Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 9153272, 14 pages
https://doi.org/10.1155/2022/9153272

Research Article

Optimal Placement of Measuring Devices for Distribution System State Estimation Using Dragonfly Algorithm

Arshia Aflaki,[1] **Mohsen Gitizadeh**,[1] **Ali Akbar Ghasemi**,[1] **and Kenneth E. Okedu**[2,3]

[1] *Department of Electronics and Electrical Engineering, Shiraz University of Technology, Shiraz, Iran*
[2] *Electrical and Communication Engineering, National University of Science and Technology, Muscat, Oman*
[3] *Electrical and Computer Engineering, Nisantasi University, Istanbul, Turkey*

Correspondence should be addressed to Mohsen Gitizadeh; gitizadeh@sutech.ac.ir

Received 16 December 2021; Revised 25 February 2022; Accepted 10 March 2022; Published 21 April 2022

Academic Editor: A. M. Bastos Pereira

This paper presents the challenges of optimal measurement devices placement (MDP) in the distribution system by considering the improvement of accuracy and speed for state estimation (SE) in the presence of distributed generations (DGs). We assumed that active and reactive power measurements (both injection and flow) with voltage magnitude measurements were used to estimate the power system's state. The paper employed phase measurement unit (PMU) and smart meters, which are the two commonly used measuring devices. For numerical evaluation of the system, the power system states are based on the angle and magnitude of voltages at every bus. The issues normally experienced in the optimal measurement devices placement in distribution networks were investigated using the binary dragonfly algorithm (BDA), in this study. As a way forward to proffer solutions to these issues, a fair compromise between accuracy, speed, and the number of measurements (NoMs) was reached, and the proposed solution was tested in two different scenarios applied in the IEEE 33-bus distribution test system. The results illustrate that by increasing the accuracy, NoMs and the cost are going to rise as well. On the other hand, by escalating the speed, NoMs decrease and the accuracy falls dramatically.

1. Introduction

Recently, distribution networks are becoming more intelligent in several ways, in order to improve their performance and effective management. State estimation is one of the most favorite tools in the power system to enhance the monitoring process. Therefore, accurate and robust state estimations are always needed in every sector of a power system. By finding the states of a power network, other tasks, such as optimal power flow, will be benefited from a reliable and accurate process. PMUs and micro-PMUs are measurement devices enhancing the state estimation process by sending the measurements from the power system for estimating the states of the smart grids [1]. For performing a state estimation, the voltage of every bus in the system is driven, and the active and reactive power flowing in the system are able to be calculated by power flow [2]. Although the distribution system is on its way to be modernized, the mentioned network under radial operations still has a large number of unbalanced loads in each phase with a high r/x ratio. In the distribution system, lack of measurements has made the system to become hardly observable, and the distribution system state estimation (SE) seems to be one of the problem-solving paths to the mentioned issue. While minimizing the number of measurements (NoMs) is a vitally important task to conduct, the accuracy and speed of the SE are both decisive features. Measurement devices placement (MDP) strategy behaves as a binary problem that calculates the being or nonexistence of the measurement unit as binary variables. Therefore, an optimization algorithm capable of handling binary problems should be proposed that can perform multiple-goal optimization.

Dragonfly algorithm (DA) proposed by Mirjalili [3] is an ongoing swarm intelligence method that mirrors the five crude standards of the amassing behavior of dragonflies. The dragonflies depend on detachment to evade crashes between people in the multitude, an arrangement to principle train the speed of all people in the multitude, attachment to relate dragonflies to an area, fascination in moving dragonflies towards the food source, interruption to move dragonflies a long way from the adversaries. These five standards require five boundaries to be controlled that are separation (S), alignment (A), cohesion (C), fascination towards the food source (F), and interruption from the enemy (E). The DA is applied effectively to tackle a few optimization issues, for example, economical dispatch [4], hybrid energy distributed power system [5], power flow management [6], picture division [7, 8], stress circulation [9], synthesis of concentric circular antenna arrays [10], basic optimization of edge structures [11], structural design optimization of vehicle components [12], filter design issue [13], newborn child cry classification [14], intent of vehicles [15], mobile sales rep problem [16], remote hub limitation in PC networks [17], 0–1 rucksack issues [18], and artificial intelligence [19]. A binary form of DA (called binary dragonfly algorithm (BDA)) was proposed in [3]. In BDA, a transfer function is utilized to plan the consistent inquiry space into binary. BDA was at first applied to the feature selection (FS) issue in [20], and the technique delivers top-notch results. As of late, a novel FS approach that utilizes an improved BDA was proposed in [19].

In [21], Singh proposed an algorithm for measurement devices selection problem using an ordinary optimization method. A multiobjective algorithm for both number and placement of the MDP leading to better accuracy is proposed in [22]. Das [23] proposed a simple rule-based algorithm for placing the devices in a radial distribution system by taking network reconfiguration into account. A comprehensive survey on MDP in power system state estimation was demonstrated in [24] by using a mixed-integer linear.

Optimization algorithm. The optimal location of PMU was presented in [25] for detecting cyber-attacks on the devices. A multiobjective method has been proposed in [26] to find the optimal placement of PMUs and intelligent electronic devices (IEDs). In reference [27], zonal SE was considered by optimal PMU placement. In reference [28, 30], optimal PMU placement based on GA and a binary-coded GA is proposed by considering observability and reliability, respectively. Due to their promising performance, swarm intelligence techniques are still attracting researchers and have been applied in several fields of power system analysis [31–34]. Mahari [35] applied a binary imperialistic competition algorithm in the optimal placement of PMU to maintain system observability. The optimal location of PMU with a limited number of channels was presented by the authors of [36]. The weight least square (WLS) technique for SE was first proposed by Ali Abur in [37], and the authors of [38], and a linear-based optimization technique for optimal MDP was proposed. In reference [29], the author used GA for PMU placement in the distribution system for observability and load loss using WLS. In reference [39], the authors used an integer-arithmetic algorithm for observability analysis of systems with SCADA and PMU measurements. Recently, the optimal location of PMUs and m-PMUs for the observability of system in the fault locations is gaining interest [40, 41]. Besides that, many papers only target full observability by using measurements such as the phasor measurement unit (PMU). A few of them performed the derivative-free optimization algorithm such as the genetic algorithm (GA) [42] and a heuristic optimization like particle swarm algorithm (PSO) [40, 43, 44] to optimize the cost function of their proposed problems which is the NoMs. The author of [42] employs a derivative-free optimizer, that is, a generalized pattern search. This algorithm is counted with GA in the MATLAB optimization library regarding the derivative-free optimizers. The authors of [30, 45] present the use of genetic algorithms (GAs) to place a minimum number of PMUs around the power network considering topological observability. The latter used a hybrid method by combining GA and BBA. m-PMUs performance in distribution systems is fully studied in [1]. In [46, 47], the authors used the interior-point method, which is a subfield of linear programming, to solve the optimal PMU placement problem in the power systems. A comparison between different MDP objectives in some previous studies in the literature is given in Table 1.

In this paper, a novel method has been proposed to solve the MDP problem by taking the accuracy, speed, and number of measurement units into consideration. Real-time measurements derived from IEEE standard systems play an important role in the convergence of the SE. The accuracy and speed of the state estimation depend on standard measurements, and for a more realistic scenario, the deviation of measurements was considered.

The rest of the paper is organized as follows: section 2 defines the WLS state estimation and its formulation. In Section 3, the mentioned BDA is introduced as an optimization method to aid in finding the best placement for measuring devices. Section 4 describes a new formulation of minimizing the number of measurements while the accuracy and speed are within the acceptable limits and formally introduce the flowchart of the mentioned method and optimization algorithm. Section 5 illustrates the simulation process and case studies in which two different scenarios are proposed and then applied in IEEE 33-bus radial distribution network with presenting the acceptable accuracy range for SE. This paper is concluded in Section 6.

2. Wight Least-Square State Estimation

State estimate is extensively used as a method to assess the current real-time time grid parameters. State estimation algorithms may suffer divergence below stressed system conditions. The minimum singular worth of gain matrix is projected to measure the space between the in-operation purpose and state estimation divergence.

A state estimator is capable of filtering the knowledge to supply an additional correct image of the state of the system. The state estimation may be outlined as a method that determines the in-operation state of the system to permit the system operator to form selections geared toward maintaining the protection of the system. The WLS method is often used for estimating the state of the system. The normal objective of the state estimation is to cut back on activity

Table 1: A comparison between different MDP objectives in the literature.

Refs	[2]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	This paper
Optimal NoMs		✓	✓	✓		✓		✓	✓	✓	✓
Quality					✓		✓	✓	✓		✓
Optimal accuracy of states	✓	✓	✓	✓	✓	✓	✓		✓		✓
Cost		✓	✓	✓	✓	✓		✓	✓	✓	✓
Presence of distributed generations (DGs)										✓	✓

errors by utilizing the redundancy obtainable within most activity systems. The root mean square metric, in particular, is used to reduce estimate variance and improve overall efficiency.

The SCADA information, measurement information, network model, and also the pseudo-measurements are types of the input for the power system SE method. The applications, such as contingency analysis, security analysis, optimal power flow, are enhanced by using the states estimated by SE.

All the SE equations in this section are derived from [37]. The process of WLS ES is illustrated in Figure 1.

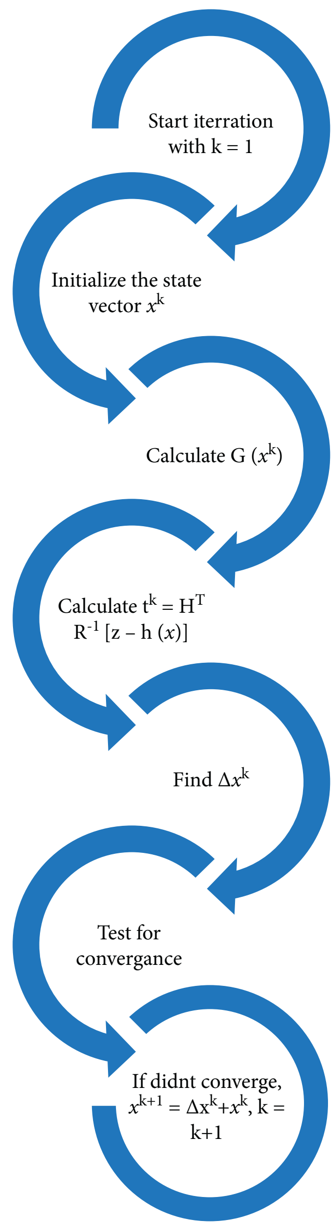

Figure 1: The WLS state estimation process.

3. Dragonfly Algorithm

The dragonfly algorithm (DA) fundamentally in-towers the conduct of chasing (called static multitude (feeding)) and relocation instruments of glorified dragonflies administrators [3]. In nature, the dragonflies fly in little gatherings looking for food sources which are called chasing.

Bigger gatherings of dragonflies fly with one another one way, so the multitude relocates in a cycle called the movement component. The two instruments of chasing and taking care of the amassing conduct of dragonflies when searching are delineated in Figure 2.

The dragonflies amassing conduct is described by five administrators:

(1) Separation is the component that guarantees to get the inquiry specialists far from one another in the area. The numerical demonstration of the detachment conduct has appeared.

$$S_i = -\sum_{j=1}^{N} X - \mathrm{Xi}. \tag{1}$$

(2) Alignment shows how the speed of a particular inquiry specialist is coordinated with the speed of other pursuit operators in the area. The numerical demonstration of the arrangement conduct has appeared.

$$A_i = \frac{\sum_{j=1}^{N} vj}{N}. \tag{2}$$

Here, V_j represents the speed of the jth neighbour.

(3) Cohesion shows how people fly from the neighbourhood region to the focal point of mass. It alludes to the propensity of people to fly towards the neighbouring focus of mass. The numerical demonstration of the Cohesion conduct is introduced.

$$C_i = \frac{\sum_{j=1}^{N} xj}{N} - X. \tag{3}$$

(4) Attraction speaks to how the food source draws in the people that fly towards it. The numerical demonstration of this conduct has appeared.

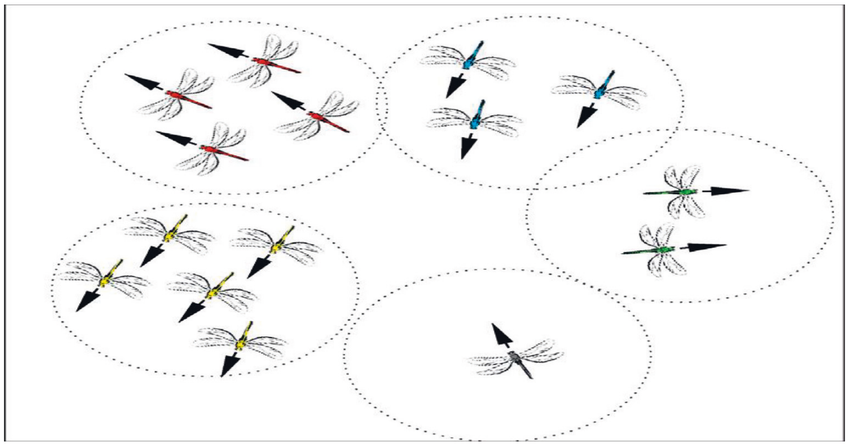

Figure 2: Chasing and taking care of amassing conduct of dragonflies when searching [3].

$$F_i = F_{\mathrm{loc}} - X, \quad (4)$$

where F_{loc} represents the position of the food source.

(5) Distraction alludes to the inclination of people to take off from a foe. The interruption between the ith arrangement and the adversary is numerically demonstrated.

$$E_i = E_{\mathrm{loc}} + X, \quad (5)$$

where E_{loc} symbolizes the enemy's position.

During the hunting cycle in the dragonfly algorithm, the wellness of the food source and the area are refreshed utilizing the competitor with the best wellness. Besides, the most noticeably terrible applicant updates the wellness and the area of the adversary. This resulted in the uniqueness of excellent hunting zones and moving indefinitely from poor hunting locations. The nonexclusive system of the particle swarm optimization algorithm is utilized by the dragonfly algorithm as it utilizes two vectors to refresh the situation of a dragonfly: the progression vector (ΔX) that is like the particle swarm optimization speed vector and the position vector. The progression vector (displayed in (6)) serves to change the dragonflies' development.

$$\Delta X_{t+1} = \left(sS_i + aA_i + cC_i + fF_i + etEi\right) + w\Delta X_t, \quad (6)$$

where *s, a, c, f,* and *e* are loads of the partition Si, arrangement A_i, attachment C_i, development speed into the food source F_i, and the foe aggravation level E_i of the ith individual separately. Figure (7) shows how these boundaries are adaptively tuned during the advancement cycle to keep up a decent harmony between investigation and exploitation. W is the latency weight, which is derived based on (8). More insights regarding the estimations of these boundaries and their impact on the dragonfly algorithm conduct can be found.

$$\begin{aligned} s &= 2 \times r \times \mathrm{pct} \\ a &= 2 \times r \times \mathrm{pct} \\ c &= 2 \times r \times \mathrm{pct} \\ f &= 2 \times r \\ et &= \mathrm{pct}, \end{aligned} \quad (7)$$

$$W = 0.9 - \mathrm{Iter} * \frac{(0.9 - 0.4)}{\mathrm{Max}_I ter}, \quad (8)$$

where *pct* is calculated as shown in (8).

$$\mathrm{pct} = \begin{cases} 0.1 - \dfrac{0.2 \times \mathrm{iter}}{\mathrm{max\_iter}}, & \text{if } (2 \times \mathrm{iter}) \leq \mathrm{max\_iter} \\ 0, & \mathrm{O.W} \end{cases}, \quad (9)$$

where r is an arbitrary number in the time period of [0,1].

The situation of an individual is refreshed as shown in (9).

$$X_{t+1} = X_t + \Delta X_{t+1}. \quad (10)$$

Here, t is the present step.

Figure 3 shows the pseudo-code of the dragonfly algorithm. At first, the algorithm makes an arbitrarily created population and instates it with step vectors haphazardly. Iteratively, the algorithm executes the accompanying strides until an end basis is met. Initially, a CO is utilized to assess every person in the populace. Second, the algorithm refreshes the primary coefficients (i.e., *s, w, a, c, f,* and *e*). Later, the administrators, separation (S), alignment (A), cohesion (C), food source (F), and enemy €, are adjusted utilizing equations (1) to (5). At long last, equations (6) and (10) are utilized to refresh the progression vectors and the dragonfly position. Subsequently, the best arrangement got so far is returned.

Initialize ΔX_i (i= 1, 2, . . . , n)
while (end condition is not satisfied) do Evaluate each dragonfly
Update (F) and (E)
Update the main coefficients (*i.*, w, *s, a, c, f, and et*)
Calculate *S, A, C, F*, and *E* (using Eqs. (1) to (5))
Update step vectors (ΔX_{t+1}) using Eq. (6)
Update X_{t+1} using Eq. (10)
Return the best solution

Figure 3: Dragonfly algorithm process.

3.1. The Binary Dragonfly Algorithm (BDA). A binary optimization issue is taken into account by a feature selection optimization. The solution space is shaped as a hypercube, where an individual area is distinguished inside the pursuit space utilizing the position vector $x = \{x_1, x_2, \ldots, x_d\}$. DA is initially proposed to deal with continuous optimization issues. The individual position is updated by adding the current position vector to the progression vector. This technique must be changed to deal with parallel optimization issues. Angular transfer function is utilized to change over the nonstop qualities into binary which is drawn as shown in Figure 4.

By utilizing the transfer functions, the positions are changed over from continuous to binary by using two stages. To start with, the value of the dth measurement of the ith step vector (speed) inside the current iteration (t) is utilized as a contribution to equation (11) to get the likelihood to set the component to binary integers (0 or 1). Second, the component is set as an incentive to 0 or 1 upheld equation (12).

$$T\left(V_D^i(t)\right) = \left|\frac{\left(V_D^i(t)\right)}{\sqrt{\left\{1 + \left(V_D^i(t)\right)\right\}^2}}\right|, \tag{11}$$

$$X(t+1) = \begin{cases} -X_t, & r < T\left(v_k^i(t)\right) \\ X_t, & r \geq T\left(v_k^i(t)\right) \end{cases}, \tag{12}$$

where r could be a function that generates a random number between 0 and 1. The value of r plays a crucial role to decide whether the value of X_t is flipped. When the value of T $(v_k^i(t))$ is little, the possibility of flipping the new value X $(t+1)$ is going to be also small.

4. Problem Formulation

The optimal MDP for SE in the distribution system solution is going to be conducted by a method in which a binary upper triangular matrix called measurement matrix (M) is proposed. By encoding the M, the placement of the measurements in the test system will be illustrated. Therefore, a binary optimization method called BDA is employed to find the optimal form of M. The solution space is divided into two sections, buses, and lines. In this article, line measurements are attached near to the superior bus, and by taking that assumption into account, diagonal elements of M are representing the bus measurement units, and nondiagonal elements introduce the line measurement units. As an example, $M_{22} = 1$ means that there is a bus measurement device (smart meter) in the second bus measuring the voltage magnitude and active/reactive power injection, and $M_{23} = 1$ means there is a line measurement in the line which connects the second bus to the third one measuring active and reactive power flows in the line. BDA generates n variable binary digits in which n is the sum of the number of buses and lines. After that, the first nb (number of buses) digits are considered to be bus measurement device placements, and the other $n_b + 1$ to $n_b + n_l$ (number of lines) digits illustrate line measurement device placement. By taking this process into account, when BDA generates a binary number, this process is able to locate the measurement devices in the power grid. Figure 5 illustrates the flowchart of the proposed method.

The problem formulation is as follows:

$$\min \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} \text{cost} \times M_{ij} \text{when } M(i, j) \geq b, \tag{13}$$

where b is a unit vector [48].

Table 2 shows the two types of measurement devices considered for SE.

The sampling rate for both is 120 samples per second in a 60 Hz distribution network [1]. Smart meters can only be installed in buses, but PMUs are able to be installed in lines too.

5. Model System Case Study

The IEEE 33-bus distribution test system is employed to examine the proposed method in two different scenarios. In one of which, the DGs are installed in some buses. It is worth noting that the one with the DGs scenario is slightly similar to that of [29]. The mentioned system is working with a three-phase symmetric structure and balanced operation and accuracy.

Two scenarios are introduced in Table 3, and the comparison between entering DGs and system performance without DGs is argued in this section while the simulation process is carried out by MATLAB 2018a in MACOS 10.15.6 with 4 GB of RAM.

As mentioned above, in scenario 1, there are no DGs installed in the grid, and the accuracy range of SE is from 92 to 94 percent, meaning that the tolerance of 0.08 to 0.06 from the standard data is acceptable. A speed limit for each part is assumed to make the simulation results more realistic. For being more comparable to prior works, DGs are included in the second scenario. In the end, by using the proposed method, the optimal MDP for the test system under the impact of both scenarios is established. It is worth noting that the speed limit (0.04 s) is less than half of the convergence speed of the load flow method for the distribution system. In global optimization algorithms, a term called efficiency is used to evaluate the performance of the method with respect to computational costs [49]. As we mentioned, a speed limit is set for the state estimation to perform faster than traditional load flows decreasing the computational cost of the state estimation compared to load flow. Another

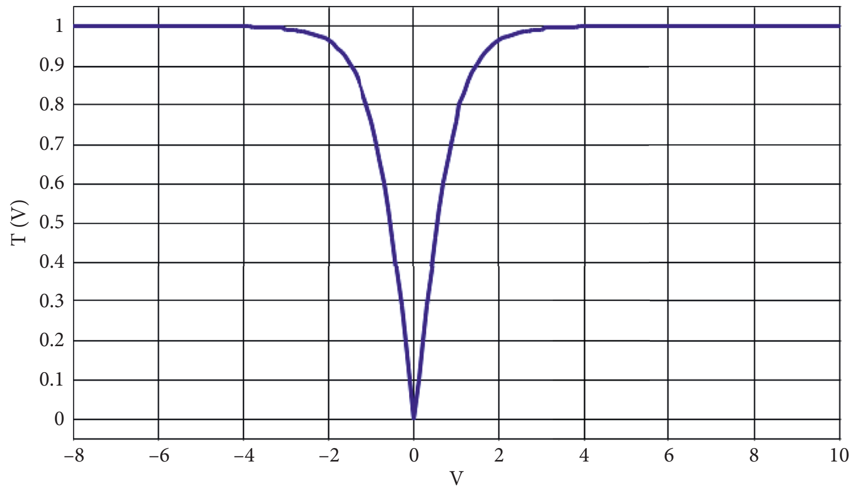

FIGURE 4: V-shaped transfer function [3].

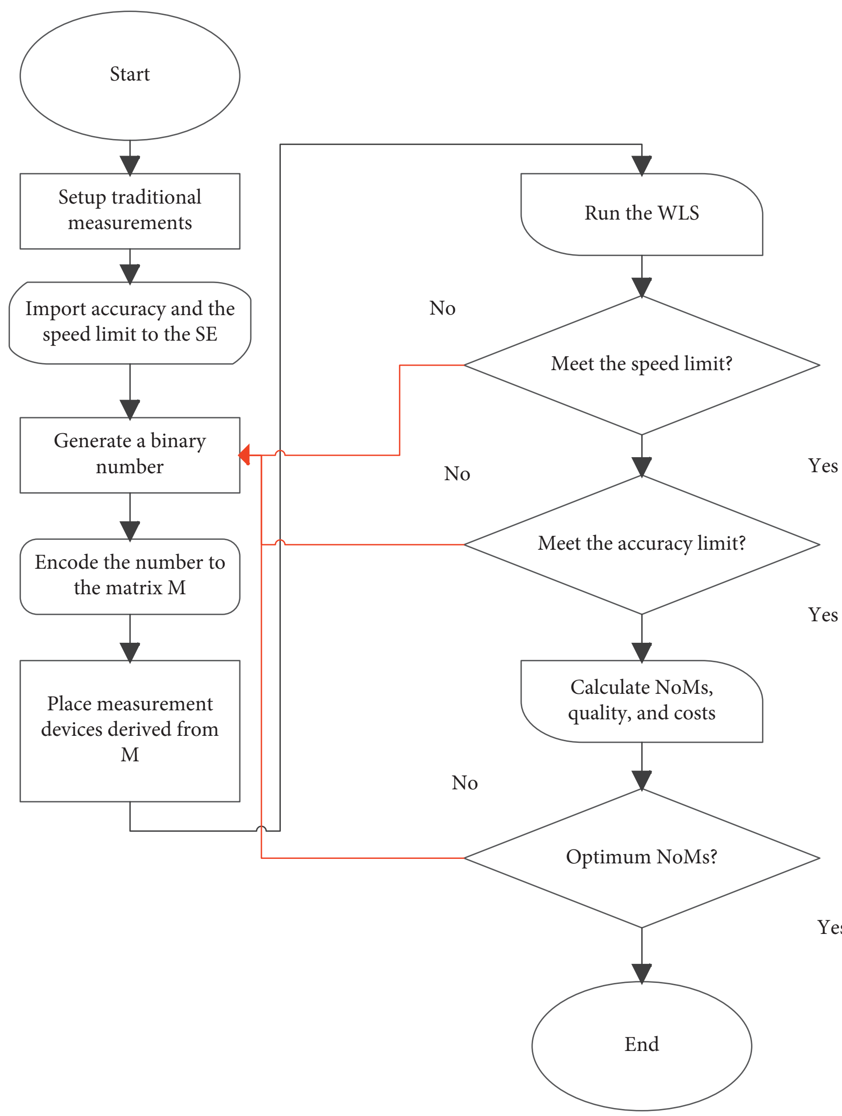

FIGURE 5: Proposed flowchart of the scheme.

Table 2: Measurement devices in which V and I are voltage and current phasor while P and Q are active and reactive power, respectively.

Measurement type	Measuring unit	Measured quantities
Branch	PMU	V, P, Q
Injection	Smart meter	Abs(V), P, Q

Table 3: Different scenarios performed in the IEEE 33-bus system.

	DGs installed	DGs placements (bus)	Accuracy range (%)	Speed limits (for each accuracy)
Scenario 1	No	—	92 to 94	0.04
Scenario 2	Yes	14, 30	92 to 94	0.04

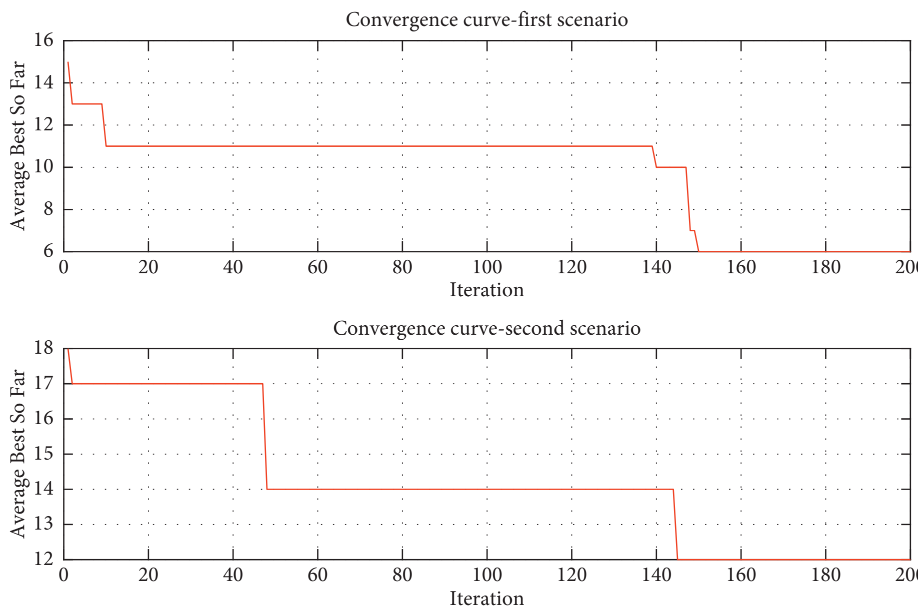

Figure 6: Convergence curve shows a minimized number of measurements with 94% accuracy from both scenarios.

term, which is also mentioned in [49], is effectiveness which is a key index that counts the algorithm's ability to find optimality.

The cost of PMU is assumed to be 2000 $, and the smart meter depends on its inputs, which are from 1000 to 3000 $ [50].

The base parameters of the mentioned system are 11 kV for voltage, 100MVA for power, 1.21 ohm for impedance, and 60 Hz for frequency. The standard deviation for bus measurements is 0.008, and for line, measurements are 0.004.

For BDA, the iteration limit is 200, and the number of particles is 200, while the number of variables is 65, and sums of nb and nl are 33 and 32, respectively.

Although SE works in the static space, the speed of convergence is a crucial element giving an advantage to the SE over the customary load flow. Therefore, with less accuracy, lower speed limitations are assumed in the test scenarios. The number of measurements and accuracy are poles apart, similar to speed and accuracy, meaning that by minimizing the NoMs, SE will be less accurate, so some boundaries are implemented in the method, such as accuracy range and speed limit.

Figure 6 describes the BDA algorithm's efficiency, the convergence speed towards optimality, and success in optimizing the problem. As mentioned before, the comparison between BDA and GA took place in Tables 4 and 5, illustrating the simulation results of the test system under first and second scenarios influences. It is worth mentioning that GA method results are driven from [29].

Figure 7 illustrates 3D figures from scenarios 1 and 2. The figure illustrates how the number of measurements changes with different accuracies when there are no DGs implemented in the test system and the number of repeats needed for SE to find the answer by the given accuracy in the first scenario.

By describing the MDP in IEEE 33-bus distribution system, Figures 8 and 9 are dedicated to simulation results for both scenarios. It is assumed that some primary measurement devices are placed in the test system, and both

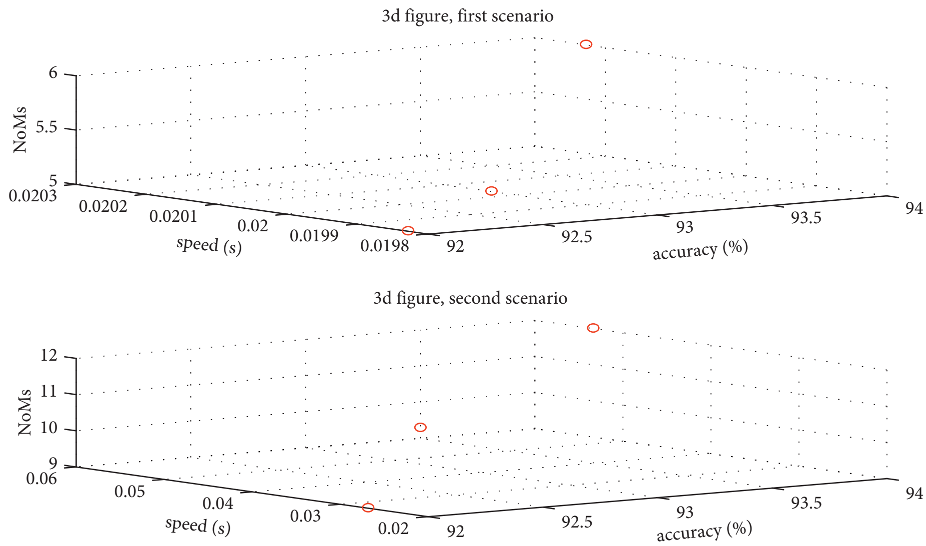

Figure 7: 3D figure from both scenarios representing the changes of accuracy, speed, and NoMs.

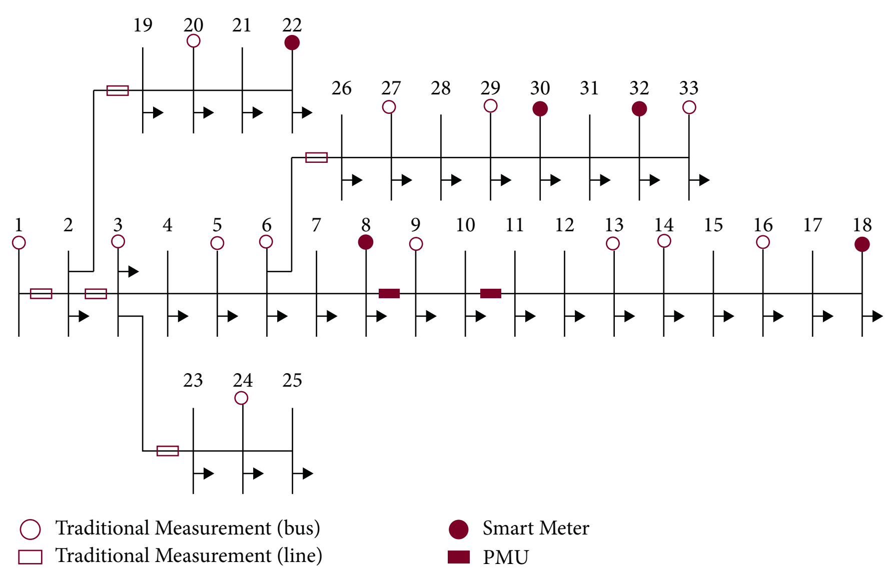

Figure 8: Measurement devices placement in the first scenario with 92% of accuracy.

proposed measurement devices are implemented, as shown in the mentioned figures. Therefore, the comparison between BDA and GA became possible.

DGs active power injections are 200 and 300 kW and are installed in buses 14 and 30, respectively, and the related measurements extracted from forward-backward load flow results in IEEE 33-bus with the installation of two DGs.

The first scenario convergence curve with 94% accuracy is shown in Figure 6, and the effectiveness of the proposed algorithm is shown with measurements per iteration in the mentioned plot. As it is visible, it is proposed in [3] that the BDA algorithm benefits from fast iteration and a sharp convergence curve. Figure 6 also describes the convergence curve of the second scenario with the given accuracy percentage. The term called effectiveness is also fully understandable in Figure 6.

While DGs are not connected to the test network, it is observed that with the same speed limit, when SE becomes more accurate, optimized NoMs increase, and for less accuracy, fewer measurement devices are needed to achieve the accuracy goal. The speed needed for SE to converge each stage of accuracy has been shown in Figure 7. For the first scenario, the mentioned figure describes that with more optimized NoMs, the speed of SE declines.

For less accuracy, however, while optimized NoMs decrease, the speed of SE slightly increases, which is logical because, with a smaller number of measurements, the speed of convergence raises dramatically, but with numerous measurements, the speed of convergence decreases.

When two DGs are implemented in the test system, it is observed that NoMs in high accuracy scenarios have changed significantly while the speed of convergence for SE

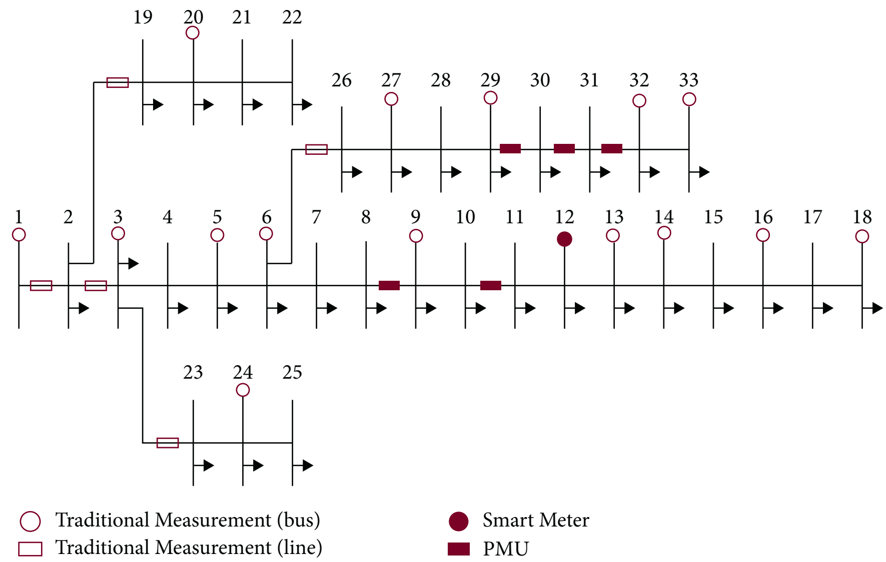

Figure 9: Measurement devices placement in the first scenario with 94% of accuracy.

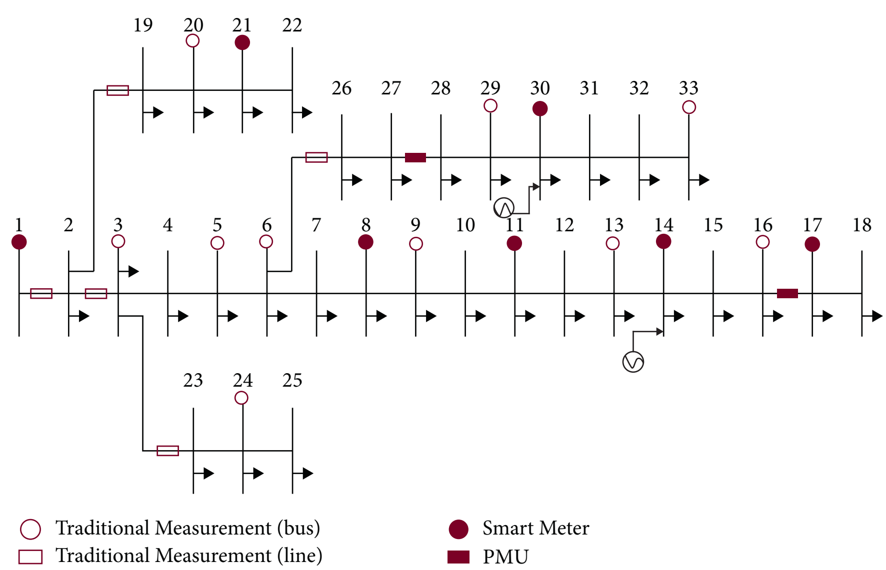

Figure 10: Measurement devices placement in the second scenario with 92% of accuracy.

decreased and exceeded the mentioned limit, as it is observable in Figure 7. As accuracy falls, NoMs drop.

The impact of traditional measurements is significant, and while for the first scenario, there are 20 prior measurements, and in the second scenario, there are 15.

The convergence speed in the second scenario rose sharply at the cost of the lower accuracy, and similar to the prior scenario, when NoMs decrease, SE can converge with more acceleration, and as shown in Figure 9, simulation results for the DG scenario describe the same data. Due to a low variety of voltage (between 0.99 and 0.92 p.u), for high accuracies, NoMs changed significantly.

Figures 8 to 11 show the place of devices in the IEEE 33-bus distribution system.

A significant fact about Figures 10 and 11 is that in buses 14 and 30, in which DGs are installed, a smart meter is implemented, which shows that the system observability depends highly on those buses.

Tables 4 to 7 illustrate a remarkable achievement by BDA compared to GA and mixed-integer linear programming (MILP), which shows that even with the highest accuracy, the optimized solution proposed by BDA is less than the lowest accuracy proposed solution GA. This is because of MDP in two DG-implemented buses presented by the BDA

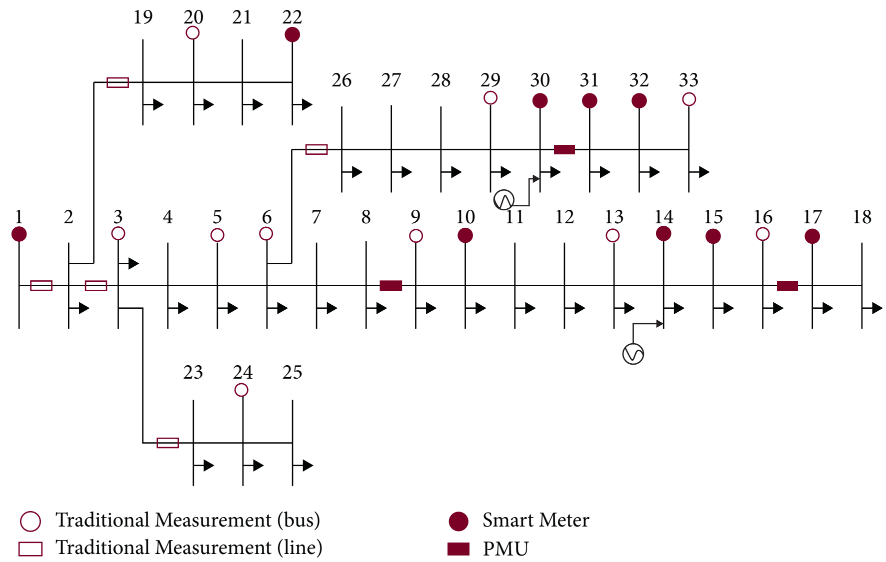

FIGURE 11: Measurement devices placement in the second scenario with 94% of accuracy.

TABLE 4: Second scenario with 92% accuracy.

	NoMs	Cost
[29]	10	28000$
This paper	9	24000$

TABLE 5: Second scenario with 94% accuracy.

	NoMs	Cost
[29]	Not observable	N/A
This paper	12	32000$

TABLE 6: First scenario with 94% accuracy.

	Quality	NoMs	Cost
[2]	6158703	11	22000$
This paper	9432851	6	15000$

TABLE 7: First scenario with 92% accuracy.

	Quality	NoMs	Cost
[2]	6197340	6	12000$
This paper	8463721	5	10000$

algorithm. It is worth noting that linear programming is also used in [46, 47].

It is illustrated from Tables 6 and 7 that when NoMs decrease, quality falls dramatically, and in the second scenario with higher accuracy, BDA finds an optimum placement. However, the WLS SE surpasses the speed limit, so the answer is not valid when the speed of the method is vitally important.

The cost of devices, compared to others, decreased due to more optimum NoMs by using BDA, showing that the study

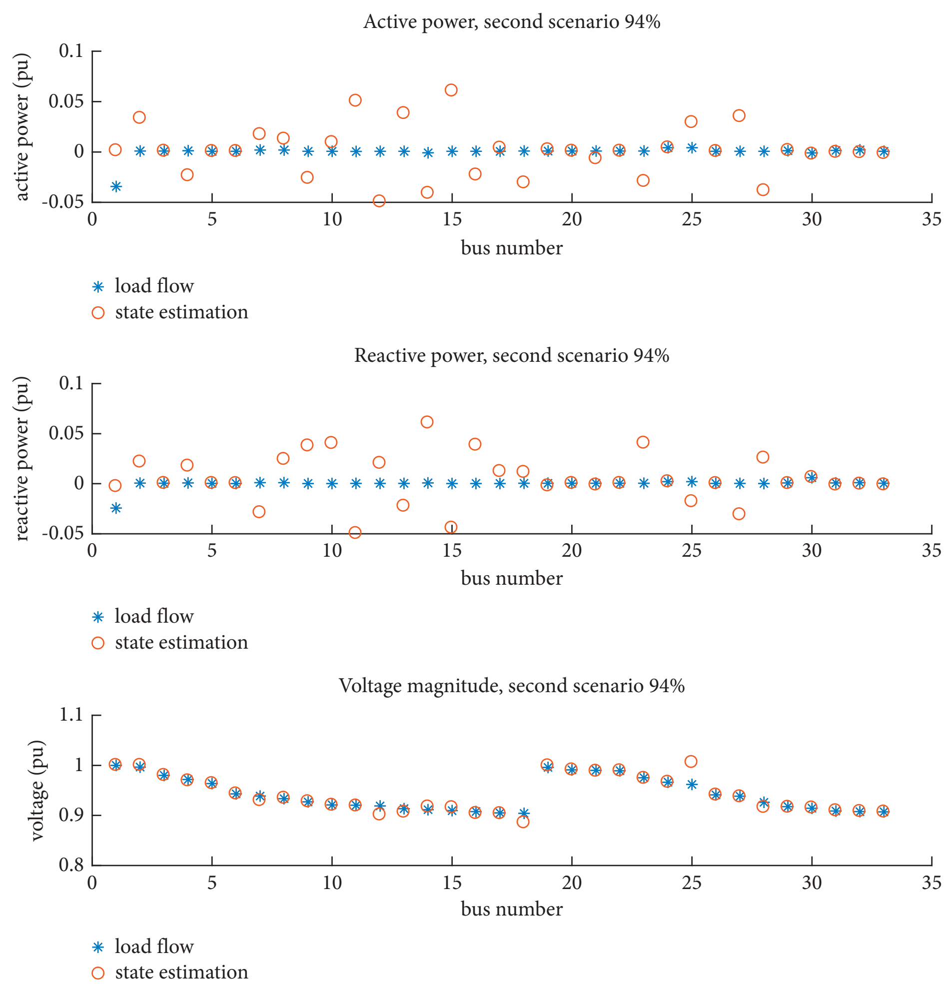

FIGURE 12: Active power, reactive power, and voltage magnitude for each bus at the second scenario with 94% of accuracy.

method in cases of quality, cost, accuracy, and the minimum number of measuring devices has excellent achievements.

Figures 12 and 13 show the test system voltages and active and reactive powers for each bus derived by using load flow and WLS state estimation techniques for 94% and 92% accuracy in the second scenario.

In light of the above results, for both scenarios within the case of different accuracies, BDA optimum answers for lower accuracy were 5 and 9 NoMs, respectively. In references [2, 29], NoMs were 6 and 10 for low accuracy. For higher accuracy as observable, by using the proposed method, NoMs are significantly lower than [2] 6 and 11, respectively. In the second scenario, the author of [29] was not able to find an optimized answer. Although the speed burdens were surpassed, this article was carried out to find the optimal answer.

It is understandable from Figure 12 that the peak deviation from the standard value was about 0.05 for the active power of bus 15 and the reactive power of bus 14. In Figure 13, the deviation reaches its highest point at bus 13 and 10 in active and reactive power, respectively.

In this article, the cost and quality in the first scenario were lower than those in [2]. The cost of measurement devices in the second scenario was lower too for the proposed method, which is one of the salient achievements of this paper.

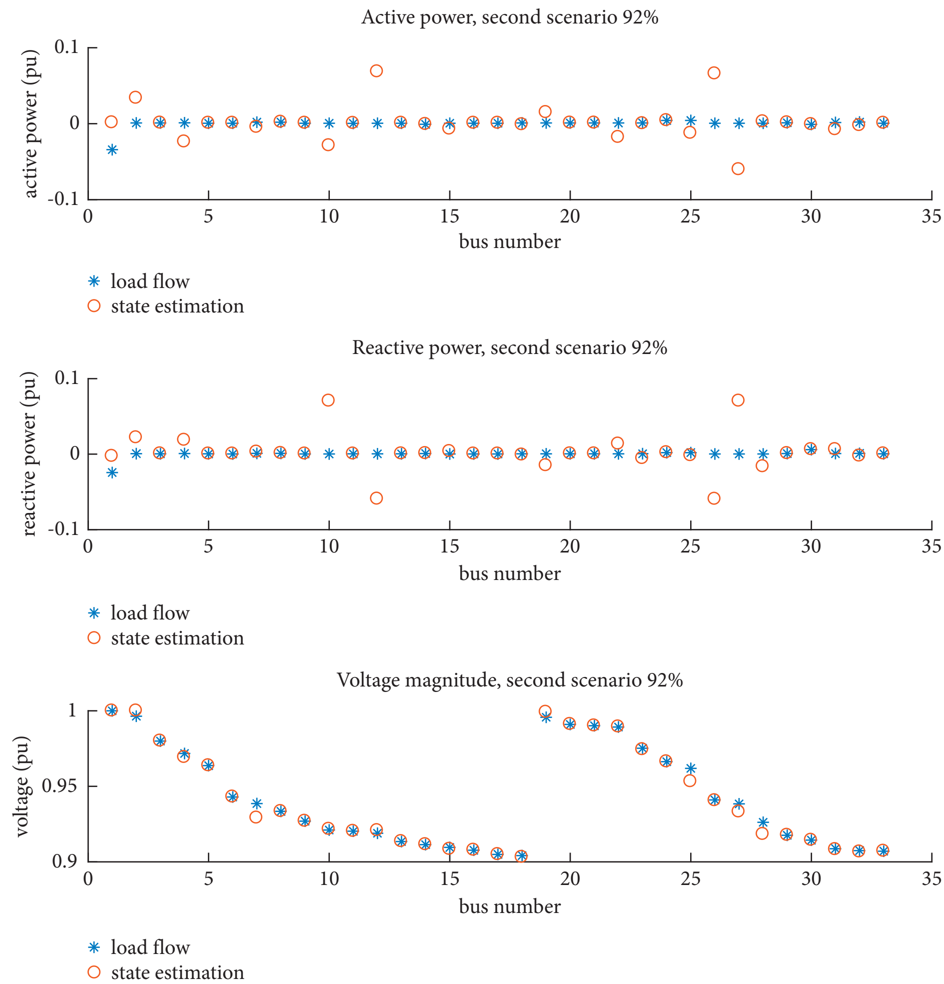

Figure 13: Active power, reactive power, and voltage magnitude for each bus at the second scenario with 92% of accuracy.

6. Conclusion

The key contribution of this article is that the methodology employed is accustomed to find adequate MDP for SE in the distribution network by considering the DG installation. BDA solves the optimization problem, and the SE problem is approached by the WLS method while the IEEE 33-bus distribution standard test system is employed to examine the mentioned method with relevant network observability under different situations and different accuracies with a speed limit which is included in the simulation for power system state estimation.

The application of the PMUs at the distribution systems can bring numerous benefits to distribution system management in a very way that overcomes the scarcity of measurements and improves the distribution system state estimation performance. However, the main obstacle to be tackled is that the PMUs are relatively costlier than smart meters. The authors thank GPS antennas and time signal distributions.

The simulation result of two different case studies shows that observability under the DG influence needs more measurement devices than the other scenario in which no DGs are installed in the tested system. When the high accuracy is implemented in SE, the number of measurement devices slightly increases in both scenarios. While the accuracy of SE is assumed to be lower, the optimization algorithm suggests a smaller number of measurement units to reach the desired accuracy for the test system observability.

This article showed how BDA outperformed GA and linear optimization algorithms. In the case of operation costs and cost of measurement devices, the mentioned method found a more economical answer than the other techniques. Concerning output quality, which was considered in the first scenario, BDA found answers with more quality of results. Therefore, the proposed method in terms of data quality, cost, and NoMs surpassed other methods.

Note that the PMU performance criteria might vary within the structure and parameters of distribution systems. The key contribution of this paper is that the methodology is accustomed find adequate PMU for better state estimation accuracy and their installation sites, which will improve the distribution state estimation performance and overall accuracy. In the end, the PMU accuracy at specific sites is often selected in accordance with the current PMU standards.

Unbalanced three-phase loads and operation are not taken into account in this article, along with observability during faults and dynamic state estimation. Consequently, as part of future work, our focus will be on dynamic state estimation and its applications such as observability of a system, while a fault occurs, and cyber-attack in the distribution system.

Abbreviations

BDA:	Binary dragonfly algorithm
DG:	Distributed generation
GA:	Genetic algorithm
Iter:	Iteration
MDP:	Measurement devices placement
MLE:	Maximum likelihood estimation
NoMs:	Number of measurements
PMU:	Phasor measurement unit
PSO:	Particle swarm optimization
SE:	State estimation
WLS:	Weight least square
e:	Error vector
$h(x)$:	Nonlinear function
k:	Number of iterations
m:	Number of measurements
nb:	Number of buses
nl:	Number of lines
s, a, c, f, and et:	Weights of the separation
x:	State vector
z:	Measurement vector
σ_{ε}:	Standard deviation
A:	Alignment
C:	cohesion
E:	Enemy disturbance level
F:	Food source
Floc:	Food location
$J(x)$:	Jacobian matrix
M:	Measurement matrix
R:	Diagonal matrix of standard deviation
S:	Separation
Vj:	Speed of the jth neighbor
Z:	The input of the algorithm generated by DA.

Data Availability

The data supporting the findings of this study are available from the first author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] E. Dusabimana and S.-G. Yoon, "A survey on the micro-phasor measurement unit in distribution networks," *Electronics*, vol. 9, p. 305, 2020.

[2] A. Hassannejad Marzouni, A. Zakariazadeh, and P. Siano, "Measurement devices allocation in distribution system using state estimation: a multi-objective approach," *Int Trans Electr Energ Syst*, 2020, https://doi.org/10.1002/2050-7038.12469, Article ID e12469.

[3] S. Mirjalili, "Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems," *Neural Computing & Applications*, vol. 27, pp. 1053–1073, 2016.

[4] V. Suresh and S. Sreejith, "Generation dispatch of combined solar thermal systems using dragonfly algorithm," *Computing*, vol. 99, pp. 59–80, 2017.

[5] D. Guha, P. K. Roy, and S. Banerjee, "Optimal tuning of 3 degree-of-freedom proportional-integral-derivative controller for hybrid distributed power system using dragonfly algorithm," *Computers & Electrical Engineering*, vol. 72, pp. 137–153, 2018.

[6] K. Sureshkumar and V. Ponnusamy, "Power flow management in micro grid through renewable energy sources using a hybrid modified dragonfly algorithm with bat search algorithm," *Energy*, vol. 181, 2019.

[7] M.-A. Díaz-Cortés, N. Ortega-Sánchez, S. Hinojosa et al., "A multi-level thresholding method for breast thermo-grams analysis using dragonfly algorithm," *Infrared Physics & Technology*, vol. 93, pp. 346–361, 2018.

[8] L. Xu, H. Jia, C. Lang, X. Peng, and K. Sun, "A novel method for multilevel color image segmentation based on dragonfly algorithm and differential evolution," *IEEE Access*, vol. 7, Article ID 19502, 2019.

[9] M. Jafari, M. Hossein, and B. Chaleshtari, "Using dragonfly algorithm for optimization of orthotropic infinite plates with a quasi-triangular cut-out," *European Journal of Mechanics - A: Solids*, vol. 66, pp. 1–14, 2017.

[10] B. Babayigit, "Synthesis of concentric circular antenna arrays using dragonfly algorithm," *International Journal of Electronics*, vol. 105, no. 5, pp. 784–793, 2018.

[11] Y. Yuan, L. Lv, X. Wang, and X. Song, "Optimization of a frame structure using the Coulomb force search strategy-based dragonfly algorithm," *Engineering Optimization*, vol. 52, pp. 1–17, 2019.

[12] B.S. Yıldız, A.R. Yıldız, "The Harris hawks optimization algorithm, salp swarm algorithm, grasshopper optimization algorithm and dragonfly algorithm for structural design optimization of vehicle components," *Mater. Test*, vol. 61, no. 8, pp. 744–748, 2019.

[13] S. Singh, A. Ashok, M. Kumar, and T. K. Rawat, *Optimal Design of IIR Filter Using Dragonfly Algorithm, in: Applications of Artificial Intelli-Gence Techniques in Engineering*, Springer Singapore, Singapore, pp. 211–223, 2019.

[14] M. Hariharan, R. Sindhu, V. Vijean et al., "Improved binary dragonfly optimization algorithm and wavelet packet based nonlinear features for infant cry classification," *Computer Methods and Programs in Biomedicine*, vol. 155, pp. 39–51, 2018, https://doi.org/10.1016/j.cmpb.2017.11.021.

[15] F. Aadil, W. Ahsan, and Z. U. Rehman, "Clustering algorithm for internet of vehicles (IoV) based on dragonfly optimizer (CAVDO)," *The Journal of Supercomputing*, vol. 74, pp. 4542–4567, 2018.

[16] A. I. Hammouri, E. T. A. Samra, M. A. Al-Betar, R. M. Khalil, Z. Alasmer, and M. Kanan, "A Dragonfly Algorithm for Solving Traveling Salesman Problem," in *Proceedings of the 2018 Eighth IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, pp. 136–141, Penang, Malaysia, November 2018.

[17] P. T. Daely and S. Y. Shin, "Range based wireless node localization using Dragonfly Algorithm," in *Proceedings of the 2016 Eighth International Conference on Ubiquitous and Future Networks*, pp. 1012–1015, ICUFN), Vienna, Austria, July 2016.

[18] M. Abdel-Basset, Q. Luo, F. Miao, and Y. Zhou, “Solving 0–1 knapsack problems by binary dragonfly algorithm,” in *Intelligent Computing Methodologies. ICIC 2017. Lecture Notes in Computer Science*, DS. Huang, A. Hussain, K. Han, and M. Gromiha, Eds., vol. 10363, Cham, Springer, 2017.

[19] M. Mafarja, I. Aljarah, Ali Asghar Heidari et al., “Binary dragonfly optimization for feature selection using time-varying transfer functions,” *Knowledge-Based Systems*, vol. 161, pp. 185–204, 2018.

[20] M. Mafarja, D. Eleyan, I. Jaber, A. Hammouri, and S. Mirjalili, “Binary dragonfly algorithm for feature selection, in: new trends in computing sciences (ICTCS),” in *Proceedings of the 2017 International Conference on*, pp. 12–17, IEEE, Amman, Jordan, October 2017.

[21] R. Singh, B. C. Pal, R. A. Jabr, and R. B. Vinter, “Meter placement for distribution system state estimation: an ordinal optimization approach,” *IEEE Transactions on Power Systems*, vol. 26, pp. 2328–2335, 2011.

[22] S. Prasad and D. M. V. Kumar, “Optimal allocation of measurement devices for distribution state estimation using multi-objective hybrid PSO- Krill Herd algorithm,” *IEEE Transactions on Instrumentation and Measurement*, vol. 66, pp. 2022–2035, 2017.

[23] H Wang, W. Zhang, and Y. Liu, “A robust measurement placement method for active distribution system state estimation considering network reconfiguration,” *IEEE Transactions on Smart Grid*, vol. 9, pp. 2108–2117, 2018.

[24] X. Chen, J. Lin, C. Wan et al., “Optimal meter placement for distribution network state estimation: a circuit representation based MILP approach,” *IEEE Transactions on Power Systems*, vol. 31, no. 6, pp. 4357–4370, 2016.

[25] Q. Yang, L. Jiang, W. Hao, B. Zhou, P. Yang, and Z. Lv, “PMU placement in electric transmission networks for reliable state estimation against false data injection attacks,” *IEEE Internet of Things Journal*, vol. 4, no. 6, pp. 1978–1986, 2017.

[26] S. Prasad and D. M. V. Kumar, “Trade-offs in PMU and IED deployment for active distribution state estimation using multi-objective evolution- ary algorithm,” *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 6, pp. 1298–1307, 2018.

[27] C. Zhang, Y. Jia, Z. Xu, L. L. Lai, and K. P. Wong, “Optimal PMU placement considering state estimation uncertainty and voltage controllability,” *IET Generation, Transmission & Distribution*, vol. 11, no. 18, pp. 4465–4475, 2017.

[28] H. H. Müller and C. A. Castro, “Genetic algorithm-based phasor measurement unit placement method considering observability and security criteria,” *IET Generation, Transmission & Distribution*, vol. 10, no. 1, pp. 270–280, 2016.

[29] Z. Wu, X. Du, W. Gu et al., “Optimal PMU placement considering load loss and relaying in distribution networks,” *IEEE Access*, vol. 6, Article ID 33645, 2018.

[30] N. P. Theodorakatos, “Optimal phasor measurement unit placement for numerical observability using branch-and-bound and a binary-coded genetic algorithm,” *Electric Power Components and Systems*, vol. 47, no. 4–5, pp. 357–371, 2019.

[31] H. H. Zeineldin, E. F. El-Saadany, and M. M. A. Salama, “Optimal coordination of overcurrent relays using a modified particle swarm optimization,” *Electric Power Systems Research*, vol. 76, no. 11, pp. 988–995, 2006.

[32] G. Li and C. Cheng, “Hybrid PSO Algorithm with Tabu Search for Hydro Unit Commitment,” *Electric Power Components & Systems*, vol. 19, no. 2, 2012.

[33] K. A. Al-anbarri and H. M. Nayyef, “Application of artificial bee colony algorithm in power flow studies,” *UHD Journal of Science and Technology*, vol. 1, no. 1, pp. 11–16, 2017.

[34] K. A. Al-anbarri and Sarah Abbas Hussain, “Load frequency control of multi- area hybrid power system by artificial intelligence techniques,” *International Tournal of Computer Application*, vol. 138, no. 7, 2016.

[35] A. Mahari and H. Seyedi, “Optimal PMU placement for power system observability using BICA considering measurement redundancy,” *Electric Power Systems Research*, vol. 103, pp. 78–85, 2013.

[36] Z. Miljanic, I. Djurovic, and I. Vujosevic, “Optimal placement of PMUs with limited number of channels,” *Electric Power Systems Research*, vol. 90, pp. 93–98, 2012.

[37] A. Abur and A. Gomez Exposito, *Power System State Estimation, Theory and Implementation*, Marcel Dekker, New York, NY USA, 2004.

[38] B. Xu and A. Abur, “Observability analysis and measurement placement for system with PMUs,” *IEEE PES Power Systems Conference and Exposition*, vol. 2, pp. 943–946, 2004.

[39] G. N. Korres, “An integer-arithmetic algorithm for observability analysis of systems with SCADA and PMU measurements,” *Electric Power Systems Research*, vol. 81, no. 7, pp. 1388–1402, 2011.

[40] N. P. Theodorakatos, “Fault location observability using phasor measurement units in a power network through deterministic and stochastic algorithms,” *Electric Power Components and Systems*, vol. 47, no. 3, pp. 1–18, 2019.

[41] T. A. Alexopoulos, N. M. Manousakis, and G. N. Korres, “Fault location observability using phasor measurements units via semidefinite programming,” *IEEE Access*, vol. 4, pp. 5187–5195, 2016.

[42] N. P. Theodorakatos, M. Lytras, and R. Babu, “A generalized pattern search algorithm methodology for solving an under-determined system of equality constraints to achieve power system observability using synchrophasors,” *Journal of Physics: Conference Series*, vol. 2090, Article ID 12125, 2021.

[43] R. Babu and B. Bhattacharyya, “Optimal allocation of phasor measurement unit for full observability of the connected power network,” *Electr. Power Energy Syst.*vol. 79, pp. 89–97, 2016.

[44] G. Koulinas, K. Lazaros, and K. Anagnostopoulos, “A particle swarm optimization based hyper-heuristic algorithm for the classic resource constrained project scheduling problem,” *Informing Science*, vol. 277, pp. 680–693, 2014.

[45] H Müller and C. A Castro, “Genetic algorithm-based phasor measurement unit placement method considering observability and security criteria,” *IET Generation, Transmission & Distribution*, vol. 10, 2016.

[46] N. P. Theodorakatos, “A nonlinear well-determined model for power system observability using interior-point methods,” *Meas J Int Meas Confed*, vol. 152, Article ID 107305, 2020.

[47] F. Potra and S. J. Wright, “F. Potra, S.J. Wright Interior-point methods,” *Journal of Applied Mathematics and Computing*, vol. 124, no. 1, pp. 281–302, 2000.

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

[49] E. M. T. Hedrix and B. Toth, *Introduction to Nonlinear and Global Optimization*, Springer, cham, 2010.

[50] T Johnson and T Moger, “A critical review of methods for optimal placement of phasor measurement units,” *Int. Trans. on Elec. Ener. Sys.*vol. 31, 2020.