A Particle Swarm Optimization for Reactive Power and Voltage Control in Electric Power Systems

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Abstract - This paper presents a particle swarm optimization (PSO) for reactive power and voltage control (RPVC) in electric power systems. RPVC can be formulated as a mixed-integer nonlinear optimization problem (MINLP). The proposed method expands the original PSO to handle a MINLP and determines an RPVC strategy with continuous and discrete control variables such as automatic voltage regulator (AVR) operating values of generators, tap positions of on-load tap changer (OLTC) of transformers, and the number of reactive power compensation equipment (RPCE). The feasibility of the proposed method is demonstrated and compared with reactive tabu search (RTS) and the enumeration method on practical power system models with promising results.

1. Introduction

One of the important operating tasks of electric power utilities is to keep voltage within an allowable range for high quality customer services. Electric power loads vary from hour to hour and voltage can be varied by change of the power load. Power utility operators in control centers handle various equipment such as generators, transformers, static condenser (SC), and shunt reactor (ShR), so that they can inject reactive power and control voltage directly in target power systems in order to follow the load change. RPVC determines an on-line control strategy for keeping voltage of target power systems considering the load change and reactive power balance in target power systems.

Current practical RPVC in control centers is often realized based on electric power flow sensitivity analysis of the operation point using limited execution time and available data from the actual target power system. Reduction of power generation cost is one of the current interested issues of electric power utilities under the current de-regulated environment of electric power systems. Therefore, an optimal control to minimize power transmission loss is required for RPVC instead of simple power flow sensitivity analysis.

RPVC can be formulated as a MINLP with continuous state variables such as AVR operating values and discrete state variables such as OLTC tap positions and the number of reactive power compensation equipment such like SC and ShR. Conventionally, the methods for RPVC problem have been developed using various methods such as fuzzy, expert system, mathematical programming, and sensitivity analysis [1-6]. However, a practical method for a RPVC problem formulated as a MINLP with continuous and discrete state variables has been eagerly awaited.

PSO is one of the evolutionary computation (EC) techniques [7]. The method is improved and applied to various problems [8-11]. The original method is able to handle continuous state variables easily. Moreover, the method can be expanded to handle both continuous and discrete variables easily as shown in this paper. Therefore, the method can be applicable to RPVC formulated as a MINLP. Various methods have been developed for a MINLP such as generalized benders decomposition (GBD) [12] and OA/ER [13]. Using the conventional methods, whole problem is usually divided to sub-problems and various methods have to be utilized for solving each sub-problem. On the contrary, PSO can handle the whole MINLP easily and naturally and it is easy to apply to various problems compared with the conventional methods. Moreover, RPVC requires various constraints that are difficult to be handled by mathematical ways. PSO is expected to be suitable for RPVC because it can handle such constraints easily.

This paper presents a PSO for RPVC formulated as a MINLP. The feasibility of the proposed method for RPVC is demonstrated and compared with RTS [14][15] and the enumeration method on practical system models with promising results.

2. Problem Formulation of RPVC

2.1 Problem Formulation

RPVC for a normal power system condition can be formulated as follows:

$$\text{minimize} \quad f_c(x, y) = \sum_{i=1}^{n} Loss_i \tag{1}$$

where, n: the number of branches,
x: *continuous* variables,
y: *discrete* variables,
$Loss_i$: power loss (ploss) at branch i,
subject to
(a) Voltage constraint

Voltage magnitude at each node must lie within its permissible range to maintain power quality.

(b) Power flow constraint

Power flow of each branch must lie within its permissible range.

Ploss of the target power system can be calculated for a certain RPVC strategy using load flow calculation [16] with both continuous variables (AVR operating values) and discrete variables (OLTC tap positions and the number of reactive power compensation equipment). Voltage and power flow constraints can be checked by the load flow calculation results, and penalty values are added if the constraints are violated. Practically, voltage security assessment (VSA) should be considered in RPVC as well [17].

2.2 State Variables

The following control equipment is considered in the RPVC problem.

(a) AVR operating values (*continuous* variable)
(b) OLTC tap position (*discrete* variable)
(c) The number of RPCE (*discrete* variable)

The above state variables are treated in load flow calculation as follows:

AVR operating values - voltage specification values,
OLTC tap positions - tap ratio to each tap position,
The number of RPCE - corresponding susceptance values.

3. Expansion of Particle Swarm Optimization for MINLP

PSO has been developed through simulation of simplified social models. The features of the method are as follows:

(a) The method is based on researches about swarms such as fish schooling and a flock of birds.
(b) It is based on a simple concept. Therefore, the computation time is short and it requires few memories.

According to the research results for a flock of birds, birds find food by flocking (not by each individual). The observation leads the assumption that every information is shared inside flocking. Moreover, according to observation of behavior of human groups, behavior of each individual (agent) is also based on behavior patterns authorized by the groups such as customs and other behavior patterns according to the experiences by each individual. The assumption is a basic concept of PSO. PSO is basically developed through simulation of a flock of birds in two-dimension space. The position of each agent is represented by XY-axis position and the velocity (displacement vector) is expressed by vx (the velocity of X-axis) and vy (the velocity of Y-axis). Modification of the agent position is realized by using the position and the velocity information.

Searching procedures by PSO based on the above concept can be described as follows: a flock of agents optimizes a certain objective function. Each agent knows its best value so far (pbest) and its XY position. Moreover, each agent knows the best value in the group (gbest) among pbests, namely the best value so far of the group. The modified velocity of each agent can be calculated using the current velocity and the distance from pbest and gbest as shown below:

$$v_i^{k+1} = w_i v_i^k + c_1 rand \times (pbest_i - s_i^k) + c_2 rand \times (gbest - s_i^k) \qquad (2)$$

where,

v_i^k	: current velocity of agent i at iteration k,
v_i^{k+1}	: modified velocity of agent i,
rand	: random number between 0 and 1,
s_i^k	: current position of agent i at iteration k,
$pbest_i$	: pbest of agent i,
gbest	: gbest of the group,
w_i	: weight function for velocity of agent i,
c_i	: weight coefficients for each term.

Using the above equation, a certain velocity that gradually gets close to pbests and gbest can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \qquad (3)$$

Fig. 1 shows the above concept of modification of searching points.

Discrete variables can be handled in (2) and (3) with little modification. The whole calculation of the right-hand side (RHS) of (2) can be discritized to the existing discrete number. Namely, the existing discrete number can be utilized for v_i^k, $pbest_i$, gbest, s_i^k, rand, and each calculated term. Then, if we utilize the original continuous equations for continuous variables and the discritized equations for discrete variables, both continuous and discrete variables can be handled in the algorithm with no inconsistency.

The features of the searching procedure can be summarized as follows:

(a) PSO utilizes several searching points like genetic algorithm (GA) and the searching points gradually get close to the optimal point using their pbests and the gbest.
(b) The first term of RHS of (2) is corresponding to diversification in the search procedure. The second and third terms of that are corresponding to intensification in the search procedure. Namely, the method has a well-balanced mechanism to utilize diversification and intensification in the search procedure efficiently.
(c) The original PSO can be applied to the only continuous problem. However, the method can be easily expanded to the discrete problem using discrete numbers like grids for XY position and its velocity.
(d) There is no inconsistency in searching procedures even if both continuous and discrete state variables are utilized

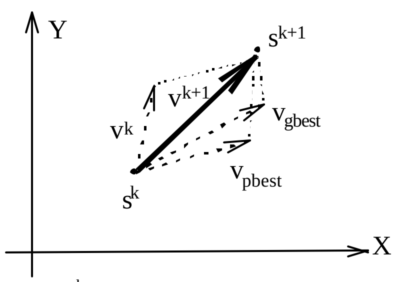
with both continuous and discrete axes for XY positions and velocities. Namely, the method can be applied to a MINLP with both continuous and discrete state variables naturally and easily.

(e) The above concept is explained using only XY-axis (two-dimension space). However, the method can be easily applied to n-dimension problem.

The above feature (b) can be explained as follows [8]. The RHS of (2) consists of three terms. The first term is the previous velocity of the agent. The second and third terms are utilized to change the velocity of the agent. Without the second and third terms, the agent will keep on "flying" in the same direction until it hits the boundary. Namely, it tries to explore new areas and, therefore, the first term is corresponding to diversification in the search procedure. On the other hand, without the first term, the velocity of the "flying" agent is only determined by using its current position and its best positions in history. Namely, the agents will try to converge to the their pbests and/or gbest and, therefore, the terms are corresponding to intensification in the search procedure. The concept of the expanded PSO for MINLP is shown in fig. 2. PSO has been also expanded using the concept of selection to obtain high quality solutions [11].

4. Formulation of RPVC Using PSO

4.1 Treatment of State Variables



s^k : current searching point,
s^{k+1} : modified searching point,
V^k : current velocity,
V^{k+1} : modified velocity,
V_{pbest}: velocity based on pbest
V_{gbest} :velocity based on gbest

Fig.1 Concept of modification of a searching point.

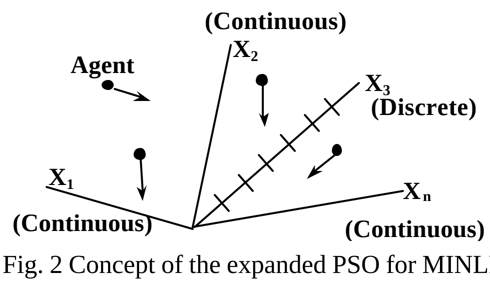


Fig. 2 Concept of the expanded PSO for MINLP in n-dimension space.

Each variable can be treated in PSO as follows.

(1) AVR

Initial AVR operating values are generated randomly between upper and lower bounds of the voltage specification values. The value is also modified in the search procedure between the bounds.

(2) OLTC

OLTC tap position is initially generated randomly between the minimum and maximum tap positions. The value is modified in the search procedure among existing tap positions. Then, the corresponding impedance of the transformer is calculated for the load flow calculation.

(3) RPCE

The number of reactive power compensation equipment is also generated from 0 to the number of existing equipment at the substation initially. The value is also modified in the search procedure between 0 and the number of existing equipment.

4.2 RPVC algorithm using PSO

The proposed RPVC algorithm using the PSO expanded for MINLP can be expressed as follows:

Step 1. Initial searching points and velocities of agents are generated using the above-mentioned state variables randomly.

Step 2. Ploss to the searching points for each agent is calculated using the load flow calculation. If the constraints are violated, the penalty is added to the loss (evaluation value of agent).

Step 3. Pbest is set to each initial searching point. The initial best evaluated value (loss with penalty) among pbests is set to gbest.

Step 4. New velocities are calculated using (2). The continuous equations are utilized for continuous variables and the discrete equations for discrete variables.

Step 5. New searching points are calculated using (3). The continuous equations are utilized for continuous variables and the discrete equations for discrete variables.

Step 6. Ploss to the new searching points and the evaluation values are calculated.

Step 7. If the evaluation value of each agent is better than the previous pbest, the value is set to pbest. If the best pbest is better than gbest, the value is set to gbest. All of gbests are stored as candidates for the final control strategy.

Step 8. If the iteration number reaches the maximum iteration number, then stop. Otherwise, go to Step 4.

If the voltage and power flow constraints are violated, the absolute violated value from the maximum and minimum boundaries is largely weighted and added to the objective function (1) as a penalty term. The maximum iteration number should be determined by pre-simulation. As mentioned below, PSO requires less than 100 iterations even for large-scale problems.

5. Numerical Examples

The proposed method has been applied to several power system models compared with RTS and the enumeration method.

5.1 IEEE 14 bus standard system

(1) Simulation conditions

Fig. 3 shows a modified IEEE 14 bus system. Table 1 shows the operating conditions of the system. The followings are control variables:

(a) *Continuous* AVR operating values of generators and synchronous compensators at node 2,3,6, and 8: Upper and lower bounds are 0.9 and 1.1 [pu].

(b) *Discrete* tap positions of transformers between node 4-7, 4-9, and 5-6: These transformers are assumed to have 20 tap positions.

(c) *Discrete* number of installed SC in node 9 and 14: Each node is assumed to have three 0.06 [pu] SC.

The proposed method tries to generate an optimal control for the operating conditions. Ploss of the original system is 0.1349 [pu]. Generation of the RPVC strategy by the proposed PSO based method, RTS, and the enumeration method is compared in the simulation. The following parameters are utilized in the simulation according to the pre-simulation.

The coefficient function w of (2) is set to the following equation [8]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \qquad (4)$$

where, w_{max}=0.9, w_{min}=0.4,
$iter_{max}$: maximum iteration number,
iter : current iteration number.

c_1 and c_2 of (2) are set to 2.0. w_{max} and w_{min} are set to 0.9 and 0.4 according to the pre-simulation as shown below. Number of agents for PSO is 10. The parameters for RTS are also determined to appropriate values through pre-simulation. The initial tabu length is 10 and increase/decrease rate for tabu length is 0.2 for RTS in the simulation. The results are compared with 300 searching iterations. RTS and the enumeration method utilizes digitized AVR operating values and the interval is 0.01 [pu]. The interval corresponds to 5 [kV] in 500 [kV] system. The formulation as the combinatorial optimization problem (COP) has about 10^9 combinations in the problem. The system has been developed using C language (egsc ver.1.1.1) and all simulation is performed using EWS (SPECint95: 12.3).

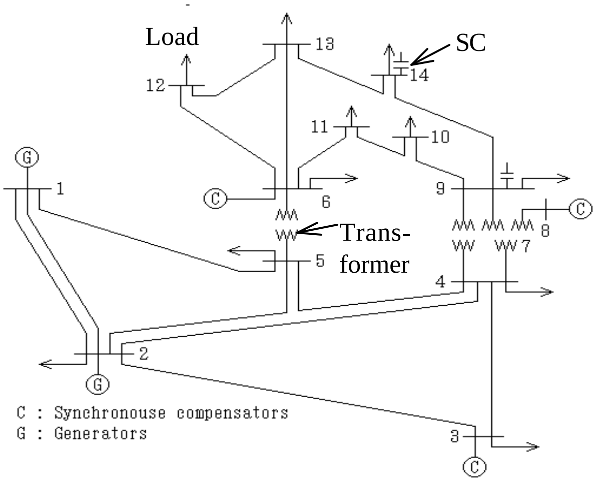


Fig. 3 A modified IEEE 14 bus system.

(2) Simulation results

Table 2 shows the best results by the proposed method, RTS, and the enumeration method. Table 3 shows the loss values and calculation time of the results. The best result by RTS is similar to that by the enumeration method (the optimal result formulated as a COP). However, the loss value calculated by PSO is smaller than the optimal value and a tap position is different between the results. When RPVC is formulated as a COP, only solutions to discrete values are searched and the objective function shape between the discretized interval is out of concern. Therefore, as it is usually pointed out, the optimal solution formulated as a MINLP and a COP is different. The results indicate necessity of formulation of RPVC as a MINLP. PSO can generate smaller loss values than RTS with 15 % possibility. The calculation time by PSO is about 15 % faster than that by RTS. Table 4 shows the parameter sensitivity analysis of PSO. In the simulation, w_{max} and w_{min} of (4) and c_i of (2) is changed. The average and minimum Ploss with 100 searching iterations in 100 trials for each case are shown in the table. The results reveal that the appropriate values for w_{max} and w_{min} are 0.9 and 0.4. The appropriate value for c_i is 1.5. However, the minimum Ploss for

Table 1 Operating conditions of IEEE 14 bus system.

Bus No.	Vol. [pu]	Node specification		SC [pu]
		P [pu]	Q [pu]	
1*1	1.060	-	-	0.0
2*2	1.045	-0.183	0.127	0.0
3*2	1.010	0.942	0.190	0.0
4		0.478	-0.039	0.0
5		0.076	0.016	0.0
6*2	1.070	0.112	0.075	0.0
7		0.000	0.000	0.0
8*2	1.090	0.000	0.000	0.0
9		0.295	0.166	0.18*3
10		0.090	0.058	0.0
11		0.035	0.018	0.0
12		0.061	0.016	0.0
13		0.135	0.058	0.0
14		0.149	0.050	0.18*3

*1 : Node 1 is slack
*2 : PV specification node
*3 : 0.06 [pu] * 3 SC

1.5, 2.0, and 2.5 are similar and 2.0 is utilized in the simulation according to the suggested value in [8]. Consequently, the appropriate parameter values for the problem are the same as the ones suggested in [8].

5.2 Practical 112 bus model system

(1) Simulation conditions

The proposed method is applied to a practical model system with 112 buses. The model system has 11 generators for AVR control, 47 OLTCs with 9 to 27 tap positions, and 13 SC installed buses with 33 SCs for RPVC. The number of agents for PSO is set to 30 in order to get a high quality solution within 1 [min]. PSO and RTS are compared in 100 searching iterations. The same parameters for IEEE 14 bus system except the above values are utilized in the simulation.

Table 2 The optimal control for IEEE 14 bus system.

Method / Cont. Variables	PSO	RTS	enumeration method
AVR 2	1.0463	1.05	1.05
AVR 3	1.0165	1.02	1.02
AVR 6	1.1000	1.10	1.10
AVR 8	1.1000	1.10	1.10
Tap 4-7	0.94	0.95	0.95
Tap 4-9	0.93	0.93	0.93
Tap 5-6	0.97	0.97	0.97
SC 9	0.18	0.18	0.18
SC 14	0.06	0.06	0.06

AVR 2 : AVR operating values [pu] at node 2
Tap 4 - 7 : Tap ratio between node 4 and 7
SC 9 : Susceptance [pu] at node 9

Table 3 Summary of calculation results by the proposed method and reactive tabu search.

Method	compared item	IEEE 14 bus system	112 bus system
PSO	Minimum loss value	0.1332276	0.1134947
	Average loss value	0.1335090	0.1175230
	Cal. Time	16.5	54.2
RTS	Minimum loss value	0.1323657	0.1208179
	Cal. Time	19.5	220.3

loss value : active power loss [pu]
cal. time : average calculation time [s]

(2) Simulation results

Fig. 5 shows the statistical evaluation results by the proposed method in 100 trials. Table 3 shows the loss values and calculation time of the results. The average loss value by the proposed method is smaller than the best result by RTS. PSO generates better solutions than RTS with 96 % possibility. Fig. 6 shows typical convergence characteristics (Ploss transition of gbest by PSO and the best result by RTS). It is clear from the figure that the solution by PSO is converged to high quality solutions at the early iterations (about 20 iterations). The average iteration to the best solution by the proposed method is 31.7. On the contrary, RTS reaches the best solution gradually. The average calculation time by PSO is about 4 times faster than that by RTS. RTS generates neighboring solutions (candidates for the next searching point) in the solution space. It performs load flow calculation for each candidate and evaluates violation of operating constraints and tabu status for all candidates. Therefore, candidates that should be evaluated are increased exponentially as the dimension of the problem increases. On the contrary, PSO just evaluate (2) and (3) for each agent and the number of load flow calculation is the same for IEEE14 and practical 112 bus system if the same number of agents are utilized for the simulation. The characteristic of PSO is suitable for the application to practical system.

5.3 Large-scale 1217 bus model system

(1) Simulation conditions

In order to evaluate the applicability of the proposed method to large-scale systems, it has been applied to a 1217 bus system. The system has 84 generators for AVR control, 388 OLTCs, and 82 SCs for RPVC. The parameters for evaluated methods are the same as that utilized for the 112 bus model system.

(2) Simulation results

Convergence characteristics for the 1217 bus system by RTS and PSO are the same as Fig. 6. RTS requires about 7.6 [hour] for 100 iterations. On the contrary, the average execution time for obtaining the optimal results (the average

Table 4 Parameter sensitivity analysis for IEEE 14 bus system (100 trials).

w_{max} / w_{min}		c_i = 0.5	1.0	1.5	2.0	2.5	3.0	4.0
0.9	ave.	0.133693	0.133573	0.133763	0.133567	0.133765	0.133986	0.134504
0.4	min.	0.133012	0.133012	0.133012	0.133012	0.133012	0.133073	0.133076
2.0	ave.	0.135519	0.135689	0.136362	0.136324	0.135763	0.136425	0.136245
0.9	min.	0.133074	0.133073	0.133073	0.133121	0.133083	0.133125	0.133315
2.0	ave.	0.134987	0.135226	0.13604	0.135661	0.135457	0.135795	0.136435
0.4	min.	0.133015	0.133012	0.133012	0.133073	0.133014	0.133075	0.133115

number of iterations for that is 27.5) by PSO is about 230 [s]. Fig. 7 shows the number of states to be evaluated at each iteration by RTS and PSO. The figure assumes that the number of agent is 30 in all cases. The number by RTS is the number of neighboring states of the current state at each iteration. Therefore, it increases drastically by increase of the dimension of the problem. On the contrary, the number by PSO corresponds to the number of agents. Therefore, it is the same even for large dimensional problems. Consequently, although PSO only evaluates the limited number of states using (2) and (3), the evaluation is efficient even for the large-scale problems and realizes the quick convergence characteristic to sub-optimal solutions. The characteristic indicates the applicability of PSO to large-scale problems.

The calculation time for evaluation of one state is increasing as the dimension of the problem increases. Therefore, if speed-up of the whole execution time have to be realized, parallel computation methods based on distributed memory tools such as PVM [18] and MPI [19] or shared memory tools such as OpenMP [20] can be utilized.

6. Conclusions

This paper presents a particle swarm optimization (PSO) for reactive power and voltage control (RPVC) in electric power systems. The proposed method formulates RPVC as a mixed integer nonlinear optimization problem (MINLP) and determines a control strategy with continuous and discrete control variables such as AVR operating values, OLTC tap positions, and the number of reactive power compensation equipment. The feasibility of the proposed method for RPVC is demonstrated on practical power systems with promising results. The results can be summarized as follows:

(a) This paper shows the practical applicability of PSO to a MINLP and suitability of PSO for application to large-scale RPVC problems. PSO has several parameters. According to the simulation results, it is not required severe parameter tuning and especially, PSO only requires less than 50 iterations for obtaining sub-optimal solutions even for large-scale systems.

(b) RPVC is sometimes formulated as a combinatorial optimization problem. However, the optimal result formulated as a MINLP and those formulated as a combinatorial optimization problem are different. Therefore, it indicates the efficiency of formulation of RPVC as a MINLP.

(c) Many engineering problems including power system problems can be formulated as a MINLP essentially. The results of this paper indicate the possibility of PSO as a practical tool for various MINLPs of engineering problems including power system operation and planning problems.

Hybrid PSO (HPSO) [11] may be more effective for RPVC. The author has applied HPSO to a state estimation problem in electric power distribution systems and found that HPSO is

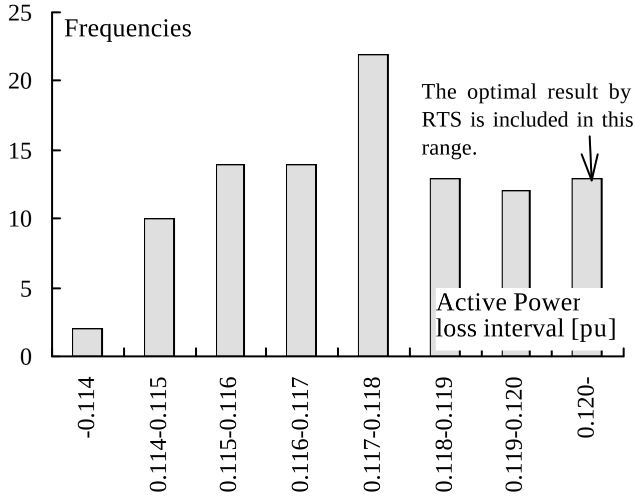


Fig. 5 Statistical results by PSO (100 trials) for practical 112 bus system.

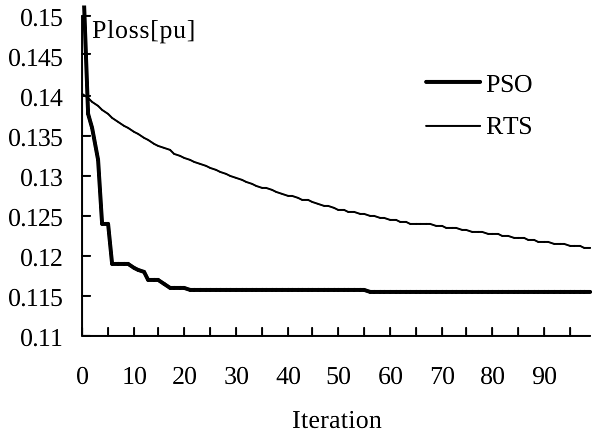


Fig. 6 Convergence characteristics by PSO and RTS for practical 112 bus system.

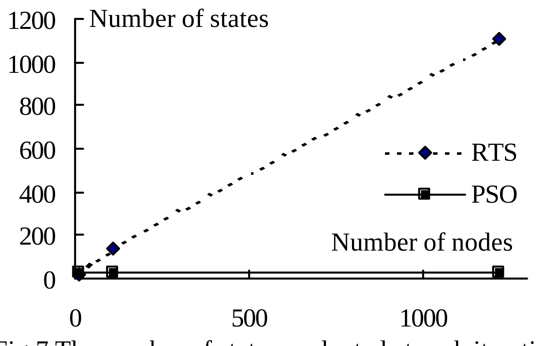


Fig.7 The number of states evaluated at each iteration by RTS and PSO.

more effective than PSO [21]. Using the same appropriate values for w_{max}, w_{min}, and c_i (0.9, 0.4, 2.0), high quality solutions can be found using wide range of the selection rate. Namely, the appropriate parameter values are the same for different power system problems. Investigation of appropriate parameter values and constriction factors for various power system problems is one of the future works [22].

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