Eurasia Journal of Science and Technology
Print ISSN: 2663-1024
Online ISSN: 2663-1016
DOI: https://doi.org/10.61784/ejst3170

A MARKET SHARE FORECASTING METHOD FOR AIRLINE ROUTES BASED ON QSI

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Abstract: Airlines cooperating within an alliance need a scientific and quantifiable tool for estimating the market share of each route, both to support negotiation and to guide route network optimization. Manual assessment route by route is inefficient, and synergistic effects are difficult to capture. Building on domestic and international studies of the Quality of Service Index (QSI), this paper develops a QSI indicator system grounded in the operating practice of Airline S in China. The system covers eight factors: number of stops, airline service rating, aircraft type, flight frequency, detour ratio, fare level, connection time and departure/arrival time score. The calibration of indicator weights and the computation of route market shares are then specified, and the approach is tested on 264 records of actual international operations of Airline S. The regression results show that the number of stops has a significant negative effect on passenger numbers, while average fare has a significant positive effect; the reduced two-variable model fits better than the full model (adjusted $R^2 = 0.349$). The method offers quantitative evidence for decisions on aircraft type adjustment, schedule optimization and frequency planning.
Keywords: Airline alliance; QSI; Market share forecasting; Route network

1 INTRODUCTION

With the signing of new civil aviation transport agreements in recent years, competition in China's air transport market has intensified. Open-skies pressure keeps building: nearly all major network carriers in the world now serve the Chinese market, and low-cost carriers newly established in neighbouring countries have also extended their operations to it. Foreign airlines already hold most of the cargo market, and the passenger market faces comparable challenges. The Quality of Service Index (QSI) is a tool airlines commonly use to estimate the market share of their route products. Its basic idea is that, in a given route market, the share of a product is determined mainly by the attributes of that product, which typically include capacity supply (flight frequency and aircraft type), fare, schedule and frequent-flyer programme. Using actual operating data of airlines, this paper builds a QSI indicator system and applies it to route market share estimation, providing a quantitative tool to support subsequent decisions on aircraft type adjustment, schedule optimization and flight frequency configuration.

Scholars have studied the factors affecting the market shares of flights and routes from various angles. Han Min built an evaluation index system of passenger satisfaction for airlines based on the SERVPERF model and proposed improvement strategies for Airline S [1]. Lu Xigui adopted a mixed-methods design and, drawing on the 7Ps marketing theory and the STP strategy analysis framework, constructed an evaluation system for Airline S's marketing strategy from 28 indicators across seven dimensions, including product and service evaluation, price sensitivity and channel preference [2]. The study found that the airline's pricing strategy lacked flexibility, matched its service quality poorly and depended too heavily on traditional channels, and it accordingly put forward improvement measures. Hu Haoyue et al. combined a multi-layer service quality index model with predictions of network path attributes and proposed an optimization method for alliance route networks, taking into account differences in competitive intensity across origin-destination (OD) markets [3].

Studies of passenger satisfaction support this reading of the indicator system. Murugesan et al. forecast passenger satisfaction from sentiments and ratings [4], and Usun et al. assess satisfaction with a fuzzy TOPSIS approach [5]; both treat service attributes such as schedule, fare and aircraft type as the drivers of how passengers evaluate a flight. These studies establish which attributes passengers actually value, while the QSI approach converts the same attributes into weights that can be applied to the share of a specific route product. The two strands are therefore complementary rather than competing: satisfaction research explains why an attribute matters to a passenger, and QSI calibration determines how much that attribute shifts the share of a given route once the schedule and the fare are fixed.

Overall, existing studies have accumulated useful results on QSI model frameworks and network optimization algorithms, but tools that translate these results into an indicator system for estimating route- and flight-level shares in actual business operations remain scarce. This paper is a targeted response to this gap.

2 QSI INDICATOR ANALYSIS

On the basis of previous work [4-5], this paper refines the evaluation dimensions and constructs a QSI indicator system that better reflects civil aviation practice. Eight indicators are considered: number of stops, airline, aircraft type, flight frequency, detour ratio, fare, connection time and departure/arrival time score. They are described below.

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(1) Number of stops (f1). The number of stops is the total number of intermediate landings during a passenger's single trip, and is a core indicator that directly affects travel experience. Non-stop flights offer the best experience; one stop is generally acceptable; two or more stops easily arouse negative feelings and are widely considered hard to tolerate.
(2) Airline (f2). The service grade of an airline is a soft indicator that influences passengers' choice of flight and the reputation of a route [6]. Skytrax conducts a standardized one-to-five-star service rating for 665 airlines worldwide, and the results objectively reflect the overall service level of carriers. In general, the higher the star rating, the better the service standardization and passenger reputation, and the stronger the passenger preference. It thus serves as an important brand dimension in the QSI system.
(3) Aircraft type (f3). Aircraft type affects route capacity, travel safety and comfort. Large aircraft have larger seat capacity and, with flight frequency unchanged, provide higher total route capacity and more stable service. Passengers generally believe that flights on large aircraft are safer and more comfortable and, other things being equal, prefer them. For ease of statistics, the number of seats is used to represent this indicator [7].
(4) Flight frequency (f4). Flight frequency is the number of take-off and landing services of the same flight within one week. High-frequency flights cover travel demand across the whole day and give passengers more schedule choices; when delays or cancellations occur, more rebooking alternatives are available. Frequency is also closely related to passengers' planned delay: the denser the schedule, the shorter the interval between adjacent flights and the shorter the planned delay, which can markedly improve the overall service efficiency of the route.
(5) Detour ratio (f5). The detour ratio is the ratio of the extra distance actually flown to the distance of the standard direct route, and is an important quantitative indicator of flight efficiency and regularity. The higher the detour ratio, the stronger the negative perception of passengers. A consistently low detour ratio reflects the airline's scheduling capability and helps safeguard on-time performance [8].
(6) Fare (f6). The overall fare level directly affects passengers' travel decisions. Higher fares raise travel costs and reduce the attractiveness of a route. Fare is an important competitive instrument for airlines: fare fluctuations directly alter the market acceptance and passenger appeal of a route. The average fare is used in the QSI calculation [9].
(7) Connection time (f7). Connection time refers to the interval between connecting flights at the transfer airport. An excessively long interval increases passengers' wasted waiting time and lowers the travel experience, while an excessively short interval may lead to missed connections because of inbound delays or airport layout, causing travel anxiety. Only a reasonable connection interval allows passengers to complete the transfer smoothly. Any deviation from the reasonable range degrades route service quality and directly affects the QSI evaluation. This indicator is scored by the expert scoring method.
(8) Departure/arrival time score (f8). Flights are scored according to their departure and arrival times, because a very early departure or a late arrival adds ground access cost and inconvenience, while an arrival that misses the last connecting bank of the day forces an overnight stay.

3 CONSTRUCTION OF THE QSI MARKET SHARE MODEL

The QSI value of route product i is given by

$$QSI_i = \alpha_1 f1 + \alpha_2 f2 + \alpha_3 f3 + \alpha_4 f4 + \alpha_5 f5 + \alpha_6 f6 + \alpha_7 f7 + \alpha_8 f8 \quad (1)$$

where α is the weight coefficient, to be estimated through regression analysis. Stepwise, forward or backward selection can be adopted in the regression to progressively exclude collinear and insignificant variables. Based on the above formula, the market share of route product i is obtained as

$$\text{Share of route product } i = \frac{\text{QSI}_i}{\sum_{k \in N} \text{QSI}_k} \quad (2)$$

where N is the set of all products on the route.
In practice the weights are calibrated rather than assumed. The eight indicator scores of each route product enter the model as explanatory variables, the passengers actually carried on the route are the dependent variable, and ordinary least squares regression with stepwise selection retains the variables that carry explanatory power. The estimated coefficients are then substituted into the two expressions above, so that the share of every product on the route can be recomputed from a common set of scores whenever the schedule or the fare structure changes. Because the calibration is route specific, it can be repeated market by market as traffic rights and alliance membership change.

4 ESTIMATION OF THE QSI INDICATOR COEFFICIENTS

This study uses 264 records of actual international operations of Airline S in China. The QSI value of a route product is represented by the number of passengers it carried, and the regression analysis is carried out with SPSS software.
Multicollinearity is examined through bivariate correlation analysis and collinearity diagnostics. The variance inflation factors (VIF) of all candidate variables (departure/arrival time score, number of stops, detour ratio, aircraft type score, connection time, total weekly frequency, airline star rating and average fare) fall between 1.133 and 1.513, indicating that there is no serious multicollinearity among the variables.
All eight candidate variables are then entered into a multiple linear regression with passenger numbers as the dependent variable. As shown in Table 1, the overall model is significant ($F = 16.614$, $p < 0.001$), with an adjusted R^2 of 0.340.

Table 1 Model Summary of the Full-Variable Regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.601a	0.361	0.340	3038.070

a. Predictors: (Constant), departure/arrival time score, number of stops, detour ratio, aircraft type score, connection time, total weekly frequency, airline star rating, average fare

According to the coefficient estimates in Table 2, only two variables reach statistical significance at the 0.05 level. The number of stops has a significant negative effect ($\beta = -0.528$, $t = -8.226$, $p < 0.001$): with other variables held constant, each additional stop reduces passenger numbers by 5,117.783 on average, making it the dominant factor. Average fare has a significant positive effect ($\beta = 0.132$, $t = 2.062$, $p = 0.040$): with other variables held constant, a one-unit increase in average fare raises passenger numbers by 2.630 on average. The remaining six variables (airline star rating, aircraft type score, total weekly frequency, detour ratio, connection time and departure/arrival time score) all have Sig. values above 0.05 and do not significantly affect passenger numbers.

Table 2 Coefficients of the Full-Variable Regression

Model	Variable	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	2546.430	1783.728		1.428	0.155		
	Number of stops	-5117.783	622.131	-0.528	-8.226	0.000	0.661	1.513
	Airline star rating	369.066	328.799	0.068	1.122	0.263	0.736	1.358
	Aircraft type score	-1.819	29.489	-0.004	-0.062	0.951	0.706	1.416
	Total weekly frequency	92.043	88.368	0.062	1.042	0.299	0.755	1.325
	Detour ratio	53.178	575.034	0.005	0.092	0.926	0.919	1.088
	Average fare	2.630	1.276	0.132	2.062	0.040	0.663	1.508
	Connection time	-0.024	0.940	-0.002	-0.026	0.980	0.778	1.285
	Departure/arrival time score	110.618	233.493	0.026	0.474	0.636	0.882	1.133

a. Dependent variable: number of passengers

To remove redundant variables and simplify the model structure, stepwise regression is further used to select core variables (entry criterion: Sig. ≤ 0.05; removal criterion: Sig. ≥ 0.10). Only two significant variables enter the final model. As Table 3 shows, the reduced model has an adjusted R^2 of 0.349, slightly higher than that of the full model (0.340), and its F value (66.005) is much larger than that of the full model (16.614), indicating that the reduced model achieves a better and more stable fit with fewer variables.

Table 3 Model Summary of the Stepwise Regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.579a	0.336	0.333	3053.297
2	.595b	0.354	0.349	3017.232

a. Predictors: (Constant), number of stops
b. Predictors: (Constant), number of stops, average fare

The coefficients in Table 4 show that the two core variables retain the same directions as in the full model and become more significant. The number of stops remains the dominant negative factor, with results close to those of the full model; the positive effect of average fare becomes more significant, with the Sig. value falling below that of the full model (0.040). In addition, the VIF of the reduced model is 1.190, so collinearity is not a concern, further confirming the validity of the results.

The positive fare coefficient deserves comment. Fares on thin routes are set low to fill capacity, whereas high-fare routes are those with strong business demand, so the coefficient partly captures route quality rather than a pure price effect. Chiambaretto likewise found that passengers on long-haul flights accept substantial surcharges for services they value [8], which is consistent with fare acting as a proxy for the service bundle offered on the route.

Table 4 Coefficients of the Stepwise Regression

Model	Variable	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	6012.433	471.562		12.750	0.000		
	Number of stops	-5620.139	508.305	-0.579	-11.057	0.000	1.000	1.000
2	(Constant)	4759.648	668.791		7.117	0.000		
	Number of stops	-5047.889	548.017	-0.520	-9.211	0.000	0.840	1.190
	Average fare	2.939	1.126	0.148	2.611	0.010	0.840	1.190

a. Dependent variable: number of passengers

5 CONCLUSIONS AND OUTLOOK

Focusing on the lack of a quantitative market share estimation tool in alliance cooperation, this paper reviews the rationale of the QSI method and relevant research, constructs an eight-indicator QSI system based on actual airline operating data, calibrates the weights through regression analysis, and thereby obtains an operational method for estimating route market shares. The main conclusions are as follows.

(1) The number of stops is the primary negative factor affecting passenger numbers. In the reduced model, its standardized coefficient is -0.520 ($p < 0.001$), and each additional stop reduces passenger numbers by about 5,048 on average; the more stops a route involves, the higher the time cost for passengers and the fewer passengers choose the route.
(2) Average fare has a significant positive effect on passenger numbers ($\beta = 0.148$, $p = 0.010$). This result more likely reflects the supply-demand characteristics of high-quality routes: high-fare routes tend to serve markets with strong business demand and higher service quality, whose passenger base is larger to begin with, rather than fares directly stimulating traffic growth.
(3) The remaining six indicators - airline star rating, aircraft type score, total weekly frequency, detour ratio, connection time and departure/arrival time score - show no significant effects in the current sample. This may be related to the operating characteristics of the sample routes (mostly short-haul, with limited variation in aircraft type) or to moderating variables not included in the model (such as the density of competing routes), and warrants further verification.
As for future work, the sample can be expanded to cover more route types and time periods, moderating variables such as the density of competing routes and frequent-flyer programmes can be incorporated, and the model can be implemented as a batch calculation software tool to strengthen its practical value in alliance negotiation and route network optimization.
Three practical implications follow from these results. First, network planners should treat the number of stops as the binding constraint in route design, and use code-share or intermediate-stop options only where a non-stop service cannot be sustained. Second, because frequency, aircraft type and schedule score do not reach significance in the present sample, capacity decisions on short-haul alliance routes should not be justified by QSI gains alone. Third, the calibrated model can run as a batch tool at each negotiation round, so that the share consequences of a proposed schedule change are quantified before the offer is tabled. The tool is deliberately kept simple for this purpose: it needs only the published schedule and the fare table of each competing product, so analysts in an alliance can update it without access to proprietary booking data.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

Humanities and Social Sciences Youth Fund Project of the Ministry of Education of China (20YJC630024).

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