[EN-A-81] Evaluation of Air Traffic Steadiness in Arrival Operations based on Statistical Analysis and Trajectories Clustering

(EIWAC 2019)

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Abstract: To improve operational efficiency and facilitate decision support in the air traffic management domain, a method is proposed to evaluate the air traffic steadiness in arrival operations, referring to the quality of arrival traffic that is steady--regular as well as unvarying, in addition, focusing on two aspects: the smoothness of intervals of flight time & distance between arrivals on final and the coherence of arrival trajectories. Firstly, the intervals of flight time & distance between arrivals when reaching 1,000ft on final are counted, then both qualitative and quantitative analyses are applied to explore the distribution form, parameter characteristics, and statistical data for illustrating the performance. Secondly, two sub-methods are used in terms of the coherence of trajectories: on the one hand, research the similarity between the arrival trajectories simplified by Douglas-Peucker algorithm and standard terminal arrival routes based on the vertical distance to show the degree of STARs' execution; on the other hand, cluster trajectories based on multiple features through DBSCAN algorithm to detect outliers, reflecting the uniformity of trajectories between each other. Finally, taking a typical Chinese airport into account, a case study comparing the performance of two periods is carried out to validate the provided methods.

Keywords: Air Traffic Steadiness, Statistical Analysis, Trajectory Clustering, Interval Smoothness, Trajectory Coherence

1. INTRODUCTION

Terminal Airspace (TMA) is a convergent area of the inbound and outbound traffic flow, having the characteristics of complex route structure, dense traffic activities, frequent flight conflicts, and narrow maneuvering space, which make TMA a bottleneck for air traffic management (ATM). Air Traffic Controllers' (ATCOs') responsibility in arrival operations is to separate arrivals from other flights and integrate them into landing sequences to each runway safely and efficiently by radar vectoring. However, the rapid growth of air traffic and the restricted use of airspace have led to an obvious trade-off between flexibility and predictability, as well as between the individual flight efficiency and overall system capacity, which brings about overload of ATCOs' work, decline in efficiency, and negative impact on travel time, environment protection, energy consumption, air incidents and etc., all of which can be simply put as "unsteadiness". Air traffic steadiness in arrival operations refers to the quality of arrival traffic that is steady--regular and unvarying.

Fine management process and quantitative performance evaluation are the basis and key to improving the efficiency of air traffic control (ATC) operations, meeting air traffic requirements, and ensuring the safety of civil aviation transportation. As practice proves in other branches of the economy, the only way to achieve visible progress in improving operational efficiency is to establish a transparent and objective performance management system that will provide decision-makers with real-time information needed for taking the necessary measures. An important advantage of this business concept is a greater responsibility of the members of the ATM community in achieving defined targets [1]. The international civil aviation organization (ICAO) [2][3][4][5], the civil air navigation services organization (CANSO) [6], the European organization for the safety of air navigation (EUROCONTROL) [1] and the federal aviation administration of USA (FAA) [7] have established respective key performance indicator (KPI) systems in succession since 2005, focusing on 11 key process areas (KPAs) including access and equity, capacity, cost-effectiveness, efficiency, environment, flexibility, global interoperability, participation by the ATM community, predictability, safety, and security. The usage of KPA and KPI to manage the system has become the most crucial source of ATM performance data in the world.

The particularity of the arrival operations and the importance of performance evaluation have attracted considerable attention from aviation researchers. Zhang et al. [8] proposed an evaluation method for operation performance of terminal control at a single-runway airport by integrating principal component analysis and K-means cluster; Dong [9] evaluated the impact of six indicators on the operational quality of the TMA based on the factor analysis method, and verified the validity by using the fuzzy comprehensive evaluation method; Zhang [10] established a road network model based on the theory of cell transmission and used the DEA model with constraint cone for evaluating the operational efficiency of approach control; Wang et al. [11] constructed a general indicator system for evaluating TMA utilization, and proposed a TMA relative utilization evaluation model based on the combination of absolute gray degree of incidence and principal component analysis; Gong [12] analyzed the impact of the arrival flight flow on the efficiency with the shortest total delay time as the optimization goal, and used the improved ant colony algorithm to realize evaluation; Xu [13] established a radar control efficiency evaluation model based on historical flight trajectories, and used clustering algorithm to grade the evaluation results; Liu and Zhang [14] proposed a data-driven method for evaluating the efficiency of ATC based on radar tracks, especially regarding arrival operations.

This paper aims to contribute to a method for evaluating the air traffic steadiness in arrival operations and is organized as follows. In section 2, distinguish air traffic steadiness from some existing transportation concepts, define two key areas of the indicator: the smoothness of intervals of flight time & distance between arrivals on final, and the coherence of arrival trajectories, then prepare data of high similarity in two periods for the following experiment. Analyze the intervals of flight time & distance between arrivals when reaching 1,000ft on final by qualitative and quantitative analysis to explore the distribution form, parameter characteristics, and statistical data in section 3. Evaluate the coherence of arrival trajectories from two aspects: the deviations of trajectories from standard terminal arrival routes (STARs) and the number of trajectory outliers in section 4, before the conclusion in section 5. The radar data from a typical Chinese airport are taken as an example of application.

2. THE DEFINITION OF AIR TRAFFIC STEADINESS AND DATA PREPARATION

2.1 The Definition of Air Traffic Steadiness

Among the eleven recommended KPAs, predictability refers to the ability of airspace users and ATM service providers to provide consistent and dependable levels of performance, additionally, there is already the concept of stability in the transportation domain, both of which may be similar to air traffic steadiness proposed in this paper literally. However, predictability takes delay measures as evaluation indicators, and stability concentrates in the quality of being enduring and free from change or variation. Air traffic steadiness focuses on the quality of being steady—regular and unvarying, resembling the combination of efficiency and reproducibility.

Two aspects of air traffic steadiness are focused on:

1) The smoothness of intervals of flight time & distance between arrivals when reaching a certain height on final;
2) The coherence of arrival trajectories.

The former is the representation of flights' landing tightness and controllers' work effectiveness, expected to be as small as possible in compliance with safety regulations, and the latter, in which more orderly is better, measures the degree of operation standardization.

2.2 Data Preparation

According to the indicator definition above, it can be found that the focus of air traffic steadiness is on analysis, and the ideal standard or scoring method in numerical form is not given. Therefore, this paper uses a comparative method, comparing the data of homologous and similar conditions to come to an evaluation conclusion.

A Chinese airport with 5 entry fixes (EF) marked from A to E was equipped with the Arrival Management (AMAN) system in 2018. This paper analyzes the radar tracks before and after the equipment of AMAN to assess the changes in air traffic steadiness of arrival operations. One of the main obstacles in conducting comparative analysis experiments is to ensure that system conditions are identical or at least closely resemble overall data collection periods. Unfortunately, the system conditions in the TMA are too complicated. There are many environmental variations during the data collection periods, which are difficult to control fully. This paper uses two criteria to identify the similarity of periods.

1) The percentage of flights that landed within 15 minutes of the estimated time of arrival (ETA);
2) The percentage of flights at each EF.

Although there are many "process quantities" of environmental variations, the impact of them on arrival operations will ultimately be reflected in whether aircraft could land at the airport on time. Therefore, we mainly judge whether the two periods are similar according to the percentage of flights that landed within 15 minutes of their ETA. If the percentages of flights that landed within 15 minutes of ETA are similar, there are no adverse weather conditions or unexpected events severely affecting the system. Then, we compare the percentages of flights at each EF. If they are not much different, it means that the workload of each control sector is not much different compared to the other period. Using the above similarity measurement method and considering both flight plans and weather conditions could be more similar in the same season (evading spring and summer when abnormal weather conditions often occur in China), the period from December 2017 to January 2018 (P1) is selected as the one without the operation of AMAN, and the period from December 2018 to January 2019 (P2) is selected as the one with the equipment of AMAN. The operating conditions of the two periods are as shown in Tab. 1.

The difference between two periods in Tab. 1 comes from two reasons: on the one hand, the adjustment of flight plans in the P2; on the other hand, some dirty flight data are eliminated in the data cleaning process. With the maximum proportion difference of 2.47%, the two phases are highly similar within an acceptable range.

Table 1 Similarity Measurement for P1 and P2

Item	P1	P2	Diff.
Landing in ETA±15min	0.4936	0.4689	0.0247
Flight at EF A	0.3053	0.2987	0.0072
Flight at EF B	0.1876	0.1796	0.0080
Flight at EF C	0.0867	0.1003	-0.0136
Flight at EF D	0.2378	0.2349	0.0029
Flight at EF E	0.1826	0.1870	-0.0044
Northbound landing	0.8936	0.8849	0.0087
Southbound landing	0.1064	0.1151	
Flight amounts	14007	14880	-873

3. EVALUATION OF THE SMOOTHNESS OF FLIGHT INTERVALS

The final refers to the final flight phase before landing, during which arrival aircraft has been aligned with the runway and is making the final speed and attitude adjustments. Intervals of flight time and distance between arrivals at a specified height on final are the representation of flights' landing tightness and controllers' work effectiveness, expected to be as small as possible in compliance with safety regulations. The existence of too many large differences means that the spatiotemporal resources of airspace are not utilized fully.

Due to the limitation of the detection scope of the control radar in the TMA, some flight data during low heights cannot be captured. So, choose 1000ft as the analysis height. This indicator is analyzed by a combination of the qualitative method based on the comparison of fitting curves, and the quantitative method based on statistics.

3.1 Qualitative Evaluation

Calculate the intervals of flight time and flight distance between arrival aircraft at 1000ft on final, and plot the distribution of intervals in Fig. 1. The large subgraph in the middle shows the linear correlation relationship between time intervals and distance intervals; the dark blue large dots in the large subgraph represent the values of the P1, and the small aquamarine dots represent the P2 values. The upper subgraph shows the frequency distribution histogram and the fitting curve of flight time intervals in both periods, while the left subgraph shows the performance of flight distance intervals.

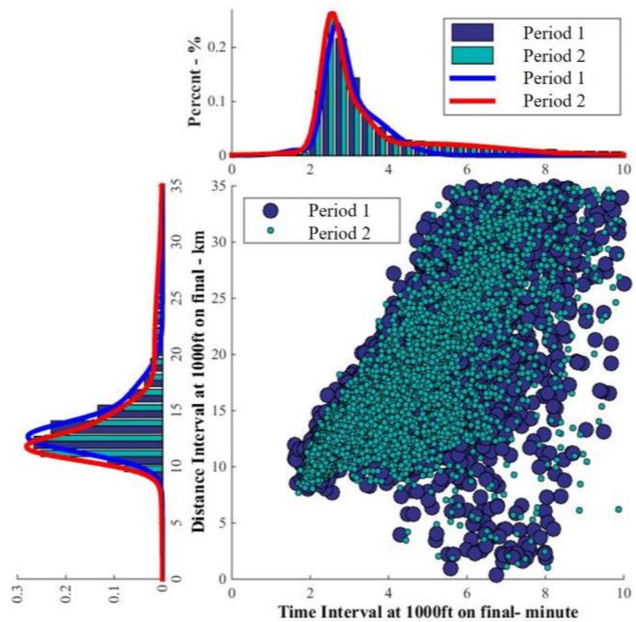

Figure 1 The Distribution of Intervals of Flight Time and Flight Distance between arrivals at 1000ft on final

Through verification, flight time intervals, and flight distance intervals obey the Gaussian distribution. The best fit can be obtained when the number of terms is 3, in which the R-square of the fitting can exceed 0.959. The fitting expression is as in (1).

$$a_1 \cdot e^{-\left(\frac{x-b_1}{c_1}\right)^2} + a_2 \cdot e^{-\left(\frac{x-b_2}{c_2}\right)^2} + a_3 \cdot e^{-\left(\frac{x-b_3}{c_3}\right)^2}, \quad (1)$$

The smaller the widths of the flight time intervals distribution curve and flight distance intervals distribution curve are, the tighter flights perform; and the more leftward the histogram and the fitting curve are, the smaller the flight time intervals and flight distance intervals are. It can be found that the fitting curve of flight time intervals in the P2 is of smaller width than in the P1 and more leftward, indicating that percentages of smaller values are higher. That performs the same in terms of flight distance intervals.

The qualitative evaluation shows the smoothness of flight intervals performs better in the P2 than in the P1.

3.2 Quantitative Evaluation

Statistical results of flight intervals are shown as Tab. 2.

Panel A of Tab. 2 presents the average intervals of flight time and standard deviations in different data samples. The flight time intervals will be larger in idle hours than in busy, so exclude the flight time intervals in idle hours by eliminating noises (large abnormal values). The noises eliminated in the table refer to the flight time intervals above 10 minutes, less than 10% of all data. According to the significance test, flight time intervals are significantly different between P1 and P2. It shows that flight time intervals performed better in the P2, indicating significant reduction by 0.1707 minutes per flight.

Panel B presents the statistical results of flight distance intervals. The noises refer to the distance intervals above 35 km, less than 14.2% of all data. Overall, the distance intervals are significantly different during the two periods. The indicator performed better in P2, indicating statistically significant reduction by 0.5372 kilometers per flight.

The quantitative evaluation shows P2 performs better, with the same result as the qualitative way.

Table 2 Intervals of Flight Time and Flight Distance at 1000ft

Panel A: Flight Time Intervals at 1000ft (min)						
	P1		P2		Diff.	Sig.*
	Avg.	St.Dev.	Avg.	St.Dev.	P1-P2	Yes/No
All	6.858	27.468	6.131	19.905	0.727	Yes
Eliminated noises	3.759	1.729	3.589	1.682	0.171	Yes
Panel B: Flight Distance Intervals at 1000ft (km)						
All	27.452	48.934	26.516	49.079	0.936	Yes
Eliminated noises	14.692	4.576	14.155	4.678	0.537	Yes
* Statistical significance at the 5% level.						

4. EVALUATION OF THE COHERENCE OF ARRIVAL TRAJECTORIES

Coherence means the state of cohering or sticking together. The coherence of arrival trajectories refers to the degree of uniformity in trajectories generated by the aircraft using the same EF and arrival route. Unified workflow and strategy often lead to great efficiency. Usually, in arrival operations, aircraft should travel the route that is in accordance with STARs on the chart. The scattered trajectories mean aircraft operations in the same route are artificially deployed, resulting in increased ATC load and reduced operational efficiency.

The coherence of arrival trajectories can be analyzed from two aspects: the coherence between arrival trajectories and STARs, showing the degree of STARs' execution, along with the coherence of trajectories between each other, which can be reflected by the number of trajectory outliers.

4.1 Deviations of Trajectories from STARs

STAR begins from the EF and ends at the initial approach fix. To compare the similarity between arrival trajectories and STARs, trajectories need to be cut out according to the range of STARs. The flight information is detected every four or five seconds by radar, which causes a big number of trajectory points, and results in low calculation efficiency if putting all trajectory points into computations. So we simplify trajectories through a Douglas-Peucker algorithm [15][16] as in Fig. 2, with ε = 500 m (i.e., roughly: remove points less than ε far from a straight line). Simplification ratio in this experiment can reach 97.05%.

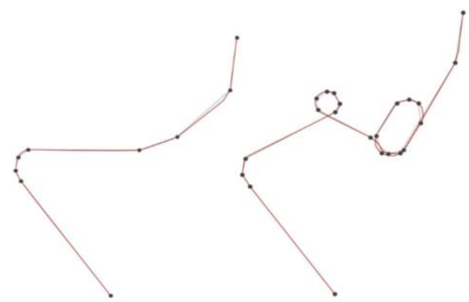

Figure 2 Douglas-Peucker Simplification of Two Sample Trajectories

The number of trajectory points is not the same as waypoints inevitably. Distances between pairs of points can't be taken into usage to measure the similarity between trajectories and STARs, which will cause great errors. Therefore, a similarity measure method based on the vertical distance of points [17] as in Fig. 3 is used, realizing the spatial correspondence of trajectory points.

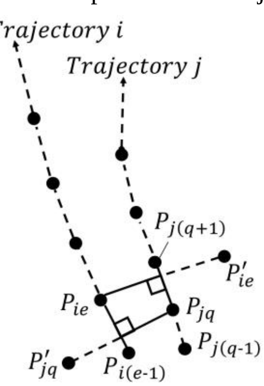

Figure 3 The Similarity Measure Based on Vertical Distance

In Fig. 3, *u* and *v* are the numbers of points in trajectory *i* and trajectory *j*. The vertical distance between trajectory *i* and trajectory *j* is as in (2).

$$\frac{1}{\min(u,v)}\left(\sum_{e=2,q=w+1}^{\min(u,v)-1}\left(\frac{d(P_{ie},P'_{ie})+d(P_{jq},P'_{jq})}{2}\right)\right), \quad (2)$$

Calculate vertical distances between arrival trajectories and STARs in two periods as in Tab. 3.

Table 3 Vertical Distances between Arrival Trajectories and STARs (km)

	P1		P2		Diff.	Sig.*
	Avg.	St. Dev.	Avg.	St. Dev.	P1-P2	Yes/No
All	2.3590	2.2290	2.5778	2.3696	-0.22	Yes
* Statistical significance at the 5% level.						

Vertical distances between arrival trajectories and STARs in the P1 and P2 are both less than 17 km (maximum is 16.92km in the P1, and 14.27km in the P2), and values less than 10 km are above 98.5% in both periods, showing the good performance in the coherence. Whereas, the P1 performed better by contrast according to Tab. 3.

4.2 Quantity of Outliers in Trajectories

The DBSCAN algorithm has outstanding performance in outlier exploration. The key work in this sub-section is to select appropriate features to characterize arrival trajectories, which is the basis of the clustering. When judging the similarity, trajectories lose their time-related features, and what to concern most is the shape. We select six features, and cluster tracks by DBSCAN algorithm after the data normalization of each feature to realize the outlier detection. The features and the result of the outliers are shown in Tab. 4 and Tab. 5.

Table 4 The Selected Features

Feature	Description
The summation of the minimum distances between track points and en route fixes on each air route of every EF	Summate the minimum distances between track points and en route fixes on each air route of every EF.
Flight distance in the terminal area	Calculate the distance traveled by the arrival flight from the EF to the runway.
The weighted average of heading	Divide 360 degrees into 120 range parts and calculate the frequency of each part according to the heading of every track point; use the median of each range part to calculate the average of heading weighted by the frequency.
Median of distances to the airport	Calculate the distance from each track point to the airport; select the median.
The presence of air holding	Determine whether the track has the holding phase. A 0/1 variable.
North / South land	Judge the land direction of the track. A 0/1 variable.

Trajectory Clustering according to the similarity based on common features has higher calculation speed as well as wider time range for evaluation than that based on distances/differences between each other. The latter would generate a diagonal symmetric similarity matrix which needs a lot of data processing time.

To ensure the similarity of conditions and the efficiency of the calculation, we select eight weeks from the P1 and P2 respectively as data sample (simplified as W1 to W8), which are of the same days, and detect outliers week by week in the experiment. What needs to be emphasized is that the maximum and minimum values of each feature used in data normalization are filtered from all samples rather than every week.

According to Tab. 5, there is a total reduction by 42 outliers in the P2, indicating the better uniformity of trajectories between each other.

Table 5 The Result of Outlier Detection

	EF A		EF B		EF C		EF D		EF E	
	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
W1	17	18	12	19	22	6	25	0	24	9
W2	11	5	20	3	29	10	4	1	21	2
W3	6	23	14	27	29	10	7	25	12	17
W4	8	20	9	11	29	11	7	10	9	1
W5	22	24	15	23	21	12	1	10	11	10
W6	0	17	6	15	15	5	19	3	3	9
W7	16	15	16	24	12	29	29	18	4	14
W8	23	14	24	13	29	28	4	23	12	21
Total	103	136	116	135	186	111	96	90	96	83
P1-P2	-33		-19		75		6		13	

5. CONCLUSIONS

Regarding the performance of P1 and P2, the air traffic steadiness is evaluated in two aspects: the smoothness and the coherence. Concerning the smoothness of flight time and distance intervals when arrivals reaching 1000ft on final, it can be found that P2 has a significant improvement over P1, which is expected that arrival flows become tighter with the operation of AMAN. Concerning the coherence of trajectories, deviations of trajectories from STARs deteriorate while the uniformity of trajectories between each other is ameliorated in the P2, which is not contradictory and caused from the forming of regular vectoring paths as well as fixed control strategies rather than STARs with the decision support of AMAN.

Regarding the work done in this paper, the definition of air traffic steadiness is set up, and the evaluation method focusing on this indicator based on statistical analysis and trajectory clustering is proposed.

Correlation analysis of feature and application of more appropriate similarity measure methods is the future direction of this paper.

6. ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (U1933117) and the Foundation of Graduate Innovation Center in NUAA (kfjj20180713).

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