The impact of estimation error on the dynamic order admission policy in B2B MTO environments

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ABSTRACT

When swarming demands cause stringent capacity situations, order promising becomes a challenging job. However, a dynamic order admission policy by utilizing the concept of revenue management may find a good way to solve the problem. Unfortunately, the expected profit under different dynamic order admission policies is sensitive to the estimation error of order forecasts. In this paper, the impact of estimation error is investigated under various order structures. The post analysis is performed and shows significant statistical difference among the optimal unbiased DSKP policy, biased DSKP policy, and FCFS policy. The results reveal the robustness and superiority of DSKP policy in most scenarios.

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1. Introduction

In the make-to-order, business-to-business (MTO B2B) environments, swarming demand caused by seasonal factor or new product launching frequently interfere with daily operations of sales or product managers. These managers sometimes may fail to fulfill all order requests because the planning capacity is insufficient to satisfy all demands in the high season. Tool machine, fashion apparel and shoe making industries frequently face this stringent capacity problem (Franco, Sridharan, & Bertrand, 1995; Sridharan, 1998). Evidences show this problem not only bothers the planners of traditional manufacturing industries, but also annoys the leading companies in the semiconductor industries, e.g., TSMC, UMC, and Chartered, etc. (David & Andy, 2007).

To handle this problem, Harris, de, and Pinder (1995) suggested applying the concept of revenue management to manufacturing industries. Because their work focused on the manufacturers with continuous production process, the order admission policy proposed by Harris and Pinder is a kind of *inventory rationing* policy for make-to-stock (MTS) environments. This inventory rationing policy is very similar to the *booking limit control* in airline, hotel, or car rental industries. Balakrishnan, Sridharan, and Patterson (1996, 1999) proposed another heuristic *capacity rationing* policy for a MTO company which segments orders into two classes by their margins. In each class, the number of orders follows Poisson distributions; therefore, the aggregate demand is an exponential random variable. Their capacity rationing policy is made according to the expected value of the approximated class demand. Later, Barut and Sridharan (2004, 2005) extended their researches for

multi-class demands and proposed a revised heuristic. However, some properties of MTO B2B environments had not been captured in previous researches. For instance, MTO B2B companies usually have limited business clients for contact and face finite planning horizon. For each order, its margin and order size are possibly distinct. Furthermore, it is difficult to identify any specific arriving pattern of orders in MTO B2B environments. In order to handle the above characteristics in MTO B2B environments, David and Andy (2007) reformulated the problem as a discrete Markov Decision Problem (MDP), or more specifically, a Dynamic and Stochastic Knapsack Problem (DSKP). It turned out that the optimal policy follows a Markov deterministic policy with revenue-threshold decision rules.

Unfortunately, all these researches assume that parameters of order size distributions are known with fixed quantities in their models. These situations rarely happen in the real world. *Production and operations managers repeatedly express the view that forecasting is a critical activity since the accuracy of the forecast significantly impacts the quality of operation plans. However, if the forecast has considerable error, even well-conceived plans and excellent operating performance against the plan may result in very disappointing productivity* (Lee & Adam, 1986). Apparently, the more estimation errors in the forecast, the less willingness planners are likely to adopt a dynamic order admission policy in practice. In the researches of Becker, Hall, and Rustem (1994) and Balakrishnan et al. (1999), they also concluded that if a model is not sensitive to estimation error, it can make the model more risk-averse and more attractive for the planners. Based on these statements, we intend to investigate the impact of different types of estimation error under various order structure. Three types of estimation error are discussed including error of spikedness, error of mean, and error of deviation. Also, various characteristics of order structure

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are explored such as margin attractiveness, capacity tightness, number of orders, demand lumpiness, and order size variation. Finally, a post analysis is performed to systematically test the model robustness and effectiveness of DSKP policy against estimation errors in order size parameters. We believe that understanding the impact of estimation error with respect to various order structures can help planners to choose the best policy to be applied.

The remainder of this paper is organized as follows: Section 2 will briefly describes an optimal dynamic order admission procedure for MTO B2B corporations based on David and Andy's work. Next, the structure of our experimental design is presented. Also, the results from our simulation experiments are analyzed in Section 4. At last, conclusions and further researches are followed.

2. Optimal order admission policy

A planner must decide whether to accept or reject an order request when it arrives if the stringent capacity situation happens in the MTO B2B environments. If the request is accepted, the order record is created and scheduled into the master production schedule (MPS).

In the order admission problem, an order can be primarily characterized by two dimensions: the margins and the required capacity of an order. The margin of an order is defined as the gross return per unit capacity required to fulfill an order. The capacity requirement of an order is determined by the capacity consumption in a bottleneck stage of production process. The margin is known and predetermined when order arrived. The capacity requirement, also referred as the size of an order, generally follows a distinguishing distribution. It is also assumed that demand visibility will increase for a B2B manufacturer as time passes by. In a normal situation, all

information about potential orders will be revealed before the end of planning horizon. The planner is risk-neutral and the objective is to achieve maximal expected revenue for the peak season.

In reality, the capacity space is finite and size distributions have a discrete form. Thus, the optimal order admission control can be modeled by a DSKP. The optimal policy can be proved as a Markov deterministic policy with revenue-threshold decision rules (David & Andy, 2007). It has been shown that the revenue improvement by taking the optimal control under unbiased forecast is huge.

Before we can explore the impact of estimation error on the dynamic order admission policy, we need to briefly introduce the mathematical model of order admission problem in this section. In Section 2.1, the formulation of the optimal control proposed by David and Andy (2007) is reviewed, and the notation used in that order admission problem formulation is summarized at Table 1. In addition, the performance measure used by our simulated experiments will be defined in Section 2.2.

2.1. Formulation of the optimal order admission control

Let Φ denotes the "real" specification and parameter sets of order size distributions. Size of potential orders follows the probability mass function f_Φ. Suppose there are T potential orders that may be arrived in the entire planning horizon. Decision epoch $t = 1, 2, \ldots, T$ is a time point when the tth order request arrives. The events of simultaneous order arrivals, order cancellation, and urgent orders are assumed to be happened with probability zero. It should be noted that t actually presents the sequence of order realization rather than explicit arrival time of orders.

A discrete-time model is constructed to present the dynamic information process. The state includes four kinds of information, i.e., the available capacity C_t, set of potential orders $\mathbf{U}_t$, identity of current arriving order $\mathbf{I}_t$, and its order size $X(\mathbf{I}_t)$. C_1 is defined as the initial available capacity estimated for the planning horizon. Information state $\xi_t \equiv (C_t, \mathbf{U}_t, \mathbf{I}_t, X)$ is observable when the tth order information gets confirmed.

$\mathbf{I}_t$ is a $1 \times T$ index vector for which the nth element is 1 if the tth arrival is order n. $\mathbf{U}_t$ is a $1 \times T$ index vector, too. Its nth element is 1 if order n has not arrived yet till epoch $t - 1$. $\mathbf{U}_1$, being the initial set of all potential orders, is an index vector with all elements being 1, i.e., $\mathbf{U}_1 = [1]_{1 \times T}$. The following example is used to illustrate the meaning of these index vectors. Suppose $T = 5$ and the arriving order at the 3rd decision epoch is order number 2, then $\mathbf{I}_3 = (0, 1, 0, 0, 0)$. If order number 1, 2, and 3 are not realized before epoch 3, then $\mathbf{U}_3 = (1, 1, 1, 0, 0)$. The setting of $\mathbf{U}_t$ and $\mathbf{I}_t$ gives a nice property of additivity in policy evaluation procedure. Thus, the $\mathbf{U}_t$ set of epoch 4 can be represented as $\mathbf{U}_4 = \mathbf{U}_3 - \mathbf{I}_3$.

The optimal order admission policy is a kind of revenue-threshold policy. Revenue threshold $R_\Phi(\xi)$ represents the opportunity/displacement cost for accepting an order. Let $P(\mathbf{I}_t)$ denote the unit margin of an arriving order $\mathbf{I}_t$. Under the revenue-threshold rules, the optimal action $a_{t,\Phi}^*$ corresponding to the tth order request can be presented below

$$a_{t,\Phi}^*(C_t, \mathbf{U}_t, \mathbf{I}_t, X) = \begin{cases} 1, & \text{if } X(\mathbf{I}_t) \leqslant C_t \text{ and } P(\mathbf{I}_t)X(\mathbf{I}_t) \geqslant R_\Phi(\xi_t), \\ 0, & \text{if } X(\mathbf{I}_t) > C_t \text{ or } P(\mathbf{I}_t)X(\mathbf{I}_t) < R_\Phi(\xi_t). \end{cases}$$

(1)

The optimal decision is to accept the current request, i.e., $a_{t,\Phi}^* = 1$, if the potential profit is equal or higher than the revenue threshold, i.e., $P(\mathbf{I}_t)X(\mathbf{I}_t) \geqslant R_\Phi(\xi_t)$. Otherwise, the optimal action is to reject, i.e., $a_{t,\Phi}^* = 0$.

The managerial interpretation of the threshold rules is intuitive. When a request is accepted, a portion of the capacity is preserved for this order and the total available capacity decreases. But this action may also induce an opportunity loss for rejecting later orders.

Table 1
Table of notations.

Φ	Real specification and parameter sets of order size distributions
f_Φ	Probability mass function of order size distributions
t	Decision epoch when the tth order request arrives, $t = 1, \ldots, T$
C_t	Available capacity at epoch t
$\mathbf{U}_t$	Set of potential orders at epoch t
$\mathbf{I}_t$	The identity of the currently arriving order
$X(\mathbf{I}_t)$	The required capacity to fulfill the corresponding order request
ξ_t	State at epoch t, $\xi_t(C_t, \mathbf{U}_t, \mathbf{I}_t, X)$
$R_\Phi(\xi_t)$	Revenue threshold at state ξ_t
$P(\mathbf{I}_t)$	The unit margin of an arriving order $\mathbf{I}_t$
$a_{t,\Phi}^*$	The optimal action, $a_{t,\Phi}^* \in \{0, 1\}$
EV_Φ^*	The expected accrued revenue under the optimal policy
ζ_t	Semi-state, $\zeta_t \equiv (C_t, \mathbf{U}_t)$
$\Pr\{\zeta_{t+1}|\zeta_t\}$	Transition probability from ζ_t to ζ_{t+1}
$\mathbf{ACC}^*(\zeta_t)$	The accepted zone under optimal policy
$\mathbf{REJ}^*(\zeta_t)$	The rejected zone under optimal policy
a_t^{fcfs}	The action under FCFS
EV_Φ^{fcfs}	The expected accrued revenue under FCFS
$\mathbf{ACC}^{fcfs}$	The accepted zone under FCFS
$\mathbf{REJ}^{fcfs}$	The rejected zone under FCFS
$\hat{\Phi}$	Estimated specification and parameter sets of order size distributions
SDBD	Standardized difference between biased DSKP and DSKP performance
SDBF	Standardized difference between biased DSKP and FCFS performance
N	The number of orders, $N = T$
P_n	Margin of order number n
S_n^l	Minimum of size of order number n
S_n^u	Maximum of size of order number n
q_n	Spikedness, it is the parameter of a Bernoulli distribution
ρ	Error multiplier of spikedness
δ	Error multiplier of mean
γ	Error multiplier of deviation
V_{ik}^{DSKP}	The total revenue brought by DSKP at scenario i replicate k
V_{ik}^{Biased}	The total revenue brought by Biased DSKP at scenario i replicate k
V_{ik}^{FCFS}	The total revenue brought by FCFS at scenario i replicate k
V_i^{DSKP}	The expect total revenue brought by DSKP at scenario i
V_i^{FCFS}	The expect total revenue brought by FCFS at scenario i