Production processes: How to apply stochastic decision optimization based on deterministic approximations

Mohan Krishnamoorthy1,2, Alexander Brodsky2 and Daniel A. Menasce2

1Argonne National Laboratory, USA
mkrishnamoorthy@anl.gov
2Department of Computer Science, George Mason University, USA
{brodsky,menasce}@gmu.edu

1. Introduction
In this paper, we motivate the need and application of the proposed algorithm called general-Stochastic Optimization Algorithm based on Deterministic Approximations (g-SODA), which solves a one-stage stochastic optimization problem to efficiently search for optimal controls of production processes. More specifically, we (1) describe the problem of performing process control and optimization in production processes, (2) provide the research gap that exists for solving this problem, (3) give an overview of g-SODA, and (4) discuss the application of g-SODA over a dynamic workflow of the production process.

2. Production process control and optimization
Production processes are ubiquitous in diverse areas such as manufacturing, supply chain management, energy systems, power grid and organizational workflows. In essence, production process networks transform certain production inputs – such as raw materials, parts, and physical or information products – into production outputs. Production process networks may involve a hierarchy of sub-processes.

Figure 1 shows an example of the production process for an assembly of a heat sink product. This service network was derived to the authors' best knowledge borrowing parts of its configuration from literature [5]. This service network consists of an aluminum base, a heat sink component, and a set of fasteners. Within the service network, each activity and physical good is represented by an image and a labeled circle, respectively. Vendors can provide raw material, i.e., Alumina Powder, or finished components, i.e., Accessory Package. As an example of a contract manufacturer, the HS Base Contract Manufacture provides the service of machining a part for the product's final assembly.

Within service networks, it is likely that there are multiple paths that provide the same physical good. Often, this is referred to as a multi-echelon supply chain [6]. Procuring the Heat Sink Base presents an example of such a situation. The Heat Sink Base can either be provided by a contract manufacturer or it can be provided by the OEM's own production line, shown in the dotted box in the middle of the diagram. This production line includes two unit manufacturing processes, namely shearing and drilling. Another such example is the procurement of the Aluminum Plate, wherein the OEM operates its own smelting plant or the aluminum bar stock is cut to specifications by another contract manufacturer. The Heat Sink's service network culminates in a relatively complex production line that includes five activities, namely shearing, anodizing, CNC machining, quality inspection, and final assembly.
To operate production processes efficiently, it is critical to solve the problem of finding control settings of underlying services, such as of manufacturing equipment, transportation, sourcing and contractual terms for supply chain components. These control settings must optimize key performance indicators (KPIs), such as cost, carbon emissions, profitability and risk, while satisfying a range of business, engineering and safety constraints.

This problem is especially hard to solve because of the dynamic nature of workflows and the stochasticity in production times, demand, prices and inventories, which effect both the KPIs and the satisfaction of engineering, business and safety constraints. Because of the stochasticity in KPIs and constraints, optimizing a (stochastic) objective means optimizing its mathematical expectation; and satisfying (stochastic) constraints, means guaranteeing that the probability of their satisfaction is above a certain threshold, e.g., 99%.

We assume that the underlying problem is that of one-stage stochastic optimization. This means that after the decision control settings are chosen, the operational environment of the production process may introduce uncertainty, which would result in stochastic outcomes (KPIs and constraints) that do not take into account a future corrective action.

3. Simulation optimization vs. mathematical programming vs. decision guidance analytics

A notable technology for solving this problem is simulation-based optimization. Because the underlying production process may be complex, it is typical to describe it using a simulation program, which computes KPIs and constraints from the input of fixed and control parameters. Simulation-based optimization uses a simulation program as a black-box and performs a search for optimized decision control settings via a trial-and-error procedure, guided by heuristics. However, the general limitation of simulation-based optimization is that the underlying mathematical structure of the model, hidden in a black box, is not utilized.

An alternative to simulation-based optimization for deterministic optimization problems (i.e., that do not have stochasticity) is mathematical programming (MP) optimization. In MP-based optimization, the problem is described in closed analytical form, through equations and inequalities that connect decision variables with the optimization objective and constraints. For deterministic optimization problems, MP utilizes the mathematical structure of the problem and hence it typically gives significantly better results in terms of optimality and computational time.
compared to simulation-based approaches. However, developing MP models is a difficult manual task, which is not modular, extensible or reusable. Even if the model is already described as a simulation program, translating it to an MP model requires operations research expertise and is costly.

Over the last decade, a new paradigm and technology of Decision Guidance Analytics Language (DGAL) and Management System (DGMS) have been developed [2,3]. The uniqueness of DGAL and DGMS lies in the modularity and composability of simulation-like analytic models without the need to manually craft mathematical programming (MP), constraint programming (CP) and machine learning (ML) models, which are instead machine-generated by the system. This results in productivity gain, as well as quality of results and computational efficiency of the best underlying MP, CP and ML algorithms, which significantly outperform simulation black-box-based algorithms. A number of deterministic production process problems were addressed using DGAL and DGMS, including Factory Optima—a system for composition and analysis of manufacturing process networks based on a reusable model repository [4]. However, while DGAL is general enough to express one-stage stochastic optimization problems, its initial implementation supported deterministic, but not stochastic, optimization problems.

4. Stochastic Optimization algorithm based on Deterministic Approximations (g-SODA)

A great advantage of describing a production process as a closed-form arithmetic simulation is that we can now extract a Mathematical Program (MP) of the deterministic approximation from the stochastic simulation by relaxing its stochastic aspects. Hence, this relaxed deterministic approximation can be used in an iterative algorithm to efficiently search for optimal controls in the stochastic search space.

This is exactly the idea behind the proposed algorithm called General Stochastic Optimization Algorithm based on Deterministic Approximations (g-SODA). In g-SODA, the deterministic approximation is used in an iterative algorithm for solving a one-stage stochastic optimization problem of finding process controls that minimize the expectation of cost while satisfying multiple deterministic and stochastic feasibility constraints with a given high probability. What makes g-SODA effective is that it solves an important problem of finding the process control so that the overall cost of operation is minimized in a stochastic environment. And, what makes g-SODA flexible is that it is general enough that it can incorporate multiple types of deterministic and stochastic constraints. Some of the deterministic constraints include upper bounds on the capacity of inventories and processes, and some of the stochastic constraints include stochastic production times and stochastic demand over a time horizon.

5. Application of g-SODA to stochastic process optimization

Using modeling tools, it becomes possible to develop dynamic workflows that accurately describe the stochastic production processes as closed-form arithmetic simulation. For such a dynamic workflow, the end-user or researcher can use the g-SODA algorithm to get precise answers to questions such as:

1. Is it possible for the production process to handle an increase in average demand of the products and/or the variation of the demand over a time horizon?
2. To keep the operational cost optimal, how should the control settings of the production process be adjusted if there is a variation in the average demand over the time horizon?
3. Sometimes it is more profitable to operate processes at a higher capacity at different times of the day or across different months. For example, in some areas, electricity is cheaper at night when the weather is cool outside and there is less demand on electricity. So, in these areas, it may be cheaper for the industry to run their machines at higher capacity during the night. By incorporating this electricity cost variability into the production process model, the question is how should the controls of the production process be set with the objective of maximizing profit?

4. What is the average time required to satisfy demand when the effects of the controls of the production process are stochastic?

5. What is maximum throughput of the production process or to put another way, what is the demand satisfaction capacity of the production process?

6. To satisfy demand, how should the control settings of the production process be adjusted if there is a local failure in one of the components such that the production cost remains optimal?

In this way g-SODA allows the end user or researcher to gain more insights into the workings of a stochastic production process and control them effectively. g-SODA combines the advantages of domain-specific tools that are generally designed for a specific task within a particular domain and that of the MP models that are more accurate in terms of optimality of results and are computationally efficient. Additionally, the workflow and results obtained using g-SODA provide a good way to obtain reusable components of processes that can then be reanalyzed in the future by merely changing certain parameter values or by adding small amount of physics for the new or modified process. An interesting point to note here is that the g-SODA algorithm is general enough that no changes need to be made to the algorithm itself when the underlying production process is updated. This enables the end-user or researcher to reuse g-SODA over many different types of stochastic production processes from different application areas.

References