

Hierarchical Coordination of Network Planning and Consumer Flexibility for DG-Integrated Distribution Systems

Minh Phong Le

Faculty of Electrical and Electronics, Thu Duc College of Technology, Ho Chi Minh City, Vietnam,

DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150900014>

Received: 11 September 2026; Accepted: 16 September 2026; Published: 30 September 2026

ABSTRACT

The growing integration of distributed generation (DG) is reshaping distribution network operation, making coordinated planning of network resources and consumer flexibility increasingly important. This study develops a hierarchical optimization framework that jointly considers DG allocation and demand response under time-of-use (TOU) pricing. The upper-level problem determines the location and capacity of DG units to improve network performance, while the lower-level problem captures consumer load adjustment in response to electricity prices. The bi-level formulation is converted into a single-level nonlinear optimization model using the Karush–Kuhn–Tucker conditions and solved by the Marine Predators Algorithm (MPA). The proposed framework is validated on IEEE 33-bus and 69-bus distribution systems and benchmarked against WOA, HHO, AOA, GBO, and SDO. Results show that MPA consistently provides the lowest daily energy loss, achieving 223.5 kWh/day and 241.7 kWh/day for the two test systems, respectively. It also delivers competitive TOU operating costs while maintaining all bus voltages within the 0.95 - 1.05 p.u. range. These findings demonstrate that coordinated DG planning and consumer flexibility can substantially improve the technical and economic performance of distribution systems compared with treating these decisions separately. The proposed framework therefore provides an effective and computationally practical approach for planning DG-integrated distribution networks under flexible electricity demand.

Keywords: Distributed generation, demand response, hierarchical optimization, time-of-use pricing; distribution networks, Marine Predators Algorithm, consumer flexibility.

INTRODUCTION

Distribution networks are increasingly evolving from conventional passive systems into active and flexible energy infrastructures. This transition is largely driven by the growing deployment of distributed generation (DG), including photovoltaic systems, small-scale wind generation, and other distributed energy resources (Kumar et al. 2023). Appropriate integration of DG can provide important technical and economic benefits, such as reducing network losses, relieving the dependence on centralized generation, improving supply resilience, and supporting the transition toward lower-carbon power systems (Siano and Sarno 2016), (Theo et al. 2017). Nevertheless, increasing DG penetration also makes network planning more challenging, particularly when the location and capacity of DG units must be determined while maintaining acceptable operating conditions.

At the same time, electricity consumers are becoming an active component of distribution system operation. Rather than maintaining fixed consumption patterns, responsive consumers can modify the timing of their electricity use in response to electricity prices and other economic signals. Time-of-use (TOU) tariffs are among the commonly adopted mechanisms for encouraging such behavioral changes, as they provide different electricity prices over predefined periods and consequently motivate consumers to transfer part of their demand from high-price periods to lower-price periods (Shahidehpour, Yamin, and Li, 2002), (T. N. Trieu et al. 2021). Demand response (DR) therefore provides an additional source of flexibility that can influence not only consumer electricity expenditure but also the operating conditions of the distribution network.

The simultaneous consideration of DG planning and consumer flexibility creates a coupled decision-making problem. Decisions concerning DG location and capacity affect power flows, voltage profiles, and network losses, while changes in consumer demand influence the same network variables and can alter the benefits obtained from DG deployment. A planning framework that considers these decisions independently may therefore fail to capture their interactions. Bi-level optimization provides a suitable mathematical structure for representing this relationship, in which the distribution system operator (DSO) makes network-level planning decisions while consumers respond to the resulting economic environment by adjusting their electricity consumption (Javadi et al. 2019).

Previous research has investigated demand-side scheduling, TOU-based load management, and bi-level optimization from different perspectives (Sun, Gao, and Wu 2008), (International Energy Agency 2023). However, the simultaneous coordination of DG siting and sizing with consumer demand response under TOU pricing remains relatively limited. This issue is particularly relevant to distribution systems in emerging electricity markets, including Vietnam, where TOU-based electricity pricing and demand-side participation are becoming increasingly important. A coordinated framework is consequently required to capture the interaction between infrastructure planning and consumer-side flexibility within a unified optimization model.

To address this issue, this study develops a hierarchical optimization framework for coordinating DG planning and consumer flexibility in distribution networks. The upper-level problem represents the DSO and determines the locations and capacities of DG units while considering network energy losses, voltage deviations, and DG investment expenditure. The lower-level problem represents responsive consumers, who modify their hourly electricity consumption to reduce their electricity bills under TOU tariffs while satisfying daily energy requirements and demand bounds. The resulting structure explicitly links network planning decisions with demand-side flexibility rather than treating them as separate optimization tasks.

Because the original hierarchical formulation is computationally difficult to solve directly, the lower-level consumer optimization problem is incorporated into the upper-level model through its Karush–Kuhn–Tucker (KKT) optimality conditions (Xie et al. 2019), (Izmailov and Solodov 2003). This transformation produces a single-level nonlinear optimization problem while retaining the interaction between the DSO and consumers. The resulting formulation remains non-convex and highly constrained because of the DG siting decisions, nonlinear distribution-network power-flow relationships, and coupling between network operation and demand response.

A Marine Predators Algorithm (MPA) based solution procedure is subsequently employed to solve the resulting optimization problem. MPA uses different search mechanisms during its exploration, transition, and exploitation stages, providing a balance between broad search and local solution refinement (Faramarzi et al. 2020). To examine the effectiveness of the proposed solution approach, its performance is compared with several established metaheuristic algorithms, including Harris Hawks Optimization (HHO) (Selim et al. 2020), Whale Optimization Algorithm (WOA) (Prakash and Lakshminarayana n.d.), Gradient Based Optimizer (GBO) (El-Rifaie et al. 2023), and Arithmetic Optimization Algorithm (AOA) (Zhang et al. 2022). The comparative evaluation is conducted using the IEEE 33-bus and IEEE 69-bus distribution systems under a 24-hour TOU pricing and demand-response framework. Each of these algorithms is inspired by distinct biological or mathematical principles and has shown competitive performance in recent studies. The proposed bi-level optimization framework is implemented on the 33-bus and 69-bus DN under 24-hour TOU pricing and demand response scenarios. Simulation results demonstrate that the MPA consistently outperforms the benchmark algorithms in minimizing technical losses, reducing operational costs, and achieving more effective DG placements. These results highlight the effectiveness of integrating advanced metaheuristics with demand side flexibility in DN planning. The proposed model serves as a mathematically tractable and scalable optimization framework for future smart grid applications, where dynamic pricing and active consumer participation are expected to play an increasingly vital role.

The main purpose of the study is therefore not only to identify suitable DG locations and capacities, but also to quantify how consumer flexibility can be coordinated with network planning decisions. By jointly

considering technical performance, investment requirements, and demand-side response, the proposed framework provides a unified approach for improving the operation and planning of DG-integrated distribution systems. The numerical results demonstrate the applicability of this coordinated strategy in reducing network energy losses and electricity-related operating costs while maintaining bus voltages within the prescribed operating limits.

Problem Formulation and Hierarchical Model

The coordination between distribution-network planning and consumer-side flexibility is represented by a hierarchical optimization model. The formulation distinguishes the strategic decisions of the distribution system operator (DSO) from the operational response of electricity consumers. This structure makes it possible to evaluate DG deployment while explicitly accounting for the changes in demand induced by TOU electricity pricing.

The DSO determines the location and capacity of DG units at the upper decision layer. Its planning objective considers network energy losses, voltage deviations, and the investment required for DG installation. At the same time, consumers respond to the applicable TOU tariffs by adjusting their hourly electricity consumption. Their scheduling problem is formulated at the lower layer, where the primary objective is to reduce electricity expenditure while maintaining the required daily energy consumption and hourly operating limits.

The two decision layers are interdependent. The consumer load profile affects network power flows, voltage magnitudes, and energy losses, whereas the DG configuration determined by the DSO influences the operating conditions experienced by consumers. The resulting interaction leads to a coupled and computationally challenging optimization problem.

To obtain a tractable formulation, the lower-level optimization is subsequently embedded into the upper-level problem through its Karush–Kuhn–Tucker (KKT) conditions. The resulting formulation eliminates the explicit nested optimization structure while maintaining the essential relationship between DG planning and consumer demand flexibility.

Network-Level Planning Model

The upper layer represents the planning actions of the DSO. Three performance measures are considered simultaneously: daily active energy loss, DG investment cost, and voltage deviation. Because these measures have different physical units and numerical ranges, they are first normalized and then incorporated into a weighted aggregate objective:

$$\min \left(w_1 \cdot \frac{A_{\Delta}}{A_{\Delta}^{\text{base}}} + w_2 \cdot \frac{C_{\text{inv}}}{C_{\text{max}}} + w_3 \cdot \frac{\sum_{t=1}^{24} \sum_{i=1}^{N_b} |V_i(t) - 1.0|}{V_{\text{norm}}} \right) \quad (1)$$

with $w_1 + w_2 + w_3 = 1$.

Where,

- A_{Δ} : Daily active energy loss (kWh/day).
- $C_{\text{inv}} = \sum_{i=1}^{N_{\text{DG}}} C_i \cdot P_{\text{DG},i}$: Total DG investment cost.
- $V_i(t)$: Voltage magnitude at bus i and time t .
- w_1, w_2, w_3 : User defined weights for loss, investment, and voltage deviation.
- $A_{\Delta}^{\text{base}}, C_{\text{max}}, V_{\text{norm}}$: Normalization factors derived from benchmark scenarios.

In the numerical implementation, the KKT conditions are not treated as post-processing conditions. They are evaluated for every candidate generated by MPA and are incorporated into the feasibility assessment of the unified problem. Stationarity and feasibility residuals are calculated directly from the lower-level formulation, while complementary slackness is evaluated from the product of each inequality multiplier and its corresponding constraint function. Candidates satisfying the prescribed KKT tolerance are considered feasible with respect to the lower-level optimality conditions. Candidates with non-negligible residuals receive a penalty proportional to the aggregate KKT violation. Thus, the KKT conditions are enforced through a combination of direct feasibility checking and penalty treatment rather than by omitting or relaxing any of the four KKT components.

The DSO planning problem is subject to the following network and DG-related constraints:

Distribution-network power flow is evaluated using the backward/forward sweep technique:

$$P_i = \sum_{j \in N(i)} f(P_j, V_j) \quad (2)$$

$$\text{Voltage limits: } V_{\min} \leq V_i \leq V_{\max}, \quad \forall i \in \mathcal{B} \quad (3)$$

$$\text{DG capacity: } 0 \leq P_{\text{DG},i} \leq P_{\text{DG}}^{\max}, \quad \forall i \in \mathcal{C} \quad (4)$$

Equation (1) provides a scalar representation of the three planning priorities, allowing technical performance and economic requirements to be considered simultaneously. The normalization factors prevent any individual objective from dominating the aggregate function merely because of its numerical scale. The constraints in (2) ensure consistency with the distribution-network power-flow relationships, while (3) maintains bus voltages within the prescribed operating range. Constraint (4) limits the capacity of installed DG units. DG investment expenditure is represented according to the installed DG capacity, with fixed or block-based charges potentially incorporated when the corresponding cost information is available.

Consumer Flexibility Model

The second decision layer describes how consumers respond to the TOU tariff. Instead of assuming an unchanged daily load curve, the model allows electricity consumption to be redistributed across the 24-hour scheduling horizon.

The consumer seeks to determine an hourly demand profile that minimizes the corresponding electricity expenditure:

$$\min_{\{P_L^t\}} \sum_{t=1}^{24} \rho_t \cdot P_L^t \quad (5)$$

The scheduling decision is restricted by two main requirements:

$$\text{Daily energy constraint: } \sum_{t=1}^{24} P_L^t = E_{\text{daily}} \quad (6)$$

$$\text{Hourly demand bounds: } P_{L,\min}^t \leq P_L^t \leq P_{L,\max}^t, \quad \forall t \quad (7)$$

Constraint (6) preserves the prescribed amount of daily energy consumption, whereas (7) prevents the demand at an individual hour from exceeding its allowable range. Consequently, the lower-level formulation captures load shifting rather than unrestricted load reduction. The resulting hourly profile represents the demand flexibility available to the distribution system under TOU pricing.

Optimality Conditions for Consumer Response

The hierarchical structure would normally require the upper-level DSO problem to account for the solution of the consumer optimization problem. Such a nested solution procedure can substantially increase

computational effort. Therefore, the lower-level model is replaced by its KKT optimality system under the convexity assumption adopted for the DR problem.

Let $P_{L,i}(t)$ be the decision variable, λ_i the Lagrange multiplier for total demand constraint, and $\mu_i^{\min}(t), \mu_i^{\max}(t)$ the dual variables for inequality constraints. The KKT system includes:

- Stationarity:

$$\frac{\partial \mathcal{L}}{\partial P_{L,i}(t)} = \rho_t - \lambda_i + \mu_i^{\min}(t) - \mu_i^{\max}(t) = 0 \quad (8)$$

- Primal feasibility:

$$\sum_{t=1}^{24} P_{L,i}(t) = E_i^{\text{daily}}, \quad P_{L,i}^{\min} \leq P_{L,i}(t) \leq P_{L,i}^{\max} \quad (9)$$

- Dual feasibility:

$$\mu_i^{\min}(t) \geq 0, \quad \mu_i^{\max}(t) \geq 0 \quad (10)$$

- Complementary slackness:

$$\mu_i^{\min}(t) \cdot (P_{L,i}^{\min} - P_{L,i}(t)) = 0, \quad \mu_i^{\max}(t) \cdot (P_{L,i}(t) - P_{L,i}^{\max}) = 0 \quad (11)$$

These four conditions jointly characterize the optimal solution of the convex consumer problem. The stationarity condition establishes the first-order optimality relationship, while primal and dual feasibility ensure satisfaction of the original constraints and their associated dual requirements. Complementary slackness establishes the relationship between active constraints and their corresponding multipliers. Accordingly, all four KKT components are retained in the reformulation. For the convex lower-level DR model, their simultaneous satisfaction is sufficient to characterize an optimal consumer response. Excluding one of these conditions would compromise the equivalence between the original lower-level problem and the reformulated model and could introduce an infeasible or non-optimal demand response into the upper-level planning problem.

Unified Optimization Representation

The KKT conditions in (8)-11) are incorporated into the DSO formulation defined by (1)-(4). In this way, the original hierarchical problem is represented by a unified single-level nonlinear optimization model. The reformulated problem still exhibits considerable computational complexity. DG location decisions introduce discrete variables, the distribution-network power-flow model is nonlinear, and the demand-response variables remain coupled with the network operating conditions. Therefore, the final formulation has a mixed-integer, non-convex, and highly constrained search space.

The Marine Predators Algorithm (MPA) is employed to search for a high-quality solution to this unified optimization problem. The algorithm is used as the numerical optimization mechanism rather than altering the mathematical formulation itself. Its exploration and exploitation phases provide a mechanism for searching the complex feasible region generated by the combined DG planning and consumer-flexibility decisions. The detailed MPA implementation is presented in the next Section.

SOLUTION METHODOLOGY

The single-level formulation obtained from the hierarchical model constitutes a challenging optimization task because of the coexistence of discrete DG siting variables, nonlinear network equations, and time-dependent demand-response decisions. The coupling between hourly demand profiles and distribution-

network operating conditions further increases the dimensionality of the search space. Consequently, conventional deterministic optimization techniques may encounter difficulties in obtaining high-quality solutions within a reasonable computational effort.

In this study, the Marine Predators Algorithm (MPA) is employed as the search mechanism for the reformulated optimization problem. MPA is a population-based metaheuristic that imitates the adaptive hunting behavior of marine predators. Its search process combines different movement patterns at successive stages, allowing the population to initially explore a broad solution region and subsequently concentrate the search around promising solutions. This characteristic is particularly useful for the mixed, nonlinear, and constrained DG planning problem considered in this work.

Search Mechanism of the Marine Predators Algorithm (MPA)

The search strategy of MPA is organized around the changing movement behavior of predators and prey. Rather than applying a single search rule throughout the optimization process, the algorithm progressively changes its search intensity as the iterations proceed. Three search stages are considered.

Stage I - Global search: At the beginning of the optimization, the population is encouraged to investigate widely separated regions of the solution space. Lévy-flight movements are used to generate relatively large search steps, increasing the probability of discovering promising regions that are distant from the current solutions.

Stage II - Guided search: As the optimization progresses, the search gradually moves toward a compromise between diversification and intensification. Candidate solutions are influenced by the current elite solution while stochastic movements are retained to avoid restricting the population to a small region prematurely.

Stage III - Local refinement: During the final stage, the search becomes increasingly concentrated around the best solution identified so far. Brownian-motion-based perturbations and localized movements are used to improve the candidate solution and refine the final DG planning and demand-response decisions.

The progressive change from broad exploration to focused refinement allows MPA to preserve sufficient population diversity during the early iterations while increasing solution accuracy during the later iterations. This exploration mechanism is adopted here to address the complex feasible region generated by the integrated DG planning and demand-response model.

Computational Procedure For Integrated DG-DR Optimization

The implementation of MPA follows a sequential procedure in which DG placement, DG sizing, and hourly responsive demand are optimized simultaneously within the single-level formulation.

Step 1: Representation of candidate solutions

Each MPA agent represents one feasible or potentially feasible planning solution. The solution is expressed using the composite decision vector:

$$X = [x_{DG}, P_{DG}, P_L^{1:24}] \quad (15)$$

Where, $x_{DG} \in \{0,1\}^{N_c}$: Binary vector indicating DG placement at candidate buses, $P_{DG} \in \mathbb{R}^+$: Real valued DG capacities (in MW), $P_L^{1:24}$: Hourly demand vector shaped by demand response at each time slot.

This representation enables the optimizer to simultaneously search the discrete DG placement space and the continuous DG sizing and load-scheduling spaces.

Step 2: Generation of the initial search population

An initial population of $(\cdot)$ predator agents is generated within the predefined bounds of the decision

variables. The initial candidates therefore contain different combinations of DG locations, DG capacities, and hourly demand profiles.

For every candidate, the network operating state is evaluated using the power-flow model. The normalized objective in (1) is then calculated, together with penalty terms associated with any constraint violations. The resulting value is used as the fitness measure for ranking the population.

Step 3: Iterative population evolution

For each generation $g = 1$ to g_{max} , update the population based on the three MPA phases:

- Phase I (Exploration): If $\text{rand} < 0.5$, use Lévy flight to simulate fast global search:

$$X_i^{g+1} = X_i^g + S \cdot \text{Lévy}() \cdot (X_i^g - X_{\text{elite}}^g) \quad (16)$$

- Phase II (Transition zone): Combine elite solution and Brownian motion for balanced search:

$$X_i^{g+1} = X_{\text{elite}}^g + r \cdot \text{Brownian}() \cdot (X_i^g - X_{\text{elite}}^g) \quad (17)$$

- Phase III: Slow convergence around elite to refine the optimum:

$$X_i^{g+1} = X_i^g + \epsilon \cdot (X_i^g - X_j^g) + \delta \quad (18)$$

Here, S, r, ϵ, δ are adaptive control parameters, and X_{elite} is the best solution found so far.

Step 4: Feasibility restoration

Following every population update, the generated solutions are checked against the operating and planning constraints. DG capacities are restricted to their allowable ranges, while the responsive load profile is adjusted to satisfy both hourly demand limits and the total daily energy requirement.

When an updated solution violates one or more constraints, penalty functions and repair procedures are applied to bring the candidate back toward the feasible region. This process prevents infeasible DG configurations or unrealistic demand schedules from being retained as competitive solutions.

Step 5: Network evaluation and objective calculation

Each repaired candidate is subjected to a distribution-network power-flow calculation. The principal performance quantities are then obtained, including daily energy loss, DG investment cost, and voltage deviation. The individual objective components are normalized according to the formulation in above Section and combined using Equation (1) to obtain the overall fitness value. This evaluation establishes the technical and economic quality of each candidate solution.

Step 6: Elite preservation and stopping criterion

After fitness evaluation, the best candidate identified in the current population is compared with the previously stored elite solution. The elite is replaced whenever an improved feasible solution is obtained. The population-update, feasibility-checking, power-flow evaluation, and elite-selection procedures are then repeated until the specified convergence condition or maximum number of generations is reached.

At termination, the retained elite solution provides the final DG installation locations, DG capacities, and responsive hourly demand profile.

The complete computational sequence establishes a direct link between the single-level mathematical formulation and the MPA search process. The procedure allows the algorithm to first investigate alternative combinations of DG placement and demand flexibility and subsequently intensify the search around high-quality feasible configurations. In this manner, the proposed approach addresses the non-convexity and constraint coupling inherent in the integrated planning problem while preserving the TOU-driven demand-response characteristics of the original hierarchical formulation. The overall computational sequence is illustrated in Figure 1.

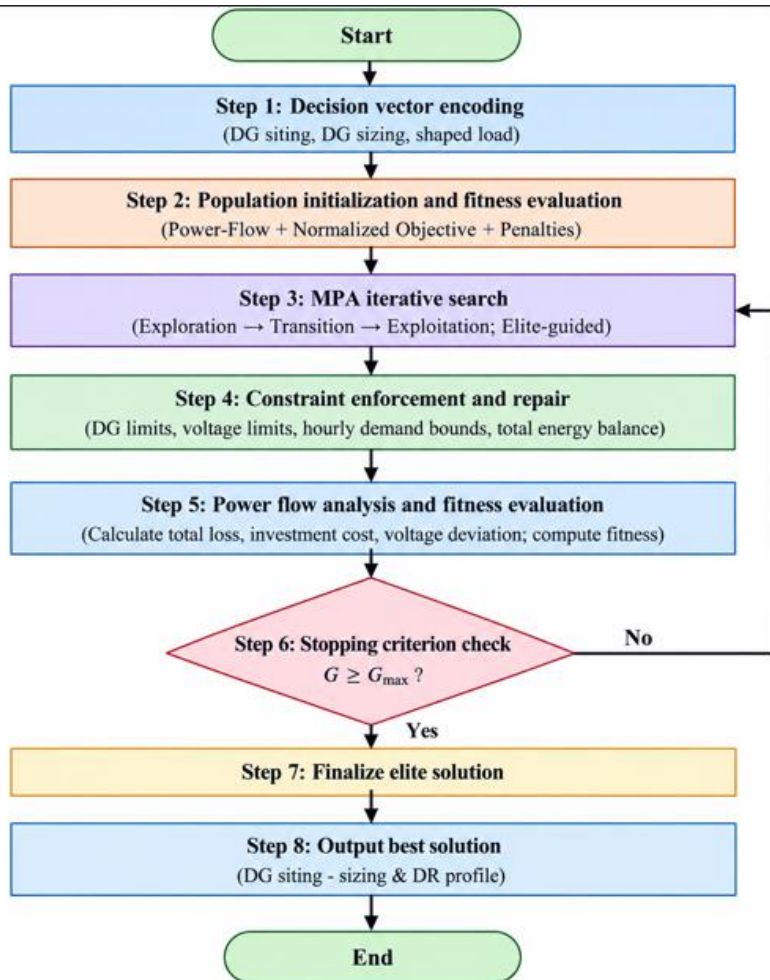


Figure 1. Computational workflow of the MPA-based DG planning and demand-response optimization.

RESULTS AND DISCUSSION

Test Systems and Computational Settings

The numerical assessment considers two widely used radial distribution-network benchmarks, namely the IEEE 33-bus and IEEE 69-bus systems. A 24-hour operating horizon is considered to represent the interaction between DG planning and consumer demand flexibility over a complete daily cycle. The hourly demand data are constructed to reflect representative residential and commercial consumption characteristics in Vietnam. Accordingly, the scheduling horizon consists of 24 consecutive one-hour periods, indexed from 00:00 to 23:00.

The benchmark feeder parameters and the 24-hour operating profile are treated separately in the numerical study. The original IEEE feeder topology and electrical parameters are retained as the reference network model. To represent daily consumer flexibility, an hourly demand profile is subsequently imposed over the 24-hour scheduling horizon. Therefore, the hourly values reported in Table 2 represent the operating demand

trajectory used in the demand-response study and should not be interpreted as modified benchmark feeder parameters.

For reference, the original peak-load conditions are also evaluated without demand-profile scaling. The corresponding peak apparent-power demand is approximately 3.72 MVA for the IEEE 33-bus system and 3.80 MVA for the IEEE 69-bus system. The unscaled peak-load power losses are reported separately as benchmark values. This distinction avoids mixing instantaneous peak power loss with the 24-hour energy-loss metric used in the optimization results.

Table1. Time based electricity tariffs (TOU) (T. N. Trieu et al. 2021)

TOU Period	Time Interval	Electricity prices (USD/kWh)
Off-peak	22:00–04:00	0.0454
Standard	04:00–09:00; 11:00–17:00; 20:00–22:00	0.0700
Peak	09:00–11:00; 17:00–20:00	0.1289

The main planning and operating assumptions are selected to maintain a consistent basis for all optimization methods. The aggregate DG capacity is restricted to 3.0 MW for each feeder, while no more than three DG units can be installed. The capacity of an individual DG unit cannot exceed 1.0 MW. These limits constrain the search to practically meaningful DG configurations and avoid excessive DG penetration relative to the considered distribution systems. The DG installation cost is fixed at 750 USD/kW.

The upper-level objective is formulated using three normalized performance indicators: daily active energy loss, DG investment expenditure, and voltage deviation. The corresponding weighting coefficients are fixed at $w_1 = 0.50$, $w_2 = 0.30$, and $w_3 = 0.20$, respectively, satisfying $w_1 + w_2 + w_3 = 1$. The adopted weights provide an explicit representation of the relative priorities assigned to network efficiency, investment expenditure, and voltage performance. No additional scalar weighting parameter is introduced. The sensitivity of the solution to these weighting coefficients is examined separately using repeated independent optimization runs. For network operation, the voltage magnitude at every bus is restricted to the interval of 0.95–1.05 p.u. Distribution-network power flow is evaluated using the backward/forward sweep technique. This approach is retained throughout the optimization so that every candidate DG configuration and responsive-load schedule is assessed under the same network operating conditions.

Before aggregation, each objective component is normalized using its corresponding benchmark value from the no-DG condition. This procedure eliminates the influence of different physical units and numerical magnitudes and allows the three criteria to contribute consistently to the composite objective.

Table 2. Hourly demand profile and load factors for the IEEE 33-bus and 69-bus systems

Hour	33-bus Load(kW)	69-bus Load (kW)	Hourly Factor
0	111	115.5	0.03
1	99.9	104.0	0.027
2	92.5	96.3	0.025
3	92.5	96.3	0.025
4	103.6	107.8	0.028

5	118.4	123.2	0.032
6	140.6	146.3	0.038
7	166.5	173.3	0.045
8	192.4	200.2	0.052
9	214.6	223.3	0.058
10	229.4	238.7	0.062
11	240.5	250.3	0.065
12	251.6	261.8	0.068
13	266.4	277.2	0.072
14	262.7	273.4	0.071
15	255.3	265.7	0.069
16	273.8	284.9	0.074
17	288.6	300.3	0.078
18	270.1	281.1	0.073
19	251.6	261.8	0.068
20	222.0	231.0	0.06
21	185.0	192.5	0.05
22	148.0	154.0	0.04
23	129.5	134.8	0.035

For the algorithmic evaluation, six population-based metaheuristic methods are considered: WOA, HHO, AOA, GBO, SDO, and MPA. To ensure that differences in performance are attributable to the search strategies rather than unequal computational settings, all algorithms use a population of 30 agents and a maximum of 100 generations/iterations. The same stopping conditions and constraint-handling strategy are applied to all methods. Constraint violations are treated using dynamically scaled penalty factors together with repair operations, allowing infeasible candidate solutions to be corrected or appropriately penalized during the search.

The MPA configuration follows its three-stage search mechanism. The initial exploration stage employs Lévy flights with $\beta=1.5$ to promote diversification. In the transition stage, Brownian motion is combined with guidance from the elite solution to establish a balance between exploration and exploitation. During the final exploitation stage, the search step is progressively reduced using $c_1=0.5$, thereby concentrating the population around the best solution identified so far. An elite-memory mechanism is also retained to preserve high-quality solutions and reduce the risk of premature convergence.

This common computational configuration provides a consistent basis for comparing the six algorithms on both distribution-network benchmarks. The resulting experiments therefore evaluate not only the quality of

the DG placement and sizing decisions, but also the ability of each optimization method to handle the coupled DG–DR problem under nonlinear power-flow constraints and time-varying electricity prices.

For the comparative numerical study, each optimization algorithm is executed independently for 30 runs using the same population size of 30 agents and a maximum of 100 iterations. The same objective function, power-flow routine, stopping criterion, variable bounds, and constraint-handling principles are applied to all algorithms. Each run uses an independent random initialization. The best, mean, and standard-deviation values of daily energy loss and TOU operating cost are recorded for statistical comparison. The computational time is also recorded for each independent run.

The 33-Bus Distribution System

The IEEE 33-bus distribution network is adopted as the first test system to assess the effectiveness of the proposed hierarchical DG planning and demand-response optimization framework. The network is a radial system operated at 12.66 kV and consists of 33 buses interconnected through 37 branches. Its relatively compact structure, together with the presence of voltage-sensitive downstream buses, makes it suitable for evaluating the impacts of DG allocation on network losses, voltage performance, and operating cost. The total system demand is approximately $(3.72 + j2.3)$ MVA. The corresponding network configuration used in the simulations is illustrated in ((Baran and Wu 1989).

The optimization results obtained using WOA, HHO, AOA, GBO, SDO, and MPA are summarized in Table 3. The algorithms were evaluated under the same population size, iteration limit, constraint-handling mechanism, and simulation conditions to ensure a consistent comparison. The results indicate that MPA provides the most favorable overall solution among the six methods. For the proposed MPA, DG units are optimally allocated at buses 4, 11, and 26, with capacities of 1.00 MW, 0.87 MW, and 0.99 MW, respectively. The resulting total DG capacity is 2.86 MW, which remains within the specified planning limit. More importantly, the MPA solution produces a daily active energy loss of only 223.5 kWh/day, representing the lowest loss among the considered optimization methods. The corresponding TOU-based operating cost is 220.3 USD/day, which is also the minimum value reported in Table 3. The computational time is 49.7 s, indicating that the improvement in solution quality is achieved without a substantial increase in computational burden.

To quantify the contribution of coordination, three baseline operating configurations are first considered: (i) No DG and No DR, in which the original network demand profile is maintained without DG installation; (ii) DG-only, in which DG planning is optimized while the demand profile remains fixed; and (iii) DR-only, in which consumer demand is optimized under TOU pricing without DG installation. These baseline cases are subsequently compared with the integrated DG–DR optimization results.

Table 3. DG Planning optimization results for the 33-bus

Algorithm	L _{DG} (bus)	P _{DG} (MW)	AΔ (kWh/day)	TOU Cost (USD/day)	Time (s)
WOA	6, 12, 28	0.98; 0.82; 0.97	259.3	234.92	48.6
HHO	8, 15, 30	0.99; 0.81; 0.95	265.7	238.38	61.4
AOA	9, 17, 25	1.0; 0.84; 0.93	250.2	230.22	53.7
GBO	7, 14, 27	0.96; 0.83; 0.92	245.1	231.32	55.2
SDO	5, 13, 24	0.95; 0.85; 0.90	238.6	229.75	58.1
Proposed (MPA)	4, 11, 26	1.0; 0.87; 0.99	223.5	220.3	49.7

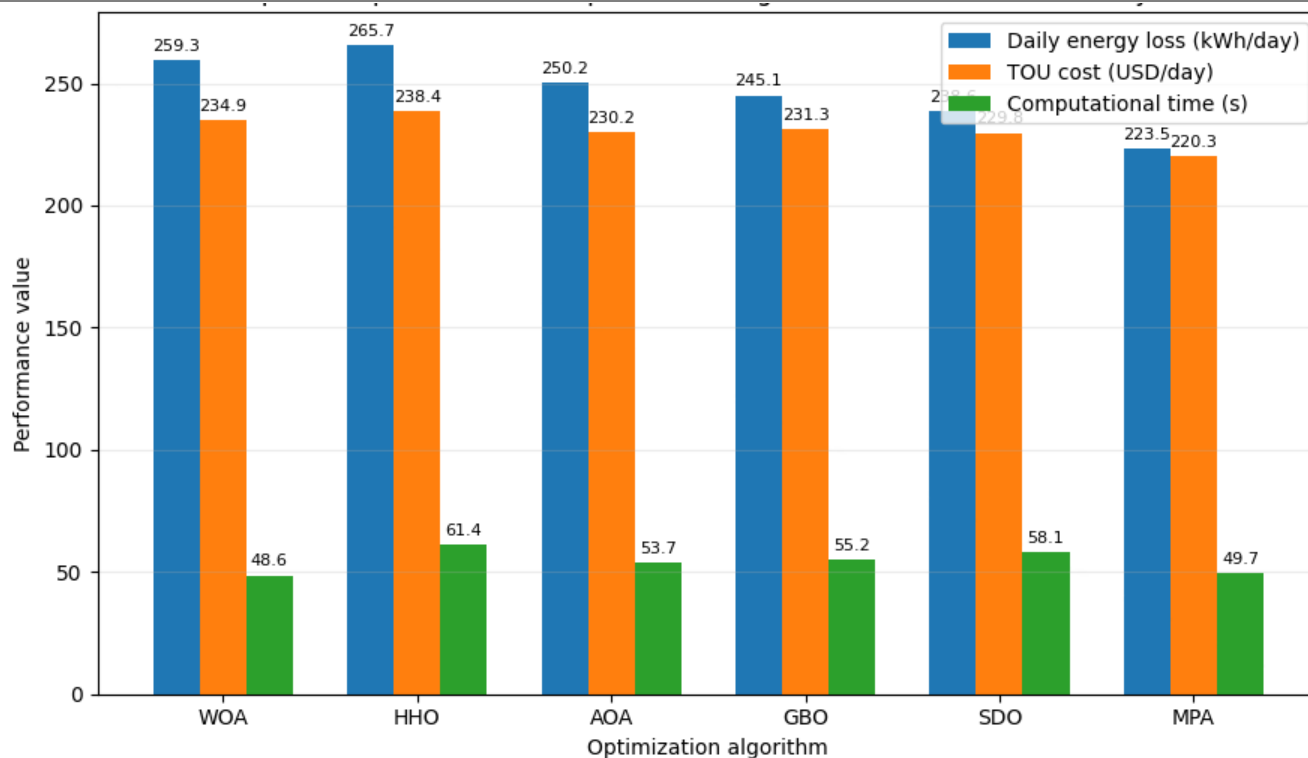


Figure 2. Comparative performance of optimization algorithms for the IEEE 33-bus distribution system

Compared with the other algorithms, WOA obtains a daily loss of 259.3 kWh/day, whereas HHO produces 265.7 kWh/day. AOA, GBO, and SDO reduce the losses to 250.2, 245.1, and 238.6 kWh/day, respectively. Thus, the MPA solution reduces the daily energy loss by approximately 6.3% compared with SDO, the second-best method in terms of loss reduction. A similar advantage is observed for the economic objective. MPA obtains a TOU cost of 220.3 USD/day, compared with 229.75 USD/day for SDO and 234.92 USD/day for WOA. These results demonstrate that the proposed search strategy is able to identify DG locations and capacities that provide a better compromise between network efficiency and operating expenditure.

The computational times range from 48.6 s to 61.4 s across the six algorithms. WOA has the shortest execution time at 48.6 s, while MPA requires 49.7 s. The difference is relatively small, indicating that the additional search mechanisms incorporated in MPA do not impose a significant computational penalty. In particular, MPA achieves substantially better loss and cost performance while remaining close to the fastest algorithm in terms of execution time. The comparative optimization results are presented in Table 3 and Figure 2.

The voltage performance of the resulting solutions is further examined across all 33 buses. As shown in Figure 3, the obtained voltage profiles remain within the prescribed operating range of 0.95 - 1.05 p.u. The MPA-based solution exhibits a relatively smooth voltage profile, particularly at the downstream buses where voltage drops are generally more pronounced.

This behavior is consistent with the objective of coordinating DG placement with network operating conditions rather than optimizing DG capacity independently. The voltage profiles therefore provide an additional indication that the MPA solution achieves a technically feasible operating point while simultaneously improving the economic and loss-related objectives.

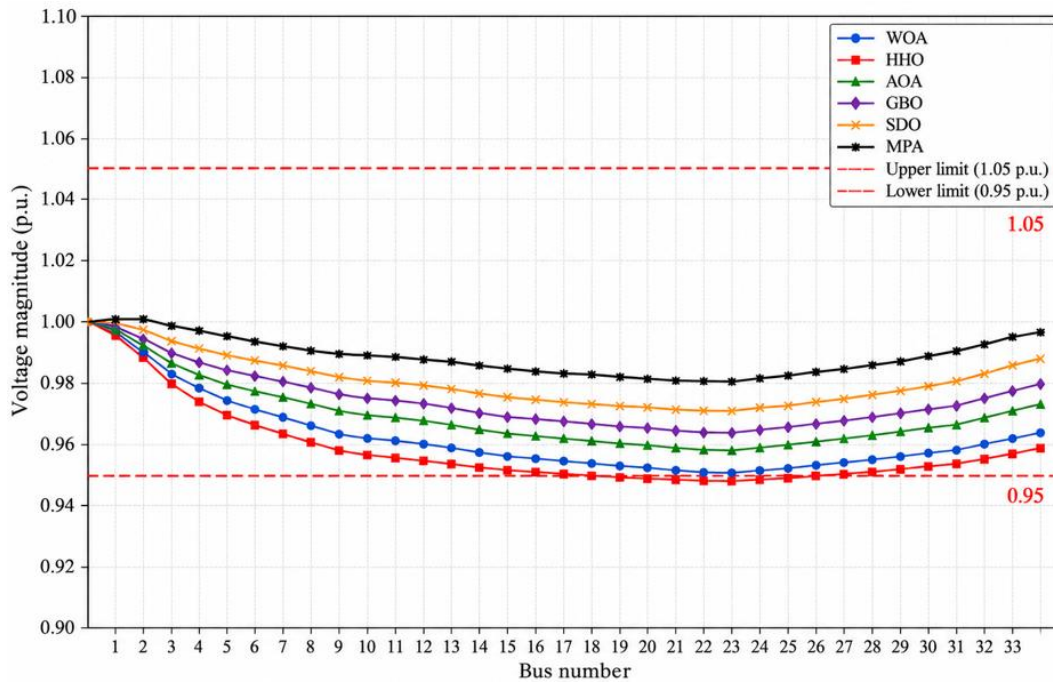


Figure 3. Voltage profiles for the IEEE 33-bus distribution system

Overall, the IEEE 33-bus case confirms the capability of the proposed hierarchical optimization framework to coordinate DG planning with consumer-side flexibility under TOU pricing. The MPA solution achieves the lowest energy loss and operating cost among the tested methods while maintaining a competitive computational time. These results provide a basis for subsequently examining the scalability and robustness of the proposed approach using the larger IEEE 69-bus distribution system.

The 69-Bus Distribution System

The IEEE 69-bus distribution network is considered as the second test system to further examine the performance of the proposed hierarchical optimization framework on a larger and more structurally complex radial network. The system operates at 12.66 kV and consists of 69 buses with a greater number of interconnected branches than the IEEE 33-bus system. The line parameters and load data are adopted from (T. N. Trieu, L. M. Phong, and L. M. Tan 2025) for modeling accuracy. With a total apparent power of about $(3.80 + j2.69)$ MVA, the network represents a medium scale real world system. Without DG integration, it incurs a power loss of 224.88 kW (Trieu et al. 2025).

Table 4 summarizes the optimization results obtained using WOA, HHO, AOA, GBO, SDO, and MPA. The comparison includes the selected DG locations, DG capacities, daily active energy loss, TOU-based electricity cost, and computational time. The results indicate that MPA provides the best performance in terms of energy-loss reduction while maintaining competitive economic and computational characteristics.

Table 4. DG Planning optimization results for the 69-bus

Algorithm	L_{DG} (bus)	P_{DG} (MW)	ΔA (kWh/day)	TOU Cost (USD/day)	Time (s)
WOA	13, 25, 63	0.95; 0.84; 0.96	268.2	239.8	48.6
HHO	12, 24, 62	0.98; 0.80; 0.95	263.1	225.88	54.3
AOA	11, 23, 61	0.99; 0.82; 0.94	258.4	236.1	60.7
GBO	14, 26, 60	0.97; 0.81; 0.93	251.7	237.6	62.9

Algorithm	L _{DG} (bus)	P _{DG} (MW)	AΔ (kWh/day)	TOU Cost (USD/day)	Time (s)
SDO	10, 22, 59	0.96; 0.83; 0.92	248.5	238.2	58.4
Proposed (MPA)	15, 27, 64	1.00; 0.86; 0.975	241.7	226.9	50.4

For the MPA-based solution, DG units are allocated at buses 15, 27, and 64, with capacities of 1.00 MW, 0.86 MW, and 0.975 MW, respectively. The resulting total installed DG capacity is 2.835 MW, which satisfies the imposed 3.0 MW system-level limit. With this configuration, the daily active energy loss is reduced to 241.7 kWh/day, representing the lowest value among all six optimization algorithms. SDO provides the next-best loss performance at 248.5 kWh/day, followed by GBO at 251.7 kWh/day. Compared with SDO, MPA achieves an additional loss reduction of approximately 2.7%, while the improvement relative to WOA reaches approximately 9.9%.

The economic results show a slightly different ranking. MPA produces a TOU-based operating cost of 226.90 USD/day, whereas HHO obtains the lowest cost of 225.88 USD/day. The difference between these two solutions is only 1.02 USD/day, indicating that MPA remains highly competitive from the economic perspective despite not attaining the absolute minimum cost. Compared with WOA, the MPA solution reduces the TOU cost by approximately 5.4%. The results also demonstrate that minimizing operating cost alone does not necessarily lead to the lowest network losses, highlighting the trade-off incorporated in the hierarchical multi-objective formulation.

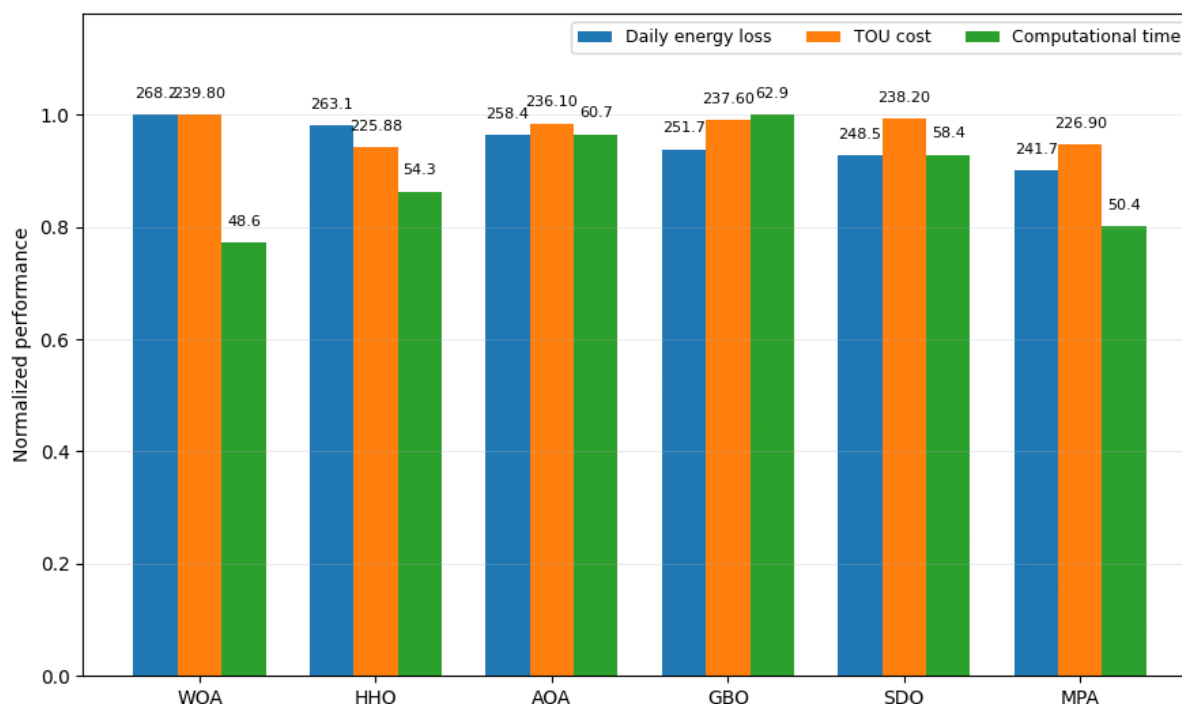


Figure 4. Comparative performance of optimization algorithms for the IEEE 69-bus distribution system

Figure 4 provides a graphical comparison of the six optimization algorithms with respect to daily energy loss, TOU cost, and computational time. The results clearly show the advantage of MPA in loss minimization. Its computational time of 50.4 s is also relatively low, being only slightly higher than WOA at 48.6 s. In contrast, AOA, GBO, and SDO require 60.7, 62.9, and 58.4 s, respectively. Therefore, the improved loss performance of MPA is not accompanied by a substantial increase in computational burden.

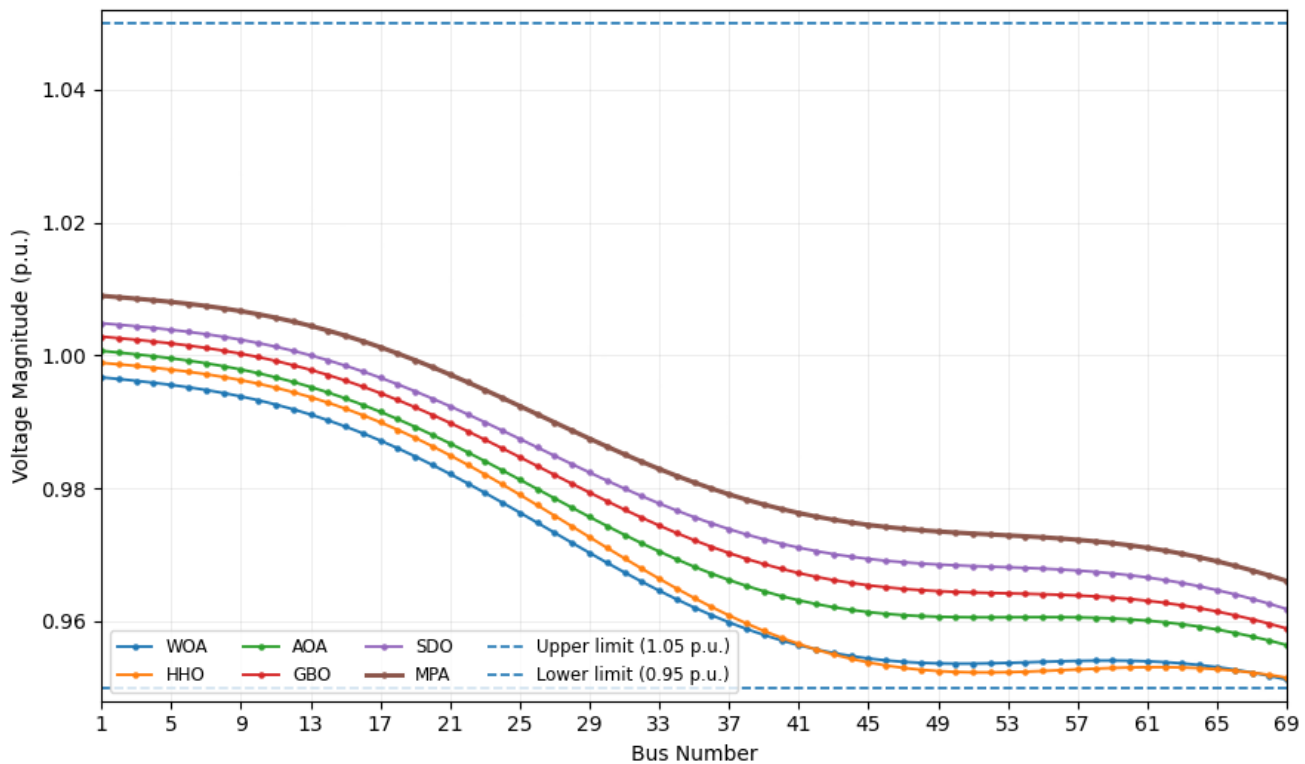


Figure 5. Voltage profiles for the IEEE 69-bus distribution system

The voltage characteristics of the optimized solutions are presented in Fig. 8. All obtained voltage profiles remain within the prescribed operating range of 0.95–1.05 p.u. throughout the 69-bus network. The voltage magnitude generally decreases along the radial feeder as the electrical distance from the substation increases. Nevertheless, the DG configurations obtained by the optimization algorithms help mitigate the voltage drop, particularly in the downstream portion of the network. Among the compared solutions, the MPA profile remains relatively higher and smoother over the remote buses, indicating improved voltage regulation capability.

Overall, the IEEE 69-bus case confirms the applicability of the proposed optimization framework to a larger distribution network. MPA identifies a DG configuration that achieves the lowest daily energy loss of 241.7 kWh/day, while maintaining a TOU cost of 226.90 USD/day and a computational time of 50.4 s. Although HHO provides a marginally lower TOU cost, MPA offers a more favorable compromise between technical performance, economic operation, and computational efficiency. The results from Figures 4 and 5 therefore support the effectiveness of the proposed approach under the increased network complexity of the IEEE 69-bus system.

DISCUSSION

The results obtained from both IEEE 33-bus and 69-bus systems demonstrate the effectiveness and consistency of the proposed hierarchical optimization framework. In particular, MPA achieves the lowest daily energy loss in both test systems, reaching 223.5 kWh/day for the 33-bus network and 241.7 kWh/day for the 69-bus network. This consistent technical advantage indicates that the proposed search strategy can effectively identify DG locations and capacities that improve power-flow conditions in radial distribution networks.

The economic results further highlight the importance of considering multiple objectives simultaneously. MPA achieves the lowest TOU cost of 220.3 USD/day for the 33-bus system. For the 69-bus system, HHO obtains a marginally lower cost than MPA; however, its energy loss is considerably higher. Thus, MPA provides a more balanced solution between network efficiency and operating cost rather than optimizing a single criterion at the expense of others.

The computational results also support the practicality of MPA. Its execution times of 49.7 s and 50.4 s for the 33-bus and 69-bus systems, respectively, remain close to those of the fastest competing methods despite the larger search space. Meanwhile, the voltage profiles remain within the required 0.95–1.05 p.u. range, confirming the feasibility of the obtained solutions.

Overall, the results demonstrate that the proposed framework does not merely seek a low-cost DG configuration, but effectively coordinates DG placement, network loss reduction, voltage regulation, and consumer flexibility under TOU pricing. The consistent performance across two different network sizes provides strong evidence of the robustness and practical relevance of the proposed MPA-based approach.

CONCLUSION

This study developed a hierarchical optimization framework for coordinating DG planning and consumer demand response under time-of-use pricing in radial distribution networks. The lower-level demand-response problem was incorporated into the network-level planning model through its KKT optimality conditions, resulting in a unified single-level optimization formulation. A dedicated constraint-handling strategy was implemented to manage binary DG-siting decisions, DG-capacity limits, daily energy balance, network constraints, and KKT feasibility within the MPA search process. The proposed framework was evaluated using the IEEE 33-bus and IEEE 69-bus distribution systems under 24-hour operating conditions. The revised numerical study includes no-DG/no-DR, DG-only, and DR-only baseline cases together with six optimization algorithms. Repeated independent runs and non-parametric statistical testing are used to assess both solution quality and stochastic consistency. The results indicate that coordinated consideration of DG planning and demand response can provide measurable improvements in network loss and TOU-based operating performance while satisfying the prescribed voltage limits. The comparison across the two benchmark systems also demonstrates the applicability of the formulation to distribution networks with different sizes and structural characteristics.

The main contribution of the work is therefore the integrated decision framework rather than the introduction of a new metaheuristic algorithm. Future research will extend the model to explicitly represent photovoltaic and wind generation profiles, renewable-generation uncertainty, energy storage systems, and larger practical distribution networks.

REFERENCES

1. Baran, M E, and F F Wu. 1989. "Network Reconfiguration in Distribution Systems for Loss Reduction and Load Balancing." *IEEE Transactions on Power Delivery* 4(2): 1401–1407., doi:10.1109/61.25627.
2. M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*, IEEE Press/Wiley-Interscience, New York, 2002, doi: 10.1002/047122412X.
3. El-Rifaie, Ali M., Abdullah M. Shaheen, Mohamed A. Tolba, Idris H. Smaili, Ghareeb Moustafa, Ahmed R. Ginidi, and Mostafa A. Elshahed. 2023. "Modified Gradient-Based Algorithm for Distributed Generation and Capacitors Integration in Radial Distribution Networks." *IEEE Access* 11(October): 120899–917. doi:10.1109/ACCESS.2023.3326758.
4. Faramarzi, Afshin, Mohammad Heidarinejad, Seyedali Mirjalili, and Amir H. Gandomi. 2020. "Marine Predators Algorithm: A Nature-Inspired Metaheuristic." *Expert Systems with Applications* 152: 1–43. doi:10.1016/j.eswa.2020.113377.
5. International Energy Agency. 2023. *International Energy Agency (IEA) Renewables 2023*. doi:10.1002/peng.20026.
6. Izmailov, A. F., and M. V. Solodov. 2003. "Karush-Kuhn-Tucker Systems: Regularity Conditions, Error Bounds and a Class of Newton-Type Methods." *Mathematical Programming, Series B* 95(3): 631–50. doi:10.1007/s10107-002-0346-6.
7. Javadi, Mohammad Sadegh, Kimia Firuzi, Maedeh Rezanejad, Mohamed Lotfi, Matthew Gough, and João P S Catalão. 2019. "Optimal Sizing and Siting of Electrical Energy Storage Devices for Smart

- Grids Considering Time-of-Use Programs.” In IEEE, IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society. IEEE, 4017–22.
8. Kumar, Ankur, Ritika Verma, Niraj Kumar Choudhary, and Nitin Singh. 2023. ““Optimal Multi-Objective Placement and Sizing of Distributed Generation in Power Distribution System: A Comprehensive Review.”” *Energy Sources, Part A: Recovery, Utilization and Environmental Effects* 45(3): 7160–85. doi:10.1080/15567036.2023.2216167.
9. Prakash, D B, and C Lakshminarayana. “Multiple DG Placements in Radial Distribution System for Multi Objectives Using Whale Optimization Algorithm”.” *Alexandria Eng. J* 57(4): 2797–2806. doi:10.1016/j.aej.2017.11.003.
10. Selim, Ali, Salah Kamel, Ali S. Alghamdi, and Francisco Jurado. 2020. “Optimal Placement of DGs in Distribution System Using an Improved Harris Hawks Optimizer Based on Single- And Multi-Objective Approaches.” *IEEE Access* 8: 52815–29. doi:10.1109/ACCESS.2020.2980245.
11. Siano, Pierluigi, and Debora Sarno. 2016. “Assessing the Benefits of Residential Demand Response in a Real Time Distribution Energy Market.” *Applied Energy* 161(October 2017): 533–51. doi:10.1016/j.apenergy.2015.10.017.
12. Sun, Huijun, Ziyu Gao, and Jianjun Wu. 2008. “A Bi-Level Programming Model and Solution Algorithm for the Location of Logistics Distribution Centers.” *Applied Mathematical Modelling* 32(4): 610–16. doi:http://doi.org/10.1016/j.apm.2007.02.007.
13. T. N. Trieu, L. M. Phong, and L. M. Tan. 2025. “Multi-Objective Optimization Strategy for Enhancing Distribution Power System Efficiency with Integrated Distributed Generation.” *The University of Danang - Journal of Science and Technology* 23(3): 7–10. doi:10.31130/ud-jst.2025.016.
14. T. N. Trieu, N. T. Thuan, T. V. Anh, and V. P. Tu. 2021. “Optimal Location and Operation of Battery Energy Storage System in the Distribution System for Reducing Energy Cost in 24-Hour Period.” *Int Trans Electr Energ Syst* e12861(February): 1–17. doi:10.1002/2050-7038.12861.
15. Theo, Wai Lip, Jeng Shiun Lim, Wai Shin Ho, Haslenda Hashim, and Chew Tin Lee. 2017. “Review of Distributed Generation (DG) System Planning and Optimisation Techniques: Comparison of Numerical and Mathematical Modelling Methods.” *Renewable and Sustainable Energy Reviews* 67: 531–73. doi:10.1016/j.rser.2016.09.063.
16. Trieu, T N, P H Loc, L M Phong, and L M Tan. 2025. “Multi-Objective Optimization of Electric Distribution Systems With Integrated Distributed Generation Using Deep Reinforcement Learning.” *Eng. Technol. Appl. Sci. Res* 15(2): 22166–22171,. doi:10.48084/etasr.10359.
17. Xie, Hua, Xiaofei Teng, Yin Xu, and Ying Wang. 2019. “Optimal Energy Storage Sizing for Networked Microgrids Considering Reliability and Resilience.” *IEEE Access* 7: 86336–48. doi:10.1109/ACCESS.2019.2922994.
18. Zhang, Jinzhong, Gang Zhang, Yourui Huang, and Min Kong. 2022. “A Novel Enhanced Arithmetic Optimization Algorithm for Global Optimization.” *IEEE Access* 10(July): 75040–62. doi:10.1109/ACCESS.2022.3190481.