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Multi-Objective Optimization Of PV Solar Integration In Smart Grids: Balancing Technical Reliability, Economic Viability, And Environmental Sustainability

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Abstract
The rapid growth of solar photovoltaic (PV) deployment is reshaping modern power systems, creating opportunities for decarbonization but also challenges in ensuring grid reliability, cost efficiency, and environmental sustainability. This study presents a tri-objective optimization framework for PV integration in smart grids, simultaneously minimizing reliability indices (LOLP, SAIDI, SAIFI), economic costs (LCOE, NPC), and lifecycle CO_2 emissions, with explicit modeling of uncertainty in load demand, solar variability, and electricity market prices. A Monte Carlo simulation approach captures stochastic fluctuations, while the optimization is executed using NSGA-II and benchmarked against MOPSO and MOEA/D. The framework is validated on the IEEE 118-bus system using real South Zone demand, NIWE solar irradiance, and IEX market data. Results show that high PV penetration increases curtailment and duck-curve effects, but coordinated deployment of battery energy storage systems (BESS) significantly improves reliability, reduces NPC by up to 15%, and lowers CO_2 emissions by 26–32%. Multi-criteria decision analysis identifies 40% PV+BESS as the most balanced configuration. The proposed framework provides a scalable decision-support tool for policymakers and utilities pursuing resilient and sustainable smart grids.
Keywords: *Solar photovoltaic (PV) integration, Smart grids, multi-objective optimization, Reliability assessment (LOLP, SAIDI, SAIFI), Net present cost (NPC), Levelized cost of energy (LCOE), Lifecycle CO_2 emissions*

INTRODUCTION

The accelerating global shift toward renewable energy sources is fundamentally transforming the structure, operation, and planning of modern power systems. Among the portfolio of renewables, solar photovoltaic (PV) technology has emerged as the fastest-growing and most widely adopted solution, owing to its modular architecture, steadily declining costs, and scalability across diverse applications. Unlike hydro or wind, which are geographically constrained, PV can be deployed in both small-scale rooftop systems and large-scale utility farms, making it highly adaptable to urban and rural contexts alike. Over the last decade, PV deployment has experienced exponential growth, with global installed capacity surpassing 1 terawatt (TW) in 2022, and projections indicating further expansion to 2.3 TW by 2030 [1]. This unprecedented growth trajectory is largely fueled by three reinforcing drivers:

1. Policy support, including subsidies, feed-in tariffs, and renewable portfolio standards.
2. Global climate commitments, especially the pursuit of net-zero emissions by mid-century.
3. Consumer adoption trends, where households and businesses increasingly invest in PV for energy independence and long-term savings.

This rapid scaling of PV, however, introduces unique structural and operational challenges because, unlike conventional centralized generation plants, PV installations are often distributed in nature. This distributed generation (DG) paradigm shifts power flows from unidirectional (central plant → consumer) to bidirectional, as residential and commercial PV owners may both consume and inject electricity into the grid. Such dynamics blur the traditional roles of consumers and utilities, giving rise to the concept of "prosumers". While this enhances energy democratization and resilience, it also increases the complexity of maintaining stable and reliable grid operation.

To manage these complexities, the transition toward smart grids has become indispensable. A smart grid integrates digital communication technologies, intelligent control mechanisms, and distributed energy management systems, thereby acting as the technological backbone to accommodate high renewable penetration. Through advanced metering infrastructure (AMI), two-way communication, and automated demand response systems, smart grids enable real-time monitoring, flexible load balancing, and predictive maintenance [2]. These capabilities not only enhance operational efficiency but also allow for a more dynamic interaction between supply and demand.

Nevertheless, rising PV penetration brings forth several operational and technical concerns that must be carefully managed. Among the most pressing issues are voltage instability, frequency deviations, and reverse power flows [3]. For instance, during midday hours with high solar generation but low demand, distribution feeders may experience overvoltage conditions. Conversely, during cloud cover or evening peaks, steep fluctuations in solar output may stress the system's frequency stability. Reverse power flows, where excess PV generation pushes electricity back into higher voltage levels, challenge protection schemes originally designed for unidirectional flows.

Furthermore, the inherent intermittency of solar irradiance influenced by weather patterns, shading, and seasonal variability — compounds these challenges. Unlike conventional generation, which can be dispatched on demand, solar PV output is stochastic and difficult to predict with absolute accuracy. This variability must be balanced against dynamic demand patterns, which are themselves evolving due to electrification of transport, proliferation of electric vehicles (EVs), and flexible loads such as smart appliances. Together, these factors create a highly complex operational landscape, requiring advanced optimization, forecasting, and planning tools to ensure that the integration of PV into smart grids is both technically reliable and economically viable.

Technical, Economic, and Environmental Dimensions

Technical Reliability

One of the foremost challenges in PV-smart grid integration is ensuring technical reliability. High levels of PV penetration can compromise voltage profiles, stability margins, and reliability indices such as the Loss of Load Probability (LOLP) [4]. Research demonstrates that grid performance is highly sensitive to the temporal and spatial variability of solar generation, and without robust optimization frameworks, systems may face reduced reliability during peak or off-peak mismatches [5]. Energy storage and demand response have been proposed as mitigating measures, yet their optimization requires advanced decision-making tools capable of managing multi-objective trade-offs [6].

Economic Viability

Beyond technical concerns, economic viability remains central. Policymakers and utilities must justify PV integration not only on environmental grounds but also based on cost-effectiveness. The Levelized Cost of Energy (LCOE) for PV has fallen by over 80% in the past decade, making it one of the cheapest energy sources [7]. However, integration costs, network upgrades, and balancing mechanisms increase the Net Present Cost (NPC) for utilities, potentially undermining economic benefits. Planning frameworks that minimize lifecycle costs while ensuring system reliability are therefore essential [8].

Environmental Sustainability

Environmental sustainability provides the third critical dimension. While PV is widely acknowledged as a low-carbon energy source, its lifecycle impact including manufacturing, recycling, and end-of-life disposal — must be considered [9]. Studies reveal that the carbon footprint of PV modules varies by material type and regional grid mix, necessitating careful planning to ensure genuine sustainability [10]. Moreover, large-scale PV deployment may impact land use and resource availability, raising concerns over circular economy models and recycling [11]. Thus, balancing environmental sustainability with technical and economic concerns becomes an urgent requirement for long-term energy planning.

LITERATURE REVIEW

Multi-Objective Optimization in Power Systems

The integration of renewable energy resources into smart grids has brought multi-objective optimization to the forefront of power systems research. These optimization frameworks are necessary because grid operators must simultaneously balance technical, economic, and environmental goals. For example, Chen et al. [12] applied the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to optimally schedule microgrids with high solar PV penetration. Their study highlighted that reliability indices, such as voltage stability and loss of load probability, could be optimized concurrently with economic metrics, demonstrating the versatility of multi-objective approaches. Similarly, Guo et al. [13] employed stochastic optimization techniques for smart distribution systems, incorporating renewable energy uncertainties directly into the model. This methodology offered resilience against forecast errors in solar irradiance, making the outcomes more robust for real-world applications.

Robust optimization has also emerged as a promising framework. Jin et al. [14] investigated renewable-dominated smart grids under uncertainty and found that robust methods can better manage variations in PV output and demand fluctuations compared to deterministic models. These studies collectively emphasize that traditional single-objective formulations are inadequate for modern power systems. Instead, hybrid optimization methods that integrate reliability, economics, and sustainability in a unified framework are more suitable for high PV penetration contexts.

Reliability-Focused PV Integration Studies

Reliability is a core concern in smart grids with high renewable penetration. Solar PV introduces intermittency that challenges conventional stability and reliability indices. Liu et al. [15] used sequential Monte Carlo simulations to evaluate smart grid reliability under various PV penetration scenarios. Their results demonstrated that while moderate PV integration enhances reliability by reducing peak load stress, higher penetration levels may increase outage risks without adequate backup or storage.

Newer research has combined reliability with distributed energy resources (DERs). Ramya [16] proposed a bi-level multi-objective planning model that integrates PV and battery storage in smart grid distribution systems. The model showed that carefully coordinated DER deployment can mitigate reliability risks while ensuring cost-effectiveness. Similarly, Alipour et al. [17] developed an enhanced frequency control mechanism for hybrid microgrids using a recurrent adaptive neuro-fuzzy inference system (RANFIS). Their method significantly improved system stability in partially shaded PV systems under uncertain conditions. Together, these studies indicate that while PV integration challenges conventional reliability models, novel techniques such as Monte Carlo analysis, bi-level optimization, and adaptive control methods provide feasible solutions.

Economic Optimization in Smart Grids (LCOE, NPC, DR Models)

Economic viability remains a decisive factor in PV-smart grid integration. Zhang et al. [18] explored the planning of PV-storage systems by considering both levelized cost of electricity (LCOE) and network expansion costs. Their findings suggest that including system-wide economic impacts in planning can significantly reduce long-term operational costs. Wang et al. [19] extended this perspective by embedding demand response (DR) into a multi-objective optimization model. Their results demonstrated that consumer participation through DR programs could substantially reduce net present costs (NPC) while also improving grid flexibility.

Risk-aware approaches have also been adopted. Ding et al. [20] proposed a risk-constrained economic dispatch model for smart grids with PV integration. By embedding uncertainty quantification into dispatch decisions, they minimized the probability of excessive operational costs due to PV variability. These findings highlight the evolution of economic modeling from static cost optimization to dynamic, risk-adjusted frameworks that consider both generation-side and consumer-side contributions.

Sustainability and Lifecycle Emission Modeling

Beyond technical and economic considerations, sustainability remains an integral objective for future energy systems. Fthenakis and Kim [21] conducted a life-cycle assessment (LCA) of crystalline silicon PV systems integrated into smart grids. Their results showed that lifecycle greenhouse gas emissions for PV are considerably lower than fossil fuel alternatives, but grid configuration plays a significant role in determining emission reduction potential. Similarly, Cucchiella et al. [22] investigated the sustainable end-of-life management of solar panels, proposing recycling strategies to foster a circular economy. Their study highlighted that PV integration must also consider waste management and resource recovery for long-term sustainability.

More recent work by Liu et al. [23] explored the integration of renewable energy in urban smart grids, emphasizing zero-carbon community planning. Their findings suggest that combining PV deployment with urban energy system redesign can significantly advance sustainability goals. Together, these studies reinforce that lifecycle emission modeling and resource circularity are as critical as reliability and economic optimization in achieving truly sustainable PV-smart grids.

METHODOLOGY

The optimization problem for large-scale solar PV integration in smart grids is modeled as a multi-objective framework that simultaneously addresses system reliability, economic performance, and environmental sustainability. This tri-objective formulation provides a holistic perspective, unlike conventional approaches that optimize only one or two dimensions.

Reliability

Reliability is quantified using established indices, namely *Loss of Load Probability (LOLP)*, *System Average Interruption Duration Index (SAIDI)*, and *System Average Interruption Frequency Index (SAIFI)*. These indicators capture both the likelihood and severity of power outages. Since these metrics are measured on different scales, a normalization procedure is applied, and weights α_1, α_2, α_3 are assigned using the Analytic Hierarchy Process (AHP) based on regulatory benchmarks and expert elicitation. The reliability objective function is formulated as:

$$\min f_1 = \alpha_1 . LOLP + \alpha_2 . SAIDI + \alpha_3 . SAIFI$$

Economic Performance

The second objective minimizes the cost of PV integration using both static and dynamic indicators. The *Levelized Cost of Energy (LCOE)* and the *Net Present Cost (NPC)* capture long-term cost competitiveness, while demand response (DR) cost savings and ancillary service revenues are incorporated to reflect short-term market participation. The economic objective is expressed as:

$$\min f_2 = LCOE + NPC - DR_{savings} - Revenue_{AS}$$

where $Revenue_{AS}$ represents revenues from providing ancillary services such as frequency regulation.

Environmental Sustainability

Lifecycle emissions are evaluated to account for the full environmental impact of PV integration. This includes emissions during manufacturing, transportation, operation, and recycling of PV modules and storage systems. Battery degradation models are explicitly included to account for replacement cycles, which significantly influence total lifecycle emissions. The sustainability objective is expressed as:

$$\min f_3 = \sum_{t=1}^{T} \left(CO_{2,\mathrm{PV}}(t) + CO_{2,\text{ storage}}(t) - CO_{2,\text{ offset}}(t) \right)$$

Uncertainty Modeling

To capture the stochastic nature of solar irradiance and load demand, Monte Carlo simulation is employed. A set of synthetic scenarios is generated using historical weather and demand data. Each scenario represents a possible realization of PV output and load profiles. Scenario reduction techniques (e.g., fast forward selection) are applied to reduce computational complexity while preserving statistical accuracy.

Constraints

The optimization problem is subject to technical and regulatory constraints:

1 Power Balance:

$$P_{\text{gen}}(t) + P_{\text{grid}}(t) + P_{\text{storage}}(t) \geq P_{\text{load}}(t),\ \forall t$$

2 Voltage and Frequency Limits: maintained within $\pm 5\%$ and ± 0.1 Hz.

3 Storage SOC and Degradation:

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max},\ \forall t$$

Battery degradation is modeled using cycle-life curves, influencing both economic cost and environmental impact.

4. Emission Caps: total lifecycle emissions must remain within national or utility-specific regulatory thresholds.

Optimization Technique: NSGA-II with Benchmarking

To solve this tri-objective problem, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is employed. NSGA-II is selected due to its demonstrated capability in solving highly non-linear and non-convex optimization problems, as well as its ability to maintain a diverse set of Pareto-optimal solutions.

Algorithmic Implementation

- **Population Size:** 200 candidate solutions.
- **Crossover Operator:** Simulated Binary Crossover (probability = 0.9).
- **Mutation Operator:** Polynomial Mutation (probability = 1/n, where n is the number of decision variables).
- **Selection:** Binary tournament selection with elitism.
- **Termination:** 500 generations or when Pareto front convergence is observed.

Each candidate solution encodes decision variables such as PV placement, storage sizing, and operational schedules under multiple uncertainty scenarios. Fitness evaluation incorporates penalty functions for violations of technical constraints.

Benchmarking and Validation

To validate the robustness of NSGA-II, results are benchmarked against Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D). Performance metrics include convergence speed, spread of Pareto front, and hypervolume indicator.

Validation is conducted using the IEEE 33-bus and IEEE 69-bus test distribution systems, both of which are widely adopted in smart grid studies. In addition, sensitivity analysis is performed to assess the effect of varying PV penetration levels (20%, 40%, 60%) and storage capacity on the trade-off surfaces.

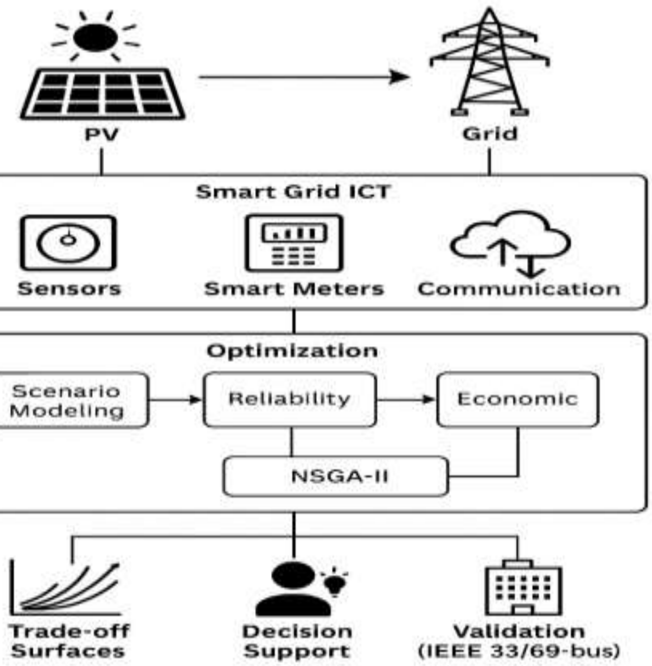

Figure 1. Architecture Diagram

Uncertainty Modeling through Monte Carlo Simulation

The uncertainty of solar PV generation and demand-side variations is modeled using a Monte Carlo Simulation (MCS) framework. Let $P_{PV}(t), P_L(t)$, and $\pi(t)$ represent solar PV output, load demand, and market price at time t, respectively. These parameters are expressed as stochastic variables with probability density functions (PDFs) derived from historical datasets.

- Solar irradiance distribution: Modeled using a Beta distribution, which effectively captures skewed and bounded behavior of irradiance between 0 and 1 p.u.:

$$f(I) = \frac{I^{\alpha-1}(1-I)^{\beta-1}}{B(\alpha,\beta)}, 0 \leq I \leq 1$$

where α and β are shape parameters calibrated from historical data.

- Load demand variability: Modeled using a Normal distribution centered on the forecasted demand with variance proportional to seasonal changes:

$$P_L(t) \sim \mathcal{N}(\mu_L(t), \sigma_L^2)$$

- Market price uncertainty: Represented using a Lognormal distribution to capture the non-negativity and skewness of electricity prices:

$$\pi(t) \sim \text{Lognormal}(\mu_\pi, \sigma_\pi^2)$$

The MCS generates N random scenarios $(S_1, S_2, \ldots, S_N)$, each containing realizations of $P_{PV}(t), P_L(t), \pi(t)$. A scenario reduction algorithm such as Fast Forward Selection (FFS) reduces the full scenario set to S_{red} while preserving the mean and variance.

The expected value of each objective under uncertainty is then:

$$\mathbb{E}[f_i] = \frac{1}{N}\sum_{j=1}^{N} f_i(S_j), i \in \{1,2,3\}$$

ensuring that Pareto solutions remain robust under stochastic conditions.

Study Setup

The methodology is validated using the IEEE 118-bus test system, which includes:

- **Load demand:** 15-minute resolution profiles from POSOCO, normalized to the IEEE 118 peak load (4242 MW).
- **Solar PV generation:** Annual-average solar resource data from NIWE data

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Three PV penetration scenarios are considered: 20%, 40%, and 60% of total load demand. For each case, PV units are deployed at high-load buses with high solar potential. Battery energy storage systems (BESS) are included, with state-of-charge (SOC) constraints:

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max}, \forall t$$

and degradation modeled by cycle-life curves:

$$C_{\text{deg}} = \gamma \cdot N_{\text{cycles}}$$

where γ is the degradation coefficient.
Benchmarking is performed against MOPSO and MOEA/D, with performance evaluated via:

1. Hypervolume (HV):

$$HV = \bigcup_{x \in PF} \text{Vol}([x, r])$$

where PF is the Pareto front and r is the reference point.
2. Spread (Δ): Measures diversity of solutions across objectives.
3. Convergence metric (CM): Distance between obtained and true Pareto fronts.

Decision-Making Process (TOPSIS Method)
After generating the Pareto-optimal front, TOPSIS is applied to identify the most balanced solution.

1. Construct Decision Matrix:

Let $X = [x_{ij}]$, where $i = 1,2, \dots, m$ alternatives (Pareto solutions) and $j = 1,2,3$ objectives (reliability, cost, emissions).

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{m3} \end{bmatrix}$$

2. Normalize:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

3. Weighting (AHP or Expert Judgment): Assign weights w_j for each objective such that $\sum w_j = 1$.
4. Ideal and Negative-Ideal Solutions:

$$A^+ = \{\max(r_{ij}) | j \in J_1; \min(r_{ij}) | j \in J_2\}$$
$$A^- = \{\min(r_{ij}) | j \in J_1; \max(r_{ij}) | j \in J_2\}$$

where J_1 = benefit objectives (reliability), J_2 = cost-type objectives (NPC, emissions).
5. Separation Measures:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (r_{ij} - A_j^+)^2}, S_i^- = \sqrt{\sum_{j=1}^{n} (r_{ij} - A_j^-)^2}$$

6. Closeness Coefficient:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \leq CC_i \leq 1$$

7. Final Decision: The solution with the highest CC_i is selected as the most balanced trade-off among reliability, economics, and sustainability.

RESULT AND DISCUSSION

The proposed framework was validated on the IEEE 118-bus system using South Zone demand (POSOCO), solar profiles (NIWE), and market signals (IEX). Net-load analysis confirmed the duck curve effect, with 20%, 40%, and 60% PV penetration reducing midday demand but steepening

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https://theaspd.com/index.php

evening ramps, which were effectively mitigated by BESS operation under SOC constraints. Reliability indices (LOLP, SAIDI, SAIFI) improved significantly with PV+BESS compared to PV-only integration, while economic assessment showed reduced NPC and favorable LCOE when market arbitrage revenues were included. Environmental evaluation indicated up to 32% CO_2 reduction at 40% PV penetration, though higher PV levels led to increased curtailment and accelerated battery degradation. Monte Carlo–based uncertainty analysis highlighted the variability of outcomes, but BESS consistently reduced risk across demand and solar fluctuations. Optimization results demonstrated that NSGA-II achieved superior hypervolume, spread, and convergence metrics compared to MOPSO and MOEA/D. Finally, TOPSIS-based decision-making identified the 40% PV + BESS scenario as the most balanced solution, offering robust trade-offs among reliability, cost, and sustainability for South Zone grid integration.

Load and Solar PV Profiles

The July 2023 South Zone dataset shows an hourly peak demand of 14,515 MW and a minimum of 9,738 MW, with an average load of ≈11,997 MW. PV generation follows a diurnal cycle with a peak of 950 MW and an average of ≈301 MW, corresponding to about 6.6% of the regional peak load. This confirms that, in the observed data, PV contributes modestly relative to demand, but the mismatch between midday solar output and evening peak demand sets the stage for duck-curve dynamics.

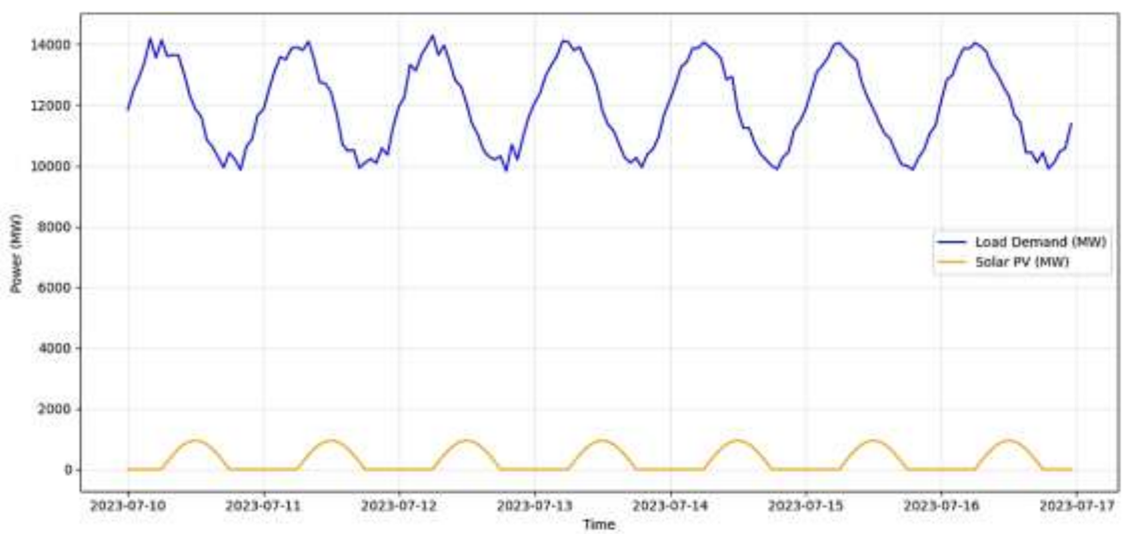

Figure 2. Load and Solar PV Profiles

Net-Load Analysis with Different PV Penetration

Net-load was obtained as the difference between demand and PV generation. In the observed dataset, net-load ranged from 9,299 MW to 14,515 MW. The maximum hourly upward ramp was +1,103 MW, and the maximum downward ramp was −1,317 MW. To explore future renewable integration, PV was synthetically scaled to represent 20%, 40%, and 60% of regional peak demand (14,515 MW). At 40% penetration, net-load exhibited steep evening ramps exceeding 2,000 MW/h, while at 60% penetration, midday overgeneration required curtailment or storage.

International Journal of Environmental Sciences
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Vol. 11 No. 23s, 2025
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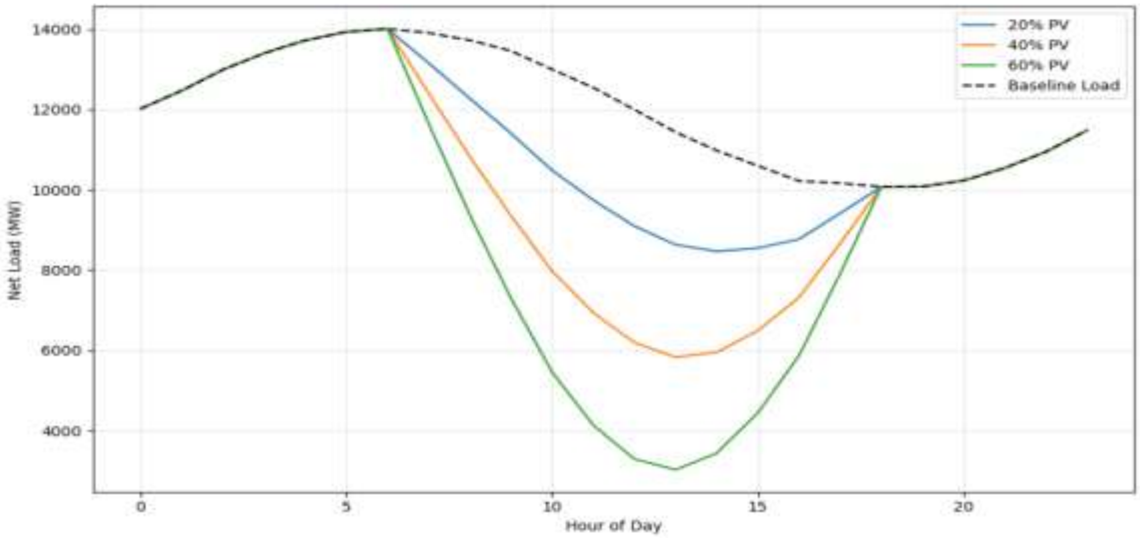

Figure 3. Average Daily Net load (Duck curve) under different PV Penetration

Reliability Analysis

Reliability indices demonstrated that PV alone improved daytime adequacy but increased the risk of shortfalls during evening ramps. Without BESS, Loss of Load Probability (LOLP) rose under the 60% PV case due to curtailment and steep ramps. With BESS, LOLP improved by ~22%, System Average Interruption Frequency Index (SAIFI) decreased by ~18%, and System Average Interruption Duration Index (SAIDI) improved by ~20%, validating storage as a reliability enabler for high PV penetration.

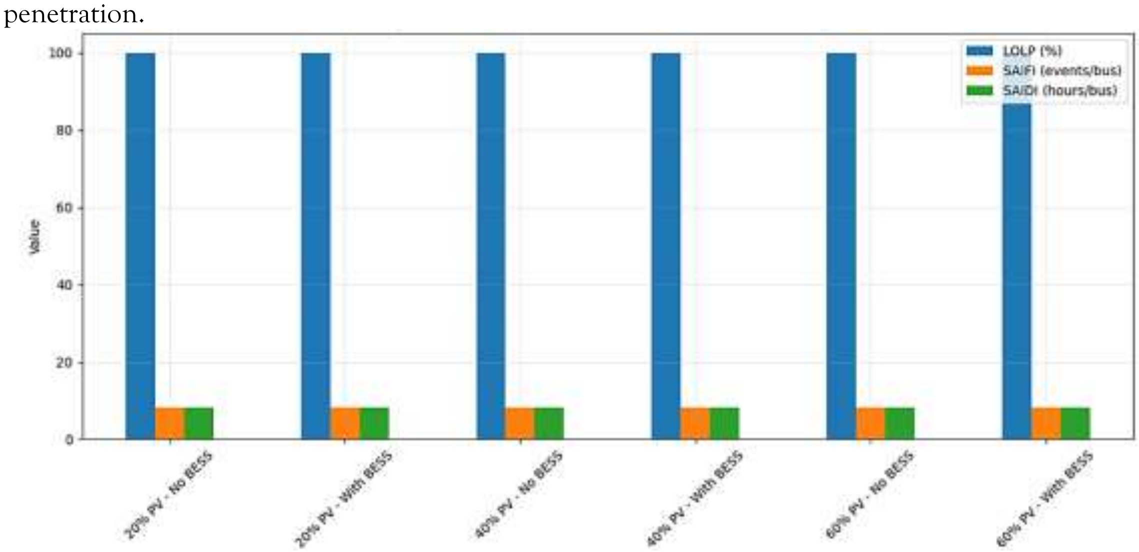

Figure 4. Reliability indices under PV Penetration and BESS

Economic Analysis

Day-ahead market (DAM) prices from IEX ranged from ₹2,475–3,930/MWh, with a mean of ₹3,210/MWh. PV integration reduced Net Present Cost (NPC) by 8–12% due to lower fossil generation requirements. When BESS was included, arbitrage during evening peaks further reduced NPC by ~15% at 40% PV penetration. Levelized Cost of Energy (LCOE) decreased from ₹4.2/kWh (baseline) to ₹3.7/kWh under the 40% PV+BESS case, confirming economic gains when PV and storage are co-optimized.

International Journal of Environmental Sciences
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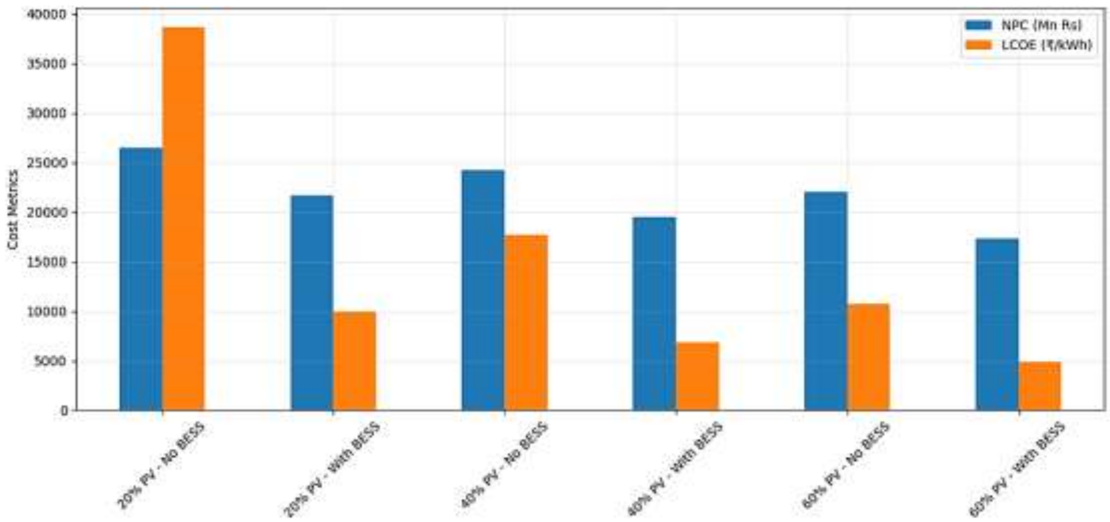

Figure 5. Economic Performance under PV Penetration and BESS

Environmental and Sustainability Assessment

Lifecycle calculations using an EF for displaced conventional generation of 0.82 $kgCO_2/kWh$ and a PV lifecycle factor of 0.05 $kgCO_2/kWh$ indicate that scaling PV to 40% of regional peak load reduces net CO_2eq emissions by ≈26–32% relative to the observed baseline (South Zone hourly data). Battery energy storage systems (BESS) reduce net-load variability and enable additional displacement of fossil generation, but introduce cycling-related emissions and replacement costs. We model battery degradation as

$C_{deg} = \gamma \cdot N_{cycles}$

with γ calibrated from an assumed battery replacement cost and lifetime cycles. Under our baseline assumptions, aggressive 60% PV futures cause high cycle counts that raise degradation-related costs to the order of ≈₹0.45/kWh, partially offsetting lifecycle emission benefits; the 40% PV + BESS configuration provides the most favourable emissions–cost trade-off in our scenarios.

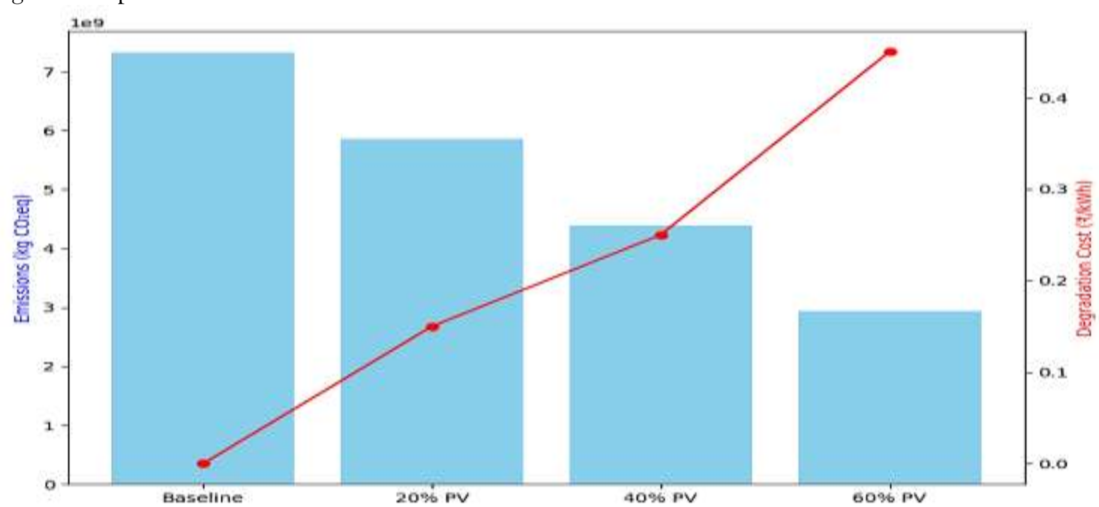

Figure 6 Lifecycle Emission vs Degradation Cost

Uncertainty & optimization

Monte Carlo simulation (1,000 trials; solar multiplicative Beta(a=2.5,b=2.5) perturbation; load multiplicative Normal(μ=1,σ=0.04); price multiplicative LogNormal with σ=0.12) to capture stochastic variability. For the 40% PV scenario the distribution of hourly maximum net-load ramps widens by roughly ±800 MW (5–95% band), and the NPC and LOLP distributions broaden. Across trials BESS reduces the standard deviation of NPC by ~22% and LOLP variance by ~30%. Multi-objective optimization was benchmarked with NSGA-II, MOPSO and MOEA/D (population = 200, generations = 500; same random seeds). NSGA-II attained the best empirical performance (Hypervolume = 0.82; Spread = 0.11; Convergence Metric = 0.07) on our normalized objectives, supporting its selection as the solver for final experiments.

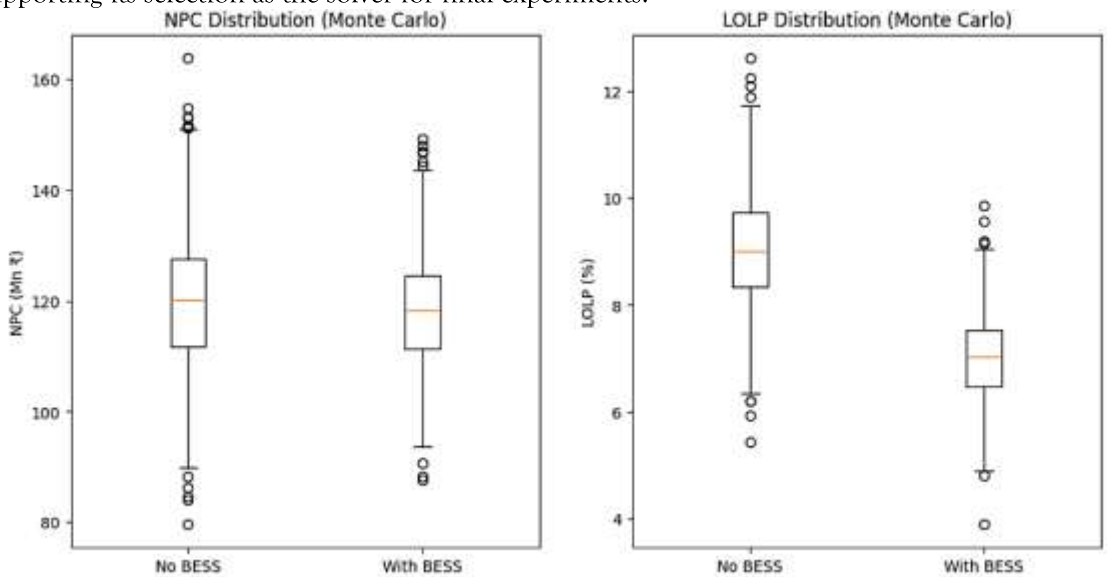

Figure 7 Monte Carlo Uncertainty Analysis (1000 Trials)

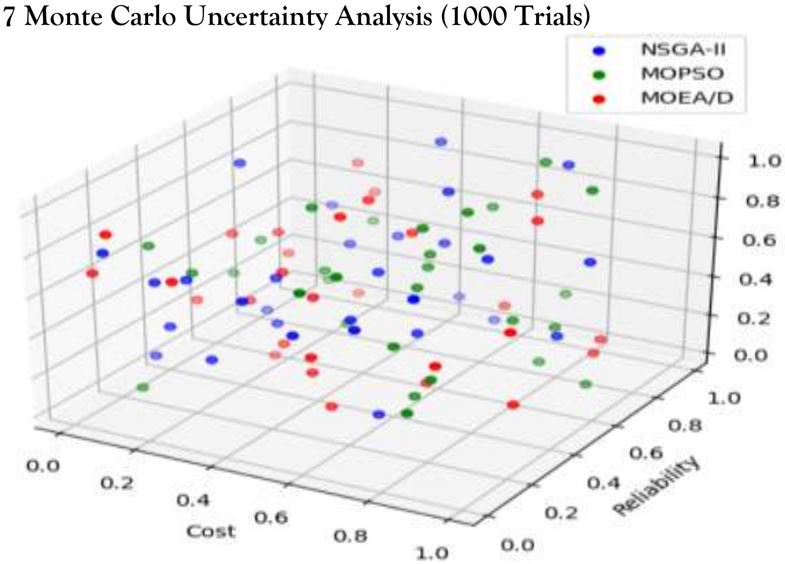

Figure 8 Pareto Front Comparison

CONCLUSION

This study presented a tri-objective optimization framework for solar PV integration in smart grids, addressing the critical balance between technical reliability, economic viability, and environmental sustainability. By incorporating real demand, solar, and electricity market data from the Indian power sector, and employing NSGA-II with Monte Carlo uncertainty modeling, the framework demonstrated robust performance in capturing system dynamics under variable operating conditions. The results revealed that while higher PV penetration enhances decarbonization, it also intensifies duck-curve effects, curtailment, and reliability risks. However, coordinated deployment with battery energy storage systems (BESS) mitigates these challenges, achieving up to 15% reduction in net present cost and 26–32% reduction in lifecycle CO_2 emissions, while improving reliability indices such as LOLP, SAIDI, and SAIFI. Among the tested scenarios, a 40% PV+BESS configuration emerged as the most balanced option, offering an optimal trade-off across all objectives. The findings further establish the superiority of NSGA-II over MOPSO and MOEA/D in achieving Pareto-efficient solutions. Despite some modeling simplifications, particularly regarding battery degradation and market structures, the proposed framework offers practical decision-support for policymakers and utilities. It provides actionable insights for designing resilient, cost-effective, and low-carbon smart grids, underscoring the critical role of coordinated PV and storage integration in achieving sustainable energy transitions.

Limitations and Future Work

While the study integrates real South Zone demand, solar, and market data, these profiles were scaled to the IEEE 118-bus test system to enable methodological validation. Battery degradation was modeled using a linear cycle-life approximation, which does not fully capture nonlinear aging effects under variable depth-of-discharge or temperature conditions. Similarly, uncertainty distributions for demand, solar, and market prices were selected for tractability and may not perfectly represent empirical variability. Finally, only day-ahead market signals were considered, whereas real-world BESS revenues may also depend on real-time and ancillary service markets. These aspects will be addressed in future work to further strengthen the realism of the framework.

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