particles update their positions and velocities as shown below:

$$v_{t+1}^i = \omega_t . v_t^i + c_1 . R_1 . (p_t^i - x_t^i) + c_2 . R_2 . (p_t^g - x_t^i) \quad (25)$$

$$x_{t+1}^i = x_t^i + v_{t+1}^i \quad (26)$$

where x_t^i represents the current position of particle i in solution space and subscript t indicates an iteration count; p_t^i is the best-found position of particle i up to iteration count t and represents the cognitive contribution to the search velocity v_t^i . Each component of v_t^i can be clamped to the range to control excessive roaming of particles outside the search space; p_t^g is the global best-found position among all particles in the swarm up to iteration count t and forms the social contribution to the velocity vector; r_1 and r_2 are random numbers uniformly distributed in the interval (0,1), wherec_1 andc_2 are the cognitive and social scaling parameters, respectively;ω_t is the particle inertia, which is reduced dynamically to decrease the search area in a gradual fashion . The variable ω_t is updated as

$$\omega_t = (\omega_{max} - \omega_{min}) . \frac{(t_{max} - t)}{t_{max}} + \omega_{min} \quad (27)$$

where ω_{max} and ω_{min} denote the maximum and minimum of ω_t respectively; t_{max} is a given number of maximum iterations. Particle i fly toward a new position according to Eq. (25) and (26). In this way, all particles of the swarm find their new positions and apply these new positions to update their individual best p_t^i points and global best p_t^g of the swarm. This process is repeated until termination conditions are met. In the paper, the velocity equation of PSO is modified as follows.

$$v_{(t+1)}^i = |r_1()| \times \left(Pbest_{ij}(t) - x_{ij}(t)\right) + |r_2()| \times \left(gbest_j(t) - x_{ij} - x_{ij}(t)\right) \quad (28)$$

The procedure of Particle Swarm optimization algorithm based on Membrane Computing (PSOMC) for solving optimal reactive power dispatch problem is described as follows.

Step 1: Initialize membrane structure and X (t), V (t) and Multi-sets are initialized as follows:

$s_0 = \lambda$
$s_1 = b_{1,1} b_{1,2}, .., b_{1,m}$
…
$s_n = b_{n,1} b_{n,2}, .., b_{n,m}$

Step 2: progress rules in each of the region 1 to n are implemented. The particle swarm optimization (PSO) based on Gaussian distribution will be carry out in every elementary membrane concurrently.

Step 3: Implement the send-out communication rules, the strings are sent to skin membrane from each elementary membrane.

Step 4: To improve the disadvantage of the premature convergence problem, the local and global neighbourhood searches are implemented in the skin membrane to improve the ability of exploration and exploitation. The equations of local neighbourhood search are defined as follows

$$LX_i = r_1 \cdot X_i + r_2 \cdot pbest_i + r_3(X_c - X_d) \quad (29)$$

$$LV_i = V_i \quad (30)$$

where X_i is the position vector of the i-th particle, $pbest_i$ is the previous best particle of P_i ; X_c and X_d are the position vectors of two random particles. $c, d \in [i+k, i-k]$.

The equations of global search are shown as follows

$$GX_i = r_4 \cdot X_i + r_5 \cdot pbest_i + r_6\big(X_e - X_f\big) \quad (31)$$

$$GV_i = V_i \quad (32)$$

where *gbest* is the global best particle, X_e and X_f are the position vectors of two random particles chosen from the entire swarm, $e, f \in [1, N]$. r_4, r_5 and r_6 are three uniform random numbers in [0, 1],

Step 5: Determine the fitness of each string object by fitness function, and save the existing best strings;

Step 6: Execute the send-in communication rules between the skin membrane and each elementary membrane concurrently. The detail explanation is as follows.

(i) First, the best strings and m -1 strings with the worst fitness are sent to the elementary membrane 1;

(ii) Subsequently, in the remaining strings, the current best strings and m-1 strings with the worst fitness are sent to the elementary membrane 2;

(iii) The above process is executed constantly until the strings from the skin membrane back to each region;

Step 7: If the stopping condition is met, then output the results; otherwise, return to step 2.

V. Simulation Results

The accuracy of the proposed PSOMC Algorithm 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 Table I, Table II, Table III and Table IV. Table V 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 I. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

TABLE I. Results of PSOMC – 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	4.3519
SVSM	0.2492

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 II 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 0.2492 to 0.2502, an advance in the system voltage stability. The Eigen values equivalents to the four critical contingencies are given in Table III. From this result, it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

TABLE II. Results of PSOMC -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	4.9980
SVSM	0.2502

TABLE III. 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 IV. 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 V. COMPARISON OF REAL POWER LOSS

Method	Minimum loss
Evolutionary programming[20]	5.0159
Genetic algorithm[21]	4.665
Real coded GA with Lindex as SVSM[22]	4.568
Real coded genetic algorithm[23]	4.5015
Proposed PSOMC method	4.3519

VI. CONCLUSION

In this PSOMC algorithm is used to solve optimal reactive power dispatch problem by including various generator constraints. The planned method formulate reactive power dispatch problem as a mixed integer non-linear optimization problem .The performance of the designed algorithm has been established well through its voltage stability evaluation by modal analysis and is effectual at various instants following system contingencies. The efficiency of the proposed method has been demonstrated on IEEE 30-bus system. Simulation results shows that Real power loss has been considerably reduced and voltage profile index within the particular limits.

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