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A Smart Hybrid Optimization Model for DSSE in Renewable Energy-Powered Distribution Networks

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Abstract

Accurate Distribution System State Estimation (DSSE) is essential for the reliable and efficient operation of modern power distribution networks, especially with the increasing penetration of renewable energy sources (RES) such as solar photovoltaics (PV) and wind energy. However, the nonlinearities, unbalanced loads, bidirectional power flows, and incomplete measurements in these networks present significant challenges. The integration of distribut-ed generation (DG) units further complicates traditional DSSE methods, requiring advanced optimization tech-niques to enhance estimation accuracy. This paper introduces a novel hybrid optimization algorithm that combines Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Egyptian Stray Dog Optimization (ESDO) to tackle these challenges in DSSE systems with high renewable energy integration. The hybrid PSO-GA-ESDO algo-rithm leverages the global search capabilities of PSO, the evolutionary principles of GA, and the adaptive social behavior of ESDO, ensuring robust optimization with faster convergence and higher accuracy. The proposed methodology is implemented on the IEEE 13-bus system using MATLAB simulations, focusing on minimizing dis-crepancies between measured and estimated state variables while accounting for the variability of distributed re-newable generation. Simulation results demonstrate that the hybrid PSO-GA-ESDO algorithm outperforms conven-tional optimization methods in terms of estimation accuracy, convergence speed, and robustness to noisy and in-complete measurements, even in scenarios with high renewable energy penetration. These findings highlight the proposed approach as an effective and scalable solution for DSSE in unbalanced, DG-integrated distribution net-works, enhancing grid reliability, stability, and efficient real-time monitoring in modern smart and sustainable en-ergy systems.

Index-words: *Distribution System State Estimation (DSSE), Metaheuristic, Egyptian Stray Dog Optimization (ESDO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), IEEE 13-bus system, MATLAB simulations.*

I. Introduction

The rapid integration of renewable energy sources (RES), particularly distributed generation (DG) such as solar photovoltaics (PV) and wind energy, has significantly transformed the operational dynamics of modern power distribution networks [1]. Unlike traditional power systems, where energy flows unidirectionally from centralized generation units to end consumers, DG-integrated smart grids introduce bidirectional power flows, increased voltage fluctuations, and greater operational uncertainties [2]. These challenges necessitate real-time monitoring, accurate power flow estimation, and efficient state estimation to ensure the stability and reliability of the power distribution system [3]. State estimation in power networks is a mathematical process that determines the most likely system state—voltage magnitudes, angles, and power flows—by processing available measurements [4]. In transmission networks, state estimation is well-established, supported by high measurement redundancy and a single-phase balanced assumption. However, distribution system state estimation (DSSE) presents unique challenges due to radial topology, untransposed feeders, unbalanced loads, and limited real-time measurement availability [5,6]. The limited observability of distribution networks, exacerbated by the increasing penetration of renewable energy-based DG, requires the incorporation of pseudo-measurements derived from historical data, load forecasting, and smart metering [7]. The basic idea of the DSSE is shown below in Figure 1.

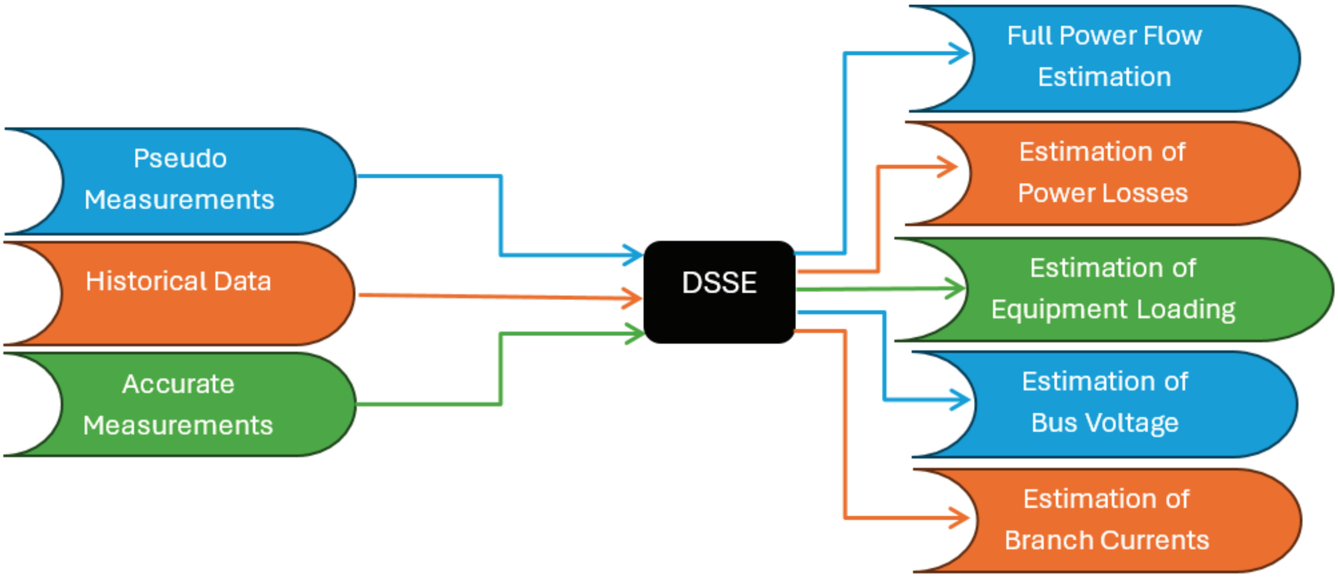

Figure 1: The block diagram of the DSSE system.

Traditional DSSE techniques are predominantly based on Weighted Least Squares (WLS) estimation, which aims to minimize estimation errors using available measurements [8]. However, WLS-based DSSE faces serious limitations in low-measurement conditions, requiring alternative estimation techniques such as Kalman filters, Bayesian methods, and compressed sensing-based approaches [9,10]. Kalman filtering techniques have been employed to improve dynamic state estimation, leveraging real-time updates, whereas Bayesian estimation incorporates probabilistic models to enhance uncertainty handling [11]. Other conventional techniques include branch-current-based and node-voltage-based formulations, offering different state variable representations [12]. Despite these advancements, traditional methods often struggle with computational complexity and scalability in large-scale renewable-rich distribution networks [13].

With the increasing complexity of modern distribution networks, artificial intelligence (AI) and machine learning (ML)-based DSSE techniques have been proposed to improve estimation accuracy and computational efficiency [14] [34]. Artificial Neural Networks (ANNs) have demonstrated strong generalization capabilities, leveraging historical measurements and pseudo-measurements to enhance estimation robustness [15] [37,38]. Physics-aware neural networks, which integrate power system constraints into learning-based estimation models, have shown improved accuracy compared to WLS estimators [16]. Hybrid approaches that combine optimization algorithms with AI techniques have also gained traction. For example, shallow neural networks have been employed to initialize Gauss-Newton optimization methods, significantly reducing convergence time [17].

Furthermore, deep neural networks (DNNs) coupled with hyperparameter optimization have exhibited strong adaptability for DSSE in modern smart grids [18] [35]. Given the limited availability of measurement devices in distribution networks, compressed sensing-based DSSE techniques have been explored to minimize the required number of measurements while maintaining accuracy [19]. Techniques such as $\ell 1$-regularized sparse voltage profile recovery, integrated with micro-phasor measurement units (μPMUs), enable reliable state estimation with fewer sensors [20]. Recent studies have also investigated Gaussian Mixture Models (GMMs) for pseudo-measurement generation, improving DSSE robustness in networks with high photovoltaic (PV) penetration [21].

Hybrid optimization-based DSSE approaches have been developed to address the nonlinear and computational challenges of traditional methods. Metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and hybrid PSO-GA techniques have demonstrated superior convergence properties and improved estimation accuracy [22]. For instance, PSO has been effectively used to estimate distributed generation and load power injections, ensuring better convergence and robustness [23]. Additionally, multi-stage estimation techniques incorporating pseudo-measurement generation from energy billing data have been explored to enhance DSSE under low-observability conditions [24]. A recent study introduced a Linearized AC Optimal Power Flow (LAOPF)-based DSSE model, which significantly reduces computational requirements while improving estimation accuracy in low-measurement environments [25].

To address these challenges, this paper presents a hybrid algorithm of particle swarm optimization, genetic Algorithm, and Egyptian stray dogs optimization (PSO-GA-ESDO) framework for solving the DSSE problem in renewable-rich distribution networks. The primary contributions of this research are as follows:

- Development of a hybrid PSO-GA-ESDO algorithm for improved DSSE accuracy, stability, and computational efficiency.
- Integration of pseudo-measurements for distributed generation units, ensuring reliable real-time state estimation.
- Application of metaheuristic-based optimization techniques to enhance DSSE in renewable-dominated unbalanced distribution systems.

The rest of this paper is structured as follows: Section 2 presents the mathematical modeling of the DSSE problem. The proposed hybrid optimization algorithm is described in Section 3, followed by case studies and validation results in Section 4. Finally, Section 5 concludes the study and discusses potential future research directions.

II. The mathematical modelling of the DSSE problem

State estimation in distribution networks (DNs) is a critical process for determining the operational state of the system, including voltages, currents, and power flows. This ensures effective monitoring, control, and optimization of the network. The DSSE problem is framed as a nonlinear optimization task, combining real-time measurements, pseudo-measurements, and physical constraints to accurately estimate the system state. To achieve this, the backward/forward sweep method is employed for power flow calculations, leveraging its suitability for radial and unbalanced distribution systems.

The objective of DSSE is to minimize the estimation error between measured and calculated variables throughout the network. Mathematically, this can be expressed as:

$$f(x,y) = \sum_{i=1}^{m} |z_i - h_i(x,y)| \tag{1}$$

Where, $f(x,y)$ is the total error, z_i represents the measured value of the i-th variable, $h_i(x,y)$ is a nonlinear function that maps the control variables x and dependent variables y to the corresponding measurement and m denotes the total number of measurements.

The control variables x include active and reactive power from loads and distributed generation (DG) units, while y comprises dependent variables such as voltages and power flows.

The optimization process is constrained by power flow equations, which connect the control and dependent variables while maintaining consistency with the physical characteristics of the network. The active power(P_i) at bus i is calculated using:

$$P_i = \sum_{j \in neighbors} V_i V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right) \tag{2}$$

Similarly, the reactive power (Q_i) at bus i is given by:

$$Q_i = \sum_{j \in neighbors} V_i V_j \left(G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}\right) \tag{3}$$

Where V_i and V_j are the voltage magnitudes at buses i and j, G_{ij} and B_{ij} are the conductance and susceptance of the line connecting them. θ_{ij} is the voltage angle difference.

These equations ensure that the active and reactive power flows are consistent with the network's physical constraints. Operational constraints are imposed to ensure safety and reliability. These include voltage limits at the buses:

$$V_{min} \le V_i \le V_{max} \tag{4}$$

Where, V_i is the voltage magnitude at bus i, V_{min} and V_{max} are the minimum and maximum allowable voltage at any bus. As well as limits on the branch power flows:

$$S_{min} \le S_i \le S_{max} \tag{5}$$

Where, S_i is the Apparent power flow through branch i, S_{min} and S_{max} are the minimum and maximum allowable apparent power flow through bus i. As well as limits on the branch power flows:

Control variables, such as active power from loads and DG units, are also bounded. For loads, the bounds are defined as:

$$P_{min,L} = P_{L,forcasted}\left(1 - \frac{e_{pm}}{100}\right) \quad (6)$$

Similarly, for DG units:

$$P_{max,L} = P_{L,forcasted}\left(1 + \frac{e_{pm}}{100}\right) \quad (7)$$

Where, $P_{min,L}$ & $P_{max,L}$ are the minimum & maximum active power limit for the load or DG unit, $P_{L,forcasted}$ is the forecasted active power for the load or DG unit, e_{pm} is the percentage margin of error in the forecast.

The backward/forward sweep method is used to solve the DSSE problem through iterative power flow calculations. During the backward sweep, branch currents are calculated, starting at the farthest buses and moving toward the source, using the equation:

$$J^{(k)}_{abc,i} = I^{(k)}_{Labc,i} + I^{(k)}_{Cabc,i} + \left(Y_{oabc,i} \cdot V^{(k-1)}_{abc,i}\right) + \sum_{l\in\alpha_i, l\neq i} J^{(k)}_{abc,l} \quad (8)$$

Where, $J^{(k)}_{abc,i}$ is the current phasor at branch i, $I^{(k)}_{Labc,i}$ and $I^{(k)}_{Cabc,i}$ are load and capacitor currents, and $Y_{oabc,i}$ is the shunt admittance. During the forward sweep, starting from the source bus, voltages are updated as:

$$V^{(k)}_{abc,i} = V^{(k)}_{abc,m} - \left(Z_{abc,i} \cdot J^{(k)}_{abc,i}\right) \quad (9)$$

Where, $V^{(k)}_{abc,i}$ is the voltage at the sending bus while $V^{(k)}_{abc,m}$ is the voltage at the receiving bus, and $Z_{abc,i}$ is the impedance of branch i.

The iterations continue until the voltage mismatch satisfies:

$$max\left|V^{(k)}_{abc,i} - V^{(k-1)}_{abc,i}\right| \leq \varepsilon_V \quad (10)$$

Real-time measurements and pseudo-measurements are integral to the DSSE process. Real-time measurements include voltages, currents, and power flows, and are simulated with noise using:

$$M_{rt} = M_0\left(1 + \frac{e_{rt}}{100}\right) \quad (11)$$

Pseudo-measurements M_{rt} are derived from historical data M_0 with added noise e_{rt}, bounded as shown in equations for load and DG limits. The accuracy of the DSSE can be evaluated using the Mean Absolute Percentage Error (MAPE), given by:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{z_i - h_i(x,y)}{z_i}\right| \quad (12)$$

Where, n is the number of measurements, z_i is the measured value, and $h_i(x,y)$ is the estimated value. This comprehensive approach ensures that the state estimation aligns with the physical constraints and measurements of the network, providing an accurate representation of its operational state.

III. The proposed hybrid optimization algorithm for solving the DSSE problem

In the quest to address the challenges of DSSE, a novel hybrid optimization algorithm has been developed by combining the strengths of Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Egyptian Stray Dog Optimization (ESDO). The integration of these algorithms ensures that the limitations of one method are compensated by the strengths of the others, achieving faster convergence, higher solution accuracy, and robustness against local optima. Below, the evolution of the hybrid Algorithm is outlined, starting from the individual contributions of each optimization method to the eventual fusion into a unified hybrid framework.

A. Particle Swarm Optimization (PSO)

Inspired by the collective behavior of bird flocks or fish schools, PSO begins by simulating a group of particles that represent candidate solutions in the search space. As shown in Figure 2, each particle adjusts its position iteratively by considering two key factors: its own best-found position (personal best) and the best position found by the entire swarm (global best) [26-28].

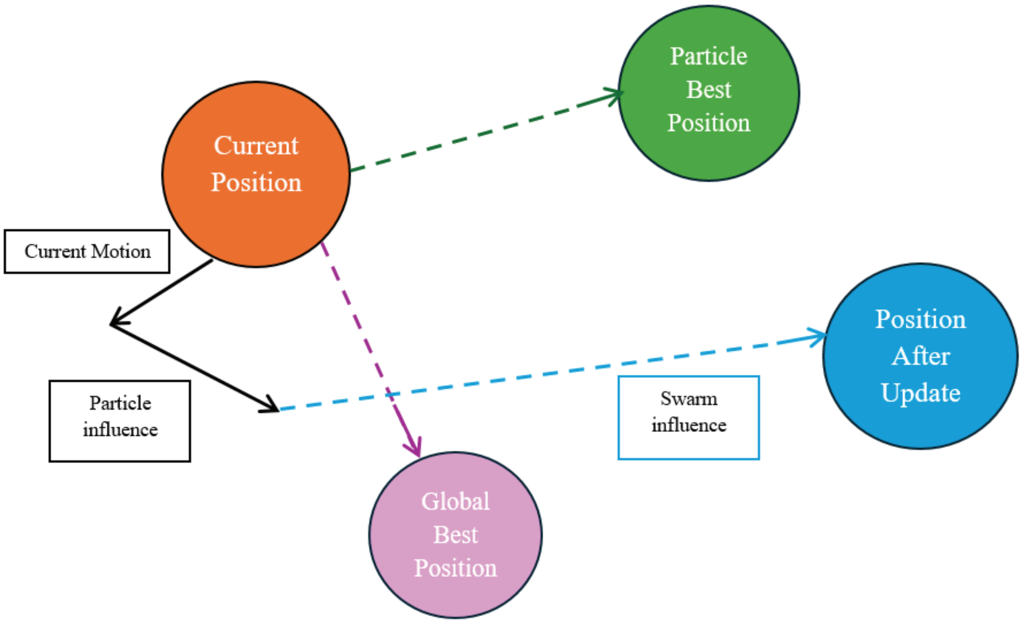

Figure 2: The main concept of the PSO algorithm.

This collaborative behavior allows the swarm to converge quickly toward promising regions of the search space. The movement of each particle is governed by two critical equations:

1. The first equation is used to update the velocity of each particle based on the inertia of its current movement, the attraction toward its personal best position, and the attraction toward the swarm's global best position as per (13):

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 (p_i - x_i^{(t)}) + c_2 r_2 (g - x_i^{(t)}) \quad (13)$$

Where, $v_i^{(t)}$ is the particle's velocity, $x_i^{(t)}$ is the current position (solution) of the i-th particle, p_i is the particle's personal best position, g is the swarm's global best position, c_1 is the cognitive coefficient, and c_2 is the social coefficient.

r_1 and r_2 are random coefficients.

2. The second equation updates the particle's position based on its newly computed velocity:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (14)$$

Where, $x_i^{(t)}$ is the current position of the particle i, $x_i^{(t+1)}$ is the updated position of particle i at iteration t+1, and $v_i^{(t+1)}$ is the updated velocity. This equation ensures that each particle moves toward a better solution, influenced by both its own past experience and the guidance of the global best solution found by the swarm. The inertia weight (ω) plays a crucial role in balancing exploration (searching new areas in the solution space) and exploitation (refining known good solutions). A higher ω value encourages broader exploration, while a lower ω value focuses on convergence toward promising regions. To improve convergence speed and prevent premature stagnation, PSO often employs adaptive techniques such as linearly decreasing inertia weight or velocity clamping to control excessive movement. Additionally, constriction factors are sometimes introduced to stabilize particle trajectories, ensuring that the swarm does not oscillate indefinitely around an optimal solution.

PSO has been widely applied in optimization problems due to its simplicity, robustness, and ability to escape local minima. However, standard PSO can struggle with premature convergence, especially in high-dimensional or multimodal optimization landscapes.

B. *Genetic Algorithm (GA)*

Unlike PSO, which focuses on swarm behavior, GA mimics natural evolution by working on a population of candidate solutions. As shown in Figure 3, the Algorithm evolves this population over generations using three main processes: selection, crossover, and mutation [29-31].

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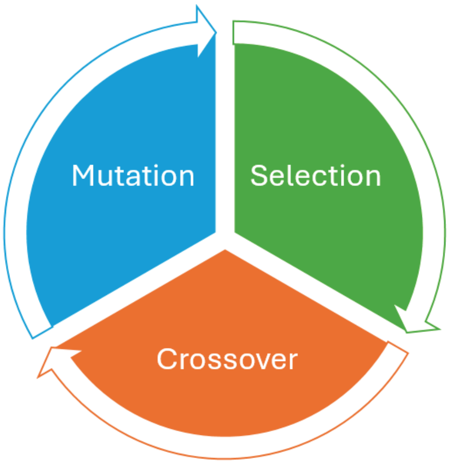

Figure 3: The main steps of the GA.

During the selection process, individuals within each generation that have better fitness are given a higher chance to reproduce. For example, tournament selection compares pairs of candidates and selects the one with the better fitness:

$$Parent = \arg\min \{f(x_{ind1}), f(x_{ind2})\} \quad (15)$$

Where, $Parent$ is the selected individual that will be used in the next generation, $arg\ min$ is a mathematical operator that returns the argument (the input value) at which a given function attains its minimum. f(x_{ind1}), f(x_{ind2}) are the fitness values (or objective function values) of two individuals, x_{ind1} and x_{ind2}, randomly selected from the population. The equation chooses the individual with the low fitness value, meaning that :

- If f(x_{ind1}) < f(x_{ind2}) then Parent = x_{ind1}) .
- Otherwise, Parent = x_{ind2}.

After this step, the crossover process starts by combining the genetic material of the selected parents to create offspring. Single-point crossover exchanges portions of two parent solutions:

$$x_{offspring} = \propto x_{parent1} + (1-\propto) x_{parent2} \quad (16)$$

Where, $\propto$ is a random weighting factor (sometimes called the crossover rate or mixing coefficient). $x_{parent1}$ & $x_{parent2}$ are the two parent solutions & $x_{offspring}$ is the newly generated offspring (solution). Finally, the mutation step starts by maintaining the diversity and avoiding local optima through introducing random variations:

$$x_{mutated} = x + \Delta x \quad (17)$$

Here, Δx is a random perturbation applied to the solution. Through these processes, GA ensures that the population evolves toward optimal solutions. However, the stochastic nature of GA can sometimes lead to slow convergence, making it ideal to integrate with faster methods like PSO.

C. *Egyptian Stray Dog Optimization (ESDO)*

In microgrid energy management, Diab and Abdelsalam initially presented the ESDO algorithm. In dynamic environments, its defensive and territorial behaviors outperformed traditional metaheuristics [32]. ElMessmary, Diab, Abdelsalam, and Moussa later compared ESDO to other metaheuristic approaches for solving multi-objective optimal power flow in transmission networks [33]. Nevertheless, DSSE in distributed, unbalanced generating systems was not covered in either work. This technique is inspired by six behaviors of stray dogs, according to Figure 4. The most important behaviors are the defensive and territorial, which enable both exploration of new territories and exploitation of the most promising areas. This Algorithm introduces a unique balance between randomness and guided search.

This Algorithm has two main behaviors:

1. Territorial behavior in which the dogs explore their territory by introducing small random perturbations to their positions:

$$x_i^{new} = x_i^{current} + \delta \quad (18)$$

Where, δ represents a random vector.

2. Defensive behavior, which exploits the best-known solution, dogs adjust their positions toward the alpha dog's (global best) position:

$$x_i^{new} = x_i^{current} + \beta(g - x_i^{current}) \quad (19)$$

Where, β controls the step size and g is the alpha dog's position.

ESDO also ensures adaptability by updating the alpha dog (best solution) regularly, combining exploration and exploitation efficiently. Its adaptive behavior makes it robust, but it benefits from hybridization with methods like PSO and GA for further refinement.

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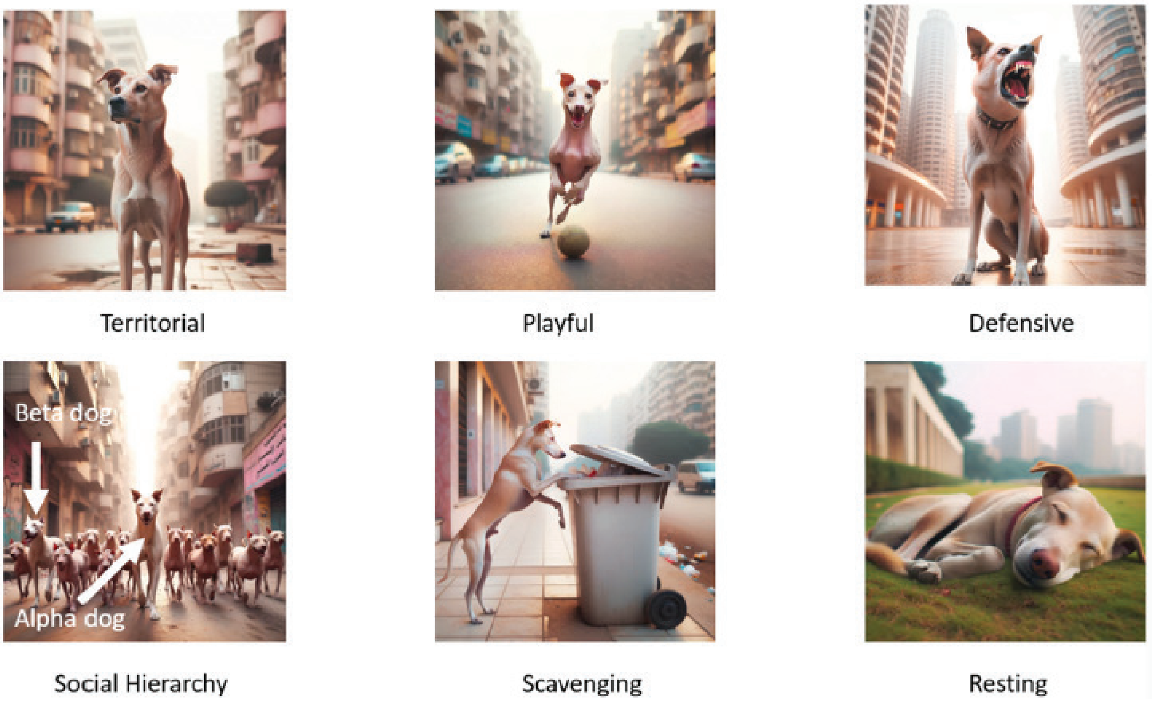

Figure 4: The ESDO main processes [32].

D. *Hybrid PSO-GA-ESDO Algorithm*

Building on fundamental work in [32,33], this paper introduces a novel sequential hybridization of PSO, GA, and ESDO specifically designed for DSSE challenges. Unlike previous implementations, our approach features: (1) phased solution refinement (PSO→GA→ESDO), (2) DSSE-optimized solution pooling, and (3) integrated pseudo-measurement handling - representing significant algorithmic innovations beyond prior combinations of these techniques.

The Algorithm starts with the initialization of the PSO particles, GA chromosomes, and ESDO dogs across the search space. Then the fitness of each candidate solution is evaluated using the objective function mentioned above in (1). The optimization process starts directly after the initialization process; this process is divided into three phases:

1. The first phase is the PSO phase in which the particle velocities and positions are updated according to (13) and (14). This is done to identify the global best solution.

2. The second phase is the GA phase which uses the best solutions produced from the PSO algorithm and converts them to agents where their population have evolved using the crossover and mutation as per (15), (16) and (17).

3. The third and final phase in the optimization process is the ESDO phase, in which the agent positions are adjusted based on the territorial and defensive behaviors according to (18) and (19).

After the evaluation of the optimization process, the following step is the solution pooling in which the best solutions from the PSO, GA and ESDO are combined into a unified pool. Then the top solutions are retained for the next iteration. The final process is the convergence check by either repeating the hybrid process until the improvements in fitness falls below a predefined threshold or the maximum number of iterations is reached. Figure 5 shows the flowchart of the proposed Algorithm.

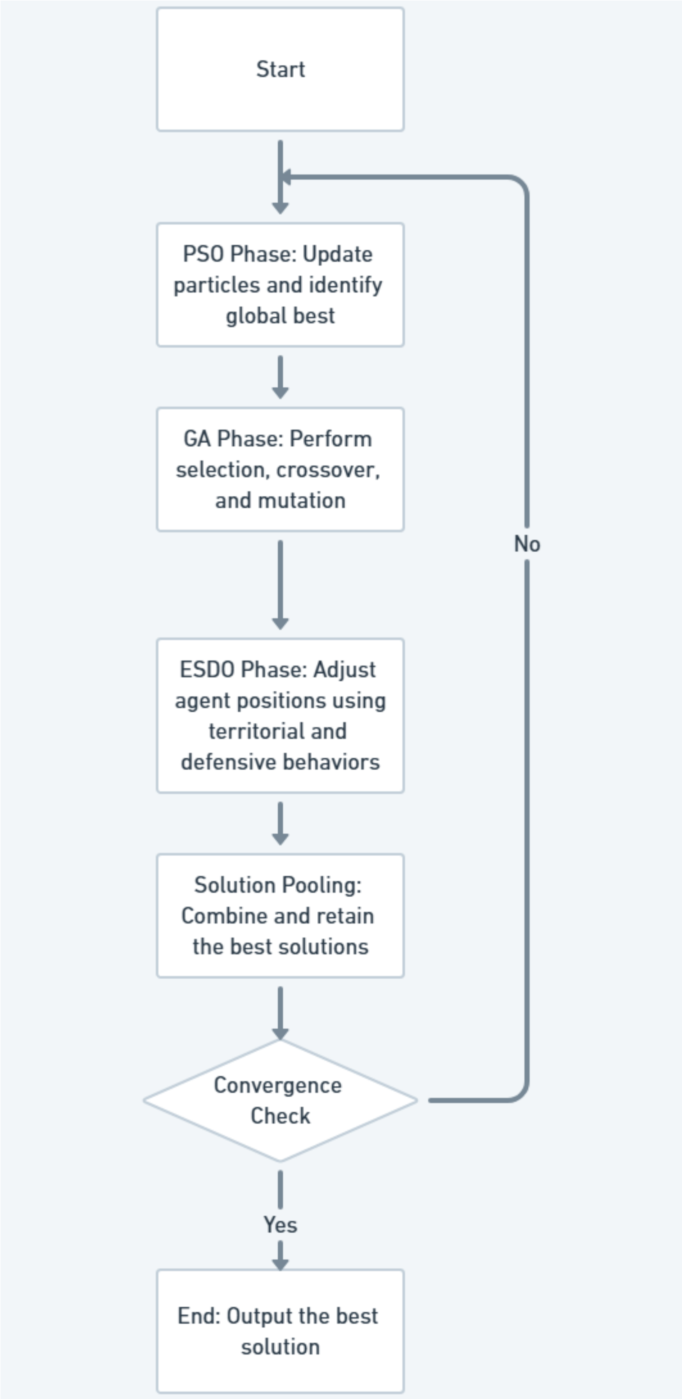

Figure 5: The flowchart of the proposed Algorithm.

As far as we are aware, this study presents the first hybrid optimization framework that sequentially integrates PSO, GA, and ESDO to address DSSE challenges in renewable-integrated distribution networks. Unlike other hybridizations that combine two techniques or apply them in parallel, our method adopts a phased structure (PSO → GA → ESDO), where each Algorithm addresses specific optimization roles: PSO accelerates early convergence, GA improves population diversity, and ESDO fine-tunes via adaptive social behavior. Additionally, this is the first time that ESDO has been implemented in a hybrid structure for any DSSE-related problem. Additionally, the Algorithm incorporates a solution pooling mechanism and DSSE-specific enhancements like pseudo-measurement integration, multi-branch error minimization, and robustness to noisy and incomplete data. Table 1 shows the main parameters for the Algorithm and their values.

Table 1: Optimization Algorithm Parameters

Algorithm	Parameter	Value/Range	Justification
PSO	Inertia weight (ω)	0.4-0.9 (linear decay)	Balances exploration-exploitation
	Cognitive Coeff. (c_1)	1.5	Standard literature value
	Social Coeff. (c_2)	1.5	Matches cognitive influence
GA	Crossover rate	0.85	Maintains population diversity
	Mutation rate	0.05	Prevents premature convergence
ESDO	Territorial Step. (β)	±0.1×(max-min)	Local search range

IV. Test cases and results

The proposed hybrid PSO-GA-ESDO algorithm was tested on the IEEE 13-bus test system to solve the DSSE problem. As shown in Figure 6, this system consists of 13 buses, 12 branches, and a mix of different load types, with various system constraints such as voltage limits, branch power flow bounds, and control variable restrictions. The test system's structure and operational characteristics make it a suitable benchmark for evaluating the performance of optimization techniques for DSSE tasks.

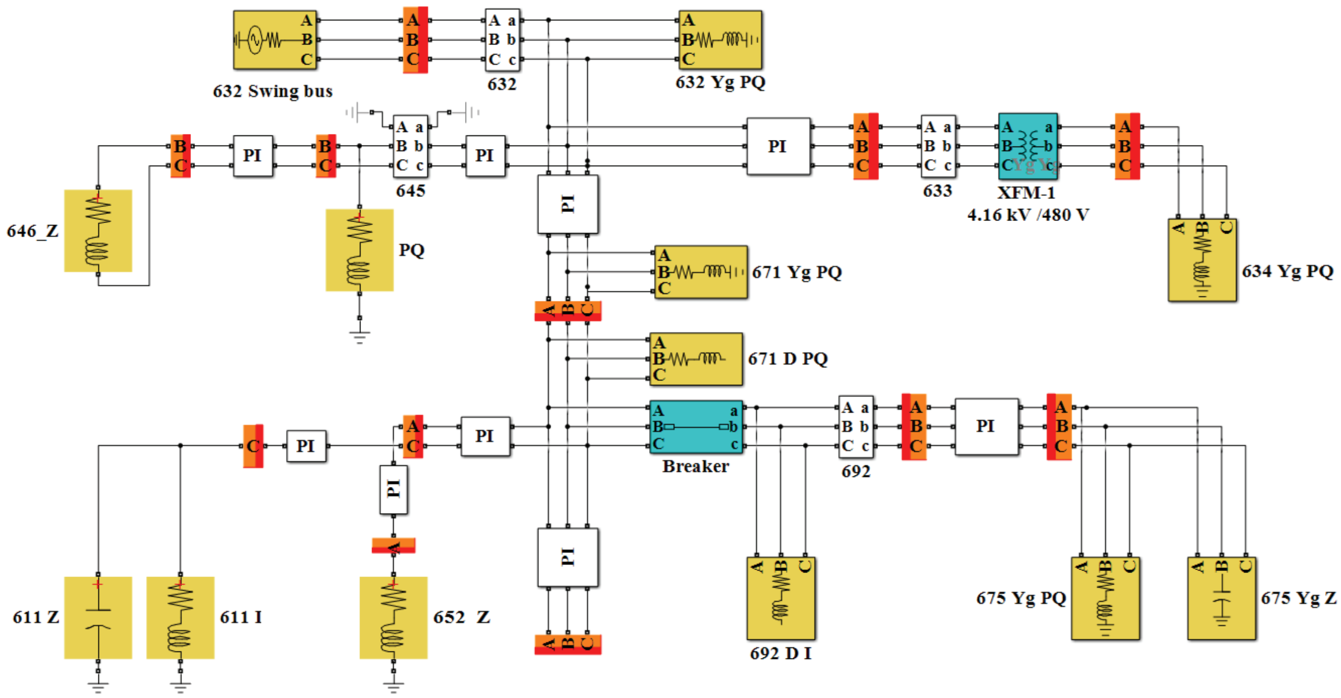

Figure 6: The diagram of the IEEE 13 bus system.

The IEEE 13 Bus System, a standardized test case used to model and analyze electrical distribution networks, is depicted in the figure in a simplified form. Bus 632, also known as the swing bus or slack bus, is at the top of the hierarchy and acts as the system's voltage and angle reference. Numerous PQ buses (such as "632 Yg PQ") are connected to it, signifying steady active (P) and reactive (Q) power loads. A wye-grounded connection, denoted by the notation "Yg," is frequently employed in distribution systems to manage unbalanced loads. Because power flows unidirectionally from the swing bus downstream to the loads in real-world distribution networks, these buses are connected in a radial (tree-like) topology.

The transformer (XFM-1), which connects the higher-voltage segment (like Bus 632) to lower-voltage loads (like Bus 614), is a crucial part of the system. It steps down the voltage from 4.16 kV to 480 V. Studying voltage regulation at various voltage levels is made possible by this transformer. The "Z"-designated buses (611 Z, 652 Z, etc.) model the resistance and reactance of distribution lines by representing line segments with inherent impedance.

In the meantime, buses marked "D I" (such as 622 D I and 672 D I) probably indicate delta-connected current injections, which might stand for specialized machinery or industrial loads. Additionally, the figure contains placeholder labels such as "P1" and "PQ," which in a complete dataset would provide precise load values in kW or kVAR. The IEEE 13 Bus System, which has radial power flow, mixed voltage levels, and unbalanced loads, is intended to resemble actual distribution networks. It is frequently employed in fault studies, load flow analysis, and the integration of dispersed energy resources (such as storage or solar panels). Voltage labels, standardized symbols for loads and generators, and a legend elucidating notations such as "Yg" or "D I" could all be added to the figure to improve clarity. It is advised to consult the complete IEEE 13-bus documentation for in-depth research, as it contains line parameters, precise load values, and capacitor banks. This system offers a strong framework for comparing theoretical models to actual distribution network behavior.

This study tests the performance of the hybrid PSO-GA-ESDO algorithm for solving the DSSE problem. The optimization was performed for five distinct test cases, each focusing on different aspects of the state estimation. For each case, we applied the Particle Swarm Optimization (PSO) algorithm, the Genetic Algorithm (GA), the Egyptian Stray Dog Optimization (ESDO) algorithm, and the hybrid PSO-GA-ESDO algorithm, which integrates the strengths of all three techniques. The aim was to compare their performance in terms of solution accuracy

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and convergence time. The following five test cases were considered to evaluate the performance of each optimization algorithm in solving the DSSE problem. For each case, the algorithms were applied individually first, followed by the hybrid approach to assess improvements in both solution quality and convergence speed.

By integrating the strengths of three optimization techniques, the hybrid algorithm achieves a higher level of precision in estimating the DSSE state compared to standalone methods. The PSO phase ensures rapid initial convergence, while the adaptive mechanisms of ESDO and the diversity-enhancing properties of GA prevent stagnation and refine the search process efficiently. The combination of PSO's global search, GA's stochastic diversity, and ESDO's adaptive mechanisms significantly reduces the risk of getting trapped in local optima.

The inclusion of ESDO ensures that the Algorithm remains flexible and robust even in highly dynamic or complex search landscapes. The hybridization enables a balanced trade-off between exploration (searching new areas) and exploitation (refining existing solutions), leading to a more comprehensive search of the solution space. The modular design of the hybrid Algorithm allows it to scale effectively for larger and more complex DSSE problems. By combining these advantages, the proposed hybrid PSO-GA-ESDO algorithm emerges as a powerful tool for solving DSSE problems, providing a compelling balance between computational efficiency and solution accuracy.

Five different test cases, each of them focused on a different facet of the DSSE problem under various operating conditions were developed in order to assess the efficacy of the suggested PSO-GA-ESDO algorithm. An overview of these test cases is given in **Table 2**, which also highlights the primary objective function focus and the associated performance metrics that were used for assessment. This organized synopsis facilitates a better comprehension of the testing process and sets the scene for the in-depth findings that are discussed in the following subsections.

Table 2: Test cases Summary

Test Case	Objective Function Focus	Targeted Evaluation Metrics
Case 1	Minimize active and reactive power errors at the substation	Substation power accuracy, total power loss, MAPE
Case 2	Minimize current magnitude and angle errors at the substation	Current estimation accuracy, power loss, MAPE
Case 3	Case 1 + minimize voltage deviation at Bus 671	Power and voltage accuracy, substation, and Bus 671 voltage profile
Case 4	Minimize power flow errors at multiple branches	System-wide power flow estimation, multi-branch accuracy
Case 5	Case 4 + voltage deviation at key buses	Comprehensive estimation accuracy (power + voltage), system-wide MAPE

A. Test Case 1

The first test case serves as a baseline scenario, where the objective function is formulated to minimize the absolute errors in active and reactive power at the substation (Branch 0-1).

This case ensures that the estimated power flows at the network's point of entry align as closely as possible with the measured values. Since the substation is a critical node in the distribution system, accurate estimation at this location is essential for maintaining the reliability of downstream power flow calculations.

B. Test Case 2

In this test case, the objective function is designed to minimize discrepancies in the magnitude and phase angle of the current at the substation. Accurate current estimation is crucial in scenarios where phasor measurement units (PMUs) or other high-precision current sensors are deployed. By focusing on the current measurements, this case enhances the reliability of the state estimation process in networks with limited voltage measurements.

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C. *Test Case 3*

Building upon Case 1, this test case incorporates an additional constraint by including voltage deviation at a key bus (Bus 671) in the objective function. The inclusion of voltage errors ensures that the estimation process maintains voltage regulation across the network while simultaneously reducing power flow discrepancies. This case is particularly relevant for distribution networks with voltage-dependent loads, where maintaining accurate voltage profiles is as important as ensuring correct power flow estimation.

D. *Test Case 4*

Unlike the previous cases, which focus primarily on the substation or a single bus, Case 4 extends the objective function to multiple branches across the distribution network. Specifically, errors in active and reactive power flows are minimized at three critical branches: the substation branch (0-1), Branch 633-634, and Branch 671-692. By incorporating multiple network locations, this case aims to enhance the overall estimation accuracy and ensure that power flows throughout the system are accurately captured.

E. *Test Case 5*

The final test case represents the most extensive and computationally demanding formulation. The objective function integrates both power flow discrepancies across multiple branches (as in Case 4) and voltage deviations (as in Case 3). This formulation ensures that the state estimation model provides an accurate representation of the system's operational state across both power and voltage domains. While computationally intensive, Case 5 offers the highest potential accuracy, making it suitable for scenarios requiring high-precision DSSE solutions.

F. *Results analysis*

The final test case represents the most extensive and computationally demanding formulation. The objective function integrates both power flow discrepancies across multiple branches (as in Case 4) and voltage deviations (as in Case 3). This formulation ensures that the state estimation model provides an accurate representation of the system's operational state across both power and voltage domains. While computationally intensive, Case 5 offers the highest potential accuracy, making it suitable for scenarios requiring high-precision DSSE solutions.

The proposed hybrid PSO-GA-ESDO optimization algorithm was evaluated across five test cases on the IEEE 13-bus system, focusing on estimation accuracy, convergence performance, and power loss minimization. The results were compared against three standalone optimization techniques: PSO, GA, and ESDO. The performance was assessed based on Ploss, Qloss, and the MAPE%.

In Case 1, which serves as a baseline scenario, the optimization was performed to minimize active and reactive power discrepancies at the substation (branch 0–1). The results in **Table 3** show that ESDO achieves the lowest active and reactive power errors at most buses, while PSO and GA result in higher errors. The hybrid PSO-GA-ESDO algorithm further enhances accuracy, exhibiting minimal error values. The total power loss estimations indicate that the hybrid approach provides a close match to the true power losses, with a Ploss error of 0.3483% and a Qloss error of 0.4988% (**Table 4**). The MAPE% error matrix confirms that the hybrid approach achieves the lowest estimation error of 0.0487%, reinforcing its superior accuracy.

Table 3: Absolute Errors of The Loading Total Power – Case 1

Bus i	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
634	21.8344	15.4574	**1.5672**	4.3962
671	7.1063	9.4979	5.5310	**3.6202**
652	14.3086	7.4604	**1.5256**	21.7629
675	1.2549	**0.5050**	1.4279	0.8852
645	**2.7574**	5.9276	7.2140	4.3863
646	1.7132	3.3458	2.9080	**0.1899**
611	6.2858	2.3460	2.8103	**2.1459**
692	0.7106	**0.2646**	10.2522	4.7148

Table 4: Absolute errors of the total active power losses, total reactive power losses, and the MAPE – Case 1

Parameter	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
Active Power Losses	0.4186	**0.1571**	0.1724	0.3483
Reactive Power Losses	1.2288	1.1684	**0.4755**	0.4988
MAPE	0.1440	0.1054	0.0524	**0.0487**

Although the hybrid PSO-GA-ESDO approach performs better in most buses and has the lowest MAPE (0.0487%), it shows an unusually high error of 21.7629% at Bus 652. The variation in the sensitivity and pseudo-measurement accuracy of some nodes

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with lower observability is the cause of this localized deviation. Some agents may converge suboptimally at buses with higher noise or weaker data support because metaheuristic optimization is stochastic and population-based. Despite this, the hybrid method maintains excellent global performance across the system, including competitive active and reactive power loss estimates, which confirms its robustness in holistic DSSE estimation.

The convergence analysis for Case 1, shown in Figure 7, reveals that the hybrid PSO-GA-ESDO algorithm reaches a low objective function value in 10–20 iterations, demonstrating the fastest and most stable convergence. GA shows slow convergence with large fluctuations, whereas PSO and ESDO take more iterations to stabilize. The hybrid approach converges much faster and exhibits a better balance between computational efficiency and estimation accuracy, despite integrating multiple optimization stages, which could increase per-iteration complexity. Its efficacy over standalone methods is confirmed by its capacity to break out of local minima and sustain consistent improvement.

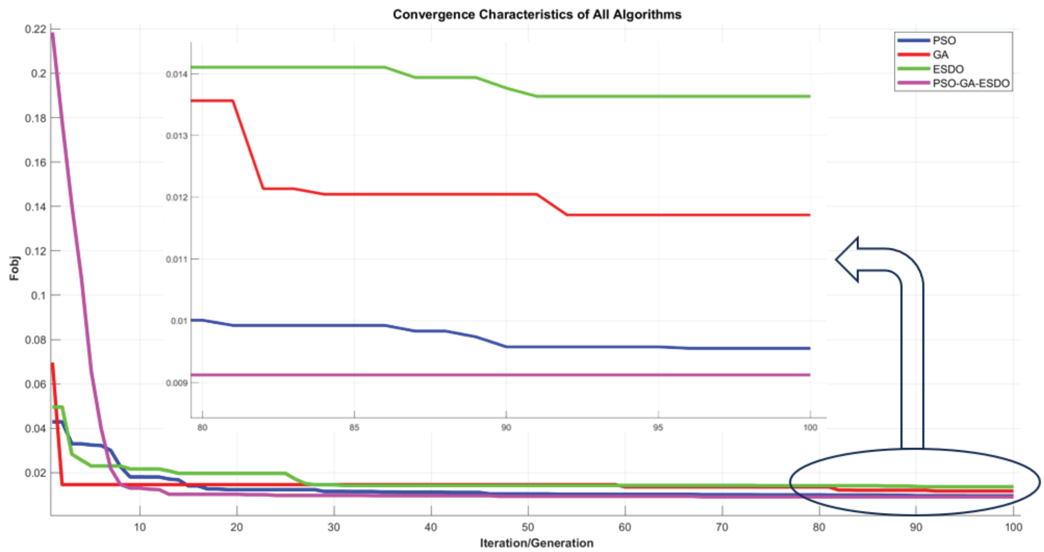

Figure 7: The convergence of different algorithms – case 1.

In Case 2, which aims to minimize current magnitude and angle errors at the substation, the results in **Table 5** indicate that GA outperforms PSO in reducing errors, while ESDO provides better accuracy in some buses. However, PSO-GA-ESDO consistently maintains the lowest overall error across all buses. The total power loss estimation results in **Table 6** confirm that the hybrid approach yields the most accurate power loss values, achieving a Ploss error of 0.5904% and a Qloss error of 0.3425%. The MAPE% results further validate that the hybrid PSO-GA-ESDO method outperforms all individual algorithms, achieving the lowest MAPE% of 0.1101%.

The convergence behavior in Case 2, shown in Figure 8, shows that the hybrid PSO-GA-ESDO algorithm performs better than any other approach by reaching the lowest objective function value in the first 20 iterations and preserving stable convergence. GA quickly stalls at a suboptimal level after making quick initial progress. After thirty iterations, PSO gradually improves but slows down, and ESDO once more converges slowly with underperforming performance. The hybrid approach, with its fewer iterations and quicker convergence to optimal solutions, turns out to be more time-efficient overall, even with its multi-phase design.

Table 5: Absolute Errors of The Loading Total Power – Case 2

Bus i	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
634	13.8798	**6.6031**	21.8541	10.1106
671	9.1845	**3.7098**	15.4918	12.5598
652	12.8660	6.3501	**4.4762**	13.3868
675	16.3969	6.2310	**5.9420**	6.1597
645	16.3969	**3.0606**	22.8280	23.8756
646	16.3969	**0.8215**	14.7727	12.6805
611	7.6921	8.5850	13.3980	**2.1671**
692	0.8480	22.0434	**0.6201**	20.4508

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Table 6: Absolute errors of: the total active power losses, total reactive power losses, and the MAPE – Case 2

Parameter	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
Active Power Losses	1.2320	1.0064	1.3032	**0.5904**
Reactive Power Losses	0.7029	**0.2190**	0.4735	0.3425
MAPE	0.1947	0.1672	0.1909	**0.1101**

When it comes to power loss estimation and MAPE (0.1101%), the hybrid approach performs better than any standalone algorithm in Case 2. A few high local errors are noted, though, especially at Bus 645 (23.8756%) and Bus 692 (20.4508%). These outliers are probably caused by current-based objective functions at nodes with sparse current measurement references being sensitive. Although GA excels at some of these specific buses, the hybrid method's overall system-wide accuracy confirms its efficacy. The steady gains in overall metrics show that the quality of the global estimation is unaffected by these local anomalies.

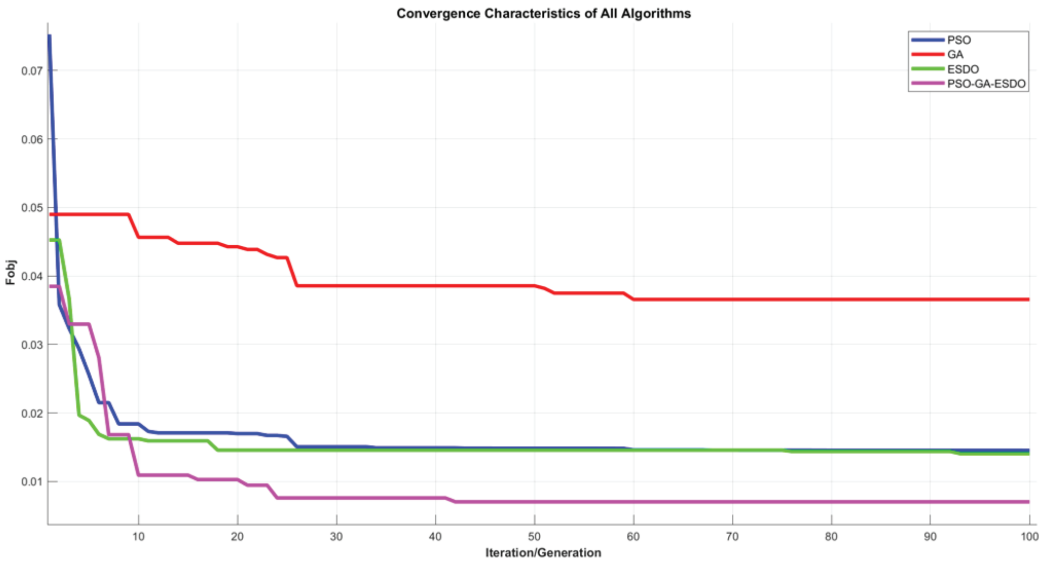

Figure 8: The convergence of different algorithms – case 2.

Case 3 extends Case 1 by incorporating voltage deviation at Bus 671. The results in **Table 7** show that PSO-GA-ESDO provides the most accurate active power estimation, outperforming GA and PSO significantly at key buses such as 652 and 634. The total power loss estimations in **Table 8** confirm that the hybrid approach minimizes discrepancies, reducing the Ploss error to 0.9284% and the Qloss error to 0.7365%. The MAPE% shows that the hybrid approach provides the lowest overall estimation error of 0.0368%, reinforcing its advantage over standalone optimization methods.

Table 7: Absolute Errors of The Loading Total Power – Case 3

Bus i	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
634	16.7394	3.3898	**0.1683**	2.3003
671	5.6252	1.7336	5.6102	**0.2164**
652	19.2739	13.1878	40.2555	**9.6901**
675	5.6252	5.0129	5.3836	**2.3003**
645	5.6252	3.1791	5.1997	**2.3003**
646	2.5669	4.7239	15.9997	**2.3003**
611	5.6232	1.3366	14.4334	**2.3003**
692	5.6252	2.6167	2.4647	**2.3003**

Table 8: Absolute errors of: the total active power losses, total reactive power losses, and the MAPE – Case 3

Parameter	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
Active Power Losses	1.1150	1.3138	**0.8512**	0.9284
Reactive Power Losses	1.9106	0.9206	**0.4167**	0.7365
MAPE	0.1479	0.0731	0.1291	**0.0368**

Although the hybrid approach still yields the lowest system-wide MAPE (0.0368%) and strong voltage estimation at Bus 671 in Case 3, an error of 9.6901% is noted at Bus 652, which is still less than PSO and much less than the 40.2555% error generated

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by ESDO. This demonstrates how resilient the hybrid Algorithm is, even in difficult estimation situations. The elevated values can be explained by localized variations in pseudo-measurement quality, especially at high-load or weakly connected nodes. However, the method's balanced performance across voltage and power objectives supports its dependability.

For Case 3, where voltage deviation is incorporated, by obtaining the lowest objective function value and stabilizing more quickly than any standalone technique, Figure 9 shows that the hybrid PSO-GA-ESDO algorithm continues to have a distinct advantage. PSO eventually reaches a higher objective value, despite initially converging more quickly than GA and ESDO. In terms of convergence speed and final accuracy, ESDO performs the worst, whereas GA takes more iterations to stabilize. These findings demonstrate the hybrid approach's superior speed-to-accuracy trade-off, effectively balancing convergence rate and solution quality in spite of its higher computational complexity per iteration.

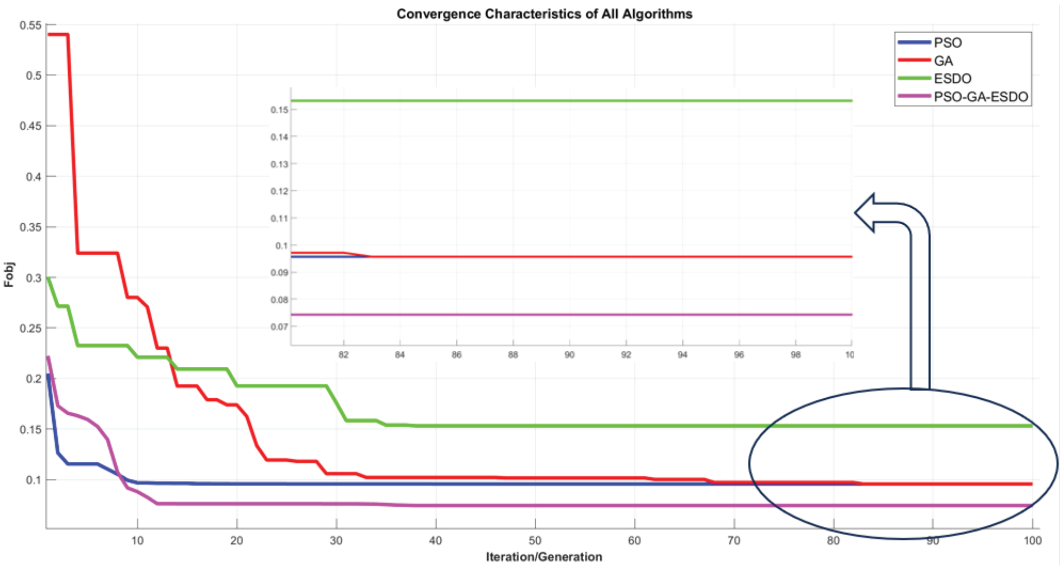

Figure 9: The convergence of different algorithms – case 3.

Case 4 extends the objective function to multiple branches, improving overall network estimation accuracy. The estimation errors for active and reactive power across the selected branches (substation, branch 633–634, and branch 671–692) are presented in **Table 9**. The results show that the hybrid PSO-GA-ESDO algorithm significantly reduces estimation errors compared to standalone methods, maintaining consistency across all key branches. The total power loss estimation results are shown in

Table 10, where PSO-GA-ESDO consistently outperforms standalone algorithms by minimizing discrepancies between the estimated and true power losses. The Ploss error is reduced to 0.0488%, while the Qloss error drops to 0.5212%, confirming the superior performance of the hybrid approach. The MAPE% values further validate that PSO-GA-ESDO achieves the lowest estimation error of 0.0513%, demonstrating higher accuracy in complex DSSE formulations.

Table 9: Absolute Errors of The Loading Total Power – Case 4

Bus i	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
634	**0.0004**	0.1250	0.6116	0.0245
671	8.3520	**5.0919**	7.5081	8.0155
652	28.4838	19.4615	**12.0894**	25.6721
675	0.7343	1.02623	1.4482	**0.0118**
645	11.2520	**4.2331**	10.6473	12.4832
646	2.8331	3.1288	18.9005	**0.5981**
611	11.9891	**0.6395**	4.1242	11.1498
692	8.3520	0.4651	23.1420	**0.0322**

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Table 10: Absolute errors of the total active power losses, total reactive power losses, and the MAPE – Case 4

Parameter	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
Active Power Losses	0.4589	0.2453	0.9444	**0.0488**
Reactive Power Losses	**0.3209**	0.5692	0.6832	0.5212
MAPE	0.0637	0.0604	0.0936	**0.0513**

The hybrid Algorithm in Case 4 produces relatively high errors at Bus 652 (25.6721%) and Bus 645 (12.4832%), despite having the lowest MAPE (0.0513%) and the best overall power loss estimation performance. These irregularities align with known issues with those buses in earlier test scenarios. The explanations once more highlight the complicated impact of multi-branch optimization targets, limited observability, and pseudo-measurement uncertainty.

The convergence trends for Case 4, Figure 10, indicate that the hybrid PSO-GA-ESDO method converges most well, stabilizing rapidly and obtaining a low objective function value in the first 10-20 iterations. PSO displays periodic oscillations, indicating early convergence to inferior solutions, whereas PSO and GA demonstrate slower and less steady convergence. When it comes to speed and overall performance, ESDO consistently falls behind. The hybrid method's quick and smooth convergence proves its resilience to complex system limitations. Its overall reduced iteration count, despite its higher per-iteration complexity, demonstrates improved computing efficiency when compared to standalone approaches.

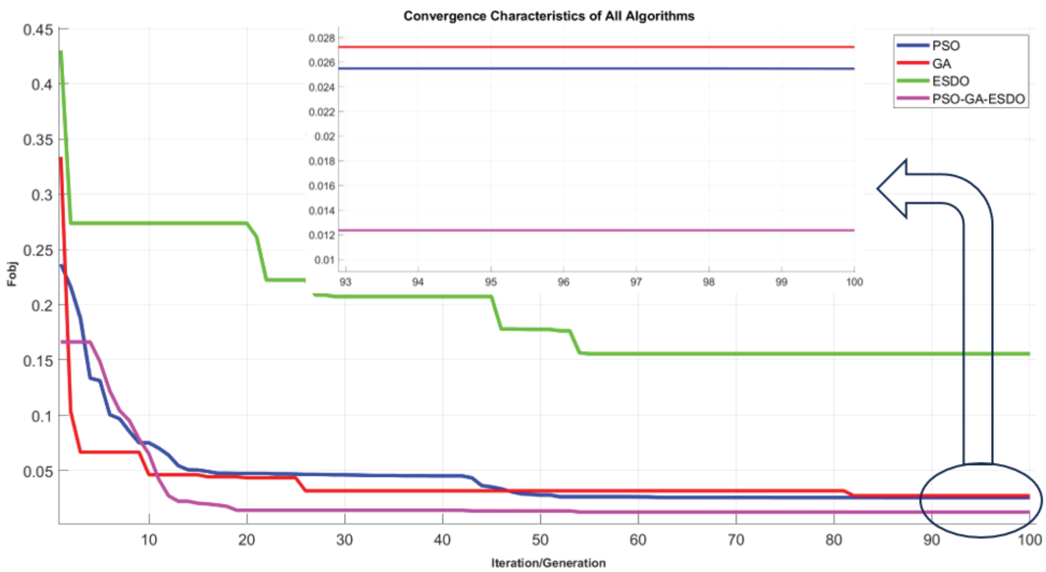

Figure 10: The convergence of different algorithms – Case 4.

Case 5 represents the most complete and computationally intensive formulation, combining multi-branch power flow errors (as in Case 4) and voltage deviations (as in Case 3) to provide a highly accurate DSSE framework. The results in **Table 11** confirm that the hybrid PSO-GA-ESDO algorithm consistently maintains the lowest active and reactive power errors across all critical buses and branches. The total power loss estimation results in **Table 12** show that the hybrid approach outperforms standalone methods, achieving a Ploss error of 0.4955% and a Qloss error of 0.2420%. The MAPE% analysis further highlights that the hybrid algorithm achieves the lowest estimation error (0.0523%), reinforcing its accuracy, efficiency, and stability in highly constrained DSSE scenarios.

Table 11: Absolute Errors of The Loading Total Power – Case 5

Bus i	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
634	**0.0001**	2.9790	0.3924	0.1472
671	4.8176	4.3783	**2.7225**	7.7553
652	7.5843	**0.9995**	18.8148	23.6442
675	**0.0534**	0.2878	3.4104	0.3425
645	7.7358	**1.4474**	1.7499	14.7029

646	4.8176	3.8254	**1.5095**	2.2864
611	1.5773	3.2523	**1.5386**	14.9411
692	**0.0391**	3.7099	4.5286	0.5276

Table 12: Absolute errors of the total active power losses, total reactive power losses, and the MAPE – Case 5

Parameter	% Error			
	PSO	GA	ESDO	PSO-GA-ESDO
Active Power Losses	0.8434	1.3194	3.1370	**0.4955**
Reactive Power Losses	1.0236	1.4962	2.9065	**0.2420**
MAPE	0.0625	0.0779	0.1937	**0.0523**

In the most comprehensive scenario (Case 5), in the majority of buses, the hybrid approach achieves the highest accuracy while maintaining the lowest total MAPE (0.0523%). Nonetheless, a number of high error values are noted, especially at Bus 652 (23.6442%), Bus 645 (14.7029%), and Bus 611 (14.9411%). When dealing with highly constrained multi-objective functions that involve both voltage and power discrepancies, these results demonstrate how sensitive the Algorithm is to local conditions. The hybrid approach provides the most globally optimal and balanced solution across all evaluation metrics, despite these local peaks, demonstrating its applicability to challenging DSSE problems.

The convergence behavior for Case 5, in Figure 11, the hybrid PSO-GA-ESDO algorithm shows a strong performance advantage, obtaining the lowest objective function value and fast convergence within the first 20 iterations. Following similar beginning trajectories, PSO and GA diverge at iteration 30, with PSO only slightly improving and GA stalling. ESDO stabilizes at a significantly higher objective value, indicating restricted and delayed improvement. The hybrid approach's scalability and efficacy in addressing complex, multi-objective DSSE situations are bolstered by the rising performance gap. Despite its more complicated structure, the hybrid Algorithm beats standalone evolutionary and swarm-based techniques in terms of total computing time because it converges with superior solutions faster.

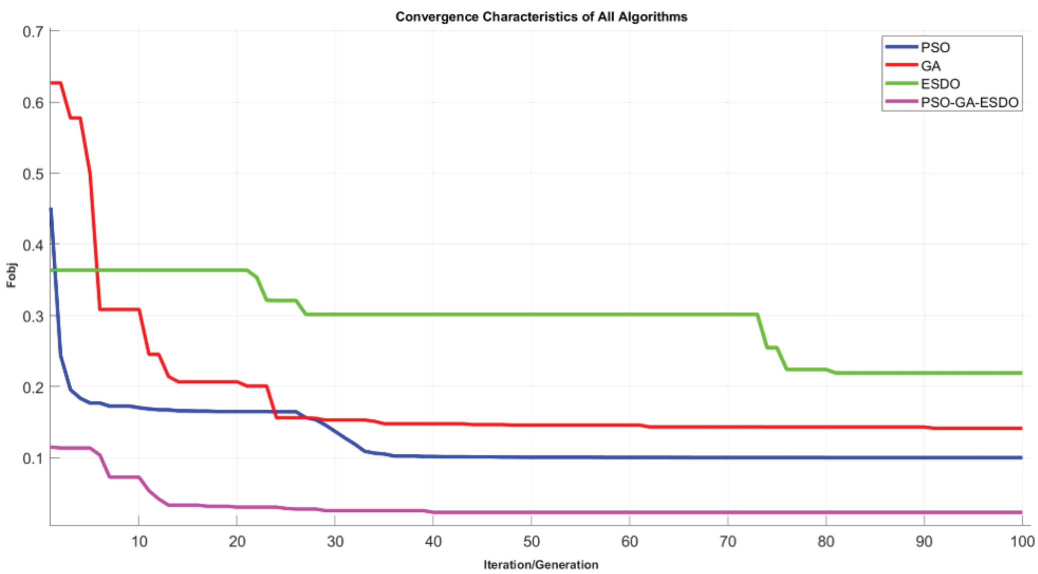

Figure 11: The convergence of different algorithms – case 5.

In terms of estimation accuracy, error minimization, and convergence speed, the Hybrid PSO-GA-ESDO algorithm continuously beats standalone optimization techniques across a set of five test cases. The synergy between its components—GA adds genetic diversity to prevent premature convergence, ESDO adds adaptive local search capabilities, and PSO offers efficient global exploration—is responsible for this performance. These components work together to help the hybrid model quickly converge toward optimal solutions while avoiding local minima.

With the lowest final objective values in each scenario, the Hybrid algorithm converges quickly and steadily in all five cases, as shown in **Table 13**, Algorithm Performance Observations Across Cases. GA, on the other hand, continuously performs

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poorly, exhibiting suboptimal final values and slow convergence. The performance of PSO and ESDO is more moderate; PSO typically performs fairly well in the beginning but lacks refinement in later stages, while ESDO is inconsistent, sometimes achieving competitive results but frequently falling short of the Hybrid model.

Table 13: Algorithm Performance Observations Across Cases

Cases	PSO	GA	ESDO	PSO-GA-ESDO
Case 1	Gradual decrease; fair performance	Early plateau; poor final value	Moderate drop; levels off	Rapid convergence and the best result
Case 2	Steady; final value close to ESDO	Slowest and highest final value	Slightly better than PSO	Quick drop and lowest final value
Case 3	Early drop, then flat	Slightly faster early drop	Very slow, plateaus early	Best convergence and lowest error
Case 4	Decent early drop, slow convergence	Sluggish with a poor final result	Consistently underperforms	Fast drop and superior stability
Case 5	Matches GA early, improves slightly	Early plateau and stagnation	Late improvement but weak result	Best convergence and lowest value

This case-based analysis demonstrates the hybrid approach's flexibility and reliability. It is particularly well-suited for real-time applications where accuracy and computing speed are critical, as it consistently provides high-quality answers in a limited number of iterations. To support these results, **Table 14** compares each Algorithm's convergence behavior, objective correctness, and computing efficiency. All essential performance indicators, including convergence speed, ultimate objective value, and result stability, outperform those of the hybrid Algorithm. Because fewer iterations are required to get optimal solutions, it is more efficient overall, while having a greater computing cost for each iteration.

Table 14: Algorithm Performance and Computational Characteristics

Category	Metric	PSO	GA	ESDO	PSO-GA-ESDO
Performance	Convergence Speed	Moderate	Slow	Moderate to Slow	Fastest
	Final Objective Value	Moderate to Low	Highest (Least optimal)	Moderate	Lowest (Most optimal)
	Stability (Plateauing)	Steady after ~60 iterations	Early plateau, slow improvements	Some fluctuations, then steady	Early convergence with minimal change
Computational Analysis	Per-Iteration Efficiency	Moderate	Low (but many iterations required)	Moderate	High (but fewer iterations needed)
	Overall Efficiency	Good balance	Poor overall	Fair but inconsistent	Best across all metrics

These computational studies demonstrate that the hybrid PSO-GA-ESDO technique offers the optimal balance of solution quality and computational cost. Even though it takes more iterations, its ability to swiftly arrive at stable, optimum solutions makes it ideal for smart grid distribution system state estimation (DSSE). Although ESDO can increase local accuracy (for example, fewer mistakes on certain buses), it is not as quick or reliable as the hybrid. Similarly, GA is less suitable for time-sensitive applications because of its sluggish convergence and lower ultimate accuracy, which outweighs its cheap per-iteration cost. Even though PSO is better balanced, it lacks the Hybrid algorithm's overall advantages.

To summarize, the Hybrid PSO-GA-ESDO algorithm provides a versatile and effective DSSE solution for today's smart grid. Its extraordinary fit for renewable-rich power distribution networks, as

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well as its ability to maintain accuracy, stability, and computational efficiency under changing conditions, enable reliable, real-time monitoring and decision-making.

V. Conclusion

The increasing integration of renewable energy sources (RES) into modern power distribution networks has introduced new challenges in Distribution System State Estimation (DSSE). Traditional state estimation methods often struggle to accommodate the complexities of unbalanced loads, bidirectional power flows, and the intermittency of distributed generation (DG) units. To address these challenges, this paper proposed a hybrid PSO-GA-ESDO optimization framework for solving the DSSE problem in renewable-rich distribution networks. The proposed hybrid algorithm combines the strengths of three metaheuristic optimization techniques: PSO, GA, and ESDO. By integrating PSO's global search efficiency, GA's stochastic diversity, and ESDO's adaptive exploratory mechanisms, the hybrid approach achieves superior estimation accuracy, faster convergence, and enhanced robustness against measurement noise and system uncertainties. The performance of the hybrid PSO-GA-ESDO algorithm was validated using the IEEE 13-bus system, considering five distinct test cases. Each case represented a progressively complex DSSE formulation, incorporating power flow errors, current magnitude and angle deviations, voltage deviations, and multi-branch constraints.

Comparative analysis demonstrated that the hybrid approach consistently outperformed standalone PSO, GA, and ESDO algorithms in all evaluation metrics, including load power error, power loss estimation accuracy, and Mean Absolute Percentage Error (MAPE%). The lowest estimation errors were observed when using the hybrid approach, confirming its effectiveness in improving DSSE accuracy. The convergence analysis of the proposed hybrid model revealed faster and more stable convergence behavior than the individual algorithms. The PSO-GA-ESDO approach achieved optimal solutions within fewer iterations, avoiding premature convergence and local minima, which are common challenges in conventional heuristic optimization methods. The hybridization process allowed for a better balance between exploration and exploitation, ensuring that the Algorithm efficiently navigates complex solution spaces while maintaining high precision in state estimation. The findings of this research confirm that PSO-GA-ESDO is a scalable and practical DSSE solution for modern distribution networks, particularly those with high penetration of renewable energy sources. The hybrid Algorithm ensures better grid reliability, stability, and enhanced real-time monitoring capabilities, making it well-suited for smart grid applications.

Although the suggested PSO-GA-ESDO algorithm was evaluated against powerful standalone optimization methods (PSO, GA, and ESDO), we recognize that a more thorough assessment requires benchmarking against additional hybrid optimization frameworks. There aren't any directly comparable hybrid models that address the same problem configuration at the moment, though, because of the novelty of our approach—specifically, the first-time integration of ESDO in a hybrid context tailored to DSSE. Furthermore, hybrid algorithms have a higher design complexity by nature, and their proven superiority over reliable individual techniques is a noteworthy accomplishment. To further confirm the generalizability and competitiveness of the suggested framework, future research will build on this study by comparing it to well-known hybrid techniques like PSO-GA, PSO-DE, or GA-ACO within the DSSE domain. Moreover, future research can extend this work by applying the hybrid optimization framework to larger-scale distribution networks, incorporating adaptive control mechanisms for real-time implementation, and exploring further enhancements using deep learning-based predictive models for DSSE in dynamic renewable-rich environments.

In conclusion, the proposed hybrid PSO-GA-ESDO algorithm offers a robust, efficient, and accurate approach to DSSE, addressing the limitations of traditional methods and ensuring optimal state estimation performance in the evolving landscape of renewable-powered smart distribution systems.

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