Research Article/Electrical Engineering http://doi.org/10.15446/ing.investig.111248

Genetic Algorithm-Based Optimization of Solar Photovoltaic Integration and Demand Response for CO_2 Reduction in Indian Coal Power

Optimización basada en algoritmos genéticos de integración de energía solar fotovoltaica y respuesta a la demanda para la reducción de CO_2 en la energía de carbón de la India

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ABSTRACT

In 2022, global coal combustion contributed significantly to global pollution, producing 15.22 billion metric tons of carbon dioxide (CO_2). This research addresses the urgent challenge of mitigating CO_2 emissions in Indian coal power plants by strategically deploying solar photovoltaic (PV) systems and integrating demand response mechanisms. The imperative to reduce greenhouse gas emissions from coal-based electricity generation underscores the critical context of climate change. Emphasizing the vital role of integrating renewable energy-based distributed generators into the existing coal infrastructure, this study positions solar PV technology as a promising solution. Optimal solar PV system allocation is achieved through the implementation of the genetic algorithm technique. Factors such as solar resource availability, electricity demand patterns, and the CO_2 intensity associated with coal power generation are considered in this process. The primary research objective is twofold: to minimize CO_2 emissions and maximize the integration of solar PV systems while mitigating power losses. The proposed approach considers the intermittent nature of solar power and the dynamic characteristics of demand. Rigorous testing on an IEEE 33-bus system powered by the studied coal power plant reveals a substantial 29.31% reduction in CO_2 generation following the implementation of the proposed strategy. This research represents a decisive step towards fostering a more sustainable and environmentally friendly energy landscape. Our study's outcomes offer valuable insights for policymakers and stakeholders in the energy sector, providing a robust foundation for the advancement of environmentally conscious practices within the coal power industry.

Keywords: bi-level optimization, distribution network, power quality, renewable energy

RESUMEN

En 2022, la combustión global de carbón contribuyó significativamente a la contaminación mundial, produciendo 15.22 mil millones de toneladas métricas de dióxido de carbono (CO_2). Esta investigación aborda el desafío urgente de mitigar las emisiones de CO_2 en las plantas de energía de carbón en India mediante el despliegue estratégico de sistemas solares fotovoltaicos (FV) y la integración de mecanismos de respuesta a la demanda. La necesidad imperiosa de reducir las emisiones de gases de efecto invernadero derivadas de la generación eléctrica a base de carbón subraya el contexto crítico del cambio climático. Destacando el papel esencial de integrar generadores distribuidos basados en energías renovables en la infraestructura de carbón existente, este estudio posiciona la tecnología solar FV como una solución prometedora. La asignación óptima de sistemas solares FV se logra mediante la implementación de la técnica de algoritmo genético. En este proceso se consideran factores como la disponibilidad de recursos solares, los patrones de demanda eléctrica y la intensidad de CO_2 asociada a la generación de energía por carbón. El objetivo principal de la investigación es doble: minimizar las emisiones de CO_2 y maximizar la integración de sistemas solares FV mientras se mitigan las pérdidas de energía. El enfoque propuesto tiene en cuenta la naturaleza intermitente de la energía solar y las características dinámicas de la demanda. Pruebas rigurosas en un sistema IEEE de 33 nodos alimentado por la planta de energía de carbón estudiada revelan una reducción sustancial del 29.31 % en la generación de CO_2 tras la implementación de la estrategia propuesta. Esta investigación representa un paso decisivo hacia la promoción de un panorama energético más sostenible y respetuoso con el medio ambiente. Los resultados de nuestro estudio ofrecen valiosos conocimientos para los formuladores de políticas y las partes interesadas del sector energético, proporcionando una base sólida para el avance de prácticas ambientalmente responsables dentro de la industria de energía a base de carbón.

Palabras clave: optimización bifásica, red de distribución, calidad de energía, energía renovable

Received: September 22nd, 2023
Accepted: September 13th, 2024

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Acronyms

$P_{\mathrm{L}\,(\mathrm{t})}$	Power transmission losses
$P_{i\,(\mathrm{t})}$	Real power at the i^{th} node at any time t
$P_{J\,(\mathrm{t})}$	Real power at the j^{th} node at any time t
$Q_{i\,(\mathrm{t})}$	Reactive power at the i^{th} node at any time t
$Q_{J\,(\mathrm{t})}$	Reactive power at the j^{th} node at any time t
$V_{i\,(\mathrm{t})}$	Voltage at the i^{th} node at any time t
$V_{J\,(\mathrm{t})}$	Voltage at the j^{th} node at any time t
r_{ij}	Resistance of the branch between the i^{th} and j^{th} nodes
$\delta_{i\,(\mathrm{t})}$	Angle of the voltage at the i^{th} node
$\delta_{j\,(\mathrm{t})}$	Angle of the voltage at the j^{th} node
$P_{R\,(t)}$	Reverse power at time t
$I_{\mathrm{G}(t)}$	Current from the grid at time t
$V_{\mathrm{G}(t)}$	Voltage of the grid at time t
$I_{\mathrm{S.}}$	Designated reverse current limit
$V_{D\,(t)}$	Penalty for voltage deviations
$V_{\mathrm{Max.}}$	Maximum permissible voltage at the nodes
V_{Min}	Minimum permissible voltage at the nodes
$P_{Gi(t)}$	Real power generation at the i^{th} node for the time period t
$P_{Di(t)}$	Real power demand for the time period t
$Q_{Gi(t)}$	Reactive power generation at the i^{th} node for the time period t
$Q_{Di(t)}$	Reactive power demand for the time period t
$P_{in,i(t)}$	Nonreceptive load at time t
$P_{el,i(t)}$	Receptive load at time t
E_i^{Total}	Energy demand per day
$L_{d,i(t)}$	Load per hour for the time period t
$P_{\mathrm{DG},i}$	Real power injection by DG
P_{DG}^{max}	Maximum value of real power generation by DG
$I_{ij(t)}$	Current flowing between the i^{th} and j^{th} nodes at t
I_{ij}^{max}	Maximum permissible current value
Y_{ij}	Admittance matrix between the i^{th} and j^{th} nodes
θ_{ij}	Angle of impedance between the i^{th} and j^{th} nodes
I_{sm}	Solar PV system current
$S_{r(t)}$	Solar irradiance at time t
S_r^r	Rated value of solar irradiance for PV systems

Introduction

Electricity plays a pivotal role across diverse sectors, underpinning industrial processes, construction activities, and daily life. However, its production predominantly relies on energy sources like coal, natural gas, uranium, and renewable resources such as solar, wind, and hydropower. The environmental footprint of electricity generation is substantial, notably contributing to global CO_2 emissions. The appropriate selection of energy generation technology is paramount in mitigating these environmental consequences, especially considering that coal, a high carbon emitter, occupies one end of the spectrum.

China, a global industrial powerhouse, relies heavily on coal-based energy, with the power industry accounting for a substantial 40% of the annual CO_2 emissions. Critiquing current carbon emission calculations, a study proposed an innovative radial basis function neural network model for enhanced accuracy in predicting emissions from coal-fired power plants, thus addressing a crucial aspect of environmental impact assessment (Cheng *et al*., 2023).

Coal-fired captive power plants, which are crucial for industrial cost savings, are confronted with significant carbon emissions. To quantify and improve low-carbon development, The study by Ma *et al*. (2022) introduced source-network-load interactive evaluation indicators, providing a scientific approach to this issue. This encourages grid participation, supports sustainable energy utilization, and aligns with global efforts towards environmental stewardship.

Samanta *et al*. (2015) proposed a partial repowering approach for a 250 MW CPP, which involved the removal of two coal mills, the utilization of a pressurized combustion chamber, and the optimization of waste heat. This innovative strategy resulted in a substantial 30.7% increase in capacity and efficiency, along with a significant reduction in CO_2 emissions (26.5%).

In China, a pivotal shift is occurring in the CPP, driven by internal improvements and external factors such as increased renewable energy integration. Zhang *et al*. (2020) conducted a comprehensive study, covering 99.7% of the operational plants, and emphasized the potential for a 265 Mt CO_2eq reduction by 2020. This study highlights regional variations and recommends tailored post-2020 decarbonization strategies, showcasing the complexity of policy effectiveness in mitigating emissions.

Addressing the challenge of harmful gas emissions from coal power plants, Smaisim *et al*. (2023) explored the integration of renewable sources such as molten carbonate fuel cells and solar farms. Their simulation results demonstrated promising energy outputs and reduced environmental impact, highlighting the potential of integrating renewables to enhance overall efficiency.

In the field of CO_2 capture, some authors have investigated energy-saving mechanisms through chemical absorption, revealing two waste heat recovery techniques while showcasing significant energy savings of 9.32 and 8.71% through optimization and heat recovery (Akbari *et al*., 2022; Eslami *et al*., 2011).

The urgency for developing clean coal technologies was underscored by Hanak *et al*. (2015), who modeled the substitution of ammonia in CO_2 capture within a supercritical coal-fired plant. The study revealed efficiency penalties ranging from 8.7 to 10.9%, emphasizing the importance of ongoing efforts to meet the EU 2050 greenhouse gas reduction target.

Distributed generators (DGs) and demand response (DR) are pivotal segments in implementing smart grid systems. DGs can be categorized into renewable and non-renewable sources, with renewable DG including solar PV systems, wind turbines, hydroelectric plants, and biomass generators, relying on naturally replenished resources. The non-renewable category includes sources like diesel generators, natural gas turbines, and fuel cells, which depend on finite fossil fuel reserves. This distinction is crucial when evaluating sustainable options for distributed energy generation.

The optimal allocation of renewable energy based DG within the distribution network (DN) hinges on factors such as load location, solar resource availability, and DN capacity. DR, characterized by consumers adjusting electricity consumption in response to cost variations, offers benefits such as peak demand reduction, enhanced grid reliability, and decreased reliance on costly infrastructure investments (Saxena *et al*., 2021a; Yaghoubi *et al*., 2022).

There are several methodologies to analyze how DR influences the optimal placement of solar PV systems in the DN. Incorporating DR and solar PV systems into smart grids makes it possible to optimize PV placement, enhance grid performance, and reduce infrastructure strain. The interplay between DR and solar PV generation constitutes a crucial area of research aiming for more sustainable and efficient energy systems (Saxena *et al*., 2022a; Eslami *et al*., 2012).

Zhong *et al*. (2021) argued that achieving sustainable development necessitates a shift towards a low-carbon economy and a reduction in energy consumption, addressing the mounting energy crises and environmental imperatives. The adoption of DGs is gaining momentum, offering not only economic benefits but also heightened system adaptability. Optimal grid-connection strategies for DGs can lead to diminished carbon emissions and reduced operating costs. In this vein, this paper introduces an algorithm designed to determine the location and scale of DGs within distribution networks to facilitate low-carbon practices.

Power prediction in PV applications plays a crucial role in optimizing energy management and integration with the grid (Al-Dahidi *et al*., 2018). Accurate PV power forecasting helps to balance supply and demand, improving the stability of power systems and reducing reliance on fossil fuels. Various machine learning techniques have been employed to enhance prediction accuracy (Al-Dahidi *et al*., 2019; Alrabai *et al*., 2022). These models account for factors like irradiance, temperature, and weather conditions, significantly impacting PV performance. The integration of such predictive models is vital for the efficient planning and operation of renewable energy systems.

Yoon *et al*. (2022) demonstrated a sophisticated system that collaborates seamlessly with distributed energy generation and storage technologies to efficiently deliver energy to users, addressing energy consumption demands. The study of model design and outcomes for regulating energy supply with a focus on carbon reduction encompasses three distinct perspectives. Firstly, an operational model is presented for an extensive examination of small-scale energy generation with minimal carbon footprints, particularly within the context of energy storage system-integrated, distributed power. Secondly, a novel supply system, attuned to fluctuations in energy demand, is outlined within a scheduling framework. Furthermore, the aim is to attain both energy self-sufficiency and carbon neutrality. This objective is pursued by overseeing and governing carbon emissions at the urban scale, facilitated by the optimized operation of DR.

In PV applications, power prediction is crucial for optimizing energy storage systems, scheduling maintenance, and enhancing overall energy production efficiency (Al-Ghussain *et al*., 2023). Hybrid models combining machine learning with physical models are also gaining attention, as they incorporate real-time data and predictive analytics (Ayadai *et al*., 2022). Moreover, advancements in data-driven techniques enable more precise short-term and long-term power forecasting, which is critical for both grid operators and energy providers (Al-Dahidi *et al*., 2024). PV power prediction plays a key role in maximizing renewable energy utilization and mitigating the challenges associated with variable solar output, contributing to more sustainable and reliable energy systems.

Viana *et al*. (2018) discussed the potential of DR and DG in facilitating sustainable DN through the active involvement of end-users. The study suggested the need for regulatory changes, *e.g.*, implementing optional time-of-use tariffs, to simultaneously enhance both DR and PVDG.

Shirazi *et al*. (2021) pointed out that the forthcoming era of intelligent microgrids holds the promise of heightened stability and resilience, in conjunction with the astute planning, precise control, and adept administration of DGs comprising wind, solar, and diesel generators. The synergistic utilization of wind and solar energy sources emerges as a potent avenue for mitigating pollution. However, orchestrating the management, scaling, and strategic siting of DGs within the electricity grid represents a formidable endeavor that is replete with challenges. This paper introduces a multi-objective model grounded in gray wolf optimization, purpose-built to enable the adequate placement of DG within intelligent microgrids (MG). The primary objectives encompass the reduction of financial costs alongside environmental impacts, spanning greenhouse gas emissions and overall pollution levels. Validation using the IEEE 30 system robustly attested to the efficacy of the proposed model, simulation outcomes unequivocally demonstrated the cost-effectiveness of the approach, effectively pinpointing the optimal DG location while entailing the smallest environmental footprint conceivable.

Wang *et al*. (2021) suggested that, in the face of escalating climate concerns, attaining carbon peak and carbon neutrality has emerged as a paramount endeavor. The pervasive integration of distributed energy resources is exerting its influence across all sectors of society. Effectively harnessing and adeptly managing this environmentally beneficial supply plays a pivotal role in curtailing carbon emissions. To this effect, this study underscores the vital importance of dispersed energy resources and their proficient management in CO_2 reduction. By incorporating the computation of carbon emission flow into the optimization of distributed energy management, the objective is to enhance emission flow dynamics, ultimately leading to more significant reductions in CO_2 emissions.

Statistics show that the energy sector, primarily due to coal burning, is responsible for 70% of greenhouse gas (GHG) emissions. To address this issue, distribution companies should utilize low-emission-coefficient generators as DG units. This reduces reliance on thermal plants, leading to decreased coal burning and GHG emissions. Therefore, a robust computational algorithm is needed for optimal DG utilization in active distribution systems which focuses on reducing emissions (Lakshmi 2023).

The Central Electricity Authority (CEA) reported a significant CO_2 emission rate of 0.975 tCO2/MWh for coal-based power plants (CEA, 2023). The optimal placement of renewable DGs in the DN offers a promising avenue to reduce these emissions. In this context, solar PV systems have gained prominence as a pollution-free form of electricity generation. The lifetime CO_2 emission for PV modules is estimated at 0.053 kg per 1 kWh of electrical energy (Rajput, 2022).

The CEA reported changes from the financial year (FY) 2000-01 to 2021-22. During this period, there was a substantial increase in coal-based capacity additions up to FY 2015-16, followed by a significant decline. In a similar vein, within the Indian grid, hydro-based capacity additions decreased starting from 2017-18.

Despite global efforts to transition towards cleaner energy sources, there is a notable research gap with regard to the reduction of CO_2 emissions from coal-based electricity generation in India. The unique challenges and opportunities posed by the integration of solar PV systems and demand response mechanisms into existing coal infrastructure constituted the focal point of this research.

The hypothesis underlying this study posits that the strategic deployment of solar PV systems, coupled with the integration of demand response mechanisms, can significantly reduce CO_2 emissions in Indian coal power plants. The hypothesis is grounded in the belief that renewable energy-based DGs, specifically solar PV technology, can play a pivotal role in transforming the environmental impact of coal power.

The primary research objectives are twofold:

To minimize CO_2 emissions. To develop and implement strategies to minimize CO_2 emissions from Indian coal power plants through the strategic deployment of solar PV systems.

To maximize solar PV integration. To optimize the integration of solar PV technology into the existing coal infrastructure while mitigating power losses and considering the intermittent nature of solar power and the dynamic characteristics of demand.

This paper is structured to provide a systematic exploration of the research topic. It unfolds through distinct sections, starting with a systematic literature review that lays the foundations of the research by surveying the existing knowledge in a methodical manner. The subsequent section states the problem, intricately detailing the formulation of the fitness function and constraints that govern the research inquiry. This establishes a clear framework for the study.

The paper then transitions into a discussion on the test system, where the methodologies selected for experimentation and analysis are outlined. The methodology section describes the systematic approach undertaken to address the research objectives, ensuring transparency and reproducibility. Implementation details follow, providing insights into the practical application of the proposed methodologies.

The core of the paper lies in the results section, where the findings are presented and analyzed. This section encapsulates the outcomes of the research, validating the proposed methodologies and shedding light on their efficacy. Following this, the paper culminates in a robust conclusion and discussion. The conclusion succinctly summarizes the key insights and contributions, while the discussion section delves into the broader implications of the findings, opening avenues for future research.

Problem statement

A substantial reduction in CO_2 emissions can be achieved by reducing reliance on electricity generated from conventional coal-fired power plants (CPPs). In light of this, this paper sets forth the following objectives to actualize the proposed framework:

Power loss minimization

The efficient operation of a power system hinges on the minimization of transmission losses within the distribution network. These losses stem from the inherent resistance in transmission wires, leading to voltage drops and energy dissipation during electricity transmission from the source to the consumers. Hence, one of our primary objectives is to minimize power losses, which is defined as follows (Meena *et al*. 2018):

$$\pounds_1 = \sum_{t=1}^{24} P_{\mathrm{L}\,(\mathrm{t})} \tag{1}$$

$$P_{\mathrm{L}\,(\mathrm{t})} = \sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_{ij\,(\mathrm{t})}\left(P_{i\,(\mathrm{t})}P_{J\,(\mathrm{t})} + Q_{i\,(\mathrm{t})}Q_{J\,(\mathrm{t})}\right) + \beta_{ij\,(t)}\left(Q_{i\,(\mathrm{t})}P_{j\,(\mathrm{t})} - P_{i\,(\mathrm{t})}Q_{j\,(\mathrm{t})}\right) \quad \forall t \tag{2}$$

where

$$\alpha_{ij\,(\mathrm{t})} = r_{ij}\cos\left(\delta_{i\,(\mathrm{t})} - \delta_{j\,(\mathrm{t})}\right) / V_{i\,(\mathrm{t})}V_{j\,(\mathrm{t})}$$

and

$$\beta_{ij\,(\mathrm{t})} = r_{ij}\sin\left(\delta_{i\,(\mathrm{t})} - \delta_{j\,(\mathrm{t})}\right) / V_{i\,(\mathrm{t})}V_{J\,(\mathrm{t})}$$

Managing reverse power flow

Reverse power flow occurs when DG units generate surplus power beyond the local demands, feeding excess power back into the grid. This phenomenon can introduce stability and safety concerns within the DN, including voltage fluctuations and potential equipment damage. To mitigate these issues, our objective is to manage reverse power flow efficiently:

$$\pounds_2 = \sum_{t=1}^{24} P_{R\,(t)} \tag{3}$$

$$P_{R\,(t)} = \begin{cases} 0, & \text{if } I_{\mathrm{G}(t)} \geq I_{\mathrm{S}} \\ \mathrm{Re}\left(V_{\mathrm{G}(t)} I^{*}_{\mathrm{G}(t)}\right) & \text{if } I_{\mathrm{G}(t)} < I_{\mathrm{S.}}. \end{cases} \tag{4}$$

Nodal voltage deviation control

Nodal voltage deviation signifies the variance between actual and standard voltage levels at specific nodes within the power system. Voltage deviations can result from various factors, including load fluctuations, reactive power flow, and line losses. These deviations can disrupt the system's efficiency, increase losses, and potentially damage equipment. To address this issue, our objective is to control voltage deviations:

$$\pounds_3 = \left(1 + \sum_{t=1}^{24} V_{D\,(t)}\right) \tag{5}$$

$$V_{D\,(t)} = \begin{cases} & \left|V_{\mathrm{Min}} - V_{i\,(t)}\right| \ \text{if } V_{i\,(t)} < V_{\mathrm{Min.}} \\ 0 & \text{if } V_{\mathrm{Min.}} \leq V_{i\,(t)} \leq V_{\mathrm{Max.}} \\ \ell & \text{if } V_{i(t)} > V_{\mathrm{Max.}} \end{cases} \tag{6}$$

where ℓ is the unacceptable value.

Fitness function

To optimize these objectives, a fitness function encompassing distinct objective functions with weighting factors is required. Below is the fitness function (Υ_1) for level-1 optimization:

$$min\left(\Upsilon_1\right) = \varphi \times M \times \pounds_3 \tag{7}$$

where $M = \pounds_1 + \pounds_2$, and φ denotes the daily to yearly conversion product.

DR planning and DG scheduling are considered at level 2 of the optimization objectives. The objective function for level 2 of the optimization problem is as follows:

$$min\left(\Upsilon_2\right) = M \times \pounds_3 \tag{8}$$

where Υ_2 is the fitness function for level 2.

Demand response aggregator

A demand response aggregator (DRA) plays a pivotal role in managing energy consumption during peak demand periods. It collaborates with energy consumers to reduce electricity usage during peak hours and sells the saved energy back to grid operators or utilities. The DRA encourages consumers through incentives like discounted electricity rates. It employs various technologies and strategies, including automated demand response systems and smart thermostats, in order to optimize the DR process (Saxena *et al*. 2021b).

DRAs play a vital role in assisting grid operators to effectively manage peak demand, mitigate energy costs, and enhance system reliability. By offering incentives to energy consumers for curtailing their energy usage during peak periods, DRAs contribute to balancing the electricity supply and demand, thereby minimizing the need for additional generation capacity. The following factors outline the constraints associated with DR that are given careful consideration:

$$P_{i(t)} = \left(P_{Gi(t)} - P_{Di(t)}\right) \quad \forall t,i \tag{9}$$

$$Q_{i(t)} = \left(Q_{Gi(t)} - Q_{Di(t)}\right) \quad \forall t,i \tag{10}$$

$$P_{Di(t)} = \left(P_{in,i(t)} + P_{el,i(t)}\right) \quad \forall t,i \tag{11}$$

$$\sum_{i=1}^{N}\sum_{t=1}^{24}\left(P_{in,i(t)} + P_{el,i(t)}\right)\times \Delta t = E_i^{Total} \tag{12}$$

$$P_{el,i}^{min} \le P_{el,i(t)} \le min\left(\left(C - P_{in,i(t)}\right), P_{el,i}^{max}\right)\forall t \tag{13}$$

$$P_{el,i}^{max} = \mu \sum_{t=1}^{24} L_{d,i(t)} \tag{14}$$

where C and μ are the contract load and the DR penetration rate, respectively.

Objective constraints

The aforementioned objective functions are subject to constraints that account for technical and operational considerations:

Solar PV output constraint:

$$0 \le P_{\mathrm{DG},i} \le P_{DG}^{max} \qquad \forall i \tag{15}$$

Feeder thermal limit constraint:

$$I_{ij(t)} \le I_{ij}^{max} \qquad \forall t,i,j \tag{16}$$

Real and reactive power constraints:

$$P_{i(t)} = V_{i(t)}\sum_{j=1}^{N} V_{j(t)} Y_{ij} \cos\left(\theta_{ij} + \delta_{j(t)} - \delta_{i(t)}\right) \ \forall t,i \tag{17}$$

$$Q_{i(t)} = -V_{i(t)}\sum_{j=1}^{N} V_{j(t)} Y_{ij} \sin\left(\theta_{ij} + \delta_{j(t)} - \delta_{i(t)}\right) \ \forall t,i \tag{18}$$

Demand modeling

Demand modeling is expressed as

$$P_{D,i(t)} = \Omega_{i(t)} P_{D,i}^{0} \qquad \forall t,i \tag{19}$$

$$Q_{D,i(t)} = \Omega_{i(t)} Q_{D,i}^{0} \qquad \forall t,i \tag{20}$$

where $\Omega_{i(t)}$ is the assigned load factor for the time period t.

Modeling the solar PV output

Solar power generation is influenced by factors such as solar panel characteristics, tilt angle, and solar irradiance. Assuming that other variables remain constant during the specified period, the current relative to the rated voltage is calculated as follows:

$$I_{sm(t)} = \begin{cases} I_{sm} \ \text{if}\ S_{r(t)} \ge S_r^r \\ I_{sm} \times S_{r(t)} / S_r^r \ \text{if}\ S_{r(t)} < S_r^r \end{cases} \tag{21}$$

In summary, this research framework encompasses multiple objectives, from minimizing power losses and managing reverse power flow to controlling nodal voltage deviation. These objectives are optimized through a fitness function with weighted factors. Additionally, the role of the DRA in managing peak energy consumption is emphasized. The framework adheres to various constraints, ensuring that both technical and operational considerations are met while modeling the demand and solar PV output to support the optimization process.

Optimization approach

The genetic algorithm (GA) is a heuristic optimization method that draws inspiration from the natural selection process. This approach is especially efficient in addressing complex, nonlinear, and non-differentiable optimization problems. The GA maintains a population of potential solutions and uses genetic operators such as crossover and mutation to progressively develop improved solutions.

The parameters and settings for the GA optimization approach in this study are outlined in Table 1, with the latter explained below:

Population size: The number of individuals in the population. This determines the diversity of solutions explored in each generation.

Crossover probability: The likelihood of crossover (recombination) occurring. This parameter controls the rate at which genetic material is exchanged between individuals.

Mutation probability: It introduces small random changes to individual solutions, helping to explore new regions of the solution space.

Number of generations: The total number of iterations or generations that the algorithm will run. It influences how thoroughly the solution space is explored.

Table 1. Simulation parameters for the genetic algorithm approach

Parameters	Level 1	Level 2
Population size	50	100
Crossover probability	0.8	0.8
Mutation probability	0.01	0.01
Number of generations	100	150

Source: Authors

These parameters were selected based on a comprehensive review of the literature, specifically drawing on the work of Saxena *et al.* (2022b, 2023). They are tailored to suit the specific characteristics and requirements of the optimization problem at levels 1 and 2. These parameters are meant to efficiently converge towards high-quality solutions within the defined computational resources.

Test system

The multilevel optimization technique proposed in this study was applied to the IEEE 33-bus system depicted in Figure 1 (Baran *et al*. 1989). The power supply for the grid was sourced from the Indian CPP. This research involved a thorough investigation and analysis of the effects of DR technologies, aiming to discern the most effective power transmission strategies while accommodating diverse conditions and constraints. The central goal was to elevate the efficiency of power distribution.

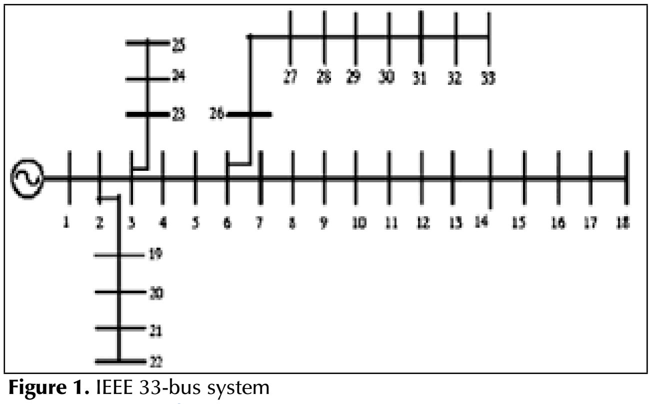

Figure 1. IEEE 33-bus system
Source: Baran *et al*. (1989)

The proposed optimization methodology was implemented using MATLAB software.

Furthermore, critical system parameters such as the base voltage, the nominal active demand, the nominal reactive demand, the power losses, *Vmin*, *Vmax,* and P_{DG}^{max} were set at 12.66 kV, 3715 kW, 2300 kVAR, 202.7 kW, 0.95 p.u., 1.05 p.u., and 2 MW, respectively. These values served as the foundational metrics for the optimization process.

Results

Case 1

This analysis explores the base scenario to assess the effectiveness of integrating solar PV technology into a 33-bus radial distribution system. The study customized the objective functions to align with daily consumption patterns, as outlined by Tazi *et al*. (2019). To quantify the system's performance, the annual energy losses were derived by averaging the losses recorded each day. The demand patterns reveal that the lowest demand occurs around 5:00 a.m., while peak demand is observed at 8:00 p.m. This variation in demand is crucial for understanding the system's performance across different times of the day. The results, detailed in Tables 2, 3, and 4, indicate the following key metrics for the base scenario: highest demand: 5397.73 kW; lowest demand: 5397.73 kW; minimum mean voltage: 0.978178 p.u.; annual energy losses: 1426 MWh; daily CO_2 emissions: 75446.33 kg.

These values highlight the system's performance and the potential impact of integrating solar PV technology, providing a comprehensive overview of the benefits and challenges associated with this approach.

Case 2

This subsection delves into the optimization of PV installations, aiming to assess the impact of integrating DGs into a DN. The optimization analysis revealed significant advancements in several key power quality parameters.

One of the most notable findings was the substantial 21.8% reduction in annual energy losses. This result emphasizes the critical role of DGs in enhancing energy efficiency by minimizing the amount of wasted energy within the network. The integration of DGs directly contributes to a more efficient and sustainable energy system by reducing the dependence on traditional power sources and cutting energy losses. In addition to energy losses reduction, our study also observed a marked improvement in voltage stability throughout the network. The minimum mean voltage experienced a significant increase from 0.978178 to 0.99634 p.u., indicating a stronger and more stable voltage profile across the system. This enhancement in voltage stability is crucial for maintaining the reliability of power distribution and ensuring consistent energy delivery to consumers.

Table 3 offers a thorough analysis of the optimal sizing and strategic placement of solar PV systems to maximize energy generation and distribution efficiency. These findings are critical in understanding how renewable energy sources can be integrated into power networks. In Figures 2, 3, and 4, the impact of DGs is further explored in relation to the network's demand patterns, voltage profiles, and active power losses, providing visual insights. These Figures collectively illustrate how the system's performance improves with the integration of solar PV technology, revealing enhanced voltage stability and reduced power losses.

A particularly notable outcome of the study is the environmental impact achieved through the integration of solar PV systems. The 26.51% reduction in CO_2 emissions attests to the effectiveness of renewable energy solutions in curbing GHG emissions. This reduction not only highlights the potential of solar PV in mitigating the environmental footprint of energy production but also underscores its role in improving the overall efficiency of the DN. In addition to its environmental benefits, this integration enhances the sustainability of the energy system, showcasing how renewable energy can contribute to a more resilient and eco-friendly power infrastructure.

Case 3

This subsection investigates the effectiveness of the DR approach by analyzing two different levels of demand elasticity in the absence of DG coordination. Demand elasticity is measured through DR rates, which reflect how responsive consumers are to shifts in electricity prices or grid demand. In this case, two DR rates (10 and 20%) are considered, assuming that DG resources are not available or deployed. The results reveal that the DR approach has a significant impact on reducing peak electricity demand. Specifically, a 10% DR rate results in a 14.72% reduction in peak demand, while a 20% DR rate achieves an 18.32% reduction. This illustrates how increasing the DR rate leads to more substantial peak demand reductions, helping to alleviate stress on the electrical grid during periods of high demand.

In addition to reducing peak demand, DR also effectively cuts down annual energy losses, with reductions of 5.96% at a 10% DR rate and 8.2% at a 20% DR rate. These results show the potential of DR to improve overall grid efficiency by minimizing energy waste. Moreover, DR reduces active power losses, contributing to the stability and reliability of the grid. However, while it enhances demand flexibility and reduces energy losses, it also causes an increase in the peak-to-valley difference, which denotes the variation between peak and off-peak electricity demand. This indicates that DR shifts demand but may amplify load fluctuations, which could affect grid stability in some scenarios.

Interestingly, this study demonstrates that DR can be highly effective even in the absence of DG resources, implying that DR alone can play a vital role in grid management. Figures 5 to 8 provide visual insights into how DR rates of 10 and 20% impact key factors such as demand, voltage profiles, and active power losses. Nevertheless, the analysis also reveals that the influence of DR rates on the voltage profile and CO_2 emissions of the system is relatively insignificant. This suggests that, while DR helps with demand management and energy losses reduction, its direct impact on voltage stability and emission reductions is minimal, especially in the absence of DG integration. Nonetheless, DR remains a valuable tool for managing energy consumption and improving grid performance.

Table 2. Effect of the coordination of DR with optimally integrated solar PV on demand

Case no.	Type of case	Maximum demand value (kW)	Reduction in the maximum demand value (%)	Demand span (kW)	% maximum loss mitigation at 20:00 h
1	Base case	6519	-	5397.73	-
2	DG	6519	-	6016.39	-
3	DR@10%	5559.3	14.7216	4166.14	25.496
	DR@20%	5324.7	18.3204	3730.6	30.9725
4	DG+DR@10%	5375.66	17.5386	4322.87	29.807
	DG+DR@20%	4794.57	26.45	3540.31	42.3061

Source: Authors

Case 4

A comprehensive analysis was conducted to assess the integration of DGs into disaster recovery coordination and planning while considering system limitations. In this scenario, DGs were incorporated into DR scheduling, factoring in these constraints. The combination of higher DR rates and smaller DGs significantly enhanced system performance, leading to a notable reduction in annual energy losses. Compared to earlier examples, the lowest mean voltage increased by 29.03-33.31% depending on the DR rate applied. As DGs help to close the gap between maximum and minimum demand, the load profile becomes more balanced and flattened. Figures 9 to 11 demonstrate the impact of DGs at a 10% DR rate on demand, voltage, and active power losses, while Figures 12 to 14 highlight the effects of a 20% DR rate on the same parameters. Notably, DR rates of 10 and 20% reduce CO_2 emissions by 29.32 and 24.87%, respectively, when diesel generators are included in the system.

Table 3. Outcomes of the coordination of DR with optimally integrated solar PV systems

Case no.	Type of case	DG location (bus no., kW)	Demand/day (kWh)	Yearly losses (MWh)	Daily losses (kWh)	Losses reduction/year (%)	PV utilization (%)	Average voltage level (p.u.)
1	Base case		73 474	1426	3906.84			0.978
2	DG	14(1343)-30(1706)-25(1078)	52 681	1115	3054.79	21.80	69.44	0.996
3	DR@10%		73 472	1341	3673.97	5.96		0.978
	DR@20%		73 411	1309	3586.30	8.20		0.978
4	DG+DR@10%	15(1163)-7(1876)-33(904)	50 684	1012	2772.60	29.03	66.33	0.996
	DG+DR@20%	18(418)-29(1820)-11(1636)	54 498	951	2605.47	33.31	64.56	0.996

Source: Authors

Table 4. Outcomes of the coordination of DR with optimally integrated solar PV systems

Case no.	Type of case	Required energy from CPP/Day (kWh)	Energy by DG/Day (kWh)	CO_2 emissions from solar PV systems (kg)	Daily energy losses (kWh)	Energy supplied from CPP/day (kWh)	Daily CO_2 emissions (kg) by the CPP	Total CO_2 emissions/ day (Kg)	% reduction in CO_2 emissions/day
1	Base case	73 474			3906.85	77 380.85	75 446.33	75 446.33	
2	DG	52 681	20 793	1102.029	3054.79	55 735.79	54 342.4	55 444.43	26.51
3	DR@10%	73 472			3673.97	77 145.97	75 217.32	75 217.32	0.30
	DR@20%	73 411			3586.30	76 997.3	75 072.37	75 072.37	0.50
4	DG+DR@10%	50 684	22 790	1207.87	2772.60	53 456.6	52 120.19	53 328.06	29.32
	DG+DR@20%	54 498	18 976	1005.728	2605.48	57 103.48	55 675.89	56 681.62	24.87

Source: Authors

Discussion

The proposed strategy for mitigating CO_2 emissions in Indian CPPs through optimal solar PV systems allocation and DR coordination was examined alongside the findings from key literature reports. Samanta *et al*. (2015) demonstrated a 30.7% increase in plant capacity and efficiency through a partial repowering approach, while Smaisim *et al*. (2023) highlighted the benefits of renewable integration in coal power plants. Zhang *et al*. (2015) focused on CO_2 capture with chemical absorption, achieving a 9.32-8.71% reduction in equivalent work consumption. Additionally, Hanak *et al*. (2015) modeled ammonia substitution in CO_2 capture, revealing efficiency penalties of 8.7-10.9%. Contrasted with these studies, our paper introduces a novel approach, directly implementing solar PV and DR mechanisms in the context of Indian CPPs. The outcomes demonstrate a noteworthy 29.32% reduction in CO_2 emissions and a substantial 69.44% penetration of renewable energy, offering a distinctive and effective strategy for emissions reduction and renewable integration within the coal-based electricity generation sector. This study not only contributes to existing literature on emissions reduction strategies but also presents a pioneering application of solar PV technology and DR coordination within Indian CPPs.

Conclusions

- This paper addresses CO_2 emissions reduction within Indian CPPs.
- The strategic allocation of solar PV systems and the synchronization of demand response are the key methods presented.
- This study uses GA to optimize solar PV placement, considering factors like solar resource availability, electricity demand trends, and CO_2 intensity from coal power.
- The goal is to minimize CO_2 emissions, maximize solar PV integration, and reduce power losses while addressing the intermittent nature of solar energy and dynamic demand.
- The approach was validated on the IEEE 33-bus system, yielding a 29.31% reduction in CO_2 emissions.
- The results demonstrate the potential of solar PV integration and DR in reducing emissions and enhancing climate change mitigation.
- DGs are effective in reducing energy losses but pose challenges wlike voltage elevation and reverse power flow as their penetration increases.
- DR helps to stabilize load profiles by reducing peak and off-peak demand gaps and alleviating system stress.
- DR also enhances demand normalization, especially with lower solar PV penetration levels.
- Case studies show significant reductions in maximum demand (26.78%), annual energy losses (34.5%), and DG penetration (67.76%).

CRediT author statement

Vivek Saxena was in charge of data collection, conceptualization, implementation, analysis, drafting, and review. Saurabh Kumar Rajput revised and reviewed the article.

Conflicts of interest

The authors declare no conflict of interest.

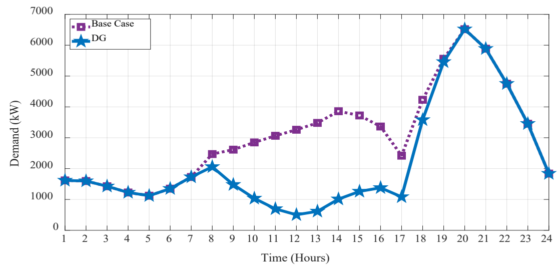

Figure 2. Impact of DG on the demand curve
Source: Authors

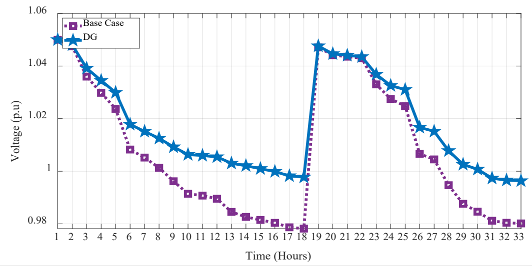

Figure 3. Impact of DG on the voltage curve
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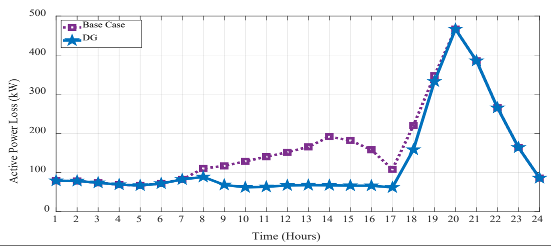

Figure 4. Impact of DG on power losses
Source: Authors

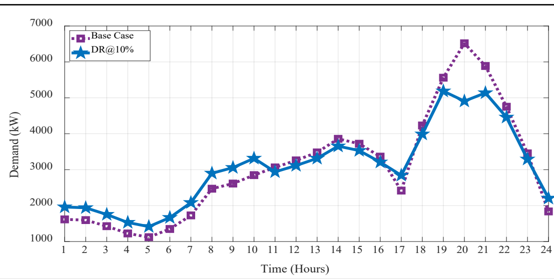

Figure 5. Impact of DR@10% on the demand curve
Source: Authors

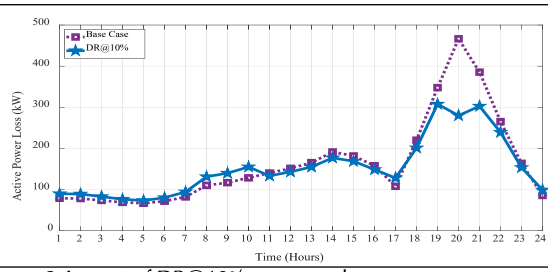

Figure 6. Impact of DR@10% on power losses
Source: Authors

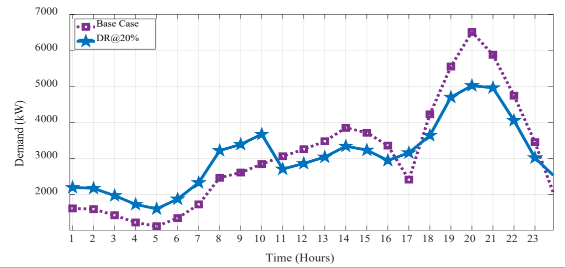

Figure 7. Impact of DR@20% on the demand curve
Source: Authors

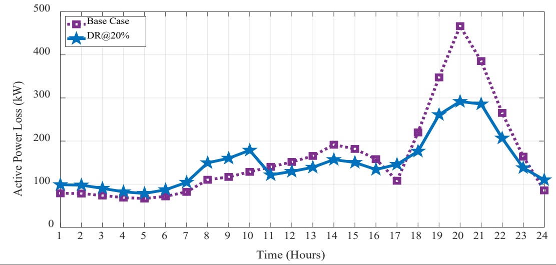

Figure 8. Impact of DR@20% on power losses
Source: Authors

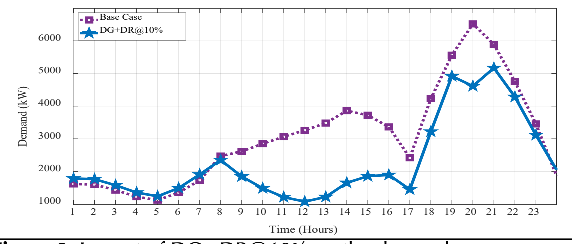

Figure 9. Impact of DG+DR@10% on the demand curve
Source: Authors

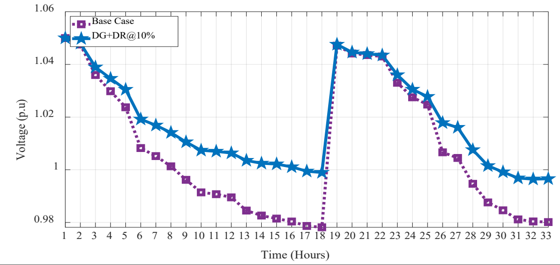

Figure 10. Impact of DG+DR@10% on the voltage curve
Source: Authors.

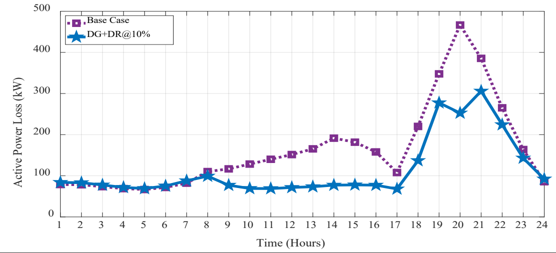

Figure 11. Impact of DG+DR@10% on power losses
Source: Authors

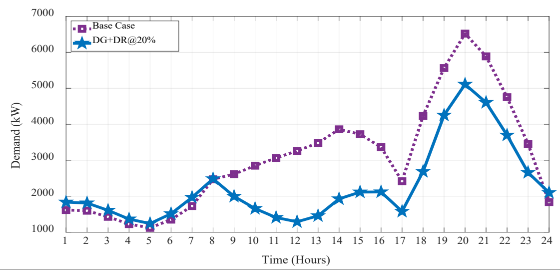

Figure 12. Impact of DG+DR@20% on the demand curve
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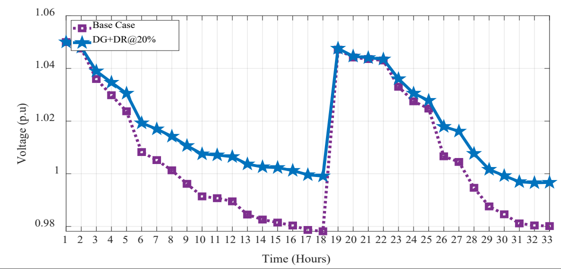

Figure 13. Impact of DG+DR@20% on the voltage curve
Source: Authors

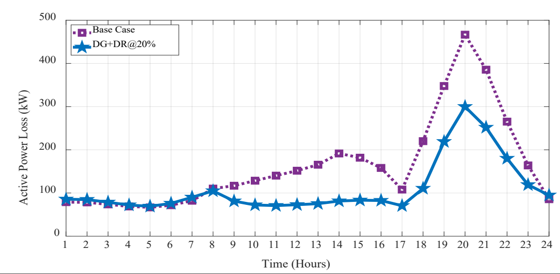

Figure 14. Impact of DG+DR@20% on power losses
Source: Authors

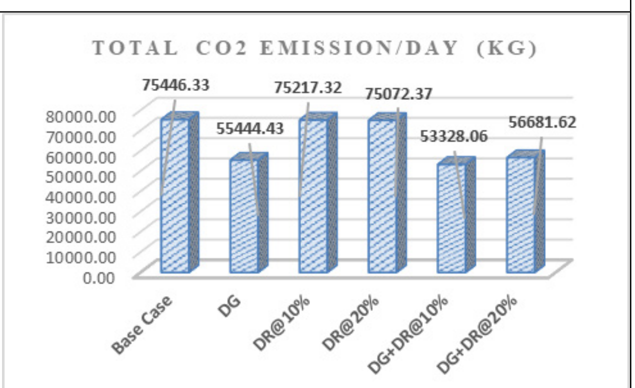

Figure 15. Total CO_2 emissions per day in different cases
Source: Authors

Data availability

Not applicable.

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