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TAILORED PARTICLE SWARM OPTIMIZATION ALGORITHM FOR SOLVING OPTIMAL REACTIVE POWER PROBLEM

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Abstract

This paper presents Tailored Particle Swarm Optimization (TPSO) algorithm for solving optimal reactive power problem. Particle Swarm optimization algorithm based on Membrane Computing is proposed to solve the problem. Tailored Particle Swarm Optimization (TPSO) algorithm 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 standard IEEE 118 & practical 191 bus test systems and compared to other specified algorithms. Simulation results show that Tailored Particle Swarm Optimization (TPSO) algorithm is superior to other algorithms in reducing the real power loss.

Keywords: Membrane Computing; Particle Swarm Optimization; Optimal Reactive Power; Transmission Loss.

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1. Introduction

The main objective of optimal reactive power problem is to minimize the real power loss and bus voltage deviation. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the complexity in managing inequality constraints. If linear programming is applied then the input- output function has to be uttered as a set of linear functions which mostly lead to loss of accuracy. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is proposed to improve 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 solve 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 evaluate 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 presents Tailored Particle Swarm Optimization (TPSO) algorithm for solving optimal reactive power problem. Particle Swarm optimization algorithm [21] based on Membrane Computing is proposed to solve the problem. Membrane computing (P systems) was initiated by Paun [22] 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 [23,24]. 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. In order to evaluate the efficiency of the proposed algorithm, it has been tested on standard IEEE 118 & practical 191 bus test systems and compared to other specified algorithms. Simulation results show that Tailored Particle Swarm Optimization (TPSO) algorithm is superior to other algorithms in reducing the real power loss.

2. Problem Formulation

2.1. Active Power Loss

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

$$F = PL = \sum_{k\in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \tag{1}$$

Or

$$F = PL = \sum_{i\in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i\neq slack}^{Ng} P_{gi} - P_d \tag{2}$$

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.

2.2. Voltage Profile Improvement

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

$$F = PL + \omega_v \times VD \tag{3}$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \tag{4}$$

2.3. Equality Constraint

The equality constraint of the problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses,

$$P_G = P_D + P_L \tag{5}$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

2.4. Inequality Constraints

The inequality constraints reflect 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:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{6}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} , i \in N_g \tag{7}$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max} , i \in N \tag{8}$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max} , i \in N_T \tag{9}$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max} , i \in N_C \tag{10}$$

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.

3. Particle Swarm Optimization Algorithm Based on Membrane Computing

Particle Swarm optimization algorithm (PSO) based on Membrane Computing is proposed to solve the problem. Tailored Particle Swarm Optimization (TPSO) algorithm designed with the framework and rules of a cell-like P systems, and particle swarm optimization with the neighbourhood search.

3.1. 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. 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,

$$\Pi = (o.T, u, s_1, .., s_n, R_1, ., R_n, i_0) \tag{11}$$

Where;

(i) O is the alphabet of objects;
(ii) T is the output alphabet, $T \subseteq O$;
(iii) $\mu$is a membrane structure consisting of $n$membranes, and the membranes labelled with 1, 2,..,n ; n is called the degree of the system Π ;
(iv) $s_i(1 \leq i \leq n)$are strings which representmulti-sets over O associated with the region 1, 2,.., n ofμ.
(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∈{1, 2,.., n} , and$s_1, s_2 \in o^*$
(Evolution rules: a rule of this type works on astring objects by the local search algorithm or various evolutionary operators, and the new strings object are created in region i.)
(b) $s_1[i] \rightarrow [i\ s_2]_i$,Where i∈{1, 2,.., n} , and$s_1, s_2 \in o^*$.
(Send-in communication rules; a string object is transmitted in the region i.)
(c) $[i\ s_1]_i \rightarrow [i]_i s_2$, where i∈{1, 2,.., n} , and
$s_1, s_2 \in o^*$.
(Send-out communication rules; a string objectis 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 anyregion. 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
```

3.2. Standard PSO

Particle Swarm optimization algorithm (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:

$$v_{t+1}^{i} = \omega_t . v_t^i + c_1 . R_1 . \left(p_t^i - x_t^i\right) + c_2 . R_2 . \left(p_t^g - x_t^i\right) \quad (12)$$

$$x_{t+1}^{i} = x_t^i + v_{t+1}^i \quad (13)$$

Wherex_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^ican 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 and c_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

$$\omega_t = (\omega_{max} - \omega_{min}) . \frac{(t_{max} - t)}{t_{max}} + \omega_{min} \quad (14)$$

Whereω_{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. (12) and (13). 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.

$$v^{i}_{(t+1)} = |r_1()| \times \left(Pbest_{ij}(t) - x_{ij}(t)\right) + |r_2()| \times \left(gbest_j(t) - x_{ij} - x_{ij}(t)\right) \quad (15)$$

The procedure of Particle Swarm optimization algorithm based on Membrane Computing 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:

$s_0 = \lambda$
$s_1 = b_{1,1}b_{1,2}, \ldots, b_{1,m}$
$\ldots$

$s_n = b_{n,1}b_{n,2}, \ldots, b_{n,m}$

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

$$LX_i = r_1 \cdot X_i + r_2 \cdot pbest_i + r_3(X_c - X_d) \quad (16)$$

$$LV_i = V_i \quad (17)$$

Where Xi 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,

$$GX_i = r_4 \cdot X_i + r_5 \cdot pbest_i + r_6\left(X_e - X_f\right) \quad (18)$$

$$GV_i = V_i \quad (19)$$

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 membrane1;
(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 out put the results; otherwise, return to step 2.

4. Simulation Results

At first Tailored Particle Swarm Optimization (TPSO) algorithm has been tested in standard IEEE 118-bus test system [25].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 1, with the change in step of 0.01.

Table 1: Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 2 and the results clearly show the better performance of proposed Tailored Particle Swarm Optimization (TPSO) algorithm.

Table 2: Comparison results

Active power loss (p.u)	**BBO [26]**	**ILSBBO/ strategy1 [26]**	**ILSBBO/ strategy1 [26]**	**Proposed TPSO**
Min	128.77	126.98	124.78	108.02
Max	132.64	137.34	132.39	114.54
Average	130.21	130.37	129.22	110.36

Then the Tailored Particle Swarm Optimization (TPSO) algorithm has been tested in practical 191 test system and the following results have been obtained. In Practical 191 test bus system – Number of Generators = 20, Number of lines = 200, Number of buses = 191 Number of transmission lines = 55. Table 3 shows the optimal control values of practical 191 test system obtained by TPSO method. And table 4 shows the results about the value of the real power loss by obtained by Tailored Particle Swarm Optimization (TPSO) algorithm.

Table 3: Optimal Control values of Practical 191 utility (Indian) system by TPSO method

VG1	1.100		VG 11	0.900
VG 2	0.760		VG 12	1.000
VG 3	1.010		VG 13	1.000
VG 4	1.010		VG 14	0.900
VG 5	1.100		VG 15	1.000
VG 6	1.100		VG 16	1.000
VG 7	1.100		VG 17	0.900
VG 8	1.010		VG 18	1.000
VG 9	1.100		VG 19	1.100
VG 10	1.010		VG 20	1.100

T1	1.000		T21	0.900		T41	0.900
T2	1.000		T22	0.900		T42	0.900
T3	1.000		T23	0.900		T43	0.910
T4	1.100		T24	0.900		T44	0.910
T5	1.000		T25	0.900		T45	0.910
T6	1.000		T26	1.000		T46	0.900
T7	1.000		T27	0.900		T47	0.910
T8	1.010		T28	0.900		T48	1.000
T9	1.000		T29	1.010		T49	0.900
T10	1.000		T30	0.900		T50	0.900
T11	0.900		T31	0.900		T51	0.900
T12	1.000		T32	0.900		T52	0.900
T13	1.010		T33	1.010		T53	1.000
T14	1.010		T34	0.900		T54	0.900
T15	1.010		T35	0.900		T55	0.900
T19	1.020		T39	0.900			
T20	1.010		T40	0.900			

Table 4: Optimum real power loss values obtained for practical 191 utility (Indian) system by TPSO method

Real power Loss (MW)	**TPSO**
Min	132.014
Max	138.002
Average	136.078

5. Conclusion

In this paper Tailored Particle Swarm Optimization (TPSO) algorithm successfully solved optimal reactive power problem. Particle Swarm optimization algorithm based on Membrane Computing is proposed to solve the problem. Tailored Particle Swarm Optimization (TPSO) algorithm 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 standard IEEE 118 & practical 191 bus test systems and compared to other specified algorithms. Simulation results show that Tailored Particle Swarm Optimization (TPSO) algorithm is superior to other algorithms in reducing the real power loss.

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