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Data-Driven Observability Enhancement in Active Distribution Networks via Optimal Co-Deployment of DGs and D-PMUs Using Hybrid APSO-ASDA

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Abstract
The increasing deployment of renewable Distributed Generators (DGs) introduces operational uncertainty and observability challenges in Active Distribution Networks (ADNs). Traditional Supervisory Control and Data Acquisition (SCADA) systems lack the temporal resolution required for real-time monitoring. This paper proposes a data-driven framework for enhancing network observability through optimal co-deployment of DGs and Distribution Phasor Measurement Units (D-PMUs) using a hybrid Accelerated Particle Swarm Optimization-Adaptive Spiral Dynamic Algorithm (APSO-ASDA). The objective is to maximize network observability with minimal measurement redundancy for improved Distribution System State Estimation (DSSE). Simulation results on the IEEE 13-bus ADN, modeled in MATLAB Simulink R2023b, showed ASDA optimal DG -D-PMU placement at buses 1, 4, with corresponding sizes of 340Kw(solar), and 445kW(wind) with D-PMU at 6, 7, 10, and 12. APSO DG placement is at bus 3 and 4 with a size of 60kW(solar), 400kW(wind), D-PMU at buses 6, 8, 9. The hybrid approach places DG at buses 1 and 3 with corresponding capacities of 110kW (solar) and 250kW (wind), and D-PMU allocation at buses 4, 6, 7, 8, 11 and 12. The hybrid algorithm achieved a rapid reduction in the cost function from 278.7 to 81.14 within the first 36 iterations, highlighting its effectiveness for real-time, data-driven applications.

Keywords: *Active Distribution Network, D-PMU, Observability, Data-Driven Control, APSO, ASDA, Distribution System State Estimation, Rate-of-Change of Frequency ROCOF.*

1.0 Introduction

The integration of DGs fundamentally transforms traditional radial distribution networks into active systems characterized by bidirectional power flows and stochastic operating conditions. While this transition enhances energy efficiency and facilitates renewable energy penetration, it also introduces significant operational uncertainties due to the uncertain nature of renewable sources such as solar and wind [1], [2]. Consequently, maintaining system stability and reliability requires high-resolution, time-synchronized monitoring, which is enabled by D-PMUs [3], [4].

To address these challenges, optimal co-deployment strategies are typically formulated as multi-objective optimization problems aimed at minimizing deployment cost, reducing power losses, and ensuring complete system observability. A critical objective in this context is to determine the minimum number of D-PMUs required to guarantee full topological observability, which is commonly achieved using Integer Linear Programming (ILP) and Nonlinear Programming (NLP) techniques [5], [6]. In parallel, optimal placement of DG units has been shown to significantly improve system performance, with reported power loss reductions of up to 81% in benchmark distribution networks [1]. The integration of D-PMU measurements further enhances the operator's ability to monitor and sustain these improvements in real time. Recent studies have extended the optimization framework to incorporate economic and reliability considerations, including capital investment, measurement redundancy, and resilience under contingency scenarios such as N-1 outages and communication failures [6], [4]. This holistic approach ensures that deployment strategies are both technically efficient and practically viable in real-world grid environments.

In situations where full D-PMU deployment is economically infeasible, data-driven methodologies have emerged as a powerful alternative for enhancing system observability. Supervised machine learning and deep learning techniques are widely employed to generate pseudo-measurements for unmonitored nodes by leveraging historical datasets and real-time D-PMU inputs [7], [2]. These approaches significantly improve the accuracy and robustness of Distribution System State Estimation (DSSE), even under limited measurement availability [5]. Beyond state estimation, data-driven techniques also enable advanced situational awareness. For instance, time-series analysis of synchrophasor data has been utilized to detect real-time switching operations and topology changes, which is particularly important in ADNs that frequently undergo network reconfiguration to optimize performance [8], [9]. Furthermore, recent advancements in multi-output deep neural networks have demonstrated

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the capability to simultaneously perform DSSE and detect False Data Injection Attacks (FDIAs), thereby enhancing both observability and cybersecurity in modern power systems [2].

The practical implementation of optimal co-deployment strategies must also consider inherent network characteristics and operational constraints. For example, zero-injection buses (ZIBs) can be strategically exploited to reduce the number of required D-PMUs while maintaining full system observability [6], [3]. Additionally, unlike traditional static placement methods, modern optimization frameworks must be adaptive, accommodating dynamic variations in load demand, renewable generation, and potential device failures [5], [10].

Advanced metaheuristic optimization techniques have emerged as valuable tools to tackle the complex problem of optimal device placement and sizing in ADNs. Accelerated Particle Swarm Optimization (APSO) is an enhanced variant of the conventional Particle Swarm Optimization (PSO) algorithm, specifically designed to improve convergence speed and mitigate the risk of premature convergence by refining the particle update mechanism [11]. Adaptive Spiral Dynamic Algorithm (ASDA), inspired by the spiral patterns found in nature, utilizes adaptive parameters to effectively guide the search for optimal solutions, potentially offering more efficient solution space exploration [12]. Both techniques are instrumental in addressing the multidimensional nature of the problem, ensuring that the deployment of D-PMUs and DG resources is optimized for performance, cost-effectiveness, and system stability.

In response to these challenges, this work proposes a data-driven co-deployment framework for DGs and D-PMUs, where optimal placement is achieved using a hybrid metaheuristic optimization approach. The proposed method not only enhances network observability and DSSE accuracy but also supports real-time control applications by leveraging high-fidelity synchrophasor data. This integrated approach provides a scalable and efficient solution for overcoming the inherent limitations of traditional DSSE in modern ADNs.

1.1 Overview of conceptual framework

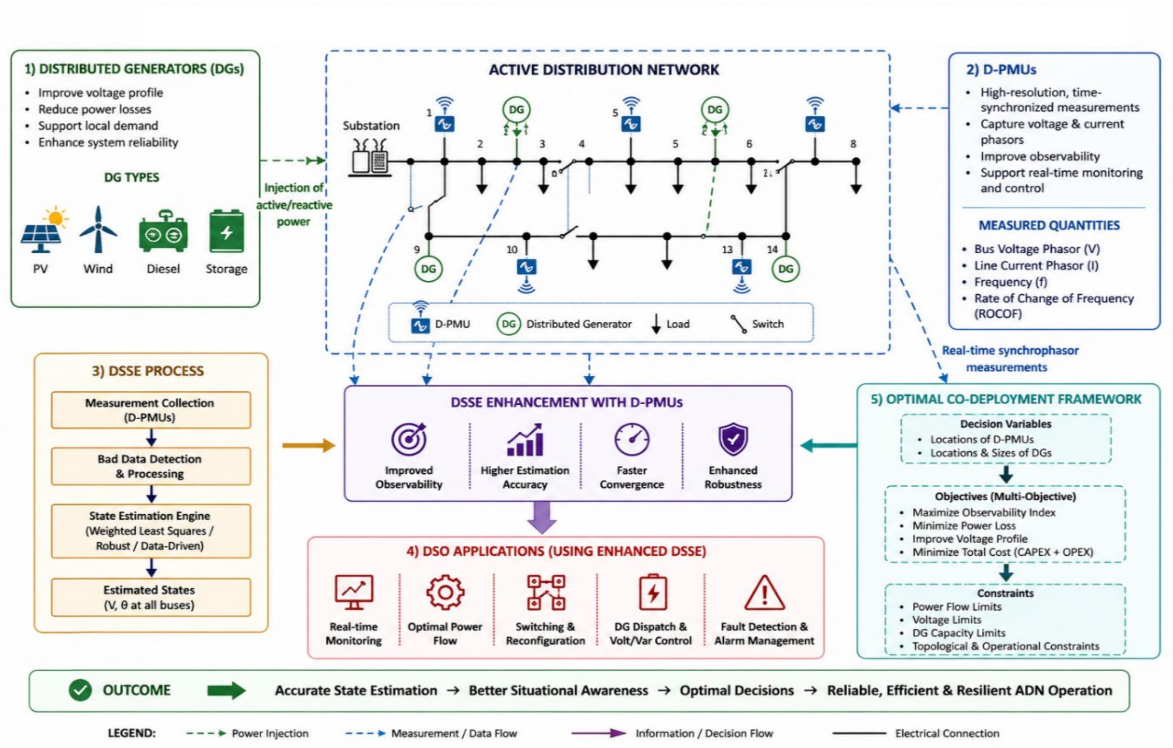

Figure 1: Conceptual framework of optimal co-ployment of D-PMUs and DGs in ADN.

A. Distributed Generations

DGs represent a class of decentralized energy systems designed to operate either autonomously or in coordination with the central grid infrastructure. Their primary strength lies in enhancing the grid's resilience and flexibility by addressing localized energy demands while promoting sustainable energy practices [13]. They are often connected directly to load centers or distribution substations, ensuring efficient power delivery closer to the point of consumption [14]. The IEEE 1547 standard defines DGs as small-scale generating units installed on the customer's side of the meter, with a maximum allowable capacity of 10 MVA. A prominent example of DG technology is solar photovoltaic (PV) systems, which harness solar irradiance and convert it into electrical energy through environmentally benign processes. The wind DG uses wind turbines to convert wind energy into electricity at a local level. When combined with solar DGs, they can provide a more consistent and reliable supply of renewable energy, balancing out fluctuations in weather conditions [15]. Different types of the DG's can be characterized as;

Type I DGs are capable of injecting only active power into the system, with photovoltaic (PV) systems and fuel cells being typical examples. These sources primarily contribute to real power support but have limited or no reactive power compensation capability.

Type II DGs are designed to inject only reactive power for voltage regulation and power quality improvement. Common examples include capacitor banks, synchronous compensators, and static VAR compensators, which are mainly employed to enhance voltage stability and reduce reactive power deficiencies within the network.

Type III DGs possess the capability to supply both active and reactive power simultaneously. Synchronous generators are a typical representation of this category, as they can actively participate in both power generation and voltage support.

Type IV DGs inject active power while consuming reactive power during operation. Induction generators commonly used in wind energy conversion systems fall within this category due to their dependence on reactive power support from the grid for excitation.

In this work, the focus is placed on Type I and Type IV DGs because of their widespread integration in modern renewable-rich active distribution networks and their significant impact on voltage stability and reactive power management.

B. Distribution Phasor Measurement Unit

The Advanced PMUs serve as critical interfaces between power system instrumentation and digital monitoring frameworks by acquiring analog voltage and current signals via current transformers (CTs) and potential transformers (PTs). Upon acquisition, the signals undergo analog conditioning through anti-aliasing filters, which constrain the bandwidth to less than half the sampling frequency. This step rigorously satisfies the Nyquist criterion, thereby eliminating the risk of aliasing and preserving signal integrity before digitization. Subsequently, high-precision analog-to-digital converters (ADCs) sample the conditioned waveforms at rates that conform to the stringent specifications outlined in IEEE C37.118 standards. D-PMUs provide high-precision, time-synchronized measurements of voltage and current phasors as shown in table 1, enabling significantly improved system observability and more accurate state estimation. By delivering real-time data with precise time alignment, D-PMUs reduce the dependency on pseudo-measurements and enhance the robustness of DSSE algorithms under dynamic operating conditions.

However, due to the relatively high cost of deployment, it is neither practical nor economical to install D-PMUs at every node in the network. This introduces a critical research problem on how to optimally deploy a limited number of D-PMUs such that maximum observability and estimation accuracy are achieved. Furthermore, while D-PMUs enhance measurement availability, their full potential can only be realized when coordinated with optimal placement of DGs, which influence network power flows and voltage profiles.

Despite existing studies on either DG placement or D-PMU allocation, the simultaneous co-optimization of DGs and D-PMUs for enhancing DSSE performance remains insufficiently explored, particularly within a data-driven control framework. This gap is further pronounced when considering the integration of real-time D-PMU data into advanced estimation and control strategies. D-PMU applications in smart grids includes (i) Improved Situational Awareness (ii) Smarter Grid Protection (Enhanced Protection) (iii) Improved Control (iv) Fault Location and Isolation (v) Power Quality Monitoring.

Table 1: Comparison between D-PMU and SCADA [19]

S/N	Attribute	SCADA	D-PMU
1	Resolution	1 sample every 2-4 s	10-60 samples/s
2	Observability	Steady state	Dynamic
3	Measurements	|V|, I	|V|, d, I, frequency, ROCOF
4	Synchronization	No	Yes
5	Phase angle	No	Yes
6	Focus	Local monitoring and control	Wide area monitoring and control

Source: Usama *et al.* (2019)

C Distribution system state estimation algorithms

Distribution System State Estimation (DSSE) algorithms are fundamental to modern Active Distribution Networks (ADNs), as they provide the Distribution System Operator (DSO) with a comprehensive and real-time representation of network states necessary for effective monitoring, control, and optimization. However, the practical deployment of DSSE in distribution environments remains significantly constrained by two inherent

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challenges: the unbalanced multi-phase structure of distribution systems and the limited availability of high-quality measurement data [17]. Unlike transmission networks, where measurements are relatively dense and balanced conditions can be reasonably assumed, distribution systems exhibit phase asymmetry, diverse load profiles, and sparse instrumentation, all of which complicate accurate state estimation. These limitations often result in low observability, reduced estimation accuracy, and increased reliance on pseudo-measurements, which are typically derived from historical or statistical data and may not accurately reflect real-time system dynamics. Consequently, conventional DSSE approaches struggle to provide the level of precision and responsiveness required for modern ADN operation, particularly under high penetration of renewable Distributed Generators (DGs), where system conditions can change rapidly and unpredictably, hence the deployment of D-PMUs.

Distribution System State Estimation (DSSE) techniques can be broadly classified into model-based, forecasting-aided, and data-driven approaches, each offering distinct capabilities and limitations in addressing the complexities of ADNs.

Model-based DSSE methods rely on detailed knowledge of network parameters and topology, which must be accurately available to the operator in advance. These approaches typically employ the Weighted Least Squares (WLS) formulation, where system states are estimated by minimizing the discrepancy between measured and calculated quantities. While mathematically rigorous, model-based methods are highly dependent on accurate network modeling and are often sensitive to parameter uncertainties, topology errors, and measurement noise.

Forecasting-aided approaches extend conventional estimation by incorporating temporal information into the estimation process. Traditional static estimators operate on a single snapshot of measurements, thereby neglecting the dynamic evolution of system states. To address this limitation, Forecasting-Aided State Estimation (FASE) introduces recursive updating mechanisms that leverage previous state estimates to improve current predictions. This enables the tracking of gradual system changes under normal operating conditions and enhances estimation continuity over time.

In recent times, data-driven DSSE algorithms have emerged as a powerful alternative, driven by the increasing integration of Information and Communication Technologies (ICT) within modern power systems. These approaches utilize machine learning and statistical techniques to infer system states directly from measurement data, reducing reliance on detailed physical models. A key advantage of data-driven methods lies in their ability to mitigate modeling inaccuracies, handle system nonlinearities, and reduce computational complexity, which are often major limitations of traditional techniques [17]. Furthermore, they exhibit improved robustness to parameter uncertainties and can adapt to evolving network conditions.

However, the effectiveness of data-driven DSSE is inherently dependent on the availability of large volumes of high-quality data, which may not always be readily accessible in practical distribution systems. This requirement highlights the critical role of advanced measurement infrastructures, such as D-PMUs, in enabling reliable and scalable data-driven state estimation frameworks.

2.0 Materials and Methods

2.1 Optimal deployment of D-PMUs and DGs in ADN

The integration of renewable DGs and D-PMUs into ADNs presents substantial technical and operational advantages, while simultaneously introducing new layers of system complexity that require careful coordination and control. From an operational perspective, DGs contribute significantly to grid performance by enhancing voltage regulation, reducing network losses through localized generation, improving supply reliability during contingencies, and increasing the overall flexibility and resilience of the distribution system. However, the stochastic and intermittent nature of renewable energy sources introduces variability that can challenge conventional monitoring and control mechanisms.

In parallel, D-PMUs provide high-resolution, time-synchronized measurements that offer a comprehensive and real-time view of the network's dynamic state. This enhanced visibility enables more accurate state estimation, faster fault detection, and improved situational awareness across the distribution system. By facilitating synchronized data exchange between distributed resources and central control units, D-PMUs support the implementation of advanced, data-driven control strategies that enhance system stability and power quality.

The synergistic integration of DGs and D-PMUs therefore establishes a more intelligent and responsive grid infrastructure, where real-time information flow enables coordinated decision-making across multiple operational layers. However, to fully realize these benefits, their deployment must be optimally planned and integrated within a unified framework, ensuring that the advantages of improved observability and distributed generation are achieved without compromising system stability or economic efficiency.

A. Optimal D-PMU placement

Conventional approaches to D-PMU placement primarily adopt a single-stage (one-time) optimization strategy, where placement decisions are derived based on network topology under normal operating conditions.

In such methods, all buses are typically treated with equal importance, which may not accurately reflect their varying impact on system observability and reliability.

Advanced D-PMU placement strategies evolve from simple topology-based methods to more sophisticated frameworks that incorporate network criticality Bus Vulnerability Index (BVI), economic considerations (multistage deployment), and system constraints (ZIBs and existing measurements). These approaches collectively enable a more efficient and practical realization of full network observability in modern ADNs.

The optimal placement of Distribution Phasor Measurement Units (D-PMUs) constitutes a critical optimization problem in Active Distribution Networks (ADNs), aimed at achieving maximum system observability and measurement redundancy with the minimum number of devices. This problem is inherently combinatorial and multi-objective, requiring a careful balance between economic constraints and monitoring performance.

(i) One-Time Optimal D-PMU Placement

The one-time placement approach focuses on determining the minimum number and optimal locations of D-PMUs required to ensure full network observability. This is typically formulated as a constrained optimization problem where each bus is assigned a binary decision variable indicating the presence or absence of a D-PMU.
To enhance efficiency, additional network characteristics such as zero-injection buses (ZIBs) and pre-existing measurement devices are incorporated into the formulation. The presence of ZIBs allows indirect observability of neighboring buses, thereby reducing the number of required D-PMUs. Similarly, if certain buses are already equipped with measurement devices, their corresponding decision variables can be fixed, effectively simplifying the optimization process and reducing computational burden [18].

(ii) Bus Vulnerability Index-Based Placement

To overcome the limitations of uniform bus treatment, the Bus Vulnerability Index (BVI) is introduced as a weighting mechanism to prioritize critical nodes within the network. The BVI quantitatively evaluates the relative importance of each bus based on factors such as observability, redundancy, connectivity, and reliability.
In this framework, buses with higher vulnerability indices are assigned greater significance during the optimization process, ensuring that measurement resources are allocated to the most critical locations. The evaluation of BVI is typically performed from a static network perspective, incorporating topological and structural characteristics of the distribution system [18]. This approach enhances the robustness of the placement strategy by focusing on weak or strategically important nodes.

(iii) Multistage Optimal D-PMU Placement

Recognizing the practical constraints associated with large-scale deployment, the multistage placement approach has been developed to support incremental implementation of D-PMUs. Unlike one-time optimization, this method considers the sequential installation of D-PMUs over multiple planning stages, allowing utility operators to distribute investment costs over time.

In this framework, previously installed D-PMUs are treated as fixed assets, and subsequent placement decisions are optimized to complement the existing configuration. The objective at each stage is to maximize observability and measurement redundancy while minimizing additional deployment cost.

B. Optimization algorithms for DG and D-PMU placement

Optimization techniques used in power systems can be broadly grouped into deterministic and stochastic approaches. Deterministic methods rely on explicit mathematical formulations and guarantee convergence under well-defined conditions, whereas stochastic techniques employ probabilistic search mechanisms to effectively navigate highly nonlinear, non-convex, and multi-modal solution spaces commonly encountered in modern power systems.

In practical applications, both classes of optimization techniques have been extensively utilized to determine optimal DG and D-PMU configurations with respect to objectives such as loss minimization, voltage profile enhancement, and observability maximization. However, hybrid optimization frameworks have emerged as a more robust and efficient alternative. As conceptually illustrated in Figure 3, hybrid methods integrate the complementary strengths of deterministic and stochastic algorithms, or even multiple stochastic strategies, to achieve superior performance.

A notable example is the hybridization of Accelerated Particle Swarm Optimization (APSO) with the Adaptive Spiral Dynamic Algorithm (ASDA) [12]. This hybrid approach leverages the fast convergence characteristics of APSO, rooted in swarm intelligence and collective particle dynamics to rapidly explore the global search space. Concurrently, ASDA enhances local search precision through a spiral motion mechanism that guides candidate solutions toward the search center, thereby increasing the likelihood of attaining the global optimum, particularly in complex and high-dimensional problem domains. By combining their strength, the hybrid APSO-ASDA framework effectively mitigates the limitations associated with individual algorithms, such as premature convergence and suboptimal accuracy.

C. IEEE 13-bus standard test network

The selection of the IEEE 13-bus test feeder of figure 2, provides a rigorous and widely accepted platform for assessing the effectiveness, robustness, and scalability of DG and D-PMU placement strategies in active distribution networks. It has a base MVA of 100MVA and a base voltage of 4.16kV, (L-L) and 2.4kV(L-N) while the total load on the line is 3.5MW and 2.1Mvar respectively. Maximum allowable DG is (30-50)% of feeder peak load resulting to 1.05MW-1.75MW else, the use of voltage regulators, smart inverters and upgrade of protection settings will apply.

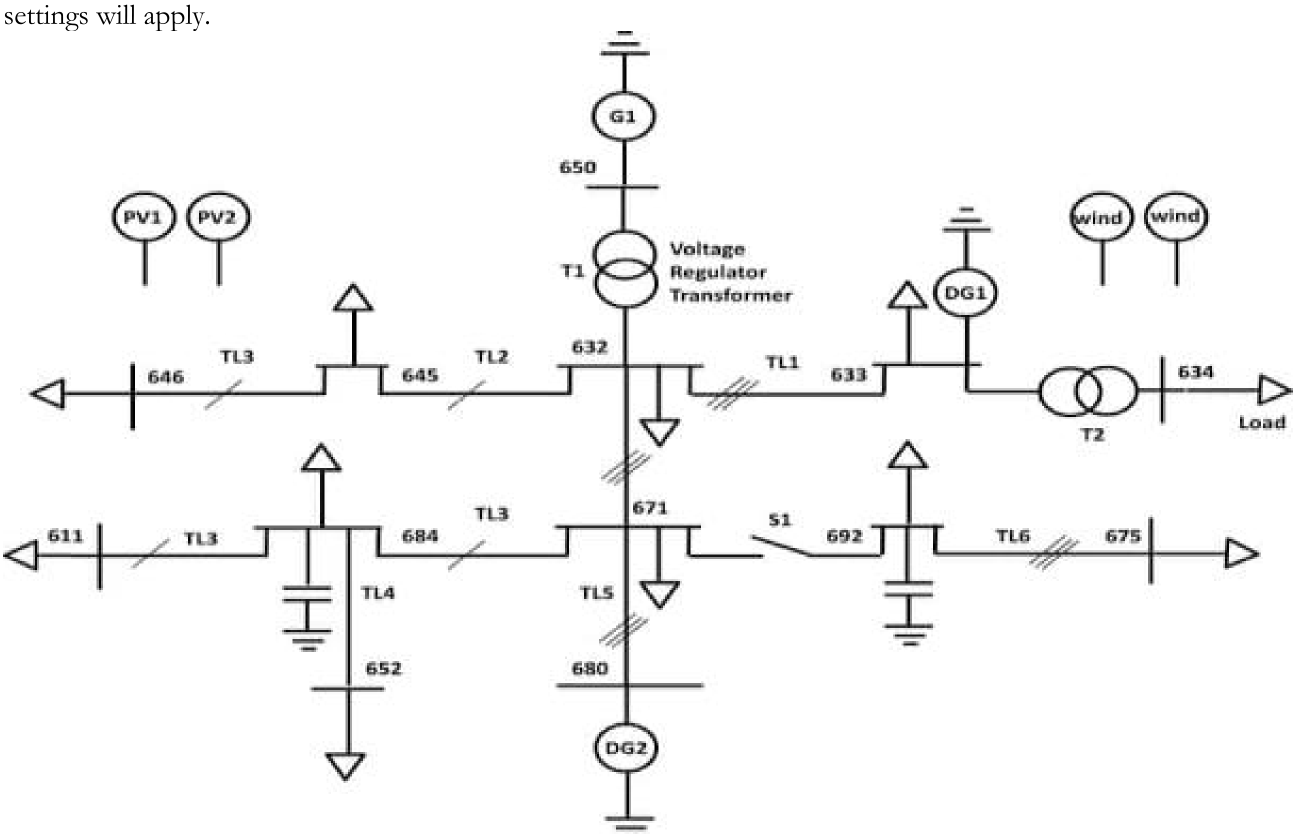

Figure 2: Single line diagram of IEEE 13-Bus ADN Network

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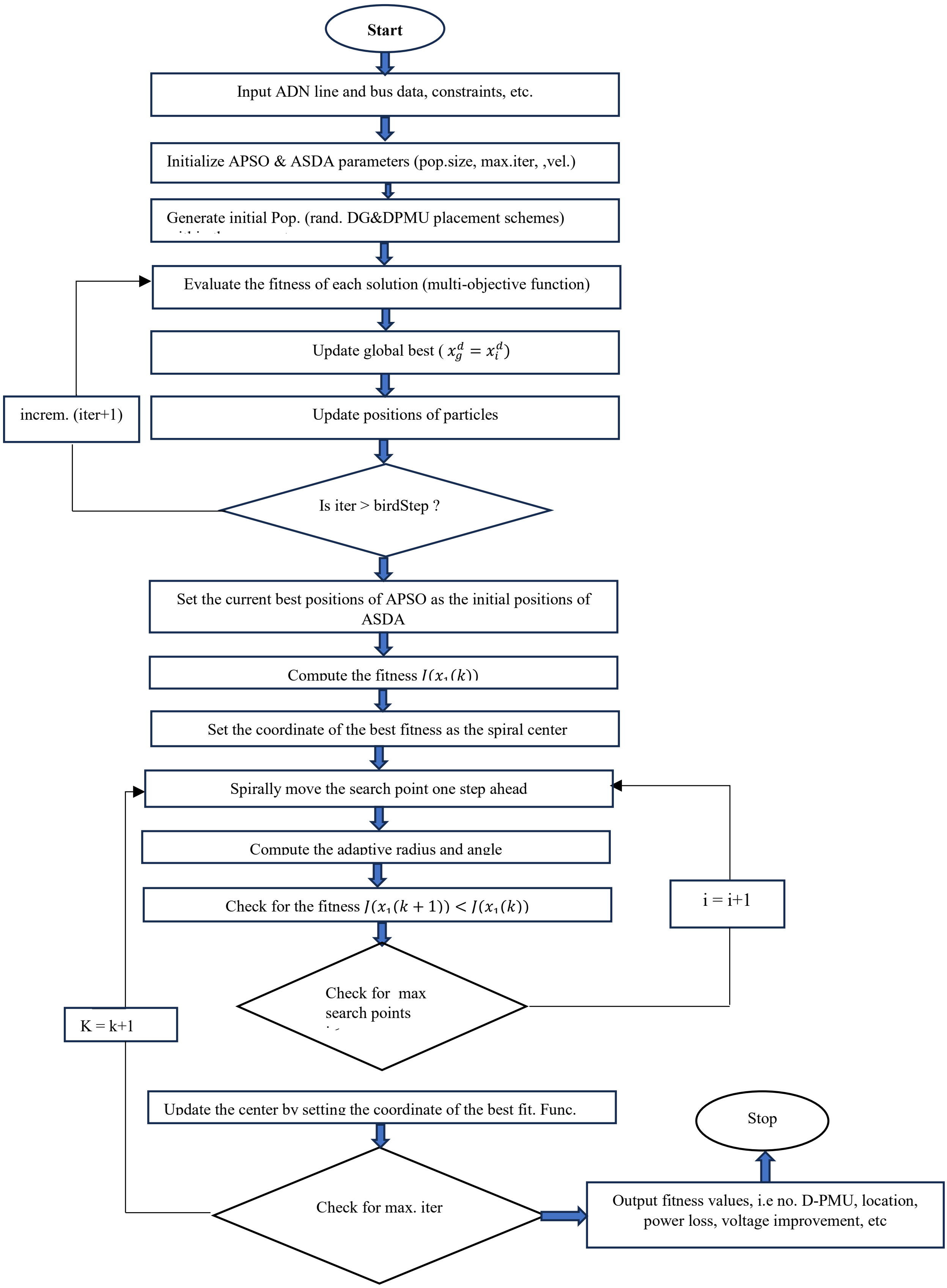

Figure 3: Implementation of combined DG-D-PMU deployment using hybrid APSO-ASDA algorithm

2.2 System Model and Problem Formulation

The main goals of optimally deploying DGs and D-PMUs in an ADN is to minimize total power losses, enhance voltage profiles across all buses, and achieve accurate state estimation with minimum number of D-PMUs.

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(i) DG deployment problem formulation.

Here we minimize operational cost, reduce losses, and enhance voltage stability while satisfying certain constraints like power balance equation, voltage limits, DG capacity etc. The DG size, location and type constitute the decision variable in the formulation. The equality constraint in the optimal allocation of DG is formulated as follows;

$$\min P_{loss} = \sum_{i-1}^{N} I_i^2 . R \tag{1}$$

$$P_{Gi} - P_{Li} = |V_i| \sum_{j=1}^{N_{bus}} |Y_{ij}||V_J| Cos(\delta_i - \delta_j - \theta_{ij}). \tag{2}$$

$$Q_{Gi} - Q_{Li} = |V_i| \sum_{j=1}^{N_{bus}} |Y_{ij}||V_j| Sin(\delta_i - \delta_j - \theta_{ij}). \tag{3}$$

where P_{Gi} denotes the active output power of the generator at bus *i*; P_{Li} is the active power of load at bus *i*, Q_{Gi} stand for the reactive output power of the generator at bus *i*, Q_{Li} is the reactive power of load at bus *i*; and Y_{ij} and θ_{ij} are the modulus and angle of *i*th element in the admittance matrix of the system related to bus *i* and bus j, respectively [20]

The inequality constraints subjected to DG setting and sizing problems includes [21],

$$V_{min} \leq |V_i| \leq V_{max} \quad i = 1,2, \ldots, N_{bus} \tag{4}$$

Where V_{min} and V_{max} are taken as 0.95 and 1.05 (p.u) respectively

$$I_i \leq I_{max} \quad i = 1,2, \ldots \ldots, N_{br} \; . \tag{5}$$

$$P_{DG}^{min} \leq |P_{DGi}| \leq P_{DG}^{max} \tag{6}$$

$$2 \leq |DG_{bus}| \leq N_{bus} \tag{7}$$

where DG_{bus} is the bus number of the *DG* installation, V_i is the bus voltage, I_i is the current of the DG at branch i, $P_{DGi}$is the total power of DG, N_{br} is the total number of branches.

(ii) D-PMU deployment problem formulation

The objective for D-PMU placement is to ensure full network observability while minimizing the number of D-PMU installed. For a placement vector Xi =1, denoting D-PMU placement at bus i, the objective function is formulated as follows;

Minimizing the number of D-PMU to be installed

$$\min \sum_{i=1}^{N} X_i \tag{8}$$

$$\text{s.t. } O_i = x_i + \sum_{j \in \mathcal{N}(i)} x_j \geq 1 \tag{9}$$

Where:

$x_i = 1$ if D-PMU is installed, O_i: observability condition

Maximizing network observability redundancy

$$\max \sum_{i=1}^{N} R_i, \tag{10}$$

where R_i is redundancy

Network observability (Obs) is quantitatively defined as the ratio of the number of observable buses to the total number of buses within the system. A bus is considered observable if it is either directly equipped with a D-PMU or is electrically connected (adjacent) to a bus hosting a D-PMU, such that its state variables can be inferred from network topology and measurement redundancy.

Accordingly, both upstream and downstream neighboring buses of each D-PMU installation contribute to the overall observability set. This topological propagation of measurement information ensures that adjacent nodes denoted as $i - 1$ and $i + 1$ relative to a D-PMU at bus i, are also rendered observable. Consequently, the observability ratio can be expressed as the proportion of all such directly measured and inferable buses to the total system buses.

$$Observability\ Ratio = \frac{Lenght(Coverage\ buses)}{Total\ Number\ of\ buses} \tag{11}$$

$$Lenght\ of\ coverge\ buses = No.of\ \ adjacent\ D - PMUs\ connected \tag{12}$$

$$\therefore\ Observability\ Ratio = \frac{No.of\ \ adjacent\ D{-}PMUs\ connected}{Number\ of\ buses} \tag{13}$$

(iii) Combined DGs and D-PMU deployment problem formulation

In the integrated optimization framework, each objective function is first normalized with respect to its corresponding base (reference) value to ensure dimensional consistency and prevent dominance of any single objective due to scale differences. The resulting normalized indices are then aggregated through a set of weighting coefficients that quantitatively represent the relative priority assigned to each objective.

This weighted aggregation transforms the original multi-objective problem into a unified scalar optimization problem, thereby enabling efficient evaluation within the solution algorithm. Consequently, the overall performance index is expressed as a composite fitness function, formulated as a weighted sum of the normalized objective components.

$$F(X) = \left[W_1 * \frac{P_{LOSS}}{P_{LOSS\_BASE}} + W_2 * \frac{V_D}{VD_{BASE}} + W_3 * 1 - Obs)\right] \tag{14}$$

$$P_{LOSS} = \sum_{i=1}^{N_{br}} R_i |I_i|^2 \tag{15}$$

$$V_D = \sum_{i=1}^{N_{bus}} (V_i - V_{rated}) \tag{16}$$

A The D-PMU Emulator

The software-based D-PMU emulator as shown in figure 3, is developed within the MATLAB/Simulink environment to replicate the functional behavior of a practical Distribution Phasor Measurement Unit. The emulator acquires input signals from instrument transformer models, which are subsequently processed through a demultiplexing stage to separate and route the measurement channels. Key electrical parameters such as voltage, current, frequency, and phase angle are initialized and extracted at the emulator output. Each measurement channel is interfaced with dedicated visualization blocks (scopes) to facilitate real-time monitoring and validation of the simulated phasor data, thereby ensuring accurate emulation of D-PMU measurement dynamics.

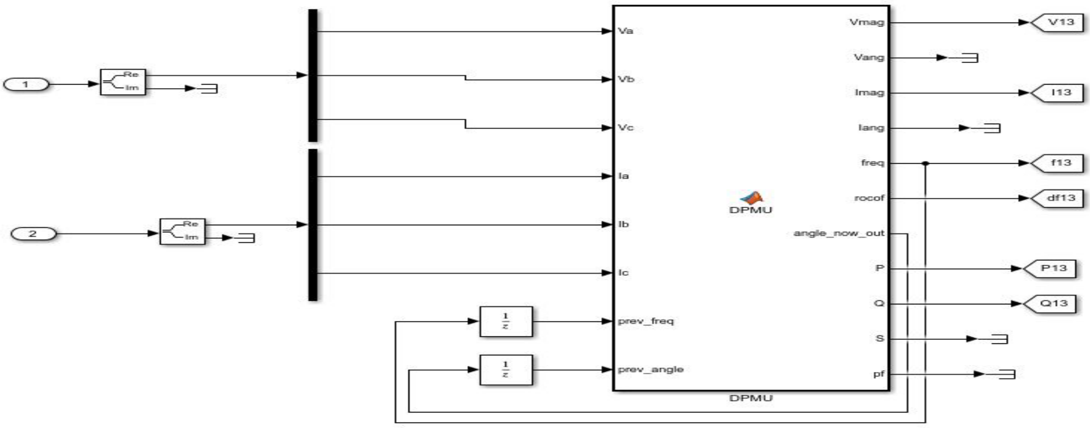

Figure 4: The D-PMU soft-ware based emulator

3.0 Results and Discussion

A comprehensive analysis of the simulation outcomes obtained from the optimal deployment of hybrid DGs and D-PMUs within the ADN is presented herein. The results below showed the individual stand-alone approaches and that of the hybrid structure. For ASDA as shown in figure 5(a-c), DGs were best installed at Bus 1 and Bus 4, with capacities of 340 kW (solar) and 445 kW (wind) units, respectively. These locations likely offer the greatest benefits in terms of improving voltage stability and reducing power losses. On the other hand, DPMUs are placed at Buses 6, 7, 10, and 12, which are spread across the middle and far ends of the feeder. This spread is a deliberate strategy to improve network visibility and ensure that the system is well monitored from different sections. There was no overlap between DG and DPMU placements. Buses 1 and 4 exhibit voltages drop slightly below 1.0 p.u. before DG placement. After DGs were placed, the voltage profile is significantly improved. The improvement is especially evident at buses with previously low voltage, showing that DG placement helped regulate and boost voltage, enhancing the overall voltage stability of the system. In APSO as in figure 6(a-c), DGs were placed at bus 3, 4 with D-PMUs at buses 6,8,9 for voltage support and loss reduction while ensuring full observability.

The hybrid optimization strategy exhibits a pronounced and rapid reduction in the objective (cost) function within the initial iterations, attaining a stable convergence state significantly earlier than its individual counterparts. Although both APSO and ASDA demonstrate progressive improvement over successive iterations, they ultimately converge to comparatively higher cost values, indicating a reduced capability in locating the global optimum. DGs were placed at buses 1 and 3, with D-PMUs at 4,6,7,8,11 and 12 respectively as showed in figure 7(a-c).

In contrast, the hybrid approach consistently achieves the lowest cost function as in figure 8, reflecting superior optimization performance and enhanced solution quality. The slower convergence rates observed in APSO and ASDA suggest susceptibility to premature convergence and entrapment in local minima, as well as limited effectiveness in fine-tuning near-optimal regions of the search space.

This improved performance can be attributed to the synergistic integration of APSO's strong global exploration capability with ASDA's adaptive local exploitation mechanism. Such a balance between exploration and exploitation enables the hybrid framework to efficiently navigate complex, high-dimensional search spaces and converge toward a more optimal solution with greater speed and robustness.

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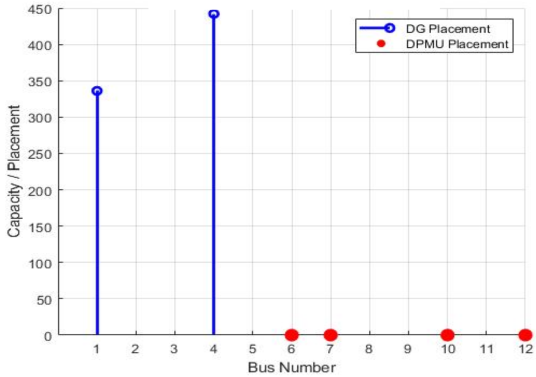

Figure 5a: ASDA DG & D-PMU placement

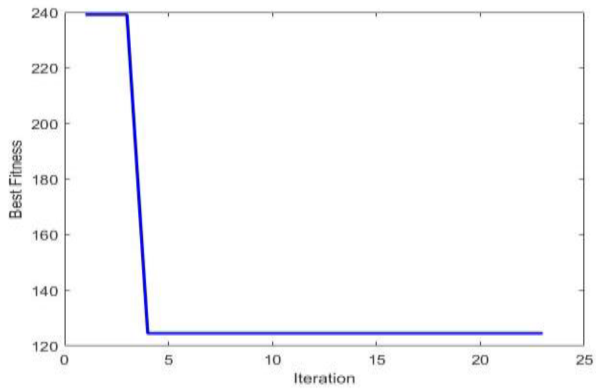

Figure 5b: Convergence characteristics of ASDA

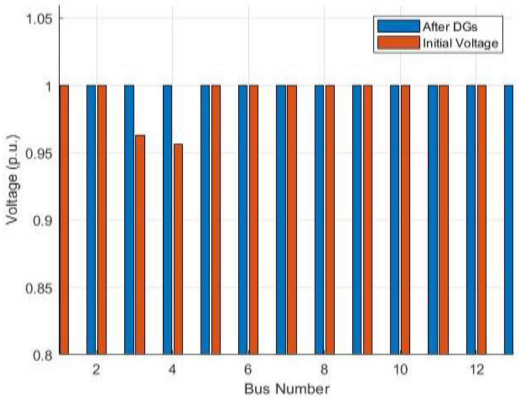

Figure 5c: Voltage profile improvement using ASDA

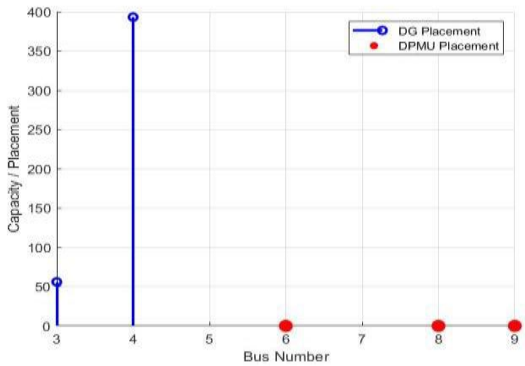

Figure 6a: DG and D-PMU deployment using APSO

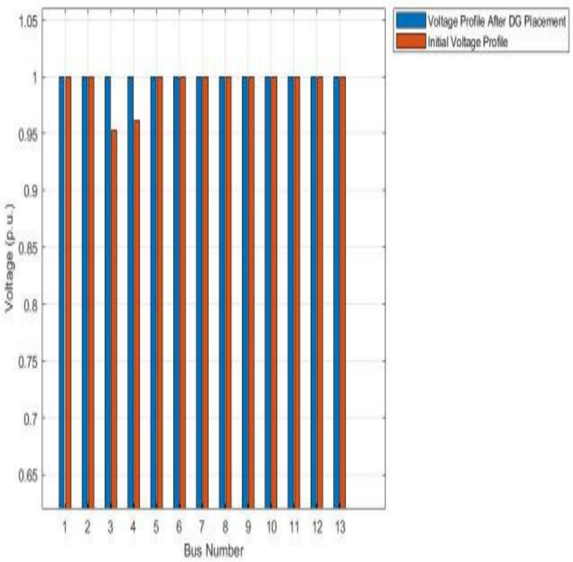

Figure 6b: Voltage profile improvement of APSO

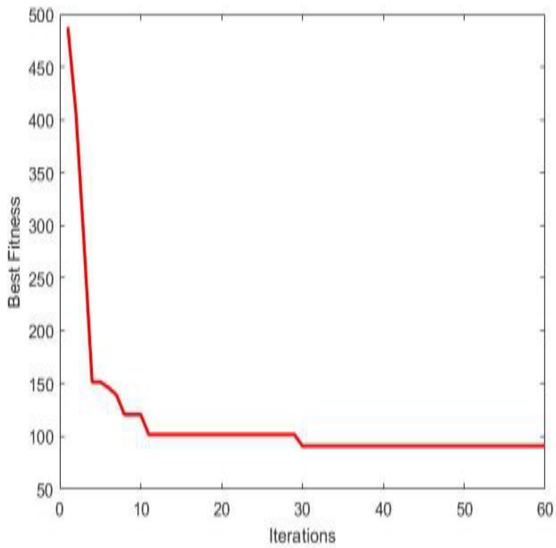

Figure 6c: Convergence characteristics plot of APSO

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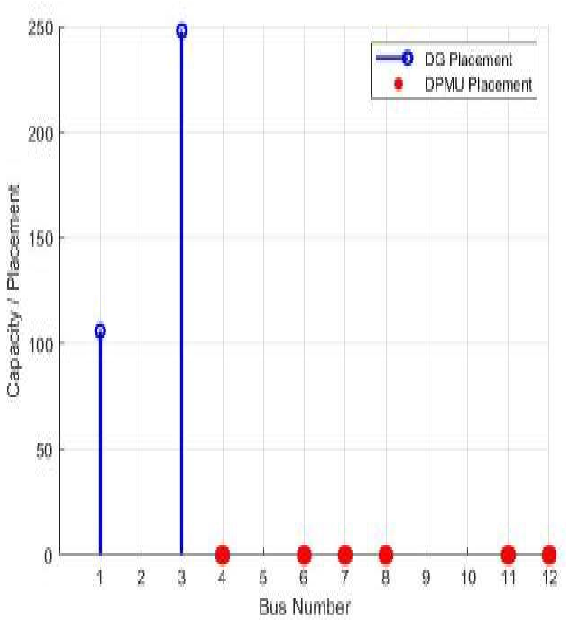

Figure 7a: Hybrid DG & D-PMU placement

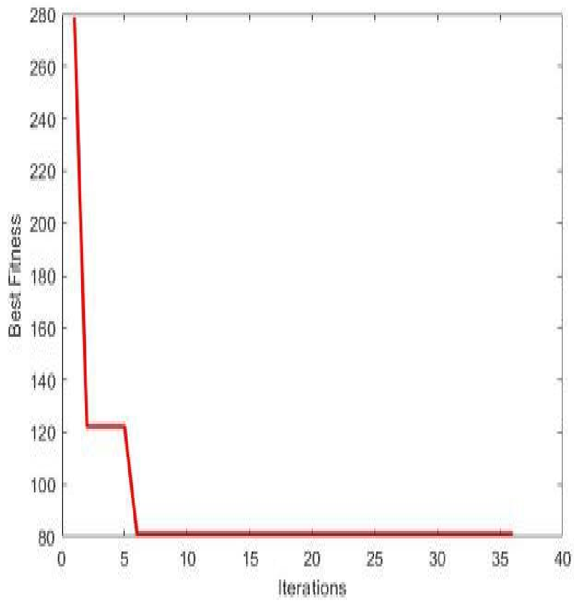

Figure 7b: Hybrid convergence Plot

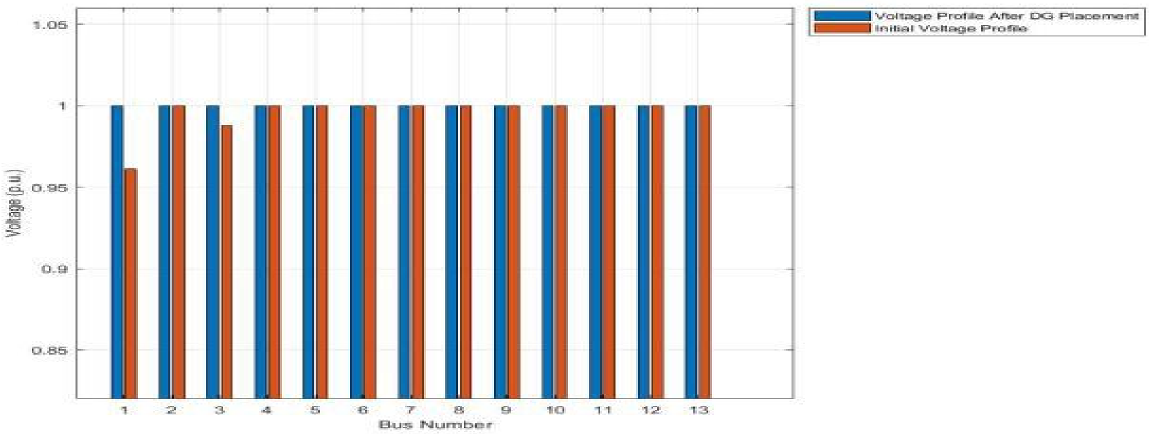

Fig. 7c: Voltage profile improvement using hybrid APSO-ASDA

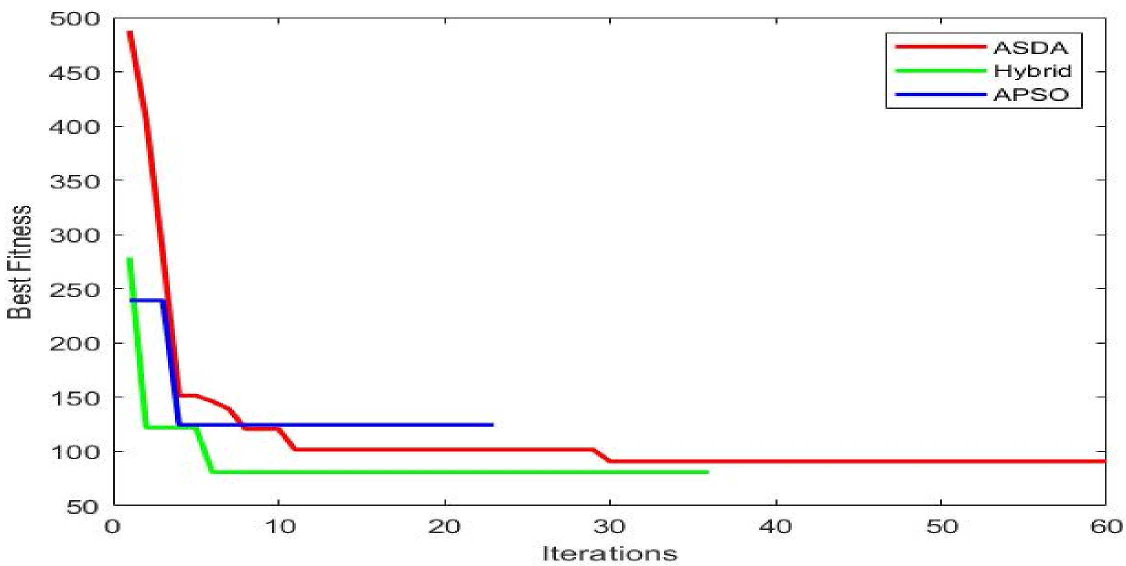

Figure 8: Combined convergence characteristics plot

4.0 Conclusion

The hybrid optimization framework markedly enhances both the efficiency and solution accuracy in the optimal deployment of DGs and D-PMUs within the ADN. It exhibits superior capability in addressing the underlying multi-objective optimization problem, consistently outperforming conventional standalone algorithms. The approach achieves rapid convergence toward near-global optimal solutions, effectively reducing transmission losses and guaranteeing complete network observability with a minimum number of D-PMUs, and demonstrates strong adaptability to varying network topologies and dynamic operating conditions.

Furthermore, the high-resolution data streams generated by the D-PMUs, when integrated with other system measurements, provide a robust dataset for training advanced data-driven control models. These models enable the derivation of optimized control actions for real-time monitoring, stability enhancement, and efficient operational management of the ADN.

References

[1] Gafari Abiola Adepoju, Baruwa Abiodun Aderemi, Sunday Adeleke Salimon, and Oladosu Jamiu Alabi "Optimal Placement and Sizing of Distributed Generation for Power Loss Minimization in Distribution Network using Particle Swarm Optimization Technique*" European Journal of Engineering and Technology Research ISSN: 2736-576X, DOI: http://dx.doi.org/10.24018/ejeng.2023.8.1.2886 Vol 8 | Issue 1 | January 2023 19.*

[2] Radhoush, S., Vannoy, T., Liyanage, K., Whitaker, B. M., and Nehrir, H., "Deep learning-based state estimation and cyber-attack detection in active distribution networks*," IEEE Trans. Smart Grid, 2023*

[3] Puvikko Chezhian, Subramanian Srikrishna, Ganesan Sivarajan and Naveen Kumar Kaliyan "Optimizing PMU Placement in Distribution Systems for Enhanced State Estimation Amid Power System Disruptions. *Journal of computer science (issn no: 1549-3636) volume 18 issue 07 july 2025*

[4] Y. Sun, X. Chen, S. Yang, Rusli, K. J. Tseng, and G. Amaratunga,"Micro PMU Based Monitoring System for Active Distribution Networks*," in Proceedings of the IEEE 12th International Conference on Power Electronics and Drive Systems (PEDS), 2017, pp. 518–522.*

[5] Kapil Chauhan and Ranjana Sodhi, "Placement of Distribution-Level Phasor Measurements for Topological Observability and Monitoring of Active Distribution Networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 6, pp. 3451–3460, 2020.

[6] S. Chauhan and R. Dahiya, "Observability enhancement using optimal PMU placement considering zero-injection buses," IEEE Systems Journal, 2021.

[7] Kai Dehghanpour , Yuxuan Yuan, Zhaoyu Wang and Fei Bu "A Game-Theoretic Data-Driven Approach for Pseudo-Measurement Generation in Distribution System State Estimation," *IEEE Transactions on Smart Grid, vol. 10, no. 6, pp. 5942–5951, 2019.*

[8] Guido Cavraro, Reza Arghandeh, Kameshwar Poolla, and Alexandra von Meier, "Data-Driven Approach for Distribution Network Topology Detection," *IEEE Power & Energy Society General Meeting, Denver, CO, USA, 2015, pp. 1–5.*

[9] Shahab Bahrami, Yu Christine Chen and Vincent W. S. Wong Dynamic Distribution Network Reconfiguration With Generation and Load Uncertainty *November 2024 IEEE Transactions on Smart Grid PP(99):1-1 DOI: 10.1109/TSG.2024.3404859*

[10] Khaoula Hassini, Ahmed Fakhfakh, and Faouzi Derbel, "Optimal Placement of μPMUs in Distribution Networks with Adaptive Topology Changes," *Energies, vol. 16, no. 20, p. 7047, 2023*

[11] K. Paul, B. Jyothi, R. Seshu Kumar, Arvind R. Singh, Mohit Bajaj, B. Hemanth Kumar, and Ievgen Zaitsev, "Optimizing sustainable energy management in grid connected microgrids using quantum particle swarm optimization for cost and emission reduction," *Scientific Reports, vol. 15, Art. no. 5843, 2025.*

[12] Sabo Miya Hassan, Rosdiazli Ibrahim, Nordin Saad, Vijanth Sagayan Asirvadam, and Kishore Bingi, "Hybrid APSO–Spiral Dynamic Algorithms with Application to Tuning of Filtered PPI Controller in a WirelessHART Environment," *Journal of Intelligent & Fuzzy Systems*, vol. 37, no. *1, pp. 597–610, 2019, doi: 10.3233/JIFS-171288.*

[13] Cavus, M. Advancing Power Systems with Renewable Energy and Intelligent Technologies: A Comprehensive Review on Grid Transformation and Integration. Electronics 2025, 14, 1159. https:// *doi.org/10.3390/electronics 14061159*

[14] Azriyenni Azhari Zakri, Rangga Eka Saputra, Makmur Saini, and Hidayat Hidayat, "Distributed Generation installed by the Phasor Measurement Unit to improve voltage," *SINERGI*, vol. 26, no. 1, pp. 37–46, *Feb. 2022, doi: 10.22441/sinergi.2022.1.006.*

[15] T. T. Tesfay, J. -Y. Le Boudec and O. Svensson (2018) Optimal Software Patching Plan for PMUs in *IEEE Transactions on Smart Grid, vol. 9, no. 6, pp. 6500- 6510, Nov. 2018, doi: 10.1109/TSG.2017.2714204*

[16] Satish Kansal, Vishal Kumar, Barjeev Tyagi (2013) Optimal placement of different type of DG sources in distribution networks Electrical Power and Energy Systems *journal homepage: www.elsevier.com/locate/ijepes http://dx.doi.org/10.1016/j.ijepes.2013.05.04*

Received: 04/05/2026; Revised: 09/05/2026; Accepted: 18/05/2026; Published: 23/05/2026

[17] Fotopoulou, M.; Petridis, S.; Karachalios, I.; Rakopoulos, D. A Review on Distribution System State Estimation Algorithms. *Appl. Sci. 2022, 12, 11073. https://doi.org/ 10.3390/app12211107*.
[18] Xiangyu Kong, Xiaoxiao Yuan, Yuting Wang, Yong Xu, and Li Yu, "Research on Optimal D-PMU Placement Technology to Improve the Observability of Smart Distribution Networks*," Energies, vol. 12, no. 22, p. 4297, 2019, doi: 10.3390/en12224297.*
[19] Muhammad Usama Usman, M. Omar Faruque (2019) Applications of synchrophasor technologies in power systems. J. Mod. Power Syst. *Clean Energy (2019) 7(2):211–226 https://doi.org/10.1007/s40565-018-0455-8*
[20] T. P. Nguyen and D. N. Vo. (2018) A Novel Stochastic Fractal Search Algorithm for Optimal Allocation of Distributed Generators in Radial Distribution Systems, *Applied Soft Computing Journal, vol. 70, pp. 773-796*.
[21] Abdelkader boukaroura, Mohammed Amroune (2022). Optimal Placement and Sizing of DGs in Distribution Networks Using Dandelion Optimization Algorithm: *Case Study of an Algerian Distribution Network*