Estimation of Standard Operation Time of Flight Legs Based on Clustering and Probability Analysis

Yuan Ligang, *Hu Minghua* *, *Xie Hua*, *Li Yinfeng*

College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, P. R. China

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Abstract: A clustering algorithm and a probability statistics method were applied to different phases of a flight to analyze operation time during aircraft ground taxiing and airborne flight. And the clustering pattern, distribution characteristics and dynamically changing rules of the two phases were identified. Further, an estimate method was established to measure operation time of flight legs, with creative steps of calculating individual segment separately and then integrating them accordingly. The method can both objectively and dynamically measure operation time, and accurately reflect real situation. It helps to better utilize airport slot resources and provides a strong support for air traffic flow management when scheduling flight plan in strategic and pre-tactic phases.

Key words: flight leg; standard operation time; clustering; probability analysis

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0 Introduction

With the rapid increase of air traffic flow in China, the imbalance between demand and supply in flight slot resources has challenged operational management. Air traffic management (ATM) has focused on how to scientifically formulate advanced flight plans and make full use of airport slot resources. Further, a standard operation time of flight legs is critical to establishing and checking flight schedules. Therefore, how to fairly and effectively estimate the standard operation time is a key issue faced by flight scheduling planners.

Some domestic and foreign airlines have carried out relevant research. Based on their operating data, they have made comparative analyses on different seasons, and set the standard operation time of flight legs in the corresponding flight route according to their respective strategies. Their estimations usually involve operation strategies (e. g. economical cruise and minimum flight time), cost control and performance assessment, etc. However, these processes are somewhat limited and selfish, and are difficult to be used as unified references for flight scheduling and coordinating. Since 2007, Eurocontrol has carried out annually periodic performance evaluation of its air traffic management[1]. Later, it cooperated with Federal Aviation Administration to contrast operations between Europe and USA[2], and discussed time deviations in different phases of flight operation as well as key phases leading to deviations. Because of its high uncertainty, taxi-out phase has been extensively studied in terms of its prediction and measurement[3-5]. Some studies focused on calculating time delay and variation related to runway and taxiway under dynamic and random conditions; others focused on the short-term prediction of taxi-out time to enhance the accuracy of prediction by queuing model[6-7] or reinforcement learning algorithm[8-9]. As most of the studies aimed at the needs of airports or airlines and adopted probability analysis based on histori-

* Corresponding author, E-mail address: minghuahu@nuaa.edu.cn.

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cal data for time calculation, they failed to fully reflect the law of change of flight leg operation. Also, with only a certain operation phase as the object, they focused on real-time operation of flights, while failing to effectively estimate the overall operation time of flight legs. Therefore, they provide only a limited support for air traffic flow management when scheduling advanced flight in the strategic and pre-tactical phases.

With regard to current relatively rough statistical methods, we explored clustering models, distribution characteristics and dynamic rules in each phase of flight leg operation from big data through data mining and probability analysis, in order to establish an overall, effective estimation method for the standard operation time of flight legs. We separately analyzed the time required by taxi-out phase, airborne flight phase and taxi-in phase and integrated them accordingly, therefore we enhanced the accuracy of operation time estimation. The method is consistent with the characteristics of flight leg operation and current control capabilities. Moreover, the feasibility of this method has been verified by typical example.

1 Analysis on Operation Time of Flight Legs

1.1 Definition of standard operation time of flight legs

Flight leg refers to the scheduled air transport route of an aircraft with a certain commercial load between two cities. The concept of standard operation time of flight legs is used to objectively measure the reference time of flight operation from one city to another, therefore to reflect the average level of flight operation under normal conditions. Definition elements include: airport of departure, airport of arrival, aircraft type and season, etc.

From the perspective of time span, flight operation starts from off-block time (push-back time) and ends at in-block time (push-in time), covering taxi-out, flight (airborne) and taxi-in phases[5,10]. Therefore, the standard operation time of flight legs is the total time spent of these three phases. Taxi-out time is defined as the duration of actual off-block to departure, taxi-in time from arrival to actual in-block, and flight time the actual airborne flight time.

1.2 Characteristic analysis of operation time of flight legs

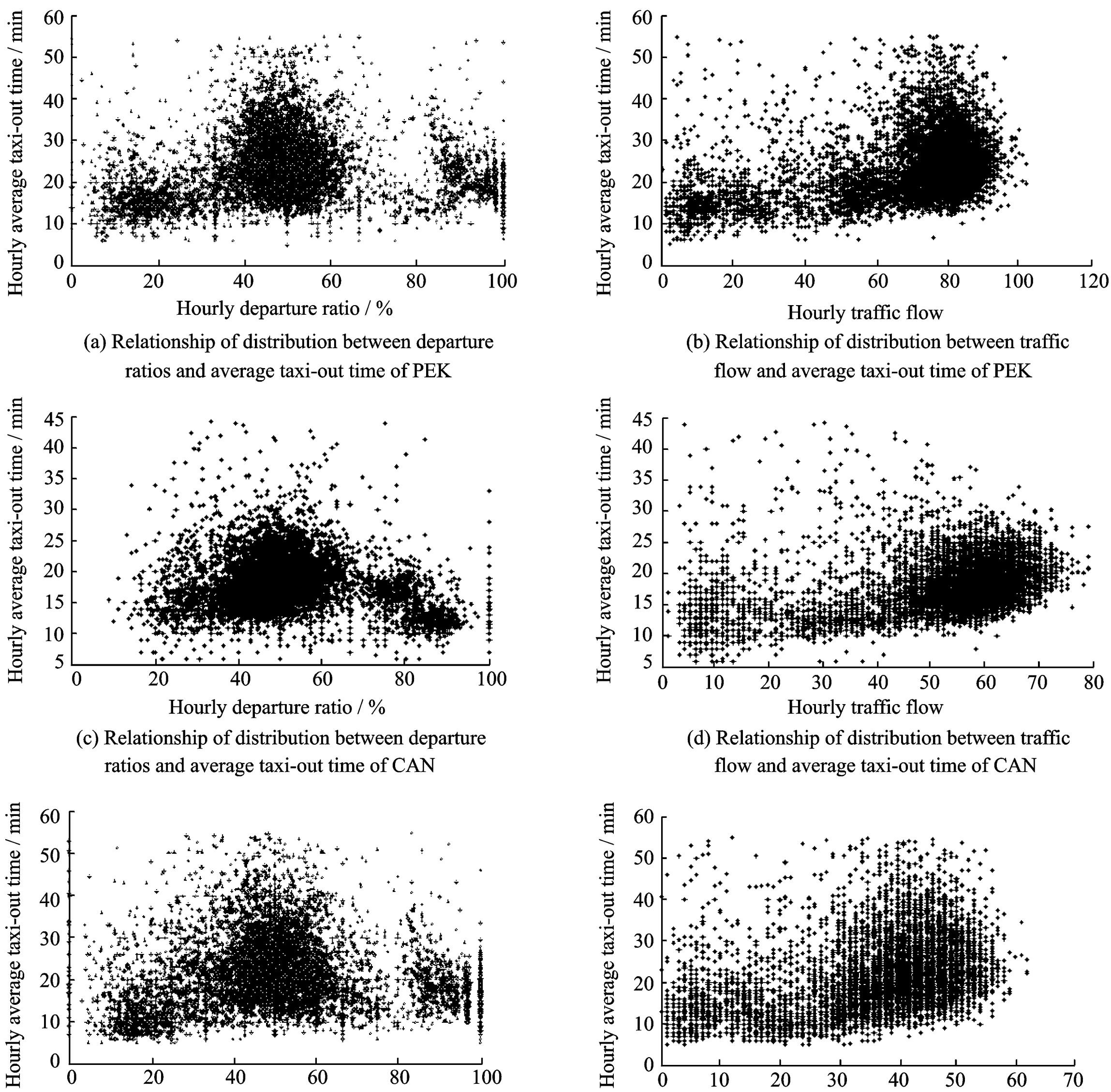
Since operations of the three phases are independent from each other and influenced by different factors, they are analyzed separately.

1.2.1 Analysis of taxiing time based on clustering algorithm

Calculating and predicting taxiing time for a certain flight can be more accurate, if positions of parking stand and runway are taken into account. However, the result cannot reflect the overall situation of airport surface operation, and therefore it is more applicable to the tactical phase of air traffic flow management (ATFM). The average taxiing time can be regarded as a reference time for taxi-out phase, which is more suitable for strategic/pre-tactic phases. In typical hub airports, the position relationships between terminal and runway, or terminal and taxiway, may lead to obviously different taxiing times, if flights parking at different terminals. For example, in 2013, at Beijing Capital International Airport (PEK), the average taxi-out time of T1 (Terminal 1), T2 (Terminal 2) and T3 (Terminal 3) was 24.1, 20.4 and 18.2 min, respectively. Therefore, a single terminal of hub airports can also serve as the object of analysis for taxiing phase.

The research data came from the flight plan management system used by air traffic control (ATC) units. The data consists of tow parts: Various flight departure/arrival time and ground taxiing information. Based on the results of correlation analysis, the relationships of relative distribution among average taxiing time, airport traffic flow and arrival/departure ratios are analyzed.

We took Guangzhou Baiyun International Airport(CAN) and PEK as examples. When increasing traffic flow in airports/terminals, taxi-out time of flights was gradually increasing; when departure or arrival ratio was high, taxi-out time remained at a relatively low level; when arrival ratio was approximate to departure ratio and the degree of mixing was high, taxi-out time significantly increased as a whole. Figs. 1(a—d) illustrate these relations. As an independent analysis object, PEK T3 followed the same change pattern, as shown in Figs. 1(e—f).



(a) Relationship of distribution between departure ratios and average taxi-out time of PEK

(b) Relationship of distribution between traffic flow and average taxi-out time of PEK

(c) Relationship of distribution between departure ratios and average taxi-out time of CAN

(d) Relationship of distribution between traffic flow and average taxi-out time of CAN

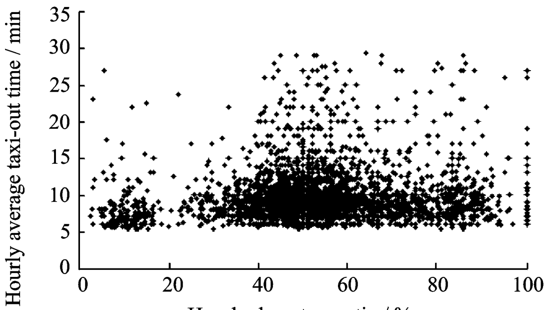
(e) Relationship of distribution between departure ratios and average taxi-out time of PEK T3

(f) Relationship of distribution between traffic flow and average taxi-out time of PEK T3

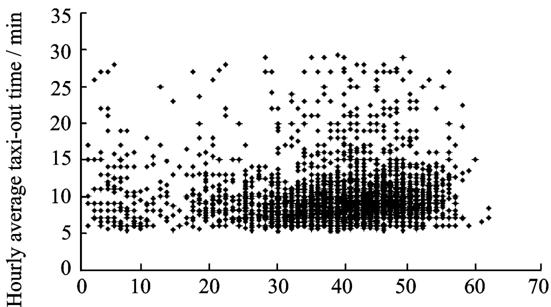
Fig. 1 Relationship of distribution between taxi-out time and other variables

Similar phenomenon also occurred in taxi-in phase of flights, as shown in Fig. 2. However, compared with taxi-out phase, its range of variation is relatively weakened.

As Figs. 1,2 show quite obvious clustering, based on the data conditions of large samples, efficient C-means clustering algorithm applicable to continuous attributes should be considered for partitioning[11]. Its main idea is to utilize iterative process to divide data set into different classes, so as to achieve intra-class compactness and inter-class independence. Clustering aims at separately exploring the characteristic patterns of taxi-in and taxi-out phases, with taxiing time, traffic flow



(a) Relationship of distribution between arrival ratios and average taxi-in time of PEK T3



(b) Relationship of distribution between traffic flow and average taxi-in time of PEK T3

Fig. 2 Relationship of distribution between taxi-in time and other variables

and arrival/departure ratios as eigenvectors[12].

Table 1 shows the clustering results of taxi-out phase for PEK and PEK T3. Partitioned data has the following characteristic patterns: (1) With high departure ratios and moderate traffic flow, the level of average taxi-out time is low; (2) With low departure ratios and moderate traffic flow, the level of average taxi-out time is the lowest; (3) With arrival ratios approximate to departure ratios and high traffic flow, the average taxi-out time markedly increases.

Table 2 shows the clustering results of taxi-in phases for CAN and PEK T3. It can be found that the level of average taxi-in time of CAN is relatively high with low departure ratios and moderate traffic flow, while the taxi-in phase for PEK T3 is the most time-consuming with relatively balanced arrival and departure ratios and high-load traffic flow. This indicates different operation characteristics between airports. Nevertheless, from the perspective of their distribution relationship, both exhibited obvious traits of classifying and clustering. Compared with taxi-out phase, taxi-in times are less different among various clusters.

Table 1 Clustering results of taxi-out phase of PEK

Attribute	Cluster1	Cluster2	Cluster3
Average taxi-out time of PEK	21.546	17.321	25.578
Traffic flow of PEK	53	31	79
Departfure ratios of PEK/%	89.13	25.21	48.46
Number of sample in cluster	813	1130	4110
Average taxi-out time of T3	18.686	15.941	25.071
Traffic flow of T3	28	20	43
Departure ratios of T3/%	84.36	23.09	49.48
Number of sample in cluster	977	1 274	3 482

Table 2 Clustering results of taxi-in phase for PEK T3 and CAN

Attribute	Cluster1	Cluster2	Cluster3
Average taxi-in time of CAN	8.41	9.09	7.59
Traffic flow of CAN	13	37	59
Arrival ratios of CAN/%	72.191 11	21.117 98	51.287 13
Number of sample in cluster	315	423	2 620
Average taxi-in time of T3	9.293 6	8.309 5	9.635 4
Traffic flow of T3	23	37	44
Arrival ratios of T3/%	79.256 27	20.107 63	51.064 9
Number of sample in cluster	576	309	1 845

Furthermore, the clustered sample data is correlated with statistical time slices for conversion to the proportional relation of samples of different clusters in each time slice. Figs. 3,4 show the data distribution of taxi-out phase for PEK and taxi-in phase for CAN, respectively. Vertical axis of the pictures refers to the percentage of the whole samples which is used in clustering. During a 24-hour operation, clustered data characteristics of taxi phases tend to vary obviously in time frame distribution. From 7:00 to 9:00, most of the flights depart from airports. The taxi-out phase is characterized by Cluster 1, while the taxi-in phase is mainly characterized by Cluster 2. From 9:00 to 23:00, due to arrivals mixing with departures as well as heavy traffic flow, the characteristics of Cluster 3 of taxi-in/taxi-out phases are obvious. From 22:00 to early morning, when flights are mainly inbound, Cluster 2 is characteristic of taxi-out phases, and Cluster 1 is characteristic of taxi-in phases.

Therefore, we attempted to extract operation characteristics according to different time distributions in airports/terminals, therefore to meas-

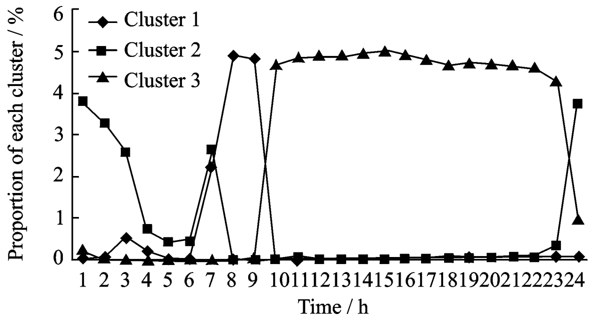


Fig. 3 24-hour sample distribution of each cluster for taxi-out phase of PKE

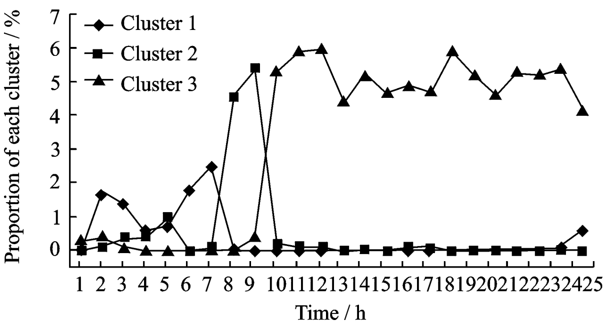


Fig. 4 24-hour sample distribution of each cluster for taxi-in phase of CAN

ure the time of taxi phases in a dynamic and differentiated way. The approach can enhance the accuracy and applicability of reference , and narrow down the deviation from actual situations.

1.2.2 Flight time analysis based on probability distribution

Compared with taxiing phases during arrival and departure, airborne flight phase is affected by numerous factors including airline flight strategies, flow control, weather (monsoon), destination airport and terminal area capacity, etc. , resulting in volatile operation times and highly discrete data. Therefore, key variables, like flight time, destination airport traffic and arrival/departure ratios, can neither reflect significant correlation in value, nor present remarkable traits for different time distribution clusters. As shown in Figs. 5,6, clustering is not as obvious as taxiing phase. All clusters are overlapped in time, without apparent changing pattern. In spite of this, clustering results, to some extent, can reflect changing characteristics of operations at destination airport. For example, the timeframes with high proportion of Cluster 1 correspond to peak hours of departure, while those of Cluster 3 mirror peak hours of arrival.

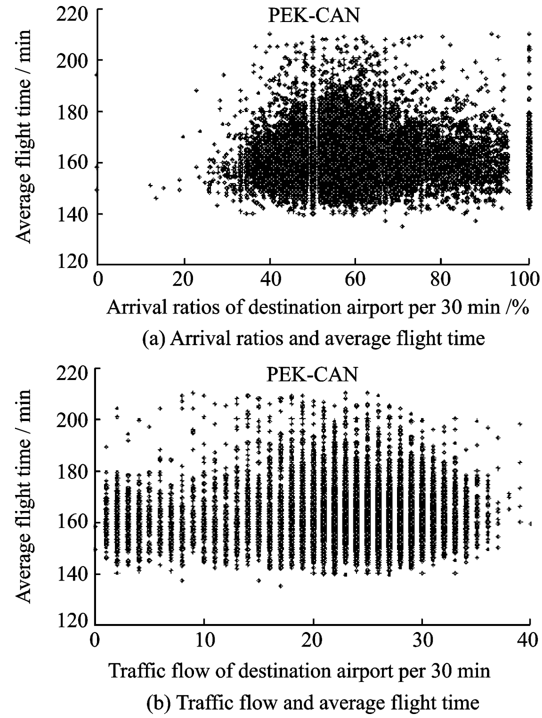


Fig. 5 Relationship of distribution between flight time and other variables

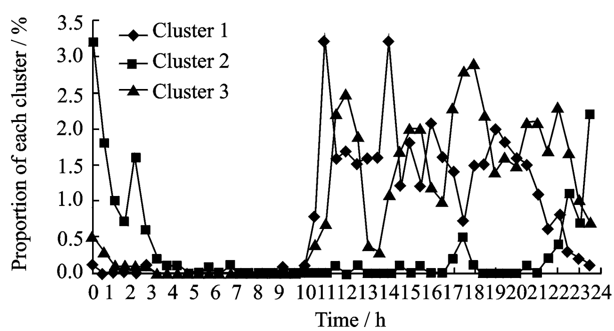


Fig. 6 24-hour sample distribution of each cluster for airborne flight phase from PEK to CAN

Operating reference times, currently adopted by airlines and ATC authorities, varies in seasons, mainly because of normal influence of monsoon on flight. The relative HL-LOW relationship between the actually measured data and the long-term mean value is compared by introducing the concept "anomaly" into meteorology. Take the flight leg from PEK to CAN as an example. the mean flight time of the leg from April 2010 to March 2013 as the long-term mean was used to measure the relative variation trend of monthly mean flight time. As shown in Fig. 7, flight time tends to periodically vary with winter-spring and

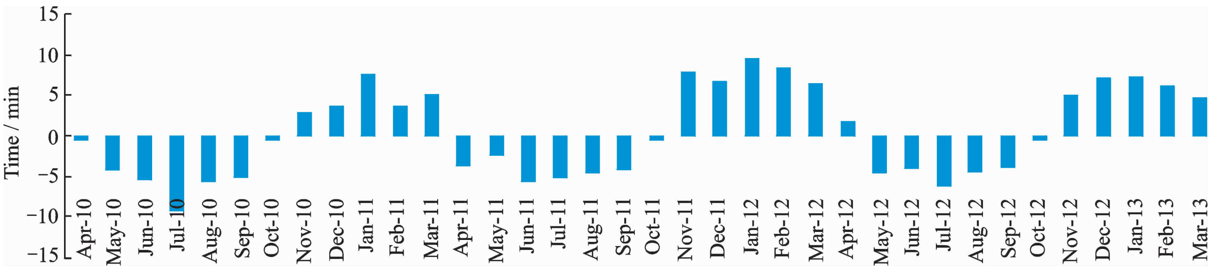


Fig. 7 Anomaly state of average flight time for PEK-CAN

summer-fall seasons. January and July witness the highest "anomaly" state due to objective factors like special weather, holiday demand variation and so forth.

Furthermore, assuming that flight time is a random variable following certain statistical distribution, non-linear fitting is made accordingly[13-14]. If meteorological and traffic control factors are ignored, cruising speed of aircraft will impose the most immediate impact on flight time. Cruise Mach number can be used as a reference to classify aircraft types. For example, we analyzed the data of flight legs from PEK to CAN in the winter and the spring of 2012 in terms of unspecified aircraft types and specified aircraft types(0.8—0.89 M), and found they followed Gaussian distribution (GaussAmp), Cauchy distribution and Logarithmic normal distribution (LogNormal). As flight time is actually in slight right-skewed distribution, the LogNormal distribution of data and logarithms has a higher degree of fitting, described as Eq. (1). The fitting results are shown in Figs. 8—9. The fitted functions are illustrated in Eqs. (2),(3). And Table 3 shows the fitting output of different distribution function.

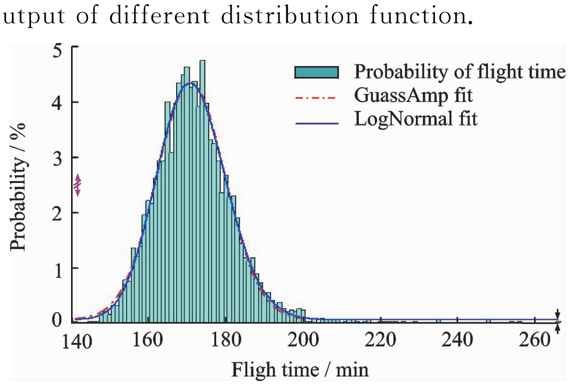


Fig. 8 Probability distribution of airborne flight time for PEK-CAN in winter and spring

$$f(x)=y_0+\frac{A}{\sqrt{2\pi}wx}\mathrm{e}^{\frac{-\left[\ln\frac{x}{x_c}\right]^2}{2w^2}} \tag{1}$$

$$f(x)_{\mathrm{all}}=0.057+\frac{95.35}{\sqrt{2\pi}\times 0.052x}\mathrm{e}^{\frac{-\left[\ln\frac{x}{171.1}\right]^2}{0.054}} \tag{2}$$

$$f(x)_{0.8}=0.088+\frac{93.48}{\sqrt{2\pi}\times 0.05x}\mathrm{e}^{\frac{-\left[\ln\frac{x}{169.9}\right]^2}{0.0048}} \tag{3}$$

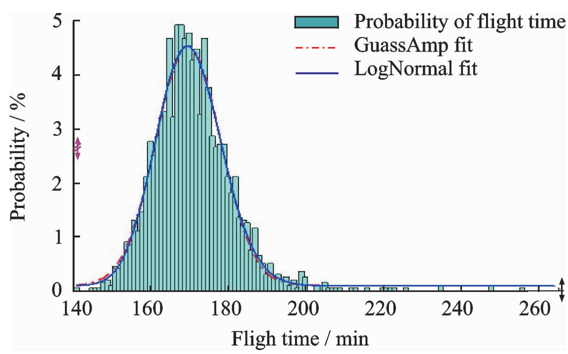


Fig. 9 Probability distribution of airborne flight time (aircraft type as 0.8—0.89 M) for PEK-CAN in winter and spring

Table 3 The comparison of different non-linear fitting

Fitting result	Unspecified aircraft type		Aircraft type (0.8—0.89 M)	
	GuassAmp	LogNormal	GuassAmp	LogNormal
Adj. R-Square	0.981 98	0.985 36	0.959 67	0.969 36
Root-MSE	0.188 63	0.180 33	0.287 16	0.275 32
Standard error	0.031 06	0.029 96	0.052 26	0.049 54
F value	2 106.407	2 306.763	941.599	1 025.852
Prob>F	0	0	0	0

Numerous fitting results demonstrated that flight time could well conform to LogNormal distribution for different time spans (seasons/months) or various aircraft in flight legs in different directions. Its stable probability distribution characteristics are conducive to flight time estimation and sample selection.

2 Design of Estimation Methods for Standard Operation Time

Based on the analysis of distribution characteristics of operation time in different phases of flight legs, an overall estimation method for the standard operation time of flight legs was designed. The specific steps are stated as follows:

Step 1 Screen abnormal data of flight operation

The historical data of flight operation, gleaned from air traffic service telegraphs and aircraft communication addressing & reporting system, contains time information, such as departure/arrival time and in-block/off-block time, aircraft type information and company information. Wild data are identified when they exhibit the following traits: (1) Inconsistency between scheduled departure/arrival airports and actual departure/arrival airports; (2) Lack of main time fields or abnormity of message decoding; (3) Flight status indicated as return, diversion or cancel; (4) Abnormal sequence of off-block time/push-back time, actual departure time, actual arrival time, and in-block time/push-in time. Based on initial screening results, operation time of different phases of a specific flight can be calculated and labeled as vector $\boldsymbol{T}_i = [T^{\text{taxiout}}_{A,i}, T^{\text{flight}}_{A-B,i}, T^{\text{taxiin}}_{B,i}]$, where $T^{\text{taxiout}}_{A,i}$ indicates the taxi-out time of flight i in airport A; $T^{\text{flight}}_{A-B,i}$ the flight time of flight i from airport A to airport B, and $T^{\text{taxiin}}_{B,i}$ the taxi-in time of flight i in airport B.

Step 2 Calculate the operation time of taxi-out/taxi-in phases

On the basis of single flight sample data, the sample set $\boldsymbol{U}^A$ of taxi-out time estimation of airport A can be defined. $\boldsymbol{U}^A = [\boldsymbol{u}^A_1, \boldsymbol{u}^A_2, \cdots, \boldsymbol{u}^A_n]$, $\boldsymbol{u}^A_i \in \mathbf{R}^3$, where $\boldsymbol{u}^A_i$ consists of hourly mean taxi-out time of airport/terminal A, hourly aircraft movements and hourly departure ratios. The departure ratio is the ratio of hourly departure flights to hourly airport traffic flow.

With reference to the analysis results of operating data of taxi phases, C-means clustering algorithm is adopted for partitioning. Its squared error criterion function and cluster center updating formula are Eqs. (4), (5), where k is the number of clusters partitioned

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} |x_j - m_i|^2 \tag{4}$$

$$m_i = \frac{1}{|C_i|} \left(\sum_{x \in C_i} x_j \right) \tag{5}$$

Since C-means algorithm is sensitive to wild value, extreme data may emerge in samples, which needs to be re-filtered during calculation. Its conditions (screening standards) should be determined depending on different airport operations. $\boldsymbol{U}^A$ is divided into n clusters via iteration, with the corresponding cluster center $\boldsymbol{P}$

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & p_{n3} \end{bmatrix}$$

where $\boldsymbol{p}_i = (p_{i1}, p_{i2}, p_{i3})$ is the component value of cluster center of Cluster i. Operation patterns can be recognized according to time distribution characteristics of different cluster samples. A single day can be divided into several timeframes, and the corresponding dynamic taxi-out time of airport/terminal A $T^{\text{taxiout}}_{A,[t_i,t_j]}$ can be set, where $0 \leqslant t_i$, $t_j \leqslant 24$, $t_i < t_j$, referring to the taxi-out reference time of airport A from t_i to t_j. The average taxi-out time component (p_{i1}) of the corresponding cluster center ($\boldsymbol{p}_i$) from t_i to t_j is used as the reference value.

The similar method can be applied to the taxi-in phase. The samples $\boldsymbol{V}^B$, $\boldsymbol{V}^B = [\boldsymbol{v}^B_1, \boldsymbol{v}^B_2, \cdots, \boldsymbol{v}^B_n]$, $\boldsymbol{v}^B_i \in \mathbf{R}^3$ are set. The attribute vector $\boldsymbol{v}^B_i$ comprises hourly mean taxi-in time, hourly aircraft movements and hourly arrival ratio. The samples are also divided into n clusters. The dynamic taxi-in time ($T^{\text{taxiin}}_{B,[t_i,t_j]}$) of airport B can be set base on the results of clustering distribution.

Step 3 Calculate operation time of flight phases

For the flight leg from airport/terminal A to airport B, based on the periodic relative variation characteristics of flight time and demand fluctuations of specific months, the time span of estimation (season/month, etc.) is set, and flight phase samples is set by aircraft types according to cruising speed, labeled as $\boldsymbol{Y}_{A-B}^{\text{flight},0.8\ \mathrm{M}}=[T_{A-B,1}^{\text{flight}},T_{A-B,2}^{\text{flight}},\cdots,T_{A-B,L}^{\text{flight}}]$, where L is the number of flights from airport A to airport B at a cruising speed of 0.8—0.89 M within a statistical timeframe.

Estimation of the standard operation time is to reflect the average level of flight operation in a normal condition, so it is necessary to remove high abnormal data from the samples. The conventional method uses confidence level and confidence interval to eliminate abnormal data, usually leaving low probability value in certain sample sets. The abnormal value recognition method based on single-value probability distribution[15] can be used to prevent abnormal value from being identified irrationally. Generally, abnormal value or isolated point occurs at extreme values. The judgment conditions of maximum and minimum abnormal values in the samples can be set as

$$\rho_{\max}=\max_{i=1,2,\cdots,L}(T_{A-B,i}^{\text{flight},k}) \tag{6}$$

$$\rho_{\min}=\min_{i=1,2,\cdots,L}(T_{A-B,i}^{\text{flight},k}) \tag{7}$$

$$L\times\int_{\rho_{\max}}^{+\infty}f(x)\mathrm{d}x\leqslant\delta \tag{8}$$

$$L\times\int_{-\infty}^{\rho_{\min}}f(x)\mathrm{d}x\leqslant\delta \tag{9}$$

where $f(x)$ refers to the fitted LogNormal distribution function of flight time, and δ the acceptable frequency of abnormal value test, generally taken as 0.2. When the maximum value $\rho_{\max}$ and the minimum value $\rho_{\min}$ in the samples satisfy the above inequality, these maximum and minimum values can be deemed as abnormal, and should be screened from the samples. Then, $\rho_{\max}$ and $\rho_{\min}$ should be updated. The judgment process will be repeated until the inequality is not satisfied.

Screened samples should serve as the estimation basis of flight time. For the sake of fairness, neglecting which airlines the flights belong to, only the overall mean value of effective samples is taken as the flight time for specific seasons/months and particular aircraft types, as described in Eq. (10), where N refers to the number of effective samples screened

$$T_{A-B}^{\text{flight},k}=\frac{1}{N}\sum_{i=1}^{N}T_{A-B,i}^{\text{flight},k} \tag{10}$$

Step 4 Measure the operation time of flight legs comprehensively

According to the definition of standard operation time of flight legs, estimation results of operation time of all phases are integrated. T_{A-B}^{k} indicates the standard operation time of k-type aircraft in the flight leg $A—B$, and is applicable to flight tasks with the scheduled departure time in $[t_i,t_j]$ and the scheduled arrival time in $[t_m,t_n]$, illustrated as

$$T_{A-B}^{k}=T_{A,[t_i,t_j]}^{\text{taxiout}}+T_{A-B}^{\text{flight},k}+T_{B,[t_m,t_n]}^{\text{taxiin}} \tag{11}$$

The applicable operation time within different timeframes of a whole day can be thus determined.

3 Case Verification

The typically busy flight leg from PEK to CAN within China was selected as the object for analysis, and PEK T3 the object for estimation of taxi-out time. Basic data was extracted from the database of "flight plan management system" which recorded the actual departure/arrival time and off-block/in-block time of flights. During winter and spring seasons from November 2012 to March 2013, there are 75 336, 3 497 and 43 707 effective samples of taxi-out, airborne flight and taxi-in phases, respectively. The operation time of each phase was estimated independently, and the results are shown in Tables 4—6. Due to space limitations, the process of calculation is not described here.

Table 4 Dynamic taxi-out reference time of PEK T3

Departure airport terminal	Departure time	Taxi-out reference time/min
PEK T3	[22:00,07:00)	16
	[07:00,09:00)	19
	[09:00,22:00)	25

Table 5 Dynamic taxi-in reference time of CAN

Arrival airport terminal	Arrival time	Taxi-in reference time/min
CAN	[00:00,07:00)	8
	[07:00,09:00)	9
	[09:00,24:00)	8

Table 6 Airborne flight reference time from PEK to CAN

Flight leg	Aircraft type	Flight reference time/min
PEK-CAN	0.7—0.79 M	174
PEK-CAN	0.8—0.89 M	167

With the scheduled departure time and aircraft type as matching conditions, the corresponding taxi-out, airborne flight and taxi-in time of flights were determined. The dynamic standard operation time reference of flight legs was obtained via accumulation of time of different phases, as shown in Table 7. Estimation results provided dynamic operation time.

Table 7 Standard operation time of flight leg ″PEK-CAN″

Scheduled departure time	Operation time/min	
Aircraft type	0.8—0.89 M	0.7—0.79 M
[22:00,04:00)	193	198
[04:00,06:00)	194	199
[06:00,07:00)	193	198
[07:00,09:00)	196	201
[09:00,22:00)	202	207
Published operation time	195	195

In order to verify the effectiveness of the methods, the values estimated with the algorithm in Table 6 were compared with actually measured values and other statistical and reference values, as shown in Table 8, where ″actually measured mean″ was obtained from calculating historical data of the flight leg from PEK T3 to CAN in November 2013. Three main effective timeframes of the airports were selected to calculate the corresponding mean operation time of this leg. Based on the same data sample, the conventional probability density method was introduced for ″statistical value″, the overall operation time was chosen as the object, and confidence ratio was set as 0.6. Results showed that 0.7—0.79 M type held the operation time of 213 min and 0.8—0.89 M 205 min. ″Published value″ was the fixed reference time published by ATM in the year; ″company reference value″ was the operation time of flight legs used by certain major airlines for internal reference.

As illustrated in Table 8, ″published value″ desirably reflects the operation time of 0.8—0.89 M type, but has a big error for 0.7—0.79 M type. This indicates that this fixed reference value focuses on the operating level of aircraft types with a high proportion in flight legs. ″Statistical value″ has certain accuracy in peak hours (departure demand approximate to arrival demand) of airport operations, but it has a larger deviation within other timeframes. Compared with measured value, ″corporate reference value″ has the largest deviation as a whole, reflecting the operation strategy of airlines, i. e. aiming at acquiring favorable slot resources through less scheduled reference time, so as to improve the utilization rate of aircraft.

Table 8 Actually measured value versus various reference values for flight leg ″PEK-CAN″

Various values	Time frame of departure/min		
	[7:00, 10:00)	[10:00, 22:00)	[22:00, 23:00)
Actually measured mean (0.7—0.79 M)	203	210	202
Actually measured mean (0.8—0.89 M)	194	202	194
Published value	195	195	195
Company reference value	190	190	190
Statistical value (0.7—0.79 M)	213	213	213
Statistical value (0.8—0.89 M)	206	206	206
Estimated value(0.7—0.79 M)	201	207	198
Estimated value (0.8—0.89 M)	196	202	193
Deviation of published value (0.7—0.79 M)	8	15	7
Deviation of published value (0.8—0.89 M)	1	7	1
Deviation of company reference(0.7—0.79 M)	13	20	12
Deviation of company reference(0.8—0.89 M)	4	12	4
Deviation of statistical value (0.7—0.79 M)	10	3	11
Deviation of statistical value (0.8—0.89 M)	11	4	11
Deviation of estimated value (0.7—0.79 M)	2	3	4
Deviation of estimated value (0.8—0.89 M)	2	0	1

Therefore, due to different proneness and single valuedness, the conventional statistical method and all reference values obtained by it can only be used as an acceptable reference within a local range, although it still holds a larger deviation which may adversely affect strategic/pre-tactical flight scheduling.

The "estimated value" based on clustering and probabilistic algorithm is the closest to the actually measured value, and deviation values within various timeframes are less than 4 min. Therefore, this algorithm is superior to others. Compared with the performances of conventional statistical methods and different fixed reference time, its estimation results can flexibly display dynamic variation models in a single day of flight leg operation. For different flights, targeted and differentiated reference values can be obtained depending on the specific conditions. Through effective estimation of the operation time of all relevant flight legs of destination airports, the accuracy of demand prediction for arrival and departure in a time window can be promoted, and the rationality of development and approval of advance/next-day flight plans can be improved, thus avoiding the waste of airport slot resources. For specific changes of flight demands(e. g. during traditional holiday) or special weather conditions, the operating data of corresponding scenarios can be collected for estimation and analysis with this algorithm, so as to provide an targeted reference time.

4 Conclusions

We first partitioned flight operation into three phases and analyzed various relationships among mean taxiing time, traffic flow and arrival/departure ratios, as well as clustering models and time distribution characteristics. The C-means data mining algorithm based on such partition was used for taxiing time analysis. Periodic variation rules of airborne flight time were analyzed and corresponding probability density functions were fitted. Thus, an estimation method was designed. This method deals with each phase independently and integrates them with different conditions, therefore to dynamically measure the standard operation time of flight legs for a single-day. Moreover, the operating data from domestic typical busy flight legs were used for verification. Results showed that the analytical process and results of this method could objectively reflect the actual flight leg operation and control capability, and provided an effective data support for the analysis of factors influencing the operation of flight legs, scientific development of advance flight plans, prediction of operation simulation, and examination of airline tasks.

Due to the lack of dynamic flight data (trajectory), we did not delve into dynamic analysis of flight time in this paper, and will further study it, so as to explore the correlation and distribution characteristics of attributes for differentiated calculation.

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Mr. **Yuan Ligang** is currently a Ph. D. candidate in College of Civil Aviation at Nanjing University of Aeronautics and Astronautics (NUAA). He received his M. S. degree in Department of Computer Science, NUAA. His Research interests are air traffic flow management and performance assessment.

Prof. **Hu Minghua** is currently a professor and doctoral supervisor in NUAA. His research interests are air traffic flow management and airspace management.

Dr. **Xie Hua** is currently a lecturer in College of Civil Aviation, NUAA. He received his Ph. D. degree from NUAA. His research interests focus on air traffic flow management and performance assessment.

Mr. **Li Yinfeng** is currently a Ph. D. candidate in College of Civil Aviation, NUAA. His research interests are Airspace management and capacity assessment.

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