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Strategic Analyses of Applying an Option-Based Hedging Mechanism in Parallel Airline Alliances

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ABSTRACT

The extant literature proposes an option-based hedging mechanism for airlines in a parallel alliance to transfer bumped passengers to their alliance partner's flight. This paper extends this literature by conducting strategic analyses and developing a two-stage simulation-based algorithm to identify the best strategy for applying the hedging mechanism. Specifically, the best strategy refers to the best number of options for the allied carriers to transact. The authors show that there exists a robust result of the best number of options, and it is obtained under the objective of maximizing alliance-wide revenue. The result of this paper can provide direct guidance to the management of airlines on the best practice of hedging ex-post overbooking risks and matching supply with demand.

KEYWORDS

Overbooking Risk, Real Options, Revenue Management, Simulation-Based Optimization, Strategic Alliances

INTRODUCTION

Overbooking refers to airlines intentionally overselling the actual number of seats on an aircraft (Coughlan, 1999). Airlines use overbooking as a revenue management instrument to minimize lost revenue due to passenger cancellations and no-shows (Rose, 2016). Although having the potential to increase capacity utilization on a flight efficiently and thus bring extra revenue to airlines, overbooking introduces a new risk that passengers in excess of the total capacity show up for a flight but are denied boarding because of oversales (Smith et al., 1992). After a temporary pause in the pandemic year 2020, air travel started to recover, and at the same time, overbooking has become common again. In 2021, around 183,000 passengers were bumped from oversold flights of the largest U.S. air carriers, up from as few as 81,000 in 2020 (U.S. Department of Transportation, 2022). Specifically, Figure 1 shows the number of passengers denied boarding voluntarily and involuntarily from 2012 to 2021. Around 11,000 passengers holding confirmed reservations were involuntarily bumped from oversold flights in 2021. Note that this figure only covers domestic and outbound international flights of ten

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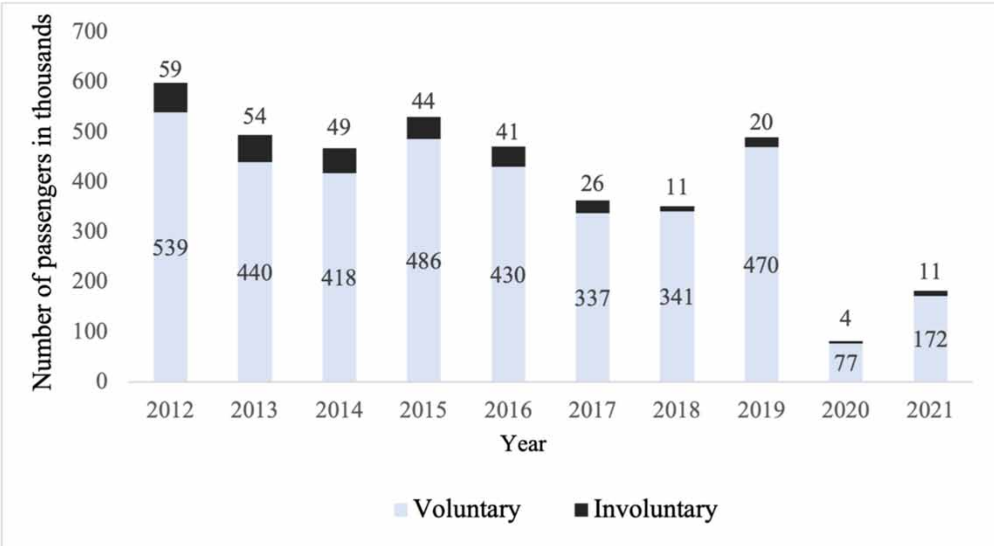
Figure 1. Number of passengers denied boarding by the largest U.S. air carriers from 2012 to 2021, by type (in thousands) (U.S. Department of Transportation, 2022)



U.S. airlines. Considering the enormous total passenger volume worldwide, the risk of oversales inherently brought by overbooking could be a big problem.

In the case of denied boarding due to overbooking, the airline must compensate the bumped passengers. Depending on how late the passenger arrives at their destination, the compensation payment can be costly (Oh & Su, 2022), let alone the reputational risk and loss of goodwill that are detrimental to the airlines' long-term survival and development (Dalalah et al., 2020; Nazifi et al., 2021; Wangenheim & Bayón, 2007; Zhang & Chen, 2013). On the other hand, airlines cannot avoid the risk of undersale, which occurs when they do not overbook flights enough, resulting in empty seats. The consequences of undersale can be equally unaffordable because the value of unsold seats will diminish upon flight departure. This issue will affect the ability of airlines to fully utilize their finite capacity and absorb the high fixed cost of operating a flight (Guo et al., 2016). Overall, it is probable that the ex-ante optimal overbooking policy ends up in ex-post oversale or undersale risk, even though overbooking per se is a risk-hedging tool used by airlines.

In a previous study, Wang and Fung (2014) proposed an option-based passenger transfer mechanism to address the issue of oversale and undersale inherent in overbooking for parallel airline alliances. Their work is the only one that studies mechanism design for airline alliances to reduce the ex-post overbooking risks. As there has been no further research aiming to extend the applicability of their mechanism, two questions remain unexplored. First, does the best strategy for applying the option-based mechanism exist? Second, if so, how to identify such a best strategy? These two unanswered questions drive the authors' interest, leading to the current study.

The remainder of this paper is organized as follows. Section 2 reviews the pertinent literature on airline overbooking. Section 3 presents a concise summary of the hedging mechanism showing the model formulation, parameter setting, and simulation procedures. Section 4 offers a comprehensive discussion of the simulation results and introduces a two-stage simulation-based algorithm to identify the best strategy for applying the hedging mechanism. Finally, Section 5 concludes this work.

LITERATURE REVIEW

The existing literature related to overbooking can be broadly divided into two categories. The first category focuses on mathematical and technical advancement in optimizing the ex-ante airline overbooking decision. The second category looks for ways to reduce the ex-post negative impacts due to overbooking.

The ex-ante overbooking decision aims to find an optimal trade-off between the expected revenue loss due to seat vacancies and the cost of oversale. The authors refer readers to Klein et al. (2020) for a review of recent research developments in revenue management, including overbooking studies that explore this optimality. While most scholars have examined overbooking problems in independent environments, Huang et al. (2013) and Chen and Hao (2013) considered the impact of carriers' collaboration in determining optimal overbooking policies.

Though the current techniques for determining the optimal overbooking policies are advanced, the ex-post risks of overbooking are inevitable. As Talluri & Ryzin (2005) pointed out, the biggest challenge in overbooking is managing the negative consequences of denying service. Therefore, the second category of the literature addresses this challenge from a different perspective by examining effective ways to mitigate the ex-post risks of overbooking. For example, Pizam (2017) discussed the causes of the United Airlines (UA) Flight 3411 incident and outlined lessons learned that can be applied to all sectors using or planning to use overbooking. Ma et al. (2019) used Twitter data to analyze crisis response and communication in the context of UA's overbooking incident. They discussed some best practices in crisis communication that can help mitigate overbooking risks and avoid crisis escalation. Recently, Dalalah et al. (2020) studied a voluntary overbooking model where some customers are willing to purchase a lower price ticket but under overbooking terms. As information is fully disclosed on the possible denied boarding consequences, passengers cooperate in the overbooking execution process so airlines can minimize potential negative consequences. Another work by Nazifi et al. (2021) proposed a practice to handle flight overbooking proactively. They demonstrated that if passengers can be informed about undesirable events before leaving for the airport, airlines can reduce negative electronic word-of-mouth (eWOM) and the cost of bumping.

Wang and Fung (2014) first addressed the issue of mitigating ex-post risks of overbooking in an airline alliance setting. They incorporated the concept of call options from the finance literature and propose an option-based mechanism to transfer bumped passengers among allied airlines to manage the negative impacts of bumping. An analytical model was built to calculate the net benefit that can be obtained by the allied airlines. Through simulation analyses, they showed that the proposed mechanism could generate mutual benefits for allied carriers under many practical conditions and thus reduce the ex-post risks of overbooking to a large extent.

This paper extends Wang and Fung (2014) and conducts a systematic analysis to examine whether the best strategy for applying the option-based mechanism exists. It also proposes a two-stage simulation algorithm for identifying such a best strategy, which refers to the best number of options the allied carriers should transact with each other. This work enriches the existing literature that addresses the potential adverse effects of overbooking. It also provides comprehensive guidance to airline management on the best practice of hedging ex-post overbooking risks and matching supply with demand.

METHODOLOGY

Review of the Hedging Mechanism

In this section, the authors briefly review how the mechanism proposed by Wang and Fung (2014) works in flight booking. On the route from City A to City B, Airlines I and J enter into a code-sharing agreement and form a parallel alliance. The two allied airlines play the roles of the operating carrier and the ticketing carrier, respectively, for flight i and swap their roles for flight j (In an airline alliance, an operating carrier is an airline that provides the aircraft, the crew, and the ground handling service. A ticketing carrier, also known as a marketing carrier, is an airline that sells tickets for a flight but does not operate it.) Both flights are overbooked, and the overbooking policy of each flight is determined by its operating carrier. The two flights depart successively, with flight j taking off shortly (e.g., within one hour) after flight i. When passengers are bumped from flight i, at least some can be transferred to flight j according to the following option-based mechanism.

Figure 2 shows the decision-making interactions between Airline I and J before and during the booking process. The authors refer readers to Section 3.1 in Wang and Fung (2014) for detailed explanations of the airlines' actions and motivations. In short, by purchasing call options from Airline J, Airline I obtains the right to purchase seats from flight j at a future time and a discounted price. This option-based approach allows Airline I to transfer bumped passengers from flight i to flight j at a lower cost and thus offers an innovative solution to manage the negative impacts of bumping. On the other hand, Airline J may increase its revenue by selling options. As a result, a win–win situation can be achieved for both airlines.

Model Formulation

To analyze the benefit brought by the hedging mechanism, Wang and Fung (2014) classified the customers of flight i into three types. Type I (disloyal) customers would choose flights offered by other alliances if they cannot board flight i. Type II (quasi-loyal) customers would choose flights offered by other airlines in the same alliance if getting bumped from flight i. Being the most loyal group, Type III customers would always choose Airline I's flights no matter whether they can fly on flight i.

Applying the same customer classification, the analyses proceed based on the benefit calculation used in Wang and Fung (2014). Table 1 shows the tabulated variable definitions. Four relevant equations are reproduced from Equations 7, 8, 10, and 3 in their paper, and the first three calculate the net benefit obtained by Airline I, J, and the alliance, respectively.

Figure 2. Decision-making interaction between Airlines I and J

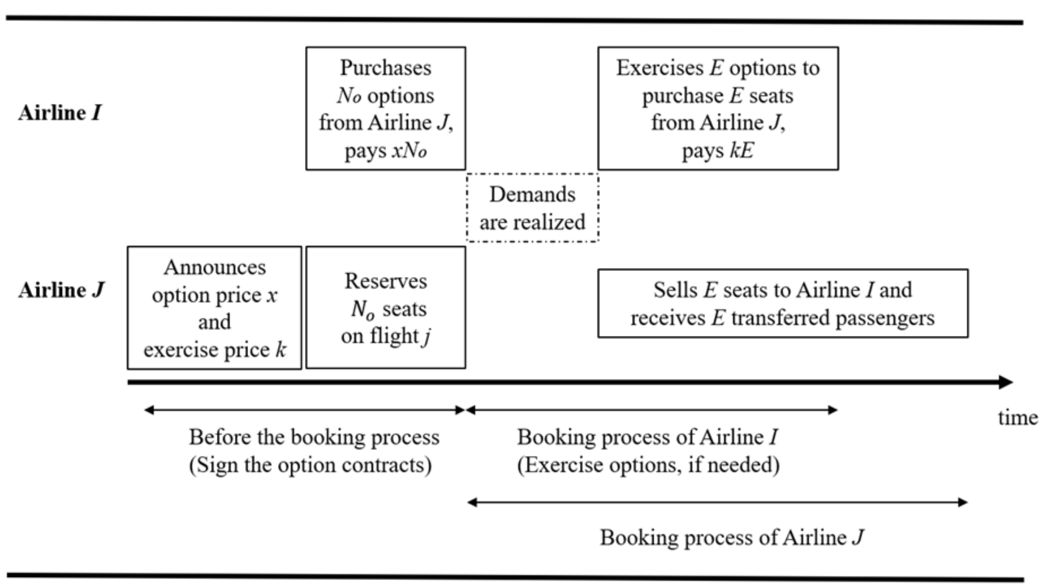


Table 1. Variable definitions

Variable	Definition
n_m	The seat capacity of flight *m*, *m* = *i*, *j*
α_m	The number of overbooked passengers on flight *m*, *m* = *i*, *j*
λ_1, λ_2	The share of Type I and Type II customers within $n_i + \alpha_i$, respectively
SH_{mc}	A binary variable coded 1 if customer c_m shows up for flight *m* (coded 0 otherwise), *m* = *i*, *j*
BP_{mc}	A binary variable coded 1 if (given that c_m shows up for flight *m*) customer c_m is denied a seat on flight *m* (coded 0 otherwise), *m* = *i*, *j*
T_{ic}	A binary variable coded 1 if (given that c_i is bumped for flight i) customer c_i is transferred to flight j (coded 0 otherwise)
$COST_{ic}$	The amount of monetary and non-monetary cost that Airline I needs to pay when bumping a passenger c_i from flight i
P'_{ic}	The ticket price that customer c_i would have paid for a seat on a future flight of Airline I
P_{jc}	The ticket price of flight j for customer c_j
L_{jc}	A binary variable coded 1 if (given that c_j shows up but bumped by flight j) customer c_j is bumped due to reservation for options (coded 0 otherwise)
x	The option price of an option
k	The exercise price of an option
N_o	The total number of options Airline I purchased from Airline J
$B_i\left(Net\right)$	The overall net benefit obtained by Airline I from the hedging mechanism
$B_j\left(Net\right)$	The overall net benefit obtained by Airline J from the hedging mechanism
$B\left(Net\right)$	The total net benefit obtained by the alliance from the hedging mechanism

$$B_i(Net) = \sum_{c_i=1}^{n_i+\alpha_i} \left\{SH_{ic} BP_{ic} T_{ic} \left(COST_{ic} - k\right)\right\} - x^{\circ} N_o - \sum_{c_i=\left(n_i+\alpha_i\right)\left(\lambda_1+\lambda_2\right)+1}^{n_i+\alpha_i} \left\{SH_{ic} BP_{ic} T_{ic} P'_{ic}\right\} \tag{1}$$

$$B_j(Net) = \sum_{c_i=1}^{n_i+\alpha_i} \left\{T_{ic}\right\} k + x^{\circ} N_o - \sum_{c_j=1}^{n_j+\alpha_j} \left\{SH_{jc} BP_{jc} L_{jc} P_{jc}\right\} \tag{2}$$

$$B(Net) = \sum_{c_i=1}^{n_i+\alpha_i} \left\{SH_{ic} BP_{ic} T_{ic} COST_{ic}\right\} - \sum_{c_i=(n_i+\alpha_i)\lambda_1+1}^{(n_i+\alpha_i)(\lambda_1+\lambda_2)} \left\{SH_{ic} BP_{ic} T_{ic} P'_{jc}\right\}$$
$$-\sum_{c_i=(n_i+\alpha_i)(\lambda_1+\lambda_2)+1}^{n_i+\alpha_i} \left\{SH_{ic} BP_{ic} T_{ic} P'_{ic}\right\} - \sum_{c_j=1}^{n_j+\alpha_j} \left\{SH_{jc} BP_{jc} L_{jc} P_{jc}\right\} \quad (3)$$

Equations 1–3 are subject to the constraint:

$$0 \leq \sum_{c_i=1}^{n_i+\alpha_i} T_{ic} \leq N_o \quad (4)$$

Equation 1 shows that the overall net benefit obtained by Airline I, $B_i\left(Net\right)$, mainly comes from the amount of $COST_{ic}$ saved by transferring bumped passengers. The transfer, however, is realized at the expense of purchasing and exercising options. The last term in Equation 1 states that $B_i\left(Net\right)$ will decrease by the reduced revenue P'_{ic} for a future flight of Airline I for each Type III passenger transferred. One condition needs to be satisfied that, as shown in Equation 4, the total number of transferred passengers cannot exceed the total number of options Airline I purchased from Airline J.

Equation 2 shows that the overall net benefit obtained by Airline J, $B_j\left(Net\right)$, includes the revenue of selling and exercising options. However, the revenue gain is reduced by the possible lost ticket revenue due to seat reservations for options. When the lost ticket revenue is smaller than the revenue of selling options, Airline J can earn a positive profit.

The overall net benefit obtained by the alliance through the option-based mechanism should be smaller than the sum of the net benefit received by Airline I and Airline J. The difference is caused by Type II (quasi-loyal) customers on flight i. If flight i transfers a Type II customer c_i to flight j, the cost saving for flight i is realized at the expense of reduced revenue for a future flight of Airline J. From the perspective of the alliance, the profit derived from Type II customers should be adjusted by the amount that traveler c_i would have paid for a seat on a future flight of Airline J.

Note that Equation 3 does not contain x and k. The option price and exercise price are inter-payment between the two alliance partners. Those option costs paid by Airline I will be offset by revenue received by Airline J. The first term in $B\left(Net\right)$ represents the monetary and non-monetary cost saved from the transferred passengers of flight i. It is the main reason the proposed mechanism can benefit the alliance, and this portion of the benefit is not affected by passenger type. However, such benefits must associate with costs, which include the reduced revenue for future flights of Airline J caused by Type II (quasi-loyal) customers on flight i, the reduced revenue for future flights of Airline I caused by Type III (loyal) customers on flight i, and the lost potential ticket revenue of Airline J due to reservation for options.

Parameter Setting

Given the rationale of the mechanism, a natural question is how many options the allied airlines should transact with each other. When applying the hedging mechanism, individual airlines are also interested in maximizing their benefit under various conditions. The authors carry out the following analyses to answer the above questions. To capture the stochastic nature of random variables $B_i\left(Net\right)$, $B_j\left(Net\right)$ and $B\left(Net\right)$, simulation experiments are used so that not only the means but also the variances of random variables can be investigated.

The authors follow the parameter specifications justified in Suzuki (2006) and Wang and Fung (2014) for similar items. For unique parameters in this paper, justifications are provided. Table 2 shows the simulation input, where $N(\mu, \sigma^2)$ and $B(1, p)$ represent a normal distribution (with mean μ and standard deviation σ) and a Bernoulli distribution (with parameter p), respectively.

Customer Type

In each experiment, the proportion of Type III customers within ($n_i + \alpha_i$) is ($1 - \lambda_1 - \lambda_2$). The equivalent share of the three types of customers aims to eliminate the effect of any potentially dominant customer type.

Overbooked Travelers on Flight j (α_j)

From the perspective of the alliance, the hedging mechanism is beneficial for both carriers in two situations. Under the assumption that the two flights have equivalent capacity (200 seats), the first situation arises when the demand of flight j has a smaller expected value than that of flight i. In this case, it is more likely that flight j has vacancies when flight i gets excessive passenger(s). This can be represented by Setting 1 of α_j. When the number of overbooked travelers on flight i lies between 20 and 40 (10% and 20% of the total capacity, respectively) 99% of the time, the number of overbooked travelers on flight j will lie between 10 and 30 (5% and 15% of the total capacity, respectively) most of the time.

The second situation is when the demand of flight j has larger volatility than that of flight i. This condition also results in a higher possibility that flight j has vacancies when flight i gets excessive passenger(s). It is represented by Setting 2 of α_j, in which case the number of overbooked travelers on flight j will lie between 15 and 45 (7.5% and 22.5% of the total capacity, respectively) 99% of the time. The two settings of α_j can be seen as realistic boundary cases where the hedging mechanism becomes most beneficial. The following simulation procedures are designed to examine all the possible scenarios falling between the boundaries for the two situations discussed above.

Table 2. Simulation parameter specifications

Parameter ($m = i, j$)	Value	Parameter ($m = i, j$)	Distribution
n_m	200	α_i	N(30, 3.52)
λ_1 *	0.33	α_j –Setting 1	N(20, 3.52)
λ_2 *	0.34	α_j –Setting 2	N(30, 5.82)
		$COST_{ic}$	N(300, 402)
		P_{mc} (refundable)	N(311, 462)
		P_{mc} (non-refundable)	N(165, 252)
		SH_{mc} (refundable)	B(1, 0.6)
		SH_{mc} (non-refundable)	B(1, 0.926)

Simulation Procedures

Part 1: For $\alpha_j \sim N\left(\mu_j, \sigma_j^{\,2}\right)$, fix $\sigma_j \; to \; 3.5$ and systematically change μ_j from 20 to 30 in the increment of 1 (11 values). For each $\mu_{jt}\left(t = 1, 2, \ldots, 11\right)$, calculate the expected net benefit for both flights and the alliance when N_o is from 1 to 10. Specifically, the procedures of calculating the net benefit are the same as the approach described in Section 4.1 of Wang and Fung (2014).

Part 2: For $\alpha_j \sim N\left(\mu_j, \sigma_j^{\,2}\right)$, fix $\mu_j = 30$ and systematically change σ_j from 3.5 to 5.8 in the increment of 0.1 (24 values). For each $\sigma_{js}\left(s = 1, 2, \ldots, 24\right)$, calculate the net benefit for both flights and the alliance when N_o is from 1 to 10.

RESULTS AND DISCUSSION

The Best Number of Options

Table 3 presents the first case of simulation Part 1 when $\alpha_j \sim N\left(20, 3.5^2\right)$. The values of (*x, k*) are set arbitrarily for illustration purpose. The expected net benefits for Airline I ($E[B_i\left(Net\right)]$), Airline J ($E[B_j\left(Net\right)]$) and the Alliance ($E\left[B\left(Net\right)\right]$) are obtained by taking an average of 1,000 experiment results, where each experiment represents one set of flight departures (i.e., one departure of flight i and one subsequent departure of flight j).

It can be observed that the best number of options N_o^* is different when the ultimate objective changes from maximizing the benefit of the alliance to maximizing the benefit of an individual airline. For example, when maximizing $E\left[B\left(Net\right)\right]$, N_o^* is 7. However, if maximizing $E[B_i\left(Net\right)]$, N_o^* changes to 5; and if maximizing $E[B_j\left(Net\right)]$, N_o^* changes to 10. Similar pattern remains for other

Table 3. Expected net benefit for Airline I, Airline J, and the alliance: Case illustration (μ_{j1} = 20, *x* = 10, *k* = 110)

N_o	$E\left[B\left(Net\right)\right]$	$E[B_i\left(Net\right)]$	$E[B_j\left(Net\right)]$
1	124.896	79.414	65.033
2	207.122	132.291	118.239
3	248.296	149.819	151.672
4	291.692	173.787	187.932
5	329.197	**180.381**	230.582
6	320.161	173.074	222.723
7	**343.798**	172.879	257.604
8	305.714	142.634	245.767
9	323.916	150.267	254.314
10	340.732	162.136	**265.438**

cases when μ_j takes other values, when σ_j takes other values, and even when the values of (*x, k*) take other combinations.

By completing simulation Part 1, results of $E\left[B\left(Net\right)\right]$, $E[B_i\left(Net\right)]$ and $E[B_j\left(Net\right)]$ for the 11 cases of μ_j are obtained. The following presents the summary. In particular, Figures 3–5 show the expected net benefit for Airline I, Airline J, and the alliance corresponding to each μ_j value calculated under the objective of maximizing $E\left[B\left(Net\right)\right]$, $E[B_i\left(Net\right)]$ and $E[B_j\left(Net\right)]$, respectively. Correspondingly, Tables 4–6 summarize the numerical values. Consistent with intuition, there is a trade-off between maximizing $E\left[B_i\left(Net\right)\right]$ and maximizing $E\left[B_j\left(Net\right)\right]$. When maximizing $E\left[B_i\left(Net\right)\right]$, $E[N_o^*]$ tends to be smaller than that obtained under the other two

Figure 3. Benefit calculated under the objective of maximizing E[B(Net)]

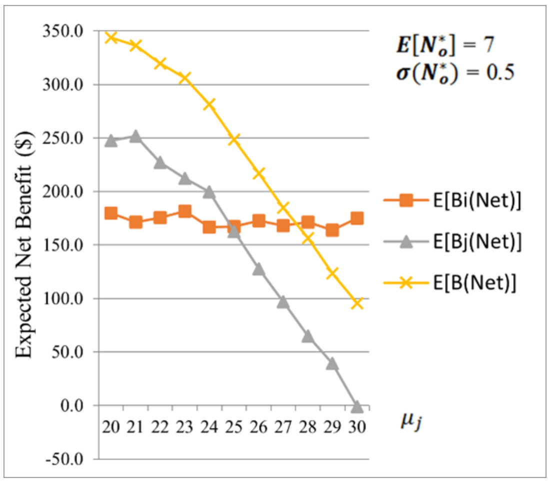


Figure 4. Benefit calculated under the objective of maximizing E[B$_i$(Net)]

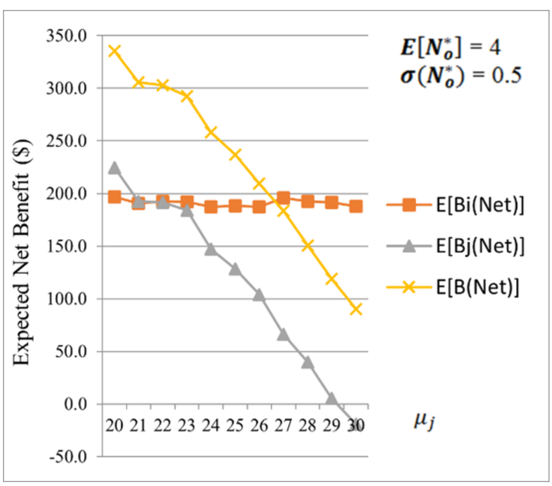


Figure 5. Benefit calculated under the objective of maximizing E[B$_j$(Net)]

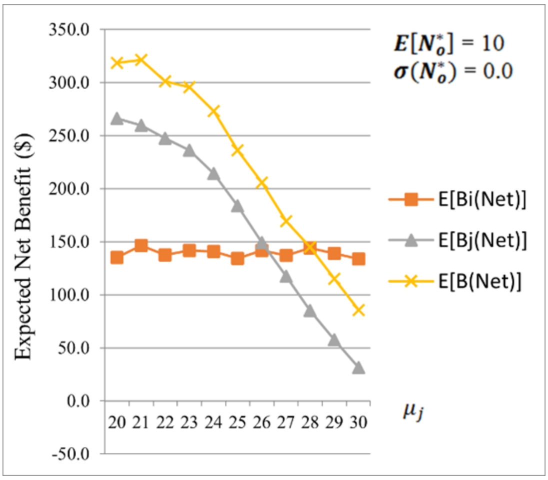


Table 4. Benefit calculated under the objective of maximizing E[B(Net)]

μ_j	N_o^*	$E[B_i(Net)]$	$E[B_j(Net)]$	$E[B(Net)]$
20	7	179.6	247.3	343.7
21	8	171.4	251.7	336.4
22	7	175.3	227.3	319.5
23	7	181.5	212.3	306.3
24	8	166.5	199.6	281.2
25	7	166.9	162.7	248.5
26	7	172.6	127.6	216.6
27	7	167.9	97.1	184.8
28	7	171.3	64.9	156.6
29	7	163.8	39.5	123.4
30	6	175.1	-1.2	95.3

maximization objectives. In this case, $E\left[B_j\left(Net\right)\right]$ is lowered because Airline J earns less revenue from selling and exercising options. When maximizing $E\left[B_j\left(Net\right)\right]$, $E[N_o^*]$ tends to be the largest possible value of N_o (10 in this simulation experiment). It is certainly to the detriment of $E\left[B_i\left(Net\right)\right]$ since Airline I needs to pay more to buy unnecessary options which will never be exercised. This trade-off effect indicates that the best number of options should be selected under the objective of maximizing $E\left[B\left(Net\right)\right]$, where $E\left[B\left(Net\right)\right]$ is the largest and the expected net

Table 5. Benefit calculated under the objective of maximizing $E[B_i(Net)]$

μ_j	N_o^*	$E[B_i(Net)]$	$E[B_j(Net)]$	$E[B(Net)]$
20	5	196.8	224.3	335.2
21	4	190.4	192.5	305.6
22	4	192.5	191.4	303.0
23	5	192.0	184.0	292.4
24	4	187.3	147.2	258.1
25	4	188.1	128.2	236.7
26	5	187.2	104.0	209.3
27	4	196.0	66.1	183.5
28	5	192.5	39.5	150.6
29	4	191.5	5.1	118.8
30	5	187.7	-19.1	90.3

Table 6. Benefit calculated under the objective of maximizing $E[B_j(Net)]$

μ_j	N_o^*	$E[B_i(Net)]$	$E[B_j(Net)]$	$E[B(Net)]$
20	10	135.1	**266.1**	318.6
21	10	146.2	**259.6**	321.1
22	10	137.4	**247.5**	301.3
23	10	141.9	**236.0**	295.5
24	10	140.7	**214.3**	273.0
25	10	134.0	**183.8**	236.4
26	10	141.7	**149.0**	205.8
27	10	137.2	**117.5**	169.2
28	10	144.1	**85.1**	145.2
29	10	138.9	**57.8**	115.2
30	10	134.0	**31.3**	85.5

benefit of the two individual airlines is comparable to that calculated under the objective of maximizing their own benefit, respectively.

A trade-off effect is observed that N_o^* is obtained under the objective of maximizing $E\left[B\left(Net\right)\right]$. Let $N_o^* = argmax\ E\left[B\left(Net\right)\right]$, $N_{oi}^* = argmax\ E\left[B_i\left(Net\right)\right]$, and $N_{oj}^* = argmax\ E\left[B_j\left(Net\right)\right]$, then $E\left[B\left(Net\right)\right]_{N_o^*} > E\left[B\left(Net\right)\right]_{N_{oi}^*}$ and $E\left[B\left(Net\right)\right]_{N_o^*} > E\left[B\left(Net\right)\right]_{N_{oj}^*}$, while $E\left[B_i\left(Net\right)\right]_{N_o^*}$ is comparable to $E\left[B_i\left(Net\right)\right]_{N_{oi}^*}$ and $E\left[B_j\left(Net\right)\right]_{N_o^*}$ is comparable to $E\left[B_j\left(Net\right)\right]_{N_{oj}^*}$.

As shown in Figure 3, when the objective is to maximize $E\left[B\left(Net\right)\right]$, the expected value of N_o^* is 7 and its standard deviation is 0.5. It is noticed that Airline J suffers a loss when flight j has the same demand pattern as flight i. In this case, it is less likely that flight i has vacancies when Flight i gets excessive passengers. As a result, flight j may need to sacrifice its own demand in most cases. Allied airlines will probably not choose the hedging mechanism under such a scenario. Therefore, the following analyses will ignore the case when μ_j equals 30.

By completing both simulations Part 1 and Part 2 for twelve $\left(x,k\right)$ combinations given in Table 7 in Wang and Fung (2014), it is found that a robust result of $E[N_o^*]$ can be obtained. Table 7 provides a summary. All the values of $E[N_o^*]$ are 7 while most of $\sigma\left[N_o^*\right]$ is small than 1. Due to demand uncertainty, there will never be a specific value of N_o^* that fits every situation. However, the results in Table 7 well suggest an expected value of N_o^*. For example, when $x = 10$ and $k = 110$, the results

Table 7. Results of $E\left[N_o^*\right]$ and $\sigma\left[N_o^*\right]$ for the twelve (x, k) combinations

Case	x	k	Simulation Part 1 Fix σ_j, change mean μ_j		Simulation Part 2 Fix μ_j, change σ_j	
			$E\left[N_o^*\right]$	$\sigma\left[N_o^*\right]$	$E\left[N_o^*\right]$	$\sigma\left[N_o^*\right]$
1	22	95	7	1.2	7	1.0
2	17	100	7	1.3	7	0.7
3	13	105	7	0.8	7	0.8
4	10	110	7	0.5	7	0.9
5	8	115	7	0.6	7	0.8
6	7	120	7	0.8	7	0.8
7	6.25	125	7	0.6	7	1.0
8	5.75	130	7	0.8	7	0.8
9	5.5	135	7	0.7	7	1.0
10	5.35	140	7	0.6	7	0.8
11	5.25	145	7	0.7	7	0.6
12	5.2	150	7	0.8	7	0.8

of ($E[N_o^*] = 7,\ \sigma\left[N_o^*\right] = 0.5$) implies that the best number of options is 7 so that airlines can tackle the problem of overbooking in most of the time. With a consistent mean value and a small variation, the result of N_o^* is considered robust.

Effectiveness of the Best Strategy

Table 8 shows the frequency of bumped cases out of 10,000 flights operated by Airline I. Nearly half of the time, flight i needs to bump passengers. For those flights with bumped passengers, the situation that no more than three passengers are bumped accounts for 60% of the cases. Nearly 98% of the time, the number of bumped passengers is less than or equal to 7. Figure 6 provides a graphical illustration. Recall that the value of $E[N_o^*]$ obtained in the above experiments is 7. It implies that by using the hedging mechanism, Airline I can tackle the problem of oversale 98% of the time. Meanwhile, the alliance as a whole can maximize its revenue. Interestingly, $E[N_o^*]$ is only 4, if the objective is to maximize Airline I's individual benefit (see Figure 4). The optimal decision for Airline I to solve the problem of bumping in 75% of the time is sub-optimal for the alliance. Therefore, the hedging mechanism is suitable for airline alliances with a medium to a high level of cooperation, where allied carriers collaborate on a network basis and concern more about the long-term benefit obtained from the alliances. If focusing on route-by-route individual benefit, the two parties may hardly achieve an agreement to cooperate.

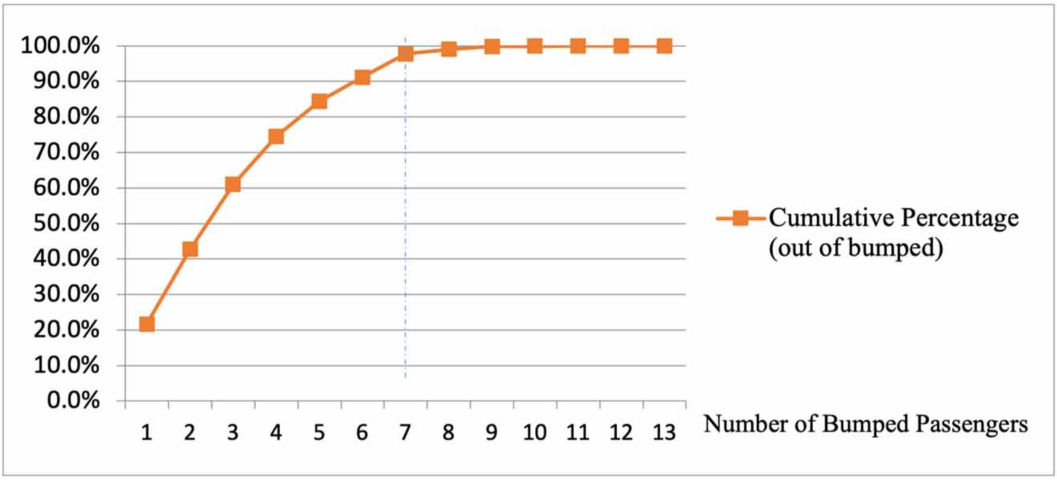
Impacts of the Option Cost on Airlines' Benefit Sharing

The authors perform simulation experiments to show the impacts of $\left(x,k\right)$ on airlines' benefit sharing when the allied carriers transact $N_o^* = 7$ options between each other. For simulation Part 1, it is

Table 8. Frequency of bumped cases

Number of Bumped Passengers	Frequency	Percentage (of Total)	Cumulative Frequency (Bumped)	Cumulative Percentage (of Bumped)
0	5,101	51.0%		
1	1,061	10.6%	1,061	21.7%
2	1,032	10.3%	2,093	42.7%
3	894	8.9%	2,987	61.0%
4	665	6.7%	3,652	74.5%
5	483	4.8%	4,135	84.4%
6	330	3.3%	4,465	91.1%
7	323	3.2%	4,788	97.7%
8	61	0.6%	4,849	99.0%
9	42	0.4%	4,891	99.8%
10	5	0.1%	4,896	99.9%
11	2	0.0%	4,898	100.0%
12	0	0.0%	4,898	100.0%
13	1	0.0%	4,899	100.0%
Sub-total of bumped cases		49%		
Total number of flights = 10,000		100%		

Figure 6. Cumulative percentage of bumped cases



found that neither a higher option price x, nor a higher exercise price k is beneficial for Airline I, which is the option buyer. In these cases, Airline I shares less benefit from the overall benefit generated for the alliance, while Airline J shares more. This pattern holds for every $\left(x,k\right)$ combination. Cases 1, 4, 12 in Table 7 are depicted in Figures 7– 9 to show the trend.

For simulation Part 2, the result is similar to that in Part 1 (see Figures 10–12). Airline I shares less benefit either when the option price x is higher or when the exercise price k is higher. Notably, Figure 10 shows that when option price x is too high, the variance of the individual airlines' net benefit is substantial. It is due to the uncertainty of exercising an option. If the option prepayment is too high, whether or not an option is exercised will cause much difference in airlines' revenue. However, when σ_j is larger, which means the demand of flight j has a more significant variation than the demand of flight i, the variance in airlines' net benefit is reduced. It supports the argument that the hedging mechanism is more beneficial when there is a larger variation in the demand patterns

Figure 7. Benefit calculation for $\left(x=22, k=95, N_o^*=7\right)$**, changing** μ_j

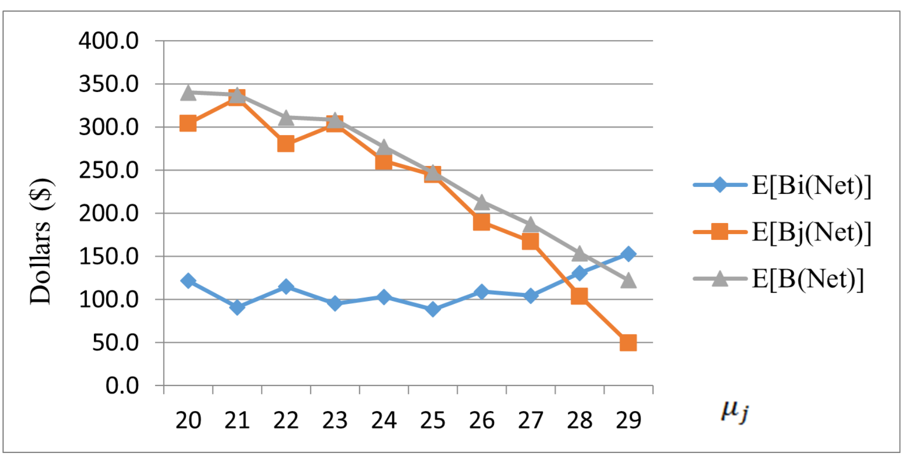


Figure 8. Benefit calculation for $\left(x = 10, k = 110, N_o^* = 7\right)$, changing μ_j

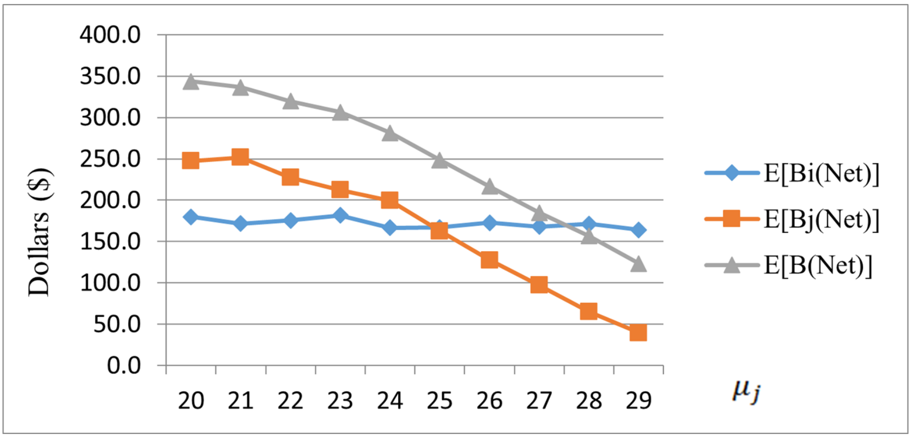
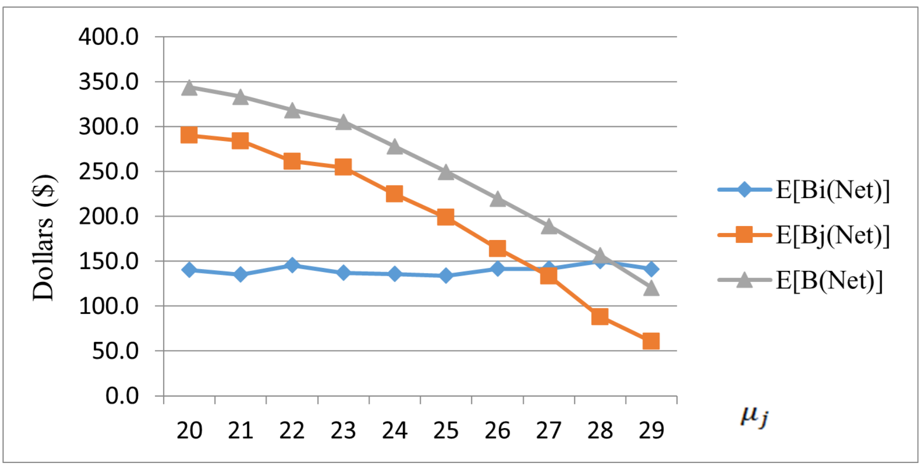


Figure 9. Benefit calculation for (x = 5.2,k = 150,N_o^* = 7), changing μ_j



of the two flights. From the perspective of Airline I, it could be more certain that the options purchased will be exercised and bring benefits most of the time.

Two-Stage Simulation-Based Algorithm

The above analyses show the best number of options for a specific scenario of airline alliances. To obtain a generalizable solution, the authors develop the following two-stage simulation-based algorithm to identify the best number of options for applying the hedging mechanism.

Stage 1 of the algorithm consists of three steps and aims to find N_o^*, which brings the largest benefit for the alliance as a whole. The rationale is first to find a range of the possible number of bumped passengers for flight i, with a specified confidence level. This confidence level is set by airlines, and it reflects the risk attitudes of the alliance. The best number of options is then identified from the range.

Figure 10. Benefit calculation for $\left(x = 22, k = 95, N_o^* = 7\right)$**, changing** σ_j

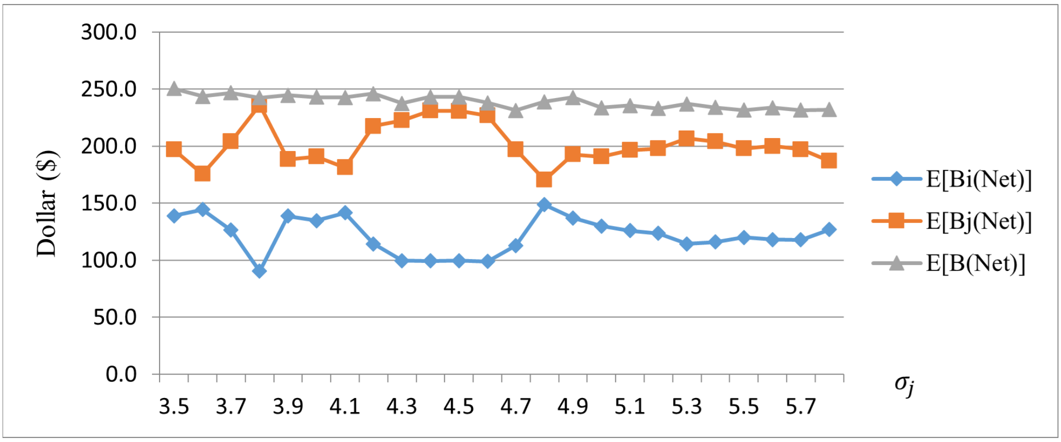


Figure 11. Benefit calculation for $\left(x = 10, k = 110, N_o^* = 7\right)$**, changing** σ_j

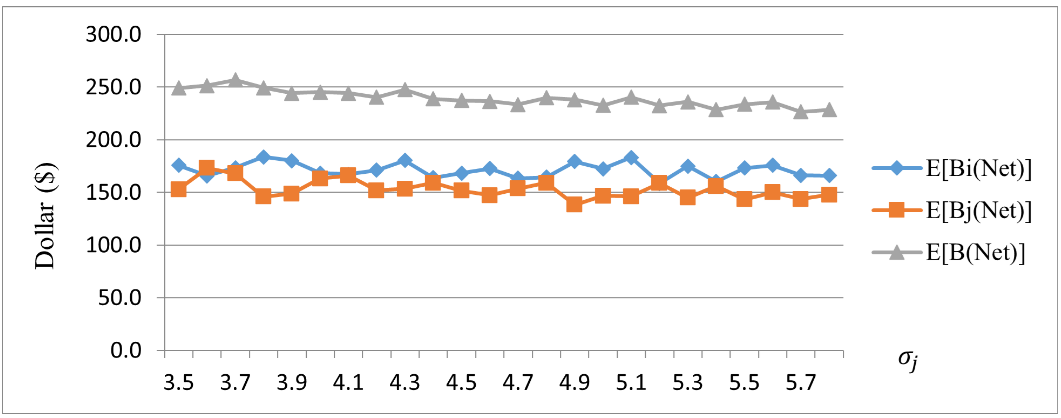
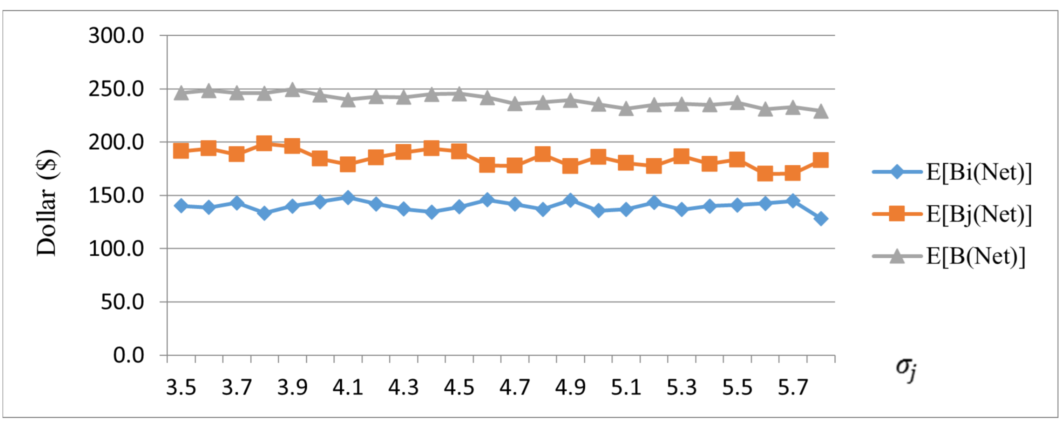


Figure 12. Benefit calculation for $\left(x = 5.2, k = 150, N_o^* = 7\right)$**, changing** σ_j



1. Calculate the mean $\bar{N}$ and the standard deviation $\sigma(N)$ of the number of bumped passengers N using historical data over a specified period:

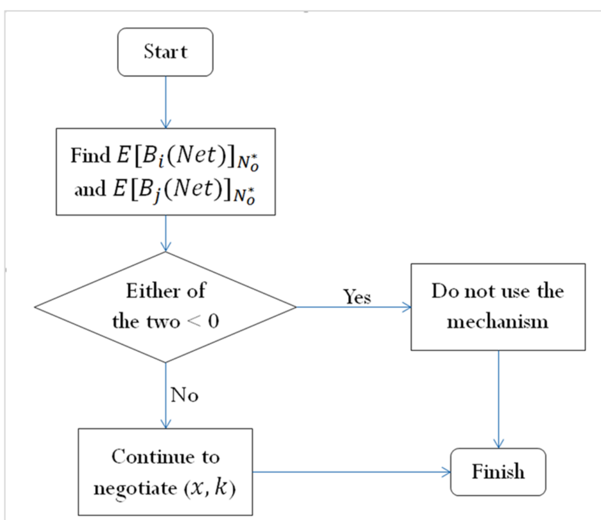
$$N = \sum_{c_i}^{n_i+\alpha_i} \left\{ SH_{ic} BP_{ic} = 1 \right\}$$

2. Find the $\theta\left(\%\right)$ confidence interval $\left[0,\tilde{N}\right]$ such that the probability that the number of bumped passengers of future flight i exceeds $\tilde{N}$ is not greater than $\left(1-\theta\right)$. Different risk attitudes of the alliance will affect the selection of θ.
3. For $N_o \in \left[0,\tilde{N}\right]$, find the best number of options N_o^* for the alliance and calculate $E\left[B\left(Net\right)\right]_{N_o^*}$. If $N_o^* > 0$ and $E\left[B\left(Net\right)\right]_{N_o^*} > 0$, proceed to Stage 2; otherwise, do not use the mechanism.

After identifying $E[N_o^*]$, decision-makers can proceed to Stage 2 (shown in Figure 13) to examine whether the individual airlines can obtain positive benefits when transacting N_o^* options between each other under a specific circumstance. The underlying assumption is that airlines are willing to cooperate if they can both obtain positive net benefits from the collaboration arrangement. As different $\left(x,k\right)$ combinations will affect the share of benefits between the allied carriers, the option pricing will depend on the bargaining power of the two airlines. This decision should be made through negotiation.

Using the result in Table 3 again as an example, if a 99% confidence level is chosen, the corresponding confidence interval of the number of bumped passengers N is [0, 8]. It is reasonable to identify N_o^* within the range of [0, 8] because this interval is likely to include the number of bumped passengers of a future flight i in 99% of the cases. It is calculated that N_o^* is 7, which brings the largest alliance-wide benefit of $343.798. In addition, Airline I and J can both obtain positive

Figure 13. Simulation-based algorithm Stage 2



benefit when transacting 7 options between each other. In this case, the best strategy for applying the option-based mechanism is identified.

CONCLUSION

Wang and Fung (2014) proposed an option-based hedging mechanism for airlines in a parallel alliance to transfer bumped passengers to their alliance partner's flight. The current work extends the literature by conducting strategic analyses of the hedging mechanism. Specifically, the authors design and perform comprehensive simulation experiments to investigate the possible scenarios in which the mechanism benefits the alliance. From the analyses, it is found that there exists the best number of options N_o^* that the allied carriers should transact with each other, and this value should be obtained under the objective of maximizing the alliance-wide revenue. The mechanism is effective since airlines can mitigate the ex-post overbooking risks in most cases.

As the hedging mechanism cannot be beneficial for both carriers under all circumstances, the authors also develop a two-stage simulation-based algorithm to identify whether the mechanism should be used; and, if yes, what the best number of options is. The algorithm can provide airlines with guidance and recommendations to identify the best strategy for applying the hedging mechanism. Using historical data and the demand forecast, airlines could follow the algorithm to obtain N_o^* for their customized scenarios. It deserves noting that, for each scenario, airlines can freely adjust their risk attitudes and get different results of N_o^*.

This work is vital because it addresses the possible negative impact of the prevalent overbooking practice and provides answers to the unexplored questions in Wang and Fung (2014). The practical deliverable of the algorithm should be application software. The airline management can use the software, input the values of key variables based on the forecast, and obtain direct guidance on the best practice of hedging ex-post overbooking risks and matching supply with demand.

DECLARATION OF COMPETING INTEREST

The authors of this publication declare there are no competing interest.

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