Monte Carlo Simulation for Reliability Assessment of Electrical Power Generation Systems with Renewable Resources

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ABSTRACT

In face of the increasing adoption of renewable sources like solar and wind, traditional reliability assessments need revision. Conventional methodologies, designed for predictable and controllable energy sources, fall short in addressing the uncertainty of renewables. This study aims to develop a methodology for assessing the reliability of Generation Systems (GS), focusing on renewable integration and analyzing a real Brazilian system. The innovation lies in incorporating probabilistic models to handle the variability and unpredictability of renewable resources, resulting in robust reliability analysis. The proposed methodology employs sequential and synchronous Monte Carlo simulations to calculate reliability indices, such as Loss of Load Expectation, Loss of Load Probability and Expected Energy Not Served. Validation was done on a real system from Minas Gerais. Results show that including renewables can significantly improve reliability indices. Thus, advanced reliability assessment methodologies are vital for addressing renewable uncertainties and enhancing system robustness.

Keywords: Generation System; Monte Carlo; Reliability; Renewable Sources; Simulation.

INTRODUCTION

The reliability of the Generation System (GS) is its ability to meet user demand, assuming perfect reliability of transmission and distribution systems [1]. Key reliability indices include LOLE (Loss of Load Expectation), expected hours per year without reserve to meet demand; LOLP (Loss of Load Probability), probability of experiencing load loss; and EENS (Expected Energy Not Served), energy not supplied per year, measured in MWh/year [1-4]. Generation modeling considers equipment availability and primary resources. A two-state model is used for equipment, based on probability distributions for outage and repair times [1].

According to the National Electric System Operator (ONS) [5], reliability studies are routinely conducted to address specific demands and cover a broad range of scenarios. These studies require proper characterization to ensure a clear understanding of the results and can be classified into three main types: composite reliability analysis, multi-area reliability analysis (as outlined in Submodule 3.3 – Medium-term energy operation planning and Submodule 2.4 – Criteria for energy and hydrological studies), and spinning reserve reliability analysis.

The predictive reliability analysis of generation and transmission employs robust tools like NH2, owned by CEPEL, and RESPROB, developed by ELETROBRAS - Centrais Elétricas Brasileiras S.A. While these well-established programs effectively address many traditional reliability analysis needs, it is essential to recognize their limitations as the energy landscape evolves with increasing renewable energy integration.

To enhance reliability assessments, implementing new methodologies is crucial. Such advancements enable meaningful comparisons of results and the proposal of innovative approaches better suited to the complexities of modern power systems. This is particularly important given the unique challenges posed by renewable energy, which requires more flexible and adaptive modeling techniques for accurate assessments.

Thus, this work aims to develop a Sequential Monte Carlo Simulation to analyze GS reliability, particularly with renewable energy integration, addressing limitations of traditional methods in handling renewable variability. This approach enhances system reliability assessment, aiding in better decision-making for modern power systems.

MATERIALS AND METHODS

The reliability analysis of the power system evaluates its adequacy over a year (8760 hours) under various random scenarios, including maximum active demand models, probabilistic models for intermittent and renewable resources (wind and solar), dispatch models, and component reliability with a failure criterion of $n-1$ (one unit out of service at a time). The simulation method used is a sequential Monte Carlo type, which is both synchronous (all random variables are updated together) and sequential (updated step by step). In each iteration, the system is evaluated hour-by-hour for the entire year. The simulation procedure is described as:

- **Start:** input data, define probabilistic models for failure times, repair times, primary resources (solar irradiance, wind), and system demand. Specify maximum capacities for generating units.
- **Processing:** update the system hourly using iterative loops with synchronous variable updates. Randomly generate failure times for units, determine power output from renewable sources, and compare it against system demand. If the demand exceeds available power, accumulate reliability indices. Repeat this process for all 8760 hours of the year.
- **Output:** at the end of each iteration, Eq. (1) to Eq. (2), calculate the reliability indices LOLE, LOLP and EENS. For the entire simulation, additional indices are calculated using Eq. (3) to Eq. (5). Record the number of

deficit hours H, the accumulated unmet demand ENS, and the number of iterations N, which is set to 1000. These indices reflect the system's performance and reliability.

$$LOLE_{single} = H \qquad \text{Eq. (1)}$$

$$LOLP_{single} = H/8760 \qquad \text{Eq. (2)}$$

$$LOLE_{simulation} = \sum_{i=1}^{N} H_j/N \qquad \text{Eq. (3)}$$

$$LOLP_{simulation} = \sum_{i=1}^{N} H_j/(N \times 8760) \qquad \text{Eq. (4)}$$

$$EENS_{simulation} = \sum_{i=1}^{N} ENS_j/N \qquad \text{Eq. (5)}$$

RESULTS AND DISCUSSION

A Monte Carlo simulation was conducted using real data from nine power plants located in the state of Minas Gerais, Brazil. The nominal generation capacities of these plants are as follows: 105 MW each for plants A, G, and H; 140 MW each for plants B, E, and F; 70 MW each for plants C and I; and 175 MW for plant D. The failure and repair rates used in the simulation are detailed in **Table 1**, calculated according to the methodology suggested by Machado [6].

Table 1. Failure and repair rates for each power plant in the system.

Plant	Failure rate (h^{-1})	Repair rate (h^{-1})
A	25.58×10^{-3}	3.03×10^{-3}
B	281.04×10^{-3}	10.55×10^{-3}
C	17.14×10^{-3}	8.10×10^{-3}
D	1288.08×10^{-3}	14.93×10^{-3}
E	110.89×10^{-3}	5.31×10^{-3}
F	43.90×10^{-3}	14.55×10^{-3}
G	90.76×10^{-3}	3.44×10^{-3}
H	118.39×10^{-3}	3.89×10^{-3}
I	13.13×10^{-3}	2.26×10^{-3}

The failure and repair rates for the plants are considered constant, and thus an exponential distribution is assumed for the failure and repair times of the units. In this case, the time T for a state transition is given by $-(1/\lambda)\ln U$, where λ is the characteristic transition rate, shown in **Table 1**, and U is a random number between 0 and 1 generated in the Monte Carlo simulation. The system's demand is modeled as uniformly distributed between 735 MW and

1155 MW, corresponding to 70% and 110% of the maximum firm generation capacity, respectively.

The reliability indices obtained from the simulation are presented in **Table 2**. The simulation for the real system considers the firm generation from the nine plants, while the designed system includes additional solar photovoltaic generation (100 MW) and wind power (twenty turbines). In this way, the wind speed at the installation site is modeled using a Weibull distribution with parameters $\alpha = 14.66$ m/s and $\beta = 2.50$ m/s. Also, the electrical power generated by a wind turbine is described by $P = 0.5\eta C_p \gamma R^2 v^3$, where η is the generator efficiency 0.90, C_p is the power coefficient of the rotor 0.45, γ the air density 1.225 kg/m³, R is the rotor radius (28 meters for turbines up to 1 MW), and v is the wind speed in meters per second. For the photovoltaic cells, solar irradiance is modeled with a normal distribution during daylight hours from 7 AM to 7 PM. The mean irradiance is $\mu = 3.07 \times 10^{-3}$ MW/m² and the standard deviation is $\sigma = 2.12 \times 10^{-4}$ MW/m².

Table 2. Reliability indices obtained for the studied scenarios, considering one thousand scenarios.

Index	Actual, considering only firm generation	Projected, considering firm generation and renewable generation
LOLE (hours/year)	2191.30	346.37
LOLP (%)	25.02	3.95
EENS (GWh/year)	1149.70	5.78

Thus, the addition of renewable generation to the real system significantly improves reliability indices. Specifically, the introduction of solar photovoltaic and wind power results in an 84.19% reduction in LOLE, an 84.19% reduction in LOLP, and a 99.50% reduction in EENS. This demonstrates that, despite the inherent intermittency of renewable resources, they provide substantial benefits for the reliable operation of the system.

CONCLUSION

This study presents a comprehensive methodology for evaluating the reliability of Generation Systems (GS) with a particular emphasis on integrating renewable energy sources. By leveraging Sequential Monte Carlo Simulations, the research introduces a robust framework that incorporates probabilistic models to effectively address the uncertainties associated with wind and solar power. The methodology was validated using real data from Minas Gerais, Brazil, demonstrating that incorporating renewable energy significantly enhances system reliability. The integration of solar photovoltaic and wind power resulted in remarkable improvements in reliability indices, including an 84.19% reduction in Loss of Load Expectation (LOLE), an 84.19% reduction in Loss of Load Probability (LOLP), and a 99.50% reduction in Expected Energy

Not Served (EENS). These reductions highlight the substantial benefits of renewable energy in enhancing system reliability, despite its inherent variability and intermittency. The findings underscore the critical need for advanced reliability assessment methodologies in the context of growing renewable energy adoption. By addressing the challenges posed by renewable resource variability, this study provides valuable contributions for improving the robustness of power systems and supports better decision-making for future energy planning.

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