Journal of the Operations Research Society of Japan
Vol. 53, No. 4, December 2010, pp. 270–288

USING ORDER ADMISSION CONTROL TO MAXIMIZE REVENUE UNDER CAPACITY UTILIZATION REQUIREMENTS IN MTO B2B INDUSTRIES

Andy Wu David Chiang Cheng-Wen Chang
National Taiwan University

(Received December 8, 2009; Revised September 10, 2010)

Abstract An order admission model is developed to introduce revenue management into MTO B2B industries. This solution is designed to resolve a common order management dilemma faced by manufacturers with severe seasonal demands. Considering the requirement that manufacturing industries be risk averse, the objective is to maximize the expected total revenue under a targeted capacity utilization constraint. The deterministic admission problem and its auxiliary model are presented and solved through an iterative dynamic programming algorithm. Through this algorithm, a reward-threshold order admission policy can be established at the beginning of the planning horizon, helping companies to achieve a balance between profitability and stability.

Keywords: Markov process, revenue management, utilization management

1. Introduction

Utilization is connected to productivity measures in manufacturing industries (e.g., Devlin et al. [16], Ptak [34], and Stonebraker [38]). In the B2B MTO (Business-to-Business Make-to-Order) environment, it is well known that capacity utilization is positively related to revenue in some high-tech industries. For instance, semiconductor manufacturing firms in Taiwan, such as Taiwan Semiconductor Manufacturing Company (TSMC) or United Microelectronics Corporation (UMC), set targeted utilization levels for annual and monthly business planning and even treat the targets as a performance measure at each foundry firm. In practice, if yearly utilization achieves more than 60-70%, they can at least break even. That is the reason these manufacturers or fabricators prefer to target utilization at 80-100% for business planning. Based on their published statistics, annual earnings increase as the utilization rate rises. In addition, most investors believe utilization is positively related to pretax earnings.

On the other hand, many manufacturers face seasonal or cyclic demands. The stringent capacity situation becomes severe in the high seasons. These problems affect not only semiconductor manufacturers, but also the apparel, shoe, glass making, and tool machine industries (see Sridharan [37]). It makes sense that capacity rationing for preferred orders can improve profit when capacity is insufficient to satisfy all incoming orders. From this angle, the relationship between utilization and revenue seems a little subtle. For a manufacturer, high utilization usually corresponds to good revenue. However, in order to raise the profitability further, utilization possibly needs to be sacrificed by employing the revenue management. This causes a kind of trade-off between utilization and revenue.

From another angle, setting a target utilization rate may be treated as a risk control manoeuvre. The action of rejecting an incoming order may result in a displacement or opportunity cost, especially due to the uneven demand pattern of incoming orders in B2B MTO environments. It is noted that key-account orders are finite, and the displacement costs of a regular rationing policy in B2B MTO environments are so huge that any errant decision cannot easily be averaged out. For this reason, managers apparently act somewhat conservatively when revenue management is suggested. Therefore, product managers may feel more comfortable if the targeted utilization is treated as a risk control mechanism to provide a baseline level of earning when adapting the concept of revenue management to reject an incoming order.

Furthermore, in addition to profit and risk concerns, there are some exogenous factors that require manufacturers to achieve at least a certain target level of utilization. For example, many B2B MTO manufacturers in China or Vietnam are small and medium enterprises, and they use more labour due to the lower wages in developing countries. Piece-rating payment, temporary hiring systems, and union forces tend to drive production managers to remain at a certain utilization level such that employees can earn enough money to support themselves.

In B2B MTO environments that are discussed in this paper, manufacturers set business plans periodically. Order management procedure can be split into two stages: order admission and order fulfilling. The order admission procedure aims to discriminate and identify the orders which contribute most to the enterprise revenue. The process is for strategic, rather than operational. By contrast, order fulfilling seeks to formulate explicit manufacturing plans and schedule specific delivery due dates for all accepted orders and corresponding components; this is an operational requirement. Being a strategic plan, order admission procedures may be simplified without considering the randomness of the machine service rate or facility capacity in detail.

This paper discusses a B2B manufacturer who sets order booking period in front of the production cycle, which is illustrated in Figure 1. During the high season, we suggest discriminating the incoming orders to improve profitability. This problem is highly related to single-leg seat control in revenue management. Nevertheless, many theories in revenue management that use the marginal contribution as the customer-discriminating factor are inappropriate for B2B MTO environments. In contrast, our work for B2B MTO order admissions is characterised by sequentially realized lumpy demands from a finite heterogeneous order population. Each realized order requires a random size of capacity to fulfil. Finite means the set of potential orders has limited components, while heterogeneous implies the discrete order-size distributions of potential orders are different from each other. Furthermore, the utilization concern leads our model to be risk-averse, a fact that apparently fits more practical situations.

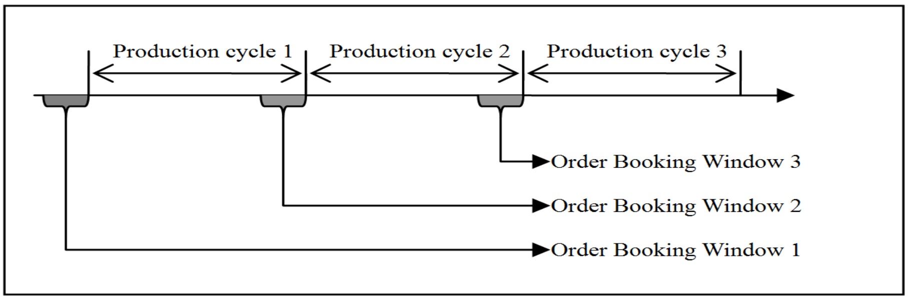

Figure 1: Order booking windows and production cycles

In this research, we use a mathematical model to present the deterministic order admission problem (DAP) with utilization constraint. It is desirable that the optimization model will indicate whether a product manager should accept or reject a realized order dynamically according to the system state. The remainder of this paper is organized as follows. A literature review is conducted in Section 2. The admission problem for limited capacity with a finite number of potential orders is explicitly modelled in Section 3. In Section 4, we propose a relaxed model and an auxiliary model in line with the primal model. The relationship between the primal, the relaxed, and the auxiliary model will be clarified. In Section 5, the iterative dynamic programming algorithm for the auxiliary model is explicitly depicted. In Section 6, a numerical example is demonstrated. Finally, concluding remarks and research extensions appear in Section 7.

2. Literature Review

Problems exist concerning how to make order admission decisions in environments of uncertain demand and limited capacity. There are several lines of literature related to this issue, such as order promising, resource allocation, extreme queuing control, inventory control in revenue management, and capacity rationing.

In terms of research on order promising, ATP (Available-to-Promise), and CTP (Capable-to-Promise) focus on selecting the most profitable orders for a fixed production cycle. For example, Chen et al. [12, 13], Zhao et al. [41], and Christou and Ponis [14] focus on providing manufacturers with a batch-processing procedure. The orders arriving within an order booking period are held, and deterministic mixed-integer-programming models are used to select the orders to be accepted. The batch-processing procedure may not be available in some industries for which a quick response is required. In contrast, this paper focuses on providing real-time dynamic admission decisions with respect to sequentially arriving orders.

For resource allocation among multiple items, Evans [17] was the first to discuss the inventory rationing issue. DeCroix and Arreola-Risa [15] extended the Evans model to one with an infinite time horizon. Glasserman [18] applied static policy to allocate production capacity for a multi-product system in multiple periods. Arreola-Risa [1], Perez and Zipkin [32], and Kogan [23] modelled production rate control problems in a single-server multi-item queuing system. Sen and Zhang [36] applied a news-vendor model to a single product with a monotonic pricing function over a multi-period horizon. Bollapragada and Rao [9] considered supply uncertainty into the multi-product inventory system. Ketzenberg et al. [20] utilised a margin analysis heuristic to allocate insufficient capacity during peak seasons. Some literature, such as Glasserman [18], de Kok [24], and Bertsimas and Paschalidis [7], include the service-level constraint in their models. Although both resource allocation and order admission discriminate demands, they are different types of strategies. Resource allocation pre-allocates resources over multiple items; by contrast the admission control process does not.

Extreme control is one type of queuing control in which the server can accept or deny an arrival in order to maximize the long-term benefit of systems. Several decades ago, Lippman [27], Lippman and Ross [28], Miller [29], and Scott [35] constructed the basis for this field. Models such as M/M/n or Semi Markov Decision Problem (SMDP) are used to present the problems within an infinite planning horizon. Under the assumption of no pre-emption, the objectives of extreme queuing control are to find the admission policies which maximize the average profit or discounted total reward. In recent research, the queuing control has been concerned with more complicated queuing networks. Ku and Jordan [25] considered a twostation multi-server tandem system with no waiting buffer. The type of optimal admission policies is a threshold policy which maximizes the expected discounted reward by inspecting the numbers of customers in stations. Carrizosa et al. [11] consider the M/G/n system. The optimal admission policy here has a structure similar to a conventional $c\mu$-rule. Thus, the optimal decision will depend on the denial surcharge per unit of service time. While previous research assumes the customer classification is based on deterministic rewards, Örmeci et al. [30] present the structural policies in the M/M/n system with two classes and random rewards. The optimal policy admits an arriving job only if the associated reward and the system load do not violate the threshold rule. Some differences between our problem and the extreme queuing control are addressed. First, the planning horizon of queuing control is infinite while, in this paper, it is planned for a finite booking period. Second, the population of customers mentioned in queuing control is infinite, but this paper models the dynamic demand structure due to a finite order set faced by a B2B MTO manufacturer.

For conventional inventory control in revenue management (ICRM), the lumpy demand or batch/group booking issue is neglected if a sufficiently large fraction of demand is from small groups (size one or two) and the capacity is reasonably large (see Talluri and van Ryzin [39]). Lee and Hersh [26] may have been the first researchers to discuss the lumpy demand situation. Their result is adjusted by Brumelle and Walczak [10]. The philosophy of revenue management has been extended to manufacturing industries by Harris and Pinder [19]. Balakrishnan et al. [2, 3] and Barut and Sridharan [4, 5] use decision trees and marginal analysis to construct a capacity ration policy for MTO industries. These capacity rationing approaches are based on the aggregate demand approximation. In fact, this case should be depicted by a dynamic and stochastic knapsack problem (DSKP). Papastavrou et al. [31] provide a discrete Markov decision problem on this subject. Their work analyses a knapsack problem in which objects with random size and reward arrive according to a stochastic process. Later, this model was extended into continuous-time formulations by Kleywegt and Papastavrou [21, 22]. However, there are three factors that make our research different from conventional DSKPs. First, since the reward and demand size of DSKPs are identically distributed for every period, we may say that all arrivals are still intrinsically equivalent. A DSKP is originally focused on transportation planning. For transportation industries that face a huge customer population, using an identical distribution to generate sequential arrivals may be an efficient approximation method. However, for B2B companies that focus on finite key-account customers, common analytical functions cannot represent the dynamics of the demand structure. One of the contributions made by this paper is modelling the demand process of a finite order set. Second, the capacity utilization constraint is considered in our model. For airline industries, profitability is much more important than utilization, and revenue management models rarely incorporate this performance measure. However, in the practice of B2B MTO industries, capacity utilization is an important assessment standard for business operation or personal performance. For industries which involve costly equipments or employ piece-rating labours, maintain a high utilization level in the high seasons is a basic requirement. Third, traditional admission controls (e.g., revenue management, extreme queuing control, and capacity rationing) include a priority rule: high-margin orders are better than low-margin orders. Such a priority rule may be inappropriate in a B2B environment. For instance, a low-margin but large-size order may benefit the manufacturer more. In this paper, the complex nature of limited capacity, order margin, and order size is presented. The order evaluation procedure is not reined by the preconceived priority rule.

3. Primal Problem Formulation

The order admission problem describes a high-season dilemma faced by sales or product managers in MTO B2B industries. It is known that many companies use a two-stage mode for order processing. The first stage, order promising, is an immediate response corresponding to the customers request. The second stage, order fulfilment, is a solid confirmation with a due date and specific delivery requirements. In this paper, we discuss the admission problem for order-promising without order-fulfilment procedure. The uncertainty of this problem is due to two random factors, i.e., stochastic arriving sequence and order size. The firms we consider have the following characteristics:

- Order set: Enterprises concentrate their attention on key-account orders. The number of orders in the potential order set is finite.
- Order realization: During a fixed booking window, potential orders arrive in a random sequence. The probability of simultaneous order arrival is assumed to be zero. For all the orders in the potential order set, their realization probabilities are equal.
- Order size: Order size means the required capacity to fulfil an order. Order size probabilities estimated by marketing department is assumed to be accurate and measurable. They follow discrete distributions with finite supports. A special event order size is zero indicates that the customer cancel their demand plan.
- Simple strategy: A certain accept-or-reject decision must be made whenever an order request realizes. The rejected request will not reoccur. Orders cannot be partially accepted and split. Operational managers need substantial guidance in practice; therefore, this research focuses on deterministic policies.

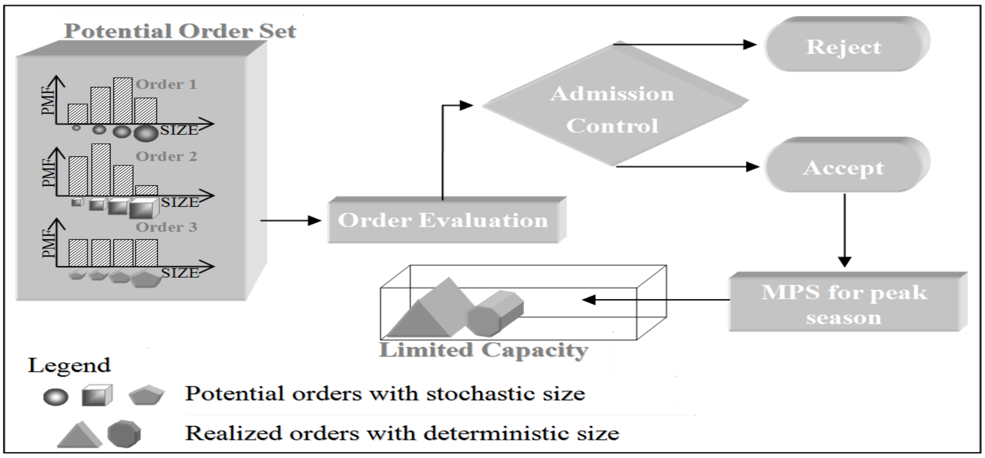

Figure 2: Deterministic order admission problem

The order admission control process requires product managers to reject undesirable orders. The controlling process is depicted in Figure 2. Managers need to make accept-or-reject decision based on some kind of order evaluation procedure. This research will figure out a policy for the order evaluation which helps the manufacturer to earn a reliable profit.

The information and decision process is illustrated in Figure 3. The initial available capacity of a production cycle is denoted by C_1. At the beginning of the order booking window, the potential order set U_1 and all order size distributions are known to the managers. There are T orders in U_1. At the first decision epoch (i.e., the time point that the first order realizes), the managers observe the order identity I_1 and the order size X_1, and then they are required to decide whether to accept or reject it. The decision is denoted by a_1, and

a_1=1 means accepting the order while a_1=0 means rejecting. After making the decision, the available capacity and potential order set changes accordingly. For instance, the available capacity at the second epoch will be C_1 minus the size committed to the first arriving order if it is accepted (i.e., C_2=C_1-X_1), and the potential order set shrinks by eliminating I_1 from set U_1 (i.e., U_2=U_1-I_1). The process continues in this manner until T^{th} order decision being made and potential order set becoming empty. In general, at decision epoch t, the manager can observe the available capacity C_t, the potential order set U_t, the arriving order identity I_t, and its order size X_t. Define $\xi_t \equiv [C_t, U_t, I_t, X_t]$ as the information state observed at t for $t = 1, \ldots, T$, and let $\zeta_t \equiv [C_t, U_t]$ be the semi-state for $t = 1, \ldots, T+1$. When the t^{th} order realizes, deterministic admission decision a_t must be made immediately. Furthermore, let h_t denote the accumulated information (history) which can be defined in a recursive form, i.e., $h_1 \equiv [\xi_1]$, $h_t \equiv [h_{t-1}, a_{t-1}, \xi_t]$ for $t = 2, \ldots, T$, and $h_{T+1} \equiv [h_T, a_T, \zeta_{T+1}]$. Let H_{T+1} denote the collection of h_{T+1}. For the order I_t, $f(I_t, X_t)$ denotes the probability of order size being X_t and $P_t(I_t)$ denote the margin per unit of job requirement.

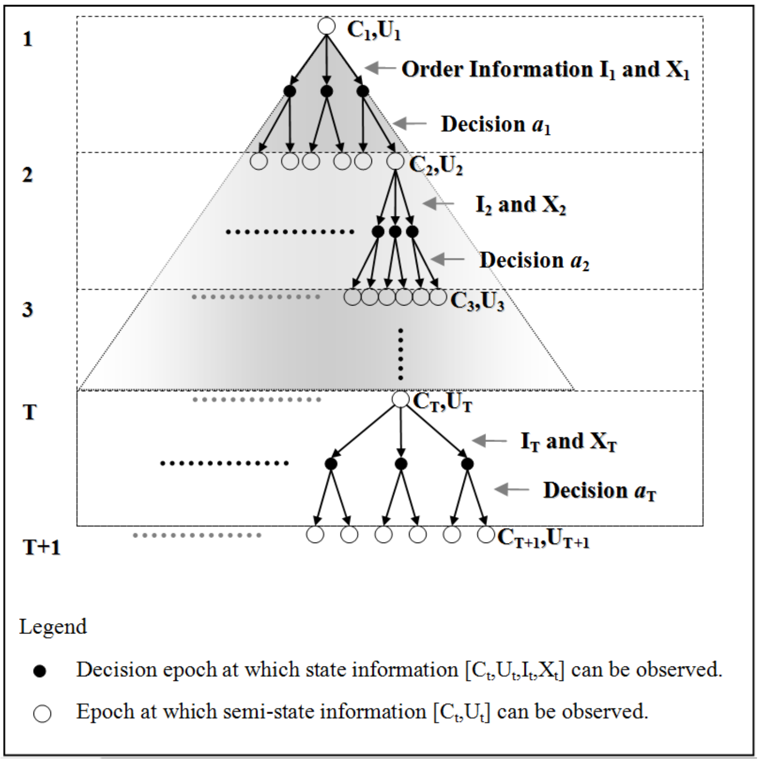

Figure 3: Tree structure of deterministic admission problem

For a profit-oriented manufacturer, the expected total revenue can be a policy evaluation criterion. Therefore, in the potential order set, if two orders have the same size distribution, it is expected that the low-margin order can be rejected easier than the high-margin one. However, rejecting a realized order to reserve the capacity for future uncertain orders is actually a highly risky strategy. For instance, if the margin difference is very tiny, and the size of the realized low-margin order is so large that accepting it may utilize a great portion of the remained capacity, is it still worthy to preserve the capacity for the uncertain high-margin order? In our opinion, we say no. Therefore, considering the utilization requirement in the order evaluation procedure helps the profitability to be more stable. In this paper, the deterministic admission problem with utilization constraint is considered. Let $a_t^{\pi}(h_t)$ denote the admission decision for the t^{th} order under policy π when h_t is observed. Π represents the collection of all the history-dependent deterministic policies that satisfy the capacity constraint. Suppose a targeted utilization level α is set by the manager. $ETR(\pi)$ is the expected total revenue and $Z(\pi)$ is the target achieving rate under policy π. Then Π, ETR, and Z are explicitly defined below.

$$\Pi \equiv \left\{ \pi \;\middle|\; \sum_{\substack{t=1 \\ h_t \subset h_{T+1}}}^{T} X_t \times a_t^{\pi}(h_t) \le C_1, \;\; a_t^{\pi}(h_t) \in \{0,1\}, \;\; \forall h_{T+1} \in H_{T+1} \right\} \tag{1}$$

$$ETR(\pi) \equiv \mathbf{E}\left[\sum_{\substack{t=1 \\ h_t \subset h_{T+1}}}^{T} P_t(I_t) \times X_t \times a_t^{\pi}(h_t) \right] \tag{2}$$

$$Z(\pi) \equiv \mathbf{E}\left[\mathbf{1}_{\alpha}\left(\left(\sum_{\substack{t=1 \\ h_t \subset h_{T+1}}}^{T} X_t \times a_t^{\pi}(h_t) \right) / C_1 \right) \right] \quad where\ \mathbf{1}_{\alpha}(s) \equiv \begin{cases} 1\ , & s \ge \alpha \\ 0\ , & s < \alpha \end{cases} \tag{3}$$

It is assumed the manager wishes to have the targeted achieving rate higher than a specific level $\beta, 0 \le \beta \le 1$. Then the deterministic admission problem (DAP) with utilization constraint is defined as follows.

$$\text{DAP}: \quad Max.\ ETR(\pi) \tag{4}$$

$$s.t.\ Z(\pi) \ge \beta \tag{5}$$

$$\pi \in \Pi \tag{6}$$

The objective of this problem is to maximize the expected total revenue by employing a history-dependent deterministic policy. Constraint (6) models the capacity restriction. Constraint (5) is a chance constraint that reflects the managers' preference for the utilization. Both α and β are set according to manufacturing or financial purposes. Managers desire a rated utilization higher than α and expect the probability of a low-utilization situation to be less than $1-\beta$. In mathematics, the utilization constraint does not involve margins in calculation thus mitigates the margin-based discriminating effect. In other words, it prevents high-margin orders dominating low-margin ones by taking utilization into consideration. On the other hand, using the chance constraint as the capacity requirement allows decision flexibility, which avoids the risk concern dominating profit orientation.

It is inefficient to handle the DAP model directly because the heterogeneous size distributions and the stochastic arriving sequence jointly induce numerous scenarios. Some searching tech could be employed to find the approximate solution. For instance, Yoshitomi et al. [40] proposed genetic algorithm for solving this kind of large-scale stochastic problem. In this research, by analyzing the model properties, an iterative dynamic programming algorithm is developed to handle the DAP model.

4. Auxiliary Model

The utilization constraint (5) restricts the decision space for the order admission problem. It is intuitive to relax this constraint by setting a penalty term in the objective function. In this section, we will clarify the relationship among the primal DAP model, the relaxed model, and the auxiliary model. Furthermore, based on the auxiliary model, an optimal deterministic policy can be achieved for DAP.

Define $G(\pi) \equiv max\{0, \beta - Z(\pi)\}$ which represents the deviation from the desired level β. Arbitrarily choose a nonnegative scalar μ as the penalty. In the case of finite scenarios, the deterministic policy space Π is finite, and the relaxed model $L(\mu)$ follows:

$$L(\mu) \equiv \max_{\pi \in \Pi} \{ETR(\pi) - \mu \times G(\pi)\} \tag{7}$$

Define $\hat{G}(\pi) \equiv max\{0, 1 - Z(\pi)\}$. Obviously, $\hat{G}(\pi) = 1 - Z(\pi)$ because $Z(\pi) \leq 1$ for all π. The solution method for problem $L(\mu)$ can be further simplified by considering the following auxiliary model $\hat{L}(\eta)$ with a nonnegative multiplier η:

$$\widehat{L}(\eta) \equiv \max_{\pi \in \Pi}\{ETR(\pi) - \eta \times \widehat{G}(\pi)\} \tag{8}$$

In fact, this auxiliary function corresponds to another dual problem shown below which takes the utilization requirement as a hard constraint.

$$\max_{\pi \in \Pi} \left\{ ETR(\pi) \;\middle|\; \mathbf{1}_\alpha \left(\sum_{\substack{t=1 \\ h_t \subset h_{T+1}}}^{T} X_t a_t^\pi(h_t) \middle/ C_1 \right) \geq 1, \;\; \forall h_{T+1} \right\} \tag{9}$$

The managerial interpretation of the auxiliary model is followed: It permits the violation of the strict utilization requirement as (9) shows, but such a violation will cause a deviation cost. These relaxed problems have their meaning in practice, while under-time cost is taken as the multiplier if workforce fails to achieve 100% efficiency.

Because of the finiteness of scenario set and action space, the optimal values of model $L(\mu)$ and $\hat{L}(\mu)$ are always attainable and the corresponding optimal policies always exist. In other words, there exist $\pi^*_\mu \in \Pi, \forall \mu \geq 0$ and $\hat{\pi}^*_\eta \in \Pi, \forall \eta \geq 0$ such that:

$$\pi^*_\mu \equiv \arg\max \{ETR(\pi) - \mu G(\pi) \,|\, \pi \in \Pi, \mu \geq 0\} \tag{10}$$

$$\widehat{\pi}^*_\eta \equiv \arg\max \left\{ETR(\pi) - \eta \widehat{G}(\pi) \,|\, \pi \in \Pi, \eta \geq 0\right\} \tag{11}$$

Lemma 1

i. $G(\pi^*_\mu)$ *is nonincreasing in* μ, *and* $\widehat{G}(\widehat{\pi}^*_\eta)$ *is nonincreasing in* η.

ii. *$ETR(\pi^*_\mu)$ is nonincreasing in μ, and $ETR(\widehat{\pi}^*_\eta)$ is nonincreasing in η.*

iii. *$L(\mu)$ is nonincreasing in μ, and $\widehat{L}(\eta)$ is nonincreasing in η.*

Lemma 2 *If $Z(\widehat{\pi}^*_\eta) \leq \beta$, then $\widehat{\pi}^*_\eta$ is also the optimal policy for the relaxed model $L(\eta)$.*

Lemma 1 illustrates the monotonicity and lemma 2 tells the relationship between $L(\mu)$ and $\hat{L}(\eta)$. The proofs of lemmas 1 and 2 are demonstrated in the appendix. Recall that the primal problem takes the utilization requirement as a chance constraint. With the support of lemmas 1 and 2, the optimal policy of the primal DAP model could be obtained or found infeasible by solving the auxiliary model $\hat{L}(\eta)$. The following proposition illustrates the link and verifies it in the appendix.

Proposition 3

i. *Given a nonnegative auxiliary multiplier η, let $\widehat{\pi}^*_\eta$ be the optimal deterministic policy for the auxiliary model. The target achieving rate under this policy is nondecreasing in η and has an asymptote $\overline{Z}$ that is equal to or less than 1, i.e., $\lim_{\eta\to\infty} Z(\widehat{\pi}^*_\eta) \to \overline{Z} \leq 1$.*

ii. *If $\overline{Z} < \beta$, then DAP is infeasible; therefore, an optimal policy which maximizes the expected revenue and satisfies the capacity requirement does not exist.*

iii. *If there exists a minimal nonnegative auxiliary multiplier $\widetilde{\eta}$ such that the target achieving rate is equal or higher than the specified level β under the auxiliary policy $\widehat{\pi}^*_{\widetilde{\eta}}$, then DAP is feasible and $\widehat{\pi}^*_{\widetilde{\eta}}$ is also its optimal policy.*

In conclusion, if all the solutions obtained from the auxiliary problems fail to raise the expected achieving rate up to the specific probability level β, then there is no feasible policy for the DAP; If there exists a nonnegative multiplier with it the auxiliary model has an optimal policy, and the expected achieving rate under this policy is equal or higher than β, then the optimal policy for the DAP can be obtained.

5. Algorithm

In the previous section it has been clarified that the deterministic admission problem with utilization constraint can be solved through an auxiliary model with the adequate multiplier. The auxiliary model can be extended as follows.

$$\hat{L}(\eta) \equiv \max_{\pi\in\Pi}\{ETR(\pi) - \eta \times \hat{G}(\pi)\}$$

$$= \max_{\pi\in\Pi} \mathbf{E}[\sum_{t=1}^{T} P_t(I_t) \times X_t \times a^\pi_t(h_t) - \eta \times (1 - \mathbf{1}_\alpha(\sum_{t=1}^{T} X_t \times a^\pi_t(h_t)/C_1))]$$

$$= \max_{\pi\in\Pi} \mathbf{E}[\sum_{t=1}^{T} P_t(I_t) \times X_t \times a^\pi_t(h_t) + u^\pi_{T+1}(h_{T+1}) - \eta] \tag{12}$$

where $u^\pi_{T+1}(h_{T+1}) \equiv \eta \times \mathbf{1}_\alpha((C_1 - C_{T+1})/C_1)$.

The constant term $-\eta$ in (12) does not affect the optimization, thus it can be omitted. After omitting $-\eta$, the terminal value u^π_{T+1} can be taken as a reward. The managerial interpretation for the revised auxiliary model is: if the utilization is above α at the end, then a fixed reward η will be granted.

Apparently, the auxiliary model can be taken as a dynamic and stochastic knapsack problem (DSKP) and solved by the backward dynamic programming. According to the characteristics considered in this paper, the orders in the potential order set have equal chance for their realization and the order sizes follow distribution f. Thus the transition probability can be defined below.

$$\text{For } t = 1, \quad \Pr\{\xi_1|\zeta_1\} = f(I_1, X_1)/T \tag{13}$$

$$\text{For } t = 2, \ldots, T, \quad \Pr\{\xi_t|\xi_{t-1}, a_{t-1}\} = \begin{cases} \frac{f(I_t,X_t)}{(T-t+1)}, & C_t = C_{t-1} - X_{t-1}a_{t-1} \geq 0 \ \&\ U_t = U_{t-1} - I_{t-1} \neq \emptyset \\ 0 & \text{, else.} \end{cases} \tag{14}$$

$$\text{For } t = T+1, \quad \Pr\{\zeta_{T+1}|\xi_T, a_T\} = \begin{cases} 1 & , C_{T+1} = C_T - X_T a_T \geq 0 \text{ and } U_{T+1} = U_T - I_T = \emptyset \\ 0 & \text{, else.} \end{cases} \tag{15}$$

It should be noted the path transition only depends on its current state, i.e., $\Pr\{h_{t+1}|h_t, a_t\} = \Pr\{\xi_{t+1}|\xi_t, a_t\}$ for $t = 1, \ldots, T-1$ and $\Pr\{h_{T+1}|h_T, a_T\} = \Pr\{\zeta_{T+1}|\xi_T, a_T\}$. Therefore, the optimal Markov deterministic policy is also the optimal history-dependent deterministic policy. Instead of $a_t^*(h_t)$, we use $a_t^*(\xi_t)$ to represent the optimal admission decision and let $EV_t(\zeta_t)$ represent the optimal expected accrued revenue for the revised auxiliary model. The Bellman optimality equation system is followed.

$$\begin{aligned} &EV_{T+1}(C_{T+1}, U_{T+1}) = \eta \mathbf{1}_\alpha((C_1 - C_{T+1})/C_1) \\ &EV_t(C_t, U_t) = \mathbf{E}[\max_{X_t a_t \leq C_t} \{P_t(I_t)X_t a_t + EV_{t+1}(C_t - X_t a_t, U_t - I_t)\}], \quad t = 1, ..., T. \end{aligned} \tag{16}$$

For $t = 1, \ldots, T$, the $EV_t(\zeta_t)$ can be extended as follows:

$$EV_t(C_t, U_t) = \sum_{\xi_t} \Pr\{\xi_t|\zeta_t\} \times \max_{\substack{X_t a_t \leq C_t \\ a_t \in \{0,1\}}} \{P_t(I_t)X_t a_t + EV_{t+1}(C_t - X_t a_t, U_t - I_t)\} \tag{17}$$

$$\text{where } \Pr\{\xi_t|\zeta_t\} = \begin{cases} f(I_t, X_t)/(T-t+1) & , U_t - I_t \neq \emptyset \\ 0 & \text{, else} \end{cases}$$

According to (17), we can get the optimal admission decisions for the revised auxiliary model as shown below.

$$a_t^*(\xi_t) = \begin{cases} 1 & , X_t \leq C_t \quad \text{and} \quad P_t(I_t) X_t \geq R(\xi_t) \\ 0 & , X_t > C_t \quad \text{or} \quad P_t(I_t) X_t < R(\xi_t) \end{cases} \tag{18}$$

$$\text{where } R(\xi_t) \equiv EV_{t+1}(C_t, U_t - I_t) - EV_{t+1}(C_t - X_t, U_t - I_t)$$

In (18) the reward threshold denoted by $R(\xi_t)$ represents the opportunity cost for accepting an order request. The managerial interpretation of the optimal decision rules is straightforward: When an order request is accepted, a portion of the capacity is preserved for this order. Thus, the available capacity decreases and leads to a loss in the opportunity to accept future uncertain orders. The reward threshold is therefore an opportunity cost. It can also be taken as a fair price for the arriving order. This price is recognized by the supplier subjectively, and therefore it cannot become a trading price negotiated between suppliers and customers. To maximize the expected revenue, a request is accepted if and only if the capacity is sufficient and the revenue brought by this order covers the opportunity cost.

Here an iterative dynamic programming algorithm will be illustrated. Define $EZ_t(\zeta_t)$ as a nonnegative function used for calculating the achieving rate under the reward-threshold policy. The algorithm encompassing backward induction and multiplier searching is illustrated by Figure 4 and explicitly presented below. For the convergence of the iterative algorithm, see Bazaraa and Shetty [6].

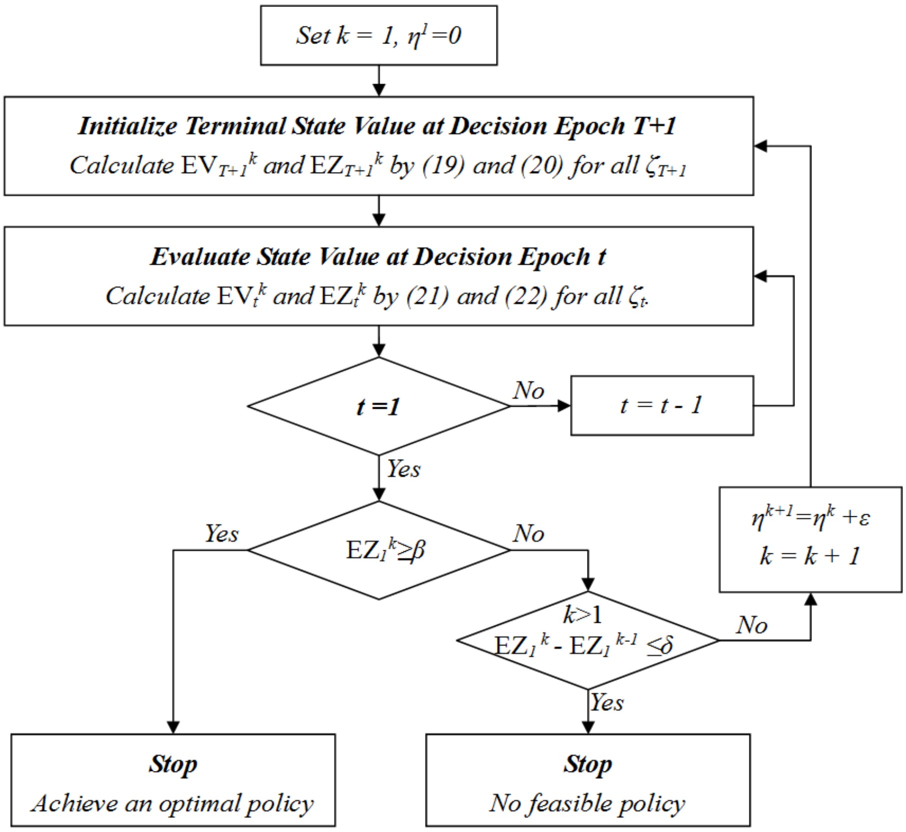

Figure 4: Algorithm

Algorithm

1. Set $k = 1$, $\eta^1 = 0$. Choose an adequate step size $\varepsilon > 0$ and a stopping value $\delta > 0$ which is sufficiently small. Then go to step 2.
2. The expected accrued revenue at stage $T + 1$ represents the reward if the requirement

on capacity utilization is satisfied. Otherwise it will be zero.

$$EV_{T+1}^{k}\left(C_{T+1},U_{T+1}\right)=\eta^{k}\times\mathbf{1}_{\alpha}\left(\left(C_{1}-C_{T+1}\right)/C_{1}\right)\qquad,\forall C_{T+1}\le C_{1} \tag{19}$$

$$EZ_{T+1}^{k}\left(C_{T+1},U_{T+1}\right)=\mathbf{1}_{\alpha}\left(\left(C_{1}-C_{T+1}\right)/C_{1}\right)\qquad,\forall C_{T+1}\le C_{1} \tag{20}$$

Then go to step 3.

3. Calculate the expected accrued revenue by backward induction for all ζ_t.

$$\begin{aligned}EV_{t}^{k}\left(\zeta_{t}\right)=&\sum_{(I_t,X_t)\in ACC(\zeta_t)}\left[P_{t}\left(I_{t}\right)X_{t}+EV_{t+1}^{k}\left(C_{t}-X_{t},U_{t}-I_{t}\right)\right]\times\Pr\left\{\xi_{t}|\zeta_{t}\right\}\\&+\sum_{(I_t,X_t)\in REJ(\zeta_t)}\left[0+EV_{t+1}^{k}\left(C_{t},U_{t}-I_{t}\right)\right]\times\Pr\left\{\xi_{t}|\zeta_{t}\right\}\end{aligned} \tag{21}$$

$$\begin{aligned}EZ_{t}^{k}\left(\zeta_{t}\right)=&\sum_{(I_t,X_t)\in ACC(\zeta_t)}EZ_{t+1}^{k}\left(C_{t}-X_{t},U_{t}-I_{t}\right)\times\Pr\left\{\xi_{t}|\zeta_{t}\right\}\\&+\sum_{(I_t,X_t)\in REJ(\zeta_t)}EZ_{t+1}^{k}\left(C_{t},U_{t}-I_{t}\right)\times\Pr\left\{\xi_{t}|\zeta_{t}\right\}\end{aligned} \tag{22}$$

The accepted zone $ACC(\zeta_t)$ and rejected zone $REJ(\zeta_t)$ are classified in line with the reward-threshold criteria shown in (18). The accepted zone is the collection of orders of which the revenue is greater than or equal to the reward threshold. It is defined below:

$$ACC(\zeta_t)\equiv\left\{[I_t,X_t]\;\middle|\;\begin{array}{c}X_t\le C_t\text{ and}\\P_t(I_t)X_t\ge EV_{t+1}^{k}(C_t,U_t-I_t)-EV_{t+1}^{k}(C_t-X_t,U_t-I_t)\end{array}\right\} \tag{23}$$

There are two reasons to reject a request. The first one is insufficient capacity, i.e., $X_t > C_t$. Another reason is that the revenue fails to surpass the reward threshold. Both of these cases will induce capacity to be the same during the semi-state transition. The rejected zone is presented below:

$$REJ(\zeta_t)\equiv\left\{[I_t,X_t]\;\middle|\;\begin{array}{c}X_t> C_t\text{ or}\\P_t(I_t)X_t< EV_{t+1}^{k}(C_t,U_t-I_t)-EV_{t+1}^{k}(C_t-X_t,U_t-I_t)\end{array}\right\} \tag{24}$$

If $t=1$, then go to step 4. Otherwise, set $t=t-1$ and return to step 3.

4. If $EZ_1^k\left(\zeta_1\right)\ge\beta$, then let $EV_1\left(\zeta_1\right)=EV_1^k\left(\zeta_1\right)$, $EZ_1\left(\zeta_1\right)=EZ_1^k\left(\zeta_1\right)$, $\widetilde{\eta}$=η^k and stop. The optimal policy is the reward threshold policy with η^k. If $EZ_1^k\left(\zeta_1\right)<\beta$, the algorithm works as follows: if k=1 or $EZ_1^k(\zeta_1)-EZ_1^{k-1}(\zeta_1)>\delta$, then set $\eta^{k+1}=\eta^k+\varepsilon$, k=k+1, and go to step 2. The evaluation process will repeat again with the greater multiplier; if k>1 and $EZ_1^k\left(\zeta_1\right)-EZ_1^{k-1}\left(\zeta_1\right)\le\delta$, then stop. It implies no feasible policy satisfying the capacity requirement.

When the algorithm stops and the optimal policy $\hat{\pi}^*_{\widetilde{\eta}}$ is attained, $EZ_1(\zeta_1)$ is the target achieving rate under the policy. $EV_1(\zeta_1)-\widetilde{\eta}$ is the objective value of the auxiliary model $\hat{L}(\eta)$ and the expected total revenue under the policy follows:

$$\text{DAP}=EV_1\left(\zeta_1\right)-\widetilde{\eta}\times EZ_1\left(\zeta_1\right) \tag{25}$$

Table 1: Input data of the numerical example

Potential Order	Margin	Capacity Requirement	
		Min. Size	Max. Size
Order 1	1.0	10	15
Order 2	1.05	5	10
Order 3	1.1	5	10
Order 4	1.15	6	10
Order 5	1.2	5	7
Order 6	1.2	4	6
Order 7	1.2	3	3
Order 8	1.25	2	6
Order 9	1.3	0	6
Order 10	1.4	0	4

6. Numerical Example

In section 4, we proved that the optimal deterministic policy is a reward threshold policy with an adequate multiplier and that this multiplier can be obtained by linear searching as the algorithm in section 5 shows. Under this policy, the expected total revenue is maximized while the capacity utilization requirement is satisfied. In this section, a numerical example is demonstrated.

In this example, we use the sales forecasting data of a saw manufacturer to simulate the performance of the order admission policy. It supplies saw blade products to home improvement tool manufacturers such as TTI or Pentair. Shift time is used as the standard capacity unit. There are two shifts in each working day. The planning horizon is one month or 48 shifts. The corporation's sales manager identified 10 potential orders in August for a factory. The accept/reject decision of each realized order is made jointly by sales and product managers. The demand estimation is shown in Table 1. The margin here does not represent the true currency value but only a relative proportionality.

For each order, we assume that the capacity requirement follows a truncated discretized Normal distribution. Let the mean sizes of orders equal to the average of the maxima and the minima and let the standard deviations (STD) equal to the range divided by (2.575×2). The size distributions are then generated. The sum of mean demands is 58.5, larger than the available 48 shifts. The numerical model is done on a notebook computer (AMD Turion, 1.60 GHz, RAM 480 MB). The algorithm is coded by VBA for Excel. Given a multiplier, the computing time to obtain the solutions is less than five minutes. For simplicity, we name the reward-threshold control as Robust DSKP policy. FCFS (First Come, First Serve) strategy is taken as the contrasting policy. Under FCFS, the manager rejects a realizing order if and only if the available capacity is insufficient to handle this job.

When the targeted capacity utilization α is given as 90%, Figure 5 reveals the relationship between the multiplier and the achieving rate of the targeted utilization. Apparently, robust DSKP policy dominates FCFS in the achieving rate.

Figure 6 represents the expected total revenue with respect to multiplier. The algorithm generates robust DSKP policies which make trade off between the expected revenue and the target achieving rate. As the multiplier increases, the expected total revenue decreases and the achieving rate of the targeted utilization increases.

Initially, the multiplier is set at zero and the expected total revenue under the robust

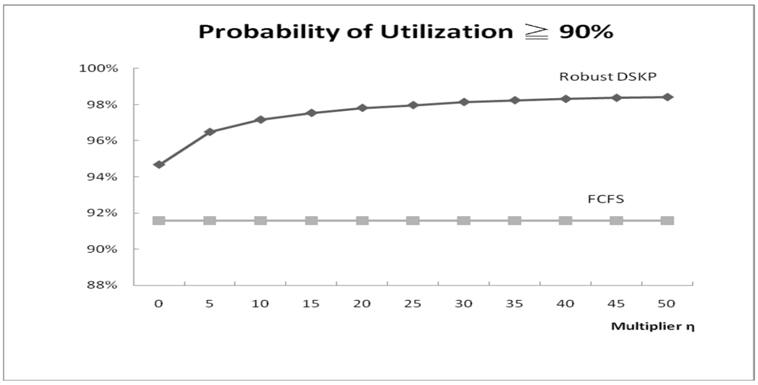

Figure 5: Multiplier and achieving rate

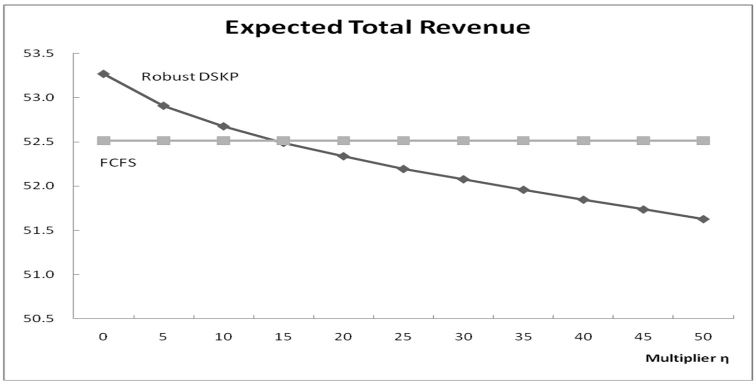

Figure 6: Multiplier and expected total revenue

DSKP policy is 53.27, while the expected total revenue under the FCFS policy is merely 52.51. The achieving rate under FCFS is 91.6%. The DSKP policy is capable of promoting the achieving rate up to 94.7%. Obviously, the DSKP policy can increase both the profitability and utilization for this saw manufacturer in the high season. If the product manager prefers to secure utilization performance and decrease risk exposure, the DSKP policy with a larger multiplier can be applied. The trade-off is decreasing profitability.

We can see in Figure 5 and Figure 6 that the achieving rate of utilization under the robust DSKP policy approaches 98%, while the expected revenue shrinks from 53.27 to 51.63. Figure 7 illustrates the trade-off between the achieving rate of targeted utilization and the expected total revenue under the robust DSKP policy. This figure can be used as an operation curve for management purposes. Managers are advised to adjust the auxiliary model according to their desired target for utilization, resulting in a robust guideline for order admission.

7. Conclusion and Research Extensions

Escalating demand in the peak season provides both a great opportunity and challenge for MTO B2B companies. The company needs a less-risky decision support model to evaluate the arriving requests in order to balance the expected total revenue with utilization downside risk.

In this paper we discuss the deterministic order admission problem with utilization constraint. The objective is to maximize the expected total revenue while restricting the

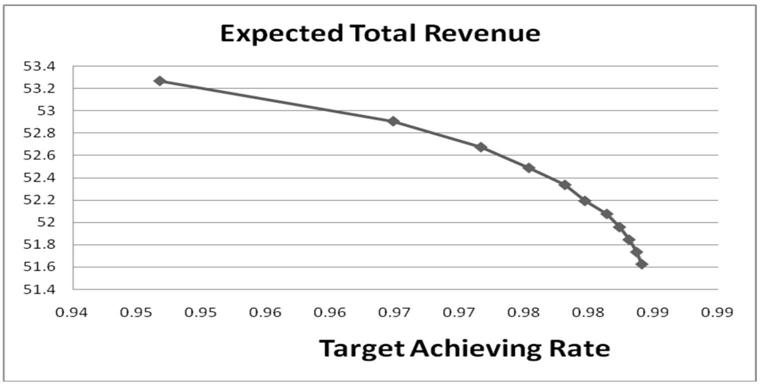

Figure 7: Target achieving rate and expected total revenue

risk of low utilization. After considering the demand patterns and decision makers' targets for capacity utilization, we propose an auxiliary model to deal with this problem. The model will indicate whether a product manager should accept or reject a realized order according to the size and margin of current order requests, available capacity in the planning horizon, and the set of unrealized orders. The optimal solutions with respect to each state then constitute an order admission policy. The preserved policy may serve a decision support function in the order-promising procedure.

The major contribution of this paper is the modelling of a deterministic order admission problem with utilization constraint and proposal of an algorithm for policy evaluation. Contrary to conventional revenue management, a high-margin order may be rejected because it includes the risk of lower capacity utilization for the factory. A low-margin order may be accepted if it fully utilizes the capacity and brings sufficient revenue. The complex nature of arriving orders means that this issue is more complicated than conventional aggregate demand planning. The results and managerial interpretations may not be so trivial. It is possible that decision-makers make mistakes by treating orders intuitively but incorrectly. This may curb the development of a heuristic requiring less computational effort, but it is still worth attempting in the future.

This paper provides a fair and quantitative evaluation process to support managers' decision procedures. It is observed that customer satisfaction is also an important factor in the MTO B2B order admission problem. Even in a set of key-account customers, some orders still have higher priority than others due to the salespeople's subjective judgment. For future studies, the rate of satisfying these orders up to a targeted level is capable of being included in a mathematical model and becoming a decision support module in operation planning systems. It is also noted that the period of the high season usually covers multiple planning periods. If we take the production capacity of each period as a knapsack, then the order admission problem will become a multiple knapsack problem. This extension also helps to relax the assumption of no order splitting applied in this research. Furthermore, if the planning horizon is a long period of time, then the waiting cost should be considered in a time-continuous model. It is possible to include these issues in future research.

8. Appendix

Proof of Lemma 1

i

Let $\lambda < \mu$. The following inequalities hold by the definition of π^*_μ.

$$\begin{cases} L(\lambda) = ETR(\pi^*_\lambda) - \lambda G(\pi^*_\lambda) \quad \geq \quad ETR(\pi^*_\mu) - \lambda G(\pi^*_\mu) & (2-\text{i}-1) \\ L(\mu) = ETR(\pi^*_\mu) - \mu G(\pi^*_\mu) \quad \geq \quad ETR(\pi^*_\lambda) - \mu G(\pi^*_\lambda) & (2-\text{i}-2) \end{cases}$$

By using $(2-\text{i}-1)+(2-\text{i}-2)$, it can be shown that $(\lambda-\mu)\left[G(\pi^*_\mu) - G(\pi^*_\lambda)\right] \geq 0$.
Because $\lambda - \mu < 0$, $G(\pi^*_\mu) \leq G(\pi^*_\lambda)$ must hold. Therefore $G(\pi^*_\mu)$ is nonincreasing in μ.
In the similar way, $\widehat{G}(\widehat{\pi}^*_\eta)$ can be verified nonincreasing in η. □

ii

$(2-\text{i}-1)$ implies the following inequality.

$$ETR(\pi^*_\lambda) - ETR(\pi^*_\mu) \quad \geq \quad \lambda G(\pi^*_\lambda) - \lambda G(\pi^*_\mu) = \lambda\left[G(\pi^*_\lambda) - G(\pi^*_\mu)\right]$$

Because $G(\pi^*_\lambda) - G(\pi^*_\mu) \geq 0$, $ETR(\pi^*_\lambda) - ETR(\pi^*_\mu)$ must be nonegative.
Therefore, $ETR(\pi^*_\mu)$ is nonincreasing in μ. Similarily, $ETR(\widehat{\pi}^*_\eta)$ is nonincreasing in η.□

iii

$(2-\text{i}-1)$ implies $L(\lambda) \quad \geq \quad L(\mu) + (\mu-\lambda)\, G(\pi^*_\mu)$.
Because $\mu - \lambda > 0$ and $G(\pi^*_\mu) \geq 0$, $L(\lambda) \quad \geq \quad L(\mu)$ is proved. □

<u>Proof of Lemma 2</u>

Let $\pi' \in \Pi$ and $\pi' \neq \widehat{\pi}^*_\eta$. By the definition of $\widehat{\pi}^*_\eta$, the following inference sustains.

$$ETR(\widehat{\pi}^*_\eta) - \eta \max\left[0, 1 - Z(\widehat{\pi}^*_\eta)\right] \geq \quad ETR(\pi') - \eta \max\left[0, 1 - Z(\pi')\right]$$
$$\Rightarrow ETR(\widehat{\pi}^*_\eta) - \eta\left[1 - Z(\widehat{\pi}^*_\eta)\right] \quad \geq \quad ETR(\pi') - \eta\left[1 - Z(\pi')\right]$$
$$\Rightarrow ETR(\widehat{\pi}^*_\eta) + \eta\left[Z(\widehat{\pi}^*_\eta)\right] \quad \geq \quad ETR(\pi') + \eta\left[Z(\pi')\right]$$
$$\Rightarrow ETR(\widehat{\pi}^*_\eta) - \eta\left[\beta - Z(\widehat{\pi}^*_\eta)\right] \quad \geq \quad ETR(\pi') - \eta\left[\beta - Z(\pi')\right]$$

Because $Z(\widehat{\pi}^*_\eta) \leq \beta$ and $-\eta\left[\beta - Z(\pi')\right] \geq -\eta \max\left[0, \beta - Z(\pi')\right]$,
$ETR(\widehat{\pi}^*_\eta) - \eta \max\left[0, \beta - Z(\widehat{\pi}^*_\eta)\right]$ is equal to or higher than
$ETR(\pi') - \eta \max\left[0, \beta - Z(\pi')\right]$.
Apparently, it implies $\widehat{\pi}^*_\eta = \arg\max_{\pi \in \Pi} \left\{ETR(\pi) - \eta \max\left[0, \beta - Z(\pi)\right]\right\}$. □

<u>Proof of Proposition 3</u>

i

It is intuitive that $Z(\widehat{\pi}^*_\eta)$ is nondecreasing in η since $\widehat{G}(\widehat{\pi}^*_\eta)$ is nonincreasing in η.
Because $Z(\widehat{\pi}^*_\eta)$ is nondecreasing but bounded by 1, there exists an asymptote $\overline{Z}$ such that $\lim_{\eta\to\infty} Z(\widehat{\pi}^*_\eta) = \overline{Z} \leq 1$. □

ii

We may use contradiction to prove the DAP is infeasible when $\lim_{\eta\to\infty} Z(\widehat{\pi}^*_\eta) < \beta$.
Suppose $\lim_{\eta\to\infty} Z(\widehat{\pi}^*_\eta) < \beta \le 1$. Because $ETR(\widehat{\pi}^*_\eta)$ is finite and $Z(\widehat{\pi}^*_\eta)$ is nondecreasing in η, it can be shown : $\lim_{\eta\to\infty}[-\eta \max\{0, \beta - Z(\widehat{\pi}^*_\eta)\}] = \lim_{\eta\to\infty}[-\eta(\beta - Z(\widehat{\pi}^*_\eta))] = -\infty$.
Therefore, $\lim_{\eta\to\infty} ETR(\widehat{\pi}^*_\eta) - \eta \max[0, \beta - Z(\widehat{\pi}^*_\eta)] = -\infty$.
According to lemma 2, $\widehat{\pi}^*_\eta = \arg\max_{\pi\in\Pi}\{ETR(\pi) - \eta \max[0, \beta - Z(\pi)]\}$ for all nonegative η.
By definition, $L(\eta) = \max_{\pi\in\Pi}\{ETR(\pi) - \eta \max[0, \beta - Z(\pi)]\} = ETR(\widehat{\pi}^*_\eta) - \eta G(\widehat{\pi}^*_\eta)$
Therefore it implies $\lim_{\eta\to\infty} L(\eta)$ approaches to $-\infty$.
Suppose DAP has a feasible policy $\pi" \in \Pi$.
That means $Z(\pi") \ge \beta$, thus $\eta G(\pi") = 0$, and $ETR(\pi") - \eta G(\pi") = ETR(\pi")\ \forall \eta$.
It is contradiction with $\lim_{\eta\to\infty} L(\eta) = -\infty$. □

iii

According to previous statement, if DAP is feasible, then $\lim_{\eta\to\infty} Z(\widehat{\pi}^*_\eta) \ge \beta$.
Given a nonnegative auxiliary multiplier η^1, suppose $Z(\widehat{\pi}^*_{\eta^1}) < \beta$. Since $Z(\widehat{\pi}^*_\eta)$ is nondecreasing in η, there exists an increasing sequence $\{\eta^k\}$ such that $Z(\widehat{\pi}^*_{\eta^{k-1}}) < \beta$ and $Z(\widehat{\pi}^*_{\eta^k}) \ge \beta$.
Let $\eta^k = \widetilde{\eta}$ and $\eta^{k-1} = \widetilde{\eta} - \varepsilon$, then the first part of proposition 3 − iii is proved since $\widehat{\pi}^*_\eta$ is a feasible policy for DAP.
Because $ETR(\widehat{\pi}^*_\eta)$ is nonincreasing on η, $ETR(\widehat{\pi}^*_{\widetilde{\eta}})$ is equal to or higher than $ETR(\widehat{\pi}^*_\eta)$ for all $\eta > \widetilde{\eta}$. Therefore it can be easily shown that $\widehat{\pi}^*_{\widetilde{\eta}}$ is the optimal policy among all the feasible policies for DAP. □

References

[1] A. Arreola-Risa: Integrated multi-item production-inventory systems. *European Journal of Operational Research*, **89** (1996), 326–340.

[2] N. Balakrishnan, V. Sridharan, and W. Patterson: Rationing capacity between two product classes. *Decision Sciences*, **27** (1996), 185–213.

[3] N. Balakrishnan, W. Patterson, and V. Sridharan: Robustness of capacity rationing policies. *European Journal of Operations Research*, **115** (1999) 328–338.

[4] M. Barut and V. Sridharan: Design and evaluation of a dynamic capacity apportionment procedure. *European Journal of Operational Research*, **155** (2004), 112–133.

[5] M. Barut and V. Sridharan: Revenue management in order-driven productions. *Decision Sciences*, **36** (2005), 287–316.

[6] M.S. Bazaraa and C.M. Shetty: *Nonlinear Programming* (John Wiley & Sons, NY, 1979).

[7] D. Bertsimas and I.CH. Paschalidis: Probabilistic service level guarantees in make-to-stock manufacturing systems. *Operations Research*, **49** (2001), 119–133.

[8] J.R. Birge and F. Louveaux: *Introduction to Stochastic Programming* (Springer-Verlag, NY, 1997).

[9] R. Bollapragada and U.S. Rao: Replenishment planning in discrete-time capacitated non-stationary stochastic inventory systems. *IIE Transactions*, **38** (2006), 583–595.

[10] S.L. Brumelle and D. Walczak: Dynamic allocation of airline seat inventory with batch arrivals. *The Conference Proceedings of the 1997 Air Transport Research Group of the WCTR Society.*

[11] E. Carrizosa, E. Conde, and M. Munoz-Marquez: Admission policies in loss queuing models with heterogeneous arrivals. *Management Science*, **44** (1998), 311–320.

[12] C.Y. Chen, Z.Y. Zhao, and M.O. Ball: Quantity and due date quoting available to promise. *Information Systems Frontiers*, **3** (2001), 477–488.

[13] C.Y. Chen, Z.Y. Zhao, and M.O. Ball: A model for batch advanced available-to-promise. *Production and Operations Management*, **11** (2002), 424–440.

[14] I.T. Christou and S. Ponis: A hierarchical system for effective coordination of available-to-promise logic mechanisms. *International Journal of Production Research*, **47** (2008), 1–16.

[15] G.A. DeCroix and A. Arreola-Risa: Optimal production and inventory policy for multiple products under resource constraints. *Management Science*, **44** (1998), 950–961.

[16] P. Devlin, C. Thielemier, and D.E. Wehrlin: Lost utilization-constraint performance management. *Semiconductor Manufacturing, 2003 IEEE International Symposium* (2003), 51–54.

[17] R. Evans: Inventory control of a multiproduct system with a limited production resource. *Naval Research Logistics*, **14** (1967), 173–184.

[18] P. Glasserman: Allocating production capacity among multiple products. *Operations Research*, **44** (1996), 724–734.

[19] F.H. de B. Harris and J.P. Pinder: A revenue management approach to demand management and order booking in assemble-to-order manufacturing. *Journal of Operations Management*, **13** (1995), 299–309.

[20] M. Ketzenberg, R. Metters, and J. Semple: A heuristic for multi-item production with seasonal demand. *IIE Transactions*, **38** (2006), 201–211.

[21] A.J. Kleywegt and J.D. Papastavrou: The dynamic and stochastic knapsack problem. *Operations Research*, **46** (1998), 17–35.

[22] A.J. Kleywegt and J.D. Papastavrou: The dynamic and stochastic knapsack problem with random size items. *Operations Research*, **49** (2001), 26–41.

[23] K. Kogan: Unbounded knapsack problem with controlled rates: the case of a random demand for items. *Journal of the Operational Research Society*, **54** (2003), 594–604.

[24] T.G. de Kok: Capacity allocation and outsourcing in a process industry. *International Journal of Production Economics*, **68** (2000), 229–239.

[25] C. Ku and S. Jordan: Access control to multiserver loss queues in series. *IEEE Transaction on Automatic Control*, **42** (1997), 1017–1023.

[26] T.C. Lee and M. Hersh: A model for dynamic airline seat inventory control with multiple seat bookings. *Transportation Science*, **27** (1993), 252–265.

[27] S.A. Lippman: Applying a new device in the optimization of exponential queuing systems. *Operations Research*, **23** (1975), 687–710.

[28] S.A. Lippman and S. Ross: The streetwalkers' dilemma: a job shop model. *SIAM Journal on Applied Mathematics*, **20** (1971), 336–342.

[29] B.L. Miller: A queuing reward system with several customer classes. *Management Science*, **16** (1969), 234–245.

[30] E.L. Örmeci, A.N. Burnetas, and H. Emmons: Dynamic policies of admission to a two-class system based on customer offer. *IIE Transactions*, **34** (2002), 813–822.

[31] J.D. Papastavrou, S. Rajagopalan, A.J. Kleywegt: The dynamic and stochastic knapsack problem with deadlines. *Management Science*, **42** (1996), 1706–1718.

[32] A.P. Perez and P. Zipkin: Dynamic scheduling rules for multiproduct make-to-stock queue. *Operations Research*, **45** (1997), 919–930.

[33] M.L. Puterman: *Markov Decision Process: Discrete Stochastic Dynamic Programming* (Wiley, NY., 1994).

[34] C.A. Ptak: *ERP : Tools, Techniques, And Applications For Integrating The Supply Chain* (Boca Raton, StateFla., 2000).

[35] M. Scott: A queuing process with some discrimination. *Management Science*, **16** (1969), 227–233.

[36] A. Sen and A.X. Zhang: The newsboy problem with multiple demand classes. *IIE Transactions*, **31** (1999), 431–444.

[37] S.V. Sridharan: Managing capacity in tightly constrained systems. *International Journal of Production Economics*, **56-57** (1998), 601–610.

[38] P.W. Stonebraker: *Operations strategy : focusing competitive excellence* (Allyn and Bacon, Boston , 1994).

[39] K. Talluri and G. Van Ryzin: *The theory and practice of revenue management* (Springer, NY, 2004).

[40] Y. Yoshitomi, H. Ikenoue, T. Takeba, and S. Tomita: Genetic algorithm in uncertain environments for solving stochastic programming problem. *Journal of the Operations Research Society of Japan*, **43** (2000), 266–290.

[41] Z. Zhao, M. O. Ball, and M. Kotake: Optimization-based available-to-promise with multi-stage resource availability. *Annals of Operations Research*, **135** (2005), 65–85.

Andy Wu
Graduate Institute of Business Administration
National Taiwan University
Floor 9, No.1, Sec. 4, Roosevelt Road, Taipei
Taiwan
E-mail: d92741003@tu.edu.tw