A Black-Box algorithm to solve Simulation-Optimization problems with chance constraints: general framework and applications

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March 24, 2015

Abstract

Many real world applications lack of reliable analytic models for optimizing the system performance. Even if it is possible to design an analytical model for the problem, this may result either too complex to be managed efficiently by the decision maker or too simple and therefore some complex dynamics of the system can be neglected. Moreover, when stochastic variables are involved in the complex system, their distribution should be known a priori in order to correctly define an analytic model. In many applications, simulation-based approaches are superior to analytic models for investigating complex stochastic systems. Indeed, the system performance can be described by means of a black-box function and there is no need to know the probability distribution of the stochastic components. Moreover, this distribution can change accordingly to the system design variables and stochastic constraints can also be included in the model, thus adding an higher level of uncertainty.

Our framework consider optimization problems where the objective is a black-box function which depends both on the design variables and on the stochastic components which distribution in turn depends on the design variable. There are also some constraints on the design and stochastic variables. In particular in this work we propose an approach that tackles the high computational cost, the black-box formulation and the stochasticity. In recent literature, these features have been addressed separately and, as in stochastic optimization, there is the underline assumption that the probability distribution of the stochastic components do not depend on the design variables.

The optimization algorithm used is based on a multi-start approach to explore the feasible region for the design variable. Then a sample of the stochastic component is generated and its size is adapted dynamically according to a defined criterion which aims to guarantee feasibility in probability. In other words, we define a confidence level to accept a point as feasible and then the sample size is accordingly adapted (it can be different by each design variable). In this way we can control the feasibility and the computational cost of evaluating the model, which is related to the sampling cost.

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