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Loss of Load Probability Calculation by Using Monte Carlo Simulation.

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ABSTRACT

This paper presents Monte Carlo simulation (MCS) to evaluate the power system reliability indexes. In this paper, loss of load probability (LOLP) is calculated based on the MCS. Simulation results are carried out based on a generation system and MCS is applied. Simulation results denote that MCS presents the results similar to the analytically method.

Keywords: Loss of Load Probability, Monte Carlo Simulation, Generation System, Reliability, Electric Power System

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INTRODUCTION

Monte Carlo simulation (MCS) is a widely used method for reliability evaluation in electric power systems. This method has also been widely used in the other engineering fields [1-5]. KMCLib is a general framework for lattice kinetic Monte Carlo (KMC) simulations [2]. The program can handle simulations of the diffusion and reaction of millions of particles in one, two, or three dimensions, and is designed to be easily extended and customized by the user to allow for the development of complex custom KMC models for specific systems without having to modify the core functionality of the program. Analysis modules and on-the-fly elementary step diffusion rate calculations can be implemented as plugins following a well-defined API. The plugin modules are loosely coupled to the core KMCLib program via the Python scripting language. KMCLib is written as a Python module with a backend C++ library. After initial compilation of the backend library KMCLib is used as a Python module; input to the program is given as a Python script executed using a standard Python interpreter. We give a detailed description of the features and implementation of the code and demonstrate its scaling behavior and parallel performance with a simple one-dimensional A–B–C lattice KMC model and a more complex three-dimensional lattice KMC model of oxygen-vacancy diffusion in a fluorite structured metal oxide. KMCLib can keep track of individual particle movements and includes tools for mean square displacement analysis, and is therefore particularly well suited for studying diffusion processes at surfaces and in solids [2]. Paper [5] discusses that accurate determination of thermodynamic properties of petroleum reservoir fluids is of great interest to many applications, especially in petroleum engineering and chemical engineering. Molecular simulation has many appealing features, especially its requirement of fewer tuned parameters but yet better predicting capability; however it is well known that molecular simulation is very CPU expensive, as compared to equation of state approaches. We have recently introduced an efficient thermodynamically consistent technique to regenerate rapidly Monte Carlo Markov Chains (MCMCs) at different thermodynamic conditions from the existing data points that have been pre-computed with expensive classical simulation. This technique can speed up the simulation more than a million times, making the regenerated molecular simulation almost as fast as equation of state approaches. In this paper, this technique is first briefly reviewed and then numerically investigated in its capability of predicting ensemble averages of primary quantities at different neighboring thermodynamic conditions to the original simulated MCMCs. Moreover, this extrapolation technique is extended to predict second derivative properties (e.g. heat capacity and fluid compressibility). The method works by reweighting and reconstructing generated MCMCs in canonical ensemble for Lennard-Jones particles. In this paper, system's potential energy, pressure, isochoric heat capacity and isothermal compressibility along isochors, isotherms and paths of changing temperature and density from the original simulated points were extrapolated. Finally, an optimized set of Lennard-Jones parameters (ε, σ) for single site models were proposed for methane, nitrogen and carbon monoxide. Paper [4] discusses that methane and ethane are the simplest hydrocarbon molecules that can form clathrate hydrates. Previous studies have reported methods for calculating the three-phase equilibrium using Monte Carlo simulation methods in systems with a single component in the gas phase. Here we extend those methods to a binary gas mixture of methane and ethane. Methane–ethane system is an interesting one in that the pure components form sI

clathrate hydrate whereas a binary mixture of the two can form the sII clathrate. The phase equilibria computed from Monte Carlo simulations show a good agreement with experimental data and are also able to predict the sI–sII structural transition in the clathrate hydrate. This is attributed to the quality of the TIP4P/Ice and TRaPPE models used in the simulations.

This paper presents Monte Carlo simulation (MCS) to evaluate the power system reliability indexes. In this paper, loss of load probability (LOLP) is calculated based on the MCS. Simulation results are carried out based on a generation system and MCS is applied.

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

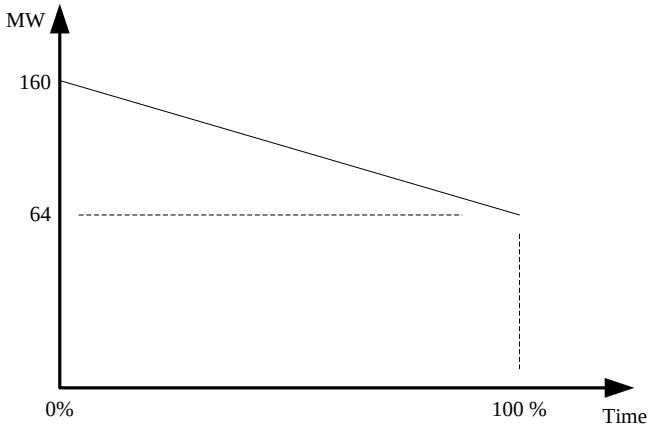

Figure 1: Load duration curve

Simulation results

Monte Carlo simulation is carried out to calculate the LOLP index. Figures 2 to 5show the MCS process for different scenarios. It is clear that with increasing the number of scenarios, the MCS convergence get better, and eventually the process is converged. The simulation results show that MCS can successfully be applied to calculate the LOLP index and the accuracy is increased with increasing the scenarios. Figure 5 shows the results for 1×10^6 scenarios and it is clear that the output is completely converged for such number of scenarios.

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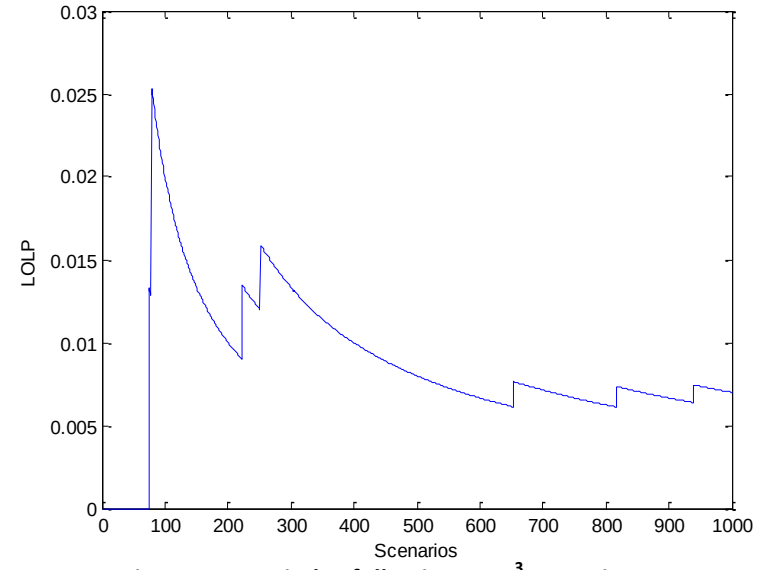

Figure 2: LOLP index following 1×10^{3} scenarious

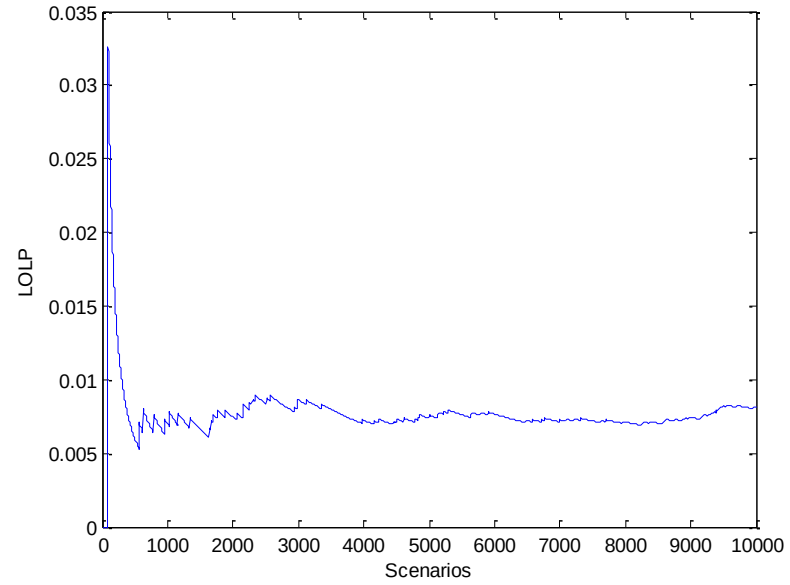

Figure 3: LOLP index following 1×10^{4} scenarious

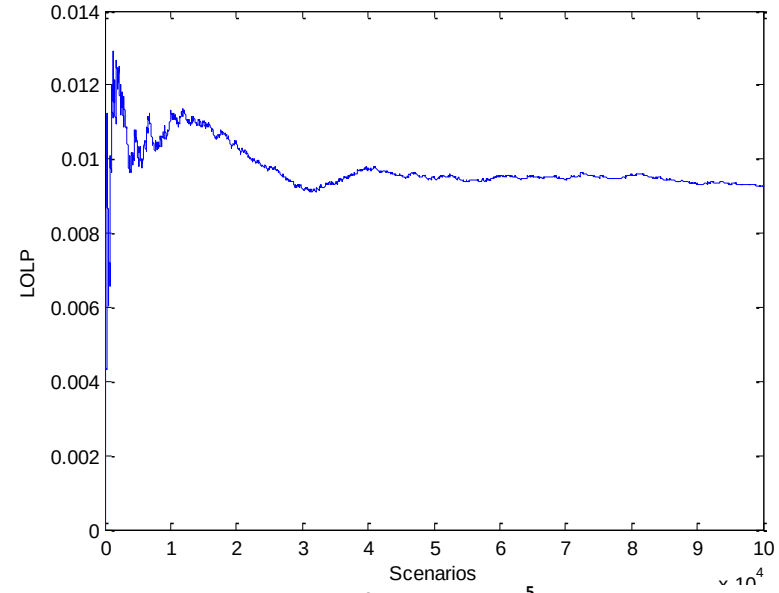

Figure 4: LOLP index following 1×10^{5} scenarious

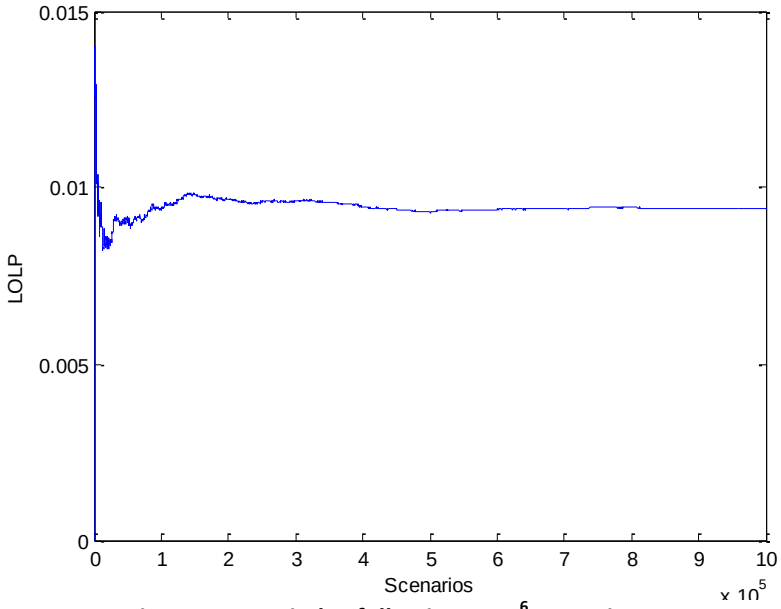

Figure 5: LOLP index following 1×10^6 scenarious

CONCLUSIONS

This paper addressed Monte Carlo simulation (MCS) to assess the power system reliability indexes, where, loss of load probability (LOLP) was calculated and assessed following different scenarios. Simulation results demonstrated that MCS could be successfully applied to calculate power system reliability indexes.

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