Proceedings of the Eastern Asia Society for Transportation Studies, Vol. 5, pp. 570 - 580, 2005

REVENUE MANAGEMENT FOR AIR CARGO SPACE WITH SUPPLY UNCERTAINTY

Kuancheng HUANG
Assistant Professor
Dept. of Transportation Technology and Management
National Chiao Tung University
No. 1001, Ta Hsueh Road, Hsinchu City
300 Taiwan
Fax: 886-3-5720844
E-mail: kchuang@cc.nctu.edu.tw

Wenhsiu HSU
Research Associate
Dept. of Transportation Technology and Management
National Chiao Tung University
No. 1001, Ta Hsueh Road, Hsinchu City
300 Taiwan
Fax: 886-3-5720844
E-mail: Wena.tem87@NCTU.edu.tw

Abstract: This study is aiming to apply the revenue management (RM) concept, a common practice in air passenger operation, to the control of air cargo space. The RM problem of air cargo differs from that of the air passenger in a lot of aspects. The most important one is the uncertainty of air cargo space supply. Meanwhile, the problem of denied boarding caused by supply uncertainty must be dealt with carefully. A single-leg air cargo RM problem is tackled by a dynamic programming (DP) model to derive the optimal control policy and the expected revenue. Numerical experiments based on the actual operational data of a Taiwanese international airline are performed to verify the model. The result shows, to raise revenue by RM, it is critical for the airlines to accurately forecast and control the cargo space supply of a flight.

Key Words: revenue management, dynamic programming, air cargo, supply uncertainty

1. INTRODUCTION

Due to world trade liberalization and global logistics operation, air cargo industry has been booming for the past decade, and recent forecasts also project a very promising development for the next two decades. For example, one of the aircraft manufactures (Boeing, 2004) estimates that the average yearly growth rate is as high as 6.2%. Particularly, for the traffic related to Asia markets, the growth rate will exceed the world average, and the share of global air cargo traffic will increase from 47.6% to 59.4% in 2023. Meanwhile, revenue management (RM) has become a common practice in air passenger operation since American Airlines successfully applied several RM techniques to raise its revenue. Nonetheless, revenue management has not become popular in air cargo industry. This study is thus aiming to apply the RM concept to the control of air cargo space, so airlines can better utilize limited resource to increase their revenue.

There exist several major differences between the revenue management of air cargo and that of air passengers. The most important one is the supply uncertainty of air cargo space available on a flight. When compared to the number of seats of a flight, the available cargo space of a flight is affected by many factors, which are uncertain by nature and cannot be determined in advance. Moreover, the problem of denied boarding caused by supply uncertainty becomes a critical issue in the decision process of airlines.

This study defines a single-leg air cargo RM problem, which take into account the supply uncertainty and the incurred penalty for denied boarding. The problem is tackled by a dynamic programming (DP) model, which comprises the booking period as the stage and the available cargo space (in terms of tons) as the state. Numerical experiments are performed to verify the model and to examine the critical factors related. Though market segmentation and price discrimination are not common in the air cargo industry, the test problems of the numerical experiment are designed based on the actual operational data of a Taiwanese international airline. The results are helpful for the airlines to understand the special features of the air cargo industry and their impacts in terms of revenue management.

This paper is organized as follows: in the next chapter, problem backgrounds are elaborated, and related previous researches are reviewed. In addition to problem definition, the dynamic programming model is developed in the third chapter. The numerical experiment together with the results of the sensitivity analysis are described in the fourth chapter. Finally, the findings of this study are concluded in the fifth chapter.

2. PROBLEM BACKGROUNDS AND PRIOR RESEARCHES

The development of RM theories and techniques has been undertaken for a long time. Particularly, after the implementation at American Airlines (Barry *et al.*, 1992) aiming to cope with the new business environment in the post-deregulation era, revenue management has become a common practice in the airline industry. Moreover, the application of revenue management has been extended to several other industries, such as rail, car rental, hotel, and many other areas of manufacturing and service industries. However, how to realize the basic concept of revenue management, "selling the right seat to the right customer at the right price," remains to be a challenge.

The employment of overbooking, an industry practice for decades, could be thought as the beginning of the application of RM techniques in the aviation industry. Prior researches in this area can be found in the paper by Rothstein (1985). However, it is later realized that, to compete with the rising low-cost carriers after the Deregulation, major carriers must carefully segment their markets, as the characteristics of the customers are diverse. Thus, the same cabin class is differentiated as many kinds of products, called fare classes. In the nested reservation scheme, sophisticated approaches with various terms and conditions are developed to implement the seat inventory control policy, which makes the accept/deny decision for the booking request of a specific fare class.

Most early seat-inventory control researches rely on the following six assumptions: 1) sequential booking classes; 2) low-before-high fare booking arrival pattern; 3) statistical independence of demands between booking classes; 4) no cancellation or no-shows; 5) single flight leg; and 6) no batch booking (McGill and Van Ryzin, 1999). For example, Belobaba (1989) develops the so-called EMSR heuristic. The key concept of the EMSR approach is to compare the marginal value of the seat with the ticket price of the fare classes while making the accept/deny decision. Though it provides the optimal solution only for the two-fare case, one advantage of the EMSR approach is that its implementation is relatively easy. Besides, the generated solution appears to be very close to the optimal solution. Nonetheless, Curry (1990), Wollmer (1992), Brumelle and McGill (1993) further develop the method to find the global optimal solution.

Above research works are often referred as the static models, as the demand for each fare class is modeled by a random variable, based on the first and the second assumption in the previous paragraph. These two assumptions greatly simplify the complexity of RM problems, but some demand characteristics are inevitably overlooked. To fully incorporate the time-dependent characteristic of demand, Lee and Hersh (1993) develop a dynamic programming (DP) model, in which the request probabilities based on Poisson arrival processes are used to represent the demand pattern. Thus, the assumption of sequential arrival of booking classes is relaxed and the booking patterns for different classes, characterized by the probabilities indexed by booking periods, are allowed to overlap in time. In addition, Lee and Hersh (1993) further generalize the sixth assumption of single-seat booking to batch booking, and the request probabilities turn out to depend on booking size as well.

Many other research works have been done with respect to seat inventory control policy. Weatherford and Bodily (1992) provides a very general approach to categorize the nature of RM problems, and the survey paper by McGill and van Ryzin (1999) serves as an excellent reference of RM research works. However, very few researches have addressed the RM problem from the viewpoint of air cargo industry. Kasilingam (1997) highlights the characteristics and complexities of air cargo revenue management, which differs from air passenger revenue management in many aspects. The most important one is the uncertainty of air cargo space supply. There are many factors related to the air cargo space available on a flight. Below are some important ones among them:

- The flight plans submitted by airlines need to be approved by the air traffic control (ATC) authorities before take-off. The air route assignment approved by the ATC authorities as well as the weather conditions along the routes can affect the amount of fuel required and, thus, the payload of the flight. In addition, the maximum take-off weight of an aircraft can also be affected by the temperature and humidity of the runway.
- In addition to the gross weight, the air cargo rating system also considers the volume of the shipment, which is converted into the so-called volume weight by being divided by a constant, 6000 cm^3/kg. The chargeable weight, on which the airlines charge the forwarders, is the greater of the gross weight and the volume weight. Thus, while selling the cargo space in terms of tons or kg's, the airlines are not sure that the aircraft can handle the shipments for the space sold. This loading issue is further complicated by the fact that the shape of the shipments can cause some problems while being loaded into the containers and the pallets of the aircraft.
- Finally, significant amount of air cargo nowadays are carried in the belly cargo space of passenger aircrafts. For this case, the luggage of passengers has a higher priority over the air cargo shipments. However, the airlines do not have the full control of the number of passengers who will actually show up, not to mention the amount of luggage to be checked.

Kasilingam (1997) provides an overbooking model, taking into account the effect of the cancellation/no-shows and the supply uncertainty, a unique characteristic for the air cargo industry. However, there is no research done to address the typical inventory control issue for air cargo. Based on the single-leg DP model in Lee and Hersh (1993), this study develops the model to provide the optimal control policy, given the supply uncertainty inherited in the air cargo RM problems.

3. DYNAMIC PROGRAMMING MODEL

While facing the uncertainty of cargo space supply, the airlines usually sell the cargo space to the forwarders based on a forecast value. The actual supply is materialized right before take-off. These two quantities are denoted by C and by $\boldsymbol{T}$ for the rest of the paper. To capture the randomness of the cargo space supply, $\boldsymbol{T}$ is modeled as a random variable with known distribution in this study. The number of denied boarding depends both on the space unsold before take-off and on the actual supply. Figure 1 illustrates the relation among these factors.

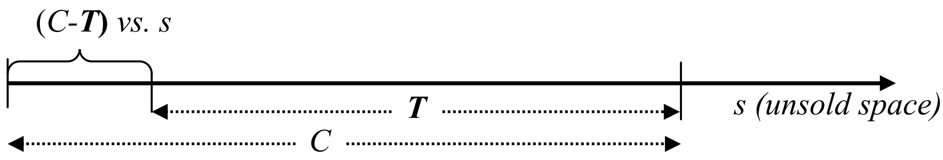

Figure 1. Number of Denied Boarding

If the actual supply is smaller than the forecasted supply, there is a chance that denied boarding could happen. However, the occurrence of denied boarding also depends on the number of space not sold before take-off, denoted by s. If the unsold space is less than the gap between the forecast and the actual supplies, a number of $b=(C-\boldsymbol{T})-s$ denied boarding is resulted in. The cost arising from denied boarding can be modeled by a function $D(b)$, which links the relation between the cost and the number of denied boarding. Of course, the choice of the function $D(b)$ depends on the policy and the cost structure of airlines. The function can incorporate the compensation paid to the customers. However, it should also consider the consequent loss such as the extra storage and handling cost incurred for holding the shipments and the degradation of company reputation or customer loyalty. The negative impact of denied boarding is modeled as a penalty for the rest of the paper and is a key issue in the numerical experiment. Based on the DP model introduced in the following paragraphs, the penalty function does not have to be linear or of any simple form. Thus, the airlines can choose the one that truly reflects their practical considerations.

Based on the model developed by Lee and Hersh (1993), the study defines and tackles a single-leg air cargo space RM problem with supply uncertainty by a dynamic programming (DP) model, which comprises the booking period as the stage and the available cargo space (in terms of tons) as the state. The air cargo demand is assumed to follow a Poisson random process, and the booking pattern is modeled by the request probabilities varying with booking period, fare class, and booking size. The supply uncertainty characteristic and the penalty for denied boarding are modeled at the last stage of the DP formulation. The optimal control policy and the expected revenue are derived by solving the DP problem.

The formulation of the DP model is as follows:
Notation:

- i: indices of fare classes (i=1 .. k, assuming i=1 is the highest-fare class and i=k is the lowest.)
- n: indices of decision periods (n=0 .. N, assuming n=0 is the period of take-off.)
- m: indices of booking size (m=1 .. M_i, which is the maximum booking size.)
- s: available cargo space
- F_i: rate of fare class i
- P_i^n: probability of booking request for fare class i at decision period n
- C: forecast of cargo space supply
- $\boldsymbol{T}$: random variable to model the actual cargo space supply
- $D(b)$: penalty function in terms of the number of denied boarding, b
- f_s^n: expected total revenue given s available space at decision period n

Based on above notation, the recursive equation of the DP model is as follows:

$$f_s^n = \begin{cases} \sum_t Pr(\boldsymbol{T} = t) D(C - \boldsymbol{T} - s) & \textit{for } n = 0, s \geq 0 \\ f_0^{n-1} & \textit{for } n > 0, s = 0 \\ P_0^n f_s^{n-1} + \sum_{i=1}^{k} P_i^n \, max(F_i + f_{s-1}^{n-1}, f_s^{n-1}) & \textit{for } n > 0, s > 0 \end{cases} \quad (1)$$

where $P_0^n = 1 - \sum_i^k P_i^n$ *, representing the probability of no booking request*

At the time of take-off (n=0), the expected revenue is determined based on the number of denied boarding and the resulted penalty, weighted by the probabilities of cargo space supply. For the case of zero available space (s=0), no decision can be made, and the expected revenue is naturally equal to that of the previous stage. As for the general case (n>0 and s>0), the expected revenue as well as the optimal control policy depends on the two quantities, $F_i + f_{s-1}^{n-1}$ and f_s^{n-1}, inside the *max* function. If the former is greater, the space should be sold to the booking request; otherwise, the space should be reserved to the next stage. This decision is made based on a concept very close to the EMSR approach in Belobaba (1989). The marginal value δ, defined as in (2), is a function of the current decision period and the number of available spaces. By comparing the marginal value with the rate of each fare class, the accept/deny decision for the optimal control policy can be determined.

$$\delta(n, s) = f_s^n - f_{s-1}^n \quad (2)$$

With the introduction of one more symbol G_{im}^n to describe the probability of the booking request with size m for fare class i at decision period n, Equation (1) can be modified to model the case of multiple-seat booking as (3), and the marginal value can be defined as (4).

$$f_s^n = \begin{cases} \sum_t Pr(\boldsymbol{T} = t) D(C - \boldsymbol{T} - s) & \textit{for } n = 0, s \geq 0 \\ f_0^{n-1} & \textit{for } n > 0, s = 0 \\ P_0^n f_s^{n-1} + \sum_{i=1}^{k} P_i^n \sum_{m=1}^{M_i} G_{im}^n \, max(F_i + f_{s-1}^{n-1}, f_s^{n-1}) & \textit{for } n > 0, s > 0 \end{cases} \quad (3)$$

$$\delta_m(n, s) = \frac{1}{m}(f_s^n - f_{s-m}^n) \quad (4)$$

4. NEMERICAL EXPERIMENT

The numerical experiment is performed based on the test problems, which includes the operational data from a Taiwanese international carrier. The actual capacities of the 747-400 freighters for the Taipei-Los Angeles route were collected during January and February in 2004. After fitting the raw data, a normal distribution is used to represent the random variable for uncertain cargo space supply. The mean of the normal distribution is chosen to be 100 tons, and the standard deviation is 3.07 tons. In the DP model, this distribution is further transformed to a discrete distribution shown in Figure 2.

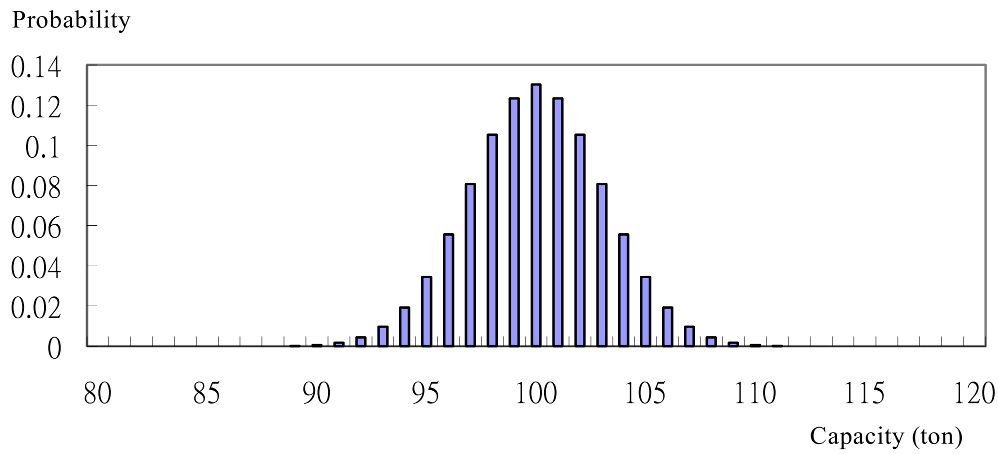

Figure 2. Distribution of Cargo Space Supply

To characterize the demand side, the airway bills of those flights were collected. In average, there are 40 airway bills per flight. The number of decision periods is chosen to be 300 to ensure that, in the Poisson arrival process, the probability of more than two booking requests resulted within a period is negligible. The analysis of the airway bills also suggests that, in terms of batch-booking size, the mean is 2.5 tons and the standard deviation is 1.78 tons. The probabilities with respect to various booking size is thus modeled by the discrete probability distribution shown in Figure 3.

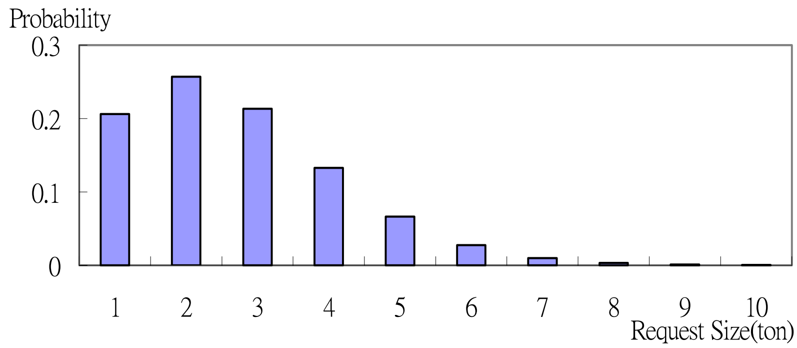

Figure 3. Distribution of Batch-Booking Size

Though market segmentation and other RM techniques are not common in the air cargo industry at this moment, the concept of fare classes have been proposed as in Ingold and Huytom (2000). In this study, three fare classes are assumed, and their associated rates and probabilities of occurrence are summarized in Table 1. Particularly, the penalty for the denied boarding in the base case of the sensitivity analysis is assumed to be the rate of the lowest booking class, i.e. $85/kg. In addition, based on the assumption of demand composition in Table 1 and the distribution of booking size in Figure 3, the request probability for each fare class of each booking size at each period can be determined according to the Poisson arrival process.

Table 1. Fare Classes in Test Problems

Classes	Rate ($/kg)	Demand Composition
Class 1	$f_1 = 125$	0.15
Class 2	$f_2 = 100$	0.60
Class 3	$f_3 = 85$	0.25

To understand the behavior of the model in terms of the expected total revenue and the optimal control policy, sensitivity analyses are conducted with respect to the two critical factors in the model, supply uncertainty and penalty for denied boarding. Particularly, the parameter *sd* stands for the level of supply uncertainty. The case of *sd*=1 represents the situation where the standard deviation is equal to 3.07, the original one calibrated from the raw data. Thus, the standard deviation of the random variable $\boldsymbol{T}$ in the test problems is 3.07×*sd*. On the other hand, the parameter *d* is used to represent the level of penalty. The case of *d*=1 is for the situation of \$85/kg, and the actual penalty paid for denied boarding in the test problems is \$85/kg×*d*. The results and the findings of the sensitivity analysis are summarized in the following sections.

4.1 Analysis of Expected Revenue

For the test problems in this numerical experiments, the expected revenue can be derived by computing the objective function value, f_s^n for s=100 and n=300. As the supply uncertainty increases, the airlines are more likely to pay the denied-boarding penalty. Therefore, the expected revenue should decrease. Moreover, the higher the penalty is, the greater the revenue decrease is supposed to be. By varying the values of the two parameters, the numerical experiment is designed to investigate the effects of the two factors. The situation of no supply uncertainty (i.e. *sd*=0) and no penalty for denied boarding (i.e. *d*=0) is used as the base case. The expected revenues for the various test problems are divided by that of the base case to evaluate the effect of revenue decrease. Figure 4 and Figure 5 show the ratios between the test cases and the base case.

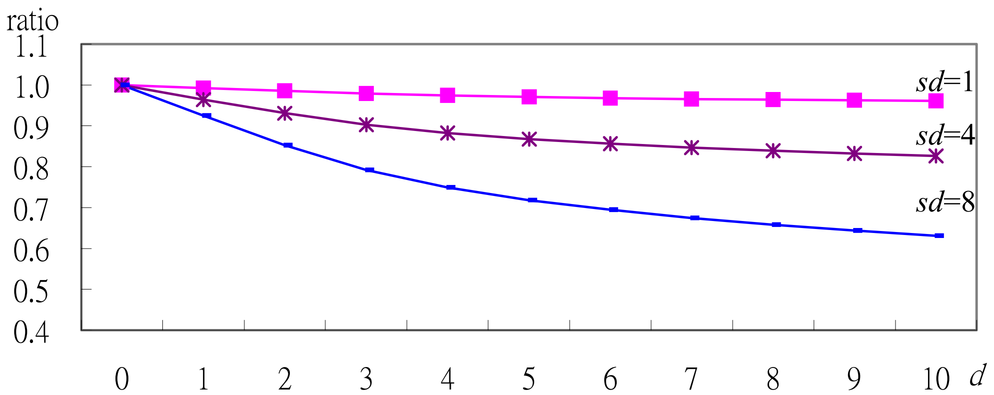

Figure 4. Effect of Penalty on Revenue for Various Levels of Supply Uncertainty

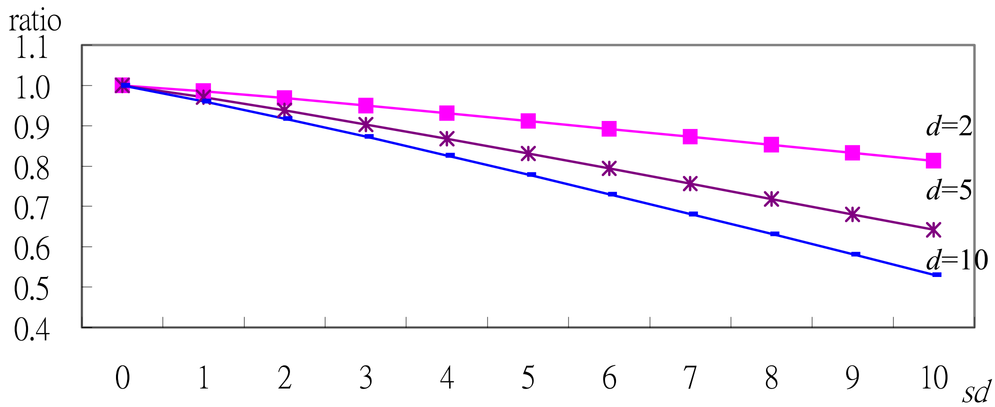

Figure 5. Effect of Supply Uncertainty on Revenue for Various Levels of Penalty

According to the cases of high, medium, and low supply uncertainty (*sd*=1, 4, 8 respectively) in Figure 4, the decrease of expected revenue become greater as the penalty for denied boarding increases (*d*=0 to 10). Nonetheless, the trend appears to be flat when the penalty is relatively high. On the other hand, the cases of high, medium, and low levels of penalty (*d*=2, 5, 10 respectively) are shown in Figure 5. As the supply certainty increases (*sd*=0 to 10), the decrease of expected revenue becomes greater, too. However, the curves become severely downward when supply uncertainty is high, indicating the expected revenue is decreased significantly. Finally, based on these two figures, the expected revenue is not affected if either factor does not exist (i.e. *sd*=0 or *d*=0).

Above results suggests that supply uncertainty cast stronger impact on expected revenue when compared to penalty level. Thus, for revenue maximization, it is critical for airlines cautiously to manage the supply of cargo space. Though inherent to air cargo operation, supply uncertainty can be reduced if good forecast techniques are applied. Particularly, if the variation of cargo space supply can be maintained within a relatively small range, the expected revenue is not very sensitive to the increase of the penalty for denied boarding. The airlines can even raise the level of penalty to attract more customers.

4.2 Analysis of Control Policy

To further evaluate the impact of supply uncertainty and penalty for denied boarding, the optimal control policies with respect to the test problems are recorded. With the example of booking size of 5, Figure 6 illustrates how these two factors affect the accept/deny decision for the booking requests of different classes.

Based on the control policies shown in Figure 6, airlines should be reserve the space for high-fare classes if the number of spaces left is small and/or it is far from the time of take-off, i.e., toward the lower-right corner in the charts. On the other hand, airlines should try their best to sell the spaces if the number of spaces left is plenty and/or the time of take-off is close, i.e., toward the upper-left corner in the charts. However, as shown in Figure 6, the "*boundaries*" representing the change of the accept/deny decisions move with respect to the cases with various levels of supply uncertainty and penalty.

When compared to the base case with light penalty and small supply uncertainty in part (a), substantially increasing the penalty to 10 times as in part (b) does not change the optimal policy much. However, if supply uncertainty is increased significantly to 8 times as in part (c), the optimal control policy is considerably modified, though the penalty remains to be low. This result is once again consistent with the argument made in the previous section that supply uncertainty is more influential than penalty level for denied boarding. Finally, as in part (d), for the situation of highly uncertain supply and heavy penalty level, airlines have to be very conservative while selling the cargo space. Many spaces have to be reserved or be sold only to higher fare classes for many occasions to counter the effect of denied boarding, which is very likely to happen.

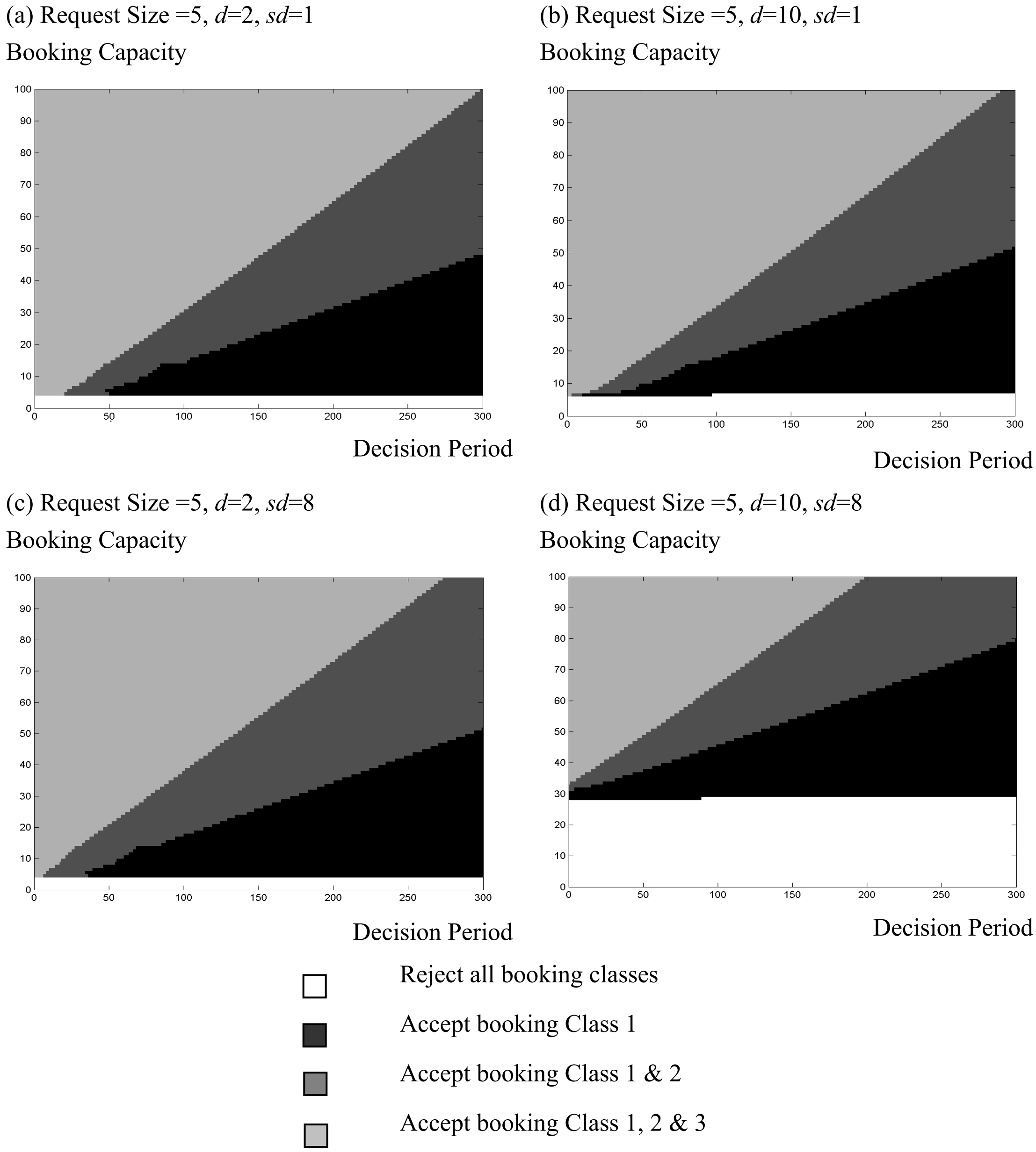

Figure 6. Effect of Supply Uncertainty and Penalty on Optimal Control Policy

5. CONCLUSIONS

This study applies the RM technique, which has been widely used in air passenger operation, to the control of air cargo space. One important difference between the RM problem of air cargo and that of air passenger is supply uncertainty. In addition, denied boarding caused by supply uncertainty must be dealt with carefully. A single-leg air cargo space RM problem is defined and tackled by a dynamic programming (DP) model in this study. The optimal control policy and the expected revenue are derived by solving the DP problem. Numerical experiments based on the actual operational data of a Taiwanese international carrier are performed to verify the model. Particularly, sensitivity analyses are conducted with respect to the most important two factors in the model, supply uncertainty and penalty for denied boarding. The result shows that supply uncertainty is more influential than penalty level.

Thus, to raise the revenue by RM techniques, airlines need to accurately forecast and control the supply of air cargo space.

The major goal of this study is to highlight the fundamental difference between the RM problems of air cargo and air passenger, and a simple dynamic single-leg problem is considered. Thus, the direction of future researches is first aiming to extend the model to the network RM problems of air cargo so as to deal with with the current hub-and-spike type of operation. In addition, practical issues such as cancellation and overbooking should be incorporated into the model. Finally, as mentioned earlier, loading is one of the sources of supply uncertainty. If the information of the shipments such as the dimensions and the gross weights is available in advance, the model can take them into consideration to further alleviate its impacts on supply uncertainty.

RM techniques are not widely applied in the air cargo industry. Especially, the concept of market segmentation is new to this industry, though some airliners have begun to offer different products such as various kinds of time-definite services. It is critical to analyze the impact of implementing this kind of mechanism, as current shippers may be unwilling to pay extra charge for late bookings. On the other hand, airlines can be reluctant to offer penalty for the shipments denied for boarding. According to the current practice, shipments denied for boarding are usually re-routed and sometimes delayed without any compensation. Nonetheless, as the value of time for many air cargo shipments are extremely high, both the suppliers and the consumers of air cargo service eventually will agree on differentiating the types of air cargo services. Therefore, future researches should focus on the strategic issues such as pricing as well as some tactical decisions such as class-dependent penalty.

REFERENCES

Barry, C.S., Leimkuhler, J.F. and Darrow, R.M. (1992) Yield Management at American Airlines, **Interfaces, Vol. 22, No.1**, 8-31.

Belobaba, P.P. (1989) Application of a Probabilistic Decision Model to Airline Seat Inventory Control, ***Operations Research*, Vol. 37, No.2**, 183-197.

Boeing (2004), World Air Cargo Forecast 2004-2005, the Webpage of Boeing Company, http://www.boeing.com/commercial/cargo/WACF_2004-2005.pdf.

Brumelle, S.L. and McGill, J.I. (1993), Airline Seat Allocation with Multiple Nested Fare Classes, **Operations Research, Vol. 41, No.1**, 127-137.

Curry, R.E. (1990), Optimal Airline Seat Allocation with Fare Classes Nested by Origins and Destinations, **Transportation Science, Vol. 24, No.3**, 193-204.

Ingold, A. and Huytom, J.R. (2000). Yield Management and the Airline Industry. In A. Ingold, U. McMahon-Beattie and I. Yeoman (eds.), **Yield Management: Strategies for the Service Industries**. Continuum, London.

Kasilingam, R.G. (1996) Air Cargo Revenue management: Characteristics and Complexities, **European Journal of Operational Research, Vol. 96**, 36-44.

Lee, T. C. and Hersh, M. (1993) A Model for Dynamic Airline Seat Inventory Control with Multiple Seat Bookings, **Transportation Science, Vol. 27**, **No.3**, 252-265.

McGill, J.I. and van Ryzin, G. J. (1999) Revenue management: Research Overview and Prospects, **Transportation Science, Vol. 33, No.2**, 233-256.

Rothstein, M. (1985) OR and the Airline Overbooking Problem, **Operations Research, Vol. 33**, 237-248.

Weatherford, L.R. and Bodily, S.E. (1992) A Taxonomy and Research Overview of Perishable-Asset Revenue Management: Yield Management, Overbooking, and Pricing, **Operations Research Vol. 40, No. 5**, 831-844.

Wollmer, R.D. (1992) An Airline Seat Management Model for A Single Leg Route When Lower Fare Classes Book First, **Operations Research Vol. 40, No.1**, 26-37.