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# State Estimation and Optimal Setting of Voltage Regulator in Distribution Systems

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**Abstract:** This paper presents a practical distribution state estimation (DSE) method and an optimal setting method for voltage regulators in distribution systems using modern heuristic techniques. The proposed DSE method utilizes hybrid particle swarm optimization (HPSO) and handles nonlinear characteristics of the practical equipment and actual measurements in distribution systems. The proposed optimal setting method for voltage regulators utilizes reactive tabu search (RTS) and enumeration method, and handles variation of load flow by introduction of distributed generation. The feasibility of the proposed methods is demonstrated on practical distribution system models.

**Keywords:** State Estimation, Optimal Setting, Distributed Generation, Modern Heuristic Techniques, Hybrid Particle Swarm Optimization, Reactive Tabu Search

## I. INTRODUCTION

Distributed generation (DG) has been introduced in distribution systems gradually. Introduction of distributed generation requires flexible planning and operation of distribution systems. Therefore, new methods are required for the flexible planning and operation, and intelligent systems can be a key technique to realize them.

In order to realize the planning and operation, observation of system condition is a basic function and distribution state estimation is becoming one of the key functions in distribution control center. DSE requires to consider error and asynchronism of measurement from actual distribution systems. Since limited measured 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 of DSE. A number of methods have been developed for DSE [1-11]. Conventional DSE methods assume that the objective function or equations related to DSE can be differentiable and continuous. However, considering the nonlinear characteristics of the practical equipment in distribution systems, the objective function and the equations cannot be differentiable and continuous, and the conventional methods cannot be applied.

Modern heuristic techniques are considered as practical tools for nonlinear optimization problems [12]. The techniques do not require that the objective function has to be differentiable and continuous. A particle swarm optimization (PSO) is one of the modern heuristic techniques [13][14] and can be applied to continuous nonlinear optimization problems such as DSE. 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 [15]. 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.

Distribution system voltage is regulated with transformers with the line drop compensation (LDC) function at substations (S/Ss) and those installed in distribution feeders, which are called step voltage regulator (SVR) in Japan. Considering various load changes in practical distribution systems, parameter setting for transformers with LDC function at S/Ss and SVR in distribution systems is one of the important tasks in distribution planning. The setting has been performed using a heuristic equation considering the lightest and the heaviest loading conditions in the target distribution system. Considering introduction of distributed generation, the conventional setting method is not appropriate any more and a new setting method has to be developed. The optimal setting problem is one of inverse problems and can be formulated as a combinatorial optimization problem. Therefore, reactive tabu search (RTS) [16] must be an appropriate method for the problem.

This paper presents a practical distribution state estimation method using a hybrid particle swarm optimization and an optimal setting method for voltage regulators in distribution systems using reactive tabu search. The proposed DSE 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 proposed optimal setting method for voltage regulators can generate sub-optimal parameter setting considering various loading conditions and power outputs of distributed generators. The feasibility of the proposed methods is demonstrated on practical distribution system models.

## II. DISTRIBUTION STATE ESTIMATION

### *Formulation of DSE problem*

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

(a) S/S: absolute value of sending voltage and current,

(b) Remote terminal unit (RTU): absolute value of voltage and current.

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

(a) A contracted load value is known at each load section.

(b) Estimated power factor of sending end at S/S and each section can be obtained.

(c) 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.

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

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

where, x : state variable,

$w_i$ : weighting factor of measurement variable i,

$z_i$ : measured value of measurement variable i,

$h_i$ : state equation of measurement variable i.

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.

$$x_{j,\min} \le x_j \le x_{j,\max} \qquad (2)$$

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) [17]. The following models have been included in BFS [18].

(a) Distributed generators
- PV, PQ specific node
- Induction generator
- Inverter connected generator (voltage control type, current control type)

(b) Load (ZIP model)

(c) Voltage regulator
- Transformer with LDC function at S/S
- SVR

(d) FACTS (SVC, UPFC, etc.)

Consequently, the state estimation problem can be formulated as a constrained nonlinear optimization problem with continuous variables.

***Hybrid particle swarm optimization***

PSO is one of the optimization techniques and belongs to EC techniques [13][14]. It has been developed through simulation of social behavior of bird flocking in two-dimension space. The position of each individual (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. Moreover, each agent knows the best value so far in the group (gbest) among pbests. Each agent tries to modify its position using the following information:
- the current positions (x, y),
- the current velocities (vx, vy),
- the distance between the current position, and pbest and gbest.

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

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

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.

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

$$s_i^{k+1} = s_i^k + v_i^{k+1} \qquad (4)$$

Hybrid Particle Swarm Optimization utilizes the mechanism of PSO and the natural selection mechanism, which is usually utilized by EC such as genetic algorithms (GAs) [12]. 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. 1 shows a general flow chart of HPSO. Fig. 2 shows concept of step. 2, 3, and 4 of the flow chart.

***Distribution state estimation by HPSO***

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 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

HPSO finds a network condition, which minimizes error between measured and calculated values.

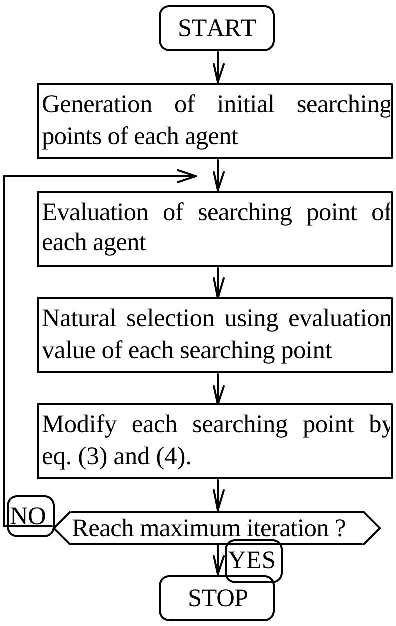


Fig.1 A general flow chart of HPSO.

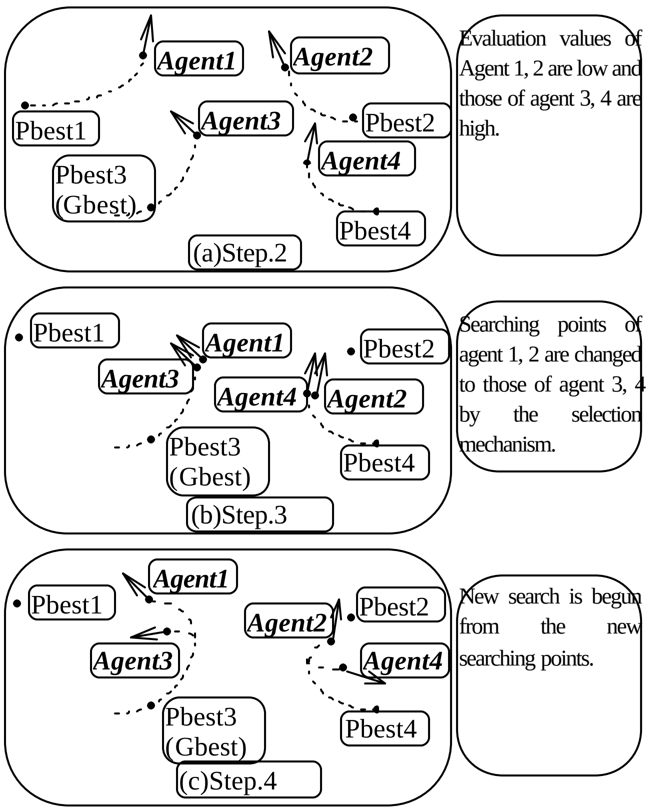


Fig. 2 Concept of searching process by HPSO.

***Numerical examples***

(1) Simulation Conditions

The proposed method and a method based on the conventional PSO are applied to a distribution model system as shown in fig. 3, which 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). The equipment causes nonlinear characteristics of the objective function. The length of the feeder is 10.5 [km]. DG capacity is 2000 [kVA].

Weighting coefficients of eq. (1) are set to 1.0. The weighting function of eq. (3) is set to the following equation :

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \qquad (5)$$

where, $w_{max}$ : Initial value of weighting coefficient,
$w_{min}$ : Final value of weighting coefficient,
$iter_{max}$ : Maximum iteration,
iter : Current iteration number.

The number of agent is set to 20. The following values are utilized for the simulations: $w_{max}$ =0.9, $w_{min}$= 0.4, $C_i$ = 2.0 according to pre-simulation. 100 trials are performed for simulations using different random numbers. At each trial, the best-evaluated value is stored within 100 searching iteration.

(2) Simulation Results

State estimation results are shown in Table 1, 2 and fig. 4. As shown in Table 1, 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. Average evaluation value by HPSO is approximately 50% of that by PSO. The results indicate HPSO can generate higher quality solutions by PSO. Table 2 and fig. 4 indicates the high quality solutions by HPSO as well.

## III. OPTIMAL SETTING OF VOLTAGE REGULATOR

***Formulation of optimal setting problem***

(1) Available data

The following data are able to obtained from actual distribution system:

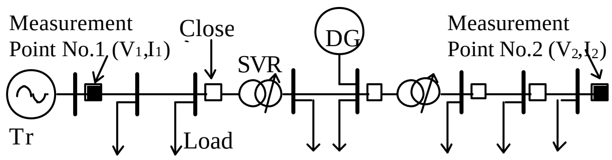


Fig.3 A distribution model system.

Table 1. Comparison of objective function values by both methods.

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

Table 2. Comparison of measured and estimated voltage and current.

| Measur-ed points | Measured values | HPSO | | PSO |
|---|---|---|---|---|
| | | Optimal estimation values | Ave. estimation values | Ave. estimation values |
| $I_1$ | 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] |

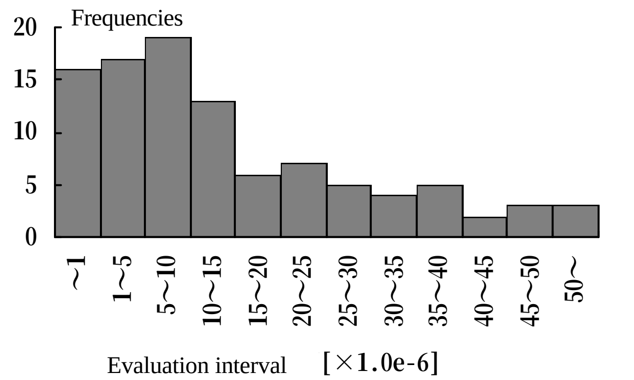

Fig.4 Convergence characteristics of the proposed method (100 trials).

(a) Setting values and ranges of control equipment,
(b) Sending end current and voltage at S/S,
(c) Major customer's contracted load value,
(d) Line type and distance (impedance) at each load section.
Each load value is able to be calculated using a ratio of each load value to the total load of the target network.

(2) State variables

The following control equipment is considered. The parenthetic values are setting steps.

(a) Transformer with LDC functions at S/S
- Reference voltage (Vref): 100.0-120.5 [V] <0.5 [V]>
- Dead band value (DB): ±1.0-±4.0 [%] <0.2 [%]>

(b) SVR with LDC functions
- Reference voltage (Vref):
  Rough setting: 95.0-115.0 [V] <5.0 [V]>
  Fine setting: 0.0-4.5 [V] <0.5 [V]>
- Dead band (DB) value: ±1.0-±4.0 [%] <0.5 [%]>
- Impedance, Rough setting: 0.0-20.0 [%] <5.0 [%]>
  (r, x) Fine setting: 0.0-4.0 [%] <1.0 [%]>

Using the above variables, one solution can be composed of a combination of setting values of various equipment. The setting values of control equipment are set using discrete values.

(3) Objective function

It is important to keep each section voltage within the permissible range. It is also necessary to consider minimization of power losses. Consequently, the object function can be formulated as follows:

$$f_c = \min\left[\sum_{t=1}^{l}\left[w_1\sum_{i=1}^{m} Loss_i + w_2\sum_{j=1}^{n}\left(V_j - V_{ref}\right)^2 + w_3 g(V,I)\right]\right] \quad (6)$$

where, $l$ : the number of target loading conditions,
m : the number of branches,
$Loss_i$ : power loss at branch j,
n : the number of nodes,
$V_j$ : voltage at node i,
$V_{ref}$ : reference voltage,
$W_k$ : weighting factor at each term,
g(V,I) : total amount of departure from voltage and current constraint.

The following constraints should be considered.

(a) Voltage constraint

Voltage magnitude at each node must lie within its permissible range.

(b) Current constraint

Current magnitude at switches and lines must lie within its permissible range.

Voltage and current can be calculated by BFS method. Consequently, the optimal setting problem can be formulated as a combinatorial optimization problem with discrete variables.

***Overview of optimal setting method***

(1) Characteristic of optimal setting problem

Fig.5 shows properties and solution methods for the optimal setting problem. Evaluation values in the optimal setting problem are calculated using the voltage profile and the power flow condition as shown in Fig.5. The setting value of the voltage control equipment is related to the evaluation value through the tap position. Using voltage profiles and power flow conditions obtained as a calculation result, setting values of each equipment, which is a cause of the result, has to be determined. Namely, the problem is a kind of inverse problem. Several sets of setting values may have the same evaluation values when a certain section voltage is comprised within the dead band value or SVR tap position cannot be

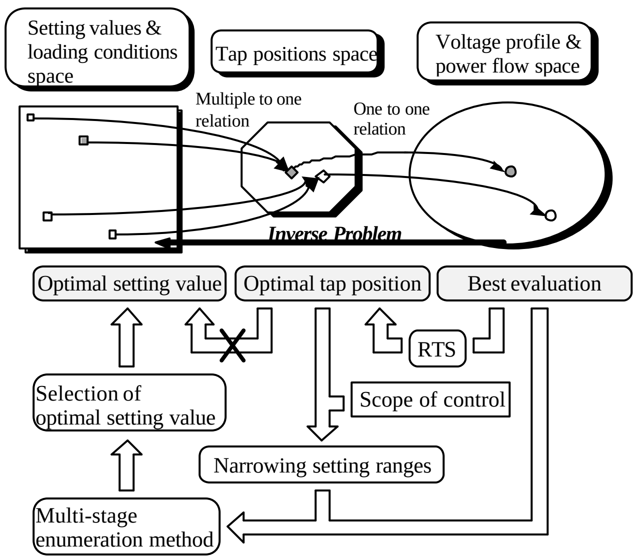

Fig.5 Concept of solutions for the optimal setting problem.

changed because of reverse power flow from distributed generators. Namely, one optimal setting value can not be calculated using SVR tap position. The enumeration method can obtain a set of the optimal setting values. However, as the number of control equipment increases, the number of solutions (combinations of setting values) increases exponentially. This paper proposes a new setting method using RTS and multi-stage enumeration method as follows:

(2) Narrowing methods of setting ranges

The setting ranges of impedance (r,x) and reference voltage of voltage control equipment (Vref) can be narrowed considering target network area of control equipment.

(a) Narrowing method of impedance setting ranges (r,x)

The voltage control equipment controls voltages from the equipment installation point to another equipment or end of the target feeder. The setting range of impedance can be narrowed considering line impedance at target network area of each control equipment.

(b) Narrowing method of reference voltage setting ranges (Vref)

Evaluation values are calculated using the voltage profile at a certain tap position and the power flow condition. Evaluation values and tap positions are one to one relations. Therefore, The optimal tap position can be obtained using RTS. The setting range of reference voltage can be narrowed considering the voltage profile at target network area of control equipment. The following algorithm is utilized for narrowing the reference voltage setting ranges.

Step.1 Searching the optimal tap position

The optimal tap position minimizing evaluation values of eq. (6) can be obtained using RTS.

Step.2 Narrowing reference voltage setting ranges

The voltage profiles at target loading conditions are determined by the optimal tap position. The reference voltage setting ranges can be narrowed considering bounds of the voltage profile at target network area of control equipment.

(3) Multi-stage enumeration method

State variables and evaluation values of the optimal setting problem are multiple to one relations. This paper develops a multi-stage setting method using the enumeration method and adjusted setting steps. The global optimal solution may not be obtained by the proposed method. However, it can realize more effective search than an ordinal (one-stage) enumeration method.

Setp.1 Reduction of combinations of the setting values including a set of the rough optimal solutions:

The enumeration method is applied to reduce the setting ranges, which include a set of the rough optimal solutions, using the narrowed setting ranges by the above-mentioned narrowing methods of setting ranges with rough setting steps.

Step.2 Searching the candidate set of the optimal solutions:

The enumeration method is applied using the reduced setting ranges by step 1 with the minimum setting steps. The step generates a set of the optimal solutions, which minimize the objective function of the target problem, (6).

The following method is utilized to determine one final optimal setting solution among a set of the optimal solutions.

(4) Selection method for one final optimal setting solution

One final optimal solution (one combination of setting values) can be selected using the following equation:

$$J = \min\left[\sum_{i=1}^{n}\left[(X_{i\max} - X_i)^2 + (X_i - X_{i\min})^2\right]\right] \qquad (7)$$

where, $n$ : the number of state variables,

$X_i$ : setting values with best evaluation,

$X_{imax}$ : maximum value of setting values with best evaluation,

$X_{imin}$ : minimum value of setting values with best evaluation.

***Numerical examples***

(1) Simulation conditions

The proposed method is applied to a distribution model system as shown in fig.3. Table 3 shows the target loading conditions. Voltage profiles calculated with the conventional setting values and the optimal setting values are compared.

(2) Simulation results

Table 4 shows the original setting values by the conventional method, original setting ranges, reduced setting ranges by the proposed narrowing methods, and the final optimal setting values by the multi-stage enumeration method and the selection method of one final optimal setting solution. The number of combination of the optimal setting values, which minimize the objective function, is 54745. Fig. 6 shows an example of voltage profiles using the optimal setting values calculated by the proposed method and the conventional setting values. The figure indicate that the proposed method can modify the voltage profiles for the target loading conditions and the practical applicability of the proposed method to the optimal setting problem.

## IV. CONCLUSIONS

This paper presents a distribution state estimation method using a hybrid particle swarm optimization and an optimal setting method for voltage regulators in distribution systems using reactive tabu search. The proposed DSE method can handle nonlinear characteristics of the practical equipment in distribution systems. It can estimate load and distributed

Table 3. Target loading conditions.

| | Maximum loading condition | Minimum loading condition |
|---|---|---|
| Total load | 1000 [kW] | 330 [kW] |
| Power factor | Lagging 0.9 | Leading -0.86 |
| Distributed Generator | - | Maximum generating power |
| Sending voltage | 6800 [V] | 6600 [V] |

Table 4. Original setting values, original setting ranges, narrowed setting ranges, and optimal setting values.

| | Setting values | Original setting values | Original setting ranges | Narrowed setting ranges | Optimal setting values |
|---|---|---|---|---|---|
| S | Vref [V] | 109.0 | 95.0～119.0 | 109.0～115.0 | 112.0 |
| V | DB [%] | ±2.0 | ±1.0～±4.0 | ±1.0～±4.0 | ±2.5 |
| R | **r** [%] | 6.0 | 0.0～24.0 | 0.0～9.0 | 4.0 |
| 1 | **x** [%] | 3.0 | 0.0～24.0 | 0.0～15.0 | 7.0 |
| S | Vref [V] | 109.0 | 95.0～119.0 | 109.0～115.0 | 110.0 |
| V | DB [%] | ±2.0 | ±1.0～±4.0 | ±1.0～±4.0 | ±1.0 |
| R | **r** [%] | 6.0 | 0.0～24.0 | 0.0～10.0 | 5.0 |
| 2 | **x** [%] | 2.0 | 0.0～24.0 | 0.0～10.0 | 4.0 |

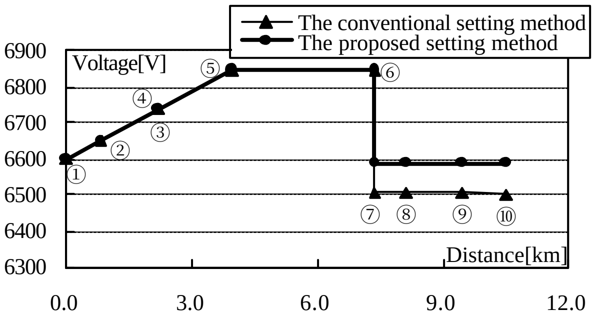


Fig.6 An example of voltage profiles at minimum loading condition.

generation output values at each node by minimizing difference between measured and calculated state variables. The proposed optimal setting method for voltage regulators can generate sub-optimal parameter setting considering various loading conditions and power outputs of distributed generators. The feasibility of the proposed methods is demonstrated on practical distribution system models.

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## REFERENCES

[1] F. F. Wu and A. F. Neyer, "Asynchronous Distributed State Estimation for Power Distribution Systems", *Proc. of 10th PSCC*, Aug. 1990.

[2] I. Roytelman and S. M. Shahidehpour, "State Estimation for Electric Power Distribution Systems in Quasi Real-time Conditions", *IEEE Trans. on Power Delivery*, Vol. 8, No. 4, October 1993.

[3] M. E. Baran and A. W. Kelley, "State Estimation for Real-time Monitoring of Distribution Systems", *IEEE Trans. on Power Systems*, Vol. 9, No. 3, August 1994.

[4] M. E. Baran, A. W. Kelley, "A Branch-Current-Based State Estimation Method for Distribution Systems", *IEEE Trans. on Power Systems*, Vol. 10, No. 1, February 1995.

[5] C. N. Lu, J. H. Teng, and W. E. Liu, "Distribution System State Estimation", *IEEE Trans. on Power Systems*, Vol. 10, No. 1, February 1995.

[6] W. M. Lin, J. H. Teng, "State Estimation for Distribution Systems with Zero-Injection Constraints", *IEEE Trans. on Power Systems*, Vol. 11, No. 1, February 1996.

[7] Ke Li, "State Estimation for Power Distribution System and Measurement Impacts", *IEEE Trans. on Power Systems*, Vol. 11, No. 2, May 1996.

[8] A. P. S. Meliopoulos, F. Zhang, "Multiphase Power Flow and State Estimation for Power Distribution Systems", *IEEE Trans. on Power Systems*, Vol. 11, No. 2, May 1996.

[9] R. C. Leou, C. N, Lu, National Sun Yat-Sen University, Taiwan, "Improving Feeder Voltage Calculation Results with Telemetered Data", *IEEE Trans. on Power Delivery*, Vol.11, No.4, October 1996.

[10] A. K. Ghosh, D. L. Lubkeman, M. J. Downey, and R. H. Jones, "Distribution Circuit State Estimation Using a Probabilistic Approach", *IEEE Trans. on Power Systems*, Vol. 12, No. 1, February 1997.

[11] W. H. E. Liu, et al., "A Practical State Estimation Algorithm for Distribution Management Systems", *Proc. of* $13^{th}$ *PSCC*, June 1999.

[12] C. R. Reeves, *Modern Heuristic Techniques for Combinatorial Problems*, Blackwell Scientific Publications, 1993.

[13] J. Kennedy and R. Eberhart, "Particle Swarm Optimization", *Proc. of IEEE International Conference on Neural Networks (ICNN)*, Vol.IV, pp.1942-1948, Perth, Australia, 1995.

[14] Y. Fukuyama, et al., "A Particle Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Security Assessment", *IEEE Trans. on Power System* (to be appeared).

[15] P. Angeline, "Using Selection to Improve Particle Swarm Optimization", *Proc. of IEEE International Conference on Evolutionary Computation (ICEC)*, Anchorage, May 1998.

[16] Y. Fukuyama, "Reactive Tabu Search for Distribution Load Transfer Operation (panel session on modern heuristics application to power systems)", *Proc. of IEEE PES Winter Meeting*, Singapore, 2000.

[17] Y. Fukuyama , et al., "Parallel Power Flow Calculation in Electric Distribution Networks", *Proc. of IEEE International Symposium on Circuit and Systems (ISCAS)*, 1996.

[18] Y. Fukuyama, et al., "Development of Equipment Models for Fast Distribution Load Flow Calculation Considering Interconnection of Distributed Generators", *Proc. of Power Technical Meeting of IEE of Japan*, PE-99-111, 1999 (in Japanese).

## BIOGRAPHY

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