A Hybrid Particle Swarm Optimization for Distribution State Estimation

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Abstract--**This paper proposes a hybrid particle swarm optimization for a practical distribution state estimation. The proposed method considers nonlinear characteristics of the practical equipment and actual limited measurements in distribution systems. The method can estimate load and distributed generation output values at each node by minimizing difference between measured and calculated voltages and currents. The feasibility of the proposed method is demonstrated and compared with an original particle swarm optimization based method on practical distribution system models. Effectiveness of the constriction factor approach of particle swarm optimization is also investigated. The results indicate the applicability of the proposed state estimation method to the practical distribution systems.**

Index Terms **-- Distributed Generation, Distribution State Estimation, Hybrid Particle Swarm Optimization, Modern Heuristic Method, Voltage Regulator**

I. 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. For example, when a DG supplies electric power to loads in a feeder, sending currents in a substation are reduced after introduction of the DG in the feeder. Namely, total load values in the feeder are estimated smaller than the actual values by the reduced sending currents in the substation. However, a power company has to supply electric power to all of the loads in the feeder when a fault occurs in the feeder. Therefore, on-line estimation of loads and DG outputs is one of the crucial tasks in the distribution systems with DG. Distribution state estimation (DSE) is required to consider error and time synchronization of measurement data from actual distribution systems. Since limited measurement values are obtained from actual distribution systems, DSE has to realize high accuracy estimation with the limited measurement.

DSE is usually formulated as a weighted least mean square (WLMS) problem. Equipment in distribution systems such as voltage control equipment, static var compensators (SVC) and DGs has nonlinear characteristics [1] and it causes nonlinear characteristics of the objective function of DSE. For example, SVCs have nonlinear output characteristics. Transformers with automatic tap changer, called step voltage regulator (SVR) in Japan, have a discrete tap control function. Output characteristics of induction generators can be described by a nonlinear function expressed by constant impedance, constant current, and constant power (ZIP) load [1]. Therefore, a target load flow equation of DSE may be changed because of the nonlinear characteristics of the actual equipment during search procedure of DSE.

A number of DSE methods have been developed as an advanced function of distribution control centers [2-12]. The methods can be divided into categories: statistical [2][4-9][12] and load adjustment SE formulation [3][10][11]. The former methods usually utilize an iterative convergence method such as Quasi-Newton method and the latter methods usually utilize sensitivity analysis. Conventional DSE 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 cannot be differentiable and continuous, and it is difficult to apply the conventional methods practically. Therefore, A practical distribution state estimation method considering the above-mentioned requirements has been eagerly awaited.

Modern heuristic algorithms are considered as effective tools for nonlinear optimization problems [13]. 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 [14-16] and can be applied to nonlinear and non-continuous optimization problems with continuous variables such as DSE. It has been developed through simulation of simplified social models. A hybrid PSO (HPSO) adds a selection mechanism of evolutionary computation (EC) to PSO and it can generate high quality solution within short calculation time [17]. 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 paper proposes a distribution state estimation method using a hybrid particle swarm optimization. The proposed method can handle nonlinear characteristics of the practical equipment in distribution systems. The method considers practical measurements in actual distribution systems and assumes that magnitude of voltage and current can be measured at the secondary side buses of substations (S/Ss) and

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remote control units (RTUs) in distribution systems. It can estimate load and distributed generation output values at each node by minimizing difference between measured and calculated voltages and currents such as the conventional methods. The feasibility of the proposed method is demonstrated and compared with the original PSO based DSE on practical distribution system models. Effectiveness of the constriction factor approach of PSO [15] is also investigated. The results indicate the applicability of the proposed DSE method to the practical distribution systems.

II. Formulation of Distribution State Estimation

A. Measurement data and assumptions

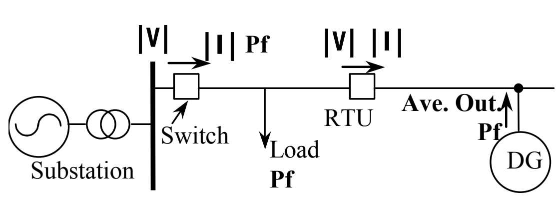
The following data are assumed to be obtained from actual distribution networks:
(a) S/S: magnitude of sending voltage and current,
(b) RTU: magnitude of voltage and current.
In addition, the following assumptions are required for the state estimation considering the actual limited measured data in distribution systems:
(c) A contracted load value is known at each load section.
(d) Estimated power factor of sending end at S/S and each section can be obtained.
(e) If output of DG is fixed, the output and power factor of DG can be obtained. If output of DG is variable, the average output and power factor of DG can be obtained.
Limited measurement values can be obtained in distribution systems. Therefore, we have large freedom for state estimation and the above assumptions are required for obtaining appropriate estimation results. Fig. 1 shows the measured and obtained data. The bold character shows the data in the figure.

B. Formulation

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

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

where, x : state variable (active power loads and active power output of DGs),
w_i : weighting factor of measurement variable i,
z_i : measurement value of measurement variable (voltages and currents) i,
h_i : state equation (power flow equation) of measurement variable i.



|V|: magnitude of voltage
|I|: magnitude of current
Pf: power factor   Ave. out.: average output

Fig. 1 Measured and obtained data.

Namely, the function is to minimize the difference between measured and calculated measurement variables. It should be noted that one of the state variables is a load value at each section rather than voltage or current 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 active power 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 "load ratio", namely a ratio of the contracted load value of the target load section to the total contracted load values of the target network. The center value of the bound of each variable output DG is the average output of the DG.

$$x_{j,\min} \le x_j \le x_{j,\max} \tag{2}$$

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

The output value of DG is omitted from state variables when we only have DGs with fixed power output values. Voltage and current can be calculated by fast distribution power flow (backward forward sweep (BFS) method) [1][18]. Consequently, the state estimation problem can be formulated as a constrained nonlinear optimization problem with continuous variables. Considering the nonlinear characteristic of actual equipment in distribution system, conventional nonlinear optimization methods based on nonlinear programming techniques cannot be applied and HPSO should be utilized as an optimization method as mentioned below.

C. Characteristics of the DSE problem

During the search procedure, PSO changes state variables (loads and DG outputs) and it may cause change of the tap positions of SVRs. In such a case, impedance of the SVR in the power flow equation is changed non-continuously. $h_i(x)$ in (1) can be calculated by the power flow equations and, therefore, the objective function may be changed non-continuously. Namely, during the search procedure, the formulation of the objective function may be changed non-continuously in the DSE problem.

The conventional method assumes that the objective function is fixed, differentiable, and continuous. Therefore, the conventional techniques cannot be applied in the DSE problem.

III. Hybrid Particle Swarm Optimization

A. Basic concept of Particle Swarm Optimization [14-16]

Natural creatures sometimes behave as a swarm. One of the main streams of artificial life researches is to examine how natural creatures behave as a swarm and reconfigure the swarm models inside a computer. Swarm behavior can be modeled with a few simple rules. School of fishes and swarm of birds can be modeled with such simple models. Namely, even if the behavior rules of each individual (agent) are simple, the behavior of the swarm can be complicated. Reynolds called this kind of agent as *boid* and tried to generate complicated swarm behavior by computer graphic (CG) animation [19]. He utilized the following three vectors as simple rules for each agent:

(a) to step away from the nearest agent,
(b) to go toward the destination,
(c) to go to the center of the swarm.

Namely, behavior of each agent inside the swarm can be modeled with simple vectors. This characteristic is one of the basic concepts of PSO.

Boyd and Richerson examine the decision process of human being and developed the concept of *individual learning and cultural transmission* (ILCT) [20]. According to their examinations, people utilize two important kinds of information in the decision process. The first one is their own experience; that is, they have tried the choices and know which state has been better so far, and they know how good it was. The second one is other people's experiences; that is, they have knowledge of how the other agents around them have performed. Namely, they know which choices their neighbors have found are most positive so far and how positive the best pattern of choices was. Namely each agent decides his decision using his own experiences and other peoples' experiences. This characteristic is another basic concept of PSO.

Moreover, Dorigo, et al, developed Ant Colony Optimization (ACO) mainly based on the social insect, especially ant, behavior [21]. They called the research field as *swarm intelligence*. Namely, they showed that the swarm behavior could be utilized as an optimization procedure.

According to the above background of PSO and simulation of swarm of bird, Kennedy and Eberhart developed a PSO concept. PSO is basically developed through simulation of bird flocking in two-dimension space. The position of each agent is represented by XY axis position and also the velocity is expressed by vx (the velocity of X axis) and vy (the velocity of Y axis). Modification of the agent position is realized by the position and velocity information.

Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its XY position. The information is corresponding to personal experiences of each agent in the concept of ILCT. Moreover, each agent knows the best value so far in the group (gbest) among pbests. The information is corresponding to knowledge of how the other agents around them have performed in the concept of ILCT. Namely, Each agent tries to modify its position using the following information:

- the distance between the current position and pbest
- the distance between the current position and gbest

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k) \tag{3}$$

where, v_i^k : velocity of agent i at iteration k,
w : weighting function,
c_j : weighting factor,
$rand$: 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.

The right-hand side (RHS) of (3) consists of three terms (vectors) like three vectors of *boid*. 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 is corresponding to a kind of inertia and tries to explore new areas. Therefore, the first term can realize 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 search 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 following weighting function is usually utilized in (3):

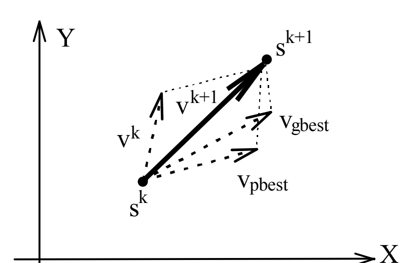
$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{4}$$

where, w_{max} : initial weight,
w_{min} : final weight,
$iter_{max}$: maximum iteration number,
$iter$: current iteration number.

The model using (4) is called "inertia weights approach (IWA)" [15]. Using the above equation, diversification characteristic is gradually decreased and a certain velocity, which gradually moves the current searching point close to pbest and gbest can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{5}$$

Fig. 2 shows a concept of modification of a searching point by PSO



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.2. Concept of modification of a searching point by PSO.

B. Constriction factor approach (CFA) [15][22]

The basic system equation of PSO ((3), (4), and (5) in IWA) can be considered as a kind of difference equations. Therefore, the system dynamics, namely, search procedure, can be analyzed by the eigen value analysis. By analyzing the eigen values of simplified equations of (3), (4) and (5), Clerc, et al., found the following equations. Namely, the velocity of CFA (simplest constriction) can be expressed as follows:

$$v_i^{k+1} = K[v_i^k + c_1 \times rand() \times (pbest_i - s_i^k) + c_2 \times rand() \times (gbest - s_i^k)] \quad (6)$$

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \ where\ \varphi = c_1 + c_2, \varphi > 4 \quad (7)$$

For example, if φ=4.1, then K=0.73. As φ increases above 4.0, K gets smaller. For example, if φ=5.0, then K=0.38, and the damping effect is even more pronounced. The convergence characteristic of the system can be controlled by φ. Namely, Clerc, et al., found that the system behavior can be controlled so that the system behavior has the following features:

(a) The system does not diverge in a real value region and finally can converge,
(b) The system can search different regions efficiently by avoiding premature convergence.

Unlike other EC methods, CFA of PSO ensures the convergence of the search procedures based on the mathematical theory. CFA can generate higher quality solutions than PSO with IWA [23]. However, CFA only considers dynamic behavior of one agent and the effect of the interaction among agents. Namely, the equations were developed with fixed best positions (pbests and gbest) although pbests and gbest can be changed during search procedure in the basic PSO equations. The effect of pbests and gbest in the system dynamics is one of the future works [22]. Details about the approach can be found in [15][22].

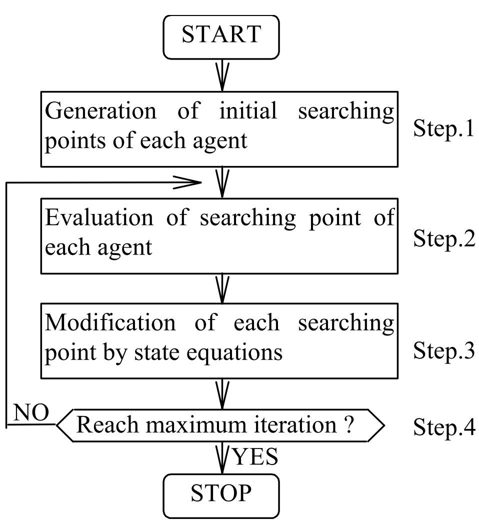


Fig.3. A general flow chart of PSO.

C. PSO algorithm [14-16]

Using the above concepts, the whole PSO algorithm can be expressed as follows (See fig.3):

1) *State variables (searching point)*
State variables (states and their velocities) can be expressed as vectors of continuous numbers. PSO utilizes multiple searching points for search procedures.

2) *Generation of initial searching points (Step.1 in fig.3)*
Initial conditions of searching points are usually generated randomly within their allowable ranges.

3) *Evaluation of searching points (Step.2 in fig.3)*
The current searching points are evaluated by using the objective functions of the target problem. Pbests and gbest can be modified by comparing the evaluation values of the current searching points, and pbests and gbest.

4) *Modification of searching points (Step.3 in fig.3)*
The current searching points are modified using the state equations ((3)(4)(5) in IWA and (6)(7)(5) in CFA)..

5) *Stop Criterion (Step.4 in fig.3)*
The search procedure can be stopped when the current iteration number reaches the predetermined maximum iteration number. The last gbest can be output as a solution.

D. Hybrid Particle Swarm Optimization [17]

HPSO utilizes the mechanism of PSO and a natural selection mechanism, which is usually utilized by EC such as genetic algorithms (GAs). Namely, the number of highly evaluated agents is increased while the number of lowly evaluated agents is decreased at each iteration. Since search procedure by PSO deeply depends on pbests and gbest, the searching area is limited by pbests and gbest. Namely, using pbests and gbest, PSO changes the current searching points successively. On the contrary, HPSO can jump the current searching points into the effective (attractive) area directly by the selection mechanism. Agent positions with low evaluation values are replaced by those with high evaluation values using the selection. The replaced rate is called selection rate (Sr). It should be noted that pbest information of each agent is maintained even if the agent position is replaced by another agent's position. Therefore, intensive search in a current effective area and dependence on the past high evaluation position are realized. Fig. 4 shows a general flow chart of HPSO. Fig. 5 shows concept of step 2, 3, and 4 of the flow chart.

The original PSO sometimes takes time to get into the current effective area in the solution space. On the contrary, HPSO moves the lowly evaluated agents to the current effective area directly using the selection method and concentrated search especially in the current effective area is realized.

IV. Distribution State Estimation By HPSO

A. 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:

(1) Load values

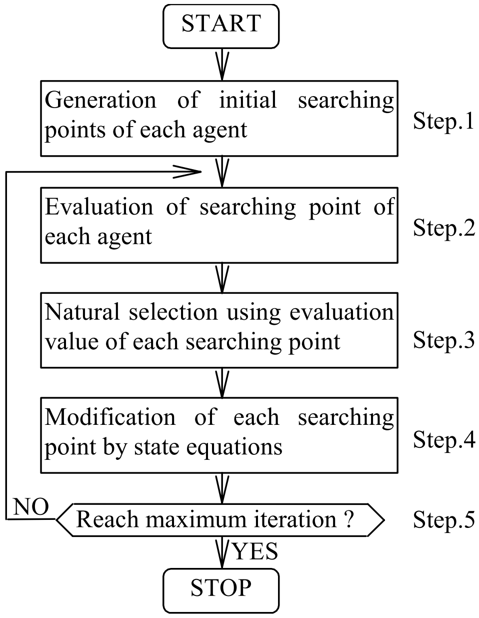


Fig.4. A general flow chart of HPSO.

Average load value at each load section can be calculated with measurement data and load ratio. 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.

(2) 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.

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.

B. 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/S, RTU, and DG)

Step 2 Set calculation conditions

(1) Calculation of initial values of state variables

- Using measurement data and load ratio, 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

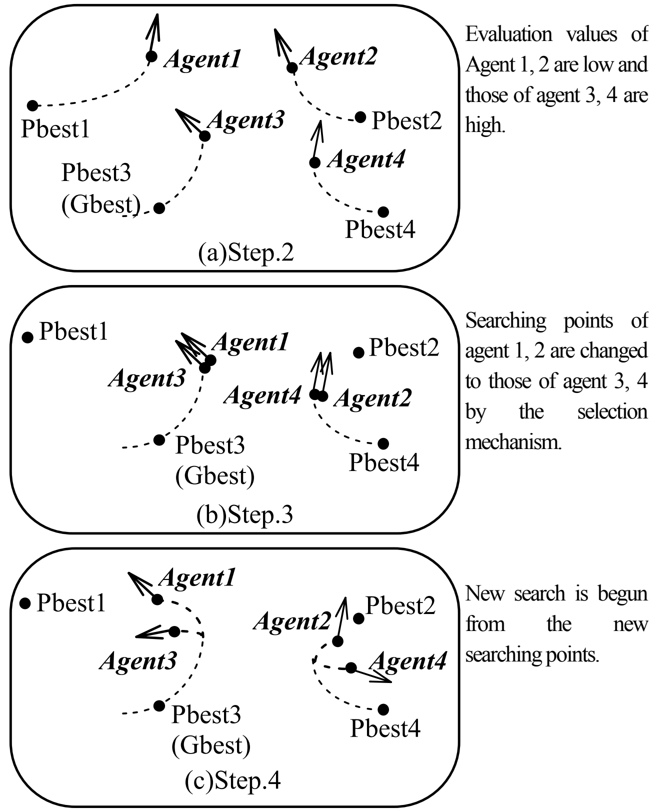


Fig. 5. Concept of searching process by HPSO.

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

Step 3 State estimation

A network condition, which minimizes error between measurement and calculated values, is found by HPSO.

The proposed distribution state estimation handles constrained nonlinear optimization problem expressed by (1) and (2). Practically, limited number of measurement values can be obtained in distribution systems and calculated voltage and currents are evaluated at limited number of nodes and branches. Therefore, a solution may have large difference between actual and calculated voltages and currents where we do *not* have measurement values even if the solution can minimize (1). However, the proposed method can generate an appropriate solution by the following reasons:

(a) Using the problem-dependent knowledge such as load ratio and average DG output values, an appropriate upper and lower limits can be set for state variables and a solution can be generated within reasonably bounded ranges.

(b) HPSO has a global optimization characteristic and can generate consistence load and DG output values, which can minimize the objective function without falling into local minima.

(c) There exists only a unique solution for radial network, while loop networks may have multiple solutions [23]. 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.

According to the observation, it can be expected that that the proposed method has a good convergence characteristic.

Moreover, solutions can be maintained within reasonable values by restriction of upper and lower limits of state variables. If solutions cannot be obtained within reasonable limits, the limits can be expanded. Then, if an impractical solution, which can minimize (1), is obtained, it can be predicted that bad data are included in measured data. Namely, when solutions are obtained by only relaxation of the constraints, inclusion of bad data in measured data can be considered as one of the reasons. The relaxation of the constraints can be considered in step 3 (state estimation) of the above-mentioned proposed algorithm.

V. Numerical Examples

The proposed HPSO based method and a method based on the conventional PSO are applied to distribution model systems. The effectiveness of CFA compared with IWA is also investigated. As pointed out above, the conventional methods cannot be applied to the DSE problems. Therefore, the proposed HPSO based method is compared with only the method based on the conventional PSO in this simulation.

A. Simulation Conditions

The followings are test cases to demonstrate two features of the proposed method. Namely, capability of the method converging to the values near to the measurement data is investigated in case No.1 and effectiveness of the method considering measurement error is evaluated in case No.2.

(1) Case No.1

The methods are applied to a model system as shown in fig. 6, which models rural area. Load flow calculation results are utilized as measurement data. The model has one DG with fixed power output 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 No.2

The methods are applied to a model system as shown in fig. 7, which models urban area with actually measured data.

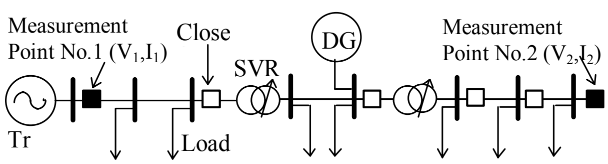


Fig.6. A distribution model system for case No.1.

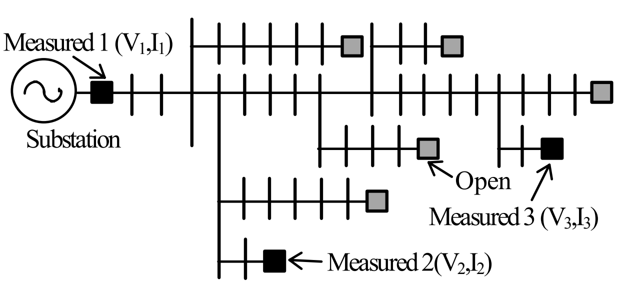


Fig.7. A distribution model for case No.2.

Weighting coefficients of (1) are set to 1.0. The number of agent is set to 20. 30 trials are performed for appropriate parameter determination simulation (table 1) and 100 trials are performed for other simulations. At each trial, Different random numbers are utilized and the best-evaluated value is stored within 100 searching iteration. IWA and CFA are compared in case No.1.

B. Simulation Results

(1) Case No.1

Parameters of HPSO with IWA are w_{max}, w_{min}, and C_i in (3) and (4), and selection rate (Sr). Table 1 shows maximum, average, and minimum values of the objective function for various optimization parameter combinations. According to the results, the following observations can be pointed out:

(a) Appropriate combination of w_{max} and w_{min} is 0.9 and 0.4. The values are the same as those recommended by other papers [14-16] and the values do *not* depend on the problems.

(b) Appropriate value ranges for C_1 and C_2 (C_1=C_2) are 1.0 to 2.0 and 2.0 is the most appropriate in many cases. The value is the same as those recommended by other papers [14-16] and the values do *not* depend on the problems.

(c) Appropriate value for S_r can be 0.3 and 0.4. However, if w_{max}=0.9 and w_{min}=0.4, almost the same characteristics can be obtained from S_r=0.3 to 0.7. Namely, the robust convergence characteristic can be obtained by setting w_{max}=0.9 and w_{min}=0.4.

According to the above observation, the following values are appropriate for DSE and utilized for other simulations: w_{max} =0.9, w_{min}=0.4, C_i=2.0. The proposed method has been applied to various loading conditions and the same characteristic has been obtained. Namely, the appropriate parameter values are *not* different among various target problems. This is one of the desirable characteristics of HPSO. DSE can be performed for various network configurations and loading conditions. Therefore, the feature is important for practical DSE problems.

State estimation results are shown in Table 2, 3 and fig. 8. As shown in Table 2, the minimum evaluation values by HPSO and PSO are the same. However, the maximum evaluation value, which means 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 3 and fig. 8 indicates the high quality solutions by HPSO as well.

Table 4 shows comparison of the objective function values with the best parameters of IWA in Table 1 (w_{max} = 0.9, w_{min} = 0.4, c_i = 2.0) and CFA (φ = 4.1 in (7)). In the simulation, S_r is set to 0.5. According to the results, maximum objective function value can be restricted to small value by CFA. Namely, even in the worst case, using CFA, the system has possibility to estimate the distribution system condition with minimum errors. As mentioned above, CFA leads state equations by eigen value analysis. Therefore, according to CFA, the appropriate values by IWA (w_{max} = 0.9, w_{min} = 0.4, c_i

= 2.0) should be related to the eigen values of the state equations of IWA. However, The state equations between IWA and CFA are different, and more mathematical analysis can be expected.

(2) Case No.2

Table 5 shows the estimation results for the model system in fig. 7 by using the appropriate values of IWA (w_{max} = 0.9, w_{min} = 0.4, c_i = 2.0). In the simulation, S_r is set to 0.5. 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. However, CT and PT at S/S is more accurate than those at RTUs. Considering communication errors from RTUs as well, the sending current should be more accurate than the voltage at RTUs in the target distribution system. Therefore, the result is acceptable by the operators. The result can be tuned by changing the weight coefficient of the objective function of each term. Table 6 shows comparison of the number of calculations (Flops by Matlab) by both methods. The number

TABLE I
SIMULATION RESULTS USING VARIOUS VALUES OF OPTIMIZATION PARAMETERS (CASE NO.1).

Sr	w_{max}		c_i							
	w_{min}		0.5	1.0	1.5	2.0	2.5	3.0	4.0	Ave.
0.3	0.9	Ave.	0.000035	0.000017	0.000014	0.000012	0.000021	0.000017	0.000032	0.000021
	0.4	Min.	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000002	0.000000
		Max.	0.000331	0.000068	0.000053	0.000055	0.000151	0.000123	0.000125	0.000129
	2.0	Ave.	0.000621	0.000336	0.000215	0.000141	0.000160	0.000109	0.000081	0.000149
	0.9	Min.	0.000008	0.000050	0.000046	0.000005	0.000003	0.000005	0.000005	0.000016
		Max.	0.000946	0.000946	0.000806	0.000806	0.000806	0.000805	0.000252	0.000632
	2.0	Ave.	0.000225	0.000183	0.000132	0.000086	0.000087	0.000067	0.000076	0.000122
	0.4	Min.	0.000000	0.000026	0.000008	0.000005	0.000002	0.000002	0.000002	0.000006
		Max.	0.000816	0.000805	0.000805	0.000230	0.000266	0.000164	0.000238	0.000475
0.4	0.9	Ave.	0.000041	0.000016	0.000013	0.000012	0.000015	0.000023	0.000037	0.000022
	0.4	Min.	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000	0.000003	0.000001
		Max.	0.000233	0.000082	0.000078	0.000050	0.000062	0.000057	0.000162	0.000103
	2.0	Ave.	0.000587	0.000364	0.000232	0.000141	0.000118	0.000093	0.000130	0.000238
	0.9	Min.	0.000117	0.000063	0.000005	0.000005	0.000004	0.000005	0.000005	0.000029
		Max.	0.000946	0.000946	0.000849	0.000241	0.000231	0.000230	0.000819	0.000609
	2.0	Ave.	0.000235	0.000168	0.000170	0.000121	0.000114	0.000084	0.000063	0.000136
	0.4	Min.	0.000024	0.000014	0.000000	0.000002	0.000005	0.000005	0.000002	0.000007
		Max.	0.000805	0.000805	0.000805	0.000230	0.000230	0.000230	0.000231	0.000477
0.5	0.9	Ave.	0.000031	0.000020	0.000018	0.000019	0.000028	0.000024	0.000039	0.000026
	0.4	Min.	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000002	0.000000
		Max.	0.000260	0.000084	0.000060	0.000106	0.000127	0.000094	0.000295	0.000147
	2.0	Ave.	0.000588	0.000332	0.000199	0.000165	0.000126	0.000152	0.000082	0.000235
	0.9	Min.	0.000000	0.000002	0.000005	0.000005	0.000002	0.000001	0.000008	0.000003
		Max.	0.000946	0.000897	0.000805	0.000822	0.000810	0.000805	0.000230	0.000759
	2.0	Ave.	0.000138	0.000112	0.000157	0.000106	0.000129	0.000109	0.000091	0.000120
	0.4	Min.	0.000000	0.000005	0.000013	0.000002	0.000002	0.000005	0.000002	0.000004
		Max.	0.000545	0.000805	0.000805	0.000303	0.000805	0.000230	0.000287	0.000540
0.6	0.9	Ave.	0.000040	0.000015	0.000020	0.000017	0.000021	0.000039	0.000033	0.000026
	0.4	Min.	0.000000	0.000000	0.000000	0.000000	0.000002	0.000001	0.000000	0.000000
		Max.	0.000215	0.000072	0.000067	0.000068	0.000085	0.000165	0.000099	0.000110
	2.0	Ave.	0.000514	0.000282	0.000155	0.000170	0.000146	0.000106	0.000127	0.000214
	0.9	Min.	0.000005	0.000005	0.000005	0.000005	0.000002	0.000002	0.000002	0.000004
		Max.	0.000946	0.000946	0.000415	0.000805	0.000634	0.000236	0.000805	0.000684
	2.0	Ave.	0.000194	0.000151	0.000141	0.000107	0.000103	0.000102	0.000047	0.000121
	0.4	Min.	0.000003	0.000005	0.000005	0.000002	0.000001	0.000001	0.000002	0.000003
		Max.	0.000805	0.000805	0.000805	0.000266	0.000327	0.000232	0.000230	0.000496
0.7	0.9	Ave.	0.000052	0.000022	0.000023	0.000024	0.000019	0.000038	0.000033	0.000030
	0.4	Min.	0.000000	0.000000	0.000000	0.000000	0.000000	0.000002	0.000004	0.000001
		Max.	0.000332	0.000138	0.000100	0.000106	0.000063	0.000140	0.000109	0.000141
	2.0	Ave.	0.000524	0.000327	0.000328	0.000122	0.000152	0.000101	0.000139	0.000242
	0.9	Min.	0.000001	0.000013	0.000033	0.000005	0.000012	0.000003	0.000002	0.000010
		Max.	0.000946	0.000946	0.000805	0.000430	0.000805	0.000230	0.000805	0.000710
	2.0	Ave.	0.000156	0.000149	0.000159	0.000107	0.000122	0.000108	0.000088	0.000127
	0.4	Min.	0.000000	0.000004	0.000005	0.000005	0.000005	0.000001	0.000005	0.000004
		Max.	0.000513	0.000895	0.000805	0.000230	0.000805	0.000230	0.000230	0.000530

TABLE II
COMPARISON OF OBJECTIVE FUNCTION VALUES BY BOTH METHODS (CASE NO.1).

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

TABLE III
COMPARISON OF MEASURED AND ESTIMATED VOLTAGES AND CURRENTS (CASE NO.1).

Measured point	Measured value	HPSO		PSO
		Optimal estimation value	Average estimation value	Average 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]

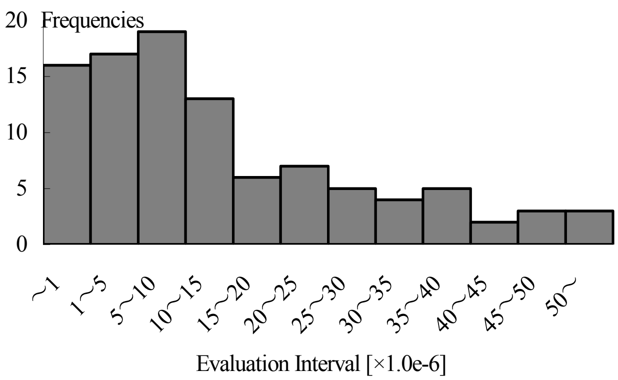


Fig.8. Convergence characteristics of the proposed method (case No.1).

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

VI. CONCLUSIONS

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

(1) This paper 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 appropriate load and distributed generation output values at each node with actual and 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 even with measurement errors.

(4) The appropriate parameter values for distribution state estimation by inertia weights approach are the same as those recommended by other PSO papers. The robust convergence characteristic of HPSO-based methods is also ensured in distribution state estimation application.

(5) HPSO with constriction factor approach has possibility to generate more accurate estimation conditions than HPSO with the inertia weight approach. However, the constriction factor approach only considers dynamic behavior of each agent and the effect of the interaction among agents. Therefore, more mathematical analysis can be expected.

The future works can be summarized as follows:

(1) The DSE presented in this paper can handle estimation of DG output. Unfortunately, we could not obtain the data with variable DG output. Therefore, verification of the estimation of DG output is one of the future works.

(2) The presented method can estimate the tap position of transformers with automatic tap changer in the distribution systems. Verification of estimation of the tap position with actual data is one of the future works.

Various problems in power system fields can be formulated as nonlinear optimization problems with non-differential and non-continuous functions practically. Therefore, the results in this paper indicate applicability of HPSO based optimization for such problems.

TABLE IV
COMPARISON OF OBJECTIVE FUNCTION VALUES BY IWA AND CFA BY THE PROPOSED METHOD (CASE NO.1).

	IWA	CFA
Ave.	0.000019	0.000019
Min.	0.000000	0.000000
Max.	0.000106	0.000072

TABLE V
COMPARISON OF MEASURED AND ESTIMATED VOLTAGES AND CURRENTS BY HPSO (CASE NO.2).

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 VI
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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