

**SPATIAL-TEMPORAL TOPOLOGY AND PERFORMANCE ANALYSIS OF AIRPORT
TAXI NETWORK**

Jianan Yin, Corresponding Author

College of Computer Science and Technology
Nanjing University of Aeronautics and Astronautics
29 Jiangjun Road, Jiangning District, Nanjing 211106
Tel: +86 (0)25 5211 2669; Email: j.yin@nuaa.edu.cn

Minghua Hu

College of Civil Aviation
Nanjing University of Aeronautics and Astronautics
29 Jiangjun Road, Jiangning District, Nanjing 211106
Tel: +86 (0)25 5211 2079; Email: minghuahu@nuaa.edu.cn

Yuanyuan Ma

State Key Laboratory of Air Traffic Management System and Technology
The 28th Research Institute of China Electronics Technology Group Corporation
8 Yongzhi Road, Qinhua District, Nanjing 210007
Tel: +86 (0)25 8228 6127; Email: mayuanyuan2121@126.com

Ke Han

Center for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London
605 Skempton Building, South Kensington Campus
London SW7 2AZ
Tel: +44 (0)20 7594 5682; Email: k.han@imperial.ac.uk

Dan Chen

College of Civil Aviation
Nanjing University of Aeronautics and Astronautics
29 Jiangjun Road, Jiangning District, Nanjing 211106
Tel: +86 (0)25 5211 2669; Email: chendan2011@nuaa.edu.cn

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ABSTRACT

This paper proposes a spatial-temporal topology from a macroscopic view to analyze the performance of airport taxi network operations. Through a macroscopic modelling of arrival and departure aircraft taxi processes in the airport taxi network, we establish a system of taxi network performance indicators (TNPIs) consisting 5 categories and 26 indicators, which includes the surface instantaneous flow indicators (SIFIs), surface cumulative flow indicators (SCFIs), aircraft queue length indicators (AQLIs), slot resource demand indicators (SRDIs) and aircraft taxi time indicators (ATTIs). Then, we analyze the correlation among different TNPIs. By identifying the key factors affecting aircraft taxi time such as takeoff and landing queue length, we provide models for predicting aircraft taxi time based on multiple regression analysis. The real-world case study in Shanghai Pudong airport demonstrates significant correlations among some of the proposed TNPIs, and the results also show the significantly improved accuracy of the proposed prediction models over some conventional models, which brings significant benefits to analyze the performance of airport taxi network and support decision making in airport operations.

Keywords: Taxi network, spatial-temporal topology, airport performance, taxi time, statistical analysis

1. INTRODUCTION

With the tremendous growth of air transport industry over the past few decades, airport taxi network and aircraft movement have become more complex. This is accompanied by a drastic increase in aircraft conflicts, airport congestion and flight delays. Despite the significant efforts undertaken to improve airspace operations, there has been a major shift of congestion from airspace to airport (1). This change has urged air navigation service providers, airports and airlines to improve, individually or collaboratively, the efficiency of their services including taxi planning (2-4), arrival and departure scheduling (5-6) and turn-around management (7). Eurocontrol (8) explored the integration of these processes and issued the implementation manual of airport collaborative decision making, which has become a mature guide in practice and effectively enhanced the airport performance.

During the entire operational period of an aircraft, airport taxi network plays a critical role in the aforementioned problems such as airport congestion and delay. The taxi network is the most significant component of airport surface supply, and is central to the mitigation of airport congestion. Due to the high complexity and uncertainties associated with aircraft movements in the taxi network, the modelling and analysis of taxi network performance is, and continue to be, a critical issue for air transport stakeholders to ensure the safety and efficiency of flight operations.

It is well known that taxi network performance is one of the main factors affecting airport efficiency, and some studies have focused on managing taxiway resources. Most of the research on taxi management is based on optimization and conflict detection / resolution. The optimization of the taxi process encompasses both spatial and temporal dimensions. The spatial planning focuses primarily on taxi routing from the gate to the point of takeoff on the runway (9-12). The temporal planning focuses on scheduling of taxi activities, which is used to assign time to aircrafts concerning when to reach certain point on the surface along its route (13-15). Regarding the optimization objective, many of the previous studies have focused on minimizing the total taxi time between the runway and the gate (16-18), while others consider multi-objective optimization. For example, Marín *et al.* (19) solve a taxi network design problem by adopting a weighted linear objective function to balance a list of performance measures including airport throughput, taxi time, flight delays and operational costs. On the constraint side of airport surface operation, minimum separation constraints, taxiing speed constraints and route priority are synthetically considered (20). Finally, most of these optimization problems are solved with heuristic methods. For example, the genetic algorithm (21), A-star algorithm (22), particle swarm optimization (23) and ant colony algorithm (24) have been adopted to solve taxi planning problems.

In the airport system, taxi time is one of the most fundamental key performance indicators (KPIs) to assess taxi network situation and effectiveness of air traffic management measures. Extended taxi times, including large queuing times before entering the threshold of runway, are direct symptoms of inefficient air traffic management and are often associated with excessive operating and maintenance costs, increased risks, as well as negative environmental impacts. The accurate prediction of taxi time, however, is a challenging undertaking because of the significant uncertainties associated with aircraft taxi processes. Along this line of research, many studies rely on statistical models that consider the probability distributions of flight delays and aircraft operation times, in order to predict aircraft taxi time (25-27). Idris *et al.* (28) identify the main factors that affect aircraft taxi-out time and establish a prediction model taking into account the most significant factors such as takeoff queue size. But the authors only consider factors related to departure aircraft, ignore the impact of arrival aircraft on the departure taxi process. Most of these prediction models focus on either the arrival taxi process or departure taxi process separately, where in reality these two processes are clearly coupled and interdependent on each other on

airport surface. Moreover, they exclusively focus on the aircraft taxi time without considering other relevant factors or performance indicators pertaining to airport surface operation. Clewlow et al. (29) analyze the impact of arrivals on departure taxi operations at airports and find that the impact increases as interaction between departures and arrivals increases. But the relationships of all influencing factors of taxi time have not yet been fully analyzed, and the values of some explanatory variables can't be estimated accurately. Balakrishna *et al.* (30-31), George *et al.* (32) define the number of arriving flights that are taxiing on the surface as one of the elements of the system state, and adopt reinforcement learning algorithm to estimate aircraft taxi-out time at airports, followed by assessment of the accuracy of these models.

We note that most of the previous studies employ a microscopic perspective for modeling aircraft taxi processes, which captures realistic aircraft dynamics at high granularity. However, microscopic models are computationally expensive and sensitive to uncertainties in the system. They are also more difficult to implement and calibrate in practice due to their complexity. On the other hand, the existing macroscopic models focus on describing the aggregate effect of the propagation of flow and congestion with fewer variables and more robust outcome. It is also computationally efficient and can be utilized for real-time decision making. There is currently a lack of macroscopic models for predicting some key indicators of taxi network performance. The main contribution of this paper can be summarized as follows.

- This paper focuses on airport network operations at the aggregate level, by establishing the taxi network spatial-temporal topology to analyze the main factors affecting the taxi process. A range of taxi network performance indicators (TNPIs) are formulated. The proposed modelling and analysis method is crucial for air traffic management and airport operations by providing critical and comprehensive information regarding the airport movements.

- Unlike existing studies, which mainly focus on the impact of departures on the taxi-out times, we use an extensive list of TNPIs to also account for the effect of arrival traffic on the taxi-out times. Thus, the framework captures more realistic surface dynamics and leads to more accurate prediction.

- We conduct an extensive correlation study on the proposed macroscopic indicators to uncover critical influencing factors of aircraft taxi time. Based on these factors, we establish some models to predict aircraft taxi time. Our prediction models differ from other models based on correlation analysis (28-29) in that we consider a range of linear or nonlinear regression models and test their statistical validity by investigating the distribution of normalized residuals.

The rest of this paper is organized as follows. Section 2 proposes a spatial-temporal topology of airport taxi network. In Section 3 we define an extensive list of TNPIs and propose ways to compute them. In Section 4 we conduct a real-world case study of taxi network performance analysis, and provide some findings and insights by analyzing the correlation between different TNPIs and prediction results of taxi time. Finally, some conclusion remarks are presented in Section 5.

2. TAXI NETWORK SPATIAL-TEMPORAL TOPOLOGY

Airport taxi network performance analysis supports air transportation stakeholders to make decisions regarding airport design, planning and management by monitoring and predicting the continuous change of network performance indicators in a dynamic environment. In order to analyze the taxi network performance, we proposed a spatial-temporal topology modelling method for aircraft taxi activities from a macroscopic view. Figure 1 illustrates a topology model of airport taxi network operations in any spatial-temporal domain, and provides a macroscopic and general description of the relationship between spatial and temporal resources. The notations are explained as follows.

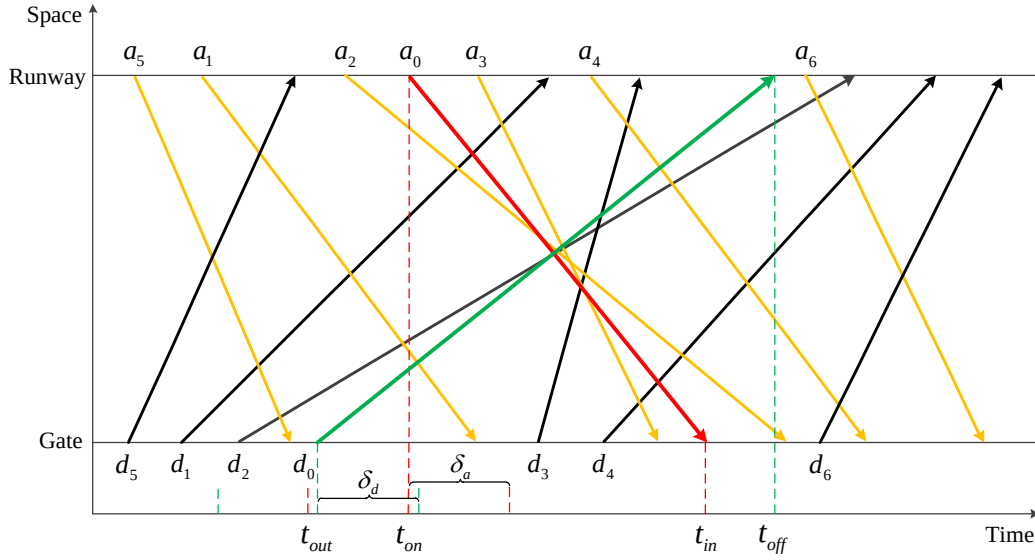


FIGURE 1 Topology of airport taxi network

a_i : Arrival aircraft, $i = 1, \dots, 4$

b_i : Departure aircraft, $i = 1, \dots, 4$

a_0, b_0 : Reference arrival and departure aircrafts, for the analysis

t_{on} : Landing time of the arrival aircraft a_0

t_{in} : In-block time of the arrival aircraft a_0

t_{out} : Off-block time of the departure aircraft d_0

t_{off} : Take-off time of the departure aircraft d_0

δ_a : Arrival slot threshold

δ_d : Departure slot threshold

We note that the slot thresholds δ_a, δ_d are generalized metrics and determine the intervals dynamically and flexibly depending on the landing or off-block times of the aircrafts.

The arrival flights $a_1, \dots, a_4$ represent four different relationships with a_0 :

$a_1 \sim a_0$: Landing Before, In-block Before (LBIB)

$a_2 \sim a_0$: Landing Before, In-block After (LBIA)

$a_3 \sim a_0$: Landing After, In-block Before (LAIB)

$a_4 \sim a_0$: Landing After, In-block After (LAIA)

Moreover, the aircraft landing simultaneously with a_0 is classified into “Landing Before” and the aircraft in-block simultaneously with a_0 is classified into “In-block Before”. It is clear that $a_1, \dots, a_4$ cover all the possible relationships between an arrival aircraft with a_0 . Moreover, as far as a_0 is concerned, a_5 and a_6 are irrelevant in the network because there is no temporal overlap with other aircrafts, which means that they have no effect on aircraft a_0 .

The classification for the departure aircrafts is entirely similar.

$d_1 \sim d_0$: Off-block Before, Take-off Before (OBTB)

$d_2 \sim d_0$: Off-block Before, Take-off After (OBTB)

$d_3 \sim d_0$: Off-block After, Take-off Before (OATB)

$d_4 \sim d_0$: Off-block After, Take-off After (OATA)

Moreover, the aircraft pushed back from the gate simultaneously with d_0 is classified as “Off-block Before” and the aircraft taking off from the runway simultaneously with d_0 is classified into “Take-off Before”. In the same way, d_5 and d_6 are also ignored in the taxi network topology.

3. TAXI NETWORK PERFORMANCE INDICATORS

We divide the TNPIs into five categories. Each category contains several indicators, then there are totally 26 indicators. Taking Figure 1 as an example, the following Sections 3.1-3.5 detail these indicators with a_0 and b_0 being the reference arrival and departure aircrafts respectively.

3.1 Surface Instantaneous Flow Indicators (SIFIs)

SIFIs refer to the numbers of taxiing aircrafts when the reference aircraft is being pushed back from the gate or landing on the runway. For any arrival aircraft a_0 , the A-SIFIs include three TNPIs:

$\partial_a^1, \partial_a^2, \partial_a^3$: The number of taxiing arrivals / departures / aircrafts when a_0 is landing on the runway

Similarly, for any departure aircraft d_0 , the D-SIFIs also include three TNPIs:

$\partial_d^1, \partial_d^2, \partial_d^3$: The number of taxiing arrivals / departures / aircrafts when d_0 is being pushed back from the gate

3.2 Surface Cumulative Flow Indicators (SCFIs)

SCFIs refer to the numbers of aircrafts that have taxied out or are taxiing on the surface during the entire taxi process of the reference aircraft. For any arrival aircraft a_0 , the A-SCFIs include three TNPIs:

$\sigma_a^1, \sigma_a^2, \sigma_a^3$: The number of arrivals / departures / aircrafts whose taxiing period has overlap with the taxiing period of a_0

Similarly, for any departure aircraft d_0 , the corresponding D-SCFIs are

$\sigma_d^1, \sigma_d^2, \sigma_d^3$: The number of arrivals / departures / aircrafts whose taxiing period has overlap with the taxiing period of d_0

3.3 Aircraft Queue Length Indicators (AQLIs)

AQLIs refer to the numbers of aircrafts that take off from or land on the runway during the entire taxi process of the reference aircraft. For any arrival aircraft a_0 , the A-AQLIs include three TNPIs:

$\lambda_a^1, \lambda_a^2, \lambda_a^3$: The number of landings / takeoffs / landings & takeoffs during the taxi process of a_0

Similarly, for any departure aircraft d_0 , the corresponding D-AQLIs are:

$\lambda_d^1, \lambda_d^2, \lambda_d^3$: The number of landings / takeoffs / landings & takeoffs during the taxi process of d_0

3.4 Slot Resource Demand Indicators (SRDIs)

SRDIs refer to the numbers of aircrafts that are pushed back from the gate or land on the runway within the time interval $[t_0 - \delta, t_0 + \delta]$ where t_0 is the off-block time or the landing time of the reference aircraft. Here the coefficients δ_a and δ_d are introduced, whose values can be set dynamically and flexibly between 10 min and 30 min, considering the possible taxi time of the aircraft. Here, slot refers to a certain time interval centered around the touch-down time of arrival aircraft and the off-block time for departure aircraft. Here the arrival slot of a_0 and departure slot of d_0 are defined to be $[t_0 - \delta_a, t_0 + \delta_a]$ and $[t_0 - \delta_d, t_0 + \delta_d]$ respectively. For any arrival aircraft, A-SRDIs include three TNPIs:

$\mu_a^1, \mu_a^2, \mu_a^3$: The number of landings / push-backs / landings & push-backs during the arrival slot of a_0

Similarly, for any departure aircraft d_0 , the corresponding D-SRDIs are:

$\mu_d^1, \mu_d^2, \mu_d^3$: The number of landings / push-backs / landings & push-backs during the departure slot of d_0

3.5 Aircraft Taxi Time Indicators (ATTIs)

ATTIs refer to the taxi time between the runway and the gate of the reference aircraft. And their definitions are relatively straightforward:

τ_a : Taxi-in time of the reference aircraft a_0 (A-ATTI)

τ_d : Taxi-out time of the reference aircraft d_0 (D-ATTI)

3.6 Illustration of the TNPIs

Taking Figure 1 as an example, we illustrate the quantities of all the TNPIs introduced in section 3.1~3.5 in Table 1.

TABLE 1 The Quantities of All the TNPIs

TNPIs		Notation	Set of relevant aircrafts	Value of index
Surface instantaneous flow indicators (SIFIs)	A-SIFI	∂_a^1	$\{a_1, a_2\}$	2
		∂_a^2	$\{d_0, d_1, d_2\}$	3
		∂_a^3	$\{a_1, a_2, d_0, d_1, d_2\}$	5
	D-SIFI	∂_d^1	$\{a_1\}$	1
		∂_d^2	$\{d_1, d_2\}$	2
		∂_d^3	$\{a_1, d_1, d_2\}$	3
Surface cumulative flow indicators (SCFIs)	A-SCFI	σ_a^1	$\{a_1, a_2, a_3, a_4\}$	4
		σ_a^2	$\{d_0, d_1, d_2, d_3, d_4\}$	5
		σ_a^3	$\{a_1, a_2, a_3, a_4, d_0, d_1, d_2, d_3, d_4\}$	9
	D-SCFI	σ_d^1	$\{a_0, a_1, a_2, a_3, a_4\}$	5
		σ_d^2	$\{d_1, d_2, d_3, d_4\}$	4
		σ_d^3	$\{a_0, a_1, a_2, a_3, a_4, d_1, d_2, d_3, d_4\}$	9
Aircraft queue length indicators (AQLIs)	A-AQLI	λ_a^1	$\{a_3, a_4\}$	2
		λ_a^2	$\{d_1, d_3\}$	2
		λ_a^3	$\{a_3, a_4, d_1, d_3\}$	4
	D-AQLI	λ_d^1	$\{a_0, a_2, a_3, a_4\}$	4
		λ_d^2	$\{d_1, d_3\}$	2
		λ_d^3	$\{a_0, a_2, a_3, a_4, d_1, d_3\}$	6
Slot resource demand indicators (SRDIs)	A-SRDI	μ_a^1	$\{a_2, a_3\}$	2
		μ_a^2	$\{d_0\}$	1
		μ_a^3	$\{a_2, a_3, d_0\}$	3
	D-SRDI	μ_d^1	$\{a_0, a_2\}$	2
		μ_d^2	$\{d_2\}$	1
		μ_d^3	$\{a_0, a_2, d_2\}$	3

4. STATISTICAL ANALYSES AND NUMERICAL RESULTS

In this paper, we conduct a case study of aircraft taxi network performance in Shanghai Pudong International Airport (PVG) on October 1, 2014. We note that the same numerical study has been conducted for multiple days in the test site. The findings presented below are generalizable to these days and hold true across all these experiments. The taxi network performance analysis is implemented for both arrivals and departures, but we only select departures as reference aircrafts here, because there is no significant difference from the view of arrival in the methodology.

4.1 Correlation Analysis of Different TNPis

There are totally 528 reference aircrafts during the test period. Since the numerical study focuses on departure traffic, we use the following TNPis to analyze the correlation among the TNPis: D-SIFIs, D-SCFIs, D-AQLIs, D-SRDIs and D-ATTI. Firstly, we use scatter plots to preliminarily interpret their correlations. Then we calculate the Pearson correlation coefficient among the TNPis, and execute quantitative correlation analysis and T test with a 526 degrees of freedom. These TNPis are computed for each aircraft, and are summarized statistically, including D-ATTI (τ_d), D-SIFI² (∂_d^2), D-SIFI¹ (∂_d^1), D-SCFI² (σ_d^2), D-SCFI¹ (σ_d^1), D-AQLI² (λ_d^2), D-AQLI¹ (λ_d^1), D-SRDI² (μ_d^2) and D-SRDI¹ (μ_d^1). The results of the correlation tests are shown in Figure 2.

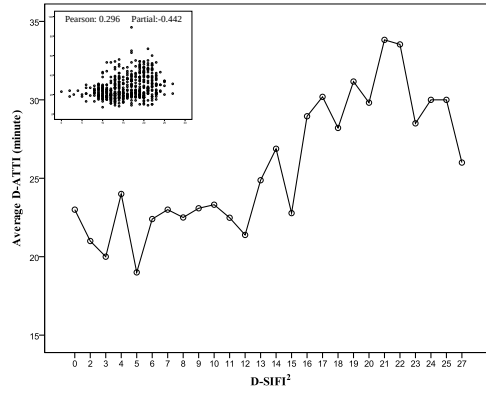
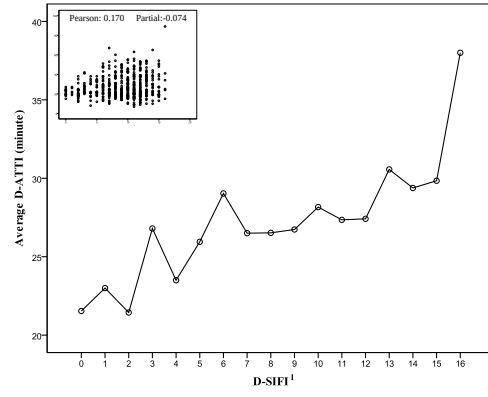
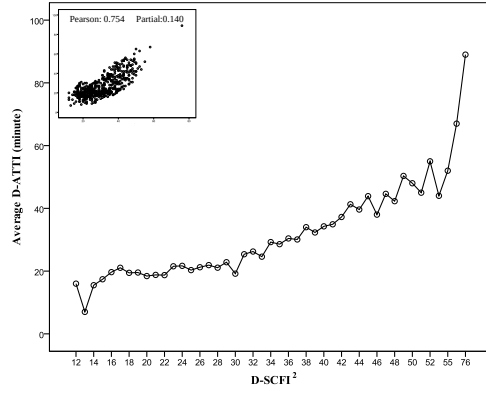
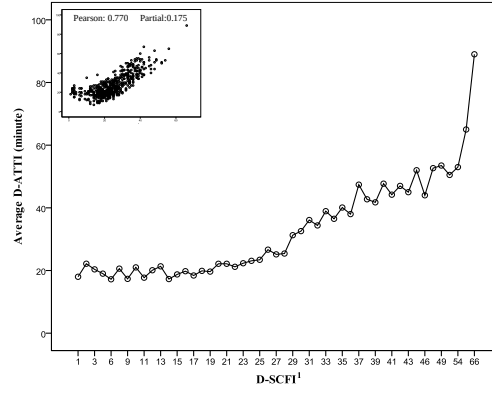
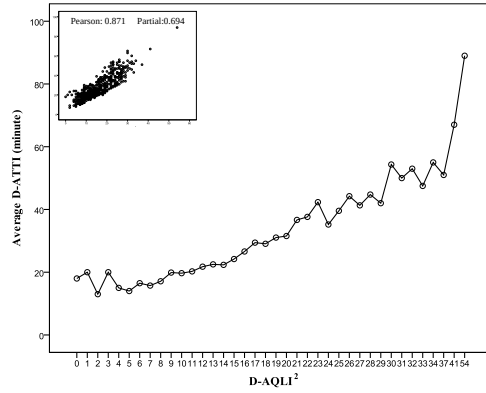
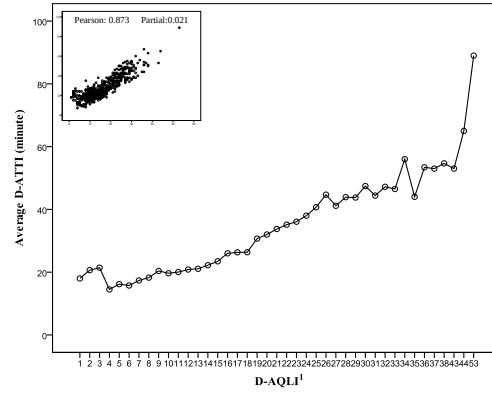
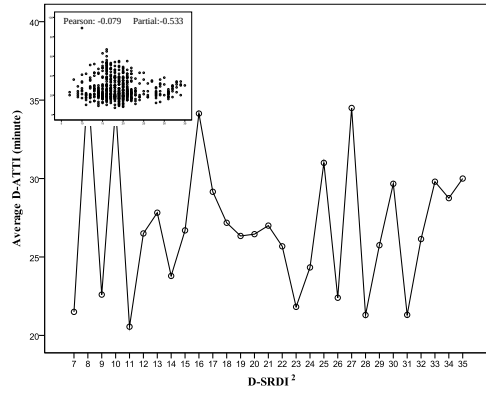
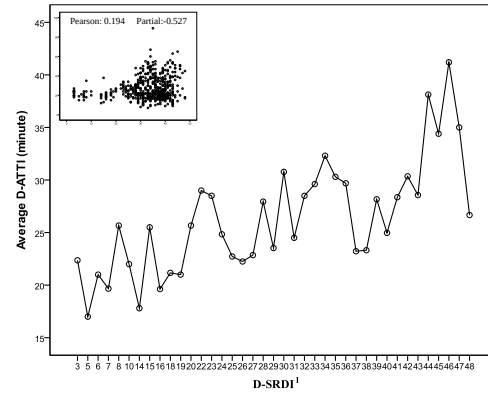
As shown in Figure 2-a, there is no strong correlation between D-ATTI (τ_d) and D-SIFI² (∂_d^2). The reason is that the quantity of taxiing departure aircrafts only reflects the instantaneous situation when the reference departure aircraft is being pushed back from the gate. However, it does not cover the entire taxi process of the reference aircraft, and therefore cannot sufficiently predict the level of congestion encountered by the reference aircraft. Similar explanation can be applied to the weak correlation between D-ATTI (τ_d) and D-SIFI¹ (∂_d^1) (see Figure 2-b).

As shown in Figure 2-c, there is a strong linear correlation between D-ATTI (τ_d) and D-SCFI² (σ_d^2). This may be due to the overlap between the taxi process of the reference aircraft and those of other departure aircrafts, which leads to the competition for surface resources and resulting taxi delays. Given that the Pearson correlation coefficient 0.754 is much larger than the partial correlation coefficient 0.140, D-SCFI² (σ_d^2) has no significant effect on the departure aircraft taxi time D-ATTI (τ_d). Actually, the correlation analysis shows that the correlation between D-ATTI (τ_d) and D-SCFI² (σ_d^2) is decided by the correlation between D-SCFI² (σ_d^2) and D-SIFI² (∂_d^2) / D-AQLI² (λ_d^2) / D-AQLI¹ (λ_d^1).

As shown in Figure 2-d, the linear correlation between D-ATTI (τ_d) and D-SCFI¹ (σ_d^1) is strong. This is for a similar reason as in Figure 2-c. Considering the Pearson correlation coefficient 0.770 is much larger than the partial correlation coefficient 0.175, D-SCFI¹ (σ_d^1) has no significant effect on D-ATTI (τ_d). Actually, we find that the correlation between D-ATTI (τ_d) and D-SCFI¹ (σ_d^1) is decided by the correlation between D-SCFI¹ (σ_d^1) and D-SIFI¹ (∂_d^1) / D-AQLI¹ (λ_d^1) / D-SRDI¹ (μ_d^1).

As shown in Figure 2-e, the linear correlation between D-ATTI (τ_d) and D-AQLI² (λ_d^2) is strong. This may be due to the fact that D-AQLI² (λ_d^2) is an indicator of the runway saturation level and hence the taxiway congestion level. Therefore D-AQLI² (λ_d^2) is positively correlated to the taxi time of the reference aircraft. Given that the difference between the Pearson correlation coefficient 0.871 and the partial correlation coefficient 0.694 is small, D-AQLI² (λ_d^2) has a significant and essential effect on D-ATTI (τ_d). We conclude that the former can be identified as a key influencing factor of the latter. As shown in Figure 2-f, similar explanation can be applied to the strong correlation between D-ATTI (τ_d) and D-AQLI¹ (λ_d^1). Note that the runway system is used for both arrivals and departures, which compete for runway resources. Thus both λ_d^1 and λ_d^2 can reflect the runway saturation level. However, for λ_d^1 , the partial correlation analysis does not pass the significant test. Therefore, the use of λ_d^1 as part of the key factors for predicting D-ATTI depends on the application scenario.

As shown in Figure 2-g and Figure 2-h, the correlation between D-ATTI (τ_d) and D-SRDI² (μ_d^2) or D-SRDI¹ (μ_d^1) is very weak. A possible explanation is that the uniformly chosen departure slot $[t_0 - \delta_d, t_0 + \delta_d]$ does not cover exactly the taxi processes of all the aircrafts throughout the test period; this is especially the case for the half interval $[t_0 - \delta_d, t_0]$, which has no overlap whatsoever with the taxi movement of the reference aircraft.

(2-a) D-ATTI and D-SIFI²(2-b) D-ATTI and D-SIFI¹(2-c) D-ATTI and D-SCFI²(2-d) D-ATTI and D-SCFI¹(2-e) D-ATTI and D-AQLI²(2-f) D-ATTI and D-AQLI¹(2-g) D-ATTI and D-SRDI²(2-h) D-ATTI and D-SRDI¹

1

2

FIGURE 2 Correlation analysis of D-ATTI and D-SIFIs / D-SCFIs / D-AQLIs / D-SRDIs

Correlation analyses have also been carried out for any pair of TNPIs, and the results are shown in Figure 3 in the form of scatter plots. For example, the subgraph labeled “9” shows the correlation between the independent variable D-AQLI² (λ_d^2) and the dependent variable D-SCFI² (σ_d^2). The red boxes indicate that the D-TNPIs have significant linear correlations with D-ATTI (τ_d). The green boxes mean the D-TNPIs have an essential effect on D-ATTI (τ_d). The blue boxes mean the D-TNPIs (excluding the D-ATTI) have a significant linear relationship with each other.

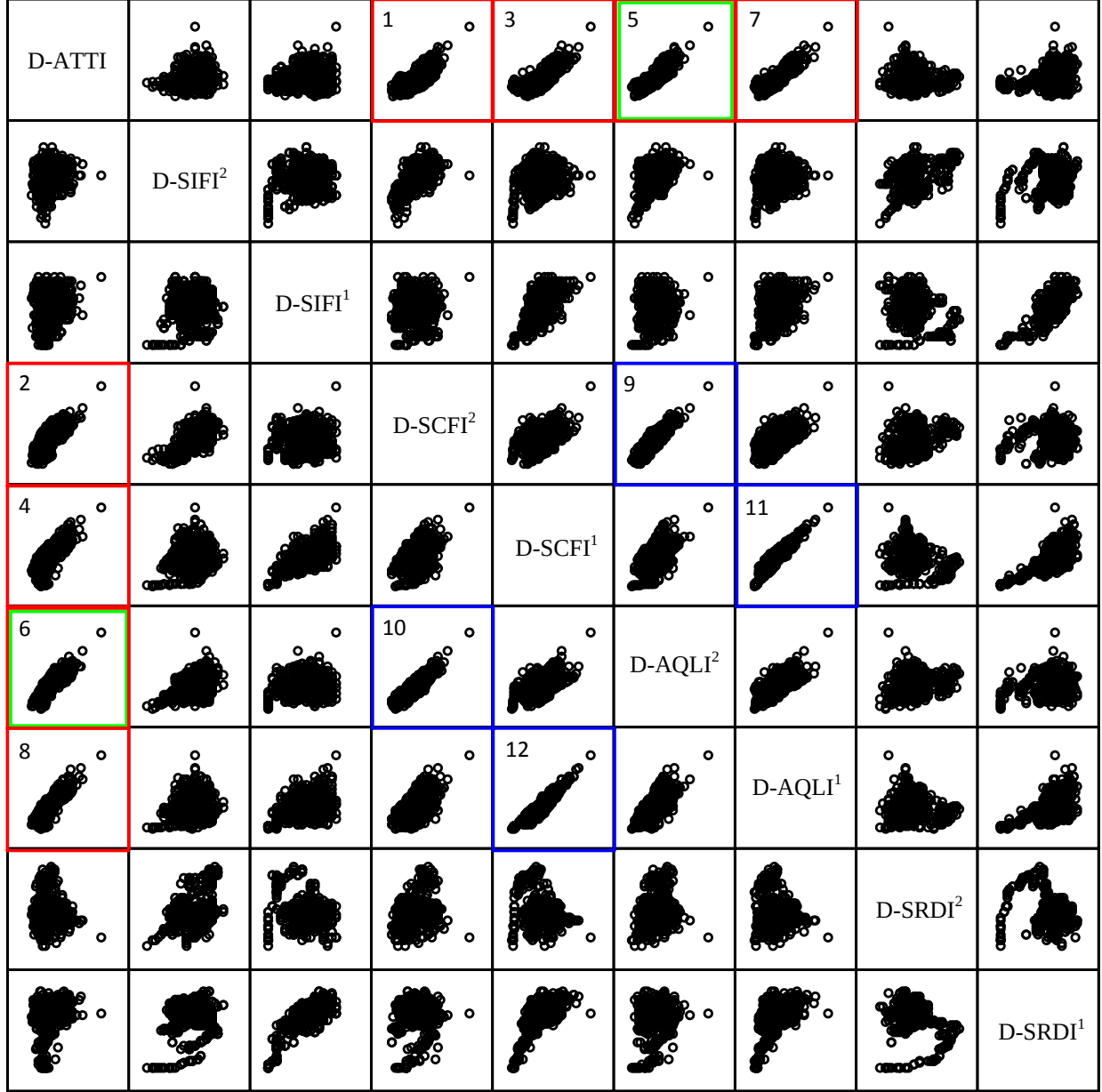


FIGURE 3 Correlation analysis of all the TNPIs

To summarize the above study, there is a significant correlation between D-ATTI (τ_d) and other four D-TNPIs including D-SCFI² (σ_d^2), D-SCFI¹ (σ_d^1), D-AQLI² (λ_d^2) and D-AQLI¹ (λ_d^1), which are the most important influencing factors of the taxi time. The correlation between D-SCFI² (σ_d^2) and D-AQLI² (λ_d^2) and the correlation between D-SCFI¹ (σ_d^1) and D-AQLI¹ (λ_d^1) are significant. The partial correlation analysis reveals that D-AQLI² (λ_d^2) is the most essential and key influencing factor of D-ATTI (τ_d).

4.2 Taxi Time Prediction Models

Considering the taxi time of aircraft is one of the most important network performance indicators in an airport system, we use the theory of multiple curvilinear regression analysis to establish the prediction models in which the D-ATTI (τ_d) is the dependent variable and D-AQLI² (λ_d^2) is the independent variable. Then we take the taxi data from 8 am to 13 pm on October 2, 2014 to validate the proposed prediction models. Here λ_d^2 is chosen because Section 4.1 shows that it is the most crucial influencing factor of taxi time. After analyzing the taxi data in the training sample data, we found that logarithmic curve, inverse function and power function are not applicable for curvilinear regression due to the existence of the value 0 for the takeoff queue length λ_d^2 . Therefore, we select six types of curvilinear regression equations to predict the departure taxi time, including linear curve, quadratic curve, cubic curve, compound curve, growth curve and exponential curve. The curvilinear regression fitting results are shown in Figure 4.

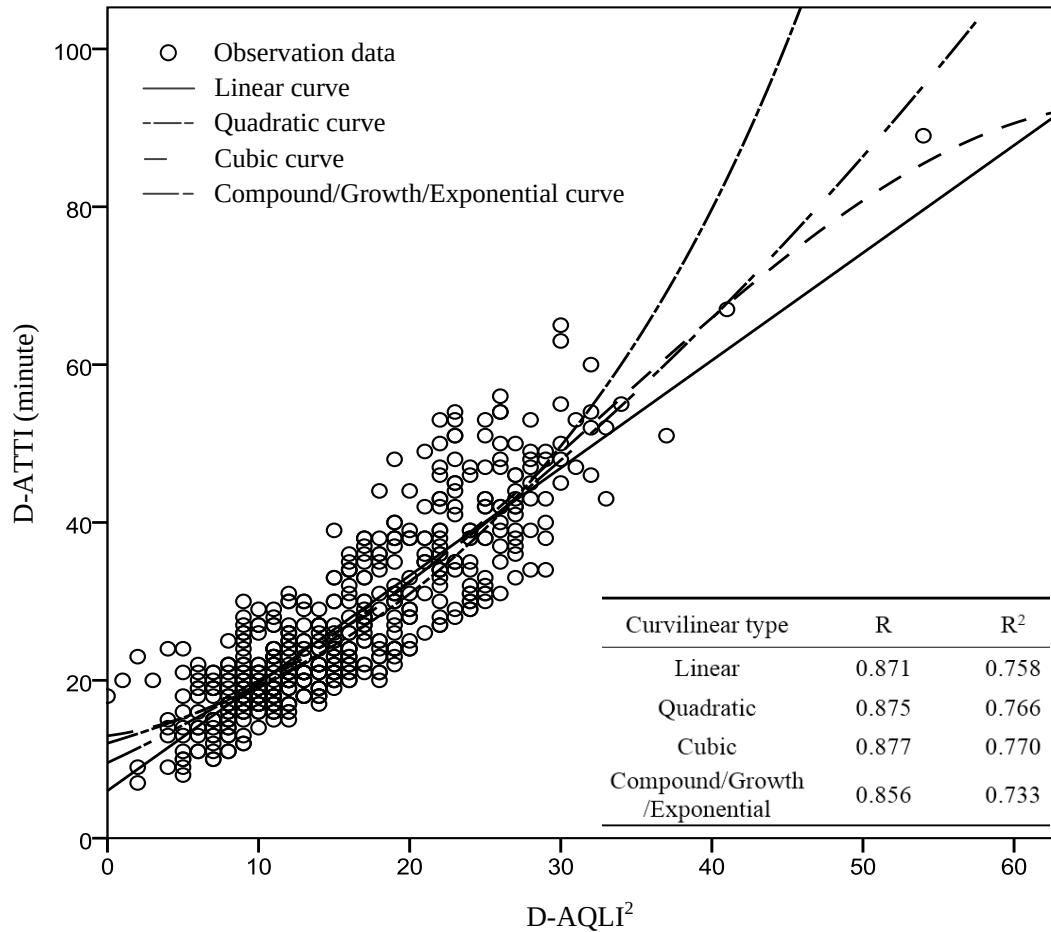


FIGURE 4 Curvilinear regression fitting for departure taxi time prediction

4.3.1 Departure Taxi Time Prediction Equations

Idris *et al.* (28) established a linear regression equation of taxi-out time, but the authors did not indicate whether their approach meets the requirements of linear regression modeling. During the process of multiple curvilinear regression fitting, we find that the linear regression equation could not meet such requirements because the normalized residuals do not follow normal distribution. In order to resolve this problem, we use the logarithmic-transformed departure taxi time data $\log(\tau_d)$ as the dependent variable to analyze the correlation between $\log(\tau_d)$ and λ_d^2 . Results show that the logarithmical linear regression equation of departure taxi time is the same as the compound /

growth / exponential curvilinear regression equation, which can be expressed in the following form.

$$\tau_{d,i} = e^{2.488+0.047\lambda_{d,i}^2} \quad (1)$$

where $\tau_{d,i}$ denotes the predicted taxi time (D-ATTI) of departure aircraft i , and $\lambda_{d,i}^2$ is the length of the take-off queue (D-AQLI²) during the entire taxi process of departure aircraft i .

It is also found that the cubic curvilinear regression equation could not meet the requirements of multiple regression modeling. Therefore, we establish a quadratic curvilinear regression equation, which can be expressed in the following form.

$$\tau_{d,i} = 0.013(\lambda_{d,i}^2)^2 + 0.89\lambda_{d,i}^2 + 9.559 \quad (2)$$

Besides the taxi time, we also selected the taxi delay as the subject of prediction, where the taxi delay is defined to be the total taxi time minus the unimpeded taxi time (UTT). Similar to taxi time, we also select the six types of curvilinear regression equations to predict the departure taxi delay, with the departure taxi delay (Δ) as the dependent variable and the relevant D-TNPIs as independent variables. It is found that the linear regression equation meets the requirements of multiple linear regression modeling, and the corresponding equation is:

$$\Delta_i = 1.086\lambda_{d,i}^1 + 0.267 \quad (3)$$

where Δ_i is the predicted taxi delay of departure aircraft i , and $\lambda_{d,i}^1$ is the length of landing queue (D-AQLI¹) during the entire taxi process of departure aircraft i . Here D-AQLI¹ is selected over D-AQLI² because it is the most essential and key influencing factor of departure taxi delay.

In addition, we also use the logarithmic-transformed departure taxi delay data $\log \Delta_i$ as the dependent variable to analyze its correlation with other D-TNPIs. The results show that the logarithmic linear regression equation coincides with the compound / growth / exponential curvilinear regression equation, and can be expressed in the following form.

$$\Delta_i = e^{1.589+0.07\lambda_{d,i}^2} \quad (4)$$

$$\Delta_i = e^{1.742+0.059\lambda_{d,i}^1} \quad (5)$$

Here, we use D-AQLI² and D-AQLI¹ to be the independent variables since they are the most significant influencing factors of departure taxi delay. Finally, the taxi time can be obtained simply by adding the UTT, which is deterministic and known, to the taxi delay:

$$\tau_{d,i} = \omega_i^d + 1.086\lambda_{d,i}^1 + 0.267 \quad (6)$$

$$\tau_{d,i} = \omega_i^d + e^{1.589+0.07\lambda_{d,i}^2} \quad (7)$$

$$\tau_{d,i} = \omega_i^d + e^{1.742+0.059\lambda_{d,i}^1} \quad (8)$$

where ω_i^d is the UTT of departure aircraft i .

4.3.2 Prediction Performance Analysis

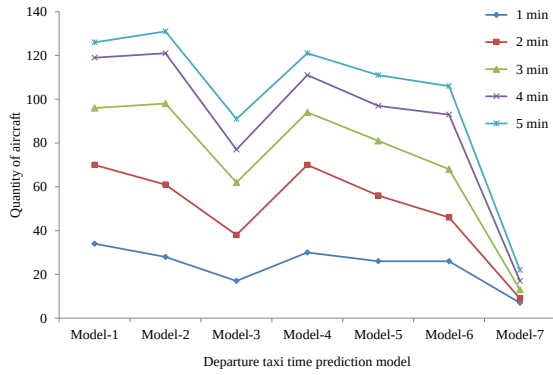
The five proposed models for predicting departure taxi time, namely Equ.1, Equ.2, Equ.6, Equ.7 and Equ.8, are compared with two benchmarks: moving average model (MAM) and arithmetic average model (AAM) frequently used in air transport industry. The AAM data was collected from Civil Aviation Administration of China which classifies the taxi time into four categories where the static average taxi time of PVG is 30 min.

We selected 138 departure aircrafts for which the taxi times need to be predicted using the aforementioned 7 models. Table 2 shows the accuracies of these prediction models (Model-1 ~ Model-7). It can be seen that the accuracies of Model-1 and Model-2 are the best and similar to each other. The remaining five models, sorted in a decreasing order of accuracy, are Model-4, Model-5, Model-6, Model-3 and Model-7.

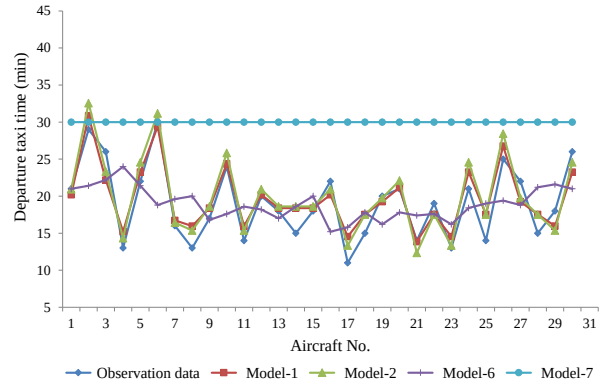
TABLE 2 Comparison of Prediction Performance of Departure Taxi Time Models

Model ID	Model description	Quantity of aircrafts within the error range				
		≤ 1 min	≤ 2 min	≤ 3 min	≤ 4 min	≤ 5 min
Model-1	Equ.1	34	70	96	119	126
Model-2	Equ.2	28	61	98	121	131
Model-3	Equ.6	17	38	62	77	91
Model-4	Equ.7	30	70	94	111	121
Model-5	Equ.8	26	56	81	97	111
Model-6	MAM	26	46	68	93	106
Model-7	AAM	7	9	13	17	22

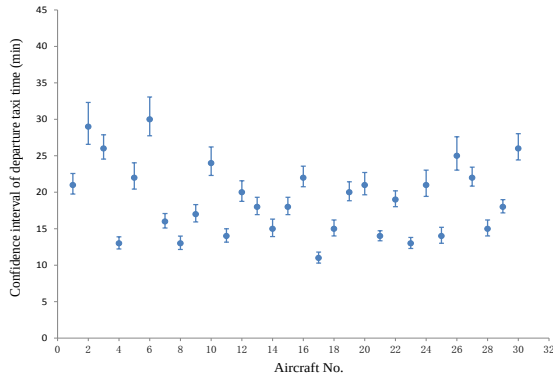
Figure 5 shows the performance of departure taxi time prediction models. Table 2 are visualized in Figure 5-a for more intuitive interpretation of the performances of these models. When Model-1 and Model-4 are applied, more than 50% of the test aircrafts have prediction errors lower than 2 min. More than 90% of the test aircrafts have prediction errors lower than 5 min if Model-1 and Model-2 are applied. Given that the taxi times range from 10 min to 30 min, the predictions by Model-1, Model-2, and Model-4 work quite well and much better than MAM and AAM. In Figure 5-b, we select 30 representative aircrafts in the test data, and plot the prediction results produced by Model-1, Model-2, Model-6, Model-7, as well as the observed data, for the further comparisons.



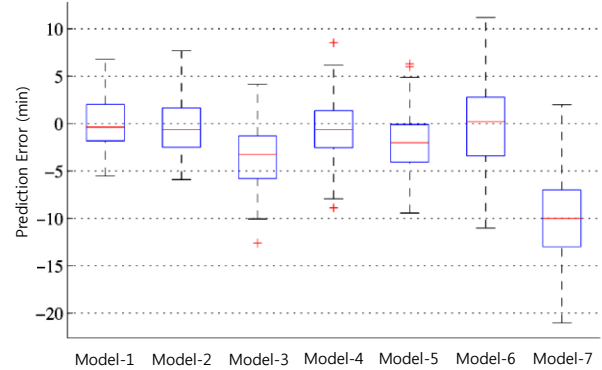
(5-a) Number of aircrafts for which the prediction errors fall below different error thresholds



(5-b) Comparison of departure taxi time prediction results and observed data



(5-c) Confidence interval of departure taxi time prediction models



(5-d) Box-plot summary of the prediction errors of the seven models

FIGURE 5 Performance analysis of departure taxi time prediction

It can be seen from Figure 5-b that Model-1 and Model-2 have very similar performances, and their predictions are very close to the observation data. The prediction errors of Model-6 and Model-7 are significant, but in different ways: Model-6, due to the moving average effect, tends to capture the overall trend of the taxi times but ignores local variations; on the other hand, Model-7 imposes a very conservative constant taxi time, which is greater than all of the actual taxi times.

We calculated the confidence interval of departure taxi time prediction models. Taking Model-1 in Equ.1 as an example, we show in Figure 5-c the 95% confidence intervals for the predicted taxi times of the 30 selected test aircrafts. These confidence intervals are constructed as follows. The confidence intervals of the linear coefficients within the exponential operator in Equ.1 are obtained as $[0.045, 0.05]$ (first-order coefficient) and $[2.446, 2.53]$ (constant); we then use the upper and lower bounds to compute the upper and lower bounds of the dependent variable, which are shown in Figure 5-c. Indeed, the larger aircraft taxi times are associated with wider confidence intervals.

Figure 5-d shows the box plots for the prediction errors over the 138 test samples. The error is defined to be the observation data minus the predicted values. It can be seen that Model-3, Model-5 and Model-7 tend to overestimate the taxi times, as the errors are mostly negative. Model-1 has the best performance, with a mean error close to 0. Overall, Model-1 ~ Model-5 outperforms the two benchmarks by a significant margin. Model-6 has a mean prediction error close to zero but with large variations, which is consistent with the moving average approach and Figure 5-b. Due to the overestimation of Model-7 on the taxi times, most of its prediction errors are negative.

5. CONCLUSIONS

This paper proposes a spatial-temporal topology from a macroscopic view to analyze airport taxi network performance, which is a crucial way to model and predict airport surface operations, and also support to assess the efficiency of airport operation and air traffic management. Advanced taxi network performance indicators can be used to schedule optimal take-off, landing, off-block and in-block times, which can increase the capacity and efficiency of airports, with the additional benefits of reduced fuel burn and emissions.

The exploration of historic data at the Shanghai Pudong Airport reveals some interesting statistical properties of TNPIs, leading to a macroscopic and reliable understanding of taxi network performance. This paper first establishes a system of TNPIs covering 5 categories and 26 indicators based on a spatial-temporal topology model for the airport taxi network movements. Then, correlation analyses are conducted to study the relationships among SIFIs, SCFIs, AQLIs, SRDIs and ATTIs. It is found that the taxi time indicators ATTIs have strong correlation with SCFIs and AQLIs. And we use the method of multiple curvilinear regression to establish several models for taxi time prediction, while the existing studies are mainly focused on the view of linear regression modelling. Finally, we conduct a comparison of several taxi time prediction models, including two traditional models used in practice, the moving average model and the arithmetic average model. The proposed models are shown to significantly outperform some conventional methods in terms of prediction accuracy.

The significance of this paper is a macroscopic and statistical perspective of airport taxi network performance modelling and analysis, and some prediction method outperforming some existing models in air transport industry, which brings significant benefits to analyze the performance of airport taxi network. It has the potential to support airport decision making and enhance the efficiency, safety, and cost-effectiveness of airport operations.

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