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An efficient method with tunable accuracy for estimating expected interruption cost of distribution systems

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ABSTRACT

The paper presents a novel efficient method with tunable accuracy for estimating expected interruption cost (ECOST) of distribution systems. ECOST index quantifies the reliability of a distribution system in monetary basis. The performance of ECOST estimation could be influenced by various factors such as time-varying load and cost models, computational limitation and random nature of component failure and repair time. Generally, the interruption cost is estimated based on an analytical method which does not consider the input and parameter uncertainties that are represented as random variables. The simulation method based on Monte Carlo (MC) simulation could provide a more accurate approximation of ECOST due to consideration of stochastic factors. However, one basic challenge related to the MC method is the high computational cost in order to run a large number of iterations for a specified high accuracy. Speed up the accurate estimation process using fast computation method could be an important feature in distribution systems management software. An advancement of the MC method with controllable accuracy is the Multilevel Monte Carlo (MLMC) estimator which is proposed to estimate the system ECOST. The proposed method could reduce the huge computational cost needed for accurately estimating the index. To illustrate the performance of this method, five different size distribution systems of Roy Billinton Test System are utilized. The impacts of the network topology, customer load type, time-varying load and cost models, failure and repair statistics on the MLMC based system ECOST assessment performance are also investigated.

1. Introduction

Expected interruption cost (ECOST) estimation is an important part of reliability analysis of distribution systems [1]. Knowing the value of a distribution system ECOST in monetary basis could play a significant role for making an optimal investment decision and for deciding the supply of which regions or sectors should be cut off during electricity shortage [2]. ECOST is a completely random variable [3] due to the dependency of random frequency and duration of interruption, time-varying load and cost levels of different customer sectors. In ECOST estimation, interruption frequency and duration are the primary variables. Load level of a given customer sector varies through the duration of the failure period. Similarly, the interruption cost for a given type of customer which is found by analysing Sector Customer Damage Function (SCDF) [4,5] and varies with the failure duration and starting time. Therefore, analytical method based on average interruption frequency, load and cost models could be replaced by simulation approach which could provide the more accurate result of ECOST estimation by considering random factors [6,7]. Through the simulation method, information of probability distribution of ECOST index could be obtained which is necessary for distribution systems expansion and future planning.

Simulation approach generally used in distribution systems reliability evaluation [8–13] including ECOST estimation is based on standard Monte Carlo (MC) simulation. MC method generates the stochastic behavior of components outage and repair times. It can be simulated in either sequential or non-sequential mode [14]. In the non-sequential mode, the states of all components are sampled and a non-chronological system state is obtained [15]. On the other hand, the up and down cycles of all components are simulated in the sequential approach and overall system operating cycle is obtained by combining all the component cycles [15]. The sequential MC mode allows chronological issues to be considered [16]. The state duration sampling approach is generally used to simulate chronological issues which provide time-related reliability indices concerning frequency and duration of load point interruption [17]. However, the slow convergence rate of the sequential MC makes it very time consuming when a large number of samples are necessary to obtain a precise

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result depending on the accuracy level and number of variables in the system; particularly it is not efficient at simulating rare events. It is mentioned that the estimation of a distribution system ECOST using any computationally inexpensive method with controllable accuracy has not been reported yet. Therefore, a new sequential Multilevel Monte Carlo (MLMC) simulation method has been applied in this study to overcome the MC based ECOST computational burden.

The MLMC estimator is an advanced MC estimator for performing stochastic simulations. In this method, the computational performance of the basic MC method is increased by maintaining the acceptable accuracy of the simulation. The idea of MLMC method is to use a hierarchy of computational meshes (levels) instead of using single time discretization level in MC method. By simulating on multiple levels, MLMC method runs most of the simulations on the computationally low-cost coarse levels and few simulations on the computationally expensive finest level. Where in MC method, all the samples are only simulated on the finest level [18]. It is simple to understand that the computational cost on a fine level is higher than on coarse level [19]. Thus most of the computational effort in MLMC method is transferred from the finest level to the coarsest one, leading to substantial computational saving. As the whole simulation is conducted using multiple approximations, therefore the less accurate estimate on the preceding coarse level can be sequentially corrected by averages of the differences of the estimations of two consecutive levels in the hierarchy. Detailed mathematical proofs of the MLMC method can be found in [20]. Initially, the method was introduced by Heinrich in the context of parametric integration [21]. The method has been extended further by Giles in the context of stochastic differential equations [18]. Since then the method is being applied for uncertainty quantification in various applications [22–28].

The objectives of this study are to investigate the application of MLMC method on estimating the system ECOST as well as to find the effect of different parameters on the computation performance. In the present study, components are represented by two-state model [29]. The operation history of each component is generated based on stochastic differential equation (SDE). Time-varying load and cost models are developed for each of the load points in the system. Milstein discretization scheme is used for the approximate numerical solution of the SDE. A benchmark Roy Billinton Test System (RBTS) [30] is used to apply the method. The performance of the proposed method is compared with the MC method in terms of computation accuracy and speed-up. The effect of different parameters on the MLMC computation method such as network configuration and load type, time-varying load and cost models, network reinforcement, transformer and line failure rate, drift and volatility values are investigated to provide insight into the variation of the ECOST with different system factors.

The remainder of this paper is organized as follows. Section 2 describes the mathematical explanation of the problem and the MLMC approach. In Section 3, ECOST evaluation methodology has been described. This Section consists of five subsections: generation of component operating history, modelling of load, modelling of per unit interruption cost, modelling of system ECOST, and simulation steps to evaluate the ECOST. In Section 4, we investigate the applicability of the proposed MLMC. We evaluate system ECOST considering different factors affecting the results to show how much the estimation results could be diversified from average value while these factors are considered. Finally, Section 5 concludes the paper.

2. Proposed approach

2.1. Problem statement

MC method is a straightforward way for the estimation of expectation arising from the stochastic simulation where ECOST is estimated by averaging over a large number of samples on a single fine grid level [31]. Let X be the ECOST for this study and $E[X]$ is the expectation or quantity of interest. Also, let $E[X_A]$ be the approximation to $E[X]$. $X_A^{(i)}$ is the *ith* sample of X_A and N_{MC} is the number of independent MC samples. Then, an unbiased MC estimator for $E[X_A]$ is

$$\widehat{Z}_{MC} = \frac{1}{N_{MC}} \sum_{i=1}^{N_{MC}} X_A^{(i)}. \tag{1}$$

where $E[\widehat{Z}_{MC}] = E[X_A]$, $N_{MC}^{-1} V[X_A]$ is the variance of this estimate and the rms error is $\mathcal{O}(1/\sqrt{N_{MC}})$.

To achieve an accuracy of ε, the simulation requires $N_{MC} = \mathcal{O}(\varepsilon^{-2})$ samples. For an increasing accuracy level, the number of samples also increases. As the samples are run on the finest level, the accuracy of evaluation is sufficiently accurate in MC method. However, the problem associated with the MC method is that huge computational burden is introduced due to large sample size. This motivates to find an alternative method which could speed up the system ECOST estimation in distribution systems planning application by maintaining an adequate level of accuracy. Hence the applicability of the proposed MLMC method is investigated in this study to perform this objective.

2.2. MLMC method

In the MC method, the calculation of system ECOST is carried out on a single fine grid level $l = L$. l is a nonnegative integer. In this level, both accuracy and estimation time of the expectation is very high.

In the MLMC method, same ECOST is evaluated but using multiple parts or levels instead of using only one level L. The multiple levels can be divided as $l = 0, 1, \cdots\cdots, L$. Here $l = 0$ and $l = L$ indicate the coarsest and finest discretisation levels, respectively. On each level, expectations are estimated using different sample size in a manner which could reduce the overall variance for a specified error tolerance. Initially, a large number of samples are run on $l = 0$. The purpose of the next level $l = 1$ is to add a correction value that initiates to decrease the bias. Based on this correction value, the expected difference from one level to the next fine level is added, until level L is reached. By this way, the less correct estimate on the coarsest grid is successively corrected by the approximations on the subsequent fine grids and thus the finest grid accuracy is obtained. The MLMC expectation can be expressed as:

$$E[X_A] = E[X_0] + \sum_{l=1}^{L} E[X_l - X_{l-1}] = \sum_{l=0}^{L} E[Z_l], \tag{2}$$

Now the estimator for the above MLMC expectation is

$$\widehat{Z}_{ML} = \widehat{Z}_0 + \sum_{l=1}^{L} \widehat{Z}_l = \sum_{l=0}^{L} \widehat{Z}_l. \tag{3}$$

where $\widehat{Z}_0$ is an unbiased estimator for $E[X_0]$ using samples N_0 on $l = 0$ and $\widehat{Z}_l$ is the estimator for $E[X_l - X_{l-1}]$ using N_l samples from .

$$\widehat{Z}_0 = \frac{1}{N_0} \sum_{i=1}^{N_0} X_0^{(i)}, \tag{4}$$

$$\widehat{Z}_l = \frac{1}{N_l} \sum_{i=1}^{N_l} (X_l^{(i)} - X_{l-1}^{(i)}), \tag{5}$$

$E[X_l - X_{l-1}]$ is approximated using the difference between the expectation of the coarse and fine level as $E[X_l^f - X_{l-1}^c]$. $E[X_l^f]$ and $E[X_{l-1}^c]$ are estimated using two different timestep sizes $h_f = 2^{-l}T$ and $h_c = 2^{-(l-1)}T$, respectively [32]. On level $l = 0$, a large and fixed value timestep is used to generate a large sample size N_0. This means that the coarsest level is the computationally cheapest level and the simulation time increases with the increase of level. The statistical properties of X_l are unchanged whether the estimation of $E[X_l - X_{l-1}]$ from level $(l-1)$ to l or $E[X_{l+1} - X_l]$ from l to $(l+1)$. This means that both $E[X_l - X_{l-1}]$ and $E[X_{l+1} - X_l]$ have the same expected value i.e. $E[X_l^f] = E[X_l^c]$. The convergence condition of the proposed method is the target rms error which could be written as follows:

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