

# **Restructuring the Backhoe Loader Product Line at Caterpillar: A New Lane Strategy**

Masha Shunko

Krannert School of Management, Purdue University

mshunko@purdue.edu, (765) 494-6725

Tallys Yunes

School of Business Administration, University of Miami

tallys@miami.edu, (305) 284-5107

Giulio Fenu

Caterpillar Inc.

fenu\_giulio@cat.com

Alan Scheller-Wolf

Tepper School of Business, Carnegie Mellon University

awolf@andrew.cmu.edu, (412) 268-5066

Valerie Tardif

SAP

vtardif@sap.com

Sridhar Tayur

Tepper School of Business, Carnegie Mellon University

stayur@andrew.cmu.edu, (412) 268-3584

# Restructuring the Backhoe Loader Product Line at Caterpillar: A New Lane Strategy

## Abstract

Caterpillar recently embarked on an ambitious program to radically change how it markets and sells key products of its Building Construction Products division (BCP). The goal was to move from a strict build-to-order strategy, in which customers selected one of millions of possible configurations, to a *Lane Strategy* in which the majority of their customers would choose machines from *just over 100* configurations. To successfully make such a radical change Caterpillar needed to quantify how customers would potentially react to the new strategy, and how such a drastic simplification of their product line would affect their manufacturing, sales, and service costs. We embarked on a study with Caterpillar to explicitly model customers' reactions to reduced product lines, to estimate the (positive and negative) effect such variety has on Caterpillar's costs – the *cost of complexity* – and ultimately help them design and implement this strategy for their flagship BCP product, the Backhoe Loader. Based on our analysis, Caterpillar began implementing the new strategy with their 2010 price list, moving completely to the new strategy in 2011. Since that time Caterpillar has expanded their Lane strategy throughout all of their product lines, fundamentally remaking their business.

*Key words:* product portfolio optimization; cost of complexity; manufacturing; machinery

## 1 Introduction

In 2010 Caterpillar (CAT) unveiled a dramatically new strategy for pricing and marketing their “BHL” series of small backhoe loaders, one of the most popular products within their Building Construction Products (BCP) division. This new strategy has radically changed how BCP markets and sells their small machines, focusing the bulk of CAT's customers on a few popular models.

Previously, BCP offered customers an almost unlimited variety of products, built-to-order, priced according to an itemized price list. This maintained very high customer satisfaction, but greatly complicated BCP's supply chain and service operations: With such broad demand dealers had to hold large amounts of inventory to give a representation of the many possible choices. Moreover, Caterpillar had to maintain documentation and provide service for an extremely heterogeneous group of machines, driving up their costs. Finally, as demand was fragmented across thousands of configurations, forecasting was problematic, leading to frustration among suppliers.

Thus CAT’s BCP division saw great potential for a rationalization of their BHL product line. Three crucial questions had to be answered before devising and implementing such a new strategy:

1. “How would customers react to a product line reduction?” Answering this question required developing an understanding of *how customers value different machines*.
2. “How much could be saved by focusing their BHL product lines?” Answering this question required developing an understanding of the *general form of the cost of complexity*.
3. “How should we configure our new BHL product line?” *Specifically, which machines should we offer, and at what prices?*

The primary contribution of this paper is to demonstrate the power of our three-step analytical framework for product line simplification. Step 1 answers question 1 by capturing customer behavior using *migration lists*; step 2 answers question 2 by creating a detailed mathematical representation of the company’s cost of complexity (CoC); and step 3 answers the final question by combining the migration lists and the CoC function into an optimization model that proposes an improved product line. The generality and flexibility of our framework stem from the fact that the mathematical and statistical techniques used in steps 1, 2, and 3 can be tailored to the situation at hand, as long as they produce the output required by each subsequent step. We also demonstrate that our framework can be used as an effective what-if tool for managers, allowing them to successfully evaluate different solutions under varying problem conditions.

To answer CAT’s first question we leveraged BCP’s extensive dealer network to gain an understanding of the segmentation, preference patterns, and price sensitivities of BCP’s customer base. We combined this dealer knowledge with the entire line’s sales history over the previous two years to construct a detailed analytical model of customer preferences and substitution (see Section 4). This produced a model of how BCP’s customers would react to changes in the product line.

To answer the second question, we built a detailed model to estimate the total direct and indirect costs of complexity, using an extensive empirical analysis of CAT’s cost data, and surveys with CAT’s engineering and marketing experts. This model captured both variety-based (driven by *number* of options offered) and attribute-based (driven by *specific complex* options) costs and benefits of product diversity, from manufacturing, to spare parts, to sales effort. (See Section 5).

We then combined the customer and cost models within a mathematical programming model, in Section 6, to evaluate different product lines against randomized demand patterns and market

scenarios. In coordination with expert input from CAT, this step determined the right product mix for the line, offering customers broad choice while also controlling the costs of complexity.

The outcome of the project was implemented as a new *Lane* strategy, offering machines within three different lanes: Lane 1, the Express Lane, featuring four built-to-stock configuration choices at an expected lead time of a few days; Lane 2, the Standard Lane, featuring 120 predefined configurations, built-to-order at an expected lead time of a few weeks; and Lane 3, the A-La-Carte Lane, built to order machines with an expected lead time of a few months.

Caterpillar committed to a phased roll-out of the project, publishing both an (old) a-la-carte price list and a (new) Lane price list in 2010, and transitioned to a single Lane price list in 2011. The Lane 1 configurations were immediately able to capture a significant portion of demand, contributing to a reduction in warranty costs on the order of 10%, as predicted by our analysis. Caterpillar has continued expanding and refining their BHL lane strategy – for example, they have now reduced the Lane 1 configurations to only *two*. In addition, Caterpillar has applied variations of our cost of complexity analysis to other divisions within the firm, helping to guide their extensions of the lane approach – a fundamental strategic change – to the entire company.

To the best of our knowledge, no previous work has ever combined an empirically-developed CoC function as detailed and comprehensive as ours, with customer preferences regarding product substitution, in an optimization algorithm that was implemented with real-life data, at an industrial scale. Moreover, our work ultimately produced recommendations that were actually implemented and verified to generate significant improvements.

In Section 2 we place our work within the product line optimization and practical application literature. Then, in Section 3 we briefly describe the BHL lines. In Section 4 we present our key tool for answering the first of Caterpillar’s questions (“How would customers react to a product line reduction?”), our customer migration list model. Next, in Section 5, we describe how we answered the second question (“How much could be saved by focusing their BHL product lines?”) by presenting our Cost of Complexity model. We then combine these in our optimization model, in Section 6, to answer the ultimate question, (“How should we configure our new product line?”). We present the results and insights from our analysis in Sections 7 and 8, and conclude in Section 9.

## 2 Literature Review

The marketing literature illustrates the difficulty of predicting the effects of reducing product line complexity: Some works describe how narrowing a product line may detract from brand image

or market share, e.g. Chong et al. (1998), while others posit that *reducing* the breadth of lines and focusing on customer “favorites” may actually *increase* sales, see for example Broniarczyk et al. (1998). Our model is consistent with both of these streams: If a customer finds a product that meets her needs (i.e. a “favorite”) she will make a purchase; if such a product and its acceptable alternatives are no longer part of the product line, she will not.

There is also a long history of empirically studying the impact of product line complexity on costs. Foster and Gupta (1990) analyze the responses to a questionnaire to assess the impacts of volume-based, efficiency-based, and complexity-based cost drivers within an electronics manufacturing company. They find that manufacturing overhead is associated with volume, but not complexity or variety. Banker et al. (1995) use data from 32 manufacturing plants to evaluate the same question; they find an association of overhead costs with both volume and transactions, which they take as a measure of complexity. Anderson (1995) examines the effect of product mix heterogeneity on overhead costs in three textile factories. Of the seven different types of heterogeneity she identifies, two are shown to be associated with higher overhead costs. Fisher and Ittner (1999) analyze data from a GM assembly plant, finding that option variety contributes to higher labor and overhead costs. We complement these works by explicitly formulating and calibrating a detailed model to estimate the total direct and indirect costs (and benefits) of complexity for the BHL line at Caterpillar, based on expert surveys and empirical analysis of cost data.

Product line optimization has a rich literature: Kok et al. (2009) and Tang (2010) provide recent surveys. Several recent papers consider the *strategic* selection of a product line via equilibrium analysis: Alptekinoglu and Corbett (2008), Chen et al. (2008), Chen et al. (2010), and Tang and Yin (2010). Our paper uses math programming to optimize a more detailed model.

Bitran and Ferrer (2007) consider the problem of determining the optimal price and composition of a single bundle of items and a single segment of customers in a competitive market. They provide extensions to multiple segments or multiple bundles based on mathematical programming, but this latter problem becomes very complex, and is left as future research. Wang et al. (2009) use branch-and-price to select a line to maximize the share of market, testing their algorithm on problems with a small number of items but many levels of product attributes on simulated and commercial data. And Schoen (2010) extends the work of Chen and Hausman (2000) to allow more general costs and heterogeneous customers. None of these algorithms have been shown to be suitable for problems anywhere near the size and complexity of Caterpillar’s (thousands of customers and millions of potential configurations). This has led to the investigation of heuristic line

optimization methods: For example Fruchter et al. (2006) apply a genetic algorithm to simulated and survey data; and Belloni et al. (2008) compare several heuristics to the optimal solution for small (up to 5-product) instances. Neither of these are actual implementations.

Kok and Fisher (2007) develop and apply a methodology to estimate demand and substitution patterns for a Dutch supermarket chain, based on empirical demand data. They develop an iterative heuristic that determines the facings allocated to different categories, and the inventory of individual elements within the categories. In contrast: (i) We develop an empirical cost of complexity function; (ii) We use a more comprehensive substitution mechanism, the *migration list*. In Kok and Fisher (2007), customers who find their first choice absent will substitute at most once (so if their second choice is absent they leave); (iii) We develop a single *product lane* strategy for use by all dealers in the network; and (iv) Our results are based on actual implementation.

Fisher and Vaidyanathan (2011) explore how to select retail store assortments; their work enhances a localized choice model to make it operational in practice. Our models share a localized choice model with randomization, location at extant configurations, and preference sets for substitution (i.e. our *migration lists*). But whereas in Fisher and Vaidyanathan (2011) all customers who prefer a particular product have the same preference set, we randomize the option utilities of each customer, so customers who purchased the same product may spawn different migration lists. Furthermore, we use an additive model of attribute utilities, theirs is multiplicative.

Other important differences include: Fisher and Vaidyanathan (2011) estimate demand intensity and substitution parameters from historical data, whereas we use expert opinion to get utilities, and generate demand by randomizing past sales. In contrast to our approach that seeks to maximize profits using our empirical cost of complexity function, they maximize revenue with greedy heuristics. Finally, they show just two examples — snack cakes and tires — implementing a small set of their recommended changes with the tires line, increasing revenue by 5.8%.

Ward et al. (2010) is another recent paper that rigorously applies an analytical framework to the product line problem, developing two tools to help Hewlett-Packard. Like Caterpillar, HP has product lines that could, in theory, span millions of different configurations.

The first tool develops a comprehensive complexity cost function, comprised of variable and fixed costs, to be used when evaluating the introduction of new products. This complexity cost function has some similarities to ours, but focuses more on inventory costs, lacking anything related to our attribute based costing. Furthermore, any substitution effects on inventory, which they term cannibalization, are subjectively estimated at a high level.

Their second tool uses a heuristic to construct a line from a selection of extant products. This tool does not use their complexity cost function, nor does it consider substitution — rather it constructs a Pareto frontier of those top  $k$  products that would cover the desired percentage of historical *order* demand (or order revenue). So while they seek the appropriate line to satisfy possibly multi-product orders assuming customers will not substitute, we find the correct line of products to satisfy orders for individual products in which customers may substitute.

Rash and Kempf (2012) recently published work on product line design and scheduling at Intel. They find the set of products to produce, for different markets, to maximize profit over a time horizon while obeying budget and availability constraints. They perform hierarchical decomposition, utilizing genetic algorithms along with MIPs. This work is quite different from ours in that their demand is viewed as deterministic, so substitution is not included in the model.

The three-step framework we use was first introduced in Yunes et al. (2007), which describes a product line simplification effort implemented at John Deere & Co. Our current work shares some of its methodology with Yunes et al. (2007), but extends their work in several dimensions.

Specifically, we: (i) Explicitly calculate and validate estimates of the parts utilities and complexity function; they were exogenous in Yunes et al. (2007). (ii) Create a sophisticated, endogenous, cost of complexity function; the function used in Yunes et al. (2007) was exogenous. (iii) Owing to the form of our endogenous function, we use a different optimization procedure, the “differential approach.” (iv) To achieve CAT’s aggressive product line goals, we make decisions at the *option* level, rather than the machine level, as in Yunes et al. (2007). We also incorporate pricing decisions and migration across models, which are not possible in Yunes et al. (2007).

### 3 BHL Product Families

Our product line simplification effort at CAT involved four models in the backhoe loader (BHL) family: 416E, 420E, 430E, and 450E. The 416E is the basic model, while the 420E, 430E and 450E provide progressively superior horsepower and capabilities. We refer to a complete machine as a *configuration*. Each configuration is composed of *features*; for each feature, a configuration specifies one of the *options* within that feature. For example, the feature *stick* has the options *standard* and *electronic*. Table 1 contains a summary of the features present in each BHL model that were included in our project, together with the number of options in each. A dash “-” indicates that a feature is not present in a model or was not included in our analysis.

To create a complete configuration, a customer selects one option for each of its features,

Table 1: Number of options in each feature of CAT’s BHL models.

Features	BHL Models			
	416E	420E	430E	450E
Sticks	2	2	2	2
Backhoe Hydraulics	3	3	3	6
Backhoe Controls	2	-	-	-
Loader Buckets	5	13	13	4
Loader Hydraulics	2	2	2	2
Cab/Canopy	5	5	4	2
Powertrain	4	3	2	-
Engine Cooling	2	2	2	-
Counterweights	4	4	4	-
Backhoe Aux Lines	3	3	3	3
Engine Coolant Heater	2	2	2	2
Product Link	2	2	2	2
Ride Control	2	2	2	-
Front Loader Mechanics	-	2	2	-

while making sure that these options are compatible. One of the difficulties faced by CAT is that the number of potential configurations is immensely large. For example, for model 416E in its most basic version, the number of feasible configurations is 37,920. When we include choices for attachments, there are 2,275,200 distinct feasible configurations. The vast majority of these configurations have never been, and most likely will never be, built. The mere fact that they *could* be purchased, however, creates overhead costs for CAT’s operations (see Section 5).

So how many configurations are built? Figure 1 depicts the number of different configurations (left panel) and options (right panel) required to capture specified revenue and sales targets for eight month’s worth of sales data for model 420E. Of the 569 built configurations, 400 were needed to capture about 95% of revenues and sales volume. Similarly, 41 out of the 45 available options were needed to capture at least 90% of revenues and sales volume. Therefore, in order to achieve the sought reductions in product offerings, it was imperative to steer purchases toward a considerably smaller subset of products and options.

## 4 Modeling Customer Behavior

The key to evaluating the potential pitfalls of reducing a product line is a good understanding of customers’ purchasing flexibility: while customers will require that the product they are buying satisfy some minimum requirements, not every feature needs to be in perfect alignment with their expectations. In addition, customers typically display some degree of price flexibility.



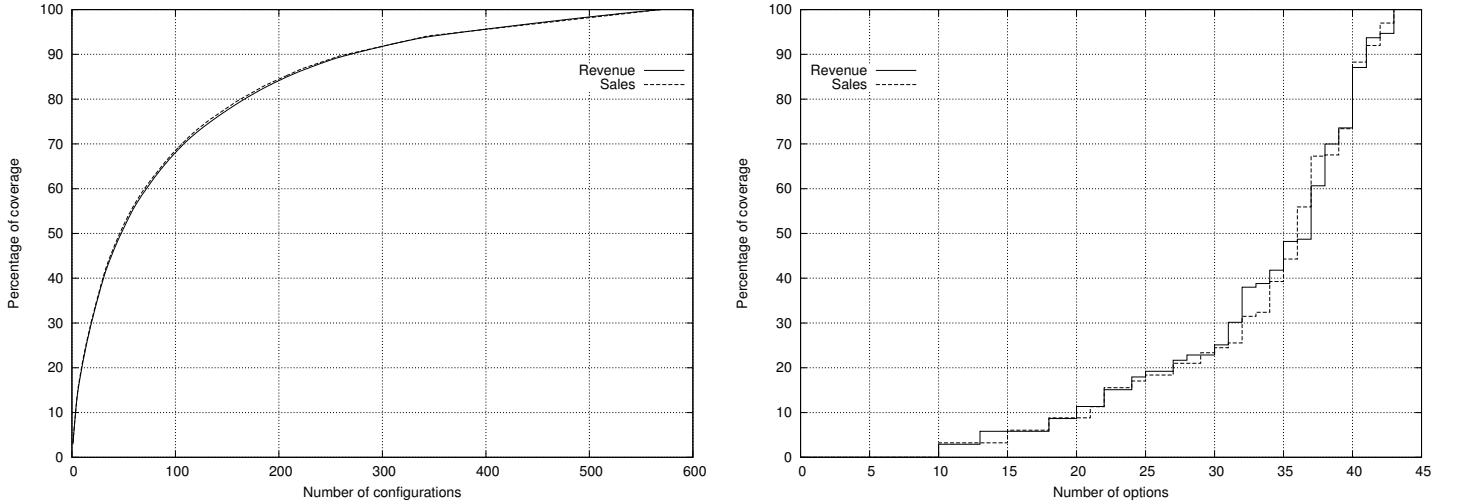


Figure 1: Number of distinct configurations (left) and options (right) required to capture given percentages of revenue and sales volume for BHL model 420E.

The centerpiece of our approach to capture flexibility is the *migration list*, an ordered list of products within the customer’s price and utility tolerance (see Yunes et al. 2007 for details). The first configuration on the list is the customer’s first choice; if available the customer will buy that configuration. If that configuration is unavailable and there is a second configuration on the list the customer will buy that if available, and so on. If none of the configurations on a customer’s list are available, that customer buys nothing (i.e. goes to a competitor). As mentioned in Section 2, this is an enhanced localized choice model, in the spirit of Fisher and Vaidyanathan (2011).

For each unique purchase in our database, we construct a corresponding migration list. Many factors come into play when constructing a customer’s migration list. Below is pseudo-code showing how the process works; each step is described in detail in a subsection below.

Construction of Migration Lists: For each customer  $C$  who bought a configuration over the past  $H$  months repeat:

1. Let  $M_C$  be the configuration (machine) bought by  $C$ .
2. Apply segmentation rules to  $M_C$  (Section 4.1) to place  $C$  in a segment  $S_C$ .
3. Based on the price and utility of  $M_C$ , and on characteristics of segment  $S_C$ , construct a *randomized* list of configurations,  $L_C$ , as acceptable alternatives to  $M_C$  (Section 4.2).
4. Sort  $L_C$  in non-increasing order of configuration utility, pruning it if it exceeds the maximum allowed length (Section 4.3).

## 4.1 Customer Segmentation

Customer segmentation plays an important role in the creation of migration lists because it affects customer flexibility. For example, customers who live in extreme weather conditions are unlikely to buy a configuration that does not include a cab with climate control, and customers who need to carry very heavy loads are not willing to sacrifice horsepower. We used focus groups composed of CAT experts and actual customers to identify the main customer segments and their characteristics. This produced six segments: *performance extreme* (PE), *performance extreme versatility* (PEV), *performance mild* (PM), *performance mild versatility* (PMV), *commodity extreme* (CE), and *commodity mild* (CM). The performance category represents customers who are less price sensitive and need powerful machines. The extreme and mild categories refer to weather conditions, and the versatility category represents customers who need their machines to perform a variety of tasks. Based on historical sales data, the fraction of customers in each of the above six segments are approximately 20, 20, 25, 10, 5, and 20 percent.

A set of *segmentation rules* was created to classify each purchase: given a configuration, its customer segment is determined by the presence and/or absence of certain options, represented as part numbers. For example, there are eight ways for a 416E loader to be placed in segment PE. One is: two out of the options 2146913, 2099929, and 2139293 must be present (89HP powertrain and e-stick), *and* one out of the options 2044161, 2044162, and 2284602 must be present (cabs), *and* the option 2120206 cannot be present (6-function hydraulics), *and* neither option 2497912, nor option 2624213 can be present (one-way and combined auxiliary lines).

In addition to the segment-specific option utilities that will be discussed in Section 4.2, the other segment-specific parameters that affect migration list generation are the reservation price and reservation utility (see Section 4.3).

## 4.2 Estimating Utilities

For each of the customer segments identified in Section 4.1, we calculate option utilities as follows. First, to estimate the importance of a model’s *features*, we asked a group of CAT employees with sales and manufacturing expertise to use the Analytic Hierarchy Process (AHP) (Saaty 1980). AHP asks experts to estimate different feature’s relative importance, on a scale from 1 (equally important) to 9 (much more important). After these pairwise relationships have been established, the scores are transformed into absolute scores, the *relative importance* of each feature. The same group of experts is then asked to rank the options *within* each feature on a scale from 0 to 100.

Table 2: AHP example: Pairwise and Normalized comparisons.

	Pairwise Comparisons			Normalized Comparisons			
	Sticks	Powertrain	Hydraulics	Sticks	Powertrain	Hydraulics	Avg. Scores
Sticks	1	1	3	$\frac{3}{7}$	$\frac{2}{5}$	$\frac{1}{2}$	0.4429
Powertrain	1	1	2	$\frac{3}{7}$	$\frac{2}{5}$	$\frac{1}{3}$	0.3873
Hydraulics	$\frac{1}{3}$	$\frac{1}{2}$	1	$\frac{1}{7}$	$\frac{1}{5}$	$\frac{1}{6}$	0.1698
Sum	$\frac{7}{3}$	$\frac{5}{2}$	6				

These option scores are scaled so that the option receiving a score of 100 is assigned a value equal to its feature’s relative importance. These scaled scores represent the *option* utilities.

We demonstrate this on a simplified example with three features: sticks, powertrain, and backhoe hydraulics. Assume the experts have ranked the pairwise importance as shown in the “Pairwise” portion of Table 2. The numbers in the “Sticks” row mean that sticks are as important as powertrain, and three times more important than hydraulics. Similarly, the second row indicates that powertrain is twice as important as hydraulics. Note that a perfectly consistent group of experts would have said that powertrain is three times as important as hydraulics, but in practice they may not be this consistent. Disparities like this are not unexpected, and are taken into account by the AHP. The AHP then calculates the column sums for each feature (last row of the “Pairwise” portion of Table 2), normalizes each column, and takes row averages to determine the final relative importance for each feature, as shown in the “Normalized” portion of Table 2. A final check is then performed to make sure that any inconsistencies are within an acceptable tolerance.

Now let us assume that the backhoe hydraulics feature has three options: 4, 5, and 6 function, assigned scores of 15, 50 and 100 by the experts, respectively. When we rescale these scores to a scale from 0 to 0.1698 (the relative importance of hydraulics from Table 2), we obtain the final utilities of these three options: 0.0255, 0.0849, and 0.1698, respectively.

The utility of a complete configuration is estimated as the sum of the utilities of its options. Although this additive method has been studied and used extensively (Keeney and Raiffa 1976), other ways of estimating option and configuration utilities are also possible (e.g. conjoint analysis and its many variations, Hauser and Rao 2004). One advantage of our migration list approach is that it is independent of the way in which utilities are calculated: The only thing it requires is a score ranking the relative desirability of each configuration.

To validate the utility values calculated for each of the options – for every BHL model in all customer segments – we conducted a survey asking actual customers to choose among alternate configurations. Caterpillar then used t-tests to examine the differences between these surveys and

the utility estimates provided by CAT experts. These differences were not statistically significant.

### 4.3 Building Migration Lists

Although customers of a given segment tend to behave similarly, they are certainly not identical. To account for variations within each segment, we modify the migration list procedure in several ways. First, for each segment we randomly perturb the relative importance (and, consequently, the option utilities) of randomly selected features. The number of features to perturb is an input parameter (for CAT, this was around three). Given a perturbation factor  $t$  (approximately ten), the change to a feature’s relative importance is randomly drawn from a uniform distribution over the interval  $[-t\%, +t\%]$ . CAT also did not want customers to have lists containing configurations too dissimilar from the one purchased. Therefore, a number called *disparity factor* (around five) limits how many options an alternative machine can have that differ from  $M_C$ . Finally, the model generates the customer’s reservation price and reservation utility; again, these values are randomly picked from a predetermined interval around the price and utility of  $M_C$ .<sup>1</sup>

We collect the above procedures into a Constraint Programming (CP) model (Marriott and Stuckey 1998) that finds feasible configurations for  $L_C$ . This CP model needs to know what constitutes a feasible configuration, i.e. which options are compatible. We use *configuration rules* to describe these interdependences. For example, for model 420E, one rule is: if a configuration has option 9R58666 and either option 2139272 or 2139273, then it cannot have option 9R5321. These rules may involve tens of different options; logical conditions of this form can be easily handled by CP models. After all feasible configurations are found, those that exceed the generated reservation price or fall short of the reservation utility are pruned from the customer’s migration list.

Next, configurations are sorted in non-increasing order of total utility and  $L_C$  is truncated, if desired, while respecting two conditions. First, if  $L_C$  is truncated  $M_C$  must always be retained. Second, we assume customers place  $M_C$  first, regardless of  $M_C$ ’s utility, with a certain probability (the  $\beta$  factor; for CAT it was between 0.3 and 0.7). This is an attempt to capture the fact that some customers are attracted to their  $M_C$  for reasons we cannot capture with utilities.

Migration across different models is also possible. In this case we apply a set of migration rules that map a purchased configuration  $M_1$  of model  $m_1$  (e.g. 416E) to its most likely counterpart  $M_2$ , of a different model  $m_2$  (e.g. 420E). Once  $M_2$  is known, we generate alternatives as if it were the

---

<sup>1</sup>Note that randomness in our choice model is restricted to the generation of option utilities and reservation values, which influence the construction of customer migration lists. Once created, these (fixed) lists serve as input to a *deterministic* optimization algorithm. Thus we refer to our model as being “randomized,” as opposed to a *random choice model*, which typically has a different meaning.

customer’s original purchase, and include them (together with alternatives to  $M_1$  in  $m_1$ ) into  $L_C$ . Because  $m_2$  configurations may have higher utilities, when  $L_C$  is sorted it may contain almost no highly ranked  $m_1$  configurations. Thus, to capture the fact that customer  $C$  originally preferred an  $m_1$  machine, we inflate the utilities of all  $m_1$  machines in  $L_C$  by a *preference factor* (between 10 and 20%). As a result,  $L_C$  ends up with machines of both models, but it does not allow utilities to overemphasize the attractiveness of  $m_2$  machines. According to CAT, the plausible model migrations are from 416E to 420E and from 430E to 420E.

As was done for option utilities, we also conducted an extensive validation study with CAT experts to evaluate the quality of our migration lists: Lists were repeatedly generated and examined to determine whether the substitution patterns indicated were realistic. Throughout this process the experts provided valuable feedback that helped us fine tune our input parameters. After a few iterations, CAT experts agreed that our migration lists could be safely used by our optimization algorithm. Before we present that algorithm, we describe how we estimate a key element of our objective function, the cost of complexity.

## 5 Capturing Cost of Complexity

We now estimate how a line reduction might affect costs. This is a significant challenge, as product variety affects many functional areas. In most areas the direction of the impact is clear: material planning costs increase as the number of options to be included increases. In some areas, however, the impact is not straightforward: sales costs may increase as variety increases because a large line may overwhelm customers and sales personnel; on the other hand, sales costs may decrease in variety if it is easier to satisfy a demanding customer. We refer to all costs impacted by the variety of product offerings, i.e. number of features and options, as *the cost of complexity*.

In this section we describe how we built a cost of complexity function for CAT. This includes both data collection and data analysis to determine and estimate the necessary parameters. The result of this process is used in our optimization model in Section 6.

### 5.1 Data collection stage

In conjunction with CAT experts we selected nine functional areas that we felt were most significantly affected by product complexity. We met with these areas’ representatives in a focus group setting that also included an information systems (IS) representative and a project manager from CAT. The primary goals of these meetings were: (i) to identify up to three major processes

Table 3: Main business processes impacted by complexity and the corresponding cost measures. A dagger (†) indicates alternative cost measures used due to lack of data availability.

<i><b>Department</b></i>	<i><b>Processes impacted</b></i>	<i><b>Measure of complexity</b></i>
<b>Purchasing</b>	Capital tooling Supplier operations	Capital tooling cost Supplier delivery performance†
<b>Customer acquisition</b>	Ordering Forecasting Quoting and training	Cost of customer acquisition†
<b>Marketing</b>	Price list creation Training Publications	Budget expenditure†
<b>Engineering</b>	Drawing changes  Original design & development	Cost of engineering changes Cost of product & component Cost of new releases
<b>Order fulfillment</b>	Attachment forecasting Sequencer work Grief resolution	Headcount cost†
<b>Product support</b>	Dealer solution network - calls Publications - manuals Warranty costs	Cost of service calls Cost of publications Cost of repairs (first 10 hours) Cost of repairs (during 11-100 hours)) Cost of repairs (above 101 hours)
<b>Material planning</b>	Inventory management  Schedule volatility Expedition	Inventory handling cost (prime product) Inventory handling cost (components) Headcount cost Freight cost
<b>Operations</b>	Initial process setup Assembly process	Man-hour cost, production planning Man-hour cost, assembly
<b>Quality</b>	Initial setup Hot test Cab test	Cost of initial setup Hot-test cost (man-hours) Cab-test cost (man-hours)

within each functional area most impacted by product complexity; (ii) to understand which cost-measures capture the impact of complexity for each major process; and (iii) to identify particular product features and/or options that have the largest impact on the complexity cost.

We then contacted an accounting representative from CAT who, working with the IS representative and the functional areas, identified which of the identified cost measures were obtainable. For some of the processes we identified there was no appropriate accounting data available; hence, we used an alternative cost measure as a proxy. Table 3 lists the functional areas, processes impacted, and measures used; when alternate cost measures are used they are denoted by a dagger (†). We elaborate on several cost measures in Table 3.

*Cost of supplier delivery performance* refers to a program aimed at improving availability; as a part of this program, CAT contacts suppliers with low delivery performance to improve their processes. We use the cost allocated to this program as a proxy for the cost of supplier operations.

In the customer acquisition department, CAT calculates sales variance cost by tracking all the discounts that go into making a sale: invoice, extended service, cost of free attachments, etc. We use this measure to approximate *cost of customer acquisition*. We rely on CAT’s accounting system for cost estimates of engineering changes (mainly consisting of payroll to engineers working on changes) and engineering of new releases (mainly consisting of the payroll of developers and engineers who work on new parts, and costs of testing and design equipment).

Another outcome of our focus group discussions was the observation that there were two distinct ways in which complexity affects different business departments: Variety Based and Attribute Based. We discuss this distinction now.

#### **5.1.1 Variety Based vs. Attribute Based complexity.**

Certain processes are impacted by the *number* of options offered for a feature, while others are more impacted by the presence of *specific* options. For example, material planners calculate requirements for each type of bucket offered, which increases their departmental cost. If one type of bucket is eliminated, the cost of complexity goes down proportionally, regardless of which option is eliminated. We refer to this effect as *Variety Based Complexity*, or *VBC*.

In contrast, for the Cab/Canopy feature, the Deluxe Cab with Air Conditioning is significantly more complicated than a canopy. Hence, if we reduce the number of options in the Cab/Canopy feature, the change in cost would be different depending on which particular option was eliminated. We refer to this effect as *Attribute Based Complexity* or *ABC*. Note that attribute based complexity is not limited to single options; it is the combination of Deluxe Cab *with* Air Conditioning that drives complexity cost. In Table 4, we summarize the features that were identified as most important during our focus group meetings, along with their VBC or ABC classifications.

In addition to the VBC/ABC classification, there were two other important considerations that came out of our focus group discussions: *time lag* and *volume drivers* of complexity.

#### **5.1.2 Time lag of the impact of complexity**

Our discussions revealed that the effect of complexity on different processes may be felt at different times. For example, assembly cost today is impacted by the product complexity being built today, while warranty costs are affected by complexity that was offered a certain time ago (positive time lag), and engineering and marketing costs may be impacted by the complexity that

Table 4: *ABC*/VBC classification of features.

<i>Department/Feature</i>	Backhoe Hydraulics	Loader Buckets	Auxiliary Lines	Quick Coupler	Hoe Buckets	Control Groups	Cab/Canopy	Sticks
<b>Purchasing</b>		VBC		VBC	VBC		VBC	VBC
<b>Customer acquisition</b>	VBC		VBC				VBC	
<b>Marketing</b>	VBC		VBC				VBC	
<b>Engineering</b>	<i>ABC</i>	VBC	VBC		VBC		<i>ABC</i>	
<b>Order fulfillment</b>	VBC	VBC	VBC	VBC	VBC	VBC	VBC	VBC
<b>Product support</b>	VBC		VBC				VBC	
<b>Material planning</b>	VBC	VBC			VBC		VBC	
<b>Operations</b>			<i>ABC</i>				<i>ABC</i>	<i>ABC</i>
<b>Quality</b>							<i>ABC</i>	

Table 5: Summary of cost time lags (in months).

<i>Department</i>	<i>Time Lag</i>	<i>Department</i>	<i>Time Lag</i>
<b>Purchasing</b>	0	<b>Product support:</b>	
<b>Customer acquisition</b>	3	Service calls	6
<b>Marketing</b>	0	Repairs in the first 10 hours	4
<b>Engineering:</b>		Repairs in 10-100 hours	9
Changes	-6	Repairs after 100 hours	9
Releases	-8	<b>Material planning:</b>	
Product and component costing	-7	Prime product inventory	2
<b>Order fulfillment</b>	0	Scrap of surplus materials	6
<b>Operations</b>	0	Inventory scrap	6
<b>Quality</b>	0		

will be offered in the future (negative time lag). Based on our focus group discussions we estimated the number of months of time lag for different cost pools. Later (in Section 5.2.1), we use this information in estimating the parameters of the cost of complexity function. Table 5 summarizes our analysis of time lag parameters.

### 5.1.3 Volume drivers for complexity

Another important aspect in understanding the impact of complexity is understanding different volume metrics and how they affect costs. Not surprisingly, most areas are affected by sales volume: costs increase as more items are produced and sold. However, costs are also driven by other volumes. For example, product support is impacted by the number of *unique* configurations *built*, because quality may decrease when employees have to work on many different configurations.



Table 6: Volume drivers.

<i>Department/Volume driver</i>	Sales volume	Complexity offered	Complexity built
Purchasing	✓		✓
Customer acquisition	✓	✓	
Marketing	✓	✓	
Engineering		✓	
Order fulfillment	✓		✓
Product support	✓		✓
Material planning	✓	✓	✓
Operations	✓		✓
Quality	✓		✓

Other processes, such as assembly planning and engineering, are impacted by the complexity *offered*, as CAT should be ready to assemble any feasible configuration offered. Later (Section 5.2.1), we use this information to determine which predictors to include in the cost model for each department. Table 6 summarizes of the most important volume drivers for each department.

## 5.2 Cost of complexity function

Before defining the cost functions and notation associated with VBC and ABC costs, we present supplementary notation that will be common to both. We use small letters for superscripts and subscripts, bold letters for sets, and capital letters for numbers coming from collected data.

### Supplementary Notation:

$d \in \mathbf{D}$	Superscript used to represent attributes pertaining to department $d$ , where $\mathbf{D}$ is the set of all departments considered in the study;
$f \in \mathbf{F}$	Superscript used to represent attributes pertaining to feature $f$ , where $\mathbf{F}$ is the set of all features in the product line;
$\mathbf{F}^d \subset \mathbf{F}$	The set of all features identified as relevant for department $d$ ;
$o \in \mathbf{O}$	Superscript used to represent attributes pertaining to option $o$ , where $\mathbf{O}$ is the set of all options in the product line;
$\mathbf{O}_f \subset \mathbf{O}$	The set of all options in feature $f$ ;
$N_f$	Number of options in feature $f$ : $ \mathbf{O}_f $ ;
$\mathbf{N}^d$	Set of cardinalities of all features relevant for department $d$ : $\mathbf{N}^d = \{N_f : f \in \mathbf{F}^d\}$ .

### 5.2.1 Estimation of VBC effect

To estimate the VBC effect for each department  $d$ ,  $\mathcal{C}_{VBC}^d$ , we use the Cobb-Douglas log-linear function. The Cobb-Douglas function is frequently used for estimating non-linear relationships

(see Greene 2000); it can capture different returns to scale and has several attractive analytical properties. Two properties are of particular convenience for us: First, the log transformation of the Cobb-Douglas function is linear and hence can be estimated using linear regression. Second, a partial derivative of the Cobb-Douglas function has a simple form that is useful in the derivation of the *differential cost of complexity* (Section 5.3). After estimating the models, we validate our Cobb-Douglas function via several goodness of fit tests (e.g. Figure 2).

Using lower-case Greek letters to represent estimated parameters, the Cobb-Douglas function for  $\mathcal{C}_{VBC}^d$  is given by

$$\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U) = \xi^d V^{\alpha^d} U^{\beta^d} \prod_{f \in \mathbf{F}^d} N_f^{\gamma_f^d}. \quad (1)$$

Where:

$V$	Total sales volume;
$U$	Total number of <i>unique</i> configurations sold;
$\xi^d$	The size of the cost pool at department $d$ relative to other departments;
$\alpha^d$	The effect of the sales volume on the cost of complexity;
$\beta^d$	The effect of the number of unique configurations sold on the cost of complexity;
$\gamma_f^d$	The effect of the cardinality of feature $f$ on the cost of complexity;

We fit this function to the data to estimate  $\xi^d$ ,  $\alpha^d$ ,  $\beta^d$ , and  $\gamma_f^d$  for all  $d$  and  $f$ , using data collected for 60 months, from 1/2001 to 12/2005, for all cost measures in the third column of Table 3. We also collected data from the price lists from 2000 to 2006 to capture all changes in the option offerings, which were used as independent variables. (Due to the time lags identified in Section 5.1.2, we collected price list data over a wider time range than cost data.) Similarly, we collected monthly sales ( $V$ ) and number of unique configurations sold per month ( $U$ ) from 2000 to 2006 and ran regression analysis to confirm our hypotheses concerning lags in Table 5.

The nature of the data suggests that there is serial correlation, which was confirmed with the Durbin-Watson statistic for all cost pools. Therefore, we use the Yule-Walker approach to fit the data to the log transformation of  $\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)$  (Greene 2000). The log transformation of  $\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)$  used for estimation, with  $\epsilon$  as the model error term, is

$$\text{Log}[\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)] = \text{Log}[\xi^d] + \alpha^d \text{Log}[V] + \beta^d \text{Log}[U] + \sum_{f \in \mathbf{F}^d} \gamma_f^d \text{Log}[N_f] + \epsilon. \quad (2)$$

Next, we fitted collected data to equation (2) and obtained statistical models for all depart-

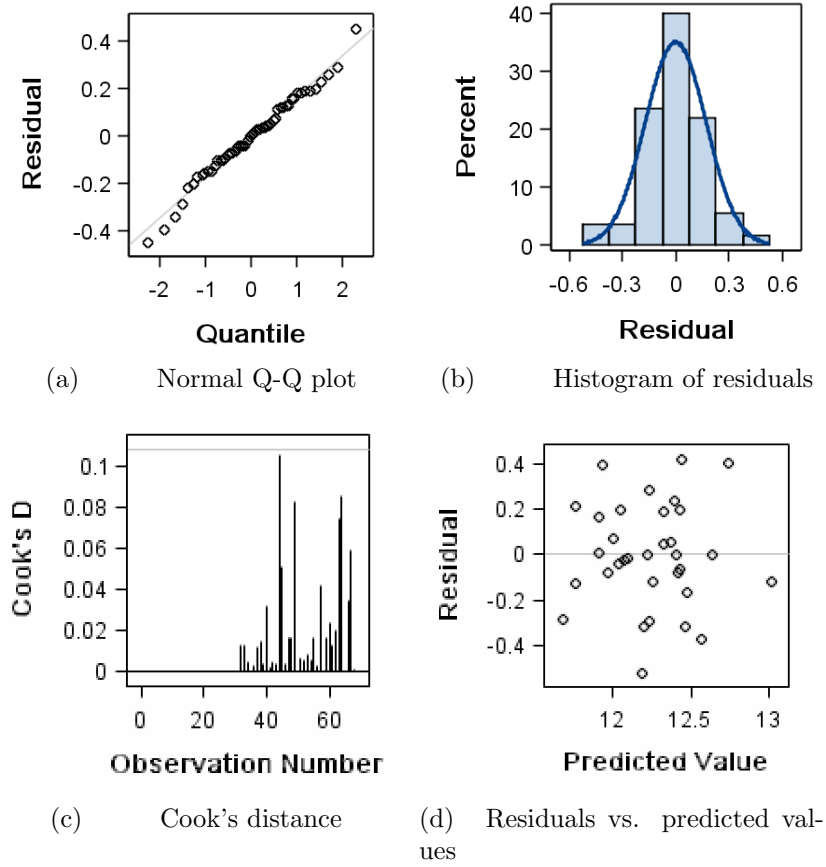


Figure 2: Goodness of fit plots for the customer acquisition cost model.

ments. We analyzed our model using both graphical and numerical tests: we examined the plots of residuals for normality, heteroscedasticity, and for influential outliers (an example of these plots for one of the cost pools, customer acquisition cost, is depicted in Figure 2). We also checked for significance of the models, and only accepted models with reasonable coefficients of variation (see Table 7) and low RMSE. The estimates that are statistically significant at the  $p = 0.05$  level are marked with an asterisk in Table 7. Hence, not all of the originally identified departments were included in the final cost of complexity function, and some of the sets  $\mathbf{F}^d$  were reduced.

First, we comment on the coefficient of determination of the models ( $R^2$ ) in Table 7. Some

Table 7: Fit results. A \* indicates statistically significant parameters at  $p = 0.05$  level. Subscripts  $HC$ ,  $C$ ,  $CW$  and  $H$  stand for hydraulic combinations, cabs, counterweights, and hydraulics.

Fn.	Cost pool ( $d$ )	$R^2$	$\xi^d$	$\alpha^d$	$\beta^d$	$\gamma_{HC}^d$	$\gamma_C^d$	$\gamma_{CW}^d$	$\gamma_H^d$
CA	Customer acquisition	0.37	962771120.4*	0.19			-1.13*		-1.68*
MP	Inventory (components)	0.29	1087617.41*	-0.03			1.04*		
MP	Inventory (prime product)	0.38	297.68	0.91*	0.91				
ENG	Engineering changes	0.41	0.00342591			4.81712*	-0.54		
ENG	Engineering product & component	0.55	6.39E-04*			4.107*		3.14*	
PS	Repair costs in the first 10 hours	0.29	26238.94*	-0.21	0.59*				
PS	Repair costs during 11–100 hours	0.32	3055.00*	-0.32	1.28*				
PS	Repair costs above 101 hours	0.55	934.63*	-1.41*	2.78*				
P	Supplier delivery performance	0.33	36.65		1.5*				

of the departmental costs are heavily impacted by factors *outside* CAT’s walls: for example, cost of customer acquisition is impacted by competitors’ actions, and cost of supplier delivery performance is impacted by the suppliers’ operations. Hence, we expect the coefficients of determination to be lower for such departments. The results in Table 7 are consistent with our expectations. Similarly, when analyzing the models for warranty costs, we expect that earlier failures would be less predictable, due to learning effects. The results are again consistent with this expectation; the coefficient of determination increases for repair costs as the time of failure increases. Nevertheless, in order to ensure that our results are robust, we use ranges of parameters in running the optimization model as described in Section 7.

We comment on some findings from Table 7. Increasing the number of options for hydraulics and cabs decreases the cost of customer acquisition:  $\gamma_H^{CA} < 0$  and  $\gamma_C^{CA} < 0$ . A large portion of the cost of customer acquisition consists of sales variance or discounts given to customers by dealers in order to attract business. Cabs and hydraulics are very important considerations for customers; having a large selection of options for these features makes it easier for the dealer to make a sale, decreasing the sales variance. This finding is in line with the intuition of sales and marketing representatives from CAT. However, this was the first time CAT was able to quantify this effect.

Another interesting observation is that sales volume has a negative impact on product support costs (i.e. repair costs). When volume goes up CAT employees assemble more machines with the same options, employees get more experienced with particular options, and the number of mistakes decreases. This intuition again seemed plausible to CAT, but had never been quantified. Guided by our study, CAT subsequently has performed similar cost of complexity analysis in other product divisions and obtained comparable results.

Finally, we tested our predictions by using the first year of data to fit the model, then calculated the predicted values for the next four years, and finally compared them to the actual data. Figure 3 shows that a large majority of the actual values lie within the 95% confidence interval around the predicted values, again for customer acquisition cost.

### 5.2.2 Estimating ABC effect

From focus groups, we identified that ABC effects were observed primarily in three departments: assembly, production planning, and engineering. The nature of work in these departments suggested that the relationship between ABC cost and complexity is linear: if it takes 5 extra minutes to install a particular option on a machine, this cost will apply to each machine that contains the option. This coincided with expert opinion, which posited that learning effects are

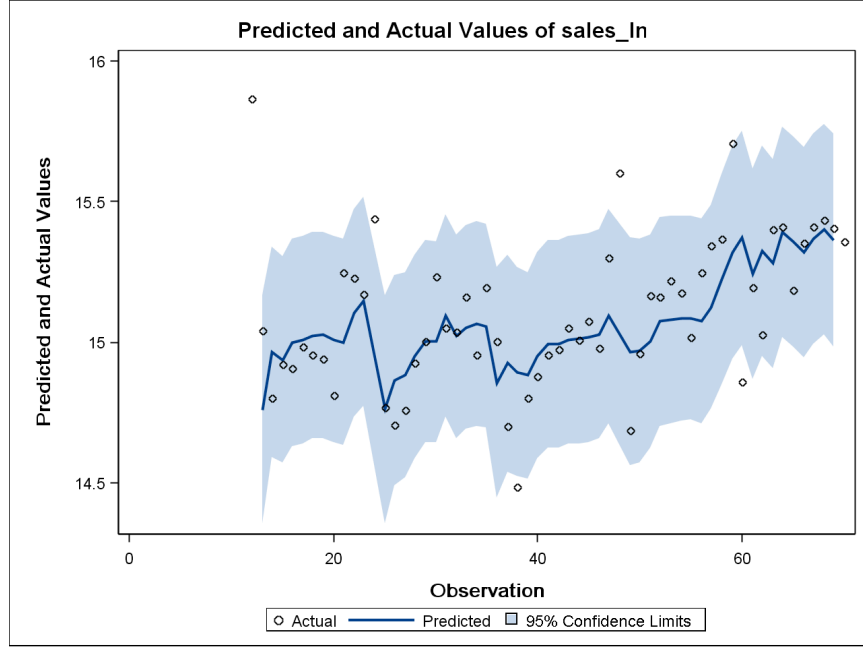


Figure 3: Actuals versus 95% confidence interval of predictions for customer acquisition.

minimal. Hence we model the total cost of offering and producing option  $o$ ,  $\mathcal{C}_{ABC}^o$ , as the sum of the one-time cost across all departments if option  $o$  is offered and the incremental cost across all departments that is incurred each time a machine with option  $o$  is built:

$$\mathcal{C}_{ABC}^o(a_o, V^o) = \delta^o a_o + \omega^o V^o.$$

Where:

$\delta^o$	Cost incurred if option $o$ is offered;
$a_o$	Binary variable that indicates whether option $o$ is offered or not;
$\omega^o$	Cost incurred <i>each time</i> option $o$ is produced;
$V^o$	Number of configurations sold that contain option $o$ ;
$\mathbf{V}$	Set of number of configurations sold for all options: $\mathbf{V} = \{V^o : o \in \mathbf{O}\}$ .

The cost parameters  $\delta^o$  and  $\omega^o$  were estimated using expert opinions, time studies, and accounting information from all functional areas that identified this option as important; see Table 8.

### 5.3 Differential cost of complexity function

Instead of computing the total revenue and total cost of each line, our complexity cost function enables us to start with the current line and compute the *estimated change in revenue* and the *estimated change in cost* as the number of features and options change. To compute this “differential” cost of complexity, we take the partial derivatives of  $\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)$  with respect to all

Table 8: ABC costs.

<b>Option</b>	$\delta^o$	$\omega^o$
Any option	\$1,000.00	
<i>In addition:</i>		
IT	\$6,000.00	\$23.61
Cab	\$14,656.25	\$53.80
E-Stick	\$125.00	\$1.30
One Way Line	\$3,593.75	\$5.64
Ride Control	\$1,281.25	\$5.86

variables, and then combine them into a differential cost of complexity function. Specifically, the change in cost of complexity when the number of options for feature  $f$  changes is:

$$\frac{d\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)}{dN_f} = \frac{\gamma_f^d}{N_f} \xi^d V^{\alpha^d} U^{\beta^d} \prod_{i \in \mathbf{F}^d} N_i^{\gamma_i^d} = \frac{\gamma_f^d}{N_f} \mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U), \quad (3)$$

substituting the definition of  $\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)$  given by (1).

This differential cost of complexity function includes the predicted value of  $\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)$ , the average size of the cost pool at department  $d$ . This is problematic for two reasons: (i) The predicted  $\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)$  contains an error term and hence may not give an accurate size of the cost pool; and (ii) Values of  $V$ ,  $N_f$ , and  $U$  change during the specified time period. Therefore we approximate  $\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)$  with the historical average cost at department  $d$  ( $\overline{D}^d$ ) attributable to complexity, taken over the period of 60 months from January 2001 to December 2005:

$$\frac{d\mathcal{C}_{VBC}^d(\mathbf{N}^d, V, U)}{dN_f} \approx \frac{\gamma_f^d}{N_f} \overline{D}^d. \quad (4)$$

Using (4) the total change in complexity cost due to a change in the number of options offered for feature  $f$  is then estimated as:

$$\overline{D}^d \frac{\gamma_f^d}{N_f} \Delta N_f, \quad (5)$$

where  $\Delta N_f$  represents the change in the number of options in feature  $f$  after line optimization; similarly we will precede  $V$ ,  $U$ ,  $V^o$ ,  $\mathbf{N}$ ,  $\mathbf{N}^d$ , and  $\mathbf{V}$  with  $\Delta$  to represent change. We will formally define these functions in Section 6 when we introduce the optimization model.

In an analogous fashion we differentiate the cost of complexity function with respect to volume and number of unique configurations. This yields the total *differential cost of complexity*  $\mathcal{D}_{VBC}^d$ :

$$\mathcal{D}_{VBC}^d(\mathbf{N}^d, V, U, \Delta \mathbf{N}^d, \Delta V, \Delta U) = \sum_{f \in \mathbf{F}^d} \overline{D}^d \frac{\gamma_f^d}{N_f} \Delta N_f + \overline{D}^d \frac{\beta^d}{U} \Delta U + \overline{D}^d \frac{\alpha^d}{V} \Delta V. \quad (6)$$

To capture the differential ABC effect, we must account for the change in the number of options offered and sold. If we eliminate an option  $o$  from the price list, the cost of complexity will decrease by  $\delta^o$  and if sales with option  $o$  deviate from  $V^o$ , the cost will change accordingly:

$$\mathcal{D}_{ABC}(\Delta \mathbf{V}, \mathbf{a}) = \sum_{o \in \mathbf{O}} \delta^o (a_o - 1) + \sum_{o \in \mathbf{O}} \omega^o \Delta V^o, \text{ where } \mathbf{a} = \{a_o : o \in \mathbf{O}\} \quad (7)$$

Finally, the total differential cost of complexity is:

$$\mathcal{D}(\mathbf{N}^d, V, U, \Delta \mathbf{N}^d, \Delta V, \Delta U, \Delta \mathbf{V}, \mathbf{a}) = \sum_{d \in \mathbf{D}} \mathcal{D}_{VBC}^d(\mathbf{N}^d, V, U, \Delta \mathbf{N}^d, \Delta V, \Delta U) + \mathcal{D}_{ABC}(\Delta \mathbf{V}, \mathbf{a}). \quad (8)$$

Because the complexity cost function is non-linear, this approach is accurate only for small changes. The accuracy of this approximation may be tested by calculating the actual change in total cost of complexity  $\mathcal{C}_{VBC}$  between the original product line and the optimized product line, and then comparing this to the result of the approximation  $\mathcal{D}_{VBC}$ . In our experiments, the differential cost approximation was within 5% of the calculated change in the cost of complexity, which was acceptable for the purposes of our project<sup>2</sup>. As a result, equation (8), with estimated parameters, becomes a part of the objective function in the optimization model of Section 6.

## 6 The Optimization Model

With the migration lists from Section 4, which capture customer flexibility information, and equation (8) of Section 5, which contains the differential complexity cost information, we can now describe our optimization model. We use a mixed-integer program to select the set of options and configurations offered, and their prices, to maximize total revenue from sales minus complexity costs. We use customer purchases in 2006 as the basis for generating our migration lists.

In addition to the data defined in Section 5, our optimization uses the following data:

- $\mathbf{I}$  — The set of all customers;
- $\mathbf{L}_i$  — The ordered set of configurations in the migration list of customer  $i \in \mathbf{I}$ ;
- $\mathbf{J}$  — The set of all possible configurations;
- $\mathbf{O}_j$  — The set of all options in configuration  $j \in \mathbf{J}$ ;

---

<sup>2</sup>If desired, this approximation may be improved by using an iterative approach built into the optimization model, in which the differential is re-estimated after each small change in variables.

- $R_i$  — Reservation price of customer  $i \in \mathbf{I}$ ; this could be made machine dependent if desired;
- $M$  — Maximum reservation price over all customers ( $M = \max_{i \in \mathbf{I}} R_i$ );
- $C_j, C'_j, B_j, P_j$  — Cost, variable cost, base price, and current sale price of configuration  $j \in \mathbf{J}$ , respectively. Variable cost  $C'_j$  is an internal CAT figure, lower than  $C_j$ , whose purpose is to enforce a constraint on the average profit margin over all machines sold (see (16)).

The decision variables are as follows ( $a_o$  was already defined in Section 5.2.2):

- $a_o = 1$  if option  $o \in \mathbf{O}$  is available, 0 otherwise.
- $q_j = 1$  if configuration  $j \in \mathbf{J}$  is bought by some customer, 0 otherwise;
- $x_{ij} = 1$  if customer  $i$  buys configuration  $j$ , 0 otherwise ( $i \in \mathbf{I}, j \in \mathbf{L}_i$ );
- $p_o$  — Price of option  $o \in \mathbf{O}$  ( $p_o \geq \delta^o$ , where  $\delta^o$  is defined in Section 5.2.2);
- $r_{ij}$  — Profit obtained from customer  $i$  if she purchases configuration  $j$  ( $i \in \mathbf{I}, j \in \mathbf{L}_i$ ).

We now provide precise definitions to the following terms that appear in (6) and (7):

$$\begin{aligned}\Delta N_f &= \sum_{o \in \mathbf{O}_f} a_o - N_f, \\ \Delta U &= \sum_{j \in \mathbf{J}} q_j - U, \\ \Delta V &= \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{L}_i} x_{ij} - V, \\ \Delta V^o &= \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{L}_i | o \in \mathbf{O}_j} x_{ij} - V^o.\end{aligned}$$

The objective function maximizes the total profit from sales ( $\sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{L}_i} r_{ij}$ ) minus the differential cost of complexity given by equation (8) of Section 5:

$$\max \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{L}_i} r_{ij} - \sum_{d \in \mathbf{D}} \mathcal{D}_{VBC}^d(\mathbf{N}^d, V, U, \Delta \mathbf{N}^d, \Delta V, \Delta U) - \mathcal{D}_{ABC}(\Delta \mathbf{V}, \mathbf{a}).$$

Our optimization model uses the following constraints, where MAX\_INC is the maximum allowed percentage price increase for a configuration:

$$q_j \leq a_o, \quad \forall j \in \mathbf{J}, o \in \mathbf{O}_j \quad (9)$$



$$x_{ij} \leq q_j, \quad \forall i \in \mathbf{I}, j \in \mathbf{L}_i \quad (10)$$

$$\sum_{k \text{ after } j \text{ in } \mathbf{L}_i} x_{ik} + q_j \leq 1, \quad \forall i \in \mathbf{I}, j \in \mathbf{L}_i \quad (11)$$

$$r_{ij} \leq B_j + \sum_{o \in \mathbf{O}_j} p_o - C_j, \quad \forall i \in \mathbf{I}, j \in \mathbf{L}_i \quad (12)$$

$$r_{ij} \leq (\min\{R_i, P_j(1 + \text{MAX\_INC})\} - C_j)x_{ij}, \quad \forall i \in \mathbf{I}, j \in \mathbf{L}_i \quad (13)$$

$$B_j + \sum_{o \in \mathbf{O}_j} p_o \leq R_i + (P_j(1 + \text{MAX\_INC}) - R_i)(1 - x_{ij}), \quad \forall i \in \mathbf{I}, j \in \mathbf{L}_i \quad (14)$$

$$C_j(1 + \text{MIN\_MARG}) \leq B_j + \sum_{o \in \mathbf{O}_j} p_o \leq P_j(1 + \text{MAX\_INC}), \quad \forall j \in \mathbf{J} \quad (15)$$

$$\text{MIN\_AVGMARG} \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{L}_i} (r_{ij} + C_j q_j) \leq \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{L}_i} (r_{ij} + (C_j - C'_j)q_j). \quad (16)$$

Constraint (9) says if option  $o$  is not available ( $a_o = 0$ ), no configuration that contains it can be bought ( $q_j = 0$ ); (10): if configuration  $j$  is not bought ( $q_j = 0$ ), make  $x_{ij} = 0$ ; (11): if  $j$  was bought by someone ( $q_j = 1$ ) it must be available; therefore customer  $i$  will not consider configurations with lower priority ( $k$  after  $j$  in  $\mathbf{L}_i$ ); (12): profit is at most equal to price minus cost; (13): profit is limited by the customer's reservation price  $R_i$ , and no purchase ( $x_{ij} = 0$ ) means no profit ( $r_{ij} = 0$ ); (14): if customer  $i$  bought configuration  $j$  ( $x_{ij} = 1$ ), price of  $j$  must be no more than  $R_i$ ; (15): configuration margins have to be at least  $\text{MIN\_MARG}$  and configuration prices cannot increase more than  $\text{MAX\_INC}$  above original values; (16): average margin over all machines has to be at least  $\text{MIN\_AVGMARG}$ .

We can turn off the price optimization aspect of the model by removing variables  $p_o$ , constraints (14)–(16), making  $\text{MAX\_INC} = 0$  in (13), and substituting  $P_j$  for  $B_j + \sum_{o \in \mathbf{O}_j} p_o$  in (12). (This additive price structure is in line with CAT's pricing rules.)

Our optimization models have around 850,000 variables and 1.8 million constraints, and they are solved using ILOG CPLEX Optimizer with default parameters. Typical solution times range from 6 to 8 hours, including preprocessing.

## 7 Results from Our Analysis

CAT's goal was to make a drastic reduction in the number of configurations offered without significantly impacting customer satisfaction and market share. How to achieve such a goal, or whether such an outcome was even possible, was unclear at the outset of the project: Optimizing

their product line required careful understanding and modeling of potential losses due to reduced offerings, and potential savings due to reduced cost of complexity. Since this reduction would present customers with fewer configurations, CAT assumed each remaining configuration could be priced a little lower; the reduced cost of complexity would allow this while maintaining profit.

Throughout our analysis, to ensure that our recommendations were robust we ran the optimization model across a range of parameters and migration list lengths.

## 7.1 Stage 1: Focusing on Configuration and Option Reduction

As an initial benchmark for our optimization, we first sought to identify the set of configurations that maximized profit at the current option prices, assuming limited customer migration (no more than a dozen configurations on a migration list, and no migration across models). While profits did increase, we obtained very little reduction in the number of configurations, except when a reduction was explicitly enforced by the constraint  $\sum_{j \in \mathbf{J}} q_j \leq (1 - \text{MIN\_CONF\_RED})|\mathbf{J}|$ . Moreover, forcing a large reduction resulted in a significant decrease of sales revenue.

Given these results, we hypothesized that further reducing the cost of complexity would require significant cuts in *options*. Hence, a new constraint was added to the model to force option reduction:  $\sum_{o \in \mathbf{O}} a_o \leq (1 - \text{MIN\_OPT\_RED})|\mathbf{O}|$ . We re-ran the optimization model forcing a reduction in the number of configurations and the number of options. Reducing options did succeed in reducing configurations, in some solutions by as much as 94%, and increased profit by generating a large cost of complexity reduction. But it also resulted in a drop in sales volume of up to 67%. This disturbed CAT team members since the company has always prided itself on its market share. Fulfilling customer demand therefore became an important new metric of the analysis.

## 7.2 Stage 2: Opening Up Choices

Thus in the next phase of our analysis we wanted to explore what results would be possible if customers were significantly more flexible, possibly as a result of price incentives. We modeled this flexibility in two ways: We increased the migration list length (to 100 configurations) and we enabled model-to-model migration.

This approach started to generate encouraging results. A solution emerged with an increase in profit of 8.8%, less than a 2% reduction in sales volume, and a reduction in configurations equal to 65%. But further analysis showed that the number of options had not decreased significantly. The increase in profit came from a decrease in the number of configurations, and increases in price paid by customers who migrated to slightly more expensive configurations. Performing

sensitivity analysis confirmed this conclusion: expecting a large reduction in options was not realistic. However, a large reduction in configurations was possible.

This resulted in a problem for CAT: Without a reduction of options, how would this new set of configurations be presented to the customers? Restaurants can get by with a 3-4 page menu that lists all their entrees. But no customer would flip through a menu of 70-90 pages listing all the possible BHL configurations. A new scheme had to be devised.

### 7.3 Stage 3: Standardization and Options Packages

We decided to try two new strategies to concentrate customer demand on a manageable number of configurations. The first strategy was standardization: Could options such as High Ambient Cooler and Engine Heater be made standard across all configurations? Optimization models with these options forced into every configuration yielded cost reductions that justified a reduction in price large enough to make the standardized configurations attractive to customers, while maintaining sales volumes and profit. Other rarely used options were eliminated using a similar approach. For example, the Cab/Canopy options were cut from five to two.

The second strategy was creating *packages* of options commonly found together. For example, guided by customer segment preferences, a single pair of loader hydraulics and powertrain options most likely to meet each segment's needs was proposed. Manual inspection and cluster analysis of the best solutions found so far led to the discovery of other options often found together.

The optimization was then run assuming standardization and option packaging, with constraints on the maximum price increase. This yielded the final product hierarchy for the 420E series, shown in Figure 4: It consists of 9 base-machine-assembly (BMA) packages, 5 finished-to-order (FTO) packages, and 3 hydraulics options, for a total of 135 possible configurations, some of them anticipated to be much more popular than others.

Pricing optimization showed that with these 135 configurations, revenue from sales could increase by almost 7% and profit by 15%, *with 99.6% demand fulfillment*. Interestingly, 76% of the projected cost of complexity savings came from reductions in finished goods inventory and warranty costs (in particular, the cost of addressing failures in the first 100 hours of machine operation). Since the goal of the project was to maintain similar profit levels (rather than seeking increases), the team determined appropriate option price *reductions* to drive dealer behavior toward these configurations while maintaining profit. The proposed pricing policy resulted in an anticipated reduction in profit from sales of 4%, which was easily made up by the reduction in cost of complexity to yield a total profit increase of 4.8%. We had finally found the very small subset

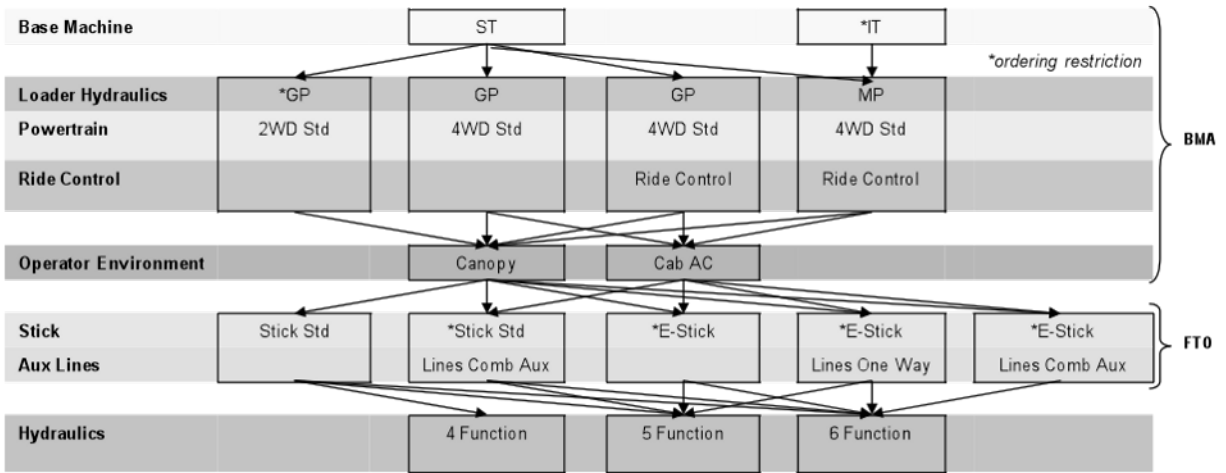


Figure 4: Final product hierarchy and packages for the BHL 420E series.

of configurations that we believed was broad enough to satisfy CAT’s customers and dealers, but also focused enough to drive operational and supply chain efficiencies.

This final recommendation was presented to CAT, and approved.

## 8 Implementation Details

### 8.1 Initial Implementation

The implementation of such a dramatic change faced challenges. The first one was a concern that our solution would restrict customer choice too much, resulting in excessive lost sales. Caterpillar therefore showed the proposed packages to a subset of dealers, including their top 15 dealers, responsible for nearly half of the North American demand. The dealers suggested configurations to add and remove, and we adapted some of the packages slightly. Caterpillar also suggested the addition of high-cost options, but the dealers did not support this, so they were excluded.

The response from the dealers was very favorable, with many dealers projecting they would be able to satisfy 80% of their demand from these packages. In contrast, dealers estimated that the machines they currently kept in stock satisfied only 5-10% of their demand. Thus, standardization and option packaging represented an effective way of potentially reducing configurations.

The second challenge came with the recession of 2009. Suddenly, every sale became crucial, and configuration reduction became a lower priority. However, with the economy showing signs of recovery in 2010 and with some changes to product sourcing at Caterpillar, reducing the number of configurations again gained importance. Caterpillar therefore put an updated price list for the 430E product line into effect in April 2010; but, in order to minimize the risk of lost sales in the

still difficult economic environment, the new price list was introduced alongside the old price list, rather than as a replacement.

Concurrent with this new price list, now featuring 124 configurations, Caterpillar introduced a 3-lane strategy for order fulfillment:

- Lane 1, the fastest lane, projected that orders on the four designated “most popular” fully configured machines would be satisfied within a few days.
- Lane 2 projected that orders on the remaining 120 choices, broken into the *Loader*, *Comfort and Convenience*, and *Excavation* packages, would be satisfied within a few weeks.
- Lane 3 projected any a-la-carte machine would be satisfied within a few months, as previously.

Upon implementation, Caterpillar experienced positive dealer feedback and large reductions in the number of unique configurations sold. This contrasted with previous attempts to reduce the size of the product line, based on a Pareto analysis of the top few dealers. These had likely been ineffective, in CAT’s opinion, because they did not effectively model the interaction of cost, customer preferences, and substitution, as we had.

It is worth noting that, to the best of our knowledge, neither standardization nor option packaging were being considered prior to the start of our project. These concepts were only developed *after* our analysis indicated that CAT needed to find a way to limit the number of configurations while *not* eliminating too many options. Our analysis gave CAT direction in implementing these new strategies, by indicating which sets of configurations were likely to be successful.

## 8.2 Moving Forward

In 2011 Caterpillar consolidated the two price lists into a single price list featuring options packages. They were able to capture over a quarter of their sales volume just in Lane 1; in contrast, the four top-selling configurations Caterpillar used to offer before this project captured 11.3% of both sales and total revenue for the 420E model (Figure 1). In addition, CAT enjoyed a reduction in warranty costs, attributable to many factors, including this project. Caterpillar has continued to focus their BHL offerings, for example reducing the 420E (now the 420F) Lane 1 offerings to three base machines by mid 2014. The other BHL lines have seen similar reductions.

Caterpillar has rolled out the lane approach to the entire company, making it an integral part of CAT’s business strategy (Thomson Reuters (2014)). While the methodologies used to determine

the lane offerings in other divisions were somewhat simpler than the analysis done here, our work provided support for the corporate-wide Lane Strategy. In particular, our cost of complexity analysis approach has been applied to other divisions, such as Wheel Loaders, with the goal of capturing all the benefits and understanding all the consequences of proposed line changes. The detailed analysis and structured optimization approach reported in this paper allowed Caterpillar to counteract skepticism toward the lane approach embarked upon by BCP, prior to the CEO mandate, and successful implementation, of this strategy for the entire company.

## 9 Conclusion

We present a three-step procedure to restructure a product line, and demonstrate its successful application on the Backhoe Loader line at Caterpillar. Our methodology hinges on (i) The construction of migration lists to capture customer preferences and willingness to substitute; (ii) Explicitly capturing the (positive and negative) cost of complexity of offering a specific product line across different functional areas; and (iii) integrating these tools within a mathematical programming framework to produce a final product line. One of the greatest strengths of our methodology is its flexibility – each step can be custom tailored to a company’s particular setting, data availability and strategic needs, so long as it produces the necessary output for the next step of the algorithm.

As Caterpillar evolves, so has their Lane Strategy. For example Thomson Reuters (2014) discusses a new variation in which lanes may contain only partially completed machines, which can be finished to customer order as needed. Ideas such as these offer opportunities to extend our work to new problem domains – analytically characterizing the performance of such a delayed differentiation strategy is an exciting and challenging problem.

Outside of Caterpillar, our work can be extended in several directions. First, explicit experimental validation of our empirical models – in particular our migration approach – would be of value. While this approach has been successfully applied in the construction equipment industry, further study could help establish how it could be applied in other sectors, and what changes might be necessary. For example, we set the list lengths based on consultation with Caterpillar executives. A better understanding of how long such lists really are, and how willing customers are to substitute (and whether there is any sort of explicit cost to this) would be of interest.

Second, as our methodology is applied to other settings, new constraints might need to be incorporated into our mathematical program. One of the benefits of our procedure is that our math

programming formulation is flexible enough to accommodate other such constraints. Nevertheless, how it performs in other settings needs to be established.

Finally, the central thrust of this paper has considered the trade-off between cost of complexity and product line breadth. Caterpillar has found what they believe to be the correct trade-off, which entailed a dramatic reduction in their product line. Different companies, in different industries, will have to answer this question for themselves. It is our hope that the methods we present in our paper can likewise help them find the answers they seek.

## References

- A. Alptekinoglu and C. Corbett. Mass customization vs. mass production: Variety and price competition. *Manufacturing and Service Operations Management*, 10(2):204–217, 2008.
- S. Anderson. Measuring the impact of product mix heterogeneity on manufacturing overhead cost. *The Accounting Review*, 70(3):363–387, 1995.
- R. Banker, G. Potter, and R. Schroederr. An empirical analysis of manufacturing overhead cost drivers. *Journal of Accounting and Economics*, 19:115–137, 1995.
- A. Belloni, R. Freund, M. Selove, and D. Simester. Optimizing product line designs: Efficient methods and comparisons. *Management Science*, 54(9):1544–1552, 2008.
- G. Bitran and J.-C. Ferrer. On pricing and composition of bundles. *Production and Operations Management*, 16(1):93–108, 2007.
- S. Broniarczyk, W. Hoyer, and L. McAlister. Consumers’ perceptions of the assortment offered in a grocery category: The impact of item reduction. *Journal of Marketing Research*, 35:166–176, 1998.
- K. Chen and W. Hausman. Technical note: Mathematical properties of the optimal product line selection problem using choice-based conjoint analysis. *Management Science*, 46(2):327–332, 2000.
- Y. Chen, A. Vakharia, and A. Alptekinoglu. Product portfolio strategies: The case of multifunction products. *Production and Operations Management*, 17(6):587–598, 2008.
- Y. Chen, J. Carillo, A. Vakharia, and P. Sin. Fusion product planning: A market offering perspective. *Decision Sciences*, 41(2):325–353, 2010.

- J. Chong, T. Ho, and C. S. Tang. Product structure, brand width, and brand share. In T. Ho and C. S. Tang, editors, *Product Variety Management: Research Advances*, pages 39–64. Kluwer Academic Publishers, 1998.
- M. Fisher and C. Ittner. The impact of product variety on automobile assembly operations: Empirical evidence and simulation analysis. *Management Science*, 45(6):771–786, 1999.
- M. Fisher and R. Vaidyanathan. An algorithm and demand estimation procedure for retail assortment optimization. *Working Paper, University of Pennsylvania*, 2011.
- G. Foster and M. Gupta. Manufacturing overhead cost driver analysis. *Journal of Accounting and Economics*, 12:309–337, 1990.
- G. Fruchter, A. Fligler, and R. Winer. Optimal product line design: Genetic algorithm approach to mitigate cannibalization. *Journal of Optimization Theory and Applications*, 131(2):227–244, 2006.
- W. H. Greene. *Econometric Analysis*. Prentice Hall, New Jersey, fourth edition, 2000.
- J. R. Hauser and V. Rao. Conjoint analysis, related modeling, and applications. In J. Wind and P. Green, editors, *Advances in Market Research and Modeling: Progress and Prospects*, pages 141–168. Kluwer Academic Publishers, Boston, MA, 2004.
- R. L. Keeney and H. Raiffa. *Decisions with Multiple Objectives: Preferences and Value Trade-offs*. Wiley, New York, 1976.
- G. Kok and M. Fisher. Demand estimation and assortment optimization under substitution: Methodology and applications. *Operations Research*, 55(6):1001–1021, 2007.
- G. Kok, M. Fisher, and R. Vaidyanathan. Assortment planning: Review of literature and industry practice. In N. Agrawal and S. Smith, editors, *Retail Supply Chain Management*, pages 1–55. Kluwer Academic Publishers, Amsterdam, The Netherlands, 2009.
- K. Marriott and P. Stuckey. *Programming with Constraints: An Introduction*. MIT Press, 1998.
- E. Rash and K. Kempf. Product line design and scheduling at Intel. *Interfaces*, 42(5):425–436, 2012.
- T. L. Saaty. *The Analytic Hierarchy Process*. McGraw-Hill Book Co., New York, 1980.



- C. Schoen. On the optimal product line selection problem with price discrimination. *Management Science*, 56(5):896–902, 2010.
- C. Tang. A review of marketing-operations interface models: From co-existence to coordination and collaboration. *International Journal of Production Economics*, 125(1):22–40, 2010.
- C. Tang and R. Yin. The implications of costs, capacity, and competition on product line selection. *European Journal of Operational Research*, 200(2):439–450, 2010.
- Thomson Reuters. Caterpillar Inc. 2014 Analyst Meeting at ConExpo edited transcript, 2014. URL `\url{http:phx.corporate-ir.net/External.File?t=1\&item=VHlwZT0yfFBhcmVudE1EPTUwODQxOTB8Q2hpbGRJRDO1MzYwODg=}`.
- X. Wang, J. Camm, and D. Curry. A branch-and-price approach to the share-of-choice product line design problem managing product variety. *Management Science*, 55(10):1718–1728, 2009.
- J. Ward, B. Zhang, S. Jain, C. Fry, T. Olavson, H. Mishal, J. Amaral, D. Beyer, A. Brecht, B. Cargille, R. Chadinha, K. Chou, G. DeNyse, Q. Feng, C. Padovani, S. Raj, K. Sunderbruch, R. Tarjan, K. Venkatraman, J. Woods, and J. Zhou. HP transforms product portfolio management with operations research. *Interfaces*, 40(1):17–32, 2010.
- T. H. Yunes, D. Napolitano, A. Scheller-Wolf, and S. Tayur. Building efficient product portfolios at John Deere and Company. *Operations Research*, 55(4):615–629, 2007.