Dependable Parallel Multi-population Global-best Brain Storm Optimization with Differential Evolution strategies for Distribution System State Estimation using Just-in-time Modeling and Correntropy in Power Systems

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Abstract— **This paper proposes dependable parallel multi-population global-best brain storm optimization with differential evolution strategies (DPMP-GBSODE) for distribution system state estimation (DSSE) using just-in-time (JIT) modeling and correntropy. In electric power distribution systems, DSSE is utilized by power utility operators to grasp whole distribution system conditions such as voltages and currents. By applying JIT modeling and correntropy to DSSE problems, voltages and currents can be correctly estimated even if false measurement values (outliers) are measured. Considering equipment of the distribution systems and penetration of renewable energies (REs), it is necessary that an evolutionary computation technique with parallel and distributed processing (PDP) is applied to the DSSE problems. When some computational processes are distributed by PDP in server systems of distribution automation systems, some calculation results from the distributed computational processes may not be returned because of various congestions of the processes. Therefore, appropriate estimation results should be obtained even if the congestions occur (dependability). The proposed DPMP-GBSODE is verified to improve dependability and computation time for the DSSE problem in comparison with conventional method even if faults of the processes occur and the outliers are measured.**

Keywords—dependability, parallel multi-population global-best brain storm optimization with differential evolution strategies, distribution system state estimation, just-in-time modeling, correntropy

I. INTRODUCTION

In power systems, electric power generated by various kinds of power generation is distributed to many customers through substations. The power generation and the high voltage substations are connected by transmission lines in which electric wires are supported with steel towers. This system with steel towers is called as a transmission system. On the other hand, the low voltage substations and the customers are connected by distribution lines in which electric wires are supported with utility poles. This system with utility poles is called as a distribution system. Power utility operators must grasp whether allowable voltage is distributed to customers or not. System conditions such as voltages and currents are measured at measurement points in the distribution systems. However, a few measurement devices are actually installed in the distribution systems. Namely, the power utility operators can check distribution system conditions only at places where measurement devices are installed. Moreover, distribution system conditions are made complex due to penetration of REs. Therefore, DSSE is utilized by the power utility operators to grasp whole distribution system conditions using limited measurement data. According to rapid penetration of REs, many DSSE methods have been investigated so far [1-10].

In conventional DSSE methods, weighted least square (WLS) has been utilized for an evaluation function [1-5]. It calculates errors between measurement values and estimation results. When measurement devices are malfunctioned, errors in measurement values are produced. The errors are called outliers, which are false measurement values. If the WLS is utilized as an evaluation function, whole estimation results are deteriorated by the outliers. Therefore, authors have proposed correntropy based DSSE methods [6-8] instead of WLS based methods. Correntropy is a technique which can ignore influence of the outliers. However, if correntropy is utilized as an evaluation function, errors between measurement values and estimation results are large at measurement points with the outliers. Therefore, authors have proposed correntropy based DSSE methods with JIT modeling for this challenge [9, 10].

In the distribution systems, equipment including static var compensators (SVCs) and step voltage regulators (SVRs) is installed. Since the equipment may cause a nonlinear characteristic of an objective function of DSSE, evolutionary computation techniques are necessary for DSSE problems. Evolutionary computation techniques can treat the nonlinear

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characteristic of the objective function of DSSE, and many evolutionary computation techniques have been investigated to apply to DSSE problems [3-10]. Moreover, multi-population is one of cooperative coevolution techniques. Using multi-population, some sub-populations are generated by dividing one population of individuals and optimization is performed independently at each sub-population. Actually, it has been verified that evolutionary computation techniques using multi-population can improve estimation accuracy for DSSE problems [6, 9, 10].

Output of REs can be changed quickly because output of REs depends on change in the weather in the distribution systems. The power utility operators must check whole distribution system conditions in a short interval considering the fluctuation of output of REs. PDP is one of solutions for the problem. PDP is easy to be applied to evolutionary computation techniques using multi-population because calculation of sub-populations is independent. Actually, it has been verified that evolutionary computation techniques using multi-population with PDP can improve computation time for DSSE problems [9, 10]. When some computational processes are distributed by PDP in server systems of distribution automation systems, some calculation results of the distributed computational processes may not be returned because of various congestions of the processes. Since the distribution system is one of social infrastructures, appropriate estimation results need to be obtained even if the congestions occur. This viewpoint is called as dependability. Namely, fast and dependable computation is necessary for DSSE problems. For this challenge, application of dependable parallel multi-population modified brain storm optimization (DPMP-MBSO) have been proposed to DSSE problems [10]. However, dependability should be improved. Multi-population global-best brain storm optimization with differential evolution strategies (MP-GBSODE) has been verified to be effective for optimal planning of smart community [11]. Consequently, dependable and PDP based MP-GBSODE has a possibility to obtain more appropriate estimation results than conventional methods for the DSSE problem.

Considering the above backgrounds, there are two contributions in this paper. Firstly, dependable parallel MP-GBSODE (DPMP-GBSODE) is proposed as a general evolutionary computation technique. Secondly, the proposed DPMP-GBSODE is applied to DSSE using JIT modeling and correntropy in order to improve dependability and computation time. Even if faults of computational processes occur and outliers are measured, the proposed DPMP-GBSODE based method is verified to improve dependability and computation time in comparison with the conventional DPMP-MBSO based method.

II. DSSE Formulation using Correntropy

Figure 1 shows a concept of the DSSE using evolutionary computation techniques. Decision variables, objective function and constraints are expressed as follows:

A. Decision Variables

Output of REs and active power loads are treated as decision variables. If the output of REs is not changeable such as hydroelectricity power generation, the output is not treated as decision variables. In search procedures, the decision variables are updated using evolutionary computation techniques.

B. Objective Function

An equation of correntropy is utilized as objective function, and shown below:

$$max f(\boldsymbol{x}) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sqrt{2\pi}}\exp(-\frac{\left(z_i - h_i(\boldsymbol{x})\right)^2}{2\sigma^2}) \quad (1)$$

where a vector $\boldsymbol{x}$ includes decision variables (outputs of REs and active power loads), N is the number of measurement points, h_i is a current or voltage calculated value at measurement point i, z_i is a current or voltage measurement value at measurement point i, σ is a kernel size.

In the DSSE problem, errors between measurement values (z_i) and estimation results ($h_i(\boldsymbol{x})$) are minimized by evolutionary computation techniques. Voltages and currents are obtained as the measurement values. The estimation results (voltages and currents) are calculated using backward forward sweep (BFS) power flow method [3]. A concept of outlier treatment by correntropy is shown in figure 2. At the initial condition, since decision variables (outputs of REs and active power loads) are

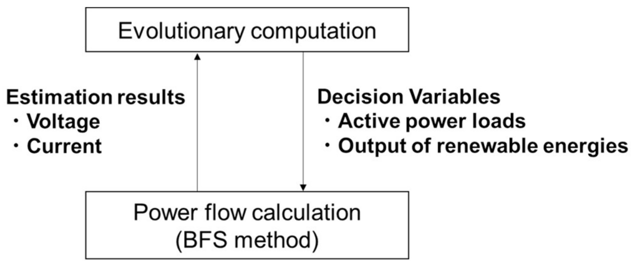

Fig. 1 A concept of DSSE using evolutionary computation techniques.

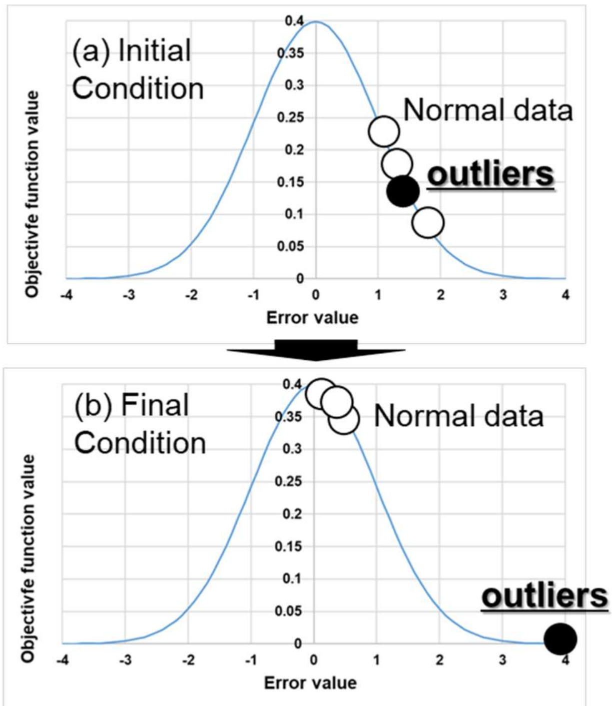

Fig. 2 A concept of outlier treatment by correntropy.

generated randomly within allowable ranges, error values for normal data and outliers are not different generally. When errors between normal data and calculated values (voltages and currents) are minimized, the objective function values of correntropy especially for normal data are moved close to 0.4. In contrast, the objective function values of correntropy especially for outliers are moved close to 0. Therefore, at the final condition, normal data and outliers can be divided by correntropy.

C. Constraints

The lower and upper limit values of decision variables are treated as constraints, and shown below:

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

where $x_{j,min}$ is the lower limit value of decision variable j, $x_{j,max}$ is the upper limit value of decision variable j.

III. The Proposed DPMP-GBSODE

A. Overview of MP-GBSODE

GBSODE [11] is an evolutionary computation technique which combines BSODE [12] and GBSO [13]. Solution search by BSODE has larger diversification than that by BSO because the algorithm of BSODE is developed by applying equations of DE to the algorithm of BSO. On the other hand, solution search by GBSO has larger intensification than that by BSO because information on a searching point with the best objective function values ($gbest$) is utilized in the algorithm of GBSO. Namely, solution search by GBSODE has larger diversification and intensification than that by BSO, and it has been verified to obtain better solution quality than BSODE and GBSO for optimal planning of smart community [11]. MP-GBSODE is an evolutionary computation technique which combines GBSODE and multi-population [11]. In MP-GBSODE, GBSODE is performed independently in each sub-population because some sub-populations are generated by dividing one population of individuals. Moreover, every certain intervals, an individual in a certain sub-subpopulation is replaced with an individual in the closest neighboring sub-populations. The process is called migration. Figure 3 shows a flow chart for generating new individuals using MP-GBSODE. Update equations using MP-GBSODE are shown below:

$$Y^t_{sij} = y^t_{sij} + \xi^t_{sij} \times rand(0,1)$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{3}$$

$$y^t_{sij} = y^t_{si1}$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{4}$$

$$y^t_{sij} = rand(0,1) \times y^t_{si1j} + \left(1 - rand(0,1)\right) \times y^t_{si2j}$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{5}$$

$$\xi^t_{sij} = rand(1,0) \times \exp(1 - \frac{T}{(T - t + 1)})$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{6}$$

$$v^t_{sij} = y^t_{sij} + F \times \left(y^t_{saj} - y^t_{sbj}\right)$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{7}$$

$$u^t_{sij} = \begin{cases} v^t_{sij}\ (random(0,1) \leq Cr) \\ y^t_{sij}\ (random(0,1) > Cr) \end{cases}$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{8}$$

$$Y^t_{sij} = \begin{cases} u^t_{sij}\ \left(f(u^t_{sij}) \geq f(y^t_{sij})\right) \\ y^t_{sij}\ \left(f(u^t_{sij}) < f(y^t_{sij})\right) \end{cases}$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{9}$$

$$y^t_{sij} = y^t_{sij} + rand(1,0) \times C \times \left(y_{sub-gbestj} - y^t_{sij}\right)$$
$$(s = 1, \cdots, S, i = 1, \cdots, I,\ j = 1, \cdots, J) \tag{10}$$

$$C = C_{min} + \frac{t}{T} \times (C_{max} - C_{min}) \tag{11}$$

where, Y^t_{sij} is a value of decision variable j of newly generated individual i in sub-population s at iteration t, y^t_{sij} is a value of decision variable j of current individual i in sub-population s at iteration t, S is the number of sub-populations, I is the number of individuals, J is the number of decision variables, y^t_{si1j} *and* y^t_{si2j} are values of decision variable j of selected existing individuals $i1$ and $i2$ in sub-population s at iteration t, $rand(0,1)$ is an uniformly distributed random real number in the range (0,1), ξ^t_{sij} is a step size function of decision variable j of individual i in sub-population s at iteration t, T is the maximum iteration number, v^t_{sij} is a value of decision variable j of newly generated individual i in sub-population s at iteration t, F is

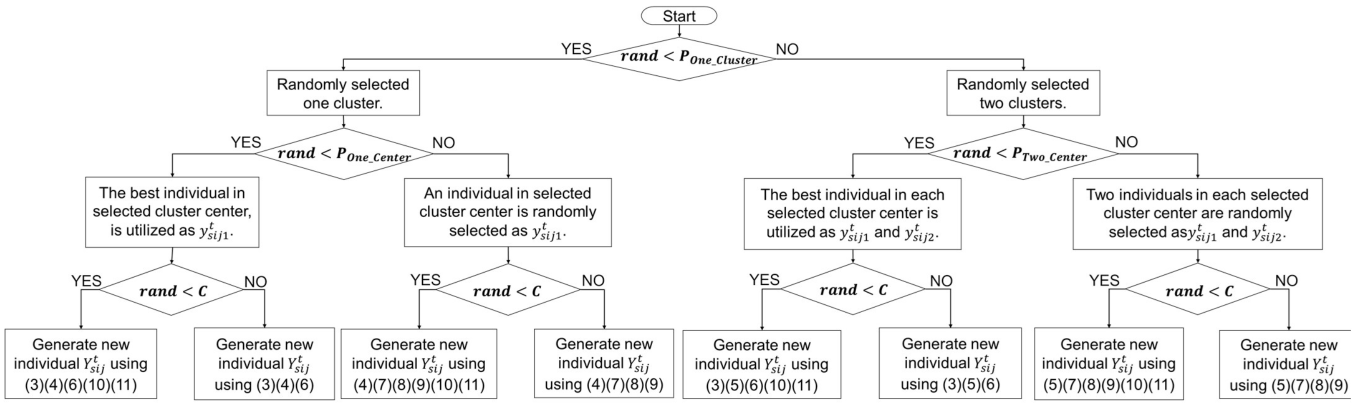

Fig. 3 A flow chart for generating new individuals using MP-GBSODE.

a mutation scaling factor, y_{saj}^t and y_{sbj}^t are values of decision variable j of randomly selected existing individuals a and b in sub-population s at iteration t $(1 \le a \ne b \le J)$, Cr is a crossover probability, $y_{sub-gbest\,j}$ is the best value of decision variable j so far found among all individuals in sub-population s, C is a calculated probability for determining whether information on $gbest$ is added or not, C_{min} and C_{max} are the minimum and the maximum values of C.

B. The proposed DPMP-GBSODE

A concept of DPMP-GBSODE using migration is shown in figure 4. The method can be utilized in various on-line optimization problems using PDP. Fast computation is necessary for the DSSE problems because DSSE is an online function in distribution automation systems. PDP is applied to MP-GBSODE to solve this challenge. Since each sub-population is distributed to each computational process as shown in figure 4, calculation of each sub-population is performed at the same time. Moreover, some calculation results of the distributed computational processes may not be returned because of various congestions of the processes. For example, it is assumed that calculation results of the process 3 cannot be returned due to the congestions as shown in figure 4. Then, appropriate estimation results must be obtained using the other processes except the process 3. Dependability is to evaluate whether appropriate estimation results are obtained or not even if the congestions occur, and is evaluated by the following equation:

$$DI = \frac{SOL_d}{SOL_{ref}} \times 100 \ [\%] \qquad (12)$$

where DI is a dependability index, SOL_d is an objective function value of an evaluated solution d, SOL_{ref} is an objective function value of the reference solution.

Since the DSSE problem using correntropy is formulated as a maximization problem, the DI value is lower than 100 [%] if SOL_d is worse than SOL_{ref}. An algorithm of DPMP-GBSODE is shown as follows:

Step 1: Individuals are initially generated at random in constraints. Objective function values of all initial individuals are calculated, and the initial individual with the best objective function value is chosen as the current best solution.

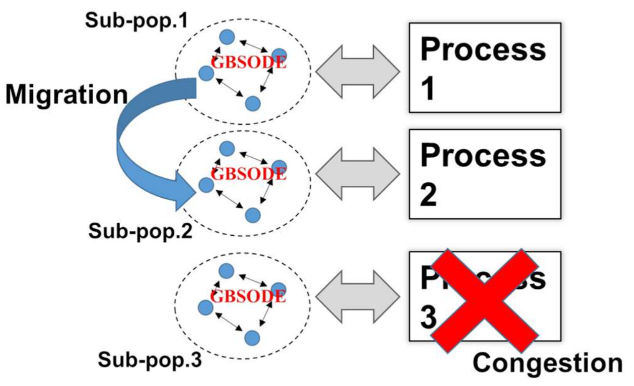

Fig. 4 A concept of DPMP-GBSODE using migration.

Step 2: Some sub-populations are generated by dividing one population of the initial individuals.

Step 3: Each sub-population is distributed to each process for speed-up of computation time. If the congestions do not occur at each process, the following procedures (Step 3-1, 3-2, and 3-3) are performed in each process.

Step 3-1: ***Clustering***: By simple grouping method (SGM) [14], individuals are divided into some clusters. The individual with the best objective function value is set as a cluster center at each cluster. In the original GBSO, clustering is performed by Fitness-based Grouping (FbG) [13]. However, since estimation results using SGM are better than those using FbG for the DSSE problem, SGM is utilized for the clustering.

Step 3-2: ***New individual generation***: If $rand(0,1) < P_{\_replace}$ at each cluster, replace the current cluster center with a randomly selected individual of the current cluster. The algorithm shown in figure 2 is utilized for generating new individuals.

Step 3-3: ***Selection***: If the objective function value of the newly generated individual is better than the existing individual at each individual, the individual is updated.

Step 4: If the newly generated individual is better than the current best solution, the current best solution is replaced with the newly generated individual.

Step 5: When the current iteration number reaches pre-set migration interval, migration is performed at each sub-population.

Step 6: When the current iteration number reaches pre-set maximum iteration number, the current best solution is output as an optimal solution. Otherwise, go back to step 3.

IV. DPMP-GBSODE FOR CORRENTROPY BASED DSSE WITH JIT MODELING

A. Overview of JIT modeling for DSSE

A concept of the correntropy based DSSE method with JIT modeling [9, 10] is shown in figure 5 and explained below:

- Firstly, DSSE using correntropy is performed ((A) in fig.5). Then, the power utility operators cannot recognize whether outliers are measured at measurement points or not. An error between measurement value and final estimation result is calculated using correntropy at each measurement point. If the error is more than a certain value (Out_{max}), the power utility operators recognize that the measurement point includes an outlier.

- The measurement value with the outlier is modified by JIT modeling ((B) in fig.5). JIT modeling keeps datasets including huge numbers of past data, and builds a local model for a target point using neighboring data in the datasets for the target point [15]. A measurement value with the outlier is modified by JIT modeling in two steps. Firstly, neighboring data for a target point are selected in datasets. Then, the actual measurement values except a measurement value which are recognized as the outlier are set as the target point. Euclidean distance between actual measurement values (the target point) and values of all data in the datasets

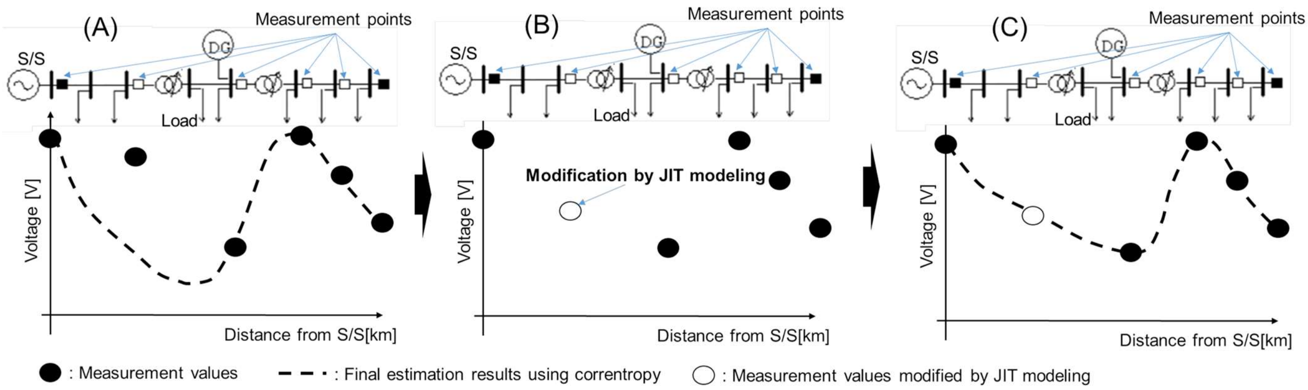

Fig.5 A concept of the correntropy based DSSE method with JIT modeling.

is calculated, and the k closest data for the target point are selected as the neighboring data. This selection method is called as k-nearest-neighbors (KNN) [16]. Secondly, a modified measurement value (a measurement value at the measurement point with the outlier) is calculated using k data selected by KNN. The outlier is replaced with the modified measurement value. The following equation is utilized for modification of the measurement value of the outlier:

$$\widehat{z_l} = \frac{\sum_{j=1}^{k} \dot{z}_{jl}}{k} \quad (l = 1, \ldots, L) \tag{13}$$

where l is a measurement point at which outliers are measured, $\hat{z}_l$ is a current or voltage estimation value at measurement point l, k is the number of data selected as datasets, $\dot{z}_{jl}$ is a current or voltage measurement value at measurement point l in jth data, L is the number of measurement points at which outliers are measured.

In figure 5, one outlier is assumed to exist as an example. If plural outliers exist, the same procedures can be utilized.

- Finally, DSSE using correntropy is performed again ((C) in fig.5). If the modified measurement value is close to a true value, errors between measurement values and final estimation results is small in all measurement points.

B. An algorithm of correntropy based DSSE with JIT modeling by the proposed DPMP-GBSODE

Step 1: Individuals are initially generated at random in constraints. For initial individuals, estimation results (voltage and current) are calculated by the BFS power flow method. Objective function values of all initial individuals are calculated using correntropy, and the initial individual with the best objective function value is chosen as the current best solution.

Step 2: S sub-populations are generated by dividing one population of the initial individuals.

Step 3: S sub-populations are distributed to S processes. If the congestions do not occur at each process, clustering (Step 3-1 explained in III-B), new individual generation (Step 3-2 explained in III-B), and selection (Step 3-3 explained in III-B) are performed in each process in parallel.

Step 4: Estimation results (voltages and currents) for the newly generated individuals are calculated using the BFS power flow method. Objective function values of newly generated individuals are calculated using correntropy. If the objective function value of the newly generated individual is better than that of the current best solution, the current best solution is replaced with the newly generated individual.

Step 5: When the current iteration number reaches pre-set migration interval, migration is performed at each sub-population.

Step 6: When the current iteration number reaches the pre-set maximum iteration number, go to step 7. Otherwise, go back to step 3.

Step 7: An error between measurement value and final estimation result is calculated using correntropy at each measurement point. If the errors are less than Out_{max} in all measurement points, output the final estimation results. Otherwise, the measurement value is modified by JIT modeling explained in IV-A, and go back to step 1.

V. SIMULATIONS

The proposed DPMP-GBSODE and the conventional DPMP-MBSO [10] are applied to benchmark systems (IEEE 33 and 69 bus systems) for verification of improving dependability and computation time by the proposed method.

A. Simulation Conditions

Figure 6 shows IEEE 33 ((a) in fig.6) and 69 ((b) in fig.6) bus systems with measurement points. In IEEE 33 bus system, both voltage and current can be obtained at measurement point No. 1, 2, and 3, and voltages in both sides can be obtained at measurement point No. 4, 5, 6, 7, and 8. In IEEE 69 bus system, both voltage and current can be obtained at measurement point No. 1, 2, 3, 8, 9, and 11, and voltages in both sides can be obtained at measurement point No. 4, 5, 6, 7, and 10. Power flow calculation results (voltage and current) are utilized as measurement values. In the simulation, Case 1, 2, 3, and 4 shown below are performed:

Case 1 - Verification of improving dependability and computation time by the proposed DPMP-GBSODE based method for IEEE 33 bus system without outliers

Case 2 - Verification of improving dependability and computation time by the proposed DPMP-GBSODE based method for IEEE 33 bus system with outliers

Case 3 - Verification of improving dependability and computation time by the proposed DPMP-GBSODE based method for IEEE 69 bus system without outliers

Case 4 - Verification of improving dependability and computation time by the proposed DPMP-GBSODE based method for IEEE 69 bus system with outliers

It is assumed that the outliers are measured at measurement point No. 2 in both systems in Case 2 and 4. Table 1 shows parameters of DPMP-GBSODE, DPMP-MBSO, JIT modeling, and correntropy in the simulations. 50000 power flow calculation results with random load values are utilized as past data in datasets for JIT modeling.

B. Simulation Results

Figure 7, 8, 9, and 10 show transitions of *DI* by the proposed DPMP-GBSODE and the conventional DPMP-MBSO based methods with 0 to 90 % fault probabilities without and with outliers for IEEE 33 and 69 bus system (Case 1, 2, 3, and 4). Since a result of the proposed DPMP-GBSODE using eight sub-populations with 0 % fault probability is the best estimation accuracy in all methods for all cases, it is set to SOL_{ref} in (12). As observed in fig. 7 and 8, *DI* values by the proposed DPMP-GBSODE based methods are superior to those by the conventional DPMP-MBSO based methods from 0 % to 50 % for both Case 1 and 2. As observed in fig. 9 and 10, *DI* values by the proposed DPMP-GBSODE based methods are superior to those by the conventional DPMP-MBSO based methods from 0 % to 40 % for both Case 3 and 4. Table 2 shows average ranks and results of Friedman test through 100 trials among the proposed DPMP-GBSODE and the conventional DPMP-MBSO based methods in all cases. As observed in table 2, average ranks of the proposed DPMP-GBSODE based methods are superior to those of the conventional DPMP-MBSO based methods for all cases from 0 % to 30 % fault probability (***bold italic numbers***). Since it is enough to consider fault probability up to 20 % in actual distribution systems, the proposed DPMP-GBSODE based method can be expected to effective in actual distribution systems even if faults of processes occur. Moreover, results in fig. 8 (Case 2 (with outliers)) and fig. 7 (Case 1 (without outliers)) are alike, and results in fig. 10 (Case 4 (with outliers)) and fig. 9 (Case 3 (without outliers)) are alike. These mean that the proposed DPMP-GBSODE based method can estimate accurate system conditions even if outliers are measured. Table 3 shows the worst estimation results by the proposed DPMP-GBSODE based method using 8 processes with 0 and 40 % fault probabilities with outliers through 100 trials for IEEE 33 bus system in Case 2. Since Case 1, 2, 3, and 4 show similar

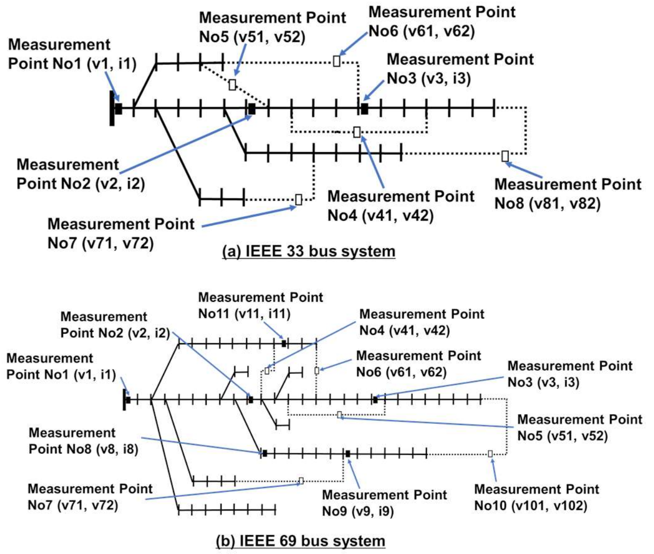

Fig. 6 IEEE 33 and 69 bus systems with measurement points.

TABLE I. PARAMETERS OF DPMP-GBSODE, DPMP-MBSO, JIT MODELING, AND CORRENTROPY IN THE SIMULATIONS.

Common parameters of evolutionary computation	
Num. of trails : 100, Num. of individuals : 144, The maximum iteration number : 200, Num. of cluster : 4, $P_{replace}$: 0.2, $P_{One\_Cluster}$: 0.8, P_{One_Center}: 0.4, P_{Two_Center}: 0.5, Num. of sub-populations : 2, 3, 4, and 8, Network topology : ring topology, Migration interval : 20, Migration policy : Worst-Best policy.	
Parameters for each method	
Method	**Parameter Settings**
DPMP-GBSODE	F: 0.6, C_r: 0.9, C_{max}: 0.9, C_{min}: 0.1
DPMP-MBSO	Pr: 0.005
JIT modeling	Num. of past data : 50000, k : 7(33 bus), 10(69 bus) Out_{max} : 0.001
Correntropy	Karnel size : 0.00045

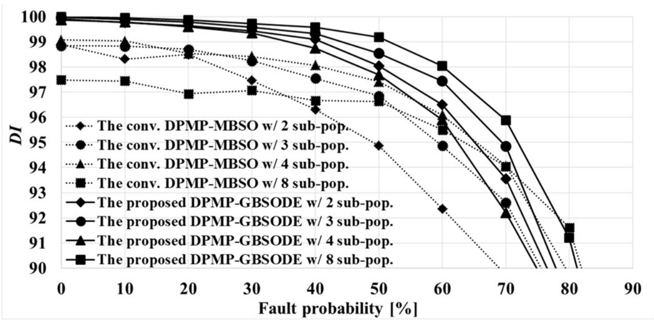

Fig. 7 Transitions of *DI* by the proposed DPMP-GBSODE and the conventional DPMP-MBSO based methods with 0 to 90% fault probabilities without outliers for IEEE 33 bus system (Case 1).

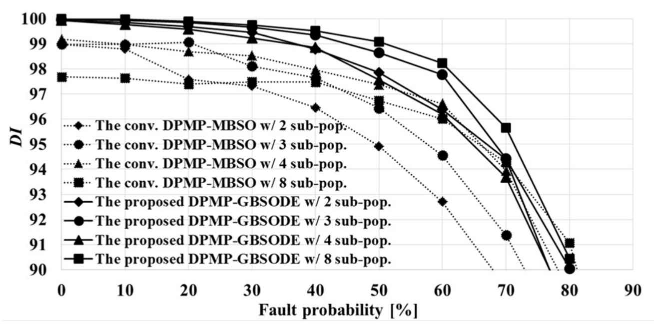

Fig. 8 Transitions of *DI* by the proposed DPMP-GBSODE and the conventional DPMP-MBSO based methods with 0 to 90% fault probabilities with outliers for IEEE 33 bus system (Case 2).

estimation results, results for Case 2 is shown as a representative. As observed in table 3, results of the proposed DPMP-GBSODE with 0 % fault probability is similar to true values even at the measure points with outliers even with the worst objective

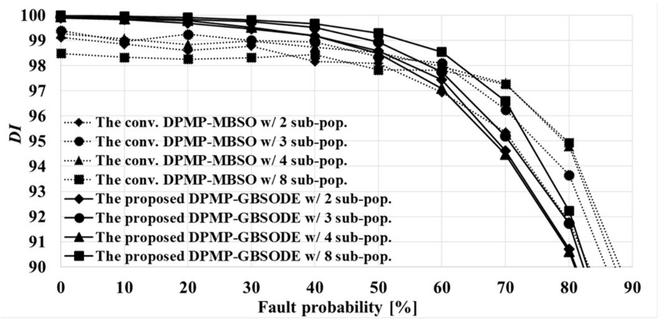

Fig. 9 Transitions of *DI* by the proposed DPMP-GBSODE and the conventional DPMP-MBSO based methods with 0 to 90% fault probabilities without outliers for IEEE 69 bus system (Case 3).

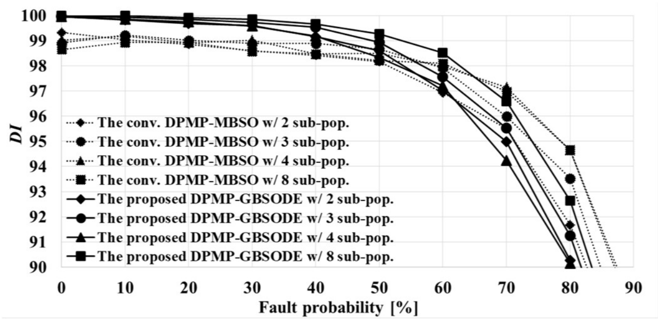

Fig. 10 Transitions of *DI* by the proposed DPMP-GBSODE and the conventional DPMP-MBSO based methods with 0 to 90% fault probabilities with outliers for IEEE 69 bus system (Case 4).

TABLE II. AVERAGE RANKS AND RESULTS OF FRIEDMAN TEST THROUGH 100 TRIALS AMONG THE PROPOSED DPMP-GBSODE AND THE CONVENTIONAL DPMP-MBSO BASED METHODS IN ALL CASES.

Fault probabilities	DPMP-MBSO				DPMP-GBSODE				*p*_value
	2 sub-pop.	3 sub-pop.	4 sub-pop.	8 sub-pop.	2 sub-pop.	3 sub-pop.	4 sub-pop.	8 sub-pop.	
Case 1									
0%	6.24	5.85	5.56	7.36	***3.16***	***2.22***	***3.55***	***2.05***	1.59E-96
10%	6.18	5.64	5.50	7.28	***3.32***	***2.61***	***3.49***	***1.97***	1.91E-86
20%	6.12	5.71	5.13	7.11	***3.58***	***2.61***	***3.75***	***1.99***	2.85E-77
30%	6.37	5.44	5.47	6.67	***3.34***	***2.68***	***3.86***	***2.17***	6.00E-70
40%	6.53	5.45	4.80	6.51	3.46	2.80	4.41	2.04	3.65E-65
50%	6.75	5.27	4.38	5.54	3.93	3.39	4.62	2.12	1.08E-46
60%	6.90	5.35	4.52	5.03	3.91	3.00	4.73	2.56	7.87E-44
70%	6.53	5.08	4.06	4.08	4.39	3.55	5.54	2.77	5.58E-32
80%	6.43	5.11	4.10	2.93	4.75	4.48	5.03	3.17	1.54E-28
90%	5.54	4.92	3.54	3.18	5.10	4.64	5.07	4.01	8.18E-15
Case 2									
0%	6.29	5.79	5.35	7.25	***3.18***	***2.59***	***3.27***	***2.27***	1.04E-85
10%	6.26	5.61	5.46	7.18	***3.18***	***2.46***	***3.79***	***2.05***	4.80E-85
20%	6.73	5.16	5.61	6.90	***3.37***	***2.23***	***3.87***	***2.12***	3.25E-85
30%	6.80	5.75	4.91	6.38	***3.51***	***2.45***	***4.01***	***2.19***	9.35E-73
40%	6.77	5.58	4.59	5.65	4.22	2.72	4.26	2.21	1.54E-54
50%	6.82	5.75	4.50	5.13	4.06	2.90	4.62	2.21	3.21E-51
60%	6.69	5.79	4.12	4.54	4.39	3.10	4.77	2.60	1.37E-40
70%	6.64	5.70	4.12	4.05	3.92	4.01	4.50	3.06	3.55E-29
80%	6.60	5.62	4.16	3.05	4.74	3.70	4.80	3.33	9.23E-33
90%	5.10	4.70	4.30	3.61	4.71	4.47	5.00	4.11	2.2E-04
Case 3									
0%	6.02	5.50	5.50	7.09	***3.86***	***2.67***	***3.27***	***2.09***	1.49E-75
10%	5.96	5.48	5.63	6.85	***3.59***	***2.57***	***3.52***	***2.39***	3.07E-67
20%	6.01	5.10	5.38	6.65	***4.03***	***2.99***	***3.56***	***2.28***	4.46E-55
30%	5.70	5.03	5.15	6.41	***4.17***	***2.80***	***4.45***	***2.29***	1.35E-45
40%	5.90	4.80	4.88	5.65	4.28	3.25	4.77	2.47	3.03E-30
50%	5.15	4.66	4.05	5.33	4.76	3.90	5.12	3.03	6.17E-13
60%	5.42	3.89	3.82	4.14	4.93	4.65	5.65	3.50	4.96E-13
70%	5.08	4.20	3.07	3.19	5.43	5.14	5.87	4.02	3.99E-24
80%	5.21	3.64	2.83	2.65	5.69	5.14	6.05	4.79	7.59E-39
90%	4.57	3.54	2.99	2.84	5.29	5.53	5.79	5.45	2.24E-33
Case 4									
0%	5.32	5.81	6.12	7.14	***3.21***	***2.77***	***3.28***	***2.35***	6.95E-78
10%	5.93	5.55	5.56	6.71	***3.53***	***2.78***	***3.89***	***2.04***	6.89E-66
20%	5.88	5.18	5.43	6.27	***4.01***	***3.06***	***3.78***	***2.39***	1.70E-45
30%	6.02	5.13	4.85	6.18	***4.10***	***3.20***	***4.26***	***2.25***	1.51E-41
40%	5.45	5.13	4.66	5.65	4.29	3.32	5.01	2.49	5.77E-27
50%	5.05	4.23	4.30	4.95	4.52	4.08	5.67	3.18	5.74E-11
60%	5.39	4.08	3.69	3.84	5.10	4.99	5.49	3.42	1.31E-14
70%	4.97	4.42	3.01	3.50	5.37	4.82	6.15	3.76	3.76E-24
80%	5.16	3.64	2.69	2.89	5.97	5.24	6.21	4.20	2.26E-42
90%	4.66	4.18	2.65	3.02	5.55	5.41	5.70	4.83	6.87E-30

TABLE III. THE WORST ESTIMATION RESULTS BY THE PROPOSED DPMP-GBSODE BASED METHOD USING 8 PROCESSES WITH 0 AND 40 % FAULT PROBABILITIES WITH OUTLIERS THROUGH 100 TRIALS FOR IEEE 33 BUS SYSTEM (CASE 2).

Measurement points and types	Measurement values (True values)	DPMP-GBSODE using 8 processes (0%)	DPMP-GBSODE using 8 processes (40%)
v1	13.250[kV]	***13.250[kV]***	***13.250[kV]***
v2(Outlier)	12.020[kV] (12.620[kV])	***12.621[kV]***	***12.622[kV]***
v3	12.257[kV]	***12.257[kV]***	***12.256[kV]***
v41	12.363[kV]	***12.364[kV]***	***12.363[kV]***
v42	12.127[kV]	12.127[kV]	12.125[kV]
v51	13.150[kV]	***13.149[kV]***	***13.149[kV]***
v52	12.445[kV]	***12.445[kV]***	***12.446[kV]***
v61	13.142[kV]	***13.141[kV]***	***13.141[kV]***
v62	12.257[kV]	***12.257[kV]***	***12.256[kV]***
v71	12.870[kV]	12.870[kV]	12.872[kV]
v72	12.444[kV]	***12.443[kV]***	***12.442[kV]***
v81	12.343[kV]	12.342[kV]	12.345[kV]
v82	12.072[kV]	***12.073[kV]***	***12.072[kV]***
i1	200.0[A]	***200.0[A]***	***200.0[A]***
i2(Outlier)	24.0[A] (48.7[A])	***48.8[A]***	***48.8[A]***
i3	25.3[A]	***25.3[A]***	***25.3[A]***

function value. Moreover, the results even with 40% fault probability are close to those with 0 % fault probability (***bold italic numbers***). Consequently, the proposed DPMP-GBSODE can be verified to obtain more appropriate estimation results than the conventional DPMP-MBSO even if faults of the processes occur and the outliers are measured.

Figure 11 shows average calculation time though 100 trials by the proposed DPMP-GBSODE based methods using 1, 2, 3, 4, and 8 processes with 0 % fault probabilities in each case. As observed in fig. 11, the proposed DPMP-GBSODE using eight processes is about two times faster than that using one process in all cases. Consequently, the proposed method can be verified to improve computation time.

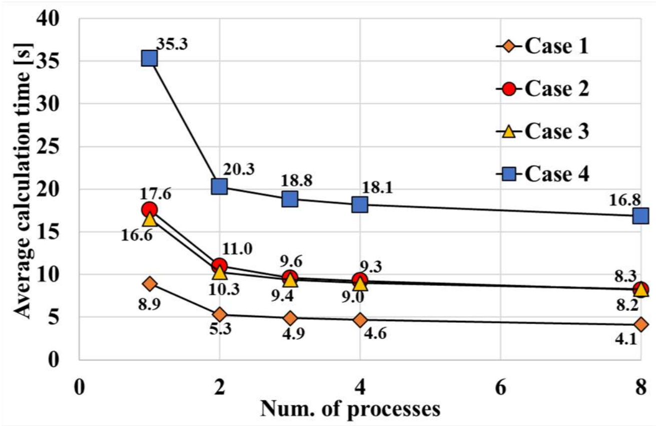

Fig. 11 Average calculation time though 100 trials by the proposed DPMP-GBSODE based methods using 1, 2, 3, 4, and 8 processes with 0 % fault probabilities in each case.

VI. CONCLUTIONS

This paper proposes DPMP-GBSODE as a general evolutionary computation technique, and it is applied to DSSE using JIT modeling and correntropy in order to improve dependability and computation time. The proposed DPMP-GBSODE based DSSE method can be verified to be effective at IEEE benchmark systems. In actual distribution systems, the proposed DPMP-GBSODE based method can be expected to improve dependability and computation time even if faults of the processes occur and outliers are measured.

As future works, new techniques will be developed for the DSSE problems in order to realize more dependable calculation.

REFERENCES

[1] F. F. Wu, et al., "Asynchronous distributed state estimation for power distribution systems", Proc. of 10th PSCC, August 1990.

[2] M. E. Baran, et al., "State estimation for real-time monitoring of distribution systems", *IEEE Trans. on Power Systems*, Vol. 9, No. 3, August 1994.

[3] S. Naka, et al., "A Hybrid Particle Swarm Optimization for Distribution State Estimation", *IEEE Trans. on Power Systems*, Vol. 18, No.1, pp. 60-68, February 2003.

[4] M.V. L. Kumar, et al., "An Artificial Bee Colony Algorithm based Distribution System State Estimation Including Renewable Energy Sources", Proc. of International Conference on Circuit, Power and Computing Technologies, March 2014.

[5] R. Khorshidi, et al., "A new smart approach for state estimation of distribution grids considering renewable energy sources", *Energy*, Vol. 94, No 1, pp 29-37, January 2016.

[6] S. Iwata, et al., "Multi-population Differential Evolutionary Particle Swarm Optimization for Distribution State Estimation using Correntropy in Electric Power Systems", Proc. of IEEE Symposium Series on Computational Intelligence, November 2017.

[7] D. Azuma, et al., "Modified Brain Storm Optimization for Load Adjustment Distribution State Estimation Using Correntropy", Proc. of IEEE TENCON, October 2018.

[8] D. Azuma, et al., "Improved Brain Storm Optimization with Differential Evolution strategies for Load Adjustment Distribution State Estimation using Correntropy", Proc. of IFAC Workshop on Control of Smart Grid and Renewable Energy Systems, June 2019.

[9] D. Azuma, et al., "Parallel Multi-population Improved Brain Storm Optimization with Differential Evolution strategies for State Estimation in Distribution Systems using Just In Time Modeling and Correntropy", Proc. of IEEE Symposium Series on Computational Intelligence, December 2019.

[10] D. Azuma, et al., "Depenbable Parallel Multi-Population Modified Brain Storm Optimization for Distribution State Estimation considering Outliers using Just-In-Time Modeling and Correntropy", *IEEJ Trans. on Power and Energy*, Vol.140, No.2,pp68-77, Fubruary 2020 (in Japanese).

[11] M. Sato, et al., "Optimal Planning of Smart Community Considering Uncertainty of Renewable Energy -Proposal and an Application of Multi-population Global-best Brain Storm Optimization with Differential Evolution Strategies-", *IEEJ Trans. on Power and Energy*, Vol.139, No.4, pp. 240-250, April 2019 (in Japanese).

[12] Z. Cao, et al., "An improved brain storm optimization with differential evolution strategy for applications of ANNs", *Mathematical Problems in Engineering*, Vol.2015 Article ID 923698, May 2015.

[13] M. El-Adb, "Global-best brain storm optimization algrithm", *Swarm & Evolutionary Computation*,Vol.37, pp27-44, December 2017.

[14] Z. Zhan, et al., "A Modified Brain Storm Optimization," Proc. of the IEEE World Congress on Computational Intelligence, June 2012.

[15] G. Cybenko, "Just-In-Time Learning and Estimation", *Identification, Adaptation, Learning*, North Atlantic Treaty Organization Advanced Science Institutes series. Series F, Computer and system sciences, pp.423-434, January 1996.

[16] J. Zhang, et al., "Intelligent selection of instances for predictions functions in lazy learning algorithms", Artificial Intelligence Review, Vol.11, pp.175-191, February 1997.