Rare Event Simulation-based Operational Safety Analysis for Complex Technological Projects: A Literature Review

Qianli Deng, Adiel Komey, Gregory B. Baecher*

Department of Civil & Environmental Engineering, University of Maryland, College Park, MD, 20742-3021, U.S.

*Corresponding author: Dr. Gregory B. Baecher

Tel.: +1 202 285 3902

E-mail address: gbaecher@umd.edu

Abstract

Natural hazards such as hurricanes, floods, and earthquakes in most cases hold very small probabilities of happening during a project life. Yet, evaluating the effects of such hazards on the of complex technological systems operation such as hydropower facilities or chemical processing plants requires prohibitively large numbers of calculations and significant computational resources. In order to address these safety issues with efficient computational resource consumption, rare event simulation techniques are widely adopted. This study reviews the past research on the simulation of rare events with very small probabilities of occurrence. These techniques not only help to accelerate the computation speed, but also increase the estimation accuracy. In the study, two major rare event simulation techniques, importance sampling and splitting, are categorized and compared with their respective advantages and disadvantages. Applications of them are also summarized, especially for the safety management of such complex technological projects. Finally, detailed reviews of the dam-reservoir systems are presented, which serves as the case study demonstrating effectiveness of rare event simulation for complex project operations.

1. Introduction

Monte Carlo simulation is a computerized mathematical technique that allows people to account for risk in quantitative analysis and decision making. To be more specific, Monte Carlo methods present a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results (Kalos and Whitlock 2008; Liu 2008). 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. The results are calculated repetitively 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 would be complete. Based on the possible outcome values, distributions of the final results could be reached.

Monte Carlo methods are widely used because of their flexibility and robustness. The modern version of the Monte Carlo method was first invented in the late 1940s by Stanislaw Ulam on the nuclear weapons projects at the Los Alamos National Laboratory (Cooper et al. 1989). Immediately after Ulam's breakthrough, John von Neumann understood its importance and programmed the Electronic Numerical Integrator And Computer to carry out Monte Carlo calculations (Neumann 2005). In engineering, Monte Carlo methods are widely used for sensitivity analysis and quantitative probabilistic analysis in process design. The need of such application arises from the interactive, co-linear and non-linear behaviors of typical process simulations (Roebuck 2012). Analytical solutions or accurate approximations are only available for a very restricted class of simple systems. These techniques are 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. In most cases, engineering systems need to resort to simulation.

However, significant computational resources are usually required in the simulation to reach the satisfied results (Bucklew 2004). Otherwise, long wait times or buffer overflows might occur. For a discrete system of moderate complexity, there are a large number of possible system states combinations. As is often the case, estimation of the probability of failure and consequences of any given system state involves computationally expensive simulation. It is commonly infeasible to analyze all possible states as the resources required (Dawson and Hall 2006).

In order to address the potential project safety issues with efficient computational resources consumption, this study reviews past research on the rare event simulation methodologies, as well as their application. The remaining paper is structured as follows: in Section 2, previous rare event simulation methodologies, including importance sampling and splitting, are reviewed. Then, Section 3 presents the corresponding applications in both engineering projects and projects in other fields. In Section 4, detailed reviews on the dam-reservoir systems are presented, which serve as the case study demonstrating effectiveness of rare event simulation for complex project operations. Conclusions are presented in Section 5.

2. Methodology of Rare Event Simulation

Rare event simulation and quantification come from the need to insure that undesirable events will not occur. Typically, such an event is the failure of industrial critical systems, for which failure is regarded as a massive catastrophic situation. Usually the system is a "black box" whose output determines safety or failure domains (Walter and Defaux 2015). A great deal of attention has been focused on the development of Monte Carlo techniques. Today, the rare event simulation applications range from lightwave and optical communication systems (Smith et al. 1997), to industrial routing problems (Chepuri and Homem-de-Mello 2005), and to financial asset pricing (Chan and Wong 2015). According to Bucklew (2004) and Rubino and Tuffin (2009), a rare event means an event that occurs infrequently with a very small probability, but is important enough to justify the study. Rare event simulation is thus an umbrella term for a group of computer simulation methods intended to selectively sample 'special' regions of the dynamic space of systems that are unlikely to visit those special regions through brute-force simulation (Juneja and Shahabuddin 2002). Based on the hazard-rate twisting method, Huang and Shahabuddin (2004) discussed a general approach to estimate rare-event probabilities in static problems.

Importance sampling and splitting are the two primary techniques to make important rare events happen more frequently in a simulation (L'Ecuyer et al. 2006). The unbiased estimator is obtained with much smaller variance than the standard Monte Carlo estimator. Comparisons of their respective advantages and disadvantages are presented in Table 1 below.

Table 1. Comparisons of Importance Sampling and Splitting

Methodology	Description	Drawback
Importance sampling	Importance sampling increases the probability of the rare event by changing the probability laws that drive the evolution of the system. Then, it multiplies the estimator by an appropriate likelihood ratio to recover the correct expectation.	The main difficulty in general is to find a good way to change the probability laws.
Splitting	In the splitting method, the probability laws remain unchanged, but an artificial drift toward the rare event is created by terminating with some probability the trajectories that go away from it and by splitting those that are going in the right direction. In general, an unbiased estimator is recovered by multiplying the original estimator by an appropriate factor.	Fewer variables are necessary to describe the system as a Markov system, the better the splitting method will work. The dimensionality of the state space negatively influences the performance of the splitting method.

2.1 Principles of Importance Sampling

Importance sampling has been extensively investigated by the simulation community in the last decade, which serves as one of the general approaches for speeding up simulations and to accelerate the occurrence of rare events. The basic ideas behind importance sampling were outlined by Kahn and Marshall (1953). Certain values of the input random variables in a simulation have more impact on the parameter being estimated than on others. If these values are emphasized by sampling more frequently, then the estimator variance can be reduced to a better accepted level. Hence, the basic methodology in importance sampling is to choose a distribution that encourages the important values, and to estimate the probability of interest via a corresponding likelihood ratio estimator. Illustration of importance sampling-based simulation is shown in Figure 1. The simulation outputs are weighted to correct for the use of the biased distribution, and this ensures that the new importance sampling estimator is unbiased. The weight is given by the likelihood ratio, that is, the Radon–Nikodym derivative of the true underlying distribution with respect to the biased simulation distribution.

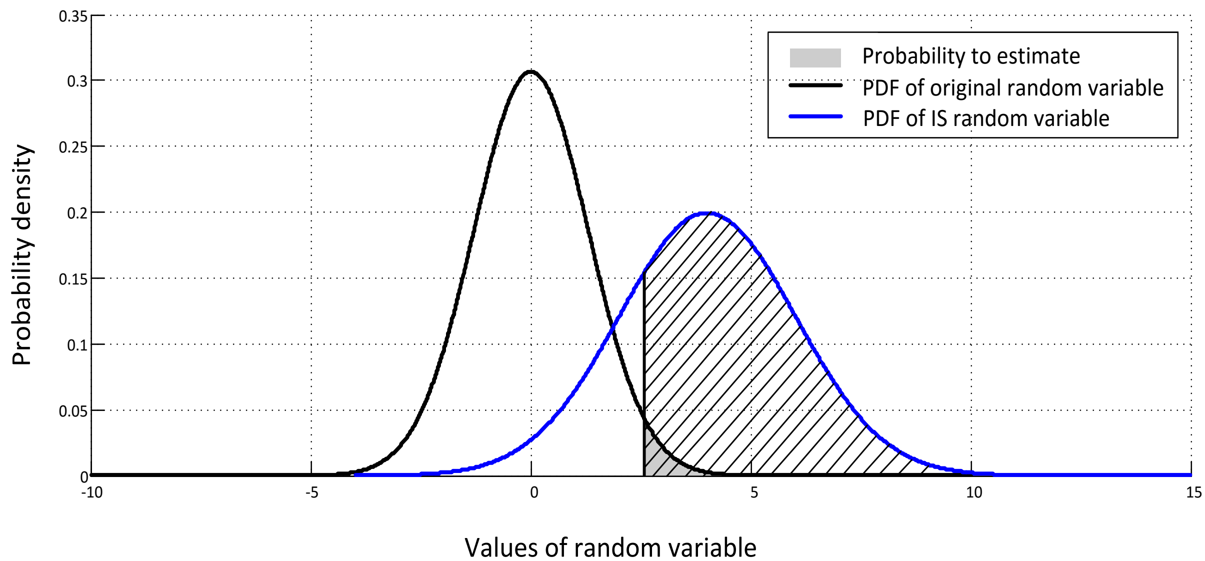

Figure 1. Graphical Illustration of Importance Sampling-Based Simulation

A considerable amount of past research has been devoted to the study of importance sampling techniques in simulation, in particular for rare-event simulation. Based on Glynn and Iglehart's (1989) research, the importance sampling idea was extended to the problems arising in the simulation of stochastic systems. Discrete-time Markov chains, continuous-time Markov chains, and generalized semi-Markov processes were covered. Shahabuddin (1995) also reviewed fast simulation techniques used for estimating probabilities of rare events and related quantities in different types of stochastic models. Based on the importance sampling technique, multiple variance reduction tools for solving rare event problems could also be found in varied areas (Ding and Chen 2013; Jacquemart and Morio 2013; Morio et al. 2010, 2013).

To be specific, Equation (1) is adopted in order to estimate the rare event probability through the importance sampling-based Monte Carlo simulation.

$$\hat{l}_{IS} = E\left(I_{\{S(X)\geq h_f\}}\right) = \frac{1}{N_{IS}} \sum_{j=1}^{N_{IS}} I_{j\{S(X)\geq h_f\}}, \quad (1)$$

where $\hat{l}_{IS}$ stands for the importance sampling Monte Carlo simulation estimator; $E(\cdot)$ stands for the function of expectation value; h_f stands for the cutting value of the probability estimation; $I_{(\cdot)}$ stands for the indicator function with binary values in [0, 1]; i stands for the index of simulation iterations; and N_{IS} stands for the iteration of simulation.

As discussed before, N_{IS} needs to be very large in order to achieve an estimation of l within the acceptable confidence intervals. Importance sampling replaces the probability density function from $f(\cdot)$ to $g(\cdot)$ as a new probability density. Detailed information is presented in Equations (2) and (3).

$$g(x) = I_{\{S(x) \geq h_f\}} f(x) = 0, \qquad (2)$$

where $g(\cdot)$ stands for the probability density function of the replaced random variables; $I_{(\cdot)}$ stands for the indicator function with binary values in [0,1]; and $f(\cdot)$ stands for the probability density function of the original random variables.

$$W(x) = \frac{f(x)}{g(x)}, \qquad (3)$$

where $W(\cdot)$ stands for the likelihood ratio function; $f(\cdot)$ stands for the probability density function of the original random variables; and $g(\cdot)$ is the importance sampling density, which stands for the probability density function of the replaced random variables.

As a result, the original random variable $\{X(t)\}$ with probability density function of $f(\cdot)$ is replaced by the updated random variable $\{Y(t)\}$ with a probability density function of $g(\cdot)$. Detailed information is shown in Equation (4) below.

$$\begin{aligned} l &= \int I_{\{S(X_i) \geq h_f\}} \frac{f(x)}{g(x)} g(x) dx \\ &= E_g\left[I_{\{S(Y) \geq h_f\}} \frac{f(y)}{g(y)} \right] = E_g\left[I_{\{S(Y) \geq h_f\}} W(y) \right], \end{aligned} \qquad (4)$$

where l stands for probability for rare event simulation; $I_{(\cdot)}$ stands for the indicator function with binary values in [0,1]; $W(\cdot)$ stands for the likelihood ratio function; $f(\cdot)$ stands for the probability density function of the original random variables; $g(\cdot)$ stands for the probability density function of the replaced random variables; and $E_g(\cdot)$ stands for the expectation function of importance sampling Monte Carlo estimation.

Thus, an updated unbiased estimator of l is shown in Equation (5) below.

$$\hat{l}_{IS} = \frac{1}{N_{IS}} \sum_{j=1}^{N_{IS}} I_{j\{S(Y) \geq h_f\}} \frac{f(y)}{g(y)} = \frac{1}{N_{IS}} \sum_{j=1}^{N_{IS}} I_{j\{S(Y) \geq h_f\}} W(y), \tag{5}$$

where $\hat{l}_{IS}$ stands for the probability estimation based on importance sampling-based Monte Carlo simulation; N_{IS} stands for the iteration times; $I_{(\cdot)}$ stands for the indicator function with binary values in [0,1]; $W(\cdot)$ stands for the likelihood ratio function; $f(\cdot)$ stands for the probability density function of the original random variables; and $g(\cdot)$ stands for the probability density function of the replaced random variables.

2.2 Principles of Splitting

The splitting methodology was first invented to improve the efficiency of simulations of particle transport in nuclear physics. It is used to estimate the intensity of radiation that penetrates a shield of absorbing material (Booth 1985; Booth and Hendricks 1984; Booth and Pederson 1992). Then, these areas remain as the splitting method primary area of application. Splitting is also used to estimate delay time distributions and losses in ATM and TCP/IP telecommunication networks (Akin and Townsend 2001; Görg and Fuss 1999). In a recent real-life application, splitting was used to estimate the probability that two airplanes get closer than a nominal separation distance, or even hit each other, in a stochastic dynamic model of air traffic where aircrafts are responsible for self-separation with each other (Blom et al. 2005).

The splitting method is based on the idea to iteratively estimate supersets of the designed set and then to estimate the corresponding probability with conditional probabilities. Assume that we want to compute the probability $P(D)$ of an event set D. The general idea for splitting is to find a series of event sets $D = D_0 \subset D_1 \subset ... \subset D_m$. Then, the calculation of $P(D)$ is successfully transformed into $P(D) = P(D_m)P(D_{m-1} | D_m)...P(D_0 | D_1)$, where each conditional event isnot rare. Illustration of splitting based simulation is shown in Figure 2.

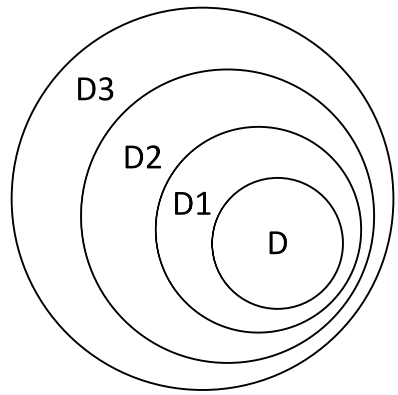

Figure 2. Graphical Illustration of Splitting Based Simulation

For $\forall D_{i-1} \subset D_i$, where $i = 1, 2, ..., m$, Equation (6) stands for the calculation relations of conditional probabilities. Here, every *j* satisfies $m \geq i > j$.

$$P\left(D_j \mid D_i\right) = \frac{P\left(D_j \cap D_i\right)}{P\left(D_i\right)} = \frac{P\left(D_j\right)}{P\left(D_i\right)} = \prod_{k=j}^{i-1} p_k \quad , \tag{6}$$

where p_k stands for the conditional probability of $P\left(D_{k-1} \mid D_k\right)$. As a result, the rare event probability is transformed to the following calculation shown in Equation (7).

$$l = \prod_{i=1}^{m} p_i \ , \tag{7}$$

where l stands for probability for rare event.

Let us define the decreasing sequence of subsets D_i where $i = 0, 1, ..., m$. Then, the corresponding rare event probability estimation is shown in Equation (8) below.

$$\hat{l}_{SP} = \prod_{i=1}^{m} \hat{p}_i = \prod_{i=1}^{m} \frac{R_i}{n_{i-1} R_{i-1}} = \frac{R_m}{\prod_{i=0}^{m-1} n_i} \quad , \tag{8}$$

where R_i stands for the simulated values. Then, the estimator for the probability of reaching the highest level shown in Equaiton (9).

$$E(\hat{l}_{SP}) = E\left(\prod_{i=1}^{m} \hat{p}_i\right) = \prod_{i=1}^{m} E(\hat{p}_i) = \prod_{i=1}^{m} p_i = l \quad , \tag{9}$$

3. Applications of Rare Event Simulation on Operational Safety Analysis

3.1 Engineering Projects

Applications of rare event simulation and importance sampling techniques could frequently be found in the reliability engineering field in past research, in order to reduce simulation expenses and increase estimation accuracy. According to Alexopoulos and Shultes (2001), importance sampling in conjunction with regenerative simulation was presented as a promising method for estimating reliability measures in highly dependable Markov systems. L'Ecuyer and Tuffin (2009) and Dai et al. (2012) also considered the Markov chain models and simulation to represent the evolution of multicomponent systems in reliability settings. This is based on dynamic importance sampling and the probability that a given set of nodes was connected in a graph where each link was failed with a given probability. According to Au and Beck (1999), an adaptive importance sampling methodology was proposed to compute the multidimensional integrals encountered in reliability analysis. In the proposed methodology, samples were simulated, as the states of a Markov chain, and then they were distributed asymptotically according to the optimal importance sampling density. Importance sampling was also adopted in structural reliability analysis (Dawson and Hall 2006; Grooteman 2008). The case studies proposed demonstrated that the risk could be a complex function of loadings, the resistance and interactions of system components and the spatially variable damage associated with different modes of system failure.

Severe blackouts due to cascading failures in the electric grid are rare but catastrophic. Consequently, the power system becomes another application focus that rare event simulation and importance sampling concentrated on. Belmudes et al. (2008) proposed an approach for identifying rare events that may endanger power system integrity. The approach was also illustrated on the IEEE 30 bus test system when instability mechanisms related to static voltage security were considered. Wang et al. (2011) also presented an effective rare-event simulation technique to estimate the blackout probability. An IEEE-bus electric network was chosen as the application case, and the most vulnerable link in the electric grid was detected, which has the highest probability of leading to a blackout event. Besides, power system security analysis is often strongly tied to contingency analysis. With variable generation sources such as wind power and due to fast changing loads, power system security analysis has to incorporate sudden changes in injected powers that are not due to generational outages. Perninge et al. (2012) used importance sampling for injected-power simulation to estimate the probability of system failure, given a power system grid state. A comparison to standard crude Monte Carlo simulation was also performed in a numerical example and it indicated a major increase in simulation efficiency.

3.2 Projects of other fields

Monte Carlo techniques and rare event simulation are also widely used in many other fields. In financial engineering, the accurate measurement of credit risk is often a rare-event simulation problem because default probabilities are low for highly rated obligors and because risk management is particularly concerned with rare but significant losses resulting from a large number of defaults. To solve these problems, Bassamboo et al. (2008) derived sharp asymptotics for portfolio credit risk that illustrated the implications of extremal dependence among obligors. Importance-sampling algorithms were then developed to efficiently compute portfolio credit risk via Monte Carlo simulation. Glasserman and Li (2005) also provided an importance sampling procedure for the widely used normal copula model of portfolio credit risk. The procedure had two parts: one that applied the importance sampling conditional on a set of common factors affecting multiple obligors, and the other that applied importance sampling to the factors themselves. The relative importance of the two parts of the procedure was determined by the strength of the dependence between obligors. Besides, in the queueing system, Blanchet and Lam (2014) developed rare-event simulation methodology for the analysis of loss events in a many-server loss system under the quality-driven regime. Heidelberger (1995) also surveyed efficient techniques via simulation for estimating the probabilities of certain rare events. In operational systems, Bee (2009) used importance sampling to estimate tail probabilities for a finite sum of lognormal distributions. And, in public health, Clemencon et al. (2013) focused, in the context of epidemic models, on rare events that might possibly correspond to crisis situations. In biochemical systems, Kuwahara and Mura (2008) proposed an efficient stochastic simulation method to analyze deviations from highly controlled normal behavior in biochemical systems.

4. Case Study on Dam-Reservoir Systems

Dam-reservoir systems are a critical component of water infrastructure, providing services such as water, power, flood control, recreation, and many economic possibilities (Vedachalam and Riha 2014). The successful performance of a dam-reservoir system depends on the aggregate satisfactory performance that prevents a failure and uncontrolled release of the reservoir. However, hundreds of dam failures have occurred throughout U.S. history that have caused immense property and environmental damage and have taken thousands of lives. Take the Lawn Lake Dam failure of 1982, for instance. The sudden release of 849,000 m^3 of water resulted in a flash flood that killed three people and caused $31 million of damage. In 1996, the Meadow Pond Dam also failed with big loss. About 350,000 m^3 of water was released, and resulted in one fatality, two injuries, and damage to multiple homes. In 2006, the Ka Loko Dam burst, resulting in a flood that caused seven fatalities and destroyed several homes. According to the Association of State Dam Safety Officials (2015), 173 dam failures and 587 incidents were reported from January 2005 through June 2013 by the state dam safety programs. Dam failures are not particularly common, but continue to occur (Baecher et al., 2011). The number of dams identified as unsafe is also increasing at a faster rate than those being repaired, as dam age and population increase. In the future, the potential for deadly dam failures will continue to grow.

Potential failure modes for dam-reservoir systems were explored by researchers. Overtopping is one of the most common failure modes for the dam-reservoir systems with significant consequences. According to national statistics, overtopping due to inadequate spillway design, debris blockage of spillways, or settlement of the dam crest account for approximately 34% of all U.S. dam failures (Association of State Dam Safety Officials 2015). Other causes include piping, seepage, internal erosion (Curt et al. 2010), and inadequate maintenance. A similar proportion has also been concluded by Kuo et al. (2008) and Zhang et al. (2009). In general, overtopping is the most common failure cause of dam-reservoir systems, particularly for the homogeneous earth-fill dams and zoned earth-fill dams. Spillways, foundations, and downstream slopes are the potential locations of the risks. Overtopping flows can erode down through an embankment dam, releasing the stored waters, potentially in a manner that can cause catastrophic flooding downstream as well as a total loss of the reservoir.

Due to the stochastic nature of a dam-reservoir system, the dynamics of system operations and corresponding overtopping risks could be modeled through Monte-Carlo simulation. According to Wang and Bowles (2006), a simulation-based model was developed on the breach process at multiple breach locations for a dam with an uneven crest under wind and wave action. Dewals et al. (2010) also applied the simulation of flows induced by several failure scenarios on a real complex of dams, involving collapse and breaching of dams in cascade. As an output, the simulation provided emergency planning and risk analysis, including the sequence of successive overtopping and failures of dams, the time evolution of the flow characteristics at all points of the reservoirs, hazard maps in the downstream valley as well as hydrographs and limnigraphs at strategic locations in the valley. Besides, Tsakiris and Spiliotis (2012) also developed an approach that combined both the simulation and semi-analytical solution, in order to address the dam breach formation caused by overtopping and the resulting outflow hydrograph. Generalized reservoir system operation models include HEC-5, which is the most widely used reservoir operation simulation model, IRIS and IRAS, the SWD SUPER Modeling System, and the WRAP Modeling System.

4.1 Research Gap

Although applications of Monte Carlo methods range widely from estimating integrals, minimizing difficult functions, to simulating complex systems, they are generally expensive and are only applied to problems that are too difficult to handle by deterministic methods. The overtopping events, in most cases, have very small occurrence probabilities. The standard Monte Carlo method is not always the most appropriate tool especially when we deal with those rare events. According to Rani and Moreira (2009), simulation without preliminary screening would be very time consuming, in view of the very large number of options of configuration, capacity and operating policy. Dawson and Hall (2006) also pointed out that the computational expense serves as one of the prohibitive reasons that the simulation technique has not been widely applied to reservoir operations. Minimizing error rates at a reasonable cost and understanding sources of errors are consequently important aspects of these practical problems. In order to save the computational expenses and increase estimation accuracy, rare event simulation has been adopted for efficient estimation, especially on small probability events. As one of the most common rare event simulation techniques, importance sampling is involved in many engineering applications in order to achieve variance reduction.

As an extension of Monte Carlo simulation, the rare event simulation techniques have been adopted in the dam-reservoir system operation. These researches mostly focus on the critical factors such as peak inflow rate, which might lead to the overtopping events (Hsu et al. 2010; Sun et al. 2012). However, overtopping is a complete process. Generally speaking, the water surface elevation in a reservoir is directly tied to the whole storage volume, with either a linear or a nonlinear relationship based on the reservoir shape. As a result, the stochastic inflow rate integrated within a certain period of time would change the reservoir storage, assuming there is no outflow releasing to the system. Overtopping would potentially occur due to the continuous high inflow volumes, even when the annual peak inflow rate is not extreme. Modeling and simulating a whole system is thus beneficial to the final overtopping estimation. Correlations between the inflow rate and the inflow volume are also proven to exist (Goodarzi et al. 2012; Klein et al. 2011; Poulin 2007).

Although overtopping results in significant consequences, in reality, such events have a very low possibility of occurrence for a specific dam-reservoir system.. Those events could be deemed as rare events. Estimation of such rare-event probabilities with crude Monte Carlo simulation requires a prohibitively large number of trials, where significant computational resources are required to reach the satisfied estimation results. Otherwise, estimation of the disturbances would not be accurate enough. Accordingly, computational expense served as one of the prohibitive reasons that the simulation technique has not been widely applied to the reservoir operation. Minimizing error rates at a reasonable cost and understanding sources of errors are consequently important aspects of these practical problems. In order to fill in the research gap, the rare-event simulation technique is thus needed and plays a critical role in evaluating the overtopping risks of dam-reservoir systems.

4.2 Future Work

Based on the current study, future efforts could be made through the following two aspects:

1) The reliable performance of dams and their appurtenant systems depends on the interactions of a large number of natural, engineering, and human systems. More information with available data resources, such as temperature, rainfall and snowfall, could be considered to be involved, as well as their inner correlations, in the future. At the same time, more failure modes would be tracked for the dam-reservoir system through both the crude and importance sampling-based simulations;

2) High performance computing generally refers to the practice of aggregating computing power in a way that delivers much higher performance than one could get out of a typical desktop

computer or workstation in order to solve large problems in science, engineering, or business. The University of Maryland has a number of high performance computing resources available for use by campus researchers requiring compute cycles for parallel codes and applications. Future work can be done in order to take use of those available computation resources and improve the simulation accuracy.

5. Conclusions

This study reviews the past research on the simulation of rare events with very small probability of occurrence. These techniques not only help to accelerate the computation speed, but also increase the estimation accuracy. In the study, two major rare event simulation techniques, importance sampling and splitting, are categorized and compared with their respective advantages and disadvantages. Applications of them are also summarized, especially for the safety management of such complex technological projects. Finally, detailed reviews on the dam-reservoir systems are presented, which serve as the case study demonstrating effectiveness of rare event simulation for complex project operations.

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