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Managing Product Availability in an Assemble-to-Order Supply Chain with Multiple Customer Segments

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Abstract

In this article, we propose a novel availability management process called Available-to-Sell (ATS) that incorporates demand shaping and profitable demand response to drive better supply chain efficiency. The proposed process aims at finding marketable product alternatives in a quest to maintain a financially viable and profitable product portfolio, and to avoid costly inventory overages and shortages. The process is directly supported by a mathematical optimization model that 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 procurement and manufacturing capabilities of a firm. We outline the business requirements for incorporating such a process into supply chain operations, and highlight the advantages of ATS through simulations with realistic production data in a computer manufacturing environment. The models featured in this paper have contributed to substantial business improvements in industry-size supply chains, including over $100M of inventory reduction in IBM's server computer supply chain.

Keywords: Availability Management; Demand Shaping; Assemble-to-Order; Configure-to-Order.

1. Introduction

In today's competitive and dynamic business environment, companies need to continually evaluate the effectiveness of their supply chain and look for ways to transform business processes to achieve superior customer service and higher profitability. In this paper we describe a novel availability management process called Available-to-Sell (ATS) that incorporates demand shaping and profitable demand response to drive better operational efficiency of the supply chain. The proposed process directly applies demand and supply data to identify intelligent sales recommendations that enable companies to take full advantage of a "sell-what-you-have" strategy. The process involves generating an availability outlook that allocates available component supplies into Available-To-Promise (ATP) quantities of saleable end products based on current supply and demand. It is directly supported by an analytical optimization model that 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 a company. The business process is most effective in an assemble-to-order (ATO) environment where end products are configured from pluggable components.

Customer demand shaping involves the integration and fusion of product alternatives, price and availability. The presentation of a seller's catalog and marketing collateral are the traditional methods of conditioning customer demand. Shipment and delivery expectations are often added to the traditional methods, primarily through the application of ATP capabilities. The ATS capabilities described in this paper are vital to making informed business decisions concerning the procurement of component inventory to build saleable end products. Therefore, to be considered a world class provider at demand shaping requires an unrelenting mixture of supply chain management, financial performance, operational culture, and creative marketing.

The models and capabilities described in this paper enable companies to maintain a financially viable, profitable, and marketable product portfolio, take effective actions to avoid excess and surplus component inventory, and articulate marketable alternate product offerings. They can easily be imbedded into supply chain operations to improve day-to-day flexibility. For example, direct sales businesses that deal with customers directly through their website or telesales system can highlight featured products on-the-fly based on current component availability and steer customers towards product configurations that they can supply easily and profitably.

Industry best practices for demand shaping and demand response include identifying entry level products suitable for up-selling, changing marketed products based on supply position, providing product alternatives, and methods of continuous up-selling and cross-selling to meet financial objectives (O'Marah and Souza 2004; Cecere 2005). To this end, a strong management system willing to make the nearly instantaneous decisions to drive the business forward is necessary, and must be supported by an integrated process and tool suite with sense and respond technologies, dynamic creation of up-sell and cross-sell relationships, and robust end-to-end analytics. Entry level products are often highlighted to customers to provide an interesting price-performance point that will establish a sound brand image and elicit a favorable customer response (i.e., buy decision) to direct or indirect marketing materials. These marketed entry or economy level products are usually forecasted at a lower rate than actual demand, driving longer product availability lead times. The seller must have a reasonable supply line for the entry or economy level products to meet regulatory and country specific business practices. The goal is to have customers contact the seller which provides the opportunity to up-sell the customer to a more richly configured solution, normally at a higher price-performance point, usually thought of as the market "sweet spot" for the product category. One of the advantages of the sweet spot products is the improved lead time to ship or delivery availability over the entry level products determined due to forecasting greater sweet spot volumes. In a consumer society driven by having a product in next to real time, improved shipment or arrival lead times can be a compelling factor in a purchase decision.

The remainder of this paper is organized as follows. In section 2 we review the related literature. In section 3 we present the underpinning principles of availability management, and discuss advantages and disadvantages of different management approaches. In section 4 we propose a mathematical optimization model that captures customer preferences to effectively mitigate supply and demand imbalances in an attempt to develop an effective demand shaping strategy. In section 5 we present a simulation framework for modeling availability management in assemble-to-order supply chains. Numerical findings and discussions of results are presented in section 6. These produce several insights into how advanced availability management can help proactively coordinating supply and sales, and quantify several business benefits in the context of assemble-to-order manufacturing. In section 7 we present our concluding remarks and future research directions.

2. Literature Review

There are two streams of research that are related to our work: (1) models from the production planning and operations literature that deal with Available-to-Promise (ATP) systems for order promising and fulfillment, and (2) models from the operations management literature that consider inventory problems with configurable products and product substitution. We provide an overview of both research streams.

There is an extensive literature in the production planning area dealing with real-time order promising and ATP (e.g., Kilger and Schneeweiss 2000; Moses *et al.* 2004; Hopp and Roof 1999). Ball et al. (2004) develop a general modeling framework for availability promising and present examples of ATP business practices from electronics companies including Dell and Toshiba. Chen *et al.* (2002) present a mixed integer programming model that provides an ATP order promising and fulfillment solution for batch orders that arrive within a predefined time interval. Ervolina and Dietrich (2001) describe an application of the implosion technology for ATP order promising in assemble-to-order (ATO) and configure-to-order (CTO) manufacturing environments. The goal is to create a feasible production plan that can be used to schedule or promise customer orders. Chen-Ritzo (2006) studies a similar availability management problem in a CTO supply chain with order configuration uncertainty. Akcay and Xu (2004) develop a two-stage stochastic integer program with recourse to allocate constrained components so as to maximize the fraction of orders assembled within a quoted maximum delay. The closest work in this stream is Dietrich *et al.* (2005) which describes a deterministic implosion model that identifies suitable product configurations for an Available-to-Sell process that consume the most surplus inventory and require minimal additional component purchasing costs. The focus of this model is on the perspective of the firm, independent of customer's flexibility ranges or propensities to buy alternative products. Market demand, customer preferences, or product substitution policies are not considered. In contrast, we explicitly model customer expectations in a dynamic setting, utilizing a customer behavior model that determines how customers evaluate product substitutions if their initial product selection is unavailable.

In the operations management literature, there are several papers in which product substitutions or flexible customer requirements are important elements. Bassok *et al.* (1999) study a multi-product inventory problem with full downward substitution where excess demand for a product can be filled using a product of higher utility. 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. Gallego *et al.* (2006) consider downward substitution to satisfy unmet demand for lower grade products in a semiconductor production environment, and propose a heuristic allocation scheme for determining near-optimal build plans. Swaminathan and Tayur (1998) determine optimal configurations of semi-finished products (vanilla boxes) along with their inventory stocking levels to enable late customization in an assemble-to-order supply chain for computer manufacturing. Balakrishnan and Geunes (2000) study a production planning problem 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 assumed to be unconstrained, the model does not address matching of demand and supply. Balakrishnan and Geunes (2003) consider a production planning problem faced by a steel manufacturer whose customers allow flexibility in product specification. In a recent work, Balakrishnan *et al.* (2005) apply concepts from revenue management to investigate how a firm can maximize profits by shaping demand through dynamic pricing.

3. Availability Management Business Processes

Availability management is the overarching task of coordinating the planning of product availability with the real-time scheduling and promising of customer orders. This task ensures that the decisions made on an order by order basis are consistent with the strategic and tactical plans of the business. To achieve this task, companies must develop business processes to coordinate the flow and integration of data, decisions, and applications along with the use of information technology and decision support systems.

3.1 Coordination of Planning and Execution

Availability management is centered on the two major subtasks of planning and execution. Planning is done on a monthly, weekly or daily basis, whereas execution happens in real-time. This disparity in “clock speed” at which each subtask operates is a fundamental reason why building a good availability management system is so difficult. As markets evolve, and efficiencies in the supply chain increase, companies are constantly challenged to transform their availability management process to remain competitive. The most common approach to Availability Management is the Available-to-Promise (ATP) process.

3.2 Available to Promise

The planning side of availability management is administered by a Sales and Operations Planning (S&OP) process. The goal of S&OP is to generate a single, integrated plan of product availability that brings together the business objectives of: finance, sales, and marketing, with the reality of the unbiased forecast and the capacity of the supply chain. This integrated supply plan is called the ATP schedule. The ATP schedule establishes a unified direction to which the sales and marketing teams will drive selling activities, the supply chain will plan to procure supply, and the finance teams will target revenue and earnings.

The execution side of availability management deals with a real-time stream of customer orders where each order must be scheduled or promised. As a customer request arrives, the order scheduling process must promise an availability date to the customer. This task involves checking the contents of the order against the ATP schedule, determining an availability promise date to the customer, and decrementing the ATP to accurately reflect the supply committed to new customer orders. The ATP schedule is the main linkage between availability management planning and execution as shown in Figure 1.

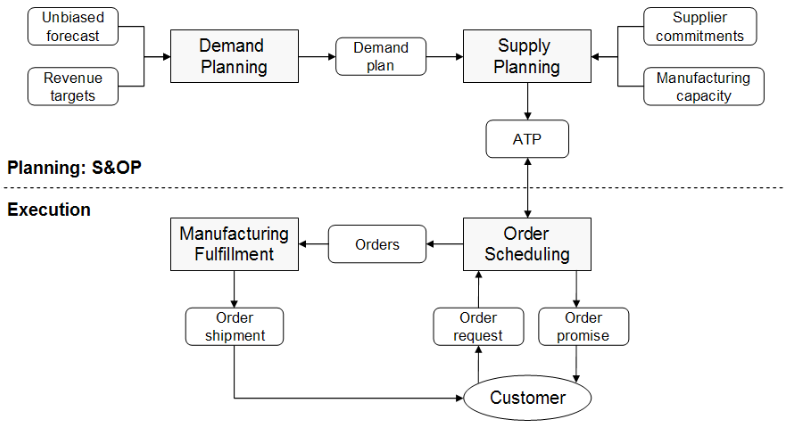

Figure 1: Availability management with Available-to-Promise (ATP)

The ATP process utilizes an analytical technique called implosion to generate an optimized ATP schedule that takes into account supplier commitments and limited manufacturing capacities (Dietrich et al. 2005). This configuration of the availability management process uses an "ask/answer" form of S&OP, where a demand planning subtask is done first ("ask") followed by the implosion process which generates the ATP ("answer") as a response to the demand. In this form, the ATP generation task seeks to satisfy, but not exceed demand and thus there is no mechanism for dealing with unallocated supply. A separate non-integrated business process is often created to manage inventory excess and overages, e.g. by exercising buy-back agreements with component suppliers or other procurement related techniques.

In today's environment, customers expect that products are available in a large variety of configurations, and, with this expanding variety, customers have become increasingly flexible in what they will purchase. The ask/answer form of availability management focuses on a specific demand target. When the capacity of the supply chain does not directly align with a fixed demand target, imbalances often lead to an ATP that falls short of the demand. As we will show in our experiments, the ATP process misses opportunities for offering alternative products to customer which may lead to poor overall supply chain performance.

3.3 Available-To-Sell (ATS)

We propose a new concept for advanced availability management, called Available-to-Sell (ATS) that is gaining more and more traction with high-technology manufacturers that rely on suppliers to provide various materials and components needed to build finished products. ATS is designed to intelligently find alternative product configurations that best consume excess supply while minimizing additional procurement investments to build “squared” sets of components (i.e., complete sets of components needed to produce the finished products). Figure 2 illustrates the integration of ATP and ATS into an event-driven availability management process. The integrated process is most effective in an assemble-to-order (ATO) supply chain environment where end products are configured from pluggable components and where customers can configure personalized products by selecting options from different feature categories such as hard disks, microprocessors, video cards, etc. In an ATO environment component supply is generally more flexible and the simplified product structure makes it more likely that product substitutions will drive customer demand.

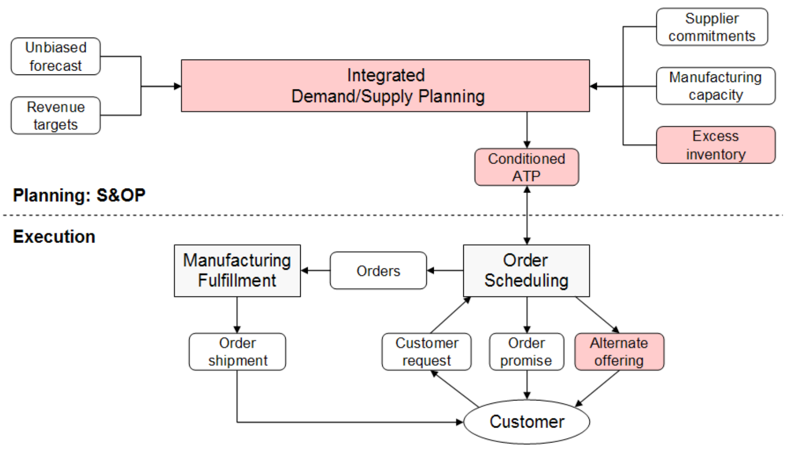

Figure 2: Availability management with Available-to-Sell (ATS)

ATS seeks to ensure that the additional product availability is sellable and not in conflict with sales and marketing goals. The key output of the integrated process is a “conditioned” ATP schedule that comprises optimized ATP quantities of core products as well as ATP quantities of saleable product alternatives. The conditioned ATP schedule may take advantage of up-sell, alternate-sell or down-sell opportunities. 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.

The proposed ATS process can drive further efficiency if the market can be segmented into customer classes with distinct lifetime value and customer behavior. Our models therefore consider unique customer preferences and financial objectives associated with a segmented market. Customers within a market segment have flexible product requirements that may differ from the requirements of customers in another market segment. Furthermore, each market segment represents a class of customers that have a certain lifetime value to the company. For example, one segment might represent long-term, strategic customers versus another segment that are one-time buys. From the perspective of ATP generation the preference will be to ensure product availability to the strategic customers, possibly at the expense of non-strategic ones.

4. Optimization Model for Demand Shaping

In this section we formulate a mathematical programming model for ATS that generates the conditioned ATP. We also define the customer behavior model and describe the simulation framework that we have developed for conducting numerical experiments.

4.1 Notation

Before we state the problem formulation, we define the notation that is used throughout the paper.

Customer model

- C : set of customer classes, indexed by c
- α^c : Price sensitivity parameter for customers in class $c \in C$.
- β^c : Quality sensitivity parameter for customers in class $c \in C$.
- γ^c : First-choice probability, i.e. the probability that a customer in class $c \in C$ will only accept its first-choice product selection and no product alternatives.

Products and components

- I : set of components, indexed by i

- M : set of core products, indexed by m
- N : set of alternative products, indexed by n
- S : set of products, indexed by s where $S := M \cup N$
- u_{is} : usage of component $i \in I$ in product $s \in S$ (bill-of-material)

Supply and demand

- S_i : supply of component $i \in I$
- D_m^c : demand forecast for core product $m \in M$ and customer class $c \in C$

Cost and profit

- h_i : inventory holding cost of component $i \in I$
- r_s : retail price of product $s \in S$
- p_s : profit of product $s \in S$
- q_s^c : utility of product $s \in S$ for customer class $c \in C$.
- b_m^c : penalty cost for backlogging one unit of demand of product $m \in M$ in customer class $c \in C$.
- w_{mn}^c : penalty cost for substituting one unit of product $n \in N$ for one unit of product $m \in M$ (price discount).

Decision variables

- X_m^c : ATP quantity for core product $m \in M$ and customer class c.
- Y_{mn}^c : ATP quantity of alternative product $n \in N$ used as a substitute for core product $m \in M$ in customer class $c \in C$.

4.2 Customer Behavior Model

Demand is principally shaped by performance, price and availability. Sound conditioning relies upon shaping client perceptions and expectations of the seller's product portfolio's value. We next describe our customer behavior model and explain how customers evaluate alternative products if their initial product selection is unavailable.

Each customer in class *c* has an associated *price sensitivity* parameter α^c that determines the incremental price that the customer is willing to pay for an alternative product, and a *quality sensitivity* parameter β^c that determines the customer's valuation of quality. The customer's price sensitivity is modeled by a reservation price. In particular, if a customer's initial selection is product *m* and r_m denotes the price of product *m*, the customer's reservation price is $(1+\alpha^c)r_m$. Similarly, the customer's quality sensitivity is modeled by a reservation utility. If q_m^c denotes the quality level of product *m* for a customer in class *c*, the customer's reservation utility is $(1-\beta^c)q_m^c$. The price sensitivity and quality sensitivity together determine whether customers will consider an alternative product $n \in N$ if their initial selection $m \in M$ is currently unavailable. Customers are willing to purchase an alternative product if its price does not exceed their reservation price and if its quality is no less than their reservation utility. If no alternative selections in the desired quality range are available or exceed the customer's reservation price, we assume that customers place a backorder for their initial selection.

We compute the quality level of a product as the (weighted) average of the quality scores of the components used in its configuration. Each component in a commodity group is assigned a quality score (a value between 0 and 100) based on its quality relative to all other components in the same commodity group. Higher scores are assigned to components with higher parts worth, e.g., a 120GB hard disk will score higher than a 60GB hard disk.

4.3 Problem Formulation

Inputs to the optimization model are a core product portfolio *N*, and extended product portfolio *M*, and the demand forecast for core products, D_m^c for $m \in M$ and all customer classes *c*. The core portfolio contains currently featured products that are offered by the seller whereas the extended portfolio contains alternative products. The alternative products may be used to fulfill unsatisfied demand for core products with additional substitution cost incurred. The components used to configure a saleable product are divided into feature categories where each component belongs to exactly one category. A bill-of-material describes the set of components needed to produce each product in the core portfolio and the extended portfolio.

The goal of the optimization is to build enough volume to satisfy the demand forecast for each core product. If that can not be achieved, the model creates a conditioned ATP schedule with alternate products. The objective is to maximize the total supply chain profit which consists of four components:

1. *Total profit from sales.*
2. *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.
3. *Inventory holding (or component liability) costs.* Costs incurred for holding excess component inventories.
4. *Product substitution costs.* Costs incurred for using an alternative product to partially fulfill demand for a core product.

The objective function is given by

$$\begin{aligned}\text{Max } Z(X_m^c, Y_{mn}^c) = & \sum_{m\in M}\left(\sum_{c\in C} p_m X_m^c + \sum_{n\in N}\sum_{c\in C} p_n Y_{mn}^c\right) \\ & - \sum_{m\in M}\sum_{c\in C} b_m^c \left(D_m^c - X_m^c - \sum_{n\in N} Y_{mn}^c\right) \\ & - \sum_{i\in I} h_i \left(S_i - \sum_{m\in M}\left(\sum_{c\in c} u_{im} X_m^c + \sum_{n\in N}\sum_{c\in C} u_{in} Y_{mn}^c\right)\right) \\ & - \sum_{m\in M}\sum_{n\in N}\sum_{c\in C} w_{mn}^c Y_{mn}^c \end{aligned} \tag{1}$$

Let us now formulate the constraints. Given the demand forecasts D_m^c for core product $m \in M$, the total build volume for this product, including the volume substituted by new alternative products, cannot exceed the demand for core product *m*:

$$D_m^c - X_m^c - \sum_{n\in N} Y_{mn}^c \geq 0 \text{ for all } m \in M, c \in C \tag{2}$$

The ATP schedule must be feasible with respect to the component supply, i.e., the number of components consumed plus any unallocated inventory must be equal to the available component supply:

$$S_i - \sum_{m \in M} \left(\sum_{c \in C} u_{im} X_m^c + \sum_{n \in N} \sum_{c \in C} u_{in} Y_{mn}^c \right) \geq 0 \text{ for all } i \in I$$
(3)

The number of product substitutions for core product $m \in M$ can not exceed the fraction of demand that can be filled with alternative products:

$$(1-\gamma^c) D_m^c - \sum_{n \in N} Y_{mn}^c \geq 0 \text{ for all } m \in M, c \in C$$
(4)

Any alternative product $n \in N$ that is used to substitute demand for core product $m \in M$ in customer class $c \in C$ must meet the reservation price and reservation utility requirements $q_n^c \geq (1-\beta^c) q_m^c$ and $r_n \leq (1+\alpha^c) r_m$. These requirements are expressed as linear constraints in the substitution quantities Y_{mn}^c as follows:

$$Y_{mn}^c \left[q_n^c - (1-\beta^c) q_m^c \right] \geq 0 \text{ for all } m \in M,\ n \in N \text{ and } c \in C \tag{5}$$

$$Y_{mn}^c \left[(1+\alpha^c) r_m - r_n \right] \geq 0 \text{ for all } m \in M,\ n \in N \text{ and } c \in C \tag{6}$$

Finally, we impose non- negativity constraints on the decision variables:

$$X_m^c \geq 0 \text{ and } Y_{mn}^c \geq 0 \text{ for all } m \in M, n \in N, c \in C \tag{7}$$

The optimization problem (1)-(7) is an LP that can be solved very efficiently even for large problem sizes.

For the purposes of scheduling, it is important to differentiate between the allocated form and the aggregated form of the ATP. In the allocated form, ATP quantities are allocated by product and customer class. In the aggregated form, ATP quantities are pooled across all customer classes for a product, and allocated into a common bucket. The optimization model computes an allocated ATP from which the aggregated ATP quantities are computed as follows:

$$\overline{X}_m = \sum_{c \in C} X_m^c \text{ for all } m \in M \text{ and } \overline{X}_n = \sum_{c \in C} \sum_{m \in M} Y_{m,n}^c \text{ for all } n \in N \tag{8}$$

The simulation model described next employs the aggregated ATP quantities in its order scheduling policies.

5. Simulation Framework

The simulation model was built using the Availability Management Simulation Tool (AMST) which has been used at IBM to develop various availability management simulation models (Lee 2006). AMST was developed using the simulation capabilities of IBM's WBM® (WebSphere Business Modeler) as a simulation modeling framework for availability management processes.

The simulation framework consists of reusable components and methods which are easily adapted to different availability management environments.. The simulation model developed for this study interfaces with the ATS optimization engine to obtain ATP quantities, generates and schedules customer orders against the ATP, and simulates supply chain dynamics such as size of customer demand, inter-arrival of customer orders, customer purchase behavior, flexibility of price and utility, and their variabilities. Figure 3 illustrates the simulation model and its interaction with the ATS optimizer described in the previous section.

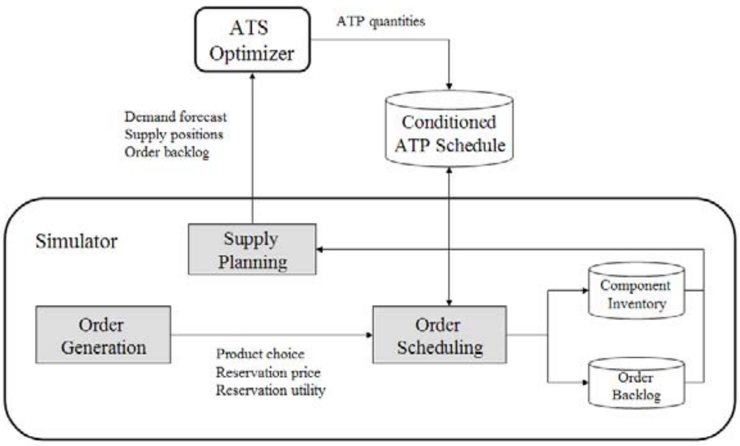

Figure 3: Availability simulation model and interface to ATS optimization.

The arrival of customer orders is generated according to a demand forecast, and each order is allocated with various attributes such as product choice, customer class, price sensitivity, quality sensitivity, and customer's willingness to purchase a substituted product when customer's first choice product is not available. The attributes are assigned using various distribution functions that are derived from the historic demand data. The orders are then processed and scheduled against ATP quantities. In this paper different order scheduling policies, such as First-Come First-Serve (FCFS) scheduling and a variety of rationing scheduling policies, are simulated.

The simplest scheduling policy is FCFS scheduling, shown in Figure 4. For each order, the scheduler in the simulation model checks the ATP quantity of the requested product. If the first-choice product is available, the order is scheduled and fulfilled. If the first choice product is not available, the scheduler determines whether the customer is willing to take a substitution, in which case the scheduler looks for a substitution product that meets the customer's price and quality tolerance. When a substitution is found, the order is scheduled and fulfilled with the product. If the customer is not willing to take a substitution or a suitable substitution is not found, the order is backlogged.

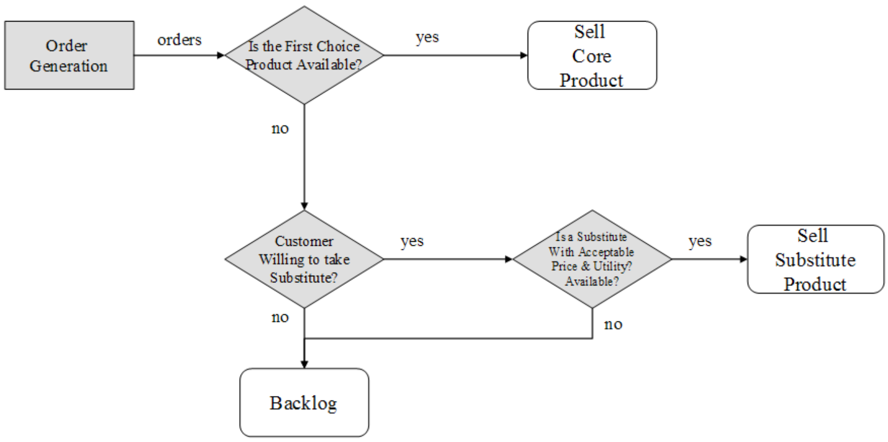

Figure 4: Simulation of First-Come First-Serve (FCFS) order scheduling

A second type of scheduling policy, called rationing, is shown in Figure 5. In a rationing scheduling policy, the ATP is rationed in a way that a customer requesting a product may be offered a substitution or be backlogged, even when the desired product is available in the ATP. There are many possible rationing schemes, including scheduling directly from the allocated ATP. The intention of a rationing scheduling policy is to drive improved profit and revenue through up-sell and intelligent Availability Management. Under rationing, the simulation model checks first whether a customer is willing to take a substitution even when the product that the customer wants to purchase is available. If a customer is willing to take a substitution, a substitution product within the price and utility tolerance of the customer is sought from the ATP. In this paper we employ a simple rationing policy where the first available substitute product within the price and quality range of a customer is sold. If there is no suitable product alternative, the ATP is searched for the customer's first choice product. If the first choice product is found, the order is scheduled and fulfilled; otherwise the order is backlogged.

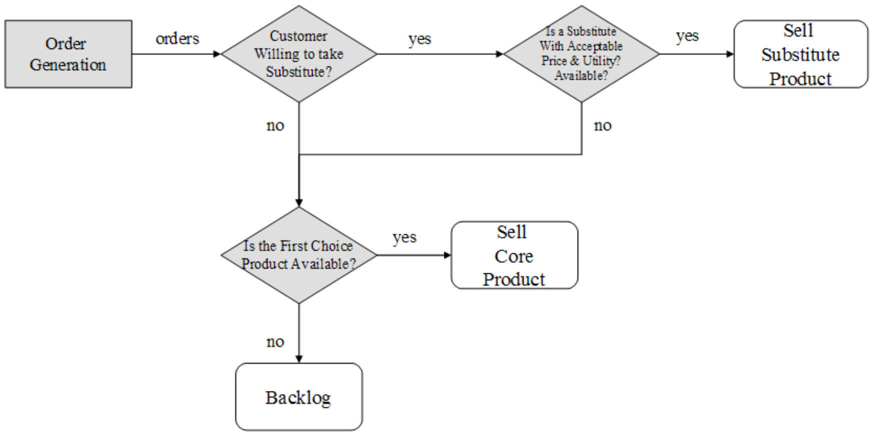

Figure 5: Simulation of rationing order scheduling

In the simulation model, the ATP quantities change as the result of three events; (1) demand event, (2) supply event and (3) roll-forward event. Each event changes the ATP quantities; the demand event (order scheduling and fulfillment) decrements the availability, the supply event increments the ATP quantities, and the roll-forward event shifts the availability from a planning period to earlier one at the end of each planning period (e.g., a week). The events are generated independently using probability distribution functions or fixed intervals. When an order is scheduled, the ATP quantity of the scheduled product is decremented, and corresponding components are decremented from the inventory of components according to the bills-of-materials. At the end of each period, the supply-planning task is triggered to invoke the ATS engine which computes optimized ATP quantities based on the updated information on supply and demand. Subsequently a new set of customer orders is generated, scheduled and fulfilled using various scheduling policies. The simulation collects statistics on all relevant business performance metrics such as order backlog, serviceability, inventory holding costs, sales revenue and profit and substitution costs.

6. Numerical Study

The previous sections provided analytical characterizations of a firm's optimal demand shaping strategy as a function of its customers' preferences and available supply. Our numerical study in this section focuses on prescribing how the firm should adjust its sales strategy when faced with different degrees of supply and demand imbalances. To address this goal, we implemented the availability management models described in the previous section and simulated them using an exemplary assemble-to-order (ATO) supply chain for mid-range server computers. In this section we present our numerical findings.

We have two objectives in conducting the numerical experiments. First, we want to test the conjecture that an intelligent demand shaping strategy that accounts for customer's price and quality preferences can provide significant financial benefits over a traditional Available-to-Promise (ATP)-based approach, particularly in environments where inventory imbalances exists. In this context, we investigate how a firm can take advantage of up-sell opportunities to advertise more richly configured solutions to customers for increased profit. We analyze the effect of customers' price sensitivity on profitability and examine how it influences the firm's demand shaping strategy. Second, we want to investigate the performance of different policies that implement the recommended demand shaping strategy using simple dynamic allocation rules in conjunction with the optimized "conditioned" ATP allocation plan.

6.1 Supply Chain Scenario

The example scenario for the numerical study is derived from an industry-size assemble-to-order supply chain of a server computer product line. The product portfolio consists of eight mainstream server computer products that represent a whole spectrum of price-performance points. The products and their bills-of-materials are depicted in Table 1. Products M1 and M2 are entry level products, M3 to M6 are mid-range systems, and M7 and M8 are high-performance computers. Each product is assembled from components of six different commodity groups: system processors, memory, hard drives, optical drives, video adapters and software preloads. For example, product M1 is assembled from a 2.8GHz system processor, a 30GB hard drive, 128MB memory, a 48X CD-RW optical drive, an Extreme 3D video card and a system software preload B.

Although in reality each server product is assembled from dozens of components, the major components represented in this study account for more than 80 percent of the cost of a product. The manufacturing operation is driven by an assemble-to-order process.

The table also shows the unit cost, gross profit margin (GPM), and quality score of every component. The quality score of a component depends on its parts worth relative to the other components in the same commodity group. Components with the highest parts worth are assigned the highest quality score, and they carry the highest profit margins. Notice that the perceived value of the components used in a product depends on the customer segment. Customers in the economy segment value have a balanced valuation of components in the six commodity groups, with 50 being the highest quality score in each group. Customers in the value segment place a higher relative importance on system processors and hard drives, whereas customers in the performance segment place their highest importance on processors, hard drives, and memory as indicated by a top quality score of 100.

Table 1: Bill-of-materials structure used in the numerical study.

Components				**Utility**			**Product Portfolio**							
Group	Technology	Cost	GPM	Economy	Value	Performance	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
SYSTEM PROCESSORS	2.8GHz/800MHz Xeon	260	10%	20	25	25	1	1	-	-	-	-	-	-
	3.0GHz/800MHz Xeon	340	15%	30	50	50	-	-	1	1	-	-	-	-
	3.2GHz/800MHz Xeon	420	20%	40	75	75	-	-	-	-	1	1	-	-
	3.4GHz/800MHz Xeon	500	30%	50	100	100	-	-	-	-	-	-	1	1
HARD DRIVES	30GB 4200 RPM	100	10%	10	20	20	1	-	1	-	-	-	-	-
	40GB 4200 RPM	140	15%	20	40	40	-	1	-	-	1	-	-	-
	60GB 4200 RPM	180	20%	30	60	60	-	-	-	1	-	1	-	-
	120GB 7200 RPM	240	30%	40	80	80	-	-	-	-	-	-	1	-
	160GB 7200 RPM	300	35%	50	100	100	-	-	-	-	-	-	-	1
MEMORY	128MB SDRAM	80	10%	10	10	20	1	-	1	-	-	-	-	-
	256MB SDRAM	120	15%	20	20	40	-	1	-	-	1	-	-	-
	512MB SDRAM	160	20%	30	30	60	-	-	-	1	-	-	-	-
	1.0GB SDRAM	200	30%	40	40	80	-	-	-	-	-	1	1	-
	2.0GB SDRAM	240	35%	50	50	100	-	-	-	-	-	-	-	1
OPTICAL DRIVES	9.5mm Slim DVD	70	10%	30	30	30	-	1	1	-	-	-	-	-
	48X CD-RW	90	15%	40	40	40	1	-	-	-	1	-	1	1
	48X CD-RW/DVD	100	20%	50	50	50	-	-	-	1	-	1	-	-
VIDEO ADAPTER	ATI Performance 2D	125	10%	30	30	30	-	1	1	-	1	-	-	-
	Extreme 3D Express	150	15%	40	40	40	1	-	-	1	-	1	1	1
	NVidia Advanced 3D	175	20%	50	50	50	-	-	-	-	-	-	-	-
SOFTWARE	Preload A	100	10%	10	10	10	-	1	-	-	-	1	-	-
	Preload B	120	10%	20	20	20	1	-	1	-	1	-	-	-
	Preload C	140	20%	30	30	30	-	-	-	1	-	-	-	-
	Preload D	200	20%	40	40	40	-	-	-	-	-	-	1	-
	Preload E	250	30%	50	50	50	-	-	-	-	-	-	-	1

Table 2 summarizes the price and quality scores of the product portfolio for the three customer segments. The price of product *m*, r_m, is the cumulative cost plus the gross profit margin of all the components used in its bill-of-materials. The quality score of product *m* in customer segment c, q_m^c, is the average of the quality scores of all components used in its bill-of material. The table also shows the unit backlog penalty, b_m^c, and the forecasted customer demand, D_m^c, for each product and each customer segment. The penalty for backlogging one unit of demand is a fraction of the price of a product; backlog penalties are lowest for economy customers and highest for performance customers. To model demand, we assume that exactly D_m^c orders arrive in each time period for product m and customer segment c (i.e., demand is deterministic).

Table 2: Sales price, sales profit, product quality, and demand and backorder costs by customer segment.

Product	Price	Profit	Economy segment			Value segment			Performance segment		
			Quality	Demand	Backlog cost	Quality	Demand	Backlog cost	Quality	Demand	Backlog cost
	r_m	p_m	q_m^1	D_m^1	b_m^1	q_m^2	D_m^2	b_m^2	q_m^3	D_m^3	b_m^3
M_1	960	92	47	800	44.6	39	200	133.8	37	-	178.4
M_2	978	95	43	800	45.5	39	200	136.4	39	-	181.9
M_3	1,002	101	43	500	46.8	40	400	140.3	38	100	187.1
M_4	1,284	190	70	500	63.0	65	400	188.9	64	100	251.9
M_5	1,218	161	57	300	58.8	56	400	176.4	54	300	235.2
M_6	1,380	233	70	200	69.1	69	400	207.4	70	400	276.5
M_7	1,656	358	83	200	86.9	85	300	260.7	84	500	347.6
M_8	1,836	450	93	100	99.0	95	300	297.0	96	600	396.0

The price and quality sensitivity parameters used in the customer behavior model are assumed to be $(\alpha_1, \alpha_2, \alpha_3) = (0.10, 0.20, 0.30)$ and $(\beta_1, \beta_2, \beta_3) = (0.30, 0.20, 0.10)$. This parameter choice is driven by the fact that customers in the economy segment tend to be highly price sensitive and may compromise on product quality, whereas customers in the performance segment are relatively price insensitive but demand a high quality level of a product. In addition to utilizing reservation prices and reservation utilities to determine whether a customer will consider an alternative product, we assume that a fraction of customers are committed to their first product choice and will not accept an alternative configuration. The first-choice probability in the baseline scenario is $\gamma_c = 0.50$ for all three customer segments, i.e., 50 percent of customer orders will not accept product alternatives if their initial product selection is unavailable.

6.2 Profit Comparison of Different Supply Strategies

Imbalances between supply and demand are the primary reason for degraded supply chain efficiency, often resulting in delinquent customer orders, missed revenue, and excess inventory. In this section, we investigate how demand shaping can help improving the operational performance of the supply chain when the component supply deviates from the ideal net component requirements. We illustrate the profit impact of employing different supply schemes for the demand scenario shown in Table 2. This enables us to quantify how the magnitude of the profit impact changes with the degree of supply imbalance, and identify conditions under which benefits to the firm are the most significant. The results presented next are generated by the optimization model for demand shaping described in section 4. The model starts with the enumeration of all possible alternative product configurations using exactly one component from each commodity group. These include down-sell products with lower price points than a core product, alternative-sell products with a similar price and quality score, and up-sell products that are priced higher than a core product.

6.2.1 Supply Skew

As indicated in the introduction, firms often feature entry level (economy) products in their marketing materials to provide customers with products at a competitive price-performance point, but usually forecast these products at a lower rate than actual demand. Once contact with the customer is established (either via telesales personnel or a direct sales website), the seller explores the opportunity to up-sell the customer to a more richly configured product at a higher price-performance point for increased revenue and profitability. For high volume and low margin businesses, the supply skew policy in conjunction with appropriate intelligent and integrated tools can provide a competitive advantage and improve financial performance.

To obtain the ideal (unbiased) supply quantity for each component under the given demand scenario, we first calculate the net component requirements by "exploding" the demand forecast through the bill-of-materials in a standard MRP-type calculation (e.g., Hopp and Spearman 2000). This calculation yields an unbiased component mix in each commodity group which we use as the baseline. Subsequently, we apply random perturbations to the baseline component mix to create artificial supply and demand imbalances while keeping the total component supply in each commodity group constant. In Table 3, we define three supply scenarios that are increasingly skewed towards higher value components within processors, hard drives and memory. The ideal supply mix derived from the net component requirements is shown in the second column.

Table 2: Supply scenarios for unbiased, low, and high component supply skew.

Components		Unbiased component mix	Biased component mix (low skew)	Biased component mix (high skew)
SYSTEM PROCESSORS	2.8GHz/800MHz Xeon	25%	24%	19%
	3.0GHz/800MHz Xeon	25%	26%	31%
	3.2GHz/800MHz Xeon	25%	25%	20%
	3.4GHz/800MHz Xeon	25%	25%	30%
HARD DRIVES	30GB 4200 RPM	25%	10%	10%
	40GB 4200 RPM	25%	28%	28%
	60GB 4200 RPM	25%	31%	26%
	120GB 7200 RPM	13%	19%	21%
	160GB 7200 RPM	13%	13%	15%
MEMORY	128MB SDRAM	25%	10%	10%
	256MB SDRAM	25%	28%	28%
	512MB SDRAM	13%	19%	19%
	1.0GB SDRAM	25%	28%	25%
	2.0GB SDRAM	13%	16%	19%

Figure 6 displays the attainable net profit (i.e., sales profit – backorder penalties – inventory holding costs) under a demand shaping strategy where the firm takes advantage of up-sell opportunities. We can see that the profit gain is monotone increasing with the degree of supply skew for the two most profitable customer segments (performance and value). The profit decreases slightly for the economy customer segment which is caused by supply constraints for low-end components, combined with limited opportunities for up-selling or alternative-selling due to the low reservation prices of entry level customers.

Figure 6: Expected net profit achieved under ATS policy under different supply scenarios.

Figure 7 shows the percentage profit gain from adopting an optimized demand shaping strategy compared to an ATP-based approach with unbiased supply, which can be interpreted as the value of demand shaping when the firm has advance knowledge about the price sensitivity and quality profiles of the customer segments. The figure depicts the net profit derived from all customer segments to be increasing as the degree of supply skew increases. The firm can be significantly better off financially (up to 10%) by recognizing opportunities for up-selling to the market sweet spots in its customer segments. The profit gain in the firm's two most profitable customer segments (value and performance) more than offsets the profit decrease in the entry level (economy) segment. Although not shown here, we note that the profit gain would eventually decrease as the supply is progressively skewed towards high-value components because the proportion of customers willing to accept up-sell products at increasingly higher price points will eventually decline. The customers willing to accept up-sells in the value and performance segments are leading edge technology adopters and operationally focused do it yourselfers. Those customers who are not willing to accept up-sells and are fixated on their first choice tend to lag in the adoption of technology and are very cost conscious.

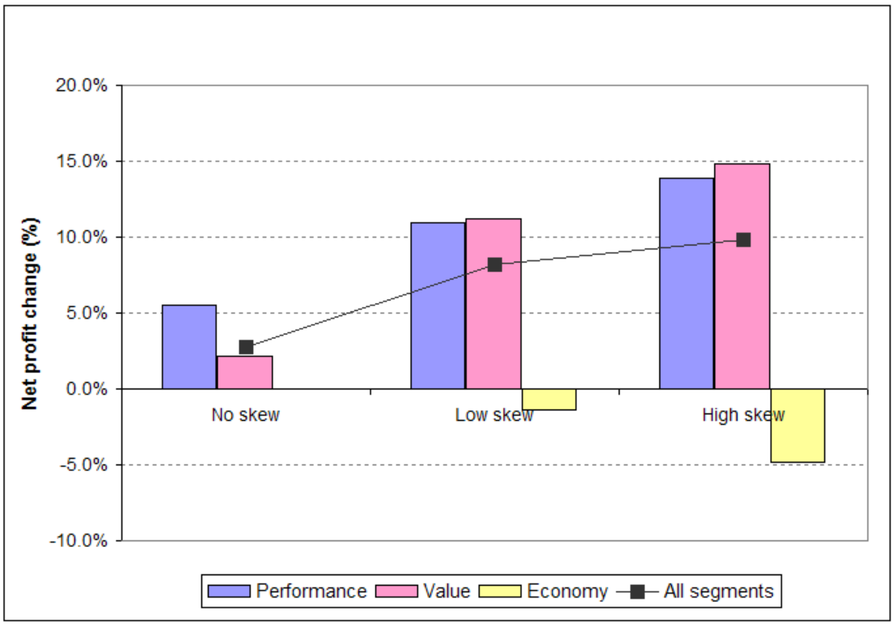

Figure 7: Expected net profit achieved under ATS policy under different supply scenarios.

For the same experiment, Figure 8 shows the order fill rate (i.e., the proportion of customer orders filled with either their initial product selection or an alternative product) and the number of alternative product purchases in the different customer segments under a demand shaping regime where the seller takes advantage of up-sell opportunities. We can make a couple of observations. First, the order fill rate averaged over all three customer segments decreases from 100 percent to 97 percent. This decline is driven entirely by backorders in the economy customer segment. The two other segments maintain a perfect order fill rate independent of the degree of supply skew. Second, the relative proportion of customers that are offered an alternative product is at its highest in the value segment (43 percent), as is the incremental profit gain for this segment as illustrated in Figure 7. Our numerical evidence from marketing analyses suggests that customers in the mid-range segment that purchase during the mid-life of the product life cycle are most likely to respond favorably to alternative product offerings. A firm should therefore focus its efforts on protecting these revenue sources and employ demand shaping actions to grow the share of the wallet from these accounts.

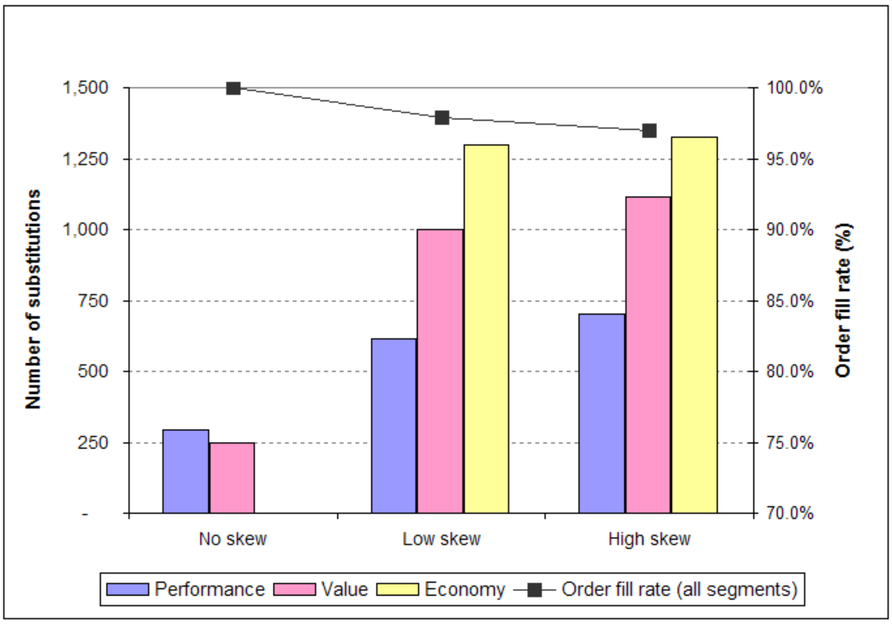

Figure 8: Order fill rate and expected number of substitutions under different supply scenarios.

6.2.2 Customer Behavior

To investigate how the product preferences of their customers can affect a firm's profitability, we applied the heavily skewed supply scenario from the previous experiment and analyzed the supply chain performance under different settings of the first-choice probability γ_c. We examined three scenarios where $\gamma_c = 0.50, 0.75$ and 1.00. Higher values of γ_c imply that customers are less willing to accept an alternative product if their initial product choice is unavailable. In the last scenario customers are fully committed to their initial selection, i.e., they do not accept alternative products regardless of price or quality. This represents the traditional ATP-based allocation model. Figure 9 displays the effect of customers' first-choice preferences on the order fill rate. As expected, we observe that as the first-choice probability increases the order fill rate decreases because a higher first-choice probability translates into fewer customers accepting an alternative configuration when their first choice selection is stocked out.

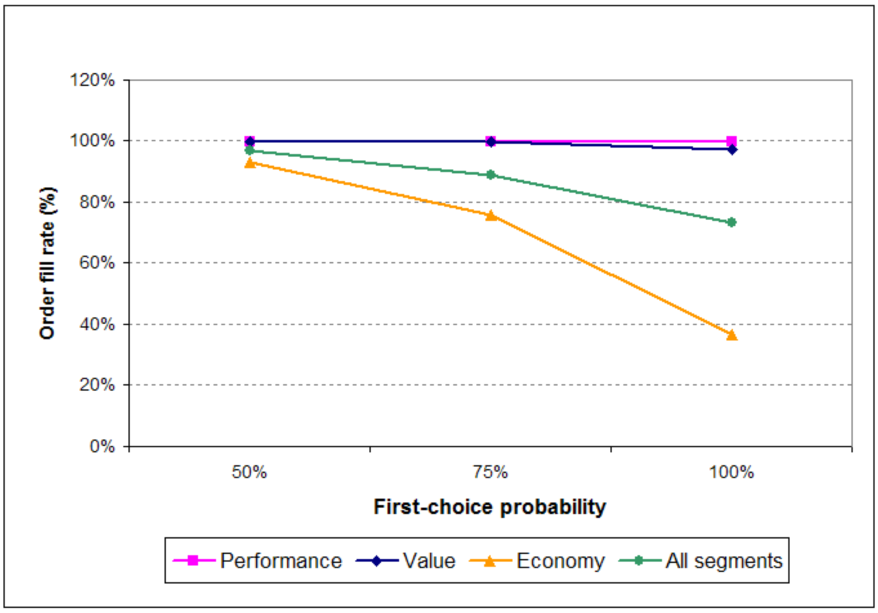

Figure 9: Effect of customer first-choice probability on order fill rate.

Table 4 depicts the average net profit, backlog cost, and inventory cost for the different values of customer first-choice probability. In the extreme case where $\gamma_c = 1.00$, the profit penalty over the baseline scenario ($\gamma_c = 0.50$) for all customer segments is 37 percent. The reason for the large profit penalty is a significant sales decline in the economy segment combined with increased inventory costs that are primarily driven by unsold high-value components. These results again demonstrate that a firm can gain significant financial benefits from acquiring information about its customer preferences, and utilizing this knowledge to develop an optimized demand shaping strategy.

Table 4: Net profit, backlog cost and inventory costs under different customer behavior models.

Customer Segment	First choice $\gamma = 0.50$			First choice $\gamma = 0.75$			First choice $\gamma = 1.00$		
	Net profit	Backlog cost	Inventory cost	Net profit	Backlog cost	Inventory cost	Net profit	Backlog cost	Inventory cost
Economy	481,398	11,242	-	341,867	38,643	-	(25,345)	100,707	-
Value	635,144	-	-	584,505	3,162	-	551,621	234	-
Performance	705,195	-	-	665,350	-	-	619,300	-	-
All Segments	1,821,737	11,242	21,120	1,591,721	41,805	78,540	1,145,576	100,941	189,640

6.3 Impact of Order Scheduling Policy

Our basic demand shaping model in section 4 and the subsequent numerical study assumed that a firm has a simple means of implementing and executing the recommended demand shaping strategy. However, the attainable performance of the demand shaping strategy depends on the order scheduling policy that matches customer orders against the availability outlook, and determines when a customer order can be shipped. For this purpose, we have developed the simulation model described in section 5 to analyze the optimized availability management process in conjunction with the demand shaping model. The simulation model consists of two phases. In the first phase, the simulator invokes the optimization model to determine the optimal allocation scheme for a given supply scenario. This step allocates components to products so as to best deal with supply and demand imbalances, which enables the demand shaping strategy. The second phase simulates the operational stage over multiple replications (in our study we conducted 10 independent replications). The simulator generates customer demands and creates a reservation price and reservation utility for each customer order to model the customer's propensity to purchase an alternative product.

The operation of the supply chain is simulated using two different order scheduling policies as described in section 5. Under the FCFS policy, the simulator first queries the availability of the customer's initial product selection. If the selected product is not stocked and the customer accepts substitutions, the simulator randomly searches the ATP schedule for the first alternative-sell product that meets the price and quality requirements of the customer. Finally, if neither the customer's initial selection nor any qualified product substitution is available the order is backlogged. Under the Rationing policy, the simulator first determines whether a customer accepts substitutions, and then randomly searches for the first alternative-sell product that meets the price and quality requirements of the customer. If no alternative-sell product is found, the simulator checks for availability of the customer's initial product choice. The outputs of this stage are statistical outcomes of the system performance metrics: sales profit, order backlog, order fill rate, and component inventory.

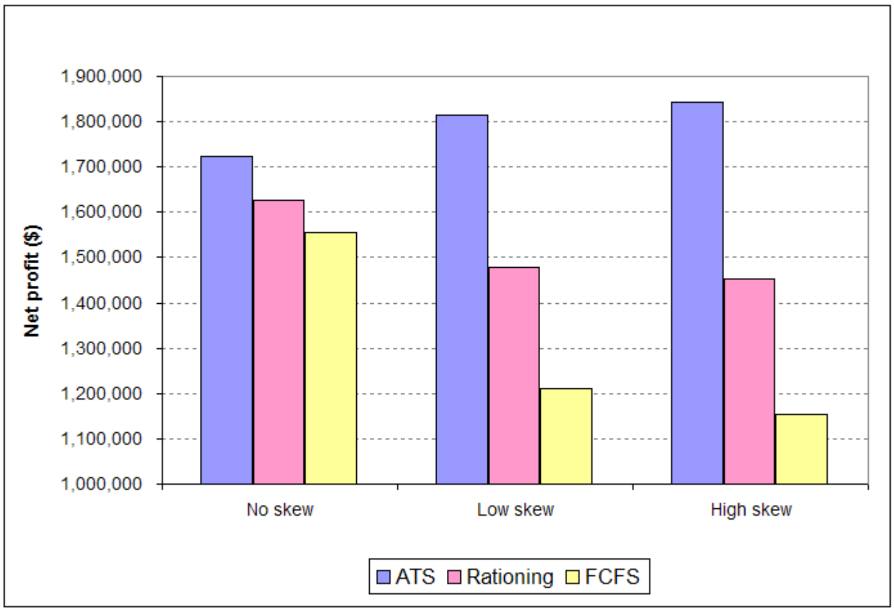

Figure 10: Expected net profit achieved under ATS, Rationing and FCFS for different supply scenarios.

Figure 10 demonstrates how skew and scheduling can drive profitability. The simulation assumes no excess inventories. The ATS engine dominates the profitability metric and drives the largest theoretical profitability improvements which are attainable through integrated sales actions. The ATS engine is optimizing the mix of sales recommendations. Rationing and FCFS order scheduling methods decrease profitability as supply is skewed to the market sweet spots. The Rationing scheduling policy seeks suitable alternatives when clients indicate their receptiveness to other product choices. FCFS scheduling policy performs the least favorably regardless of supply skew. FCFS may achieve a sense of equality amongst clients. However, when supply is skewed or constrained, FCFS decreases the profitability of the enterprise. Therefore, the scheduling policies implemented in an enterprise's application suite can have a profound effect on profitability when an enterprise seeks to condition demand to market sweet spots.

Table 5: Order fill rate achieved under ATS, Rationing and FCFS for different supply scenarios.

Customer Segment	No supply skew			Low supply skew			High supply skew		
	ATS	Rationing	FCFS	ATS	Rationing	FCFS	ATS	Rationing	FCFS
Economy	100.0%	94.7%	93.2%	95.0%	80.5%	73.1%	92.9%	76.7%	70.2%
Value	100.0%	97.5%	96.0%	100.0%	88.9%	80.2%	100.0%	89.0%	79.0%
Performance	100.0%	99.1%	97.4%	100.0%	96.3%	85.9%	100.0%	96.1%	84.6%
All Segments	100.0%	96.7%	95.2%	97.9%	87.1%	78.7%	97.0%	85.5%	76.6%

Table 5 shows the order fill rates achieved by supply skew, scheduling policy and customer segment. The details by customer segment show the ATS engine driving sales to value and performance products as supply is skewed increasingly to those products. Overall, the Rationing and FCFS scheduling methods demonstrate increasing gaps to ATS scheduling in order fill rates as supply is skewed to value and performance products, thereby leaving more pended orders in each sales cycle which has an undesirable effect on revenue and profitability.

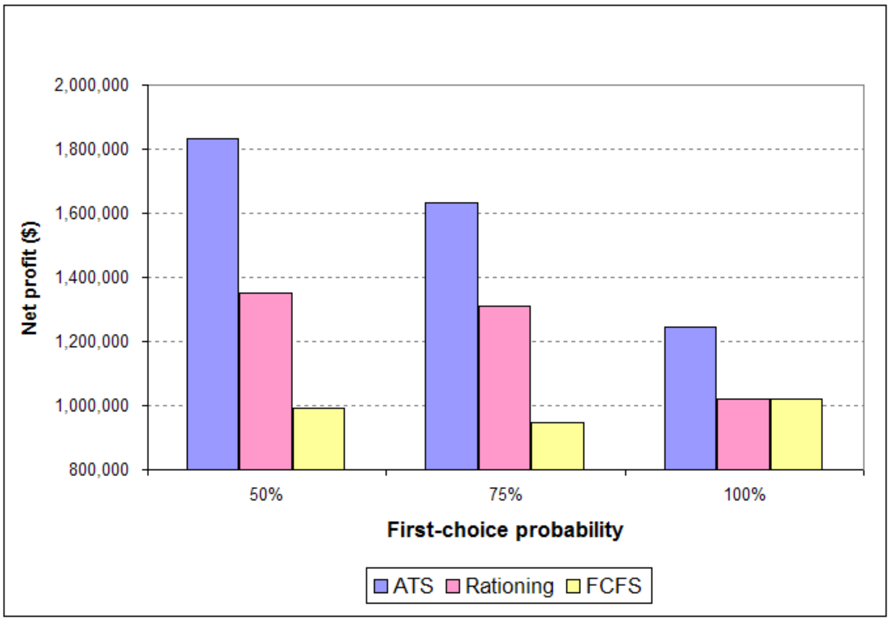

Figure 11: Expected net profit achieved under ATS, Rationing and FCFS for different customer behavior models.

Figure 11 shows the effect on profitability based on the scheduling regime and customers' flexibility on their first choice. Clients with a first choice fixation (i.e., probability equals 100%) provide an overall drag on profitability. Clients that are more flexible in their final product selections increase the profitability of the enterprise, and are more valuable to the business. Again, the ATS engine takes excellent advantage of the optimal mix to drive the highest profitability regardless of first choice probability, with the rationing scheduling method a distant second.

Table 6: Order fill rate achieved under ATS, Rationing and FCFS for different customer behavior models.

Customer Segment	First-choice $\gamma = 0.50$			First-choice $\gamma = 0.75$			First-choice $\gamma = 1.00$		
	ATS	Rationing	FCFS	ATS	Rationing	FCFS	ATS	Rationing	FCFS
Economy	92.9%	76.7%	70.2%	75.7%	73.9%	67.1%	36.8%	59.3%	59.3%
Value	100.0%	89.0%	79.0%	97.4%	85.7%	75.4%	99.8%	75.9%	75.9%
Performance	100.0%	96.1%	84.6%	100.0%	96.3%	84.8%	100.0%	90.3%	90.3%
All Segments	97.0%	85.5%	76.6%	88.8%	83.3%	74.3%	73.1%	72.5%	72.5%

Table 6 provides detailed insight into Figure 11 by evaluating the scheduling method and customer segment on order fill rates. The ATS policy consistently outperforms the rationing and FCFS scheduling methods across order fill rates regardless of customer segment.

7. Concluding Remarks

7.1 Summary

In this paper we have developed and simulated an advanced availability management process for assemble-to-order supply chains and have outlined the business requirements for incorporating such a process into supply chain operations. We have described a mathematical model that aims at finding marketable product alternatives in a product portfolio that best utilize inventory surplus and replace demand on supply-constrained products, and have highlighted business benefits through simulations with realistic production data. The models featured in this paper have already contributed to substantial business improvements in real-world supply chains. IBM has implemented an ATS process in its complex-configured server supply chain in 2002. The realized savings include $100M of inventory reduction in the first year of implementation and over $20M reduction annually in the subsequent years.

Our numerical results point out that more flexible customers are more profitable customers. Market intelligence and data analytics can identify these more flexible customers via market models. The integration of marketing insight with the number and types of sales recommendations are the key to fully attaining these results and are beyond the ability of this simulation construct. For example, a very price-sensitive client may only be presented with two sales recommendations – both of which are alternative-sells or one alternative sell and one down sell. A more price insensitive client may be presented with five dynamic sales recommendations – three are up-sells and two are alternative sells (no down sells). This stratification of clients by price sensitivity and the approach to dynamic sales recommendations will be essential to achieving the business results we have identified. Moreover, the use of the ATS model as an intelligent and dynamic engine for sales recommendations on the Internet and for sales professionals, and the integration of the ATS output with sales activities will be imperative for attaining a sustainable competitive advantage.

7.2 Future Research

Credible product alternatives must be contained in any product portfolio and be presented to customers during the sales process. The business benefits of doing so in conjunction with an optimized ATS process are increased revenue, profitability, market share, and client satisfaction. Additional financial benefits that directly impact the profit and loss statement are the cost avoidance of brokering, scrapping and inventory obsolescence, reduction of inventory carrying costs, return cash for additional investments, and improved cash-to-cash cycle times.

Future work requires the integration of the ATS engine with demand and supply processes, data and applications. This is important when large product portfolios are in place and automation is necessary for speed and accuracy of calculations. We recognize that ATS substitution proposals will be near real time due to the latency caused by booked orders, forecast changes, supply updates, and the requirement to recalculate the various sales (up-sell, alternative-sell and down-sell) recommendations based on individual customers. The benefit of the ATS and market intelligence integrated process and application architecture is to migrate ATS closer to sales execution and allowing automation to make the communication and presentation of credible sales recommendations a push selfservice capability (instead of a pull) for customers. This will minimize the amount of effort of the customer and supporting sales staffs as automation masks the complexity of the product portfolio and business considerations such as profitability from the customer, and presents viable product alternatives that have attractive price-performance characteristics.

The major prerequisite to integrate ATS into the process and application architecture is a robust market intelligence capability. The rationale for this dependency is to identify the customer's flexibility concerning their first product selections or amenability to another set of sales recommendations. As the customer's flexibility range is identified in the various types of market intelligence models such as propensity to buy and share of the wallets profiles, this business insight into customer buying behavior can be exploited by ATS modeling by proposing credible and dynamic sales recommendations based on the customer's buying characteristics. Customer flexibility and their spending patterns are highly relevant inputs into the ATS and may determine the sequence and number of sales recommendations presented to the customer based on enterprise business rules.

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