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Product Offering Conditioning In Assemble-To-Order Supply Chains[1]

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Product offering conditioning aims at creating marketable product alternatives to mitigate misalignments of supply and demand and to enable companies to take full advantage of a "sell-what-you-have" strategy. A well executed conditioning process benefits the customers through improved delivery times, and it benefits the enterprise through higher inventory turns, fewer supply overages and shortfalls, and reduced inventory liability exposure. We describe an analytical optimization model that determines profitable product offerings that minimize inventory liabilities and lost sales risks over the entire supply chain. The model provides dynamic, real-time sales recommendations based on current availability, price, performance and customer demand information. It not only improves the coordination of supply and sales in terms of optimizing profit, but also helps managing major product and technology transitions. It is most effective in an assemble-to-order environment with sales building blocks where end products are configured from pluggable components.

Keywords: Assemble-to-order; configure-to-order; demand conditioning; demand–supply matching; inventory liability; product variety.

1. Introduction

In a rapidly shifting global economy, product proliferation combined with declining product life cycles make it increasingly difficult for manufacturers to balance supply with customer demand. Often the linkage between a company's marketing and sales organization, procurement and manufacturing operations is inefficient and leads to misalignment of supply and demand decisions. Sales teams are unable to react intelligently to constraint situations with alternative sales

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recommendations that satisfy customer needs. This invariably leads to situations of component shortfall on one hand, and component excesses on other hand, which can have dramatic effects on a company's top-line performance through missed revenue, and its balance sheet through inventory liabilities or write-downs.

Supply chain performance can often be improved by the intelligent application of trend analysis that results in the company's ability to position itself to condition demand for existing and planned supply (Sheffi 2005; Cachon and Terwiesch 2005; Kapoor *et al.* 2005; Butner and Buckley 2004). Such actions, known as conditioning actions, may touch on three dimensions of the supply chain: demand, supply and product offerings. Supply conditioning actions focus on working with suppliers to resolve supply imbalances, such as negotiating for additional supply or rebalancing supply between sales regions. Demand conditioning actions focus on adjusting the sales plan to affect demand in a desirable way. Examples are sales promotions for a surplus product or price reductions on an alternative product in order to transfer demand from a constrained product. Product offering conditioning actions focus on creating new product models that use excess components or substitutions for supply-constrained components. The success of the conditioning process depends on the timely and proactive identification of supply imbalances and the degree to which the conditioning plan is optimized to meet business objectives. A well-executed conditioning process benefits the customers through improved delivery times, and it benefits the enterprise through higher inventory turns, reduced inventory, and lower component liabilities which lead to higher profits.

In this paper, we describe an analytical optimization model for product offering conditioning. The model determines profitable product offerings to minimize inventory liabilities and lost sales risks over the entire supply chain. A major goal is to create a financially viable, marketable product portfolio that meets customer demand and best utilizes available component inventory. The model is most effective in an assemble-to-order (ATO) environment with sales building blocks where end products are configured from pluggable components. It provides dynamic, real-time sales recommendations based on current availability, price, performance and customer demand information. This enables on demand up-selling, alternative-selling and down-selling to better integrate the supply chain horizontally, connecting the interaction of customers, business partners and sales teams to the procurement and manufacturing capabilities of the company.

An up-sell opportunity is where a customer or business partner is sold a more richly configured solution above the customer's initially selected price range. Incentives may be used to entice the customer to agree to an up-sell. An alternative-sell relates to a sale of a similar product that falls within the selected price range. An alternative-sell is performed when an up-sell is not available or the customer opts for a similarly priced product. A down-sell opportunity refers to a sale of a product that falls below the price range selected by the customer.

Conventional methods of up-selling, alternative-selling, and down-selling include scanning the product portfolio and estimating other recommended products that provide the customer with what they are looking for, in addition to meeting the company's revenue and profit targets. These approaches typically require sales personnel to have expert knowledge of the offerings and financial benefits, as well as require that the product portfolio be small and uncomplicated. Large-scale product offerings and automation use an approach to up-selling, alternative-selling, and down-selling wherein static product substitutions are created by marketing or product planning personnel who have detailed product knowledge. A significant problem with these static approaches is that they are manually created and entered into automated systems, and they are often limited to a single product family. Another significant problem is that the substitutions are predetermined and remain unchanged for an indeterminate length of time, even though certain criteria such as product or component availability, pricing, or technological features may have changed.

Product offering conditioning is by no means limited to dealing with oversupply situations. Assume that a company's demand-supply process for analyzing forecasted demand versus supply position identifies a short-term constraint (1-2 weeks) of an 80 GB hard drive used in high-end laptop products. While procurement evaluates the constraint posture against additional supply actions, sales teams are informed of the constraint that to ensure that promotions and marketing campaigns for the affected products are suspended. Sales personnel are advised of product alternatives via special scripts to exercise the conditioning recommendations as they take orders. Product alternatives may include configurations that use 120 GB hard drives that may be in ample supply. For Internet orders, product alternatives that were identified are presented to the customer via sales prompts on the web. The alternative products may further be discounted to mitigate customer dissatisfaction that the desired product is unavailable. The end result is improved customer satisfaction because the company is selling readily available finished goods and components. End-to-end integration of the company's demand-supply and sales processes would enable alternative product offerings immediately when a constraint is recognized.

The contributions of this paper are as follows. First, we formulate the problem of finding marketable product alternatives in a given product portfolio that best utilize the available component supply as an optimization problem. We present two variants of the problem that overcome the deficiencies of conventional product offering conditioning methods: a single-period model that aims at creating new product models that either use surplus components or substitutions for supply-constrained components; and a multi-period model that assists planners in managing major product and technology transitions as well as pending orders for improved revenue attainment. Second, we develop an efficient column generation procedure for solving these problems. The procedure involves solving a master optimization problem and a slave problem in an iterative algorithm. The master problem generates an optimal build plan for a recommended set of product configurations. The slave problem utilizes column generation to determine the best new configurations to be added to the existing set such that an overall financial objective is optimized. And third, we demonstrate the efficacy of product offering conditioning by numerical experiments with realistic production data. This produces several insights into how the proposed models help proactively coordinate of supply and sales, and it quantifies business benefits of product offering conditioning in assemble-to-order systems.

The rest of the paper is organized as follows. In section 2 we review the related literature. In section 3 we present the single-period offering conditioning problem and derive an efficient column-generation procedure for solving it. In section 4 we present its extension to a multi-period model and explain its application to product transitioning. Computational findings and discussions of results are presented in section 5. Section 6 concludes the paper.

2. Literature Review

The model developed in this paper spans several streams of literature. One stream of research is the literature on available-to-promise (ATP) systems for order promising and fulfillment. Ball *et al.* (2005) provide a classification of ATP models as either push-based or pull-based. Their paper presents a general optimization framework for ATP models that have been described in the literature, as well as several examples of actual ATP business practices in the electronics industry. Chen *et al.* (2002) present a mixed integer programming model that provides an ATP order promising and fulfillment solution for a batch of orders that arrive within a predefined time interval. A variety of constraints, such as raw material availability, production capacity, material compatibility, and customer preferences, are considered. Dietrich *et al.* (2005) describe an implosion technology that takes into account parts availability and solve a resource allocation problem to determine which products should be produced so that an overall profitability objective is maximized. Ervolina and Dietrich (2001) describe an application of the implosion technology for ATP order promising in an assemble-to-order (ATO) or configure-to-order (CTO) environment. The goal is to create a feasible production plan that can be used to schedule (or promise) orders against. Another application of the implosion technology that is closely related to our work is available-to-sell (ATS). The goal of ATS is to provide a squared set analysis for the consumption of excess inventory, and finding marketable products that consume the excess while minimizing additional purchase. Dietrich *et al.* (2005) describe a basic ATS implosion model where the set of new product configurations is predetermined. No explicit demand statement is provided and the configurations are assumed to have infinite demand.

A second stream of research is related to the product substitution problem. Balakrishnan and Geunes (2000) describe a manufacturing planning method with flexible bills-of-materials and component substitution. A dynamic programming solution method is developed to find production and substitution quantities that satisfy demands at minimum total cost, comprising setup, production, substitution, and inventory holding cost. Because supply is unconstrained, the model does not address matching of demand and supply. Another particular type of substitution is the so-called downward substitution where high-end products can substitute for low-end products when the latter are out of stock. Bassok *et al.* (1999) study the single-period and infinite horizon, multi-product, downward substitution problem and provide proof for the concavity of the profit function. Hale *et al*. (2001) extend the analysis of the downward substitution problem to an ATO system with two end-products where each product is composed of two components. Substitutions are carried out at the component level. Chen and Plambeck (2005) study a single-item production-inventory system with periodic replenishments where customers may accept substitutes or choose not to buy when a product is out of stock. They show that learning about the demand distribution and customer substitution behavior influences the optimal inventory levels. Although it is not the focus of this paper, pricing can also be an effective part of demand conditioning. For a review the reader is referred to Chan *et al.* (2004).

A third stream of related literature deals with disassembly decisions in reverse logistics supply chains, see Dekker (2003) and Fleischmann *et al.* (2005) for an overview. In reverse logistics, products which by themselves are no longer marketable may be disassembled to recover components or subassemblies. The recovered components may serve as spare parts or as components in new configurations that are resold in secondary markets. Gupta and Taleb (1994) and Taleb *et al.* (1997) develop effective disassembly configurations with common components among products and limited inventory of products available for disassembly. Veerakamolmal and Gupta (1998) present a mathematical programming model for component recovery that computes the number of products to disassemble in order to fulfill the demand of the components at the minimal disassembly and disposal costs. Veerakamolmal *et al.* (2002) examine the costs and benefits of different product take-back (PTB) scenarios for used electronics equipment. The model determines a theoretical optimal cost scenario for PTB programs. Meacham *et al.* (1999) determine optimal disassembly configurations to meet a specified demand for recovered components and subassemblies from an available supply of recovered products. Products are represented through their bills-of-materials. As in our approach, a fast column generation algorithm is proposed to determine maximum revenue disassembly configurations for individual products.

Finally we mention the literature on ATO and CTO systems. Product offering conditioning is more likely to be implemented in a build-to-order environment because of its flexibility in responding to changing customer demand; refer to Song and Zipkin (2004) for a review of research to date on ATO systems. Among other issues, multi-component, multi-product ATO systems pose challenging inventory management problems. Xu and Akcay (2004) formulate a two-stage stochastic integer program with recourse for allocating constrained components and selecting base-stock levels to maximize the fraction of orders assembled within a quoted maximum delay. They develop a heuristic method based on a simple, order-based component allocation rule. Cheng *et al.* (2002) study the problem of minimizing average component inventory holding cost subject to product family dependent fill rate constraints in a CTO system. Plambeck and Ward (2003) employ diffusion approximation to allocate supply-constrained components to outstanding customer orders in an ATO system to maximize expected discounted profit.

3. Single Period Product Offering Conditioning Model

In this section, we formulate the single period product offering conditioning problem and develop an efficient solution algorithm that uses decomposition and column generation to enable a conditioning process.

We are given a portfolio of existing product offerings and their demand forecasts. Existing offerings are grouped into product categories such as economy, value and performance products. Our goal is to build enough volume to satisfy the demand forecast for each existing offering. If that can not be achieved, we create new product offerings (with new configurations) to sell in each product category. A new offering created for a product category can be used to fulfill unsatisfied demand for an existing offering in the same category with additional subsitution cost incurred.

The components used to configure (assemble) end products are grouped into commodity groups with each component belonging to exactly one commodity group. A bill-of-materials that describes the component consumption is given for each existing product offering. For each product category, we also have product configuration rules that restrict the components that can be used in every commodity group to create new product offerings for this category. Product configuration rules represent technical and manufacturing restrictions that dictate how various parts can be assembled into a product. For example, the power consumption requirements of a specific component could limit the product category in which this component can be used and would thus be expressed as a product configuration rule. The product offering conditioning model compares and analyzes product alternatives to create a set of recommended new product configurations. The analysis is based on optimizing financial objectives and includes liability costs for excess inventory and penalty costs for violating desired customer services levels.

3.1 Notation

Before we discuss the formulation, let us define the notation required.

Products, commodities, and components

I : Number of components (indexed by i, $i = 1, \ldots, I$)

K : Number of commodity groups (indexed by k, $k = 1, \ldots, K$)

P : Number of product categories (indexed by p, $p = 1, \ldots, P$)

M_p : Number of existing product offerings in category p (indexed by m, $m = 1, \ldots, M_p$)

Demand and supply

D_m^p : Demand forecast for the existing product offering m in category p

$S_i^{\min}$: Downside supply flexibility for component i (minimum supply quantity supported by the component supplier)

$S_i^{\max}$: Upside supply flexibility (maximum supply quantity supported by component supplier)

Bills-of-materials

B_{ik} : 1 if part i belongs to commodity group k, 0 o/w

u_{im}^p : 1 if part i is used to assemble existing product offering m in category p, 0 o/w (BOM)

w_i^p : 1 if part i can be used to assemble products in category p, 0 o/w (*selection menu*)

Costs

h_i : Unit holding cost of component i (liability cost)

b_m^p : Unit lost-sales (or backorder) cost of existing product offering m in category p

c^p : Unit substitution cost for product category p. Building one unit of a new offering in product category p to fulfill the demand forecast of an existing offering in the same category will incur the cost c^p

Decision Variables

X_m^p : Build volume of existing product offering m in category p

N_p : Number of models to build for product category p (indexed by n, $n = 1, \ldots, N_p$)

v_{in}^p : 1 if component i is used to assemble new product offering n in product category p; 0 o/w

Y_{mn}^p : Build volume of new product offering n in product category p that is used to substitute existing offering m in the same product category

S_i : Quantity of component *i* ordered from supplier based on the build volumes

3.2 Problem Formulation

We can now formulate the single period product offering conditioning model. The objective function given by (1) is to minimize the total supply chain cost which consists of three components:

1. Lost-sales (or backorder) costs. If the build volume allocated to an existing product offering falls short of the demand forecast, a lost-sales cost is incurred.
2. Product substitution costs. Costs incurred for using a new product offering to (partially) fulfill demand for an existing product offering.
3. Inventory holding (or component liability) costs. Costs incurred for holding excess component inventories.

$$\begin{aligned}\text{Min } Z(X_m^p, v_{in}^p, Y_{mn}^p) = \ & \sum_{p=1}^{P}\sum_{m=1}^{M_p} b_m^p \left(D_m^p - X_m^p - \sum_{n=1}^{N_p} Y_{mn}^p \right) + \sum_{p=1}^{P} c^p \sum_{m=1}^{M_p}\sum_{n=1}^{N_p} Y_{mn}^p \\ & + \sum_{i=1}^{I} h_i \left(S_i - \sum_{p=1}^{P}\sum_{m=1}^{M_p} u_{im}^p X_m^p - \sum_{p=1}^{P}\sum_{n=1}^{N_p} v_{in}^p \sum_{m=1}^{M_p} Y_{mn}^p \right)\end{aligned} \tag{1}$$

Let us now formulate the constraints. The consumption of component *i*, S_i, is bounded by a maximum and minimum order quantity:

$$S_i \le S_i^{\max}, \forall i \tag{2}$$

$$S_i \ge S_i^{\min}, \forall i. \tag{3}$$

Given the demand forecasts D_m^p for existing offering *m* in category *p*, the total build volume for this offering (including the volumes substituted by new product offerings) cannot exceed the demand forecast D_m^p :

$$D_m^p - X_m^p - \sum_{n=1}^{N_p} Y_{mn}^p \ge 0 \tag{4}$$

The number of components consumed must be less than or equal the number of components ordered from the supplier:

$$S_i - \sum_{p=1}^{P}\sum_{m=1}^{M_p} u_{im}^p X_m^p - \sum_{p=1}^{P}\sum_{n=1}^{N_p} v_{in}^p \sum_{m=1}^{M_p} Y_{mn}^p \ge 0 \tag{5}$$

The components used in a new product offering must not violate the *selection menu* specified for the product category of the new product offering:

$$v_{in}^{p} \leq w_{i}^{p}, \forall i, p, n \tag{6}$$

Each new product offering must be a squared set configuration, i.e., it uses one and only one component from each commodity group:

$$\sum_{i=1}^{I} B_{ik} v_{in}^{p} = 1, \forall k, p, n \tag{8}$$

Finally, we also have non-negativity and integrality constraints on the decision variables.

$$X_{m}^{p} \geq 0, \forall p, m \tag{8a}$$

$$S_{i} \geq 0, \forall i \tag{8b}$$

$$Y_{mn}^{p} \geq 0, \forall p, m, n \tag{8c}$$

$$N_{p} \geq 0 \ \& \ Integer, \forall p \tag{8d}$$

$$v_{in}^{p} \in \{0,1\}, \forall i, n, p \tag{8e}$$

It is important to note that, even if the number of new product configurations in product category p, N_p, were fixed, there is a nonlinear term ($v_{in}^{p} Y_{n}^{p}$) in (1) and (4). It is possible to linearize this term using standard techniques and convert the problem into a mixed integer program (e.g., Barnhart *et al.* 1998). However, given that industry-size problems involve hundreds of components and dozens of product categories (which results in thousands of binary variables), finding the optimal solution of the MIP is likely to take a prohibitively long time. Because speed of execution is essential for a timely resolution of demand–supply imbalances, we have developed an iterative procedure based on column generation to efficiently solve this problem. The algorithm is described next.

3.3 Computational Algorithm

The basic idea is that new product offerings are columns that are introduced into the problem one at a time in an iterative algorithm. The problem is decomposed into two sub-problems: a master problem (*MP*) that aims at finding the optimal build volumes for a given set of new and existing product offerings, and a set of slave problems (SP_{m}^{p} , $p = 1, \ldots, P$ and $m = 1, \ldots, M_{p}$) that generates new product offerings and supplies them to *MP*. The two sub-problems are solved iteratively until the optimal solution is reached. The master problem is given in (9) as follows:

Master Problem (MP):

$$\text{Min } Z(X_m^p, Y_{mn}^p) = \sum_{p=1}^{P}\sum_{m=1}^{M_p} b_m^p \left(D_m^p - X_m^p - \sum_{n=1}^{N_p} Y_{mn}^p \right) + \sum_{p=1}^{P} c^p \sum_{m=1}^{M_p}\sum_{n=1}^{N_p} Y_{mn}^p + \sum_{i=1}^{I} h_i \left(S_i - \sum_{p=1}^{P}\sum_{m=1}^{M_p} u_{im}^p X_m^p - \sum_{p=1}^{P}\sum_{n=1}^{N_p} v_{in}^p \sum_{m=1}^{M_p} Y_{mn}^p \right) \tag{9}$$

subject to constraints (2), (3), (4), (5), (8a), (8b) and (8c)

Note that the bills-of-materials of the new product offerings, v_{in}^p, are not decision variables in *MP* and are fixed along with N_p. Thus, the master problem (9) is a linear program that can be solved very efficiently even for large problem sizes.

Let λ_i, $i = 1,\ldots, I$, denote the shadow prices pertaining to the liability constraint (5), and β_m^p, $m = 1\ldots, M_p$ and $p = 1, \ldots, P$, denote the shadow prices pertaining to the build volume constraint (4), in the optimal solution to *MP*. We can now formulate the slave problems SP_m^p for $p = 1, \ldots, P$ and $m=1, \ldots, M_p$ as follows.

Slave Problem (SP_m^p):

$$\text{Min } Z_2^p(\bar{v}_i^p) = \sum_{i=1}^{I}(-h_i + \lambda_i)\bar{v}_i^p - b_m^p + \beta_m^p + c^p \tag{10}$$

subject to constraints (6), (7), (8d) and (8e)

We use a standard column generation procedure to solve the problem (e.g., Barnhart 1998). In the initial step of the algorithm, *MP* is solved without any new product offerings and its solution is fed into the slave problems. The slave problems subsequently try to improve the solution by introducing new product offerings for every product category. Any new product offerings are then added back into *MP* after updating the corresponding values of N_p for $p = 1, \ldots, P$, and the master problem *MP* is resolved. This process iterates until no further improvement is possible. Below is a detailed description of the algorithm.

Algorithm 1: Single-period problem

Step 1: Initialize $N_p := 0$ and set $\{v_{in}^p\} = \phi$ for all *p*, i.e., there are no new product offerings.

Step 2: Solve the master problem, *MP*, and obtain the optimal values of λ_i and β_m^p.

Step 3: Solve the slave problems SP_m^p. Because the solutions for all the existing product offerings in a given product category *p* differ by a constant term $-b_m^p + \beta_m^p$, we only solve problem (10) for a single existing offering *m* in each category *p*. The existing offering *m* selected is the one with the smallest $-b_m^p + \beta_m^p$ value since (10) is a minimization problem.

Step 4: If $Z_2^p(\cdot) \geq 0$, $\forall p$, we have found the optimal solution; STOP and print the results from the current master problem solution. Otherwise, go to Step 5.

Step 5: Select the category $p*$ that has the minimum $Z_2^p(\cdot)$ value and update the number of new product offerings of this category by $N_{p*} := N_{p*} + 1$. Append the new product offering $\bar{v}_i^{p*}$ to the set of new product offerings of category $p*$ as $\{v_{in}^{p*}\} = \{v_{in}^{p*}, \bar{v}_i^{p*}\}$ and go to Step 2.

In Step 3, we generate a new product offering that will improve the LP solution. In Step 4, all $Z_2^p(\bar{v}_i^p) \geq 0$ means no improvement is possible and we have found the optimal solution; otherwise, we continue to the next iteration.

Although the slave problem SP_m^p is an integer program, it has a special structure that can be exploited to solve it easily: For each commodity group, first consider the parts that belong to this group and are allowed in the selection menu w_i^p. Compare their $(-h_i + \lambda_i)$ values and choose the one with the minimum $(-h_i + \lambda_i)$ value. It is easy to see that repeating this procedure for all commodity groups produces a squared set product offering that minimizes $Z_2^p(\bar{v}_i^p)$. This procedure is efficient in terms of the computational requirement per iteration. To further improve the runtime performance of the algorithm, we modified Step 5 of the above procedure to introduce multiple columns (new product offerings) per iteration instead of just one. This is achieved by simultaneously introducing all columns that yielded a negative $Z_2^p(\cdot)$ value.

4. Multi-Period Product Offering Conditioning Model

The single period model discussed in the previous section captures the dynamics of a product offering conditioning process on an aggregate basis, say, at a quarterly level. Having developed a procedure to design new product offerings that enable supply-demand matching for the aggregate problem, we will discuss its extension into a multi-period model where we capture the inventories and back-orders at a much more granular level, say, on a weekly basis. The new product offerings recommended by the model are available for marketing throughout a quarter, although the recommended build volumes differ from week to week to reflect available supply. The multi-period model described next helps planners gain more detailed insights into supply consumption and demand satisfaction and it enables better decision making as explained below:

- *Managing excess inventory to reduce liability*. A multi-period model helps distinguish between excess inventory costs and liability costs. Although supply commitments for components are usually updated every week, excess components inventory will incur liabilities only at the end of a quarter. Excess supply within the quarter may incur a (comparatively small) inventory holding cost.
- *Managing pending orders to improve revenue attainment.* A multi-period model also helps distinguish between backorders and pending orders at the end of a financial quarter. Backordered demand within a quarter imposes a smaller penalty to the business compared to orders that are left pending across quarters because pending orders directly affect a company's top-line revenue.
- *Managing technology transitions.* Most importantly, a multi-period model helps planners to better manage product and technology transitions. For example, when a new technology (say a faster CPU) is announced, a supplier might offer price or other incentives to accelerate the ramp-up of the new technology during product introduction and to rapidly phase out the predecessor technology. While the new component will carry a higher profit margin, the component it replaces may expose a manufacturer to inventory liabilities and obsolescence costs. The multi-period model captures the detailed sales ramp-up and ramp-down processes during product transitions, and it enables product planners to create transition plans that balance the trade-offs between costs and profits.

4.1 Notation

Before we formulate the multi-period model, let us define the required notation. Most of the notation carries over from the single period model with an additional subscript *t* for the time period. The additional notation required is defined below.

Inputs

H : Number of time periods or length of horizon (indexed by t, $t = 1, \ldots, H$)

δ_m : Unit cost of horizon-end pending orders for existing product offering m

θ_i : Unit cost of liability for excess inventory of part i at end of horizon

Decision Variables

B_{mt} : Backorders of existing product offering m at end of period t

I_{it} : Excess inventory of part i at the end of period t

4.2 Problem Formulation

We next formulate the master problem, MP^H, and slave problems, SP_{pt}, for each product category p and time period t. The master problem, MP^H, can be stated as follows:

Master Problem (MP^H):

$$\begin{aligned}\min Z_1\left(X_{mt}, Y_{mt}^{(n,p)}\right) = & \sum_{t=1}^{H-1} \sum_{p \in P} \sum_{m \in M_p} b_{mt} B_{mt} + \sum_{p \in P} \sum_{m \in M_p} \beta_m B_{mH} \\ & + \sum_{i \in I} \sum_{t=1}^{H-1} h_i I_{it} + \sum_{i \in I} \theta_i I_{iH} + \sum_{t} \sum_{p \in P} \sum_{m \in M_p} \sum_{n \in N_p} c_m^p Y_{mt}^{(n,p)}\end{aligned} \tag{11}$$

subject to the following constraints:

$$B_{mt} = B_{m,t-1} + D_{mt} - X_{mt} - \sum_{n \in N_p} Y_{mt}^{(n,p)} \tag{12}$$

$$S_{it}^{\min} \le S_{it} \le S_{it}^{\max}, \forall i, t \tag{13}$$

$$I_{it} = I_{i,t-1} + S_{it} - \sum_{m \in M} u_{im} X_{mt} - \sum_{p \in P} \sum_{m \in M_p} \sum_{n \in N_p} u_{in}^{(p)} Y_{mt}^{(n,p)} \tag{14}$$

$$X_{mt} \ge 0, \forall m, t \tag{15a}$$

$$Y_{mt}^{(n,p)} \geq 0, \forall n, m, p, t \tag{15b}$$

$$S_{it} \geq 0, \forall i, t \tag{15c}$$

$$I_{it} \geq 0, \forall i, t \tag{15d}$$

$$B_{mt} \geq 0, \forall m, t \tag{15e}$$

As in the single period model, the objective of MP^H is to decide the build volumes, given the existing product offerings and a given number of new product offerings for the product categories. The objective function (11) is the sum of the backorder costs, horizon-end pending orders costs, excess inventory costs and liability costs. Constraints (12) give the volume balance equations to set the backorders at the end of each period for the existing product offerings. Constraints (13) bound the order quantities to the supplier based on the available supply flexibilities. Constraints (14) involve volume balance equations to set the excess inventories carried over at the end of every period based on the consumption due to the build volumes. Constraints (15) are non-negativity constraints. As can be seen from the above model, the optimal build volumes provide period-by-period (e.g., weekly) allocations for the various product offerings that are fully aligned with the available component supply.

Let us next discuss the structure of the slave problems, SP_{pt}, for the multi-period problem. As is obvious, we now have to solve several slave problems per iteration. Let λ_{it} be the shadow prices pertaining to the inventory non-negativity constraints, (15d), and μ_{mt}, be the shadow prices pertaining to the backorders for product offerings, (15e), in the optimal solution to the master problem. We can now formulate a slave problem, SP_{pt}, for every product category p and time period t as follows:

Slave Problem (SP_{pt}):

$$\begin{aligned} \min Z_2^{(p,t)}\left(\bar{v}_i^{pt}\right) = \sum_{i \in I_p} \left[\sum_{r=t}^{H-1} \left(-h_{ir} + \lambda_{ir}\right) + \left(-\theta_i + \lambda_{iH}\right) \right] \bar{v}_i^{pt} \\ + \sum_{r=t}^{H-1} \left(-b_{mr} + \mu_{mr}\right) + \left(-\beta_m + \mu_{mH}\right) + c_m^p \end{aligned} \tag{16}$$

subject to constraints

$$\bar{v}_i^{pt} \leq w_i^p, \forall i \tag{17}$$

$$\sum_{i=1}^{I} B_{ik}\bar{v}_i^{pt} = 1, \forall k \tag{18}$$

$$\bar{v}_i^{pt} \in \{0,1\}, \forall i \tag{19}$$

Constraints (17), (18) and (19) are similar to those in the single period model. The objective function also has the same structure as the single period model. As in the single period model, for every product category p, we choose the model $m \in M_p$ that has the lowest value of $\sum_{r=t}^{H-1}\left(-b_{mr} + \mu^{(m,r)}\right) + \left(-\beta_m + \mu^{(m,H)}\right) + c_m^p$ in the objective function.

4.3 Computational Algorithm

We will use the column generation procedure similar to the one developed for the single period model. Below is a detailed description of the algorithm.

Algorithm 2: Multi-period model

Step 1: Initialize $N_p = 0$ and set $\{v_{in}^p\} = \phi$ for all p, i.e., there are no new product offerings.

Step 2: Solve the mater problem and obtain the optimal values of λ_{it} and μ_{mt}.

Step 3: Solve the following slave problems, for every category p and time period t.

Step 4: If $Z_2^{p,t}(\cdot) \geq 0$, $\forall p, t$, we have found the optimal solution, STOP and print the results from the current master problem solution. Otherwise, go to Step 5.

Step 5: Append all the columns, $\bar{v}_i^{pt}$, that yielded a negative $Z_2^p(\cdot)$ value as $\{v_{in}^p\} = \{v_{in}^p, \bar{v}_i^{p,t}\}$ after updating the appropriate N_p. and go to Step 2.

In each iteration of the procedure we may introduce more than one column for every product category. We found that this was more efficient than introducing one column at a time, given the large number of slave problems. The master problem for the multi-period model remains an LP that can be solved efficiently and all the slave problems can still be solved using a greedy heuristic similar to the one described for the single period model. Thus, the procedure we have developed is efficient in terms of computational requirements.

Finally, let us discuss how we can model product transitions using this model. For a new component being introduced, the minimum supply commit at the end of every period, $S_{it}^{\min}$, can be set such that the desired ramp-up pattern is captured within the horizon. Given that the model aims at reducing inventory costs, it will make build decisions that best accommodate the desired ramp-up targets. Also, to encourage the design of product offerings that use the new component, one can give sufficient upside flexibility by making the difference between $S_{it}^{\min}$ and $S_{it}^{\max}$ large for the new component being introduced. For the component that becomes obsolete, one can set $S_{it}^{\min}$ such that the end-of-life inventory is consumed and inventory write-offs are minimized. The upside supply flexibility can be set to be equal to the downside supply flexibility, discouraging the model to consume more old components than needed. In addition to capturing technology transitions, the model also allows planners and the sales teams to test ramp-up and ramp-down patterns for their practicality with respect to the availability of supply in other commodities and demand satisfaction other product offerings that may not use the transitioning parts. These advantages make the multi-period model extremely valuable in practice.

5. Numerical Results

In this section we present and discuss our numerical findings. The numerical study focuses on

1. evaluating the benefits of offering conditioning (in terms of expected backorder and liability costs) relative to a conventional Material Requirements Planning (MRP) approach with a static portfolio of product configurations;
2. assessing the impact of supply quantity flexibility on supply chain performance when combined with product offering conditioning; and
3. managing product transitions to minimize exposure to inventory liabilities and pending orders.

We illustrate the capabilities of the models by implementing the solution procedures and applying them to an assemble-to-order system for personal computers (PCs). The product portfolio in our numerical study consists of three PC product families representing low-end, mid-range and high-end portable computers. Each product family comprises a number of predefined product configurations with bills-of-materials as depicted in Table 1. The data set resembles a real-world problem compiled from actual PC supply chain data.

PC Components		Low-End (Economy)				Mid-Range (Value)			High-End (Performance)			Supply Requirements	Supply Commitment
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10		
PANELS	14" XGA	1	1	1	1	-	-	-	-	-	-	6,000	2,500
	15" XGA	-	-	-	-	1	1	1	-	-	-	4,500	10,000
	15" SXGA+	-	-	-	-	-	-	-	1	1	1	4,500	2,500
HARD DRIVES	30GB 4200rpm	1	1	1	-	-	-	-	-	-	-	4,500	4,000
	40GB 5400rpm	-		-	1	-	-	1	-	-	-	3,000	5,000
	60GB 7200rpm	-	-	-	-	1	1	-	1	-	-	4,500	4,000
	80GB 5400rpm	-	-	-	-	-	-	-	-	1	1	3,000	2,000
PROCESSORS	Pentium M725	1	1	-	1	-	-	-	-	-	-	4,500	4,000
	Pentium M735	-	-	1	-	1	1	-	-	1	-	6,000	7,000
	Pentium M765	-	-	-	-		-	1	1	-	1	4,500	4,000
OPTICALS	CD-RW 24X	-	1	-	-	1	-	1	1	1	-	7,500	6,000
	COMBO 24X	1	-	1	1	-	1	-	-	-	1	7,500	9,000
Demand forecast		1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500		
MRP build plan		1,000	1,500	-	-	1,500	1,500	1,500	1,000	-	1,500		

Table 1. Bill-of-materials, supply requirements, and supply commitments for example scenario.

Product configurations P_1 to P_4 are low-end systems, P_5 to P_7 are mid-range systems, and P_8 to P_{10} are high-end computers. Each configuration is assembled from components of the four commodity groups: panels, hard drives, processors, and optical drives. For example, product P1 is assembled from a 14"XGA panel, a 30GB hard drive, a Pentium M725 processor, and a 24X optical combo drive. Notice that all configurations within a product family use the same type of panel (i.e., 14"XGA for low-end systems, 15"XGA for mid-range systems, 15"SXGA+ for high-end configurations).

We assume that the top-level demand forecast for configuration *m* in product family *p* is $D_m^p = 1{,}500$ units. To determine the supply requirements for each PC component, the demand forecast is exploded through the bills-of-materials in a standard MRP calculation. The two rightmost columns of Table 1 show the supply requirement and a sample supply commitment pertaining to the top-level demand forecast. The supply commitment indicates a suppliers' capability to deliver to the manufacturer's supply requirements. For now, we assume that the minimum supply quantity $S_i^{\min}$ is equal to the maximum supply quantity $S_i^{\max}$, i.e., there is no supply flexibility. Comparing the supply requirements with the supply commitment indicates supply constraints on 14"XGA and 15"SXGA+ panels. To mitigate the constrained supply, the panel supplier committed a higher than requested supply volume of 10,000 units for the 15"XGA panel. Notice that the supply commitment matches the supply requirements at the commodity group level, although the individual component mix deviates from the requirements.

Given the supply commitment, a conventional MRP system would match the available supply to the demand forecast and provide an optimized build plan. A build plan created by such a tool is displayed in the bottom row of Table 1. Notice that the constrained supply of 14"XGA and 15"SXGA+ panels results in 3,500 backorders of low-end systems and 2,000 backorders of high-end systems. Next, we apply the single-period model described in Section 3 to the example scenario. Table 2 shows the selection menu w_i^p for the three product families.

Selection menu		Low-End (Economy)	Mid-Range (Value)	High-End (Performance)
PANELS	14" XGA	1	-	-
	15" XGA	1	1	1
	15" SXGA+	-	-	1
HARD DRIVES	30GB 4200rpm	1	-	-
	40GB 5400rpm	-	1	-
	60GB 7200rpm	-	1	-
	80GB 5400rpm	-	-	1
PROCESSORS	Pentium M725	1	-	-
	Pentium M735	1	1	-
	Pentium M765	-	1	1
OPTICALS	CD-RW 24X	1	1	1
	COMBO 24X	1	1	1

Table 2. Selection menu for low-end, mid-range, and high-end product categories.

Recall that the master problem begins with the initial set of product configurations, their demand forecasts and the component supply commitments. Once a feasible production plan is determined, the algorithm executes a slave problem to generate new product configurations until the inventory costs can not be further reduced. In this example, the algorithm creates a total of four new product configurations. The bills-of-materials of the new configurations are shown in the shaded areas of Table 3. The conditioned build plan is displayed in the bottom row. As a result of offering conditioning, backorders for low-end systems are reduced from 3,500 to 500, and backorders for high-end systems are reduced from 2,000 to 1,000.

PC Components		Low-End (Economy)						Mid-Range (Value)				High-End (Performance)			
PANELS	14.1" XGA	1	1	1	1	-	-	-	-	-	-	-	-	-	-
	15.0" XGA	-	-	-	-	1	1	1	1	1	1	-	-	-	1
	15.0" SXGA+	-	-	-	-	-	-	-	-	-	-	1	1	1	-
HARD DRIVES	30GB 4200rpm	1	1	1	-	1	1	-	-	-	-	-	-	-	-
	40GB 5400rpm	-	-	-	1	-	-	-	-	1	1	-	-	-	-
	60GB 7200rpm	-	-	-	-	-	-	1	1	-	-	1	-	-	-
	80GB 5400rpm	-	-	-	-	-	-	-	-	-	-	-	1	1	1
PROCESSORS	Pentium M725	1	1	-	1	1	-	-	-	-	-	-	-	-	-
	Pentium M735	-	-	1	-	-	1	1	1	-	1	-	1	-	1
	Pentium M765	-	-	-	-	-	-		-	1	-	1	-	1	-
OPTICALS	CD-RW 24X	-	1	-	-	-	-	1	-	1	1	1	1	-	1
	COMBO 24X	1	-	1	1	1	1	-	1	-	-	-	-	1	-
Base forecast		1,500	1,500	1,500	1,500	-	-	1,500	1,500	1,500	-	1,500	1,500	1,500	-
Conditioned build plan		-	-	1,000	1,500	2,500	500	1,000	1,500	1,500	500	1,500	-	1,000	1,000

Table 3. Conditioned build plan and bills-of-materials of new product offerings.

Table 4 compares the allocated supply and excess component inventories that result from the two build plans. We observe that a substantial portion of the component supply in the MRP build plan remains unallocated, in particular 5,500 units of 15"XGA panel and 5,000 units of 30GB and 40GB hard drives. The reason for the large overage is that none of the existing product offerings in Table 1 is configured with a 15"XGA panel with a low-end hard drive. To prevent such overages, the offering conditioning model creates three new configurations in the low-end and mid-range category, each of which utilizes a 15"XGA panel and a 30GB or 40GB hard drive in its bill-of-material. As a result, the total excess component inventory is reduced from 22,000 to 6,000 units.

PC Components		Supply Commitment	MRP allocation		Offering conditioning	
			Allocated supply	Excess inventory	Allocated supply	Excess inventory
PANELS	14" XGA	2,500	2,500	-	2,500	-
	15" XGA	10,000	4,500	5,500	8,500	1,500
	15" SXGA+	2,500	2,500	-	2,500	-
HARD DRIVES	30GB 4200rpm	4,000	2,500	1,500	4,000	-
	40GB 5400rpm	5,000	1,500	3,500	3,500	1,500
	60GB 7200rpm	4,000	4,000	-	4,000	-
	80GB 5400rpm	2,000	1,500	500	2,000	-
PROCESSORS	Pentium M725	4,000	2,500	1,500	4,000	-
	Pentium M735	7,000	3,000	4,000	5,500	1,500
	Pentium M765	4,000	4,000	-	4,000	-
OPTICALS	CD-RW 24X	6,000	5,500	500	5,500	500
	COMBO 24X	9,000	4,000	5,000	8,000	1,000

Table 4. Supply and excess inventory for MRP allocation and product offering conditioning.

If we assume that the inventory liability cost for component i is $h_i = 5$, the build plan generated by the offering conditioning model yields an inventory cost of 30,000 which is significantly less than the cost of 110,000 produced by the MRP allocation. If we further assume that the backorder cost per unit of unfilled demand is $b_m^p = 50$ and the product substitution cost is $c^p = 10$, the offering conditioning model yields a backorder cost of 75,000, a substitution cost of 45,000 and a total cost of 150,000. Given that the total cost arising from the MRP allocation is 385,000 the percent cost improvement gained by employing the offering conditioning model is more than 60 percent when compared to the MRP-based approach. The individual costs pertaining to the two approaches are depicted in Table 5.

	Unit cost	MRP allocation Quantity	Cost	Offering conditioning Quantity	Cost
Backorders	50	5,500	275,000	1,500	75,000
Inventory liability	5	22,000	110,000	6,000	30,000
Substitutions	10	-	-	4,500	45,000
Total cost			385,000		150,000

Table 5. Cost comparisons between MRP allocation and product offering conditioning.

Next we investigate the benefit of supplier quantity flexibility in conjunction with product offering conditioning on supply chain cost. Quantity flexibility can be specified in a supply contract that allows a manufacturer to adjust its order quantities after an initial purchase order is placed. In addition to a committed order quantity, a manufacturer can purchase option contracts or other derivative instruments for risk management to protect its supply chain against demand risk. Such flexibility enables the buyer to reduce its risk in over- or under-stocking, but it generally comes at an extra cost which gives the supplier an incentive to offer flexibility while undertaking more risk.

As before, the top-level demand forecast for configuration m in product family p is $D_m^p = 1{,}500$ units and the minimum supply commit for component i, $S_i^{\min}$, is as shown in the rightmost column of Table 1. To model quantity flexibility, let $S_i^{\max} := (1+\alpha)S_i^{\min}$ denote the maximum supply quantity, where α is a contingency factor that determines the amount of upside supply flexibility. With quantity flexibility the supplier is committed to provide up to $S_i^{\max}$ units of component i. The manufacturer assumes inventory liabilities only if the allocated supply is less than $S_i^{\min}$. Figure 1 shows the optimized inventory cost, backlog cost, and total cost when the contingency factor takes on values $\alpha =$ 0, 0.1, 0.2, and 0.3. The secondary y-axis shows the number of new product configurations generated by the conditioning model in each instance. We observe that the total cost improves from 150,000 for the based scenario (no upside flexibility) to 80,000 for the scenario with 30 percent flexibility. This result is intuitive because higher supply flexibility provides more opportunities for building squared set configurations without increasing inventory liability exposure. Furthermore the results confirm that even a modest level of upside flexibility can results in significant percentage cost improvements. When $\alpha = 0.1$, the backorder cost decreases by 40 percent and the total cost decreases by 25 percent compared to the base case. Such numerical analysis can help procurement managers to quantify and price flexible supply contracts.

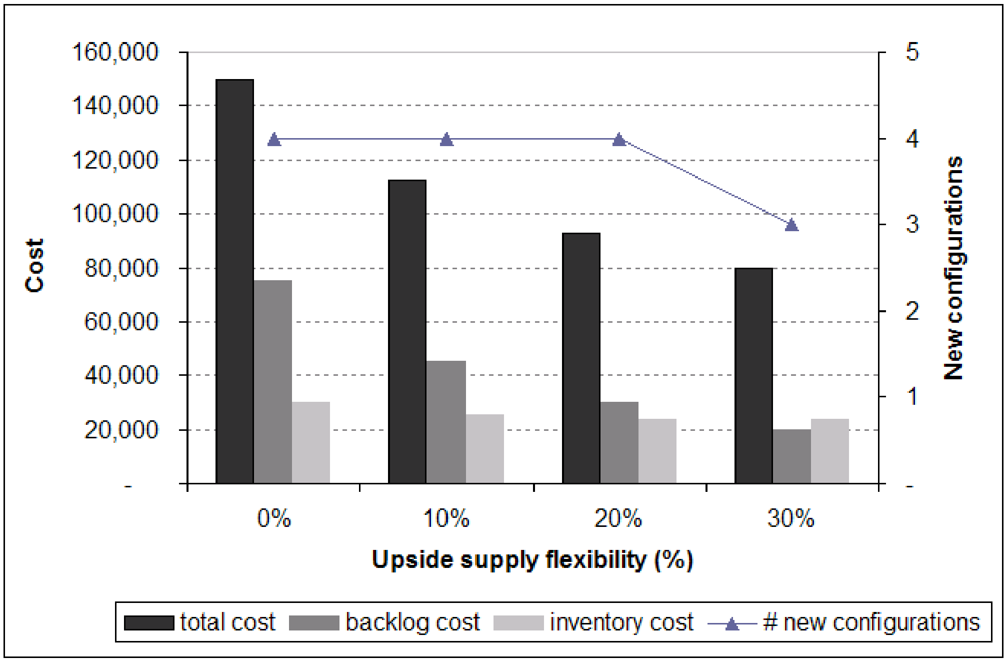

Figure 1. Optimal cost of conditioned build plan as a function of supply quantity flexibility.

Finally, we apply the multi-period model to investigate the impact of product transition plans on costs. In assemble-to-order systems, transition plans are often expressed at the component level as the relative proportion of supply of a new technology during its introduction phase (ramp-up). In our PC assembly example, assume that the 14"XGA panel is replaced by a 15"XGA panel. We investigate three transition plans over three time periods (e.g., months): slow, moderate, and fast. In the slow transition plan, denoted as (10%-50%-90%), the 15"XGA panel accounts for 10 percent of the total volume in the first month; 50 percent in the second month, and 90 percent in the third month. In the moderate and fast transition plans, the transition rates are (30%-60%-90%) and (50%-75%-90%), respectively. In all transition plans, the total combined supply of 14"XGA and 15"XGA that is available in each of the three months is 4,000 units. The supply commit for the two panels and the other components is shown in Table 6. We assume that the top-level demand forecast for configuration m in product family p and time period t is $D_{mt}^{p} = 500$ units.

PC Components		Slow transition			Moderate transition			Fast transition		
		Period 1	Period 2	Period 3	Period 1	Period 2	Period 3	Period 1	Period 2	Period 3
PANELS	*14" XGA*	*3,600*	*2,000*	*400*	*2,800*	*1,600*	*400*	*2,000*	*1,000*	*400*
	15" XGA	*400*	*2,000*	*3,600*	*1,200*	*2,400*	*3,600*	*2,000*	*3,000*	*3,600*
	15" SXGA+	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
HARD DRIVES	30GB 4200rpm	1,400	1,300	1,300	1,400	1,300	1,300	1,400	1,300	1,300
	40GB 5400rpm	1,700	1,700	1,600	1,700	1,700	1,600	1,700	1,700	1,600
	60GB 7200rpm	1,400	1,300	1,300	1,400	1,300	1,300	1,400	1,300	1,300
	80GB 5400rpm	700	700	600	700	700	600	700	700	600
PROCESSORS	Pentium M725	1,400	1,300	1,300	1,400	1,300	1,300	1,400	1,300	1,300
	Pentium M735	2,400	2,300	2,300	2,400	2,300	2,300	2,400	2,300	2,300
	Pentium M765	1,400	1,300	1,300	1,400	1,300	1,300	1,400	1,300	1,300
OPTICALS	CD-RW 24X	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
	COMBO 24X	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000

Table 6. Supply commitments for multi-period scenario.

The results of applying the multi-period offering conditioning model are shown in Table 7. Our first observation is that the fast transition plan incurs a significantly lower cost than the slow and moderate transition plans. The total cost of the fast transition plan is 172,500. This is 11 percent less than the cost of the moderate transition plan and 45 percent less than the cost of the slow transition plan. Table 7 further illustrates that the main cost driver is the backorder cost which accounts for up to 67 percent of the total cost. To understand why the backlog cost is at its lowest in the fast transition plan, we tracked the backlog separately for the three product categories low-end, mid-range and high-end. We observe that the largest difference between the transition plans is in the backlog cost of the mid-range product category. The order backlog in the mid-range category contributes a cost of 110,000 in the slow transition plan, 15,000 in the moderate transition plan, and zero in the fast transition plan.

	Slow transition (10%-50%-90%)	**Moderate transition** (30%-60%-90%)	**Fast transition** (50%-75%-90%)
Backorder cost	210,000	120,000	95,000
Low-end	-	-	-
Mid-range	110,000	15,000	-
High-end	100,000	105,000	95,000
Inventory liability cost	87,500	51,500	41,500
Substitution cost	15,000	23,000	36,000
Total cost	312,500	194,500	172,500

Table 7. Backorder, inventory, and substitution costs of different transition plans.

The technology selection menu in Table 2 shows that the 15"XGA panel can be substituted in each one of the three product categories whereas the 14"XGA panel can only be used in low-end products. This explains why the fast transition plan incurs the lowest backlog costs. With the fast transition plan there is enough supply of 15"XGA panels in the first two months which reduces backlog cost and consequently the total cost. With a slow transition plan there is an over-supply of 14"XGA panels and a supply shortage of 15"XGA in the first two periods which sharply increases the order backlog for mid-range and high-end systems and thus drives up the total supply chain cost.

In the electronics industry that is characterized by short product lifecycles and a proliferating product variety, development teams deal with technology transitions that occur simultaneously and often involve multiple predecessors or multiple successors. The experiments illustrate that product planners have to be aware of feasible supply plans, component substitutions, and squared set allocations when deciding on target ramp-up and ramp-down profiles during product transitions. The models presented of this paper help automate the decisions by enabling planners to test different transition plans, tune ramp-up patterns for technology introductions based on the results, and choose a transition plan that is most cost effective.

6. Summary and Conclusions

In this paper we have described a novel approach to demand-supply imbalance resolution in assemble-to-order supply chains that overcomes many deficiencies of conventional methods. The approach aims at finding marketable product alternatives in a product portfolio that best utilize inventory surplus and replace demand on supply-constrained components. We formulated the problem as a nonlinear program and developed efficient computational procedures based on decomposition and column generation to generate optimal solutions. We demonstrated the benefits of product offering conditioning through numerical experiments with realistic production data. We quantified business improvements in the context of assemble-to-order supply chains, and showed how offering conditioning can help manage major product and technology transitions. Given that companies are facing significantly uncertain demand and that point forecasts are invariably wrong, we are currently investigating how the proposed models can be extended to accommodate stochastic demand. Hedging against demand risk in conjunction with supply flexibility arrangements will ultimately help create a more responsive supply chain that can react to demand and supply fluctuations even when not anticipated. Another extension would be to develop a revenue-based objective function. While this is straightforward to do and does not affect our solution procedure, it helps capture the revenue aspects of up-sell, down-sell or alternative-sell opportunities. Finally, we also plan to incorporate pricing decisions into the model.

Most companies recognize that imbalances will differ in magnitude and severity, but rarely invest resources to develop a systematic approach for resolution. Some leading companies in the industry have begun to implement conditioning processes that seek to dynamically adjust product offerings to guide marketing and sales teams. However, these are almost always entirely manual processes that rely on expert's knowledge and partial sets of data. With hundreds or even thousands of product offerings in a typical product portfolio it is impossible for a person to assemble the data and reach an optimal conclusion. An automated approach based on optimization not only ensures that the resources invested have the likelihood of producing a successful result, but offers the additional advantage of speed in execution which is critical for a timely resolution of short-term demand-supply imbalances.

The models proposed in this paper can play a pivotal role in helping companies to recover from supply disruptions or other disruptive supply chain events as quickly as possible. Companies with a lean supply chain design are more robust to supply chain disruptions since they carry very little inventory and rely on last minute supply of components. An assemble-to-order model combined with flexible sales processes and postponed assembly enables such companies to take full advantage of a "sell-what-you-have" strategy. The conditioning principles and models described in this paper can be imbedded in supply chain operations and substantially improve day-to-day flexibility. Companies with a direct sales business model deal with customers directly through their website or telesales system can highlight featured models on-the-fly based on current component availability and steer customers towards product configurations that they can supply easily and profitably.

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