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Improving spare parts inventory control at a repair shop ☆

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ABSTRACT

We study spare parts inventory control for an aircraft component repair shop. Inspection of a defective component reveals which spare parts are needed to repair it, and in what quantity. Spare part shortages delay repairs, while aircraft operators demand short component repair times. Current spare parts inventory optimization methods cannot guarantee the performance on the component level, which is desired by the operators. To address this shortfall, our model incorporates operator requirements as time-window fill rate requirements for the repair turnaround times for each component type. In alignment with typical repair shop policies, spare parts are allocated on a first come first served basis to repairs, and their inventory is controlled using (s, S) policies. Our solution approach applies column generation in an integer programming formulation. A novel method is developed to solve the related pricing problem. Paired with efficient rounding procedures, the approach solves real-life instances of the problem, consisting of thousands of spare parts and components, in minutes.

A case study at a repair shop reveals how data may be obtained in order to implement the approach as an automated method for decision support. We show that the implementation ensures that inventory decisions are aligned with performance targets.

1. Introduction

High availability of aircraft is crucial for airline operator profitability. Therefore, defective components are replaced by components in good condition during line maintenance, instead of being repaired inside the aircraft. The defective component is then repaired separately, allowing operators to reduce the duration of line maintenance. Independent repair shops perform these repairs on a commercial basis. Component repairs (non-military) generated a turnover of $9 billion in recent years [4].

To enable efficient planning and execution of aircraft line maintenance, airline operators use their bargaining power to pressure repair shops into achieving short repair turnaround times (TATs) [11]. In case of in-house shops, the need for efficient line maintenance planning is typically reflected in business targets for repair TATs [1]. In either case, timely availability of the resources needed for component repairs is key. Assuring spare parts availability is particularly challenging: components may consist of hundreds of parts, any number of which may need replacement to complete a repair. Only inspection reveals which parts are needed in each repair. Thus, demand for each spare part is unpredictable, forcing repair shops to keep large spare parts safety stocks.

Stochastic inventory control methods for safety stock optimization typically set availability targets based on price, leadtime and demand volume. A simple example illustrates the limitations of such approaches: consider a 10-day time-window fill rate target of 98% for each spare part, and a repair of a *critical* component that uses 20 different spare parts. The repair delay exceeds 10 days with a probability of roughly $1-0.98^{20} \approx 33.2\%$ (depending on demand correlations). This disrupts the operators' ability to efficiently perform line maintenance, causing eventual loss of market share for the repair shop. But repair times of 40 days may be acceptable for another component, if it is less critical, if an exchange stock is available, or if it is only used in heavy line maintenance that takes more than 40 days. The spare parts availability targets thus result in overperformance for that component, causing excessive spare parts inventories. So even though short repair times are the prime reason for stocking spare parts, current stochastic inventory models do not provide sufficient control over those repair times.

On initiative of the manager of a repair shop owned by Fokker Services, we developed a model and algorithm to support the inventory analysts in dealing with the above-mentioned difficulties. In the model, availability targets are set on the level of *components*,

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and spare parts inventories follow from those targets. This is the central idea of the spare parts algorithm developed in this paper.

The approach we propose addresses the following properties of the repair shop stocking problem:

1. Inventory decisions are taken for spare parts, while performance is measured on the component repair level. Repairs require multiple spare parts.
2. The shop repairs hundreds of components and stocks thousands of spare parts.
3. Spare parts are slow moving: Demand during leadtime is discrete.
4. Many spare parts are relatively inexpensive and ordering involves fixed costs, so parts should preferably be ordered in batches.

In particular, our algorithm for optimizing (s, S) policies scales to systems of thousands of spare parts and components.

Repair shop performance is measured on the level of component repairs, while each repair requires multiple different spare parts. This distinguishes our work from the majority of the literature on spare parts inventory control. For a review, see Kennedy et al. [16]. In particular, studies of large-scale spare parts networks assume that demands for different spare parts are independent; see Caggiano et al. [8] and references therein. *Multi-indenture* models distinguish components and spare parts, but assume that each component failure is caused by a single spare part failure [22]. The so-called repair kit models form an exception, but the repair kit model differs significantly from our model. In particular, the repair kit problem involves only a single replenishment without leadtime [31,7], whereas our setting involves many replenishments with positive leadtimes over an infinite time horizon.

From a modeling perspective, the problem we consider is an assemble-to-order (ATO) system, yet the interpretation differs from the classical ATO context. In ATO systems, products are assembled from multiple components, while in our setting multiple spare parts are required to repair a component (see Fig. 1). Inventory optimization of ATO systems is well studied, but none of the proposed methods are scalable to the large instances arising at the repair shop. Ettl et al. [13] and Cheng et al. [10] test their methods on 18 product and 17 component systems. These methods might scale to larger systems, but assume base-stock policies, while batching is important at the repair shop. Moreover, their analysis fits normal distributions to demand during leadtime, which gives poor results for slow moving spare parts demands. Indeed, Fig. 2 shows that a normal distribution is a very bad fit for a typical slow moving spare parts demand. Other studies in the periodic review setting include Hausman et al. [14], Zhang [35], Agrawal and Cohen [2], and Akçay and Xu [3]. In a continuous review setting, Lu et al. [21] consider back-order minimization under a budget constraint and Lu and Song [20] investigate cost

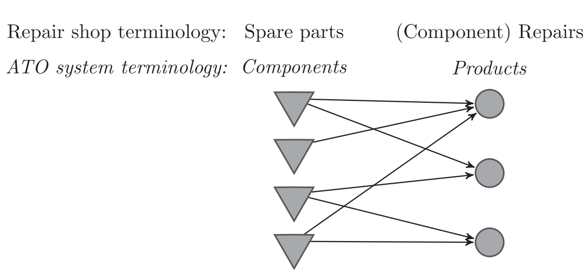

Fig. 1. Schematic representation of a repair shop/*assemble-to-order*(*ATO*) *system*. Inventory is kept for spare parts/*components*, while availability is measured for repairs/*products*.

minimization for product specific back-order costs, but the proposed algorithms can only solve small cases. Song [26] and Zhao and Simchi-Levi [36] study evaluation of performance measures under (r,Q) policies, but optimization is not addressed.

Repair shops typically allocate spare parts on a first come first served (FCFS) basis to component repairs, while spare part inventories are controlled using independent (s, S) policies (de Jong [11], Aerts [1]). These approaches are prevalent in practice because they are easy to implement. For example, once the (s, S) parameters are known one may determine whether a product should be ordered by inspecting the supply chain of that part alone. Mathematical treatises of ATO systems have shown that optimal control would involve coordination of replenishment orders and complex allocation rules (cf. Benjaafar and El Hafsi [6], Doğru et al. [12], Reiman and Wang [23], Lu et al. [19]), but concrete policies have only been proposed and tested for very small systems. Our modeling assumptions match the practice of FCFS allocation and independent (s, S) policies, reflecting our goal to develop a method that is easily implementable in practice. This pragmatic approach matches that of the majority of studies on ATO systems, including those reviewed in the previous paragraph.

We use bounds on performance measures to obtain a surrogate optimization problem, a commonly used approach to handle the intractability of performance measures in ATO systems (see e.g. Zhang [35], Song and Yao [28], Cheng et al. [10], Kapuscinski et al. [15] and Lu et al. [21]). Van Jaarsveld and Scheller-Wolf [33] find that this approach typically has only a limited detrimental effect on the quality of the optimum.

Our algorithm is based on column generation; we appear to be the first to use this approach in an ATO setting. (Others have used the approach for different inventory problems, e.g. Wong et al. [34], Kranenburg and van Houtum [17,18], Topan et al. [32].) The related pricing problem reduces to a separate optimization of the inventory policy for each spare part. These optimizations are carried out efficiently by a novel algorithm which is based on a grid of parallelograms covering the policy space. We derive a lower bound for the costs of policies enclosed in such a parallelogram, which is utilized to determine which areas of the grid need refinement. This pricing algorithm is interesting by itself, because it works under more general conditions than existing algorithms for the single-item problem.

In a numerical study, we find that our automated method for determining (s, S) policies at repair shops solves systems consisting of hundreds of components and thousands of spare parts in a practical time-scale. Our case study reveals that implementing the method at a repair shop improves inventory control by assuring that spare parts inventories are aligned with business targets on component repairs.

The remainder of this paper is organized as follows. In Section 2 we formulate the optimization problem. In Section 3, we describe the optimization algorithm and in Section 4, we present a computational study to evaluate the performance of the algorithm. In Section 5, we report on the implementation of the method at the repair shop. We conclude in Section 6.

2. The optimization problem

In this section, we formulate the optimization problem and the model underlying it. The model is described in Section 2.1. In Section 2.2, we derive bounds on performance measures that are used to formulate the optimization problem, which is given in Section 2.3. In Section 2.4 we discuss the pricing problem associated with our optimization problem.