IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal
IEEE POWER & ENERGY SOCIETY SECTION

Received 6 December 2022, accepted 22 January 2023, date of publication 1 February 2023, date of current version 8 February 2023.
Digital Object Identifier 10.1109/ACCESS.2023.3241754

RESEARCH ARTICLE

Developing an Optimal Framework for PMU Placement Based on Active Distribution System State Estimation Considering Cost-Worth Analysis

AMIN SALEHI[1], MAHMUD FOTUHI-FIRUZABAD[1,2], (Fellow, IEEE), SAJJAD FATTAHEIAN-DEHKORDI[1,2], (Graduate Student Member, IEEE), MOHAMMAD GHOLAMI[1], AND MATTI LEHTONEN[2]
[1]Department of Electrical Engineering, Sharif University of Technology, Tehran 1458889694, Iran
[2]Department of Electrical Engineering and Automation, Aalto University, 02150 Espoo, Finland
Corresponding author: Matti Lehtonen (matti.lehtonen@aalto.fi)

ABSTRACT Due to low levels of observability and automation in active distribution networks (ADNs), the deployment of accurate measurement devices would be inevitable to increase the network observability. This work develops an optimal framework for phasor measurement unit (PMU) placement considering the accuracy of the distribution system state estimation (DSSE) process. In this regard, first, considering the significance of active power in supplying network loads, an active power sensitivity analysis is conducted in which the accuracy of active power injection at each bus is multiplied by its value of lost load. In this way, the accuracy of active power estimation could be transformed into a monetary value. Then, based on the determined sensitivity criterion, the optimal placement of PMUs has been performed with the aim of appropriate accuracy for the DSSE. On the other hand, the accuracy of the results obtained in the state estimation procedure can affect the estimation of line-loadings and lead to load shedding due to the low accuracy of estimated line-loadings. It is noteworthy that due to the high integration of distributed energy resources in distribution systems, ADNs would be prone to congestion issues. Therefore, in the next stage, this perspective is also used for determining the optimal number and location of PMUs in ADNs to improve their observability based on the operational conditions of the network. Finally, the developed algorithm is applied on the 77-bus-UK-test distribution network to investigate its effectiveness in improving the DSSE accuracy and mitigating interrupted loads. The numerical results indicate that implementing the proposed framework not only increases the DSSE accuracy but also decreases the cost of compensating the accuracy of active power by 7% compared to the typical network without PMUs. Further, the results show that the proposed model significantly mitigates the total curtailed loads due to the low accuracy of estimated line-loadings.

INDEX TERMS Active distribution network, state estimation, phasor measurement units, active power sensitivity, line-loadings.

ABBREVIATIONS

DER	Distributed energy resource.
ADN	Active distribution network
APS	Active power sensitivity.
PMU	Phasor measurement unit.
DSSE	Distribution system state estimation.
SEP	State estimation process.
ADMS	Active distribution management system.
EMS	Energy management system.
GA	Genetic algorithm.
MOGA	Multi-objective genetic algorithm.

The associate editor coordinating the review of this manuscript and approving it for publication was Ravindra Singh.

VoLL Value of lost load.
CCAAP Cost of compensating the accuracy of active power.
LLE Line-loadings error.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

The increasing penetration of distributed energy resources (DERs) in local energy systems has led to increased operational challenges in active distribution networks (ADNs). In ADNs, operators can manage and coordinate the flow of electrical energy using an active distribution management system (ADMS). It is noteworthy that the main features of the ADMS include: congestion management, automatic voltage control, capacitor switching, conservation voltage reduction, distribution transformer usage optimization, control of switches and reclosers, price signal determination, fast reconfiguration and service restoration, optimization and loss management, demand side management, and fault detection [1], [2], [3], [4].

In ADNs structure, distribution system state estimation (DSSE) and energy management system (EMS) are essential elements for optimizing the utilization of DERs, energy storage systems as well as responsive loads [5]. In the present situation, ADMS controls and monitors the distribution network with low levels of observability and automation which will not meet the challenges of ADNs. Nonetheless, network monitoring, control, and protection must be developed based on the operational condition of the network [6]. Therefore, DSSE as one of the essential elements of ADMS can be used to achieve accurate and reliable network conditions. Figure 1 demonstrates the role and importance of DSSE.

B. RELATED WORKS

DSSE has been widely studied considering the accuracy of the state estimation process (SEP), measurement placement, network observability, and investment cost issues [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]. In these works, traditional measurements such as substation measurement, line flow measurements, pseudo-measurements based on historical network data, and modern measurements such as phasor measurement units (PMUs) as well as smart metering measurements have been used for an effective state estimation. Note that the state estimation utilizing PMU measurements has been widely investigated for transmission systems. PMU placement is often recognized as a very promising tool in these networks by improving the accuracy of state estimation and increasing the network observability [9], [12], [13], [14], [17].

Nevertheless, in ADNs due to a number issues (e.g. low x/r value, renewable energy integration, observability problem, network configuration problem, communication infrastructure constraints, and cyber-security), it is not suitable to simply employ the transmission state estimation and PMU placement methods [2]. In these networks, AC state estimation is often used to estimate network variables, and heuristic algorithms are employed for optimal placement of measurement devices. It is noteworthy that the basic PMU placement problem has been developed in recent years due to sophisticated operation conditions and limitations including communication infrastructure and PMU channel constraints, reliability of network components and data acquired by measurements, and contingencies due to the PMU failures and/or line outages [8], [13], [16], [18], [19], [20].

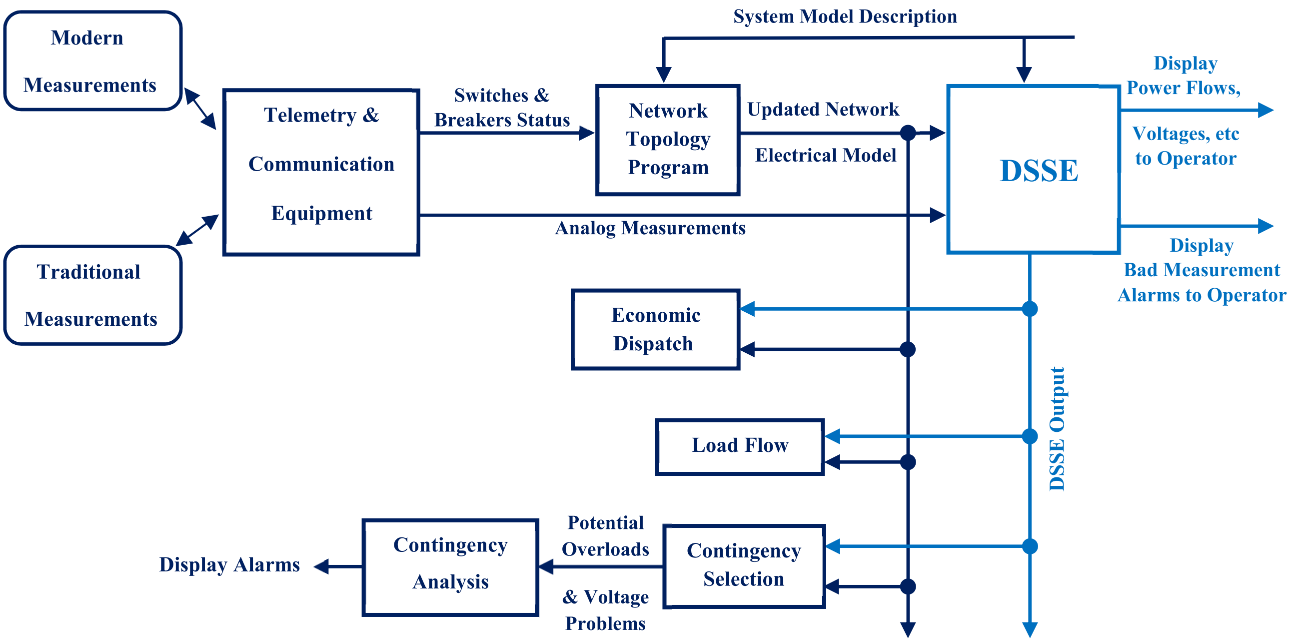

FIGURE 1. Architecture for the role and importance of DSSE.

On the other hand, in the current ADNs, due to the limitations of real-time measurements and the use of pseudo-measurements, it is not possible to achieve the results of state estimation with the desired accuracy. Therefore, meter placement would be necessary to improve the accuracy and efficiency of the SEP and the observability of distribution grids. In this regard, the distribution of PMUs, smart meters, and other measurement equipment is studied in [6]. Accordingly, the optimal deployment of PMUs and smart meters along with substation measurements and pseudo-measurements have been considered using the genetic algorithm (GA) while satisfying the constraints related to state estimation errors in ADN. Authors in [7] presents a probabilistic method based on Monte Carlo simulation for locating voltage and power flow measurements to reduce the relative magnitude and voltage phase error of all buses below the threshold defined in 95% of the simulated cases. In [20], due to the fact that any failure in measurement devices can affect the DSSE results, a PMU placement approach has been investigated based on reliability and accuracy of the DSSE results. A method for optimizing the location and the number of PMUs in distribution systems with the presence of distributed generation sources, variable loads, and voltage regulators with the aim of least error in the SEP is proposed in [21]. As stated in [22], the data transmission rate by smart meters is unsuitable for real-time monitoring of future distribution systems. Therefore, considering the limited number of voltage magnitude meters and PMUs, a sub-modular saturation algorithm could provide a robust method for meters placement to conduct the DSSE. In [23], the placement of a limited number of meters including the optimal number and type of measurements is suggested to minimize the voltage profile estimation error in the worst-case scenario of all possible scenarios. In [24], the authors present a multi-objective optimization model based on the state estimation function in distribution networks. In the proposed model, the total cost of PMUs, smart meter devices, and the average relative percentage of state estimation errors are considered as the objective function. Eventually, the optimal answer is calculated using a multi-objective hybrid PSO-Krill Herd algorithm.

Furthermore, the appropriate functioning of the DSSE under different operational conditions would be an essential issue. In this regard, the DSSE should be enabled to provide suitable outputs under various contingencies, including PMU failure, line outages, network reconfiguration, communication system failures, load variations, measurement error degradation, and lines congestion. According to the aforementioned facts, in [27], an optimal PMU placement method is developed to minimize the cost of PMUs and line relays considering the network observability and the minimum load loss with different configurations. Also, as taken into consideration in [28], an integer linear programming method is used to optimize measurement costs and network observability. The effects of state estimation accuracy in different contingencies have been analyzed in this regard. Furthermore, optimal PMU placement subject to availability of PMU channels, single PMU loss, and single branch outage is investigated in [13] and [19]. The optimal allocation of PMUs aiming to minimize the PMU-cost and line relays is also introduced in [25]. In this regard, the network observability and the minimization of load loss with different configurations have been considered. The optimization of measurement costs and network observability is investigated in [26] by an integer linear programming framework. Furthermore, the accuracy of DSSE results in different network conditions, such as reconfiguration, alteration in load consumption, and measurement error degradation is addressed to assess the impact of the proposed placement.

As can be seen from the related literature, in most of the studies performed in this field, there are generally two different strategies for optimal meter placement in distribution networks:

1) Specifying the least number of required measurement devices (due to economic issues) and their optimal placement (pursuant to the precision of obtained results).

2) Optimal placement of a prespecified number of measurements based on the desired precision of the results.

Finally, Table 1 reports a simplified comparison of previously developed schemes with the proposed framework in this paper from viewpoints of DSSE accuracy, optimal PMU placement, contingency analysis, and relating the DSSE accuracy to the cost value.

TABLE 1. Taxonomy of research works on the DSSE.

Ref.	State Estimation Accuracy	Optimal Measurement Placement	Contingency Analysis	Relating the DSSE Accuracy into the Cost Value
[8]	✓	✓	-	-
[9], [10]	✓	-	-	-
[12], [13], [25], [27]	-	✓	✓	-
[6], [11], [15], [23], [24]	✓	✓	-	-
[14], [16], [18], [19]	-	✓	✓	-
[20]	-	✓	-	-
[26]	✓	✓	✓	-
This Paper	✓	✓	✓	✓

C. MAIN CONTRIBUTIONS

The desired goal of ADMS is to supply all consumers without power interruptions and with appropriate quality in their voltage profile. In this regard, active power and voltage at load points play major roles in operational management of the system. Therefore, the supply of network loads would be important from the ADMS point of view. In this regard, the primary step to reaching this goal is accurately estimating voltage profile and active power in the ADN. On the other hand, the increasing penetration of renewable energy resources in distribution grid can affect the operating conditions and reliability of the system, especially line-loadings [28], [29].

Motivated by the aforementioned facts, the major contributions of this paper can be briefly rendered as the following points:

- An active power sensitivity (APS) analysis is performed to enhance the estimated active power injection of all network buses considering the allowable range of the bus voltage magnitudes. Furthermore, this framework investigates a method that relates the state estimation accuracy to the cost of compensating accuracy of active power injection at each bus. Then, based on the determined sensitivity criterion, the placement of PMUs has been performed with the aim of proper accuracy for the DSSE process and minimizing the number of PMUs. Furthermore, in the developed procedure, the effects of incorrect input data in PMUs (intentional or unintentional) are evaluated on the system cost.
- Monitoring of network line-loadings is studied as a result of state estimation output. In other words, since the state estimation output affects load flow calculations, in case that the DSSE results are not accurate, the calculated line-loadings based on the DSSE will not be precise either. Therefore, PMUs are optimally located with the least number to perform the DSSE with the appropriate accuracy. Respectively, the amount of energy not served to the consumers is minimized due to incorrect estimation of line-loadings. In other words, a contingency analysis is performed for network line-loadings.
- The idea employed in this paper to study the state estimation considering operational condition of the system would enable the utility to determine the best configuration of PMUs based on the condition of the grid.

Additionally, several scenarios are considered as random measurement errors to take into account the measurement uncertainty and different operating conditions. These scenarios are generated using the K-means clustering process.

D. PAPER ORGANIZATION

The rest of the paper is organized as follows. Section II describes the DSSE concept and its process. Mathematical modeling and performance indices are discussed in Section III-A. The optimization methodology and measurement placement are also described in Sections III-B and III-C, respectively. Section IV illustrates the case study, simulation assumptions, and the performance assessment of the developed framework. Finally, the conclusion is drawn in Section V.

II. DISTRIBUTION SYSTEM STATE ESTIMATION

A. STATE ESTIMATION CONCEPT

State estimation is a computational process that provides the best evaluation of system states using limited measurements that are subjected to noise and measurement errors. In this paper, similar to the previous studies performed in [2], [6], [30], and [31], the weighted least square (WLS) method is used for the SEP. If there are n numbers of state variables and m measurements, then the mathematical relationship between the set of measurements (z) could be modelled as follow:

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix} = \begin{bmatrix} f_1(x_1, x_2, \ldots, x_n) \\ f_2(x_1, x_2, \ldots, x_n) \\ \vdots \\ f_m(x_1, x_2, \ldots, x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_m \end{bmatrix} = f(x) + e \tag{1}$$

where, $f(x)$ is the vector of the non-linear relationship between the measured variables and the state vector x. Moreover, $x^T = [x_1, x_2, \ldots, x_n]$ is the system state vector which consists of bus voltage magnitudes and phase angles. Additionally, $e^T = [e_1, e_2, \ldots, e_m]$ is the vector of measurements uncertainty (i.e., measurements errors).

Generally, the optimization problem in the SEP is modeled with the following objective function:

$$Min_X J(x) = \sum_{i=1}^{N_m} \frac{[z_i^{meas} - f_i(x)]^2}{\sigma_i^2} \tag{2}$$

where, $J(x)$ is the measurement residual, z_i^{meas} is the i^{th} measured quantity, σ_i is the standard deviation for the i^{th} measurement, and N_m is the number of independent measurements.

Equation (2) can be written in a compact form as follows:

$$Min_X J(x) = [z^{meas} - f(x)]^T [W]^{-1} [z^{meas} - f(x)] \tag{3}$$

where, $W = diag\{\sigma_1^2, \sigma_1^2, \ldots, \sigma_m^2\}$ is the covariance matrix of measurement errors.

B. MEASUREMENTS

As mentioned, the presence of PMUs in the network is essential to improve the DSSE accuracy and distribution network observability. On the other hand, due to the limited number of PMUs installed in the network, phasor measurements should be used together with other measurements for the DSSE. In this work, the measurement vector (Z^{meas}) is considered as follows:

$$Z^{meas} = [V_{mag}, V_{ang}, I_{mag}, I_{ang}, P_{flow}, Q_{flow}, P_{inj}, Q_{inj}]^T$$

where, V_{mag} and V_{ang} are sub-vectors that include the voltage magnitude and phase angle measurements in the substation bus (slack bus) and buses with PMUs, respectively. Moreover, the flow current magnitude and phase angle measurements for the lines connected to the buses with PMUs are considered in I_{mag} and I_{ang} sub-vectors, respectively. Additionally,

P_{flow} and Q_{flow} consist the active and reactive power flow measurements; while the active and reactive power injection measurements (pseudo-measurements) are considered as P_{inj} and $Q_{inj.}$

Therefore, based on the aforementioned measurement vector, the objective function (3) could be formulated as below:

$$J = [E]^T [W]^{-1} [E] \tag{4}$$

where:

$$E = \begin{bmatrix} V_{mag}^{meas} - f_{V_{mag}}(x) \\ V_{ang}^{meas} - f_{V_{ang}}(x) \\ \vdots \\ Q_{inj}^{meas} - f_{Q_{inj}}(x) \end{bmatrix};$$
$$W = diag(W_{V_{mag}}, W_{V_{ang}}, \ldots, W_{Q_{inj}}) \tag{5}$$

Finally, by applying the iterative WLS process, the state variable x can be calculated according to:

$$x_{j+1} - x_j = [G(x_j)]^{-1} [H(x_j)]^T [W]^{-1} [z^{meas} - f(x_j)] \tag{6}$$

where, x_j is the estimated state vector from the j^{th} iteration of x, $G(x) = [H]^T [W]^{-1} [H]$ is the gain matrix, and $H(x)$ represents the Jacobian matrix obtained by taking partial derivatives from $f(x)$ with respect to x.

III. METHODOLOGY AND OPTIMIZATION OF MEASUREMENT PLACEMENT

A. MATHEMATICAL MODELING OF PERFORMANCE INDEXES

Increasing the level of distribution network observability and monitoring to improve the DSSE accuracy will increase the designing cost of the state estimation system. Therefore, focusing on the DSSE accuracy function in ADMS and the network sensitivity to not-scheduled power outages, measurement placement cost is optimized in proportion to the desired accuracy and sensitivity. In this regard, an APS analysis is performed to enhance the estimated active power injection of all network buses considering the allowable range of the bus voltage magnitudes. Note that the minimum and maximum acceptable range of the bus voltage magnitudes are considered between 0.95 to 1.05 per-unit (p.u.), respectively. Furthermore, the increasing penetration of renewable resources in distribution grid can affect the operating conditions and reliability of the system, especially line-loadings. In this respective, monitoring of grid line-loadings is also studied as a result of state estimation output.

1) ACTIVE POWER SENSITIVITY ANALYSIS

As stated before, the optimal condition in power systems is to supply all network loads without power interruptions while appropriate quality in the network voltage profile is met. For example, some buses have sensitive loads (such as large malls or factories), and it would be crucial from the ADMS point of view to supply the load of these buses. Active power and voltage at load points play a pivotal role in this regard. The primary step to reaching this goal is accurately estimating voltage profile and active power in the ADN. Therefore, an APS analysis has been performed so that the accuracy of estimated active power injection for each bus (the difference between the actual and the estimated active power injection) is represented by a monetary value. This is done by multiplying the accuracy at each bus times its value of lost load (VoLL). Then, based on the determined sensitivity criterion, the placement of PMUs has been performed with the aim of proper accuracy for the DSSE process and minimizing the number of allocated PMUs. It should be noted that, in the proposed approach without loss of generality, VoLL has been used as a parameter to compare the value of increasing the accuracy of bus estimation. Therefore, in this way, the cost of compensating the accuracy of active power in the network would be calculated. Furthermore, the optimization problem is developed in a way that the voltage magnitudes of network buses would be within their allowable range.

$$P^{sensitivity} = \frac{1}{N_{scn}} \sum_{sc=1}^{scenarios} \sum_{i=1}^{N} VoLL_{sc,i} * \left| (P_{inj}^{base})_{sc,i} - (P_{inj}^{est})_{sc,i} \right| \tag{7}$$

where, $P^{sensitivity}$ is the APS function, P_{inj}^{base} is the actual active power injection (based on the power flow results), and P_{inj}^{est} is the estimated active power injection of each bus. Moreover, N, and N_{scn} are the total number of network buses and scenarios, respectively. $VoLL_i$ is also the value of lost load of the i^{th} bus. In (7), first, the APS function is computed in each generated scenario for all network buses taking into account the localized PMUs. Then, by averaging all the scenarios, the APS value is calculated for the mentioned PMU configuration.

2) NETWORK LINE-LOADINGS

One of the critical issues that the accuracy of the state estimator output can affect is the estimated loading of network lines. As mentioned earlier, since the state estimation output affects load flow calculations, in case that the DSSE results are not accurate, the calculated line-loadings based on the DSSE will not be precise either. In this situation, the distribution network operator is forced to shed the downstream loads until the loading of the lines returns to their normal values. Consequently, the distribution network consumers will face a lot of damage and interruption costs. Therefore, with different criteria that will be expressed, the minimized number of PMUs are optimally located to perform the DSSE with the appropriate accuracy. Respectively, the amount of energy not served to the consumers is minimized due to incorrect estimation of line-loadings. In this regard, line-loading is calculated by the following equation:

$$line\_loading = \sqrt{\frac{P_l^2 + Q_l^2}{|V|^2}} \tag{8}$$

where, P_l and Q_l are the active and reactive power flows and $|V|$ is the voltage magnitude at the beginning of the line.

The operating conditions in the distribution network are normal at most of the time intervals, but sometimes abnormal conditions (i.e., over-loading on network lines) may occur. It is noteworthy that the high integration of DERs could result in the over-loading in distribution networks. Therefore, the scenarios of this part of the study have been produced according to the operational condition of the system. In this regard, there will be two aspects associated with the scenarios:

1- In normal scenarios, if the SEP has not worked properly, the state estimator may show the loading percentage of each line above 100%. This means the over-loading condition in the respected lines. Therefore, based on the state estimator results, the network operator is forced to shed the downstream loads of these lines to ensure normal loading.

2- In abnormal scenarios, where the actual loading of some lines is above 100% (e.g., $(100+\lambda)\%$), we could consider two special conditions based on the operation of the over-current relay. It should be noted that in reality, when the loading percentage of a line is $100+\varepsilon$, the over-current relay with a predefined tolerance cuts off all the downstream loads of the mentioned line. Note that, λ illustrates the actual over-loading, while η represents the over-loading that is estimated by state estimator. Moreover, ε illustrates the threshold of the over-current relay.

a) If the state estimator shows the loading of a line above 100% (e.g., $(100+\eta)\%$) and $\eta > \lambda > \varepsilon$, then the network operator sheds the downstream loads of the line as much as $\eta\%$. In this condition, the over-current relay doesn't work and $\eta\%$ of the downstream load would be curtailed.

b) If the state estimator shows the loading of a line above 100% (e.g., $(100+\eta)\%$) and $\eta < \varepsilon < \lambda$, then the network operator sheds the downstream loads of the line as much as $\eta\%$. However, despite this action by the operator, since loading of the line in this case is still higher than the threshold of the over-current relay, the over-current relay would cut off all the downstream loads of the line.

B. OPTIMIZATION OF MEASUREMENT PLACEMENT AND GA

Based on the aforementioned performance criteria in the previous sections, different objective functions are proposed for DSSE accuracy and APS improvement. Respectively, minimizing load shedding due to incorrect estimation of line-loadings are investigated as follows:

1) PMU placement based on APS analysis

$$Min \begin{cases} \mathrm{obj}_1 = \mathrm{PMU}^{\cos t} \\ \mathrm{obj}_2 = \mathrm{P}^{sensitivity} \end{cases} \tag{9a}$$

$$\text{Subject to: } \left|V_i^{\min}\right| < |V_i| < \left|V_i^{\max}\right| \tag{9b}$$

where, $\mathrm{P}^{sensitivity}$ is the APS function and $\mathrm{PMU}^{\cos t}$ is the total cost of PMUs that are optimally located in the network which is found using the following equation.

$$PMU^{\cos t} = \sum_{i=1}^{N} x_i \tag{10}$$

where, x is a binary variable that is equal to one if there is a PMU at a bus and zero if there is no PMU. Moreover, N is the total number of network buses. Furthermore, in (9), $\left|V_i^{\min}\right|$ and $\left|V_i^{\max}\right|$ are the minimum and maximum voltage magnitude of the i^{th} bus, respectively. According to (9), it is considered that the voltage magnitudes of buses would be in the allowable range. Otherwise, inappropriate responses, which would not satisfy the constraint (9), will be penalized by adding a large number to their cost functions in the multi-objective optimization.

2) line-loadings and PMU placement

For this part of the study, different objective functions are considered:

2.1. PMU placement based on minimizing line-loading errors

$$Min \begin{cases} \mathrm{obj}_1 = \mathrm{PMU}^{\cos t} \\ \mathrm{obj}_2 = \sum Line\ \mathrm{Loading}\_Errors \end{cases} \tag{11a}$$

$$\text{Subject to : } \left|V_i^{\min}\right| < |V_i| < \left|V_i^{\max}\right| \tag{11b}$$

where, $\sum Line\ \mathrm{Loading}\_Errors$ is the summation of line-loading errors due to low accuracy and incorrect state estimation in the studied lines.

2.2. PMU placement based on minimizing APS & line-loading errors

$$Min \begin{cases} \mathrm{obj}_1 = \mathrm{PMU}^{\cos t} \\ \mathrm{obj}_2 = \mathrm{P}^{sensitivity} \\ \mathrm{obj}_3 = \sum Line\ \mathrm{Loading}\_Errors \end{cases} \tag{12a}$$

$$\text{Subject to: } \left|V_i^{\min}\right| < |V_i| < \left|V_i^{\max}\right| \tag{12b}$$

2.3. PMU placement based on minimizing the amount of load shedding

$$Min \begin{cases} \mathrm{obj}_1 = \mathrm{PMU}^{\cos t} \\ \mathrm{obj}_2 = \Delta\mathrm{P}^{total} \end{cases} \tag{13a}$$

$$\text{Subject to: } \left|V_i^{\min}\right| < |V_i| < \left|V_i^{\max}\right| \tag{13b}$$

where, $\Delta\mathrm{P}^{total}$ indicates the summation of interrupted loads. $\Delta\mathrm{P}^{total}$ would be calculated by the following equation:

$$\Delta P^{total} = \frac{1}{N_{scn}} \sum_{sc=1}^{scenarios} \sum_{k=1}^{m} \Delta P_{line\ \mathrm{k,sc}} \tag{14}$$

where, $\Delta P_{line\ \mathrm{k}}$ is the amount of downstream interrupted loads of *line k* based on explanations of section A.2, and m is the number of monitored lines.

C. MEASUREMENT PLACEMENT USING GENETIC ALGORITHM

PMU placement is a polynomial-time hard, non-deterministic problem that requires many computational efforts and may not have a single answer [32]. Respectively, effective algorithms cannot be applied to solve these types of problems. In this regard, metaheuristic optimization methods are considered to be suitable tools to solve these types of problems [33]. GA is one of the common optimization algorithms in engineering that has been used in the face of complex optimization problems [6]. Therefore, in this paper, due to the multi-objective nature of each optimization section, a multi-objective genetic algorithm (MOGA) is used for the optimal PMU placement in the ADN. Implementing a MOGA usually begins with generating a population of volunteer individuals (N_{pop}), which are the vector of possible measurement locations. Elements of these individuals are binary variables relating to the presence/absence of a measurement device at a given location. Input data for the optimization process are:

- MOGA settings like population size of individuals, exit criteria, etc.,
- Distribution topology data,
- Distributed productions and load data,
- Measurements uncertainty,
- The objective functions relate to the DSSE accuracy and PMU placement.

Then, DSSE outputs and performance indexes are calculated for each individual, assuming that the proposed buses are equipped with PMUs. Subsequently, one of the multi-objective cost functions presented in the section III-B is used as the competency function for the MOGA, which is then used to assess the competency values of all individuals in the population. However, the competency values of individuals that do not meet the accuracy constraints are increased by a large number to penalize them as impractical responses. Then, after assessing the competency of all individuals in the population, the optimization process is stopped. In this regard, if the exit criteria of MOGA are met, the best configuration of PMUs in the network would be reported. Otherwise, a new population is created by crossing over and mutating the individuals with the best competency values (lowest values). This process is repeated until the MOGA criteria are met. Figure 2 demonstrates the optimization flowchart based on the MOGA technique.

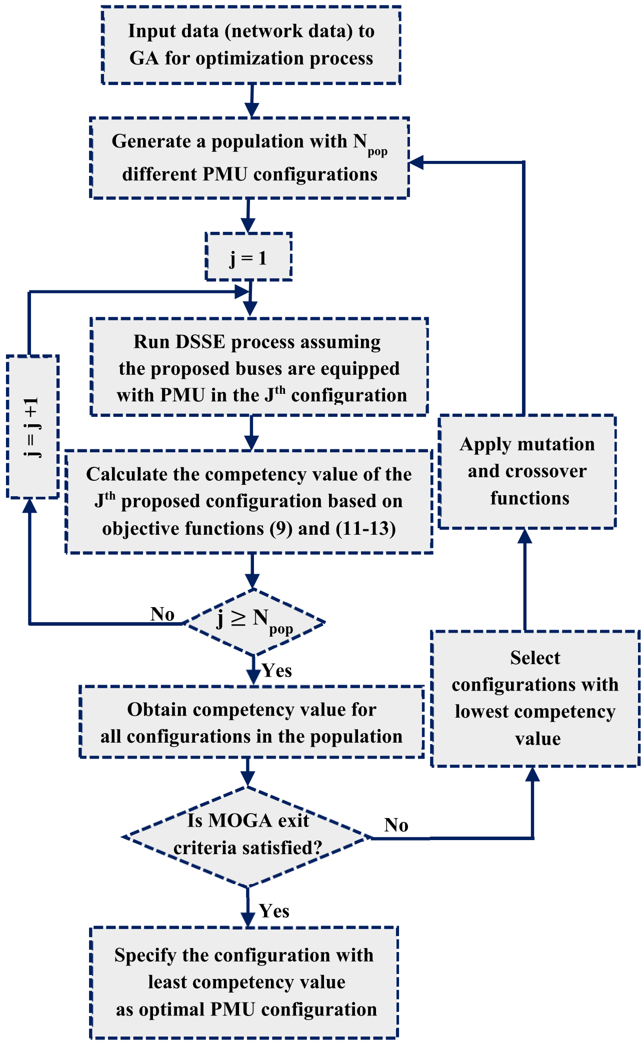

FIGURE 2. Optimization flowchart based on GA.

IV. CASE STUDY

A. SIMULATION CONDITIONS

A set of input data is generated for the DSSE process, which includes both real-time and pseudo-measurements. These measurements are obtained from the power flow results in test cases as reference values. Furthermore, deviation in measurements is determined by Gaussian distribution as measurements noise. It is assumed that the network default real-time measurements consist of the main substation voltage phasor measurement (i.e., slack bus) as well as active and reactive power flow measurements. Moreover, pseudo-measurements consist of active and reactive power injections of all buses with loads and distributed generations, which are employed to achieve full observability of the network.

The measurement distributions are assumed to have a Gaussian shape and a standard deviation of one-third of their error values [34]. Depending on the type of measurements, the maximum error percentages are assumed to be:

- 1% for substation measurement,
- 3% for power flow measurements,
- 50% for pseudo-measurements,
- 0.7% and 0.7 centiradian for magnitude and phase angle in PMU measurements, respectively [6], [35].

Finally, a K-means clustering process [36] is used for generating different scenarios to take into account the measurement's uncertainty and various operating conditions. In the first step, 10000 measurement data were generated for all measurement devices using the normal distribution. In this regard, the power flow and the error associated with the measurements were considered as the mean values and standard deviations, respectively. Then, employing the K-means clustering algorithm, 10000 data were divided into 500 clusters. Eventually, clusters' centroids are considered as 500 final measurement scenarios.

B. CASE STUDY ON UK 77-BUS TEST SYSTEM

The 77-bus UK distribution network [37] has been chosen for the performance evaluation of the proposed algorithm. The modified network is a three-phase balanced system which includes one grid supply in the substation bus, 2 transformers, 7 DGs (PV plants), and 75 load points, which are demonstrated in Fig. 3.

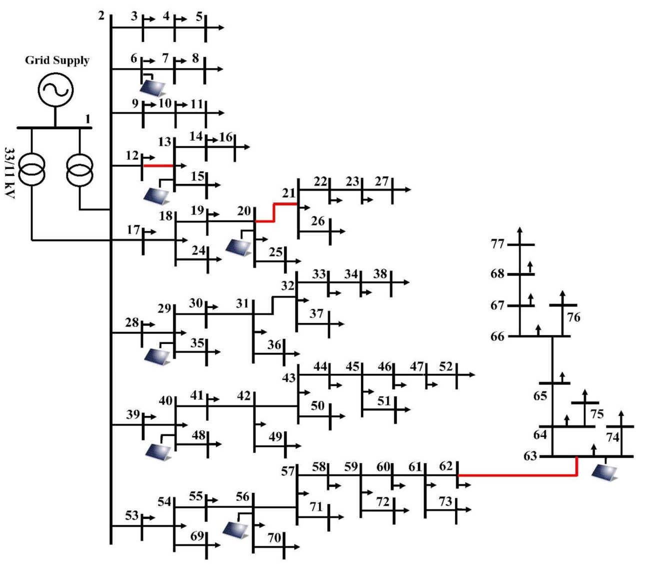

FIGURE 3. UK 77-bus test system.

After running the GA for the optimization problem of APS, different optimal PMU locations to improve the DSSE accuracy, and decrease the cost of compensating the accuracy of active power (CCAAP) are summarized in Table 2.

It is noteworthy that, the VoLL is assumed to be 6000 $\$/MWh$ (for buses: 5, 8, 11, 14, 16, 23, 24, 25, 26, 27, 34, 35, 36, 37, 38, 44, 46, 47, 48, 49, 50, 51, 52, 58, 60, 62, 65, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77), 9000 $\$/MWh$ (for buses: 4, 7, 10, 15, 20, 22, 32, 33, 43, 56, 59, 61, 64, 67), and 12000 $\$/MWh$ (for buses: 1, 2, 3, 6, 9, 12, 13, 17, 18, 19, 21, 28, 29, 30, 31, 39, 40, 41, 42, 45, 53, 54, 55, 57, 66).

It should be noted that, in the proposed approach without loss of generality, VoLL has been used as a parameter to compare the value of increasing the estimation accuracy of bus parameters. On the other hand, the input data of the estimator (including active power) is taken from the network load flow in one hour. Therefore, the active power in such condition is also made of energy. So, by multiplying the APS function (in p.u. form) times the base apparent power (100 MVA), we can calculate the amount of CCAAP for each PMU configuration. Moreover, the total cost of PMUs is considered to be equal to their numbers, taking into account that the price of one PMU is one per-unit.

As can be traced in Table 2, the DSSE accuracy is improved by locating PMUs and increasing their number. Consequently, the sensitivity of active power and CCAAP are reduced.

TABLE 2. Optimal PMU configurations with minimum Costs, APS function, and its related CCAAP for the UK 77-bus distribution network.

Config. number	PMU Locations (Bus number)	PMU^{cost} (p.u.)	APS (p.u.)	CCAAP ($)
1	[-]	0	967.142	967142
2	[10, 13, 21, 30, 46, 55, 63]	7	929.587	929587
3	[13, 21, 30, 44, 55, 64, 75]	7	926.362	926362
4	[3, 9, 12, 19, 22, 41, 53, 62]	8	919.68	919680
5	[7, 14, 17, 21, 28, 39, 57, 64]	8	918.758	918758
6	[10, 13, 17, 21, 30, 37, 42, 55]	8	912.151	912151
7	[9, 12, 13, 19, 23, 28, 31, 32, 53, 54]	10	901.822	901822
8	[4, 7, 9, 13, 15, 17, 23, 30, 32, 39, 53, 69]	12	899.328	899328

As the results show, CCAAP can be reduced to 67814 \$ per hour by placing PMUs at optimal points of the network. Therefore, implementing the proposed framework results in not only an increase in the DSSE accuracy but also a decrease in CCAAP by 7% compare to the typical network without PMUs. However, by increasing the number of PMUs, the investment costs would also increase. Therefore, based on the cost-based analysis and minimum acceptable accuracy, ADMS can choose one of the schemes in Table 2. Figure 4, illustrates the results of Table 1 schematically.

In the following, two approaches are considered to show the effects of incorrect input data in PMUs on the system operational costs. In the first one, the impact of different error percentages in the input of one of the installed PMUs is analyzed on the APS function, while the second one investigates the effects of errors in the input of two installed PMUs on the APS function.

The obtained results for the configurations in Table 2 are summarized in Table 3 and Table 4. As can be seen, by increasing the measurement error for the PMUs (and generally all measurement devices), the estimation errors of SEP outputs, the values of the APS function, and the CCAAP are increased in the network. Also, a comparison between the results of Tables 3 and 4 demonstrates that applying errors in

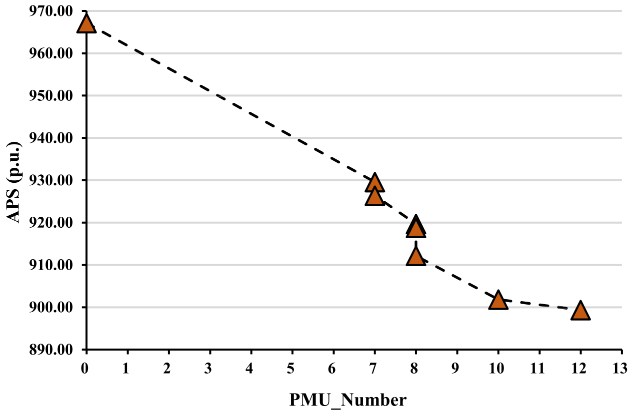

FIGURE 4. PMU placement considering APS analysis.

TABLE 3. Effect of different error percentages on the input of one PMU on the APS function.

Config. number	PMU^{cost} (p.u.)	APS (p.u.)			
		0%	15%	30%	45%
1	0	967.142	-	-	-
2	7	929.587	932.736	969.062	1059.763
3	7	926.362	928.896	945.1	993.946
4	8	919.68	923.827	947.865	1011.379
5	8	918.758	923.827	945.408	992.947
6	8	912.151	914.15	934.195	989.338
7	10	901.822	902.4	906.47	915.456
8	12	899.328	899.712	902.707	909.619

the input of more measurement devices has more destructive effects on the output accuracy of the state estimation and operational costs.

As mentioned in section III, DSSE results affect the estimated line-loadings. To study this effect, three network lines are studied, assuming different loadings and under various operating conditions. These three lines are: the connecting lines of buses 12 -13, buses 20 – 21, and buses 62 – 63 (shown in Figure 3 with red lines), which have 85%, 95%, and 110% loading, respectively. Note that, in this study, it is assumed that only these three lines will face over-loading.

In this regard, the line-loading errors (LLEs) are first analyzed based on the approach described in Section III-A. The obtained results are summarized in Table 5. Note that LLE_1, LLE_2 and, LLE_3 are related to lines 12-13, 20-21 and, 62-63, respectively. According to the results, by increasing the number of allocated PMUs in the network, the accuracy of DSSE output increases while the number of errors in

TABLE 4. Effect of different error percentages on the input of two PMUs on the APS function.

Config. number	PMU^{cost} (p.u.)	APS (p.u.)			
		0%	15%	30%	45%
1	0	967.142	-	-	-
2	7	929.587	943.718	1045.25	1250.765
3	7	926.362	936.8	991.334	1115.29
4	8	919.68	932.045	1004.08	1161.216
5	8	918.758	932.89	991.488	1109.99
6	8	912.151	918.22	970.829	1096.166
7	10	901.822	903.552	912.538	932.045
8	12	899.328	900.48	907.622	925.594

line-loadings decreases. Therefore, the distribution network operator will have to cut fewer loads in such cases. Also, as can be seen from $\sum LLE$, allocating PMUs near the monitored lines and increasing the measurement accuracy significantly reduces the total number of loading errors (about 26 %).

So far, APS analysis and line-loadings have been studied separately. Yet, we can evaluate the effects of both parameters on the network operation considering the cost function of (11a). The results are illustrated in Table 6.

As can be concluded in Table 6, increasing the DSSE accuracy as a result of PMU placement, improves the APS function accuracy and reduces the number of LLE. The amount of downstream interrupted loads will also decrease by reducing the number of incorrect estimated line-loadings, which could eventually improve the network reliability.

However, by defining an accuracy index (AI) for the APS function as well as using a cost-benefit diagram, the optimal point between the parameters "total PMU placement cost," "APS function accuracy" and, "number of LLE" can be obtained. This process would determine the economically optimal scheme.

$$AI(\%) = \frac{APS^{without\ PMU} - APS^{with\ PMU}}{APS^{without\ PMU}} \times 100 \qquad (15)$$

where, $APS^{withoutPMU}$ is the value of the APS function without any PMU in the network and, $APS^{withPMU}$ is the value of APS function if the PMU schemes in Table 6 are located in the network.

Based on the obtained cost-benefit diagram illustrated in Fig. 5, the PMU configuration schemes 2 or 3, can be chosen as the optimal scheme. Although both schemes have almost the same APS function, scheme 3 has fewer number of LLE than scheme 2 and could be a better choice for ADMS.

TABLE 5. **Optimal PMU configurations based on minimizing line-loadings error.**

Config. number	PMU Locations (BUS NUMBER)	LLE_1	LLE_2	LLE_3	$\sum LLE$
1	[14, 33, 46, 73]	23	96	71	190
2	[5, 14, 23, 57, 76]	23	80	71	174
3	[5, 8, 10, 22, 26, 74]	28	66	69	163
4	[13, 16, 22, 23, 26, 29, 74]	24	66	71	161
5	[5, 8, 13, 22, 23, 26, 29, 35, 57, 74]	24	53	71	148
6	[5, 8, 13, 14, 21, 22, 23, 26, 35, 37, 57, 71, 74]	23	52	66	141

TABLE 6. **Optimal PMU configurations based on minimizing APS and LLE.**

Config. number	PMU Locations (BUS NUMBER)	PMU^{cost}	APS (p.u.)	$\sum LLE$
1	[2, 6, 21, 29, 46, 53, 55]	7	928.59	223
2	[7, 13, 17, 21, 30, 37, 42, 55]	8	919.142	218
3	[6, 8, 22, 23, 26, 28, 29, 39, 55]	9	918.835	206
4	[4, 8, 22, 23, 26, 28, 29, 39, 56]	9	914.38	205
5	[12, 13, 22, 24, 26, 28, 35, 39, 53, 55]	10	914.304	195
6	[6, 10, 13, 15, 17, 21, 23, 30, 35, 39, 53, 55]	12	912.307	195

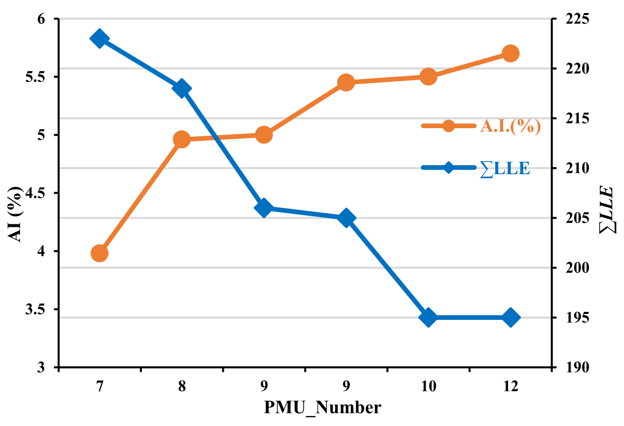

FIGURE 5. **Cost-benefit diagram for schemes in Table 6.**

As mentioned earlier, incorrect line-loading estimation due to the low accuracy of the state estimator outputs will cause the downstream loads to be shed by the network operator or over-current relay. Therefore, according to (11b), PMU placement has been done to minimize the interrupted downstream loads, as illustrated in Table 7.

TABLE 7. **Optimal PMU configurations based on minimizing interrupted downstream loads.**

Config. number	PMU Locations (BUS NUMBER)	PMU^{cost}	ΔP^{total} (p.u.)
1	[-]	0	0.0098
2	[54, 65]	2	0.0073
3	[7, 54, 65, 76]	4	0.0064
4	[7, 27, 54, 65, 76]	5	0.0062
5	[7, 22, 49, 54, 55, 65, 76]	7	0.0058

In Table 7, ΔP^{total} represents the average total curtailed load from the downstream loads of the three monitored lines, for all scenarios. The results clearly show that the use of PMUs reduces the interrupted loads from approximately 1 to 0.6 MW, due to improving the DSSE accuracy. On the other hand, the improvement rate may appear to be a small value in the interrupted loads. It is worth mentioning that the values obtained in Table 7 are, firstly, the amounts of interrupted loads for the downstream loads of only three monitored lines of the entire network lines, and secondly, for the one-time run of the DSSE process.

V. CONCLUSION

Based on the network operation condition, we presented a new approach for optimal PMU placement in this study. In this regard, since insufficient accuracy of DSSE results can significantly affect the CCAAP and estimation of line-loadings, an APS analysis and a line-loading approach were investigated for specifying the optimal number and location of PMUs to improve the DSSE accuracy based on predefined indices. To evaluate the effectiveness of the developed algorithm, the proposed optimization problem was applied to the 77-bus UK ADNs considering different cases and operating scenarios. The results demonstrated that employing the APS analysis and line-loading approach leads to PMU configurations that improve DSSE accuracy and minimize CCAAP and load interruptions due to the low accuracy of estimated line-loadings. In this regard, the proposed framework not only increased the DSSE accuracy but also decreased CCAAP by 7% compared to the typical network without PMUs. Furthermore, the proposed model significantly mitigated the total curtailed loads. Also, as observed, incorrect input data injection in PMUs significantly increases operating costs.

Although using more PMUs in the network will improve the accuracy of the state estimator results, network monitoring, and reliability, it would also increase the network investment costs. Therefore, ADMS could choose the optimal scheme based on the proposed analysis procedure. Notably, the developed framework is based on the application of state estimation in the operation of distribution networks. In this regard, this concept could be updated according to the condition and operation of any network.

Future works can focus on developing a PMU placement framework to decrease the CCAAP and interrupted loads considering unbalanced distribution networks. Another future research direction to extend the proposed model is about considering the limitations of PMU components to enhance the designing costs of the state estimator.

REFERENCES

[1] A. Primadianto and C.-N. Lu, "A review on distribution system state estimation," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3875–3883, Sep. 2017.

[2] K. Dehghanpour, Z. Wang, J. Wang, Y. Yuan, and F. Bu, "A survey on state estimation techniques and challenges in smart distribution systems," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2312–2322, Mar. 2018.

[3] M. Gholami, A. Abbaspour, M. Moeini-Aghtaie, M. Fotuhi-Firuzabad, and M. Lehtonen, "Detecting the location of short-circuit faults in active distribution network using PMU-based state estimation," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1396–1406, Mar. 2020.

[4] M. Gholami, F. Dehkordi, S. H. Mazaheri, and A. Tehrani-Fard, "Active distribution management system," in *Active Electrical Distribution Network: A Smart Approach* 1st ed., B. Khan, J. M. Guerrero, S. Padmanaban, H. H. Alhelou, O. P. Mahela, and S. Tanwar, Eds., Hoboken, NJ, USA: Wiley, 2021.

[5] F. Pilo, G. Pisano, and G. G. Soma, "Optimal coordination of energy resources with a two-stage online active management," *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4526–4537, Oct. 2011.

[6] J. Liu, J. Tang, F. Ponci, A. Monti, C. Muscas, and P. A. Pegoraro, "Trade-offs in PMU deployment for state estimation in active distribution grids," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 915–924, Jun. 2012.

[7] R. Singh, B. C. Pal, and R. B. Vinter, "Measurement placement in distribution system state estimation," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 668–675, May 2009.

[8] G. Celli, P. A. Pegoraro, F. Pilo, G. Pisano, and S. Sulis, "DMS cyber-physical simulation for assessing the impact of state estimation and communication media in smart grid operation," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2436–2446, Sep. 2014.

[9] M. Kabiri and N. Amjady, "A new hybrid state estimation considering different accuracy levels of PMU and SCADA measurements," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 9, pp. 3078–3089, Sep. 2019.

[10] Z. Jin, P. Wall, Y. Chen, J. Yu, S. Chakrabarti, and V. Terzija, "Analysis of hybrid state estimators: Accuracy and convergence of estimator formulations," *IEEE Trans. Power Syst.*, vol. 34, no. 4, pp. 2565–2576, Jul. 2019.

[11] M. Picallo, A. Anta, and B. de Schutter, "Comparison of bounds for optimal PMU placement for state estimation in distribution grids," *IEEE Trans. Power Syst.*, vol. 34, no. 6, pp. 4837–4846, Nov. 2019.

[12] B. Cao, Y. Yan, Y. Wang, X. Liu, J. C.-W. Lin, A. K. Sangaiah, and Z. Lv, "A multiobjective intelligent decision-making method for multistage placement of PMU in power grid enterprises," *IEEE Trans. Ind. Informat.*, early access, Oct. 19, 2022, doi: 10.1109/TII.2022.3215787.

[13] S. Kundu, M. Alam, and S. S. Thakur, "State estimation with optimal PMU placement considering various contingencies," in *Proc. IEEE 8th Power India Int. Conf. (PIICON)*, Dec. 2018, pp. 1–6.

[14] Y. Shi, H. D. Tuan, T. Q. Duong, H. V. Poor, and A. V. Savkin, "PMU placement optimization for efficient state estimation in smart grid," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 1, pp. 71–83, Jan. 2020.

[15] S. Prasad and D. M. V. Kumar, "Trade-offs in PMU and IED deployment for active distribution state estimation using multi-objective evolutionary algorithm," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 6, pp. 1298–1307, Jun. 2018.

[16] R. Andreoni, D. Macii, M. Brunelli, and D. Petri, "Tri-objective optimal PMU placement including accurate state estimation: The case of distribution systems," *IEEE Access*, vol. 9, pp. 62102–62117, 2021.

[17] J. De La Ree, V. Centeno, J. S. Thorp, and A. G. Phadke, "Synchronized phasor measurement applications in power systems," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 20–27, Jun. 2010.

[18] S. Kumar, B. Tyagi, V. Kumar, and S. Chohan, "Optimization of phasor measurement units placement under contingency using reliability of network components," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 12, pp. 9893–9906, Dec. 2020.

[19] N. M. Manousakis and G. N. Korres, "Optimal allocation of phasor measurement units considering various contingencies and measurement redundancy," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 6, pp. 3403–3411, Jun. 2020.

[20] M. Gholami, A. Abbaspour, S. Fattaheian-Dehkordi, M. Lehtonen, M. Moeini-Aghtaie, and M. Fotuhi, "Optimal allocation of PMUs in active distribution network considering reliability of state estimation results," *IET Gener., Transmiss. Distribution*, vol. 14, no. 18, pp. 3641–3651, Sep. 2020.

[21] M. Haghifam, M.-R. Haghifam, and B. S. Chabok, "State estimation in electric distribution networks in presence of distributed generation using the PMUs," in *Proc. Workshop, Integr. Renewables Distrib. Grid*, 2012, pp. 1–4.

[22] M. G. Damavandi, V. Krishnamurthy, and J. R. Marti, "Robust meter placement for state estimation in active distribution systems," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1972–1982, Jul. 2015.

[23] Y. Yao, X. Liu, and Z. Li, "Robust measurement placement for distribution system state estimation," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 364–374, Jan. 2019.

[24] S. Prasad and D. M. Vinod Kumar, "Optimal allocation of measurement devices for distribution state estimation using multiobjective hybrid PSO–krill herd algorithm," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 8, pp. 2022–2035, Aug. 2017.

[25] Z. Wu, X. Du, W. Gu, Y. Liu, P. Ling, J. Liu, and C. Fang, "Optimal PMU placement considering load loss and relaying in distribution networks," *IEEE Access*, vol. 6, pp. 33645–33653, 2018.

[26] K. Chauhan and R. Sodhi, "Placement of distribution-level phasor measurements for topological observability and monitoring of active distribution networks," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 6, pp. 3451–3460, Jun. 2020.

[27] S. Teimourzadeh, F. Aminifar, and M. Shahidehpour, "Contingency-constrained optimal placement of micro-PMUs and smart meters in microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1889–1897, Mar. 2019.

[28] S. Fattaheian-Dehkordi, A. Rajaei, A. Abbaspour, M. Fotuhi-Firuzabad, and M. Lehtonen, "Distributed transactive framework for congestion management of multiple-microgrid distribution systems," *IEEE Trans. Smart Grid*, vol. 13, no. 2, pp. 1335–1346, Mar. 2022.

[29] M. Tofighi-Milani, S. Fattaheian-Dehkordi, M. Fotuhi-Firuzabad, and M. Lehtonen, "Decentralized active power management in multi-agent distribution systems considering congestion issue," *IEEE Trans. Smart Grid*, vol. 13, no. 5, pp. 3582–3593, Sep. 2022.

[30] A. Abur and A. G. Exposito, *Power System State Estimation: Theory and Implementation*. Boca Raton, FL, USA: CRC Press, 2004.

[31] A. J. Conejo and L. Baringo, *Power System Operations*. Cham, Switzerland: Springer, 2018.

[32] N. M. Manousakis, G. N. Korres, and P. S. Georgilakis, "Taxonomy of PMU placement methodologies," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 1070–1077, May 2012.

[33] X.-S. Yang, *Engineering Optimization: An Introduction With Metaheuristic Applications*. Hoboken, NJ, USA: Wiley, 2010.

[34] R. Singh, B. C. Pal, and R. A. Jabr, "Choice of estimator for distribution system state estimation," *IET Gener., Transmiss. Distrib.*, vol. 3, no. 7, pp. 666–678, Jul. 2009.

[35] K. E. Martin, "Synchrophasor measurements under the IEEE standard C37.118.1–2011 with amendment C37.118.1a," *IEEE Trans. Power Del.*, vol. 30, no. 3, pp. 1514–1522, Jun. 2015.

[36] T. Kanungo, D. M. Mount, N. S. Netanyahu, C. D. Piatko, R. Silverman, and A. Y. Wu, "An efficient K-means clustering algorithm: Analysis and implementation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, pp. 881–892, Jul. 2002.
[37] *DTI Centre for Distributed Generation and Sustainable Electrical Energy, United Kingdom Generic Distribution System, Generic HV Underground Network*. Accessed: Mar. 28, 2015. [Online]. Available: http://monaco.eee.strath.ac.uk/ukgds/United

AMIN SALEHI received the B.Sc. and M.Sc. degrees in electrical engineering from the Shiraz University of Technology, in 2018 and 2021, respectively. His research interests include power system planning and operation, distribution system state estimation, integration of distributed and renewable energy resources in electric power and energy systems, and the application of control theory in power system control.

MAHMUD FOTUHI-FIRUZABAD (Fellow, IEEE) received the B.Sc. degree in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 1986, the M.Sc. degree in electrical engineering from the University of Tehran, in 1989, and the M.Sc. and Ph.D. degrees in electrical engineering from the University of Saskatchewan, Canada, in 1993 and 1997, respectively. He is currently a Professor with the Electrical Engineering Department, Sharif University of Technology. He is also a Visiting Professor at Aalto University, Finland. His research interests include power system reliability, distributed renewable generation, demand response, and smart grids. He is a member of the Center of Excellence in Power System Control and Management with the Electrical Engineering Department. He was a recipient of several national and international awards, including the 16th Khwarizmi International Award, the World Intellectual Property Organization (WIPO) Award for the Outstanding Inventor, in 2003, the PMAPS International Society Merit Award, for Contributions in Probabilistic Methods Applied to Power Systems, in 2016, and the 2014 Allameh Tabatabaei Award. He was the Editor-in-Chief of the IEEE Power Engineering Letters, from 2017 to 2022.

SAJJAD FATTAHEIAN-DEHKORDI (Graduate Student Member, IEEE) received the M.Sc. degree in electrical engineering and power systems from the Sharif University of Technology, Tehran, Iran, in 2014. He is currently pursuing the Ph.D. degree with the Sharif University of Technology and Aalto University, Espoo, Finland. His research interests include power systems planning, operations, and economics, with focus on issues relating with the integration of renewable energy resources into the systems.

MOHAMMAD GHOLAMI received the M.Sc. degree in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 2015, where he is currently pursuing the Ph.D. degree in electrical engineering. His research interests include smart grid, active distribution networks, distribution system state estimation, distribution system automation, power system reliability, and transformer protection.

MATTI LEHTONEN received the master's and Licentiate degrees in electrical engineering from the Helsinki University of Technology, in 1984 and 1989, respectively, and the Doctor of Technology degree from the Tampere University of Technology, in 1992. He has been a Professor with the Helsinki University of Technology (now Aalto University), where he is currently the Head of Power Systems and High Voltage Engineering. His main research interests include power system planning and asset management and power system protection, including earth fault problems, harmonic related issues, and applications of information technology in distribution systems.