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# Probabilistic Reliability Assessment of Power Systems with Demand-Side Flexibility Using Monte Carlo Simulation

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**ABSTRACT**

The increasing penetration of renewable energy sources such as wind and solar power presents significant challenges due to their intermittent nature. This research explores a probabilistic approach to assessing power system reliability by incorporating demand-side flexibility (DSF) using Monte Carlo Simulation (MCS). The study evaluates key reliability indices, including Loss of Load Probability (LOLP) and Expected Energy Not Supplied (EENS), under various renewable energy uncertainty scenarios. Without integrating DSF, LOLP obtained was 0.1288, while EENS obtained was 5.92 MWh. By integrating a 100 MW demand response adjustment, LOLP and EENS was noticeably reduced (LOLP-0.0127 and EENS-0.38 MWh) compared to a system without flexibility. Additionally, the impact of demand response as a mitigation strategy for supply shortages was analyzed, providing valuable insights into improving grid stability and reducing reliance on conventional generation. The MCS model was implemented in MATLAB, enabling statistical analysis and graphical representation of results to observe convergence.

**Keywords:** Monte Carlo Simulation, Demand-Side flexibility, Reliability Assessment, Renewable Energy Sources.

## INTRODUCTION

Reliance on renewable energy sources keeps increasing due to the shift in the global energy landscape transitions toward sustainability. Traditional power distribution systems are designed as unidirectional networks, delivering electricity from centralized generation sources to end-users [1]. The integration of distribution generation can provide benefits such as reduced transmission losses and improved voltage support, but also introduces challenges related to voltage regulation, protection coordination, and reverse power flow, the increasing penetration of distributed generation requires a re-evaluation of traditional distribution system planning and operation practices [2]. To ensure a reliable electrical power system, probabilistic methods such as Monte Carlo Simulation (MCS) are essential for evaluating supply adequacy, the steps involved in using MCS for stability assessment typically include defining the input parameters and their associated probability distributions, running a large number of simulations with randomly sampled parameter values, and analyzing the resulting output to estimate the probability of instability [3]. The implementation of MCS for power system stability evaluation involves the use of specialized software tools and platforms, these tools can be integrated with MCS algorithms to perform probabilistic stability assessment [4]. This study focuses on a power system consisting of conventional generation, wind, and solar energy, with the integration of demand-side response mechanisms as a potential solution to mitigate reliability issues. The analysis is conducted using Monte Carlo Simulation implemented in MATLAB.

## LITERATURE SURVEY OF THE STUDY

Power system stability is a critical aspect of ensuring reliable electricity supply, and it can be classified into several categories, including rotor angle stability, frequency stability, and voltage stability [5]. The increasing integration of renewable energy sources (RES), such as wind and solar, introduces new challenges due to their intermittent and variable nature These sources can cause fluctuations in both frequency and voltage, making it more difficult to maintain system stability. Therefore, advanced analysis techniques are essential to ensure grid reliability in the face of these challenges [6].

**Power System Reliability Metrics:** To measure and quantify the reliability performance of different power systems, various metrics can be used. These depend on the reliability dimension, data availability, some common examples are Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), Expected Energy Not Supplied (EENS), System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and voltage and frequency deviations [7] this study focuses on LOLP and EENS. LOLP Represents the probability that the available power supply will be insufficient to meet demand at any given time, while EENS Measures the expected shortfall in energy supply over a given period [8].

**Demand-Side Flexibility in Power Systems:** Demand flexibility refers to the ability of electrical consumers to change or adjust the electricity consumption in response to an external condition, such as electricity price, financial incentives, and technical requirements [9].

In [10] the growing role of demand-side response (DSR) in enhancing system stability and reducing energy shortfalls was highlighted, [11] discussed advanced MCS techniques for power system reliability, showcasing their application in real-world scenarios, [12] explored hybrid systems combining solar, wind, and conventional power, presenting probabilistic models for reliability assessment, [13] investigated the impact of solar intermittency on power system reliability, [14] applied machine learning algorithms to enhance MCS-based reliability assessments, [15] investigated strategies for ensuring grid resilience with increasing renewable shares, [16] reviewed the impact of distributed generation (DG) on system reliability and probabilistic load balancing, [17] provided an overview of recent advances in reliability analysis and probabilistic modeling, [18] discussed the integration of probabilistic methods in smart grid planning and operation.

Existing literatures extensively explores power system reliability assessment using Monte Carlo Simulation (MCS), significant gaps remain in integrating demand response and renewable generation in a unified reliability framework. Most studies either focus on the probabilistic modeling of renewables or the role of demand-side flexibility, but very few have holistically evaluated their combined effects on LOLP and EENS.

## METHODOLOGY

**System Modelling:**

The modeled power system consists of:

**Renewable generation:** Wind and solar power, modeled using normal distributions to account for variability. The stochastic behaviour of wind and solar general follows a normal distribution [11] express as

$$P_{solar} = \max(N(\mu_{solar}, \sigma_{solar}), 0) \quad (1)$$

$$P_{wind} = \max(N(\mu_{wind}, \sigma_{wind}), 0) \quad (2)$$

Where:

$P_{solar}$ and $P_{wind}$ are the respective power outputs (MW)

$N(\mu, \sigma)$ represents a normal distribution with mean $\mu$ and standard deviation $\sigma$

The max function ensures that negative values (which are not physically meaningful) are set to zero

**Conventional generation:** A stable, dispatchable power source providing baseline capacity

The total available power is determined as:

$$P_{total} = P_{solar} + P_{wind} + P_{conv} \quad (3)$$

Where:

$P_{conv}$ is the firm capacity from conventional sources

**Load demand:** A dynamic energy demand profile with integrated demand response capabilities

Demand side flexibility is incorporated to adjust the required load dynamically, and can be express as:

$$D_{adjusted} = D_{base} - P_{total} \quad (4)$$

$$D_{flexible} = (\max D_{adjusted} - P_{demand\ response}, 0) \quad (5)$$

Where:

$D_{base}$ is the base demand (MW)

$P_{demand\ response}$ is the demand-side flexible capacity (MW)

$D_{flexible}$ represents the remaining demand after response actions

**Loss of Load Probability (LOLP):** LOLP is defined as the probability that the available generation is insufficient to meet demand, it is computed as

$$\text{LOLP} = \frac{N_{loss}}{N_{total}} \quad (6)$$

Where:

$N_{loss}$ is the number of times a shortfall occurred

$N_{total}$ is the total number of Monte Carlo iterations

**Expected Energy Not Supplied (EENS):** this represents the average amount of unmet demand across all simulations, it is computed as

$$\text{EENS} = \frac{\sum_{i=1}^{N} S_i}{N} \quad (7)$$

Where:
$S_i$ is the shortfall energy in iteration i
N is the total number of Monte Carlo simulations
All the above models are dynamically implemented in MATLAB software.

## RESULTS AND DISCUSSION

**Table 1:** Parameters used for the Monte Carlo Simulation

| Parameters | Values/Unit |
|---|---|
| Number of Simulations $(N_{sim})$ | 10,000 |
| Base Load Demand $(D_{base})$ | 1000 (MW) |
| Mean solar Power Output $(\mu_{solar})$ | 200 (MW) |
| Solar Power Standard Deviation $(\sigma_{solar})$ | 50 (MW) |
| Mean wind Power Output $(\mu_{wind})$ | 300 (MW) |
| Wind Power Standard Deviation $(\sigma_{wind})$ | 75 (MW) |
| Conventional Generation Capacity $(P_{conv})$ | 600 (MW) |
| Demand Respond Capacity $(P_{demand})$ | 100 (MW) |
| Loss of Load Probability $(LOLP)$ | Computed |
| Expected Energy Not supplied $(EENS)$ | Computed (MWh) |

**First Analysis Approach:** Without Demand-side flexibility
The following results shows simulation results without Demand -side response flexibility:

**Loss of Load Probability (LOLP): 0.1288**
**Expected Energy Not Supplied (EENS): 5.92 MWh**

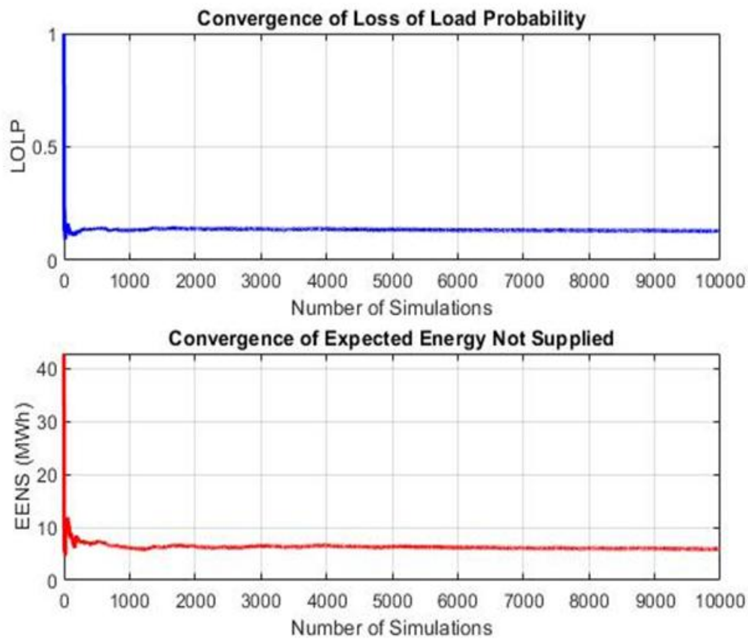


*Figure 1: LOLP and EENS Simulation Results without Demand-Side flexibility.*

**Second Analysis Approach: With Incorporated Demand-Side Flexibility**
The following results shows simulation results with integrated Demand -side response flexibility:

**Loss of Load Probability (LOLP): 0.0127**
**Expected Energy Not Supplied (EENS): 0.38 MWh**

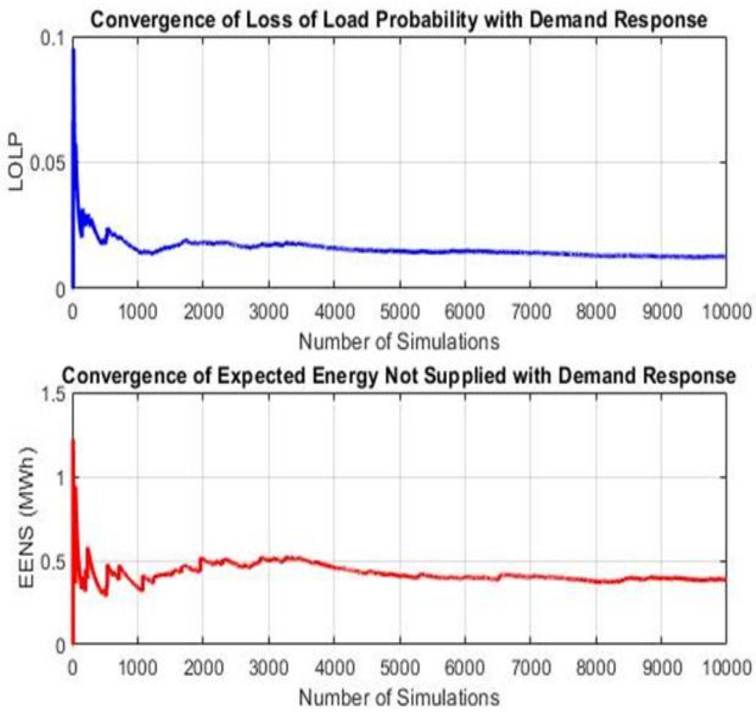


*Figure 2: LOLP and EENS Simulation Results with Integrated Demand-Side flexibility*

## DISCUSSION

The computed LOLP represents the probability that power generation is insufficient to meet demand, without incorporating demand response, (LOLP, figure 1), The simulation reveals that LOLP fluctuates initially but stabilizes as more Monte Carlo iterations are performed. This trend suggests that random fluctuations in wind and solar generation impact system reliability. By integrating a 100 MW demand response adjustment, LOLP is noticeably reduced compared to a system without flexibility. This confirms that demand-side adjustments can significantly lower the likelihood of power shortages as shown in (LOLP, figure 2).

A high EENS means that the system regularly fails to meet demand, which could lead to power outages or the need for costly emergency power purchases (EENS, figure 1), the EENS results show that while some energy shortages remain, the magnitude of unserved energy is reduced compared to a system without demand-side flexibility The plotted EENS curve stabilizes over multiple iterations, reflecting the robustness of Monte Carlo methods in reliability assessments as shown (EENS, figure 2).

## CONCLUSION

Integrating demand-side flexibility strategies into the power system under study, shows significant improvements in reliability of the system. The probability of supply shortages decreases, and the amount of unserved energy is reduced, demonstrating the effectiveness of demand response strategies in balancing supply and demand. Since wind and solar generation are stochastic (unpredictable), demand-side response can balance unexpected supply fluctuations without requiring additional generation. The simulation results provided a clear understanding of how demand response influences system reliability.

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