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

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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 primarily 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 try to give a representation of the many possible choices as well as to satisfy those customers who were unwilling to wait through the build-to-order lead time. 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; and step 3 answers the final question by combining the migration lists and the cost of complexity 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).

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 cost 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. In Section 3 we briefly describe the BHL lines. Sections 4, 5, and 6 present our customer behavior, cost of complexity, and optimization models in a generic fashion that is neither company- nor product-specific. In Section 7, we provide details on how the steps in the three preceding sections were tailored to suit CAT's specific products and business requirements. Finally, we present the results and insights from our analysis in Sections 8 and 10, and conclude in Section 11.

2 Literature Review

Some marketing research describes how narrowing a product line may detract from brand image or market share, e.g. Chong et al. (1998), while other works 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) 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), using data from 32 manufacturing plants, find an association of overhead costs with both volume and transactions, which they take as a measure of complexity. Anderson (1995) identifies seven different types of product mix heterogeneity in three textile factories, and finds that two are 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.

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); they focus on deriving general insights via analysis of abstract models. Our paper uses math programming to optimize a detailed model of a company, their customers and products based on data and expert opinion. In addition, we implement our solution in practice.

Bitran and Ferrer (2007) determine 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. Chen and Hausman (2000) demonstrate how choice-based conjoint analysis can be applied to the product portfolio problem; Schoen (2010) extends this work 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 methods: For example, Fruchter et al. (2006) and Belloni et al. (2008). 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) develops two analytical tools to apply to Hewlett-Packard's product line problem. Like Caterpillar, HP has product lines that could, in theory, span millions of different configurations. The first tool develops a comprehensive cost of complexity function, comprised of variable and fixed costs, to be used when evaluating the introduction of new products. This function has some similarities to ours, but focuses more on inventory costs, lacking anything related to our attribute based costing. Furthermore, cannibalization, which is how they refer to any substitution effects on inventory, are in their words "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 cost of complexity 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) find the set of products for Intel 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. 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 extends their work in several dimensions. Specifically, we: (i) Explicitly calculate and validate estimates of the parts utilities; 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, absent in Yunes et al. (2007).

Compared to the literature, our work is unique in that cost of complexity, utility estimation and substitution behavior is modeled, estimated, *and* incorporated into a flexible, modular solution framework for product portfolio problem, applicable across different industries and problem settings. In addition, we demonstrate how our solution can be used in practice; describing a dramatic redesign of the product portfolio at Caterpillar.

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 their 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*. In the marketing literature, what we call a feature is also known as an *attribute*, and what we call on option is also known as an *attribute level*. Table 1 summarizes the features and number of corresponding options present in each BHL model in our project. 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	1	1	1	1
Product Link	1	1	1	1
Ride Control	1	1	1	-
Front Loader Mechanics	-	2	2	-

ensuring that these options are compatible. The number of such configurations is immensely large: For model 416E in its most basic version, there are 37,920 feasible configurations. Including choices for attachments yields 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. Moreover, every unique option offered incurs a cost for Caterpillar, due to the engineering and support costs it requires. We discuss this in detail in Section 5.

So how many configurations are actually built? Figure 1 depicts the minimum number of different configurations (left panel) and options (right panel) required to capture given percentages of revenue and sales, respectively, for eight month's worth of sales data for model 420E. The left-hand graph was created by sorting the configurations sold by decreasing value of revenue and sales and plotting the cumulative revenue/sales amount for a given number of configurations. The right-hand graph shows the maximum revenue and sales that could have been obtained had the number of available options been limited to each one of the values between 1 and 42. Of the 569 built configurations, 400 were needed to capture about 95% of revenues and sales volume. Similarly, 36 out of the 42 available options were needed to capture at least 95% of revenues and sales volume. Therefore, to achieve the sought reductions in product offerings, it was imperative to steer purchases toward a considerably smaller subset of products and options.

As we will see in Section 10, CAT ultimately converged on a lane system in which configuration

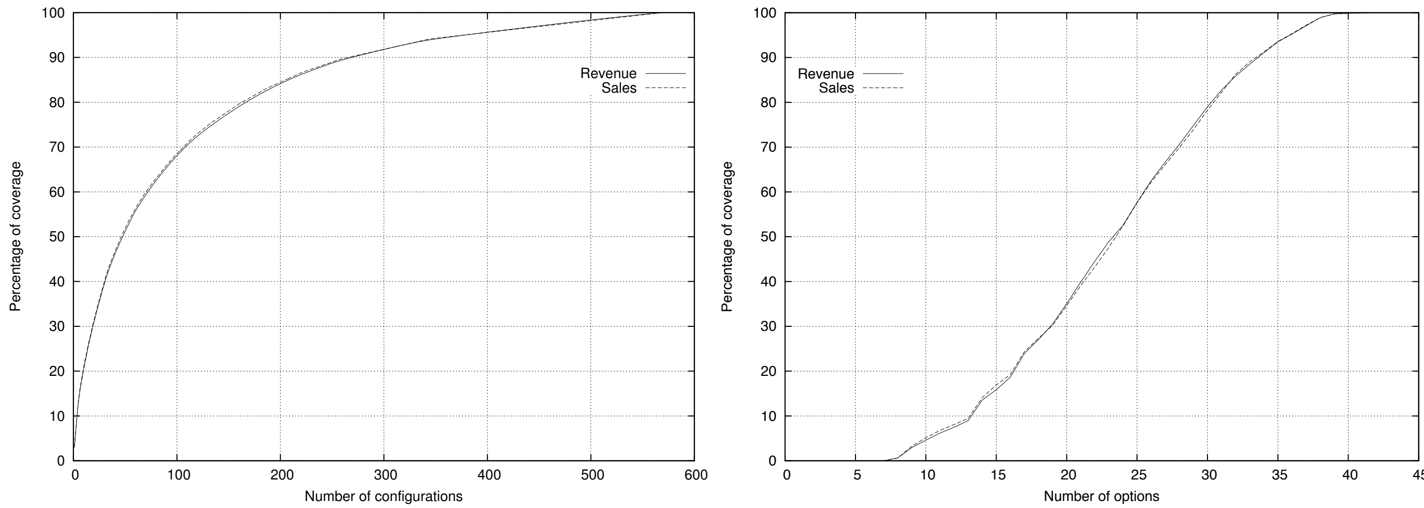

Figure 1: Minimum number of distinct configurations (left) and options (right) required to capture given percentages of revenue and sales volume for BHL model 420E.

lead times depend on the lane to which they belong. Although not part of our original algorithm, our modeling framework can incorporate such a structure assuming the number and lead time of each lane are given. We will illustrate our algorithm under this more general assumption.

Specifically, lanes, with corresponding lead times, can be treated as options of an additional configuration feature, which we will call *Availability*. With respect to the customer choice model described in Section 4, this new feature can be treated exactly the same way the other features are. In addition, just as customers can be modeled as having tolerances for price and utility, there can be a maximum availability threshold per customer as well.

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 configuration 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.

The centerpiece of our approach to capture customer flexibility is the *migration list*, an ordered list of configurations within the customer's price, utility, and availability 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 it. If that configuration is unavailable and there exists a second one 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).

One advantage of this methodology is that it is independent of the way migration lists are created; the only requirement is that there be one list, L_i, per customer i, consisting of a collection of configurations sorted in decreasing order of *preference*, where preference is defined by some *ranking function*. This ranking function could map configurations to utilities (as calculated by conjoint analysis (Hauser and Rao, 2004)), or to purchase probabilities (as in a multinomial logit model (Guadagni and Little, 1983)), or to any other quantitative measure of choice.

The configurations on customer i's migration list L_i could also be determined by sales history. If customer i purchased machine M_i, L_i should contain configurations "similar enough" to M_i to satisfy i. There are several ways to define a *similarity function*. It could be as sophisticated as a formal metric in the space of configurations, or as simple as a conjunction of conditions. For example: their utilities and prices do not differ too much, *and* the number of features on which they differ is not too great, *and* they share compatible options for a few crucial features, etc. To illustrate the last condition, assume customer i needs a machine with large towing capacity (engine power is a crucial feature for i). All acceptable substitutes for M_i need to have an engine at least as powerful as M_i's engine. Once those machines "similar enough" to M_i are determined, they would be ranked and placed in L_i. In some settings, L_i may need to be truncated once its length reaches a certain threshold value to capture possible limits on customer willingness to substitute.

Finally, if creating different ranking and/or similarity functions for each customer is too burdensome, customers can be clustered into market segments.

In summary, the following steps are repeated for each customer i in the optimization (assume, for the sake of illustration, we use the method based on sales history):

1. Let s be the customer segment to which i belongs (possibly unique for each customer);

2. Let g_{is} and h_{is} be, respectively, the *similarity* and *ranking* functions tailored for i and/or s;

3. Apply g_{is} to M_i to obtain a list L_i of configurations that are acceptable substitutes for M_i;

4. Sort the elements of L_i in non-increasing order according their h_{is} value;

5. Truncate L_i to a maximum acceptable length and save it for the optimization step.

In Section 7.1, we explain how CAT performed these operations.

5 Capturing Cost of Complexity

Our next task is to estimate how a line reduction might affect costs. Product variety affects many functional areas in heterogeneous ways, and in some areas, the impact on costs 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. As a result, complexity has to be understood in each functional area and individually modeled in different departments. We refer to all costs impacted by the variety of product offerings, i.e. number of features and options, as the *cost of complexity*.

We describe important elements of cost of complexity, propose a cost of complexity function that captures these elements, and derive a differential cost of complexity function in Sections 5.1, 5.2, and 5.3 respectively. The result of this process is used by our optimization model in Section 6. In Section 7.2, we describe our experience estimating cost of complexity with CAT.

5.1 Important Elements of Cost of Complexity

5.1.1 Option Effects

Complexity may affect the costs of different processes in different ways. We distinguish between two main effects: Certain processes are impacted by the *number* of options offered for a feature, while other processes are more impacted by the presence of *specific* options or combinations of options (within one feature or across features). For example, material planners need to calculate stocking requirements for each SKU offered. If one SKU is eliminated, the cost of complexity will go down proportionally, regardless of which SKU is eliminated. We refer to this effect as *Variety Based Complexity*, or *VBC*.

In contrast, some processes are highly impacted by the *type* of part or SKU involved. For example, a feature may include simple and complex options; engineering cost for releasing a complex option may be much higher than that for releasing a simple option. Hence, the reduction in the cost of complexity will depend on the particular option eliminated. We refer to this effect as *Attribute-level Based Complexity* or *ABC*. ABC is not limited to single options; there may be cases in which a combination of options drives the cost of complexity.

5.1.2 Temporal Effects

Building the cost of complexity function also requires understanding the lagged impact of complexity on costs. For example, assembly cost today is impacted by the product complexity being built today, while warranty costs are affected by the complexity that was offered a certain time ago (positive time lag), and engineering and marketing costs may be impacted by the complexity that will be offered in the future (negative time lag). Some of these time lags may already be incorporated into the cost data, e.g. accounting may allocate costs for material write-offs to the month when an option was discontinued. In contrast, expenses paid to sub-contractors involved in development of a new set of options are likely to be recorded in the month when the work is being done, not in the months when the options will be added to the price list. Hence, it is important to talk to accounting about potential lags in data.

5.1.3 Volume Effects

Finally, the cost of complexity is impacted by different volume metrics. Not surprisingly, most processes 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. Other processes, such as engineering, are impacted by the complexity *offered*, as engineers have to prepare releases for all options and each associated feasible configuration, while sales volume is unlikely to have impact on the engineering cost.

5.2 Cost of Complexity Function

We estimate two separate components of the cost of complexity function: $VBC^d(\cdot)$ is the cost of complexity caused by variety and is specific to each functional area or department d, and $ABC_o(\cdot)$ is the cost of complexity caused by offering a specific option o. We summarize this and additional notation used in this section in Table 2. We use small letters for superscripts and subscripts, bold letters for sets, and capital letters for numbers coming from collected data.

5.2.1 Estimation of VBC

We use the Cobb-Douglas log-linear function to estimate the variety-based effect on the cost of complexity for each department d. 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* function (Section 5.3).

Using lower-case Greek letters to represent estimated parameters, the Cobb-Douglas cost of complexity function at time t is given by:

Table 2: Table of notation

$d \in \boldsymbol{D}$	Superscript used to represent attributes pertaining to department d, where $\boldsymbol{D}$ is the set of all departments considered in the study;
$f \in \boldsymbol{F}$	Subscript used to represent attributes pertaining to feature f, where $\boldsymbol{F}$ is the set of all features in the product line;
$\boldsymbol{F^d} \subset \boldsymbol{F}$	The set of all features identified as relevant for department d;
$o \in \boldsymbol{O}$	Superscript used to represent attributes pertaining to option o, where $\boldsymbol{O}$ is the set of all options in the product line;
$\boldsymbol{O_f} \subset \boldsymbol{O}$	The set of all options in feature f;
N_f	Number of options in feature f: $\lvert\boldsymbol{O_f}\rvert$;
$\boldsymbol{N^d}$	Set of cardinalities of all features relevant for department d: $\boldsymbol{N^d} = \{N_f : f \in \boldsymbol{F^d}\}$;
$VBC^d(\cdot)$	The cost of complexity caused by variety at department d;
$ABC_o(\cdot)$	The cost of complexity caused by offering a specific option o;
$DVBC^d$	The differential cost of complexity caused by variety at department d;
$DABC_o$	The differential cost of complexity caused by offering a specific option o;
$DCoC$	The total differential cost of complexity;
V	Total sales volume;
O	Number of configurations sold that contain option o;
$\boldsymbol{V}$	Set of configurations sold for all options: $\boldsymbol{V} = \{V^o : o \in \boldsymbol{O}\}$;
U	Total number of *unique* configurations sold;
l^d	Time lag parameter at department d;
ξ^d	The size of the cost pool at department d relative to other departments;
α^d	The effect of the sales volume on the cost of complexity at department d;
β^d	The effect of the number of unique configurations sold on the cost of complexity at department d;
γ_f^d	The effect of the cardinality of feature f on the cost of complexity at department d;
δ_o^d, $\delta_o = \sum\limits_{d \in \boldsymbol{D}} \delta_o^d$	One time cost incurred if option o is offered at department d and total across departments respectively;
a_o	Binary variable that indicates whether option o is offered or not;
ω_o^d, $\omega_o = \sum\limits_{d \in \boldsymbol{D}} \omega_o^d$	Cost incurred *each time* option o is produced at department d and total across departments respectively.

$$VBC_t^d = \xi^d V_{t+l^d}^{\alpha^d} U_{t+l^d}^{\beta^d} \prod_{f \in \boldsymbol{F^d}} \left(N_{f,t+l^d}\right)^{\gamma_f^d}. \tag{1}$$

The $\prod_{f\in\boldsymbol{F^d}} \left(N_{f,t+l^d}\right)^{\gamma_f^d}$ term captures the complexity *offered*, by accounting for the number of options for each feature on the price list, and the $U_{t+l^d}^{\beta^d}$ term accounts for the complexity *built*.

We log-transform this function to use linear regression analysis to estimate needed parameters:

$$Log[VBC_t^d] = Log[\xi^d] + \alpha^d Log[V_{t+l^d}] + \beta^d Log[U_{t+l^d}] + \sum_{f\in\boldsymbol{F^d}} \gamma_f^d Log[N_{f,t+l^d}] + \epsilon_t. \tag{2}$$

Within our optimization model we evaluate the effect of a one-time change to the product portfolio on the long-term cost. Hence we do not need the time dimension for further analysis and will suppress time subscript t, using a functional representation $VBC^d(\boldsymbol{N^d}, V, U)$ instead[1].

5.2.2 Estimation of ABC

Introducing a specific complex option may have different effects: 1) There may be a fixed cost associated with offering the option (e.g. part design cost); and 2) There may be variable costs incurred each time the option is produced (e.g. additional testing each time the part is installed). Hence we model the total cost of offering and producing option o, ABC_o, as the sum of the one-time cost across all departments if option o is offered (complexity *offered*) and the incremental cost across all departments incurred each time a configuration with option o is built (complexity *built*):

$$ABC_o(a_o, O) = a_o \sum_{d\in\boldsymbol{D}} \delta_o^d + O \sum_{d\in\boldsymbol{D}} \omega_o^d. \tag{3}$$

5.3 Differential Cost of Complexity Function

To facilitate optimization, instead of computing the total cost of each offering, we build a cost of complexity function that starts with the current line and computes the *estimated change in cost* as the numbers of features and options change. For the variety-based component, we take the partial derivatives of $VBC^d(\boldsymbol{N^d}, V, U)$ with respect to all variables, and then combine them into an aggregate differential cost of complexity function.

For example, the change in VBC with the number of options for feature f is:

[1] Alternatively, one can refine this approach by keeping the time lags in the model and computing the net present value of future cash flows.

$$\frac{dVBC^d(\boldsymbol{N^d}, V, U)}{dN_f} = \frac{\gamma_f^d}{N_f}\xi^d V^{\alpha^d} U^{\beta^d} \prod_{i \in \boldsymbol{F^d}} N_i^{\gamma_i^d} = \frac{\gamma_f^d}{N_f} VBC^d(\boldsymbol{N^d}, V, U),$$

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

This differential cost of complexity function includes the predicted value of $VBC^d(\boldsymbol{N^d}, V, U)$. This is problematic for two reasons: (i) The predicted $VBC^d(\boldsymbol{N^d}, V, U)$ 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 $VBC^d(\boldsymbol{N^d}, V, U)$ with the historical average cost at department d ($\overline{D^d}$) attributable to complexity, taken over an appropriate period:

$$\frac{dVBC^d(\boldsymbol{N^d}, V, U)}{dN_f} \approx \frac{\gamma_f^d}{N_f}\overline{D^d}. \tag{4}$$

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

$$\overline{D^d}\frac{\gamma_f^d}{N_f}\Delta N_f, \tag{5}$$

where ΔN_f represents the change in the number of options in feature f after line optimization; similarly we will precede V, U, O, $\boldsymbol{N}$, $\boldsymbol{N^d}$, and $\boldsymbol{V}$ with Δ to represent change. These differential quantities depend on the market response to the options offered in the product portfolio, and will be computed within the optimization model by leveraging our customer migration model. 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. Aggregating these differences yields the total variety-based *differential cost of complexity* $DVBC^d$:

$$DVBC^d = \sum_{f \in \boldsymbol{F^d}} \overline{D^d}\frac{\gamma_f^d}{N_f}\Delta N_f + \overline{D^d}\frac{\alpha^d}{V}\Delta V + \overline{D^d}\frac{\beta^d}{U}\Delta U. \tag{6}$$

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 $\delta_o = \sum_{d \in \boldsymbol{D}} \delta_o^d$ and if sales with option o deviate from O, the cost will likewise change:

$$DABC = \sum_{o \in \boldsymbol{O}} \delta_o(a_o - 1) + \sum_{o \in \boldsymbol{O}} \omega_o \Delta O, \text{ where } \boldsymbol{a} = \{a_o : o \in \boldsymbol{O}\}. \tag{7}$$

Finally, the total differential cost of complexity is:

$$DCoC = \sum_{d \in \boldsymbol{D}} DVBC^d + DABC. \tag{8}$$

Equation (8), with estimated parameters, becomes a part of the objective function in the optimization model of Section 6. Because the cost of complexity function is non-linear, this approach is accurate only for small changes. In practice, the accuracy of this approximation may be tested by calculating the actual change in the total cost of complexity for the original product line $VBC^d(\boldsymbol{N^d}, V, U)$ and for the optimized product line $VBC^d(\boldsymbol{N^d} + \Delta\boldsymbol{N^d}, V + \Delta V, U + \Delta U)$, and then comparing this to the result of the approximation $DVBC^d$.

6 The Optimization Model

With the migration lists from Section 4 and Equation (8) from Section 5, we are now ready to describe our optimization model. We use a mixed-integer linear program to select the set of options and configurations offered, and their prices, to maximize total profit from sales minus the change in cost of complexity (the objective function value increases when this change is negative).

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

- $\boldsymbol{I}$ — The set of all customers;
- $\boldsymbol{L_i}$ — The ordered set of configurations in the migration list of customer $i \in \boldsymbol{I}$. Each member of L_i is represented by a pair (j, k), where k identifies the lane choice and j identifies the specific options chosen for all remaining features. Therefore, the same j can appear in several pairs with different values of k, but only one (j, k) pair will appear in the final portfolio.
- $\boldsymbol{J}$ — The set of all configurations appearing on migration lists ($\boldsymbol{J} = \bigcup_{i \in \boldsymbol{I}} \boldsymbol{L_i}$);
- $\boldsymbol{O_{jk}}$ — The set of all options in configuration $(j, k) \in \boldsymbol{J}$;
- R_i — Reservation price of customer $i \in \boldsymbol{I}$; this could be configuration-dependent if desired (i.e. R_{ijk} instead of R_i);
- M — Maximum reservation price over all customers ($M = \max_{i \in \boldsymbol{I}} R_i$);
- C_{jk}, B_{jk}, P_{jk} — Cost, base price, and current sale price of configuration $(j, k) \in \boldsymbol{J}$, respectively. Base price is the starting price of an incomplete configuration before any of its options

are included. The value of P_{jk} equals of B_{jk} plus the prices of all options contained in configuration (j,k). We use this additive price structure to illustrate option pricing optimization, but it is not a requirement of our model, i.e., other price structures are also possible.

The decision variables (a_o was defined in Table 2, but we repeat it here for completeness):

- $a_o = 1$ if option $o \in \boldsymbol{O}$ is available, 0 otherwise.
- $q_{jk} = 1$ if configuration $(j,k) \in \boldsymbol{J}$ is bought by at least one customer, 0 otherwise;
- $x_{ijk} = 1$ if customer i buys configuration (j,k), 0 otherwise ($i \in \boldsymbol{I}$, $(j,k) \in \boldsymbol{L_i}$);
- p_o — Price of option $o \in \boldsymbol{O}$ ($p_o \geq \delta_o$, where δ_o is defined in Table 2). These variables enable changing the prices of individual options; one could eliminate these variables entirely, or replace them with variables p_{jk} to price configurations. Using p_{jk} instead of p_o would result in simple changes to some of the constraints we present below;
- r_{ijk} — Profit if customer i purchases configuration (j,k) ($i \in \boldsymbol{I}$, $(j,k) \in \boldsymbol{L_i}$).

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

$$\Delta N_f = \sum_{o \in \boldsymbol{O_f}} a_o - N_f,$$

$$\Delta U = \sum_{(j,k) \in \boldsymbol{J}} q_{jk} - U,$$

$$\Delta V = \sum_{i \in \boldsymbol{I}} \sum_{(j,k) \in \boldsymbol{L_i}} x_{ijk} - V,$$

$$\Delta O = \sum_{i \in \boldsymbol{I}} \sum_{(j,k) \in \boldsymbol{L_i} \,|\, o \in \boldsymbol{O_{jk}}} x_{ijk} - O.$$

The objective function maximizes the total profit from sales minus the differential cost of complexity given by (8):

$$\max \sum_{i \in \boldsymbol{I}} \sum_{(j,k) \in \boldsymbol{L_i}} r_{ijk} - DCoC.$$

Our optimization model uses the following constraints, where MAX_INC is the maximum allowed percentage price increase for any configuration:

$$q_{jk} \leq a_o, \qquad \forall\, (j,k) \in \boldsymbol{J},\ o \in \boldsymbol{O_{jk}} \tag{9}$$

$$x_{ijk} \leq q_{jk}, \qquad \forall\, i \in \boldsymbol{I},\ (j,k) \in \boldsymbol{L_i} \tag{10}$$

$$\sum_{k \,|\, (j,k) \in \boldsymbol{J}} q_{jk} \leq 1, \qquad \forall\, j \mid (j,k) \in \boldsymbol{J} \text{ for some } k \tag{11}$$

$$\sum_{(j',k') \text{ after } (j,k) \text{ in } \boldsymbol{L_i}} x_{ij'k'} + q_{jk} \leq 1, \qquad \forall\, i \in \boldsymbol{I},\ (j,k) \in \boldsymbol{L_i} \tag{12}$$

$$r_{ijk} \leq B_{jk} + \sum_{o \in \boldsymbol{O_{jk}}} p_o - C_{jk}, \qquad \forall\, i \in \boldsymbol{I},\ (j,k) \in \boldsymbol{L_i} \tag{13}$$

$$B_{jk} + \sum_{o \in \boldsymbol{O_{jk}}} p_o \leq P_{jk}(1 + \text{MAX\_INC}), \qquad \forall\, (j,k) \in \boldsymbol{J} \tag{14}$$

$$r_{ijk} \leq (\min\{R_i, P_{jk}(1{+}\text{MAX\_INC})\} - C_{jk})x_{ijk}, \qquad \forall\, i \in \boldsymbol{I},\ (j,k) \in \boldsymbol{L_i} \tag{15}$$

$$B_{jk} + \sum_{o \in \boldsymbol{O_{jk}}} p_o \leq R_i + (P_{jk}(1{+}\text{MAX\_INC}) - R_i)(1 - x_{ijk}), \qquad \forall\, i \in \boldsymbol{I},\ (j,k) \in \boldsymbol{L_i} \tag{16}$$

The purpose of each constraint is as follows. (9): If option o is not available ($a_o = 0$), no configuration that contains o can be bought ($q_{jk} = 0$); (10): If customer i buys configuration (j,k) ($x_{ijk} = 1$), then (j,k) must have been bought ($q_{jk} = 1$); (11): Configurations can be assigned to at most one lane; (12): If (j,k) is bought by someone ($q_{jk} = 1$), it must be available, therefore customer i cannot buy less desirable configurations (j',k') that appear after (j,k) in $\boldsymbol{L_i}$ (all $x_{ij'k'} = 0$); (13): Profit cannot exceed price ($B_{jk} + \sum_{o \in \boldsymbol{O_{jk}}} p_o$) minus cost; (14): Configuration prices cannot increase by more than MAX_INC; (15): No purchase ($x_{ijk} = 0$) means no profit ($r_{ijk} = 0$) and, if a purchase happens ($x_{ijk} = 1$), the term in parenthesis is a ceiling on the value of r_{ijk}; (16): If customer i buys configuration (j,k) ($x_{ijk} = 1$), (j,k)'s price must not exceed R_i.

We can turn off the price optimization aspect of this model by removing variables p_o and constraints (14)–(16), and changing the right-hand side of (13) to $(P_{jk} - C_{jk})x_{ijk}$. Lane assignment decisions can be removed by deleting constraint (11) and all occurrences of index k.

7 CAT-Specific Modeling Details

In this section we detail the assumptions and decisions made to create the CAT-specific instantiation of the generic framework we describe in sections 4, 5, and 6. CAT experts participated in the entire process, making sure they understood and, when necessary, validated, the inputs and outputs of each intermediate step.

7.1 Modeling the Behavior of CAT's Customers

The pseudo-code below shows how migration lists were constructed for CAT. (We use customer purchases in 2006 as the basis for generating our migration lists.)

For each customer $i \in \boldsymbol{I}$ who bought a configuration over the past H months repeat:

1. Let M_i be the configuration (i.e. machine) bought by i.
2. Apply segmentation rules to M_i (Section 7.1.1) to place i in a customer segment S_i.
3. Based on the price and utility of M_i, and on characteristics of segment S_i, construct a *randomized* list of configurations, L_i, as acceptable alternatives to M_i (Section 7.1.2).
4. Sort L_i in non-increasing order of configuration utility, pruning it if it exceeds the maximum allowed length (Section 7.1.3).

7.1.1 Customer Segmentation

Customer segmentation is important in CAT's business 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: *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 discussed in Section 7.1.2, the segment-specific reservation prices and reservation utilities also affect migration list generation (Section 7.1.3).

7.1.2 Estimating Utilities

For each of the customer segments identified in Section 7.1.1, 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 the *relative importance* between every pair of features on a scale from 1 (equally important) to 9 (much more important). The pairwise scores are then transformed into absolute scores of relative importance for each individual feature. The same group of experts is then asked to rank the options within each feature on a scale from 0 to 100. 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 final option utilities. The utility of a complete configuration is estimated as the sum of the utilities of its options.

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. Using t-tests, Caterpillar determined that differences between the utilities derived from the survey results and those estimated by experts were not statistically significant.

7.1.3 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 θ (approximately ten), the change to a feature's relative importance is randomly drawn from a uniform distribution over the interval $[-\theta\%, +\theta\%]$. 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 configuration can have that differ from M_i. 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_i.[2]

We collect the above procedures into a Constraint Programming (CP) model (Marriott and Stuckey 1998) that finds feasible configurations for L_i. 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. 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_i is truncated, if desired, while respecting two conditions. First, if L_i is truncated, M_i must always be retained. Second, we assume customers place M_i first, regardless of M_i's utility, with a certain probability (the β *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_i 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 customer's original purchase, and include them (together with alternatives to M_1) onto L_i. Because m_2 configurations may have higher utilities, when L_i is sorted it may contain almost no highly ranked m_1 configurations. Thus, to capture the fact that customer i originally preferred an m_1 configuration, we inflate the utilities of all m_1 configurations on L_i by a *preference factor* (between 10 and 20%). As a result, L_i ends up with configurations of both models, but it does not allow utilities to overemphasize the attractiveness of m_2 configurations. 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. 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.

[2]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.

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.

Department	***Processes impacted***	***Measure of complexity***
Purchasing	Capital tooling Supplier operations	Capital tooling cost Supplier delivery performance†
Customer acquisition	Ordering Forecasting Quoting and training	Cost of customer acquisition†
Marketing	Price list creation Training Publications	Budget expenditure†
Engineering	Drawing changes Original design & development	Cost of engineering changes Cost of product and component Cost of new releases
Order fulfillment	Attachment forecasting Sequencer work Grief resolution	Headcount cost†
Product support	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)
Material planning	Inventory management Schedule volatility Expedition	Inventory handling cost (prime product) Inventory handling cost (components) Headcount cost Freight cost
Operations	Initial process setup Assembly process	Man-hour cost, production planning Man-hour cost, assembly
Quality	Initial setup Hot test Cab test	Cost of initial setup Hot-test cost (man-hours) Cab-test cost (man-hours)

7.2 Estimating the Cost of Complexity at CAT

7.2.1 Understanding the Impact of Complexity at CAT

The first step was to identify the areas impacted the most by complexity; in conjunction with CAT experts, we selected nine functional areas. We met with these areas' representatives in a focus group setting that also included an information systems representative and a project manager from CAT. Our primary goals were: (i) to identify up to three major processes 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 cost of complexity.

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

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

We then contacted an accounting representative from CAT who, working with the information systems 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 (†). Below we elaborate on several cost measures in Table 3.

Cost of supplier delivery performance refers to a program targeted towards improving availability, in which 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 the *cost of customer acquisition*. We rely on CAT's accounting system for cost estimates of engineering changes (primarily consisting of payroll to engineers working on changes) and engineering of new releases (primarily consisting of the payroll of developers and engineers who work on new parts, and costs of testing and design equipment).

7.2.2 Option Effects for CAT

The next step was to understand which features have VBC and/or ABC effects on identified processes. We continued our focus group discussions, restricted to processes identified as important in the previous step. The results of VBC/ABC classification are summarized in Table 4.

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

Department	*Time Lag*	*Department*	*Time Lag*
Purchasing	**0** - *0 (0)*	**Product support:**	
Customer acquisition	**3** - *3 (0.71)*	Service calls	**6** - *5.75(0.5)*
Marketing	**0** - *0 (0)*	Repairs in the first 10 hours	**4** - *4 (0)*
Engineering:		Repairs in 10-100 hours	**9** - *8.5 (0.58)*
Changes	**-6** - *5.67 (0.58)*	Repairs after 100 hours	**9** - *8.75 (0.5)*
Releases	**-8** - *8 (0)*	**Material planning:**	
Product and component costing	**-7** - *7 (0)*	Prime product inventory	**2** - *2 (0)*
Order fulfillment	**0** - *0 (0)*	Scrap of surplus materials	**0*** - *5.8 (1.1)*
Operations	**0** - *0 (0)*	Inventory scrap	**0*** - *6.2 (1.3)*
Quality	**0** - *0 (0)*		

* Time lag accounted for through cost allocation. Bold numbers represent the time lag selected for the models; italic numbers represent the mean (standard deviation) of experts' opinions.

7.2.3 Temporal Effects for CAT

We also used our focus group discussions to estimate the time lag for different cost pools. First, we collected expert opinions from the members of each focus group, followed by a group discussion to come to consensus regarding any discrepancies in estimates. Finally, we consulted the accountant who helped us determine which departments already included the lag in the cost data. Table 5 summarizes our analysis of time lag parameters: The bold numbers represent the final time lag selected, the numbers in italic represent the raw estimates of the focus group experts with standard deviations in parentheses. We use this information in Section 7.2.5 to estimate the parameters of the cost of complexity function.

7.2.4 Volume Effects for CAT

The final piece of the initial focus group discussion was to identify the primary volume drivers for different cost pools. Similar to the time lags, we collected initial estimates from the experts in each department, summarized the results, and held a group discussion to come to consensus. Table 6 provides a summary of the most important volume drivers for each department.

7.2.5 Estimation of the VBC Effect

With a good understanding of the costs, time lags, and volume drivers, we collected data to estimate parameters ξ^d, α^d, β^d, and γ^d_f for all d and f. We collected data from January 2001 to December 2005, for all cost measures summarized in the third column of Table 3. We then collected data from the price lists from 2000 to 2006 to capture all changes in option offerings, which were used as independent variables. (We had to collect a larger range of data due to the time lags identified in Section 7.2.3.) Similarly, we collected monthly sales (V_t) and the number

Table 6: Main volume drivers.

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

of unique configurations sold per month (U_t) from 2000 to 2006.

The nature of the data suggested that there may be serial correlation, hence, we examined partial auto-correlation function plots and checked for auto-correlation using the generalized Durbin-Watson statistics using the AUTOREG procedure in SAS. For those cost pools having autocorrelation (All three "Cost of repairs" measures), we used the autocorrelation order identified by SAS (all three were a lag of one) and used the Yule-Walker approach to fit the data (Greene 2000).

Next, we obtained statistical models for all departments by fitting collected data to (2). We evaluated our models using both graphical and numerical tests using standard statistical techniques (e.g. examined the plots of residuals for normality, heteroscedasticity, and influential outliers). Although our cost data exhibited seasonality, the seasonality in cost (our dependent variable) is driven mainly by the seasonality in the volume (an independent variable) and, hence, it is likely to be automatically taken into account by our model. We checked this by analyzing residuals: In each model we group the residuals for each month; F-tests show that there are no statistically significant differences between the means of the groups. We also checked for significance, and only accepted those factors with reasonable coefficients of determination and low RMSE. Hence, not all of the originally identified departments were included in the final cost of complexity function. Table 7 summarizes all models/departments included in the optimization model. The estimates that are statistically significant at the 0.05 significance level are marked with an asterisk[3].

We comment on the coefficient of determination (R^2) of the models in Table 7. Some 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 suppliers' operations. Hence, we expect the coefficients of determination to be lower

[3]Some data is masked to preserve confidentiality. The signs and magnitudes have been preserved.

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

Fn.	Cost pool (d)	R^2	RMSE	ξ^d	α^d	β^d	γ^d_{HC}	γ^d_C	γ^d_{CW}	γ^d_H
CA	Customer acquisition	0.37	0.18	962771120.4*	0.19			−1.13*		−1.68*
MP	Inventory (components)	0.29	0.16	1087617.41*	−0.03			1.04*		
MP	Inventory (prime product)	0.38	0.4	297.68	0.91*	0.91				
ENG	Engineering changes	0.41	0.52	0.00342591			4.81712*	−0.54		
ENG	Engineering product & component	0.55	0.9	6.39E-04*			4.107*		3.14*	
PS	Repair costs in the first 10 hours	0.29	0.37	26238.94*	−0.21	0.59*				
PS	Repair costs during 11–100 hours	0.32	0.24	3055.00*	−0.32	1.28*				
PS	Repair costs above 101 hours	0.55	0.47	934.63*	−1.41*	2.78*				
P	Supplier delivery performance	0.33	0.58	36.65		1.5*				

for such departments. 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 help ensure that our results are robust, we evaluate ranges of parameters in running the optimization model, as described in Section 8.

Some other findings in Table 7 are noteworthy. Increasing the number of options for hydraulics and cabs decreases the cost of customer acquisition, i.e., $\gamma_H^{CA} < 0$ and $\gamma_C^{CA} < 0$: A large proportion of this cost consists of sales variance or discounts given to customers 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 to make a sale, decreasing the sales variance. This finding is in line with the intuition of sales and marketing representatives from CAT. Nevertheless, this was the first time that CAT was able to quantify this effect.

Another 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, and learning effects reduce the number of mistakes. This intuition again seemed plausible to CAT, but had never been quantified. On the other hand, sales volume has a positive impact on the cost of inventory of prime product. As CAT subsidizes dealers for carrying final product inventory for time sensitive customers, and the lead time demand increases when volume increases, subsidies increase. Guided by our study, CAT subsequently has performed similar cost of complexity analyses in other product divisions and obtained comparable results.

Finally, we validated our model by using the first two years of data to fit the model, then, compared the predicted values for the next three years to actual data. A large majority of the actual cost pool values were within the 95% confidence interval around their predictions.

Table 8: ABC costs.

Option	δ_o	ω_o
Any option	\$1,000.00	
In addition:		
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

7.2.6 Estimation of the 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 a linear relationship between ABC cost and complexity: 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 minimal learning effects. This supported the form of our proposed ABC_o function having a fixed and variable cost component.

The cost parameters δ_o and ω_o were estimated using expert opinions, time studies, and accounting information from all functional areas that identified this option as important (see Table 8).

7.3 CAT's Optimization Model

CAT used the optimization model in Section 6 without its lane-assignment features. In addition to the constraints described therein, CAT's optimization model includes two constraints that deal with profit margins. Let MIN_MARG and MIN_AVGMARG be, respectively, the minimum required profit margin on each configuration sold, and the minimum required average margin over all configurations sold. The margin constraint per configuration is written as

$$C_j(1 + \textsc{min\_marg}) \leq B_j + \sum_{o \in \boldsymbol{O}_j} p_o, \qquad \forall\, j \in \boldsymbol{J} \tag{17}$$

CAT provided a specific formula they use to enforce the minimum average margin over all configurations sold. Besides the configuration cost C_j defined in Section 6, CAT uses another cost figure, denoted $C'_j \leq C_j$, which they refer to as *variable cost*. The sole purpose of C'_j is to enforce this average margin constraint[4]:

$$\text{MIN\_AVGMARG} \sum_{i \in \boldsymbol{I}} \sum_{j \in \boldsymbol{L_i}} (r_{ij} + C_j q_j) \leq \sum_{i \in \boldsymbol{I}} \sum_{j \in \boldsymbol{L_i}} (r_{ij} + (C_j - C'_j) q_j). \tag{18}$$

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

8 Results from Our Analysis

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

8.1 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 $\sum_{j \in \boldsymbol{J}} q_j \leq (1 - \text{MIN\_CONF\_RED})|\boldsymbol{J}|$. 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: $\sum_{o \in \boldsymbol{O}} a_o \leq (1 - \text{MIN\_OPT\_RED})|\boldsymbol{O}|$. 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.

[4]CAT did not explain the rationale behind (18); they just asked us to enforce this requirement.

8.2 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 presumed to be 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 machines. 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.

8.3 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 2: It consists of 9 base-machine-assembly (BMA) packages, 5 finished-to-

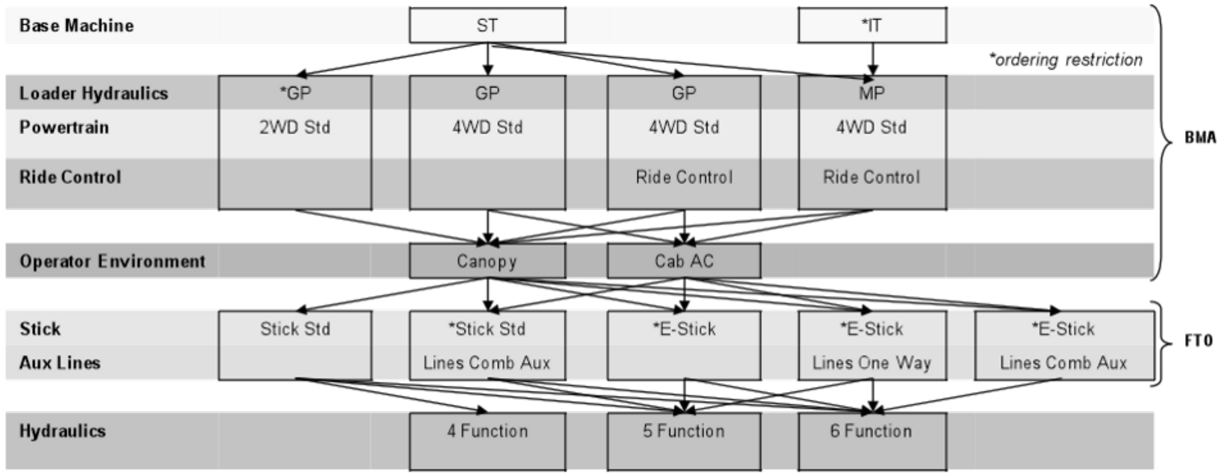

Figure 2: Final product hierarchy and packages for the BHL 420E series.

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 could increase by 15%, *with 99.6% demand fulfillment.* The standardization and bundling of options greatly reduced the universe of feasible configurations, which led to inventory and quality savings: 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 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.

9 Sensitivity Analysis and Insights

In order to generate additional insights from our model, we conducted an extensive sensitivity analysis of our framework by running a large number of experiments in which we vary the main input parameters over a range of values and record key output measures. Because of space limitations, we do not include all of the experiments here; they are available in a separate online supplement to this article. This section summarizes the main findings generated by this analysis.

9.1 Modeling Customer Behavior

9.1.1 Customer Flexibility: The More the Better

As customers become more flexible and willing to accept a wider range of configurations, the expected effects include a decrease in the number of configurations needed to satisfy them, a reduced number of required options, decreased complexity costs, and higher profits. These trends are supported by our experiments, as these output measures improve as customer flexibility increases, which happens when any of the following parameters increases in value: maximum migration list length, reservation price, disparity factor, and percentage of novel configurations in the portfolio. Varying the number of features whose utilities are perturbed and/or the amount of perturbation around the point estimate (perturbation factor) seems to add some noise, but does not ultimately change the observed outcomes significantly.

9.1.2 Role and Effect of Migration Lists

Longer lists correlate, as expected, with improvements in profit, increased portfolio reduction, a decrease in options needed, increased number of new configurations, etc. These all follow from the fact that longer lists correspond to more flexible customers. We note, however, that the increase in profit with list length is more pronounced for smaller lists—once lists are of moderate size (about forty) profit is largely flat with further increases in length. When it comes to purchase rank, more choices lead to purchases being more spread through migration lists, decreasing the number of top-ranked purchases, as these are knocked out of the portfolio in favor of more universally appealing configurations.

To better explain the role of migration lists, Figure 3 shows how many times, out of 3825 customers, a customer's original choice ended up at a given position on that customer's (100 configuration long) migration list (note the log scale on the vertical axis). The rightmost, tallest bar indicates that for 2601 customers (68% of the time) a customer's original choice would not have appeared anywhere in the first 100 positions of the customer's list. For Caterpillar this means that, for over two thirds of their customers, there are many products that provide them with higher utility than the first product they had in mind. Figure 3 emphasizes that, within the context of product portfolio reduction, the main purpose of migration lists is *not* to predict what a given customer would buy. Rather, the migration list's job is to determine which products

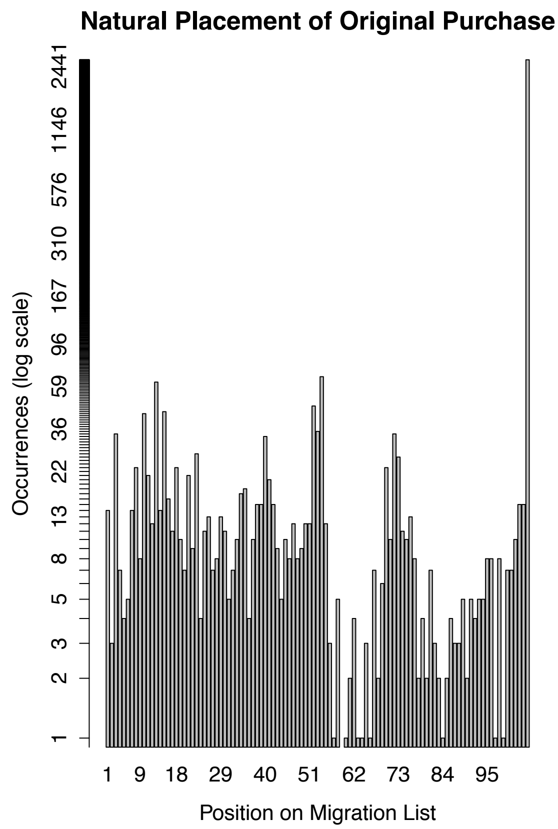

Figure 3: Number of migration lists, out of 3825, containing original purchase.

would provide high utility to each customer, thus forming a pool of configurations from which to select the ultimate product portfolio. To explore this point further, assume a company had a perfect forecasting algorithm that could always guess exactly what any customer's first choice of product would be. Despite being useful for several things (such as targeted advertising, as well as production and inventory planning), if the universe of customers' first choices were very heterogeneous, this algorithm would not allow the company to reduce the size of its product portfolio because it would not provide *any* information about customers' flexibility and willingness to substitute. Instead, a migration list, as defined in our framework, tries to predict, *given* a customer's first choice of product, what *other* products would likely be acceptable to that customer. In doing so, if a large number of customers happen to like the same not-so-large collection of products, there is a chance that significant savings can be achieved by focusing the portfolio on that smaller collection, even if some of those products are not the first choice of many, or even any, of the original customers.

9.1.3 Varying the β Factor

As β goes up, the probability of buying the first configuration on the migration list goes down. This is likely because many of the originally purchased configurations are pruned from the portfolio in an effort to concentrate customers. As for profit, it is largely insensitive to β, even though the composition of the portfolio may change.

9.1.4 Reservation Price vs. Reservation Utility

As expected, when customers are willing to pay more, everything improves for the company. Customers whose β factor does not force their originally purchased configuration to appear first on the list are more likely to buy their top choice, as it will likely be a high-utility, high-price machine. The remaining customers are more likely to purchase configurations further down their migration lists, as their top, lower utility/lower priced choices get pruned. At the same time, having customers willing to accept lower utility machines is not as impactful as their becoming less price sensitive. That is because accepting machines with lower utility does not remove the higher utility machines from consideration, and the latter get placed ahead of the lower utility machines on the migration lists anyway.

9.2 Constraints on Sales Volume and Unique Configurations

For CAT, the best course of action appears to be to lose as much sales volume as permitted (see Figure 4). (Recall that early profit maximizing solutions decreased sales volume by as much as 67% and were thus rejected.) Most savings due to volume come from inventory cost reduction and quality control savings: quality level is impacted highly by the total volume (not so much by options) as you have more time to spend on machines when the volume is low. Inventory cost is also reduced based on volume because lower volume implies less inventory held at dealers and, hence, CAT has to subsidize less. In CAT's specific case, these two cost pools have a large enough impact to explain the change in profit. This is why the strategic constraint on market share is so important—CAT wants to hold the line on market share, which restricts the portfolio reductions they will tolerate. In contrast, the number of unique configurations can be easily reduced by up to 80% in CAT's case, without side effects on other performance measures, indicating it is not nearly as important as the minimum market share requirement.

9.3 Insights Related to Cost of Complexity

Section 7.2.5 provided evidence for two insights that, although intuitive, had never been empirically verified by CAT. First, for some features, increasing the number of options decreases the

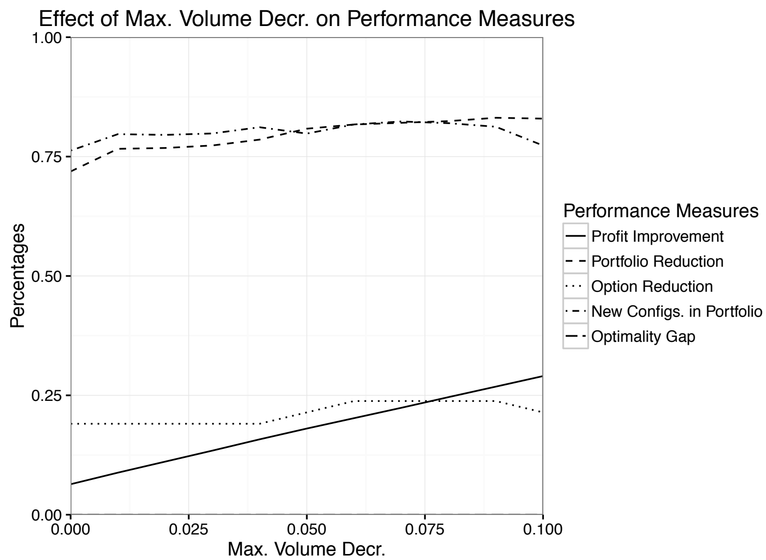

Figure 4: Maximum Sales Volume Decrease vs. Other Outputs

costs of customer acquisition. Second, sales volume has a negative impact on product support costs (i.e. repair costs) and, at the same time, a positive impact on the cost of prime product inventory. In addition, we emphasize three complexity-related takeaways from our analysis: (i) There are two types of impact of product portfolio complexity on cost, which need to be modeled separately: complexity driven by the number of options offered (VBC) and complexity driven by specific options (ABC); (ii) There are time lags and leads on the impact of complexity that have to be incorporated into the models that estimate the cost of complexity, and time impact reflected in cost data is impacted by the accounting methods used; (iii) Costs can be impacted in either direction (increase or decrease) by complexity.

9.4 Data Collection

As we collected data to implement and run our models, we found some data particularly useful, while there were other instances when we wished we had certain types of data that were not available, forcing us to go with the next-best thing. Hence, as an added insight, we believe that tracking the following data, whenever possible and practical, would enhance a company's ability to improve their product portfolio: (i) Whether or not the product purchased by a customer was the one they originally had in mind to buy and, if not, record both the original choice and the final purchase; (ii) Record what options/features the product support costs are associated with. Having this data could have revealed that some options had an ABC effect on the cost pool.

10 Implementation Details

10.1 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.

Overall, the response from 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 while a dealer would not be able to keep all the packages in stock, this sentiment confirmed that standardization and option packaging represented an effective way of concentrating demand.

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 some regions in April 2010; but, in order to minimize the risk of lost sales, customers could still order a-la-carte machines according to the old price list.

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

- Lane 1, the fastest lane: Orders on the four designated "most popular" fully configured machines would be satisfied within a few days;
- Lane 2: 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: 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, and the lane strategy they support, 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 then gave CAT direction in implementing these new strategies, by indicating which sets of configurations were likely to be most successful.

This evolution of the solution strategy also affected how the results of our algorithm were applied. Specifically, we initially modeled a problem setting in which there would be a reduced set of products offered to customers differentiated by price, but not by leadtime. The solution Caterpillar implemented (in principle) still includes all possible configurations within Lane 3, and differentiates these from the first two lanes by leadtime. Thus our forecasts of the savings in cost of complexity, which would be accurate if only the first two lanes were offered, are only an approximation given the continued possibility of a-la-carte ordering. Caterpillar felt that the flexibility of retaining Lane 3 outweighed any reductions in cost of complexity savings. Likewise, although leadtime differences could be incorporated into our framework as shown in Sections 4 and 6, Caterpillar felt comfortable enough with the main conclusions of the analysis to forgo additional analysis.

10.2 Moving Forward

In 2011 Caterpillar released a single price list featuring options packages for use in all regions. They were able to capture over a quarter of their sales volume just in Lane 1; in contrast, the four top-selling configurations Caterpillar offered 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.

11 Conclusion

We present a three-step procedure to restructure a product line, demonstrating 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 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 tailored to a company's particular setting, data availability and strategic needs, so long as it produces the necessary output for the next step.

As Caterpillar has evolved, 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 list 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 optimization model is flexible enough to accommodate 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.

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Online Supplement for the Manuscript Entitled
Restructuring the Backhoe Loader Product Line at Caterpillar: A New Lane Strategy

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1 Sensitivity Analysis

In this section we investigate how sensitive a number of key outputs produced by our framework are with respect to its main input parameters. In doing so, we bring to light several managerial insights that can be useful to companies considering reducing their product portfolio.

1.1 Experimental Settings

Table 1 shows the default values of the main parameters in our framework. In each of our sensitivity analysis tests, parameters whose values are not being altered for the test are set to their default values. Optimization models were run with a time limit of two hours, except for the tests in Section 1.4, which ran for up to 24 hours each, which was necessary to obtain meaningful output with the longer migration lists in this section. When a positive optimality gap is shown, we report the results of the best solution found within the given time limit.

Parameter	**Default Value**
β factor: probability original purchase is first on migration list	50%
maximum migration list length	5
customers' reservation price: max. acceptable price increase	2%
customers' reservation utility: max. acceptable utility decrease	10%
disparity factor: max. # features differing from original purchase	5
# features to have importance score perturbed	3
perturbation factor for features' importance score (±)	10%
maximum decrease in sales volume	3%
minimum decrease in # unique configurations sold	0%
maximum percentage of novel configurations in portfolio	100%
maximum price increase per configuration (when price opt. is on)	0.5%
minimum margin per configuration	2%
minimum weighted average margin over all configurations	15%

Table 1: Default values of the main list-generation and optimization parameters.

1.2 Placement of Original Purchase on Migration Lists

Figure 1 shows how many times, out of 3825 customers, a customer's original choice ended up at a given position on that customer's (100 configuration long) migration list (note the log scale on the vertical axis). The rightmost, tallest bar indicates that for 2601 customers (68% of the time) a customer's original choice would not have appeared anywhere in the first 100 positions of the customer's migration list. For Caterpillar this means that, for over two thirds of their customers, there are many products that provide them with higher utility than the first product they had in mind.

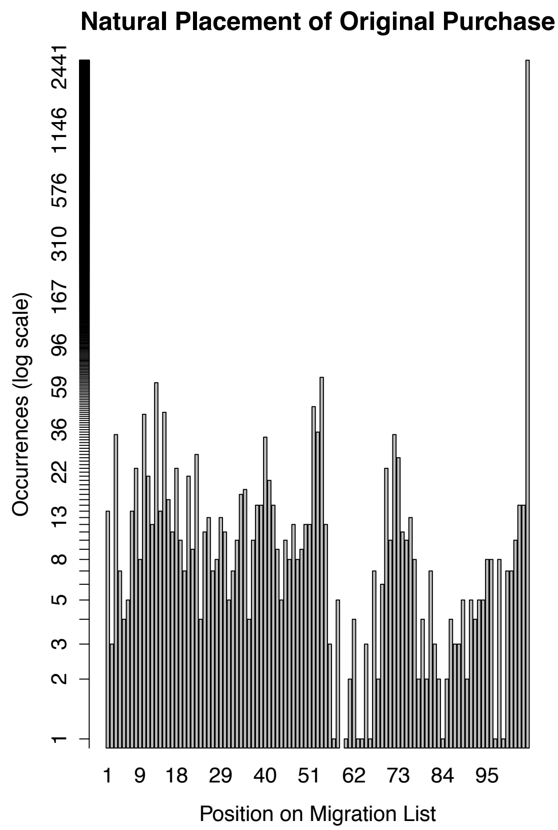
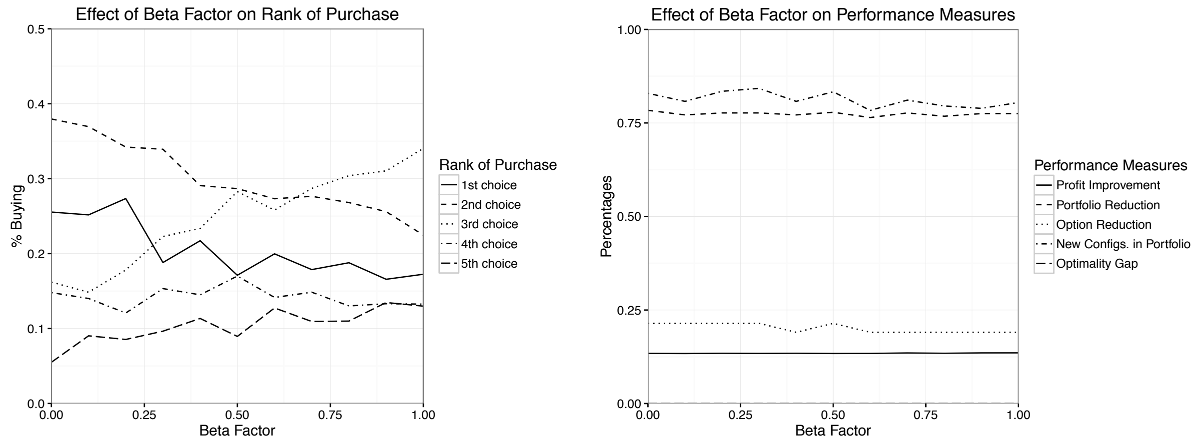


Figure 1: Number of migration lists, out of 3825, containing original purchase.

Figure 1 emphasizes that within the context of product portfolio reduction, the main purpose of migration lists is *not* to predict what a given customer would buy. Rather, the migration list's job is to find out which products would provide high utility to each customer, thus forming a pool of configurations from which to select the ultimate product portfolio. To see why, assume a company had a perfect forecasting algorithm that could always guess exactly what any customer's first choice of product would be. Despite being useful for several things (such as targeted advertising, as well as production and inventory planning), if the universe of customers' first choices were very heterogeneous, this algorithm would not allow the company to reduce the size of its product portfolio because it would not provide *any* information about customers' flexibility and willingness to substitute.

Instead, a migration list, as defined in our framework, tries to predict, *given* a customer's first choice of product, what *other* products would likely be acceptable to that customer. In doing so, if a large number of customers happen to like the same not-so-large collection of products, there is a chance that significant savings can be achieved by focusing the portfolio on that smaller collection, even if some of those products had not been the first choice of many, or even any, of the original customers.

1.3 Varying the Beta Factor



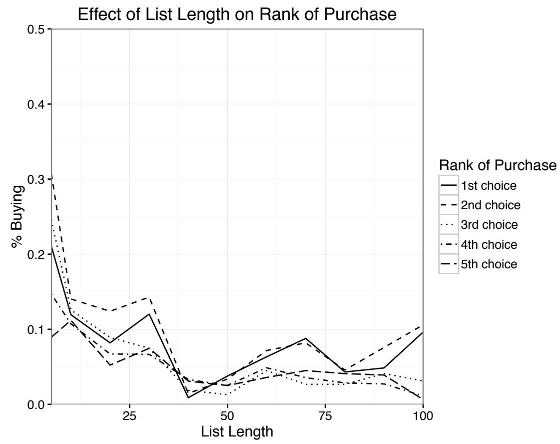
(a) Beta Factor vs Purchase Rank

(b) Beta Factor vs Other Outputs

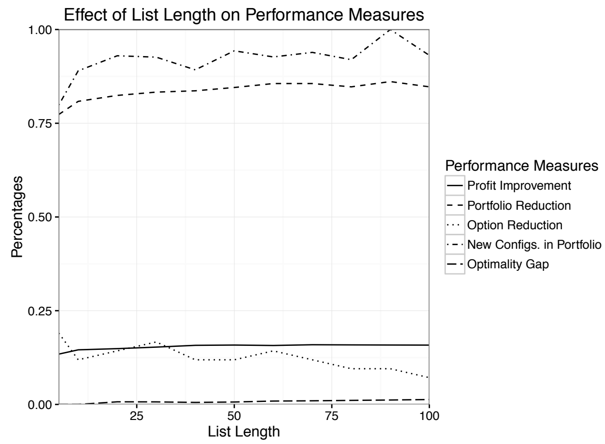
Main insights from graphs:

- From (a): Some go up, some go down, but no clear pattern is visible. Customers appear to have idiosyncratic preferences. It is potentially informative that as the probability that the purchased configuration is forced to be first (β) goes up, the probability of buying the first configuration goes down. This is likely because many of the purchased configurations are pruned from the portfolio in an effort to concentrate customers.
- From (b): Profit is largely insensitive to the beta factor, even though the composition of the portfolio may change. Again, probably because most of these configurations get pruned, so it does not really matter much where they reside on the lists.

1.4 Varying Migration List Length



(a) List Length vs Purchase Rank

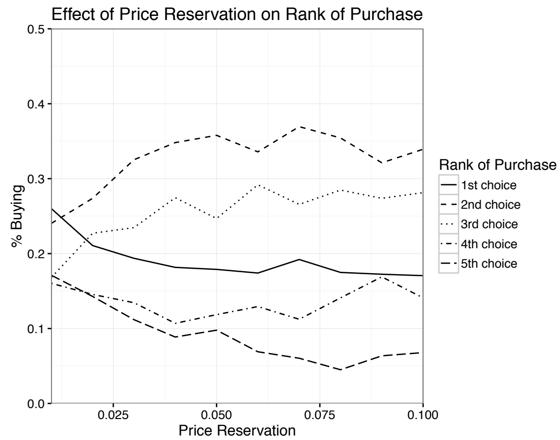


(b) List Length vs Other Outputs

Main insights from graphs:

- From (a): More choices lead to purchases being more spread through migration lists, decreasing the number of top-ranked purchases.
- From (b): Longer lists correlate, as expected, with improvements in profit, increased portfolio reduction, decrease in options needed, increased number of new configurations, etc. These all follow from the fact that longer lists correspond to more flexible customers. We note though that the increase in profit with list length is more pronounced for smaller lists—once lists are of moderate size (about forty) profit is largely flat with further increases in length.

1.5 Varying Customers' Reservation Price



(a) Price Reservation vs Purchase Rank

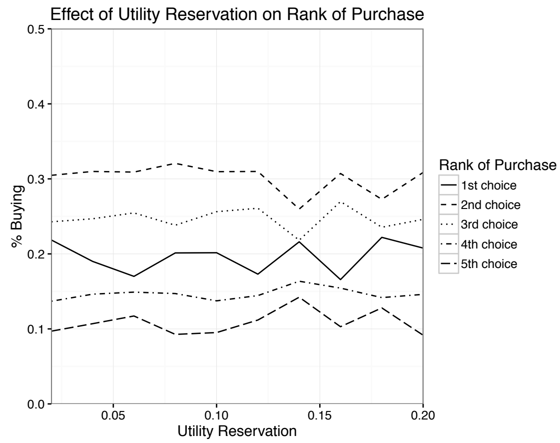
(b) Price Reservation vs Other Outputs

Main insights from graphs:

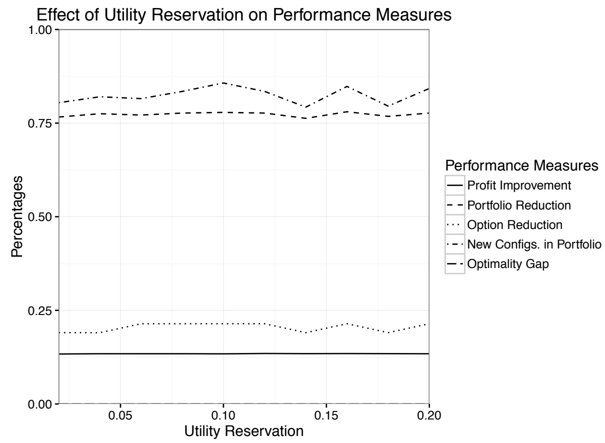
- From (a): As customers become more flexible, they are more likely to be steered away from their top choice (which with probability $\beta = .5$ is the purchased configuration) to a more expensive one. Customers whose β did not force their purchased configuration to appear first on the list are more likely to buy their top choice, as it will likely be a high-utility, high-price machine.

- From (b): As expected, when customers are willing to pay more, everything improves for the company.

1.6 Varying Customers' Reservation Utility



(a) Utility Reservation vs Purchase Rank

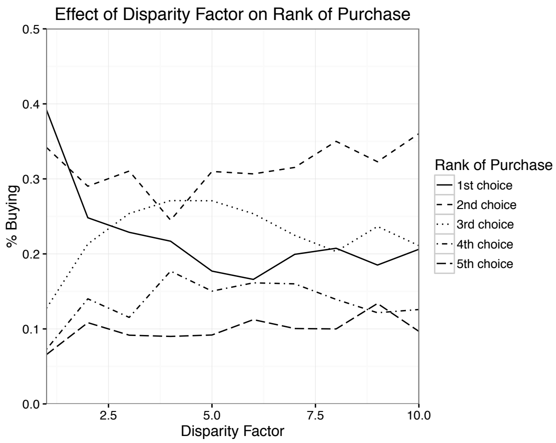


(b) Utility Reservation vs Other Outputs

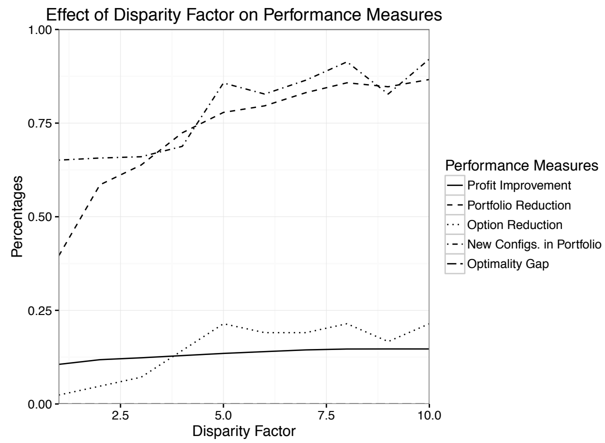
Main insights from graphs:

- Customers willing to accept lower utility machines is not as impactful as their becoming less price sensitive (Section 1.5). This insensitivity to changes in utility reservation can be explained as follows: the fact that customers accept machines with lower utility does not remove the higher utility machines from consideration, and the latter get placed ahead of the lower utility machines on the migration lists as usual.

1.7 Varying the Disparity Factor



(a) Disparity Factor vs Purchase Rank



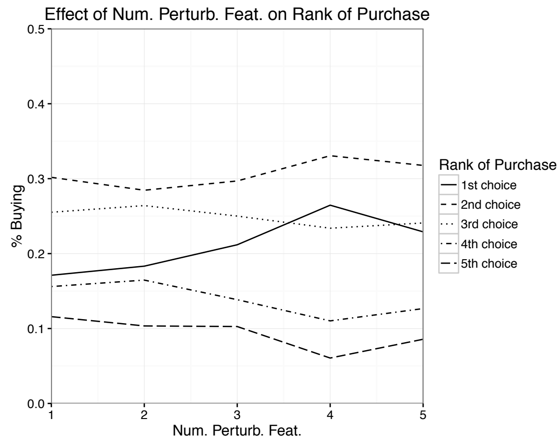
(b) Disparity Factor vs Other Outputs

Main insights from graphs:

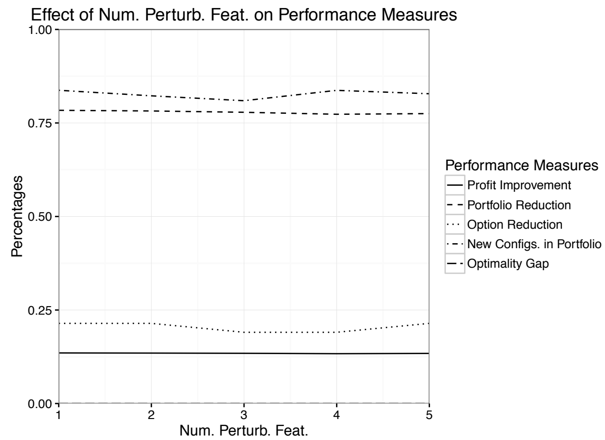
- From (a): The first-choice purchase line is down dramatically, for reasons similar to those discussed in 1.5: For those customers for whom their purchased configuration is forced to be their first choice, greater flexibility gives us greater ability to steer them to other configurations, concentrating the portfolio.

- From (b): As customers become more flexible in terms of disparity, lists become more concentrated on key configurations, driving up these measures. Relatively little disparity seems to go a long way.

1.8 Varying the Number of Features Whose Utilities Are Perturbed



(a) # Feat Perturbed vs Purchase Rank

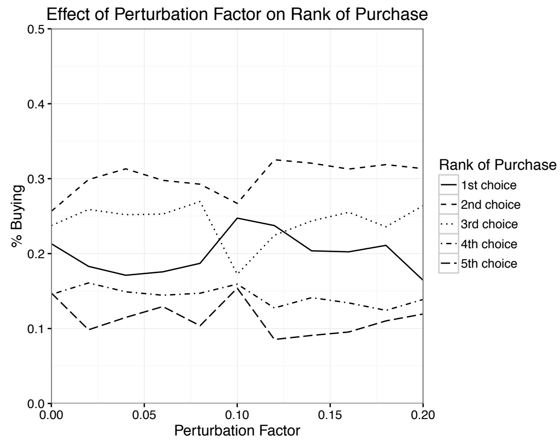


(b) # Feat Perturbed vs Other Outputs

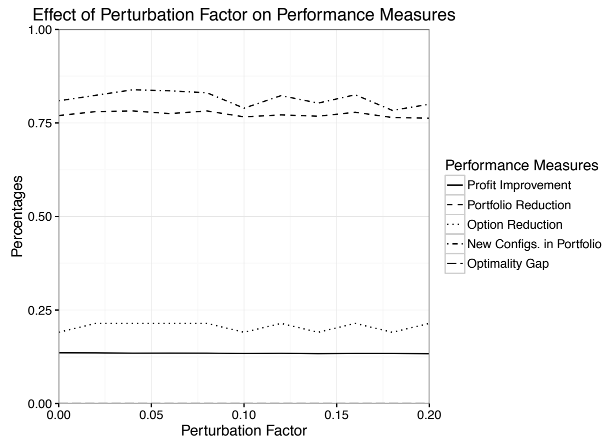
Main insights from graphs:

- No clear pattern/insight visible.

1.9 Varying the Feature Perturbation Factor



(a) Perturbation Factor vs Purchase Rank

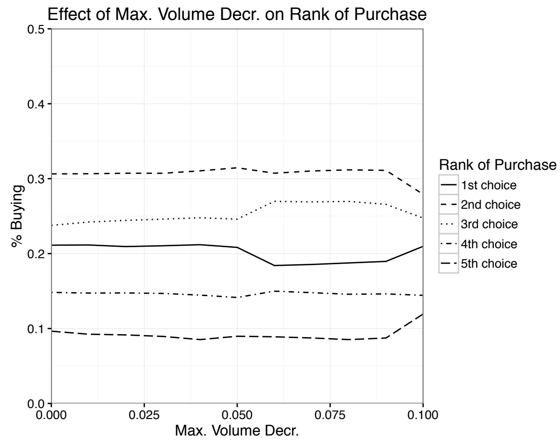


(b) Perturbation Factor vs Other Outputs

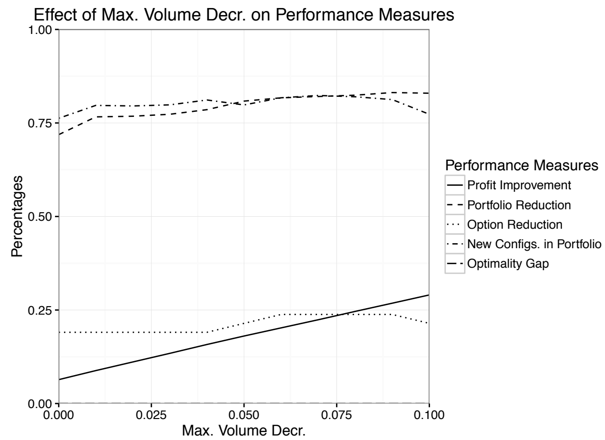
Main insights from graphs:

- No clear pattern/insight visible. Varying perturbation factors seems to add some noise, but not change ultimate results.

1.10 Varying the Maximum Sales Volume Decrease



(a) Max Vol Decr vs Purchase Rank

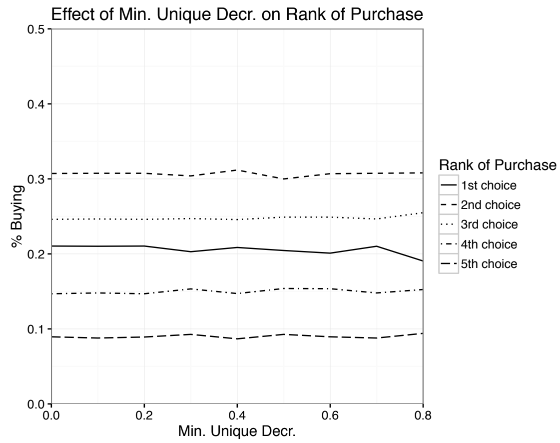


(b) Max Vol Decr vs Other Outputs

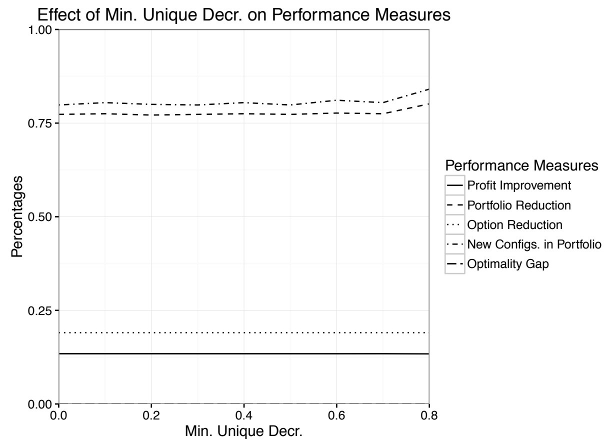
Main insights from graphs:

- From (a): No clear patter/insight visible.
- From (b): Interesting, strong effect of maximum allowed volume decrease (lost sales) on profit increase. This constraint was binding for all optimal solutions, that is, the best course of action was to lose as much sales volume as possible. Most savings due to volume come from inventory cost reduction and quality control savings: Quality level is impacted highly by the total volume (not so much by options) as you have more time to spend on machines when the volume is low. Inventory cost is also reduced based on volume because lower volume implies less inventory held at dealers and hence, CAT has to subsidize less. In CAT's specific case, these two cost pools have a large enough impact to explain the change in profit. This is why the strategic constraint on market share is so important—CAT wants to hold the line on market share, which restricts the portfolio reductions they will tolerate.

1.11 Varying the Minimum Decrease in Unique Configurations



(a) Min Unique Decr vs Purchase Rank

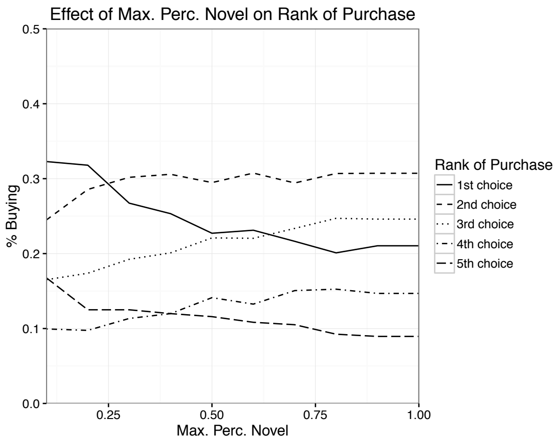


(b) Min Unique Decr vs Other Outputs

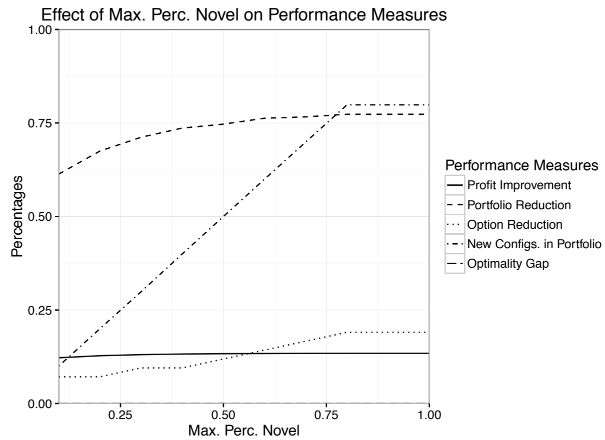
Main insights from graphs:

- All curves relatively flat, indicating that the number of unique configurations can be easily reduced by up to 80% in CAT's case, without side effects on other performance measures. Together with the previous graph this emphasizes that minimum market share is a much more important constraint than decrease in configurations.

1.12 Varying the Percentage of Novel Configurations in Portfolio



(a) Percent Novel vs Purchase Rank



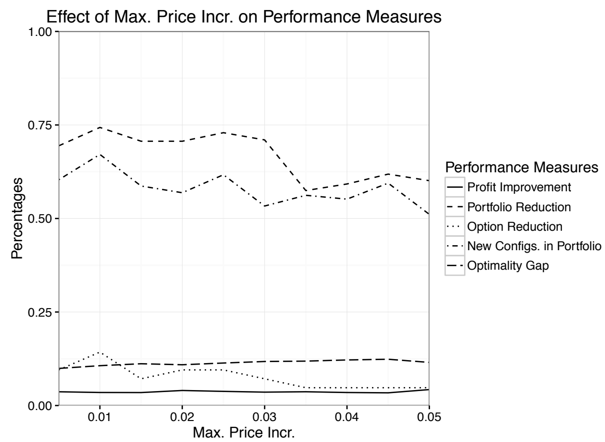
(b) Percent Novel vs Other Outputs

Main insights from graphs:

- From (a): Customers steer away from first choice (50% of which are forced to be first by the beta factor), as a larger and larger percentage of novel configurations are allowed in the portfolio.
- From (b): Increasing the presence of novel configurations in the portfolio allows it to shrink further by steering customers to a smaller set of novel, satisfactory configurations. The fourth curve flattens a bit after 75% indicating the need to still keep some of the original configurations there.

1.13 Varying the Maximum Price Increase per Configuration

(a) Max Price Increase vs Purchase Rank

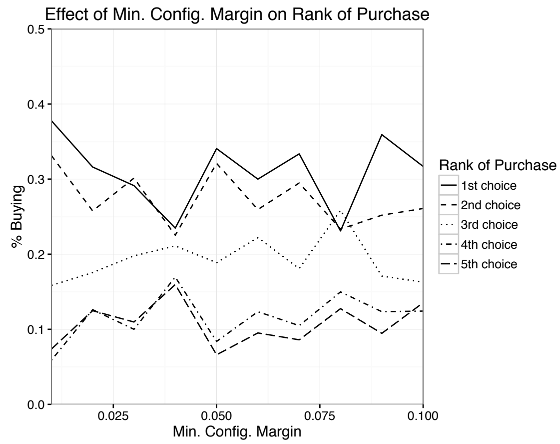


(b) Max Price Increase vs Other Outputs

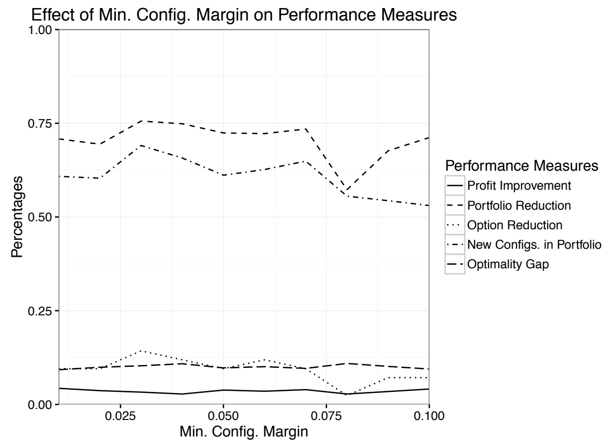
Main insights from graphs:

- The optimization problem becomes very hard to solve as the solution space expands dramatically as price becomes a more important lever. It is difficult to draw conclusions from a collection of suboptimal solutions because they are not necessarily comparable. They represent different trade-offs on the way to optimality.

1.14 Varying the Minimum Margin per Configuration



(a) Min Config Margin vs Purchase Rank

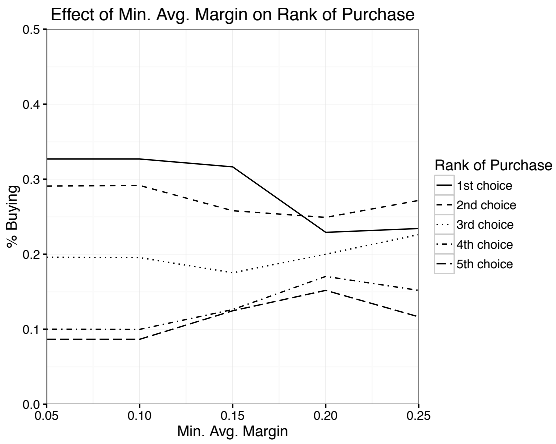


(b) Min Config Margin vs Other Outputs

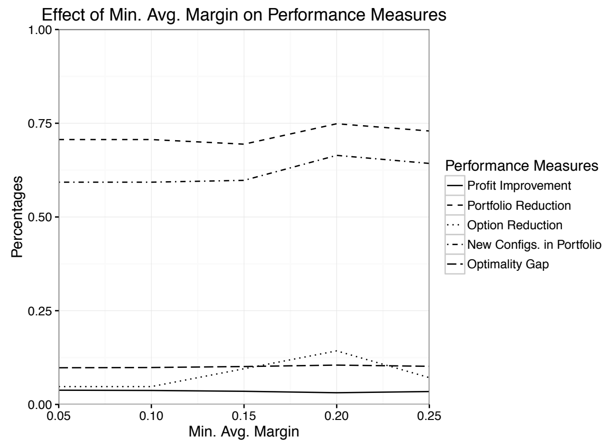
Main insights from graphs:

- Once again the optimization problem becomes very hard to solve as the solution space expands. It is difficult to draw conclusions from a collection of suboptimal solutions because they are not necessarily comparable. They represent different trade-offs on the way to optimality.

1.15 Varying the Minimum Average Weighted Margin over All Configurations



(a) Min Avg Margin vs Purchase Rank



(b) Min Avg Margin vs Other Outputs

Main insights from graphs:

- And again the optimization problem becomes very hard to solve as the solution space expands. It is difficult to draw conclusions from a collection of suboptimal solutions because they are not necessarily comparable. They represent different trade-offs on the way to optimality.