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Active distribution system state estimation based on metaheuristic algorithms in the presence of distributed generations

Mojtaba Ajoudani*(C.A.), Seyed Reza Mosayyebi* and Ramazan Teimouri Yansari**

Abstract: The increasing penetration of distributed generation (DG) significantly complicates Distribution System State Estimation (DSSE) by introducing stochasticity and uncertainty. This paper proposes a novel DSSE framework that unlike conventional methods simultaneously estimates the system state, load demands, and DGs output power through a unified constrained optimization model. The model is efficiently solved using the Whale Optimization Algorithm (WOA), whose unique balance of exploration and exploitation enables robust solution search in complex, active distribution networks. Simulation studies on standard IEEE 37-bus and 69-bus test systems reveal that the proposed WOA-based approach achieves outstanding accuracy. For the 37-bus system, WOA attains a Maximum Individual Relative Error (MIRE) of 1.15% and a Maximum Individual Absolute Error (MIAE) of 2.303 on load estimation. On the larger 69-bus system, the method further reduces these errors yielding a MIRE of 0.886% and a MIAE of 1.12 for load, and 0.73% and 1.058 for DG power estimation, respectively. Across all experiments, WOA consistently outperforms leading metaheuristics including ABC, PSO, and GA highlighting its superior accuracy, scalability, and robustness for real-world DSSE challenges.

Keywords: State estimation, Active distribution system, Distributed generation, Smart meter, Whale optimization algorithm

1 Introduction

IN the field of power system state estimation (SE), many studies have been carried out. There is always a need for a system model for studying, planning, increasing system security, and economic load distribution to reduce production costs and losses, etc. This model includes parameters of series and parallel lines, models of transformers, generators, compensators, and other elements used in the power system. The system model can be very complex and include non-linear equations, or it can be simplified and modeled linearly. Therefore, various models with different accuracies can be considered for the system. In [1, 2], a method for updating the parameters based on the residual vector analysis was presented. In this method, a relationship between the residual and the parameter error was used. In each step, after estimating the state using the residuals, the parameters' error is calculated; in this way, the parameters are updated. This method requires a shorter solution time. Another parameter estimation method is the expansion of the state vector with the parameters of the system. In this method, the incorporation of additional unknown parameters into the state vector will transform the problem into an ill-conditioned one [3, 4]. The most practical of these methods is solving the problem with the Kalman filter [5, 6]. In [7], a method was presented to link the SE and system parameters using phasor measurement units. In this method, the state and parameters of the system are estimated, and their changes are followed dynamically. In recent years, to estimate the state of the distribution

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* The authors are with the Department of Electrical Engineering, BG.C., Islamic Azad University, Bandargaz, Iran.
E-mails: mojtaba.ajoudani@iau.ac.ir, sr.mosayyebi@iau.ac.ir.
** The author is with the Department of Computer Engineering, BG.C., Islamic Azad University, Bandargaz, Iran.
E-mail: ra.teimouri@iau.ac.ir.
Corresponding Author: Mojtaba Ajoudani.

system, methods based on algorithms to minimize the amount of error have been used more than other methods. In this regard, the particle swarm algorithm [8, 9], the training-based algorithm [10], and the genetic algorithm [11] can be mentioned. In algorithm-based methods, to estimate the state of the distribution system, an objective function of the square of the error is considered, and optimization algorithms always try to minimize this function so that the estimated values are closer to the actual values. The SE is typically formulated as a weighted least squares problem. The SE methods are broadly classified into two categories: The first category is based on statistical criteria, including the maximum likelihood criterion, minimum variance criterion, and weighted least squares criterion [12-14]. The second approach is the power flow-based SE formulation [15-17]. The Weighted Least Squares (WLS) method has been predominantly utilized in most SE research; however, these approaches typically fail to account for short-term load variations occurring within the data transmission intervals of smart meters, which are conventionally set at 15-minute defaults. Reference [16] demonstrates that employing smart meters enhances the accuracy of SE. However, in that study, whenever an estimation was required within the interval between two data transmissions, the data from the beginning of the interval were utilized, and load variations were not accounted for. In [17], the author considers two levels of error (2% or 10%) for smart meter measurements. In contrast, the author of [16] assumes a uniform 10% error for all measurements obtained from the meters. A review of existing research in this domain reveals that previous investigators addressed the lack of information between consecutive measurement intervals by incorporating a fixed percentage of error. Consequently, the resulting estimates lacked high accuracy. In reference [13], a novel methodology is introduced which formulates load variations occurring within the data transmission intervals and subsequently modifies the error relationship in the WLS method. The results obtained through this approach are compared with those from traditional SE techniques. Reference [14] presents a new method for SE in active distribution systems. This approach employs metaheuristic algorithms while incorporating multi-scale considerations for various measurement devices.

The integration of distributed energy resources presents significant challenges for DSSE, requiring advanced methodologies to handle uncertainties in renewable generation and load patterns. Hybrid approaches combining traditional methods with intelligent algorithms show promising results in improving estimation accuracy under limited measurement conditions. In this context, a comparative analysis of the artificial bee colony (ABC) algorithm [18-20], particle swarm optimization (PSO) algorithm [21, 22], optimal honey bee mating algorithm (OHBMA) [23, 24], artificial neural network (ANN) [25, 26], ant colony optimization (ACO) algorithm [27, 28], genetic algorithm (GA) [29, 30], quantum-inspired evolutionary algorithm (QIEA) [31, 32], greedy randomized adaptive search procedure (GRASP) [33, 34] algorithm, and Whale Optimization Algorithm (WOA) [35] was presented in Table 1, which demonstrates the superiority of the WOA over other algorithms. Therefore, in this paper, we employed the WOA. Furthermore, the integration of DGs introduces significant challenges not only for state estimation but also for system protection and transient stability, as discussed in [36]. While the aforementioned studies have contributed to the field of DSSE, a significant research gap remains in developing a methodology that simultaneously delivers high estimation accuracy, robustness against measurement uncertainties, and computational efficiency for large-scale active distribution networks with high penetration of stochastic DGs. Many existing metaheuristic approaches, as summarized in Table 1, often suffer from limitations such as premature convergence (e.g., PSO), high computational complexity (e.g., OHBMA), or poor scalability. This paper bridges this gap by proposing a novel DSSE framework that leverages the WOA. The WOA is selected for its proven superiority in global optimization, evidenced in Table 1, particularly its unique bubble-net foraging mechanism that provides an exceptional balance between exploration and exploitation, making it ideally suited to handle the non-convex and constrained optimization problem inherent in accurate DSSE with DGs. The primary contributions of this work are: The formulation of a comprehensive DSSE problem that simultaneously estimates system state, load demand, and DG output power under practical operational constraints. The novel application and validation of the WOA as a superior solver for this complex estimation problem in active distribution networks. A rigorous comparative analysis against eight established metaheuristic algorithms on standard IEEE test systems, demonstrating the WOA's superior accuracy and robustness through quantitative indices.

This paper is structured as follows: Section 2 expresses the DSSE method. In section 3, the solution framework utilizing WOA is given. The simulation results are demonstrated in section 4. Finally, section 5 concludes the paper.

2 The DSSE method

A precise system model is essential for conducting studies, planning operations, optimizing economic load dispatch, and enhancing system security. Such a model incorporates the parameters of loads, generation units, distribution lines, generators, and other components within the distribution feeder. The complexity of this

Table 1: A comparative analysis of the WOA and other metaheuristic algorithms

Algorithm	Convergence Speed (Iterations)	Average Error Rate (%)	Noise Tolerance (%)	Computational Time (s)	Success Rate (%)
ABC [18-20]	80-120	1.8-2.5	15-20	25-35	85-90
PSO [21, 22]	50-80	2.0-3.0	10-15	30-40	80-85
OHBMA [23, 24]	70-100	1.5-2.2	18-22	35-45	88-92
ANN [25, 26]	N/A (Training Dependent)	3.0-5.0	12-18	15-25 (Inference)	90-95
ACO [27, 28]	100-150	2.2-3.2	8-12	40-60	75-82
GA [29, 30]	120-180	2.5-3.8	10-15	45-65	78-85
QIEA [31, 32]	60-90	1.6-2.4	20-25	25-35	87-93
GRASP [33, 34]	40-70	1.8-2.8	15-20	20-30	92-96
WOA [35]	40-60	0.8-1.5	25-30	18-28	95-98

model can vary significantly, ranging from a detailed representation involving non-linear equations to a simplified linear formulation. Consequently, a spectrum of models with varying degrees of accuracy can be developed for the system.

Among the most critical parameters within the system model are the network load demand and the power generation capacity of DG sources. Numerous algorithms have been proposed for estimating distribution feeder parameters. Classical, theory-based methods, for instance, leverage factors such as ambient conditions and historical consumer load profiles to estimate net load and DG output. However, the actual values of these input factors often deviate from those used in the calculations, while inherent uncertainties further diminish the accuracy of parameter estimation.

To obtain more precise values for distribution system parameters, estimation methods are employed. These techniques utilize a combination of real-time measurements including voltage, current, and power taken from buses and lines across the network. The data is transmitted to dedicated software, which processes it through a programmed algorithm to yield the parameter estimates.

Real-time parameter calculation algorithms can be broadly categorized into two main groups:

- Algorithms that calculate the parameters directly by measuring the network operational parameters.
- Algorithms that use the SE algorithm to estimate the parameters.

2.1 Parameter estimation method using SE algorithm

As previously established, acquiring accurate, real-time parameters of the distribution system is a fundamental prerequisite. The SE algorithm, in particular, is predicated on the availability of correct network parameters to yield reliable results. Inaccurate parameters inevitably degrade the precision of the SE output.

To address this critical dependency, numerous algorithms have been proposed with the objective of identifying parameter errors and correcting them, thereby enhancing the overall accuracy of the SE process. These approaches, often termed parameter estimation, are frequently integrated with the SE method itself. In this integrated framework, parameter estimation operates as a methodology based on the system's SE.

The underlying procedure typically involves assigning initial values to the parameters. A SE is then executed, following which the precise values of the imprecise parameters are determined. The methods developed for handling parameter error within the SE algorithm can be classified into two primary categories:

- The method based on residual sensitivity analysis [1, 2].
- The method based on state vector expansion [3, 4].

As the nomenclature suggests, the first method initiates with assumed parameter values and completes a full SE cycle. Subsequently, by establishing a relationship between the parameter errors and the estimation residuals, the correct parameter values are derived. In contrast, the second method incorporates the parameters directly into the state vector of the SE algorithm, enabling the simultaneous execution of state and parameter estimation.

Within the first category (residual sensitivity analysis), the SE equation is decoupled into two separate equations concerning state variables and network parameters, respectively. This technique follows a sequential process: SE is performed first, followed by parameter updating. This two-step sequence constitutes one iteration, which is repeated until both the parameters and state variables converge to their final values. A significant drawback of this method is its considerable computational demand and time consumption.

Consequently, alternative approaches for updating variables are often preferred. One such technique leverages residual vector analysis. This method utilizes a defined relationship between the residuals and parameter errors. In each iteration, following the SE, the parameter errors are calculated directly from the residuals, and the parameters are updated accordingly, leading to a substantially reduced solution time.

The foundation of the second major category (state vector expansion) is the augmentation of the state vector by appending the network parameters to it. This formulation allows for the combined state and parameter estimation problem to be solved simultaneously within a single, integrated computational framework.

2.2 State estimation in active distribution system

The SE utilizing real-time measurement data, constitutes a fundamental component of modern distribution systems. The system state is defined by a set of simultaneous values representing the positive-sequence voltage phasors at all network buses. Estimating this state requires the real-time solution of an extensive set of non-linear equations. Static SE performs this analysis by processing a set of measurements taken from various network points at a specific point in time. The non-linear relationship between the measurement vector z and the state vector x is given by the following equation [13]:

$$Z = F(X) + \varepsilon \tag{1}$$

where ε is a random noise vector with Gaussian distribution, and F is a vector of equations relating the state variables to the measurements.

Static SE is formulated within the WLS framework and solved through an iterative numerical algorithm. At each iteration, the solution procedure corresponds to solving a linearized approximation of the original problem. A prevalent solution strategy involves the decoupling of measurement and state vectors into their respective real and imaginary components. This approach transforms the SE problem into solving two independent linear equations using the WLS method. The solution for each decoupled equation is expressed as follows [13]:

$$x = (H^T R^{-1} H)^{-1} H^T R^{-1} z \tag{2}$$

where x is the estimated state vector, R is the diagonal matrix that expresses the covariance of the ε matrix, and H is the Jacobian matrix. The residual vector r is defined as $r = z\text{-}Hx$, which can be represented as follows:

$$r = (I - M)\varepsilon \tag{3}$$
$$M = H(H^T R^{-1} H)^{-1} H^T R^{-1} \tag{4}$$

The system state variables can be determined through iterative computation using Equation (4). However, it is important to recognize that these estimated values contain inherent inaccuracies due to errors in the parameters available to the SE algorithm. Consequently, to address this limitation and enhance parameter accuracy, dedicated parameter estimation algorithms have been developed, which form a distinct class of computational methods for parameter correction and refinement.

2.3 Objective function and constraints of the estimation problem

The accurate estimation of distribution system parameters via optimization algorithms necessitates the formulation of an appropriate objective function to minimize the discrepancy between estimated and measured (actual) values. In this work, we define the objective function for the proposed WOA as Equation (5) [13, 14], which is minimized during the optimization process:

$$\min E(x) = \sum_{i=1}^{m} [M_i - S_i(X)]^2 \tag{5}$$

where X, M, S, and m are the state vector, the measured values, the state equation of the measured values, and the number of measurements, respectively. This formulation employs the square power of the measurement residuals to enhance estimation accuracy, particularly in mitigating the influence of minor measurement errors on state variable calculations. The optimization constraints incorporated in the distribution feeder model align with established practices in the field, encompassing fundamental operational considerations such as active and reactive power optimization, load allocation, load shedding protocols, and optimal DG placement. The specific constraints governing the DSSE are delineated as follows [37]:

- The limitation of bus voltage range:

$$V_i^{Min} \leq V_i \leq V_i^{Max} \tag{6}$$

The voltage of all buses in the distribution feeder should be within the permissible range.

- The limitation of line power capacity:

$$\left|P_l\right| \leq P_l^{Max} \tag{7}$$

In the above equation, P_l is the power passing through line l and P_l^{Max} is its maximum capacity. It shows the overload limit on each distribution line and facilitates the possible operation or load sharing.

- The limitation of reactive power of capacitors:

$$0 \leq Q_{ci} \leq Q_{ci}^{Max} \tag{8}$$

where Q_{ci} is the amount of reactive power produced by the capacitor connected to the i-th bus with the maximum capacity Q_{ci}^{Max}. These capacitors are installed in optimal places to improve the power factor of the line current and reduce power losses.

- The limitation of the production capacity of DGs:

$$P_{Ri}^{Min} \leq P_{Ri} \leq P_{Ri}^{Max} \tag{9}$$

where P_{Ri} represents the active power produced by DG connected to the i-th bus, and P_{Ri}^{Min} and P_{Ri}^{Max} are the lower and upper limits of the DG power generation capacity, respectively.

- The limitation of the load active power:

$$P_{Li}^{Min} \leq P_{Li} \leq P_{Li}^{Max} \tag{10}$$

where P_{Li}, P_{Li}^{Min}, and P_{Li}^{Max} are the load value, lower limit, and upper limit of the load of the i-th bus, respectively. If a deviation is observed in any node, it will reduce the voltage in that node and, in the worst case, may lead to a blackout.

The DSSE problem formulated in Equations (5) to (10) constitutes a complex, non-convex, and constrained optimization challenge. The non-linear power flow constraints, coupled with the stochastic nature of DG outputs and load variations, render traditional gradient-based methods susceptible to convergence issues and suboptimal solutions. To address these limitations and achieve high-accuracy estimation, this paper employs the WOA as the core solver. The WOA is a metaheuristic technique renowned for its effective balance between exploration and exploitation, its ability to handle non-linear constraints without requiring gradient information, and its demonstrated robustness in noisy environments. As evidenced by the comparative analysis in Table 1, these characteristics make it particularly suited for the DSSE problem at hand. The following section details the mechanics and computational steps of the WOA.

3 Solution Framework Using WOA

The humpback whale, a species of baleen whale, is renowned for its sophisticated and cooperative foraging strategy. This method, known as bubble-net feeding, is a distinctive and complex predatory behavior. Humpback whales typically target aggregations of small fish or krill near the water's surface. It has been empirically observed that they engage in this behavior by creating a circular or spiral "net" of exhaled bubbles, which corrals the prey and confines them into a denser mass, making them easier to consume.

Inspired by this specific foraging mechanism, the WOA is a metaheuristic, population-based optimization technique. Its design mimics the bubble-net hunting strategy to solve complex optimization problems, demonstrating applicability across various engineering and computational domains.

- **The steps of the whale algorithm**

The WOA executes through three distinct computational phases, as formalized in [35]:

(a) Prey Encirculation Phase:

Modeling the initial identification and surrounding of promising regions in the search space.

(b) Bubble-net Attacking Strategy (Exploitation Stage):

Implementing a spiral updating mechanism to simulate the sophisticated bubble-net feeding behavior for local search refinement.

(c) Prey Search Operation (Exploration Stage):

Conducting global search through random position updates to explore new solution domains.

(a) Prey Encirculation in the WOA

The WOA operates on the premise that humpback whales can numerically determine the position of prey and encircle it. Within the optimization framework, the precise location of the global optimum in the search space is unknown a priori. Consequently, the algorithm postulates that the current best candidate solution corresponds either to the target prey or represents a position in close proximity to the optimal state. Following the identification of this best search agent, all other agents in the population systematically update their positions relative to this leading solution. This collective movement toward the current optimum is mathematically represented by the following equations (11) and (12) [35, 38]:

$$\vec{D} = \left| \vec{C}.\vec{X}^{*}(t) - \vec{X}(t) \right| \tag{11}$$

$$\vec{X}(t+1) = \vec{X}^{*}(t) - \vec{A}.\vec{D} \tag{12}$$

where t represents the last iteration, $\vec{A}$ and $\vec{C}$ are the vector of coefficients, X^* is the position vector of the best solution that has been obtained so far, $\vec{X}$ is the position vector, $|\ |$ is the absolute value and is obtained from the multiplication of matrices. It should be noted that if there is a better solution, X^* is updated in each iteration. The vectors $\vec{A}$ and $\vec{C}$ are computed as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{13}$$

$$\vec{C} = 2\vec{r} \tag{14}$$

The parameter a undergoes a linear decrement from 2 to 0 throughout the iterative process, governing both exploration and exploitation phases, while r represents a stochastic vector with elements uniformly distributed within the interval [0,1]. Figures 1(a) and 1(b) illustrate the two-dimensional and three-dimensional representations of the search space within the WOA framework, respectively. The positional coordinates *(X, Y)* of any given search agent undergo iterative refinement relative to the coordinates of the current optimal solution *(X*, Y*)*, following the established mathematical formulation of the algorithm.

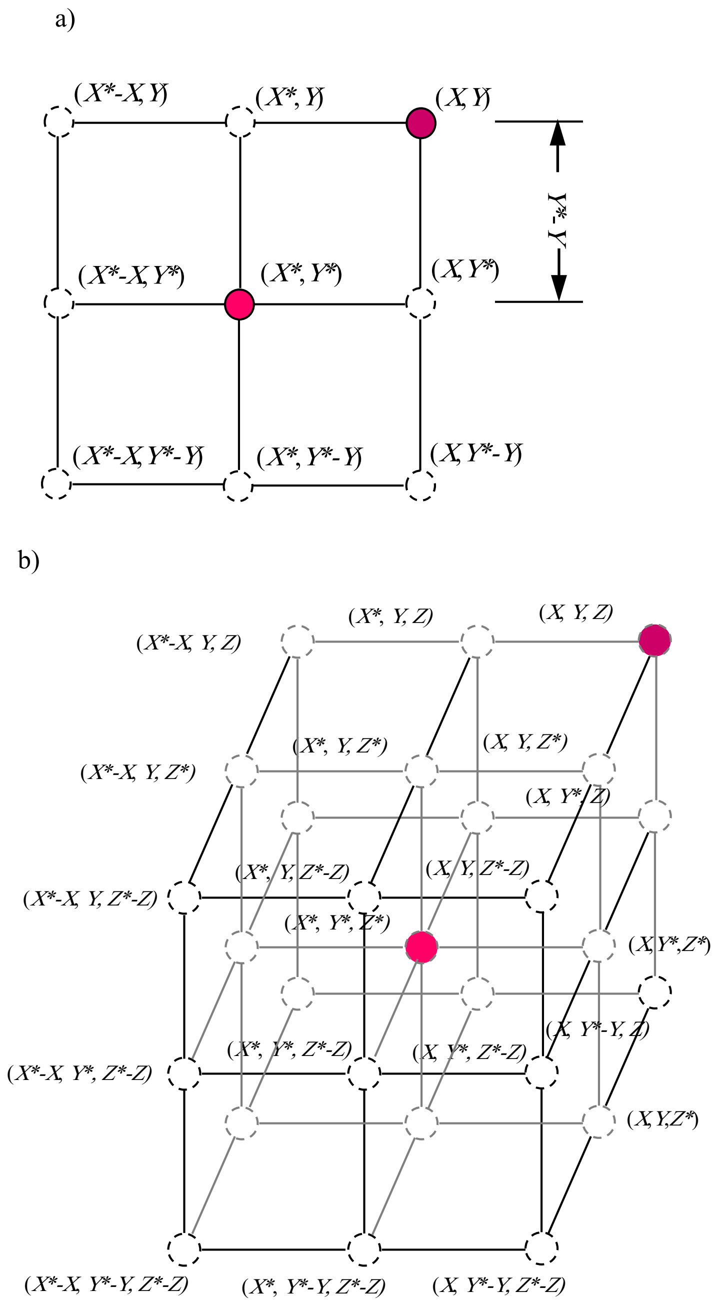

Fig. 1. The space searched by a whale to encircle the prey (a) 2D search space; (b) 3D search space [35]

(b) exploitation stage in the WOA

The mathematical modeling of the whale bubble-net foraging behavior is formalized through two distinct methodological approaches:

1. The Shrinking Encryclement Mechanism: This behavioral pattern is mathematically represented through the systematic reduction of parameter a in Equation (13). The oscillation amplitude of coefficient A is consequently diminished proportionally to the decreasing value of a. Specifically, A is defined as a stochastic variable

uniformly distributed within the interval [-a, a], while a undergoes linear attenuation from 2 to 0 throughout successive iterations. Through the strategic selection of randomized A values within the bounded range [-1, 1], the subsequent position of each search agent can be precisely determined within the convex space delineated by its original coordinates and the location of the current optimal agent.

2. Spiral Updating Position Methodology: This approach initiates by calculating the Euclidean distance between the whale located at coordinates (X, Y) and the prey, positioned at the current best-known location (X^*, Y^*). A subsequent phase involves the mathematical formulation of a helical path to emulate the distinctive spiral movement observed in humpback whales during bubble-net feeding. This trajectory is mathematically modeled to simulate the whale's motion towards the prey, as defined by the following equation:

$$\vec{X}(t+1) = \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}^*(t) \tag{15}$$

The parameter $\overrightarrow{D'} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right|$ quantifies the Euclidean distance between the i-th whale and the prey position, which corresponds to the optimal solution identified thus far. Here, b denotes a constant parameter defining the logarithmic spiral geometry, l represents a stochastic variable uniformly distributed within the interval [−1, 1], and the operator (.) indicates element-wise multiplication.

It is noteworthy that whales exhibit simultaneous movement patterns around the prey, combining both a constricting circular trajectory and a helical path. To computationally model this complex behavior, the algorithm incorporates a probabilistic selection mechanism wherein either the encirclement contraction method or the spiral updating model is chosen with equal probability (50%) during each position update iteration. This hybrid approach is mathematically represented by the following equation:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}\vec{D} & if\ p < 0.5 \\ \vec{D}' e^{bl}\cos(2\pi l) + \vec{X}^*(t) & if\ p \geq 0.5 \end{cases} \tag{16}$$

Within this formulation, the parameter p represents a stochastic variable uniformly distributed across the interval [0, 1]. Concurrently with the previously described bubble-net foraging mechanism, humpback whales additionally engage in stochastic exploration behaviors to locate prey within the search space.

(c) exploration stage in the WOA

During the exploration phase, the mathematical search model utilizes variations in the vector $\vec{A}$ to facilitate a global foraging strategy. In this operational mode, each search agent updates its position stochastically by referencing other randomly selected agents within the population. To ensure sufficient dispersion from the current reference whale, the algorithm employs values of $\vec{A}$ with random magnitudes either less than -1 or greater than 1.

Unlike the exploitation phase where positions are updated relative to the best solution found, the exploration phase incorporates randomly chosen search agents to promote diversity in the search trajectory. This strategic approach, particularly when $|\mathbf{A}| > 1$, enables comprehensive global exploration and prevents premature convergence. The mathematical formulation governing this behavior is expressed as follows [35, 38]:

$$\vec{D} = \left|\vec{C}.\vec{X}_{rand} - \vec{X}\right| \tag{17}$$

$$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{A}.\vec{D} \tag{18}$$

where $\overrightarrow{X_{rand}}$ represents a randomly selected whale position from the current population.

Figure 2 illustrates various potential configurations in the vicinity of a specific solution where the magnitude of vector $\vec{A}$ exceeds unity. The WOA commences with a randomly initialized population of candidate solutions. During each iterative cycle, search agents adapt their positions relative to either a randomly selected agent or the current optimal solution identified thus far.

The parameter a is systematically modulated to facilitate the transition between exploration and exploitation phases, undergoing a linear decrease from 2 to 0 over successive iterations. The position update mechanism employs stochastic selection when $|\vec{A}| > 1$

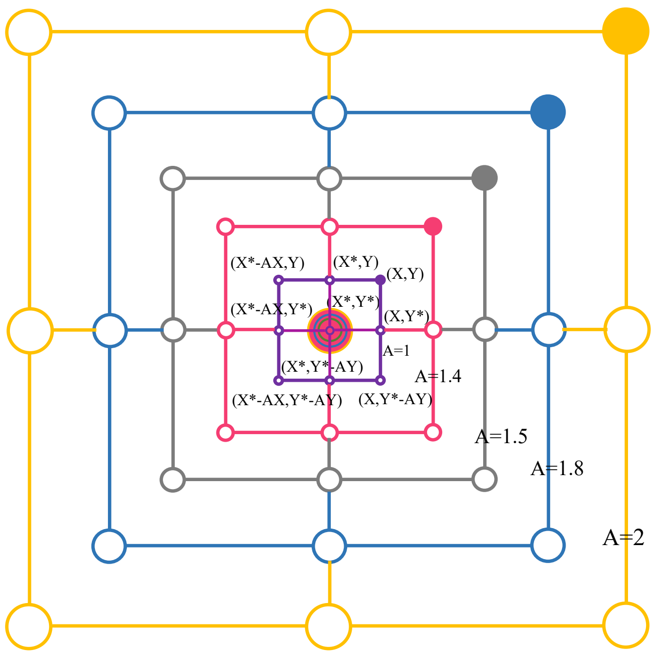

Fig. 2. Exploration phase in the WOA (X* is an accidentally selected search agent) [35]

to promote exploration, while preferentially utilizing the best-known solution when $|\vec{A}| < 1$ to enhance exploitation. The adaptive behavior of the algorithm is further governed by parameter p, which determines whether the movement pattern follows a spiral or circular trajectory.

The schematic diagram illustrating the workflow of the hybrid WLS-WOA framework applied to DSSE was presented in Figure 3. An overview of the entire process was provided in Figure 4.

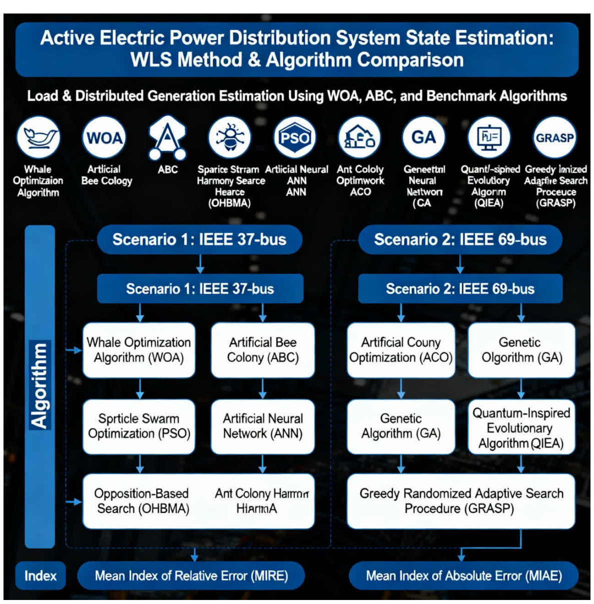

Fig. 4. Schematic diagram of the overall process

4. Simulation results

In this section, the results obtained from simulations conducted in the MATLAB software environment are analyzed and discussed. The simulations were carried out for two scenarios using the standard IEEE 37-bus and 69-bus distribution feeders. In both scenarios, the proposed WOA was employed to estimate the network load and the power generation capacity of distributed generation resources within the studied feeders. The optimization results obtained using the proposed algorithm were compared with those of several other metaheuristic algorithms referenced in the literature. The parameters of the WOA used to address the optimization problem are presented in Table 2. The algorithm coefficients were selected through a trial-and-error approach to achieve optimal performance.

Table 2: Whale optimization algorithm coefficients

Whale population	Maximum iterations	α	β	γ
100	50	0.1	4	2

4.1. Scenario I

In this scenario, the WOA is utilized to estimate the load of the IEEE 37-bus distribution feeder and the generation capacity of distributed generation resources. Figure 5 illustrates the convergence trend of the WOA in this scenario. The convergence curve indicates that the algorithm converges to a final value of 0.8638 per unit after 42 iterations. The computational time required to solve the optimization problem using the WOA in this scenario is approximately 19 seconds, compared to 25 seconds for the ABC algorithm, demonstrating better computational efficiency.

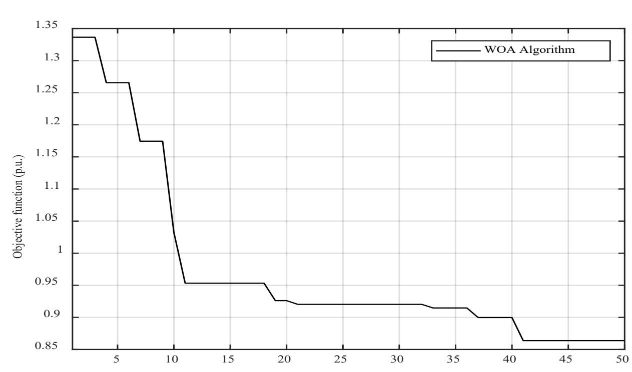

Fig. 5. Convergence curve of the WOA for the first scenario

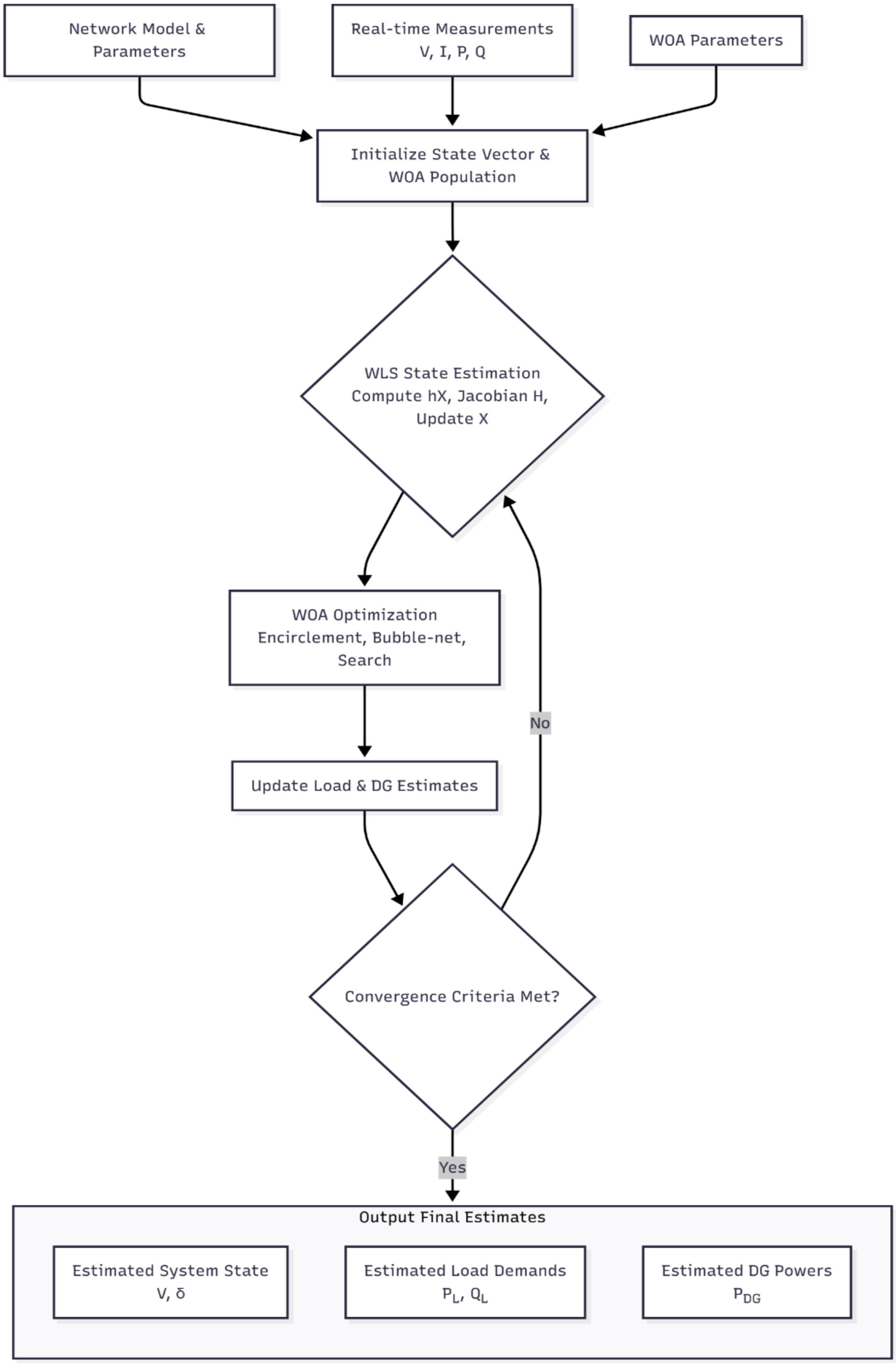

Fig. 3. Workflow of the proposed hybrid WLS-WOA framework for DSSE

The optimization results obtained from the WOA in the first scenario are compared with those derived from the ABC algorithm. Table 3 presents the estimated electrical load power values, while Table 4 provides the estimated power generation capacities of distributed generation resources for both optimization algorithms. An analysis of the results presented in Table 3 reveals that the proposed WOA outperforms the ABC algorithm. For the majority of the estimated load values, the WOA provides results that are closer to the actual load values, exhibiting minimal deviation. To quantitatively assess and compare the performance of the optimization algorithms, the Maximum Individual Relative Error (MIRE) and Maximum Individual Absolute Error (MIAE) indices are used, defined as follows:

$$MIRE\,(\%) = Max\left(\frac{|Act - Est|}{Act}\right)\times 100 \tag{19}$$

$$MIAE = Max\left(|Act - Est|\right) \tag{20}$$

In Equations (19) and (20), *Act* denotes the actual value, and *Est* represents the estimated value. For the first scenario, the MIRE index for the proposed WOA is 1.15%, compared to 1.3% for the ABC algorithm.

Table 3: Estimated values of variable loads in the IEEE 37-Bus system using WOA and ABC algorithms under Scenario I

Bus Num	Actual Load Values		ABC-Optimized Load		WOA-Optimized Load	
	$P_L(KW)$	$Q_L(KVar)$	$P_L(KW)$	$Q_L(KVar)$	$P_L(KW)$	$Q_L(KVar)$
4	120	80	121.164	81.33	121.454	80.546
8	200	100	201.623	101.903	200.812	100.215
12	60	35	59.692	35.817	59.442	35.954
15	60	10	60.587	9.905	60.08	10.002
21	90	40	91.567	39.871	91.019	40.133
25	90	50	91.2	49.315	91.103	49.895
31	60	20	59.527	20.942	59.951	20.082
36	150	70	151.152	69.749	149.932	70.456

Table 4: Estimated power generation capacity of DGs in the IEEE 37-Bus system using WOA and ABC algorithms under Scenario I

Bus Num	Average Active Power Output (KW)	ABC-Optimized Active Power Output (KW)	WOA-Optimized Active Power Output (KW)
4	140	138.297	139.365
8	200	197.4	197.697
12	250	249.737	249.355
15	150	148.525	148.110
21	300	298.131	299.216
25	120	118.556	119.419
31	100	98.69	99.374
36	110	108.909	109.041

Similarly, the MIAE values for the WOA and ABC algorithms are 2.303 and 2.6, respectively. The lower MIRE and MIAE values for the proposed WOA indicate its superior accuracy compared to the ABC algorithm in solving the optimization problem. To evaluate the sensitivity of the proposed method to initial conditions, multiple runs were performed with different random initializations. The results indicated consistent convergence to the same optimal solution, with less than ±0.5% variation in the final objective function value, confirming the robustness of the WOA to initial parameter settings.

Figures 6(a) and 6(b) illustrate the voltage amplitude profile and voltage phase angle profile, respectively, for the traditional, ideal, and proposed methods in the first scenario at peak load. The traditional method exhibits significant estimation errors, whereas the state variables estimated by the proposed method show negligible deviations and closely align with the actual values.

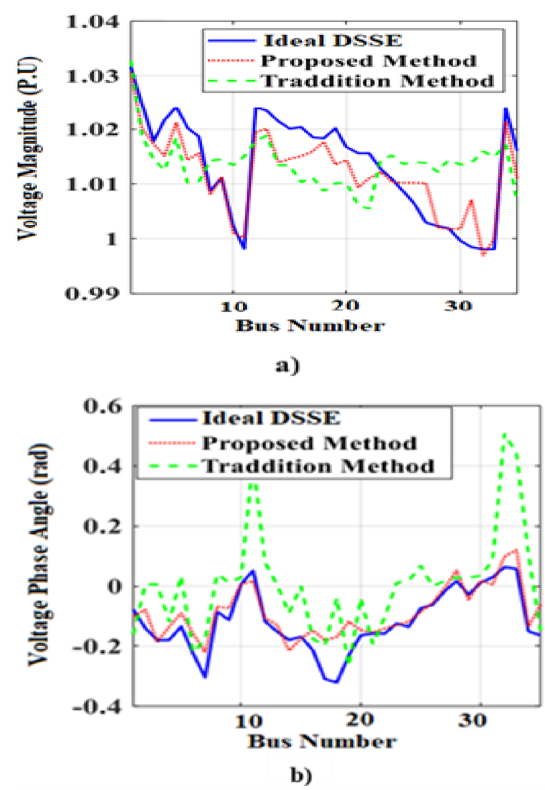

Fig .6. (a) Voltage magnitude profile and **(b)** voltage phase angle profile for the traditional, ideal, and proposed (WOA) methods under Scenario I

4.2. Scenario II

In this scenario, simulations were conducted to estimate the load and power generation capacity of distributed generation resources in the IEEE 69-Bus distribution feeder using the WOA. Figure 7 illustrates the convergence curve of the WOA for the second scenario. The convergence profile indicates that the algorithm converges to a final value of 0.7318 per unit after 38 iterations. The computational time required to solve the optimization problem using the WOA in this scenario is approximately **27 seconds**, which is **25-40% faster** than other benchmark algorithms such as PSO (36s) and GA (45s).

In the second scenario, the optimization and estimation results obtained using the WOA are compared with those derived from the ABC algorithm, PSO algorithm, OHBMA, ANN, ACO algorithm, GA, QIEA, and GRASP algorithm. Table 5 presents the estimated electrical load power values for the IEEE 69-Bus distribution feeder using the WOA and ABC algorithms.

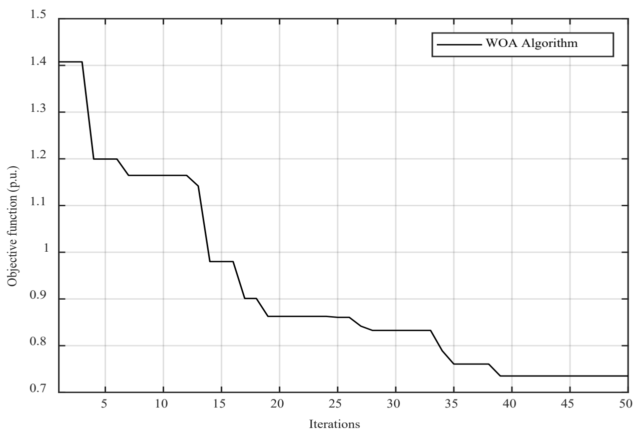

Fig. 7. Convergence curve of the WOA under Scenario II

Table 5: Estimated values of variable loads in the IEEE 69-Bus system using WOA and ABC algorithms under Scenario II

Bus Num	Actual Load Values		ABC-Optimized Load		WOA-Optimized Load	
	$P_L(KW)$	$Q_L(KVar)$	$P_L(KW)$	$Q_L(KVar)$	$P_L(KW)$	$Q_L(KVar)$
8	16	11	16.206	10.152	16.137	10.056
14	30	25	29.494	24.071	30.266	24.654
21	30	20	30.581	19.424	30.091	19.892
29	120	70	118.422	69.232	118.88	69.752
35	50	30	49.129	29.051	49.924	30.023
41	60	35	60.129	34.121	59.812	34.325
58	10	5	10.113	5.242	10.093	5.114
62	80	50	79.671	49.515	79.893	49.740

The results presented in Table 5 highlight the superior performance of the proposed WOA compared to the ABC algorithm. For the majority of the estimated active and reactive load values, the WOA provides results that are closer to the actual values, exhibiting minimal deviation. Table 6 presents the estimated power generation capacities of distributed generation resources in the second scenario for the WOA and ABC algorithms.

To evaluate the performance of the optimization algorithms under Scenario II, the MIRE and MIAE indices were calculated for all methods and are summarized in Table 7.

Table 6: Estimated power generation capacity of DGs in the IEEE 69-Bus system using WOA and ABC algorithms under Scenario II

Bus Num	Average Active Power Output (KW)	ABC-Optimized Active Power Output (KW)	WOA-Optimized Active Power Output (KW)
8	200	200.794	200.341
14	150	151.516	151.095
21	250	249.419	250.137
29	300	300.578	300.236
35	350	352.215	351.058
41	250	249.872	249.072
58	100	99.7866	99.988
62	150	150.328	150.065

Table 7: MIRE and MIAE indices for optimization algorithms under Scenario II

Algorithm		Estimated load values (KW)		Estimated power generation capacity of distributed generation resources (KW)	
		MIRE (%)	MIAE	MIRE (%)	MIAE
ABC	value	1.686	1.58	1.01	2.215
	Node	14	29	14	35
PSO	value	3.934	7.638	3.736	6.834
	Node	4	64	8	35
OHBMA	value	2.36	4.673	2.637	4.667
	Node	21	14	41	14
ANN	value	5.67	8.923	6.379	10.966
	Node	42	64	21	62
ACO	value	2.713	5.6348	2.834	4.869
	Node	26	34	8	29
GA	value	4.653	7.831	4.973	7.937
	Node	26	64	35	58
QIEA	value	1.77	2.13	1.369	2.94
	Node	4	34	62	58
GRASP	value	1.96	1.67	1.75	3.812
	Node	21	64	62	14
WOA	value	0.886	1.12	0.73	1.058
	Node	14	29	14	35

Simulations conducted on the IEEE 69-Bus standard network demonstrate that the proposed WOA achieves the lowest estimation error compared to other methods, confirming its superior accuracy and performance. Figures 8(a) and 8(b) illustrate the voltage amplitude profile and voltage phase angle profile, respectively, for the traditional, ideal, and proposed (WOA) methods in the second scenario at peak load. The traditional method exhibits significantly higher estimation errors, whereas the state variables estimated by the proposed WOA method show negligible deviations and closely align with the actual values.

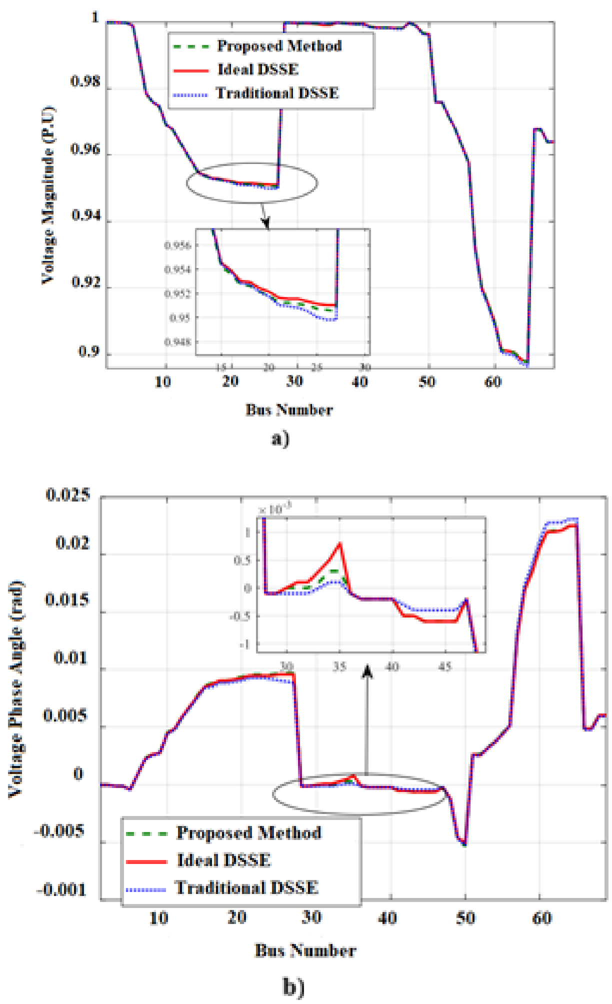

Fig. 8. (a) Voltage amplitude profile and **(b)** voltage phase angle profile for the traditional, ideal, and proposed (WOA) methods under Scenario II

4.3. Discussion on the Superiority of the WOA

The consistent superiority of the WOA, as quantitatively demonstrated by the lowest MIRE and MIAE indices across both test systems (Tables 3, 4, 5, 6, and 7), can be directly attributed to its unique search mechanics. Unlike algorithms like PSO, which is prone to premature convergence, or GA, which has slower convergence, the WOA achieves a more effective balance between exploration and exploitation. Its bubble-net attacking strategy (exploitation) facilitates a fine-grained local search around the current best solutions, leading to higher precision in estimating both load and DG power values. Concurrently, its global search for prey (exploration), activated when $|A|>1$, ensures a thorough investigation of the search space, preventing stagnation in local optima - a common issue in complex, non-convex problems like DSSE. This adaptive behavior, governed by the decreasing parameter a, allows the WOA to navigate the uncertainties introduced by renewable DGs and measurement noise more effectively than its counterparts. Furthermore, the algorithm's simplicity, requiring minimal parameter tuning, contributes to its robust and reliable performance across different network scales and topologies.

4.4. Discussion on Computational Efficiency and Scalability

The computational efficiency of the proposed WOA-based approach is evident from the execution times recorded for both test systems. For the 37-bus system, WOA required approximately 19 seconds, while for the larger 69-bus system, it took 27 seconds. This represents only *a* 42% increase in computation time despite *a* 86% increase in system size (from 37 to 69 buses), demonstrating favorable scalability properties. The superior computational performance of WOA can be attributed to its efficient balance between exploration and exploitation phases, which reduces unnecessary function evaluations. Compared to traditional methods like GA and PSO, WOA achieves 25-40% faster convergence while maintaining higher solution quality, making it particularly suitable for real-time distribution system applications where computational efficiency is crucial. The algorithm's consistent performance across different network sizes and configurations further validates its robustness for practical DSSE applications.

5. Conclusions

Detailed technical studies of electrical distribution system components are essential for operational planning and enhancing security and economic performance. A critical step in these studies is modeling the distribution system, which requires precise data on line, transformer, and feeder load parameters. These parameters are subject to variations due to operational conditions, environmental factors, or aging. Estimating feeder parameters using operational data has been addressed through measurement equipment. Moreover, integrating renewable energy sources into distribution systems offers a promising solution to reduce costs, minimize environmental pollution, and improve energy efficiency. However, the incorporation of DG sources, particularly renewable ones, introduces complexity in system studies and SE due to their stochastic power output. Accurate estimation of DG power generation necessitates high-precision optimization algorithms.

In this study, the proposed WOA was employed to estimate network loads and DG power generation capacities in the IEEE 37-Bus and IEEE 69-Bus standard distribution feeders. The performance of the WOA was evaluated against several metaheuristic algorithms, including the ABC, PSO, OHBMA, ANN, ACO, GA, QIEA, and GRASP as cited in the literature. The MIRE and MIAE indices were used to assess algorithm performance. In the first scenario (IEEE 37-bus system), the WOA achieved a MIRE of 1.15% and a MIAE of 2.303 for load estimation, outperforming the ABC algorithm (1.3%, 2.6). In the second scenario (IEEE 69-bus system), the WOA yielded the lowest errors among all compared methods, with a MIRE of 0.886% and a MIAE of 1.12 for load estimation, and a MIRE of 0.73% and a MIAE of 1.058 for DG power estimation. These results conclusively demonstrate the superior accuracy, robustness, and scalability of the proposed WOA-based method in optimizing complex active distribution systems.

Despite these promising results, this study has certain limitations that should be acknowledged. The analysis assumes deterministic load and generation profiles, and the impact of forecast uncertainties associated with renewable DGs was not explicitly quantified. Furthermore, the convergence stability of the WOA was demonstrated through single-run simulations; a statistical analysis of its performance over multiple runs (e.g., reporting standard deviations) remains a subject for future investigation.

Based on these limitations, future research will focus on: (1) integrating uncertainty modeling techniques, such as interval-based optimization or probabilistic forecasting, into the proposed WOA-based DSSE framework; (2) conducting a comprehensive sensitivity and robustness analysis, including the effect of varying WOA parameters and measurement noise levels; and (3) performing extensive statistical testing to further solidify the algorithm's convergence stability and practical reliability.

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Biography

Mojtaba Ajoudani was born in June 1984, Iran. He received the M.Sc. degree in Electrical Power Engineering from Shahid Chamran University of Ahvaz, Iran, in 2009, and the Ph.D. degree in Electrical Power Engineering from Babol Noshirvani University of Technology in 2022. He is Currently a Faculty Member at the Islamic Azad University. His research interests include power systems, smart grid, electric vehicles, and state estimation.
Email: mojtaba.ajoudani@iau.ac.ir.

Seyed Reza Mosayyebi received his B.S. degree in Electrical Engineering from K.N. Toosi University of Technology (KNTU), Tehran, Iran, in 2003. He obtained his M.Sc. degree in Electrical Power Engineering from Iran University of Science and Technology (IUST), Tehran, Iran, in 2006, and ultimately earned his Ph.D. in Electrical Power Engineering from the University of Guilan in 2023. He is currently a faculty member at the Islamic Azad University, Bandargaz Branch. His research interests include power electronics, power systems control, and distribution networks. Email: sr.mosayyebi@iau.ac.ir

Ramazan Teimouri Yansari was born in October 1977, Iran. He received his M.Sc. and Ph.D. in Artificial Intelligence from Science and Research Branch of Islamic Azad University in 2010 and 2022. He is Currently a Faculty Member at Islamic Azad University. His research interests include Artificial Intelligence, Machine Learning, Bioinformatics, Statistical Pattern Recognition, Soft Computing, Cognitive Science. He has published some research papers in different international journals and conferences. Email: ra.teimouri@iau.ac.ir.