Multi-Objective Dynamic Self-Healing of Unbalanced and Harmonic-Rich Smart Distribution Networks Using Improved Whale Optimization Algorithm

Tung Linh Nguyen[1], Quynh Anh Nguyen[2], and Vu Long Pham[1,3,*]
[1] Faculty of Control and Automation, Electric Power University, Hanoi, 100000, Vietnam
[2] Faculty of Information Technology, Electric Power University, Hanoi, 100000, Vietnam
[3] Institute of Energy, 6 Ton That Tung, Hanoi, 100000, Vietnam
Email: linhnt@epu.edu.vn (T.L.N.), anhnq@epu.edu.vn (Q.A.N.), longpv@ievn.com.vn (V.L.P.)

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*Corresponding author

***Abstract*—The increasing penetration of intermittent Renewable Energy Sources (RES), coupled with the decentralized architecture of modern power distribution networks, has introduced substantial challenges in maintaining system stability and ensuring power quality—particularly under fault conditions and nonlinear operating regimes. This paper proposes a dynamic self-healing model for smart distribution systems based on an Improved Whale Optimization Algorithm (IWOA), with the objective of simultaneously optimizing active power loss, voltage deviation, Total Harmonic Distortion (THD), and Phase Voltage Unbalance Ratio (PVUR). The proposed IWOA incorporates a nonlinear shrinking mechanism, discrete solution mapping, and a normalized, equally weighted multi-objective function structure. These enhancements significantly improve convergence behavior, solution accuracy, and optimization performance in complex combinatorial search spaces. The proposed framework is validated on a modified IEEE 33-bus distribution system featuring unbalanced topologies, harmonic disturbances, and distributed RES integration. Simulation results demonstrate that IWOA outperforms conventional metaheuristics such as Particle Swarm Optimization (PSO), Differential Evolution (DE), and the original WOA in terms of convergence speed, energy efficiency, and power quality enhancement. This study highlights a promising direction for advanced automated optimization strategies in resilient and sustainable energy distribution infrastructures.**

***Index Terms*—self-healing distribution networks, Improved Whale Optimization Algorithm (IWOA), power quality optimization, voltage unbalance, harmonic distortion, smart microgrid reconfiguration**

I. Introduction

The transition toward modern distribution power systems with deep integration of renewable energy sources, such as Photovoltaic (PV) and wind power, presents both tremendous opportunities and significant challenges in ensuring system stability and power quality. These RES are inherently intermittent and rapidly fluctuating in nature, and are typically interfaced through power electronic converters, which are well-known contributors to harmonic distortion and severe phase voltage unbalance in distribution networks [1–3]. These issues become even more critical in the context of smart microgrids, where the combination of nonlinear loads, dynamically reconfigurable topologies, and widespread single-phase DER integration exacerbates local instability and deteriorates overall Power Quality (PQ) [4, 5].

To address these challenges, numerous studies have proposed Distribution Network Reconfiguration (DNR) strategies aimed at minimizing power losses and improving voltage profiles [6–8]. However, many conventional approaches tend to focus solely on these two objectives, while largely neglecting important power quality metrics such as Total Harmonic Distortion (THD) and Phase Voltage Unbalance Ratio (PVUR) particularly critical in networks with single-phase RES [9, 10].

Several recent studies have made initial attempts to incorporate PQ considerations into reconfiguration frameworks. For example, Elazim *et al*. [11] introduced the Modified Sperm Swarm Optimization algorithm (MSSO) algorithm to enhance distribution system reliability, but without addressing harmonics or phase imbalance. Babu *et al*. [12] applied a CS-GWO-based approach to optimize network reconfiguration with improvements in loss reduction, yet PQ metrics were not incorporated. Liu *et al* [13] employed an Improved Whale Optimization Algorithm (IWOA) but restricted the formulation to single-objective optimization. Mohammad Nadimi-Shahraki *et al*. [14] enhanced WOA for optimal capacitor placement with emphasis on voltage profile enhancement, without addressing THD or unbalance. Lu *et al*. [15] extended IWOA for microgrid scheduling but did not consider its application in self-healing under harmonic disturbance scenarios.

More recently, some advanced approaches have emerged that incorporate multiple power quality objectives into the reconfiguration problem. Wang *et al*. [16] conducted a comprehensive review of WOA improvements for multi-objective optimization;

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Hakim *et al*. [17] utilized binary PSO for reconfiguring PV-integrated networks, though PQ-related objectives were not considered and Fayumi *et al*. [18] introduced a Selective Particle Swarm Optimization and Interior Point Optimization (SPSO-IPOPT) algorithm-based framework for dynamic reconfiguration with integrated Distributed Energy Resources (DERs).

Overall, the literature reveals a clear progression from single objective to multi-objective optimization frameworks that address PQ. Although several recent studies have investigated optimization-based reconfiguration, they still exhibit significant methodological gaps in scope or objective coverage. For instance, Liu *et al*. [13] proposed an IWOA-based approach for grid operation scheduling but focused solely on power loss minimization without addressing PQ metrics such as harmonics or voltage imbalance. Fayumi *et al*. [17] developed a dynamic reconfiguration method using SPSO-IPOPT, considering DER integration but without incorporating harmonic distortion or PVUR. Similarly, Hakim *et al*. [18] addressed PV-based reconfiguration using binary optimization but did not account for phase unbalance or nonlinear harmonic propagation. These comparisons highlight that while multi-objective optimization is gaining traction, a comprehensive treatment that simultaneously considers power loss, voltage deviation, THD, and PVUR—especially in unbalanced and harmonic-rich networks—remains largely unexplored. The present study directly addresses this gap through a unified multi-objective, discrete-optimization framework with real-world operational constraints.

Nevertheless, several critical gaps remain unaddressed. First, no existing study has proposed a framework that optimizes all four objectives: power losses, voltage deviation, THD, and PVUR. Second, dynamic self-healing models that accommodate unbalanced loading, RES intermittency, and nonlinear harmonic distortion are still lacking. Third, many metaheuristic-based methods suffer from premature convergence or get trapped in local optima—especially in discrete combinatorial search spaces [19].

To address these deficiencies, this paper proposes a dynamic self-healing system based on an Improved Whale Optimization Algorithm (IWOA) designed to concurrently optimize P_{loss}, V_{dev}, THD, and PVUR. The algorithm is enhanced with an adaptive search mechanism, solution diversity preservation, and discrete-space mapping to improve convergence characteristics and solution robustness in nonlinear, unbalanced, and harmonically polluted environments.

Compared to recent studies such as [13, 17, 18], which omit key PQ metrics, our model incorporates harmonics and phase imbalance.

The proposed model is validated on the IEEE 33-bus distribution test system, modified to reflect practical grid conditions including single-phase and unbalanced loads, harmonic injection, and multiple fault scenarios (N-1, N-2). This study aims to fill the research gaps while offering a robust and scalable tool for real-time, power-quality-aware operation of modern smart distribution systems.

II. Mathematical Model and Optimization Function

A. Overview of the Problem Formulation

In the context of modern distribution systems with high penetration of renewable energy sources, network reconfiguration must not only aim for fast service restoration following contingencies (self-healing) but also ensure the continuous optimization of PQ. Dynamic Network Reconfiguration for Self-Healing (DNR-SH) refers to the process of determining the optimal combination of switch states (open/close) to restore power delivery, maintain system stability, and enhance operational performance under conditions involving dynamic faults, load unbalance, and harmonic distortion.

The problem addressed in this study is formulated as a constrained multi-objective combinatorial optimization task. The decision variables represent the configuration of switching devices across the distribution network. The objective function is designed to simultaneously minimize four critical indicators: active power loss (P_{loss}), voltage deviation (V_{dev}), Total Harmonic Distortion (THD), and Phase Voltage Unbalance Ratio (PVUR).

B. Multi-Objective Function and Constraints

The composite objective function is formulated using a weighted-sum approach, enabling the simultaneous optimization of multiple criteria by converting the problem into an equivalent single-objective framework.

Minimize:

$$F = w_1\tilde{P}_{\text{loss}} + w_2\tilde{V}_{\text{dev}} + w_3\widetilde{\text{THD}} + w_4\widetilde{\text{PVUR}} \quad (1)$$

where $w_i \in [0,1]$ represents the weighting coefficient assigned to the ith objective, subject to the constraint $\sum w_i = 1$. In this study, equal weights are adopted. $w_1 = w_2 = w_3 = w_4 = 0.25$ to ensure a balanced and comprehensive optimization across all objectives. The terms $\tilde{P}_{\text{loss}}, \tilde{V}_{\text{dev}}, \widetilde{\text{THD}}, \widetilde{\text{PVUR}}$ denote the normalized values of each respective objective, computed relative to their base-case values in the original (unreconfigured) network.

C. Detailed Objective Functions

We will consider the objective functions as described below.

1) Active power loss:

$$P_{\text{loss}} = \sum_{(i,j)\in\mathcal{L}} R_{i,j}\frac{(P_{i,j}^2+Q_{i,j}^2)}{V_i^2} \quad (2)$$

where $R_{i,j}$ is the resistance of the distribution line between buses i and j, $P_{i,j}$ and $Q_{i,j}$ are the active and reactive power flows on branch (i, j), and V_i is the voltage magnitude at bus i.

Note: This formulation is adopted as a real-valued approximation consistent with standard test system implementations. For exact modeling, the complex form $P_{\text{loss}} = R\left|\frac{S^*}{V}\right|^2$ can also be used.

2) Voltage deviation:

$$V_{\text{dev}} = \sum_{i=1}^{N}|V_i - V_{\text{ref}}| \quad (3)$$

where V_{ref} is the nominal voltage reference value (typically set to 1.0 p.u.)

3) Total Harmonic Distortion (THD):

$$\text{THD}_{\text{i}} = \left(\sum_{h=2}^{H}\left(\frac{I_{h,i}}{I_{1,i}}\right)^2\right)^{1/2}.100\% \tag{4}$$

where $I_{h,i}$: denotes the current of the hth harmonic order at bus i, $I_{1,i}$ represents the fundamental component. Therefore, the total harmonics objective function is

$$\widetilde{\text{THD}} = \sum_{i=1}^{N}\text{THD}_i.$$

4) Phase voltage unbalance ratio $\widetilde{\text{PVUR}}_i$

$$\widetilde{\text{PVUR}}_{\text{i}} = \frac{\max(V_{R,i}, V_{S,i}, V_{T,i}) - \min(V_{R,i}, V_{S,i}, V_{T,i})}{V_{\text{avg},i}}100\% \tag{5}$$

where $V_{R,i}, V_{S,i},$ and $V_{T,i}$ are the voltages of phases R, S, and T at bus i, and $V_{\text{avg},i} = \frac{V_{R,i}+V_{S,i}+V_{T,i}}{3}$ is the average phase voltage at bus i.

D. Objective Normalization

To ensure consistency in units and scale across all evaluation metrics, a linear normalization approach is employed, formulated as follows:

$$\widetilde{f_i} = \frac{f_i}{f_i^{\text{base}}} \tag{6}$$

where f_i is the denotes the current value of the ith objective and f_i^{base} represents its corresponding value in the base-case (i.e., the unreconfigured network scenario).

E. Constraint Conditions

The optimization model is subject to a set of operational and physical constraints to ensure feasibility and compliance with power system requirements:

- *Voltage magnitude limits at each bus:*

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \forall i \in \mathcal{N} \tag{7}$$

Typically, 0.95 p.u. $\le V_i \le$ 1.05 p.u.

- *Branch current limits:*

$$I_{ij} \le I_{ij}^{\max} \qquad \forall (i,j) \in \mathcal{L} \tag{8}$$

This constraint ensures that the thermal capacity of the branches is not exceeded under any loading condition.

- *Radial topology constraint:*

$$\text{Number of closed switches} = N_{\text{bus}} - 1 \tag{9}$$

This ensures that the network remains radial and avoids meshed configurations that may compromise protection coordination.

- *Nodal power balance:*

$$\sum_{j\in\mathcal{N}} P_{ij} = P_{L,i} - P_{G,i} \qquad \forall i \in \mathcal{N} \tag{10}$$

where $P_{L,i}$ is the load and $P_{G,i}$ is the generation at node i

- *Switching operation limit:*

$$N_{\text{switch}}^{\text{change}} \le N_{\max} \tag{11}$$

This constraint restricts the number of switching actions during reconfiguration, aiming to reduce mechanical wear and limit control complexity

III. Improved Whale Optimization Algorithm

A. Overview of the Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm (WOA), originally proposed by Mirjalili and Lewis [20], is a prominent metaheuristic inspired by the hunting behavior of humpback whales. WOA simulates two primary stages of whale predation: the encircling phase and the bubble-net attacking phase. In continuous search spaces, this strategy allows the algorithm to approach the global optimum in a flexible and relatively efficient manner for simple optimization problems.

The Whale Optimization Algorithm has been applied across various domains of electrical engineering, particularly in solving problems related to power loss minimization and voltage regulation [16]. However, when extended to more complex multi-objective combinatorial problems—such as distribution network reconfiguration under nonlinear and harmonic-rich environments—the standard WOA framework reveals several critical limitations:

- Premature convergence: Due to its linearly decreasing control parameter, the algorithm is prone to being trapped in local optima.
- Inadaptability to discrete search spaces: The on/off configuration of switches in network reconfiguration constitutes a discrete combinatorial problem, which the basic WOA is ill-equipped to handle effectively.
- Inefficiency in handling heterogeneous multi-objective problems: The standard WOA does not account for discrepancies in units and scales across multiple objectives (e.g., THD in percentage vs. Ploss in kilowatts).

To overcome these limitations, this study proposes an enhanced version of the algorithm, referred to as the Improved Whale Optimization Algorithm (IWOA), incorporating several key modifications to address the above challenges and improve performance in complex grid optimization tasks.

B. Enhancements in the Proposed IWOA

1) Nonlinear contraction mechanism (cubic contraction)

In the original WOA, the vector A—which governs the search space contraction behavior—linearly decreases from 2 to 0 as follows:

$$A = 2.a.r - a, \quad \text{with } a = 2 - \frac{2.t}{T} \tag{12}$$

Here, $r \in [0,1]$, t is the current iteration, and T is the maximum number of iterations.

In the proposed IWOA, the parameter a is updated using a cubic decay function to enhance convergence flexibility:

$$a = 2.\left(1 - \left(\frac{t}{T}\right)^3\right) \tag{13}$$

2) Discrete search space (discrete mapping)

The standard WOA operates in a continuous search space $[0,\ 1]^{\text{D}}$, which is unsuitable for combinatorial optimization problems such as switch configuration.

In the proposed IWOA, each element X_d of the whale position vector is projected onto a discrete value set via a rounding function, as follows:

$$X_d^{\text{disc}} = \arg\min_{x \in S_d} |X_d - x| \tag{14}$$

where S_d denotes the set of feasible discrete values (e.g., {0,1} for switch open/close states).

3) Adaptive parameter control mechanism

The IWOA incorporates an adaptive weighting function to dynamically balance exploration and exploitation capabilities throughout the optimization process, governed by the parameter $\lambda(t)$

$$\lambda(t) = \lambda_{\max}\,(1 - \tfrac{t}{T}) \tag{15}$$

Remark: As t increases, $\lambda(t)$ decreases, thereby increasing the emphasis on local exploitation.

4) Normalized multi-objective fitness function

The IWOA addresses the four-objective optimization problem by applying normalization and assigning equal weighting to each criterion (as referenced in Eq. (1)). This approach enables consistent evaluation of objectives with heterogeneous units such as kilowatts (kW), percent (%), and per unit (p.u.) within a unified assessment framework.

C. Pseudocode for Problem

Input: Network data, population size N, maximum iterations T, objective weights w_i
1. Initialize a population of N individuals X_i with random switch configurations
2. Evaluate the objective function F(X_i) using (1)
3. Identify the best individual X_best
For t = 1 to T do:
    For each individual X_i in the population do:
        - Update vectors A and C according to (12) and (13)
        - If rand < 0.5 then:
            - Apply shrink encircling or spiral bubble-net attack
        - Else:
            - Perform random exploration
        - Project solution to discrete search space using (14)
    End For
    Update X_best if a better solution is found
End For
Output: Optimal switch configuration with minimized objective function F

D. Convergence and Computational Complexity Analysis

Convergence: The integration of cubic parameter decay and adaptive control mechanisms significantly enhances global search capability and accelerates convergence. Experimental evaluations (as presented in later sections) demonstrate that IWOA achieves convergence approximately 30% to 40% faster than the original WOA in terms of the number of iterations required.

Computational Complexity: For a population of N individuals and T iterations, the total time complexity of the IWOA is:

$$\partial(NTf_{\text{evalf}}) \tag{16}$$

where f_{evalf} denotes the computational cost of evaluating the objective function. This complexity is comparable to that of PSO and GWO; however, due to its faster convergence behavior, IWOA achieves a reduced overall runtime in practice.

The proposed algorithm is illustrated in Fig. 1, and its operational steps are described as follows:

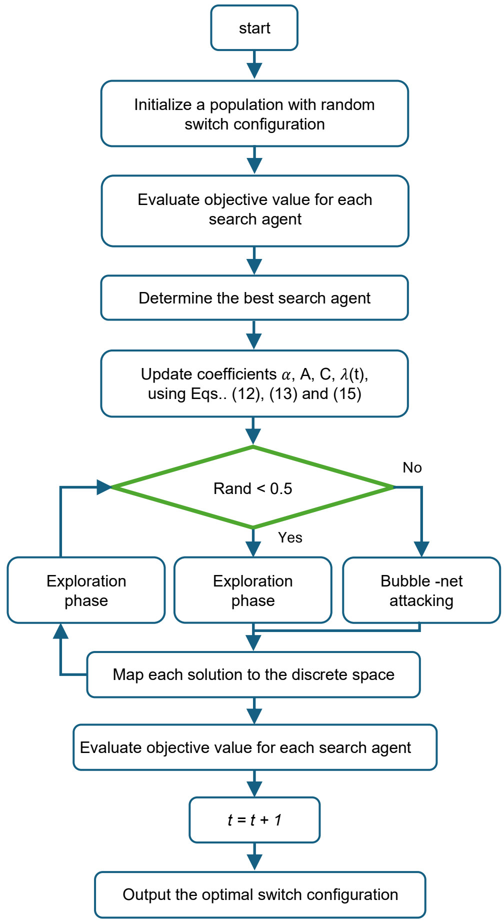

Fig. 1. Improved Whale Opimization Algorithm (IWOA).

Step 1: Population Initialization: Generate a set of individuals (agents), where everyone represents a randomly generated switch open/close configuration within the distribution network.

Step 2: Objective Function Evaluation:Compute the multi-objective fitness function—including power loss, voltage deviation, THD, and PVUR—for each individual in the population.

Step 3: Best Individual Identification: Record the individual with the best (i.e., lowest) objective function value as X_{best}

Step 4: Algorithmic Coefficient Update: Update the control parameters *a, A, C,* and $\lambda(t)$ according to (12), (13), and (15), which govern the search behavior.

Step 5: Behavior Phase Selection:
If rand <0.5 select the exploitation phase — direct movement toward X_{best}
Else: select the bubble-net attack phase, applying either spiral motion or contraction.
Otherwise: perform the exploration phase through random search.

Step 6: Discrete Solution Mapping: Project each continuous solution vector onto a feasible combinatorial space (e.g., map each value to 0 or 1 for binary switch status).

Step 7: Fitness Reevaluation: Recalculate the objective function values for all individuals in the updated population.

Step 8: Iteration Loop: Increment the iteration counter $t=t+1$ and repeat the above steps until the maximum number of iterations T is reached.

Step 9: Output Result: Return the optimal switch configuration corresponding to the minimum objective function value found during the optimization process.

IV. Improved Whale Optimization Algorithm

A. Test System Setup

To evaluate the effectiveness of the proposed IWOA under realistic operating conditions, simulations were conducted on a modified IEEE 33-bus distribution system. (Detailed data for unbalanced phase loads and DER integration are provided in Appendix A) The test system includes four interconnected microgrid clusters, each integrating various types of renewable energy sources such as Photovoltaic (PV), wind turbines, Battery Energy Storage Systems (BESS), and Distributed Generation (DG). The model incorporates three-phase unbalanced load conditions as well as time-varying harmonic injection profiles to closely reflect practical scenarios. Two fault scenarios are considered: 1) an N–1 contingency involving the loss of a single branch during peak PV generation hours, and 2) an N–2 contingency involving the simultaneous loss of two branches during the system's peak load period.

The performance of the proposed IWOA is compared against three benchmark algorithms: Particle Swarm Optimization (PSO), Differential Evolution (DE), and the original Whale Optimization Algorithm (WOA).

B. Node-Wise Power Quality Assessment

Following the application of each optimization algorithm for network reconfiguration, the Total Harmonic Distortion (THD) and Phase Voltage Unbalance Ratio (PVUR) indices were computed for every node in the system. Fig. 2 and Fig. 3 illustrate the comparative performance of IWOA versus the original WOA in terms of node-level THD and PVUR distributions, respectively.

Overall, under the coordination of IWOA, the THD is tightly regulated, maintaining values within the range of approximately 2.0% to 2.7%, which is significantly lower than those observed with the original WOA—where many nodes exceed the 5.0% threshold. Similarly, the Phase Voltage Unbalance Ratio (PVUR) under IWOA remains below 1.0% at all nodes, whereas WOA exceeds the 2.0% margin at several nodes with single-phase PV integration. These results clearly demonstrate the superior capability of IWOA in managing harmonic distortion and phase balance on a node-by-node basis.

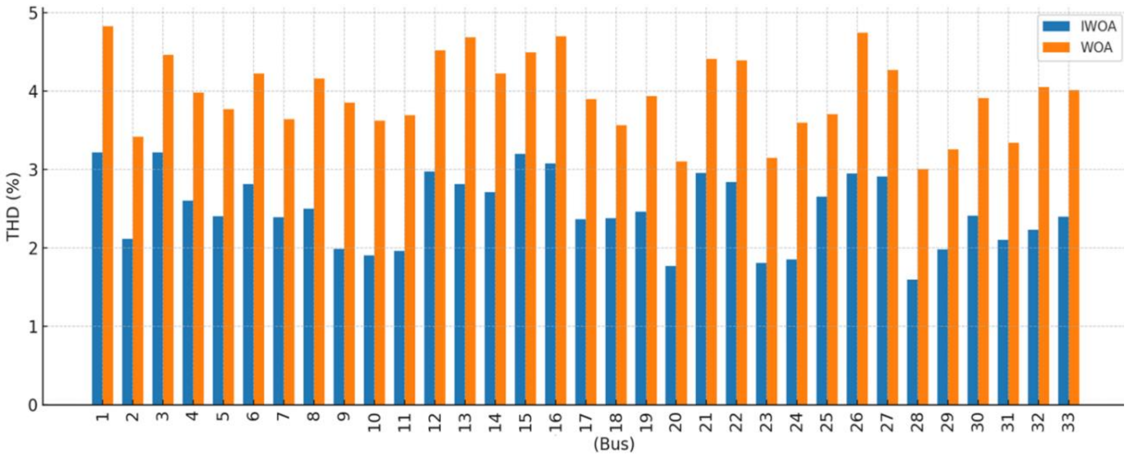

Fig. 2. Node-wise THD comparison between IWOA and WOA.

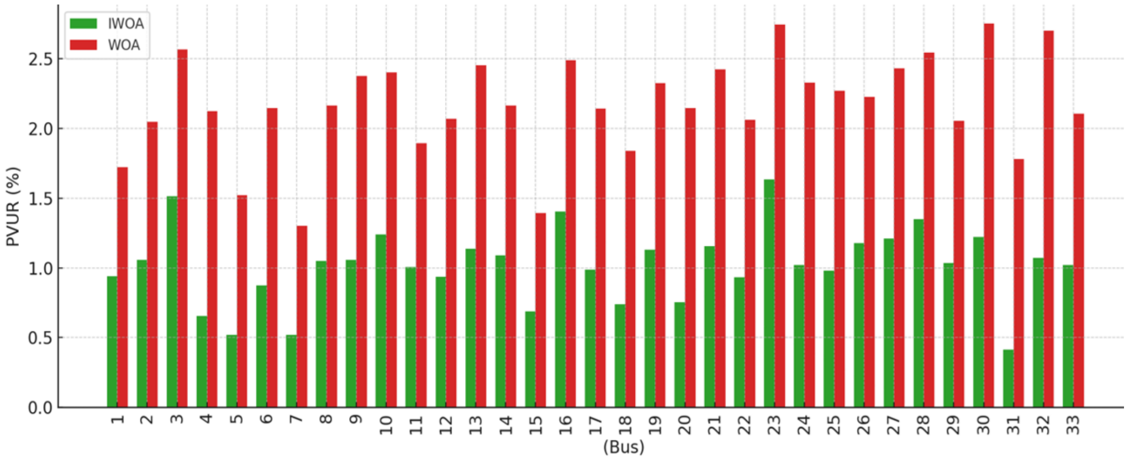

Fig. 3. Node-wise PVUR comparison between IWOA and WOA.

C. Assessment Convergence Behavior of the Objective Function

One of the key aspects in any optimization problem is the speed and stability of convergence. Fig. 4 illustrates the convergence trajectories of the considered algorithms.

The IWOA achieves rapid convergence within approximately 12 iterations and stabilizes at a lower objective function value compared to the other methods. It should be noted that Table I presents the number of iterations required for each algorithm to achieve convergence based on the termination criteria (i.e., minimal change in objective value over successive iterations). In contrast, Fig. 4 illustrates the complete convergence trajectories across all iterations up to the predefined maximum. This distinction highlights not only the efficiency but also the stability of the proposed IWOA compared to other algorithms. While WOA and DE exhibit slower or oscillatory convergence patterns, IWOA stabilizes within fewer than 12 iterations, demonstrating faster convergence and robustness. PSO and DE require 18–21 iterations to reach a steady state, while the original WOA converges earlier but becomes trapped in local optima, yielding inferior solution quality. These observations underscore the practical effectiveness of the proposed nonlinear contraction vector and discrete-space mapping strategies employed in IWOA.

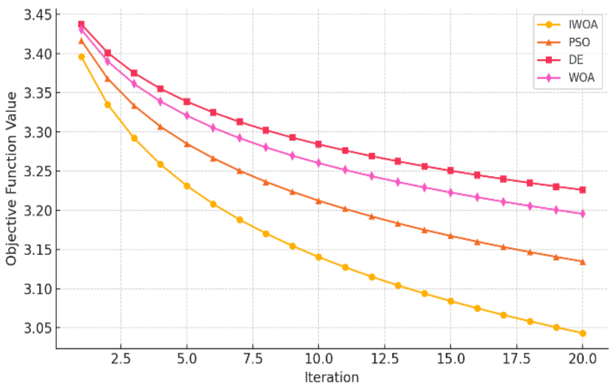

Fig. 4. Convergence curves of the objective function.

TABLE I: SUMMARY OF OPTIMIZATION ALGORITHM PERFORMANCE

Algorithm	TDH TB(%)	PVUR TV(%)	Plosse (kW)	Iteration	DeltaU (pu)
IWOA	2.32	0.61	0.121	12	0.015
PSO	2.68	0.78	0.124	18	0.018
DE	2.59	0.69	0.126	21	0.020
WOA	4.15	1.17	0.221	15	0.026

D. Power Loss Comparison

In Fig. 5 illustrates the total active power loss obtained by each algorithm following network reconfiguration.

The IWOA achieves the lowest power loss at 0.121 MW, representing an improvement of approximately 5–7% compared to PSO and DE, and a substantial reduction of nearly 45% relative to the original WOA, which records a loss of 0.221 MW. This result not only validates the efficiency of IWOA in power flow coordination but also suggests its potential for long-term economic benefits in grid operation.

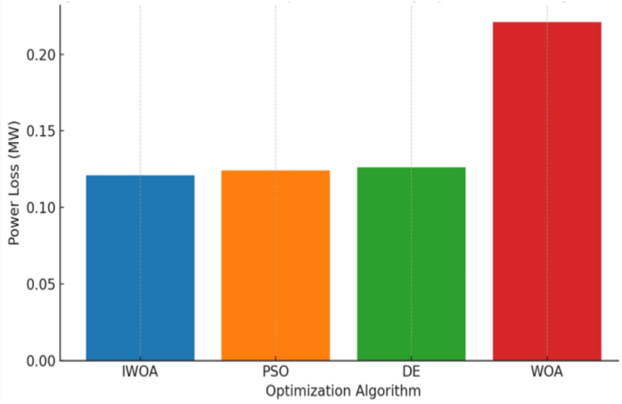

Fig. 5. Power loss comparison among optimization algorithms.

While [13, 18] focus on loss minimization or PV support, they do not explicitly address phase unbalance or THD. Our method addresses all four objectives simultaneously.

E. Summary of Algorithm Performance

The overall performance metrics of all algorithms are consolidated in Table I. From the results presented in Table I, it is evident that IWOA delivers superior overall performance. It achieves the lowest average THD (2.32%), the lowest PVUR (0.61%), the least power loss, the fastest convergence rate, and the smallest voltage deviation among all compared algorithms. While PSO and DE demonstrate reasonable effectiveness, they fall short of the holistic consistency achieved by IWOA. The original WOA clearly exhibits limitations when applied to nonlinear, multi-objective optimization in distribution systems.

F. Sensitivity Analysis of Weighting Factors

A sensitivity analysis was conducted by varying the weights assigned to each objective in the composite fitness function. The results indicate that increasing the weight of THD from 0.25 to 0.4 reduces THD by approximately 0.3–0.4% but leads to a 6–8% increase in power losses. Conversely, lowering the weight of power loss improves power quality but degrades energy efficiency. Therefore, the configuration with equal weights w_i=0.25 provides the most stable and robust performance across all metrics. Increasing the weight assigned to THD (e.g., from 0.25 to 0.40) results in a more aggressive minimization of harmonic distortion, reducing average THD by approximately 0.3% to 0.4%. However, this prioritization compromises energy efficiency, leading to a 6% to 8% increase in total active power loss. Similarly, assigning lower weights to power loss improves PQ indicators but degrades overall system efficiency. This behavior highlights the inherent trade-offs among the four objectives, reinforcing the rationale for using uniform weighting. Such balanced weighting enables robust and stable performance across various operating scenarios, without overfitting the optimization toward any single objective.

G. Factors Overall Evaluation and Discussion

Considering power quality enhancement, energy efficiency, convergence speed, and algorithmic stability, IWOA consistently outperforms the alternative methods. Its integration of a nonlinear contraction strategy, discrete solution mapping, and normalized multi-objective formulation enables faster convergence, greater accuracy, and more robust optimization under highly dynamic and uncertain distribution system conditions. These enhancements collectively empower IWOA to serve as an effective solution for complex reconfiguration tasks in smart distribution grids.

V. CONCLUSION

This study presents a comprehensive and technically rigorous self-healing reconfiguration framework for unbalanced and harmonic-rich distribution networks, leveraging the Improved Whale Optimization Algorithm to address four simultaneously critical operational objectives: active power losses, voltage deviation, total harmonic distortion, and phase voltage unbalance ratio. The proposed approach significantly advances existing literature by unifying multi-objective optimization, discrete decision variables, and nonlinear grid dynamics into a coherent and scalable control solution—particularly suited for modern distribution systems with high penetration of distributed energy resources and nonlinear loads.

Methodologically, the IWOA integrates several key algorithmic enhancements, including nonlinear cubic contraction for balanced exploration-exploitation dynamics, discrete solution space mapping for effective handling of switching configurations, and an equally weighted normalization scheme to standardize heterogeneous objectives. These innovations collectively enable superior convergence speed, global optimality, and robustness in complex combinatorial search spaces. Simulation results on the modified IEEE 33-bus test feeder demonstrate consistent improvements over benchmark algorithms such as PSO, DE, and classical WOA, across all performance indicators—namely power quality, energy efficiency, and convergence behavior.

Nonetheless, the study acknowledges several limitations. First, validation is currently confined to a standard-scale benchmark system, which may not fully encapsulate the spatial and temporal diversity of real-world grids. Second, the model assumes idealized communication and actuation infrastructure, while practical deployments must contend with latency, noise, and switching delays. To address these constraints, future research will explore extensions to large-scale systems, incorporation of delay-aware and transient constraints, and hybridization with deep reinforcement learning to enable adaptive, context-aware control. Hardware-In-the-Loop (HIL) testing is also envisioned to bridge the gap between simulation and field-level implementation.

In essence, this research not only delivers a high-performance algorithmic tool but also lays a strategic foundation for the development of resilient, intelligent, and self-healing power distribution infrastructures in the era of decentralized energy systems.

APPENDIX

A. Unbalanced Load and DER Profiles for IEEE 33-Bus System

This appendix provides the complete unbalanced load distribution (Table AI) and distributed energy resources (DER) allocation (Table AII) used in the modified IEEE 33-bus test system. The system simulates realistic conditions with unbalanced three-phase loads and DER integration including PV, Wind, DG, and BESS.

TABLE AI: UNBALANCED PHASE LOAD DISTRIBUTION

Bus No.	Phase A Load (kW/kVar)	Phase B Load (kW/kVar)	Phase C Load (kW/kVar)	Total Load (kW/kVar)
1	50 / 30	0 / 0	42 / 23	92 / 53
2	60 / 36	46 / 23	49 / 26	155 / 85
3	70 / 42	0 / 0	0 / 0	70 / 42
4	80 / 48	30 / 15	42 / 23	152 / 86
5	40 / 24	0 / 0	49 / 26	89 / 50
6	50 / 30	46 / 23	0 / 0	96 / 53
7	60 / 36	0 / 0	42 / 23	102 / 59
8	70 / 42	30 / 15	49 / 26	149 / 83
9	80 / 48	0 / 0	0 / 0	80 / 48
10	40 / 24	46 / 23	42 / 23	128 / 70
11	50 / 30	0 / 0	49 / 26	99 / 56
12	60 / 36	30 / 15	0 / 0	90 / 51
13	70 / 42	0 / 0	42 / 23	112 / 65
14	80 / 48	46 / 23	49 / 26	175 / 97
15	40 / 24	0 / 0	0 / 0	40 / 24
16	50 / 30	30 / 15	42 / 23	122 / 68
17	60 / 36	0 / 0	49 / 26	109 / 62
18	70 / 42	46 / 23	0 / 0	116 / 65
19	80 / 48	0 / 0	42 / 23	122 / 71
20	40 / 24	30 / 15	49 / 26	119 / 65
21	50 / 30	0 / 0	0 / 0	50 / 30
22	60 / 36	46 / 23	42 / 23	148 / 82
23	70 / 42	0 / 0	49 / 26	119 / 68
24	80 / 48	30 / 15	0 / 0	110 / 63
25	40 / 24	0 / 0	42 / 23	82 / 47
26	50 / 30	46 / 23	49 / 26	145 / 79
27	60 / 36	0 / 0	0 / 0	60 / 36
28	70 / 42	30 / 15	42 / 23	142 / 80
29	80 / 48	0 / 0	49 / 26	129 / 74
30	40 / 24	46 / 23	0 / 0	86 / 47
31	50 / 30	0 / 0	42 / 23	92 / 53
32	60 / 36	30 / 15	49 / 26	139 / 77
33	70 / 42	0 / 0	0 / 0	70 / 42

Note: The loads are representative synthetic values to reflect phase unbalance across the network.

TABLE AII: DISTRIBUTED ENERGY RESOURCES (DER) ALLOCATION

Bus No.	DER Type	Rated Capacity (kW)	Phase Connection
6	PV	50	Phase A
13	Wind	75	Three-phase
18	BESS	40	Phase B
22	DG	60	Phase C
30	PV	45	Phase B

CONFLICT OF INTEREST

The authors have no conflicts of interest to declare.

AUTHOR CONTRIBUTIONS

Tung Linh Nguyen: Conceptualization, algorithm development, and manuscript supervision. Quynh Anh

Nguyen: Simulation and performance evaluation. Vu Long Pham: Draft writing and manuscript revision. All authors had approved the final version.

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Nguyen Tung Linh was born in 1982. He earned his bachelor's and master's degrees in electrical and electronic engineering from Hanoi University of Science and Technology (2005, 2010). He received his Ph.D. degree in 2018 from the Vietnam Academy of Science and Technology with the dissertation "building artificial intelligence algorithms for the problem of reconfiguration network distribution." He is currently affiliated with the Faculty of Control and Automation, Electric Power University (EPU), Hanoi, Vietnam. His research focuses on smart electrical systems, renewable energy, distribution network reconfiguration, AI applications, and digital energy transformation. He has published over 45 papers in national and international journals and conferences.

Nguyen Quynh Anh is a lecturer at the Faculty of Information Technology, Electric Power University, Vietnam. She received her master's degree in computer science from the Faculty of Information Technology, Posts and Telecommunications Institute of Technology, Vietnam. Her research interests are primarily in the field of biomedical engineering, particularly in Electroencephalogram (EEG) signal processing. Her has published more than 10 articles in national and international journals, workshops, and conferences.

Pham Vu Long was born in 1980. He earned his bachelor's and master's degrees in electrical and electronic engineering from Hanoi University of Science and Technology (2003, 2010). He is currently a research fellow at the Vietnam Institute of Energy. At present, he is also a Ph.D. candidate at the Faculty of Automation Control, Electric Power University. His research focuses on smart grids and power quality, and reconfiguration distribution network. He has co-authored five published research papers with his collaborators.