AN ASSESSMENT OF FACTORS AFFECTING AIRLINE COALITIONS USING DECISION AND COOPERATIVE GAME THEORY

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Abstract

Because of the rigorous competition in the air travel market, more airlines tend to form alliances to extend market shares and to enhance their competitiveness. Cooperation among airlines includes code sharing, equity sharing, merging and acquisition, but we only focus on code sharing and merging in this study. We first formulate payoff functions under various airline coalition scenarios. Then, we assess the effectiveness of code sharing and merging by the estimation of Shapley values. By applying TOPSIS, we create several priority rankings of target airlines in the games of code sharing and merging. A case study based on Taiwan's domestic airlines was used for demonstration.

Keywords: Code sharing; Airline merging; Cooperative games; Multi-criteria decision methods
Topic area: A3 Airports and Aviation

1. Introduction

1.1 Motivation of airline coalitions, merging and acquisitions

Taiwan's deregulation of air travel market began in 1987. Since then, the number of domestic airlines increased from four to nine, and the flights between Taipei and other major cities were so frequent that made Taipei domestic airport became one of the most busiest airports in Asia.

Unfortunately, the benefits of low airfare and high flight frequency resulted from deregulation did not last long. In 1998, several local air traffic accidents along with the Asian financial crisis caused most of the domestic airlines suffering from severe losses in revenue and patronages.

Motivated by strengthening air travel safety and enhancing the quality of services, Taiwan's Civil Aviation Bureau (TCAB) released new regulations in 1999 to offer incentives for merging and penalties for those who refused to comply. As a result, merging and acquisitions among airlines reduced the number of airlines from nine to six and the cutthroat competition among domestic airlines was ended.

Similarly, merging and acquisition were quite often in the last decade for international airlines. For instance, American Airlines merged with TWA in 2001; Swissair acquired three local airlines in France, i.e., Air Liberte, Air Littoral, and AOM, and owned 49.5% shares of Sabena, in order to extend their services in Western Europe; In China, ten airlines were merged into China Southern Airlines, China Eastern Airlines, and China International Airlines in 2000.

Usually, the effectiveness of merging and acquisitions would not be revealed in a short period of time. To find good candidates as well as to assess the potential benefits before merging or acquisitions take place are crucial issues to all airlines. The goal of the study is to develop an evaluation scheme for this task.

1.2 Factors affecting airline's code sharing and merging

According to our survey to higher-ranked managers from various airlines, the only factor affecting airline's code sharing is profit. However, the major factors affecting airline's merging or acquisitions might include: 1) the performance of profitability; 2) the financial creditability and stability; 3) the extension of service network; 4) the compatibility of maintenance and logistic systems; and 5) the coordination of human resources.

It should be noted that the performance of profitability may be the most important factor in the games of airline's merging or acquisitions, but the other factors, such as the financial creditability and stability, may also be critical in the games. For instance, an airline with good performance on profitability but poor creditability on financial stability was usually the target airline while an airline with solid financial support but average performance on profitability was often the bidder in the merging or acquisition games. In other words, these factors not only affect airlines' long-term profitability and competitiveness, but also link to the keys of success or survival in the market.

As a result, the study would first focus on the estimation of coalition effectiveness by the cooperative game approach. Nest, the paper applies multi-criteria decision method, i.e., the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) developed by Hwang and Yoon (1981), to incorporate these factors and provide a priority ranking of target airlines in code sharing and merging games.

1.3 Literature review

Numerous papers had dealt with airline cooperation issues. Carlton, Landes, and Posnner (1980) compared the benefits and costs before and after the merging of North Central Airlines and Southern Airways. Their analysis showed that increasing returns to scale was probably one of the major incentives for airline merging. Hviid and

Prendergast (1993) were interested in the bidding game of airline merging. They assumed that the target airline had private information of its own profits and both the target and the bidder airlines played the Cournot game in a duopolistic market before merging took place. In the equilibrium, the bidder's offer would be rejected only if the operating costs of the target airline were lower than the bidder's expectation. Youssef and Hansen (1994) found that code-sharing agreement between Swissair and Scandinavian Airlines System (SAS) had produced higher load factor resulted from better quality of service for customers. Oum, Park, and Zhang (1996) developed an analytical procedure for the impact assessment of code sharing between follower and leader airlines. They found that if the follower airlines formed a code-sharing alliance, the leader airline would have to lower airfares in response to the new alliance. In the equilibrium, the leader would have higher load factor due to lower airfares. Park (1997) further pointed out that code sharing might produce higher consumer's surplus if the allied airlines had similar quality of service and the service frequency on their routes were low. Chen (1999) studied the merging of China Airline (CAL) and Formosa Airline by analyzing financial data to explore the relationship among bidding prices, financial stability, and profitability. Ko (1999) predicted airline's benefits from parallel code sharing cooperation by the use of travelers' revealed and stated preference data in discrete choice demand modeling. He then applied cooperative game approach to solve for the benefit distribution problem for domestic airlines. Chang (2001) compared the customer's surplus before and after international airline's complementary code sharing by following Ko's approach. Button (2003) started from the idea of core, which is a fundamental concept in cooperative game, to analyze the long-term effect of deregulation around the world. Button suggested that appropriate policy reactions, e.g., removal of some restrictions on airline merging and coalitions, might allow a more sustainable market structure to survive.

As for the applications of decision theory, Pen (1998) compared the competitiveness index of five domestic airlines in Taiwan by applying multi-criteria decision approaches. She defined the components of competitiveness index as operations efficiency, service quality, productivity, and the advantages of lower airfares or lower costs. Using Entropy and TOPSIS methods, Pen concluded that her index consisted of two major factors: operations efficiency and service quality. By analyzing the data of the past few years, she found that her index was consistent with profitability.

This study applies TOPSIS method for analyzing managers' preferences on code sharing and merging due to two reasons: 1) TOPSIS was derived based on managers' utility functions and was proven to be effective in many empirical works; 2) with managers' order data, we are able to calibrate the priority ranking of various coalition alternatives regarding merging or code sharing.

1.4 The framework of the study

The framework of the study is demonstrated by the flowchart shown as Figure 1. First, we collect airlines' financial and operating data and design the questionnaires for airline managers and travelers. Next, we calibrate the payoff functions and the weights of various factors affecting merging and code sharing. Then, the payoff functions are validated by historical data and a consistency test was performed for the TOPSIS analysis. Finally, we present three case studies for model applications: 1) the complementary code sharing among international flights; 2) the parallel code sharing among domestic flights; and 3) the merging of domestic airlines.

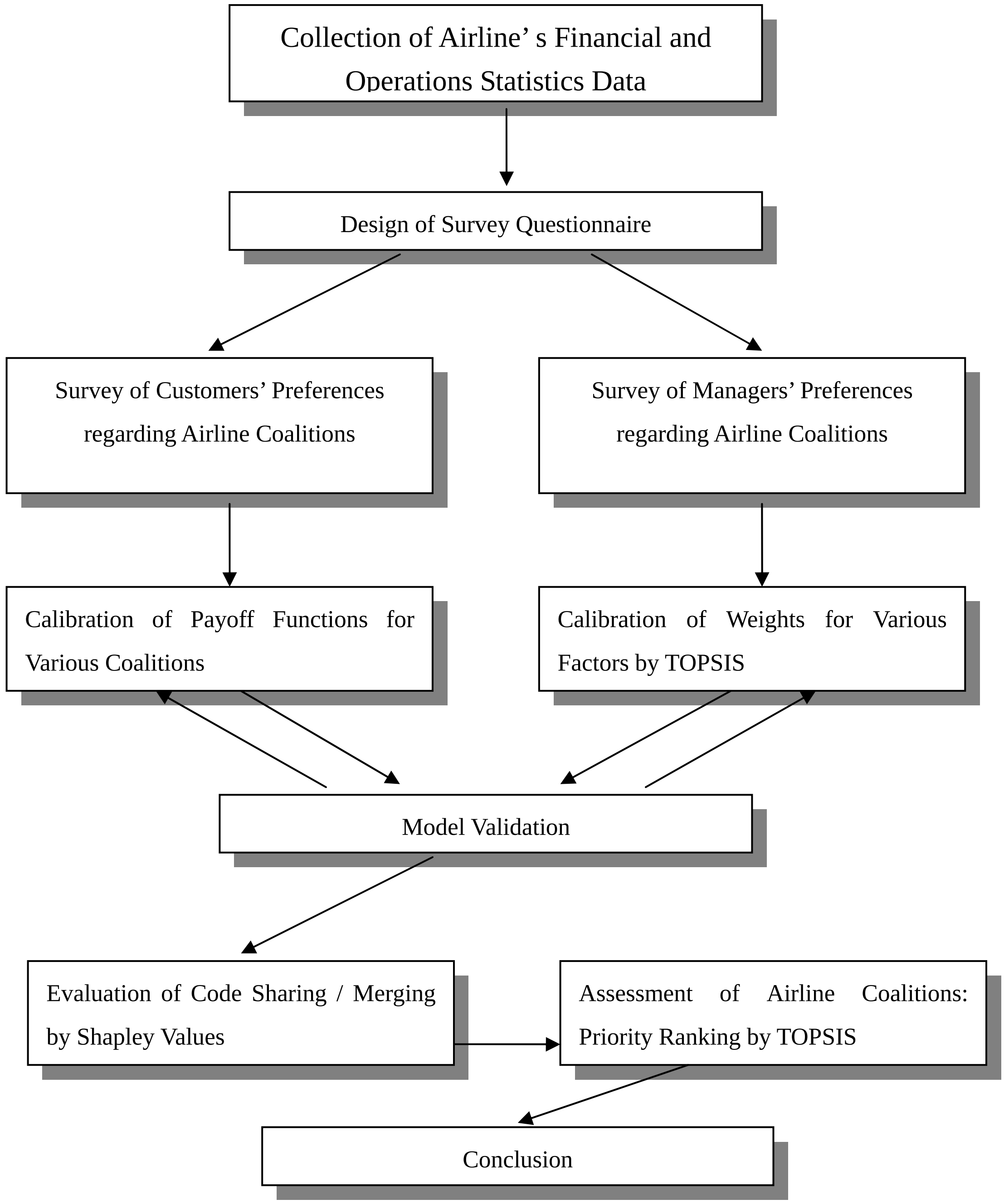

Figure 1: Solution Approach to Airline's Merging and Acquisitions

2. Formulation of airline's payoff function

The assumptions of the study are as follows:

1) All airlines are candidates of targets or bidders in the merging games;

2) Before and after code sharing or merging, all airlines play Bertrand Games;

3) The decision regarding code sharing or merging is rational.

The first assumption addresses the fact that all airlines would be looking for any good opportunities of cooperation. The second assumption states that the market is oligopoly and airlines were competing in airfares. The last assumption describes the fact that the motivation for code sharing or merging is driven by profits or profit related factors.

Next, we develop a payoff function that could be used for various coalition relationships. The payoff function consists of an air travel demand function of any O-D pair, an airline's load factor function, and a cost function that could reveal different cooperation scenarios. The specification of payoff function is as follows:

$$\pi_{ijk} = p_{ijk} \cdot q_{ijk} - Cost_{ijk} \cdot F_{ijk} \tag{1}$$

where

π_{ijk} = the profit of airline alliance k generated from the (i, j) O-D pair;

p_{ijk} = the average airfare set by airline alliance k on the service route of the (i, j) O-D pair;

q_{ijk} = the air travel demand of airline alliance k on the service route of the (i, j) O-D pair;

$Cost_{ijk}$ = the cost per flight of airline alliance k on the service route of the (i, j) O-D pair;

F_{ijk} = the flight frequency of airline alliance k on the service route of the (i, j) O-D pair.

The air travel demand q_{ijk} is formulated as follows:

$$q_{ijk} = F_{ijk} \cdot Seats_{ijk} \cdot R_{ijk} \tag{2}$$

$$R_{ijk} = \frac{1}{1 + e^{-U_{ijk}}} \tag{3}$$

where,

$Seat_{ijk}$ = the number of seats per flight of airline alliance k of the (i, j) O-D pair;

R_{ijk} = the load factor of airline alliance k of the (i, j) O-D pair;

U_{ijk} = the utility function of passengers choosing airline alliance k of the (i, j) O-D pair.

The specification of load factor was a logistic function such that the value of load factor would lie between 0 and 1. The utility function of passenger's choice on airline was set to be a linear function of airfares, frequencies, and seasonal adjustment factors. In addition, the load factor model could be calibrated by linear regression approach with the following transformation:

$$-\ln\left(\frac{1}{R_{ijk}} - 1\right) = U_{ijk}$$

$$= b_0 + b_1 \cdot p_{ijk} + b_2 \cdot p_{ijl} + b_3 \cdot \ln F_{ijk} + b_4 \cdot \ln F_{ijl} + b_5 FFP_k + b_6 D_1 + b_7 D_2 + e \qquad (4)$$

where,
p_{ijl} = the average airfare set by opponent airline l on the service route of the (i, j) O-D pair;
F_{ijl} = the flight frequency of opponent airline l on the service route of the (i, j) O-D pair;
FFP_k = the frequent flyer dummy variable, 1 if member of airline k, 0, otherwise;
D_1 = the seasonal adjustment factor, 1 for January, February, April, July, August, December, 0 for other months;
D_2 = the accident adjustment factor, 1 for the following 4 months of accident, 0, otherwise;
b's = the coefficients of the utility function;
e = the random error.

Because the load factors of airline alliances under various scenarios could not be observed in current practices, we would have to collect survey data to obtain passenger's revealed and stated preferences on airlines. In other words, the load factor function was estimated by using potential demand predicted by a passengers' choice model under various scenarios. Meanwhile, using monthly airlines' load factor data in the past five years, we were able to validate the load factor function with data fusion techniques.

The cost function was calibrated according to the general practices in merging and code sharing. The cost function consisted of four parts: 1) direct flight costs, i.e., fuel costs; 2) airport holding costs, i.e., landing and holding fees, passengers and cargos logistic costs; 3) variable costs, i.e., passenger service and crew costs; and 4) other costs, i.e., maintenance and leasing costs. It should be noted that the costs vary from code sharing to merging. For instance, code sharing would affect cargo logistic costs, passenger service costs, etc.; merging on the other hand, would affect crew costs, maintenance and leasing costs if two merging airline reschedule their crews and flights.

3. Solution approach

To estimate the potential benefits of code sharing and merging, this study derived a set of all possible coalition scenarios and then solved for the market equilibrium with respect to airfares for each coalition scenario. The solution concept of Shapley value was applied to compute the allocation of profits among airlines derived from various coalition scenarios. The following steps summarized the solution approach:

1. Form a set of all possible coalitions;
2. Calibrate the payoff function, especially the load factor model, for each coalition;
3. Find the market equilibrium by solving the airfares that maximize the payoff functions of all competitors under each coalition scenario;
4. Calculate Shapley values of all airlines with various coalition payoffs from Step 3.

Next, TOPSIS was adopted to assess the importance of factors affecting airlines' merging. These factors included profitability, financial stability, coverage of service network, compatibility of maintenance/logistic systems, and coordination of human resources. A set of weights for theses factors was derived based on the preferences of airline managers. The results were then applied to evaluate various coalition strategies among airlines.

The solution approach to TOPSIS is as follows:

Step 1: Normalization of indices

$$\overline{X}_{ij} = \frac{\left(X_{ij} - X_{\min.j}\right)}{\left(X_{\max.j} - X_{\min.j}\right)} \tag{5}$$

$$V_{ij} = W_j \times \overline{X}_{ij} \quad , j = 1,2,\cdots n \tag{6}$$

where,

X_{ij} = the j^{th} index value for the i^{th} alternative,

$X_{\max.j} = \max\{X_{ij}, \forall i\}$, $X_{\min.j} = \min\{X_{ij}, \forall i\}$,

$\overline{X}_{ij}$ = the normalized index, lies between 0 and 1,

V_{ij} = the weighted normalized index value, lies between 0 and 1,

W_j = the weights.

Step 2: Calculation of ideal solutions and negative ideal solutions

$$A^* = \left\{\left(\max_i V_{ij} \middle| j = 1\right), \left(\min_i V_{ij} \middle| j = J'\right) \middle| i = 1,2,\cdots m\right\} = \left\{V_1^*, V_2^*, \cdots V_j^*, \cdots V_n^*\right\} \tag{7}$$

$$A^- = \left\{\left(\min_i V_{ij} \middle| j = 1\right), \left(\max_i V_{ij} \middle| j = J'\right) \middle| i = 1,2,\cdots m\right\} = \left\{V_1^-, V_2^-, \cdots V_j^-, \cdots V_n^-\right\} \tag{8}$$

Where J is the set of utility indices and J’ is the set of cost indices, A^* and A^- are the positive and negative ideal solution, respectively.

Step 3: Computation of Separation Measure

If the ideal solution is positive for utility indices, then

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - V_j^*\right)^2} \quad ,i = 1,2,\ldots\ldots,m \tag{9}$$

If the ideal solution is negative for cost indices, then

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - V_j^-\right)^2} \quad ,i = 1,2,\ldots\ldots,m \tag{10}$$

Step 4: Calculation of Relative Closeness (RC) for various factors or alternatives

$$RC_i = \frac{S_i^-}{S_i^- + S_i^+} \qquad 0 \le RC_i \le 1 \tag{11}$$

If $A_i = A^*$, then $RC_{i^*} = 1$; if $A_i = A^-$, then $RC_{i^*} = 0$.

Step 5: Creation of priority ranking for various factors or alternatives

From Step 4, we could find the RC values for various factors and coalition alternatives. By ranking the RC's in descending order, we are able to create a priority list of different alternatives for airline coalitions.

4. Case study

Because of limited budget, we only selected four destinations, i.e., Bangkok, San Francisco, Sydney, and Amsterdam, in the case study of code sharing effects for international travelers from Taiwan. As for merging, we focused on the merging game among domestic airlines due to fact that Taiwan's authority would not approve the merging between domestic and international airlines.

The survey data consist of two parts: 1) travelers' stated and revealed preferences, and 2) managers' preferences on merging among domestic airlines. The survey of travelers' preferences on code sharing and merging was performed by the use of choice-based sampling. In other words, the random sampling was performed at the waiting lines of airport counters for travelers flying from Taipei to four selected destinations. Figure 2 shows the airlines that are flying these routes. Currently, Qantas and EVA are code sharing in flying between Taipei and Sydney. Table 1 is the sample distribution of the case study. The sample was consistent with the market shares of airlines serving these routes.

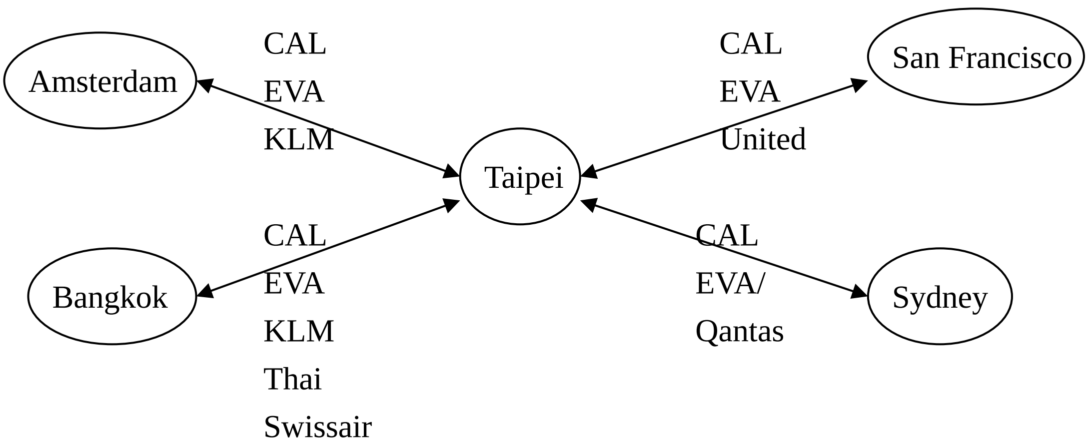

Figure 2: Airlines flying from Taipei to various destinations

We had completed 21 interviews in the survey of managers' preferences. For each merging scenario, we provided the estimation of three factors, i.e., profitability, coverage of network, and financial conditions based upon our model or hypothesis. Then, managers were asked to provide their evaluations on two other factors, i.e., compatibility of maintenance/logistic systems, and coordination of human resources, before and after code sharing or merging. Finally, they ordered their preferences on these five factors and various merging scenarios.

4.1 Calibration of load factors and costs for various coalitions

Without historical load factor data for code sharing and merging, we first apply multinomial Logit model to calibrate airline's market share by using travelers' stated preference data. Then, we calibrate the load factor model by using the prediction data drawn from market share under various coalition scenarios. On the other hand, because the historical load factor data were available in the case of pre-coalition, we were able to calibrate the historical load factor models. Then, by applying data fusion technique, we were able to combine two models and produce the results as shown in Table 2.

Due to the limitation of context length, we could only show the estimation results for airlines providing flights from Taipei to Amsterdam. Detail results could be found in the theses written by Kuo (2003) and Chang (2001). Table 3 shows the estimation results for the code sharing between CAL and KLM. Table 4 shows the results for the merging of CAL and EVA.

Except for the insignificant signs of seasonal factor, the estimated parameters are consistent with our *a priori*. For instance, the signs for airfares, opponents' frequency, and accident are negative; while the signs for frequency and opponents' airfares are positive.

Table 1: Sample distribution for travelers flying from Taipei to various destinations (Market shares in parentheses)

Airline	Destinations			
	Amsterdam	San Francisco	Sydney	Bangkok
CAL	31 (30%)	35 (34%)	53 (52%)	0 (0%)
EVA	32 (32%)	36 (35%)	0 (0%)	0 (0%)
KLM	39 (38%)	0 (0%)	0 (0%)	0 (0%)
United	0 (0%)	32 (31%)	0 (0%)	0 (0%)
EVA/Qantas	0 (0%)	0 (0%)	49 (48%)	0 (0%)
Swiss Air	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Thai	0 (0%)	0 (0%)	0 (0%)	0 (0%)

Table 2: Parameters of Airline's Load Factor Models from Taipei to Amsterdam: the Pre-Coalition Case (t values in parentheses)

Variables \ Airline	CAL	EVA	KLM
Constant	7.799 (6.476)	12.280 (11.823)	12.997 (14.200)
CAL's Airfare (in 1000 $NTD)	-2.354 (-10.041)	0.695 (3.435)	0.667 (3.741)
EVA's Airfare (in 1000 $NTD)	0.532 (3.985)	-1.736 (-15.086)	0.274 (2.702)
KLM's Airfare (in 1000 $NTD)	1.137 (5.805)	0.969 (5.738)	-2.107 (-14.154)
CAL's frequency (flights / week)	0.542 (1.250)	-3.872 (-10.353)	-3.337 (-10.125)
EVA's frequency (flights / week)	-1.663 (-4.016)	1.684 (4.715)	-1.498 (-4.757)
KLM's frequency (flights / week)	-2.900 (-6.821)	-3.494 (-9.528)	0.555 (1.716)
CAL's Membership Dummy Variable	5.486 (7.369)	-1.459 (-1.615)	-1.613 (-2.851)
EVA's Membership Dummy Variable	-0.421 (-0.557)	4.656 (7.141)	-1.112 (-1.936)
KLM's Membership Dummy Variable	-1.348 (-1.286)	-1.459 (-1.615)	5.878 (7.381)
Seasonal Dummy Variable: D1	-1.329 (-3.407)	-0.201 (-0.596)	0.09463 (0.319)
Accident Dummy Variable: D2	-0.481 (-0.850)	-0.444 (-0.909)	-0.565 (-1.314)
Adjusted R^2	0.710	0.903	0.904
F Value	501.713	226.250	90.229

Note: the rate of exchange: 33 New Taiwan Dollars ($NTD) = 1 US Dollar ($USD).

For the calibration of cost functions, we used Boeing 747-400 as an example to demonstrate the cost estimation. Table 5 shows the total operating costs for each flight from Taipei to four destinations in the pre-coalition case. These figures were derived based upon the data provided by Tseng (2000). We further assume that the estimated operating costs per flight remain the same for code sharing cases while the reduction of costs per flight is 15% for the merging cases.

4.2 Assessment of code sharing and merging

Based on the estimated costs as shown in Table 5 and the calibrated load factor model as shown in Table 2, Table 3, and Table 4, we apply software Mathematica (Varian, 1993) to solve for the optimal airfares in the Bertrand games. The results of the various coalition cases for flights from Taipei to Amsterdam are shown in Table 6. Comparing these Tables, we found that merging of CAL and EVA or code sharing among airlines would result in lower airfares and higher load factors for all airlines. The results were consistent with Park's findings (1997). However, the estimated profits were not increased by code sharing or merging according to the load factor model calibrated by passengers' stated preferences. In other words, unless the costs could be significantly reduced due to code sharing or merging, airlines flying from Taipei to Amsterdam would have no incentive for code sharing or merging.

Table 3: Parameters of Airline's Load Factor Models from Taipei to Amsterdam: the case of code sharing between CAL and KLM (t values in parentheses)

Variables \ Airline	CAL	EVA	KLM
Constant	8.337 (2.404)	5.440 (1.954)	16.541 (7.337)
CAL's Airfare (in 1000 $NTD)	-2.670 (-5.416)	0.290 (1.732)	0.847 (2.644)
EVA's Airfare (in 1000 $NTD)	0.385 (1.872)	-1.451 (-3.937)	1.290 (4.324)
KLM's Airfare (in 1000 $NTD)	0.858 (1.869)	0.251 (1.708)	-2.362 (-8.228)
CAL's frequency (weekly flights)	1.855 (3.422)	-0.872 (-2.005)	-2.416 (-6.857)
EVA's frequency (weekly flights)	-1.178 (-2.399)	0.178 (1.417)	-3.023 (-8.745)
KLM's frequency (weekly flights)	-2.328 (-4.378)	-0.917 (-2.326)	-1.347 (-4.223)
CAL's flight time (hours)	-0.442 (-3.972)	0.242 (2.703)	0.329 (4.544)
EVA's flight time (hours)	0.114 (1.023)	-0.312 (-3.486)	0.203 (2.808)
KLM's flight time (hours)	0.206 (1.848)	0.162 (1.819)	-0.765 (-10.581)

Adjusted R^2	0.769	0.742	0.935
F Value	10.622	5.452	42.810

Table 4: Parameters of Airline's Load Factor Models from Taipei to Amsterdam: the case of merging between CAL and EVA (t values in parentheses)

Variables \ Airline	CAL and EVA	KLM
Constant	7.258 (4.025)	11.077 (2.222)
CAL/EVA's Airfare (in 1000 \$NTD)	-1.078 (-3.595)	1.641 (1.979)
KLM's Airfare (in 1000 \$NTD)	0.127 (1.347)	-2.124 (-2.102)
CAL/EVA's frequency (weekly flights)	-1.425 (-3.623)	-4.346 (-3.998)
KLM's frequency (weekly flights)	-1.326 (-3.929)	-1.876 (-2.010)
Adjusted R^2	0.824	0.778
F Value	10.394	8.007

Table 5: Estimated Operating Costs for Each Flight from Taipei to Four Destinations

Category \ Destination	Amsterdam	San Francisco	Sydney	Bangkok
Fuel Costs \$NTD	1,594,573	1,359,918	2,145,968	309,131
Holding Costs \$NTD	378,703	325,227	310,781	259,490
Other Costs \$NTD	93938.844	330077	325227	116,760
Total \$NTD	2,090,036	2,015,222	2,781,976	685,381

Table 6: Optimal Airfares in Bertrand Game for Flights from Taipei to Amsterdam

Scenario	Airlines	Weekly Flights	Airfares in \$NTD	Load Factor %	Weekly Profits in \$NTD
Pre-Coalition	CAL	7	36,724	69	47,802,675
	EVA	4	38,048	70	28,681,838
	KLM	7	39,634	77	57,599,006
Parallel Code Sharing CAL and KLM	CAL	7	26,406	86	42,969,477
	EVA	4	24,769	72	19,240,338
	KLM	7	30,801	86	49,923,309
Merging of CAL and EVA	CAL/EVA	11	32,558	72	72,856,154
	KLM	7	30,279	85	48,410,644

As for complementary code sharing, currently both CAL and EVA provide direct services from Bangkok to San Francisco with transfer at Taipei. United Airline, on the other hand, would have to code sharing with Thai Airways, KLM, or Swissair to provide the same services. As a result, we assume that all these six airlines are the players of the game, and United Airline could be simultaneously code sharing with more than one airline in competing with CAL and EVA. Table 7 shows the estimated profits and optimal airfares for complementary code sharing of flights from Bangkok to San Francisco. Consumers' surplus was calculated as follows:

$$CS_i = \int_0^{p_i^*} Q_i(p_i)dp_i - p_i^* \cdot q_i^* \qquad (12)$$

where,

CS_i = consumers' surplus of passengers flying with airline i;

p_i = airfares of airline i;

p^*_i = the airfares of airline i at market equilibrium;

q^*_i = the number of boarding passengers of airline i at market equilibrium;

$Q_i(p_i)$ = the demands function of airline i.

The computation of Shapley values were derived based on the following coalition structures:

1) Players: CAL (C), EVA (E), United (U), Thai (T), KLM (K), and Swissair (S);
2) Dummy Coalitions: no complementary code sharing could be formed by the members, for example, {C, E}, {T, K, S}, etc. in these cases, the payoffs would be set to zeros;
3) Effective Coalitions: complementary code sharing could be formed by the members, for example, {U, T}, {U, K, S}, {U, T, K, S}, etc., in these cases, the payoffs would be set to the profits of United Airline code sharing with other airlines in competing with CAL and EVA.
4) Hybrid Coalitions: complementary code sharing could be formed by part of the members, for example, {C, U, T}, {E, U, K}, etc., in these cases, CAL and EVA were dummy members in the coalitions.

Table 7 provides the estimated payoff of {U, T, K, S}, while the estimated payoffs of other coalitions could be found in the thesis written by Chang (2001). By applying software Mathematica (Varian, 1993), we compute the Shapley values for six players as shown in Table 8. In other words, Table 8 provides the profit distributions of complementary code sharing among United Airline, Thai Airways, KLM, and Swissair. If United Airline is allowed to code sharing with one airline only, then the profit split could be derived based on Table 8 to produce the profit splits as shown in Table 9. From Table 9 we learned that the code sharing between United Airline and KLM would generate the maximum profits among three scenarios. Moreover, the code sharing between United

Airline and KLM produced the largest consumers' surplus. In other words, for passengers flying from Bangkok to San Francisco, the code sharing of United and KLM was very attractive in comparing to the direct flight services provided by CAL and EVA.

Table 7: Optimal Airfares in Bertrand Game: the case of Complementary Code Sharing from Bangkok to San Francisco

Airlines	Transfer Time in Hours	Airfares in \$NTD	Market Share %	Weekly Profits in \$NTD	Consumers' Surplus in \$NTD/week
CAL	0.83	18,053	12%	2,579,927	18,138
EVA	1.5	16,891	9%	1,440,495	13,022
United-Thai	1.5	18,312	8%	2,023,385	13,961
United-KLM	0.67	11,977	36%	3,772,755	31,651
United-Swissair	1	11,574	35%	3,450,132	29,739

Table 8: Shapley Values of Code Sharing for Bangkok-San Francisco Flights

Airline	CAL	EVA	United	Thai	KLM	Swissair
Shapley Values	0	0	223,643	16,466	148,991	5,051
% Share	0	0	56.74%	4.18%	37.80%	1.28%

Table 9: Effects of Code Sharing and Profit Splits for Bangkok-San Francisco Flights

Scenarios	Profits (\$NTD)			Profit Splits (\$NTD)			
	Before	After	Change	United	Thai	KLM	Swissair
United-Thai	1,805,930	1,905,030	+129,100	120,247	8,853	0	0
United-KLM	3,592,350	3,986,500	+394,150	236,556	0	157,594	0
United-Swissair	4,413,320	4,473,930	+60,610	59,271	0	0	1,339

Table 10 shows the estimated profit changes after code sharing and merging for five Taiwan's airlines, i.e., China Airlines (CAL), EVA Air (EVA), Far Eastern Air Transport (FAT), TransAsia Airways (TRA), and UNI Air (UNA). In Table 10, the figures of the diagonal elements represent the profits before code sharing, the figures in the upper triangular area are the additional profits derived from code sharing, and the figures in the lower triangular area are the additional profits derived from merging. The estimations of profit changes are based on the calibration results provided by Ko (1999). Currently, CAL and EVA provide international services while FAT, TRA, and UNA fly to all domestic destinations with very limited international services. Figures shown in Table 10 were derived based on estimated profits of sample routes. From Table 10 we learned that code sharing between FAT and UNA was the best choice among all code sharing alternatives while merging of CAL and EVA produced the largest profits in all coalition alternatives.

As for the financial performances, Table 11 shows the financial data of 2001 provided by five domestic airlines. Because CAL, EVA, and FAT are the only three airlines that offer stock exchange trading in Taiwan stock market, therefore, the financial data for UNA and TRA were derived based on data provided by TCAB. From Table 11 we learned that CAL's EPS was not the highest in Taiwan's airline industry, but CAL's stocks value were often the highest among the three because CAL has always been the largest airline in Taiwan. As a result, CAL is often a bidder in the merging game.

Table 10: The estimated profits before and after code sharing or merging

Airlines	Airlines				
	CAL	EVA	FAT	TRA	UNA
CAL	1,325,142	199,010	—	—	—
EVA	19,223,718	2,136,313	—	—	—
FAT	—	—	1,330,104	2,264,967	3,239,363
TRA	—	—	5,234,160	806,657	2,659,184
UNA	—	—	7,245,740	5,550,520	1,725,899

4.3 Priority ranking of coalitions by TOPSIS

The weights of five factors affecting airline merging were calibrated by TOPSIS as shown in Table 12. Form Table 12, we found that financial stability was the major concern in merging decision, followed by profitability, network coverage, maintenance compatibility, and human coordination. The results were consistent with the fact that CAL or EVA often played as bidders in the airline merging games.

Assuming CAL and FAT were the bidders, their preferences on merging targets were shown as Table 13. Based on the TOPSIS analysis, the best target for CAL would be EVA, and the second choice would be UNA. Likewise, FAT's best target is EVA, and the second choice would be CAL.

For other domestic airlines, if the ranking of alternatives depend on profitability only, then the order of various coalitions scenarios would be shown as Table 14. The results showed that: 1) code sharing options were less attractive than merging for FAT, TRA, and UNA; 2) FAT was the best target for TRA and UNA in the merging games; 3) the worst alternative would be no coalition with any other airlines, in other words, cooperation among airlines were in the top priority for all airlines in Taiwan.

5. Conclusion

From the TOPSIS analysis we found that the most important factors affecting airline coalition were profitability and credibility in financial status. Meanwhile, domestic airlines in Taiwan would gain more profits through merging rather than code sharing in current practices, and the worst alternative would be no coalition with any other airlines.

Table 11: Financial Data for Major Airlines in Taiwan

Category		Airlines				
		CAL	EVA	FAT	TRA	UNA
Financial Structure	Debt Asset Ratio	69.89	74.00	71.26	66.02	84.88
	Long Term Capital and Fixed Asset Ratio	105.13	137.00	136.45	89.12	83.29
Liquidity Ratio	Current Ratio	78.22	74.00	102.10	32.31	56.88
	Quick Ratio	44.88	38.00	67.98	20.09	21.28
	Times-Interest-Earned	140.15	9	NA	(0.54)	(0.82)
Asset Management Ratio	Account Receivable Turnover Rate	12.59	NA	34.46	18.99	26.25
	Average Collection Period (days)	28.99	NA	10.59	19.23	14
	Fixed Asset Turnover Ratio	0.60	0.84	0.64	0.90	0.63
	Total Asset Turnover Ratio	0.47	0.46	0.41	0.59	0.33
Profitability Ratio	Return on Assets	3.38	NA	(5.08)	(2.04)	(5.82)
	Return on Equity	4.09	(10.00)	(23.64)	(20.03)	(95.07)
	Basic Earning Power Ratio	6.77	(15.00)	(21.28)	(9.49)	(168.95)
	Profit Margin on Sales	2.55	(6.00)	(19.24)	(10.10)	(30.26)
	Earnings per Share ($NTD)	0.74	(1.44)	(2.12)	(1.08)	(15.39)
Cash Flow Management	Cash Flow Ratio	23.90	2.00	106.57	3.33	(8.22)
	Affordable Cash Flow Ratio	16.79	43.00	19.10	8.64	(35.04)
	Cash Reinvestment Ratio	2.34	NA	6.88	1.32	(5.79)
Leverage	Operating Leverage	3.28	125.16	NA	NA	(3.09)
	Financial Leverage	(4.31)	(0.10)	NA	NA	0.48

Note: NA for Not Available; figures shown in parentheses are estimated values.

As for parallel code sharing among international flights, we found that merging of CAL and EVA or code sharing among airlines would result in lower airfares and higher load factors for all airlines flying from Taipei to Amsterdam. The results were consistent with Park's findings and suggested that international flights may not be benefited unless the costs could be significantly reduced due to code sharing or merging.

On the other hand, the analysis of consumer surplus suggested that the complementary code sharing between United Airline and KLM produced the largest consumers' surplus. As a result, for passengers flying from Bangkok to San Francisco, the code sharing of United and KLM was very attractive in comparing to the direct flight services provided by CAL and EVA.

In conclusion, by analyzing the Shapley Values of all airlines and the changes in consumer surplus, the study was able to evaluate the impacts of strategic alliances and merging on airlines and on passengers.

Table 12: Relative Closeness for various factors

Factors	RC values	Ranking
Profitability	0.3019	2
Human Coordination	0.0625	5
Financial Stability	0.3587	1
Network Coverage	0.2927	3
Maintenance Compatibility	0.2500	4

Table 13: Ranking of Merging Preferences

Target \ Bidder	CAL	FAT
CAL	NA	2
EVA	1	1
FAT	4	NA
TRA	3	4
UNA	2	3

Table 14: Ranking of Domestic Airline's Preferences on Coalition Alternatives

Alternative\Airlines	Far Eastern Air	Trans Asia	Uni Air
No Coalition	5	5	5
Code Sharing with FAT	-	3	3
Code Sharing with TRA	3	-	4
Code Sharing with UNI	3	4	-
Merging with FAT	-	1	1

Merging with TRA	1	-	2
Merging with UNA	2	2	-

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