

Optimal Network Partition and Edge Server Placement for Distributed State Estimation

Lyuzerui Yuan, Jie Gu, Jinghuan Ma, Honglin Wen, and Zhijian Jin

Abstract—This paper investigates network partition and edge server placement problem to exploit the benefit of edge computing for distributed state estimation. A constrained many-objective optimization problem is formulated to minimize the cost of edge server deployment, operation, and maintenance, avoid the difference in the partition sizes, reduce the level of coupling between connected partitions, and maximize the inner cohesion of each partition. Capacities of edge server are constrained against underload and overload. To efficiently solve the problem, an improved non-dominated sorting genetic algorithm III (NSGA-III) is developed, with a specifically designed directed mutation operator based on topological characteristics of the partitions to accelerate convergence. Case study validates that the proposed formulations effectively characterize the practical concerns and reveal their trade-offs, and the improved algorithm outperforms existing representative ones for large-scale networks in converging to a near-optimal solution. The optimized result contributes significantly to real-time distributed state estimation.

Index Terms—Network partition, edge server placement, distributed state estimation, edge computing, non-dominated sorting genetic algorithm (NSGA).

I. INTRODUCTION

AS an essential task for monitoring and controlling power systems, state estimation should provide a real-time estimate of system states, where real-time means that the response time of estimation operation is within two seconds [1]. This requirement, however, is hardly satisfied in a large-scale network, as its control center spends considerable computational time on dealing with high-dimensional state variables. To address the issue, a mainstream countermeasure is distributed state estimation (DSE), which divides the overall estimation problem into many low-dimensional subproblems and then solves them in parallel [2]–[8]. Although the control center is capable of parallel computing, it still suffers from great communication burdens caused by the massive

measurements transmitted from remote data sources. This will result in long delays to increase the response time of DSE [9].

Fortunately, the emerging edge computing can provide strong technical support for the real-time DSE [10]. It moves the estimation subproblems from the control center into multiple edge servers (ESs) that are distributed near data sources, to deliver low communication delays and timely data processing [11]. Based on this, we should decompose a large-scale network into several subareas, where an ES is placed in each subarea as the local controller to acquire information and perform DSE [12]. In this scenario, the network partition and the ES placement are two critical factors to facilitate the real-time performance of DSE, as the network partition can balance the sizes of subareas to shorten the runtime of DSE [13], and the ES placement aims to shorten the average distance between ES and data sources to reduce communication delays [11].

Existing works have studied the network partition with fixed network size [13]–[15] or the ES placement based on potential locations [16]–[18], while coupling of the two factors, as a non-negligible impact on the performance of DSE, has not been fully addressed. Specifically, a partition scheme that ignores ES placement is unfavorable for reducing delays of servers, since the potential ES locations in subareas could be remote from some data sources. In contrast, without considering network partition, the determined ES locations may be unevenly distributed to result in unbalanced partition sizes. Hence, their coupling should be considered to enhance real-time DSE operation.

In this paper, we propose to combine the two factors to form an integrated optimization problem of network partition and edge server placement (NPESP). Concerns on network partition are characterized by the coupling of subareas and the state variable balance. The coupling of subareas indicates the extent of connections between subareas, which is minimized to reduce exchanged information and communication burden [15]. We also minimize the state variable balance that refers to the difference in sizes of subareas, to lead to shorter runtime of DSE [13]. Next, a metric named cohesion of served nodes, i.e., the ratio of subarea density and the average distance between ESs and data sources, is used to represent the timeliness of communication in a subarea. It is maximized to reduce delays of ESs. Economic concern, which refers to the costs of purchasing, operating and maintaining ESs, is also characterized by a metric of cost. The

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L. Yuan, J. Gu (corresponding author), J. Ma, H. Wen, and Z. Jin are with the School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China (e-mail: ylzr.z@sjtu.edu.cn; gujie@sjtu.edu.cn; mjhdte@sjtu.edu.cn; linlin00@sjtu.edu.cn; zjjin@sjtu.edu.cn).

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metric is minimized for obtaining economical ES placement scheme. In addition, we constrain capacities of ES within a range to prevent underload and overload. Hence, coupling of the two factors, i.e., trade-off between the network partition and the ES placement, can be indicated by a negative correlation between the number of subareas and the cost of ES related issues, the impact of partitions on the determination of ES locations, and the restriction on the size of subareas posed by capacities of ES.

Based on the above-mentioned four criteria, we formulate a many-objective optimization problem (MaOP), which refers to the optimization problem with more than three objectives [19], constrained by the maximum and minimum capacities of ES, of which the objectives are to minimize the cost, the coupling of subareas, and the state variable balance, while maximizing the cohesion of served nodes. The proposed MaOP is a non-convex mixed-integer nonlinear program that is not tractable by continuous relaxation [19]. Thus, we choose the non-dominated sorting genetic algorithm III (NSGA-III), which has competitive convergence and diversity for MaOPs, as a basic solution algorithm [20], [21]. To enhance the efficiency of NSGA-III in dealing with large-scale MaOPs, we modify the basic NSGA-III to an improved one. Specifically, the real-number encoding is applied to map the decision variable matrix for saving computational resources. Conforming to topological characteristics of partitions, we design a directed mutation operator for accelerating convergence. Besides, a gene restriction is established to readily guarantee the feasibility of offspring solutions.

Experiments are implemented on the IEEE 118-bus system [22] and the Polish 2383-bus system [23]. The results illustrate that there are trade-offs among the four objectives, whereas the proposed MaOP can provide various sub-optimal NPESP schemes to achieve a compromise between objectives without degrading any of them. Under NPESP schemes, the runtimes of distributed weighted least squares (DWLS) [7], distributed unscented Kalman filter (DUKF) [3], [4], and distributed particle filter (DPF) [6] are shortened. Moreover, the exceptional convergence, diversity, and evenness of the improved NSGA-III for large-scale networks are testified by two popular metrics, i.e., inverse generational distance (IGD) and spacing [21].

The main contributions of this study are summarized as follows. ① We present an integrated NPESP problem in the scenario where DSE is supported by edge computing. ② We formulate the NPESP problem as a constrained MaOP, in which the coupling between network partition and ES placement is considered. ③ We design an improved NSGA-III with rapid convergence for the proposed MaOP in large-scale networks. ④ The trade-offs between objectives are demonstrated, i.e., the four criteria are indispensable for NPESP to acquire a compromise scheme without sacrificing any one of the real-time DSE, the economy of ESs, or the strength of partition.

This paper is organized as follows. Section II reviews the related work. Section III introduces the DSE model based on edge computing framework. A constrained NPESP MaOP is proposed in Section IV. Section V presents the solution algo-

rithm. Section VI uses case study to evaluate the proposed MaOP and show the performance of the improved NSGA-III. Conclusion is drawn in Section VII.

II. RELATED WORK

Network partition is a basic problem in multiple distributed scenarios such as distributed optimal power flow [24], [25], distributed energy resource aggregation [26], DSE, etc. Since real time is a main concern on state estimation, researchers mostly focus on state variable balance. Reference [14] adopts the branch-line layer method and postorder-traversal algorithm to develop a graph-based partition approach that can ensure balance of subarea sizes. Reference [15] proposes a single-objective optimization problem solved by genetic algorithm (GA) to obtain size-balanced subareas. In addition, the effect of coupling between subareas on communication time of DSE is mentioned in [27]. To balance subarea sizes and reduce coupling level, the studies in [13] and [28] use *K*-means and spectral clustering to cluster nodes into several subareas, respectively. Nevertheless, the interaction between coupling and the number of subareas is ignored due to the predetermined number of clusters. For observable networks, [29] develops a heuristic method which combines the integer-linear-programming eigenvector based approach and interchange method to obtain several observable subareas. In [30], a network is transformed into a spanning tree that is traversed and partitioned based on Markov chains to guarantee the observability of subareas. However, the partition strategies are invalid in case of unobservable networks.

The ES placement has been investigated in communication field recently. The concerns mainly include cost of service, delay, and communication network robustness. In [16], the service cost is represented by the sum of resource usage cost and one-time deployment cost. Then a constrained single-objective optimization problem is formulated to address the trade-off between cost and user coverage. Reference [17] proposes a prediction-mapping optimization heuristic algorithm to minimize the user cost that consists of calculation cost and migration cost. For delay reduction, [18] aims to minimize the response time and maximize the response time fairness of base stations through a game-theory-based method, where the response time is calculated as the sum of communication delays and task execution delays. Reference [31] formulates a multi-objective constraint optimization problem to minimize communication delays and to balance the workload difference between ESs, which is solved by GA and local search algorithm. Communication network robustness is proposed in [32], which is assessed by a metric that refers to the number of mobile users co-covered by two ESs, and a compromise programming is formulated to trade off communication network robustness and user coverage. In these studies, some concerns (e.g., user coverage [16], [32], response time fairness [18], and migration cost [17]) on the basis of mobile edge computing, are non-essential in the scenario presented in this paper, since power system has high-speed fiber-optic private network and fixed workload [33].

Furthermore, the coupling between network partition and ES placement is disregarded in aforementioned studies. This

paper will take it into consideration to formulate a constrained NPESP MaOP. However, the above-mentioned solution methods such as GA and K -means are not adept in dealing with MaOPs. The reason is that more than one objective have to be changed into a single objective by weighted summation, which may result in non-equivalence between the original MaOP and weighted single-objective problem [34]. Hence, an efficient solution method for the proposed MaOP needs to be developed.

III. DSE MODEL BASED ON EDGE COMPUTING FRAMEWORK

In this section, we integrate DSE into a general three-level framework of edge computing in [11]. As shown in the left side of Fig. 1, the left part of the three-level framework is the perceptual layer, where abundant edge devices, e.g., pha-

sor measurement unit (PMU) and feeder terminal unit (FTU), are deployed on nodes to collect measurements for DSE. The middle is the edge layer with several ESs distributed near edge devices. An ES can receive measurements from its associated edge devices, communicate with other ESs, execute DSE algorithms, etc. There is a significant reduction of communication delays because of the ES close to data sources. In addition, some sensitive information such as residential electricity consumption can be processed by ESs rather than being sent to the remote data center, which means better data security and privacy. The right part is the cloud layer with a large data center to perform global applications, e.g., power system security analysis, based on all DSE results. Since global applications in the cloud layer are not the focus of this paper, they are not mentioned below.

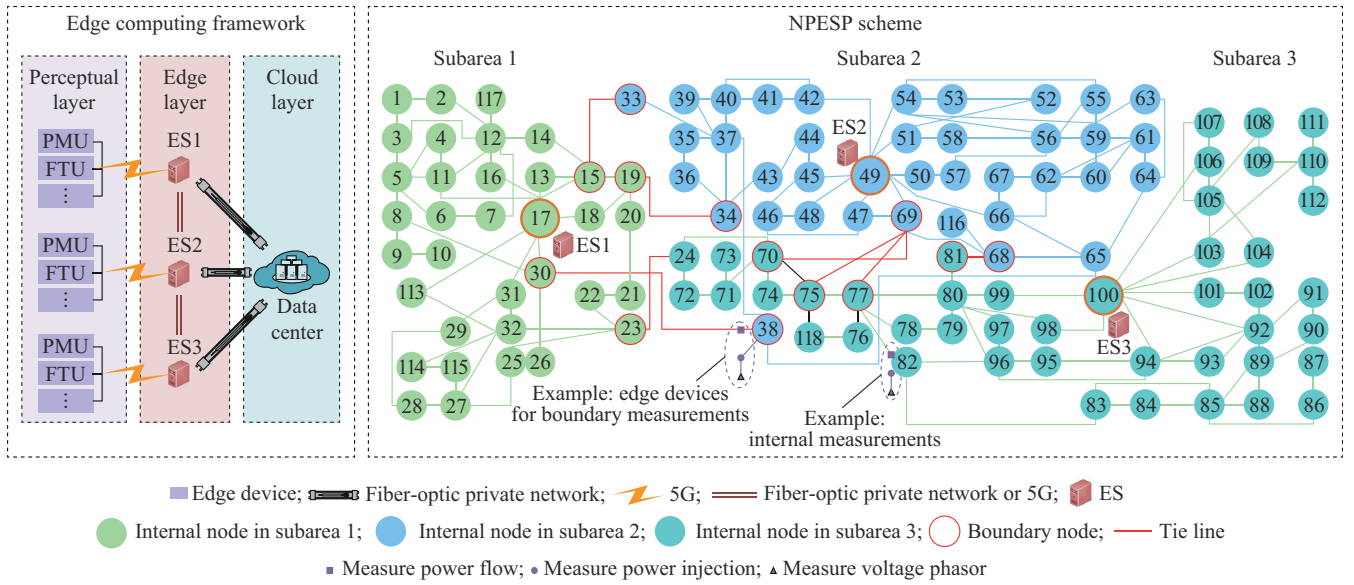


Fig. 1. A three-level edge computing framework for DSE and IEEE 118-bus network with three partitions.

As shown in the right side of Fig. 1, a tripartite IEEE 118-bus test system [22] is considered as the intended scenario. Three ESs, denoted as ES_i ($i=1,2,3$), are located at node 17, 49, and 100 as local controllers of subareas 1, 2, and 3, respectively. In terms of DSE approaches [2]-[8], ES_i should receive local measurements z_i in subarea i and shareable measurements z_{ej} ($j \neq i$) from ES_j . Then, it calculates the optimal estimation $\hat{x}_i$ of state variable vector x_i in two steps. Firstly, the local estimation $\hat{x}_i^l$ is acquired by minimizing the error between measurement functions $h_i(x_i)$ (i.e., power flow equations [7]) and local measurements z_i , i.e.,

$$\hat{x}_i^l = \arg \min_{x_i} r_i(x_i) \quad (1)$$

$$r_i(x_i) = z_i - h_i(x_i) \quad (2)$$

Secondly, $\hat{x}_i^l$ is corrected into the optimal estimation $\hat{x}_i$, i.e.,

$$\hat{x}_i = \hat{x}_i^l + \Delta x_i \quad (3)$$

$$\Delta x_i = g_i(\chi_i) \quad \chi_i \in \{z_{ej}, \hat{x}_j^l, \theta, j=1,2,3\} \quad (4)$$

where θ is the other shareable information except measurements; and $g_i(\cdot)$ is the function mapping χ_i to Δx_i . The di-

mension of $\hat{x}_i$, which has a significant impact on DSE runtime, is determined by network partition. The ES placement influences communication delays of ESs receiving or delivering z_i and χ_i . To realize real-time DSE under edge computing, NPESP problem should be paid attention to.

Before formulating the problem, we present some basic notations. An undirected graph $G=\{V,E\}$ is applied to describe the topology of a network. $V=\{v_i|i=1,2,\dots,n\}$ is the set of nodes, where v_i represents node i and n is the total number of nodes. $Y=(y_{ij})_{n \times n}$ is the adjacency matrix of G . We denote the distance matrix of G as $D=(d_{ij})_{n \times n}$, where d_{ij} calculated by Dijkstra's algorithm is the minimum number of edges between v_i and v_j . In addition, the workload vector of the network is represented as $W=[w_1, w_2, \dots, w_n]^T$, where w_i ($i=1,2,\dots,n$) is the amount of measurements in v_i at a timestamp. To indicate partitions and ES locations, a binary matrix $A=(a_{ij})_{n \times n}$ named NPESP matrix is defined, i.e.,

$$a_{ij} = \begin{cases} 1 & v_i \text{ is served by the ES at } v_j \\ 0 & v_i \text{ is not served by the ES at } v_j \end{cases} \quad (5)$$

When $i=j$, $a_{ii}=1$ means that v_i has an ES. Thus, the num-

ber of ESs is represented by the trace of $\mathbf{A}$, i.e., $\text{trace}(\mathbf{A}) = \sum_{i=1}^n a_{ii}$.

IV. CONSTRAINED NPESP MAOP

In this section, a constrained NPESP MaOP is proposed, in which the objectives and constraints characterize essential practical concerns on NPESP. To simply deliver the basic idea, we make three assumptions: ① the partition is non-overlapping and each subarea has one ES; ② referring to [31], [32], the price, capacity, and hardware performance of ESs are supposed to be the same, as they have little influence on problem formulation; ③ since measurement devices are usually inadequate for DSE in large-scale power systems, both actual and pseudo measurements are considered as the workload to meet the observability of network.

A. Cost Minimization

Economic concerns on purchasing, operating, and maintaining ESs can be represented by a cost minimization. The purchasing cost contains the prices of an ES and related hardware accessories and application softwares. The operating cost and maintaining cost refer to the discounted values of daily operation expenses and estimated breakdown maintenance costs within service life of an ES, respectively. We denote the sum of three costs of an ES as P_{cost} . The cost minimization function is expressed as:

$$\min F_1 = \sum_{i=1}^n P_{\text{cost},i} a_{ii} = P_{\text{cost}} \cdot \text{trace}(\mathbf{A}) \quad (6)$$

where $P_{\text{cost},i}$ is the sum of the purchasing, operating, and maintaining costs of the i^{th} ES.

B. High Cohesion

The topology of each subarea is required to be connected and preferably densely connected [14]. In addition, we should shorten the average distance between an ES and the served nodes [11]. A metric named cohesion of served nodes (called cohesion hereafter) is designed to judge both the density of topology and the average distance. Inspired by the intra-cluster density [34], the density of subarea topology is defined as:

$$\rho_i = \begin{cases} \frac{\frac{1}{2} \sum_{j=1}^n \left(\sum_{k=1}^n a_{ki} y_{kj} \right) a_{ji}}{\sum_{k=1}^n a_{ki}} & a_{ii} = 1 \\ 0 & a_{ii} = 0 \end{cases} \quad (7)$$

Nodes in the subarea with larger ρ_i are denser. The average distance between an ES and its served nodes is calculated as:

$$\gamma_i = \begin{cases} \frac{\sum_{k=1}^n a_{ki} d_{ki}}{\sum_{k=1}^n a_{ki}} & a_{ii} = 1 \\ \infty & a_{ii} = 0 \end{cases} \quad (8)$$

A smaller γ_i represents that the ES at v_i is closer to its data sources. Consequently, the cohesion can be defined as:

$$\delta_i = \begin{cases} \frac{\rho_i}{\gamma_i} & a_{ii} = 1 \\ 0 & a_{ii} = 0 \end{cases} \quad (9)$$

To make subareas cohesive and reduce communication delays, we minimize the reciprocal of the average cohesion, i.e.,

$$\min F_2 = \frac{\text{trace}(\mathbf{A})}{\sum_{i=1}^n \delta_i} \quad (10)$$

C. Low Coupling

The coupling of subareas (called coupling hereafter), which is a criterion for network partition, estimates the extent to which the subareas are connected. Based on inter-cluster density [34], the coupling is measured by the number of tie lines that equals the total number of lines in the network minus the number of internal lines. Since the low level of coupling indicates less exchanged information and communication resource consumption [27], the third objective is to minimize the coupling, i.e.,

$$\min F_3 = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n y_{ij} - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n a_{ki} y_{kj} a_{ji} = \frac{1}{2} \text{trace}(\mathbf{Y}^T \mathbf{Y}) - \frac{1}{2} \text{trace}(\mathbf{A}^T \mathbf{Y} \mathbf{A}) \quad (11)$$

D. State Variable Balance

State variables refer to voltage magnitudes and phase angles estimated in the DSE. Thus, the number of state variables are twice that of nodes. For improving the real-time performance of DSE, a network should be partitioned into several similarly-sized subareas to balance the computational burden of subareas. We use a metric named state variable balance, i.e., the largest difference between subarea sizes, to evaluate the impact of network partition on the runtime of DSE. Thus, the last objective is to minimize state variable balance, i.e.,

$$\min F_4 = \max_{j \in \Psi} \left(\sum_{i=1}^n a_{ij} \right) - \min_{j \in \Psi} \left(\sum_{i=1}^n a_{ij} \right) \quad (12)$$

where $\Psi = \{j | a_{jj} = 1, j = 1, 2, \dots, n\}$ is the set of node numbers for ES locations.

E. Constraints

1) Partition Constraints

Considering non-overlapping subareas, each row of the NPESP matrix has one and only one element equal to 1, i.e.,

$$\begin{cases} \sum_{j=1}^n a_{ij} = 1 \\ a_{ij} \in \{0, 1\} \quad i, j = 1, 2, \dots, n \end{cases} \quad (13)$$

In each column, we need to ensure $a_{ij} = 0$ ($\forall v_i \in V$) when no ES is deployed at v_j and $a_{jj} = 1$ when the measurements of v_i are allocated to the ES at v_j . The other partition constraint can be expressed as:

$$a_{jj} - a_{ij} \geq 0 \quad i, j = 1, 2, \dots, n \quad (14)$$

2) Capacity Constraints

Due to finite measurements received by an ES in a time-stamp, the maximum workload capacity $C_{\max}$ and the minimum workload capacity $C_{\min}$ are set to prevent overload and underload of ES, respectively, i.e.,

$$a_{jj} \sum_{i=1}^n w_i a_{ij} \leq \alpha C_{\max} \quad j = 1, 2, \dots, n \quad (15)$$

$$a_{jj} \sum_{i=1}^n w_i a_{ij} \geq (\beta C_{\min} + 1)^{a_j} - 1 \quad j = 1, 2, \dots, n \quad (16)$$

where α ($0 < \alpha < 1$) and β ($\beta > 0$) are the maximum and minimum capacity margins, respectively.

V. SOLUTION ALGORITHM

This section presents an improved NSGA-III with a designed directed mutation for the proposed MaOP.

A. Basic NSGA-III

NSGA-III, as a variant of GA, is one of the best heuristic algorithms for MaOPs [20], [21]. It has the same procedures as GA, i.e., encoding, crossover, mutation, and selection, in which the selection operator is quite different from GA. Thus, its selection operator is introduced briefly. We denote an MaOP as $F = \{ \min f_i(x), i = 1, 2, \dots, k, k > 3 \}$, where $f_i(x)$ is the i^{th} objective function. The three basic definitions about the MaOP are given below.

1) Definition 1: Pareto domination. Supposing there are two different feasible solutions (π_a, π_b) for F , we deem that π_a dominates π_b if π_a and π_b satisfy the following conditions:

$$\begin{cases} f_i(\pi_a) \leq f_i(\pi_b) & \forall f_i \in F \\ f_j(\pi_a) < f_j(\pi_b) & \exists f_j \in F \end{cases} \quad (17)$$

2) Definition 2: non-dominated solutions. Let Π denote the feasible solution set of F . We deem that π^* is a non-dominated solution, i.e., Pareto solution, of F when π^* dominates π , given the condition of $\forall \pi \in \Pi$ and $\pi \neq \pi^*$.

3) Definition 3: non-dominated level. Based on k objectives, the members, each of which represents a solution of F , are sorted in accordance with Pareto domination. The final non-dominated solutions are recorded as a non-dominated level.

The selection operator of NSGA-III classifies members of the population into different non-dominated levels by reference-point-based non-dominated sorting and then selects elite members. Specifically, the parent population with z members in the t^{th} generation is denoted as $\mathbf{P}^t = \{\mathbf{p}_i^t, i = 1, 2, \dots, z\}$, and the offspring population $\mathbf{O}^t$ with z members is created from $\mathbf{P}^t$ by crossover and mutation operators. To generate the next generation $\mathbf{P}^{t+1}$, we should select z elite members from the combined parent and offspring population $\mathbf{R}^t = \mathbf{P}^t \cup \mathbf{O}^t$ (with size of $2z$). First, we sort $\mathbf{R}^t$ into different non-dominated levels $R_1^t, R_2^t, \dots, R_r^t$, where the members of R_i^t dominate anyone of R_{i+1}^t . Next, superior members are selected into $\mathbf{P}^{t+1}$ starting from R_1^t , until the size of $\mathbf{P}^{t+1}$ equals z . There is no extra work when the size of $R_s^t = R_1^t \cup R_2^t \cup \dots \cup R_s^t$ ($s < r$) is equal to z . In most situations, however, the size of R_{s-1}^t denoted as u is smaller than z , while

the size of R_s^t is larger than z . Therefore, $z - u$ members have to be chosen from the last accepted level R_s^t . To maximize diversity of members in the s^{th} level, the elitist selection strategy based on the reference point is proposed. For further details, please refer to [35].

B. Improved NSGA-III

The basic NSGA-III converges slowly when solving MaOPs with high-dimensional decision variables. Hence, an improved NSGA-III is presented. We use real-number encoding to compress the sparse NPESP matrix. The capacity and partition constraints are easily calculated by penalty function and gene restriction, respectively. To accelerate convergence, a directed mutation operator is designed with regard to topological characteristic of partitions.

1) Real-number Encoding

Since the NPESP matrix $\mathbf{A}$ has numerous zero elements to occupy storage and computing resources, we adopt real-number encoding to compress it into one-dimensional sequence with n real numbers. The chromosome of a member in $\mathbf{P}^t$, i.e., a real-coded form of $\mathbf{A}$, is represented as:

$$\mathbf{p}^t = (p_{ij}^t)_{1 \times n} \quad p_{ij}^t \in \Omega, i = 1, 2, \dots, z, j = 1, 2, \dots, n \quad (18)$$

where $p_{ij}^t = l$ means that v_j is served by the ES at v_i ; and Ω is the set of potential ES locations. In this paper, we set the nodes with more than three degrees as the potential ES locations.

2) Penalty Function

The capacity constraints in (15) and (16) are represented by the penalty function, i.e.,

$$PF = \begin{cases} 0 & \forall a_{jj}, (\beta C_{\min} + 1)^{a_j} - 1 \leq a_{jj} \sum_{i=1}^n w_i a_{ij} \leq \alpha C_{\max} \\ \infty & \exists a_{jj}, a_{jj} \sum_{i=1}^n w_i a_{ij} < (\beta C_{\min} + 1)^{a_j} - 1 \text{ or } a_{jj} \sum_{i=1}^n w_i a_{ij} > \alpha C_{\max} \end{cases} \quad (19)$$

As a result, the final objectives of the proposed MaOP are to minimize F_1, F_2, F_3, F_4 , and PF .

3) Gene Restriction

The gene restriction is used to simplify the partition constraints, which makes p_{ij}^t equal to j on condition of $p_{ii}^t = j$ ($v_i \in V$). It only corresponds to the constraint in (14), as the constraint in (13) is naturally satisfied by the real-number encoding. We perform the gene restriction after each mutation operator.

4) Directed Mutation

There are multiple mutation operators, e.g., uniform mutation and inversion mutation, which randomly mutate members to lead to slow evolution. Therefore, we design a new mutation operator named directed mutation based on the topological characteristic of partitions. For the directed mutation of a chromosome, we randomly select an initial mutation node v_i and sort its distance sequence $\{d_{ij}, j = 1, 2, \dots, n\}$ in ascending order to get the corresponding node number sequence $N_a(v_i)$. Next, the potential ES location v_{n_j} closest to v_i is found according to $N_a(v_i)$ and Ω . Finally, the genes corresponding to the first η nodes in $N_a(v_i)$ are changed into n_j , where the mutation scale η determines the number of mutat-

ed genes. This step ensures that the η nodes closest to v_i are assigned to the same subarea. Through directed mutation operator, partial genes of the chromosome are mutated purposely, accelerating the evolution of population towards the targets. Algorithm 1 conducts the procedure of the directed mutation for the t^{th} generation. The flowchart of the improved NSGA-III is shown in Fig. 2. Furthermore, we present an analysis of the computational complexity of the algorithm in Appendix A.

Algorithm 1: directed mutation for the t^{th} generation

Input: parent population $\mathbf{P}' = \{p'_i, i = 1, 2, \dots, z\}$; mutation rate $\zeta \in (0, 1)$; mutation scale $\eta \in \{1, 2, \dots, n\}$; set of potential ES locations $\mathcal{Q}$; distance matrix $\mathbf{D}$

Output: filial population $\mathbf{P}^{t+1}$

```

1:  $k = 0$ 
2: repeat
3:    $k = k + 1$ 
4:   generate a random integer  $\omega$  from  $[0, 1]$ 
5:   if  $\omega > \zeta$  then
6:      $p_k^{t+1} = p'_k$ 
7:   else
8:     generate a random number  $i$  from  $[1, n]$  as the initial mutation node number
9:     find the potential ES location closest to  $v_i$  and record its number as  $n_f$ 
10:    sort  $\{d_{ij}, j = 1, 2, \dots, n\}$  in ascending order to get the corresponding sequence of node numbers  $N_a(v_i)$ 
11:     $j = 0$ 
12:    repeat
13:       $j = j + 1, l = N_a(v_i)[j], p_{kl}^{t+1} = n_f$ , where  $N_a(v_i)[j]$  is the  $j^{\text{th}}$  element of  $N_a(v_i)$ 
14:    until  $j = \eta$ 
15:  end if
16: until  $k = z$ 

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VI. CASE STUDY

In this section, the test results based on IEEE 118-bus system and Polish 2383-bus system are used to validate the enhancement in real-time DSE by the NPESP schemes and reveal trade-offs among four objectives of the proposed MaOP. The performance of the improved NSGA-III for large-scale networks is illustrated as well. The simulations are run on a computer with Intel-i5-10400F CPU and 16 GB memory.

A. Metrics

The four proposed objectives in (6), (10), (11), and (12) are considered as metrics for NPESP schemes. To measure the impact of NPESP schemes on real-time performance of DSE, the time to perform a DSE approach is used, i.e.,

$$t_{DSE} \approx t_{area, \max} + t_{correction} \quad (20)$$

where $t_{area, \max}$ is the runtime of local state estimation in the largest subarea; and $t_{correction}$ is the execution time to correct local estimations. Besides, a popular metric in community detection, i.e., modularity Q [36], is applied to evaluate the strength of partition of a network into subareas, which can be calculated as:

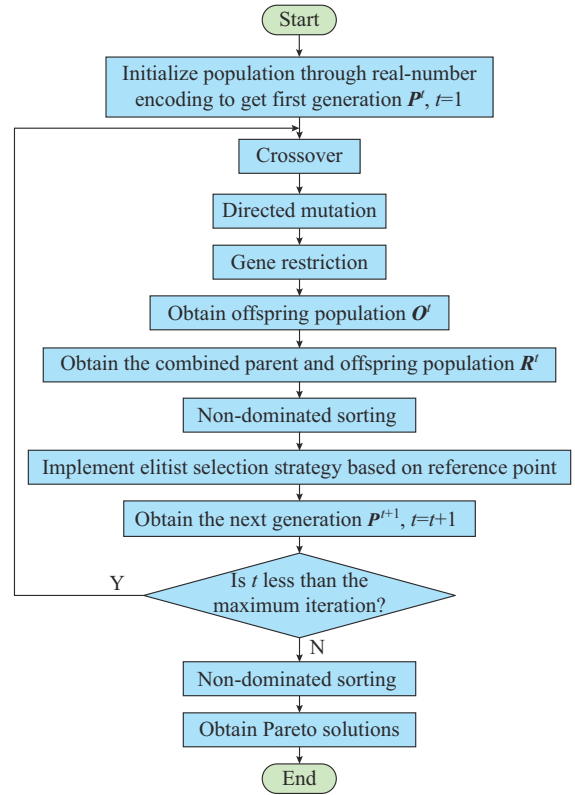


Fig. 2. Flowchart of improved NSGA-III.

$$Q = \frac{1}{2m} \sum_{i \neq j} \left(y_{ij} - \frac{k_i k_j}{m} \right) \delta_{ij} \quad (21)$$

where $m = \sum_{i,j} y_{ij}$; $k_j = \sum_i y_{ij}$; and $k_i = \sum_j y_{ij}$. The situation that v_i and v_j are in the same subarea is represented by $\delta_{ij} = 1$; otherwise, by $\delta_{ij} = 0$. The partitions with higher Q have more internal lines but less tie lines.

To assess performance of the improved NSGA-III, we select two metrics named IGD and spacing [21]. The IGD can be used to estimate both convergence and diversity of solutions to MaOP, i.e.,

$$IGD(\mathbf{P}, \mathbf{P}^*) = \frac{1}{|\mathbf{P}^*|} \sum_{x \in \mathbf{P}^*} \left(\min_{y \in \mathbf{P}} dis(\mathbf{x}, \mathbf{y}) \right) \quad (22)$$

where $dis(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|_2$; and $\mathbf{P}$ and $\mathbf{P}^*$ are the obtained solutions and the target points uniformly distributed on Pareto-optimal surface, respectively. We approximate $\mathbf{P}^*$ with all obtained solutions after ten times of optimization. The smaller IGD indicates the better convergence and diversity of solutions. The spacing measures the standard deviation of the minimum distance from each solution to other solutions, i.e.,

$$Spacing(\mathbf{P}) = \sqrt{\frac{1}{|\mathbf{P}| - 1} \sum_{m=1}^{|\mathbf{P}|} (\bar{d}_P - d_m)^2} \quad (23)$$

$$d_m = \min_j \left\{ \sum_{i=1}^k |f_i(\mathbf{x}_m) - f_i(\mathbf{x}_j)|, \mathbf{x}_m, \mathbf{x}_j \in \mathbf{P} \right\} \quad (24)$$

$$\bar{d}_P = \frac{1}{|\mathbf{P}|} \sum d_m \quad (25)$$

The smaller spacing represents the better evenness of solu-

tions.

B. IEEE 118-bus System

The IEEE 118-bus system integrated with five distributed generators (DGs), as shown in Fig. 1, is selected as a test network. With reference to [37], its hybrid measurement system consists of 54 PMUs and a supervisory control and data acquisition (SCADA) system. PMUs acquire voltage phasors of buses and current phasors of branches, and the SCADA system can collect voltage magnitudes, injection power of buses, and power flow of branches. We assume that the measurements from SCADA system cover 50% buses and branches, whereas the pseudo injection power measurements are generated for the remaining 50% buses to guarantee the observability of subareas. The total workload in the test network is 728.

Three popular partition schemes of IEEE 118-bus network are chosen as benchmarks, i.e., three partitions in [22], six partitions in [8], and eight partitions in [3], which are denoted as REF118-3, REF118-6, and REF118-8, respectively. However, the locations of ESs, i.e., local control centers, are not specified in [3] or [8]. For the convenience of comparison, we consider the node with the shortest average distance in each subarea as the ES location. Table I provides the details of the three benchmarks. To compare runtimes of DSE under different NPESP schemes, three DSE algorithms, i.e., DWLS [7], DUKF [3], [4], and DPF [6], are adopted as testing algorithms. The maximum iterations for each DWLS estimation is 10, and the number of particles in DPF are 100. We apply the finite-time average consensus to modify local estimations [3]. Other parameters for the three algorithms can be referred to [3].

TABLE I
DETAILS OF THREE BENCHMARKS

Benchmark	ES location	Subarea size
REF118-3	S1: v_{17} ; S2: v_{49} ; S3: v_{100}	S1: 35; S2: 38; S3: 45
REF118-6	S1: v_{12} ; S2: v_{28} ; S3: v_{37} ; S4: v_{80} ; S5: v_{59} ; S6: v_{100}	S1: 16; S2: 10; S3: 32; S4: 18; S5: 17; S6: 25
REF118-8	S1: v_{12} ; S2: v_{19} ; S3: v_{27} ; S4: v_{49} ; S5: v_{59} ; S6: v_{80} ; S7: v_{89} ; S8: v_{103}	S1: 16; S2: 17; S3: 13; S4: 16; S5: 19; S6: 13; S7: 14; S8: 10

In terms of the workload, $C_{\max}$, $C_{\min}$, α , and β of an ES are set to be 500, 50, 0.9, and 1.1, respectively, which are appropriate to obtain NPESP schemes with the same number of partitions as benchmarks. Without loss of generality, P_{cost} is set to be 1. An NPESP scheme is represented as NPESP118- j , where j is the number of subareas. In the improved NSGA-III, we apply the partial-mapped crossover operator [20], and set the mutation rate and scale of directed mutation operator to be 0.8 and 10, respectively. The population size can be three to six times the network size, and more than 40 iterations are recommended via extensive simulations. To obtain robust solutions, the test cases are iterated 100 times with 700 members.

1) NPESP Scheme Analysis

The non-dominated solutions to the proposed MaOP con-

tain 21 NPESP schemes, from which six schemes are selected for comparison. The details about the six schemes are given in Appendix B. As shown in Table II, the real-time performance of DWLS, DUKF, and DPF under NPESP schemes exceeds that under the corresponding benchmarks, e.g., the runtimes of DWLS under NPESP118-3, NPESP118-6, and NPESP118-8 are reduced by 19.25%, 36.93%, and 20.00% compared with those under REF118-3, REF118-6, and REF118-8, respectively. Besides, NPESP118-5 outperforms REF118-6 by 11.50%, 17.72%, and 11.08% on runtimes of DWLS, DUKF, and DPF, respectively, while it costs less than REF118-6 according to their F_1 values. A similar situation occurs in NPESP118-7 and REF118-8. Hence, the proposed MaOP can provide cost-effective schemes to facilitate real-time DSE.

TABLE II
COMPARISON OF SIX NPESP SCHEMES AND BENCHMARKS

Scheme	Runtime (s)			F_1	F_2	F_3	Q	F_4
	DWLS	DUKF	DPF					
NPESP118-3	0.495	0.264	1.870	3	1.71	9	0.62	4
REF118-3	0.613	0.282	2.111	3	1.74	8	0.61	10
NPESP118-4	0.373	0.190	1.492	4	1.70	20	0.64	9
NPESP118-5	0.254	0.130	1.035	5	1.61	22	0.67	11
NPESP118-6	0.181	0.109	0.702	6	1.60	27	0.68	12
REF118-6	0.287	0.158	1.164	6	1.63	29	0.64	22
NPESP118-7	0.011	0.007	0.318	7	1.45	28	0.69	6
NPESP118-8	0.008	0.006	0.157	8	1.43	32	0.70	3
REF118-8	0.010	0.007	0.306	8	1.64	48	0.59	9

In case of the same ES costs (F_1), most NPESP schemes have higher cohesion (F_2) and lower coupling (F_3) compared with benchmarks, e.g., F_2 and F_3 values of NPESP118-8 are 12.8% and 31.25% less than those of REF118-8, respectively. This indicates that NPESP schemes are stronger with enhanced connectivity within a subarea and weakened connections between subareas. It is further testified by the modularity Q , as Q values of NPESP118-3, NPESP118-6, and NPESP118-8 are 1.62%, 5.88%, and 16.05% better than those of REF118-3, REF118-6, and REF118-8, respectively. Nevertheless, we find that the modularity increases with larger F_1 , which implies a trade-off between the ES cost and the strength of partition. From the perspective of state variable balance, F_4 values in NPESP118-3, NPESP118-6, and NPESP118-8 are reduced by 60.00%, 45.45%, and 66.67% compared with those in REF118-3, REF118-6, and REF118-8, respectively. With the fixed number of subareas, the proposed MaOP has the ability to balance the computational burdens of ESs. This is the main reason why the runtimes of DSE in NPESP schemes are shorter than those in the corresponding benchmarks. To sum up, the proposed MaOP provides a set of near-optimal NPESP schemes, in which we can select a suitable one to satisfy a single or weighted target without degrading other objectives.

2) Trade-offs Among Four Objectives

We use the ordinary least square method to fit Pareto front of the proposed MaOP. As shown in Fig. 3, there are

linear correlations among the ES cost (F_1), the cohesion (F_2), and the coupling (F_3). Although the state variable balance (F_4) is not significant correlated with other objectives according to Fig. 3(d), (e) and (f), it has an effect on them, e.g., one NPESP scheme has small F_2 (1.452), F_4 (2) but large F_1 (8), F_3 (32), whereas another NPESP scheme has small F_1 (5), F_2 (1.618), F_3 (19) but large F_4 (30). To further demonstrate their trade-offs, we remove one objective of the proposed MaOP in turn to generate four multi-objective optimization problems (MoOPs), i. e., $T_1=\{F_2, F_3, F_4\}$, $T_2=\{F_1, F_3, F_4\}$, $T_3=\{F_1, F_2, F_4\}$, and $T_4=\{F_1, F_2, F_3\}$. Through the improved NSGA-III, the Pareto fronts of T_1 , T_2 , T_3 , and T_4 are obtained as illustrated in Fig. 4.

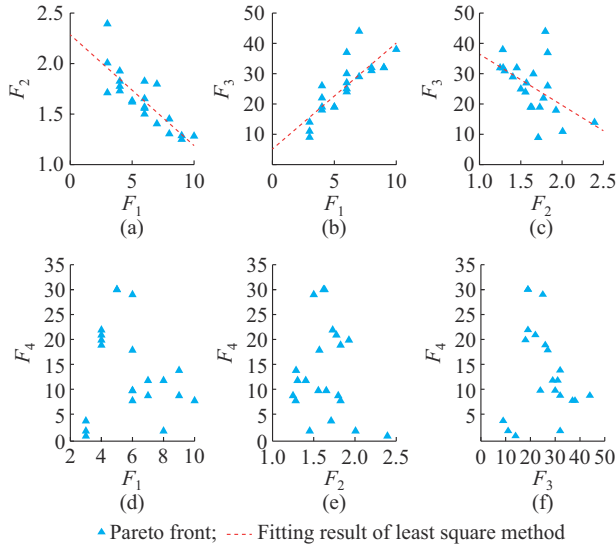


Fig. 3. Pareto fronts of proposed MaOP in IEEE 118-bus network. (a) F_1 and F_2 . (b) F_1 and F_3 . (c) F_2 and F_3 . (d) F_1 and F_4 . (e) F_2 and F_4 . (f) F_3 and F_4 .

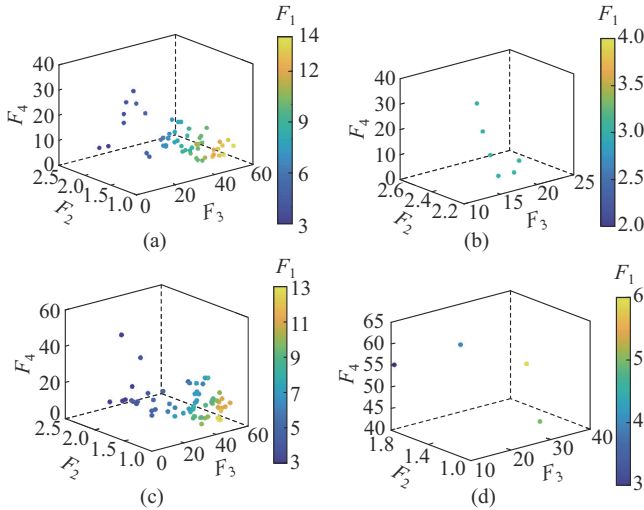


Fig. 4. Pareto fronts of four MoOPs in IEEE 118-bus network. (a) Pareto front of T_1 . (b) Pareto front of T_2 . (c) Pareto front of T_3 . (d) Pareto front of T_4 .

In Fig. 4(a), F_1 values are quite dense in the range of 8 to 14, whereas those in Fig. 3 vary between 1 and 10. Thus, F_1 is not well optimized in T_1 . The Pareto front in Fig. 4(b) is

lack of diversity, as F_1 values are equal to 3 and those of F_2 are greater than 2. We can infer that T_2 fails to trade off the cost against the cohesion. Compared with Fig. 3, Fig. 4(c) shows smaller F_2 but larger F_3 , which indicates that the cohesion and the coupling are not balanced in T_3 . In Fig. 4(d), the solutions are sparse and perform poorly on F_4 . In summary, the solutions to each MoOP are unsatisfactory on the abandoned objective, i.e., the four objectives are indispensable in the NPESP problem due to their trade-offs.

3) Performance of Improved NSGA-III

We compare the improved NSGA-III with three evolutionary algorithms, i.e., traditional GA [15], GA with directed mutation (GADM), and the basic NSGA-III. Since GA and GADM are single-objective GAs, their objective is set to be $\min F_{GA} = F_1 + 4F_2 + 0.5F_3 + F_4 + PF$, where 4 and 0.5 are coefficients to modify the order of magnitude differences. Based on the number of non-dominated solutions, we regard the first 100 members with the smallest F_{GA} as solutions of GA and GADM. The changes in IGD and spacing of four algorithms, as illustrated in Fig. 5, validate that the solutions solved by the improved NSGA-III have the best convergence, diversity, and evenness, followed by GADM.

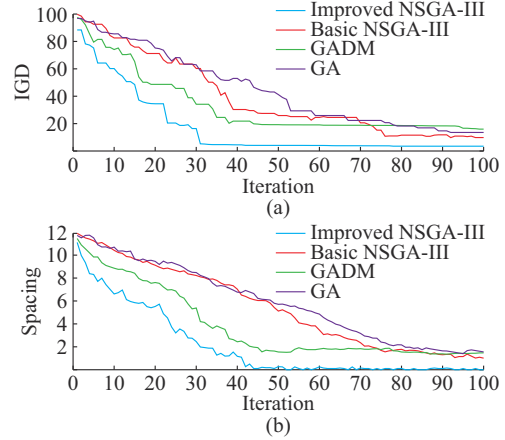


Fig. 5. Changes in IGD and spacing of four evolutionary algorithms based on IEEE 118-bus network. (a) IGD. (b) Spacing.

C. Polish 2383-bus Test System

To verify effectiveness of the improved NSGA-III for large-scale networks, the Polish 2383-bus system in Matpower [23] is selected as a test network. It has six zones, in which there are only 8 buses in the sixth zone. We assign the 8 buses to other five zones with regard to electrical connections. It is assumed that PMUs are only placed on the buses with generators or DGs. The proportions of SCADA measurements and pseudo measurements are the same with those in IEEE 118-bus system. Table III provides the details about the modified zones. For the improved NSGA-III, the population sizes and iterations in zones 1, 2, and 5 are set to be 1500 and 150, respectively, whereas those in zones 3 and 4 are 3000 and 150, respectively. Others are referred to the parameter setting in IEEE 118-bus network.

Figure 6 demonstrates the performance of the four evolutionary algorithms in the largest zone, i.e., zone 3. In terms

of IGD and spacing, the improved NSGA-III still has the fastest convergence and its solutions are the most diverse and well-distributed, compared with other three algorithms. Furthermore, GA and the basic NSGA-III fail to converge within 150 iterations, while GADM and the improved NSGA-III have found local optimal solutions after 106 and 75 iterations, respectively. This indicates that the directed mutation operator can remarkably promote convergence of high-dimensional NPESP MaOP.

TABLE III
MODIFIED ZONES OF POLISH 2383-BUS TEST SYSTEM

Zone	Bus number
1	367 buses with 1875 workloads: 1-22, 187-195, 197-299, 301-312, 314-398, 400-423, 425-429, 431-469, 471-538
2	283 buses with 1587 workloads: 23-55, 181, 183, 300, 424, 430, 539-656, 658-774, 776-785
3	887 buses with 4651 workloads: 56-110, 180, 184, 185, 399, 470, 657, 775, 786-1601, 1745, 1802, 1803, 1872, 2043, 2083, 2088, 2089, 2092
4	570 buses with 3122 workloads: 111-154, 182, 186, 196, 1602-1744, 1746-1801, 1804-1871, 1873-2042, 2044-2082, 2084-2087, 2090, 2091, 2093-2115, 2176, 2192, 2197, 2201, 2202, 2215, 2217, 2237, 2244, 2247, 2253, 2273, 2274, 2278, 2289, 2310, 2333, 2346, 2376, 2383
5	276 buses with 1482 workloads: 155-179, 313, 1842, 2054, 2116-2175, 2177-2191, 2193-2196, 2198-2200, 2203-2214, 2216, 2218-2236, 2238-2243, 2245, 2246, 2248-2252, 2254-2272, 2275-2277, 2279-2288, 2290-2309, 2311-2332, 2334-2345, 2347-2375, 2377-2382

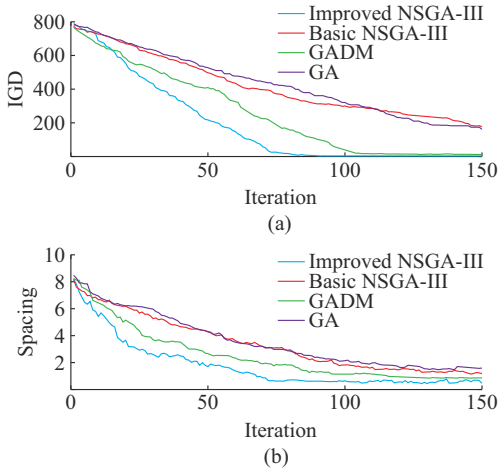


Fig. 6. Changes in IGD and spacing of four evolutionary algorithms based on zone 3 of Polish 2383-bus network. (a) IGD. (b) Spacing.

Trade-offs among the four objectives, which have been demonstrated in Section VI-B, are further proven by Pareto fronts of the five zones, as shown in Figs. 7 and 8. Specifically, in addition to the remarkable correlations between F_1 , F_2 , and F_3 , Fig. 8(d) and (f) presents that F_4 is negatively correlated with F_1 and F_3 , respectively. The relationship between F_2 and F_4 is not obviously illustrated, which may result from the complex and discontinuous expressions of F_2 and F_4 on decision variables.

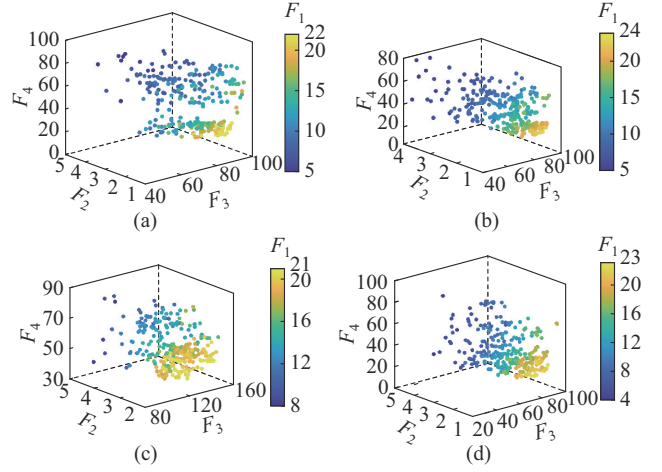


Fig. 7. Pareto fronts of proposed MaOP for zones 1, 2, 4, and 5 of Polish 2383-bus network. (a) Zone 1. (b) Zone 2. (c) Zone 3. (d) Zone 4.

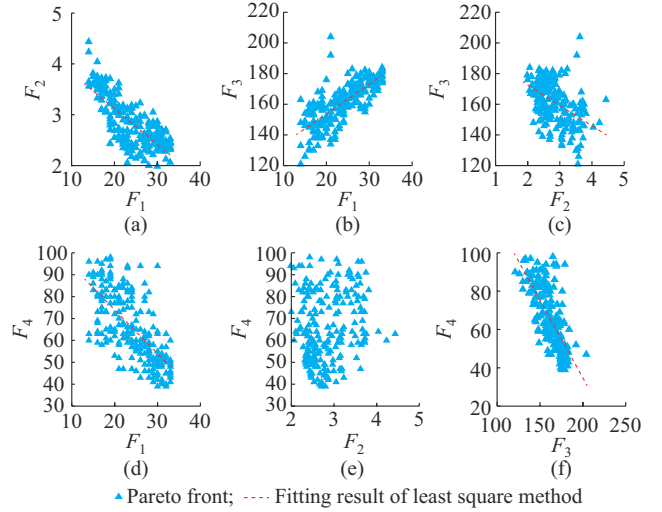


Fig. 8. Pareto front of proposed MaOP for zone 3 of Polish 2383-bus network. (a) F_1 and F_2 . (b) F_1 and F_3 . (c) F_2 and F_3 . (d) F_1 and F_4 . (e) F_2 and F_4 . (f) F_3 and F_4 .

VII. CONCLUSION

Based on DSE supported by edge computing, this paper proposed an NPESP problem to find satisfactory partitions and ES locations in a large-scale network. We formulated NPESP as a constrained MaOP which considers the economy of ES placement, cohesion within each subarea, coupling of subareas, and state variable balance. Then, an improved NSGA-III was developed for the proposed problem in large-scale networks. The experiments, which were implemented on IEEE 118-bus system and Polish 2383-bus system, testified that the solutions to the proposed problem can trade off the objectives and significantly reduce the runtime of DSE. Finally, we evaluated the excellent convergence, diversity, and evenness of the improved NSGA-III by two popular metrics, i.e., IGD and spacing. In future, we will take the convergence of DSE and the reliability of ESs into account in the proposed NPESP problem, and demonstrate the impacts of edge computing on the scalability and response time of DSE.

APPENDIX A

For the basic NSGA-III with the population of size z and k ($k \geq 3$) objective functions, its worst-case complexity at one generation is $O(z^2 k)$ or $O(z(\lg z)^{k-2})$, whichever is larger [35]. The presented solution method modifies the basic NSGA-III by adding real-number encoding and gene restriction, and replacing the random mutation operator with the designed mutation operator. Hence, we should analyze the computational complexity of the modified parts, and compare it with $O(z^2 k)$ and $O(z(\lg z)^{k-2})$. The real-number encoding and the gene restriction require $O(z)$ and $O(z^2)$ computations, respectively. The directed mutation operator with the maximum mutation scale, i.e., $\eta = n$ in Algorithm 1, requires $O(zn^2 \lg n)$ computations, where n is equal to the number of genes of a chromosome. The value of z is generally several times that of n . With all above computations considered, the worst-case complexity

of the improved NSGA-III is $O(z(\lg z)^{k-2})$ or $O(zn^2 \lg n)$, whichever is larger.

The proposed NPESP problem has four objectives and one penalty function, i.e., $k=5$. To solve it, the basic NSGA-III and the improved NSGA-III require no more than $O(z^2)$ and $O(zn^2 \lg n)$ computations at each generation, respectively. The improved NSGA-III has larger computational complexity, since the worst-case complexity of its directed mutation operator is $O(zn^2 \lg n)$, which is larger than $O(z^2)$. Hence, rapid convergence of the improved NSGA-III is achieved by sacrificing the computational complexity.

APPENDIX B

Table BI shows the partitions and ES locations of the six competitive NPESP schemes for IEEE 118-bus system.

TABLE BI
PARTITIONS AND ES LOCATIONS OF SIX COMPETITIVE NPESP SCHEMES FOR IEEE 118-BUS SYSTEM

Scheme	Subarea	Node number	ES location	Subarea size	Number of tie lines
NPESP118-3	1	1-33, 71-73, 113-115, 117	v_{17}	40	5
	2	34-69, 116	v_{49}	37	7
	3	70, 74-112, 118	v_{100}	41	6
NPESP118-4	1	1-20, 33-37, 117	v_{12}	25	9
	2	18, 21-32, 38, 69, 70-76, 113-115, 118	v_{32}	26	13
	3	39-68, 77, 78, 116	v_{49}	33	14
	4	79-112	v_{94}	34	4
NPESP118-5	1	1-16, 33, 36, 117	v_{12}	19	7
	2	17-32, 113-115	v_{32}	19	8
	3	34, 35, 37-45, 49-67	v_{49}	30	10
	4	46-48, 68-84, 96, 97, 116, 118	v_{69}	24	13
	5	85-95, 98-112	v_{100}	26	6
NPESP118-6	1	1-20, 117	v_{12}	21	7
	2	21-23, 25-32, 38, 65, 113-115	v_{25}	16	10
	3	24, 33-37, 43-48, 68-75, 116	v_{47}	21	15
	4	39-42, 49-64, 66, 67	v_{49}	22	8
	5	76-82, 95-99, 118	v_{80}	13	9
	6	83-94, 100-112	v_{100}	25	5
NPESP118-7	1	1-16, 117	v_{12}	17	5
	2	17, 20-23, 25-32, 113-115	v_{32}	16	7
	3	18, 19, 33-44	v_{37}	14	8
	4	48-67	v_{49}	20	7
	5	24, 45-47, 68-75, 116, 118	v_{69}	14	11
	6	76-87, 94-97, 99	v_{77}	17	11
	7	88-93, 98, 100-112	v_{100}	20	7
NPESP118-8	1	1-12, 14, 16, 117	v_{12}	15	4
	2	13, 15, 17-20, 30, 33-39	v_{15}	14	12
	3	21-29, 31, 32, 72, 113-115	v_{32}	15	6
	4	40-49, 65-68, 81, 116	v_{49}	16	14
	5	50-64	v_{56}	15	6
	6	69-71, 73-80, 82, 96, 97, 118	v_{75}	15	11
	7	83-95, 101, 102	v_{92}	15	6
	8	98-100, 103-112	v_{100}	13	5

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Lyuzerui Yuan received the B.E. degree in electrical engineering and automation from South China University of Technology, Guangdong, China, in 2017. She is currently pursuing the Ph.D. degree in electrical engineering at Shanghai Jiao Tong University, Shanghai, China. Her current research interests include situational awareness, edge computing, and deep learning applications in power system.

Jie Gu received the bachelor's, master's, and Ph.D. degrees in electrical engineering from Shanghai Jiao Tong University, Shanghai, China, in 1992, 1995, and 2000, respectively. She then worked with Shanghai Jiao Tong University, where she is currently an Associate Professor with the School of Electronic Information and Electrical Engineering. Her main interests include power system planning, electricity markets, smart grids, microgrids, and intelligent algorithms.

Honglin Wen received the bachelor's degree in electrical engineering from Shanghai Jiao Tong University, Shanghai, China, in 2017, where he is currently working toward the Ph.D. degree with the Research Center for Big Data Engineering Technology. His research interests include machine learning applications in power system, time series forecasting, uncertainty quantification, and decision-making under uncertainty.

Zhijian Jin received the Ph.D. degree in electrical engineering from Shanghai Jiao Tong University, Shanghai, China. Since 1990, he has been with the Electrical Engineering Department, Shanghai Jiao Tong University, where he currently serves as a Tenured Full Professor and the Deputy Director of the National Smart Grid Research and Development Center in Shanghai Jiao Tong University. His research interests include smart grids and applied superconductor.