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Lot size optimization in manufacturing systems: The surrogate method

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ABSTRACT

In this paper we extend a stochastic discrete optimization approach so as to tackle the lot-sizing problem in manufacturing systems. In practice, with the surrogate methodology, the lot sizes are continuously adjusted on-line by the gradient-based approach. The lot sizing determines the number of parts batched together for production. We utilize the queueing approach that evidences the existence of a convex relationship between batch size and waiting time (including processing). Large lot sizes will cause long lead times (the batching effect), as the lot size gets smaller the lead time will decrease but once a minimal lot size is reached a further reduction of the lot size will cause high traffic intensities resulting in longer lead times (the saturation effect). The congestion phenomenon is due to the increased number of setups (and thus total setup time). In this paper, we consider the Surrogate method and the Stochastic comparison algorithm. According to our findings, the Surrogate method finds the optimal solution of the original discrete problem and exhibits a very fast convergence. Some numerical results are reported.

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1. Introduction

The design and control of *discrete event* and *hybrid systems* frequently involve discrete parameters. In designing manufacturing systems, for instance, the determination of buffer sizes and numbers of equipment of some type, fixture or pallets are crucial. Similarly, operating such systems often reduce the control of integer valued thresholds and the so-called *hedging point*. Given the combinatorially explosive nature of the discrete search spaces involved in such systems, they are usually analyzed on the basis of stochastic discrete optimization. The problem of *stochastic optimization* for arbitrary objection functions presents a dual challenge. First, one needs to repeatedly estimate the objective function, when no closed form expression is available, this is only possible via simulation. Second, one has to face the possibility of determining local, rather the global optima. One common approach to solve the *continuous optimization problem* is based on estimated gradient information which drives the optimization process to a minimal point. However, this approach can easily lead to a local minimum. To overcome this problem, it is necessary to allow the optimization process to occasionally move to a bad neighboring point so as to provide the opportunity to jump out of a local minima. While the area of stochastic optimization over continuous decision space is rich and usually involves gradient-based techniques as in several well-known stochastic approximation algorithms, the literature in the area of *discrete stochastic optimization* is relatively limited. Most known approaches are based on some form of random search, with the added difficulty of having to estimate the cost function at every step. Such algorithms have been proposed by Yan and Mukai (e.g., Yan and Mukai, 1992) and Gong et al. (e.g., Gong and Ho, 1987). For this reason the *surrogate method* is proposed (e.g., Gokbayrak and Cassandras, 2001), with this approach the original discrete set is transformed into a continuous set over which a surrogate optimization problem is defined and subsequently solved. As in earlier works an important feature of this approach is that every discrete state in the optimization process remains feasible, so that this scheme can be used on line to adjust the decision vector as operating conditions change over time. Thus, at every step of the continuous optimization process, the continuous state obtained is mapped back into a feasible discrete state; based on a realization under a feasible state, new sensitivity estimates are obtained that drive the surrogate problem to yield the next continuous state. The proposed scheme, therefore, involves an interplay of sensitivity-driven iterations and continuous-to-discrete state transformation. In practice, with the *surrogate methodology*, the discrete optimization is transformed into a surrogate continuous problem where the gradient based approach is used and the discrete problem solution is continuously adjusted on line. The construction of the neighbor is relatively simple and through a careful choice of the step size it is also possible to overcome the possibility of getting stuck in a local minimum. This method has given good results in different areas of application (see Adacher and Cipriani, 2010; Adacher, 2012).

In this paper, we extend a surrogate problem approach so as to tackle the *lot sizing problem* in manufacturing systems (Cassandras and Rui, 2000).

Most research on lot size optimization has focused on single-stage batch production systems. However, in practice it is of interest to optimize performance over multiple processing stages, where stages are not independent. The models in this study consider also

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two stages, where multiple products are produced using the processing stages sequentially. The objective is to minimize total lot flow times across both stages by selecting the optimal lot sizes for each product, and subjecting the remaining constant across both stages.

The paper is organized as follows: in Section 2 we report the literature review, in Section 3 we introduce the lot sizing problem. In Section 4 we show the basic concepts of the stochastic optimization and the stochastic comparison algorithm is extended to our problem. Section 5 provides a framework for the surrogate approach and in Sections 6 and 7 we propose a formulation of the surrogate approach for the lot sizing problem. In Sections 6 and 7 we present some representative numerical results from the application of those optimization approaches to the lot sizing problem. The conclusion is drawn in Section 8.

2. Literature review

In the manufacturing system literature, the main concern is to determine lot sizes of manufactured parts for several future periods that minimize the sum of setup and inventory holding costs over a planning horizon, while satisfying a known demand in discrete time. The study of this problem has its origins in the Economic Order Quantity (EOQ) extended through the years (see Harris, 1913), and eventually formulated mathematically as a mixed integer programming problem with binary variables representing setups for each job-period combination. The problem is NP-hard (Florian et al., 1980), so that various heuristics have been proposed as in Maes and Wassenhove (1988), Absi and Kedad-Sidhoum (2007), Belvaux and Wolsey (2000), Akartunah and Miller (2009), Federgruen and Meissner (2007), Karimi and Ghomiand (2006), Kim and Han (2010) and Kucukyavuz (2009). In addition, extensions to multi-stage lot-sizing problems have been considered in Afentakis et al. (1984), Simpson and Erengue (2005), Sahling and Buschkuhl (2009), Sadtler (2003), and Tempelmeier (2009), where users (parts) go through a sequence of resources (machines) leading to formidable complexity even if one assumes unlimited resource capacities. This line of work is based on discrete-time models, usually assuming fixed setup costs and inventory holding costs, and it ignores random effects in the job arrival and service processes since there is actually no notion of "jobs" in such discrete-time models.

Since the 1980s, several researchers have dealt with stochastic lot interarrival times and the prediction of lot queue or flow times. Karmarkar was one of the earliest to examine the effects of lot-sizing policies using queuing models. Several papers were published describing the impact of the lot sizes on flow times and work-in-process (WIP) inventory. Analysis of the single-product, single-stage problem Karmakar (1987) dealt primarily with M/M/1 and M/G/1 queuing assumptions. Later extensions included multiple product, multiple stage models. The single-stage lot sizing problem of most relevance to manufacturing is one that allows general interarrival time assumptions. Only approximate GI/G/1 queuing relationships can be used since no closed form solution exists. Fowler et al. (2002) investigated lot size optimization in a multiple product, multiple stage production environment through the use of queuing relationships and Genetic Algorithm search techniques. Finally, in Enns and Li (2004) the authors considered the problem of auto-correlation between lot interarrival times in manufacturing systems. It was demonstrated that lot size optimization based on GI/G/1 assumptions worked poorly in a multiple product, single stage environment where lot arrivals were derived from accumulated independent customer demand. A methodology was developed that used dynamic performance feedback to adjust queuing relationships so as to compensate for auto-correlation effects. In general, the costs considered by lot-sizing models are restricted to production, inventory and setup. Some recent reviews of lot-sizing problems can be found in Karimi et al. (2003) and in Brahimi et al. (2006). A new way to solve the "lot-sizing" problem viewed as a stochastic noncooperative resource contention game is presented for a single station in Chen and Cassandras (2012). In Vroblefski et al. (2000) the author puts in evidence that transportation costs are one of the highest costs in the logistics of distributed warehousing. The objective of a firm is to improve the performance of their operations through the adoption of continuous improvement programmes, e.g., reducing set-ups times, increasing production capacity and eliminating rework. The learning curve can be used to describe and predict such improvements see Jaber and Bonney (2003) and Mohamad and Mehmood (2010).

3. The "Lot Sizing" problem

In this paper, we consider the *lot sizing* problem in manufacturing systems. A "lot" in manufacturing systems is a group of parts of similar types that are processed together at a workstation following a "setup" to accommodate this particular part type. When a lot has completed processing, the workstation switches over to a new part type through a setup associated with this new type. Clearly, during a setup the workstation is idle, so it is desirable to minimize the total setup time over a given production period. If lots are small, the workstation engages in frequent setups. If, on the other hand, lots are large, then part types must experience long queueing delays as they await their turn.

Recently the idea of combining batching and queueing models has attracted great attention from many researchers, as it introduces the aspect of time from queueing into inventory theory. Despite queueing delay is an aspect that was almost ignored in the classical inventory models, it is clear that it constitutes a major part of the manufacturing (Hafner, 1991; Karmakar et al., 1985; Karmakar, 1987). Models relating queueing delay to batching represent the production facility as a queueing system with one or more servers where orders (or batches) represent individual customers. We analyze a queue of orders in front of the production facility, but there is no finished goods inventory (once produced, products are immediately delivered to the customer). Karmarkar initiated pioneering work (Karmakar et al., 1985; Karmakar, 1987), the main result from this queueing approach is the existence of a convex relationship between batch size and waiting time (including processing). Large lot sizes will cause long lead times (the batching effect), as the lot size gets smaller the lead time will decrease but once a minimal lot size is reached a further reduction of the lot size will cause high traffic intensities resulting in longer lead times (the saturation effect). The congestion phenomenon is due to the increased number of setups (and thus total setup time).

3.1. Single station

The model can be described as follows: assume a demand process, characterized by individual customer arrivals per time unit. Next we wait until n customers have arrived (batch collection; the batch size n is the decision variable) after which the production facility incurs a setup using τ time units. Finally, the customers are served on a first come, first served basis. Once the individual customer is served, the customers have to wait until the complete batch is finished and then leave the system. We are interested in the time W that customers spend in the system (sojourn time).

The lot sizing problem is a complex optimization problem: lot sizes take integer values defining a large discrete state space, while the system itself operates in a stochastic environment where one can typically only estimate average part system times through direct observation or simulation. The interarrival and process time

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