Comparing Scheduled Block Time Setting in Europe and China Based on Multiple Linear Regression

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Abstract—Improving air transport system performance while not impeding and supporting traffic growth is a big challenge in civil aviation all over the world. Scheduled block time plays an important role in airline flight scheduling, which in return is a driver of capacity-demand-balance of air traffic management. In this context, a proper method of setting the scheduled block time is beneficial to air transport performance. In this study, the setting behavior was analyzed by comparing between China and Europe. A model based on multiple linear regression was developed and fitted separately with Chinese and European operational data. A hub airport analysis was carried out to support the fitting. The coefficients of the fitting results were compared and discussed according to the differences in ATM system characteristics between both regions. In general, the fitted model explains the schedule block time setting well with R² of above 0.8 for both regions, however significant differences exist for the different coefficients.

Keywords - air transportation; scheduled block time; behavior analysis; multiple linear regression; collaboration;

I. INTRODUCTION

The world’s air traffic industry is in an era of quick development. In 2016, the number of controlled flights increased by 2.4%, and the total growth of passenger numbers was 5.1% in Europe [1]. At the same time, China have been seeing great increase in traffic volume in recent 10 years. The average annual growing rate of air transport was 9.7% from 2006 to 2016 [2]. While the increasing number of flights brings economic thrive to the nations, there is also increasing operational pressure on air navigation service providers (ANSP) to limit constraints on flight operations. Scholars from all over the world are seeking solutions to enhance aviation system performance while not impeding and supporting traffic growth.

Flight scheduling is the central element of an airline’s planning process, aimed at optimizing the deployment of the airline’s resources in order to meet demand and maximize profits [3]. Flight scheduling is a systemic problem of a combination of route development, schedule design, fleet assignment, maintenance routing and crew pairing [4]. The approach varies between different airlines, because of their market position, selection of city accessed, and allocation of other resources. Schedule design is the part of airline business planning that concerns air traffic management (ATM) most. It plays a core role in determining air traffic demand and affects air transport system performance by influencing the capacity-demand-balance.

Block time (also called aircraft hours) is based on “block-to-block” time (i.e. from the moment the aircraft is pushed back from the gate or starts taxiing from its parking stand for take-off to the moment it comes to a final stop at a gate or parking stand after landing) [5]. A flight timetable is formed with several block times together with turnaround times. Normally airline schedulers prepare flight timetables six months before operation. The foreseen flight time in the timetable is named scheduled block time (SBT). Fig. 1 illustrates the different components of SBT [6].

![Figure 1. Decomposition of Flight Time](image)

When schedulers set SBTs for flight legs (i.e. airport pairs), they have to make compromises to balance airlines’ operational profit and passengers’ on-time expectations. A longer SBT leads to higher flight punctuality but with lower profit because of the reduced number of flight legs, while a shorter SBT increases the risk of flight delays and results in
passenger complaints and associated economic costs [7]. In addition to the direct impact on airlines, SBT setting influences the operational performance of the air traffic network as limited ANSP resources (capacity) are planned on the basis of the flight schedule (planned demand). Thus, an optimized SBT setting solution benefits in both airline operation and ATM system performance.

There are many drivers influencing the actual block time / flight time (FT) of a flight which need to be taken into consideration in SBT setting. Therefore, achieving a commonly used SBT setting approach requires a mapping between those drivers and SBT. In other words, optimization of SBT setting needs a proper SBT model. Practices in SBT setting differ from airline to airline and may be also affected by regional governance and regulations. Aiming at enhancing ATM system performance with SBT optimization, the work reported in this paper provides the following contributions:

- a SBT model based on multiple linear regression was developed and fitted with operational data of Europe and China;
- an analysis of hub airport characteristics was conducted considering the throughput and regional & non-regional connections, in order to support the SBT model;
- a comparison of the coefficients of the fitted European and Chinese SBT model was performed with a view to identify and discuss regional differences;

II. BACKGROUND

A. ICAO – Regional ATM Performance Benchmarking

Operational performance analysis of air transportation and air navigation is essential to address the capabilities of local or regional systems. Operational performance monitoring and reporting has gained a higher visibility through the recent Global Air Navigation Plan (GANP). As part of the GANP process, ICAO promotes regional ATM performance benchmarking. For this a series of commonly accepted key performance indicators (KPI) have been proposed [8].

As part of the establishment of an initial China/Europe ATM comparison report, Civil Aviation University of China (CAUC) and EUROCONTROL’s Performance Review Unit (PRU) collaborate under the ICAO GANP framework. The current set of GANP KPIs addresses actual ATM performance (e.g. punctuality, capacity / throughput, and efficiency). However, the framework lacks of proposed KPIs to assess the level of demand satisfaction. SBT modelling can fill the gap by supporting a measure of planned user demand between airport pairs.

B. China/Europe Comparison Work and System Descriptions

China and Europe show similarities in civil aviation systems. In terms of airspace volume, China covers an area of 10.8 million km², while Europe has 11.5 million km².

In China, Air Traffic Management Bureau (ATMB) of Civil Aviation Administration of China manages the national air traffic services, civil aviation communications, navigation, surveillance (CNS) and aviation meteorology and flight information. In 2016, there are 8522 registered air traffic controllers in China, providing ATC service for 4.96 million flights. Air traffic service provision in Europe is predominantly performed on national level resulting in 62 en-route centers (ACCs) and a high number of local air traffic service units. The only multi-state unit is the Maastricht Upper Area Control Centre serving traffic over 4 states. In total, air traffic services are provided by 17 370 controllers to 10 million flights. Next to airspace and associated procedure design, the Network Manager ensures in collaboration with the national and local flow management functions strategic through tactical flow management. The Network Manager represents therefore a pan-European centralized function.

Fig. 2 illustrates the busyness of Chinese and European airspaces by yearly flight hours per squared kilometer. It can be seen that high-density-areas are located in the middle in China, which can be considered as corridors. A similar traffic concentration is visible in Europe. Given the nature of air traffic in Europe traffic characteristics are expressed as complexity score rather than density. The annual complexity score shown in Fig. 3 combines traffic density (concentration of traffic in space and time) and the intensity of potential interactions between traffic (structural complexity). Within the EUROCONTROL area the complexity score increased further in 2016 and reached 6.9 minutes of potential interactions with other aircraft per flight hour in the airspace [1].

Figure 2. Traffic density in China
On the airport level there is a stronger difference between China and Europe in terms of traffic characteristic. Fig. 4 shows the airports’ yearly throughput distribution from 2014 to 2016. 30 main airports in each region were taken into consideration. The throughput at European airports ranges between 150 thousand and 500 thousand yearly movements. In particular, a group of 3 major airports accrue 400 to 450 thousand flights per year. A different distribution is seen in China, where at the top airports an annual throughput of more than 600 thousand was observed. Very few airports fall into the middle scale of the figure with a larger number of airport throughputs ranging between 100 and 200 thousand. In a word, main airports in Europe have similar operating capacities, while greater variance is seen in Chinese airports. This phenomenon is better shown in Fig. 5, where annual number of arrivals and departures at Chinese and European airports are illustrated. Within China, 2 airports (ZBAA and ZSPD) show a yearly traffic share of more than 250 thousand arrivals and departures, while most of the airports are ranging below 100 thousand. On the contrary, top airports in Europe fall into the range between 200 thousand and 250 thousand, well below the top Chinese airports. Nevertheless, the majority of the Europeans range between 100 thousand and 200 thousand. In other words, air transport demands in China reveal a higher concentration at the biggest airports. In Europe, however, main airports are contributing shares of traffic demand in a relatively equal way. The air traffic is therefore wider spread across Europe (c.f. Fig. 2 and 3) with several major airports forming the core nodes of the European network.

C. Literature Reviews

SBT setting has been studied by several scholars and there exists a body of knowledge in the literature. Steven Coy built an SBT estimation model based on operational data, while block time reliability was not considered in the work [9]. Milind Sohoni et al. defined metrics of service level based on block time reliability, and further developed a model to maximize airlines’ profit by changing flight departure time [10]. Christopher Mayer et al. studied the record of 67 million flights between 1988 and 2000 and found that SBT is approximately equal to the median of actual block time of flights without departure delay [11]. Lu Hao et al. analyzed flight time from a predictable point of view, and modeled SBT setting behavior of airlines using multiple regression [12].

III. Methodology

The overall workflow of the research reported in this paper is illustrated by Fig. 5.
Firstly, the state-of-the-art was studied. Based on scholars’ previous results, together with industry practice, a model based on multiple linear regression was developed to model SBT setting behavior in China and Europe. Afterwards, operational data of China and Europe for the years 2014 through 2016 were pre-processed separately, to form datasets for SBT modeling of each region. Then a study to empirically characterise hub airports was conducted by analyzing airports’ connectivity in operation. This supported the definition of “hub airport” in a generally admitted way in both regions. Based on the preparatory work, the model was fitted to model SBT setting behaviors. Last but not least, values of fitting coefficients in each region were compared to identify the differences in SBT setting between China and Europe.

A. Model Configuration

In China, Flight Planning Office (FPO) of Operational Monitoring Center in Civil Aviation Administration of China (CAAC) publishes a table of Standard Block Time (StaBT) every year, covering all city pairs (origin: O, destination: D) with regular flights in China. Airlines in China take the StaBT table as a reference, and make decisions of their SBTs. The FPO was interviewed for their method of StaBT setting. They use software developed by a research group, with the input of the historical flight data of the previous year, to generate a draft version of new StaBT table. The algorithm used in the software is not open to public. Then they compare the table with the one of the previous year and identify the mostly changed StaBTs. They send the found ones to relevant airlines together with new OD pairs with scheduled flights. At last, the FPO organize a meeting with the airlines to decide the final StaBT table.

In the table, StaBT changes according to OD pair, season (Winter-Spring or Summer-Fall) and cruise speed of aircraft (Mach number). Table I is a sample line of StaBT.

<table>
<thead>
<tr>
<th>OD Pair</th>
<th>Season</th>
<th>M0.8</th>
<th>M0.7</th>
<th>M0.6</th>
<th>M0.5</th>
<th>M0.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZLXY-ZSOF</td>
<td>Summer-Fall</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>130</td>
</tr>
<tr>
<td></td>
<td>Winter-Spring</td>
<td>95</td>
<td>105</td>
<td>110</td>
<td>110</td>
<td>130</td>
</tr>
</tbody>
</table>

In industrial practice, the airlines don’t have to set SBT strictly according to StaBT table. They take StaBT as a reference and set SBT according to their own pattern of operation.

There is no centralized SBT process in Europe. Similar to the practice in China, airlines set their final SBT based on their internal business priorities and the availability of airport slots. Within certain limits and for slot controlled airports, the IATA slot coordination process acts as a centralized process where demand and airport capacity, including local and national constraints, are balanced. The local airport capacity declaration also considers the capability of the air navigation system to satisfy airspace user demand. All the European airports in this study are fully coordinated (i.e. summer and winter season). Accordingly, the flights operating between the study airports represent a ‘centrally’ coordinated network. The derived airline schedule therefore builds on the slot coordination system and the SBT process reflects the accessibility of city pairs in light of this system.

According to relevant departments or companies, statistics of historical FT records form the basis of SBT setting in Europe and China. In order to study the mechanism how the historical block time distribution affects SBT setting, a multiple linear regression model was developed based on former work [12] and StaBT setting approach in China and the approximation of a European network between fully slot controlled airports.

A daily schedule for an aircraft comprises turnaround times, departure delays, taxi-out times, en-route flying times and taxi-in times. The historical analysis of these times supports the setting of the SBT except turnaround times. Table II shows the result of summary statistics of the operational time between Beijing Capital International Airport (ZBAA) and Shanghai Pudong International Airport (ZSPD) while Table III shows the example of London Heathrow Airport (EGLL) and Frankfurt International Airport (EDDF). Departure delays, with the greatest standard deviation and coefficient of variation, are the major drivers of variance in both regions. Similarities are also shown in en-route flying times and taxi-in times. The time of these two phases are relatively stable. The biggest
difference is in the taxi-out times. Greater variance is shown in China compared with Europe. This can be seen as a result of different strategies in push back orders. According to these, the contribution of departure delay and taxi-out time was emphasized, while en-route flying time and taxi-in time were the contribution of departure delay and taxi-out time was different strategies in push back orders. According to these, China compared with Europe. This can be seen as a result of difference is in the taxi-out times. Greater variance is shown in China compared with Europe. The three combined in SBT modeling.

In the modeling of SBT, flight time is divided into three parts to capture the variation of different phases. The three parts are:

- taxi-out (TO) time: TO is the time difference between wheels-off time and actual off-block time (AOBT);
- non-taxi-out (nonTO) time: nonTO is the time difference between actual in-block time (AIBT) and wheels-off time, as a combination of en-route flying time and taxi-in time; and
- departure delay (dep); dep is the time difference between AIBT and scheduled departure time.

The SBT model is defined as (1):

$$\text{SBT}_{f,y} = a_1 \times \text{TO}_{f,y} + a_2 \times \text{nonTO}_{f,y} + a_3 \times \text{dep}_{f,y} + \sum_{i=1}^{5} \beta_i \times \text{dTO}_{f,i+4,j+5} + \sum_{i=1}^{5} \lambda_i \times \text{dnonTO}_{f,i+4,j+5} + \varepsilon_y \times \text{HUB}_{f,y} + \delta \times \text{Vortex} + \pi \times \text{GCD} + \mu \times \text{Season} + \text{const}$$

where

- $\text{SBT}_{f,y}$ is the SBT of flight leg $f$ in year $y$. 
- $\text{TO}_{f,y}$, $\text{nonTO}_{f,y}$, and $\text{dep}_{f,y}$ refer to the 50th percentile or median of the taxi-out time, non taxi-out time, or departure delay.
- $\text{dTO}_{f,i+4,j+5}$, $\text{dnonTO}_{f,i+4,j+5}$, and $\text{ddep}_{f,i+4,j+5}$ represent the the difference between every adjacent pair of 10th percentiles of $\text{dTO}$, $\text{dnonTO}$ and $\text{ddep}$ above the median. E.g. $\text{dTO}_{f,i} = \text{TO}_{f,i} - \text{TO}_{f,5}$.
- Generally speaking, the 100th percentile refers to the most extreme condition. In these circumstances, the main factor influencing flight time is the extreme condition instead of most common operations, which should not be taken into account for the SBT setting. In this study, the 100th percentiles were replaced by the 99th to remove the effect of outliers.
- $\text{HUB}_{0}$ and $\text{HUB}_{2}$ is a pair of dummy variables indicating whether the origin or destination airport is a hub airport. They are used in investigating the influence of SBT setting by hub airports. If the origin/destination airport is hub, $\text{HUB}_{0}/\text{HUB}_{2}$ is set to 1. As reported above, an empirical approach to describing the hub characteristic of an airport was applied in this study.
- $\text{Vortex}$ is a dummy variable indicating the aircraft is either a wide-body or narrow-body, and is set to 1 for wide-body aircrafts, and to 0 for narrow-body aircrafts.
- $\text{Season}$ is another dummy variable to study the influence of seasonal changes in SBT. In China, the StaBT is varying according to the season. In Europe, there are seasonal changes in terms of flight connections between the selected study airports. The Winter-Spring season starts on the last Sunday of October and ends on the last Saturday of March. $\text{Season}$ is set to 1, if the date of the flight is in Winter-Spring season, and to 0 if it’s in Summer-Fall season.
- $\text{GCD}$ refers to the great circle distance between OD pairs and is calculated as:

$$\text{GCD} = R \times \arccos(\cos(Lat_o) \times \cos(Lat_d) + \sin(Lat_o) \times \sin(Lat_d) \times \cos(Lon_o - Lon_d))$$

where $Lat_o$ and $Lat_d$ are latitudes of the OD pair while $Lon_o$ and $Lon_d$ are longitudes. $R$ is the radius of earth (6371km).

B. Data Preparation

As presented in Fig. 6, this study included careful data pre-processing based on a harmonized interpretation of available data or their generation was conducted before the regression.

The work aimed at studying SBT setting behavior in China and Europe. Thus, only flights within China or within Europe were taken into consideration. Overflights and cross border flights were deleted firstly for this reason. Because of the
incompletion of dataset, key information to the modeling was missing in some of the flight records, thus these pieces of data were given up. In the regression, we assume that SBT is only resulted from historical data of the previous year, which means data of 2014 was used in the fitting of SBT in 2015, and data of 2015 was used in the fitting of SBT in 2016. To fulfill this idea, for every available SBT data in 2015 or 2016, values of its variables should be able to be calculated. In other words, flight records are only considered, if there are flights with the same OD pair in the previous year.

In the fitting of Chinese SBT model, a dataset consisting several kinds of messages recorded from flight operation were introduced. It includes date, flight number, aircraft type, mission type (domestic, overflight or cross border flight), scheduled departure time, scheduled arrival time, actual off-block time (AOBT), wheels off time (take off time), wheels on time (landing time), actual in-block time (AIBT), etc. The data covers all flights within China’s airspace from year 2014 to 2016, which is totally 17.1 million flights. Among which, 5.77 million flights in 2015 and 5.99 million in 2016 directly became SBT information contributors while flights in 2015 together with 5.35 million flights in 2014 supported historical time distributions calculation in the model. After data pre-processing, approximately 7.55 million pieces of data were finally used in the modeling.

The European air traffic network was approximated by all flights between 20 main airports. These 20 main airports were chosen based on the cumulative number of flight connections of OD pairs. The associated operational data is collected by PRU through the airport operator data flow for each airport under the EUROCONTROL Performance Review System. These data comprise the aforementioned timestamps and flight related data. For the approximated network, the respective arrivals and departures between the chosen airport pairs were mapped to establish a flight-by-flight record. The dataset covered all flights within the network from 2014 to 2016. After data processing, approximately 2.55 million pieces of data were used in the fitting of European SBT model.

C. Hub Airport Analysis

The regional comparison made it necessary to harmonise the understanding of what a “hub” airport is. Despite the pervasive use of the term, there is not a globally accepted definition. Conceptually, the term applies to the “hub-and-spoke” network model. This model foresees the concentration of passenger and flight operations at a set of major airports. Traditionally, the hub-and-spoke optimizes airline resources when operating between many destinations and across different regions. Accordingly, the term hub airport is also related to a high number of international air traffic.

One element of the operating model of an airline is the choice of the route network and application of a hub-and-spoke or more point-to-point network approach. It must be noted that both concepts are to be understood as extremes in the establishment of the route network. Although the hub-and-spoke model is attributed to legacy flag carriers, and point-to-point to low cost carriers, neither form of route choice is applied in its pure form by both. However, this decision has a direct bearing on the SBT setting.

Figure 7. Ratio of non-regional connections to total number of connections

In the absence of a globally accepted definition of hub airport, this project studied a numerical approach to qualify hub characteristic. Based on the aforementioned route choice concept, the ratio of non-regional connections to the total number of air services at an airport has been studied. Fig. 7 depicts the results for the airports considered in this study. For readability reasons not all airport location indicators are shown.

In general, the 20 European airports used in this study show a higher level of non-regional flight connections and total connections. Working with a qualitative threshold of 100 non-regional connections, ZGGG, ZSPD, and ZBAA range above the threshold and show a ratio of above 0.45 which is illustrated by the red line. In Europe this applies to EGLL, EDDF, and LFPG. While in Europe the concentration effect is dispersed over a high share of the airports, there seems to be a power law distribution in China that directly correlates with the traffic numbers and geographic concentration of air traffic (c.f. Fig 2 and Fig 4)

D. Regression Coefficients Estimation

Ordinary least-square (OLS) method was used to estimate coefficients of fitting. Table IV shows the result, where $R^2$ in both regions are more than 0.8, showing that the model followed SBT setting behavior well.

A low p value in the fitting result means a significant relationship between the variable and SBT. In China, all of the variables have a p value less than 0.01% except for $d_{dep_{0,5}}$ and a p value of 1.51% is tolerable in most cases. Despite a similar $R^2$, the fitting results for Europe question the expressiveness of
certain model variables. In particular 6 out of 24 variables have an insignificant relationship with SBT. Fortunately, the study is aimed at analyzing SBT setting behavior instead of predicting SBT values. Therefore, it is not a bad result.

### TABLE IV. COEFFICIENT ESTIMATION RESULT

<table>
<thead>
<tr>
<th>Variables</th>
<th>China</th>
<th>Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coefficient</td>
<td>p value</td>
</tr>
<tr>
<td>Intercept</td>
<td>13.6613</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>T0h,5</td>
<td>0.1845</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>nonT0h,5</td>
<td>0.5421</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>dep,5</td>
<td>0.0317</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>dT0h,6</td>
<td>0.0823</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>dT0h,7</td>
<td>0.0262</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>dT0h,8</td>
<td>0.0267</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>dT0h,9</td>
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<td>&lt; 0.0001</td>
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<td>dT0h,10</td>
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<td>&lt; 0.0001</td>
</tr>
<tr>
<td>dnonT0h,5</td>
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</tr>
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<td>dnonT0h,9</td>
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<td>ddep,5</td>
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<td>ddep,9</td>
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<td>HUBh</td>
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<td>HUBD</td>
<td>2.3286</td>
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<tr>
<td>Vortex</td>
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<tr>
<td>GCD</td>
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<td>Season</td>
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<tr>
<td>R²</td>
<td>0.8499</td>
<td></td>
</tr>
</tbody>
</table>

### E. Comparison between China and Europe

The result of the fitting shows the similarities and differences in SBT setting between China and Europe. The three medians showing a general length of operation, are main factors of flight time, and obviously influence the SBT. Their coefficients refer to the weights of the medians in SBT setting. nonT0h,5 has the largest coefficient among the three medians, while dep,5 has the smallest. It can be summarized that in both regions, SBT is set mainly according to historical actual block time, and departure delay plays a minor role. Fig. 8 illustrates the coefficients of the percentile variables where the Chinese coefficients are shown in red and the Europeans in blue. Peaks can be found on the medians. Moreover, the coefficients of the percentiles of TO and nonTO show a descending trend, indicating that the effect of historical actual block time on SBT setting is decreasing with the location of its distribution moving towards 100th percentile. This is in line with the general observation that the 100th percentile would include also the extreme observations potentially distorting the predictive power of common operations. More variations are shown in the coefficients in Europe. They also show a decreasing trend, but reverses exist in dT0h,8, dnonT0h,8 and ddep,5. This phenomenon indicates SBT is mainly influenced by the median and the 70th percentile.

The coefficients of HUBh and HUBD are positive in China, but negative in Europe, which reflects differences in the operation of hub airports. In China, business passengers contribute a big share in air traffic, which leads to huge air traffic demand in big cities, as mentioned in previous section of this paper. Nevertheless, airport capacities in these cities
cannot satisfy the demand, leading to inefficiencies at hub airports. Thus, the flight time increases when the flight leg services a hub airport, and this leads to an increasing SBT. In Europe, punctuality at hub airports remain at a high level, and the flight delay ratio is not necessarily higher than other airports. Moreover, air traffic is widely spread across the approximated airport network. As a result, coefficients of the hub variables in Europe are small negative numbers.

The cruise speed of wide-bodied aircraft is generally faster than of narrow bodied. The coefficient of Vortex follows this observation. Its negative value shows that SBT are shorter when it comes to an aircraft with a wake vortex type of heavy.

The temperature in winter and spring is lower than summer and autumn. Low temperature leads to higher density of the air, and further result in lower airspeed if the aircraft’s lift remains the same. This phenomenon confirms the negative coefficients in both regions.

A very interesting result is shown in the coefficients of GCD. The value is positive in China while negative in Europe. Conceptually, great circle distance and flight time should be positively correlated. The coefficient in China follows this rule. Nevertheless, the negative value of coefficient in Europe contradicts the general rule. A possible explanation of the result is that the great circle distance is linearly related to the percentiles of the different flight time phases. The coefficients of TO$_{0.5}$, nonTO$_{0.5}$ and dep$_{0.5}$ in Europe are all greater than in China. Obviously, this is not necessarily showing that flight time in Europe is longer than China. Actually, the negative coefficient of GCD weakens the effect of great values of the medians’ coefficients. In a word, this phenomenon is a result of the behavior of the multiple linear regression, instead of an anti-natural effect.

V. CONCLUSIONS AND DISCUSSIONS

In this paper, SBT setting in China and Europe were studied. For both regions a model based on multiple linear regression was fitted with operational data for 2014 through 2016. Results show that the model well follows SBT setting. Comparison between China and Europe were made according to coefficients in the fitting result. And the differences in SBT setting behaviors were discussed.

Multiple linear regression is a data driven method for mapping between dependent and independent variables. It is an effective approach when an obvious quantitative relationship between dependent and independent variables does not exist. Normally, analysis on the linear correlation among the variables, which supports multiple linear regression model, should be carried out. In this study, the model developed covered all potential variables related to SBT setting in order to capture the SBT setting behavior. The analysis of the linear correlation among the variables was absent. As a result, many of the variables were clearly correlated. Under this condition, some variables’ coefficients were negative even though they should be positively related to SBT. This phenomenon leads to misleading results of model fitting.

To carry out a further investigation on SBT setting, the flight time can be disintegrated according to different phases. And studies on the phases can be conducted separately. In this paper, discussions were limited to the SBT setting behavior and its relationship with ATM system characteristics. Based on the developed model a study on the relationship between SBT setting behavior and flight schedule performance can be achieved in future. New SBT can be calculated by using new coefficient values which represent different SBT setting strategies. An associated flight schedule can be generated with such new SBT and the shift of demand can be analyzed by comparing the generated schedule with the original. What’s more, flight time prediction can be achieved with the developed model. The model can be simplified by removing variables with duplicated contribution through principle component analysis, to form a more concise model.

This study is the first application of linear regression to investigate regional SBT behavior as part of an international benchmarking project. It builds a basis for further collaborative work in the future and can serve as an additional metric for regional comparison projects under the ICAO GANP framework.

REFERENCES


