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An interval-based approach to model input uncertainty in M/M/1 simulation

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ABSTRACT

This paper presents an interval-based discrete-event simulation (IBS) mechanism to help improve the robustness of simulations that incorporate input uncertainty. This proposed simulation mechanism is based on imprecise probability and models the parameter and model-form uncertainty without the need of sensitivity analysis in traditional simulation practice. The imprecise probabilistic measure given in an interval form is used as the input of simulation in our proposed IBS mechanism, where the statistical distribution parameters have interval values. A parameterization technique for interval probability distributions is proposed in this paper. An interval random variate generation method is used to run the simulation. Uncertainty propagation is achieved by applying Kaucher interval arithmetic. The proposed mechanism is illustrated with an M/M/1 queueing system.

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1. Introduction

In building stochastic simulation models, the maximum likelihood estimation (MLE) method is typically used to choose the statistical distributions and to estimate their parameters from available data. The resulting distributions and parameters used in simulations have precise values. One can argue that the assumption of precise input models is too strong given the epistemic uncertainty associated with the system under study.

Epistemic uncertainty is due to the lack of perfect knowledge about the system. It is also called reducible uncertainty or incertitude and can be reduced by gaining more knowledge to fill the information gap. In contrast, aleatory uncertainty is due to the inherent randomness and dispersion in the system. It is also referred to as irreducible uncertainty, stochastic uncertainty, and variability.

The most important source of epistemic uncertainty related to simulation is due to the lack of data and information. The unavailability of reliable sources of data and information is a common issue when knowledge about the system is sought for. Nevertheless, in some cases multiple data sources are available with conflicting information, which will also puzzle the analyst over which source to rely on. Similarly the solicited experts' judgments and opinions may be conflicting because of their subjectivity and diverse background. The effect of these epistemic uncertainties gets amplified when the analyst does not have the necessary time to deliberate about the most possibly accurate description of physical systems. In addition, measurement errors are embedded in collected data because of the limitations of device, measuring environment, process

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of measurement, and human errors. Finally, the knowledge of dependencies among variables and their time dependency is usually not available.

Given the different nature and sources of epistemic uncertainty, it needs to be differentiated from the aleatory component of uncertainty [27,57]. Probability has been widely used to represent both components of uncertainty. Yet it has limitations in representing epistemic uncertainty. The accuracy of simulation prediction heavily depends on the fundamental understanding of the underlying physical processes. Lack of perfect knowledge and fundamental insight inevitably makes models imperfect. Any assumption made about distributions in simulation has introduced a bias. The most significant limitation of probability is that it does not differentiate total ignorance from other probability distributions. Total ignorance means that the analyst has zero knowledge about the system under study. Based on the principle of maximum entropy, uniform distributions are usually assumed. A problem arises because introducing a uniform or any particular form of distribution has itself introduced extra information that is not justifiable by the zero knowledge. The commonly used uniform distribution where all possible values are equally likely is not guaranteed to be true because we are totally ignorant. This leads to the Bertrand-style paradoxes. Although the Bayesian approach has been proposed to reduce the bias introduced in the distribution assumption, and it serves the purpose well in an ideal situation where we have plenty of data supply to perform Bayesian update extensively, without systematic error or bias in measurement. Yet its limitation remains in the real-world applications where lack of data or imperfect measurement lingers. Other limitations of probability in the context of subjective probability include its lack of mechanisms in capturing the true subjective belief for those who have hesitation and indeterminacy. Inconsistency within a group and ambiguity about beliefs cannot be represented either.

The consideration of input uncertainty in stochastic simulation will improve the robustness of the prediction. Ignoring input parameter uncertainty can significantly reduce the coverage of confidence intervals for the mean hence their reliability is also decreased [6,7]. Epistemic uncertainty needs to be accounted for separately in simulation-based decision making when there is lack of knowledge on probabilities [28], simulation parameters [41], or risk events [26]. Traditionally, sensitivity analysis is conducted by running simulations with modified input parameters, where confidence intervals of the parameters are derived from asymptotically normal distributions and simulations are run with combinations of confidence interval end points. Yet, the drawbacks include the computational cost of multiple simulation runs and the possible abrupt changes of the system performance because the parameter values vary by levels.

The straightforward approach to study the effect of epistemic uncertainty is second order Monte Carlo (SOMC) [39,49,37]. In SOMC, an analyst uses a probability distribution to model distributions' parameters. For instance, a random variate X follows the distribution exponential(Uniform(a, b)). The uniform distribution function here is superimposed on the exponential distribution to characterize the epistemic uncertainty associated with its rate parameter. This representation requires two loops of sampling. The inner loop is the variability loop, whereas the outer loop represents the incertitude of the input parameters. SOMC is easy to implement. Yet, the double-loop simulation is computationally costly. In each replication of the outer loop, the simulation output captures one of the possible scenarios associated with the uncertain parameters. As the number of replications for the outer loop increases, the simulation robustness increases. Usually the analyst is not aware of the number of replications required to achieve a certain level of robustness representing all possible scenarios. Another criticism about SOMC is that it assumes that there is no effect of epistemic uncertainty in a single simulation run. The additional question that has to be asked is whether the analyst has enough information to select the distributions of the input parameters in the outer loop [48].

Bayesian methods were also applied to account for input uncertainty where a prior distribution on each input parameter in the simulation is placed initially then updated based on the observed data [22]. Glynn [33] first proposed a general Bayesian approach to continuously update input distributions with real-world data. Chick [18] established the Bayesian approach into the simulation as an uncertainty quantification technique and suggested a broader range of application areas. Andradóttir and Bier [2] also proposed a Bayesian analysis approach for input uncertainties and model validation. A Bayesian model average (BMA) method was developed by Chick [19–21] where both model and parameter uncertainties are included in the simulation prediction. BMA runs the simulation multiple replications by sampling distribution types and input parameter values and the output is the average of the replication results [44]. The idea of BMA was further improved by Zouaoui and Wilson [58–61] to have more control on the number of simulation replications to be performed. Recently, a Bayesian model that handles many correlated inputs while accounting for epistemic uncertainties was proposed by Bahar and Gunes [5]. The Bayesian methods have been widely used by the simulation practitioners. Nevertheless, the selection of prior distributions as a subjective expression of uncertainty is not helpful to resolve conflicting beliefs when data are limited [25]. Bayesian update itself is computationally costly. The output is not helpful for giving guidance of how to reduce uncertainty.

Resampling was also used in quantifying input uncertainty. Cheng and Holland [15,17] used bootstrapping to quantify the effect of parameter uncertainty for the parametric formulation. Barton and Schruben [7] proposed three non-parametric resampling methods to incorporate the error due to input distributions. These methods use empirical distribution functions to model the distribution functions of independent input random variables. The resampling associated with this method generates new observations which are used to continuously update the input parameters using the MLE to account for its uncertainty. The percentile confidence intervals based on ordered data are recommended for bootstrap calculations. Their estimates are based on a convolution of the epistemic and aleatory uncertainties [35]. Hence, it is not clear how these confidence intervals behave when input uncertainties are included. Recently, Barton et al. [8] introduced metamodel-assisted bootstrapping that produces confidence intervals for the simulation outputs accounting for both types of uncertainties.

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