WORKING PAPER SERIES

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Working Paper No. 29/2012

OTTO VON GUERICKE
UNIVERSITÄT
MAGDEBURG

FACULTY OF ECONOMICS
AND MANAGEMENT

Impressum (§ 5 TMG)

Herausgeber:
Otto-von-Guericke-Universität Magdeburg
Fakultät für Wirtschaftswissenschaft
Der Dekan

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http://www.fww.ovgu.de/femm

Bezug über den Herausgeber
ISSN 1615-4274

How Yield Process Misspecification Affects the Solution of Disassemble-to-order Problems

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Abstract

Random yields from production are often present in manufacturing systems and there are several ways that this can be modeled. In disassembly planning, the yield uncertainty in harvesting parts from cores can be modeled as either stochastically proportional or binomial, two of these alternatives. A statistical analysis of data from engine remanufacturing of a major car producer fails to provide conclusive evidence on which kind of yield randomness might prevail. In order to gain insight into the importance of this yield assumption, the impact of possible yield misspecification on the solution of the disassemble-to-order problem is investigated. Our results show that the penalty for misspecifying the yield method can be substantial, and provide insight on when the penalty would likely be problematic. The results also indicate that in the absence of conclusive information on which alternative should be chosen, presuming binomial yields generally leads to lower cost penalties and therefore preferable results.

Keywords: Remanufacturing, Disassembly, Random yields, Disassemble-to-order problem, Binomial yields, Stochastically proportional yields.

1 Introduction and Literature Review

1.1 Motivation

Conducting sustainable operations demands that firms incorporate environmental concerns and stakeholder points of view alongside shareholder profit. Product recovery management (PRM) and reverse logistics have been seen as an integral part of sustainability, allowing for increased revenue and reduced environmental burden, as shown in e.g. Atasu et al. (2008), Wu and Pagell (2011). Within PRM, remanufacturing, when a firm takes returned products, disassembles them, inspects the parts, and reassembles these parts into "good as new" products has received much attention and is generally accepted as one of the more advantageous (both in terms of revenue as well as environmental burden) product recovery options. Examples of products that are remanufactured include relatively simple products such as Kodak single use cameras (Guide et al. (2003)) and waste electronic and electrical equipment (shown in Webster and Mitra (2007)) to complicated items like jet turbine engines (Guide and Srivastava (1998)) and Xerox photocopiers (Guide et al. (2003)).

Remanufacturing is usually done in an industrial setting where varying products from a certain manufacturer are disassembled and reassembled. In order to reassemble products, a certain number of parts must be available, as can be calculated by examining products' bills of material. These parts are gained (mostly) from the disassembly of returned products, and might be obtainable from external vendors. A disassemble to order problem concerns itself with how many of each type of returned product to disassemble in order to meet this demand. This problem is complicated by several factors. First, the same part might be contained in several products, an aspect referred to as commonality. Second, since these returned products differ in regard to quality, a stochastic yield problem results in which one is never sure how many good quality parts will be harvested from the disassembly of a certain returned product (see e.g. Guide (2000) p. 474-475 and 479-480). This is somewhat akin to a production yield problem in which one is unsure how many good quality items will be produced by an unreliable production process, as is seen in practice e.g. semiconductor manufacturing. The impact of random yields can be seen not only in operational issues like production scheduling (e.g. New and Mapes (1984)) but also in strategic-tactical level decisions like location and capacity (Bohn and

Terwisch (1999)). As a matter of fact, this problem with stochastic yields is more complex than standard stochastic production yield problems. This is because in the most general case, with many products, some of whom have common parts with other products, joint disassembly decisions must be made which consider not only each leaf contained in the considered product, but also other disassembly decisions of products with common parts and their yields. In this manner, the disassembly decisions of the products are linked through the stochastic yields of the others which contain common parts. In general, it is not possible to simply separate these problems to allow for a decomposed optimal solution.

Until now, most approaches to incorporate stochastic yields into planning have assumed stochastically proportional random yields, which presumes that the yield rate distribution does not change by increasing or decreasing the number of products disassembled. Another stochastic yield modeling approach, binomial random yields, deviates from this property and assumes independence of each unit's yield within an assembly lot. There has been absolutely no attention paid in the literature as to how to discern between these two approaches in practice, i.e. how to test whether or not this critical assumption can be presumed.

Using actual yield data obtained confidentially from an industrial partner, we will first test to see if it can be concluded which modeling approach is more fitting for the data. This will first require selecting an appropriate statistical test, since literature provides little advice. The contribution will also aim at exploring the sensitivity of decisions to assumptions of random yield modeling methodologies. Our results will (1) highlight differences between these two modeling alternatives, (2) provide guidance to others on statistical tests to use in testing the assumption in practice, (3) show the practical application of testing real world data and illustrate typical results, and (4) explore how misspecification of the yield type might impact the results.

1.2 Relevant Literature

In this section, we will start by examining stochastic yield literature in general, where differing modeling approaches are presented. We will then review some contributions to random yield literature in remanufacturing and finally focus on the disassembly problems with stochastic yields.

Yano and Lee (1995) provide a classic reference, a comprehensive review of dozens of contributions to the field of stochastic yields in lot sizing. The review starts by discerning modeling approaches, something we will later draw on. In their work, they review contributions differentiating between continuous and discrete time, single and multiperiod models, also including assembly, rework, and coproduction systems.

Another noteworthy review is afforded by Grosfeld-Nir and Gerchak (2004), where the emphasis is more on multistage production systems.

A more specific recent review of modeling for semiconductor manufacturing is given by Kumar et al. (2006). Several issues unique to the industry, viz. special defects and radial yield losses, are examined. The work also contains remarks concerning the periphery of the system in complex manufacturing systems.

Ben-Zvi and Grosfeld-Nir (2007) examine serial systems that must fulfill a rigid demand. Their analysis includes binomial, interrupted geometric, and all-or-nothing yields, and the work provides a heuristic for such serial production systems.

Tajbakhsh et al. (2010) examine lotsizing under binomial yields in a context where the yields can be improved by increasing the order cost and unit costs. They formulate and compare two models, a return model and a repair model.

Teunter and Flapper (2006) examine random yields in production and rework, in a context stemming from their work with a pharmaceutical concern. Here, the decisions include when to remove a batch from the production tank and send it to bottling, since rework can only take place before bottling.

Production planning at a sawmill is planned by Zanjani et al. (2010), where random yields are incorporated by way of a recourse model where different scenarios result in yield coefficients which are subject to certain probabilities. In this work, they are obtaining a yield distribution that can be employed by sampling output obtained from 300 logs, yielding a yield distribution which can be utilized by the recourse model.

One outcome of surveying these contributions is that several different types of yield randomness are modeled, mainly stochastically proportional, binomial, and interrupted geometric yield. Additionally, no literature is found which uses real-world yield data in order to test which yield model might fit best. This also holds for the next articles which deal with yield uncertainty in remanufacturing systems, providing some recent, more problem-specific contributions from literature.

Bakal and Akcali (2006) deliberate the effects of yield uncertainty on remanufacturing systems and its impact on pricing. In their paper, the demand for remanufactured items as well as supply of returned products is influenced by the prices offered. They also examine the impact of yield uncertainty on profitability of the remanufacturing operation as well as the value of information in the context.

Galbreth and Blackburn (2006) point out that through sorting policies, policies which decide which returns are to be remanufactured and which returns would be relegated to material recycling, yield uncertainty can be diminished. The authors analyze how many returned products should be obtained from a third party. Naturally, the more unsorted returns acquired, the more selective the remanufacturer can be on deciding which returns to remanufacturer. This work was extended in Galbreth and Blackburn (2010) by more completely incorporating the trade-off between acquisition cost, remanufacturing cost, and disposal costs in the system. The authors show how their methods are applied on cases stemming from their experience with cell phone and imaging equipment manufacturers.

Ferguson et al (2009) analyze a remanufacturing system based on experience with postage and mailing machines. Here, the yields of disassembly were random and influenced by the quality of the returned products. The returned products were able to be graded and customers would receive a higher amount for better quality returns, and due to better yields these returns also resulted in less remanufacturing cost. Through incentivizing better quality returns and receiving better returns resulting in lower remanufacturing costs, substantial cost savings were realized.

Mukhopadhyay and Ma (2009) consider a joint system where new and recovered components can be used for remanufacturing, discerning between long and short lead times for new parts. They model yields from product recovery using the stochastic proportional approach and provide insight into the value of information in this context, which also includes demand stochasticity.

Teunter and Flapper (2011) consider multiple classes of returned products and develop optimal procurement and disassembly decisions for both deterministic and stochastic demand, emphasizing the impact of yield uncertainty. Here, unlike in a disassemble-to-order problem, there is only one part needed for remanufacturing, commonly interpreted as a single critical major part for which yields are random.

Panagiotidou et al (2012) examine optimal procurement decisions under random yields in remanufacturing, where a recovered item is either remanufacturable or not. The authors illustrate the impact of sampling on this context, where Bayesian learning allows for better return procurement decisions.

Lastly, and most recently, Tao et al. (2012) probe a remanufacturing setting with stochastic yields, demand, and supply of returned products. Here, like Teunter and Flapper (2011) they restrict their analysis to one product and one item needed for remanufacturing.

The last group of articles is more specifically concerned with yield uncertainty in disassemble-to-order systems with complete disassembly, most closely related to this contribution.

In this area, Inderfurth and Langella (2003) provide the first contribution to disassemble to order systems under stochastic proportional yields. The work was extended in Inderfurth and Langella (2006) providing single period heuristics of varying complexity developed by decomposition. Langella (2007) extends this somewhat for planning multiple periods, providing and testing heuristics for the multiperiod problems in addition to developing heuristics for deterministic yield cases with and without constraints on returned items. Inderfurth and Langella (2008) provide recourse model formulations for both the single and multiple period problem with stochastic yields and provide a glimpse into the computational complexity of models.

A similar stream examined the disassemble-to-order problem under multiple decision criteria. Imtanavanich and Gupta (2004) first extend the deterministic yield problem put forth by Kongar and Gupta (2002) utilizing the adjusted yield values put forth in Inderfurth and Langella (2006). This is then further extended to the multiple period case by Imtanavanich and Gupta (2005). Most recently, Kongar and Gupta (2006) examine multicriteria decisions under uncertainty in disassemble to order systems by using fuzzy goal programming to determine the right mix of products to be disassembled to meet a specific demand for the leaves.

In the preceding remarks, we have focused only on disassemble to order problems with complete disassembly under stochastic yield conditions. For a more broad and comprehensive review, including deterministic yield, multi period, and incomplete (single product) disassembly, the reader is referred to Langella (2007, pp. 12-16).

The unique contribution of this study is twofold. First, based on an analysis of empirical data from the disassembly area, we investigate which types of random yield processes can be identified in practice. Given these findings, we show how different yield models can be incorporated in disassemble-to-order problems and analyze which drawbacks we have to expect in solving these problems if we misspecify the yield process and use the wrong yield model.

1.3 Outline

The remainder of this paper is organized as follows. In the following section, we will begin by introducing the disassemble-to-order problem and the impact of yield uncertainty in complicating its solution. In the third section, we will examine the two relevant (stochastically proportional and binomial) methods to model yield uncertainty and describe how real industrial data was tested to determine whether one of the two modeling approaches best fit. In the fourth section, we will examine how sensitive solutions to the problem are when the yield process is misspecified. Concluding comments and an outlook on future research is afforded in the final section.

2 Disassemble-to-order problem and yield uncertainty

In this section, we will begin by introducing the disassemble-to-order problem. This will be followed by an examination of the effects of yield uncertainty on planning in this realm.

2.1 The disassemble-to-order problem

The disassemble-to-order problem stems from demand driven remanufacturing planning. In remanufacturing, products are taken back from consumers either at the end of their useful lives or the end of their use by consumers. These returned products, called *cores*, are collected and transported back to a remanufacturing facility where they await disassembly. Once disassembled, the parts, called *leaves,* are inspected to good as new quality standards. Any leaves which fail to meet these standards are either replaced by new components or leaves harvested from the disassembly of another core. The leaves are then reassembled into a remanufactured product that by its very definition meets the quality standards of a newly produced item. From the firm's side, it produced additional revenue and from the planet's point of view it saves the landfill space needed to dispose of the core and the virgin material consumption needed to produce the new product.

In demand-driven remanufacturing, a certain specified demand for remanufactured products is given. In the authors' experience with automotive engine remanufacturing operations, it is very often the case that the demand is specified by marketing and distribution. Once the demand for remanufactured products has been specified, the number of leaves which must be obtained can be calculated through a material requirements planning bill of material explosion. A disassemble to order problem is concerned with calculating the number of cores to disassemble in order to fulfill this demand.

As shown in *Figure 1*, the cores, represented by numbered boxes on the left side of the diagram, are collected from the marketplace, transported to the remanufacturing facility, and sorted by type, to await disassembly. On the demand side, remanufactured units are requested and this translates itself into a gross requirement of various leaves by a bill of materials explosion. The leaves are shown as lettered circles. With demand for leaves described above, the question becomes how many of each core should be disassembled in order to meet this demand, given that some of the leaves are contained in more than one core, and the yields of these leaves are stochastic. This disassembly decision is also affected by the opportunity to procure missing leaves externally, usually, however, at a higher cost.

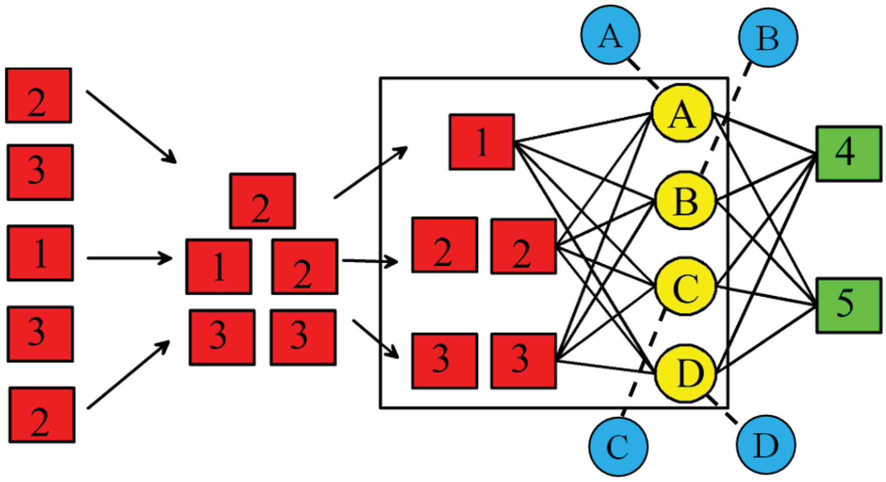

Figure 1: A depiction of the disassemble-to-order problem in remanufacturing

Disassemble-to-order problems can be classified according to several criteria. One can first discern between single and multiple core problems, where the former simply seeks to determine the number of single products to disassemble, and the latter must make disassembly decisions for several cores. It can be seen that in the absence of (any) commonality, multiple product problems can be separated into single product problems, and a decomposed solution will be optimal in the multiple product case.

Next, we can differentiate between single and multiple period problems. In the former, only one period's demands are specified, and there is no need or ability to hold leaves obtained by disassembly for future demands. In the latter, holding leaves harvested in one period and not immediately needed for reassembly can satisfy future demand, with given holding costs.

Additionally, one can discern between single or multilevel problems. In the former, only cores and leaves are considered and a decision to disassemble a core results in complete disassembly to the leaves. In multi-level disassembly, additional items called intermediate items, which are neither cores nor leaves, but subassemblies of some leaves contained in a core, are considered. In these models, partial disassembly can take place where some subassemblies are immediately further disassembled and others are not. Here, one can hold the subassembly for further disassembly (in e.g. a capacitated disassembly situation) or dispose of the subassembly should the leaves contained therein be redundant.

Lastly, one can additionally distinguish between problems which contain stochastic elements and those who do not. Stochastic elements could include the yield, which we have previously discussed results from the quality uncertainty surrounding the recovered core, and the demand for parts, as would be the case if parts harvested for disassembly were being used to fulfill demand for spare parts.

Within this classification, our contribution would fall within the group where multiple products are disassembled (including part commonality) in a single period, under complete disassembly conditions (i.e. single level) with deterministic demands and stochastic yields from disassembly. There are several costs which are relevant to this decision. First, the cost to procure the core, transport it to the facility, disassemble it completely, and inspect the leaves is called the *core cost*. Leaves which must be replaced must be obtained at a *leaf procurement cost* and they will be sourced either from the same supplier who supplied manufacturing operations or from an alternative supplier due to the typically small amounts of demand once the product is no longer manufactured in mass. Lastly, a *leaf disposal cost* is incurred when an unneeded leaf is disposed of. This cost can be positive or negative, the former being a landfill cost and the latter occurring when revenue is generated from e.g. material recycling. In the authors' experience with several industrial partners, this can often be negligible, since a small amount of revenue is gained but the leaves must be handled and transported to the recycler.

There are a couple of reasons why this disassemble-to-order problem is difficult to solve. First, it is often the case that there is commonality in the leaves, i.e. a certain leaf is contained in more than one core. This is due to component commonality in manufacturing, a commonly known mechanism to reap scale economies in production and procurement. With commonality present, a leaf can be harvested from several different cores, and this will require deliberating which core is best to source the demand from. This will depend on several things, most obviously the core cost, but less obviously on the fact that the disassembly of a core will result generally in some leaves which will be immediately needed and others which may not be immediately needed. This becomes even more complicated in a multi-period setting where inventory of leaves will effectively decouple supply and demand. The second complication of planning disassembly for remanufacturing is the fact that yields from disassembly are almost always stochastic.

Since our contribution is focused on the impact of the yield model choice on the quality of disassembly decisions, we will restrict our analysis to a more simple to analyze single-period problem setting. In this case, the disassemble-to-order problem under stochastic yields can be formulated as a non-linear optimization problem. To this end we introduce some general notation which will be used in the following section. The size Q_i of a disassembly lot for a specific core i from a set of I cores generates a random yield $\tilde{Y}_{ik}(Q_i) \leq Q_i$ for each part k from a set K incorporated in this core.

The optimization problem then can be described as follows:

$$\begin{aligned} MIN\ \ C(Q_i \mid i \in I) = \sum_{i \in I} c_i^z \cdot Q_i &+ \underset{\tilde{Y}_{ik}}{\mathrm{E}}\left[\sum_{k \in K} c_k^p \cdot \max\left\{ D_k - \sum_{i \in I} \tilde{Y}_{ik}(Q_i); 0 \right\} \right] \\ &+ \underset{\tilde{Y}_{ik}}{\mathrm{E}}\left[\sum_{k \in K} c_k^d \cdot \max\left\{ \sum_{i \in I} \tilde{Y}_{ik}(Q_i) - D_k; 0 \right\} \right] \end{aligned} \tag{1}$$

Here it is already incorporated that under the described conditions it is always optimal to satisfy demand D_k for part k and purchase new parts if demand exceeds the respective yield, and to dispose of excess parts if the yield is higher than demand. The corresponding purchasing and disposal costs per leaf k are given as c_k^p and c_k^d respectively. Therefore, the remaining decision variables are the disassembly batch sizes Q_i of the different cores which always have to be non-negative. Each disassembling operation results in disassembly costs c_i^z for core type i. From this problem description it is obvious that the optimal solution strongly depends on the specific yield process $\tilde{Y}_{ik}(Q_i)$ that transforms the cores' batch quantities in yield quantities for the respective parts.

2.2 Uncertainty in the yield of disassembly

In our remanufacturing setting, it is easy to see why yield randomness might present even more of a problem than it does in traditional settings. First, the yields from disassembly will depend on how the product was used (and otherwise treated, e.g. stored) during its life or use by the consumer. Second, each leaf might be more or less able to withstand or resist wear and tear i.e. leaves will have differing degrees of durability. Lastly, disassembly is known to be a very manual process, and operator skill will also affect the yields of disassembly with more skilled workers being presumably better able to successfully harvest leaves from cores.

It is also the case here that commonality further complicates this since different cores will very likely have differing disassembly yields for the same leaf. This will, in a similar fashion to differing core costs, make a straightforward decision far less likely.

In the following we will assume that the yields of different parts (or groups of parts) from the same core are not correlated, since from literature we did not find any evidence for correlation. The outcome of each disassembly lot Q_i can be described by its yield rate, defined as $\tilde{Z}_{ik} = \tilde{Y}_{ik}(Q_i)/Q_i$. Depending on the type of the yield process, the yield rate mean and variance might be affected by the batch size Q or not. Since this will have a major impact on the optimal disassembly policy, it is important to identify which yield model will represent the underlying random yield process in the best way. In the next section we will describe the most important yield models in this context and discuss their appropriateness, based on an empirical study.

3 Types of yield randomness: Theoretical models and empirical findings

In this section, we will start by reviewing various methods for modeling yield uncertainty, concentrating on the two methods most applicable to this research. We will then present some empirical findings obtained by testing real disassembly yield data from a large automotive manufacturing partner.

3.1 Theoretical modeling alternatives

There are several methods to model yield uncertainty, e.g. addressed in the classic reference Yano and Lee (1995). In our study we only concentrate on two types that are commonly used in literature to model supply uncertainty: stochastically proportional and binomial yields. They will each be briefly described in the following:

- **Stochastically proportional.** Under this method, the quantity of remanufacturable parts is the product of input (i.e. lot size Q) and a random variable representing the proportion of good (reusable) items (the yield rate $\tilde{Z}$). This can be denoted as $\tilde{Y}_{ik} = \tilde{Z}_{ik} \cdot Q_i$. Here the yield rate's distribution, along with its mean and variance, can be independently specified and does not depend on the lot size itself, allowing for greater modeling freedom. As noted in Yano and Lee (1995), this is an appropriate modeling approach when production is affected by process conditions which vary randomly from lot to lot or when the quality of input materials will change unpredictably in different lots. In the remanufacturing context, especially varying skills within and working conditions for different disassembly teams might cause such a yield type.
- **Binomial.** Here, the yield of the disassembling process follows a typical Bernoulli process, where the yield that results depends on the probability of success of each trial and the number of trials which is equal to the lot size Q. The total yield $\tilde{Y}_{ik}(Q_i)$ is binomially distributed with success probability $\hat{p}_{ik}$ which is equal to the expected yield rate. Under these conditions, the yield rate variance equals $\hat{p}_{ik} \cdot (1 - \hat{p}_{ik}) / Q_i$ and, thus, obviously depends on the lot size. Assumptions of this method include dichotomous outcomes with a fixed probability of success and independence of the outcome of one trial from another one. Such a situation can be expected if the disassembly process is stable and the quality of cores is independent between cores within a lot.

As mentioned in Yano and Lee (1995) there exist more than these two options to model the outcome of production processes. Additional modeling approaches would include (1) all or nothing, where a process will either yield perfect output or no good output at all, (2) stochastically decreasing (sometimes referred to as interrupted geometric) where after a random amount of time a process delivers only bad quality items, before which it delivers only perfect items, and (3) stochastically increasing, where after a certain amount of time a process will deliver perfect output, before which it delivered only bad items. We can note that examining the actual yield data makes it clear that none of these three alternatives appear relevant. For disassembly operations both stochastic proportional and binomial models seem to be relevant, but up to now we are not aware of any literature that analyzes if one of the yield modeling approaches can be used to model a real data set that stems from a disassembly process. In the following subsection, we will test actual disassembly yield data to see which of the modeling approaches best fit the data.

3.2 Empirical testing of industrial disassembly data

The given dataset was obtained from a German car manufacturer that disassembles used engines and remanufactures parts that are reusable. Amongst others it contains the daily amount of disassembled engines of about three months, that is more precisely 19 days for engine type one (*E1*) and 37 days for engine type two (*E2*). In the following histogram (see *Figure 2*) one can see that the quantity of engines that are disassembled per day (disassembly lot) for *E1* is in between 2 (once only) and 13 (six times) whereas it varies between 1 and 19 for *E2*.

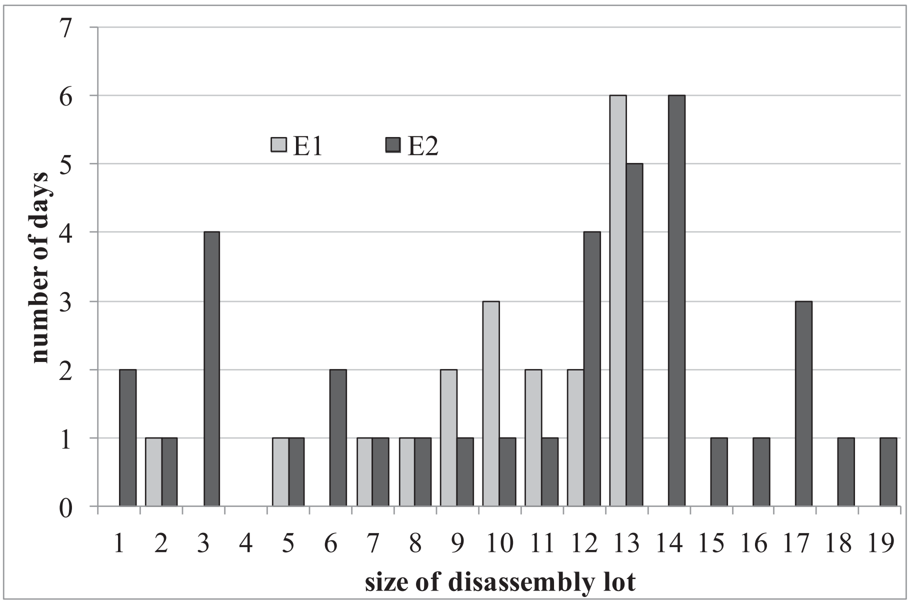

Figure 2: Number of days and disassembly lot for each engine type

Additionally to the daily quantity of disassembling operations we received information about the outcome (disassembly yield) of the disassembly process for roughly 30 major parts whether or not it is possible to remanufacture them and reuse them as a good as new part to satisfy the customer demand. This yield data set consists of streams of zeroes and ones where a one indicates that the part was successfully harvested and is available for remanufacturing and zero if not. With this data on hand we were able to calculate the percentage of reusable parts (yield rate) for each disassembly lot and determined the frequency distribution and corresponding box-and-whisker plots for three different parts of *E2* (see *Figure 3*).

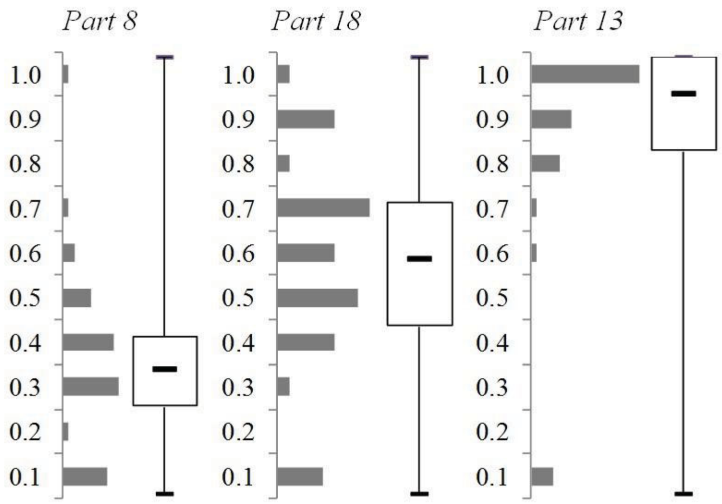

Figure 3: Histograms of yield rates for three different parts that are contained in *E2*

Here we can see that there is not only a high yield rate variability for a part itself but also the differences between the yield rates of parts that stem from the same engine type can be very different.

In order to test the industrial data, we must first identify characteristics of the two contrasted yield modeling alternatives that can be used to discern between the two. Considering first the stochastically proportional yield, we are reminded that the variance of the yield rate σ_Z^2 must remain constant for differently sized lots. For this, we will use the Brown-Forsythe test (Brown and Forsythe (1974)) for equality of variances between two groups of lots, one large and one small. With binomial yields, however, we expect an independent occurrence of defectives. Here, a chi-squared test can be used to test if the total yield resulted from a binomial process with an expected success probability. We will further elaborate on each in the following paragraphs in turn.

To test for proportional yield, we conducted a test comparing small lots to large lots. In doing this, we selected two of the five engine types to analyze in more detail, the engine types *E1* and *E2* since we gain the most extensive data sets for these engines. For engine type *E1* we created a group called “large” that contains lots with an amount of 12 and 13 and a group called “small” with all lots between 5 and 11. In each case, the lots were standardized to 12 and 5 respectively by discarding remaining yield values. This results in nine lots in each group. For the "small" group of engine type *E2* we composed lots with a size between 6 and 13, while the "large" group contained lots of an amount between 14 and 19. Again, the lots were standardized to lot size of 6 and 14, with remaining values discarded as well as lots of less than 6. Following this procedure we get 16 "small" lots and 13 large lots. Having these small and large lot-groups on hand we employed a *Brown-Forsythe-Test* to test for equality of variances between the two groups, see Brown and Forsythe (1974). In testing for binomial yields, a *Chi-Square-Test* (χ^2) was used to test if the yields resulting from each group fit the binomial distribution.

The results of these tests are summarized in *Tables 1 and 2* for some parts of *E1* and *E2* respectively for a significance level of 0.05, where a minus sign (-) indicates that the null hypothesis, that the data can stem from one of the two mentioned yield models, is rejected and a positive sign (+) that it fails to reject the null hypothesis. As it can be seen in the tables, there is no clear picture which yield model might fit better. It can be seen for some parts the binomial model is rejected while for others it is not. For most parts (and this also holds for the ones omitted in the tables) both yield types are candidates for explaining the empirical findings. To some extent, this ambiguity might be caused by small sample sizes of our empirical data. Be that as it may, on the basis of the available data set none of the two yield models can be excluded from the set of potential approaches when modeling the random yield situation. Since this might be the case in many practical situations it is important to get some insight into the extent of error that occurs when decisions are made under misspecification of the yield process.

Table 1: Results for engine type *E1*

Part #	χ^2 *(lot size 5)*	χ^2 *(lot size 12)*	**Brown-Forsythe**
1	-	+	+
2	-	+	+
3	-	+	+
…			
11	+	+	+
12	+	+	+
…			
27	+	+	-
28	+	+	+
29	+	+	-

Table 2: Results for engine type *E2*

Part #	χ^2 *(lot size 6)*	χ^2 *(lot size 14)*	**Brown-Forsythe**
1	-	-	+
2	-	-	+
3	-	-	+
…			
11	+	+	-
12	+	+	-
…			
27	-	-	+
28	+	+	+
29	+	+	+

4 Comprehensive performance study on yield misspecification

4.1 Design

In this section, we will examine how sensitive decisions are to the selection of the modeling approach and ascertain the quality of solutions in situations where the modeling approach has been misspecified. We can begin by defining two cases:

- Case *SP* comprised the situation in which the yields were assumed to be binomial but in fact were stochastically proportional and
- Case *BI* occurs when yields are binomial in reality, but were falsely presumed to be stochastically proportional.

In each of these cases, a penalty will result from using the wrong modeling alternative. The respective penalties (cost deviations in percent) are given below:

$$\Delta_{SP} = 100 \cdot \frac{C_{SP}(Q_{BI}^*) - C_{SP}(Q_{SP}^*)}{C_{SP}(Q_{SP}^*)} \tag{2}$$

and

$$\Delta_{BI} = 100 \cdot \frac{C_{BI}(Q_{SP}^*) - C_{BI}(Q_{BI}^*)}{C_{BI}(Q_{BI}^*)} \tag{3}$$

where C_{SP} and C_{BI} represent the costs for stochastically proportional and binomial models, respectively, and analogously Q_{SP}^* and Q_{BI}^* represent optimal decisions of the proportional and binomial models, respectively.

For this study, we rely on a simple product structure for which optimal policies and expected costs can be calculated. This simple two core three leaf structure, originally utilized in Inderfurth and Langella (2006) is shown in *Figure 4*. Note that 1 and 2 represent the cores (engine type *E1* and *E2*) and A, B, and C represent the leaves. We can see that leaves A and C are unique to cores 1 and 2 respectively while leaf B is common to both cores. This is a simplification worthy of some justification. With this relatively simple two core three leaf structure, we can analyze a multiple core problem where each core has one unique leaf and share one common leaf. More complicated and realistic structures would not allow for an easy calculation of optimal decisions necessary for the analysis. Empirically the simplification can be thought of as a situation where there is one common part which is expensive or particularly critical for remanufacturing.

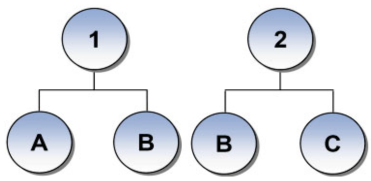

Figure 4: Product structure of the underlying study

Under stochastically proportional yield and for the given product structure the cost function given in (1) results in

$$
\begin{aligned}
C_{SP}(Q_1,Q_2) = {} & \left(c_1^z \cdot Q_1 + c_2^z \cdot Q_2\right) \\
& + c_A^p \cdot E\left[\max\left\{\left(D_A - \tilde{Z}_{1A} \cdot Q_1\right);0\right\}\right] + c_B^p \cdot E\left[\max\left\{\left(D_B - \tilde{Z}_{1B} \cdot Q_1 - \tilde{Z}_{2B} \cdot Q_2\right);0\right\}\right] \\
& + c_C^p \cdot E\left[\max\left\{\left(D_C - \tilde{Z}_{2C} \cdot Q_2\right);0\right\}\right] + c_A^d \cdot E\left[\max\left\{\left(\tilde{Z}_{1A} \cdot Q_1 - D_A\right);0\right\}\right] \\
& + c_B^d \cdot E\left[\max\left\{\left(\tilde{Z}_{1B} \cdot Q_1 + \tilde{Z}_{2B} \cdot Q_2 - D_B\right);0\right\}\right] + c_C^d \cdot E\left[\max\left\{\left(\tilde{Z}_{2C} \cdot Q_2 - D_C\right);0\right\}\right]
\end{aligned} \tag{4}
$$

Assuming binomial yields the cost function in (1) can be reformulated as

$$
\begin{aligned}
C_{BI}(Q_1,Q_2) = {} & (c_1^z \cdot Q_1 + c_2^z \cdot Q_2) \\
& + c_A^p \cdot \sum_{Y_A=0}^{\min\{D_A-1;Q_1\}} \left[\left(D_A - Y_A\right) \cdot \binom{Q_1}{Y_A} \cdot (\hat{p}_{1A})^{Y_A} \cdot (1-\hat{p}_{1A})^{Q_1-Y_A} \right] \\
& + c_B^p \cdot \sum_{Y_B=0}^{\min\{D_B-1;Q_1+Q_2\}} \left[\left(D_B - Y_B\right) \cdot \sum_{j=\max\{Y_B-Q_2;0\}}^{\min\{Y_B;Q_1\}} \left[\begin{matrix} \binom{Q_1}{j} \cdot (\hat{p}_{1B})^{j} \cdot (1-\hat{p}_{1B})^{Q_1-j} \cdot \\ \binom{Q_2}{Y_B-j} \cdot (\hat{p}_{2B})^{Y_B-j} \cdot (1-\hat{p}_{2B})^{Q_2-Y_B+j} \end{matrix} \right] \right] \\
& + c_C^p \cdot \sum_{Y_C=0}^{\min\{D_C-1;Q_1\}} \left[\left(D_C - Y_C\right) \cdot \binom{Q_2}{Y_C} \cdot (\hat{p}_{2C})^{Y_C} \cdot (1-\hat{p}_{2C})^{Q_2-Y_C} \right] \\
& + c_A^d \cdot \sum_{Y_A=D_A+1}^{Q_1} \left[\left(Y_A - D_A\right) \cdot \binom{Q_1}{Y_A} \cdot (\hat{p}_{1A})^{Y_A} \cdot (1-\hat{p}_{1A})^{Q_1-Y_A} \right] \\
& + c_B^d \cdot \sum_{Y_B=D_B-1}^{Q_1+Q_2} \left[\left(Y_B - D_B\right) \cdot \sum_{j=\max\{Y_B-Q_2;0\}}^{\min\{Y_B;Q_1\}} \left[\begin{matrix} \binom{Q_1}{j} \cdot (\hat{p}_{1B})^{j} \cdot (1-\hat{p}_{1B})^{Q_1-j} \cdot \\ \binom{Q_2}{Y_B-j} \cdot (\hat{p}_{2B})^{Y_B-j} \cdot (1-\hat{p}_{2B})^{Q_2-Y_B+j} \end{matrix} \right] \right] \\
& + c_C^d \cdot \sum_{Y_C=D_C-1}^{Q_2} \left[\left(Y_C - D_C\right) \cdot \binom{Q_2}{Y_C} \cdot (\hat{p}_{2C})^{Y_C} \cdot (1-\hat{p}_{2C})^{Q_2-Y_C} \right]
\end{aligned} \tag{5}
$$

For this study, we set the procurement cost for the leaves equal to 10 and disposal costs for leaves to zero. We can justify this with the following remarks. The leaf procurement cost is an arbitrary standardization of sorts, following and previous research in Inderfurth and Langella (2006) and Langella (2007). With respect to disposal costs, it is often the case that leaves obtained from disassembly which are not needed can be recycled for material resulting in a small amount of revenue that generally offsets the required handling.

The first factor of experimentation is the *profitability of disassembly*, defined as the ratio between the core cost and the summed procurement cost of the resulting leaves. Here, we have chosen three levels: Low (90%), Medium (50%) and High (10%). The next experimental factor is the *demand symmetry*, the relative demands of the leaves. Here we have four levels of symmetric demand (called *Sdem*, with a ratio of 1:2:1 for A, B, and C, since B is contained in both cores), common demand (*Cdem*, ratio of 1:3:1), and unique demand (*Udem*, 2:1:2) as well as level of asymmetric demand (*Adem*, ratio of 2:2:1 for A, B and C). Next, we explored *demand level*, and we have also chosen three levels here for the demand of the leaf with the smallest demand, viz. 5, 10, and 30.

The last two factors both deal with the yields. First, we explore the *average yield rate* for *SP*-yield, choosing three average levels of 0.5, 0.6, and 0.7. These values correspond to the success probability p for *BI*-yield. Lastly, we examine the role of yield dispersion in case of stochastically proportional yield assuming a uniform yield rate distribution and choosing three levels for *yield rate variance*, high, medium and low shown below in *Table 3* (with the corresponding upper (p+) and lower (p-) bounds):

Table 3: Lower and upper bounds for the uniformly distributed yield rate in case of *SP*-yield

$\mu_Z = p$	***Hvar*** $(\sigma_Z = 0.1732)$		***Mvar*** $(\sigma_Z = 0.1155)$		***Lvar*** $(\sigma_Z = 0.0577)$	
	p^+	p^-	p^+	p^-	p^+	p^-
0.50	0.80	0.20	0.70	0.30	0.60	0.40
0.60	0.90	0.30	0.80	0.40	0.70	0.50
0.70	1.00	0.40	0.90	0.50	0.80	0.60

Since under binomial yield the ordering decision is independent of the yield rate variability these lower and upper bounds are not taken into account in the optimal order size determination procedure for *BI*-yield.

This full factorial design results in a total of 324 possible parameter constellations. For each of them we determined the optimal order sizes for each engine type and the corresponding costs in dependency of the underlying yield model as well as the costs that result from using the falsely presumed order size. These cost parameters are then used to calculate the penalty (using formula (2) and (3)) that stems from misspecifying the model.

4.2 Results

We will start by examining average and maximum relative cost deviations for each of the two cases generally as shown in *Table 4*. These values represent the average as well as the maximum value over 324 parameter constellations for each case.

Table 4: Average and maximum of cost deviations in percent over all constellations

	Δ_{SP}	Δ_{BI}
Average cost deviation	0.84	1.37
Maximum cost deviation	12.32	19.73

Obviously, the average deviations are only minor while under worst case parameter constellations yield misspecification can result in an unacceptable cost increase above optimum. Furthermore, as we can see, there are lower averages and maximum deviations for case Δ_{SP}, where binomial yields are falsely presumed. For a more detailed analysis we will now juxtapose the respective average und maximum values for some of the specific parameters that have been considered in the study. The complete results are given in *Appendix Tables A1* and *A2* for Δ_{SP} and Δ_{BI} respectively. We can start with the impact of the profitability of disassembly as given in *Table 5*.

Table 5: Average and maximum of cost deviations in percent for each case of disassembly profitability

Profitability of disassembly		***Low***	***Medium***	***High***
Δ_{SP}	*Avg*	0.41	0.13	1.98
	Max	3.46	1.01	12.32
Δ_{BI}	*Avg*	0.37	0.13	3.15
	Max	3.09	2.45	19.73

In general, the relative deviations increase with increasing profitability. This can be most evidently seen when examining the deviations in the high profitability cases, where maximum deviations exceed 10 percent. This effect is quite intuitive since with higher profitability of disassembly less parts are procured externally so that along with the increasing importance of demand fulfillment from disassembly a misspecification error has a larger impact.

We can now turn our attention to the impact of demand symmetry using *Table 6* below.

Table 6: Average and maximum of cost deviations in percent for each case of demand symmetry

Demand symmetry		***Sdem***	***Cdem***	***Udem***	***Adem***
Δ_{SP}	*Avg*	1.65	0.65	0.45	0.93
	Max	12.32	5.86	3.29	3.32
Δ_{BI}	*Avg*	1.91	0.86	1.04	1.32
	Max	19.73	12.89	11.10	11.21

From *Table 6* we observe that the relative as well as the maximum cost deviations decrease in order from symmetric to common to asymmetric to unique for each type of misspecification. One can also clearly see here that, different from other demand structures, the penalties for symmetric demand are substantial ranging between 10 and 20 percent. Also that the penalties for falsely presuming *SP* yields exceed those of falsely presuming *BI* yields for all average and maximum values in the table for the respective cases. Lastly, we can add that the maximum penalties for falsely presuming *SP* yields exceed 10 percent for each type of demand symmetry. The extraordinary high misspecification effect for the *Sdem* case is surprising since this demand structure fits best with the yield expectation from disassembling the same number of core types. However, this is just the situation where external procurement caused by a mismatch from core disassembly and parts' demand plays only a minor role so that internal procurement and, in this context, misspecification gains importance.

Next, we can examine the impact of the average yield rate using *Table 7* below. Referring to *Table 7*, we can see a clear progression where penalties generally decrease with an increasing average yield rate.

Table 7: Average and maximum of cost deviations in percent for each considered average yield rate

Average yield rate		***0.5***	***0.6***	***0.7***
Δ_{SP}	*Avg*	0.96	0.85	0.71
	Max	12.20	12.32	11.05
Δ_{BI}	*Avg*	1.43	1.25	0.96
	Max	19.73	16.05	14.21

Also here the penalties for falsely presuming *SP* yields exceed those of falsely presuming *BI* yields for all average and maximum values in the table for their respective cases. Lastly, in every average yield rate setting, the maximum deviation exceeded 10 percent.

The remaining factors, yield rate variance and demand level, are slightly more challenging to interpret. Here, we introduce the following boxplots in *Figures 5* and *6* for Δ_{SP} and Δ_{BI} respectively. In each of these figures, high and low variability are in the plots on the left and right, and within each plot, demand levels are shown. As one can see, the penalties increase with increasing demand level for high yield rate variability but decrease for low yield rate variability in both cases of misspecification, both for Δ_{SP} and Δ_{BI}. This finding can be interpreted as follows. Different from the *SP* yield case, the yield rate variance in case of *BI* yield decreases with increasing production lot size. Since this lot size is rising with growing demand level the variance is relatively high for a demand of 5 and relatively low for a demand of 30 items. For the low demand level the *BI* yield rate variance is nearly of the same magnitude as for high variability (*Hvar*) in the *SP* case, while for high demand level the *BI* variance resembles the low level (*Lvar*) of *SP* yield. It turns out that the penalty is quite low if the yield rate variances in the *BI* and *SP* case are of similar size while it quickly grows with increasing variance deviations. This explains the reverse direction of change of performance for the *Hvar* and *Lvar* case in *Figures 5* and *6* when the demand level increases. From that we see that it might not only be important to specify the yield type in a correct manner, but also estimate the yield rate variability more or less precisely.

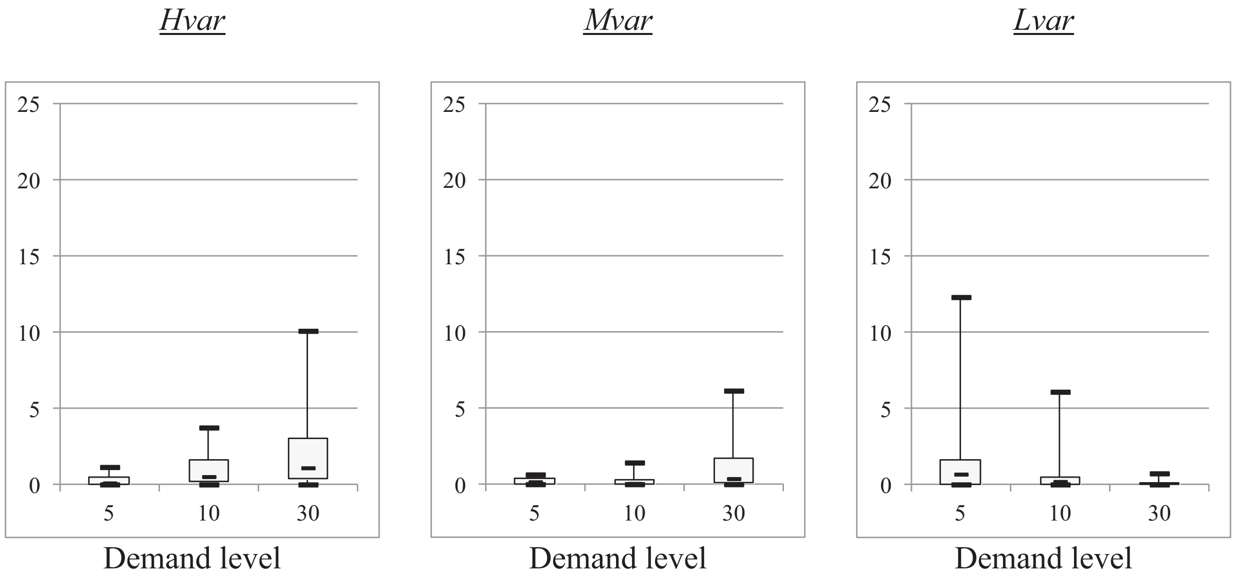

Figure 5: Box plots for case Δ_{SP}

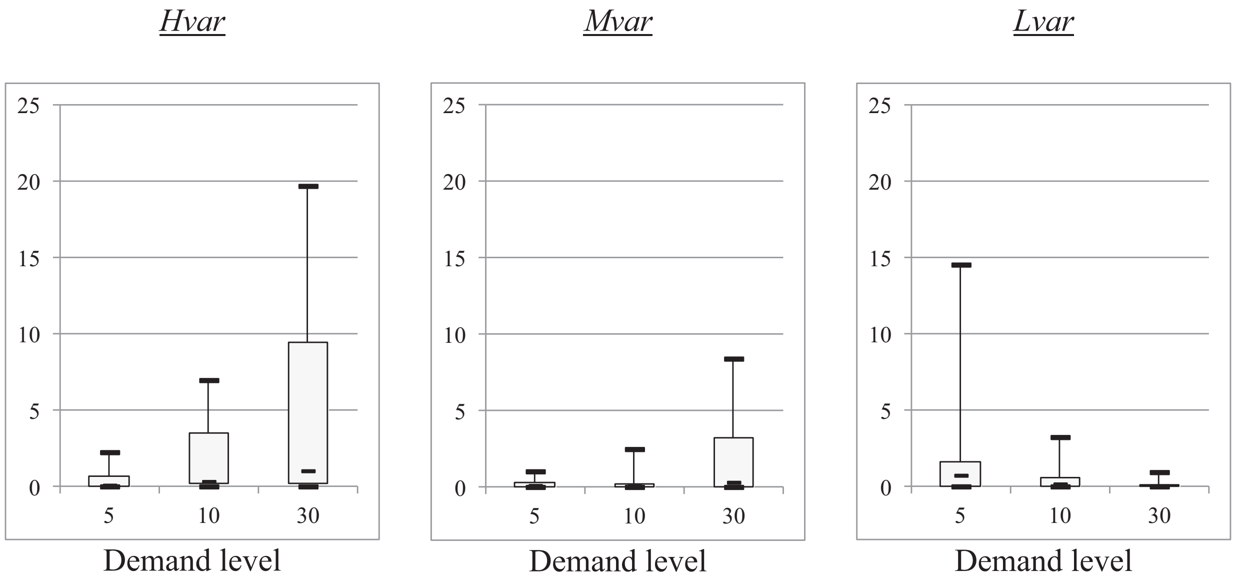

Figure 6: Box plots for case Δ_{BI}

Examining the entire results tables (see Appendix *Table A1* and *A2*) and counting the relative cost deviations that exceeds a given value, we discover that planning the disassembling process assuming stochastically proportional yield when yields are actually binomial leads in 24 parameter constellations to relative cost deviations greater than 5 % and in 2 cases the deviations exceed a high percentage rate of 15 % (see *Table 8*). This is in stark contrast to results for the opposite case when binomial is presumed but yields are proportional, where 9 cases exhibit deviations exceeding 5% and no cases show deviations exceeding 15%.

Table 8: Amount of parameter constellations greater than 5%, 10% or 15% for each case

Relative cost deviation is greater than	Amount of constellations for case	
	Δ_{SP}	Δ_{BI}
5 %	9	24
10 %	4	9
15 %	0	2

Additionally, we can examine cases where one modeling alternative dominates the other, using *Table 9*. As can be seen, in 118 cases the penalty from falsely presuming binomial exceeds the penalty of falsely presuming stochastically proportional, where in 142 cases the penalty of falsely presuming proportional exceeds that of falsely presuming binomial. As there are 324 cases in total, in the remaining 69 cases there were equal penalties for either false assumption. In order to examine the magnitude of these differences, the table also provides average penalties for each group of cases. Here we can see that in the 118 cases where $\Delta_{BI} < \Delta_{SP}$ the difference between the penalties was less than 0.4% where in the 142 cases where $\Delta_{BI} > \Delta_{SP}$ the difference was above 1.1%. We can draw that not only is it more likely to have $\Delta_{BI} > \Delta_{SP}$, it is also so that when that is the case, the penalties for falsely presuming stochastic proportional yields is approximately four times as large as the penalties for the opposite case.

Table 9: Number of cases and average deviations for cases where one modeling approach dominates the other

	$\Delta_{BI} < \Delta_{SP}$	$\Delta_{SP} < \Delta_{BI}$
Number of cases	118	142
Average Δ_{SP}	0.948 %	1.130 %
Average Δ_{BI}	0.569 %	2.301 %
Average $\Delta_{SP} - \Delta_{BI}$	0.378 %	---
Average $\Delta_{BI} - \Delta_{SP}$	---	1.171 %

Examining the complete results given in the appendix reveals parameter combinations where penalties are particularly high or low. Here we observe that the highest deviations occur in case of symmetric demand with a demand level of 30 for the part with the smallest demand (30:60:30), high disassembly profitability and for high yield rate variability. The penalty is higher also for other demand symmetry cases under the same demand level and profitability scenarios, particularly penalties where proportional is falsely presumed. Additionally, cases with low demand level, symmetric demand, low yield variation and high profitability also have pronounced penalties. In no cases involving medium or low profitability did any penalty exceed 3% with most cases having marginal penalties. In the following section, we draw implications based on these results.

4.3 Managerial insights

We can draw some insight from the analysis and provide managers with actionable advice on planning remanufacturing operations. First, as we have seen our set of real world data does not allow us to specify one modeling alternative or the other. Where some parts studied tend to suggest that stochastically proportional yield is more likely, other parts results are inconclusive, even within the same core. For practice this means that collection of a sufficiently large amount of yield data is necessary and recommendable in order to get a valid picture of the yield type that prevails. Considering the results of our numerical experiments, it turns out that a correct specification of the true yield type can be very valuable as best evidenced by examining the worst case performances. Moreover, also correct estimation of the yield rate variance in case of *SP* yield is of major importance for avoiding excessive penalties.

From our analysis we are also able to give some advice in which cases a correct yield specification might be of specific importance. As we have seen from the results, high disassembly profit cases tended to have higher penalties, particularly with higher demand levels and yield variability, but also for lower demands and lower yield variability under symmetric demand. For this reason, in such cases it is worthwhile to exert special effort to test yields to determine which modeling alternative is appropriate. Here, the tests we have employed can be used to attempt to ascertain which alternative is appropriate.

Furthermore, the results clearly indicate that penalties for falsely presuming proportional yields exceed that of falsely presuming binomial yields. In such cases where there is either uncertainty regarding which alternative is appropriate, i.e. it has not been tested, or when such tests fail to provide a conclusive result, a wise manager will assume binomial yields since this usually provides a better result.

Finally, from our findings we can also give some more insight into the effects of quality testing prior to disassembly decisions. While testing certainly can save costs by avoiding unnecessary disassembly of bad-quality cores, its effect on misspecification penalties can be ambiguous. If we assume that the information from testing results in a higher mean yield rate and lower yield rate variance of the cores remaining for disassembly, due to the ambiguous effect of yield rate variability for small and high demand levels it might happen that in case of a low demand for parts a testing-based decrease in the yield risk results in an increase of the misspecification risk.

5. Conclusion and Outlook

As we have seen, remanufacturing specifically and product recovery management generally fits well within the current push towards more sustainability in business. Since remanufacturing requires parts to be harvested from returned products, disassembly planning is an important component to remanufacturing operations. The yields of disassembly are subject to uncertainty since the condition of the returned products varies and disassembly processes are not entirely predictable.

There are several alternative methods to model stochastic yields, two of which viz. stochastically proportional and binomial, come into question for disassembly planning. Analysis of industrial disassembly yield data obtained from an automotive manufacturer failed to yield a conclusive result as to which method is applicable. For this reason, we examined the performance of disassemble-to-order problems when the yield process is misspecified.

The results from this sensitivity study indicate that decisions are most sensitive for instances where the profitability of disassembly is high, particularly when demand level and yield variances are high. In these cases, it is especially important to try to ascertain which method is appropriate for the specific products being disassembled. That said, the results may well indicate a complicated picture where there is no single dominant method. Our results also generally indicate that assuming binomial yields is preferable to presuming proportional yields. For this reason, when one is unsure about the method, presuming binomial yields will generally give a better chance of obtaining closer to optimal results.

This work can be extended in a couple of directions. First, it would be interesting to see if other products yields also result in an inconclusive result with respect to the appropriate modeling alternative. This will require industrial yield data from other manufacturers and that that data be tested. Second, extending the sensitivity analysis for more complicated problems would also be interesting. This will be difficult as more realistic product structures will be computationally difficult to analyze. Third, for real-world situations with more than 10 cores, up to 100 parts per core and a high level of part communality determining optimal solutions to the disassembly-to-order problem might be computationally intractable so that heuristic solution procedures are necessary. While for stochastic proportional yields powerful disassemble-to-order heuristics are available in the literature (see Inderfurth and Langella (2006)), heuristics for binomial yields must be developed and tested. Armed with these, managers will be in a better position to plan disassembly, even for realistically complex product structures.

Appendix

Table A1: Entire penalties for misspecification in case Δ_{SP}

			Δ_{SP}									
			Hvar			*Mvar*			*Lvar*			*Z Var*
Dis. profit.	*Demand symmetry*	*Demand level*	*0.5*	*0.6*	*0.7*	*0.5*	*0.6*	*0.7*	*0.5*	*0.6*	*0.7*	*Z Avg*
low	*Sdem*	*5*	0.00	0.00	0.08	0.32	0.40	0.50	1.55	1.31	0.79	
		10	0.46	0.37	0.81	0.00	0.00	0.00	1.07	1.04	0.56	
		30	3.46	2.65	1.98	1.15	0.80	0.51	0.00	0.01	0.07	
	Cdem	*5*	0.00	0.00	0.00	0.37	0.48	0.00	1.34	1.09	0.10	
		10	0.52	0.50	0.26	0.00	0.00	0.00	0.48	0.34	0.47	
		30	1.49	1.18	0.94	0.52	0.40	0.30	0.00	0.00	0.00	
	Udem	*5*	0.12	0.16	0.00	0.35	0.42	0.00	0.77	0.76	0.27	
		10	0.00	0.00	0.00	0.06	0.02	0.07	0.36	0.26	0.28	
		30	0.20	0.15	0.11	0.02	0.02	0.01	0.06	0.06	0.06	
	Adem	*5*	0.07	0.02	0.00	0.13	0.02	0.12	0.75	0.54	0.58	
		10	0.66	0.22	0.51	0.16	0.03	0.13	0.18	0.33	0.13	
		30	1.25	0.81	0.81	0.50	0.30	0.34	0.05	0.03	0.04	
medium	*Sdem*	*5*	0.31	0.00	0.00	0.00	0.00	0.00	0.81	0.00	0.00	
		10	0.53	0.41	0.05	0.09	0.13	0.00	0.10	0.00	0.00	
		30	0.79	0.58	0.26	0.20	0.18	0.06	0.00	0.01	0.00	
	Cdem	*5*	0.20	0.07	0.00	0.00	0.00	0.00	0.02	0.00	0.00	
		10	0.36	0.04	0.15	0.03	0.00	0.04	0.00	0.00	0.00	
		30	0.42	0.22	0.13	0.04	0.03	0.03	0.01	0.00	0.00	
	Udem	*5*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Adem	*5*	0.51	0.64	0.56	0.35	0.37	0.26	0.11	0.00	0.00	
		10	0.96	0.42	0.59	0.31	0.05	0.19	0.01	0.00	0.00	
		30	1.01	0.66	0.42	0.31	0.24	0.14	0.01	0.00	0.00	
high	*Sdem*	*5*	0.88	0.27	0.42	0.50	0.44	0.00	12.20	12.32	11.05	
		10	3.74	3.24	3.63	0.63	0.29	0.00	4.79	6.10	4.88	
		30	10.10	9.80	9.01	6.16	4.78	3.67	0.05	0.08	0.16	
	Cdem	*5*	1.01	0.27	0.00	0.31	0.64	0.00	4.16	4.98	2.80	
		10	2.71	1.84	1.54	0.05	0.03	0.24	1.11	1.08	0.41	
		30	5.86	4.51	2.90	1.54	1.22	0.99	0.05	0.03	0.00	
	Udem	*5*	0.17	0.90	1.15	0.00	0.34	0.28	2.24	0.61	0.00	
		10	1.11	1.62	2.35	1.02	1.01	1.43	0.00	0.00	0.00	
		30	2.28	2.88	3.29	2.67	2.52	2.48	0.73	0.43	0.35	
	Adem	*5*	0.43	0.70	1.14	0.00	0.23	0.18	2.24	1.87	0.00	
		10	1.39	1.60	1.97	0.68	0.79	1.04	0.75	0.20	0.00	
		30	3.32	2.96	3.19	2.36	2.13	2.29	0.53	0.29	0.24	

Table A2: Entire penalties for misspecification in case Δ_{BI}

			Δ_{BI}									
			Hvar			*Mvar*			*Lvar*			*Z Var*
Dis. profit.	*Demand symmetry*	*Demand level*	*0.5*	*0.6*	*0.7*	*0.5*	*0.6*	*0.7*	*0.5*	*0.6*	*0.7*	*Z Avg*
low	*Sdem*	*5*	0.00	0.00	0.01	0.78	1.02	0.31	3.09	1.02	2.09	
		10	0.23	0.31	0.19	0.00	0.00	0.00	0.87	0.99	0.78	
		30	1.45	1.28	1.23	0.59	0.45	0.49	0.00	0.06	0.02	
	Cdem	*5*	0.00	0.00	0.00	0.11	0.17	0.00	0.80	1.29	1.31	
		10	0.34	0.38	0.26	0.00	0.00	0.00	0.30	0.20	0.16	
		30	1.12	0.94	0.86	0.45	0.31	0.30	0.00	0.00	0.00	
	Udem	*5*	0.05	0.08	0.00	0.05	0.08	0.00	0.39	0.62	0.63	
		10	0.00	0.00	0.00	0.03	0.10	0.08	0.15	0.35	0.08	
		30	0.22	0.15	0.14	0.04	0.01	0.02	0.05	0.05	0.06	
	Adem	*5*	0.17	0.08	0.00	0.35	0.40	0.16	1.08	1.52	0.66	
		10	0.30	0.21	0.14	0.08	0.05	0.05	0.50	0.51	0.36	
		30	0.88	0.70	0.57	0.29	0.23	0.21	0.09	0.10	0.05	
medium	*Sdem*	*5*	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		10	1.24	0.61	0.53	0.14	0.03	0.00	0.00	0.00	0.00	
		30	2.45	1.13	0.63	0.44	0.24	0.07	0.03	0.01	0.00	
	Cdem	*5*	0.13	0.16	0.00	0.00	0.00	0.00	0.06	0.00	0.00	
		10	0.31	0.14	0.01	0.02	0.00	0.01	0.02	0.00	0.17	
		30	0.23	0.07	0.02	0.02	0.01	0.00	0.03	0.00	0.00	
	Udem	*5*	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00	
		10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Adem	*5*	0.79	0.07	0.25	0.24	0.25	0.25	0.08	0.00	0.25	
		10	0.69	0.31	0.16	0.15	0.09	0.01	0.09	0.00	0.14	
		30	0.48	0.14	0.04	0.09	0.02	0.00	0.09	0.00	0.00	
high	*Sdem*	*5*	1.16	0.91	1.02	0.28	1.02	0.00	8.83	14.56	6.55	
		10	6.98	4.98	4.64	0.59	0.21	0.52	3.24	2.39	2.32	
		30	19.73	16.05	14.21	8.41	6.42	4.75	0.00	0.01	0.10	
	Cdem	*5*	2.25	0.74	0.00	0.26	0.07	0.00	3.08	3.89	0.97	
		10	5.82	3.81	1.66	0.20	0.24	0.07	0.81	0.68	0.59	
		30	12.89	8.31	5.64	2.63	2.31	1.92	0.08	0.02	0.00	
	Udem	*5*	0.86	1.99	0.68	0.00	0.32	0.68	1.20	1.45	0.00	
		10	3.74	3.77	4.88	2.48	2.21	1.11	0.00	0.00	0.00	
		30	10.49	10.92	11.10	7.69	6.64	5.99	0.94	0.67	0.52	
	Adem	*5*	0.59	1.25	0.52	0.00	0.18	0.42	1.83	2.03	0.00	
		10	4.21	3.15	3.42	1.61	1.55	0.96	0.42	0.51	0.00	
		30	11.21	9.46	9.46	6.38	5.30	4.98	0.63	0.44	0.38	

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ISSN 1615-4274