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Airline network competition in inter-continental market

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Abstract

As the number of countries liberalizing their skies increases, some airlines, notably carriers in the Middle East, have extended their hub-and-spoke networks beyond domestic borders. This allows them to serve international destinations without the need to go through traditional gateway hubs, so that they can compete with airline alliances relying on the traditional dual-gateway, or the so-called "dog-bone" networks. This paper proposes a stochastic optimization model to address the location choice issue of additional gateway airports, with a consideration of the competition between airlines running traditional dog-bone networks and hub-and-spoke networks in a liberalizing inter-continental market. A two-stage approach is adopted to model the effects of demand uncertainty. In the first stage, the future passenger demand is not observable and thus airlines or airline alliances aim to maximize their own expected profit by choosing additional gateway airports from the set of candidate gateway airports pre-specified by the regulator. In the second stage, with the passenger demand observed and the gateway scheme fixed, airlines determine their aircraft sizes and service frequencies to maximize their own profit, and air passengers choose routes that minimize their own travel disutility. Based on a calibration of the demand dispersion parameters in elastic demand function, the proposed model is applied to the China-Europe aviation market, which includes the inter-continental international market and the associated Chinese and European domestic markets, so that to ascertain the comparative advantages of different network configurations. The social welfares of the system under different demand scenarios and different gateway schemes are compared, and the sensitivity analyses of some parameters are also implemented.

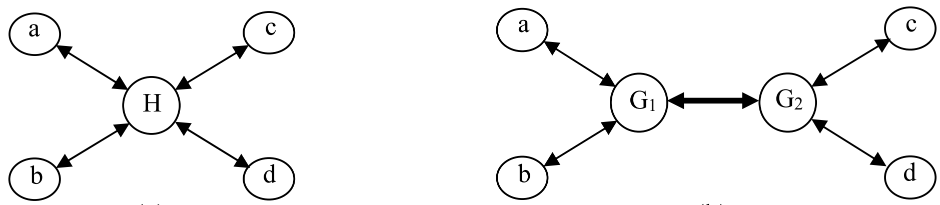
Keywords: Network cooperation and competition; Hub-and-spoke network; Dog-bone network; International gateway hub; Demand uncertainty; Parameter calibration.

1. Introduction

It has widely been recognized that one of the most important innovations in the aviation industry is the development of hub-and-spoke (HS) networks. HS networks can yield "economies of traffic density" by combing traffic volumes on feeder routes and funneling them to a central hub, where aggregated traffic is then channeled to domestic or international markets – a process that ensures high load factors and enhanced revenues for network airlines (Lei and O'Connell, 2011). As a result, airlines have an incentive to enhance their service qualities with increased flight frequencies, and to compete more strategically (Caves et al., 1984; Brueckner and Spiller, 1994; Zhang, 1996; Brueckner and Zhang, 2001; Brueckner, 2004)[1]. Following deregulations in the US and European countries, HS networks have been extensively adopted in the aviation industry. However, in international especially inter-continental markets, the primary network configuration is the so-called "dog-bone" networks with two gateway hubs[2] (Button, 2009, 2012). This is partly due to the fact that most countries forbid a foreign airline to freely serve their domestic cities, so that airlines in the origin-destination (OD) countries have to jointly offer international services via their gateway hubs by forming an international alliance or code-share agreement. Fig. 1 illustrates a pure HS network and a dog-bone network. Clearly, the latter is essentially an extended/linked HS network. In the case of an inter-continental market, it consists of two gateway hubs, G_1 and G_2, located in two continents respectively, each connected to local spoke markets via domestic feeder flights. One example of such a configuration is the alliance network by Lufthansa and Air China in the China-Europe market. In such a case, G_1 may represent Lufthansa's hub at Frankfurt serving the intra-European market, whereas G_2 may represent Air China's hub in Beijing which has extensive services to mainland China and some Asian destinations. Both Lufthansa and Air China are members of Star Alliance and have developed extensive cooperation agreement through joint venture. They could thus jointly provide a connecting service for passengers flying from Manchester UK to Zhengzhou China via their respective hubs in Frankfurt and Beijing. The local spoke sections from Manchester to Frankfurt and from Beijing to Zhengzhou are, respectively, served by Lufthansa and Air China.

[1] It is worth noting that recent empirical studies suggest that PoP (Point-to-Point) networks may also offer airlines competitive advantages through specific types of network effects (See for example the study on Southwest Airlines' network development pattern by Fu et al. (2019)).

[2] In the literature, the dog-bone network is also referred to as the "dumb-bell" network. Because HS airlines may use more than one hub to serve markets with large geographic coverage, for clear reference we will consistently use the term of "dog-bone network" instead of alternative names such as dual-gateway or dual-hub networks.



(a) (b)

Fig. 1. Airline network configurations: (a) a pure HS network, and (b) a dog-bone network.

The adoption of dog-bone networks is largely due to both operational and regulatory considerations. First, aircraft sizes for inter-continental flights are generally large, which are not economically feasible for direct flights linking two spoke destinations. In the case of a dog-bone network, large-sized aircraft can be used to serve hub-to-hub routes, while smaller aircraft may be used to serve hub-to-spoke/spoke-to-hub routes. Second, international regulations often prohibit airlines to develop extensive networks in foreign countries (Fu et al., 2010). As a result, airlines have usually resorted to forming alliances (e.g., OneWorld, Star Alliance and Sky Team) or enter into code-sharing agreements to jointly offer international services via their existing hubs. This allows airlines to consolidate traffic volumes through their gateway hubs so as to further leverage the advantages of HS networks, such as increased frequencies and decreased operating costs.

However, in the past decades, the aviation industry has been experiencing some changes in technologies and regulatory policies. For example, relatively small-sized aircraft are introduced which can serve long-distance routes efficiently (e.g., A350 and B787 can serve long-distance routes with a seating capacity of about 300). As more countries are liberalizing their skies, it is now possible for airlines to expand their networks extensively across national borders. Carriers in the Middle East, such as Emirates, have been able to expand their HS networks to serve a large number of destinations in Europe, Asia, and North America. Thus, they can by-pass regional gateways and compete with airline alliances relying on dog-bone networks. Emirates, for example, now serve 144 destinations around the world directly out of Dubai[3], where passengers only need to connect once for their inter-continental flights. Turkish Airlines, which developed extensive networks over Europe and Africa, has been adopting the similar strategy to expand its network in Asia Pacific.

[3] According to OAG (Official Airline Guide) database, as of late 2017 these include 40 destinations in Europe and 42 destinations in Asia, respectively.

The fast expansion of the Middle East carriers has led to on-going policy debates and competition concerns. International aviation operates within the framework of the 1944 Chicago Convention, under which airlines' rights are primarily regulated by bilateral air services agreements (ASAs) between each country-pair. Other than a few regional open-skies in EU and ASEAN, most aviation liberalizations have been implemented on a bilateral basis. This has led to the formation of dog-bone networks which are jointly operated by alliance airlines in the origin and destination (OD) countries. As HS networks expand beyond national borders, airlines in a third country can also compete in that OD market by utilizing the 6th freedom. This could significantly change the ways that airlines compete and thus the traditional bilateral negotiations of air transport liberalization. For example, the EU and China should consider the competitiveness of Middle East airlines in the inter-continental aviation market during the process of negotiating bilateral ASAs, even though the Middle East carriers are not directly involved in these negotiations. Regulations on airline alliances or code share agreement need also to be re-evaluated, because they significantly influence airline competition and operation.

Airlines' competitive strategies and network development also need to be revisited. Each type of networks has its own advantages and disadvantages. The dog-bone network is likely to bring airlines substantial cost savings via traffic consolidation on the hub-to-hub links. However, passengers will spend more time on flight connection. Global HS network is more convenient because the passengers can just transfer one time at its global hub airport. However, it can only serve sufficiently large destinations, which can fill long-range wide-body aircraft, and may need to be authorized the sixth freedom by the origin and destination countries. Despite the inter-continental HS network expansion by major Middle East carriers, it is unclear how the airlines' HS network developments influence those of traditional dog-bone networks. Would these two network configurations each secure certain niche market with distinctive competitive advantages? Should governments take into account airline competition in ASA negotiations or should they focus on providing general infrastructures such as airport capacities? These policy and managerial issues need to be thoroughly addressed, as more countries are liberalizing their skies. For example, mainland China has been adopting more liberalized policies in the international markets, notably those to Europe and ASEAN countries under its Belt-and-Road initiative. If the dog-bone network will continue to dominate the future aviation market, more investments should be made on existing and potential gateway hubs. Otherwise, European and Chinese airlines should re-think their alliance strategies and try to build their own global HS networks with more long-range aircraft.

As afore-mentioned, a dog-bone network in the inter-continental aviation market consists of at least two sub-networks, each of which also serves the associated intra-continental aviation market. Obviously, the passenger demand in the local or domestic markets has significant impacts on the inter-continental market and the locations of the new gateway airports in the dog-bone network. On one hand, the inter-continental travelers may make trips in the destination continent, which contributes to the passenger demand of the local or domestic markets. On the other hand, most of the air passengers on the spoke-to-hub/hub-to-spoke links are the domestic air passengers. Ignoring the passenger demand of the domestic aviation market may lead to significant biases of modeling the airlines' decisions and evaluating the competition between dog-bone network and HS network.

In summary, an investigation on the effects of airline network competition is important for both airlines and regulators. For airlines, they could optimize and reconfigure their networks to improve their competitiveness. For regulators such as the Civil Aviation Administration of China (CAAC), a good assessment of the competition effects will help them design the related policies, such as aviation liberalization (Fu et al., 2010, 2015), slot allocation at major airports (Li et al., 2010; Sheng et al., 2015, 2019), and the approval of airline alliances or code share agreements. More importantly, regulators should not only take care of their national carriers, but also customers. If Chinese passengers enjoy substantially better services at lower costs due to increased competition (possibly the competition from Middle East carriers), then the Chinese government should promote liberalization even if Chinese airlines may lose some market shares.

To address these important issues in this paper, a stochastic optimization model accounting for the effects of passenger demand uncertainty is first proposed. In the proposed model, the interactions between two types of stakeholders, namely the airlines and the air passengers, are explicitly considered. A two-stage approach is used to deal with the effects of demand uncertainty. In the first stage, the future passenger demand is not observable, and thus airlines or airline alliances maximize their own expected profits through deciding the locations of new gateway airports from a set of candidate gateway airports pre-specified by the regulator. In the second stage, with passenger demand observed and the gateway scheme fixed, airline alliances operating the dog-bone networks and an airline running an inter-continental HS network compete for the inter-continental aviation market. Furthermore, the related domestic markets are also discussed simultaneously. Both the airline alliances and the airlines operating HS networks maximize their own profits by optimizing their aircraft sizes and frequencies. A heuristic solution algorithm combining the diagonalization method and the Hooke-Jeeves method is proposed to solve the proposed model. Then, a parameter calibration method is presented to estimate the value of the demand dispersion parameter in the elastic demand function for each OD pair. The value of such a demand dispersion parameter in the previous studies is usually assumed to be the same across OD pairs, and is seldom calibrated based on real market demand data. This may lead to an increased gap between the estimated and actual realized passenger demand. Therefore, a parameter calibration method should be presented to estimate the demand dispersion factor for each OD pair through collecting real data of the OD passenger demand matrix. Finally, a case study of the China-Europe aviation market (including the inter-continental international market and the Chinese and European domestic markets) is analyzed to illustrate the applications of the proposed model. The effects of aviation liberalization on passengers' preferences for different aviation routes, airline network competition, and the total social welfare of the system are also evaluated, which allow relevant recommendations on regulatory policies and managerial strategies to be made.

Such an analysis allows us to make contributions in multiple ways. A few carriers using HS networks, notably gulf carriers (i.e. Emirates, Etihad and Qatar Airways), have been quite successful in expanding their global networks. As a result, certain countries turned conservative in giving them market access.[4] Our study models the market equilibrium when airlines compete with different networks. As illustrated in the case study of the China-Europe inter-continental market, such an analysis allows regulators to better assess different types of airlines' strengths and weakness, and the likely outcomes of alternative liberalizing policies (e.g. what types of markets/routes are ideal for dog-bone network operators vs. inter-continental HS network carriers; the likely market outcome and impacts to domestic airlines if more liberal market access is given to gulf carriers), and the choices of alternative international gateway hubs. As elaborated in the literature review section, existing network

[4] For example, instead of awarding access to major international hubs, the Chinese government first allowed Emirates to serve the Chinese markets through Yinchuan, a non-hub third-tier airport in the country. Emirates' services to the cross Tasman market also raised policy debates in Australia.

competition models cannot be easily adapted for such an analysis.[5] In addition to industrial insights, our study also contributes to the modeling of airline competition over networks. To the best of our knowledge, few network competition studies have explicitly modeled the effect of demand uncertainty on airline rivalry. Our analysis formally addresses this issue by considering airlines as maximizing the expected profit when alternative demand scenarios are possible. Combined with traditional sensitivity analysis of key parameters, our study not only allows a robustness check of modeling results (e.g. ranking of additional gateway hubs), but also serves as a step toward a more systematic modeling of the effects of uncertainty. In addition, whereas we follow the usual practice adopted by previous investigations to calibrate the model using empirical estimates obtained from other markets, a maximum likelihood approach is introduced for the calibration of key parameter in the elastic demand function. This allows the model to reproduce observed market outcomes, and the calibration process to be performed in a more systematic and objective manner.

The remainder of this paper is organized as follows. Section 2 reviews previous relevant studies. Section 3 presents the model formulation. Section 4 applies the proposed model to the China-Europe aviation market so that the likely market equilibrium can be identified. Section 5 concludes the paper and provides recommendations for future studies.

2. Literature Review

In the literature, some studies have modeled the effects of airline network configuration and the competition between airlines. However, to the best of our knowledge, most of the previous studies about airline network competition focus on the interactions between HS networks or between an HS network and a full connected network. The competition between HS network and traditional dog-bone network has not been properly explored yet. The choices of alternative airline networks have been studied by Lederer and Nambimadom (1998) and Adler and Hashai (2005). However, the primary objective was to minimize the total costs of airlines and passengers, and thus airline competition was not considered explicitly. Adler (2001) adopted a two-stage best-response game model to identify the profitable hub choices and resultant market equilibria. This model was further extended by Adler (2005) to examine the most adaptable and profitable HS networks under airline competition in Western Europe.

[5] Although not discussed in details in the literature review, our gateway hub choice analysis also complements location choice studies, which usually focus on the cost/distance minimization or service equality maximization, without explicitly considering inter-firm competition.

Adler and Smilowitz (2007) discussed the competition between dog-bone networks with and without airline alliances or mergers. However, possible rivalry with HS networks was not modeled and their study focused on airlines' decisions only. Hansen and Kanafani (1990) explored the network competition between one-hub airlines and two-hub airlines in the US-Asia aviation market by a computer simulation model (but not a mathematical optimization model as presented in our paper). Moreover, the airlines analyzed in their study belong to either of the two continents but not cross both. Hansen (1990) and Takebayashi and Kanafani (2005) investigated the competitions between airlines running HS networks and point-to-point (PoP) networks. Alderighi et al. (2005) analytically demonstrated that HS networks and PoP networks may coexist at equilibrium. Pels et al. (2000) proposed a nested multinomial logit model to analyze airport competition and airline competition simultaneously. Silva et al. (2014) investigated how two symmetric airlines choose between fully connected networks and HS networks in the competition. They concluded that in addition to airport charges, other regulatory instruments on airlines' route choices may be necessary to maximize social welfare. Network-based modeling has also been used to analyze a wide range of issues, such as airline competition, slot allocation, airline-airport arrangements over simplified HS networks (see for example, Hansen, 1990; Hong and Harker, 1992; Takebayashi and Kanafani, 2005; Li et al., 2010; Takebayashi, 2011; Saraswati and Hanaoka, 2014; Sheng et al., 2015). Therefore, they cannot be used directly to examine the international markets in the presence of alternative network configurations.

For airlines, important strategic decisions include the choice of gateway hubs and the design of their service networks. In certain cases, airlines use multi-hub networks to serve markets with a large geographic coverage. For example, United Airlines and American Airlines each developed multiple hubs in the US.[6] Air China has also been developing hubs in Beijing, Chengdu and Shenzhen of China. Therefore, it is important for the airlines to determine the location for adding an alternative gateway hub in response to competition. This may alleviate the capacity shortage and congestion issue at the saturated gateway airport. In most markets, however, such a strategy cannot be implemented without strong government support, because substantial changes in airline and airport designations,[7] slot allocation and capacity

[6] Over the years, United Airlines has developed hubs in San Francisco, Denver, Chicago and Washington D.C., whereas American Airlines has developed domestic hubs in Dallas, Chicago, Miami, St. Louis, New York, and Los Angeles.

[7] Absent full open-sky liberalization, only designated airlines can provide international services between designated/approved destinations in the OD countries under ASAs' regulations related to designation and capacity.

investments at the new gateway airports are needed. In certain markets like China, the strategic planning for airports is developed or endorsed by the regulator CAAC.[8] In other cases, governments invest in airport infrastructures but have limited influence over airlines' hub choices.[9] Regardless of the regulatory frameworks and aviation market developments, it would be useful to take into account the (additional gateway) hub choice in the model so that such strategic decisions are reasonable and accurate. The seminal work by Hansen and Kanafani (1990) investigated the effects of developing additional hubs on Tokyo's role as the transpacific gateway under the situation of network competition. However, their computer simulation model only considered a single kind of aircraft for all airlines' flight services and assumed that airlines only optimize the frequencies, which may not be consistent with the current situation because the aviation industry has been experiencing many changes in aircraft technologies. Besides, passengers' route choice only depends on traveler's preference of the types of routing, transcontinental service frequency and service circuity. Adler (2005) developed a multinomial logit model to compute different airlines' market shares and then formulated a mathematical model to investigate the HS network design under competition. According to the p-hub median model, Adler and Smilowitz (2007) proposed a game-theoretic model to study the airline merger and hub location decisions. However, the responses of air passengers to airlines' services and the airport congestion delay were not explicitly considered in both studies. Yang (2009, 2010) proposed a two-stage stochastic model to study the hub location issue and the flight routes and flow allocations. However, the interaction between airlines and air passengers, the demand-supply equilibrium, and the passengers' route choices were not discussed yet, which will be considered in our present study.

In addition, it should be mentioned that the model parameters in the previous studies were seldom calibrated for real aviation markets. For example, the passenger demand dispersion parameter in the elastic demand function is very important because it determines the resultant passenger demand and thus airlines' service decisions. However, most previous studies

[8] For example, in the 13th Five Year Plan for Civil Aviation Airports Development released by CAAC, which covers the plan during 2016-2020, it was indicated that 10 international hub airports will be developed, including the airports in Beijing, Shanghai, Guangzhou, Chengdu, Kunming, Shenzhen, Chongqing, Xi'an, Urumqi, and Harbin.

[9] For example, Odoni and De Neufville (2003) noted that the Dulles airport in Washington DC and the Newark airport in New York/New Jersey experienced severe under-utilization for extended periods, because airlines are reluctant to switch their operations from existing hubs. In comparison, regulators in China, Korea and France can designate certain airlines/aviation services to selected airports.

usually applied a single or uniform value for the passenger demand dispersion factor for all the OD pairs in the network (Zhang and Wei, 1993; Zhou et al., 2005; Li et al., 2010; Saraswati and Hanaoka, 2014; Sheng et al., 2015). There are also several studies that mentioned the importance of using different demand dispersion factors for different OD pairs (see Yang and Bell, 1997; Yang et al., 2004; Szeto and Lo, 2004). However, few studies implemented the calibration work of such parameters for real cases, which will be done in this paper.

Hub location, similar to other network design problems (NDPs), is a strategic long-term decision, relying on the forecast of future passenger demand. However, it is difficult to precisely predict future demand in the planning stage. Therefore, it is important to consider passenger demand uncertainty in NDPs. Lee and Dong (2009) explored the design of reverse logistics networks with both demand and supply uncertainty, and concluded that the results from the stochastic problem are more suitable for practical decisions. Ukkusuri and Patil (2009) developed a multi-time-period NDP formulation considering both demand uncertainty and elasticity to model the future network investment. Compared to a single-stage NDP, this formulation can lead to 10%-30% higher expected consumer surplus. Yin et al. (2009) proposed three different stochastic models to determine the robust optimal improvement schemes for road networks. Chen et al. (2010) discussed an NDP with demand uncertainty by adopting three stochastic multi-objective models and obtained a Pareto optimal solution set. These studies mostly modeled uncertainty by generating a substantial number of samples from the pre-given probability distribution. However, it is usually difficult to ascertain a probability distribution of future passenger demand in the first place. Instead, there are usually clear seasonal patterns in the aviation industry. Therefore, Yang (2009, 2010) incorporated seasonal demand variations into a two-stage stochastic programming model to study an airline network design problem. Such an approach is also adopted in this study to account for the effects of demand uncertainty.

3. Model formulation

Network configuration strategies are fundamental decisions of airlines. In this study, we consider a network with a set of nodes (airports) and a set of arcs (links), which are respectively denoted as N and A. A link $a \in A$ is defined as the direct linkage between a pair of airports. A route may consist of several links. Let K denote the set of airlines, and k be a generic element of K. $A_k \subseteq A$ is the set of associated links in the sub-network of airline k. $G \subseteq N$ is the set of all international gateways, whereas $\bar{G} \subseteq N$ is the set of candidate gateway airports to be added. Let W be the set of all OD pairs, $W_1 \subseteq W$ be the set of inter-continental OD pairs, and $W_2 \subseteq W$ be the set of local/domestic markets' OD pairs.

The choice of gateway airports is strategic and cannot be changed in the short term. However, it is extremely difficult to forecast long-term travel demand at route level or airport level (Xiao et al., 2013, 2017). Therefore, it is important to explicitly consider the effects of passenger demand uncertainty. Because air passenger demand usually exhibits clear seasonal patterns and airlines adjust their service offerings regularly[10], it would be useful to model some demand scenarios in the analysis which correspond to flight seasons or quarterly changes. To simplify the presentation of the problem while sufficiently characterize the key dynamics in the aviation market, the following assumptions are made in this study.

A1. Two types of airlines are considered for the inter-continental aviation market, which include the carriers operating HS networks and the carriers operating traditional dog-bone networks. In practice, the latter often refers to the airlines in the OD markets which jointly offer the flight services through alliance or code-share agreements (e.g., Air China and Lufthansa in the China-Europe market). Additionally, the local or domestic aviation markets in intra-continent are also considered, which are served by their own airlines in the continents concerned. Certainly, the inter-continental aviation market is the focus of our research. The airports are classified into the feeder airports and the hub/gateway airports. The hub/gateway airports play the role of concentrating and distributing air passengers. An HS network involves only one hub airport, while the dog-bone network usually contains two international gateway airports, each in one continent. In a dog-bone network, the feeder airports are assumed to connect to all gateway airports at the same continent for the purpose of inter-continental transportation. In an HS network, the feeder airports are all connected to the unique global hub airport (e.g. Dubai for Emirates). A passenger route for the inter-continental OD pair involves at most two transfers/connections, which is in line with the industry reality. However, for the local or domestic markets, we assume that the passengers can fly directly

[10] For example, there are two flight seasons per year, for which airlines systematically update their operation plans of frequencies, aircraft schedules and flight destinations. Moderate changes can also be introduced upon the approval and confirmation of regulators, air traffic controllers and airports.

from the origin airport to the destination airport. All the airports and airlines are pre-given, and thus no entrant airlines are considered in our model.

A2. The members in an alliance jointly set service qualities for the inter-continental OD pairs (i.e., airline alliance with anti-trust immunity), as if they were one single airline (Takebayashi, 2011). In this study, the proposed model is mainly for long-term planning purpose at a strategic level, and thus it is a stationary-state model. A concept of average airfare for each route is adopted, as done in Hansen (1990), Hsu and Wen (2003), and Li et al. (2010). Such an average airfare for each route can be pre-determined through the data collected from industry database or airlines' official websites. Each airline is allowed to join at most one alliance. It is further assumed that airlines are allowed to serve all city pairs, so that airlines' operational decisions can be endogenously modeled (Berechman and de Wit, 1996; Yang, 2008).

A3. The potential OD demand on each route is a random variable due to seasonal demand variation and forecasting error, and is assumed to have a discrete distribution with a finite number of possible realizations called demand scenarios (Li et al., 2012; Yang, 2009, 2010).

A4. Two types of players are considered in the aviation market, namely the airlines and air passengers. For the airlines, a two-stage model is used to determine the decision variables: locations of gateway airports and flight services (i.e., aircraft sizes and flight frequencies). In the first stage, the locations of gateway airports are determined to maximize the expected net profit of airlines before actual travel demand is observed. In the second stage, for a realized demand scenario and a given gateway scheme, each airline alliance or HS network airline aims to maximize its own profit by optimizing the associated flight services (including aircraft sizes and flight frequencies). An elastic demand function is applied to capture the responses of air passengers to airlines' services. Airlines running the dog-bone networks are assumed to jointly make their decisions of flight services, as if they were one company operating within an open-sky market. Therefore, we consider the joint profits for the airline alliances in this paper for simplicity. This is a restrictive assumption. However, additional assumptions and justification will be needed if specific agreements of code-sharing, revenue pooling or capacity sharing are modeled, which will also impose unknown limitation on the generality. Note that if airlines agreed to a fixed sharing ratio, there will be little change in our model. Besides, airlines, especially those already within the same global alliance such as Star Alliance and OneWorld, often form close cooperative arrangements. For example, Lufthansa had signed a Group Route Joint Venture with Air China in September 2016, allowing the two airlines to make many joint decisions. The set of alternative aircraft sizes for each airline is assumed to be pre-given, and each airline schedules only one type of aircraft on each link (or an average aircraft size on that link).

A5. The effects of congestion delay at the hub airports are considered. If an airport is subject to capacity constraint, then the airlines landing at or taking off from that airport would incur congestion cost. The capacity of an airport is the maximum number of flights (i.e., aircraft movements) that the airport can serve.

3.1. Scenario-based air passengers' route choices

Let Ω be the set of finite demand scenarios under the situation of stochastic demand, and $\xi \in \Omega$ be a realized demand scenario. According to assumption A4, for a given gateway scheme and demand scenario $\xi \in \Omega$, the potential OD demand is pre-given and the air passengers are assumed to make route choices based on their own perceptions of the disutility on alternative routes and services. Let R_{kw} denote the set of all possible routes served by airline k between OD pair $w \in W$. For a specific demand scenario and the temporarily fixed service levels provided by all airlines, the travel disutility function u_{krw}^{ξ} of route $r \in R_{kw}$ served by airline k is computed as a weighted sum of the line-haul travel time t_{krw}^{ξ}, the schedule delay time at airports d_{krw}^{ξ}, an additional penalty term Δ_{krw} to reflect passengers' preferences over different trip patterns (i.e., non-stop, one-stop, or two-stop), the congestion delay time at the capacitated hub airports C_{krw}^{ξ}, and the airfares p_{krw}^{ξ} (Kanafani and Ghobrial, 1985; Hsu and Wen, 2003; Li et al., 2010, 2011). The passengers using the HS networks transfer just once during their trips. However, passengers may make at most two connections when they travel with airline alliances operating dog-bone networks. u_{krw}^{ξ} can, therefore, be expressed as follows

$$u_{krw}^{\xi} = \alpha_1 t_{krw}^{\xi} + \alpha_2 d_{krw}^{\xi} + \alpha_3 \Delta_{krw} + \alpha_4 C_{krw}^{\xi} + p_{krw}^{\xi},\ \forall r \in R_{kw}, w \in W, k \in K, \xi \in \Omega, \tag{1}$$

where α_1 is the passenger's value of line-haul travel time, α_2 is the value of schedule delay time, α_3 converts the additional penalty term into monetary cost, and α_4 is the passenger's value of time for the congestion delay at the capacitated hub airports.

The line-haul travel time t_{krw}^{ξ} on route $r \in R_{kw}$ can be expressed as the sum of the travel times on all links along route *r*, specified as

$$t_{krw}^{\xi} = \sum_{a \in A_k} t_{ka}^{\xi} \delta_{ar}, \ \forall r \in R_{kw}, w \in W, k \in K, \xi \in \Omega, \tag{2}$$

where t_{ka}^{ξ} is the travel time on link *a*, assumed to be dependent on the distance of link *a* and the velocity of the aircraft of airline *k* allocated for that link. δ_{ar} equals 1 if link *a* is on route *r*, and 0 otherwise.

The schedule delay time at an airport refers to the time difference between passengers' preferred departure time and the time of a schedule flight, which decreases with the flight frequency. The schedule delay time on route $r \in R_{kw}$, d_{krw}^{ξ} , can be specified as the sum of the schedule delays on all links along this route

$$d_{krw}^{\xi} = \sum_{a \in A_k} d_{ka}^{\xi} \delta_{ar}, \ \forall r \in R_{kw}, w \in W, k \in K, \xi \in \Omega, \tag{3}$$

where d_{ka}^{ξ} is the schedule delay on link *a*, which can be approximated as the quarter of the average headway according to Kanafani and Ghobrial (1985), expressed as

$$d_{ka}^{\xi} = \frac{T}{4 f_{ka}^{\xi}}, \ \forall a \in A_k, k \in K, \xi \in \Omega, \tag{4}$$

where *T* is the average operating duration of the airport over the period of analysis (*T* usually takes 18h/day, and thus it can be converted to 22.5 days/month), and f_{ka}^{ξ} is the flight frequency of airline *k* on link *a*.

The congestion delay time on route $r \in R_{kw}$, C_{krw}^{ξ}, can be expressed as the sum of the congestion delays at all the hub airports subject to the capacity constraints along this route

$$C_{krw}^{\xi} = \sum_{H} \sum_{a \in A_k} d_H \delta_{ar} \delta_{Ha}, \ \forall r \in R_{kw}, w \in W, k \in K, \xi \in \Omega, \tag{5}$$

where d_H is a flight's delay at airport *H*, δ_{Ha} equals 1 if airport *H* is on link *a*, and 0 otherwise. A flight's delay time d_H can be calculated as the ratio of the total number of flights to the capacity of airport *H* (Borger and Dender, 2006; Basso and Zhang, 2007; Yang and Zhang, 2011; Benoot et al., 2013; Gillen and Mantin, 2014; Silva et al., 2014), given as

$$d_H = \frac{F_H}{C_H}, \tag{6}$$

where $H \in G$ represents a capacitated hub airport. F_H is the sum of all aircraft movements (i.e. landing and taking off flights) at airport *H*, and C_H is the capacity of airport *H*.

The expected disutility function φ_w^ξ between OD pair *w* can, therefore, be expressed by the following formula (Oppenheim, 1995)

$$\varphi_w^\xi = -\frac{1}{\theta}\ln\left(\sum_{k\in K}\sum_{r\in R_{kw}}\exp\left(-\theta u_{krw}^\xi\right)\right),\ \forall w \in W, \xi \in \Omega, \tag{7}$$

where θ measures the error in the passenger perceptions of travel disutility u_{krw}^ξ. A higher value of θ means a smaller passenger perception error, and vice versa (Huang, 2002; Huang and Li, 2007; Li et al., 2010).

For each demand scenario $\xi \in \Omega$, define $\bar{Q}_w^\xi$ as the potential travel demand between OD pair *w*. An elastic demand function is adopted to capture the responses of passengers to airlines' services and airfares (Li et al., 2010, 2011; Saraswati and Hanaoka, 2014). Let Q_w^ξ be the resultant OD demand, specified as follows

$$Q_w^\xi = \bar{Q}_w^\xi \exp\left(-\beta_w \varphi_w^\xi\right),\ \ \forall w \in W,\ \xi \in \Omega, \tag{8}$$

where β_w is the demand dispersion factor that reflects the demand sensitivity to the expected travel disutility φ_w^ξ between OD pair $w \in W$. The value of β_w may be different for different OD markets (Yang and Bell, 1997; Yang et al., 2004), and $\boldsymbol{\beta}=\{\beta_w, w \in W\}$ is the vector of the demand dispersion factors. Therefore, the passenger volume q_{krw}^ξ on route $r \in R_{kw}$ served by airline *k* can be obtained by a multinomial logit formulation, which has been applied in many previous studies to model the route choice behavior of air passengers (Davis, 1994; Lam et al., 2002; Li et al., 2010; Saraswati and Hanaoka, 2014).

$$q_{krw}^\xi = Q_w^\xi \frac{\exp\left(-\theta u_{krw}^\xi\right)}{\sum_{k\in K}\sum_{r'\in R_{kw}}\exp\left(-\theta u_{kr'w}^\xi\right)},\ \forall r \in R_{kw}, w \in W, k \in K, \xi \in \Omega. \tag{9}$$

The aggregated passenger flow q_{ka}^ξ on link $a \in A_k$ in the sub-network of airline *k* can be calculated by

$$q_{ka}^\xi = \sum_{w\in W}\sum_{r\in R_k} q_{krw}^\xi \delta_{ar},\ \forall a \in A_k, k \in K, \xi \in \Omega. \tag{10}$$

3.2. Scenario-based airlines' decisions on aircraft size and service frequency

According to assumption A**2**, alliance airlines are considered as one single decision-maker in this paper. We can thus formulate the profit maximization problem for the HS network airline and for the airline alliances, respectively. Airlines usually adjust their operations and flight schedules according to the seasonal variations in the passenger demand. According to assumption A4, for a given gateway scheme and demand scenario $\xi \in \Omega$, the airlines maximize their own profits by competing in airfares, flight frequencies and types of aircraft. However, owing to the fluctuation in the daily airfares of airlines, an average airfare for each air route is adopted and pre-determined according to the actual data collected from industry database and airlines' official websites. The profit function π_k^ξ of airline $k \in K$ is defined as the difference between the total revenues and the total costs on all routes operated by airline *k*, expressed as

$$\pi_k^\xi\left(\mathbf{f}_k^\xi, \mathbf{s}_k^\xi, \mathbf{f}_{-k}^\xi, \mathbf{s}_{-k}^\xi\right) = \sum_{w \in W} \sum_{r \in R_{kw}} p_{krw}^\xi q_{krw}^\xi - \sum_{a \in A_k} \left(\mu_a q_{ka}^\xi + \eta_{ka}^\xi f_{ka}^\xi\right)$$
$$-\gamma \sum_H \sum_{a \in A_{k-}(H) \cup A_{k+}(H)} d_H f_{ka}^\xi, \ \forall k \in K, \xi \in \Omega, \tag{11}$$

where $\mathbf{f}_k^\xi$ and $\mathbf{s}_k^\xi$ are the vectors of frequencies and aircraft sizes of airline *k* under demand scenario ξ, whereas $\mathbf{f}_{-k}^\xi$ and $\mathbf{s}_{-k}^\xi$ are the vectors of corresponding variables for other airlines excluding airline *k* under demand scenario ξ. p_{krw}^ξ denotes the airfare of airline *k* on route $r \in R_{kw}$ under demand scenario ξ. q_{krw}^ξ and q_{ka}^ξ are determined by the passenger route choice model (1) - (10). μ_a is the marginal cost per passenger on link *a*, which includes the passenger-related costs, such as the baggage handling cost, and costs of meals on board. η_{ka}^ξ is the marginal cost per flight on link *a* in the network of airline *k* under demand scenario ξ, which includes various flight-based costs, such as the pilot and crew wages, fuel costs, and maintenance cost. γ is the marginal congestion cost that airlines incur at the capacitated airports. $A_{k-}(H)$ (or $A_{k+}(H)$) denotes the set of links with a tail (or head) node *H* in airline *k*'s network. d_H is a flight's delay at airport *H*. f_{ka}^ξ is airline *k*'s frequency on link *a* under demand scenario ξ. The first term on the right-hand side of Eq. (11) represents the total revenue of airline *k*. The second term contains the total passenger-related costs and the flight-related costs of the airline. The third term is the total congestion costs of airline k that are incurred in the capacitated hub airports.

According to the empirical study of Swan and Adler (2006), the link distance and aircraft size (in terms of the number of seats) are two important factors determining the marginal cost per flight. They suggested determining η_{ka}^{ξ} by

$$\eta_{ka}^{\xi} = \left(D_a + \tau_0\right) \times \left(s_{ka}^{\xi} + \tau_1\right) \times \tau_2,\ \forall a \in A_k, k \in K, \xi \in \Omega, \tag{12}$$

where D_a is the distance of link $a \in A_k$, s_{ka}^{ξ} is the type of aircraft operated on link a by airline k under demand scenario ξ. τ_0, τ_1, and τ_2 are the parameters determined by the link distance.

Accordingly, the profit maximization problem for airline k can be formulated as

$$\max_{\left\{\mathbf{f}_k^{\xi}, \mathbf{s}_k^{\xi}\right\}} \pi_k^{\xi}\left(\mathbf{f}_k^{\xi}, \mathbf{s}_k^{\xi}, \mathbf{f}_{-k}^{\xi}, \mathbf{s}_{-k}^{\xi}\right),\ \forall k \in K, \xi \in \Omega, \tag{13}$$

subject to

$$q_{ka}^{\xi} \le s_{ka}^{\xi} f_{ka}^{\xi},\ \forall a \in A_k, k \in K, \xi \in \Omega, \tag{14}$$

$$\mathbf{f}_k^{\xi} \ge 0, \mathbf{s}_k^{\xi} \ge 0,\ \forall k \in K, \xi \in \Omega, \tag{15}$$

where $\left\{\mathbf{f}_k^{\xi}, \mathbf{s}_k^{\xi}\right\}$ are the decision variables of airline k. The optimization model (13) - (15) maximizes the profit of airline k given other airlines' services. Constraint (14) indicates that the aggregated passenger volume of link $a \in A_k$ must not exceed the available number of seats provided by airline k on this link. Constraint (15) ensures that the flight frequencies and capacities of aircraft are nonnegative.

For profit maximization model (13) - (15), the Lagrangian relaxation and penalty function approaches are applied to incorporate the above side constraints into the objective function (13). The augmented Lagrangian penalty function for airline k can be formulated as

$$L_k^{\xi}\left(\mathbf{f}_k^{\xi}, \mathbf{s}_k^{\xi}, \boldsymbol{\lambda}_k^{\xi}\right) = \pi_k^{\xi}\left(\mathbf{f}_k^{\xi}, \mathbf{s}_k^{\xi}, \mathbf{f}_{-k}^{\xi}, \mathbf{s}_{-k}^{\xi}\right) - \frac{1}{2\rho} \sum_{a \in A_k} \left[\max{}^2\left\{0, \lambda_{ka}^{\xi} + \rho\left(q_{ka}^{\xi} - s_{ka}^{\xi} f_{ka}^{\xi}\right)\right\} - \left(\lambda_{ka}^{\xi}\right)^2\right], \tag{16}$$

where ρ is a penalty constant. λ_{ka}^{ξ} is the Lagrangian multiplier associated with constraint (14), and $\boldsymbol{\lambda}_k^{\xi}$ is the corresponding vector. Therefore, the constrained maximization problem (13) - (15) can be transformed into the following unconstrained maximization problem

$$\max_{\{\mathbf{f}_k^\xi,\mathbf{s}_k^\xi,\boldsymbol{\lambda}_k^\xi\}} L_k^\xi\left(\mathbf{f}_k^\xi,\mathbf{s}_k^\xi,\boldsymbol{\lambda}_k^\xi\right),\ \forall k\in K,\xi\in\Omega. \tag{17}$$

Following the study of Li et al. (2010), the unconstrained maximization problem (17) can be solved by a heuristic solution algorithm that combines the diagonalization method and the Hooke-Jeeves method (Bazaraa et al., 2006, p. 370).

3.3. Airline's gateway airport location problem

Investment of additional gateway airports is a strategic decision of airlines, which can facilitate airlines' efforts to optimize their network configuration, improve service qualities, and alleviate the congestion at busy hub airports. In addition, other regulatory changes may also be necessary, such as ASA specifications of airline and airport designations, flight frequency and airport slot allocation. Such strategic decisions may significantly affect the performance of aviation service systems, and thus need to be carefully made, particularly in the presence of demand uncertainty. As is stated above, the aviation demand shows obvious seasonal variations, thus a two-stage approach is used to deal with such effects of demand uncertainty. Assume that airline k' aims to choose the locations of gateway hubs to maximize its own expected profit, we formulate a two-stage model of gateway airport locations as follows

$$\max_{\mathbf{x}} E[\pi_{k'}(\mathbf{x})]=\sum\nolimits_{\xi\in\Omega} P^\xi \pi_{k'}^\xi(\mathbf{x}), \tag{18}$$

subject to

$$\sum_{g\in\bar{G}} x_g \le M, \tag{19}$$

$$x_g=\begin{cases}1, & \text{if airport } g \text{ is set to be a gateway,}\\ 0, & \text{otherwise,}\end{cases} \quad \forall g\in\bar{G}, \tag{20}$$

where $\pi_{k'}^\xi(\mathbf{x})$ can be calculated by solving the scenario-based airlines' profit-maximization problem (13)-(15).

In this model, $g\in\bar{G}$ is a candidate gateway airport. $\mathbf{x}=\{x_g\}$ is the vector of the decision variable, and x_g equals 1 if airport g is a gateway and 0 otherwise. P^ξ and $\pi_{k'}^\xi(\mathbf{x})$ are, respectively, the probability and the profit of airline k' under demand scenario $\xi\in\Omega$. M is the allowed maximum number of gateway airports that airline k' plans to develop.

The two-stage model is a 0-1 integer programming problem with the binary decision variable $\{x_g\}$. The objective function (18) maximizes the expected profit of airline k'. Constraint (19) means that the total number of new gateway hubs must be less than the pre-given value *M*. Constraint (20) states that the location variables are binary. In order to solve the 0-1 integer programming problem (18)-(20) and (13)-(15), we propose the following heuristic solution algorithm, as depicted by the flowchart in Fig. 2.

Step 1. Initialization. Define a set of candidate gateway airports $\bar{G}$ and a set of demand scenarios Ω.

Step 2. First loop operation. Set $E[\pi_{k'}]^* = -\infty$ as the lower bound of the expected profit of airline k', $E[\pi_{k'}]$ in Eq. (18) and $\mathbf{x}^* = \{x_g = 0,\ g \in \bar{G}\}$ as the initial gateway scheme. Based on $\bar{G}$, check all possible gateway schemes sequentially. Set the scheme counter $i = 1$.

Step 3. Second loop operation. Perform all demand scenarios sequentially and set the scenario counter $\xi = 1$.

Step 4. Third loop operation (demand-supply equilibrium). For a given gateway scheme and demand scenario, do the interactive process of demand and supply. Set counter $j = 1$.

Step 4.1. Solve airline's profit maximization model (13) - (15) and passengers' route choice model (1) - (10) separately and sequentially for all airlines, so as to obtain the passenger demand $\mathbf{Q}^{\xi(j)} = \left\{Q_w^{\xi(j)}\right\}$, optimal frequencies $\mathbf{f}^{\xi(j)}$, aircraft sizes $\mathbf{s}^{\xi(j)}$, and the corresponding airlines' profits $\boldsymbol{\pi}^{\xi(j)} = \left\{\pi_k^{\xi(j)}\right\}$. Then, calculate the relative variations in resultant passenger demand $r\left(\mathbf{Q}^{\xi(j)}\right)$ and airlines' profits $r\left(\boldsymbol{\pi}^{\xi(j)}\right)$ respectively by Eqs. (21) and (22) below (Hsu and Wen, 2003).

$$r\left(\mathbf{Q}^{\xi(j)}\right) = \sum_{w \in W} \frac{\left|Q_w^{\xi(j)} - Q_w^{\xi(j-1)}\right|}{0.5\left(Q_w^{\xi(j)} + Q_w^{\xi(j-1)}\right)}, \tag{21}$$

$$r\left(\boldsymbol{\pi}^{\xi(j)}\right) = \sum_{k \in K} \frac{\left|\pi_k^{\xi(j)} - \pi_k^{\xi(j-1)}\right|}{0.5\left(\pi_k^{\xi(j)} + \pi_k^{\xi(j-1)}\right)}. \tag{22}$$

Step 4.2. Termination check for the third loop operation. If $r(\mathbf{Q}^{\xi(j)}) < \varepsilon_1$ and $r(\boldsymbol{\pi}^{\xi(j)}) < \varepsilon_2$ (ε_1 and ε_2 are pre-defined), then go to Step 5. Otherwise, set $j = j + 1$ and go to Step 4.1.

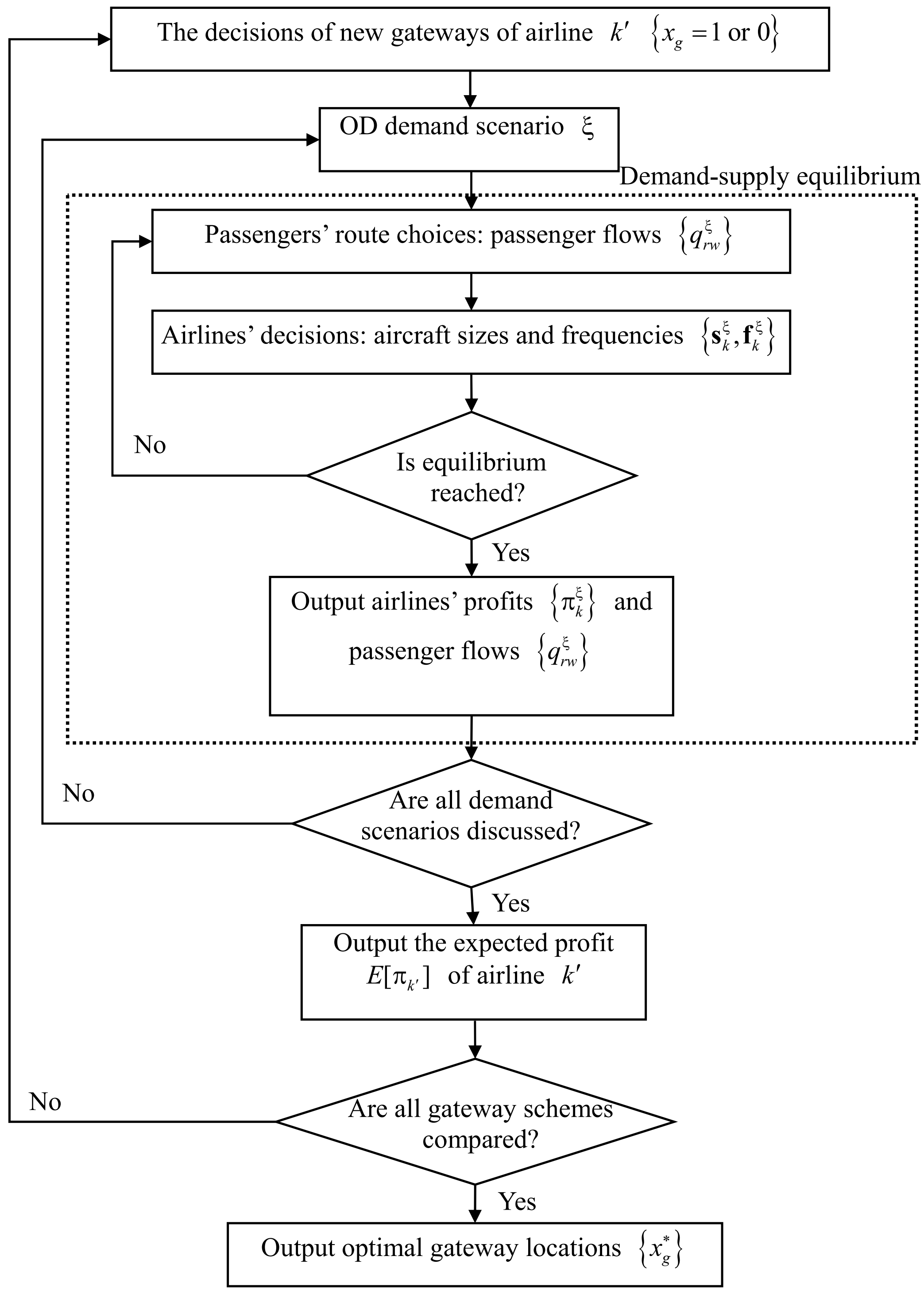


Fig. 2. Flowchart of the solution algorithm.

Step 5. Termination check for the second loop operation. If all demand scenarios are performed, compute the expected profit of airline k', $E[\pi_{k'}]^{(i)}$, by Eq. (18) for gateway scheme i. If $E[\pi_{k'}]^{(i)} > E[\pi_{k'}]^{*}$, then let $E[\pi_{k'}]^{*} = E[\pi_{k'}]^{(i)}$ and obtain the optimal gateway scheme $\mathbf{x}^{*} = \left\{x_g^{(i)}\right\}$. Otherwise, set $\xi = \xi + 1$ and go to Step 4.

Step 6. Termination check for the first loop operation. If all possible gateway schemes are checked, terminate the algorithm and report the optimal gateway scheme $\mathbf{x}^{*}$ and the corresponding expected profit, $E[\pi_{k'}]^{*}$, of airline k'. Otherwise, set $i = i + 1$, and go to Step 3.

Note that in Step 4, when the relative variations in the resultant passenger demand and airlines' profits are small enough, one can conclude that a demand-supply equilibrium is reached. At equilibrium, airlines' market share on each OD pair is at optimal level, thus that their profit-maximizing decisions on the service qualities will not change given the competitors' strategies. Similarly, passengers have no incentive to change their route choices, and so the demand-supply interaction convergences.

3.4. Parameter calibration

Note that there are many parameters in the proposed stochastic optimization model in the previous sections. The values of some parameters can be found in previous empirical studies based on some real market data. However, some parameters were not empirically estimated in the previous related studies yet. Additional parameter calibrations are thus needed here. Specifically, the demand dispersion factors $\boldsymbol{\beta}=\{\beta_w, w \in W\}$ in the elastic demand function, i.e., Eq. (8), as important parameters, need to be calibrated for each OD pair. They reflect the demand sensitivity to the expected travel disutility φ_w^{ξ} and determine the actual travel demands of the aviation markets, which further determine the profits of associated airlines and the social welfare of the system. It should be pointed out that the data of the OD demand matrices collected are the actual realized aviation passenger demand. For calibration purpose, the potential passenger demand in Eq. (8) is assumed to be an appropriate multiplier of the actual realized passenger demand. The values of $\boldsymbol{\beta}$ can then be adjusted and calibrated such that the resultant OD passenger demand matrices are nearly consistent with the actual realized OD passenger demand matrices.

In order to calibrate the values of $\boldsymbol{\beta}$, the maximum likelihood method is adopted and stated as follows. Define the likelihood function L and correspondingly the calibration model as

$$\max_{\beta} L=\frac{Q^0\,!}{\prod_{w\in W} Q_w^0\,!}\left(\frac{Q_w(\beta)}{Q(\beta)}\right)^{Q_w^0}, \tag{23}$$

subject to Eqs. (1)-(10) and (13)-(15),

where Q_w^0 is the actual realized passenger demand of OD pair $w\in W$, and $Q^0=\sum_{w\in W} Q_w^0$ is the total actual realized passenger demand of the system. $Q_w(\beta)$ and $Q(\beta)=\sum_{w\in W} Q_w(\beta)$ are, respectively, the forecasted passenger demand of OD pair $w\in W$ and the forecasted total passenger demand by the model. Both can be obtained by solving airlines' profit-maximization model (13)-(15) and passengers' route choice model (1)-(10) for given demand scenario and gateway scheme. It is not easy to quickly obtain an optimal solution of $\beta=\{\beta_w, w\in W\}$ based on the maximization problem (23) due to a large size of the calibrated parameters β. Therefore, according to Boyce and Zhang (1998), an alternative condition, $\sum_{w\in W}(Q_w^0/Q)\varphi_w=\sum_{w\in W}(Q_w(\beta)/Q(\beta))\varphi_w$, is adopted as the termination rule for calibrating the values of $\beta=\{\beta_w, w\in W\}$, where the right-hand side and the left-hand side of the equation denote the actual and estimated average expected travel disutility of the system, respectively. A heuristic solution algorithm for calibrating the demand dispersion parameters $\beta=\{\beta_w, w\in W\}$ is shown as follows.

Step 1. Choose an initial vector for $\beta=\{\beta_w, w\in W\}$, denoted as $\beta^{(1)}=\{\beta_w^{(1)}, w\in W\}$, and set the iteration counter to $i=1$.

Step 2. Calculate $\{Q_w^{(i)}(\beta^{(i)}), w\in W\}$ based on airlines' profit-maximization model (13)-(15) and passengers' route choice model (1)-(10) by using the demand-supply equilibrium algorithm stated in Section 3.3.

Step 3. If $\left|\frac{\sum_{w\in W}(Q_w^{(i)}(\beta^{(i)})/Q^{(i)}(\beta^{(i)}))\varphi_w}{\sum_{w\in W}(Q_w^0/Q^0)\varphi_w}-1\right|<\varepsilon$ (ε is a pre-defined precision), stop and output the optimal solution $\beta^*=\{\beta_w^*, w\in W\}$; otherwise, update the value of $\beta=\{\beta_w, w\in W\}$ by Eq. (24) , set $i=i+1$ and return to Step 2,

$$\beta_w^{(i+1)}=\beta_w^{(i)}\left(\frac{\sum_{w\in W}(Q_w^{(i)}(\beta^{(i)})/Q^{(i)}(\beta^{(i)}))\varphi_w}{\sum_{w\in W}(Q_w^0/Q^0)\varphi_w}\right),\ \forall w\in W. \tag{24}$$

Based on the collected passenger demand data of Year 2015 and the solution procedure above, the calibrated values of demand dispersion parameters $\boldsymbol{\beta}^* = \{\beta_w^*, w \in W\}$ can be obtained, which can be applied for future passenger demand forecast for each aviation market concerned.

4. Case study: China-Europe inter-continental aviation market

4.1. Parameter specifications

In this case study, the China-Europe inter-continental aviation market, the Chinese domestic aviation markets and European domestic aviation market are used to illustrate the proposed model. Two kinds of airline decision-makers are considered in the aviation market. One is the airline alliances, which may represent the Air China-Lufthansa alliance (both are Star-alliance members), the China Eastern-Air France alliance (both are SkyTeam members), and the China Southern-British Airways alliance. The airlines in an alliance are modeled as a whole (i.e., one decision-maker) in our study. For the China-Europe inter-continental aviation market, all the alliance airlines have been together operating the dog-bone networks via their own hubs. For the domestic market in China or Europe, point-to-point aviation networks are assumed for simplicity and modeling tractability. The other competitor is an HS network carrier, which may represent the Emirates Airlines. The Middle East airline has secured significant market shares in the China-Europe inter-continental aviation market using its HS network. Therefore, in the "base case", the dog-bone network of Air China-Lufthansa alliance contains two international gateway hubs, namely the Beijing Capital International Airport (PEK) in China and Frankfurt Airport (FRA) in Europe. In the dog-bone network of the China Eastern-Air France alliance, the Shanghai Pudong International Airport (PVG) in China and Charles de Gaulle Airport (CDG) in Paris serve as alliance's gateway hubs. In the dog-bone network of the China Southern-British Airways alliance, the Guangzhou Baiyun International Airport (CAN) and Heathrow Airport (LHR) in London are the gateway hubs. In the HS network, the Dubai International Airport serves as the Emirates Airlines' unique global hub. Three airports located in Western China, namely airports of Chengdu, Kunming and Xi'an, are considered by the Air China-Lufthansa alliance as candidates for new additional international gateways in China. Such a scenario is consistent with the strategic plan of the regulator CAAC (i.e., the 13th Five Year Plan for Civil Aviation Airports Development).

Real market data for OD passenger volumes between China and Europe in 2015 are compiled from the OAG and IATA PaxIS databases, and the top 14 airports in China and top 10 airports in Europe are chosen for simulations. The list of airports is reported in Tables 1 and 2. Fig. 3 illustrates the locations of all relevant airports (including 14 airports in China, 10 airports in Europe and the airport in Dubai). Because Shanghai Pudong Airport and Shanghai Hongqiao Airport are both located in Shanghai, they are modeled as one airport with the combined traffic volume (the same treatments applied to the Xiamen Gaoqi Airport and Fuzhou Changle Airport). For simplicity, we assume that the two-way traffic volumes of the inter-continental OD markets are symmetric. The OD demands for the China-Europe inter-continental aviation market and for the Chinese and European domestic aviation markets are set according to the 2015 actual traffic volumes. Tables 3-5 show the average monthly OD demand matrices for these aviation markets.

The other input parameters used in the numerical study are also from real market data where possible. Note that the values of demand dispersion factors $\boldsymbol{\beta}=\{\beta_w, w \in W\}$ of the model were not empirically estimated in the previous related studies for the aviation markets concerned in this paper. Thereby, a validation and calibration of the model parameters is carried out here. Specifically, the potential passenger demand is assumed to be an appropriate multiplier of the actual passenger demand (assumed as 1.3 times in view of the average market growth). Given that the values of other parameters are taken from previous empirical studies and the passenger demand data of Year 2015 for each OD market are collected based on the real case, the values of the demand dispersion parameters $\boldsymbol{\beta}=\{\beta_w, w \in W\}$ can be calibrated by the proposed procedure and are shown in Table 6, with an average relative error of 0.93% between the actual and estimated passenger demand and the maximum relative error of 1.92%.

The data for the flight distances of links (D_a) are from the website of http://www.gcmap.com. The velocity of aircraft is assumed to be 700km/h, which is used to calculate the flight time between airports. The average airfares of airlines used in the model are calculated with the actual ticket prices during November 21, 2019 and November 28, 2019. Based on the database of aircraft fleets from airlines' official websites, aircraft size in the dog-bone networks is assumed to be [200, 550] seats for the hub-to-hub routes, and [150, 400] seats for the hub-to-spoke/spoke-to-hub routes. In the HS network, aircraft size is assumed to be [354, 615] seats. The PEK airport is assumed to be subject to capacity constraint with capacity C_H of 7796 flights per month for both international services between China and Europe and domestic services of Chinese aviation market. Passengers' value of time parameters in the travel disutility function, α_1, α_2, and α_3, are respectively \$20.5/h, \$26.65/h and \$20.5/h (Hsu and Wen, 2003; Li et al., 2010; Saraswati and Hanaoka, 2014). The coefficient θ is set to be 0.02 (Takebayashi and Kanafani, 2005). The passengers' value of time for flight delay α_4 and the airlines' marginal congestion cost γ are assumed to be \$40 and \$2500, respectively (Basso and Zhang, 2008). The marginal cost per passenger μ_a is chosen as \$20 (Li et al., 2010). The coefficients τ_0, τ_1 and τ_2 in the equation of marginal cost per flight are set to 722, 104 and \$0.019 for flights with a travel distance below 5000 km; and 2200, 211 and \$0.0115 for flights with a distance equal to or greater than 5000 km, respectively (Swan and Adler, 2006; Alder and Smilowitz, 2007).

Additionally, based on the historical data and empirical data in the previous related studies, three demand scenarios, namely the middle level (based on the real data of 2015), the low level (80% of the middle level) and the high level (120% of the middle level), are adopted to model the seasonal variation in the air travel demand, which are reported in Table 7. The solution algorithms were coded in Matlab and run on a Thinkpad X1 computer with an Inter® Core ™ i5 CPU (2.4-GHz) and 8 GB of RAM.

Table 1 14 Chinese airports considered.

No.	Airports	Code
1	Beijing Capital Airport	PEK
2	Shanghai Pudong Airport	PVG
3	Guangzhou Baiyun Airport	CAN
4	Chengdu Shuangliu Airport	CTU
5	Kunming Changshui Airport	KMG
6	Shanghai Hongqiao Airport	SHA
7	Xian Xianyang Airport	XIY
8	Chongqing Jiangbei Airport	CKG
9	Hangzhou Xiaoshan Airport	HGH
10	Nanjing Lukou Airport	NKG
11	Xiamen Gaoqi Airport	XMN
12	Wuhan Tianhe Airport	WUH
13	Shenyang Taoxian Airport	SHE
14	Fuzhou Changle Airport	FOC

Table 2 10 European airports considered.

NO.	Airports	Code
1	London Heathrow Airport	LHR
2	Paris Charles de Gaulle Airport	CDG
3	Amsterdam Schiphol Airport	AMS
4	Frankfurt Airport	FRA
5	Istanbul Ataturk Airport	IST
6	Madrid Barajas Airport	MAD
7	Barcelona El Prat Airport	BCN
8	München Airport	MUC
9	Rome Fiumicino Airport	FCO
10	Milan Malpensa Airport	MXP

Fig. 3. Geographical locations of Chinese and European airports considered.

Table 3 OD demand matrix for the China-Europe inter-continental aviation market (passengers/month).

Origin \ Destination	LHR	CDG	MXP	MUC	FCO	AMS	IST	BCN	MAD	FRA
PVG	16964	15034	7381	6186	4786	4632	4978	4358	3374	14988
CAN	3099	3599	796	410	829	1178	2855	657	717	1127
WUH	615	1371	112	92	152	140	121	47	80	288
SHE	461	575	184	794	140	170	48	108	61	688
CKG	589	544	297	121	405	108	119	102	186	274
HGH	405	530	336	100	276	774	174	478	818	192
NKG	455	341	118	206	91	113	44	64	97	2323
XMN	1221	467	353	112	567	1153	73	231	540	432
XIY	486	794	113	105	120	100	80	34	59	249
KMG	265	976	76	49	139	104	28	36	50	217
CTU	1755	1857	508	242	524	1161	508	210	293	1660
PEK	16396	15386	5103	5642	4520	4883	4113	3147	3348	9576

Table 4 OD demand matrix for the Chinese domestic aviation market (passengers/month).

Origin \ Destination	PEK	PVG	CAN	CTU	KMG	XIY	CKG	HGH	NKG	XMN	WUH	SHE
PEK	0	279256	162147	193294	95887	96102	89166	89267	35940	95821	54377	38615
PVG	278260	0	192231	122964	78686	105909	100698	0	1858	177357	65422	80421
CAN	161918	190894	0	107833	63944	66876	88491	88132	70512	58658	37194	26447
CTU	193470	123606	108087	0	61222	45105	6	42303	34806	29613	28964	6617
KMG	96359	78981	64094	61253	0	58251	67861	37245	35725	40152	45578	4505
XIY	94959	106709	66977	45447	58224	0	38419	58941	34580	32121	22683	17248
CKG	89230	100852	89822	7	67920	38447	0	46875	38670	44035	19054	5987
HGH	89259	0	88259	42263	37214	58997	46859	0	0	38872	21800	27985
NKG	35934	1853	70627	34766	35714	34561	38724	0	0	61931	14	21311
XMN	95964	177544	58875	29532	40157	32163	43987	38814	61902	0	58725	8796
WUH	54410	65426	37206	28920	45525	22538	19088	21804	13	58833	0	15695
SHE	38459	80266	26417	6636	4491	17311	5984	27943	21300	8785	15689	0

Table 5 OD demand matrix for the European domestic aviation market (passengers/month).

Destination / Origin	LHR	CDG	AMS	FRA	IST	MAD	BCN	MUC	FCO	MXP
LHR	0	21772	36986	32840	18421	28154	18533	33243	23666	6216
CDG	21952	0	13807	13639	17391	28826	34244	20844	22644	27113
AMS	39123	12495	0	7970	14807	18830	33840	16067	25107	16212
FRA	32375	12187	8077	0	15987	14249	21820	13888	10724	3034
IST	19244	17798	15336	16519	0	5199	5056	9874	6299	5736
MAD	22420	29412	18661	14526	5010	0	58953	14170	13951	10909
BCN	19738	34614	33970	22307	5052	57670	0	19255	36961	25509
MUC	32218	19798	16098	13149	10113	14099	18991	0	17993	9485
FCO	22487	21517	24161	10872	5950	14295	36552	17538	0	5958
MXP	6568	26084	15958	2764	5412	12254	24510	9912	7871	0

Table 6 The calibrated demand dispersion factors β_w for all OD pairs ($\times 10^{-3}$).

	PEK	PVG	CAN	CTU	KMG	XIY	CKG	HGH	NKG	XMN	WUH	SHE	LHR	CDG	AMS	FRA	IST	MAD	BCN	MUC	FCO	MXP
PEK	0	1.511	0.987	1.309	1.007	1.410	1.511	1.410	1.813	1.108	1.410	1.612	0.272	0.232	0.232	0.252	0.242	0.242	0.232	0.242	0.272	0.181
PVG	1.511	0	2.014	1.511	1.309	2.115	1.712	0	1.007	2.317	1.712	2.216	0.222	0.252	0.212	0.272	0.262	0.242	0.262	0.282	0.262	0.262
CAN	0.987	2.014	0	2.317	2.619	2.518	2.518	2.619	3.928	2.518	2.317	1.108	0.191	0.181	0.171	0.181	0.191	0.181	0.181	0.181	0.181	0.181
CTU	1.309	1.511	2.317	0	1.712	2.216	0	1.410	1.410	1.511	2.216	1.108	0.232	0.181	0.212	0.201	0.222	0.191	0.222	0.212	0.201	0.242
KMG	1.007	1.309	2.619	1.712	0	2.317	4.029	1.410	1.712	1.410	1.813	0.705	0.181	0.171	0.171	0.111	0.111	0.181	0.181	0.111	0.181	0.171
XIY	1.410	2.115	2.518	2.216	2.317	0	4.900	2.417	2.719	1.511	2.216	1.712	0.201	0.171	0.181	0.111	0.121	0.181	0.171	0.121	0.181	0.171
CKG	1.511	1.712	2.518	0	4.029	4.900	0	2.014	2.317	1.813	2.014	1.108	0.212	0.181	0.191	0.140	0.141	0.191	0.171	0.141	0.181	0.171
HGH	1.410	0	2.518	1.410	1.410	2.417	2.014	0	0	3.525	2.921	2.014	0.191	0.181	0.181	0.111	0.141	0.181	0.181	0.111	0.191	0.181
NKG	1.813	1.007	3.928	1.410	1.712	2.719	2.317	0	0	2.921	0	2.216	0.212	0.171	0.171	0.181	0.181	0.181	0.191	0.191	0.191	0.191
XMN	1.108	2.317	2.518	1.511	1.410	1.511	1.813	3.525	2.921	0	3.223	1.209	0.161	0.131	0.181	0.111	0.080	0.111	0.171	0.121	0.151	0.131
WUH	1.410	1.712	2.400	2.216	1.813	2.216	2.014	2.921	0	3.223	0	1.813	0.191	0.181	0.171	0.151	0.151	0.181	0.181	0.151	0.181	0.181
SHE	1.612	2.216	1.108	1.108	0.705	1.712	1.108	2.014	2.216	1.209	1.813	0	0.222	0.141	0.151	0.181	0.181	0.161	0.161	0.181	0.161	0.191
LHR	0.272	0.212	0.191	0.232	0.181	0.201	0.212	0.191	0.212	0.161	0.201	0.222	0	0.705	0.806	0.705	0.504	0.604	0.604	0.604	0.604	0.604
CDG	0.232	0.252	0.201	0.191	0.171	0.171	0.191	0.191	0.181	0.131	0.191	0.151	0.705	0	0.604	0.604	0.504	0.705	0.906	0.705	0.806	0.705
AMS	0.232	0.212	0.161	0.212	0.111	0.131	0.191	0.171	0.171	0.201	0.201	0.141	0.725	0.604	0	0.806	0.604	0.705	0.705	0.906	0.806	0.705
FRA	0.252	0.262	0.201	0.212	0.111	0.106	0.201	0.201	0.191	0.111	0.222	0.191	0.705	0.604	0.806	0	0.604	0.705	0.705	0.604	0.504	0.504
IST	0.242	0.252	0.191	0.222	0.111	0.121	0.201	0.201	0.191	0.081	0.222	0.201	0.504	0.504	0.705	0.604	0	0.403	0.408	0.705	0.614	0.604
MAD	0.232	0.232	0.181	0.191	0.181	0.181	0.212	0.201	0.191	0.111	0.212	0.161	0.604	0.705	0.806	0.705	0.403	0	0.705	0.604	0.705	0.604
BCN	0.222	0.252	0.191	0.222	0.181	0.171	0.212	0.201	0.201	0.171	0.222	0.161	0.604	0.906	0.856	0.705	0.453	0.705	0	0.806	0.806	0.906
MUC	0.242	0.272	0.201	0.222	0.111	0.121	0.201	0.222	0.201	0.121	0.252	0.201	0.604	0.705	0.906	0.604	0.705	0.604	0.806	0	0.806	0.705
FCO	0.262	0.252	0.181	0.212	0.181	0.181	0.201	0.201	0.201	0.141	0.222	0.171	0.604	0.806	0.806	0.504	0.609	0.705	0.806	0.806	0	0.554
MXP	0.181	0.252	0.191	0.242	0.171	0.171	0.191	0.201	0.201	0.141	0.222	0.191	0.604	0.705	0.705	0.504	0.604	0.604	0.906	0.705	0.554	0

Table 7 Three demand scenarios.

Demand scenario	OD demand	Probability
Low demand	80% of the medium demand	33%
Medium demand	Average monthly actual OD demand of Year 2015	50%
High demand	120% of the medium demand	17%

4.2. Analysis of results

In order to evaluate the effects of introducing new gateway airports on the aviation system, the concept of social welfare is used and defined as the sum of consumer surplus and producer surplus (i.e., airlines' profits). According to Williams (1977) and Evans (1987), the consumer surplus represents the net benefits received by passengers. The consumer surplus CS^{ξ} under demand scenario ξ is specified as

$$CS^{\xi} = \sum_{w \in W} \int_0^{Q_w^{\xi}} \varphi_w^{\xi}(\mathrm{y})\mathrm{d}y - Q_w^{\xi}\varphi_w^{\xi}\left(Q_w^{\xi}\right), \tag{25}$$

where $\varphi_w^{\xi}(\cdot)$ is the inverse of demand function Q_w^{ξ} in Eq. (8). The first term on the right-hand side of Eq. (25) is the total willingness to pay of all the passengers and the second term is the total travel costs.

Note that the inverse demand function $\varphi_w^{\xi}(\cdot)$ can be obtained, in terms of Eq. (8), as follows

$$\varphi_w^{\xi}(Q_w^{\xi}) = \frac{1}{\beta_w}\left(\ln \bar{Q}_w^{\xi} - \ln Q_w^{\xi}\right), w \in W, \xi \in \Omega, \tag{26}$$

Combining Eqs. (25) and (26), the system's consumer surplus CS^{ξ} under demand scenario ξ can be rewritten as

$$\begin{aligned} CS^{\xi} &= \sum_{w \in W} \int_0^{Q_w^{\xi}} \varphi_w^{\xi}(y)\mathrm{d}y - \sum_{w \in W} Q_w^{\xi}\varphi_w^{\xi}\left(Q_w^{\xi}\right) \\ &= \sum_{w \in W}\left(\int_0^{Q_w^{\xi}} \varphi_w^{\xi}(y)\mathrm{d}y - Q_w^{\xi}\varphi_w^{\xi}\left(Q_w^{\xi}\right)\right) \\ &= \sum_{w \in W} \frac{1}{\beta_w}\left(\left(y \ln \bar{Q}_w^{\xi} - y \ln y + y\right)\Big|_0^{Q_w^{\xi}} - Q_w^{\xi}\left(\ln \bar{Q}_w^{\xi} - \ln Q_w^{\xi}\right)\right) \\ &= \sum_{w \in W} \frac{Q_w^{\xi}}{\beta_w}. \end{aligned} \tag{27}$$

The total social welfare Z^{ξ} under demand scenario ξ is thus defined as

$$Z^{\xi} = \sum_{w \in W} \frac{Q_w^{\xi}}{\beta_w} + \sum_{k \in K} \pi_k^{\xi}, \tag{28}$$

where $\{\pi_k^\xi\}$ is determined by airlines' profit maximization model (13) - (15).

In order to look at the effects of stochastic fluctuation in passenger demand on the stakeholders' decisions and the aviation system performance, we compare the results with deterministic OD demand and stochastic OD demand, which are discussed as follows.

4.2.1. The results with deterministic OD demand

For the deterministic case, the data of actual realized OD demand in 2015 are adopted for the China-Europe aviation market and the Chinese and European domestic aviation markets, meaning that there is only one demand scenario. Assuming that Air China is planning to develop one more international gateway hub in addition to Beijing airport in China among three candidate airports (airports of Chengdu, Kunming and Xi'an).

Table 8 shows the results generated by various gateway schemes with actual OD passenger demand of Year 2015, including the profits of all airline alliances, the profit of the Emirates Airlines operating the HS network, the resultant market demand, total number of flights per month in the PEK airport, and the total social welfare of the whole aviation system. It can be seen that Chengdu is the best choice for the additional gateway hub for the dog-bone network of the Air China-Lufthansa alliance, leading to the highest total profit of $340.088 million per month. Xi'an is the worst choice with the lowest total profit of $339.301 million per month. The scheme with Chengdu airport as the gateway hub can also lead to the highest total social welfare of $9.885 billion per month and the highest passenger demand of the whole aviation system (9951353 passengers per month). These results are consistent with the fact that the Chengdu Shuangliu Airport (CTU) was ranked the fourth among all the Chinese airports in terms of the actual passenger throughputs of Year 2015.

Table 8 Results with different gateway schemes for actual demand of Year 2015.

Model solution	Base case	Chengdu	Kunming	Xi'an
Total profit of the Air China-Lufthansa alliance (million $/month)	327.656	340.088	339.639	339.301
Total profit of the China Southern-British Airways alliance (million $/month)	213.148	210.364	207.334	207.339
Total profit of the China Eastern-Air France alliance (million $/month)	367.886	372.642	372.254	371.970
Profit of the Emirates Airlines (million $/month)	121.092	114.090	114.311	115.197
Total resultant demand of the aviation system	9943596	9951353	9945443	9946226

(passengers/month)				
Resultant demand of inter-continental market (passengers/month)	414485	415030	414773	414750
Resultant demand of domestic markets (passengers/month)	9529111	9536323	9530670	9531476
Total number of flights at PEK airport (flights/month)	7875	7273	7643	7636
Total social welfare (billion $/month)	9.870	9.885	9.876	9.877

It can also be seen in Table 8 that introducing an extra gateway airport (either in Chengdu, Kunming or Xi'an) would lead to an increased social welfare and an increased number of air passengers in the China-Europe inter-continental aviation market and in the domestic aviation markets. However, the changes in the profits of airlines are different. Specifically, after introducing an additional gateway airport, the profits for both the Air China-Lufthansa alliance and the China Eastern-Air France alliance would increase, whereas the profits of the Emirates Airlines and China Southern-British Airways alliance would decrease, compared to the base case.

Table 9 Market shares with different gateway schemes for actual demand of Year 2015.

Airline alliance or airline	Base case		Chengdu		Kunming		Xi'an	
	Int. market	Dom. markets	Int. market	Dom. markets	Int. market	Dom. markets	Int. market	Dom. markets
Air China + Lufthansa	11.51%	14.64%	14.80%	14.84%	14.41%	14.97%	14.30%	14.93%
China Southern + British Airways	9.04%	29.42%	8.89%	28.44%	8.92%	28.33%	8.95%	28.42%
China Eastern + Air France	0	55.94%	0	56.72%	0	56.70%	0	56.65%
Emirates Airlines	79.45%	0	76.31%	0	76.67%	0	76.75%	0

Table 9 further shows the market shares under various gateway schemes for the inter-continental market and the domestic markets. For the inter-continental market, the market share of the Emirates Airlines is always much higher than those of airline alliances regardless of the gateway schemes adopted. This may be due to a shorter connection time and a lower congestion delay cost of the HS network, which would lead to reduced passenger travel disutility, more inter-continental passengers, and more revenue, compared to the airline alliances in the dog-bone networks. Moreover, the large passenger volumes in the (Chinese and European) domestic markets can also significantly influence the flight services in the inter-continental market. When a new gateway airport is developed for the dog-bone network of the Air China-Lufthansa alliance, the market shares of both inter-continental and domestic markets for the Air China-Lufthansa alliance become larger than those in the base case. On one hand, more gateway airports mean more route choices for the inter-continental journey, which can reduce the travel disutility and attract more inter-continental travelers. On the other hand, the transfer of the inter-continental passengers from the busy routes to the new ones can leave more resources to serve the domestic passengers, thus the market share of the domestic market may also increase. For the China Southern-British Airways alliance, the market shares of both inter-continental market and domestic market will decrease. Specially, for the China Eastern-Air France alliance, the market share of the inter-continental market is zero. Such results are mainly due to the fact that we are considering the China-European international market only. The geographic location of China Eastern's hub at Shanghai is ideal for east-bound China-American flights but probably the worst choice for western bound China-European flights. Indeed, Shanghai has never been a gateway for Chinese traffic toward European destinations.

Table 10 indicates the effects of network competition on the total profit of the Air China-Lufthansa alliance, the total social welfare, and the resultant demand of the aviation system. It can be firstly found that the scheme with Chengdu is always the best choice for the Air China-Lufthansa alliance, leading to a total profit of $340.0875 million per month and $532.672 million per month, respectively for the situations with and without network competition. This scheme can also produce the highest total social welfare and the largest passenger demand. Secondly, such network competition can help generate more passenger demand and improve the total social welfare. This is intuitive as increased competition encourages airlines to improve the qualities of flight service for travelers, and Chengdu is geographically located in Western China, ideal for China-European services.

Table 10 Comparison of the results with and without network competition.

Model solution	**Base case**		**Chengdu**		**Kunming**		**Xi'an**	
	Only dog-bone network	HS vs. dog-bone network	Only dog-bone network	HS vs. dog-bone network	Only dog-bone network	HS vs. dog-bone network	Only dog-bone network	HS vs. dog-bone network
Total profit of the Air China-Lufthansa alliance (million $/month)	482.941	327.656	532.672	340.0875	522.162	339.639	526.298	339.310
Total social welfare (billion $/month)	9.827	9.870	9.876	9.885	9.864	9.876	9.870	9.877
Resultant demand of the system (passenger/month)	9887001	9943596	9914503	9951353	9908988	9945443	9914377	9946226

However, it should be noted that although the total resultant demand increases with the network competition, the total profit of the Air China-Lufthansa alliance decreases with the competition, which are consistent with the market shares in Tables 11 and 12. Tables 11 and 12 show that aviation network configuration and competition have significant impacts on the market shares of airline alliances. For the inter-continental market (see Table 11), the market share of the Air China-Lufthansa alliance is always higher than others. Specifically, without network competition, the Air China-Lufthansa alliance occupies more than 60% of the inter-continental market. However, after introducing the network competition, the market share of the Air China-Lufthansa alliance decreases dramatically and thus its profit decreases accordingly, implying that the HS network is very competitive for the China-Europe inter-continental aviation market. This probably explains why gulf airlines have been quite successful in the Asia-Europe routes. For the domestic aviation markets (see Table 12), regardless of the network competition, the China Eastern-Air France alliance would have a much higher market share than others. However, the changes of airlines' market shares in the domestic market before and after introducing the network competition are trivial, given the large size of domestic markets.

Table 11 Comparison of airline alliances' market shares for the inter-continental market with and without network competition.

Airline alliance	Base case		Chengdu		Kunming		Xi'an	
	Only dog-bone network	HS vs. dog-none network	Only dog-bone network	HS vs. dog-none network	Only dog-bone network	HS vs. dog-none network	Only dog-bone network	HS vs. dog-none network
Air China + Lufthansa	68.52%	11.51%	76.15%	14.80%	75.45%	14.41%	75.99%	14.30%
China Southern + British Airways	13.31%	9.04%	11.88%	8.89%	12.00%	8.92%	11.98%	8.95%
China Eastern + Air France	18.17%	0	11.97%	0	12.55%	0	12.03%	0

Table 12 Comparison of airline alliances' market shares for the domestic markets with and without network competition.

Airline alliance	Base case		Chengdu		Kunming		Xi'an	
	Only dog-bone network	HS vs. dog-none network	Only dog-bone network	HS vs. dog-none network	Only dog-bone network	HS vs. dog-none network	Only dog-bone network	HS vs. dog-none network
Air China + Lufthansa	15.13%	14.64%	15.29%	14.84%	15.28%	14.97%	15.26%	14.93%
China Southern + British Airways	29.22%	29.42%	28.21%	28.44%	28.15%	28.33%	28.39%	28.42%
China Eastern + Air France	55.65%	55.94%	56.50%	56.72%	56.57%	56.70%	56.35%	56.65%

In addition, the introduction of new gateway airport can significantly affect the total number of flights landing at and taking off from the PEK hub airport. Specifically, before introducing the new gateway airport, all flights served by the Air China-Lufthansa alliance fly the routes linking to Beijing, and the total number of flights at the PEK airport is 7875 flights per month (see Table 8), which is slightly higher than the maximum number of flights per month that it can serve. However, after introducing the new gateway airport, this number decreases to 7273, 7643, and 7636 for the gateway schemes of Chengdu, Kunming, and Xi'an, respectively. According to Tables 8, 10, 11 and 12, it can be found that the development of new gateways can alleviate the congestion of saturated hub airports, but not reduce the total passenger volume, social welfare and the total profit of airlines. On the contrary, it can improve industry surplus although the benefits are not distributed evenly among all stakeholders.

4.2.2. The results with stochastic OD demand

In order to look at the effects of seasonal variations of passenger demand, three demand scenarios are considered. The levels of the demand scenarios and the corresponding probability of each scenario are given in Table 7. Similar to the deterministic demand case, one more gateway airport in addition to the PEK airport is considered for the dog-bone network of the Air China-Lufthansa alliance.

Table 13 Results with different gateway schemes under three demand scenarios.

Model solution	Base case	Chengdu	Kunming	Xi'an
Total profit of the Air China-Lufthansa alliance at the low demand level (million $/month)	283.180	290.722	289.096	284.905
Total profit of the Air China-Lufthansa alliance at the medium demand level (million $/month)	327.656	340.088	339.639	339.301
Total profit of the Air China-Lufthansa alliance at the high demand level (million $/month)	392.006	408.562	400.631	402.435
Total expected profit of the Air China-Lufthansa alliance (million $/month)	323.918	335.438	333.328	332.083
Total social welfare of the system at the low demand level (billion $/month)	7.866	7.873	7.870	7.867
Total social welfare of the system at the medium demand level (billion $/month)	9.870	9.885	9.876	9.877
Total social welfare of the system at the high demand level (billion $/month)	11.865	11.876	11.872	11.873
Total expected social welfare of the system (billion $/month)	9.548	9.560	9.553	9.553

Table 13 shows the results of gateway schemes under different demand scenarios. It can be noted that the Chengdu gateway scheme is always the best choice for the dog-bone network of the Air China-Lufthansa alliance, yielding the highest total profit of $290.722 million per month, \$340.088 million per month, and \$408.562 million per month under the three demand scenarios, respectively. The Chengdu scheme can also lead to the highest total social welfare and the largest number of passengers. In addition, Table 13 also shows that from the perspective of the expectation of all scenarios (the expected profit of the Air China-Lufthansa alliance and expected social welfare), Chengdu is the best choice for the new gateway airport. However, it can be noted that the priority ranking of the candidate airports in the alternative gateway schemes changes for different demand scenarios. Specifically, for the low and medium demand scenarios, Kunming is a better choice than Xi'an in terms of the total profit of the Air China-Lufthansa alliance. However, under the high demand scenario, Xi'an becomes better than Kunming. This is because when demand is low, the Air China-Lufthansa alliance can take advantage of the scale economy effects caused by the large passenger volume of Kunming airport to reduce airline's operating cost and thus increase the profit. However, as the passenger demand increases, the gap of the scale economy effects of different airports is narrowed. Moreover, compared to Kunming, Xi'an is closer to European airports and the majority of the Chinese airports in terms of flight distance. Therefore, choosing Xi'an as the new gateway can effectively reduce the passenger travel disutility and attract more passengers. Similar observations can be found in terms of the social welfare of the Kunming and Xi'an schemes.

The aviation demand has been growing over the recent years. It is thus meaningful to look at the effects of the forecasted future demand level on the locations of the new additional gateway airports. By the end of Year 2015, the passenger volume of China-Europe inter-continental aviation market had increased by 61% over the level of Year 2010, leading to an average annual growth rate of about 10%. For Chinese domestic market, the average growth rate is about 10% in the past years. For the European domestic market, the average growth rate is about 6.1%. Therefore, it is assumed that the demand growth rates for China-Europe inter-continental market, Chinese domestic market and European domestic market are, respectively, 10%, 10% and 6.1% for the next decade. Then, we obtain that the passenger demands in 2025 will be 259%, 259% and 181% of the demand levels in 2015.

We now consider the case of at most three additional gateway airports to be developed in China. This leads to seven possible gateway schemes according to constraint (19), namely three schemes with only one more gateway airport, three schemes with two more gateway airports and one scheme with three more gateway airports in addition to the PEK airport.

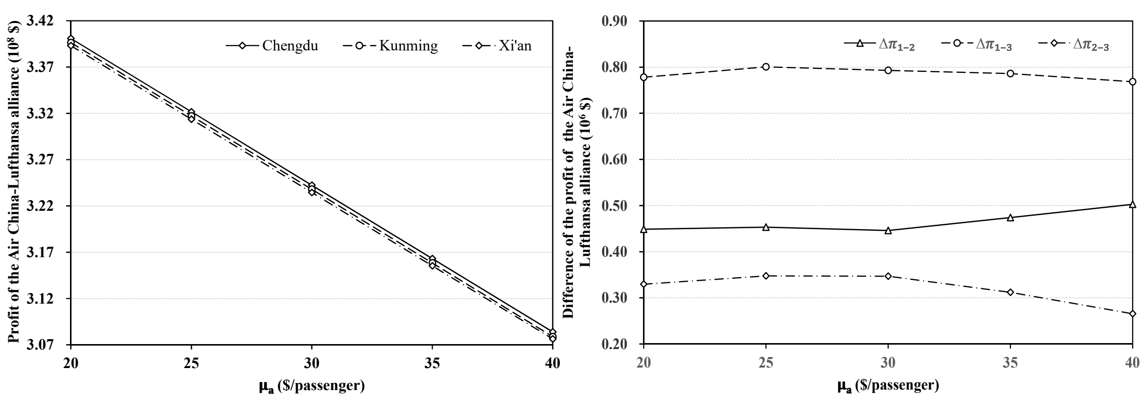
Table 14 summarizes the optimal gateway schemes in the case of one, two or three more gateway airports, respectively. It can be seen that for the demand level of 2025, the scheme of Chengdu and Xi'an as additional gateways is the optimal choice in terms of the total profit of the Air China-Lufthansa alliance, which is $166.873 million and $27.837 million per month higher than those of the Chengdu scheme and the scheme with three new gateways, respectively. This means that introducing more gateway airports is not always a good choice in terms of airline's or airline alliance's profit (in this case, two gateways are better than three gateways). It should be pointed out that although the scheme of Chengdu and Xi'an is the best choice in terms of the total profit of the Air China-Lufthansa alliance, the scheme of Chengdu, Kunming and Xi'an will be best in terms of the resultant passenger demand and the total social welfare. This is because more gateway airports imply more route choices for travelers, which can facilitate the passengers and thus reduce travel disutility and increase social surplus. It should be noted that in our analysis, the fixed costs of developing these additional hub airports are not considered due to lack of such financial information in the public domain.

Table 14 Results with different gateway schemes for forecasted demand of 2025.

Candidate gateway schemes	**Chengdu**	**Chengdu + Xi'an**	**Chengdu + Kunming + Xi'an**
Total profit of the Air China-Lufthansa alliance (million $/month)	603.965	770.838	743.001
Total social welfare (billion $/month)	23.247	23.302	23.307
Total resultant demand of the system (passenger/month)	24450997	24497848	24498010

4.2.3. Sensitivity analysis of model parameters

Figs. 4 and 5 show the impact of the airline's marginal cost imposed by an additional passenger μ_a on the total profit of the Air China-Lufthansa alliance and the total social welfare of the system for different gateway schemes, at the actual travel demand level of Year 2015. As previously stated, the marginal cost μ_a is the passenger-related costs, including the baggage handling cost and costs of meals on board and so on. It can be firstly observed that the increase of μ_a will dramatically reduce the total profit of the Air China-Lufthansa alliance (Fig. 4a) and the total social welfare of the system (Fig. 5a). In Fig. 4a, the profit curves for the three gateway schemes are very close, meaning that the gap among Air China-Lufthansa alliance's profits with these gateway schemes is very small regardless of the value of μ_a. Fig. 4b further shows how the profit difference among different gateway schemes changes with μ_a. For ease of presentation, we denote the Chengdu scheme, the Kunming scheme and the Xi'an scheme as scheme 1, scheme 2 and scheme 3, and thus $\Delta\pi_{1\text{-}2}$ in Fig. 4b represents the curve of profit difference between scheme 1 and scheme 2, and so forth. It can be found that the profit difference between the Chengdu and Kunming schemes, Chengdu and Xi'an schemes or Kunming and Xi'an schemes is positive, showing that for a given value of μ_a, the priority ranking of the three alternative gateway schemes is always Chengdu, Kunming and Xi'an. As for the social welfare, the welfare curve with Chengdu gateway scheme in Fig. 5a is far above that with Kunming or Xi'an gateway scheme, suggesting that the social welfare with the Chengdu gateway scheme is much higher than that with Kunming or Xi'an gateway scheme. Fig. 5b further shows the welfare difference curves among three gateway schemes. In Fig. 5b, $\Delta Z_{1\text{-}2}$ represents the curve of the welfare difference between scheme 1 and scheme 2, and so forth. It can be noted that the welfare difference between Kunming and Xi'an schemes is negative. Therefore, although the profit of the Air China-Lufthansa alliance with Kunming scheme is higher than that with Xi'an scheme, Xi'an scheme is more beneficial for improving the total social welfare than Kunming scheme. All these observations show that, in terms of the total profit of the Air China-Lufthansa alliance or the total social welfare of the system, Chengdu is superior to Kunming and Xi'an as the gateway airport, but either of them is also a good choice.



(a) (b)

Fig. 4. Effects of airline's marginal cost parameter μ_a on: (a) total profit of the Air China-Lufthansa alliance; (b) difference of the profit of the Air China-Lufthansa alliance with different schemes.

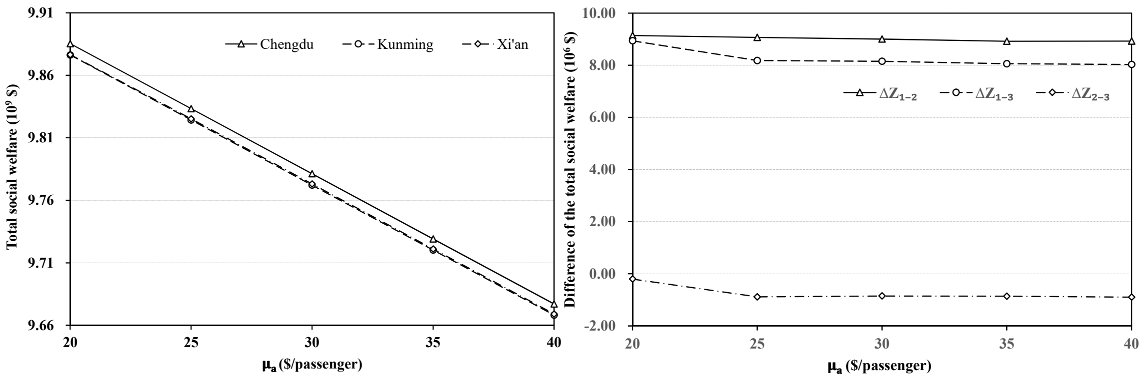
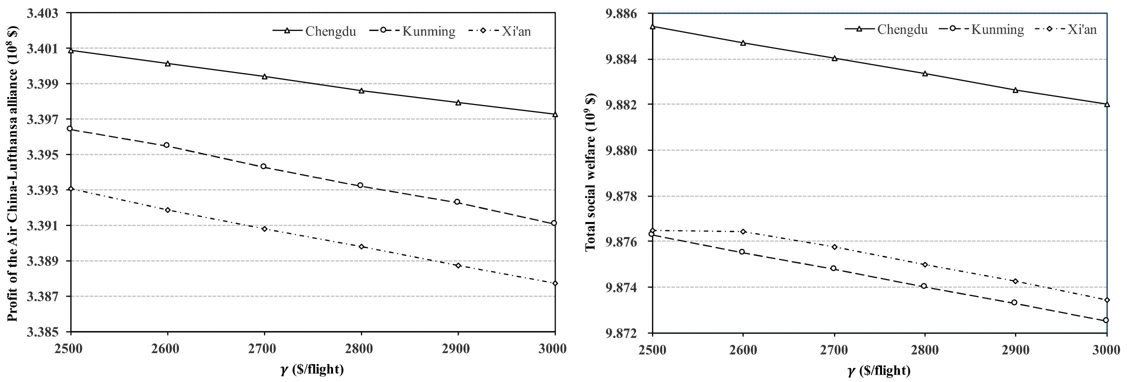


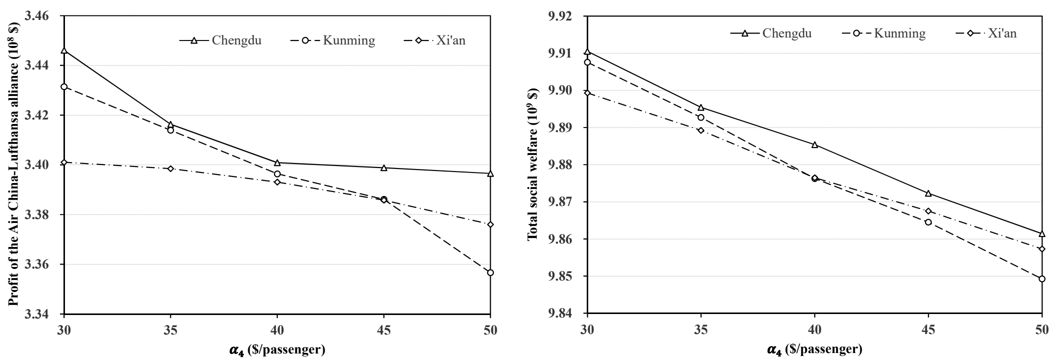
Fig. 5. Effects of airline's marginal cost parameter μ_a on: (a) total social welfare of the system; (b) difference of the total social welfare with different schemes.

Recently, some major hub airports in China become increasingly congested with sustained growth in demand and traffic volume. For example, the throughput of the Beijing (PEK) airport exceeds 100 million passengers in 2018. However, its design capacity is only 76 million passengers per year. As a result, the airport congestion becomes increasingly serious. In order to ascertain the effects of airport congestion, Fig. 6 illustrates the changes of the total profit of the Air China-Lufthansa alliance and the total social welfare of the system with the airline's marginal congestion cost parameter γ at the PEK airport. It shows that as γ increases, both the total profit of the Air China-Lufthansa alliance and the total social welfare of the system decrease. However, choosing Chengdu as the gateway airport is better than choosing the other two airports as the gateway airport in terms of either the total profit of the Air China-Lufthansa alliance or the total social welfare. In addition, in terms of the profit of the Air China-Lufthansa alliance (Fig. 6a), the priority ranking of the gateway schemes (Chengdu, Kunming, and Xi'an) does not change. However, it can be found that in Fig. 6b, the Xi'an scheme is better than the Kunming scheme in terms of the total social welfare, similar to the effects of μ_a.



(a) (b)

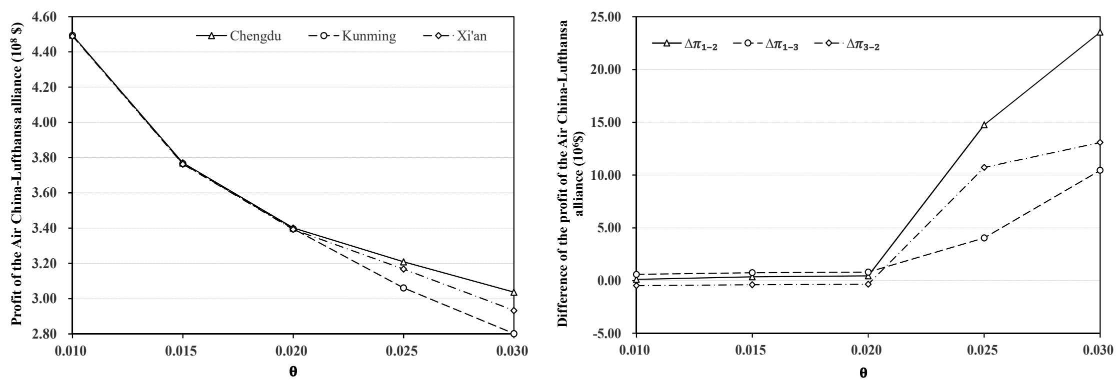
Fig. 6. Effects of flight's marginal congestion cost parameter γ at PEK hub airport on: (a) total profit of the Air China-Lufthansa alliance; (b) total social welfare of the system.



(a) (b)

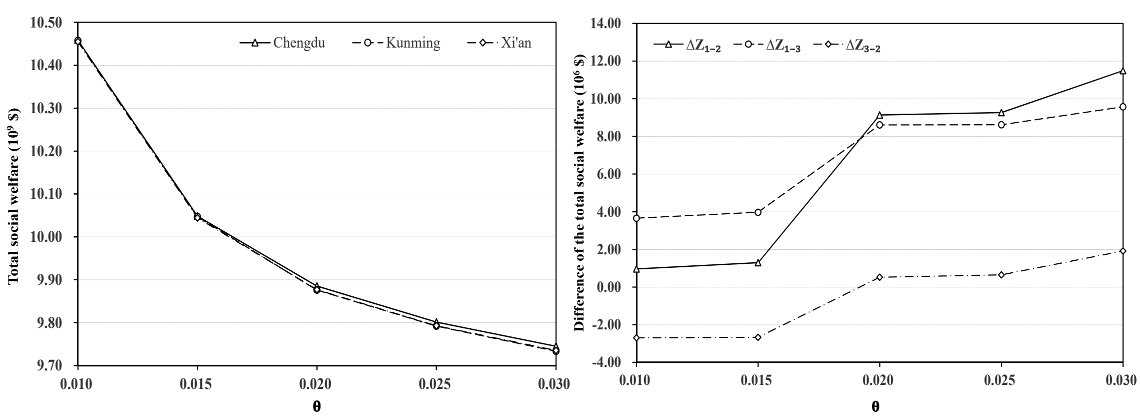
Fig. 7. Effects of passenger's value of time for the congestion delay α_4 at PEK hub airport on: (a) total profit of the Air China-Lufthansa alliance; (b) total social welfare of the system.

Fig. 7 shows the effects of passenger's value of time α_4 for the congestion delay at the PEK airport on the total profit of the Air China-Lufthansa alliance and the total social welfare of the system. It can be seen that as α_4 increases, the total profit and the total social welfare for each gateway scheme decrease, but the Chengdu scheme is always superior to the other two schemes. The impact of α_4 on the total profit of the Air China-Lufthansa alliance and the total social welfare of the system for different gateway schemes are different from the impacts of μ_a and γ. In Fig. 7a, as the value of α_4 is smaller than \$45 per passenger, the Kunming scheme is better than the Xi'an scheme in terms of the Air China-Lufthansa alliance's profit, but it is reverse for the value of α_4 larger than \$45 per passenger. Similarly, from the perspective of the total social welfare (see Fig. 7b), the change point between the Kunming and Xi'an schemes occurs at the location of $\alpha_4 = 40$. These observations mean that as the passengers are not sensitive to the airport congestion (i.e., α_4 is small enough), the Kunming scheme is better than Xi'an scheme, in terms of the profit or the total social welfare. Contrarily, as the passengers are sensitive to the airport congestion (i.e., α_4 is high enough), Xi'an scheme can attract more passengers, and generates more profit and total social welfare than Kunming scheme.



(a) (b)

Fig. 8. Effects of parameter θ on: (a) total profit of the Air China-Lufthansa alliance; (b) difference of the profit of the Air China-Lufthansa alliance with different schemes.



(a) (b)

Fig. 9. Effects of parameter θ on: (a) total social welfare of the system; (b) difference of the total social welfare with different schemes.

Figs. 8 and 9 show how the parameter θ influences the profit of the Air China-Lufthansa alliance and the total social welfare of the system, respectively. It can be seen that both the profit and the social welfare decrease quickly with the increasing value of θ regardless of the gateway schemes. This may be due to the fact that a higher value of θ leads to a higher expected disutility and a lower resultant passenger demand, thereby reducing the profit and the social welfare. Figs. 8b and 9b further depict the profit differences and welfare differences among three different gateway schemes. It can be noted that the Chengdu scheme is always a better choice than other two schemes because the corresponding profit differences and welfare differences are positive. Additionally, the higher the value of the parameter θ is, the larger the difference of the Air China-Lufthansa alliance's profit or the total social welfare with different schemes is. This is because a larger value of θ means fewer routes to be chosen by passengers and larger demand differences among different travel routes to be obtained. However, the profit difference or the welfare difference between the Xi'an and Kunming schemes changes from a negative value to a positive value, as the value of θ varies from 0.01 to 0.03. In other words, the Xi'an scheme is better than the Kunming scheme when the value of θ is high enough, and vice versa.

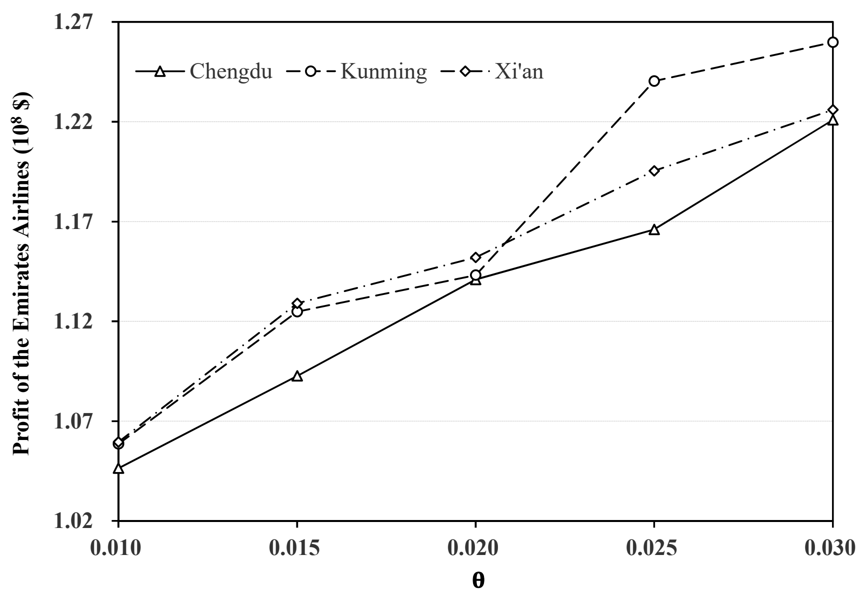


Fig. 10. Effects of parameter θ on the profit of the Emirates Airlines.

Finally, we look at how the parameter θ influences the profit of the Emirates Airlines, as shown in Fig. 10. As stated above, the additional gateway scheme would reduce the profit of the Emirates Airlines. It can be further noted in Fig. 10 that the Chengdu scheme has a more serious negative effect on the profit of the Emirates Airlines. Besides, as the value of θ increases, the profit of the Emirates Airlines increases, which is different from the profit curve of the Air China-Lufthansa alliance and the total social welfare curve (see Figs. 8a and 9a).

This is because the higher the value of θ is, the larger the difference in the passenger volume among alternative travel routes or airlines' networks is. From Table 9, the market share of the Emirates Airlines is always much higher than those of airline alliances regardless of the gateway schemes adopted. Therefore, more passengers prefer to choose the Emirates Airlines for their journeys rather than other airlines, and such a situation may become more obvious for a larger value of θ.

5. Concluding remarks and further studies

Significant changes are taking place in the global aviation industry, as more and more countries are liberalizing their skies to promote the aviation industry and the associated sectors such as trade, tourism and logistics. To cater for the changes of the aviation industry, medium-sized aircraft capable of long-range flights are being introduced. As a result, some airlines have incentives to expand their HS networks to serve inter-continental markets that have been dominated by dog-bone network operators. Such market dynamics have raised some important and intriguing issues to the aviation industry. A proper understanding of the best responses of airlines and regulators to such market dynamics is important. For airlines, they would seek to optimize and reconfigure their networks in order to strengthen their competitiveness. For regulators, a good assessment of the competitive effects can help them design related policies, such as aviation liberalization, slot allocation at major airports, and the approval of airline alliances or code share agreements. Where needed, additional investments may be made to promote the development of new gateway hub airports. However, few studies have explicitly addressed the competition between these aviation networks, and thus the implications for airline network configurations, government policies, and the resultant impacts on passengers are not properly revealed.

This paper aims to provide some insights for better understanding these aforementioned questions through developing an integrated model of the locations of additional gateway airports and the airline network rivalry (i.e., HS network versus dog-bone network). The effects of passenger demand uncertainty due to seasonal demand variations are explicitly considered by modeling the OD passenger demand as a discrete distribution with finite demand scenarios. A two-stage approach is adopted to model the effects of demand uncertainty. In the first stage, the future passenger demand is not observable and thus airlines or airline alliances maximize their own expected profits by optimizing the locations of new additional gateway airports from the set of candidate gateway airports pre-specified by the regulator. In the second stage, with passenger demand observed and the gateway scheme fixed, airlines determine their aircraft sizes and service frequencies to maximize their own profits, and air passengers choose routes that minimize their own travel disutility. Furthermore, based on the actual data of passenger demand matrix, a maximum likelihood method is adopted to calibrate the passenger demand dispersion parameter in the elastic OD demand function. The calibrated values of the parameters are then used as inputs of the above two-stage stochastic model. Such a model allows the identification of market equilibrium when airlines compete with different types of networks, thus that the effects of alternative network configurations can be tested and quantified. Such a framework can help airlines identify their strength and weakness, and optimize and reconfigure their networks to strengthen their competitiveness. It can also help the regulators to evaluate the effects of new additional gateway airports in liberalizing markets on the social welfare.

Applying the proposed stochastic model to the China-Europe aviation market (including the inter-continental international market and the Chinese and European domestic markets), some interesting and meaningful findings are obtained. First, in terms of the profits of decision-makers, the priority ranking of candidate airports for new gateway with deterministic demand changes with the realized demand scenario. Specifically, in our case, in terms of the total profit of the Air China-Lufthansa alliance, the priority ranking of the gateway airport schemes is Chengdu, Kunming and Xi'an for a low and a medium demand level (80% and 100% of the actual passenger demand in 2015). At a high demand level (120% of the 2015 passenger demand), the priority ranking of the gateway airport schemes becomes Chengdu, Xi'an and Kunming. Furthermore, the Chengdu scheme is always better than others regardless of the changes of the related parameters (i.e., the marginal passenger cost μ_a, airlines' marginal congestion cost γ, passenger's value of time for the congestion delay α_4 and the parameter of the logit model θ), while the priority ranking of Kunming and Xi'an will change in terms of profit or the total social welfare. Second, as passenger demand grows, the number of the optimal gateway airports for the dog-bone aviation network may increase. For example, for the forecasted demand of 2025 in this paper, the optimal gateway scheme for the Air China-Lufthansa alliance contains two airports, namely Chengdu and Xi'an, leading to higher total profit of the Air China-Lufthansa alliance, compared to other gateway schemes. Third, if the number of the gateway scheme is given and fixed, the optimal gateway scheme may achieve the highest profit for the decision-marker, total social welfare and the resultant demand simultaneously. Otherwise, this may not the case. At the forecasted demand level of 2025, both total social welfare and the resultant passenger demand for the scheme with Chengdu and Xi'an are less than those for the scheme with Chengdu, Kunming and Xi'an. Fourth, the pure HS network (i.e., the Emirates Airlines) can lead the inter-continental market to have a higher market share than other airline alliances, although the development of the new gateway airport may decrease its market share and the profit of the Emirates Airlines. For the inter-continental market between China and Europe, the market share of the Air China-Lufthansa alliance is higher than that of the China Southern-British Airways alliance or China Eastern-Air France alliance, which is reverse for the domestic aviation market. Finally, the competition between different kinds of aviation networks can generate more aviation passengers and improve the social welfare of the system, although such competition may harm the interests of some airlines.

It should be noted that we have modeled the airline competition between airlines operating different types of networks in the China-Europe markets. One should be cautious to generalize our modeling results to the competition between dog-bone networks and inter-continental HS networks in general. In the case of Middle East carriers, their HS network is significantly affected by their geographic location as well as small domestic market. In other words, this does not necessarily indicate general trade-offs between HS and "dog-bone". Discussion of the strength and weakness of each network type without considering the geographic location is misleading, and there is a need to consider market-specific characteristics in analysis similar to that used in this study.[11]

Although we have tried to develop and implement our model carefully and rigorously, some simplifying assumptions were introduced, which could limit the accuracy and applicability of the modeling results. These are areas that should be cautioned, and may provide research opportunities for further extensions. First, we considered a relatively small network with only 14 Chinese airports and 10 European airports and a handful of airlines or airline alliances in the case study. Intuitively, to better control for airline network effects and competition from other airlines and alternative routes, it is better to model more airports and airlines. This however requires collecting much larger datasets and likely more assumptions on additional

[11] We are thankful to an anonymous referee for pointing out this to us.

airlines and routes.[12] If not done properly, including more airports and airlines could reduce, instead of increasing, the accuracy and reliability of the model. In practice, some simplifications will have to be made by focusing on specific markets and airlines. Such an approach is similar to the "residual demand" assumption that is frequently used in anti-trust analysis. It effectively assumes that there will be limited interaction between the network/market under investigation and other parts of the network/market. However, there has been no clear guidance in the literature what is the proper scope of analysis (i.e., how many airports and airlines should be included when analyzing inter-continental markets). Second, passengers are assumed to be homogenous in this paper. However, classifying the passengers into business and leisure passengers according to income and travel preference may further improve the accuracy of the model. Therefore, there is a need to consider the heterogeneity of the passengers in a further study. Third, we consider the total profit of airline alliance and do not investigate the revenue distribution among allied airlines. Obviously, this is an important issue involving whether the collaboration between airlines is successful or not, and deserves a further study. Finally, a likely better approach of model calibration is to conduct empirical studies on the market first, thus that parameters can be chosen based on estimates from the markets being analyzed. This is however a challenging task involving large amount of data and careful analysis. More importantly, before the proposed services are provided, there may be no data available at all. Developing a better approach for model calibration would be a valuable contribution to the literature. Our study is a modest step toward obtaining accurate and reliable modeling of aviation networks. More advanced studies are needed in this important research field.

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[12] For example, a Chinese passenger may also fly through Hong Kong, Bangkok or Istanbul to European destinations using the aviation services provided by Cathay Pacific, Thai Airways and Turkish Airlines, respectively. To formally control for such services and networks, more data and assumed parameters will be needed to model the service quality, passenger disutility and airline operation and competition situations. Similarly, Lufthansa has extensive network and operations between Europe and North America, whereas Air China has extensive services to Asia and other destinations that are not currently included in our study. Due to network effects, such operations may influence these airlines' hub operations and costs. To properly and fully control the related influences, more data and assumptions are needed. In addition, one also needs to find proper treatments on the competition imposed by other airlines serving these extended networks.

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