International Journal of Production Economics 185 (2017) 266–274

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

A heuristic solution method for disassemble-to-order problems with binomial disassembly yields

Karl Inderfurth[a], Ian M. Langella[b,*], Sandra Transchel[c], Stephanie Vogelgesang[a]

[a] *Otto-von-Guericke University, Magdeburg, Germany*
[b] *Shippensburg University, Shippensburg, PA, USA*
[c] *Kuehne Logistics University, Hamburg, Germany*

ARTICLE INFO

Keywords:
Remanufacturing
Disassemble-to-order problem
Binomial yields
Heuristics

ABSTRACT

In disassemble-to-order problems, where a specific amount of several components must be obtained from the disassembly of several types of returned products, random disassembly yields create a formidable challenge for appropriate planning. In this context, it is typically assumed that yields from disassembly are either stochastically proportional or follow a binomial process. In the case of yield process misspecification, it has been shown (see Inderfurth et al. (2015)) that assuming binomial yields usually results in a lower penalty than assuming stochastically proportional yields. While there have been heuristics developed for the disassemble-to-order problem with stochastically proportional yields, a suitable, powerful heuristic for binomial yields is needed in order to facilitate solving problems with complex real-world product structures. We present a heuristic approach that is based on a decomposition procedure for the underlying non-linear stochastic optimization problem and that can be applied to problems of arbitrary size. A comprehensive numerical performance study using both randomly generated instances as well as a full factorial experimental design and, additionally, the data of a practical case example reveals that this heuristic delivers close-to-optimal results.

1. Introduction

In operations management, sustainability requires that demand be fulfilled considering not only shareholder profit but also environmental impact and stakeholder effects, commonly referred to as the triple bottom line. With this aim, reverse logistics and product recovery management have made a substantial contribution, allowing demand to be fulfilled while preserving natural resources and avoiding landfill use (see recent reviews in Agrawal et al. (2015) and Govindan et al. (2015)). Once products are recovered, there are several options on their disposition, classically defined in Thierry et al. (1995). These include material recycling, where products are physically transformed and their material recovered, refurbishing, where returned products are brought to a specified (less than "good as new") quality, and remanufacturing, where products are brought back to a "good as new" standard. Here, remanufacturing has been accepted as an advantageous option for some products, avoiding energy used in material recycling and keeping the value added through component manufacturing, while ensuring that the remanufactured product (in contrast with refurbishing) meets the quality standards of newly produced items and is commonly termed "good as new" (see Lage Junior and Godinho Filho (2012) for a review). There are many examples of remanufactured products, from relatively simple products like single-use cameras to very complicated products like automobile engines (see Priyono et al. (2015) for a detailed process description and several case studies).

Remanufacturing is often (though not always, and our work is not restricted by this) accomplished by the original equipment manufacturer themselves, often in the same facility where newly produced items are made. The process of remanufacturing requires that returned products, called *cores,* are disassembled into their requisite components, called *leaves*. These leaves are inspected, and if found to meet the quality standards of newly produced components, are reassembled into a remanufactured product. Components failing to meet these standards can be made up for be either disassembling more cores or through external procurement. In this scenario, the manufacturer has received certain amounts of several product types back from the sphere of the consumer, and faces a given demand for various types of remanufactured products. With this demand given, the amount of leaves necessary can be computed simply by considering the bills of material, translating demand for products into a dependent demand for the components. A *disassemble-to-order* (DTO) problem then results where a decision must be made as to how many of each core

* Corresponding author.
E-mail address: IMLangella@ship.edu (I.M. Langella).

http://dx.doi.org/10.1016/j.ijpe.2017.01.006
Received 17 February 2016; Received in revised form 20 December 2016; Accepted 7 January 2017
Available online 12 January 2017

should be disassembled to meet this demand. A recent, detailed overview of remanufacturing with several case studies illustrating typical characteristics can be found in Lage Junior and Moacir Godinho (2016).

While this might seem at first glance to be simple, DTO problems are complicated by several issues. Firstly, component part commonality in manufacturing results in the same leaf being present in more than one core type. Secondly, there is substantial uncertainty surrounding the quality of the core and therefore the harvest yield of the leaves. Thirdly, disassembling a certain core results in the release of all of the contained leaves. Considering all three issues it becomes apparent that the disassembly decisions for each core depend on decisions for the other cores, having been made dependent through the leaves they have in common. Further, these decisions must take into account random yields of the leaves, and that in disassembling a core to meet a demand for a certain leaf we may obtain other leaves for which there is no demand and therefore must be disposed of. In this manner, stochastic yields in this context might be thought of as even more complex than in typical production settings where this coupling and interdependence of decisions is not present.

Yano and Lee (1995) and Grosfeld-Nir and Gerchak (2004) provide classic overviews of random yields in lot sizing problems and list the various methods in which stochastic yields can be modelled. These include binomial, stochastically proportional, interrupted geometric, and all-or-nothing yield types. Due to properties of disassembly processes, the two most relevant forms of modeling yield uncertainty for DTO problems are stochastically proportional (*SP*) yield where the yield rate distribution is independent of the lot size and binomial (*BI*) yield where the outcome of a non-defective unit follows a Bernoulli process. From a more technical point of view, both modeling forms have their advantages and disadvantages. While *SP* yield allows to specify both mean and variance of the yield rate, its disadvantage is the assumption that the yield rate must be independent of the lot size. On the other hand, *BI* yield only needs to specify a single parameter, however, it does not allow the variance of the yield rate to be specified independently of the lot size. Empirical data concerning the yield types in disassembly operations are hardly found in literature. Only Inderfurth et al. (2015) have analyzed actual yield data from an engine remanufacturer in the automobile industry to determine which yield type results in a best fit. In this work, it turned out that neither of the two yield types, *BI* and *SP* could definitively be rejected in explaining the empirical yield observations. Additionally, they have examined the impact of a misspecification of the underlying yield type and found that if the yield type is unknown, one should prefer assuming the *BI* yields. Thus, the development of decision support for DTO problems under *BI* yield conditions is obviously a relevant issue.

While the DTO problems with SP yields have already been addressed in literature, solution methods for DTO problems with *BI* yield have not yet been considered in scientific contributions up to now. Due to the specific solution properties, a full enumeration is necessary to determine the optimal disassembly lot sizes for the specific product structure with many cores, many parts and including part commonality under *BI* yield. Thus, for practical problem sizes a well-performing heuristic must be developed to arrive at a solution with reasonable computational effort. This paper now proposes a heuristic approach that is based on a decomposition procedure for the underlying non-linear stochastic optimization problem, which can be applied to problems of arbitrary size. A numerical performance study reveals that this heuristic delivers close-to-optimal results.

The rest of this paper is organized as follows. In the next section, we give an overview of the relevant literature. In Section 3, we will provide a complete problem description and an exact solution method. In Section 4, we will propose a heuristic solution approach which can be used to solve problems of industrially relevant size. In Section 5, we conduct a performance study of the proposed heuristic. Section 6 provides concluding remarks and suggests some possible future extensions for the work.

2. Literature review

In literature, we find many contributions which model production systems with random yields that follow a binomial distribution. Many of them, like Grosfeld-Nir (1995), Braha (1999), and Depuy and Usher (2001), refer to problems of multiple lot sizing in (single- and multi-stage) production-to-order systems where yield losses can be compensated by multiple production runs in order to satisfy a rigid demand level. An overview of this type of random yield production problems which also covers extensions to multiple quality grades and systems with rework activities is found in Grosfeld-Nir and Gerchak (2004). While these contributions refer to single-period problems with random (and often binomial) yields like in our problem setting they do not address the field of product remanufacturing. This is different for a second group of papers which deal with the problem of how many cores should be acquired in a single-period setting with deterministic or random demand if the yield from disassembling is random because of an unknown core quality. In Galbreth and Blackburn (2010) the tradeoff between acquisition, scrapping, and remanufacturing costs is probed in order to arrive at the optimal amount of returned products to acquire. It is shown to which extent the quantity of acquired cores should exceed the demand in order to lower the remanufacturing costs by exploiting cores with higher quality levels. This paper also points out the practical relevance of a single-period planning situation with firm demand, a problem environment that our paper is focusing on. Panagiotidou et al. (2013) also look at the impact of yield uncertainty on returned product acquisition and use sampling and Bayesian learning to decide on how many products to acquire and how much sampling should be done. Zikopoulos et al. (2010) also examine the value of sampling of returns in order to better make procurement and disassembly decisions in a remanufacturing setting where they consider binomial yields and stochastic demands. Teunter and Flapper (2011) address the core acquisition problem under the aspect of multiple core quality classes with multinomial quality distributions for each class. They derive optimal procurement and remanufacturing decisions for both deterministic and uncertain demand. All these contributions deal with procurement decisions of cores in the presence of yield randomness but do it on a very aggregate level. So, only a single core type is considered, and the specific disassembly process into different parts with different yield characteristics is not taken into account. This also holds for papers that refer to the part level in hybrid manufacturing-remanufacturing systems, like the article by Mukhopadhyay and Ma (2009), where the optimal procurement mix of newly manufactured and used components with uncertain recovery yield is determined as input of a production process. Also this type of contribution remains on the level of a single part and a single product and, thus, does not reflect the planning situation where procurement and disassembly decisions are made concerning several types of used products which contain different sets of (partly common) components which are needed in specific quantities as inputs to a remanufacturing process. This issue is, however, specifically accounted for in the following group of articles dealing with general DTO problems which consider many cores with many leaves and include component part commonality.

Within the group of DTO papers, Kongar and Gupta (2002) provide an integer programming solution under deterministic yield assumptions using goal programming to optimize various objectives, one of which is cost. More relevant to the current contribution, Inderfurth and Langella (2003) provide the first contribution to DTO systems under random yields, assuming a *SP* yield model. This work was motivated by the automotive industry where disassembling and remanufacturing of engines has gained particular importance as car manufacturers aim to supply their customers with spare parts as long as possible. In this context, they have developed different procedures to decompose the complex original problem into smaller sub-problems that are easier to handle. In the original DTO problem "many" different parts can be