

## Chapter 13

### Power System Controls: Particle Swarm Technique

**Abstract:** This chapter presents two application of particle swarm optimization to power system control related problems. One is an application on voltage and reactive power control formulated as a mixed integer nonlinear optimization problem. Another one is an application on distribution state estimation formulated as a nonlinear continuous optimization problem. Moreover, constriction factor concept has been applied to a distribution state estimation problem and efficiency of constriction factor has been indicated. Numerical results of both applications have shown the efficiency of particle swarm optimization to power system control related problems.

**Keywords:** Particle Swarm Optimization, Voltage and Reactive Power Control, Mixed Integer Nonlinear Optimization Problem, Hybrid Particle Swarm Optimization, Distribution State Estimation, Nonlinear Continuation Problem

#### 1. INTRODUCTION

This chapter presents two applications of particle swarm optimization (PSO) to power system control related problems.

One is an application on voltage and reactive power control (Volt/Var Control: VVC) formulated as a mixed integer nonlinear optimization problem (MINLP). PSO has been basically developed for continuous optimization problems. This section expands PSO to handle MINLP and the PSO has been applied to a VVC problem. The developed method has been applied to up to 1217 node model systems. Numerical simulation results indicate the efficiency of PSO for practical VVC problems formulated as a MINLP.

Another one is an application on distribution state estimation (DSE) formulated as a nonlinear continuous optimization problem (NCOP). In order to handle the problem efficiently, this section utilizes a hybrid particle swarm optimization (HPSO). Moreover, constriction factor (CF) concept has been applied to a distribution state estimation problem and efficiency of HPSO with CF has been shown.

The numerical simulation results of both applications indicate the followings:

- (1) The appropriate optimization parameters of PSO can be the same in both applications and they do *not* depend on target problems.
- (2) The usage of CF concept has possibility of obtaining high quality solutions.

This chapter organizes as follows. Section II shows application of PSO to a VVC problem. Section III shows application of HPSO with CF concept to a DSE problem. Section IV shows some remarks through two applications.

#### 2. VOLTAGE AND REACTIVE POWER CONTROL – PARTICLE SWARM TECHNIQUE –

##### 2.1 Introduction

One of the important operating tasks of 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. Voltage and reactive power control (Volt/Var Control: VVC) 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 VVC in control centers is often realized based on 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 power utilities. Therefore, an optimal control to minimize power transmission loss is required for VVC instead of simple power flow sensitivity analysis. Since many voltage collapse accidents have been occurred over the last three decades [1], voltage security problems have been dominated and the consideration of the problem has been required in VVC problem [2,3]. Two evaluations should be performed to consider voltage security. First one is to calculate the distance between the current operating point and the voltage collapse point. The calculation can be realized by drawing a P-V curve using the continuation power flow (CPFLOW) technique [4]. The authors has been developed a practical CPMFLOW and verified it with practical power systems [5]. Another one is to suppose various faults for the current operating point in the target power system and calculate the distance between the post-fault operating points and voltage collapse points for each contingency. The calculation is called voltage contingency analysis [1]. If a sufficient distance can be kept for both calculations, the new operating condition calculated by VVC can be evaluated as a secure one. Thus, the advanced VVC requires optimal control strategy considering power loss minimization and voltage security.

VVC 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 as SC and ShR. The objective function can be varied according to the

power system condition. For example, the function can be minimization of power transmission loss of the target power system for the normal operating condition as described above. Conventionally, the methods for VVC problem have been developed using various methods such as fuzzy, expert system, mathematical programming, and sensitivity analysis [6-11]. However, a practical method for a VVC problem formulated as a MINLP with continuous and discrete state variables has been eagerly awaited.

PSO is one of the evolutionary computation (EC) techniques [12]. The method is improved and applied to various problems [13-16]. 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. Therefore, the method can be applicable to VVC formulated as a MINLP. Various methods have been developed for a MINLP such as generalized benders decomposition (GBD) [17] and OA/ER [18]. Using the conventional methods, whole problem is usually divided to sub-problems and various methods are 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, VVC requires various constraints that are difficult to be handled by mathematical ways. PSO is expected to be suitable for VVC because it can handle such constraints easily.

This section presents a PSO for VVC formulated as a MINLP considering VSA. Voltage security assessment is considered using a CPFLOW technique and a fast voltage contingency selection method. The feasibility of the proposed method for VVC is demonstrated and compared with RTS [19][20] and the enumeration method on practical system models with promising results.

## 2.2 Problem formulation of VVC

### 2.2.1 Problem Formulation

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

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

where, n: the number of branches,

x: *continuous* variables,

y: *discrete* variables,

Loss<sub>i</sub>: active 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.

#### (c) Voltage security

The Determined VVC strategy should keep voltage security of the target power system.

Ploss of the target power system is calculated for a certain VVC strategy using load flow calculation 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 at the load flow calculation and penalty values are added if the constraints are violated.

P-V curves for the determined VVC strategy and various contingencies are generated and checked whether the VVC candidate can keep sufficient voltage security margins. The constant power load model is used because the load model is the severest to the voltage security problem. However, if a more complicated load model is required, the proposed method can be easily expanded using a ZIP load model [21].

### 2.2.2 State Variables

The following control equipment is considered in the VVC problem.

(a) AVR operating values (*continuous* variable)

(b) OLTC tap position (*discrete* variable)

(c) The number of reactive power compensation equipment (*discrete* variable)

The above state variables are treated in load flow calculation as follows: AVR operating values are treated as voltage specification values. OLTC tap positions are treated as tap ratio to each tap position. The number of reactive power compensation equipment is treated as corresponding susceptance values.

## 2.3 Overview of particle swarm optimization [12][13]

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.

(c) It was originally developed for nonlinear optimization problems with continuous variables. However, it is easily expanded to treat problems with discrete variables.

Therefore, it is applicable to a MINLP with both continuous and discrete variables such as VVC.

The above feature (c) is suitable for the VVC problem because practically efficient methods have not been developed for VVC with both continuous and discrete variables. The above features allow PSO to handle the VVC problem and require short computation time.

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 all information are 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  $v_x$  (the velocity of X-axis) and  $v_y$  (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:

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

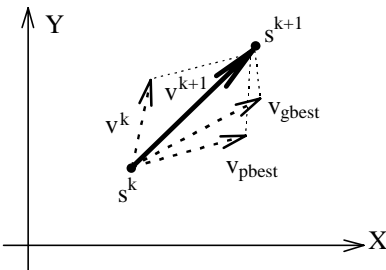
where,

- $v_i^k$  : 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<sub>i</sub> : 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:

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

Fig. 1 shows the above concept of modification of searching points. Discrete variables can be handled in (2) and (3) with little modification. Discrete numbers can be used to express the current position and velocity. If a discrete random



- $S^k$  : 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.

number is used in (2) and the whole calculation of right-hand side (RHS) of (2) is discretized to the existing discrete number, both continuous and discrete number 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 expanded to the discrete problem using discrete numbers like grids for XY position and its velocity easily.
- (d) There is no inconsistency in searching procedures even if continuous and discrete state variables are utilized with continuous axes and grids for XY positions and velocities. Namely, the method can be applied to a MINLP with 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 [13]. 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 expanded PSO for MINLP is shown in fig. 2. The original PSO has been applied to a learning problem of neural networks and Schaffer f6, the famous benchmark function for GA, and efficiency of the method has been confirmed [12].

#### 2.4 Voltage Security Assessment

The static P-V curve represents the relation between load increase and voltage drop. Namely, the P-V curve can be calculated by increasing total loads in the target power system gradually and plotting the dropped voltage. CPFLOW utilizes power system loads as parameters and calculates the P-V curve by modification of the parameters using a continuation method. The continuation method is one of the methods in applied mathematics and it calculates transition of equilibrium points (e.g. P-V curve) by

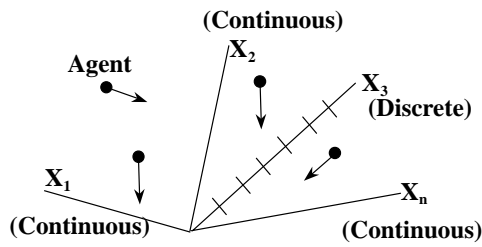


Fig. 2 Concept of expanded PSO for MINLP.

modification of parameters. In order to avoid the ill condition around the saddle node bifurcation point (nose point), an arclength along the P-V curve is introduced as an additional state variable and the power flow equation is expanded. The continuation method is applied to the expanded power flow equation and the P-V curve can be generated rapidly without ill condition around the nose point. CPFLOW can generate a P-V curve automatically and can be applied to large-scale power systems easily [4][5].

The proposed method generates a P-V curve using the CPFLOW technique and calculates a MW margin, distance between the current operating point and the nose point, for the determined control strategy. The proposed method also utilizes the fast voltage contingency analysis method using CPFLOW [22]. Then, the method checks whether the MW margin is enough or not compared with the predetermined value. The procedure for voltage security assessment can be expressed as follows:

Step. 1 Evaluation of the control strategy

It is checked whether the new power system condition after applying the current control strategy has an enough MW margin or not.

Step. 2 Evaluation of various contingencies

The several severe contingencies for the new power system condition after applying the current control strategy are selected by the fast voltage contingency analysis method. The MW margin for the only severe contingencies are calculated using CPFLOW.

If the MW margins for the current control strategy and the severe contingencies are large enough, the current control strategy is selected. Otherwise it is not selected. Using the procedure, the method checks whether the target power system can keep voltage security by the control or not.

VSA consists of static and dynamic VSA and the proposed method only considers the static VSA because of the limited calculation time for on-line VVC. If the dynamic VSA is still required, the VSA used in the proposed method can be replaced with a dynamic VSA tool such as QSS described in [1]. However, in such a case, we have to face the problem of execution time and we may have to develop a parallel computation method for the VSA based on distributed memory tools such as PVM [23] and MPI [24] or shared memory tools such as OpenMP [25].

## 2.5 Formulation of VVC using PSO

### 2.5.1 Treatment of State Variables

Each variable is treated in PSO as follows: 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. 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. 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.

### 2.5.2 VVC algorithm using PSO

The proposed VVC algorithm using PSO 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).
- Step 5. New searching points are calculated using (3).
- 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 go to Step 9. Otherwise, go to Step 4.
- Step 9. P-V curves for the control candidates and various contingencies are generated using the best gbest among the stored gbests (candidates). If the MW margin is larger than the predetermined value, the control is determined as the final solution. Otherwise, select the next gbest and repeat the VSA procedure mentioned above.

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). The maximum iteration number should be determined by pre-simulation. As mentioned below, PSO requires less than 100 iterations even for large-scale problems. There are several ways to formulate VVC considering VSA. Maximization of MW margin instead of

loss minimization is one option. However, the purpose of the paper is to develop VVC algorithm for steady state operation. In this case, we can think that we still have enough voltage stability margins. Therefore, the author decided to utilize only loss minimization as the objective function and check whether the control strategy has enough voltage stability margins or not after loss minimization. Moreover, evaluation for each state is extremely time-consuming considering VSA during optimization procedure, and it is difficult to realize on-line VVC. Considering the trade-off between the optimal control and the execution time, the proposed method selected the way to handle the contingencies after generation of the optimal control candidates. If maximization of MW margin is required as the objective function, approximation method such as the look-ahead method with parallel computation should be used during the search procedure for on-line VVC.

## 2.6 Numerical examples

The proposed method has been applied to several power system models compared with RTS and the enumeration method. Our target VVC problem is formulated as a MINLP with discrete and continuous variables. OPF basically only handles continuous variables and some papers such as [26] tried to handle discrete variables in OPF formulation. Unfortunately, the authors does not have OPF program with such treatment. Therefore, the proposed method is compared with available combinatorial optimization soft wares in the simulation.

### 2.6.1 IEEE 14 bus system

#### (1) Simulation conditions

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

- Continuous AVR operating values of node 2,3,6, and 8: Upper and lower bounds are 0.9 and 1.1 [pu].
- Discrete tap positions of transformers between node 4-7, 4-9, and 5-6: These transformers are assumed to have 20 tap positions.
- Discrete number of installed SC in node 9 and 14: Each

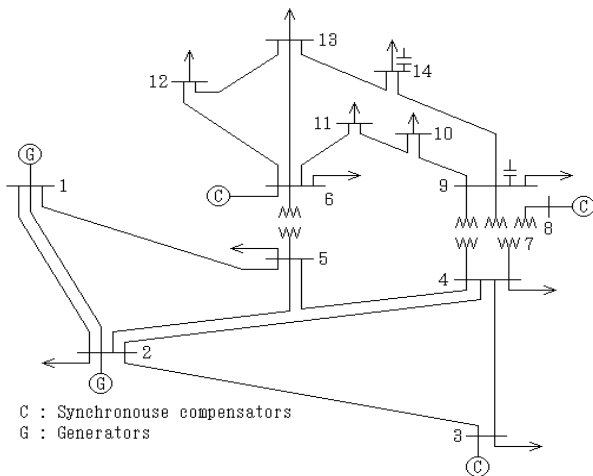


Fig. 3 A modified IEEE 14 bus system.

node is assumed to have three 0.06 [pu] SC.

The proposed method tries to generate an optimal control for the operating condition. Ploss of the original system is 0.1349 [pu]. Generation of the VVC candidates (Step 1 - 7 in the proposed VVC algorithm) 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 [13]:

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

where,  $w_{\max}$  : initial weight,  
 $w_{\min}$  : final weight,  
 $iter_{\max}$  : 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).

#### (2) Simulation results

Table 1 Operating condition of IEEE 14 bus system.

Bus No.	Vol. [pu]	Node specification		SC [pu]
		P [pu]	Q [pu]	
1 <sup>*1</sup>	1.060	-	-	0.0
2 <sup>*2</sup>	1.045	-0.183	0.127	0.0
3 <sup>*2</sup>	1.010	0.942	0.190	0.0
4		0.478	-0.039	0.0
5		0.076	0.016	0.0
6 <sup>*2</sup>	1.070	0.112	0.075	0.0
7		0.000	0.000	0.0
8 <sup>*2</sup>	1.090	0.000	0.000	0.0
9		0.295	0.166	0.18 <sup>*3</sup>
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 <sup>*3</sup>

\*1 : Node 1 is slack

\*2 : PV specification node

\*3 : 0.06 [pu] \* 3 SC

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 VVC is formulated as a COP, only solutions to discrete values are searched and the objective function shape between the discretized intervals 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 VVC 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 1.5, 2.0, and 2.5 are similar and 2.0 is utilized in the simulation according to the suggested value in [13]. Consequently, the appropriate

parameter values for the problem are the same as the ones suggested in [13].

The proposed method generates a P-V curve for the optimal control strategy using the CPFLOW technique and performs the voltage contingency analysis. It is verified that the strategy can keep voltage security when the load margin to 0.95 [pu] voltage is larger than 10 % load increase point in the simulation. The evaluation criteria depend on the target power system and they should be determined for each system through pre-simulation. Fig. 4 shows an example of a P-V curve for node 12 with the optimal control strategy.

## 2.6.2 Practical 112 bus model system

### (1) Simulation conditions

The proposed method is applied to a practical model system with 112 buses. The system models the EHV system of Kansai Electric Practical system. 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 VVC. 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	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 items	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]

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	<b>0.133567</b>	0.133765	0.133986	0.134504
	Min.	0.133012	0.133012	0.133012	<b>0.133012</b>	0.133012	0.133073	0.133076
2.0	Ave.	0.135519	0.135689	0.136362	0.136324	0.135763	0.136425	0.136245
	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
	Min.	0.133015	0.133012	0.133012	0.133073	0.133014	0.133075	0.133115

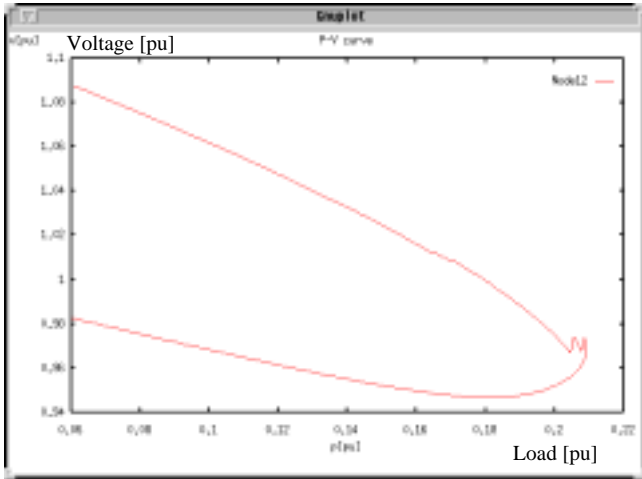


Fig. 4 A P-V curve of the optimal control (Node 12) for IEEE 14 bus system.

## (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 solution 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 result by the proposed method is 31.7. On the contrary, RTS reaches the best result 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. The determined VVC strategy candidate is evaluated as a secure one using a CPFLOW technique. Voltage contingency analysis is also performed for the candidate and it is evaluated as secure. The calculation time for voltage contingency ranking is 11.0 [s] (112 contingencies) and the time for one CPFLOW calculation is 2.0 [s] for the 112 bus model system. Therefore, for example, the total calculation time for voltage security assessment is 19.0 [s] if CPFLOW is performed for the severest three contingencies (one CPFLOW calculation, contingency ranking and three CPFLOW calculation). As described above, large penalty is added at the evaluation of the objective function if the voltage and power flow constraints are violated. Therefore,

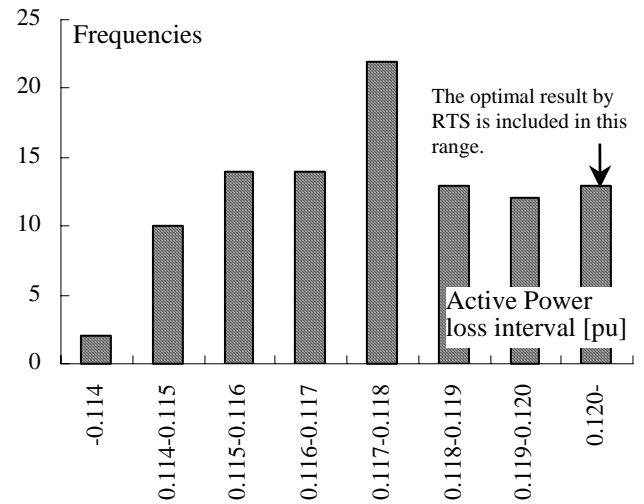


Fig. 5 Statistical results by PSO (100 trials) for practical 112 bus system.

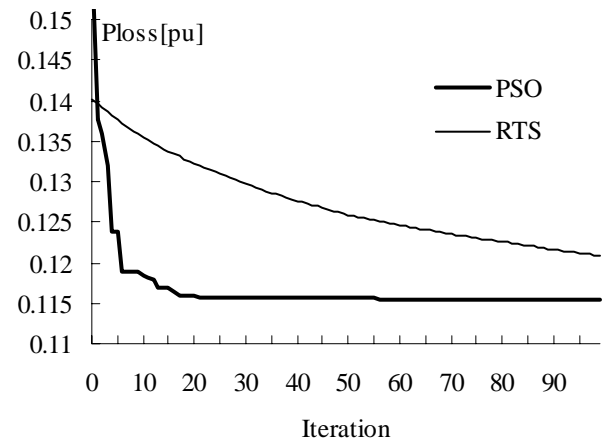


Fig. 6 Convergence characteristics by PSO and RTS for practical 112 bus system.

all of the best solutions by both PSO and RTS within 100 searching iterations are feasible solutions without voltage and power flow constraints violation in the simulation. Although the best VVC strategy is evaluated as secure in the model system, voltage security assessment can become more important when the utilization rate of power equipment is increased and in the deregulation environment.

### 2.6.3 Large-scale 1217 bus model system

#### (1) Simulation conditions

The proposed method has been developed to apply the practical EHV system. Therefore, the applicability of the proposed method to the target system is already evaluated with the 112 bus system. However, in order to evaluate the applicability of the proposed method to large-scale systems, it has been applied to a 1217 bus system. The model system is composed by doubling the full scale Kansai Electric power system. The system has 84 generators for AVR control, 388 OLTCs, and 82 SCs for VVC. 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 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 [23] and MPI [24] or shared memory tools such as OpenMP [25] can be utilized for the optimization part in a similar manner for the VSA part.

## 2.7 Summaries of PSO application to VVC problems

This section presents a particle swarm optimization (PSO) for reactive power and voltage control (VVC) considering voltage security assessment (VSA). The proposed method formulates VVC 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 method also considers voltage security using a continuation power flow (CPFLOW) and a voltage contingency analysis technique. The feasibility of the proposed method for VVC is demonstrated on practical

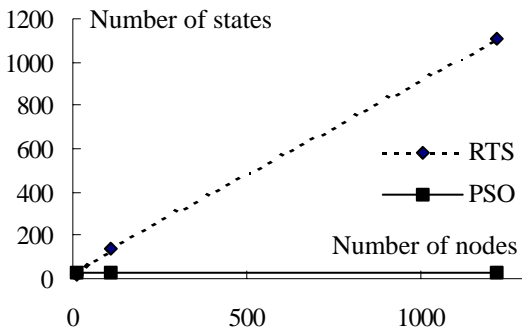


Fig.7 The number of states evaluated at each iteration by RTS and PSO.

power systems with promising results. The results can be summarized as follows:

- (a) This section shows the practical applicability of PSO to a MINLP and suitability of PSO for application to large-scale VVC 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) Many power system problems can be formulated as a MINLP and the results indicate the possibility of PSO as a practical tool for various MINLPs of power system operation and planning.
- (c) VVC is sometimes formulated as a combinatorial optimization problem. However, discrete variables of 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 VVC as a MINLP.
- (d) Consideration of VSA is one of the important practical functions of VVC. The results reveal that the possibility of treatment of the security by the proposed PSO-based method in VVC.

In addition to the proposed method, the following additional features make the proposed VVC more practical.

- (e) Avoidance of control concentration to a specific equipment
- (f) Tracking to load change
- (g) Look-ahead control using load forecast

Especially, for handling (e)(f), an optimal control strategy in several control intervals should be considered simultaneously. Improvement of the proposed method considering the above features and parallel computation are one of the future works.

## 3. DISTRIBUTION STATE ESTIMATION – HYBRID PARTICLE SWARM TECHNIQUE –

### 3.1 Introduction

On-line state estimation is becoming one of the key functions in distribution control centers considering deregulation environment and introduction of distributed generator (DG) in distribution systems. Distribution state estimation (DSE) is required to consider error and asynchronism of measurement from actual distribution systems. Since limited measurement values are obtained from actual distribution systems, DSE has to realize high accuracy estimation with limited measurement.

DSE is usually formulated as a weighted least mean square (WLMS) problem. Equipment in distribution systems such as SVC and DG causes nonlinear characteristics of the objective function for DSE. For example, static var compensators (SVCs) have nonlinear output characteristics. Transformers with automatic tap changer have a discrete tap control function. Therefore, target load flow equations may

be changed because of automatic tap changing function of voltage controllers during convergence. Output characteristics of induction generators can be described by a nonlinear function expressed by constant impedance, constant current, and constant power (ZIP) load. A number of methods have been developed as an advanced function of distribution control centers [27-37]. The methods can be divided into categories: statistical and load adjustment SE formulation. The former methods usually utilize an iterative convergence method such as Quasi-Newton method and the latter methods usually utilize sensitivity analysis. Since conventional distribution state estimation methods belonging to both categories assume that the objective function or equations related to DSE can be differentiable and continuous. However, considering the above-mentioned nonlinear characteristics of the practical equipment in distribution systems, the objective function and the equations can not be differentiable and continuous, and the conventional methods can not be applied. Therefore, A practical distribution state estimation method has been eagerly awaited considering the practical requirements.

Modern heuristic algorithms are considered as practical tools for nonlinear optimization problems [38]. The algorithms do not require that the objective function has to be differentiable and continuous. A particle swarm optimization (PSO) is one of the modern heuristic algorithms [12][39] and can be applied to continuous nonlinear optimization problems such as DSE. It has been developed through simulation of simplified social models. A hybrid PSO (HPSO) adds a selection mechanism of the evolutionary computation (EC) to PSO and it can generate high quality solution within short calculation time [39]. Since the state estimation is one of the on-line functions in distribution control centers, HPSO must be an appropriate method for the target problem.

This section proposes a practical distribution state estimation method using a hybrid particle swarm optimization. The proposed method considers practical measurements in actual distribution systems and assumes that absolute values of voltage and current can be measured at the secondary side buses of substations (S/Ss) and remote terminal units (RTUs) in distribution systems. The method can handle nonlinear characteristics of the practical equipment in distribution systems. It can estimate load and distributed generation output values at each node by minimizing difference between measured and calculated state variables. The feasibility of the proposed method is

demonstrated and compared with the original PSO on practical distribution system models.

### 3.1 Formulation of distribution state estimation

#### 3.1.1 Measurement data and assumptions

The following data are assumed to be obtained from actual distribution networks:

- (1) S/Ss: absolute value of sending voltage and current,
- (2) RTUs: absolute value of voltage and current.

In addition, the following assumptions are required for the state estimation considering the above limited measured data:

- (1) A contracted load value is known at each load section.
- (2) Estimated power factor of sending end at S/S and each section can be obtained.
- (3) If output of DG is fixed, the output and power factor of DG can be obtained. If output of DG is variable, the estimated output and power factor of DG can be obtained.

Fig. 8 shows the measured data.

#### 3.1.2 Problem formulation

The objective function of the distribution state estimation is the same as that of conventional state estimation as follows:

$$\min J(x) = \sum_{i=1}^m w_i (z_i - h_i(x))^2 \quad (5)$$

where,  $x$  : state variable,

$w_i$  : weighting factor of measurement variable  $i$ ,

$z_i$  : measurement value of measurement variable  $i$ ,

$h_i$  : state equation of measurement variable  $i$ .

Namely, the function is to minimize the difference between measured and calculated state variables. It should be noted that one of the state variables is a load value at each section rather than voltage as utilized by the conventional state estimation. Load power factor is assumed to be fixed as mentioned above. Therefore, only an active power load value is utilized as a state variable. The output value of DG is also utilized as a state variable. The state variables are calculated among the following bounds. The center value of the bound at each load is calculated using the total input power to the target network and the ratio of the target load section to the total loads of the target network. The center value of the bound of each variable output DG is average output of the DG.

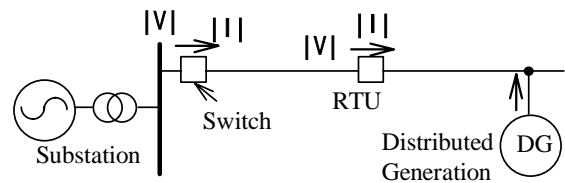


Fig. 8 Measured Data.

$$x_{j,\min} \leq x_j \leq x_{j,\max} \quad (6)$$

where,  $x_{j,\min}$  : minimum value of state variable j,  
 $x_{j,\max}$  : maximum value of state variable j.

Voltage and current can be calculated by fast distribution power flow (backward forward sweep (BFS) method) [40]. Consequently, the state estimation problem can be formulated as a constrained nonlinear optimization problem. Considering the nonlinear characteristic of actual equipment in distribution system, conventional nonlinear optimization methods based on nonlinear programming techniques can not be applied and HPSO should be utilized as an optimization method as mentioned below.

### 3.3 Hybrid particle swarm optimization [41]

HPSO utilizes the mechanism of PSO and the natural selection mechanism that is usually utilized by EC such as genetic algorithms (GAs). Since search procedure by PSO deeply depends on pbest and gbest, the searching area is limited by pbest and gbest. On the contrary, by introduction of the natural selection mechanism, effect of pbest and gbest is gradually vanished by the selection and broader area search can be realized. Agent positions with low evaluation values are replaced by those with high evaluation values using the selection. On the contrary, pbest information of each agent is maintained. Therefore, intensive search in a current effective area and dependence on the past high evaluation position are realized. Fig. 9 shows a general flow chart of HPSO. Fig. 10 shows concept of step. 2, 3, and 4 of the flow chart.

### 3.4 Constriction factor [42]

The basic system equation of PSO ((2), (3), and (4)) can be considered as a kind of difference equations. Therefore, the system dynamics, namely, search procedure, can be analyzed by the eigen value analysis. The constriction factor approach utilizes the eigen value analysis and controls the system behavior so that the system does not diverge in a real value region and can search different regions efficiently. The velocity of the constriction factor approach can be expressed as follows instead of (2) and (4):

$$v_i^{k+1} = K[v_i^k + c_1 \times rand() \times (pbest_i - s_i^k) + c_2 \times rand() \times (gbest - s_i^k)] \quad (7)$$

$$K = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}, \text{ where } \varphi = c_1 + c_2, \varphi > 4 \quad (8)$$

### 3.5 Distribution state estimation by HPSO

#### 3.5.1 State Variables

DG output and load values are considered to be state variables as mentioned above. The variables can be calculated as follows in HPSO algorithm:

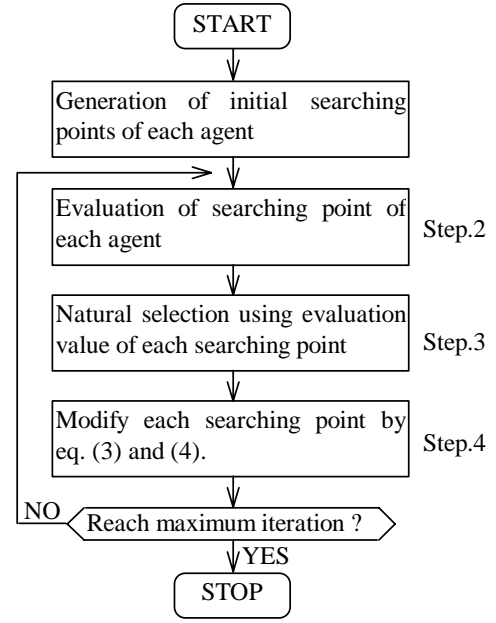


Fig.9 A general flow chart of HPSO.

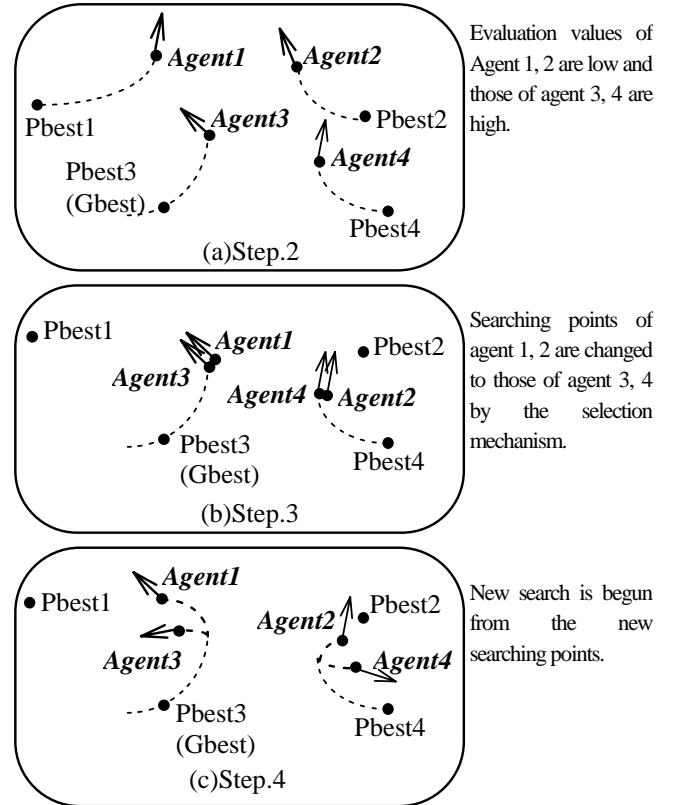


Fig. 10 Concept of searching process by HPSO.

#### (1) DG output

If the output of a DG is fixed, it is not utilized as a state variable and can be utilized as a specified value in load flow calculation. On the contrary, if the output of a DG is variable, the average and upper and lower limits of the

output is set considering the target power system conditions.

An initial value of DG output can be calculated between upper and lower limits of the output at each agent. The state variables can be modified between the limits in search procedures.

## (2) Load values

Average load value at each load section can be calculated with the ratio of the contracted section load value to the total contracted load values, and total injection power to the target power system. Upper and lower limits of the load values can be calculated considering heavy and light loading conditions of the target power system.

An initial value of the load can be calculated between upper and lower limits of the load value at each agent. The state variables can be modified between the limits in search procedures.

### 3.5.2 The proposed algorithm

The following algorithm is utilized for the state estimation:

#### Step 1 Input data

The following data are input.

- network configuration, line impedance
- contracted load value
- measurement data (S/Ss, RTUs, and DGs)

#### Step 2 Set calculation conditions

##### (1) Calculation of initial values of state variables

- Using total power input to the target network and ratio of the contracted load value of each load section to the total contracted load values of the target network, initial value of each load is calculated.
- Using average power output of each DG, initial value of each DG is calculated.

Using initial values of state variables, initial load flow calculation by BFS is performed.

##### (2) Set upper and lower bounds of state variables

- Using the results of initial load flow calculation, upper and lower bounds of each state variable can be calculated.

#### Step 3 State estimation

Find a network condition that minimizes error between measurement values and calculated values by HPSO.

The proposed distribution state estimation handles constrained nonlinear optimization problem expressed by (1) and (2). Generally, it is difficult to give a suboptimal initial solution to the optimization problem. However, using the problem-dependent knowledge, initial load and DG output values can be given for the target problem as shown before. Therefore, it can be estimated that the proposed method has a good convergence characteristic.

Practically, it is necessary to satisfy limited number of relations between measured and calculated values. Therefore, there may exist many solutions which can satisfy the constraints. HPSO has a global optimization characteristic

and can generate consistent load and DG output values, which can minimize the objective function without falling into local minima. Therefore, if upper and lower limits of state variables are set to impractical values, the variables may be converged to impractical values. Namely, impractical values of state variables can minimize the objective function more than practical values. However, there exists only a unique solution for radial network load flow, while loop networks have multiple solutions [43]. Therefore, the algorithm can generate practical state variable values if measured values are reasonable. According to authors' experiences, solutions have always converged to appropriate values.

Solutions can be maintained within reasonable values by restriction of upper and lower limits of state variables. If solutions can not be obtained within reasonable limits, the limits can be expanded. Then, if an impractical solution is obtained, it can be predicted that bad data are included in measured data. Namely, using the expansion, detection of bad data can be realized. The detection of bad data can be considered in step 3 of the above-mentioned proposed algorithm.

### 3.6 Numerical examples

#### 3.6.1 Simulation Conditions

The proposed method and a method based on the conventional PSO are applied to distribution model systems. The followings are test cases:

##### (1) Case 1

The methods are applied to a model system as shown in fig. 11 that models rural area. Load flow calculation results are utilized as measured data. Namely, capability of the methods converging to the values near to the measured data is compared. The model has one DG and two voltage regulators (SVR). SVR is widely utilized in Japan and it automatically changes tap position of the transformer to regulate the voltage at a target point in distribution systems. The equipment causes nonlinear characteristics of the objective function.

##### (2) Case 2

The methods are applied to a model system as shown in fig. 12, which models urban area with actually measured data. Namely, Effectiveness of the methods considering measured error is evaluated.

Weighting coefficients of (1) are set to 1.0. The weighting function of (3) is set as shown in (4).

The number of agent is set to 20. 30 trials are performed for appropriate parameter determination simulation and 100 trials are performed for other simulations using different random numbers. At each trial, the best-evaluated value is stored within 100 searching iteration.

#### 3.6.2 Simulation Results

(1) Case 1

HPSO have parameters:  $w_{max}$ ,  $w_{min}$ , and  $c_i$  in eq. (4). Table 5 shows average values of objective function values for various parameter combinations. According to the results, appropriate combination of  $w_{max}$  and  $w_{min}$  is 0.9 and 0.4, and appropriate  $c_i$  is 1.0 to 2.0. The values are the same as those recommended by other papers [12][13]. The following values are appropriate for DSE and utilized for other simulations:  $w_{max}=0.9$ ,  $w_{min}=0.4$ ,  $c_i = 2.0$ . Namely, the appropriate parameter values are not different among various target problems. This is one of the desirable characteristics of PSO.

State estimation results are shown in Table 6, 7 and fig. 13. As shown in Table 6, the minimum evaluation values by HPSO and PSO are the same. However, the maximum evaluation value, which has a maximum error between measurement data and calculated value, by HPSO is approximately 59% of that by PSO and average evaluation value by HPSO is approximately 50% of that by PSO. The results indicate HPSO can generate higher quality solutions by PSO without measurement errors. Table 6, 7 and fig. 13 indicates the high quality solutions by HPSO as well.

Table 8 shows comparison of the objective function values with the best parameters in table 5 ( $w_{max} = 0.9$ ,  $w_{min} = 0.4$ ,  $c_i = 2.0$ ) and the constriction factor ( $\phi = 4.1$  in (8)). According to the results, maximum objective function value can be restricted to small value. Namely, even in the worst case, using the constriction factor, the system can estimate the distribution system condition with minimum errors.

(2) Case 2

Table 9 shows the estimation results for the model system in fig. 12 with best parameters. The proposed method gradually decreases load values in order to match it with the sending current value. As a result, calculated voltage values are higher than the measured values. The results are obtained considering measurement errors and the appropriate results are obtained. Table 10 shows comparison of the number of calculations (Flops by Matlab) by both methods. The number

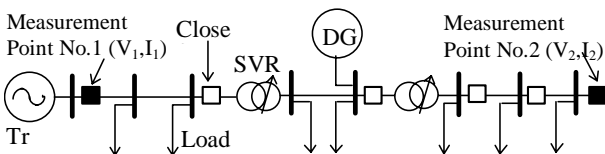


Fig.11 A distribution model system for case No.1.

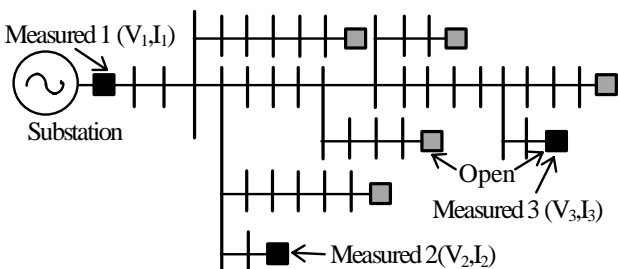


Fig.12 A distribution model for case No.2.

Table 5 Average values of objective function values to various parameter combinations (case No.1, 30 trials).

$c_i$	$w_{max}, w_{min}$		
	0.9, 0.4	2.0, 0.9	2.0, 0.4
0.5	0.000031	0.000588	0.000119
1.0	<b>0.000020</b>	0.000332	0.000112
1.5	<b>0.000018</b>	0.000199	0.000157
2.0	<b>0.000019</b>	0.000165	0.000106
2.5	0.000028	0.000126	0.000129
3.0	0.000024	0.000152	0.000120
4.0	0.000039	0.000085	0.000129

Table 6 Comparison of the objective function values by both methods (case No.1, 100 trials).

Methods	Max.	Min.	Ave.
HPSO	0.000106	0.000000	0.000015
PSO	0.000180	0.000000	0.000030

Table 7 Comparison of measured and estimated voltage and current (case No.1).

Measur- ed Point	Measured value	HPSO		PSO
		Optimal estimation value	Ave. estimation value	Ave. estimation value
$I_1$	150.00[A]	150.01[A]	149.98[A]	150.22[A]
$V_2$	6500[V]	6503[V]	6481[V]	6538[V]
$I_2$	0.00[A]	0.00[A]	0.00[A]	0.00[A]

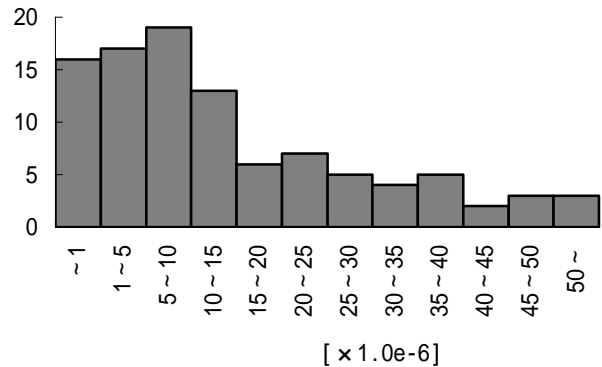


Fig.13 Convergence characteristics of the proposed method (case No.1, 100 trials).

Table 8 Comparison of the objective function values with the best parameters and the constriction factor for case No.1 (HPSO, 30 trials).

	Best parameters	Constriction factor
Ave.	0.000019	0.000019
Min.	0.000000	0.000000
Max.	0.000106	0.000072

\*)Best parameters :  $w_{max} = 0.9$ ,  $w_{min} = 0.4$ ,  $c_i = 2.0$   
Constriction factor :  $\phi = 4.1$

by HPSO is almost the same as that by PSO. Namely, the results indicate possibility of HPSO to generate high quality solutions compared with the original PSO.

### 3.6 Summaries of application of HPSO to DSE

This section proposes a distribution state estimation method using a hybrid particle swarm optimization. The results of the section can be summarized as follows:

- (1) This section develops a hybrid particle swarm optimization which can handle the non-differential and non-continuous objective function of distribution state estimation caused by nonlinear characteristics of the practical equipment such as SVC, SVR.
- (2) The proposed method can estimate load and distributed generation output values at each node with practical limited measurement values in distribution systems.
- (3) The results of the numerical simulations indicate that the proposed method can estimate the target system conditions more accurate than the original PSO. Moreover, it can estimate the appropriate target system conditions with measurement errors.
- (4) Constriction factor approach has possibility to generate more accurate estimation conditions by the conventional HPSO.

## 4. CONCLUSIONS

This chapter presents two application of particle swarm optimization to power system control related problems. One is an application on voltage and reactive power control formulated as a mixed integer nonlinear optimization problem. Another one is an application on distribution state estimation formulated as a nonlinear continuous optimization problem. Moreover, constriction factor concept has been applied to a distribution state estimation problem and efficiency of constriction factor has been indicated. Numerical results of both applications have shown the efficiency of particle swarm optimization to power system control related problems.

The numerical simulation results of both applications indicate the followings:

- (1) The appropriate optimization parameters of particle swarm optimization can be the same in both applications and they do *not* depend on target problems.
- (2) The usage of constriction factor approach has possibility of obtaining high quality solutions. More detailed efficiency evaluation of the constriction factor approach for various problems is one of the future works.

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Table 9 Comparison of measured and estimated voltage and current for case No.2 by HPSO.

Target	Measured values	Optimal estimated values
$I_1$	320.00[A]	320.03[A]
$V_2$	6705[V]	6744[V]
$V_3$	6675[V]	6706[V]

Table 10 Comparison of number of calculation by HPSO and PSO.

	Case No.1		Case No.2	
	HPSO	PSO	HPSO	PSO
# of Nodes	20		41	
# of Measurement	4		6	
Flops	12834882	12328668	14550867	14543764

\*)Flops means the calculation number counted in Matlab.

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