Research Article

Measures for Airlines to Reduce Airport Congestion Fees: Scheme Design and Performance Assessment

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Congestion at busy airports has become one of the major bottlenecks to air transportation development around the world. Airport congestion pricing is one of the most popular market-based mechanisms to relieve airport congestion. This study develops a steady-state congestion model, which considers the market power of airlines and the costs of externalities (i.e., airlines, passengers, and the environment), to estimate congestion fees for different times and queue lengths. To reduce airport congestion fees, we propose and discuss two different options for airlines: schedule adjustment and flight merging in detail from the views of economic, operational, and environmental benefits, and provide a comparative performance analysis of two different measures using an empirical example of Guangzhou Baiyun International Airport (CAN). Our analysis shows that: (1) during the peak period, the congestion fees for one specific flight (operated by B738) may exceed 10,000 RMB, even reach 25,000 RMB; (2) both the methods can relieve congestion and effectively reduce congestion fees; (3) in the CAN case, flight merging by a bigger aircraft B744 is more effective in congestion relief, total fees reduction, and emission mitigation; and (4) schedule adjustment has a better performance of reducing fees per adjusted flight and is more simple and straightforward. We also provide several recommendations to relieve congestion and cut congestion fees.

1. Introduction

Air transportation has historically shown strong growth during the last several decades and is expected to have continuous growth with about a 5-6% annual rate in the future [1, 2]. The rapid development of the civil aviation sector has imposed increased pressure on airport operations and resulted in flight delays and airport congestion. Unfortunately, more and more airports are suffering from severe airport congestion, and airport congestion is becoming one of the major bottlenecks to air transport growth. As a potential demand management tool, congestion pricing has been proposed and widely discussed in the literature.

Economists first studied congestion pricing for the case of roads as variable road tolls that are higher under congested conditions and lower at less congested times and locations. The concept of congestion pricing can be traced back to Pigou [3], and Knight [4] further developed the theory. This pricing strategy regulates demand, making it possible to manage congestion without increasing supply. The essence of congestion pricing is making users conscious of the real costs they impose upon each other during the peak period and thus eliminating negative external effects by charging.

Similarly, researchers have extended the theory to the airport since congestion has become a significant issue in air transportation. Beginning with Levine [5] and Carlin and Park [6], congestion pricing was put forward and explored as one solution to the congestion problem. Unlike traditional pricing based on total aircraft weight, congestion pricing calls for a toll to airlines with the cost of the congestion delay they impose on other flights and passengers. Under such a pricing system, airport capacity will match demand, and the pattern of overcrowded peak periods will be changed.

Extensive research has been performed to explore the airport congestion pricing, and the literature has mainly focused on three aspects of this topic. The first set of studies has focused on the congestion pricing models and
equilibrium analysis. Daniel [7] applied a bottleneck model to airport congestion pricing and to calculate equilibrium congestion fees, schedule frequencies, traffic patterns, landing and takeoff costs, airport revenues, and resource savings from peak-load congestion fees. Daniel [8] further extended the previous stochastic bottleneck model in Daniel [9] by dynamically adjusting traffic rates, queuing delays, and congestion fees to include elastic demand, heterogeneous operating time preferences, and heterogeneous lay-over and queuing time values. Morrison and Winston [10] compared the welfare gains from the optimal congestion tolls and traditional congestion tolls. They found that traditional congestion charges have a higher likelihood than optimal tolls have of actually being implemented.

The second set of studies has discovered the influential factors of airport congestion pricing. Brueckner [13] first pointed out that airlines cannot be treated as “atomic” as they usually have “market power,” and he analyzed airport congestion pricing when carriers are under monopoly and oligopoly conditions. The result shows when the atomistic model is abandoned, and the verdict on congestion is softened. Pels and Verhoef [14] also adopted “market power” and developed a model in which airlines have a part of external travel delays that aircraft impose are internal to an operator and hence should not be accounted for in congestion tolls. The type of travelers is another important influential factor in congestion pricing. Czerny and Zhang [15, 16] explored airport congestion pricing with two types of travelers (business and leisure passengers) in a model with a public and congested airport. Their results showed that increasing airport charges could help protect business passengers from excessive congestion caused by leisure passengers who are less sensitive to congestion. Lin and Zhang [17] found that while charging per-local and per-connecting passengers differently at hub airports leads to the social optimum, in general, levying a pure per-flight charge cannot achieve the first-best outcome. Silva and Verhoef [18] investigated and compared airport pricing policies under various types of competition. They found that optimal congestion pricing would bring more significant welfare gains and congestion reductions than what had been advanced before.

The third set of studies has checked the effectiveness of airport congestion pricing for some real airport examples. Daniel [7] used the data from the Minneapolis-St. Paul Airport to validate the effectiveness of a bottleneck model for airport congestion pricing. Janić [19] applied his models to the New York LaGuardia Airport to illustrate their ability to handle more realistic congestion scenarios. Johnson and Savage [20] selected Chicago O’Hare Airport as a study case to calculate congestion fees that help the airport reduce delays. Morrison and Winston [10] found that airport congestion charges would significantly reduce delays at the congested US airports. Hu et al. [21] revealed that airport congestion pricing could offer many benefits, including congestion mitigation, energy conservation, and emission reduction, with the example of Guangzhou Baiyun International Airport.

Most of the previous studies are theoretically complicated. They concentrate more on congestion pricing models and their effectiveness, efficiency, or welfare analysis. Meanwhile, airlines’ responses cannot be ignored when facing high airport congestion fees, such as flight schedule adjustment, flight merging, and flight transfer to nearby or other airports. Under the congestion pricing model in Kara et al. [22], Kara [23] analyzed the effect of “noncompliance” of airlines with regard to the allocation of runway access to the flights (i.e., airlines reject the runway access slot allocated to them and choose further delay or potential cancelation of their flights). Janić [24] pointed out that airport congestion charging might stimulate the additional flights to be carried out by larger aircraft. Johnson and Savage [20] and Hu et al. [21] both found that airport congestion pricing could motivate airlines to relocate their flights from the peak time to off-peak time, and to slightly alter the scheduled departure time of other flights for reducing the cost caused by airport congestion. However, further discussions and comparative analyses of airline options are still lacking. Moreover, we note that the environmental awareness of air transportation is being strengthened, and congestion pricing can generate environmental benefits by reducing queues and emissions. Similarly, certain countries have begun to take market means to control air pollution. In 1999, engine emission charges were in place only at some Swiss and Swedish airports, and these charges were targeted only at local emissions [25]; by 2008, more airports had pollution-related charges, like London Heathrow Airport, London Gatwick Airport, Frankfurt Airport, and Munich Airport, etc. [26, 27]; and in 2010, due to the charge regulations, an emission-based charge was introduced to Copenhagen Airport [28].

In sum, airport congestion pricing is among the most important issues of high-efficient and low-carbon airport development. Understanding the characteristics of different measures to reduce airport congestion fees is crucial to making the best market response for airlines to cut congestion fees in the future. However, previous research rarely provided a comprehensive performance analysis of fee reduction measures for airlines considering environmental impacts. We aim to fill this research gap.

In light of these, first, this study introduces a steady-state congestion model and derives the socially optimal airport charge when environmental costs are considered. Then, we design and evaluate the performance of two potential airlines’ choices in which airlines seek the minimum fees of airport congestion. The main contributions of this study are to (1) develop an airport congestion pricing model with considerations of environmental externality (i.e., the external cost for gas emissions) and market power of airlines, (2) propose two different measures—schedule adjustment and flight merging—for airlines when facing airport congestion pricing, and (3) contrast the performance of two measures in detail from a more comprehensive perspective (i.e., from the perspective of economic, operational, and...
environmental benefits). Our research approach is grounded since airport congestion mitigation and aircraft emission reduction are both critical challenges for the future of aviation.

The rest of this study is organized as follows. Section 2 presents the primary model of airport congestion pricing and the basic principles of the two measures. Section 3 introduces the empirical example and data sources. Section 4 presents empirical results and discussions. Concluding remarks, policy recommendations, and suggestions for future research are given in Section 5.

2. Methodology

2.1. Model of Airport Congestion Pricing. This study employs a steady-state bottleneck congestion model, which is based on marginal cost pricing. In particular, airlines need to pay for the flights operating during congested periods to offset the externality, which is equal to marginal social cost minus marginal private cost, thereby the social net revenue will reach the maximum. In contrast to the previous empirical congestion models [9, 29–31], the steady-state bottleneck congestion model is simpler and more transparent [20]. This study gives some insight into the magnitude of airport congestion fees before and after adopting measures for a congestion fee reduction.

This study treats the entire airfield rather than the runway as a bottleneck because congestion has already been manifested on the taxiways leading to the runways. The congestion pricing model is shown in Figure 1. The horizontal axis refers to the queue length of departure aircraft wishing to take off at time \( t \), defined as the number of aircraft that has pushed back from the gate but has yet to take off. The vertical axis refers to the cost of the taxi-out time, which we will define as the time between push-back and wheel-off. The cost is a function of the taxi-out time and combines the airlines’ operating costs, passengers’ time costs, and environmental costs.

The marginal private cost (MPC) curve represents the “private” costs incurred by a specific aircraft and its passengers for different lengths of the departure queue. It must be noted that a departure queue does not necessarily imply congestion, because a departure flight needs a minimum time to push back from the gate, taxi to the assigned runway, and take off immediately. If there are relatively few aircraft in the departure line, the taxi-out time will not sharply increase because, by the time a flight arrives at its assigned runway, the previous aircraft in the departure queue has already taken off. Therefore, there is an acceptable queue length at an airport, which can be called the threshold of congestion queue (shown as \( L_0 \) in Figure 1). The threshold of congestion queue is closely related to the layout of the airport, taxi routes, and gate assignments. Only when the queue length is longer than the congestion queue threshold is it proper to charge.

The marginal social cost (MSC) curve represents the total “social” costs incurred by an additional flight. The total social costs of an additional flight are not merely the direct costs undertaken by the specific aircraft and its passengers, but also include costs to other aircraft and their passengers who are behind it in the queue and the environment. In general, MSC includes both marginal private cost and marginal external cost. The gap between the two curves represents the externalities. Please note that the MSC in this study is always greater than the MPC since the environmental cost is considered.

For a fixed capacity, the standard economic model suggests that, in the short term, society maximizes social welfare when the price of a good equals its marginal cost. As at an airport, the number and configuration of runways, taxiways, and terminals are fixed in the short run; social welfare will reach the maximum when the cost of a flight equals its marginal cost in the airport congestion pricing model. In Figure 1, time \( t_1 \) represents a situation where a queue has developed and exceeded the congestion threshold value. Without congestion pricing, airlines equate their demand with their marginal private costs, which is the intersection of the demand function \( D_{1I} \) and MPC (shown as point A) and is where \( L_1 \) aircraft wish to depart. However, to maximize social welfare, the optimal queue length is \( L_2 \), where the demand function \( D_{1I} \) intersects MSC (shown as point B). At this point, the marginal social cost exceeds the marginal private cost by distance \( BC \), which means the costs imposed on aircraft that are already in the queue when the marginal aircraft takes off. Technically, assuming that price changes are not so dramatic, they significantly reduce the effective real revenue of airline passengers and twist the demand function; a congestion fee of \( BC \) will generate an optimal number of flights.

Unlike road users, which are treated as “atomistic,” airport users, airlines usually have market power. At most congested airports, one or two airlines, especially base airlines, have the dominant position in market shares. Brueckner et al. [32, 33] pointed out that an additional flight at peak time from an airline with a high market share will delay its planes and those of other airlines, and the cost imposed on its other flights will be “internalized” by itself. Furthermore, a monopolistic airline would fully internalize
of the congestion, and an oligopolistic airline would internalize the congestion that they imposed on themselves [13]. Consequently, a congestion price should only reflect delays imposed on other airlines and their respective passengers. Therefore, the congestion fee charged to a flight should be calculated as \((1 - \text{proportion of an airline’s market share of departures}) \times \text{distance} \times BC\).

2.2. Measures of Airport Congestion Fee Reduction. While facing airport congestion fees, airlines certainly will consider the impact of tolls on their market revenue and flight operations. If the fees are high enough, airlines will take additional actions to reduce the negative impact of congestion pricing. These further actions include but are not limited to altering the scheduled departure time, transferring flights to a nearby airport, or even canceling the flights. In this study, we investigate two different measures—flight schedule adjustment and flight merging—to reduce congestion fees from the perspective of airlines.

2.2.1. Rules of Schedule Adjustment. At a congested airport, the most congestions are created by imbalances between demand and airport capacity [34], which will occur when too many flights wish to depart at the same time or in a short period, and this would lead to a “flight peak.” Meanwhile, there could be several off-peak periods of flights, such as late night or early morning. So, shifting flights from peak time to off-peak time may be an effective means to reduce the number of departure flights and relieve congestion during rush hours.

In general, schedule adjustment means adjusting the scheduled departure time in the flight schedule. However, the scheduled departure time cannot be directly used for congestion fee calculation. In addition, in most cases studied in this study, the gap between push-back time and scheduled departure time is limited. Thus, this study adopts push-back time instead of scheduled departure time for schedule adjustment analysis.

Kinds of adjustment plans may be produced based on different sets of objectives and constraints. In this study, the adapted schedule adjustment plan is limited in order to have less disruption to passengers and be more convenient for airlines and airports. The basic principles are as follows:

(1) Push-back time used to accommodate the new flights must originally have a sufficiently short queue length.

(2) Adjustments are considered for the flights suffering extreme congestion. In other words, those flights that suffer longer queue length or taxi-out time will be given priority to alter their scheduled departure time.

(3) There is a 30 min limit on the adjustable time span, meaning that push-back time can just be postponed by a maximum of 30 minutes for the convenience of slot management due to the latest regulations of the Civil Aviation Administration of China (CAAC, 2018a [35]), and we also consider it an acceptable time span for both airlines and passengers (Pyrgiotis and Odoni, 2016 [36]).

2.2.2. Rules of Flight Merging. For some hot routes, there are large quantities of flights to the same destination airport in short time intervals. Thus, we can merge two or more flights operated by small aircraft into one flight by a larger aircraft without seat loss in a short time span. In this study, it means that only when the push-back time interval of two flights is less than an acceptable threshold value, and two flights to the same destination airport will be merged into a larger aircraft.

For comparative analysis of these two methods—schedule adjustment and flight merging, we also set some further principles as follows:

(1) The same 30 min time span limitation of flight merging means that only two flights with a push-back time interval of fewer than 30 minutes can be merged.

(2) The new push-back time of the merged flight is set to be the same as the original flight with a shorter queue length or the same as the later flight if two flights are equal in queue length.

(3) The seating capacity of the merged flight is limited, which should not be less than the total number of two original flights.

(4) The new congestion pricing after flight merging cannot exceed the sum of two original congestion pricings.

The flight merging is feasible because new congestion fees are reduced, which proves to be a mutually beneficial business for airlines.

In reality, airlines from the same alliance often merge flights through code-sharing agreements to expand market share. Moreover, on some air express routes, such as “Beijing—Shanghai,” airlines from different alliances also merge their flights according to their administration agreements.

3. Empirical Example and Data Sources

3.1. Empirical Example. This airport congestion pricing model was applied to Guangzhou Baiyun International Airport (IATA: CAN). In 2019, CAN was the third busiest airport nationwide, with a total passenger throughput of 73.38 million. Massive flight delays are common at CAN because of Guangzhou’s geographic location and tight airspace resources. Moreover, except for CAN, there are several large airports in Pearl River Delta, like Shenzhen Bao’an International Airport (SZX), Hong Kong International Airport (HKG), and Macao International Airport (MFM), making the airspace of Guangzhou complicated. Furthermore, as one of the three major international hub airports in China, CAN had a rapid development in the past five years, yielding an average annual growth rate of 7.38% on passenger throughput [37], and is expected to continuously grow in the future. Consequently, CAN suffered serious flight delays and congestion. The on-time departure rate of
CAN was only 76.72% from January 2018 to December 2019, with an average 30 minutes delay per delayed flight [38]. There would be a huge cost caused by these delays for airlines, passengers, and the environment. Massive delays, serious congestion, and vigorous development pose a great challenge to future growth for CAN. Research on congestion mitigation at CAN is increasingly urgent and necessary. Hence, CAN was selected as an example for empirical analysis.

3.2. Data Sources. Different data sources are needed in this study. First, we use the same flight schedule data as Hu et al. [21] from an Operation Monitoring Center of the Civil Aviation Administration of China (CAAC) airline on-time database, which covers the actual push-back time from the gate, the wheel-off time, original and destination airport, aircraft type, scheduled departure time, etc. The queue length is obtained by counting the number of aircraft that have been pushed back from the gate but not had wheels off. One should note that this is just an approximation due to complicated circumstances. For example, an aircraft that pushes back later can “jump the queue,” and an aircraft already in line for take off may be taken out of the queue due to the bad weather at the destination airport.

Second, the threshold of the congestion queue is a critical parameter for calculating congestion fees. As there is almost no congestion from midnight to 7 a.m., we figured out the average taxi-out time of all departure flights from midnight to 7 a.m. from March 1 to March 31, 2013, at CAN, which was 10.5 minutes. This figure would be used to determine the threshold of the congestion queue in Section 4.1.

Third, this study divided external costs during taxi-out into three parts: airline cost, passenger cost, and environmental cost. For airline costs, we use combined and modified data from Eurocontrol [39] and Chen et al. [40] considering the delay time and load factor for the empirical study. For passenger costs, we classified the passengers into three categories: domestic leisure passengers, domestic business passengers, and international passengers, and each category had a different time value. Data from the Annual Report of Civil Aviation Transportation of China [41] and Xu and Li [42] were used for passenger cost calculation in this study. The environmental externality during the taxi-out time is mainly from gas emissions. There are two types of waste gas: one is pollutant gas, such as CO, HC, and NOx, which have harmful effects on human health, and the other is greenhouse gas, like CO2, which contributes to global warming. The level of the environmental cost depends on the amount of gas emission and the unit social cost of each gas. The parameter data of gas emission and the unit social cost of each gas have been extracted from ICAO Aircraft Engine Emissions Databank [43], and the social costs of each exhaust pollutant in China have been extracted from the results of Chen [44] and Lu [45].

Finally, in consideration of currency inflection, all costs were inflated to the target year 2013 by applying the Chinese inflation rates published in the Annual Statistics Book of China [46]. The final external costs of aircraft studied in this study (i.e., Boeing 738, Boeing 744, and Airbus 333) are listed in Table 1. The total cost per minute during taxiing out (including the environmental cost) is estimated as 493, 1299, and 927 RMB in 2013, respectively.

The data are obtained by the methods of curve fitting using data from Eurocontrol [39].

4. Results and Discussions

4.1. Estimation of Congestion Pricing. The taxi-out time is the difference between push-back time and wheel-off time. It varies from 4 minutes to 60 minutes, mainly from 13 to 21 minutes in this case. The average taxi-out time is 18 minutes. A considerable variation exists in taxi-out time even though these aircraft have the same queue length, mainly due to different gates and assigned taxing paths. Figure 2 depicts the relationship between the queue length and taxi-out time.

In general, the taxi-out time is positively correlated with the queue length [20, 21]. We tested various functional forms and chose the one with the best fit. It is estimated as follows [21]:

\[
T = 8.068e^{0.0629L} + \epsilon, \quad R^2 = 0.5149, \tag{1}
\]

where \(T\) is the taxi-out time, \(L\) is the queue length, and \(\epsilon\) is the error term. This curve is plotted as the dashed line in Figure 2.

We assume that the minimum average taxi-out time is \(t_0\), which is the necessary time for the aircraft to taxi to the runway and take off from the gate without congestion. As mentioned in Section 3.2, 10.5 minutes that was calculated by using historical taxi-out data of departure flights operated from midnight to 7 a.m. could be used as a reasonable and acceptable value of \(t_0\). Thus, the value that needs to be calculated in congestion pricing is the actual taxi-out time minus \(t_0\). Consequently, taking B738 as an example (as B738 accounts for the largest proportion of the departures with 31% in this case), the atomistic \(MPC\) curve in Figure 1 will take the form as follows:

\[
MPC = 493 \times (8.068e^{0.0629L} - t_0) \tag{2}
\]

\[
MPC = 3977.52e^{0.0629L} - 493t_0.
\]

\[
MSC = \frac{dT\ C}{dL} = \frac{d (MPC \cdot L)}{dL} \tag{3}
\]

\[
MSC = 3977.52 (0.0629L + 1)e^{0.0629L} - 493t_0.
\]

\[
MSC - MPC = 250.19L \cdot c^{0.0629L}. \tag{4}
\]
We calculated the congestion fees of all departure flights and computed the average congestion fees per flight every half an hour. The fees considering market share and environmental externalities are shown in Figure 3.

As mentioned earlier, no departure congestion exists during the period from midnight to 7 a.m. Thus, we focus on the flights operating during the period from 7 a.m. to midnight. The average congestion fees are approximately 2000 to 6000 RMB at most time intervals. From 8:30 a.m. to 10:59 a.m., average congestion fees always exceed 5500 RMB, even reaching 7500 RMB, which suggests the great congestion at peak hours. In fact, congestion fees for one certain flight exceed 10,000 RMB and even reach 25,000 RMB at peak hours. At off-peak hours, fees are only no more than 3000 RMB. Moreover, fades away at dusk, with the lowest continuous level of fees from 5:30 p.m. to 6:29 p.m.

We can imagine that faced with such high congestion fees, airlines will take various measures to minimize the loss as much as possible. Next, two methods—schedule adjustment and flight merging—are compared from the view of fees reduction for the case study because of the limited revenue data. Please note that all the fees include environmental costs and market share.

4.2. Schedule Adjustment. According to the data of Guangzhou Baiyun International Airport, the more detailed principles of schedule adjustment are as follows:

1. Flights will be increased when the queue length is no more than 11 aircraft (the original average and median queue lengths are 11 and 10 in this case).
2. Flights will be postponed when the queue length exceeds 20 aircraft, meaning whose taxi-out time is longer than 30 minutes.
3. The push-back time can be postponed by a maximum of 30 minutes.

In total, there are ten flights with queue lengths of more than 20, and only six flights meet all the three rules above. Four flights cannot be adjusted because of the congestion duration during morning rush hours, which illustrates the limitation of this method. Table 2 shows the most economical adjustment plan for those flights.

The change in queue length caused by schedule adjustment is shown in Figure 4. The queue length of six flights at peak hours has been significantly reduced, with the longest queue length from 30 to 8. Total congestion fees of six adjusted flights decrease from 128,146 RMB to 19,999 RMB, falling by a total of 108,147 RMB with 18,025 RMB per flight. The result is inspiring that cost drops by 5.3% by adjusting only 1.1% of total flights. In addition, with shifting these six flights, more than 70 flights are affected by queue length shortening by 1. What is more important, the flights with longer queue length achieve more benefits, which shows a powerful point of attraction for airlines in this method.

4.3. Flight Merging. In this study, B744 (with 524 seats) and A333 (with 335 seats) are selected aircraft types as a case study for flight merging, due to their high seating capacities and good airport adaptability in China. In addition, three schemes of flight merging are tested as follows:

(a) Flights are merged only by B744;
(b) Flights are merged only by A333;
(c) Flights are merged by B744 and A333 according to the total seat number after merging.

As a result, scheme (a) merges 18 flights to 9; scheme (b) merges 18 flights to 9; and scheme (c) merges 30 flights to 15. Please note that congestion pricing shown in Table 3 for three plans all included 30 flights and other affected flights for comparative purposes.

With the most significant change in the value of congestion fees, scheme (c) is the best choice for flight merging.
Table 2: Queue length and congestion fees before and after the schedule adjustment.

| Flight number | Original push-back time | Original queue length | Original congestion fees (RMB) | Current push-back time | Current queue length | Current congestion fees (RMB) | Change in value of fees (RMB) |
|---------------|-------------------------|-----------------------|--------------------------------|------------------------|-----------------------|--------------------------------|--------------------------------|
| UEA2236       | 10:38                   | 30                    | 49,441                         | 10:50                  | 8                     | 3304                           | −46,137                        |
| CSN3157       | 13:51                   | 22                    | 11,375                         | 13:53                  | 11                    | 2847                           | −8528                          |
| CHH7733       | 14:32                   | 21                    | 18,458                         | 14:42                  | 9                     | 3719                           | −14,739                        |
| CHN3637       | 15:19                   | 21                    | 10,196                         | 15:43                  | 7                     | 1409                           | −8787                          |
| CHH7373       | 16:54                   | 21                    | 18,458                         | 17:14                  | 10                    | 4400                           | −14,058                        |
| CCA4304       | 20:43                   | 22                    | 20,218                         | 21:07                  | 10                    | 4320                           | −15,898                        |

Figure 4: Change in the queue length.

Table 3: Comparison of three schemes for flight merging.

| Scheme     | Congestion fees (RMB) | Change in value of fees (RMB) | Percentage change (%) | Change in value of fees per flight (RMB) |
|------------|-----------------------|--------------------------------|-----------------------|------------------------------------------|
| Original   | 879,296               | —                              | —                     | —                                        |
| Scheme (a) | 687,474               | −191,822                       | −21.82                | −1442                                    |
| Scheme (b) | 781,452               | −97,844                        | −11.13                | −1193                                    |
| Scheme (c) | 639,497               | −239,799                       | −27.27                | −1453                                    |

Table 4: A typical example of flight merging.

| Flight number | Push-back time | Aircraft | Seating capacity | Original queue length | Current queue length | Original congestion fees (RMB) | Current congestion fees (RMB) | Change in value of fees (RMB) |
|---------------|----------------|----------|------------------|-----------------------|----------------------|--------------------------------|--------------------------------|--------------------------------|
| CSZ9617       | 10:17          | A320     | 150              | 15                    | —                    | 8930                           | 4233b                          | −4697                          |
| CSN3599       | 10:31          | A320     | 150              | 10                    | —                    | 2431                           | 1152b                          | −1279                          |
| Postmerging   | 10:31          | A333     | 335              | —                     | 9                    | 11,361                         | 5385                           | −5976                          |

Note. Current congestion fees are calculated with the same proportion of original congestion fees. Details are as follows: 5385 * (8930/11361) = 4233 and 5385 * (2431/11361) = 1152.
Table 5: Queue length and congestion fees for affected flights after CSZ9671 merged.

| Flight number | Original queue length | Current queue length | Original congestion fees (RMB) | Current congestion fees (RMB) | Change in value of fees (RMB) |
|---------------|-----------------------|----------------------|--------------------------------|------------------------------|-----------------------------|
| CSN3803       | 11                    | 10                   | 2847                           | 2431                         | −416                        |
| CSC8793       | 8                     | 7                    | 3254                           | 2674                         | −580                        |
| CCA1330       | 7                     | 6                    | 2504                           | 2016                         | −488                        |
| CES5288       | 14                    | 13                   | 7843                           | 6839                         | −1004                       |
| UEA2236       | 30                    | 29                   | 49441                          | 44879                        | −4562                       |
| CES5732       | 9                     | 8                    | 3681                           | 3073                         | −608                        |
| Total         | —                     | —                    | —                              | 61912                        | −7658                       |

Table 6: Performance contrast of two methods.

| Scope                        | Index                              | Original | Schedule adjustment | Scheme (a) | Scheme (b) | Scheme (c) |
|------------------------------|------------------------------------|----------|---------------------|------------|------------|------------|
| The number of flights        | Total flights                      | 529      | 529                 | 520        | 520        | 514        |
|                             | The number of charged flights      | 448      | 444                 | 439        | 439        | 433        |
|                             | The number of adjusted flights     | —        | 6                   | 18         | 18         | 30         |
|                             | The number of affected flights     | —        | 73                  | 115        | 64         | 135        |
| Economic benefits            | Total congestion fees (RMB)        | 2,028,678| 1,877,689           | 1,705,346  | 1,716,655  | 1,650,033  |
|                             | Fees per charged flight (RMB)      | 4429     | 4100                | 3993       | 4145       | 3957       |
|                             | Fees per flight (RMB)              | 3835     | 3550                | 3448       | 3579       | 3410       |
|                             | Fees per seat (RMB)                | 22.04    | 20.40               | 19.37      | 20.31      | 19.02      |
|                             | Change in value of total fees (RMB)| —        | −150,989            | −172,344   | −76,314    | −211,065   |
|                             | Change in value of fees for all adjusted flights (RMB) | —       | −108,146            | −92,365    | −29,499    | −109,951   |
|                             | Change in value of fees per adjusted flight (RMB) | —       | −42,843             | −79,979    | −46,815    | −101,114   |
|                             | Change in value of fees per affected flight (RMB) | —       | −18,024             | −5131      | −1639      | −3665      |
|                             | Change in value of total emissions (kg) | —       | −587                | −695       | −731       | −749       |
| Operational benefits         | The longest queue length           | 30       | 30                  | 30         | 30         | 30         |
|                             | The shortest queue length          | 0        | 0                   | 0          | 0          | 0          |
|                             | The average queue length           | 10.74    | 10.41               | 10.35      | 10.57      | 10.21      |
|                             | The longest span in queue length   | —        | 22 (30 ⟷ 8)         | 17         | 6 (15 → 9, 13 → 7) | (30 → 13) |
|                             | The number of flights with a queue length of 16–20 | 2       | 1                   | 2          | 1          |
|                             | The number of flights with a queue length of 21–25 | 8       | 3                   | 8          | 6          |
|                             | The number of flights with a queue length of 26–30 | 23      | 23                  | 19         | 21         | 19         |
|                             | The number of flights with a queue length of 11–15 | 200     | 185                 | 178        | 182        | 169        |
|                             | The number of flights with a queue length of 6–10 | 215     | 232                 | 235        | 226        | 238        |
|                             | The number of flights with a queue length of 1–5 | 21       | 25                  | 21         | 21         | 21         |
|                             | The number of flights slot without queuing | 60      | 60                  | 60         | 60         | 60         |
| Environmental benefits       | Total emissions (kg)               | 169,210  | 156,616             | 152,739    | 156,743    | 150,289    |
|                             | Total environmental costs (RMB)    | 78,184   | 72,365              | 70,803     | 72,491     | 69,703     |
|                             | Change in value of total emissions (kg) | —       | −12,594             | −16,471    | −12,467    | −18,921    |
|                             | Change in value of total environmental costs (RMB) | —       | −5819               | −7381      | −5693      | −8481      |

Note. Bold italic numbers have the best performance of each index.
It is easy to understand this result, as scheme (c) has the advantages of the other two schemes by using two types of aircraft. Here, scheme (a) and scheme (b) are further discussed.

Scheme (a) should have more merged flights than scheme (b) because B744 has more seats than A333. However, they have an equal number of merged flights. This is mainly due to rule (4) (see Section 2.2.2)—new fees cannot exceed the sum of two original fees. It implies that some flights that could be merged by B744 are finally removed because new fees become higher. There are two reasons for higher fees: first, the congestion pricing per minute of B744 is nearly three times that of B738 (Table 1); second, the difference in queue length is quite small between the two merged flights. In other words, flight merging with B744 requires an extraordinary shortening queue length, and only in this way can we offset high congestion pricing per minute of B744. In contrast, flight merging with A333 will not bring higher fees because congestion pricing per minute of B738 is less than half of A333’s cost (Table 1).

In general, there are three critical factors of flight merging. First is congestion pricing per minute for the aircraft before and after merging. When the new aircraft’s congestion pricing per minute is lower than the sum of the original aircraft, congestion fees will decrease. Second, the aircraft’s seating capacity determines how well the new aircraft matches the original two. High attendance of the new flight is inclined to bring an economical result. Third, the queue length of certain flights pushed back after the merged flight also gets shorter, which means the congestion fees will be correspondingly reduced.

As mentioned before, the feasibility of flight merging is based on win-win cooperation. Table 4 illustrates the operation of this example.

Merging CSZ9671 and CSN3599 into one larger flight operated by A333, congestion fees are reduced from 11,361 RMB to 5385 RMB, decreasing by over 52%. Six flights get shorter queue lengths when CSZ9617 is merged, and these so-called affected flights, whose push-back time is between CSZ9617’s push-back time and its wheel-off time, are shown in Table 5. Affected flights also get benefits from flight mergers. Total congestion fees are reduced from 69,570 RMB to 61,912 RMB, decreasing by over 11%.

4.4. Comparison of the Two Methods. The above two methods are further compared, and Table 6 shows the final results from four different scopes: number of flights, economic benefits (i.e., lower congestion fees), operational benefits (i.e., shorter queue length), and environmental benefits (i.e., lower emissions and external costs). Moreover, Figure 5 depicts the distribution of flights with different queue lengths for each scheme.

The schedule adjustment is quick and straightforward. It can have a better result with these flights with an extremely long queue. For example, the number of flights with a queue length from 21 to 30 is the least, as shown in Figure 5. The change in the value of fees per adjusted flight also shows that schedule adjustment has a powerful economy and practicability. However, even if we set the push-back time that can just be postponed by a maximum of half an hour, promoting flights shifting from peak periods to off-peak periods implies that the ticket price may also drop, which is not desirable for airlines. Furthermore, schedule adjustment plays a relatively minor role in emission reduction.

The flight merging has a significant effect on congestion fees reduction, and scheme (c)—merging by B744 and A333—has the lowest total congestion fees. However, from the view of the change in the value of fees per adjusted flight, flight merging is less effective in congestion fee reduction. Flight merging contributes substantially to congestion relief by offering more seats in bigger aircraft, decreasing the total number of departure flights. Moreover, the effect of this method will be more prominent when the flight schedule is balanced, which means the flight schedule does not have prominent flight peak and off-peak periods. In addition, flight merging will lower operating costs for airlines because the unit cost per seat of bigger aircraft is lower than that of smaller aircraft (Givoni and Rietveld [47]). Nevertheless, at the same time, flight merging will decrease frequencies and cannot satisfy the various demands of travelers, especially business travelers. Furthermore, there is still one more question about the allocation of reduced fees, shown as a change in the value of total fees in Table 4. In other words, how should we charge two airlines with fairness after flight merging (here, in Table 7, we charged by the same proportion of original congestion fees)? Hence, it will be the direction for future research.

Table 7 gives summarized comparison results of two methods according to the above analysis. Each method has its advantages and disadvantages and should be chosen according to the requirement, or be used in combination.
5. Conclusions and Policy Implications

5.1. Conclusions. Air transportation has realized impressive growth in the last few decades. However, this did not occur along with a corresponding growth in airport capacity. Consequently, airport congestion has become serious trouble, which brings a loss for airlines, passengers, and the environment.

To complete the externality, a steady-state airport congestion model that includes the costs of airlines, passengers, and the environment is developed to calculate airport congestion fees for different times and different queue lengths under consideration of airlines’ market shares. To reduce airport congestion fees for airlines, two different measures—flight schedule adjustment and flight merging—were proposed and studied for Guangzhou Baiyun International Airport. The main conclusions are as follows:

1. Congestion cost varies from aircraft to aircraft, but the proportion of each subcost is similar. Airline operating cost is the highest, about 55%–57%, and environmental cost is the lowest, at 3%–6%. This study calculates the overall cost during the taxi-out time with an environmental cost. Taking B738 as an example, average congestion fees are approximately 2000 RMB to 6000 RMB at most time intervals. However, during the peak period, the congestion fees would exceed 10,000 RMB and even reach 25,000 RMB at CAN.

2. Based on congestion pricing, two different options for congestion fee reduction are under discussion. Schedule adjustment stimulates airlines to change flight schedule planning at congested airports. Flight merging reduces queue length by merging two flights into one flight by using a larger aircraft. The results of the empirical analysis indicate that both methods can relieve congestion and reduce congestion fees at Guangzhou Baiyun International Airport. In other words, these two methods both have positive economic, operational, and environmental benefits.

3. In this case, flight merging by B744 and A333 achieves a better result on most performance indices, although schedule adjustment is significantly more effective at congestion fees change per adjusted flight. Additionally, schedule adjustment is flexible and straightforward, which is better for congestion relief by “peak shaving and valley filling.” Under this method, the utilization of slot resources is better balanced and improved. However, several flights cannot be adjusted because of the congestion duration during peak periods.

4. Flight merging can fundamentally reduce the total number of departure flights, which means airport demand reduction. Nevertheless, it is constrained by many factors in operation, such as the aircraft type and the queue length of the original flights. Moreover, the reason for the airline having two flights instead of a single one could be various: offer more frequencies to capture a greater market share (especially significant for business travelers), for operational reasons (one aircraft can then continue to one destination while the other to a second one), for not losing slots at congested airports, etc. Also, one should note that improper choice of aircraft type for flight merging will lead to higher fees, which makes this method infeasible.

Therefore, with both the methods, airlines can choose one or even use them in combination according to the actual requirements.

5.2. Policy Implications. As we can see from the previous results, congestion is evident during the peak period, which needs urgent improvement. Thus, we propose the following specific policy options.

First, airlines need to have a clear idea of the total cost at different slots. A rush hour means high ticket prices and severe delays, which suggests an implicit but not negligible loss. Thus, a better balance in resource allocation at the
initial moment is critical for airlines. Airlines are suggested to pay more attention to peak time at busy airports and undertake a cost-benefit analysis to decide how to optimize the slots.

Second, airlines are advised to expand the scope of flight merging on the most popular route. Like the Beijing-Shanghai air express route, which cooperates with five airlines from different alliances to operate this route, one can board the earliest flight no matter who the carrier is and which airline your ticket is from. That is, flight merging is no longer limited to the same airlines or alliances. Notably, in the high-dense market, flight merging is strongly recommended to relieve congestion.

Third, facing the rapid growth of air transportation, it is unlikely that the congestion will be relieved soon at busy airports like CAN. Thus, to reduce taxing time and emissions from aircraft during the taxi-out process, the Airport Operation Center (AOC) should take advantage of management reform of aerodrome control, which is ongoing now in China to improve aircraft ground operations, such as aircraft taxiing route optimization and gate-holding strategy.

In addition, congestion pricing revenue redistribution needs to be further explored. There are several options for the airport to relocate congestion fees, such as runway expansion that increases airport capacity and financial subsidies for airlines that encourage flight schedule adjustment to help "shave peak and fill valley". The airport authority is suggested to evaluate different redistribution schemes and have the best balance between short-term and long-term interests of congestion mitigation.

Finally, it should be noted that in this study, we provided a general approach and a combined perspective to assess the performance of different measures for airport congestion fees reduction with the research case of Guangzhou Baiyun International Airport. The specific value of congestion fees at CAN may be different from other selected examples. Therefore, other airports/airlines are suggested to consider these differences before taking further action.

Although the current research has drawn some interesting results on the design and assessment of measures for airlines to reduce airport congestion fees, it also has some limitations. Due to the lack of flight revenue data, we adopted a minimum of congestion fees as the optimization objective rather than the maximum profits. Moreover, we used push-back time instead of scheduled departure time in schedule adjustment and did not consider the network effects that the two measures may have. These need to be explored in the future.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares that they have no conflicts of interest.

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