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Airline Network Choice and Configuration

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ABSTRACT: As an increasing number of countries liberalize their skies, some airlines, notably carriers in the Middle East, have been able to extend their hub-and-spoke networks beyond domestic borders. This allows them to serve international destinations without going 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 model to investigate the competition between airlines running traditional dog-bone and hub-and-spoke networks in a liberalizing inter-continental market. The proposed model considers the interactions among three types of stakeholders, namely a regulator that aims to maximize the expected social welfare by designating the locations of new gateways; airlines that maximize profits by optimizing the service offerings and airfares; passengers that minimize their own travel disutility. Such a model is applied to analyze the Europe - China aviation market, so that the comparative advantages of different networks can be examined and quantified. The modeling results provide evidence-based recommendations on airline competition and airport development, and infrastructure investment needs in markets being liberlized.

KEY WORDS: ***Network cooperation and competition; Hub-and-spoke network; Dog-bone network; International gateway hub; Demand uncertainty***

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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 allow airlines to achieve "economies of traffic density" by combing traffic volumes on feeder routes, to enhance service quality with increased flight frequency, and to compete more strategically (Caves et al. 1984, Brueckner and Spiller 1994, Zhang 1996, Brueckner and Zhang 2001, and Brueckner 2004). Following deregulations in the US and European countries, hub-and-spoke networks have been extensively used in the aviation industry. However, in international especially inter-continental markets, the primary network configuration has been the so-called "dog-bone" networks which employs two gateway hubs[1] (Button 2009, 2012). This is partly due to the fact that most countries forbid a foreign airline to serve its domestic markets (i.e. cabotage), 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. Figure 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 comprises of two gateway hubs, G_1 and G_2, located in two continents respectively, each connected to local spoke markets via feeder flights. One example of such a configuration is the alliance network by Lufthansa and Air China in the Europe-China market. In such a case G_1 may represent Lufthansa's hub at Frankfurt serving the intra-Europe market, whereas G_2 may present 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, thus they could jointly provide a connection service for passengers flying from Manchester, UK to Zhengzhou, China via their hub airports in Frankfurt and Beijing.

[1] 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.

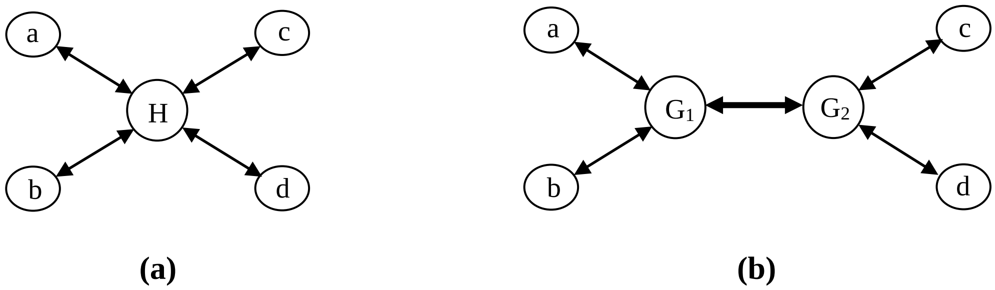

Fig. 1. Airline network configurations: (**a)** a pure HS network, and (**b) a** dog-bone network.

The popular use of dog-bone networks was 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 small spoke destinations. In the case of a dog-bone network, large-sized and small-sized aircraft can be used to serve the hub-to-hub and hub-to-spoke/spoke-to-hub routes, respectively. Second, international regulations often prohibit airlines to develop extensive networks in foreign countries (Fu et al. 2010). As a result, airlines often have to form 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 that to further leverage the benefits of HS networks such as increased frequencies and lowered operation costs.

However, in the past decades, the aviation industry has been experiencing some changes in technologies and regulatory policies. On the one hand, 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 around 300 or less). Meanwhile, 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, Etihad Airways and Qatar Airways, have been able to expand their HS networks to serve a large number of destinations in Europe, Asia, and North America. This allowed them to by-pass regional gateways and compete with airline alliances relying on dog-bone networks.

Emirates, for example, can now serve 144 destinations around the world () directly out of Dubai[2], where passengers only need to connect once for their inter-continental flights. Turkish Airlines, which developed extensive networks over Europe and Africa, has been following the similar strategy to expand its network in Asia Pacific.

The fast expansion of the Middle East carriers has led to on-going policy debates and competition concerns. International air transport 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 liberalization 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, now airlines in a third country can also compete in this OD market by utilizing the 6th freedom. This could significantly change the ways airlines compete and thus the traditional bilateral negotiations of air transport liberalization. That is, when EU and China negotiate bilateral ASAs, they may have to consider the roles played by Middle East carriers, thus that the negotiation cannot be purely bilateral any more. Regulations on airline alliances or code share agreement may also be re-evaluated, as they significantly influence airline competition and operation.

Airlines' strategies of competition and network development also need to be revisited. Each type of networks has its own strength and weakness. The dog-bone network is likely to bring airlines substantial cost savings via traffic consolidation over existing networks. However, passengers will spend more time on flight connection. Global HS network is more convenient but can only serve sufficiently large destinations that can fill long-range wide-body aircraft. Despite the inter-continental HS network expansion by major Middle East carriers, it is unclear which network configuration, HS or dog-bone, will win the competition in the long

[2] According to OAG database, as of late 2017 these include 40 destinations in Europe and 42 destinations in Asia, respectively.

term. If the two types of networks can co-exist, would they each secure certain niche markets with distinctive competitive advantage? 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 policy 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.

In summary, a better understanding of such a problem is important for both airlines and regulators. Airlines can identify their strength and weakness, and how they could optimize and reconfigure their networks in order to win competition with higher efficiency and better services. 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), slots allocation at major airports (Li et al., 2010; Shen et al., 2015) 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 competition, possibly from the competition from Middle-East carriers, then the Chinese government should promote liberalization even if Chinese airlines may lose some market shares.

In the literature, a number of studies have modelled airline network configuration and airline competition. However, to the best of our knowledge, few have examined the rivalry between HS and dog-bone networks. 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 costs of airlines and passengers, thus airline competition was not considered explicitly. Adler (2001) modelled a two-stage best-response game 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. 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 modelled and the study focused on airlines' decisions only. 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 conclude 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 and 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; Shen et al., 2015). Therefore, they cannot be used directly to examine the international markets in the presence of alternative network configurations.

An associated strategic decision of airlines is the choice of gateway hubs. In certain cases, airlines use multi-hub networks to serve markets with large geographic coverage. For example, United Airlines and American Airlines each developed multiple hubs in the US.[3] Air China has also been developing hubs in Beijing, Chengdu and Shenzhen in mainland China. Therefore, where necessary it may be possible for these airlines to add an alternative gateway hub in response to competition. This may also alleviate the capacity shortage and congestion issue at the saturated gateway airport. In most markets, however, such a strategy cannot be

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

implemented without strong government support, because substantial changes in airline and airport designation,[4] slot allocation and capacity investments at the (new) gateway airports are needed. In certain markets like China, the strategic planning for airports are developed or endorsed by the central regulator (e.g. CAAC).[5] In other cases, governments invest on airport infrastructures but have limited influence over airlines' hub choices.[6] Either way, it would be useful to incorporate the (additional gateway) hub choice in the model, so that such strategic decisions can be made based on systematic analysis. As many other network design problems (NDPs), hub location is a strategic long-term decision. However, it is very difficult to precisely predict future demand in the planning stage. Therefore, it is important to incorporate demand uncertainty into 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 with 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 modelled uncertainty by generating a substantial number of samples from the assumed probability distributions. However, it is usually difficult to ascertain a probability distribution of future demand in the first place. Instead, there are usually clear seasonal patterns in the aviation industry. Therefore, Yang (2009, 2010) incorporated seasonal

[4] Absent full open-sky liberalization, only designated airlines can provide international services between designated/approved destinations in the OD countries under ASAs.

[5] 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, which include the airports in Beijing, Shanghai, Guangzhou, Chengdu, Kunming, Shenzhen, Chongqin, Xi'an, Urumqi, Harbin.

[6] For example, De Neufville and Odoni (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.

demand variations into a two-stage stochastic programming model to study airline network designs. Such an approach is adopted in this study to model demand uncertainty.

In order to fill the gap in research and contribute to the associated policy and managerial decision-making, this study proposes a stochastic model to investigate the competition and cooperation between airlines running dog-bone and HS networks in an inter-continental aviation market. The model considers the interactions among three types of stakeholders, namely a regulator, airlines and passengers. Before the actual passenger demand is observed, the aviation regulator maximizes the expected social welfare by choosing the additional gateway airports. Such a modelling approach is used to capture the important roles played by regulators in forming policies related to ASAs, slot allocation and capacity choices of gateway airports etc. Based on the chosen gateway and observed demand, airlines involved in the related markets, including two alliance airlines jointly operating a dog-bone network and an airline running an inter-continental HS network, compete by optimizing aircraft sizes, frequencies and airfares to maximize their own profits. The model is used to analyze the Europe - China aviation market, thus that the optimal gateway hub can be identified for different demand scenarios. The effects of aviation liberalization on airlines, passengers, and social welfare are evaluated respectively, allowing relevant recommendations on regulatory policy and managerial strategies to be made.

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

2. 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. $G \subseteq N$ denotes the set of all international gateways, whereas $\bar{G} \subseteq N$ represents the set of candidate gateway airports, and W represents the set of all 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, 2015). Therefore, it is important to explicitly consider demand uncertainty. Because air demands usually exhibit clear seasonal patterns and airlines adjust their service offerings regularly[7], it would be useful to model 2 to 4 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 a carrier operating a HS network and the other is an airline that operates a traditional dog-bone network. In practice, the latter refers to two airlines in the OD markets which jointly offer the service through alliance or code-share agreements (e.g. Lufthansa and Air China in the Europe-China market). The airports are classified as the feeder airports and hub/gateway airports. The hub/gateway airports play the role of concentrating and distributing air passengers. A HS network involves only one hub airport, while the dog-bone network usually contains two international gateway airports, one for each 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 hub airport. A passenger route involves at most two transfers/connections, which is in line with the industry reality. All the airports and airlines are

[7] For example, there are two flight seasons a 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.

pre-given, thus no entrant airlines are considered in our model.

A2. The members of alliance jointly set airfares (i.e. airline alliance with anti-trust immunity) as if they are one single airline (Takebayashi, 2011). 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 modelled (Berechman and de Wit, 1996; Yang, 2008).

A3. The potential OD demand on each route is assumed to have a discrete distribution with a finite number of possible realizations called scenarios (Li et al., 2012; Yang, 2009, 2010). Let Ω be the set of finite scenarios and $\omega \in \Omega$ be a realized demand scenario.

A4. Three types of players are considered in the inter-continental aviation market, namely an aviation regulator, airlines and passengers. The regulator aims to maximize the expected social welfare by optimizing the locations of gateways before travel demands are observed. This can be a strong assumption as governments tend to maximize the benefits to their own countries. However, since the aviation sector offers significant positive externalities to the global economy, it is difficult to precisely allocate the associated benefits among different countries. Such an assumption is also consistent with the modeling of joint decisions of airlines running the dog-bone network, or markets when multilateral open-skies have been achieved (e.g. the EU single aviation market). With a given demand scenario and a gateway scheme, each airline aims to maximize its own profit by optimizing the associated services (i.e. the choices of aircraft and flight frequencies) and airfares taking into account of passengers' travel decisions. An elastic demand function is applied to capture the responses of air passengers to the airlines' services and airfares.

A5. We also consider the effects of congestion delay at the airports. If an airport is subject to capacity constraint, the airlines and air passengers landing or taking off this airport would incur congestion cost. The capacity of an airport is the maximum number of flights (i.e.

aircraft movements) that this airport can serve.

A6. In this problem, we do not consider the yield management issue and the average airfares are considered as basic and static values (Hansen, 1990; Hsu and Wen, 2003). The types of aircraft of airlines are given in advance, and each airline is assumed to schedule only one type of aircraft on each link.

2.1. Air passengers' route choices

For a given demand scenario $\varpi \in \Omega$, the potential OD demand is fixed 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 $w \in W$. The travel disutility function u_{krw}^{ϖ} of route $r \in R_{kw}$ served by airline k is computed as the weighted sum of the line-haul travel time t_{krw}^{ϖ}, the schedule delay time at airports d_{krw}^{ϖ}, an additional penalty term Δ_{krw} to reflect passengers' preferences over different trip pattern (i.e., non-stop, one-stop, or two-stop), the congestion delay time at the capacitated hub airports C_{krw}^{ϖ}, and the airfares p_{krw}^{ϖ} (Kanafani and Ghobrial, 1985; Hsu and Wen, 2003; Li et al., 2010, 2011). When travel with HS network airlines, the passengers transfer just once. However, passengers may make at most two connections when they travel with airline alliances operating dog-bone networks. u_{krw}^{ϖ} can therefore be expressed as follows

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

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 passenger's value of time for the congestion delay at the capacitated hub airports.

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

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

where t_{ka}^{ϖ} is the travel time on link *a*, assumed to be dependent on the distance of link *a* and the velocity of the aircraft that 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 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}^{ϖ}, can be specified as the sum of the schedule delays on all links along this route

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

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

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

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

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

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

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 between the total number of flights and the capacity of airport *H* (Borger and Dender, 2006; Basso and Zhang, 2008; Gillen and Mantin, 2014; Silva et al., 2014), which is specified 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*, C_H is the capacity of airport *H*.

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

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

where θ measures the variation in passenger perceptions of travel disutility u_{krw}^{ϖ}. A higher value of θ corresponds to smaller variation in passenger perceptions, and vice versa.

For each demand scenario $\varpi \in \Omega$, let $\tilde{Q}_w^{\varpi}$ be 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^{ϖ} be the resultant OD demand, which is specified as follows

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

where β is the demand dispersion factor that reflects the demand sensitivity to the expected travel disutility φ_w^{ϖ} between OD pair *w*.Therefore, the passenger volume q_{krw}^{ϖ} 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 behaviors of air passengers (Davis, 1994; Lam et al., 2002; Li et al., 2010; Saraswati and Hanaoka, 2014).

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

The aggregated passenger flow q_{ka}^{ϖ} on link $a \in A_k$ in the sub-network of airline *k* can be calculated with Eq. (9) as follows

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

2.2. Airlines' decisions on service qualities and airfares

According to assumption A2, alliance airlines can be treated as one single decision-maker. Thus we can formulate the profit maximization problem respectively for the HS network airline as well as for the airline alliance. Airlines usually adjust their operations and flight schedules according to the seasonal variations of demand. For a given demand scenario $\varpi \in \Omega$, the airlines maximize their profits by competing in airfares, flight frequencies and types of aircraft. The profit function π_k^{ϖ} of airline $k \in K$ is defined as the difference between the total revenues and the total costs on all routes that this airline operates, which can be specified as follows

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

where $\mathbf{p}_k^{\varpi}$, $\mathbf{f}_k^{\varpi}$ and $\mathbf{s}_k^{\varpi}$ are the vectors of airfares, frequencies and capacities of aircraft of airline *k*, whereas $\mathbf{p}_{-k}^{\varpi}$, $\mathbf{f}_{-k}^{\varpi}$ and $\mathbf{s}_{-k}^{\varpi}$ are the vectors of corresponding variables for other airlines excluding airline *k*. p_{krw}^{ϖ} denotes the airfare on route $r \in R_{kw}$, which is served by airline *k*. q_{krw}^{ϖ} and q_{ka}^{ϖ} are determined by the passenger route choice model (**Error! Reference source not found.**) - (10). μ_a is the marginal cost per passenger on link *a*, which includes the passenger-related costs such as the baggage handling cost, costs of meals on board and so on. η_{ka}^{ϖ} is the marginal cost per flight on link *a* in the network of airline *k*, which includes various flight-based costs such as the pilot and crew wages, fuel costs, maintenance cost and so on. γ is the marginal congestion cost that airlines incur at the capacitated airports. $A_{k-}(H)$ ($A_{k+}(H)$) denotes the set of links with a tail (head) node *H* in airline *k*'s network. d_H is a flight's delay at airport *H*. f_{ka}^{ϖ} is airline *k*'s frequency on link *a*. The first part on the right-hand side of Eq. (11) represents the total revenue of airline *k*. The second part contains the total passenger-related costs and the flight-related costs of the airline. The third part 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 number of seats) are two important factors determining the marginal cost per flight. They suggested to formulate η_{ka}^{ϖ} as follows

$$\eta_{ka}^{\varpi} = \left(D_a + \tau_0\right) * \left(s_{ka}^{\varpi} + \tau_1\right) * \tau_2, \ \forall a \in A_k, k \in K, \varpi \in \Omega, \tag{1}$$

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

Therefore, the profit maximization problem for airline *k* can be formulated as follows

$$\max_{\left\{\mathbf{p}_k^{\varpi}, \mathbf{f}_k^{\varpi}, \mathbf{s}_k^{\varpi}\right\}} \ \pi_k^{\varpi}\left(\mathbf{p}_k^{\varpi}, \mathbf{f}_k^{\varpi}, \mathbf{s}_k^{\varpi}, \mathbf{p}_{-k}^{\varpi}, \mathbf{f}_{-k}^{\varpi}, \mathbf{s}_{-k}^{\varpi}\right), \ \forall k \in K, \varpi \in \Omega, \tag{2}$$

subject to

$$q_{ka}^{\varpi} \le s_{ka}^{\varpi} f_{ka}^{\varpi}, \ \forall a \in A_k, k \in K, \varpi \in \Omega, \tag{3}$$

$$\mathbf{p}_k^{\varpi}, \mathbf{f}_k^{\varpi}, \mathbf{s}_k^{\varpi} \ge 0, \ \forall k \in K, \varpi \in \Omega, \tag{4}$$

where $\left\{\mathbf{p}_k^{\varpi}, \mathbf{f}_k^{\varpi}, \mathbf{s}_k^{\varpi}\right\}$ are the decision variables of airline *k*. The optimization model (13) – (15) maximizes the profit of airline *k* given other airlines' services and airfares. 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 (154) ensures that the airfares, flight frequencies and capacities of aircrafts 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 follows

$$\max_{\{\mathbf{p}_k^{\varpi},\mathbf{f}_k^{\varpi},\mathbf{s}_k^{\varpi}\}} L_k\left(\mathbf{p}_k^{\varpi},\mathbf{f}_k^{\varpi},\mathbf{s}_k^{\varpi},\boldsymbol{\lambda}_k^{\varpi}\right)=\pi_k^{\varpi}\left(\mathbf{p}_k^{\varpi},\mathbf{f}_k^{\varpi},\mathbf{s}_k^{\varpi},\mathbf{p}_{-k}^{\varpi},\mathbf{f}_{-k}^{\varpi},\mathbf{s}_{-k}^{\varpi}\right)-\frac{1}{2\rho}\sum_{a\in A_k}\left[\max^2\left\{0,\lambda_{ka}^{\varpi}+\rho\left(q_{ka}^{\varpi}-s_{ka}^{\varpi}f_{ka}^{\varpi}\right)\right\}-\left(\lambda_{ka}^{\varpi}\right)^2\right], \quad (5)$$

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

$$\max_{\{\mathbf{p}_k^{\varpi},\mathbf{f}_k^{\varpi},\mathbf{s}_k^{\varpi}\}} L_k^{\varpi}\left(\mathbf{p}_k^{\varpi},\mathbf{f}_k^{\varpi},\mathbf{s}_k^{\varpi},\boldsymbol{\lambda}_k^{\varpi}\right),\ \forall k\in K,\varpi\in\Omega. \quad (6)$$

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.

2.3. Regulator's decision on the additional international gateway airports

Investment of additional gateway airports can facilitate airlines' efforts to optimize their network configuration, improve flight frequency and thus passenger service quality, and alleviate the congestion at existing hub airports. In addition, other regulatory changes may also be necessary, such as ASA specifications of airline and airport designation, flight frequency and airport slot allocation. Such strategic decisions need to be made in the presence of demand uncertainty. Therefore, we consider a regulator aiming to maximize the expected social welfare of the whole system by optimizing the locations of gateway hubs. Its objective function is specified as follows

$$\max_{\{x_g\}} E[Z]=\sum\nolimits_{\varpi\in\Omega}P^{\varpi}Z^{\varpi}, \quad (7)$$

subject to

$$\sum_{h\in\bar{G}} x_g \le M, \quad (19)$$

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

where $g \in \bar{G}$ is a candidate gateway airport. x_g is the decision variable, x_g equal 1 if airport g is set to be a gateway and 0 otherwise. P^{ϖ} and Z^{ϖ} are respectively the probability and social welfare of the specific demand scenario $\varpi \in \Omega$. M is the maximum number of gateways that the regulator plans to develop. For each demand scenario $\varpi \in \Omega$, the social welfare is calculated as the sum of the consumer surplus and the producer surplus (i.e. airlines' profits). According to Williams (1997) and Evans (1987), the consumer surplus represents the perceived benefits experienced by actual passenger demand and is measured in monetary units, which is specified as $\sum_{w \in W} q_w^{\varpi} / \beta$. Thus, the total social welfare Z^{ϖ} is specified as follows.

$$\mathrm{Z}^{\varpi}\left(\mathbf{q}^{\varpi}\left(\mathbf{u}\left(\mathbf{Y}^{\varpi}\left(\mathbf{x}\right)\right)\right), \pi_k^{\varpi}\left(\mathbf{Y}^{\varpi}\left(\mathbf{x}\right)\right)\right) = \frac{1}{\beta} \sum_{w \in W} Q_w^{\varpi}\left(\mathbf{u}^{\varpi}\left(\mathbf{p}^{\varpi}\left(\mathbf{x}\right), \mathbf{f}^{\varpi}\left(\mathbf{x}\right), \mathbf{s}^{\varpi}\left(\mathbf{x}\right)\right)\right) + \sum_{k \in K} \pi_k^{\varpi}\left(\mathbf{p}^{\varpi}\left(\mathbf{x}\right), \mathbf{f}^{\varpi}\left(\mathbf{x}\right), \mathbf{s}^{\varpi}\left(\mathbf{x}\right)\right), \tag{21}$$

where $\mathbf{x}$ is the vector of regulator's decisions $\left\{x_g\right\}$. $\mathbf{Y}^{\varpi}\left(\mathbf{x}\right) = \mathbf{Y}^{\varpi}\left(\mathbf{p}^{\varpi}\left(\mathbf{x}\right), \mathbf{f}^{\varpi}\left(\mathbf{x}\right), \mathbf{s}^{\varpi}\left(\mathbf{x}\right)\right)$ is the vector of airlines' strategies. Vector $\mathbf{Q}^{\varpi}$ is a function in $\mathbf{x}$ through airfare $\mathbf{p}^{\varpi}$, frequency $\mathbf{f}^{\varpi}$ and the types of aircrafts $\mathbf{s}^{\varpi}$, and is determined by the passenger choice model (1) - (10). Vector $\boldsymbol{\pi}_k^{\varpi}$ is also a function in $\mathbf{x}$ through $\mathbf{p}^{\varpi}$, $\mathbf{f}^{\varpi}$ and $\mathbf{s}^{\varpi}$, which is determined by the airline's profit maximization model (13) - (15).

The maximization model (**Error! Reference source not found.**) - (21) is a 0-1 integer programming problem with the binary decision variable $\left\{x_g\right\}$. The objective function (18) maximizes the expected social welfare. Constraint (19) means that the total number of new gateway hubs must be less than the predefined value M. Constraints (20) state that the location variables are binary. In order to solve the 0-1 integer programming problem (18) – (21), we propose the following heuristic solution algorithm as depicted by the flowchart illustrated in Fig. 2.

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

Step 2. First loop operation. Set $E[Z]^* = -\infty$ as the lower bound of the expected social welfare $E[Z]$ in Eq. (18) and $\mathbf{x}^* = \{x_h = 0,\ h \in \bar{H}\}$ as the initialized gateway scheme. Based on $\bar{H}$, 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 $\varpi = 1$.

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 that to obtain the resultant passenger demand $\mathbf{Q}^{\varpi(j)} = \{Q_w^{\varpi(j)}\}$, the optimal frequencies, the types of aircrafts and airfares $\mathbf{f}^{\varpi(j)}$, $\mathbf{s}^{\varpi(j)}$ and $\mathbf{p}^{\varpi(j)}$, and the corresponding airlines' net profits $\pi^{\varpi(j)} = \{\pi_k^{\varpi(j)}\}$. Then, calculate the relative variations in resultant passenger demand $r(\mathbf{Q}^{\varpi(j)})$ and airlines' profits $r(\boldsymbol{\pi}^{\varpi(j)})$ respectively by Eq. (22) and (23) (Hsu and Wen, 2003).

$$r(\mathbf{Q}^{\varpi(j)}) = \sum_{w \in W} \frac{\left| q_w^{\varpi(j)} - q_w^{\varpi(j-1)} \right|}{0.5(q_w^{\varpi(j)} + q_w^{\varpi(j-1)})}, \tag{22}$$

$$r(\boldsymbol{\pi}^{\varpi(j)}) = \sum_{k \in K} \frac{\left| \pi_k^{\varpi(j)} - \pi_k^{\varpi(j-1)} \right|}{0.5(\pi_k^{\varpi(j)} + \pi_k^{\varpi(j-1)})}. \tag{23}$$

Step 4.2. Termination check for the third loop operation. If $r(\mathbf{Q}^{\varpi(j)}) > \varepsilon_1$ and $r(\boldsymbol{\pi}^{\varpi(j)}) > \varepsilon_2$ (ε_1 and ε_2 are predefined), then compute the social welfare Z^{ϖ} for the current demand scenario ϖ and go to Step 5. Otherwise, set $j = j + 1$ and go to Step 4.1.

Step 5. Termination check for the second loop operation. If all demand scenarios are performed, compute the expected social welfare $E[Z]^{(i)}$ by Eq. (18) for gateway scheme i. If $E[Z]^{(i)} > E[Z]^{*}$, $E[Z]^{*} = E[Z]^{(i)}$ and the optimal gateway scheme $\mathbf{x}^{*} = \left\{ x_h^{(i)} \right\}$.Then go to Step 6. Otherwise, set $\varpi = \varpi + 1$ 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 social welfare $E[Z]^{*}$. 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, we 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 and airfares will not change given the competitors' strategies. Similarly, passengers have no incentives to change their route choices, and so the demand-supply interaction convergences.

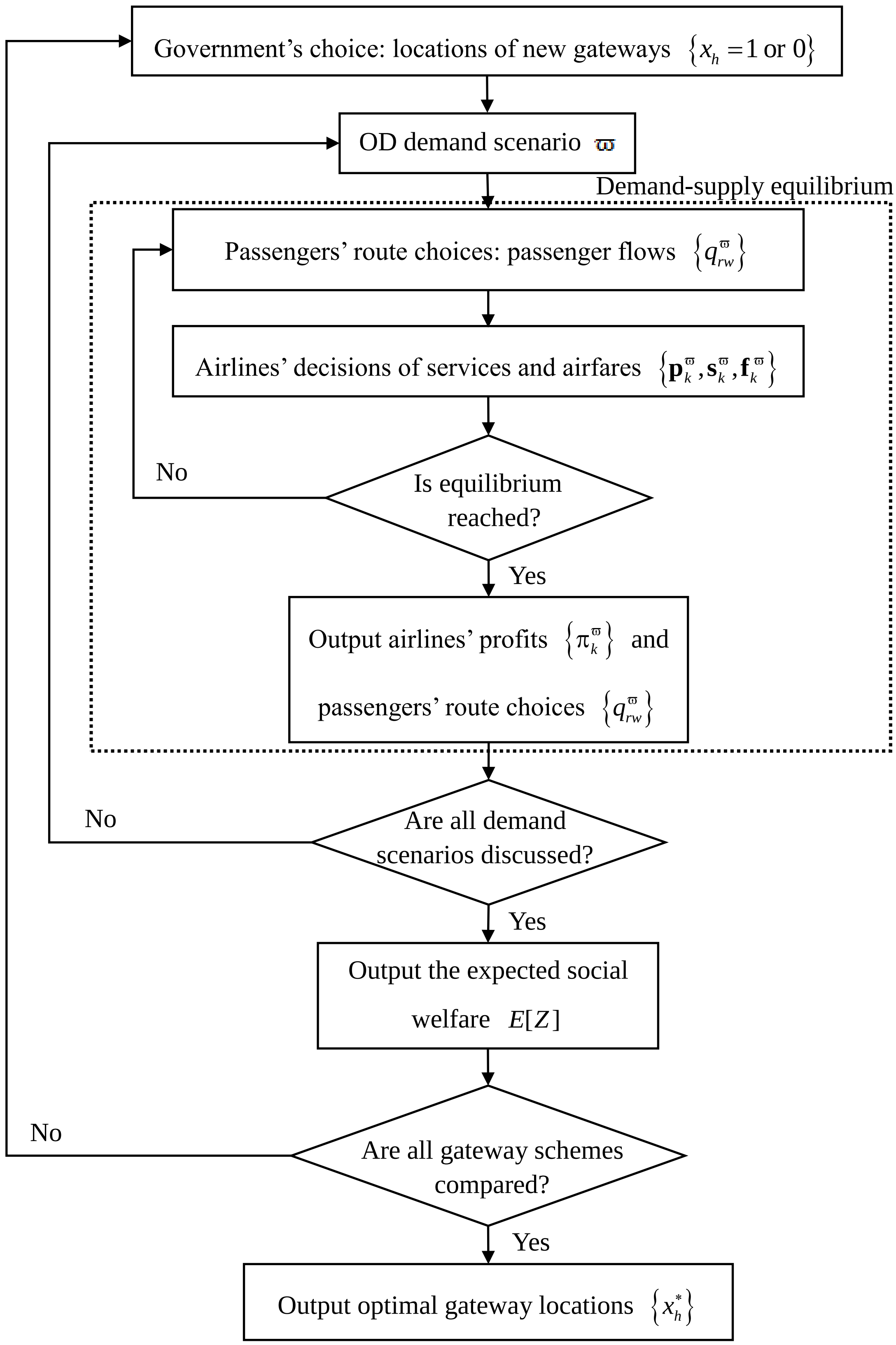

Fig. 2. Flowchart of the solution algorithm.

3. Case study for the China-Europe inter-continental aviation market

3.1. Parameter specifications

The specified model is used to study the China-Europe aviation market. Two airline decision-makers are considered for the China-Europe market. One is an airline alliance, which may represent the Star-alliance member airlines of Air China and Lufthansa. The two airlines have been together operating a dog-bone network via their hubs at Beijing and Frankfurt, and is modeled as one airline in our study Another is a HS network carrier, which may represent the Emirates. The Middle East airline has secured significant market shares in the China-Europe aviation market using its HS network. Therefore, in the “Base case”, the dog-bone network contains two international gateway hubs, namely the Beijing Capital Airport in China and Frankfurt Airport in Europe. In the HS network, the Dubai International Airport serves as the airlines’ global hub. Three candidate airports in Western China, namely the airports in Chengdu, Kunming and Xi’an, are considered by the aviation regulator for developing 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).

For simplicity, we first assume that the traffic volumes are symmetric, and so the analysis can be restricted to one-way traffic. Real market data of OD traffic volumes between China and Europe in 2015 are compiled from the OAG and PaxIS databases, and the top 14 airports in China and top 10 airports in Europe are chosen for simulations. The list of airports are 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 modelled as one airport with the combined traffic volume. The time period considered is one month, and the corresponding OD demand matrix constructed based on the 2015 traffic volumes is reported in Table 3.

All other input parameters are obtained from real market data where possible or estimated based on previous studies. The flight distances of links (D_a) are compiled 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 (including time for landing and take-off). The aircraft sizes are treated as continuous variables. Therefore, in the dog-bone network, aircraft capacity ranges (measured in seats) are assumed to be [250, 450] for the hub-to-hub routes, and [150, 400] for the hub-to-spoke/spoke-to-hub routes. In the HS network, aircraft capacity is assumed to take values in [250, 400]. The Beijing Capital Airport is assumed to be subject to capacity constraint and C_H is set to 461 flights per month for international services between China and Europe based on the statistics in 2015. 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 demand dispersion factor β is set to be 0.0002, and the coefficient θ is set to be 0.02 (Takebayashi and Kanafani, 2005). Passengers' value of time for flight delay α_4 and 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 respectively, for flights with a travel distance below 5000 km; and 2200, 211 and \$ 0.0115 respectively, for flights with a distance equal to or greater than 5000 km (Swan and Adler, 2006; Alder and Smilowitz, 2007). Additionally, based on the historical data and previous studies, three demand scenarios, namely the middle level (based on real data of 2015), the low level (about 80% of the middle level) and the high level (about 120% of the middle level), are adopted to model the seasonal/ uncertainty of air travel demand, which are reported in Table 4. 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 local airports.

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.

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. Locations of all relevant airports.

Table 3 OD demand matrix for the China-Europe 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 Three demand scenarios.

Demand scenarios	OD demand	Probability
Low demand	80% of the medium demand	0.33
Medium demand	Real OD demand of 2015	0.50
High demand	120% of the medium demand	0.17

3.2. Analysis of results

The proposed model, which investigates the choices of gateway hubs and the competition between different kinds of airlines, is applied to the China-Europe inter-continental aviation market. The results with deterministic OD demand and stochastic OD demand are summarized and analyzed below.

3.2.1. The results with deterministic OD demand

In this part, the real OD demand of 2015 for China-Europe aviation market is considered, which means there is only one demand scenario. Assuming that the aviation regulator plans to develop one more international gateway hub in addition to Beijing in China (i.e., $M = 1$), there are three possible gateway schemes, each with one candidate airport. Table 5 lists the total social welfare of the whole system, the profits of two kinds of airlines and the resultant travel demand respectively for the three different gateway schemes as well as the base case, when the deterministic demand of 2015 is considered. It can be observed that Chengdu is the best choice for the additional gateway hub, leading to the highest social welfare of $ 1.1529 billion. Kunming is the worst choice with the lowest social welfare. Also, the gateway scheme of Chengdu leads to the highest total profits (the sum of all airlines' profits) and the resultant passenger demand, which are $ 153.8203 million and 199807 passengers per month, respectively. Such modelling results are consistent with the fact that in 2015, the Chengdu Shuangliu Airport was ranked fourth among all the Chinese airports based on the yearly passenger throughput.

Comparing the results of the base case with those of new gateway airport, we can conclude that developing an additional gateway airport (either in Chengdu, Kunming or Xi'an) would improve the total social welfare and the total profits and attract more air passengers. However, the changes of the profits for the two kinds of airlines are different. Table 6 shows suggests that with additional gateway hub, the net profit of the Emirates is much less than that of the airline alliance, while in the base case, the Emirate earns more than the airline alliance. Consistent results can be found in changes of market shares. In the base case, the market share of the airline alliance is slightly smaller than that of Emirates. However, when a new gateway airport is developed, the market share of the airline alliance become much larger than that of Emirates. On the one hand, developing one more gateway airport in China may lead to reduced flight frequency on certain routes. On the other hand, it means that there is one more route option for each OD pair in the dog-bone network. Although services offered by Emirates have one less stop, passengers may fly shorter distances by taking the airline alliance's flights. Shorter flying distance means lower time cost, cheaper ticket and correspondingly lower travel disutility. As a result, the airline alliance can increase its market share and the net profits with additional gateway.

Table 5 Comparing different gateway schemes with deterministic demand of 2015.

Gateway schemes	Social welfare (billion $)	The sum of profits (million $)	Resultant demand (passengers/month)
Base case	1.1415	147.3122	198844
Chengdu	1.1529	153.8203	199807
Kunming	1.1471	149.4837	199521
Xi'an	1.1480	149.8602	199635

Table 6 Market share and net profits under different gateway schemes with deterministic demand of 2015.

Gateway schemes	**Airlines**	**Net profits (million $)**	**Market share**
Base case	Airline Alliance Emirates	60.3142 86.9980	41.59% 48.41%
Chengdu	Airline Alliance Emirates	124.9019 28.9184	80.91% 19.19%
Kunming	Airline Alliance Emirates	99.1866 50.2971	67.08% 32.92%
Xi’an	Airline Alliance Emirates	125.4040 24.4562	81.38% 18.62%

Tables 7 and 8 investigate the effects of network competition on total social welfare and resultant air passengers. Comparing the results with and without network competition, we can find that Chengdu is always the best choice for the new gateway, with the total social welfare of $ 1.1529 and $ 1.1459, respectively. Furthermore, the network competition between the dog-bone network and the HS network leads to higher passenger demand and social welfare. This is intuitive as increased competition encourages airlines to improve the qualities of service and reduce airfares. However, it should be noted that the total welfare changes are moderate. Table 8 suggests that this is probably due to the fact that the overall market size only increased moderate. Table 6 suggests that different network configuration and competition scenarios will have significant impacts on the distribution of airlines’ market shares.

Table 9 reports the total number of flights in Beijing Capital Airport under different choices of gateways. In the base case, all flights served by the dog-bone network are routed through Beijing, leading to a total of 475 flights per month in the China-Europe market. However, with an additional gateway developed, this number decreases to 359, 383, and 427 respectively for the gateway schemes of Chengdu, Kunming, and Xi’an. With results reported in Tables 5, 7 and 8, it is clear that the development of new gateways can alleviate the congestion at the saturated hub airports without reducing total traffic volume, welfare and industry profits. On the contrary, it improves the overall industry performance although such benefits are not distributed evenly among all stakeholders.

Table 7 Comparing the total social welfares with and without airlines' competition.

Gateway schemes	**Social welfares (billion $)**	
	Only dog-bone network	**HS vs. dog-bone network**
Base case	1.1042	1.1415
Chengdu	1.1459	1.1529
Kunming	1.1395	1.1471
Xi'an	1.1454	1.1480

Table 8 Comparing the resultant demand with and without airlines' competition.

Gateway schemes	**Resultant travel demand (passengers/month)**	
	Only dog-bone network	**HS vs. dog-bone network**
Base case	185809	198844
Chengdu	197918	199807
Kunming	192578	199521
Xi'an	195210	199635

Table 9 Total number of flights at Beijing Capital Airport for different gateway schemes.

Gateway schemes	Base case	Chengdu	Kunming	Xi'an
Total number of flights	475	359	383	427

3.2.2. The results with stochastic OD demand

To control for demand uncertainty and seasonal variations, three demand scenarios are considered. The levels of the demand and the corresponding probability of each scenario are summarized in Table 4. As in the deterministic demand case, one more gateway in addition to Beijing capital airport is considered for the dog-bone network (i.e., M = 1). Table 10 reports the optimal gateway schemes under the three different demand scenarios. It is noted that with low and medium levels of demand, the optimal choice of the additional gateway is always Chengdu, which lead to the social welfare values of $ 0.9199 and $ 1.1529 billion, respectively. However, when the demand further increases (i.e., the high demand scenario modelled), the optimal gateway to be added is Xi'an. When demand is relatively low, the Beijing Capital Airport is capable of serving almost all passengers from Beijing and some passengers originating from other cities. The newly added gateway airport mainly attracts passengers in its surrounding areas. The throughput of Chengdu is much larger than those of other candidate gateways. Therefore, choosing Chengdu as the new gateway leads to lower passenger disutility than Kunming and Xi'an. However, when the demand is quite high, the Beijing Capital Airport becomes saturated which forces many passengers, including the passengers originated from Beijing, to fly through the new gateway airport rather than through Beijing. Compared with Chengdu, the travel distances between Xi'an-Beijing, and Xi'an-Frankfurt are shorter. This leads to slightly higher welfare when Xi'an is chosen compared to the case of Chengdu gateway. Table 11 summarizes the expected social welfare for different candidate gateways. That is, considering all possible demand levels, Chengdu is the best choice for the new gateway airport.

Table 10 Optimal gateway schemes for three demand scenarios.

Demand scenarios	Low demand	Medium demand	High demand
Optimal gateway airport	Chengdu	Chengdu	Xi'an
Social welfare (billion $)	0.9199	1.1529	1.3894

Table 11 Expected social welfare for different gateway schemes.

Gateway schemes	**Expected social welfare (billion $)**
Base case	1.1037
Chengdu	1.1158
Kunming	1.1104
Xi'an	1.1127

Passenger volumes for the China-Europe aviation market have been increasing over the years. By the end of 2015, the traffic volume of China-Europe aviation market had increased by

61% over the 2010 level, corresponding to an average annual growth rate of about 10%. Assuming a demand growth rate of 10% for the next decade, traffic demand in 2025 will be 259% of the traffic level in 2015. We consider the case when at most two new gateway airports can be added in China (i.e., M = 2). This leads to six possible gateway schemes according to constraint (19), namely three schemes with only one more gateway airport and three schemes with two more gateway airports in addition to Beijing. Table 12 summarizes the optimal gateway schemes in the case of one more gateway and two more gateway airports, respectively. It can be observed that Xi'an and Chengdu + Xi'an are respectively the best choices. The social welfare of the Xi'an gateway scheme is \$ 4.6 million/per month lower than that of the scheme with Chengdu + Xi'an. This suggests that when the level of the passenger demand is sufficiently high, it is better to add two new gateways rather than one, with the optimal choices being Chengdu and Xi'an in addition to the established gateway in Beijing.

Table 12 Results for different gateway schemes with forecasted demand of 2025.

Optimal gateway scheme	**Social welfare (billion \$)**	**Resultant demand (passengers/month)**
Xi'an	3.0055	521070
Chengdu + Xi'an	3.0101	522902

4. Summary and conclusions

Significant changes are taking place in the global aviation industry. More countries are liberalizing their skies to promote the aviation industry and the associated sectors such as trade, tourism and logistics. Meanwhile, medium-sized aircraft capable of long-range flights are being introduced. As a result, some airlines are able to expand their HS networks to serve inter-continental markets that have been dominated by dog-bone network operators. Such market dynamics have raised important questions to the aviation industry. A better understanding of such a scenario is important for both airlines and regulators. Airlines can identify their strength and weakness, and how they could optimize and reconfigure their networks in order to win competition with higher efficiency and better services. For regulators, a good assessment of the competition effects will help them to design the related policies such as aviation liberalization, slots allocation at major airports, and the approval of airline alliances or code share agreements. Where needed, additional investments may be needed to promote the development of additional gateway hubs. However, few studies have explicitly modelled the competition between these aviation networks. Even less is known on their implications to airline network configurations, government policies, and resultant impacts to passengers. This paper aims to answer these questions with an integrated model on airline network rivalry and configuration taking into account the possible addition of gateway airports in the dog-bone networks. Passenger demand uncertainty and seasonal variations are explicitly considered by modelling the OD demands to have a discrete distribution with finite growth scenarios. A stochastic model is developed to characterize the decisions of a welfare-maximizing regulator, profit-maximizing airlines and disutility-minimizing passengers. Such a model allows the identification of market equilibrium when airlines compete with different types of networks, where the effects of alternative network configurations can be tested and quantified. Such a framework can help airlines to identify their strength and weakness, and how they could optimize and reconfigure their networks in order to win competition with higher efficiency and better services. It also helps regulators to design the related policies such as aviation liberalization, slots allocation at major airports, and the approval of airline alliances or code share agreements. It also helps government to develop and promote new gateway airports in liberalizing markets.

The proposed model is applied to study the China-Europe aviation market, which leads to some interesting and meaningful findings. For example, the optimal gateway location with deterministic demand is different from that with uncertain demand. In the market studied with deterministic demand, the optimal choice of the new gateway is Chengdu at relatively low demand levels (80% and 100% of the actual traffic volumes in 2015). However, Xi’an becomes the optimal choice at a higher demand level (120% of the 2015 traffic volume). When the demand is stochastic, Chengdu is the best choice which leads to the highest expected social welfare. In addition, our model also suggests that as demand grows, more gateway airports are needed for the benefits of the aviation industry and the overall economy. Last, the competition between the airline networks will benefit the air passengers as well as the whole system.

Although we have tried to provide some useful insights for the governments and airlines based on the current model, we were forced to impose a few simplifying assumptions and calibrations. For example, we considered a relatively small network with 12 airports in China and 10 airports in Europe. This is mainly due to the difficulties in compiling data for a large OD demand matrix, and the computational challenges in solving the proposed stochastic model for a large network. It would be valuable to develop new methods to solve large-scale network problems effectively in future research, so as the developed model can solve the market equilibrium in realistic inter-continental markets. For the same consideration, it would be useful to model more airlines and alliances. Finally, both Beijing and Chengdu are constructing their second airports. It would be useful to incorporate multi-airport systems in our models. These extensions will further enhance the value of the proposed model.

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