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Determinants of wave-system structures of network airlines at hub airports

Yonglei Jiang [a,b,*], Jing Lu [c], Tao Feng [d], Zhongzhen Yang [e]

[a] School of Traffic and Transportation, Beijing Jiaotong University, Beijing, 100044, PR China
[b] Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Ministry of Transport, Beijing Jiaotong University, Beijing, 100044, PR China
[c] Department of Air Transportation Management, Nanjing University of Aeronautics and Astronautics, PR China
[d] Department of the Built Environment, Eindhoven University of Technology, the Netherlands
[e] Faculty of Maritime and Transportation, Ningbo University, Ningbo, 315211, PR China

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ABSTRACT

This paper attempted to analyze the factors influencing the existence and configuration of wave-system structures of large network airlines at hub airports based on the statistical data of daily flight schedules. A bootstrapped binary logistic regression model was used to analyze the relationship between wave-system structure and its influential factors. Further, a partial least squared regression model was employed to uncover the determinants of wave-system structures' configuration. It is found that the interaction effects of two types of flight rates positively determine the existence of a wave-system structure, and the rate of airline's daily flights had the biggest impact on the configurations of wave-system structures.

1. Introduction

A wave-system structure at a large hub airport consists of connecting waves, which means 'a complex of incoming and outgoing flights, structured such that all incoming flights connect to all outgoing flights […]'(Bootsma, 1997). This concept has been considered as an effective method to improve flight connection and enlarge the market size of airlines with a small scale of fleet by the decision makers of a series of large airlines. For example, American Airlines (AA) and Deutsche Lufthansa (LH) have organized different types of wave-system structures at their main hub airports (Dallas-Fort Worth International Airport, DFW and Flughafen München, MUC), respectively. Meanwhile, some other large network airlines do not employ or are gradually abandoning the organizing of wave-system structures at their hub airports. For example, most flight schedules of Southwest Airlines (WN) and Delta Air Lines (DL) at their main hub airports (e.g., Dallas Love Field airport, DAL; Hartsfield-Jackson Atlanta International Airport, ATL) do not follow the shape of wave-system structures. However, at present organizing wave-system structures at hub airports is still considered by many countries as one of the effective methods to improve the airlines' operation. Recently, the fast development of China civil aviation industry has brought fierce competition to both airlines and airports in China. Three Largest network airlines in China are trying to take large hub airports as their base airports to construct their own hub-spoke networks to improve the quality of their air transport service.

Thus, this paper aims to find out the existence of wave-system structures, uncover the impact factors of wave-system structures at hub airports, and identify the determinants of wave-system structures' configuration based on the statistical data of daily flight schedules. Meanwhile, related suggestions and future researches are proposed and discussed.

The structure of this paper is as follows. Section 2 is the literature reviews on flight scheduling. Section 3 introduces the data source and employed models. In section 4, the impact factors of both wave-system structures and their configuration are analyzed. Finally, discussions and suggestions are given in the section of Conclusions and suggestions.

2. Literature reviews

Since the ideal type of connection wave (wave-system structure) and the measuring indices for a hinterland hub were firstly proposed by Bootsma (1997) to organize flight of European hinterland hubs, related studies have been concentrated on two aspects:1) identification of wave-system structures of different airlines at different hub airports 2) assessment of airlines' connectivity and coordination assessment of airlines at hub airports considering wave-system structures.

* Corresponding author. School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, PR China.
E-mail address: yljiang1@bjtu.edu.cn (Y. Jiang).

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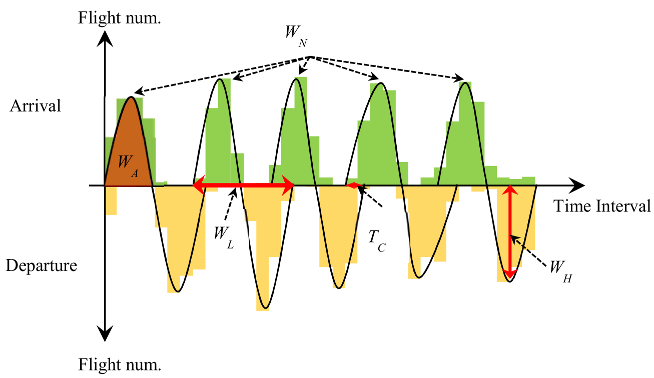

Fig. 1. Theoretical configuration of wave-system structure.
Source: Bootsma (1997) and own compilation by authors.

According to the identification of wave-system structures, Burghouwt and Wit (2005) analyzed the development and configuration of wave-system structures at European hub airline hubs since the deregulation of European Union (EU) airline industry in the 1990s. They found that a temporal concentration trend existed among European airlines by adopting or intensifying wave-system structures. Kraus and Koch (2006) discussed various types of airports based on 24 h demand profile form O-D to continuous hub. Later, Burghouwt (2007) analyzed the network development of KLM-Royal Dutch Airlines, British Airways and Iberia. He found that deregulation resulted that hub-and-spoke networks were built or intensified by all these three carriers. In addition, the ideal hub-and-spoke operation was determined by both a wave-system structure and a central location of the hub airport. Kim and Park (2012) analyzed the interconnectivity of airfreight networks at hub airports from a temporal perspective. The airfreight transshipment of Korean Air and Asiana Airlines at Incheon International Airport was analyzed. They found the existence of wave-system structures of scheduled flights meant three concentrations of airfreight transshipment at the airport. Huang and Wang (2017) compared the indirect connectivity of the top ten hub airports in China between 2010 and 2015 from the perspective of wave-system structures. Further, Huang and Wang (2018) identified the existence of wave-system structures among the top ten hub airports in China, and analyzed the spatial evolution of indirect connections of hub airports with obvious wave-system structures. They found that the wave-system structures were significant at Beijing Capital International Airport, Shanghai Pudong International Airport, Guangzhou Baiyun International Airport and Kunming Changshui International Airport. The indirect connections of these four hub airports were deterred by airlines' network expansion instead of geographic proximity.

Meanwhile, several researchers tried to explore the efficiency of operations at hub airport and capacity management under wave-system structure. In the opinion of Dennis (2001), policies including improved flight scheduling (more waves in the wave-system structure) should be implemented at European hub airports. Danesi (2006) proposed a new index, "weighted connectivity ratio", to measure airline hub timetable co-ordination and connectivity according to the so-called "connectivity ratio" by Doganis (2002) with higher accuracy. Mirkovi and Tošić (2016) proposed an extended apron capacity estimation model considering the impacts of wave-system structure. Based on the apron capacity analysis, Mirkovi and Tošić (2017) concluded the impact factors of apron capacity at non-hub and hub airports to define the runway-apron relationship, and considered this relationship in the estimation of airside capacity under the wave-system structure of airlines. O'Connell and Bueno (2018) assessed efficiency (connectivity and coordination) of three main Gulf carriers at local hub airports based on the wave-system structure theory. They found that the degree of connectivity and temporal coordination of Gulf hub airports was greater than European hubs.

However, existing research have been focusing on the identification of wave-system structures or the measuring of airport temporal connectivity of hub airports when the flight schedule follows a wave-system structure. The impact factors of the existence of wave-system structures at hub airports were supposed to be the same, which was listed by Burghouwt and Wit (2005). However, wave-system structures are not organized at all the hub airports by all the network airlines worldwide. It is necessary to analyze the impact factors on the existence of wave-system structures and the structural configurations according to the existing definition and measurement of wave-system structure.

3. Methodology and data collection

3.1. Methodologies

In order to uncover the factors influencing the existence of wave-system structure at hub airports of network airlines and their structural configurations, the existence of wave-system structures were firstly identified according to the existing definition of an ideal connection wave (Bootsma, 1997). Second, considering the constraint of sample size, a bootstrapped binary logistic regression model is employed to uncover the determinants of wave-system structures of network airlines at hub airports. Finally, the factors influencing wave-system structures' configuration is analyzed using a partial least square regression (PLSR) model.

3.1.1. Configuration of wave-system structures

There are five indices describing the configuration of wave-system structures (Fig. 1):

- Wave density (W_N): the number of daily waves at the hub airport.
- Wave Degree (W_A): the total number of flights in an arrival wave or a departure wave.
- Wave length (W_L): the time interval of a total wave (hours), which is the time gap between the last departure flight and the first arrival flight in a flight wave.
- Wave height (W_H): the peak number of flights in an arrival wave or a departure wave. To improve the description of wave-system structure, we proposed this index.
- Wave connection time (T_C): the connection time (minutes) between two neighboring flight waves, which is the time gap between the last departure flight of the $(N\text{-}1)^{th}$ wave and the first arrival flight of the N^{th} wave.

In addition, to compare the timetable co-ordination and connectivity of airline hubs, the so-called connectivity ratio (CR) of each airline at its hub airport is calculated according to equation (1) proposed by Doganis (2002):

$$\mathrm{CR} = \frac{n_c}{n_r} = \frac{n_c}{n_d \frac{MACT-MCT}{T}} = \frac{N_c/n_a}{n_d \frac{MACT-MCT}{T}} \tag{1}$$

suppose that $i = 1, \ldots, n_a$ is a flight arriving at the airline hub during the time period T, $j = 1, \ldots, n_d$ a flight departing form the hub during the time period T. When the time interval between the departure time of flight j ($t_{d,j}$) and arrival time of flight i ($t_{a,i}$) belongs to the scope of [MCT, MACT],[1] $m_{ij} = 1$; otherwise $m_{ij} = 0$. $N_c = \sum_i \sum_j m_{ij}$. N_r is the approximate number of viable connections that is expected to occur in case of a purely random arrival and departure distribution across T. T is one airline operational day, usually 15–18 h.

[1] MCT is the minimum connect time, which is usually 45 min; MACT is the maximum acceptable connect time, which is usually 90 min.

Table 1
Descriptive information of sample airlines at hub airports.

Variable	Description	Num.	Unit	Min	Max	Mean
Flightnum_airlines	Total number of airlines' daily flight	29	thou.	1.580	80.253	36.771
Flightnum_airport	Total number of airport's daily flight	29	thou.	2.665	15.978	6.521
Flightnum_aa	Total number of airline's daily flight at the hub airport	29	thou.	0.734	12.657	3.625
Flightrate_airlines	The rate of airline's daily flight at the hub airport in the total daily flight of the airlines	29	%	3.93	71.77	19.76
Flightrate_airport	The rate of airline's daily flight at the hub airport in the total daily flight of the hub airport	29	%	22.15	94.65	55.11
Flightdist_airlines	Average distance of airline's daily flight at the hub airport	29	km	0.865	5.048	1.958
Intflight_rate1	The rate of airline's daily international flight at the hub airport	29	%	0.00	100	35.16
Intflight_rate2	The rate of airline's daily international flight at the hub airport (flights in the same IATA regional code are not international ones)	29	%	0.00	74.29	20.17
Fleet_airlines	Airline's fleet scale at the end of 2016	29	thou.	0.082	1.603	0.708

Table 2
Configuration information of 14 wave-system structures.

Region	Airport-Airlines	W_N	Avg. W_A	Avg. W_L (hr)	Avg. W_H	Avg. T_C (min)
Europe	AMS-KL	5	280	2	150	30
	FRA-LH	5	730	4	430	45
	MUC-LH	5	560	4	60	45
	CDG-AF	7	660	4	120	30
U.S.A.	DFW-AA	9	1240	2	100	30
	CLT-AA	9	800	2	150	45
	MIA-AA	9	530	2	400	30
	ATL-DL	12	1360	2	300	15
	ORD-UA	9	450	2	150	30
	IAH-UA	10	670	2	200	30
	DEN-UA	10	430	2	175	30
	HOU-WN	7	290	2.5	160	30
Asia	ICN-KE	2	350	4	80	30
	TPE-CI	4	130	2.5	35	15
Avg.		**7**	**600**	**2.5**	**179**	**30**

3.1.2. Bootstrapped binary logistic regression

A binary logistic regression model can describe the relationship between a dependent variable and multiple independent variables. This approach models the probability of presence and absence of the binary dependent variable, while the independent variables could be a mixture of continuous and categorical or binary variables (Ozdemir, 2011). Supposed that when the dependent variable (Y), flight schedule of an airlines at a hub airport, follows a wave-system structure, we set Y = 1; otherwise, we set Y = 0. Meanwhile, there are m independent variables (x_i, i = 1, ,m). The probability (π) of Y = 1 can be predicted according to equations (2)–(5):

$$\pi = \mathrm{P}(\mathrm{Y}=1|x_1,\quad x_2,\ldots,x_m) = \frac{e^{\left(\beta_0+\sum_i \beta_i x_i\right)}}{1+e^{\left(\beta_0+\sum_i \beta_i x_i\right)}} \tag{2}$$

$$\mathrm{P}(\mathrm{Y}=0|x_1,\quad x_2,\ldots,x_m) = 1-\pi \tag{3}$$

$$\text{odds} = \frac{\Pr(Y=1)}{\Pr(Y=0)} = \frac{\Pr(Y=1)}{1-\Pr(Y=1)} = \frac{\pi}{1-\pi} \tag{4}$$

$$\text{Logit}\quad \mathrm{P} = \ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_m x_m \tag{5}$$

where β_0 is the constant; β_i are the parameters of the independent variables to be estimated. Details of the binary logistic regression model can be found in Hosmer and Lemeshow (2000). The odds is the probability of Y = 1 divided by the probability of Y = 0, and it takes value between 0 and ∞. If the probability of Y = 1 is higher than the probability of Y = 0, odds is larger than 1. Logit P is the logarithmic conversion of the odds (called the Logit), which is supposed to have linear relationships with the independent variables.

Considering the sample size is less than 30, in order to ensure the reliability and significance of parameter estimation, the parameters of the binary regression model are estimated on 3000 bootstrapped data by using bootstrap resampling method (Vinod, 1993).

3.1.3. Partial least square regression (PLSR) model

After analyzing the determinants of wave-system structure, the determinants of configuration of wave-system structures (five indices) are further analyzed by a PLSR model. The PLSR is to extract the latent factors considering as much of the manifest factor variations as possible while modeling the responses well (Wang et al., 2008). Supposed that $x_1, x_2, \ldots, x_m$ is from the data matrix, X $= [x_1, x_2, \ldots, x_m]$, and y is the size of samples with n dimensions. X can be decomposed into a bilinear form as equation (6):

$$\mathrm{X} = t_1 p_1' + t_2 p_2' + \ldots + t_h p_h' + E_h \tag{6}$$

where $p_1', \ldots, p_h'$ are the loading vectors; $t_1, \ldots, t_h$ are the latent factors; E_h is the residual matrix of X when the first h latent factors are included in the PLSR model. The relation between X and y can be conveyed by the latent variables in equation (7):

$$\mathrm{y} = q_1 t_1 + q_2 t_2 + \ldots + q_h t_h + f_h \tag{7}$$

where the scalar $q_1, \ldots, q_h$ are the loading value of y and f_h is the residual vector of y when the first h latent factors are included in the PLSR model. The details of calibration were described in Wang et al. (2013).

3.2. Data collection

To identify the determinants of wave-system structures, three types of statistical data were collected from the database of Official Airline Guide (OAG), and both typical network airlines and hub airports from three main air transport regions (North America, West Europe and Asia-Pacific) were taken as study objects:

- The daily flight information of 16 large network airlines on January 2, 2017, including 4 European carriers, 4 American carriers, 4 carriers from Mainland China and Hong Kong and 4 carriers from Chinese Taipei & other Asian countries (see Appendix 1).
- According to the network structures of these airlines, data of 27 hub airports was also collected.
- Data of several variables related to airlines and airports were collected and calculated in Table 1.

According to existing study, the number of flights with indirect connections should be considered and introduced into the identification of wave-system structure. However, as we know, the fast development of e-commerce and internet technology gave birth to the of online travel agency platforms (Castillo-Manzano and López-Valpuesta, 2010). According to the consolidated information of flight schedules on the platforms, passengers can easily arrange their flight schedules and book their online air tickets (Jeon et al., 2019). It reveals that any viable connecting flights in a whole flight wave can be booked at the hub airports by the passengers own. Thus, instead of flights with indirect connections, the numbers of both arrival and departure flights were

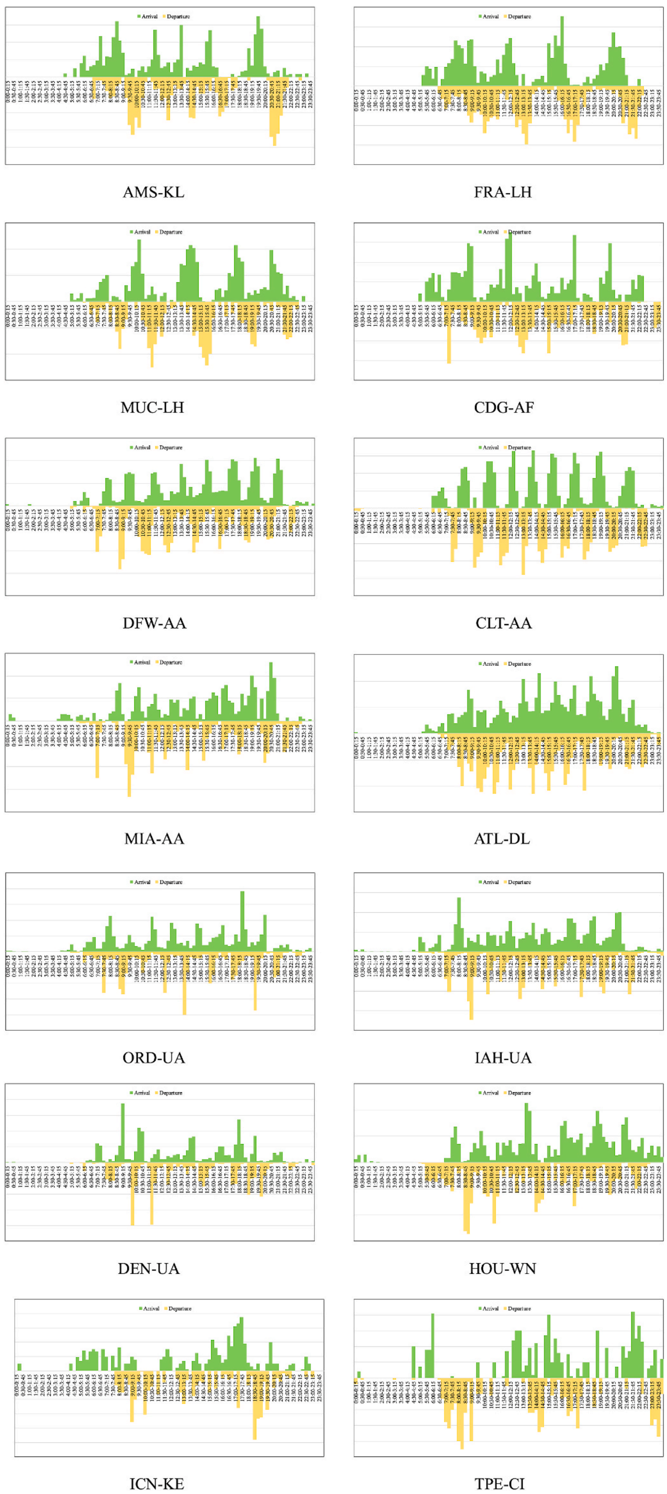

Fig. 2. Wave-system structures of 9 airlines at 14 hub airports.

collected and took into consideration.

4. Results analysis

4.1. The identification of wave-system structures

According to the timetable of 16 airlines' daily flights at 27 hubs and the suggestions of both airport and airline operators, the numbers of flights in each 15-min interval of a whole day were tallied. Out of the 29 airlines-airport pairs, the flight schedules of 9 airlines at 14 hub airports followed the wave-system structure. The configuration information of wave-system structures was shown in Table 2 and Fig. 2, respectively. Meanwhile, the CR value of each airline-hub, computed based on Table 2 and Equation (1), is shown in Table 3.

Table 3
Connectivity ratios (CRs) of 29 airline hubs.

Airline-hub with wave-system structure		Airline-hub with no wave-system structure	
AMS-KL	6.61	LHR-BA	1.75
FRA-LH	2.57	EWR-UA	1.27
MUC-LH	2.40	DEN-WN	1.68
CDG-AF	1.83	BWI-WN	1.24
DFW-AA	1.39	DAL-WN	1.22
CLT-AA	2.12	LAS-WN	1.14
MIA-AA	1.83	MDW-WN	1.05
ATL-DL	2.73	PHX-WN	1.29
ORD-UA	1.25	HND-NH	1.32
IAH-UA	1.91	SIN-SQ	1.11
DEN-UA	1.36	HKG-CX	1.24
HOU-WN	1.25	PEK-CA	0.98
ICN-KE	0.64	PVG-MU	0.98
TPE-CI	1.63	SHA-MU	0.35
		CAN-CZ	1.31

Table 4
Classification table.

Observed		Predicted		
		Feedback (FB)		Percentage Correct
		0	1	
Feedback (FB)	0	13	2	86.7
	1	2	12	85.7
Overall Percentage				86.2

Note: The cut value is 0.500.

According to the statistical results in Table 2, we found that some results can be concluded as following. First, in Europe, all the network airlines organized the wave-system structures at their hub airports except the British Airways (BA). The British Airways (BA) considered the London Heathrow International Airport (LHR) as a rolling/continuous hub instead. In the U.S.A., although network airlines also organized wave-system structures at their hub airports, the flight schedules of Southwest Airlines (WN) at other hub airports were not following the wave-system structure. In Asia, the wave-system structure was not widely organized by network airlines at their hub airports. Only Korean Air (KE) and China Airlines (CI) organized wave-system structures at their hub airports, respectively.

Second, three largest Chinese network airlines (Air China, CA; China Southern Airlines, CZ; China Eastern Airlines, MU) did not organize wave-system structures at their hub airports, which is against the results of Huang and Wang (2018). In addition, according to the results of other researches (Sun and Su, 2013; Li et al., 2016), some network airlines organized wave-system structures at their hub airports between domestic arrival flights and international departure flights or domestic departure flights and international arrival flights. However, there are no wave-system structures existed in the left 15 pairs of airlines-hub airports when considering the schedules of domestic arrival flights and international departure flights or schedules of domestic departure flights and international arrival flights according to the statistic results of flight schedules.

Third, the configurations of wave-system structures of different airlines are largely different at each hub airport. It reveals that the American network airlines have organized more flight waves at their hub airports (in most cases 9 or more) than those of other network airlines at their hub airports (<6 waves per day) in the world. The average wave

Table 5
Bootstrap for variables in the equation.

Variable	B	Bootstrap[a]				
		Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
					Lower	Upper
Constant	−7.028	−57.161[b]	402.825[b]	0.002[b]	−346.902[b]	−3.795[b]
Fleet_airlines	0.006	0.047[b]	0.355[b]	0.008[b]	0.002[b]	0.277[b]
Flightnum_aa × Intflight_rate2	−0.002	−0.014[b]	0.094[b]	0.074[b]	−0.164[b]	0.000[b]
Flightrate_airlines × Flightrate_airport	52.311	391.216[b]	2433.193[b]	.002[b]	30.339[b]	2606.053[b]

Note:
[a] Unless otherwise noted, bootstrap results are based on 3000 bootstrap samples.
[b] Based on 2999 samples.

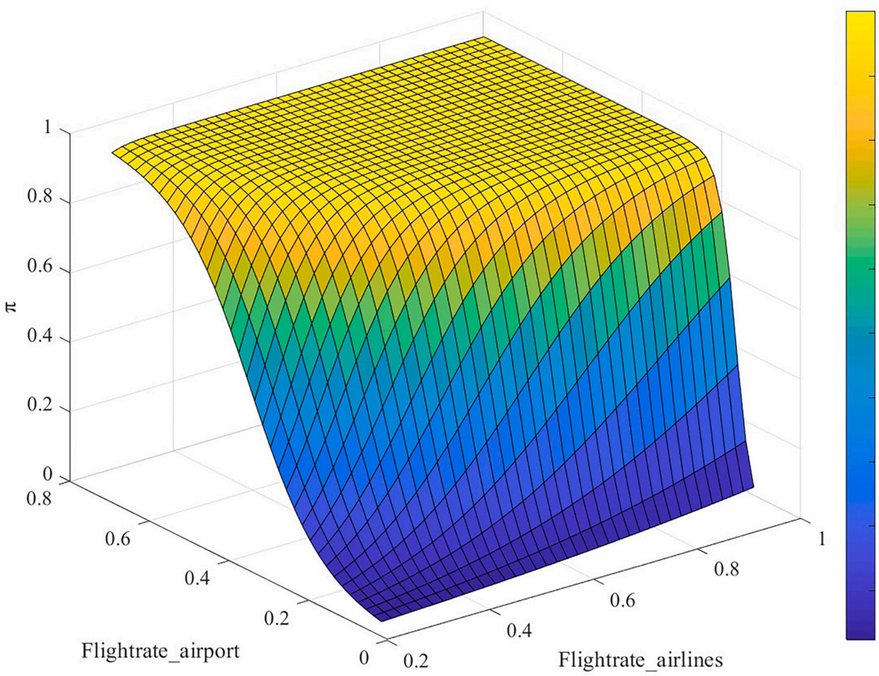

Fig. 3. Interaction surface plot of Flightrate_airlines and Flightrate_airport.

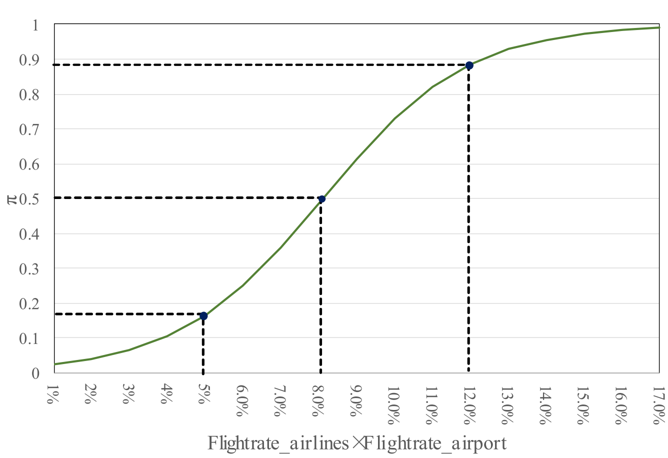

Fig. 4. Interaction curve plot of Flightrate_airlines and Flightrate_airport.

density (W_N) is 7 per day, average wave degree (W_A) is 600 flights per arrival-wave or departure-wave, the average wave length (W_L) is 2.5 h and the average wave connecting time (T_C) is 30 min. Last but not the least, the height of wave is related to the degree (W_A), and the average wave height is about 150 fights.

Finally, the connectivity ratios (Avg. value = 2.13) of airline-hubs with a wave-system structure are higher than those (Avg. value = 1.17) without a wave-system structure. The KLM-Royal Dutch Airlines (KL) has the highest connectivity ratio at Airport Schiphol (CR = 6.61) based on the rational structure of wave systems while most Asian airlines have the lowest connectivity ratios at their hub airports ($CR_{SHA\text{-}MU}$ = 0.35, $CR_{ICN\text{-}KE}$ = 0.64, $CR_{PEK\text{-}CA}$ = 0.98, $CR_{PVG\text{-}MU}$ = 0.98, $CR_{SIN\text{-}SQ}$ = 1.11). Thus, the relationship between structures of wave system and airline-hub connectivity ratios needs further investigation.

4.2. Factors influencing wave-system structures

Considering the variables in Table 1 as potential impact factors, the possible correlations among independent variables were tested and considered into the estimation. According to Pearson Correlation Test in Appendix 2, the correlations between some variables is high. Thus, the interaction effects of these variables were also included into the bootstrapped binary logistic regression model. The results of parameters estimation are shown in Table 4 and Table 5.

According to Table 4, the overall percentage of correctness by the bootstrapped binary logistic regression model is 86.2%, which reveals that this model has a good fitness for uncovering the impact factors of wave-system structure of network airlines at their hub airports. The significant values in Table 5 reveal that only 1 variable and 2 interaction

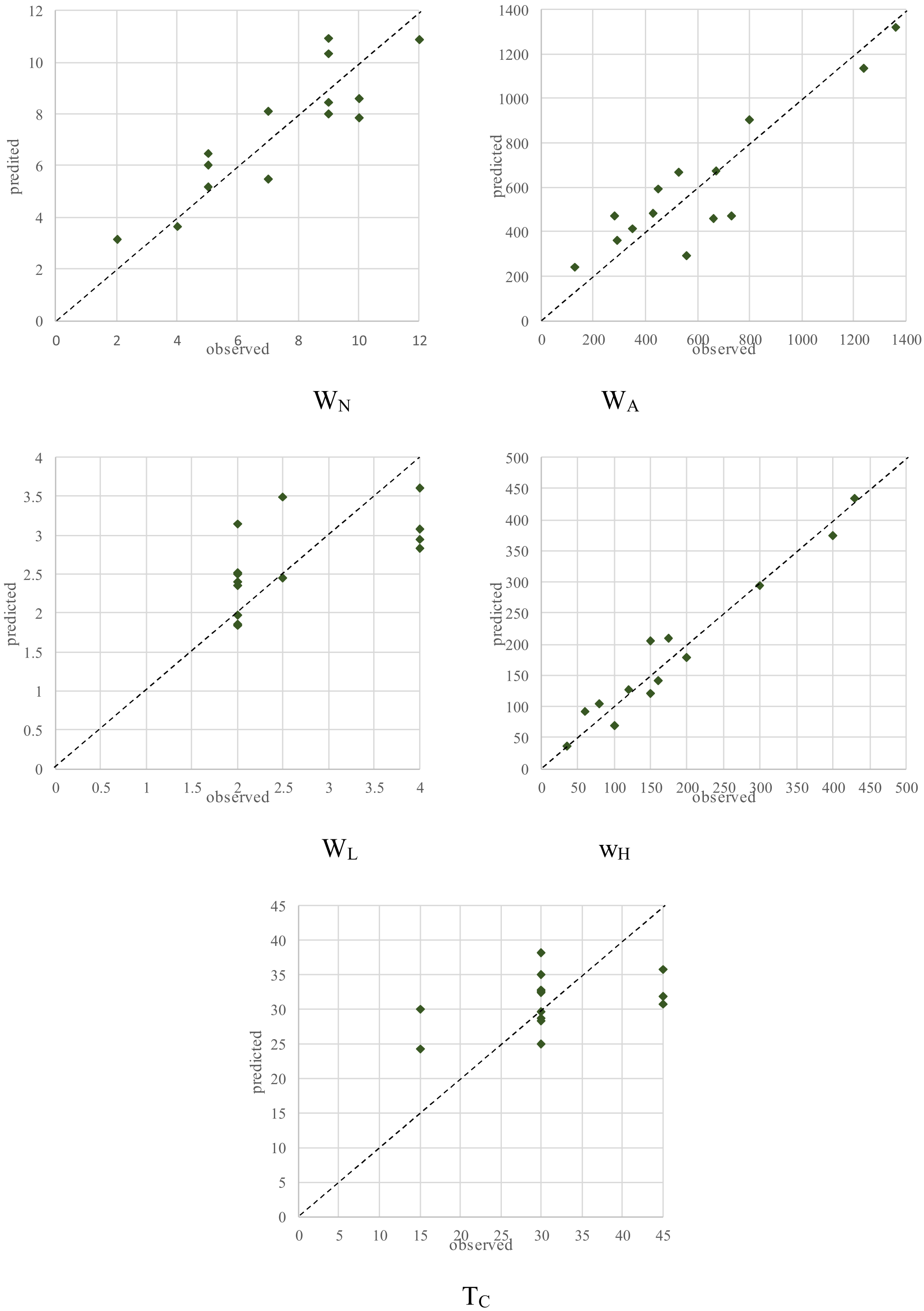

Fig. 5. Fitting plot of PLSR models.

items have significant impacts (at least at 10% significant level) on the organization of wave-system structures of airlines.

First, the negative value of constant (−7.208) indicates that the baseline odds is $e^{-7.028} = 0.001$, and airlines are unwilling to organize wave-system structures initially. Meanwhile, the positive parameter (0.006) implies that a larger fleet scale of the airlines leads to slightly higher probability (odds $= e^{0.006} = 1.006$) of organizing a wave-system structure at hub airports.

Second, out of our expectation, the number of daily flights of airlines at hub airports has no significant impact on the organization of wave-system structures. Further, considering the close relations with the ratio of international flights, the interaction effect of number of daily flights of airlines at hub airports and the ratio of international flights also has slightly negative impacts (exp(-0.002) = 0.998) on the probability of organizing a wave-system structure.

Third, the interaction effects of Flightrate_airlines and Flightrate_airport has the most important and positive impact (exp(52.311) = 5.268E+22) on the probability of organization of wave-system

Table 6
Estimated parameters of PLSR models.

Variables	W_N	W_A	W_L	W_H	T_C
Constant	4.6822	−77.9903	3.2280	−60.9179	39.3048
Fleet_airlines	0.0011	0.1316	−0.0003	0.0499	−0.0001
Flightrate_airport	2.1468	120.1197	−0.4916	52.0802	2.6072
Flightrate_airlines	−1.9237	376.6013	0.4654	112.2962	−12.7475
Intflight_rate2	−2.4373	152.4318	0.5730	35.6805	−9.1695
Flightnum_aa	0.0003	0.0811	−0.0001	0.0283	−0.0011

Note: Number of principal components = 2, cross-validation = −0.018514.

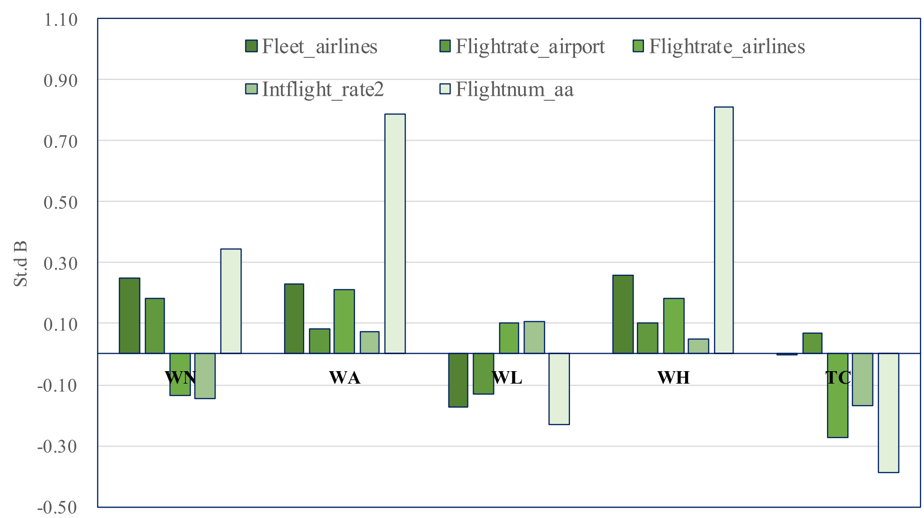

Fig. 6. Standardized estimated parameters of the PLSR models.

structures. While holding other variables, including Fleet_airlines, Flightnum_aa and Intflight_rate2, in the model constant at their mean value (707.59, 3624.55 and 0.202, respectively), the estimated probabilities for an interaction plot of Flightrate_airlines and Flightrate_airport is shown in Fig. 3 and Fig. 4. When the value of interaction effect is within the range of [0.05, 0.12], the probability of organizing a wave-system structure presents a nearly linear increase. Further, if the value of interaction effect is large than 0.0811, the probability of wave-system structure organization would be higher than 0.5. Taken the probability of 0.6 as the bottom line of organizing the wave-system structure, a network airline company could organize flights at a hub airport when the product of its Flightnum_aa and Intflight_rate2 is 0.55, and the product of its Flightrate_airlines and Flightrate_airport is 8.9% with a fleet scale of 707. Furtherly, the potential combinations of two types of product provide the airlines with different types of operational mode.

4.3. Determinants of wave-system structures' configuration

Taking the five indices of wave-system structures as dependent variables and those discussed in section 4.2 as independent variables, a PLSR model was estimated. The goodness of fit of the model is shown in Fig. 5. Although both W_L and T_C are numeric variables, the actual value of them seems to belong to three categories. Thus, except W_L and T_C, the PLSR models have a good fitness for the configurations of wave-system structures.

The results of estimated parameters and related standardized parameters are shown in Table 6 and Fig. 6, respectively. According to the estimated results of standardized parameters in Fig. 6, some findings can be drawn as following. First, among the 5 independent variables, Flightnum_aa (as high as 0.8095) has the foremost absolute impact on the configurations of wave-system structures. The airlines' fleet scale (as high as 0.2597) has the second important impact on the configuration of wave-system structures while Flightrate_airlines and Intflight_rate2 have similar impacts on the configurations of wave-system structure. Similar to the role in organizing the wave-system structures, the impact of Intflight_rate2 (as low as 0.0505) on the configuration of wave-system structures is the smallest.

Second, according to the definitions, wave density (W_N) has a negative relationship with wave length (W_L), compared with wave density (W_N), independent variables have opposite impacts on the wave length (W_L). The airline which organizes a larger number of daily flights (Flightnum_aa) to get a higher flight share (Flightrate_airport) at the hub airports prefer to organize higher wave density (W_N) at hub airports when the fleet size (Fleet_airlines) of the airline is larger. However, the number of airline's daily flight at the hub airports (Flightrate_airlines) should be a small part of its total daily flight scale, while its international flights (Intflight_rate2) should be a smaller part of the total number of hub airport's daily flights. Thus, the airlines have to organize their daily flight schedules at their hub airports to balance the wave density and wave length. Meanwhile, the impacts of both wave degree (W_A) and wave height (W_H) have high similarity with each other because both two indices are used to describe the shape of wave-system.

Finally, except Flightrate_airport, other independent variables have different impacts on wave connection time (T_C). The independent variable of Fleet_airlines has smaller impact on T_C than other dependent variables including Flightnum_aa. Meanwhile, other four independent variables have negative impacts on the wave connection time, which is a trade-off between the wave shape (W_N, W_A, W_L and W_H) and wave connection gap (T_C) for the decision makers of airlines.

5. Conclusions and suggestions

Organizing wave-system structures of at hub airports has been considered as one of the efficient strategies to improve the operational performance for network airlines worldwide. Based on the flight schedules of several largest airlines at their hub airports and existing theory of wave-system structure, this paper tries to uncover the impact factors of both wave-system structures and its configurations using bootstrapped binary logistic regression model and partial least square regression model, respectively. Three main findings can be concluded.

First, among the 29 airline-hub pairs only 14 pairs organized different shapes of wave-system structures, and the CRs reveal that airline-hubs with wave-system structures have higher connectivity ratios than those without any shapes of wave-system structures. However, Asian airline-hubs have the lowest connectivity ratios.

Second, the interaction effect of two types of flight rates (Flightrate_airlines and Flightrate_airport) has the biggest and positive impact on the probability of organization of wave-system structures, which is against the existing opinions that the wave-system structure is determined by the rate of airlines' daily flight at the hub airport in the total daily flight of the hub airport[2] (Flightrate_airport).

Third, when considering the configuration of wave-system structures at hub airports, the variable, Flightnum_aa, has the biggest impact on five indices of wave-system structures. However, the decision makers have to balance the negative relations between wave density (W_N) and wave length (W_L), and different impact directions of independent variables on different indices of wave-system structures.

In addition, this paper uncovered the determinants of wave-system structures of network airlines at hub airports based on the wave-system structure theory. Future research, including detailed wave-system structure identification, wave-system structures comparison, and measurement of hub airport's connectivity and temporal coordination under different flight schedules, should be given fully consideration to improve the organization of wave-system structures at hub airports by network airlines.

Author statement

Yonglei Jiang: Conceptualization; Writing - original draft; Jing Lu: Data curation; Tao Feng: Writing - review & editing, Formal analysis. Zhongzhen Yang: Writing - review & editing, Formal analysis.

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Appendix 1. Sample Information

Region	Airlines	Hub airports
Europe	Air France (AF)	Paris Charles de Gaulle Airport (CDG)
	British Airways (BA)	London Heathrow International Airport (LHR)
	KLM-Royal Dutch Airlines (KL)	Airport Schiphol (AMS)
	Lufthansa German Airlines (LH)	Flughafen München (MUC)
America	American Airlines (AA)	Charlotte/Douglas International Airport (CLT)
		Dallas-Fort Worth International Airport (DFW)
		Miami International Airport (MIA)
	Delta Air Lines (DL)	Hartsfield-Jackson Atlanta International Airport (ATL)
	United Airlines (UA)	Denver International Airport (DEN)
		Newark Liberty International Airport (EWR)
		George Bush Intercontinental Airport (IAH)
		O'Hare International Airport (ORD)
	Southwest Airlines (WN)	Baltimore-Washington International Thurgood Marshall Airport (BWI)
		Dallas Love Field airport (DAL)
		Denver International Airport (DEN)
		William P. Hobby Airport (HOU)
		Las Vegas McCarran International Airport (LAS)
		Midway International Airport (MDW)
		Phoenix Sky Harbor International Airport (PHX)
Mainland China & Hong Kong	Air China (CA)	Beijing Capital International Airport (PEK)
	China Southern Airlines (CZ)	Guangzhou Baiyun International Airport (CAN)
	China Eastern Airlines (MU)	Shanghai Pudong International Airport (PVG)
		Shanghai Hongqiao International Airport (SHA)
	Cathay Pacific Airways (CX)	Hong Kong International Airport (HKG)
Chinese Taipei & other Asia countries	China Airlines (CI)	Taiwan Taoyuan International Airport (TPE)
	Singapore Airlines (SQ)	Singapore Changi Airport (SIN)
	Korean Air (KE)	Incheon International Airport (ICN)
	All Nippon Airways (NH)	Tokyo International Airport/Haneda Airport (HND)

[2] http://editor.caacnews.com.cn/mhb/html/2013-01/24/content_112324.htm.

Appendix 2. Pearson Correlations between variables

	Flightrate_airport	Intflight_rate1	Intflight_rate2	Flightrate_airlines	Flightdist_airlines	Flightnum_aa	Flightnum_airport	Flightnum_alines	Fleet_airlines
Flightrate_airport	1	-.465*	-.497**	-.487**	-.591**	.581**	.041	.692**	.624**
Intflight_rate1	-.465*	1	.831**	.880**	.785**	-.403*	-.325	-.794**	-.671**
Intflight_rate2	-.497**	.831**	1	.749**	.918**	-.351	-.217	-.640**	-.485**
Flightrate_airlines	-.487**	.880**	.749**	1	.755**	-.266	-.142	-.771**	-.644**
Flightdist_airlines	-.591**	.785**	.918**	.755**	1	-.514**	-.324	-.659**	-.609**
Flightnum_aa	.581**	-.403*	-.351	-.266	-.514**	1	.790**	.570**	.740**
Flightnum_airport	.041	-.325	-.217	-.142	-.324	.790**	1	.317	.545**
Flightnum_alines	.692**	-.794**	-.640**	-.771**	-.659**	.570**	.317	1	.875**
Fleet_airlines	.624**	-.671**	-.485**	-.644**	-.609**	.740**	.545**	.875**	1

*: Correlation is significant at the 0.05 level (2-tailed); **: Correlation is significant at the 0.01 level (2-tailed).

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