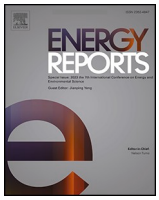
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Research paper



Bi-level optimization for demand response integration with solar pv and battery energy storage systems: Enhancing distribution network efficiency and sustainability

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ABSTRACT

The integration of distributed energy resources (DERs) offers significant potential to enhance the efficiency and resilience of distribution networks (DNs). Yet, high penetration of distributed generation (DG), particularly solar photovoltaic (PV), can introduce voltage instability, higher losses, and reverse power flows. Addressing these challenges, this study presents a novel bi-level optimization framework that jointly coordinates DG placement, battery energy storage systems (BESS), and price-based demand response (DR). In the upper level, a Grey Wolf Optimizer (GWO) determines the optimal siting and sizing of DG and BESS; the lower level schedules real-time BESS dispatch with DR participation. Metaheuristic GWO is adopted for its strong exploration–exploitation balance in the nonlinear, mixed-integer search space of AC power-flow constraints. Using the IEEE-33 bus test system, six integration scenarios were evaluated. The best configuration—Case 6 (DG + BESS + DR)—reduced annual energy losses by 46.8 %, improved the average voltage profile to 1.01 p.u., shaved the peak demand by ~50 %, and achieved a payback period of 4.4 years with the lowest levelized cost of energy (LCOE). These findings demonstrate that coordinated DER planning and real-time control can significantly improve technical and economic performance, providing actionable guidance for utilities seeking smarter and more sustainable power-distribution systems.

1. Introduction

The integration of renewable energy resources into DNs has become a central priority in modern power systems. To achieve efficient, reliable, and economically sustainable operation, advanced control, storage, and demand-side management strategies are required. Smart grids, through real-time data acquisition and advanced communication technologies, enable coordinated interaction between operators and consumers, thereby enhancing demand flexibility and facilitating renewable energy utilization (Ziadi et al., 2014). Among these strategies, DR has been extensively investigated, demonstrating its ability to shift loads from peak to off-peak hours and to improve the integration of variable renewable resources (Saxena et al., 2021).

The rapid deployment of DG, particularly solar PV systems, has transformed the operational dynamics of DNs. The optimal siting and sizing of DG units is essential, as improper allocation can lead to power losses, voltage deviations, and reverse power flows (Da Costa et al., 2019; Ehsan et al., 2019). While DG integration offers technological, financial, and environmental benefits, conventional networks face challenges in accommodating the variability and intermittency of renewable resources (Hung et al., 2014a, 2014b). To mitigate these challenges, BESS have emerged as a complementary technology. Importantly, extensive literature exists on BESS capacity expansion, as well as on optimal siting and sizing in distribution systems. Recent

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studies and reviews (Chreim et al., 2024; Carpinelli et al., 2024; Apribowo et al., 2024) have addressed these issues using deterministic, probabilistic, and metaheuristic techniques to achieve objectives such as loss minimization, voltage profile enhancement, and stability support.

Smart grids leverage real-time data and advanced communication technology to enable seamless collaboration and consensus between grid operators and consumers (Ziadi et al., 2014). Extensive research has thoroughly examined the concept of responsive load management using dynamic pricing. This study constantly emphasizes the advantages of redistributing demand from peak to off-peak hours in order to optimize the use of renewable energy-based generation (Saxena et al., 2021).

The evolution of technology in small-scale power generation has prompted distribution system operators (DSOs) to incorporate more DGs into DNs. Efficient DN performance hinges upon determining the optimal size and placement of DGs, as inefficient allocation of resources can be detrimental (Da Costa et al., 2019; Ehsan et al., 2019). While the integration of DGs achieves various objectives such as technological, financial and environmental, traditional DNs encounter difficulties in effectively accommodating a substantial increase in renewable energy sources owing to their inherent variability (Hung et al., 2014a, 2014b).

In addition to planning aspects, operational factors—such as charging and discharging patterns, depth of discharge, and lifetime management—are critical in determining the effectiveness of BESS (Saxena et al., 2024a). Several recent contributions emphasize coordinated strategies where BESS supports DG while interacting with network reconfiguration, ancillary services, or DR (Saxena et al., 2024b; Zhang et al., 2017). DR, in particular, has proven to be a valuable complement to both DG and BESS, reducing peak demand, mitigating intermittency, and lowering investment requirements (Hussain et al., 2020; Meena et al., 2018). Studies investigating combined DR and DG operation further confirm their potential to improve DN efficiency and to generate benefits for stakeholders including consumers, operators, and utilities (Bazrafshan et al., 2019; Kanwar et al., 2015).

Despite these advances, comparatively few studies provide a unified optimization framework that simultaneously:

i. determines the optimal siting and sizing of DG and BESS,
ii. coordinates real-time BESS dispatch with price-based DR, and
iii. evaluates the combined techno-economic performance across multiple scenarios.

Existing works often consider these elements in isolation or focus exclusively on either planning or operational aspects. Reviews of heuristic and metaheuristic algorithms, including variants of the Grey Wolf Optimizer (GWO), confirm their suitability for solving such nonconvex, mixed-integer optimization problems (Saxena et al., 2024c). However, the joint treatment of DG/BESS planning, DR-coordinated real-time operation, and scenario-based techno-economic evaluation remains underexplored.

The novelty of this study lies in the development of a bi-level optimization framework that integrates DG and BESS siting and sizing at the planning level with coordinated real-time BESS dispatch and DR participation at the operational level. The framework consistently applies the GWO algorithm at both levels, ensuring robustness and uniformity in addressing the underlying nonlinear power-flow formulation. A comprehensive techno-economic evaluation across six IEEE-33 bus scenarios quantifies improvements in annual energy loss reduction, peak demand reduction, average voltage profile, LCOE, and payback period. Unlike prior approaches, the proposed framework highlights trade-offs between technical and financial performance, thereby offering actionable insights for utilities and policymakers.

The remainder of this manuscript is organized as follows. Section 2 introduces the mathematical models of PV, BESS, and DR. Section 3 formulates the optimization problem and details the proposed bi-level GWO methodology. Section 4 presents and discusses the simulation results. Finally, Section 5 concludes the study and outlines future research directions.

1.1. Contributions of this work

The main contributions of this study can be summarized as follows:

- *Bi-level optimization framework*: A novel architecture is developed where the upper level determines the optimal siting and sizing of DG and BESS, while the lower level coordinates hourly BESS dispatch with price-based DR strategies.
- *Consistent GWO-based methodology*: The GWO is applied across both levels to solve the mixed-integer, nonconvex AC power-flow problem, ensuring methodological consistency and robust convergence.
- *Integrated techno-economic assessment*: Six IEEE-33 bus test scenarios are designed to evaluate technical and economic performance, including annual loss reduction, peak demand reduction, voltage profile improvements, payback period, and LCOE.
- *Policy-relevant insights*: Results show that modest DR participation can offset additional BESS investments, offering utilities actionable guidance for balancing financial viability with technical performance.
- *Research gap addressed*: Unlike prior works that study DG, BESS, and DR either in isolation or pairwise, this paper provides a validated framework that jointly integrates siting/sizing, real-time dispatch, and economic scenario ranking — a combination not adequately represented in the existing literature.

2. Mathematical modelling

In this research, a multi-objective function is created to implement the recommended strategy. The function considers the following objectives for the minimization:

2.1. Power distribution losses

Minimizing power distribution losses is a crucial goal for optimizing the efficiency of DNs. The occurrence of these losses can be attributed to factors such as conductor resistance, transformer inefficiencies, and use of reactive power. Reducing these losses is crucial for improving the overall efficiency and dependability of the power system. Therefore, minimizing power loss is taken into consideration as one of the objective functions, which is defined as follows:

$$f_1 = \sum_{T=1}^{24} P_{\text{Loss}}^T \tag{1}$$

$$P_{\text{Loss}}^T = \sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_{ij}^T \left(P_i^T P_J^T + Q_i^T Q_J^T\right) + \beta_{ij}^T \left(Q_i^T P_j^T - P_i^T Q_j^T\right) \forall T \tag{2}$$

where $\alpha_{ij}^T = r_{ij}\cos\left(\delta_i^T - \delta_j^T\right)/V_i^T V_j^T$ and $\beta_{ij}^T = r_{ij}\sin\left(\delta_i^T - \delta_j^T\right)/V_i^T V_J^T$

P_{Loss}^T, P_i^T, P_J^T, Q_i^T, Q_J^T, V_i^T and V_j^T are power distribution losses at time T, real power level, reactive power level and voltage level at i^{th} and j^{th} node at time T.

2.2. Power to grid

The minimization of reverse power flow refers to the reduction or mitigation of the flow of electrical power in the opposite direction of its intended path within a power system. Reverse power flow occurs when there is an imbalance between generation and consumption, resulting in excess power being fed back into the distribution or transmission network. The objective of the power flow in the opposite direction might be stated as:

$$f_2 = \sum_{T=1}^{24} P_R^T \tag{3}$$

$$P_R^T = \begin{cases} 0, & \text{if } I_{\text{Grid}}^T \geq I_{\text{Spc}} \\ \text{Re}\left(V_{\text{Grid}}^T I_{\text{Grid}}^{T^*}\right) & \text{if } I_{\text{Grid}}^T < I_{\text{Spc.}} \end{cases}. \tag{4}$$

P_R^T, V_{Grid}^T, $I_{\text{Grid}}^{T^*}$ and I_{Spc} are the reverse power flow, voltage level of grid, current level of grid at time T and the specified value of current level.

2.3. Charging discharging losses

The minimization of converter losses is required for effective integration of BESS. Therefore, taking into consideration and may be written as:

$$f_3 = \left(\sum_{T=1}^{24} P_c^T\right) \tag{5}$$

$$P_c^T = (1-\eta) P^T_{BESS\left(\frac{C_i}{D_i}\right)} \tag{6}$$

P_c^T and $P^T_{BESS\left(\frac{C_i}{D_i}\right)}$ are the charging-discharging losses and power level of BESS at time T.

Eq. (6) models the converter losses P_c^T of the BESS system using a constant round-trip efficiency factor η. While actual efficiency is affected by SOC, temperature, and load dynamics, a fixed efficiency assumption (e.g., 90–95 %) is adopted here to simplify computation and maintain focus on high-level coordination strategies. This simplification is acknowledged as a limitation in conclusion section.

2.4. Voltage variation

The minimization of node voltage deviation is a critical objective in the optimization of power distribution systems. This entails reducing the variation or deviation in voltage levels across different nodes within the network. By minimizing voltage deviations, the stability and reliability of the DNs can be improved, ensuring that voltage levels remain within acceptable limits and written as:

$$f_4 = \left(1 + \sum_{T=1}^{24} V_D^T\right) \tag{7}$$

$$V_D^T = \begin{cases} \left|V_{\text{Min}} - V_i^T\right| \text{ if } V_i^T < V_{\text{Min.}} \\ 0 \quad \text{if } V_{\text{Min.}} \leq V_i^T \leq V_{\text{Max.}} \\ \not{\ell} \quad \text{if } V_i^T > V_{\text{Max.}} \end{cases} \tag{8}$$

V_D^T, $V_{\text{Max.}}$, V_{Min} and V_i^T are voltage deviation, voltage, maximum and minimum value of voltage level and voltage level at i^{th} node at time T while l denotes the unacceptable solution. High level of voltage level is a major problem, which is required to keep in consideration during the optimization process. As a result of the low demand case, the rise in voltages may continue to worsen, eventually reaching such high levels that it may have an effect on the protection shield and insulation collapse may happen in a number of the equipment that are linked. Increased voltage is the primary barrier that prevents a deeper penetration of DGs in DN. Because of this, hard constraint was employed whenever there was a violation of the higher voltage limit. However, compared to the maximum voltage, the minimum voltage has been treated as more of a flexible limitation. It means that there can be a small deviation from the minimum voltage as long as there is a good penalty factor.

2.5. Fitness function

The bilevel optimization process consist the following fitness function for level and level 2 respectively:

The fitness function ($F_{\ell 1}$) is given as:

$$\min(F_{\ell 1}) = \Psi \times L \times f_4 \tag{9}$$

where $L = f_1 + f_2 + f_3$

The fitness function ($F_{\ell 2}$) is given as:

$$\min(F_{\ell 2}) = \kappa \times f_4 \tag{10}$$

where $\kappa = f_1 + f_2$

Ψ is the daily to annual conversion factor. The charging discharging losses are not considered for the level 2 of optimization.

Here, Ψ and κ are dimensionless scaling parameters empirically selected to normalize and balance the relative magnitudes of the loss and smoothness terms for improved optimization performance. Their values are chosen based on the dynamic range of the respective components and kept constant during the analysis.

2.6. Demand response aggregator

The DR aggregator has an impact on how customers schedule their demand in accordance with their participation in DR, and this scheduling is also subject to a number of different technological restrictions. This study focuses the majority of its attention on the technological challenges faced by the DS as a direct result of the widespread use of PVs. In its most basic form, DR implementation makes use of the information provided by dynamic tariff and, based on that information, schedules the load in order to achieve the greatest possible reduction in set technical targets. The financial objectives are not considered for this study; rather, attention is directed toward the technological problems.

The following are some of the DR limitations that are taken into consideration (Safdarian et al., 2014):

$$P_i^T = \left(P_{Gi}^T - P_{Di}^T\right) \forall T, i \tag{11}$$

$$Q_i^T = \left(Q_{Gi}^T - Q_{Di}^T\right) \forall T, i \tag{12}$$

$$P_{Di}^T = \left(P_{in,i}^T + P_{el,i}^T\right) \forall T, i \tag{13}$$

$$\sum_{i=1}^{N} \sum_{T=1}^{24} \left(P_{in,i}^T + P_{el,i}^T\right) \times \Delta t = E_i^{Total} \tag{14}$$

$$P_{el,i}^{\min} \leq P_{el,i}^T \leq \min\left(\left(C - P_{in,i}^T\right), P_{el,i}^{\max}\right) \forall T \tag{15}$$

$$P_{el,i}^{\max} = \chi \sum_{T=1}^{24} L_{d,i}^T \tag{16}$$

$$P_{el} = \left[P_{el}^1, P_{el}^2, P_{el}^3, P_{el}^4 \ldots\ldots\ldots\ldots\ldots\ldots P_{el}^T\right] \forall T.$$

P_i^T, Q_i^T, P_{Gi}^T, Q_{Gi}^T, P_{Di}^T, Q_{Di}^T, $P_{in,i}^T$, $P_{el,i}^T$, E_i^{Total} and $L_{d,i}^T$ are the real power level, reactive power level, real power generation, reactive power generation, real power demand, reactive power demand, unshifted demand, shifted demand, energy level and hourly load at i^{th} node for time T while, C and χ are the contract load and DR rate.

2.7. Constraints for the optimization

2.7.1. DG constraint

$$0 \leq P_{\text{PV},i} \leq P_{PV}^{\max} \forall i \tag{17}$$

$P_{\text{PV},i}$ are the power penetration of PV at i^{th} node and maximum power generation by PV system.

2.8. BESS constraints

$$0 \le E_{BESS,i} \le E_{BESS}^{\text{Max}} \forall i \tag{18}$$

$$P_{BESS}^{\text{Min.}} \le P_{BESS(C_i/D_i)}^{T} \le P_{BESS}^{\text{Max.}} \forall T, i \tag{19}$$

$$SOC^{\text{Min.}} \le SOC_i^T \le SOC^{\text{Max.}} \forall T, \text{I} \tag{20}$$

$$SOC_i^T = \begin{cases} SOC_i^{T-1} + P_{BESS(C_i/D_i)}^{T} \eta_c \Delta t \Big/ E_{BESS}^{R} & \text{if } P_{BESS(C_i/D_i)}^{T} > 0 \\ SOC_i^{T-1} + P_{BESS(C_i/D_i)}^{T} \Delta t \Big/ \eta_d E_{BESS}^{R} & \text{else} \end{cases} \tag{21}$$

$$\sum_{T=1}^{24} \eta_c P_{BESS(C_i/D_i)}^{T} + P_{BESS(C_i/D_i)}^{T} \Big/ \eta_d = 0 \tag{22}$$

$E_{BESS,i}$, $P_{BESS(C_i/D_i)}^{T}$ and SOC_i^T are energy level, power level and SOC of BESS while η_c and η_d are the charging and discharging efficiency.

It is important to note that the SOC model used herein assumes ideal charge/discharge cycles and does not incorporate battery degradation effects such as DOD, temperature, or cycling history. While this idealization aids in computational tractability, integrating degradation-aware models (e.g., cycle-life models or rainflow counting techniques) is a potential avenue for future work.

2.9. Power balance constraints

$$\&P_i^T = V_i^T \sum_{j=1}^{N} V_j^T Y_{ij} \cos\left(\theta_{ij} + \delta_j^T - \delta_i^T\right) \forall T, i \tag{23}$$

&

$$Q_i^T = -V_i^T \sum_{j=1}^{N} V_j^T Y_{ij} \sin\left(\theta_{ij} + \delta_j^T - \delta_i^T\right) \forall T, i \tag{24}$$

2.10. Demand modeling

The demand modeling of the system is given in the following equations:

$$\&P_{D,i}^T = \kappa_i^T P_{D,i}^0 \forall T, i \tag{25}$$

&

$$Q_{D,i}^T = \kappa_i^T Q_{D,i}^0 \forall T, i \tag{26}$$

$P_{D,i}^0$ and $Q_{D,i}^0$ are the initial level of real power and reactive power demand while κ_i^T is the allocated load factor.

2.11. PV generation modeling

The power generation from PV systems depends on the level of solar radiation (SR). The relationship between the current generated by PV systems and SR can be expressed as follows (Rajput and Dheer, 2022):

$$I_{pv}^T = \begin{cases} \&I_{PV} \text{ if } R_{PV}^T \ge R_{PV}^r \\ \&I_{PV} \times R_{PV}^T / R_{PV}^r \text{ if } R_{PV}^T < R_{PV}^r \end{cases} \tag{27}$$

R_{PV}^T, R_{PV}^r, I_{pv}^T and I_{PV} are SR level at time T, rated level of solar radiation, current generation from PV at time T and current generation from PV.

3. Economic evaluation of integration scenarios

To enhance the practical relevance of the proposed optimization framework, a brief economic assessment is performed considering the following cost metrics:

Capital Expenditure (CAPEX):

Initial investment covering the installation of DG, BESS, and DR enablement (Yang et al., 2024)

Operational Savings (OS):

Benefits derived from reduced technical losses, peak demand shaving, and improved voltage profile.

Payback Period (PP):

Time required to recover CAPEX through annual operational savings:

$$\text{PP} = \frac{CAPEX}{Annual\ Operational\ Savings} \tag{28}$$

Levelized Cost of Energy (LCOE):

A key metric indicating the per-unit cost of energy over system lifetime (IEA, 2020):

$$\text{LCOE} = \sum_{t=1}^{N} \frac{CAPEXt + OnM(t)}{Energy\ Output(t)} \tag{29}$$

where N is system lifetime (20 years), and operation and maintenance (OnM) denotes annual operation and maintenance costs.

3.1. Key assumptions

- Lifetime of system: 20 years (IEA, 2020)
- Discount rate: 6 %
- Energy price: ₹6/kWh
- Peak demand reduction benefit: ₹250/kW
- DR enablement cost: ₹500/kW
- DG cost: ₹40,000/kW
- BESS cost: ₹20,000/kWh (energy) + ₹10,000/kW (power) (Li et al., 2022)
- OnM cost: 2 % of CAPEX annually (Yang et al., 2024)

4. Optimization technique

In the scenario described earlier, the optimization objectives required the use of a sophisticated optimization technique capable of addressing complex nonlinear problems. The GWO is selected for this study due to its balanced exploration and exploitation capabilities, low computational complexity, and strong convergence behavior in constrained, non-linear optimization problems. Unlike particle swarm optimization (PSO) and differential evolution (DE), which may suffer from premature convergence or stagnation in local optima under high-dimensional search spaces, GWO mimics the leadership hierarchy and hunting behavior of grey wolves, enabling more adaptive search dynamics. Moreover, comparative studies (Mirjalili et al., 2014; Ansari et al., 2020) have demonstrated that GWO achieves better or comparable performance in terms of solution quality and convergence speed in DER optimization problems. Additionally, its parameter-free design (compared to PSO's inertia and acceleration coefficients) makes it well-suited for the bilevel optimization structure adopted in this study. The algorithm's stability across diverse scenarios and its capability to handle multi-modal, constrained objective functions justify its application to optimize the coordinated operation of DR, BESS, and DG.

Given the constraints associated with SOC levels and their availability, the presence of BESS necessitates a multilevel optimization approach.

During the initial stage of optimization, the optimal distribution (size and location) of PVs and the BESS is identified. Subsequently, the hourly power scheduling of the BESS is synchronized with DR programs in a second level of optimization. This ensures that the operational benefits realized by the DSO are maximized to the fullest extent possible (Chen et al., 2013). To enhance the multilevel optimization process under consideration, the GWO method can be employed as an effective

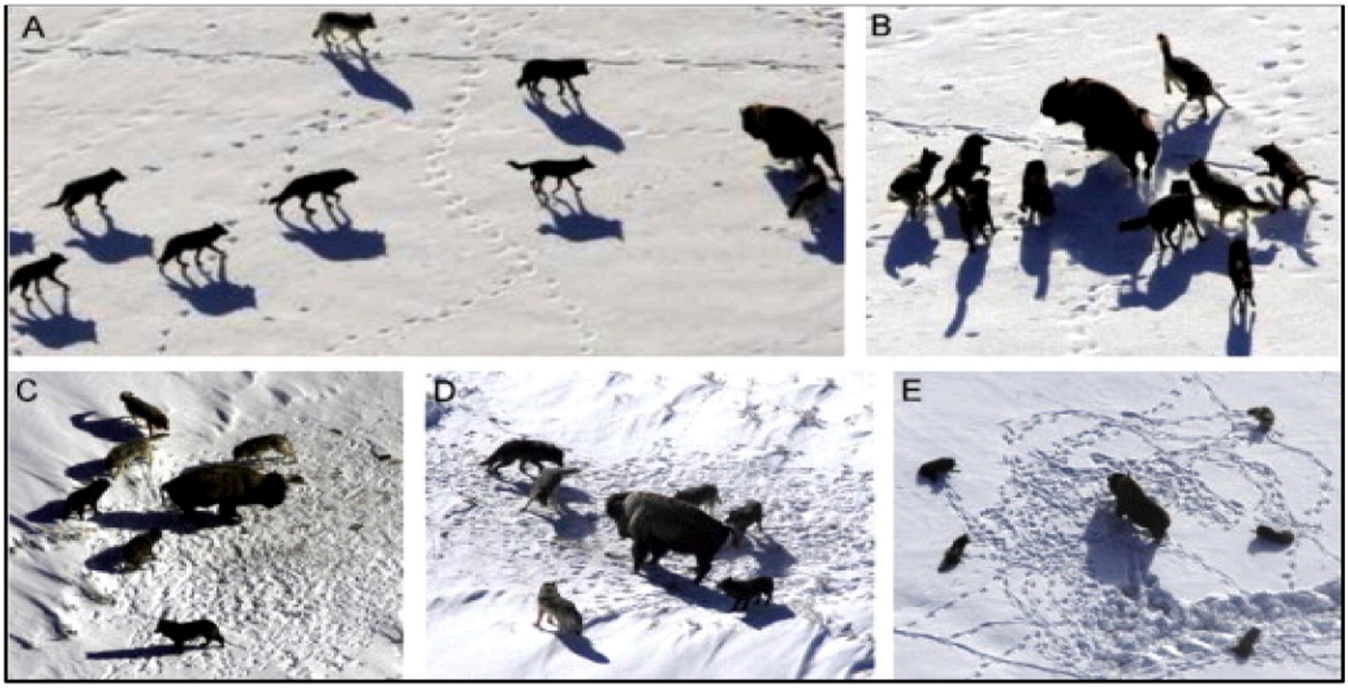


Fig. 1. Grey Wolf Optimizer: leadership hierarchy and search mechanism (Mirjalili et al., 2014).

evolutionary technique. GWO offers unique advantages for addressing complex optimization challenges in power systems (Mirjalili et al., 2014; Saxena et al., 2023).

GWO is a population-based meta-heuristic algorithm known for its capability to efficiently search for global or near-global solutions in challenging optimization problems. To apply GWO effectively to the multilevel optimization task at hand, the following steps should be undertaken:

- Initialization: Begin by initializing a population of grey wolves, representing potential solutions to the optimization problem.
- Hunting Mechanism: Implement the hunting behaviour of grey wolves, including alpha, beta, delta, and omega wolves. This involves updating the position of each wolf based on its role in the pack.
- Fitness Evaluation: Evaluate the fitness of each potential solution (wolf) based on predefined objective functions related to the multilevel optimization problem.
- Iterative Improvement: Iterate through generations of wolves, updating their positions and evaluating their fitness in each iteration.
- Convergence Criterion: Define a convergence criterion to determine when the optimization process should terminate, based on reaching a satisfactory solution or exceeding a specified number of iterations.

By applying GWO to the multilevel optimization process, the goal is to efficiently explore the solution space and achieve optimal or near-optimal solutions for power system optimization challenges. This approach leverages the collective intelligence and hunting behaviour of grey wolves to effectively navigate complex optimization landscapes. Fig. 2 illustrates the flowchart depicting the optimization process of the proposed framework.

5. Test system

The parameter values for the test system, based on IEEE 33 (Baran and Wu, 1989), are as follows: the base voltage is 12.66 kV, with a real power demand of 3715 kW and a reactive power demand of 2300 kVAr (Mazidi et al., 2014). The power loss in the system is 202.7 kW. The voltage limits range from 0.95 pu to 1.05 pu. The minimum and maximum power limits for the BESS are −1 MW and 1 MW, respectively, and the SOC ranges from 0 to 1. The maximum capacity for DG is 2 MW, and the maximum energy capacity of the BESS is 5 MWh. Table 1 outlines the simulation parameters for both level-1 and level-2 in the implementation of GWO within the proposed framework.

6. Results

Case 1. - ***Base Case*:** In the base case scenario, the peak demand was recorded at 6520 kW with a significant difference between peak and valley demand levels. The annual energy losses were 1424 MWh, and the voltage level averaged at 0.978178 pu. No specific mitigation approach was applied in this case, serving as a reference point for comparison with subsequent cases.

Case 2. - ***DG Integration*:** Introducing DG led to a reduction in the peak demand value, with the peak demand remaining at 6520 kW. However, there was a notable reduction in the difference between peak and valley demand levels, indicating improved demand variability. The annual energy losses decreased to 1106.44 MWh, and the voltage level improved to an average of 0.996344 pu. The DG penetration reached 69.1 %. All pertinent results are illustrated in Figs. 3–5.

Case 3. - ***DR Implementation*:** Implementing demand response at 10 % and 20 % levels resulted in further reductions in peak demand levels and improvements in demand variability. The reduction in yearly losses and loss reduction percentage suggests that DR implementation contributes positively to network optimization and efficiency. The DG penetration remained constant, while the voltage level averaged at 0.978444 pu and 0.978547 pu for DR at 10 % and 20 %, respectively. All pertinent results are illustrated in Figs. 6–11.

Case 4. - ***Combined DG and DR*:** Combining DG and demand response at 10 % and 20 % levels led to significant reductions in peak demand levels and demand variability. The integration of both strategies resulted in substantial improvements in network performance metrics, including yearly losses and loss reduction percentage. The DG penetration and

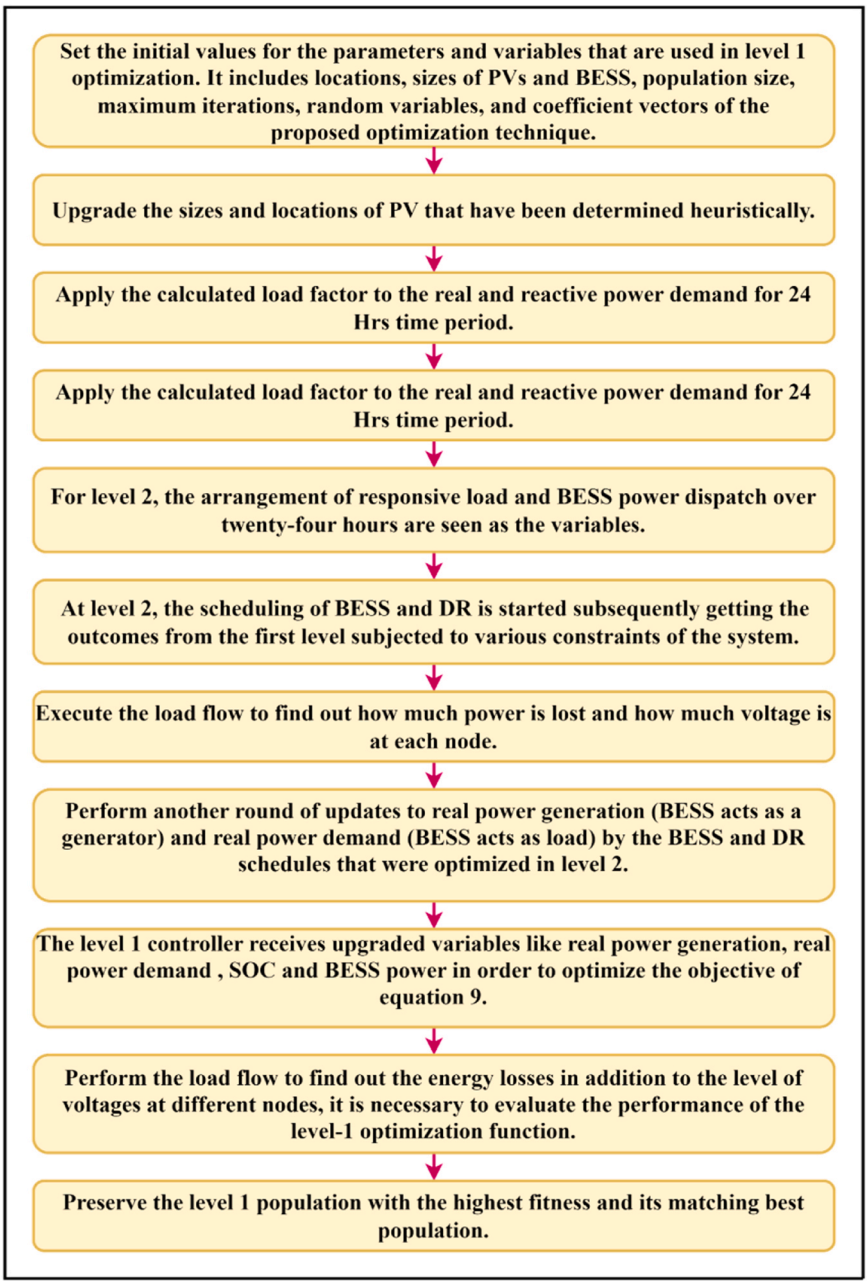


Fig. 2. Bi-level optimization framework for coordinated DG, BESS and DR integration.

Table 1
Tuning parameters for the optimization.

Parameters	First Level	Second Level
Grey Wolf Population size	50	100
Number of iterations	100	200
Random vectors r1 and r2	0, 1	0, 1
Coefficient vector $\vec{v}$	0.5	0.5

voltage level varied with the implementation of DG and DR strategies. All pertinent results are illustrated in Figs. 12–17.

Case 5. - ***DG and BESS Integration*:** Integrating DG with BESS resulted in notable reductions in peak demand levels and demand variability. The addition of BESS further enhanced network performance, as evidenced by reductions in yearly losses and loss reduction percentage. The DG penetration increased to 90.41 %, and the voltage level improved to

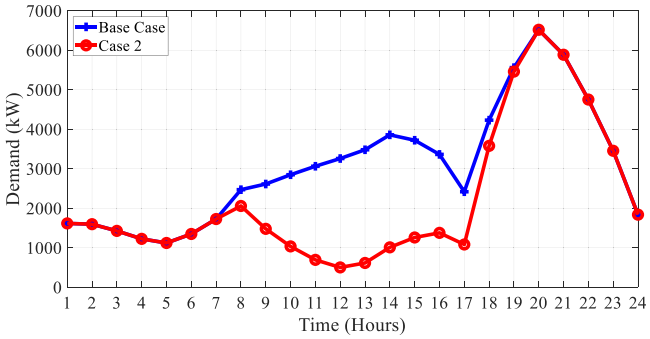


Fig. 3. Case 2: 24-hour system demand profile after DG allocation.

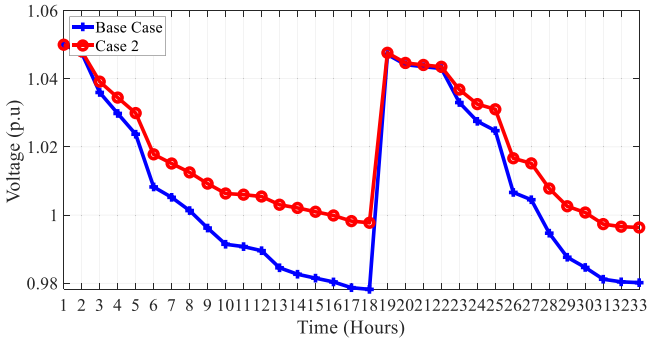


Fig. 4. Case 2: Node voltage profile after DG allocation (per-unit).

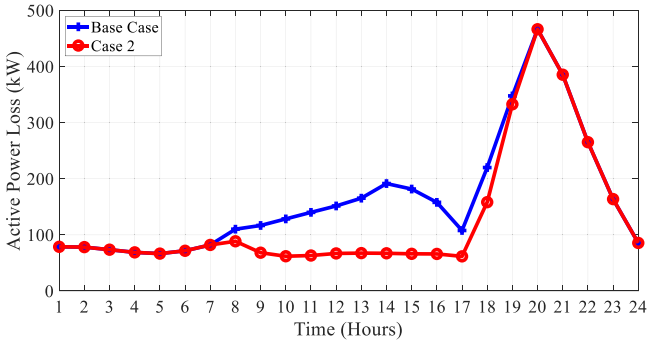


Fig. 5. Case 2: Feeder active power losses after DG allocation.

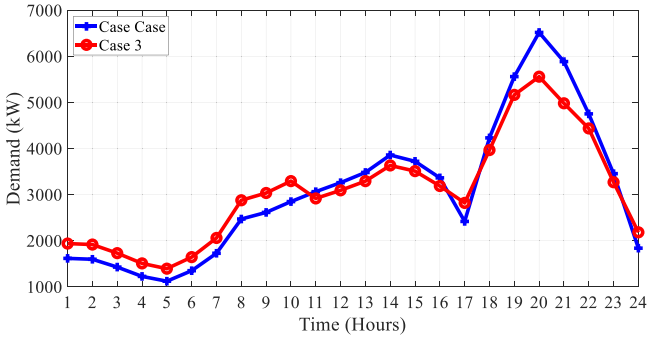


Fig. 6. Case 3 (DR 10 %): 24-hour system demand profile with demand response.

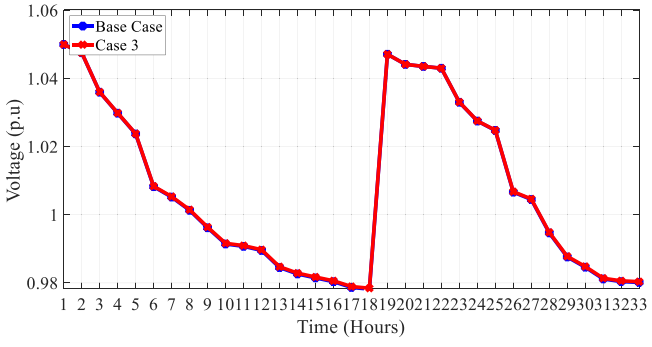


Fig. 7. Case 3 (DR 10 %): Nodal voltage profile with demand response (per-unit).

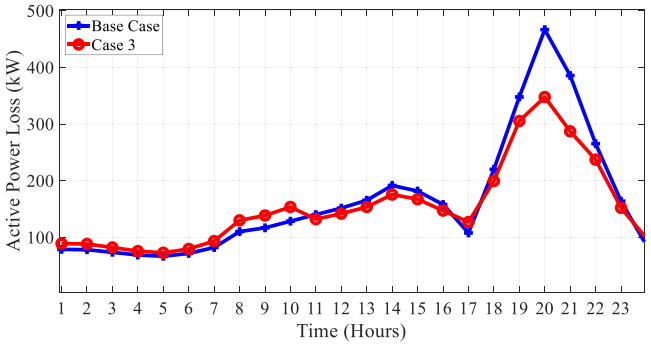


Fig. 8. Case 3 (DR 10 %): Feeder active power losses with demand response.

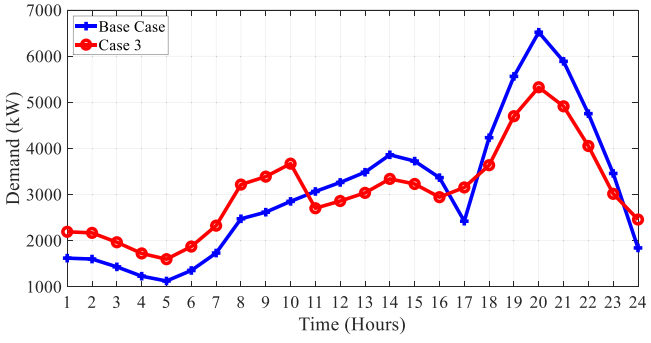


Fig. 9. Case 3 (DR 20 %): 24-hour system demand profile with demand response.

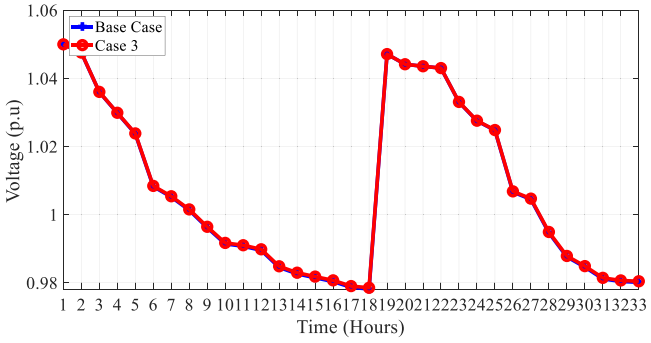


Fig. 10. Case 3 (DR 20 %): Nodal voltage profile with demand response (per-unit).

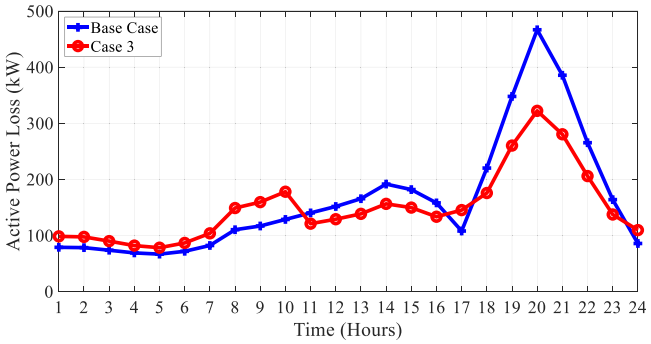


Fig. 11. Case 3 (DR 20 %): Feeder active power losses with demand response.

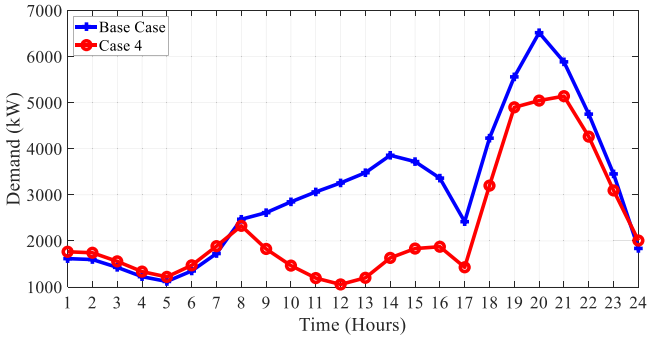


Fig. 12. Case 4 (DG + DR 10 %): 24-hour demand profile after coordinated DG and DR.

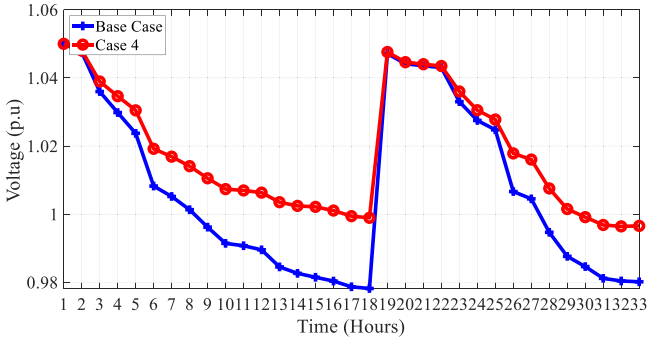


Fig. 13. Case 4 (DG + DR 10 %): Nodal voltage profile after coordinated DG and DR (per-unit).

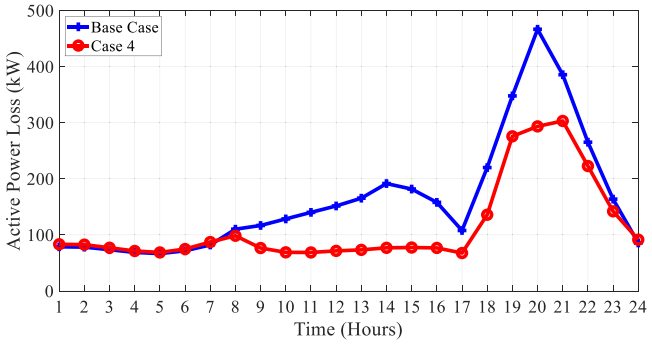


Fig. 14. Case 4 (DG + DR 10 %): Feeder active power losses after coordinated DG and DR.

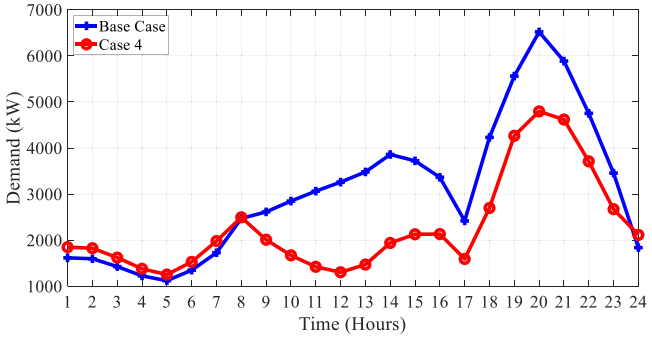


Fig. 15. Case 4 (DG + DR 20 %): 24-hour demand profile after coordinated DG and DR.

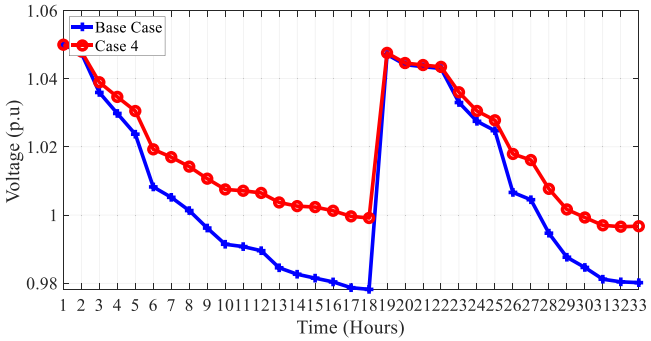


Fig. 16. Case 4 (DG + DR 20 %): Nodal voltage profile after coordinated DG and DR (per-unit).

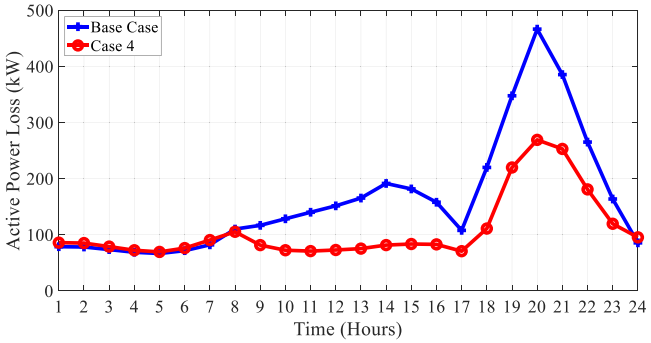


Fig. 17. Case 4 (DG + DR 20 %): Feeder active power losses after coordinated DG and DR.

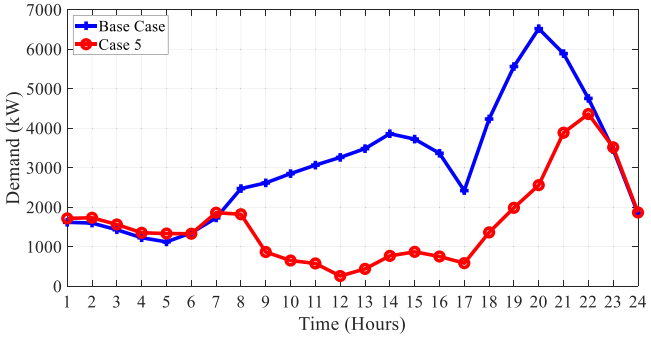


Fig. 18. Case 5 (DG + BESS): 24-hour demand profile with DG and battery energy storage.

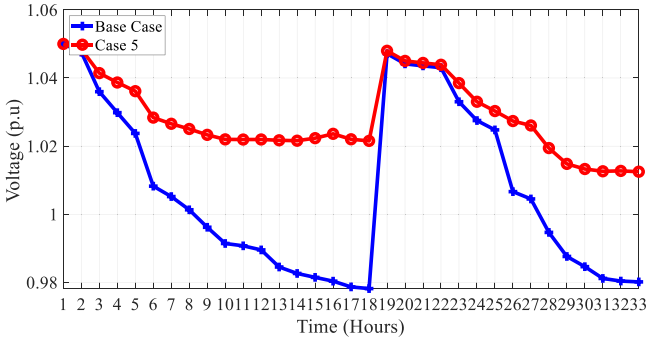


Fig. 19. Case 5 (DG + BESS): Nodal voltage profile with DG and BESS (per-unit).

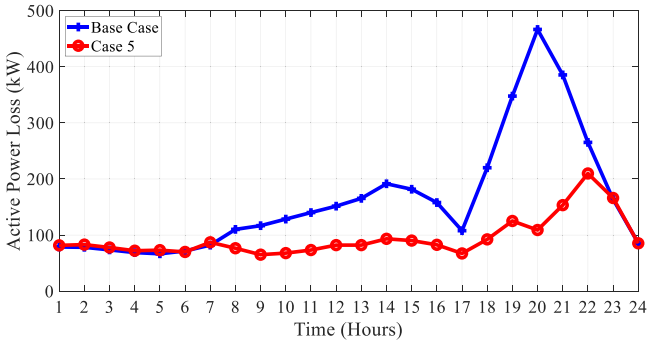


Fig. 20. Case 5 (DG + BESS): Feeder active power losses with DG and BESS.

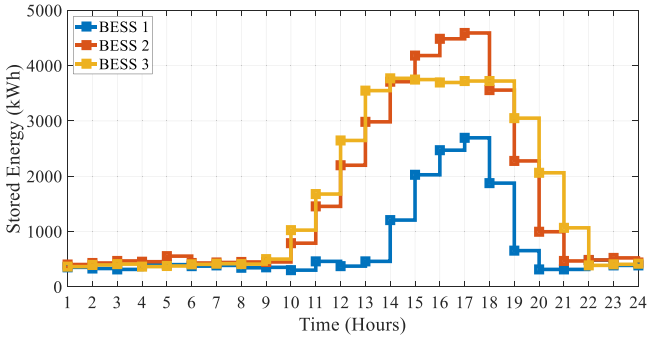


Fig. 21. Case 5 (DG + BESS): BESS stored energy / SOC profile at selected buses.

an average of 1.01249 pu. All pertinent results are illustrated in Figs. 18–21.

Case 6. - ***Combined DG, DR and BESS*:** In the DN the integration of DG, DR and BESS at 10 % and 20 % levels led to the most significant improvements in peak demand reduction and demand variability. The comprehensive approach resulted in substantial reductions in yearly losses and loss reduction percentage, highlighting the synergistic effects of combining multiple optimization strategies. The DG penetration and voltage level further improved with the combined approach. All pertinent results are illustrated in Figs. 22–29.

Table 2: The impact of the proposed approach on the level of demand reveals varying levels of reduction in peak demand and differences between peak to valley levels across different cases and approaches.

Table 3: The impact of the proposed approach on the considered objectives, including size and location of PV and BESS, average voltage level, DG penetration, yearly losses, and loss reduction percentages, further demonstrates the effectiveness of the integrated approach in

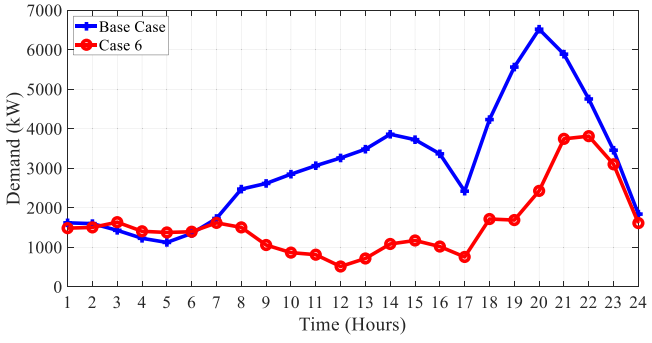


Fig. 22. Case 6 (DG + BESS + DR10 %): 24-hour demand profile for combined strategy.

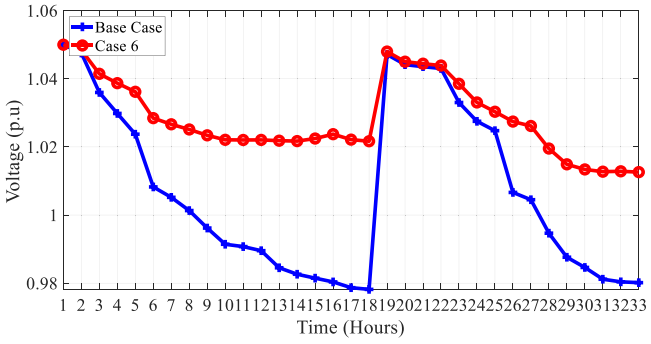


Fig. 23. Case 6 (DG + BESS + DR10 %): Nodal voltage profile for combined strategy (per-unit).

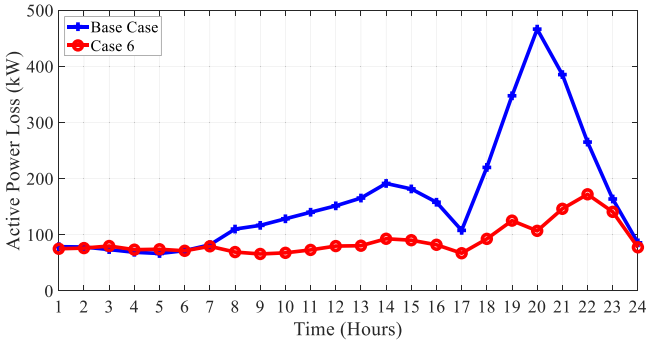


Fig. 24. Case 6 (DG + BESS + DR10 %): Feeder active power losses for combined strategy.

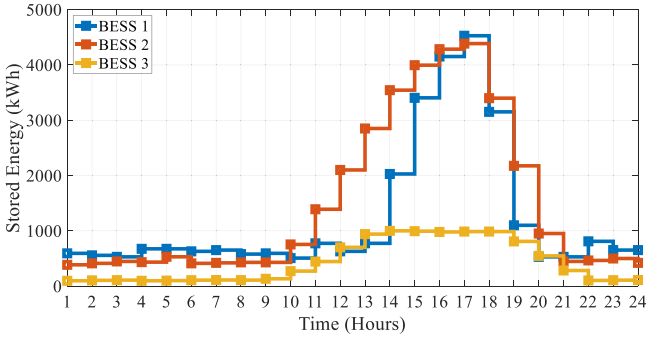


Fig. 25. Case 6 (DG + BESS + DR10 %): BESS stored energy / SOC profile with DR coordination.

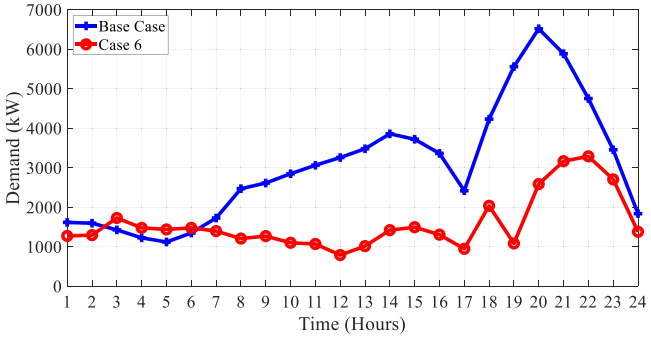


Fig. 26. Case 6 (DG + BESS + DR20 %): 24-hour demand profile for combined strategy.

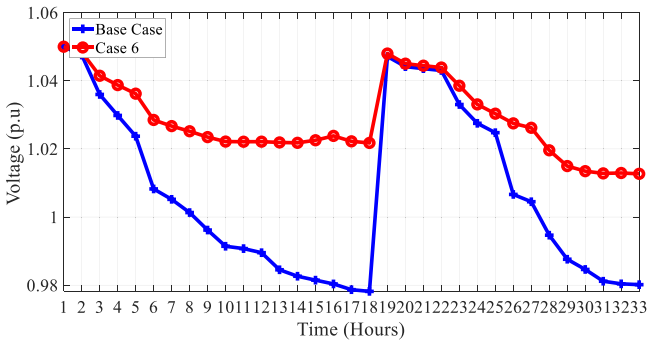


Fig. 27. Case 6 (DG + BESS + DR20 %): Nodal voltage profile for combined strategy (per-unit).

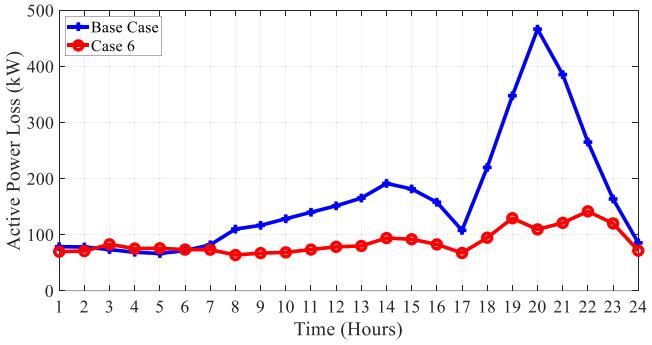


Fig. 28. Case 6 (DG + BESS + DR20 %): Feeder active power losses for combined strategy.

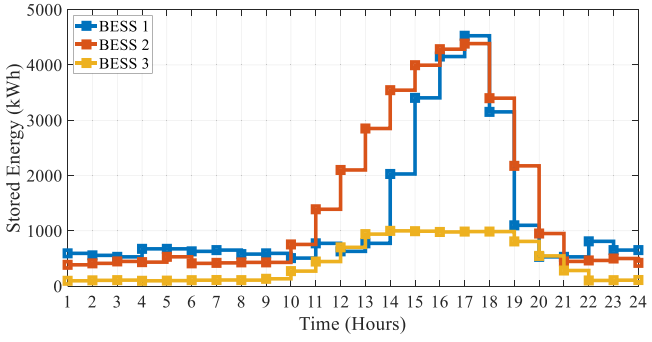


Fig. 29. Case 6 (DG + BESS + DR20 %): BESS stored energy / SOC profile with DR coordination.

achieving the desired outcomes.

Table 4 reveals that:

Case 6. (DG + BESS + DR at 20 %) provides the shortest payback period (4.43 years) and the lowest LCOE (₹4.91/kWh) among hybrid configurations, making it the most economically attractive option.

- Cases with DR only (e.g., Case 3) offer the lowest absolute LCOE, but their standalone impact is limited due to lower energy displacement.
- DG-only solutions have longer payback periods and higher LCOE, indicating the need for combined strategies.

These results validate that the optimal integration of multiple DERs not only enhances technical performance but also offers cost-effective solutions in distribution system planning, as also reported in similar optimization frameworks (IEA, 2020; Li et al., 2022).

Fig. 30 presents a comparative ranking of the integrated scenarios based on key performance indicators: **(a)** annual energy loss reduction, **(b)** peak demand reduction, **(c)** peak–valley demand difference, **(d)** average voltage profile improvement, and **(e)** payback period. Each subfigure systematically illustrates the relative effectiveness of the configurations under study with respect to these critical operational and economic metrics.

Table 2
Impact of proposed approach on the level of demand.

Case	Approach	Level of Peak Demand	Reduction in the Peak value of Demand (%)	Difference between Peak to Valley level of Demand
1	Base Case	6520	-	5380.3
2	DG	6520	-	6009.45
3	DR rate 10 %	5724	12.2	4166.14
	DR rate 20 %	5079	22.1	3730.6
4	DG and DR rate 10 %	5581	14.4	4322.87
	DG and DR rate 20 %	5020	23.0	3540.31
5	DG and BESS	4357	33.15	4100.89
6	DG, BESS and DR rate 10 %	3749	42.5	3299.7
	DG, BESS and DR rate 20 %	3298	49.51	2498.53

Figs. 3–5 — DG-only (Case 2). Figs. 3–5 present demand profile, voltage profile and power-loss distribution for Case 2 (DG only) and are intended to isolate the technical impact of distributed generation integration. Note that Case 2 increases DG penetration to 69.1 % and improves the average voltage to 0.996344 p.u., while annual losses fall to 1106.44 MWh (22.30 % reduction versus the Base Case). These quantitative values are summarized in Table 3.

Figs. 6–11 — DR-only (Case 3 at 10 % and 20 %). Figs. 6–11 show the effects of price-based DR at 10 % and 20 % participation levels. DR reduces peak demand (e.g., from 6520 kW baseline to 5724 kW at 10 % DR and 5079 kW at 20 % DR) and produces modest loss reductions (6.97 % and 9.10 % respectively), as reported in Table 2 and Table 3. These panels compare DR trials directly with the Base Case to demonstrate the incremental benefit of demand shifting alone.

Figs. 12–17 — Combined DG + DR (Case 4, 10 % and 20 %). These figures compare combined DG and DR strategies against earlier single-resource cases. Combined operation achieves larger loss reductions and peak shaving than either strategy alone (e.g., DG+DR20 % reduces yearly losses to 932.57 MWh, a 34.51 % reduction vs. Base Case). See Table 3 for bus-level allocation details.

Figs. 18–21 — DG + BESS (Case 5). Figs. 18–21 display results where BESS is included for the first time (Case 5). Because BESS is absent in Cases 1–4, SOC and BESS energy-level plots only appear in these panels; this is why certain figures (e.g., SOC profiles) show Case 5 (and Case 6) only. DG+BESS yields the largest single-technology improvement in losses (813.10 MWh; 42.90 % reduction) and raises average voltage to 1.01249 p.u. (Table 3).

7. Scalability and real-world implementation

The proposed bi-level optimization framework demonstrates significant potential for real-world deployment in utility-scale distribution networks. Scalability is facilitated by the modular nature of the optimization structure, enabling seamless integration of additional DG units, BESS, and DR programs across larger grid segments. However, effective real-time implementation requires robust communication infrastructure, high-resolution demand and generation data, and advanced control architectures to coordinate distributed assets. While the GWO exhibits low computational overhead, ensuring real-time responsiveness in larger systems may necessitate hierarchical or decentralized control schemes. Moreover, compatibility with existing SCADA systems and smart metering infrastructure is essential for practical adoption. Future

Table 3
Impact of proposed approach on the considered objectives.

Case	Approach	Size and location of PV (Bus No. and kW)	Size and location of BESS (Bus No. and kWh)	Vavg	DG Penetration (%)	Yearly Losses (MWh)	Loss reduction (%)
1	Base Case	-	-	0.978178	-	1424	-
2	DG	16(1352)-24(1715)-28(1079)	-	0.996344	69.10	1106.44	22.30
3	DR rate 10 %	-	-	0.978444	-	1324.74	6.97
	DR rate 20 %	-	-	0.978547	-	1294.4	9.1
4	DG and DR rate 10 %	17(1172)-8(1905)-30(912)	-	0.9964	66.48	1013.46	28.83
	DG and DR rate 20 %	18(435)-26(1805)-14(1649)	-	0.996575	64.81	932.57	34.51
5	DG and BESS	15(1912)-27(1648)-30(1865)	13(2697)-33(4593)-16(3773)	1.01249	90.41	813.10	42.90
6	DG, BESS and DR rate 10 %	16(1532)-32(1765)-26(1798)	16(4529)-32(4386)-20(982)	1.01226	84.91	757.85	46.78
	DG, BESS and DR rate 20 %	18(990)-14(2045)-30(1765)	16(4591)-33(4388)-18(985)	1.01263	80.00	792.17	44.37

Table 4
Economic performance of integration scenarios.

Rank	Case	CAPEX (₹ Lakhs)	Annual Savings (₹ Lakhs)	Payback Period (Years)	LCOE (₹/kWh)
1	Case 6 (DG + BESS + DR20 %)	185.0	41.7	**4.43**	**4.91**
2	Case 6 (DG + BESS + DR10 %)	170.0	35.5	**4.79**	5.15
3	Case 5 (DG + BESS)	160.0	31.8	5.03	5.34
4	Case 4 (DG + DR20 %)	145.0	26.2	5.53	5.63
5	Case 4 (DG + DR10 %)	140.0	21.9	6.39	5.88
6	Case 2 (DG only)	120.0	17.1	7.02	6.42
7	Case 3 (DR only, 20 %)	30.0	6.1	4.92	3.75
8	Case 3 (DR only, 10 %)	18.0	3.8	4.74	3.91
9	Case 1 (Base)	–	–	–	–

work could explore adaptive control strategies and edge computing techniques to further reduce latency and improve scalability across diverse operational contexts.

8. Limitations

While the proposed optimization framework demonstrates promising performance, several simplifying assumptions have been adopted that may limit its applicability under real-world conditions. Firstly, DR participation is modeled using fixed curtailment rates (10 % and 20 %), without accounting for dynamic elasticity, user-specific behavior, or temporal preferences. This static representation may not fully capture the variability and responsiveness of end-users in actual DR programs. Secondly, the framework assumes ideal forecasts for both load and renewable generation, without explicitly modeling uncertainty or incorporating probabilistic error margins. Such deterministic treatment could affect the robustness and adaptability of the proposed real-time coordination strategy under forecast deviations. The power system environment is also considered to be fully deterministic, excluding factors such as communication delays, data losses, hardware constraints, and electricity market dynamics. These real-world complexities—particularly important in smart grid implementations—are beyond the scope of the current study and represent key directions for future research. Subsequent work will aim to integrate stochastic elements, adaptive DR modeling, and hardware-in-the-loop (HIL) validations to enhance the practical viability of the proposed approach.

Regarding the modeling of the BESS, converter losses have been simplified using a constant efficiency factor. However, actual BESS efficiency is influenced by SOC, ambient temperature, and real-time loading conditions. Incorporating these dynamic characteristics may further improve the accuracy of system modeling. Moreover, the present study assumes ideal BESS operation, neglecting long-term degradation effects such as DOD, thermal stress, and aging. While such assumptions are common in initial optimization studies, future extensions will incorporate battery degradation models to better reflect lifecycle costs and long-term operational performance.

9. Conclusions

This study presented a bi-level optimization framework integrating DG, BESS, and DR for enhancing the operational and economic performance of distribution networks. The findings from the six IEEE-33 bus scenarios provide the following key insights:

*DG integration alone (*Case 2*)* reduced annual network losses by 22.3 % (from 1424 MWh to 1106.44 MWh) and improved average bus voltage from 0.978 pu to 0.996 pu. However, the payback period remained relatively high at 7.02 years, with an LCOE of ₹6.42/kWh, indicating limited economic viability when DG is deployed in isolation.

*DR participation (*Case 3*)* provided meaningful improvements in peak demand reduction without requiring significant capital investment. At 20 % DR, peak demand fell by 22.1 %, annual losses decreased by 9.1 %, and the payback period was 4.92 years with an LCOE of ₹3.75/kWh. Although technically less effective than DG or BESS, DR offers a cost-efficient solution for utilities.

*Combined DG and DR (*Case 4*)* further enhanced performance, achieving up to 34.5 % annual loss reduction and a 23.0 % decrease in peak demand under 20 % DR. The average bus voltage improved to 0.9966 pu, with a payback period of 5.53 years. This demonstrates the value of coupling generation-side and demand-side resources.

*DG with BESS (*Case 5*)* yielded substantial technical improvements, reducing annual losses by 42.9 %, cutting peak demand by 33.2 %, and increasing DG penetration to 90.4 %. The payback period, however, was 5.03 years, highlighting the cost intensity of BESS deployment despite its technical benefits.

*Full integration of DG, BESS, and DR (*Case 6*)* produced the most significant outcomes. Under 20 % DR, peak demand dropped by nearly 50 % (from 6520 kW to 3298 kW), annual losses declined by 44.4 %, and average voltage rose to 1.0126 pu. Economically, this case achieved the best results, with a payback period of only 4.43 years and the lowest LCOE of ₹4.91/kWh. Even at 10 % DR participation, Case 6 remained highly effective, with a 42.5 % peak demand reduction and a 46.8 % loss reduction.

Overall, the results confirm that coordinated deployment of DG, BESS, and DR significantly outperforms isolated strategies in both technical and economic terms. While DG reduces losses and improves voltage, and DR offers cost-effective peak management, BESS integration delivers strong stability and efficiency benefits. The bi-level optimization approach ensures optimal siting/sizing and real-time coordination, providing utilities with actionable pathways to reduce

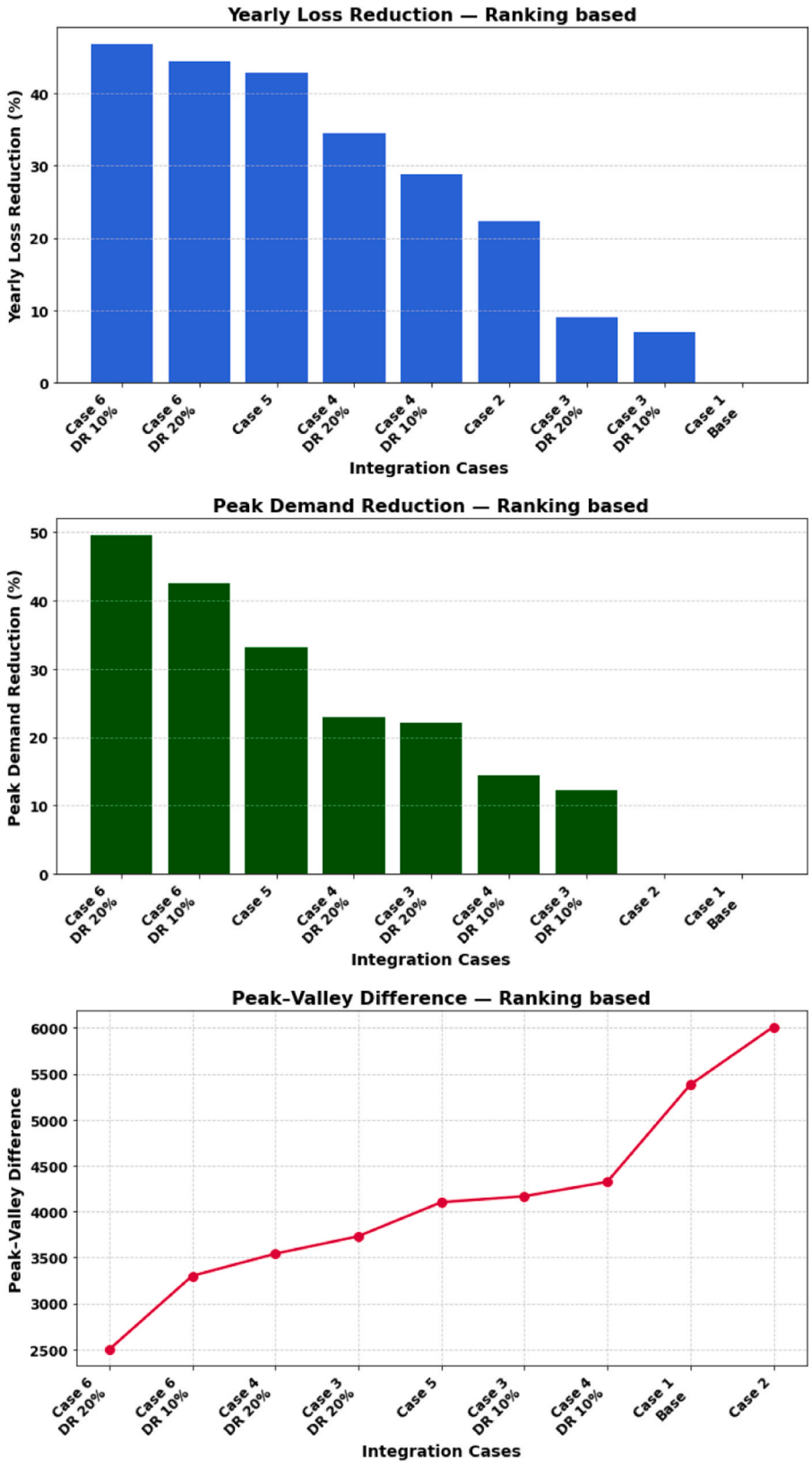


Fig. 30. **(a)** Ranking based yearly loss reduction for various integrated cases. **(b)** Ranking based peak demand reduction for various integrated cases. **(c)** Ranking based peak-valley difference for various integrated cases. **(d)** Ranking based average voltage profile for various integrated cases. **(e)** Ranking based payback period for various integrated cases.

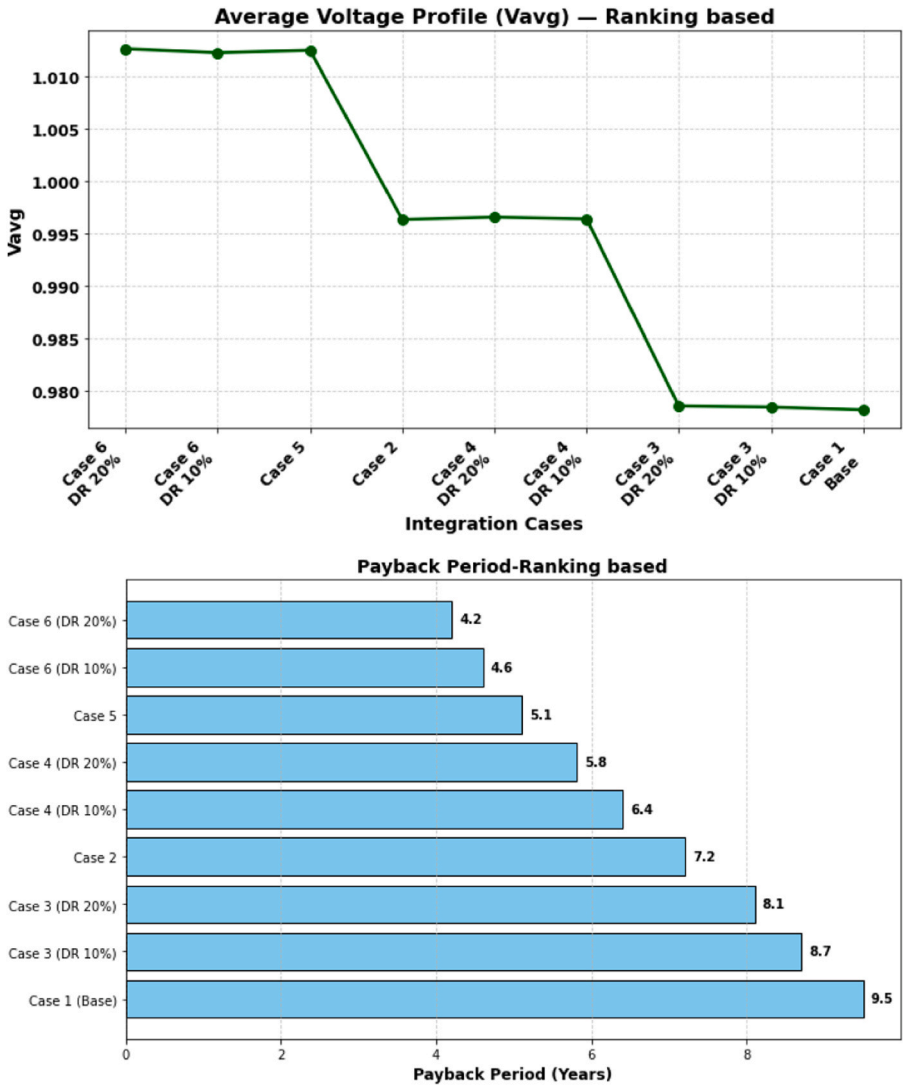


Fig. 30. (*continued*).

losses, improve voltage stability, and achieve competitive payback periods.

Future research should address scalability to larger and more diverse grid topologies, incorporate stochastic renewable generation models, and evaluate regulatory and policy frameworks to support real-world deployment of integrated DER coordination.

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Author Statement

Vivek Saxena: performed the experiments, analyzed and interpreted the data, wrote the paper. **Saurabh Kumar Rajput**: conceived and designed the experiments. **Saibal Manna**: analyzed tools or data and interpreted the data, materials. **Amaresh Gantayet**: performed the experiments. **Kusum Lata Agarwal**: conceived and designed the experiments. **Mohammed H. Alsharif**: contributed reagents and designed the experiments. **Mun-Kyeom Kim**: conceived and designed the experiments, contributed reagents

CRediT authorship contribution statement

Kusum Lata Agarwal: Investigation, Formal analysis, Data curation. **Mohammed H. Alsharif:** Writing – review & editing, Investigation, Conceptualization. **Saibal Manna:** Visualization, Resources, Data curation. **Amaresh Gantayet:** Supervision, Software, Conceptualization. **Mun-Kyeom Kim:** Writing – original draft, Validation, Conceptualization. **Vivek Saxena:** Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Saurabh Kumar Rajput:** Resources, Project administration, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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