순차적으로 출발하는 여객노선에서 고객의 의사결정을 고려한 좌석재고 통제문제에 대한 모의실험 분석

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Simulation Experimental Analysis on a Seat Inventory Control Problem for Sequential Multiple Flights with Customer Choice Behavior

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■ Abstract ■

We conduct the future studies suggested by Park and Seo [3]. They considered a seat inventory control problem in which flights depart sequentially during a similar time-interval and passengers purchase available seats depending on individual customer choice behavior. Customer choice behavior can lead to one among a horizontal shift, a diversion-up, and a booking loss when a desired fare class is unavailable. We investigate how seat availability calculation method, booking limit control mechanism, seat inventory capacity, number of booking class, type of seat demand influence on revenues in an airline industry through thorough computer simulation experiments.

Keywords : Seat Inventory Control, Revenue Management, Customer Behavior, Heuristic Algorithm, Airlines

1. Introduction

In this paper, we consider a seat inventory control problem in which flights depart sequentially during a similar time-interval and passengers purchase available seats depending on individual customer choice behavior. Under the seat inventory control problem, we examine several seat inventory control alternatives that consist of the booking policy. The theme of this paper is the extension of Park and Seo [3], which was suggested as future studies. Through thorough computer simulation experiments, analyzed is how the seat inventory control alternatives impact on revenues in an airline industry. The considered seat inventory control alternatives include booking limit control mechanism, seat availability calculation method, type of seat demand, seat inventory capacity, and number of fare class.

First, <Figure 1> depicts the problem situation in which computer simulation experi-

ments are conducted. We consider a single flight leg with a fixed seat inventory capacity (e.g., a one-way flight from location A to location B), but each flight departs sequentially during a similar time-interval. It is assumed that customers arrive separately in the system and that each customer's arrival is statistically independent. Each customer requests a single seat; multiple-seat requests, in which an arriving customer attempts to book more than one reservation, are not permitted. Passengers purchase available seats based on individual customer choice behavior. When a desired fare class is unavailable, customer choice behavior can lead to one among a horizontal shift to consider the next flight, a diversion-up to accept a seat in the next lowest fare class, and a booking loss to leave the system.

We also make the simplified assumption that there is no uncertainty involved with accepting and rejecting passenger requests : all accepted passengers purchase a seat; no rejected pas-
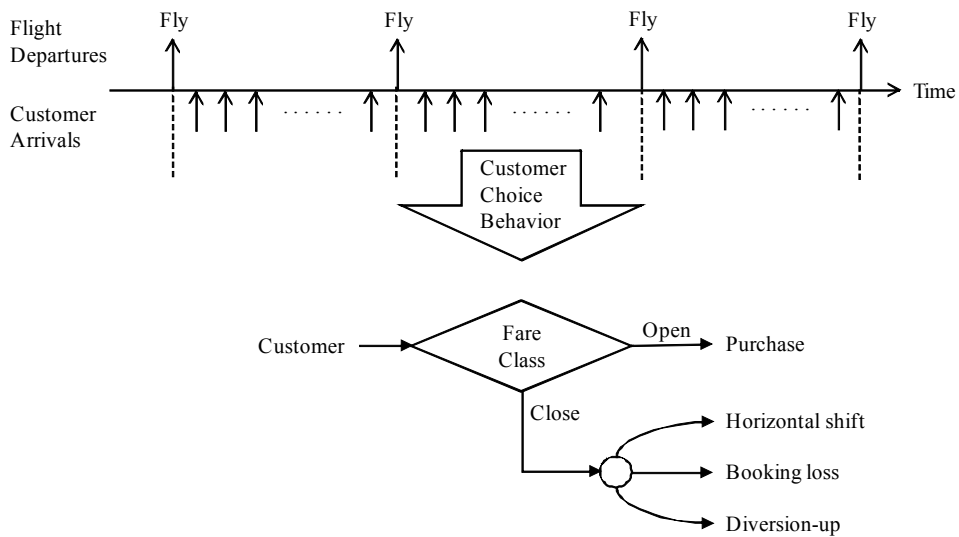
〈Figure 1〉 Scheme of the Problem Situation

sengers do. This assumption sidesteps the important issues of no-shows and the accompanying overbooking, cancellation penalties, and bump compensation. Under the conditions described above, the problem can be defined to identify the optimal number of seats allocated to each fare class to maximize expected total revenue (ETR) for a scheduled future flight leg departure.

We owe the literature review to Park and Seo [3] because this paper conducts the future studies suggested by them. Park and Seo [3] provided the summary of fundamental seat inventory control literature. Further they reviewed literatures on the strategic customer behavior, on the seat inventory control problem with multiple flights, and on the simulation-based optimization approach in airline revenue management. We also utilize the simulation-based greedy grid-search algorithm (SBGGSA) developed by Park and Seo [3] in order to analyze how the seat inventory control alternatives impact on revenues in an airline industry.

In the rest of this paper, section 2 describes the main tools for seat inventory control alternatives, which are used in simulation experiments. Section 3 presents the results of simulation experiments conducted by utilizing the SBGGSA. Section 4 concludes this paper.

2. Seat Inventory Control Alternatives

This section describes three main tools which are commonly used for seat inventory control alternatives.

2.1 Booking Limit Control Mechanism

Booking limit is the maximum number of seats that can be sold to a particular booking class. The booking limit is either non-nested (i.e., partitioned) or nested. A non-nested control divides the available capacity into separate blocks (or buckets)-one for each fare class-that can be sold only to the designated fare class. The booking classes are independent of each other. This implies the possibility that a lower fare class is open for sale while a higher fare class is closed for sale. With nested controls, the capacity available to different fare classes overlaps in a hierarchical manner-with higher-ranked classes having access to all the capacity reserved for lower-ranked classes. <Figure 2> illustrates the non-nested control and typical variations of nested control such as parallel, serial, and hybrid nesting controls. The number in each class box means the booking limit.

Parallel nesting control is an improvement over non-nested control because all the lower-ranked classes are nested into the highest-ranked class, guaranteeing that the highest-ranked class has always the same or higher availability than the lower-ranked classes [4]. In the serial nesting control, seats that are available for sale to a particular booking class are also available to bookings in any higher fare class, but not the reverse. This guarantees that a lower-ranked class will never be open when a higher-ranked class is closed for sale. Lastly, hybrid nesting control is a variant where there are two or more independent nesting structures which are kept separate.

2.2 Seat Availability Calculation Method

To calculate seat availability for each fare class, two basic methods have been proposed in

(a) Non-Nested Control

(b) Parallel Nesting Control

(c) Serial Nesting Control

(d) Hybrid Nesting Control
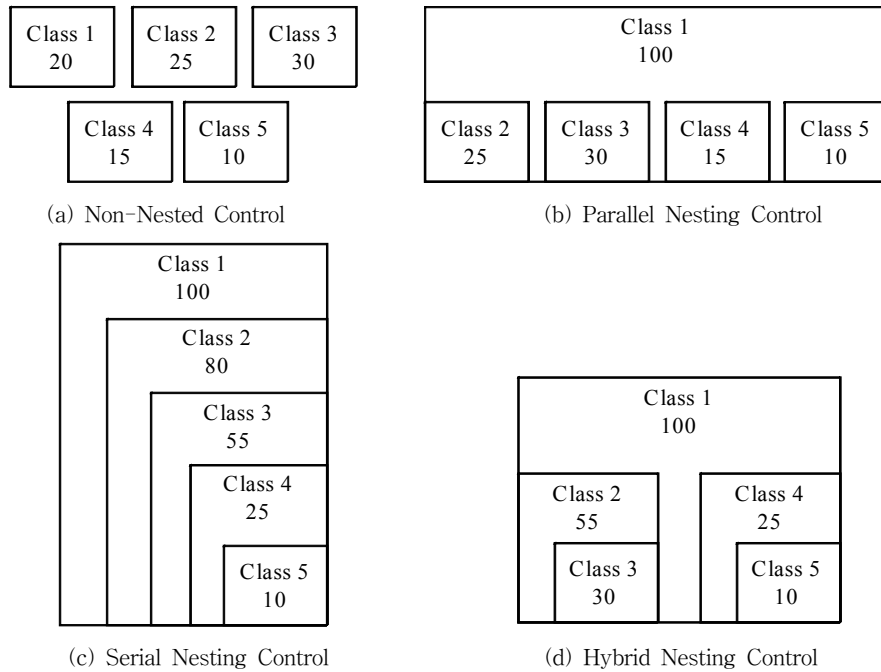
〈Figure 2〉 Booking Limit Control Structures

the literature, namely, standard nesting and threshold nesting. At another time or place, standard nesting is called as net nesting and threshold nesting as theft nesting. Standard nesting is the most natural and common way to calculate seat availability for each fare class. With standard nesting, seat inventory calculation action is taken in the requested class, and all classes above the requested class in the class line hierarchy, up to the highest class. The number of available seats (NAS_i) for class i is calculated as follows.

$$NAS_i = \begin{cases} BL_i - \sum_{k=1}^{N} NSS_k & \text{for } i = 1 \\ BL_i - \sum_{k \in SUB_i} NSS_k & \text{for } i = 2, 3, \cdots, N \end{cases}$$

BL_i is the booking limit for class i, N is the total number of fare classes, NSS_i is the number of seats sold in class i, and SUB_i is the set of fare classes below i and itself in the class line hierarchy.

<Figure 3> shows the results of applying standard nesting policy for serial nesting and parallel nesting controls. To visualize a booking process, <Figure 3> includes the nesting table proposed by Haerian et al. [2]. In the nesting table with C columns and N rows corresponding to capacity and number of fare classes, respectively, each column represents one seat and can be filled with only one entry in any of the rows, which correspond to the class. Crossed out cells in each row represent the seats that are protected from the corresponding class and are reserved for higher-ranked classes only.

With threshold nesting, a booking in any fare class affects all the fare classes in the class line hierarchy, therefore maintaining the protection

(a) Serial nesting control

Arrival sequence	0	1	2	3	4	5	6	7	8	9	10	11
Requested seat		2	3	2	3	2	1	3	2	1	2	1
Decision		A	A	A	A	A	A	R	A	A	R	R

Class	Seat availability											
1	8	7	6	5	4	3	2	2	1	0	0	0
2	6	5	4	3	2	1	1	1	0	0	0	0
3	2	2	1	1	0	0	0	0	0	0	0	0

Nesting table — Fill from the right

						1	1
		2	2	2	2	X	X
3	3	X	X	X	X	X	X

A = Accept
R = Reject

(b) Parallel nesting control

Arrival sequence	0	1	2	3	4	5	6	7	8	9	10	11
Requested seat		2	3	2	3	2	1	3	2	1	2	1
Decision		A	A	A	A	A	A	A	A	R	R	R

Class	Seat availability											
1	8	7	6	5	4	3	2	1	0	0	0	0
2	5	4	4	3	3	2	2	1	0	0	0	0
3	3	3	2	2	1	1	1	0	0	0	0	0

Fill from the right

	X				1	X	X
2			2	2	2	X	X

			X	1	X	X	X
3	3	3	X	X	X	X	X

〈Figure 3〉 Applying Standard Nesting Policy

level across all classes, except for those that are closed, regardless of what fare class was sold. The number of available seats is calculated as follows.

$$NAS_i = \begin{cases} BL_i - \sum_{k=1}^{N} NSS_k & \text{for } i = 1 \\ Max\left[0,\ BL_i - \sum_{k \in LINE_i} NSS_k\right] & \text{for } i = 2, 3, \cdots, N \end{cases}$$

$LINE_i$ is the set of fare classes belonged to the class line hierarchy of fare class i. <Figure 4> shows the results of applying threshold nesting policy for serial nesting and parallel nesting controls.

2.3 Type of Seat Demand

It is known that modeling seat demand is not easy task. Depending on how seat demands are defined, there exist significant differences in forecasting and optimization algorithms. Boyd and Kallesen [1] classified seat demands into yieldable demand and priceable demand based on how much passengers are sensitive to price. Under a yieldable model of seat demand, the higher fare class passenger is specifically inter-

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(a) Serial nesting control

Arrival sequence	0	1	2	3	4	5	6	7	8	9	10	11
Requested seat		2	3	2	3	2	1	3	2	1	2	1
Decision		A	A	A	R	A	A	R	A	A	R	A

Class	Seat availability											
1	8	7	6	5	5	4	3	3	2	1	1	0
2	6	5	4	3	3	2	1	1	0	0	0	0
3	2	1	0	0	0	0	0	0	0	0	0	0

Nesting table — Fill from the left

				1		1	1
2		2	2		2	✕	✕
	3	✕	✕	✕	✕	✕	✕

A = Accept
R = Reject

(b) Parallel nesting control

Arrival sequence	0	1	2	3	4	5	6	7	8	9	10	11
Requested seat		2	3	2	3	2	1	3	2	1	2	1
Decision		A	A	A	A	A	A	R	A	A	R	R

Class	Seat availability											
1	8	7	6	5	4	3	2	2	1	0	0	0
2	5	4	4	3	3	2	1	1	0	0	0	0
3	3	3	2	2	1	1	0	0	0	0	0	0

Fill from the left

			1		1	X	X
2	2	2		2	✕	✕	✕

		1	1	X	X	X	X
3	3		✕	✕	✕	✕	✕

⟨Figure 4⟩ Applying Threshold Nesting Policy

ested in the higher fare class ticket and will pur-chase that ticket even when a less expensive fare class ticket is available. The traditional seat demand model used in the vast majority of pub-lished research is a yieldable demand.

However, using a seat demand model that as-sumes passengers will buy the lowest available fare class-either because fare class restrictions are minimal or because price is more important than restrictions-leads to a priceable demand. Under a priceable model of seat demand, the higher fare class passenger is primarily con-cerned with price and will purchase a less ex-pensive fare class ticket.

3. Experimental Results

In this section, we describe computer simu-lation experiments that were performed by uti-lizing the SBGGSA to analyze how the seat in-ventory control alternatives impact on revenues in an airline industry. The experimental setup is as follows. First, flights are set to depart se-quentially at every 100 unit time. The arrival of customers for each fare class follows the non-homogeneous Poisson process. In order

words, the inter-arrival times of customers are set to follow the exponential distribution with different mean time depending on the interval of unit time. <Figure 5> shows how customers of each fare class arrive in the system in the case of booking 5 fare classes.
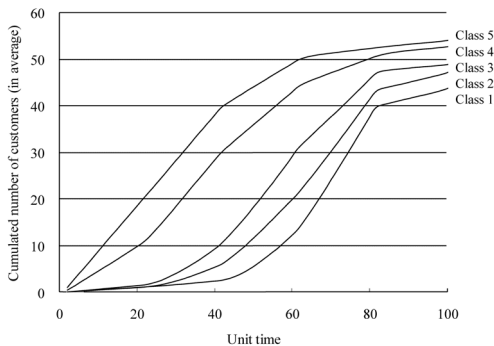
〈Figure 5〉 Customer Arrival Distributions for 5 Fare Classes

Since simulation experiments consider three cases of having 2, 3, and 5 fare classes, we combine 5 fare class customers into 2 and 3 fare class customers in order to keep the same total customer demands when comparing experiment results. Customers of classes 4 and 5 are combined and customers of classes 2 and 3 are combined for the case of booking 3 fare classes, while customers of classes 3, 4 and 5 are combined and customers of classes 1 and 2 are combined for the case of booking 2 fare classes.

Other parameters such as revenue (or price), fraction of horizontal shift, fraction of booking loss, and fraction of diversion-up are shown in <Table 1>. Parameters in <Table 1> are designed to have the same fractions of horizontal shift, booking loss, and diversion-up for all fare classes but fare class 1. When all fare classes are closed, fractions of horizontal shift and booking loss are set as 0.5 and 0.5.

〈Table 1〉 Parameters for the Experimental Problem

Case	Class				
2 fare classed	1				2
3 fare classed	1		2		3
5 fare classed	1	2	3	4	4
Revenue($)	100	90	80	75	70
Horizontal shift	0.50	0.30	0.30	0.30	0.30
Booking loss	0.50	0.20	0.20	0.20	0.20
Diversion-up		0.50	0.50	0.50	0.50

The SBGGSA was encoded in a Visual Basic module in MS-Access (taking advantage of the databases). For each grid point during the search of optimal booking limits, the algorithm ran the computer simulator 1000 times to calculate ETR. Each simulation run collected necessary statistics from the 10th flight that showed a steady-state condition.

3.1 Validation of the SBGGSA performance

Even though the performance of SBGGSA was evaluated by Park and Seo [3], this section validates the SBGGSA performance under this paper's problem situation. The genetic algorithm (GA) was designed as the same way as Park and Seo [3].

<Table 2> shows ETR values of the best (or optimal) booking limits obtained by the GA and total enumeration for various classes, capacities, seat availability calculation methods, and booking limit control mechanisms. For the case of booking 2 fare classes, the total enumeration was conducted to search the optimal booking limits. However, for the cases of booking 3 and 5 fare classes, the GA was conducted due to the computational size. The ETR values obtained by the GA are average of 5 independent runs. <Table 3> shows ETR values of the best book-

〈Table 2〉 ETR Values of the Best Booking Limits Obtained by the GA and Total Enumeration

Class	Capacity	Non-nested	Serial nesting		Parallel nesting		Hybrid nesting	
			Standard	Threshold	Standard	Threshold	Standard	Threshold
2	200	19217.70	19217.70	19217.70				
	250	20177.90	20177.90	20179.48				
	300	20200.60	20200.60	20205.54				
	350	20200.60	20200.60	20205.54				
3	200	17058.70	16999.28	17004.30	17060.40	17096.90		
	250	19002.56	19031.45	19043.54	19084.22	19023.21		
	300	19589.06	19616.01	19610.82	19617.15	19524.77		
	350	19621.18	19621.11	19621.26	19622.27	19618.37		
5	200	17077.03	17155.23	17182.61	17158.77	17269.30	17155.84	17175.08
	250	19535.22	19912.40	19929.88	19901.55	19556.27	19910.52	19829.41
	300	20501.82	20600.23	20566.12	20595.97	20090.10	20598.26	20443.23
	350	20591.60	20605.56	20589.18	20604.77	20388.05	20605.63	20542.31

〈Table 3〉 ETR Values of the Best Booking Limits Obtained by the SBGGSA

Class	Capacity	Non-nested	Serial nesting		Parallel nesting		Hybrid nesting	
			Standard	Threshold	Standard	Threshold	Standard	Threshold
2	200	19217.70	19217.70	19217.70				
	250	20177.90	20177.90	20179.48				
	300	20200.60	20200.60	20205.54				
	350	20200.60	20200.60	20205.54				
3	200	17062.10	17001.65	17004.45	17062.10	17096.90		
	250	19007.83	19038.50	19043.37	19084.23	19033.78		
	300	19589.60	19616.01	19616.01	19617.22	19530.34		
	350	19622.27	19621.11	19621.26	19622.27	19618.58		
5	200	17089.51	17155.06	17185.44	17160.58	17162.11	17158.30	17182.70
	250	19656.40	19912.18	19932.41	19906.87	19568.81	19910.70	19828.69
	300	20516.80	20600.23	20600.23	20599.57	20128.52	20600.23	20471.14
	350	20599.68	20605.87	20605.62	20605.66	20405.59	20605.64	20593.93

ing limits obtained by the SBGGSA.

Comparing the results in 〈Table 2〉 and 〈Table 3〉, the SBGGSA demonstrates outstanding performance. For the case of booking 2 fare classes, the SBGGSA identifies the optimal booking limits which are identical to the total enumeration. For the cases of booking 3 and 5 fare classes, the SBGGSA identifies better booking limits than GA.

3.2 Influence of Seat Availability Calculation Method and Booking Limit Control Mechanism

This section investigates the influence of seat availability calculation method and booking limit control mechanism on revenues. We considered standard nesting and threshold nesting as seat availability calculation method, while non-nest-

ed control, serial nesting control, parallel nesting control, and hybrid nesting control as booking limit control mechanism. <Table 3> shows ETR values of the best booking limits obtained by the SBGGSA for various classes, capacities, seat availability calculation methods, and booking limit control mechanisms.

First, we compare seat availability calculation methods to examine whether there is a significant dominance in revenues generated by standard nesting and threshold nesting. If we look at the example in <Figure 3> and <Figure 4>, standard nesting policy rejects the requested seats of classes 3, 2, and 1 for serial nesting control and the requested seats of classes 1, 2, and 1 for parallel nesting control, while threshold nesting policy rejects the requested seats of classes 3, 3, and 2 for serial nesting control and the requested seats of classes 3, 2, and 1 for parallel nesting control.

According to this example, the threshold nesting policy seems to generate higher revenues than the standard nesting policy does by protecting more capacity for higher-ranked classes. Can we conclude that the threshold nesting policy always generates higher revenues than the standard nesting policy does? In order to verify this question, we conducted a statistical test (t-test) of the paired comparison between standard nesting and threshold nesting for each fare class. However, experiment outputs in <Table 3> do not support that there is a significant difference in revenues generated by standard nesting and threshold nesting for each fare class (p-value > 0.1).

Secondly, we compare booking limit control mechanisms to examine whether there is a significant dominance in revenues generated by non-nested, serial nesting, parallel nesting, and hybrid nesting. We conducted a statistical test (t-test) of the paired comparison between serial nesting and parallel nesting for 3 and 5 fare classes, and two-factor analysis of variance for 5 fare classes with booking limit control mechanisms (e.g., serial, parallel, and hybrid nesting) as one factor and combination of capacity and seat availability calculation methods as another factor. In addition, we conducted another two-factor analysis of variance for 5 fare classes with capacity as one factor and combination of booking limit control mechanisms and seat availability calculation methods including non-nested control as another factor.

According to these 4 statistical tests based on experiment outputs in <Table 3>, we cannot conclude that there is no significant difference in revenues among booking limit control mechanisms (p-value = 0.521 at the paired comparison test for 3 fare classes case, p-value = 0.091 at the paired comparison test for 5 fare classes case, p-value = 0.045 at ANOVA for serial, parallel, and hybrid nesting, and p-value = 0.003 at ANOVA for non-nested, serial, parallel, and hybrid nesting).

Based on the above two comparisons and experiment outputs in <Table 3>, we can infer that there is the best combination of seat availability calculation method and booking limit control mechanism case by case. Thirdly, we conducted three-factor analysis of variance with seat availability calculation method, booking limit control mechanism, and capacity as each factor. The result of three-factor ANOVA shows that there is a statistically significant interaction between seat availability calculation method and booking limit control mechanism (p-value = 0.042).

3.3 Influence of Seat Inventory Capacity and Number of Booking Class

If we look at <Table 3>, the value of ETR is non-decreasing as capacity increases, no matter what number of booking class, seat availability calculation method, and booking limit control mechanism are used. From <Table 3>, we can infer that the value of ETR will stay the same if capacity increment passes a certain point of value that sufficiently covers seat demands. As shown in <Figure 5>, the total average seat demands for a certain flight are about 250, ignoring the turnover demands from prior flights due to customer choice behavior. In case of booking 2 fare classes, the value of ETR reaches a maximum at the capacity of 300. However, in the other cases, the value of ETR is still increasing at the capacity of 300, because the variance of seat demands increases as the number of considered fare class increases.

In order to examine how the number of booking classes impacts on revenues, we reorganized the ETR values of the best booking limits in <Table 4>. From <Table 4>, it is hard to notice any pattern as the number of booking class increases. However, the ETR values of booking 3 fare classes are generally less than others. After carefully reviewing various causes, we recognized that the requested seat demands in the case of booking 3 fare classes were distributed to yield less revenue than other cases. Thus we can infer that prices of fare classes and distribution of seat demands give more impact on revenues rather than the number of booking classes itself.

3.4 Influence of Type of Seat Demand

As mentioned in section 2.3, there exist significant differences in forecasting and optimization algorithms depending on how seat demands are modeled. We can infer that an inappropriate modeling of seat demand will incur revenue dilution. This section illustrates the revenue dilution using simulation experiments. The first experiments were performed according to <Figure 6>. <Table 5> shows the experi-

〈Table 4〉 Rearrangement of 〈Table 3〉

Capacity	Class	Non-nested	Serial nesting		Parallel nesting		Hybrid nesting	
			Standard	Threshold	Standard	Threshold	Standard	Threshold
200	2	19217.70	19217.70	19217.70				
	3	17062.10	17001.65	17004.45	17062.10	17096.90		
	5	17089.51	17155.06	17185.44	17160.58	17162.11	17158.30	17182.70
250	2	20177.90	20177.90	20179.48				
	3	19007.83	19038.50	19043.37	19084.23	19033.78		
	5	19656.40	19912.18	19932.41	19906.87	19568.81	19910.70	19828.69
300	2	20200.60	20200.60	20205.54				
	3	19589.60	19616.01	19616.01	19617.22	19530.34		
	5	20516.80	20600.23	20600.23	20599.57	20128.52	20600.23	20471.14
350	2	20200.60	20200.60	20205.54				
	3	19622.27	19621.11	19621.26	19622.27	19618.58		
	5	20599.68	20605.87	20605.62	20605.66	20405.59	20605.64	20593.93

ment results when the SBGGSA is run based on a priceable demand. By comparing the experiment results of <Table 3> and <Table 5>, we can infer that revenue dilution will occur if we make a mistake of forecasting type of seat demand. <Table 6> and <Table 7> show the experiment results when there are mismatches on type of seat demand. By comparing the experiment results of <Table 3> and <Table 6>, and <Table 5> and <Table 7>, we can infer that revenue dilution will occur if we use an inappropriate optimization algorithm.

<Table 5> ETR Values of the Best Booking Limits for a Priceable Demand When an Actual Demand is Priceable

Class	Capacity	ETR
2	200	19230.30
	250	20179.50
	300	20179.50
	350	20197.70
3	200	16883.30
	250	18155.78
	300	18218.72
	350	18218.72
5	200	14472.40
	250	16850.35
	300	17331.72
	350	17335.08

In this section, we consider another type of seat demand that is derived from a priceable demand. We call it an aggregate demand. Under the aggregate model of seat demand, passengers behave like a priceable demand, that is, passengers will buy the lowest available fare class. However, unlike a priceable model of seat demand, an aggregate demand does not consider the originally intended fare class of passengers,

		Demand	
		Priceable	Yieldable
Search algorithm	Priceable demand	Good <Table 5>	Revenue dilution <Table 6>
	Yieldable demand	Revenue dilution <Table 7>	Good <Table 3>

<Figure 6> Experiment Framework for Revenue Dilution

<Table 6> ETR Values of the Best Booking Limits for a Priceable Demand when an Actual Demand is Yieldable

Class	Capacity	Non-nested	Serial nesting		Parallel nesting		Hybrid nesting	
			Standard	Threshold	Standard	Threshold	Standard	Threshold
2	200	19217.70	19217.70	19217.70				
	250	20177.90	20177.90	20179.48				
	300	20196.90	20196.90	20198.33				
	350	20196.90	20196.90	20198.33				
3	200	16961.50	16961.50	16957.10	16961.50	16955.34		
	250	18834.65	18984.01	18749.06	19012.15	18775.73		
	300	15098.33	19499.49	19281.80	19499.49	19411.55		
	350	18664.13	19500.43	19281.60	19500.43	19411.90		
5	200	6794.98	16411.99	16651.81	15741.09	15712.43	16639.44	16631.65
	250	4694.98	19911.94	19929.94	15920.08	15920.98	17746.55	17747.66
	300	4064.98	20600.23	20600.58	15820.78	15820.88	17581.06	17581.36
	350	6754.98	20605.62	20605.70	15839.98	15840.08	17607.66	17608.46

〈Table 7〉 ETR Values of the Best Booking Limits for a Yieldable Demand When an Actual Demand is Priceable

Class	Capacity	Non-nested	Serial nesting		Parallel nesting		Hybrid nesting	
			Standard	Threshold	Standard	Threshold	Standard	Threshold
2	200	19230.30	19230.30	19230.30				
	250	20179.50	20179.50	20179.50				
	300	20194.80	20194.80	20192.70				
	350	20194.80	20194.80	20192.70				
3	200	16725.70	16645.30	16618.90	16725.70	16414.60		
	250	18125.26	18105.60	17404.22	17934.78	17379.74		
	300	18156.82	18028.00	17330.60	18055.26	18147.44		
	350	18064.94	17878.25	17334.87	17879.61	17872.48		
5	200	10495.97	9208.93	9048.12	9422.78	9598.52	9682.74	9178.69
	250	11813.08	12381.60	16648.16	11967.86	11344.90	12291.11	11660.61
	300	11636.44	13228.60	17330.04	12397.67	11410.75	12969.19	12262.23
	350	12265.93	13070.01	17334.87	12830.36	12020.77	12539.27	14538.80

that is, an aggregate demand only concerns whether a current customer purchases a presently open fare class. An aggregate demand is estimated from the ticket sales data ignoring the purchase propensity of passengers.

The second experiments were performed according to <Figure 7>. <Table 8> shows the experiment results when the SBGGSA is run based on an aggregate demand. The aggregate demand is estimated from the ticket sales data obtained by simulation experiments in <Table 3>. By comparing the experiment results of <Table 3> and <Table 8>, we can recognize that revenues are generally inflated because the aggregate model of seat demand overestimates high fare class demands at the expense of low fare class demands. <Table 9> shows the experiment results of the search algorithm run based on an aggregate demand when an actual demand is yieldable. By comparing the experiment results of <Table 3> and <Table 9>, we can also infer that revenue dilution would occur if we use an inappropriate optimization algorithm.

		Demand	
		Aggregate	Yieldable
Search algorithm	Aggregate demand	Overestimate of high fare demands <Table 8>	Revenue dilution <Table 6>
	Yieldable demand		Good <Table 3>

〈Figure 7〉 Experiment Framework for an Aggregate Demand

4. Conclusion

In this paper, we conducted the future studies suggested by Park and Seo [3]. Park and Seo [3] considered a seat inventory control problem in which flights depart sequentially during a similar time-interval and passengers purchase available seats depending on individual customer choice behavior. We analyzed how seat inventory control alternatives impact on revenues in an airline industry through thorough simulation experiments.

〈Table 8〉 ETR Values of the Best Booking Limits for an Aggregate Demand When an Actual Demand is Aggregated

Class	Capacity	Non-nested	Serial nesting		Parallel nesting		Hybrid nesting	
			Standard	Threshold	Standard	Threshold	Standard	Threshold
3	200	17761.00	17896.40	17666.30	17761.00	16991.30		
	250	17989.20	19387.32	19089.90	19376.96	17404.70		
	300	17855.70	24758.00	24758.00	19876.10	18393.20		
	350	19811.52	24764.10	24764.10	19811.52	18132.30		
5	200	19718.20	19978.90	19974.90	19976.70	19065.20	19975.10	19974.60
	250	21606.32	23956.70	23969.40	23058.80	21426.55	23956.80	23961.40
	300	22143.30	24758.00	24758.00	22282.02	22124.24	24758.00	24737.20
	350	22172.90	24764.10	24764.10	22287.69	22470.56	22287.69	24726.40

〈Table 9〉 ETR Values of the Best Booking Limits for an Aggregate Demand When an Actual Demand is Yieldable

Class	Capacity	Non-nested	Serial nesting		Parallel nesting		Hybrid nesting	
			Standard	Threshold	Standard	Threshold	Standard	Threshold
3	200	16487.30	16424.30	15877.46	16487.30	16513.97		
	250	15981.80	18193.86	15833.51	18086.12	17271.69		
	300	15931.30	15735.50	15735.50	16540.00	15845.07		
	350	16819.04	15735.50	15735.50	18129.14	15845.07		
5	200	14351.60	14350.20	14350.20	14350.20	14528.70	14350.2	14350.2
	250	13874.96	14350.20	14351.60	14350.20	16065.29	14350.2	14320.8
	300	11917.24	14350.20	14350.20	16065.29	16119.43	14350.2	14294.8
	350	12117.24	14350.20	14350.20	16065.29	16119.43	16065.29	15167.9

First, we recognized that it is rarely possible to find analytically optimal booking limits that maximize the ETR of seat inventory control problem for sequential multiple flights with customer choice behavior, because distributions of seat demands for a certain flight (e.g., the kth flight in the sequential multiple flights) depend on the booking limits and customer choice behavior. Thus, we selected the SBGGSA as a promising alternative approach and evaluated again the performance of the SBGGSA by comparing with the GA.

Next, we conducted simulation experiments using the SBGGSA to investigate how seat availability calculation method, booking limit control

mechanism, seat inventory capacity, number of booking class, type of seat demand influence on revenues. The results of simulation experiments showed that :

- There is a significant interaction between seat availability calculation method and booking limit control mechanism. This implies that there is the best combination of seat availability calculation method and booking limit control mechanism to maximize the ETR.

- The revenues will stay the same if capacity increment passes a certain value that sufficiently covers seat demands. Prices of fare classes and distribution of seat demands give more impact on revenues rather than the

number of booking classes itself.

- Revenue dilution would occur if we make a mistake of forecasting type of seat demand and use an inappropriate optimization algorithm.

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