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ELECTRICAL ENGINEERING

Harnessing Solar PV and Demand Response for Carbon Reduction in Gas-Fired Power Plants Using Ant Colony Optimization

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ABSTRACT. Addressing climate change requires urgent efforts to reduce carbon dioxide (CO_2) emissions from gas-fired power plants (GFPPs), which remain integral to India's energy sector. While various mitigation strategies have been explored, the integration of solar photovoltaic (PV) systems with demand response (DR) in GFPPs remains under examined. This study evaluates the effectiveness of combining solar PV and DR for emissions reduction using Ant Colony Optimization (ACO) to optimize PV allocation, considering solar variability, demand profiles, and the carbon intensity of gas-fired generation. Unlike previous research focused on single energy sources or isolated optimization techniques, this study integrates PV generation with demand-side management to enhance both emissions reduction and energy efficiency. Tested on the IEEE 33-bus system with real-world Indian GFPP data, the proposed approach achieves a 27.66% CO_2 reduction, demonstrating its viability. The findings provide a strategic framework for policymakers and industry stakeholders to implement low-carbon technologies in gas-fired power generation.

Keywords: Ant colony optimization; CO2; Gas fired power plant; Renewable energy.

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Introduction

Electricity is the bedrock of modern civilization, driving industrial activities, infrastructure development, and daily life. The generation of electricity, however, is heavily dependent on various energy sources such as coal, lignite, natural gas, uranium, solar, wind, and hydropower. Despite its critical role, electricity generation has profound environmental implications, particularly through its substantial contribution to global CO2 emissions. As a result, the choice of generation technology becomes a critical factor in mitigating the environmental consequences of energy production. Renewable energy sources, especially solar and wind are increasingly recognized as more sustainable alternatives to fossil fuels like coal, with a carbon footprint nearly 20 times smaller in comparison (Saxena et al., 2021; Saxena et al., 2022; Saxena, 2025; Sharma et al., 2025).

The Central Electricity Authority (2023) of India reported in its 2022 CO2 Baseline Database that GFPP emit approximately 0.975 tons of CO2 per megawatt-hour (tCO2 MWh^{-1}) of electricity produced. In this context, the integration of renewable DG within DN is a promising solution to reduce these emissions. Solar PV systems, in particular, are crucial for this transition. However, it is important to acknowledge that the manufacturing of solar PV systems depends on electricity derived from thermal power plants, thereby contributing to CO2 emissions. The lifecycle CO2 emissions associated with PV module production are estimated at approximately 0.053 kg per kWh of electricity generated (Rajput et al., 2022, Rajput et al., 2025).

The evolving energy landscape in India, particularly from fiscal years 2000-01 to 2021-22, has been marked by notable shifts in capacity additions. Coal-based capacity expanded significantly from 2000-01 until 2015-16, after which it began to decline from 2016-17 to 2021-22. Simultaneously, hydro-based capacity has experienced a downward trend since 2017-18, while other generation capacities have shown minimal growth. Although there was a slight increase in coal-based generation in 2021-22 due to increased demand, gas and hydro-based generation witnessed a decline, and the share of imported coal reduced from 9% to 4% compared to the previous fiscal year.

This paper is structured as follows. The introduction presents the research background, emphasizing the need for CO_2 reduction in GFPPs through solar PV integration and DR coordination. The literature review analyzes existing studies on emissions mitigation and renewable energy integration. The mathematical modeling formulates the problem, incorporating emissions and energy loss calculations. The optimization approach details the application of ACO for optimal solar photovoltaic allocation. The results and discussion assess the impact of solar PV integration with DR on emissions reduction and system performance. Finally, the conclusion summarizes key findings, policy implications, and future research directions.

Literature review

The following literature review examines significant studies addressing these areas, highlighting key innovations and methodologies aimed at reducing CO2 emissions and improving energy efficiency. By comparing different approaches, the review provides insights into the most effective strategies for fostering sustainable energy systems. This comparison not only underscores the importance of innovation in energy systems but also serves as a basis for further research into optimizing energy management for a carbon-neutral future. Table 1 presents a comparative summary of key studies on emission reduction and energy integration strategies. It highlights the range of methods and findings that collectively emphasize the potential for CO_2 mitigation through optimized system design.

Table 1. Comparison of Studies on Emission Reduction and Energy Integration Strategies.

Study	Main Focus	Methodology	Findings	CO2 Reduction Potential
(Cheng et al., 2023)	CO2 emission prediction in coal-fired plants	RBF neural network model	Improved accuracy in emission predictions	Enhances predictive accuracy, vital for emission control
(Ma et al., 2022)	Carbon emissions in coal-fired captive power plants	Source-network-load interactive evaluation	Supports grid participation and low-carbon development	Scientifically grounded approach for carbon reduction
(Samanta et al., 2016)	Efficiency improvement in coal-fired power plants	Partial repowering strategy	30.7% efficiency increase, 26.5% CO2 reduction	Substantial efficiency gains and emission reductions
(Li et al., 2020)	National CO2 reduction strategies	Analysis of 99.7% of operational plants	Regional disparities and decarbonization strategies post-2020	265 Mt CO2eq reduction potential by 2020
(Smaisim et al., 2023)	Integration of renewables in coal-fired plants	Molten carbonate fuel cells and solar farms	Increased energy output and reduced environmental impact	Significant emission reduction through renewable integration
(Zhang et al., 2015)	CO2 capture energy savings	Chemical absorption with heat recovery	Identified 9.32% and 8.71% energy savings	Improved energy efficiency in CO2 capture processes
(Hanak et al. 2015)	Clean coal technologies	Ammonia substitution in CO2 capture	Efficiency penalties of 8.7% to 10.9%	Supports EU 2050 greenhouse gas reduction goals
(Saxena et al. 2024a)	Role of DG in sustainable grid integration	Classification of DGs (renewable and non-renewable)	Critical for assessing sustainable energy generation	Promotes renewable energy utilization
(Saxena et al. 2024b)	Optimal placement of solar PV in DN	Integration of DR in PV placement	Enhances voltage stability and grid performance	Optimizes infrastructure usage for emission reduction
(Zhong et al. 2021)	DG placement optimization	Chaotic-particle swarm methodology	Optimized grid connection for reduced emissions	Carbon reduction in low-carbon practices
(Yoon et al. 2022)	Energy generation and carbon reduction	Energy storage integration and supply system adaptation	Improved carbon management at the urban scale	Enhanced energy self-sufficiency and carbon neutrality
(Viana et al. 2018)	DR and PVDG integration in DNs	Framework for evaluating DR and PVDG benefits	Provides cost-effective strategies for utility planning	Facilitates economic and sustainable energy consumption
(Shirazi et al. 2021)	Intelligent microgrids and DG optimization	Gray Wolf optimization model for DG placement	Cost-effective and environmentally minimal solutions	Reduces environmental impact and financial costs
(Wang et al. 2021)	Carbon emission flow optimization	Emission flow computation in distributed energy	Enhances carbon management	Significant emission reduction through efficient energy management
(Lakshmi et al. 2023)	GHG emission mitigation	Computational algorithms for DG integration	Encourages use of low-emission DG units	Reduces GHG emissions from coal-based generation

Mathematical modeling

Fitness function

In light of the imperative to mitigate CO2 emissions, there exists a pressing need to bolster the adoption of renewable energy sources while concurrently addressing energy losses within the existing energy infrastructure (Saxena et al., 2025). The reduction of CO2 emissions hinges significantly on diminishing dependence on electricity derived from GFPP. Thus, this paper endeavours to delineate a comprehensive framework aimed at achieving this goal. To this end, the following objectives are proposed to guide the realization of the framework:

Minimizing power distribution losses

$$¥_1 = \sum_{t=1}^{24} P_{\mathrm{L}\,(\mathrm{t})} \tag{1}$$

Reverse power flow

$$¥_2 = \sum_{t=1}^{24} P_{R\,(t)} \tag{2}$$

Node voltage deviation

$$¥_3 = \left(1 + \sum_{t=1}^{24} V_{D\,(t)}\right) \tag{3}$$

Where, $P_{\mathrm{L}\,(\mathrm{t})}$, $P_{R\,(t)}$ and $V_{D\,(t)}$ denotes the power distribution losses, reverse power flow and voltage deviation at time t respectively (Saxena et al., 2025).

The fitness function (ξ) for the optimization process is given as

$$min(\xi) = © \times \alpha \times ¥_3 \tag{4}$$

$$\alpha = ¥_1 + ¥_2 \tag{5}$$

Where © is used to convert daily to annual conversion factor.

DR Constraints

$$P_{i(t)} = \left(P_{Gi(t)} - P_{Di(t)}\right)\forall t, i \tag{6}$$

$$Q_{i(t)} = \left(Q_{Gi(t)} - Q_{Di(t)}\right)\forall t, i \tag{7}$$

$$P_{Di(t)} = \left(P_{in,i(t)} + P_{el,i(t)}\right)\forall t, i \tag{8}$$

$$P_{el,i}^{max} = \mu \sum_{t=1}^{24} L_{d,i(t)} \tag{9}$$

where $P_{i(t),}$ $Q_{i(t)}$ $P_{Gi(t)}$, $Q_{Gi(t)}$, $P_{Di(t)}$, $Q_{Di(t)}$, $P_{in,i(t)}$, $P_{el,i(t),}$ denotes the real power level, reactive power level, real power generation, reactive power generation, real power demand, reactive power demand, nonresponsive load, responsive load at i^{th} node at time *t* respectively while μ, and $L_{d,i(t)}$ denotes the DR rate and hourly load.

$$0 \leq P_{\mathrm{DG},i} \leq P_{DG}^{max} \forall i \tag{10}$$

Equation (10) represents the DG penetration limit.

The configuration of the IEEE 33-bus test system employed for analysis is shown in Figure 1.

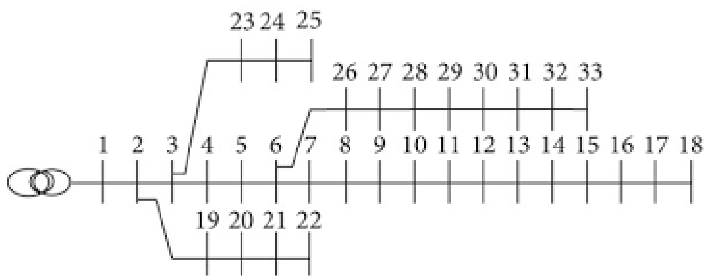

Figure 1. IEEE 33 bus system.

Optimization approach

Ant Colony Optimization (ACO) is a bio-inspired optimization technique based on the foraging behavior of ants. ACO solves optimization problems by simulating how ants find the shortest paths to food sources through pheromone trails. In this algorithm, a population of artificial ants constructs potential solutions by moving through the search space, influenced by pheromone intensity and heuristic information. As ants traverse paths, they deposit pheromones, which guide subsequent ants towards promising regions of the search space. Over time, pheromone evaporation prevents stagnation by reducing the likelihood of repeatedly selecting the same paths.

ACO is particularly effective for combinatorial optimization problems, such as the traveling salesman problem or network routing, where finding the best solution involves evaluating numerous possible configurations. The technique's adaptability allows it to handle dynamic environments and incorporate constraints. ACO is known for its ability to balance exploration (discovering new paths) and exploitation (refining known solutions), making it robust for finding near-optimal solutions in complex search spaces (Saxena et al., 2021b; Saxena et al., 2023). The flowchart of the proposed optimization techniques is demonstrated in Figure 2.

For the simulation of ACO, an ant population of 30 is used, with the pheromone evaporation rate set at 0.5 to allow a balance between exploring new paths and reinforcing good solutions. The importance of pheromone and heuristic information is controlled by parameters α (1.0) and β (2.0), respectively. The algorithm runs for 100 iterations, with each iteration representing one complete cycle of solution construction and pheromone update. These parameters are selected to ensure efficient convergence towards optimal paths while maintaining diversity in the search process.

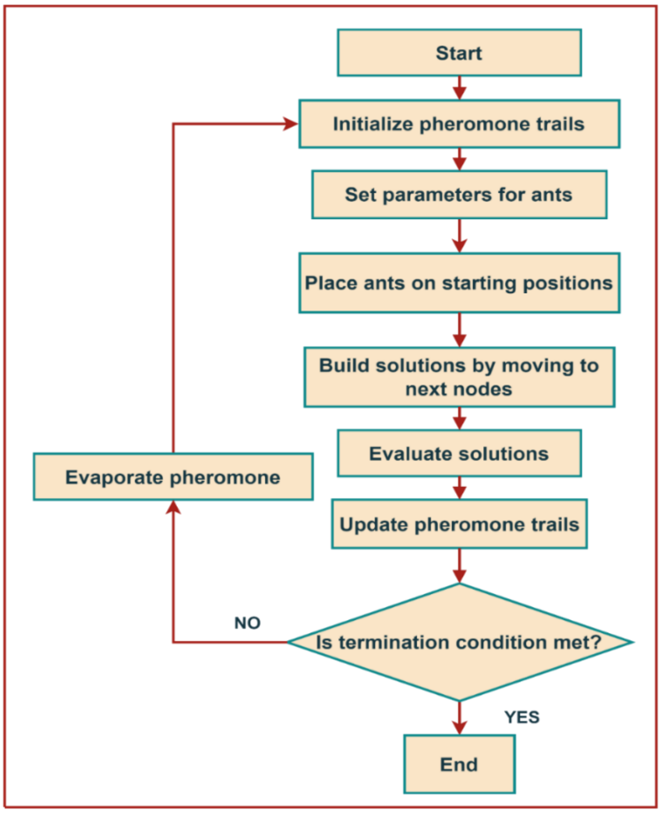

Figure 2. Proposed ACO technique.

Results and discussion

Case-1: base case

In the Base Case, the energy demand is 73,474 kWh day^{-1}, and there are annual energy losses of 1,430 MWh, translating to daily losses of 3,917.81 kWh. The average voltage level is 0.9781 p.u. With no DG or DR implemented, the system operates with higher losses and a relatively low voltage level, leading to total CO2 emissions of 35,987.19 kg day^{-1}. This scenario serves as the baseline for evaluating the impact of DG and DR integration on system performance and emissions.

Case-2: DG-only scenario

In the DG scenario, DG units are optimally allocated at Bus 15 (1,290 kW), Bus 28 (1,740 kW), and Bus 29 (1,092 kW), which significantly reduces the energy demand from the GFPP to 52,681 kWh day^{-1}. The energy supplied by DG units amounts to 20,793 kWh day^{-1}, leading to a considerable decrease in CO2 emissions from the GFPP to 25,908.23 kg day^{-1}. The total CO2 emissions are reduced to 27,010.26 kg day^{-1}, reflecting a 24.94% reduction compared to the base case. Annual losses are also reduced to 1,108 MWh, and daily losses drop to 3,035.62 kWh, representing a 23% reduction in losses. The DG penetration level reaches 68.7%, and the voltage level improves to 0.9963 p.u., indicating better system stability and performance. The real power losses are demonstrated in Figure 3.

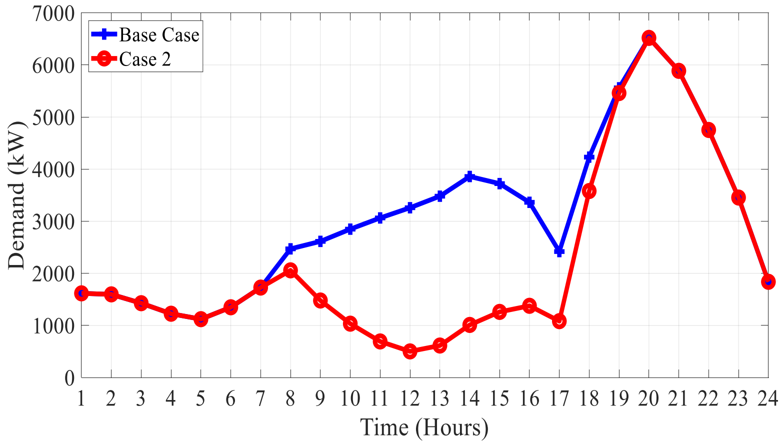

Figure 3. Real power losses after integration of DG.

Case-3: DR-only scenarios

In the DR-only scenarios, the results demonstrate marginal improvements in losses and CO2 emissions. At 10% DR, the energy demand remains nearly the same at 73,472 kWh day^{-1}, with annual losses reduced to 1,298 MWh, corresponding to daily losses of 3,556.16 kWh. CO2 emissions are slightly reduced to 35,818.10 kg day^{-1}, yielding a minimal reduction of 0.47%. At 20% DR, energy demand is slightly reduced to 73,411 kWh day^{-1}, and daily losses drop to 3,504.11 kWh. CO2 emissions decrease to 35,765.53 kg day^{-1}, representing a 0.62% reduction. The minimal impact of DR-only scenarios indicates that demand response alone is not sufficient to achieve significant energy or emission reductions. The real power losses are demonstrated in Figures 4 and 5 for DR rate of 10% and 20% respectively.

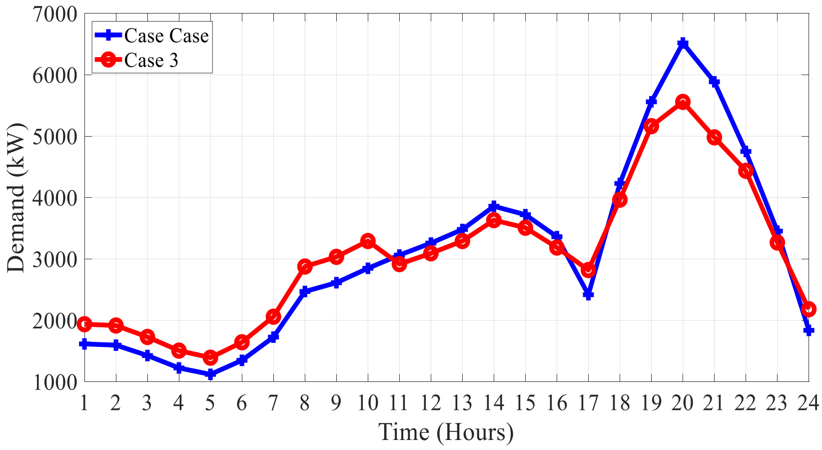

Figure 4. Real power losses at DR rate of 10%.

In the combined DG and DR scenarios, the results show substantial improvements. With 10% DR and DG units optimally placed at Bus 9 (1,116 kW), Bus 17 (1,880 kW), and Bus 29 (878 kW), the energy demand from the GFPP decreases to 50,684 kWh day^{-1}. The DG units supply 22,790 kWh day^{-1}, leading to a total CO2 emission reduction to 26,034.61 kg day^{-1}, representing a 27.66% decrease. Annual energy losses drop to 988 MWh, with daily losses reduced to 2,706.85 kWh, marking a 30.15% reduction in losses. The DG penetration level is 64.56%, and the voltage level improves further to 0.9964 p.u., indicating enhanced system performance.

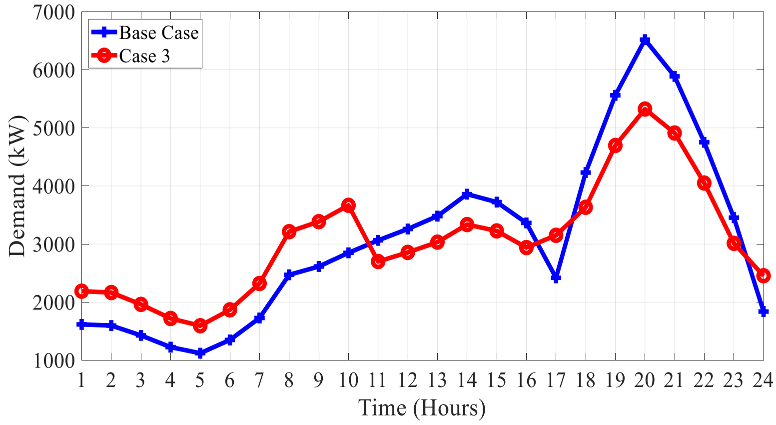

Figure 5. Real power losses at DR rate of 20%.

Case-4: combined DG and DR scenarios

At 20% DR with DG, DG units are placed at Bus 8 (502 kW), Bus 9 (1,790 kW), and Bus 16 (1,498 kW). The energy demand from the GFPP is slightly higher at 54,498 kWh day^{-1}, while DG supplies 18,976 kWh day^{-1}. The total CO2 emissions amount to 27,519.35 kg day^{-1}, showing a 23.53% reduction compared to the base case. Annual energy losses drop to 920 MWh, with daily losses at 2,520.55 kWh, resulting in a 34.5% reduction in losses. The DG penetration level is 63.16%, and the voltage level improves to 0.9967 p.u., demonstrating continued system enhancement with combined DG and DR strategies. The real power losses are demonstrated in Figures 6 and 7 for DR rate of 10% and 20% in the coordination of DG respectively.

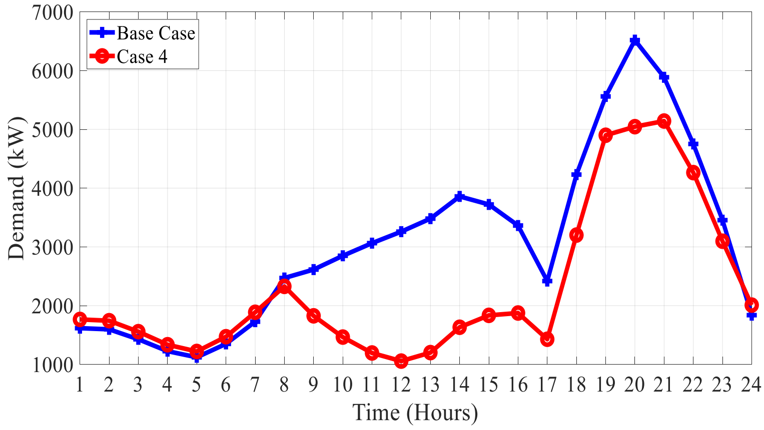

Figure 6. Real power losses after integration of DG and at DR rate of 10%.

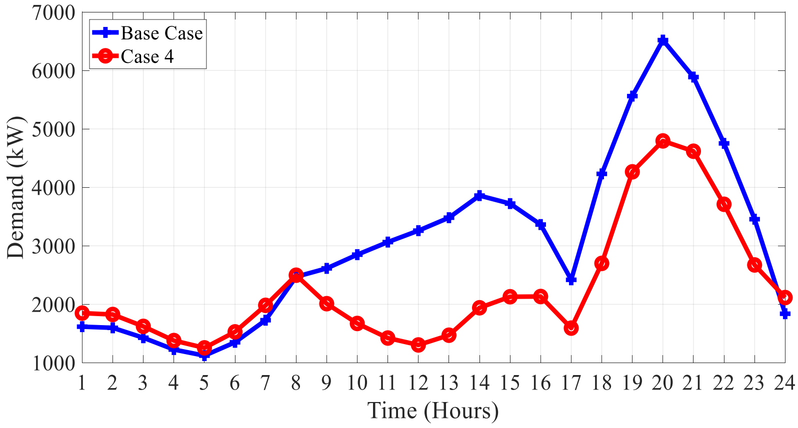

Figure 7. Real power losses after integration of DG and at DR rate of 20%.

In summary, the combined DG and DR scenarios yield the most significant reductions in both energy losses and CO2 emissions, with the 10% DR and DG scenario achieving the highest reduction in emissions (27.66%) and a considerable decrease in losses (30.15%). The DG-only scenario also shows notable improvements, while DR alone has minimal impact on system performance and emissions. The integration of DG significantly enhances the system's energy efficiency, reduces emissions, and improves voltage levels, especially when combined with demand response measures. Figure 8 illustrates the CO_2 reduction percentages across different scenarios. The highest emission reduction is achieved through solar PV integration coordinated with 10% DR. Table 2 presents the outcomes of coordinating DR with optimally integrated solar PV. The results clearly show that while DR alone reduces annual losses moderately, its combination with DG yields significant improvements in loss reduction, DG penetration, and average voltage levels. Table 3 highlights the impact of the proposed framework on CO_2 emissions in gas-fired power plants. It demonstrates that integrating DG with DR substantially reduces daily CO_2 emissions compared to the base case, confirming the environmental benefits of the combined strategy.

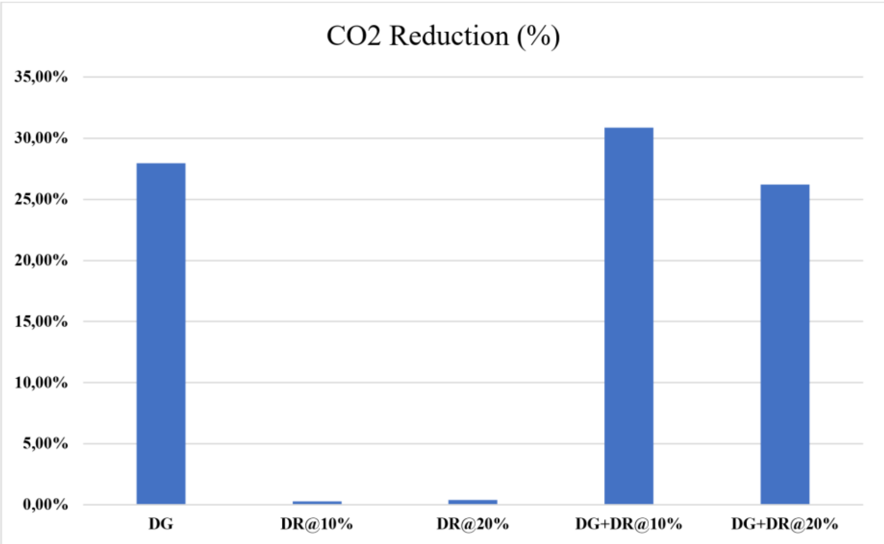

Figure 8. Total CO2 reduction percentage per day in different cases with GFPP.

Table 2. Outcomes of the coordination of DR with optimally integrated solar PV.

Case No.	Category	Optimal Allocation of DG (Bus No., kW)	Demand /Day (kWh)	Annual Losses (MWh)	Losses /Day (kWh)	Reduced losses / Year (%)	DG Penetration (%)	Average Voltage level (p.u.)
1	Base Case	-	73474	1430	3917.81		-	0.9781
2	DG	15(1290)-28(1740)-29(1092)	52681	1108	3035.62	23	68.7	0.9963
3	DR@10%	-	73472	1298	3556.16	8.69	-	0.9784
	DR@20%	-	73411	1279	3504.11	9.53	-	0.9785
4	DG+DR@10%	9(1116)-17(1880)-29(878)	50684	988	2706.85	30.15	64.56	0.9964
	DG+DR@20%	8(502)-9(1790)-16(1498)	54498	920	2520.55	34.5	63.16	0.9967

Table 3. Impact of proposed framework on CO2 emission of GFPP.

Case No.	Case	Energy Demand from GFPP/Day (kWH)	Energy Supplied from DG/Day (kWh)	CO2 emission from SPV (Kg)	Energy Losses / Day (kWh)	Energy Supplied from GFPP/Day (kWH)	CO2 emission/Day (Kg) by CPP	Total CO2 emission/Day (Kg)	% Reduction in CO2 emission /Day
1	Base Case	73474			3917.81	77391.81	35987.19	35987.19	
2	DG	52681	20793	1102.03	3035.62	55716.62	25908.23	27010.26	24.94%
3	DR@10%	73472			3556.16	77028.16	35818.10	35818.10	0.47%
	DR@20%	73411			3504.11	76915.11	35765.53	35765.53	0.62%
4	DG+DR@10%	50684	22790	1207.87	2706.85	53390.85	24826.74	26034.61	27.66%
	DG+DR@20%	54498	18976	1005.73	2520.55	57018.55	26513.62	27519.35	23.53%

Conclusion

- Effective emissions reduction strategy: Integrating solar PV systems with DR significantly reduces CO2 emissions in gas-fired power plants, achieving a 27.66% reduction in emissions and a 30.15% decrease in energy losses under the optimal scenario.
- Optimization using Ant Colony Algorithm: The study employs ACO to determine the optimal allocation of solar PV units, demonstrating that hybrid strategies combining distributed generation and DR yield superior environmental and operational benefits.
- Comparative performance of DR: DR alone has limited impact, with emissions reductions of only 0.47% (10% DR) and 0.62% (20% DR), but when combined with solar PV, even modest participation enhances overall system efficiency and sustainability.
- Policy and practical implications: The findings provide a strategic framework for low-carbon energy transitions, particularly in India, where gas-fired power remains a key component of the energy mix, offering valuable insights for policymakers and energy stakeholders.
- Broader contribution to sustainable energy: By validating the effectiveness of hybrid approaches that integrate renewable energy with demand-side management, this research advances the discourse on decarbonization and sustainable energy optimization in fossil-fuel-based power plants.

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