ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

# Calculation of Expected Energy Not Served Based on the Monte-Carlo Simulation.

**Hossien Hemmati[1*], Ali Zarei[2], and Mahvash Najafi Harsini[3].**

[1,2,3] Department of Electrical Engineering, College of Engineering, Islamshahr Branch, Islamic Azad University, Tehran, Iran.

**ABSTRACT**

This paper addresses the calculation of expected energy not served (EENS) based on the Monte-Carlo simulation (MCS) for a typical generation system. EENS is considered for evaluation and assessment due to its importance in electric power systems and generation systems. Simulation results demonstrate that MCS can be successfully used to calculate the power system reliability indexes.
**Keywords:** Expected Energy Not Served, Monte Carlo Simulation, Reliability, Power Systems

**Corresponding author*

## INTRODUCTION

Expected energy not served is a well known and widely used index in power system reliability evaluation [1-5]. Paper [4] presents the forecast uncertainties into EENS for wind turbine studies. This paper discusses that the rapid increase in wind power generation around the world has stimulated the development of applicable technologies to model the uncertainties of wind power resulting from the stochastic nature of wind and fluctuations of demand for integration of wind turbine generators (WTGs). In paper [4], the load and wind power forecast errors are integrated into the expected energy not served (EENS) formulation through determination of probabilities using the normal distribution approach. The effects of forecast errors and wind energy penetration in the power system are traversed. The impact of wind energy penetration on system reliability, total cost for energy and reserve procurement is then studied for a conventional power system. The results show a degradation of system reliability with significant wind energy penetration in the generation system. This work provides a useful insight into system reliability and economics for the independent system operator (ISO) to deploy energy/reserve providers when WTGs are integrated into the existing power system. Paper [1] discusses that in deregulated electricity market environment, the power system works with lower stability margin due to demand fluctuations. Therefore, in restructured power systems all generation companies attempt to increase reliability of their own power plants. The arrangement of the busbar layouts in power stations has a great effect on the power system reliability. This paper develops a sequential Monte Carlo simulation (SMCS) to evaluate the effect of generator breaker and bus-section on the reliability indices of one and half and two-breaker busbar layouts. Karun III power station layout in Iran national grid (ING) is considered as a real world system case study. The most commonly used reliability indices such as loss of load expectation (LOLE), expected energy not supplied (EENS) and expected load curtailment (ELC) are used to evaluate the reliability in this paper. Economic and technical evaluations of reliability indices variation in presence of generator breaker and bus-section are presented. Simulation results show that how variation of forced outage rate (FOR) of generator and generator breaker affect on the reliability indices. Paper [3] presents a multi-state Markov model for a coal power generating unit. The paper proposes a technique for the estimation of transition intensities (rates) between the various generating capacity levels of the unit based on field observation. The technique can be applied to such units where output generating capacity is uniformly distributed. In order to estimate the transition intensities a special Markov chain embedded in the observed capacity process was defined. By using this technique, all transition intensities can be estimated from the observed realization of the unit generating capacity stochastic process. The proposed multi-state Markov model was used to calculate important reliability indices such as the Forced Outage Rate (FOR), the Expected Energy Not Supplied (EENS) to consumers, etc. These indices were found for short-time periods (about 100 h). It was shown that these indices are sensibly different from those calculated for a long-term range. Such Markov models could be very useful for power system security analysis and short-term operating decisions.

This paper addresses the calculation of expected energy not served (EENS) based on the Monte-Carlo simulation (MCS) for a typical generation system. EENS is considered for evaluation and assessment due to its important in electric power systems and generation systems. Simulation results demonstrate that MCS can be successfully used to calculate the power system reliability indexes.

**Monte Carlo simulation**

Monte Carlo simulation is a computerized mathematical technique that allows people to account for risk in quantitative analysis and decision making. The technique is used by professionals in such widely disparate fields as finance, project management, energy, manufacturing, engineering, research and development, insurance, oil & gas, transportation, and the environment. Monte Carlo simulation furnishes the decision-maker with a range of possible outcomes and the probabilities they will occur for any choice of action.. It shows the extreme possibilities—the outcomes of going for broke and for the most conservative decision—along with all possible consequences for middle-of-the-road decisions.The technique was first used by scientists working on the atom bomb; it was named for Monte Carlo, the Monaco resort town renowned for its casinos. Since its introduction in World War II, Monte Carlo simulation has been used to model a variety of physical and conceptual systems.

Monte Carlo simulation performs risk analysis by building models of possible results by substituting a range of values—a probability distribution—for any factor that has inherent uncertainty. It then calculates results over and over, each time using a different set of random values from the probability functions. Depending upon the number of uncertainties and the ranges specified for them, a Monte Carlo simulation could involve thousands or tens of thousands of recalculations before it is complete. Monte Carlo simulation produces distributions of possible outcome values. By using probability distributions, variables can have different probabilities of different outcomes occurring. Probability distributions are a much more realistic way of describing uncertainty in variables of a risk analysis. Monte Carlo simulation provides a number of advantages over deterministic analysis:

- Probabilistic Results. Results show not only what could happen, but how likely each outcome is.
- Graphical Results. Because of the data a Monte Carlo simulation generates, it’s easy to create graphs of different outcomes and their chances of occurrence. This is important for communicating findings to other stakeholders.
- Sensitivity Analysis. With just a few cases, deterministic analysis makes it difficult to see which variables impact the outcome the most. In Monte Carlo simulation, it’s easy to see which inputs had the biggest effect on bottom-line results.
- Scenario Analysis: In deterministic models, it’s very difficult to model different combinations of values for different inputs to see the effects of truly different scenarios. Using Monte Carlo simulation, analysts can see exactly which inputs had which values together when certain outcomes occurred. This is invaluable for pursuing further analysis.
- Correlation of Inputs. In Monte Carlo simulation, it’s possible to model interdependent relationships between input variables. It’s important for accuracy to represent how, in reality, when some factors goes up, others go up or down accordingly.

## Test system

A generation system with 5-generation units is considered as case study. The system data are listed in Table 1. Load duration curve is also depicted in Figure 1. It is clear that maximum load is 160 MW and minimum load is 64 MW.

**Table 1: The system data for generation system**

| Generation unit | Size (MW) | FOR |
|---|---|---|
| G1 | 40 | 0.01 |
| G2 | 30 | 0.01 |
| G3 | 50 | 0.02 |
| G4 | 20 | 0.02 |
| G5 | 60 | 0.03 |

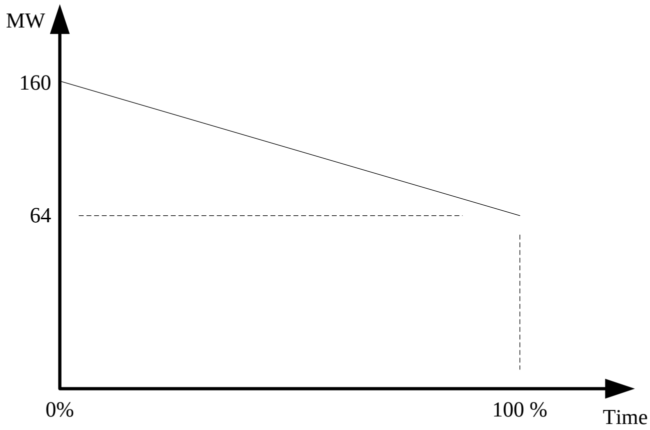


**Figure 1: Load duration curve**

## Simulation results

In this section, EENS index is calculated by using Monte-Carlo simulation. Numbers of scenarios are considered as 10000 and 100000 and two cases are simulated as depicted in Figures 2 and 3. It is clear that the output is converged for 100000 scenarios and the simulation is completed. The simulation results show that MCS can be successfully applied to calculate the power system reliability indexes such as EENS. Nevertheless, the simulation times for several scenarios are listed in Table 2 and it is clear that simulation time is more than analytically methods.

**Table 2: The simulation time for MCS following different scenarios**

| Number of scenarios | Simulation time (s) |
|---|---|
| $1\times10^3$ | 0.5 |
| $1\times10^4$ | 1 |
| $1\times10^5$ | 2.2 |
| $1\times10^6$ | 5 |

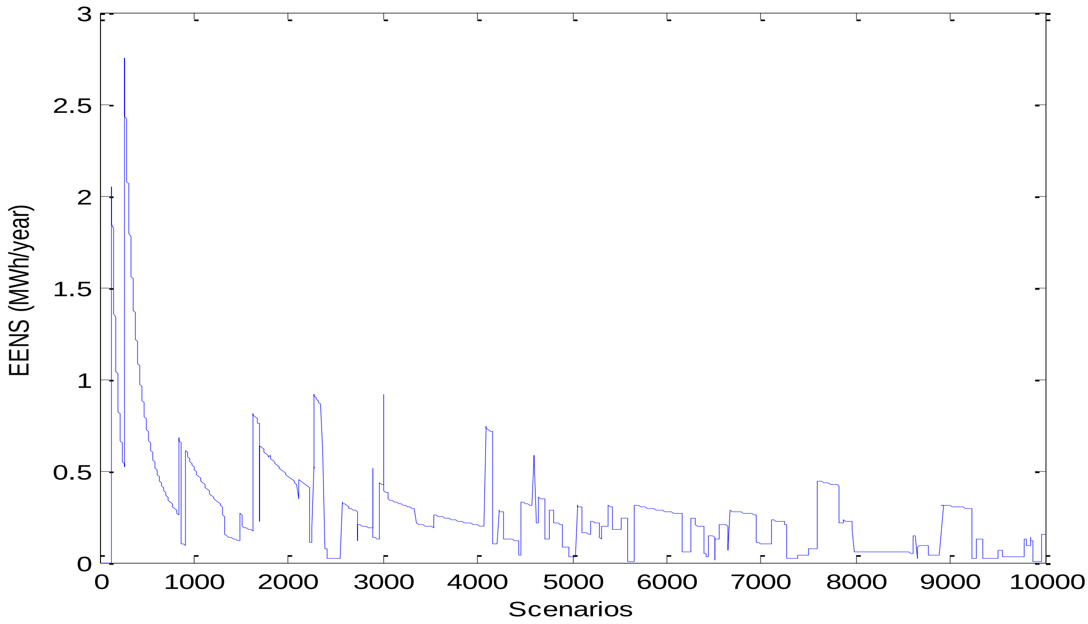


**Figure 2: EENS index for 10000 scenarios**

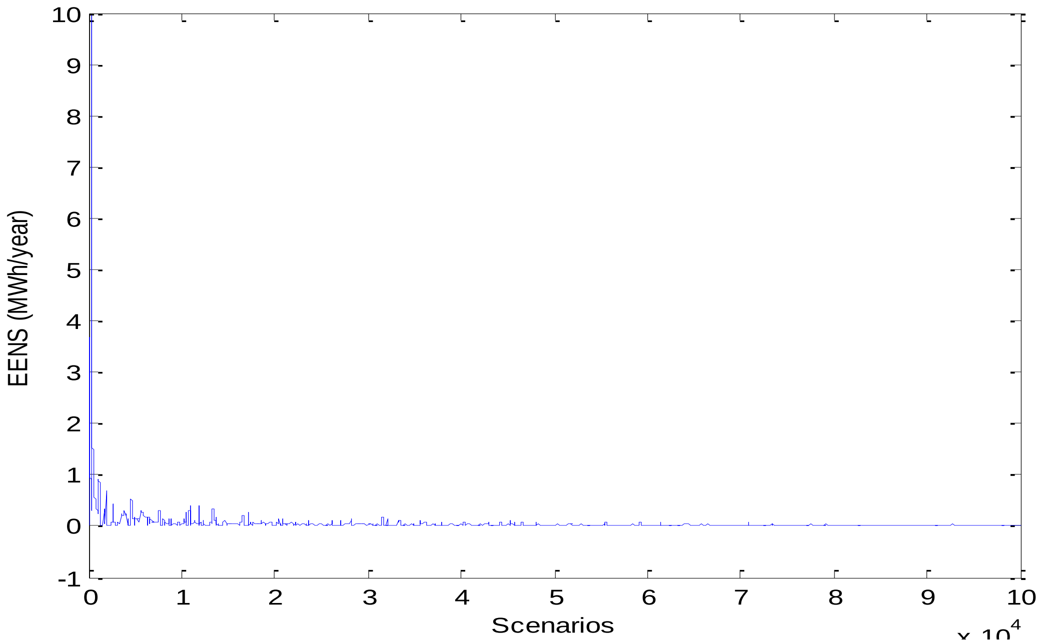


**Figure 3: EENS index for 100000 scenarios**

## CONCLUSIONS

This paper presented the calculation of EENS index by using MCS for a typical generation system. Simulation results demonstrated that MCS could be successfully used to calculate the power system reliability indexes. The results denoted that simulation time of MCS is more than analytically methods.

## ACKNOWLEDGEMENT

The authors gratefully acknowledge the financial and other support of this research, provided by Islamic Azad University, Islamshahr Branch, Tehran, Iran.

## REFERENCES

[1] Moazzami M, Hemmati R, Haghighatdar Fesharaki F, Rafiee Rad S. Int J Electr Power Ener Syst. 2013;53: 987-993.
[2] Li YF, Zio E. Reliab Eng Syst Saf 2012;106: 28-36.
[3] Lisnianski A, Elmakias D, Laredo D, Ben Haim H. eliab Eng Syst Saf 2012;98:1-6.
[4] Toh GK, Gooi HB. Electr Power Syst Res 2011;81: 430-439.
[5] Tanrioven M, Alam MS. J Power Sour 2006;157:401-410.