Airport taxi situation awareness with a macroscopic distribution network analysis

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Abstract

This paper proposes a framework for airport taxi situation awareness to enhance the assessment of aircraft ground movements in complex airport surfaces. Through a *macroscopic distribution network* (MDN) of arrival and departure taxi processes in a spatial-temporal domain, we establish two sets of *taxi situation indices* (TSIs) from the perspectives of single aircraft and the whole network. These TSIs are characterized into five categories: taxi time indices, surface instantaneous flow indices, surface cumulative flow indices, aircraft queue length indices, and slot resource demand indices. The coverage of the TSIs system is discussed in detail based on the departure and arrival reference aircraft. A real-world case study of Shanghai Pudong airport demonstrates significant correlations among some of the proposed TSIs such as the *aircraft taxi time indices* (ATTIs), *surface cumulative flow indices* (SCFIs) and *aircraft queue length indices* (AQLIs). We identify the most crucial influencing factors of the taxi process and propose two new metrics to assess the taxi situation at the aircraft and network levels, by establishing taxi situation assessment models instead of using two systems of multiple TSIs. The findings can provide significant references to decision makers regarding airport ground movements for the purposes of air traffic scheduling and congestion control in complex airports.

Keywords Macroscopic distribution network; Situation awareness; Complexity; Airport performance; Air Traffic Management

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Nomenclature

ATM	*Air Traffic Management*
MDN	*Macroscopic Distribution Network*
TSI	*Taxi Situation Index*
ATTI	*Aircraft Taxi Time Index*
SIFI	*Surface instantaneous flow index*
SCFI	*Surface Cumulative Flow Index*
AQLI	*Aircraft Queue Length Index*
SRDI	*Slot Resource Demand Index*

1 Introduction

With the tremendous growth of air transport industry over the past few decades, airport network structure, aircraft ground movement, and airport operational environment have become increasingly more complex. This is accompanied by a drastic increase in aircraft conflicts, airport congestion and flight delays. With the significant efforts undertaken to improve en-route operation, there has been a major shift of congestion from en-route airspaces to airport surface (Smeltink et al., 2003). This change has urged air navigation service providers, airports and airlines to improve, individually or collaboratively, the efficiency of their services or processes including taxi planning (Marín, 2006; Clare et al., 2009; Mori, 2013), arrival and departure scheduling (Bohme et al., 2007; Hesselink and Basjes, 1999) and turn-around management (Norin, 2008). Integration of all these processes is explored by Eurocontrol (2005) by issuing the implementation manual of airport collaborative decision making, which, since then, has become a mature guide and effectively enhanced the performance of hub airports.

During the entire operational period of an aircraft, airport ground movement plays a critical role and contributes to airport congestion and delay. The taxiway network is the most significant component of airport capacity, and is central to the mitigation of congestion. Due to the significant complexity and uncertainties associated with aircraft movements in taxi network, the accurate awareness of airport taxi situation is, and continue to be, a critical issue for air transport decision makers to ensure the safe and efficient operation of Air Traffic Management (ATM) systems.

Most literature on taxiway network management focuses on the optimization. The optimization of the taxi process encompasses both spatial and temporal dimensions. The spatial planning focuses primarily on taxi routing between the gates and the runways (Balakrishnan and Jung, 2007; Keith et al., 2008; Gerdes and Temme, 2012; Guépet et al., 2016). The temporal planning focuses on scheduling of taxi activities, which is used to assign time stamps to aircraft concerning when to reach certain point on the airport surface along its taxi route (Smeltink and Soomer, 2004; Rathinam et al., 2008; Montoya et al., 2010). Regarding the objective of these optimization problems, many of the previous studies focus on minimizing the total taxi time between the runway and the gate (Pesic, et al., 2001; Deau et al., 2009; Ravizza et al., 2013), while others consider multi-objective optimization. For example, Marín and Codina (2008) solve the problem of taxi network design by adopting a weighted linear objective function to balance a list of conflicting performance measures, including airport throughput, aircraft taxi time, flight delays and operational costs. On the constraint side of airport surface operation, minimum aircraft separation constraints, taxiing speed constraints, arrival/departure time constraints and route priorities are synthetically considered based on the theory of conflict detection and resolution (Atkin et al., 2010; Smeltink et al., 2003). Finally, most of these optimization problems are solved with heuristic methods due to the complexity of the dynamics and constraints. For example, the genetic algorithm (Gotteland et al., 2001), A-star algorithm (Brinton et al., 2002), particle swarm optimization (Liu et al., 2011) and ant colony algorithm (Nogueira et al., 2014) are adopted to solve the taxi planning problems. Most of the literature reviewed above focuses on the spatial-temporal information of single aircraft, rather than the entire aircraft fleet in the taxiway system. Given that the efficient taxiway network management requires precise and reliable assessment of the entire traffic situation, we propose a macroscopic distribution network model to assess the airport taxi situation, aiming at providing precise information of airport taxi situation for airport managers and air navigation service providers.

In the airport system, taxi time is one of the key performance indicators to analyze the airport taxi situation. Extended taxi-out time and taxi-in time, including large queuing times before entering the runway, are direct consequences of inefficient air traffic management, and are often associated with excessive operational and maintenance costs, increased risks, as well as negative environmental impacts. Regarding taxi time, many studies rely on statistical models that rely on probability distributions of flight delays and aircraft operation times, in order to predict aircraft taxi time (Shumsky, 1995; Signor and Levy, 2006). Idris et al. (2001) identify some factors that affect aircraft taxi time and establish a prediction model taking into account the most significant factors such as takeoff queue size. Clewlow et al. (2010) analyze the impact of arrivals on departure taxi operations at airports and find that the impact increases as interaction between departures and arrivals increases. Balakrishna et al. (2008, 2010), George and Khan (2015) define the number of arrivals that are taxiing on the surface as one of the elements of system state, and adopt reinforcement learning algorithm to estimate aircraft taxi time, followed by assessment of the accuracy of these models.

Most of the aforementioned taxi situation 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. Moreover, they exclusively focus on the aircraft taxi time without considering other relevant factors or performance indicators pertaining to airport taxi situation, such as taxi delay, pushback rate, runway queue length, traffic volume and the interactions between arrivals and departures. Although taxi time is a key performance indicator of airport ground movements, it alone cannot sufficiently represent airport taxi situation in its entirety. [1] In additional, much attention of existing studies was focused on the situation of single aircraft while ignoring the analysis of taxi situation on the network level. For these and other reasons that will become clear when we present the results, it is necessary to identify all relevant performance indicators at the levels of aircraft and network, independent or correlated, in order to distinguish and identify the correct taxi situation, which is the focus of this paper.

From the literature review, we conclude that there is a lack of systematic taxi situation awareness methods that rely on indicators beyond taxi time; nor is there a study on the complexity of airport taxi situation. Aiming at modelling, analyzing and assessing the taxi situation in complex airport systems with full consideration of the influencing factors of aircraft taxi process, this paper proposes a novel method for characterizing airport taxi situation based on a macroscopic distribution network (MDN) and a full list of TSIs. Specific contributions and findings are as follows.

- This paper focuses on airport taxi situation awareness at the aggregate level, by establishing a MDN to analyze the spatial-temporal characteristics of aircraft taxi process. With a given reference aircraft, we divide all the departures and arrival aircraft into 8 categories with the consideration of airport traffic in its entirety.
- Two sets of taxi situation indices (TSIs) are formulated, from the perspectives of a single aircraft (hereafter referred to as Level-1 indices) and network (hereafter referred to as Level-2 indices). The TSIs at Level-1 and Level-2 include 5 categories and 19 indices based on the proposed MDN model. Then, we investigate the coverage of the TSIs system.
- A three-step hierarchical framework is proposed to assess the airport taxi situation at both aircraft and network levels. This consists of data analysis (TS-1), situation indices refinement (TS-2) and multiple situation awareness (TS-3). In TS-3, we conduct a comprehensive correlation study for all the TSIs and identify the most key influencing factors of aircraft taxi time indices. The proposed framework can be used for taxi situation awareness at pre-tactical, tactical, and post operations in a complex airport system.
- We propose two new metrics CTS_a, CTS_n to assess the taxi situation at Level-1 and Level-2 respectively, instead of using two systems of multiple TSIs. A significant relationship is revealed between the taxi delay and CTS_a at Level-1, and the taxi time and CTS_n at Level-2, which provides strong reference to airport ground movements for control and management purposes.

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[1] For example, aircraft with a long taxi route has a relatively larger taxi time, even if there is no conflict or congestion involved.

The rest of this paper is organized as follows. Section 2 presents the macroscopic distribution network (MDN) of aircraft taxi process to describe the relationship between spatial and temporal resources. In Section 3 we define two systems of TSIs from the perspective of aircraft and network, and propose ways to compute them. Section 4 analyzes the coverage of the proposed TSIs system. In Section 5 we conduct a real-world case study of airport taxi situation awareness, and provide findings and insights by analyzing the correlation between different TSIs and complexity assessment results of airport taxi situation. Finally, some conclusion remarks are presented in Section 6.

2 Macroscopic Distribution Network

We propose a novel macroscopic distribution network (MDN) of airport ground movements in any spatial-temporal domain at any airport system shown in Figure 1. Note that the arrows in Figure 1 represent the macrscopic resource flow at airport system, not the microscopic trajectory of individual aircraft. The arrivals (departures) are represented by the arrows pointing from the runways (gates) to the gates (runways), with relevant times marked in the figure.

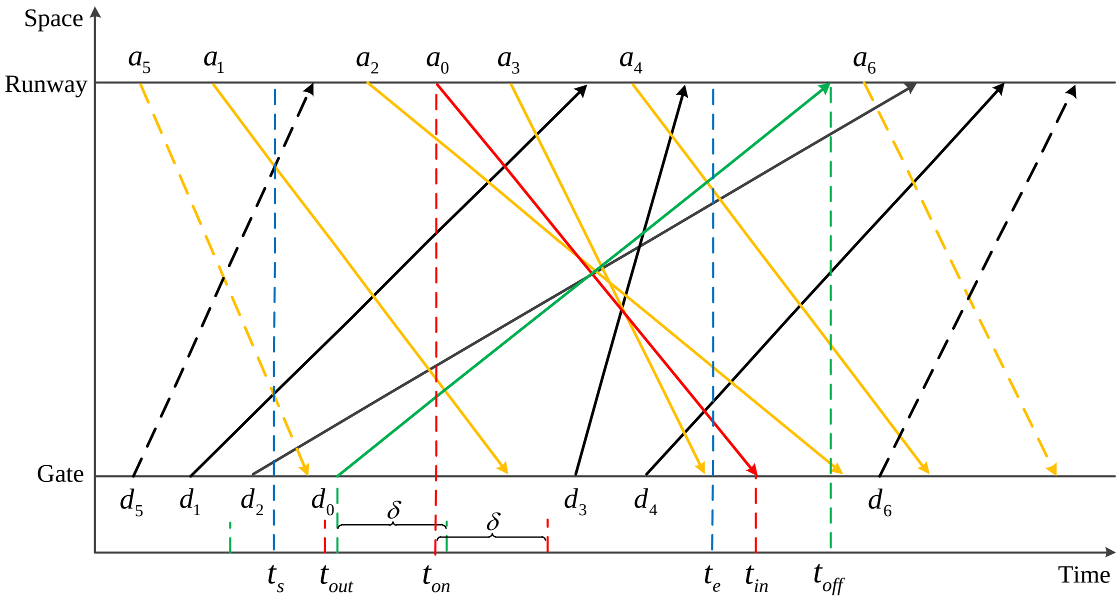


Figure 1. Macroscopic distribution network of airport ground movements

The MDN model covers all the types of air traffic with the reference aircraft a_0, d_0 and reference interval $[t_s, t_e]$ as the benchmarks for comparison, and provides a macroscopic and general description of the relationship between spatial and temporal resources. The notations in Figure 1 are explained as follows.

a_i: Arrival aircraft, $i = 1, \dots, 6$

d_i: Departure aircraft, $i = 1, \dots, 6$

a_0, d_0: Reference arrival and departure aircraft, for the analysis of TSIs

t_{on}: Landing time of arrival aircraft a_0

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

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

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

t_s, t_e: Start and end time of a certain time-slice, for the analysis of TSIs

δ: A pre-defined statistic threshold

The departures $d_1, \dots, d_4$ represent four different relationships between any departure aircraft with the reference departure aircraft d_0:

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

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

$d_3 \sim d_0$: 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". Here, by 'simultaneous' we mean that the two events occur within the same time step or are not distinguishable by the time resolution selected for the model. It is clear that $d_1, \dots, d_4$ cover all the possible relationships between any departure aircraft with the reference departure aircraft d_0. Moreover, as far as d_0 is concerned, d_5 and d_6 are irrelevant in the TSIs classification because there is no temporal overlap with the other departures, which means that they have no effect on the environment surrounding the departure aircraft d_0.

Similarly, the arrivals $a_1, \dots, a_4$ represent four different relationships between any arrival aircraft with the reference arrival aircraft a_0:

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

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

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

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

Moreover, the aircraft landing simultaneously with a_0 is classified into "Land-on Before" and the aircraft in-block simultaneously with a_0 is classified into "In-block Before". In the same way, a_5 and a_6 are also ignored in the TSIs classification of arrival aircraft.

3 Taxi Situation Indices (TSIs) System

TSIs can be divided into 5 categories and 19 indices, aircraft taxi time indices (ATTIs), surface instantaneous flow indices (SIFIs), surface cumulative flow indices (SCFIs), aircraft queue length indices (AQLIs) and slot resource demand indices (SRDIs). Each category of TSIs are calculated from two perspectives including the single-aircraft (Level-1) and whole-network (Level-2). The aircraft perspective focuses the taxi situation of airport ground movements during the taxi process of each aircraft. The network perspective focuses the taxi situation of airport ground movements in the airport network during a certain period such as one time-slice, of which the range can be set to 15 minutes, 30 minutes or 1 hour. Taking Figure 1 as an example, the following Sections 3.1-3.2 detail the definitions and calculation methods of these indices at Level-1 and Level-2.

3.1 *Level-1: Aircraft TSIs system*

Table 1 illustrates the quantities of aircraft TSIs system in Figure 1 at Level-1, with d_0 and a_0 being the reference departure and arrival aircraft respectively.

Table 1. Illustration of Aircraft TSIs system at Level-1.

TSIs	Notation	Taking d_0 as the reference departure		Taking a_0 as the reference arrival	
		Relevant aircraft	Value of index	Relevant aircraft	Value of index
ATTIs	τ_d/τ_a	$\{d_0\}$	$\tau_d = t_{off} - t_{out}$	$\{a_0\}$	$\tau_a = t_{in} - t_{on}$
SIFIs	∂_d	$\{d_1, d_2\}$	2	$\{d_0, d_1, d_2\}$	3
	∂_a	$\{a_1\}$	1	$\{a_1, a_2\}$	2
SCFIs	σ_d	$\{d_1, d_2, d_3, d_4\}$	4	$\{d_0, d_1, d_2, d_3, d_4\}$	5
	σ_a	$\{a_0, a_1, a_2, a_3, a_4\}$	5	$\{a_1, a_2, a_3, a_4\}$	4
AQLIs	λ_d	$\{d_1, d_3\}$	2	$\{d_1, d_3\}$	2
	λ_a	$\{a_0, a_2, a_3, a_4\}$	4	$\{a_3, a_4\}$	2
SRDIs	μ_d	$\{d_2\}$	1	$\{d_0\}$	1
	μ_a	$\{a_0, a_2\}$	2	$\{a_2, a_3\}$	2

3.1.1. Aircraft taxi time indices (ATTIs)

The ATTIs at Level-1 refers to the taxi time between the runway and the gate of the reference aircraft. Its definition is relatively straightforward, for any reference departure or arrival aircraft, the ATTIs include one TSI τ_d or τ_a. The ATTIs related to the reference departure aircraft d_0 is defined as follows:

τ_d: Taxi-out time of the reference departure aircraft d_0

Similarly, the ATTIs related to the reference arrival aircraft a_0 is defined as follows:

τ_a: Taxi-in time of the reference arrival aircraft a_0

Note that the ATTIs is only concerned with the reference aircraft and not any other aircraft.

3.1.2. Surface instantaneous flow indices (SIFIs)

The SIFIs at Level-1 refer to the number of taxiing aircraft when the reference aircraft is being pushed back from the gate or landing on the runway. For any reference departure or arrival aircraft, the SIFIs include two TSIs ∂_d and ∂_a. The SIFIs related to the reference departure aircraft d_0 are defined as follows:

∂_d: Number of taxiing departures when d_0 is being pushed back from the gate

∂_a: Number of taxiing arrivals when d_0 is being pushed back from the gate

Similarly, the SIFIs related to the reference arrival aircraft a_0 are defined as follows:

∂_d: Number of taxiing departures when a_0 is landing on the runway

∂_a: Number of taxiing arrivals when a_0 is landing on the runway

3.1.3. Surface cumulative flow indices (SCFIs)

The SCFIs at Level-1 refer to the number of aircraft that have taxied out or are taxiing on the surface during the entire taxi process of the reference aircraft. For any reference departure or arrival aircraft, the SCFIs include two TSIs σ_d and σ_a. The SCFIs related to the reference departure aircraft d_0 are defined as follows:

σ_d: Number of departures whose taxiing period has overlap with the taxiing period of d_0

σ_a: Number of arrivals whose taxiing period has overlap with the taxiing period of d_0

Similarly, the SCFIs related to the reference arrival aircraft a_0 are defined as follows:

σ_d: Number of departures whose taxiing period has overlap with the taxiing period of a_0

σ_a: Number of arrivals whose taxiing period has overlap with the taxiing period of a_0

3.1.4. Aircraft queue length indices (AQLIs)

The AQLIs at Level-1 refer to the number of aircraft that take off from or land on the runway during the entire taxi process of the reference aircraft. For any reference departure or arrival aircraft, the AQLIs include two TSIs λ_d and λ_a. The AQLIs related to the reference departure aircraft d_0 are defined as follows:

λ_d: Number of departures that take off from the runway during the taxi process of d_0

λ_a: Number of arrivals that land on the runway during the taxi process of d_0

Similarly, the AQLIs related to the reference arrival aircraft a_0 are defined as follows:

λ_d: Number of departures that take off from the runway during the taxi process of a_0

λ_a: Number of arrivals that land on the runway during the taxi process of a_0

3.1.5. Slot resource demand indices (SRDIs)

The SRDIs at Level-1 refer to the number of aircraft that is pushed back from the gate or land on the runway in 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, and δ is the statistic threshold coefficient introduced in Figure 1, whose value can be set dynamically and flexibly. In general, considering the normal departure and arrival taxi time of the aircraft, the statistic threshold δ can be set between 10 min and 30 min, or adjusted according the air traffic manager. For any reference departure or arrival aircraft, the SRDIs include two TSIs μ_d and μ_a. The SRDIs related to the reference departure aircraft d_0 are defined as follows:

μ_d: Number of departures that are pushed back during the statistic time interval of d_0

μ_a: Number of arrivals that land on the runway during the statistic time interval of d_0

Similarly, the AQLIs related to the reference arrival aircraft a_0 are defined as follows:

μ_d: The number of departures that are pushed back during the statistic time interval of a_0

μ_a: The number of arrivals that land on the runway during the statistic time interval of a_0

3.2 *Level-2: Network TSIs system*

Besides the TSIs set $\{\tau_d/\tau_a, \partial_d, \partial_a, \sigma_d, \sigma_a, \lambda_d, \lambda_a, \mu_d, \mu_a\}$ related to the single-aircraft, we also establish a similar system of TSIs from the perspective of whole-network, which is similar with Section 3.1.1~3.1.5. Note that the values of ATTIs, SIFIs, SCFIs and AQLIs from the perspective of network are counted in each time-slice, not focused on the single-aircraft but the whole-network, just like the definition of SRDIs introduced in Section 3.1.5. The quantities of the network TSIs system of the reference time-slice $[t_s, t_e]$ in Figure 1 at Level-2 are illustrated in Table 2.

Table 2. Illustration of Network TSIs system at Level-2.

TSIs	Notation	Taking the horizontal ordinate domain $[t_s, t_e]$ as the reference time-slice	
		Relevant aircraft	Value of index
ATTIs	$\bar{\tau}_d$	$\{d_0, d_1, d_2, d_3, d_4\}$	$\bar{\tau}_d = Avg(\tau_d^i), i = 0,1,2,3,4$
	$\bar{\tau}_a$	$\{a_0, a_1, a_2, a_3, a_4\}$	$\bar{\tau}_a = Avg(\tau_a^i), i = 0,1,2,3,4$
SIFIs	∂_s	$\{d_1, d_2, a_1\}$	3
	∂_e	$\{d_0, d_2, d_4, a_0, a_2, a_4\}$	6
SCFIs	$\tilde{\sigma}_d$	$\{d_0, d_1, d_2, d_3, d_4\}$	5
	$\tilde{\sigma}_a$	$\{a_0, a_1, a_2, a_3, a_4\}$	5
AQLIs	$\tilde{\lambda}_d$	$\{d_1, d_3\}$	2
	$\tilde{\lambda}_a$	$\{a_0, a_2, a_3, a_4\}$	4
SRDIs	$\tilde{\mu}_d$	$\{d_0, d_3, d_4\}$	3
	$\tilde{\mu}_a$	$\{a_0, a_2, a_3, a_4\}$	4

3.2.1. *Aircraft taxi time indices (ATTIs)*

The ATTIs at Level-2 refer to the average taxi time in the reference time-slice at the whole airport network. For any reference time-slice $[t_s, t_e]$, the ATTIs include two TSIs $\bar{\tau}_d$ and $\bar{\tau}_a$. The ATTIs related to the departure measurement is defined as follows:

$\bar{\tau}_d$: Average taxi-out time of all the departures in time-slice $[t_s, t_e]$

Similarly, the ATTIs related to the arrival measurement is defined as follows:

$\bar{\tau}_a$: Average taxi-in time of all the arrivals in time-slice $[t_s, t_e]$

Note that the τ_d^i and τ_a^i in Table 2 are the taxi-out time of departure aircraft i and the taxi-in time of arrival aircraft i respectively.

3.2.2. *Surface instantaneous flow indices (SIFIs)*

The SIFIs at Level-2 refer to the number of taxiing aircraft at the start or end time of the reference time-slice at the whole airport network. For any reference time-slice $[t_s, t_e]$, the SIFIs include two TSIs ∂_s and ∂_e. The SIFIs related to the measurement of start time is defined as follows:

∂_s: Number of taxiing aircraft at the start time of time-slice $[t_s, t_e]$

Similarly, the SIFIs related to the measurement of end time is defined as follows:

∂_e: Number of taxiing aircraft at the end time of time-slice $[t_s, t_e]$

3.2.3. *Surface cumulative flow indices (SCFIs)*

The SCFIs at Level-2 refer to the number of aircraft that have taxied out or are taxiing on the surface in the reference time-slice at the whole airport network. For any reference time-slice $[t_s, t_e]$, the SCFIs include two TSIs $\tilde{\sigma}_d$ and $\tilde{\sigma}_a$. The SCFIs related to the departure measurement is defined as follows:

$\tilde{\sigma}_d$: Number of departures whose taxiing period has overlap with time-slice $[t_s, t_e]$

Similarly, the SCFIs related to the arrival measurement is defined as follows:

$\tilde{\sigma}_a$: Number of arrivals whose taxiing period has overlap with time-slice $[t_s, t_e]$

3.2.4. *Aircraft queue length indices (AQLIs)*

The AQLIs at Level-2 refer to the number of aircraft that take off from or land on the runway in the reference time-slice at the whole airport network. For any reference time-slice $[t_s, t_e]$, the AQLIs include two TSIs $\tilde{\lambda}_d$ and $\tilde{\lambda}_a$. The AQLIs related to the departure measurement is defined as follows:

$\tilde{\lambda}_d$: Number of departures that take off from the runway in time-slice $[t_s, t_e]$

Similarly, the AQLIs related to the arrival measurement is defined as follows:

$\tilde{\lambda}_a$: Number of arrivals that land on the runway in time-slice $[t_s, t_e]$

3.2.5. *Slot resource demand indices (SRDIs)*

The SRDIs at Level-2 refer to the number of aircraft that is pushed back from the gate or land on the runway in the reference time-slice at the whole airport network. For any reference time-slice $[t_s, t_e]$, the SRDIs include two TSIs $\tilde{\mu}_d$ and $\tilde{\mu}_a$. The SRDIs related to the departure measurement is defined as follows:

$\tilde{\mu}_d$: Number of departures that are pushed back in time-slice $[t_s, t_e]$

Similarly, the SRDIs related to the arrival measurement is defined as follows:

$\tilde{\mu}_a$: Number of arrivals that land on the runway in time-slice $[t_s, t_e]$

4 Coverage analysis of the TSIs system

The coverage of the proposed index system refers to its capability to cover all the individual aircraft to be analyzed, and that no aircraft is left unaccounted for in the formulation of these indices. This characteristic is very important since, otherwise, there would be aircraft that influences the taxi process in reality but are not reflected in any of the indices. Based on the 5 categories of TSIs proposed in Section 3, we establish in this section the mathematical relationship of TSIs $\tau_d, \partial_d, \partial_a, \sigma_d, \sigma_a, \lambda_d, \lambda_a, \mu_d, \mu_a$, and analyze the coverage of the TSIs system. The relationships among TSIs are quantitatively analyzed as follows. Note that the coverage analysis of the TSIs $\bar{\tau}_d, \bar{\tau}_a, \partial_s, \partial_e, \tilde{\sigma}_d, \tilde{\sigma}_a, \tilde{\lambda}_d, \tilde{\lambda}_a, \tilde{\mu}_d, \tilde{\mu}_a$ at Level-2 are generalized to that of the TSIs $\tau_d, \partial_d, \partial_a, \sigma_d, \sigma_a, \lambda_d, \lambda_a, \mu_d, \mu_a$ at Level-1, but the only difference is that all the time-slices (not one time-slice just like $[t_s, t_e]$) in the study period of airport should be discussed, which is similar with the analysis at Level-1 and not described in detail here.

4.1 *Coverage of departure measurement*

For any reference departure aircraft d_0, we denote the number of departure aircraft in the categories OBTB, OBTA, OATB and OATA (see Section 2) by N_d^1, N_d^2, N_d^3 and N_d^4, respectively. The SIFIs, SCFIs and AQLIs of d_0 satisfy

$$\partial_d = N_d^1 + N_d^2 \quad (1)$$

$$\sigma_d = N_d^1 + N_d^2 + N_d^3 + N_d^4 \quad (2)$$

$$\lambda_d = N_d^1 + N_d^3 \quad (3)$$

We can see from (1)-(3) that there is a correlation between ∂_d and σ_d because they share two additive variables N_d^1 and N_d^2, same goes for σ_d and λ_d for a similar reason. Considering the two TSIs ∂_d and λ_d are correlated, we can find the relationships among ∂_d, σ_d and λ_d

$$\sigma_d = \partial_d + N_d^3 + N_d^4 \quad (4)$$

$$\lambda_d = \partial_d - N_d^2 + N_d^3 \quad (5)$$

Moreover, for the SRDIs, the relationship between μ_d and the other two TSIs ∂_d and λ_d depends on the statistic threshold coefficient δ. Therefore, for any departure aircraft d_0, the TSIs ∂_d, σ_d, λ_d and μ_d cover all the four departure cases OBTB, OBTA, OATB and OATA. Similarly, for any reference arrival aircraft a_0, the TSIs ∂_d, σ_d, λ_d and μ_d also cover all the four departure cases OBTB, OBTA, OATB and OATA. Based on the above discussion, we establish the coverage analysis of the TSIs system from the perspective of departure measurement.

4.2 *Coverage of arrival measurement*

Similarly, for any reference arrival aircraft a_0, we let the number of arrival aircraft in the categories LBIB, LBIA, LAIB and LAIA (see Section 2) be N_a^1, N_a^2, $N_a^3$and N_a^4 respectively, then SIFIs, SCFIs and AQLIs of a_0 satisfy

$$\partial_a = N_a^1 + N_a^2 \tag{6}$$

$$\sigma_a = N_a^1 + N_a^2 + N_a^3 + N_a^4 \tag{7}$$

$$\lambda_a = N_a^3 + N_a^4 \tag{8}$$

We can see from (6)-(8) that there is a correlation between ∂_a and σ_a because they have two shared additive factors N_a^1 and N_a^2. For similar reason, σ_a and λ_a are correlated. Variables ∂_a and λ_a are independent, as they share no common factors. Based on this, we can write

$$\sigma_a = \partial_a + \lambda_a \tag{9}$$

Furthermore, for the SRDIs, the relationship between μ_a and the other two TSIs ∂_a and λ_a depends on the statistic threshold coefficient δ. Therefore, for any arrival aircraft a_0, the TSIs ∂_a, σ_a, λ_a and μ_a cover all the four arrival cases LBIB, LBIA, LAIB and LAIA. Similarly, for any reference departure aircraft d_0, the TSIs ∂_a, σ_a, λ_a and μ_a also cover all the four arrival cases LBIB, LBIA, LAIB and LAIA. Based on the above discussion, we establish the coverage analysis of the TSIs system from the perspective of arrival measurement.

5 Numerical results and analysis

In this paper, we conduct a case study of airport taxi situation awareness in the Shanghai Pudong International Airport (PVG) to analyze the relationship among the TSIs and assess the taxi situation from the perspective of single-aircraft and whole-network at both Level-1 and Level-2, based on the proposed conceptual framework of airport taxi situation awareness.

5.1 *Conceptual framework*

The conceptual framework of airport taxi situation awareness has three hierarchies: data analysis (TS-1), situation indices refinement (TS-2) and multiple situation awareness (TS-3), which are shown in Figure 2.

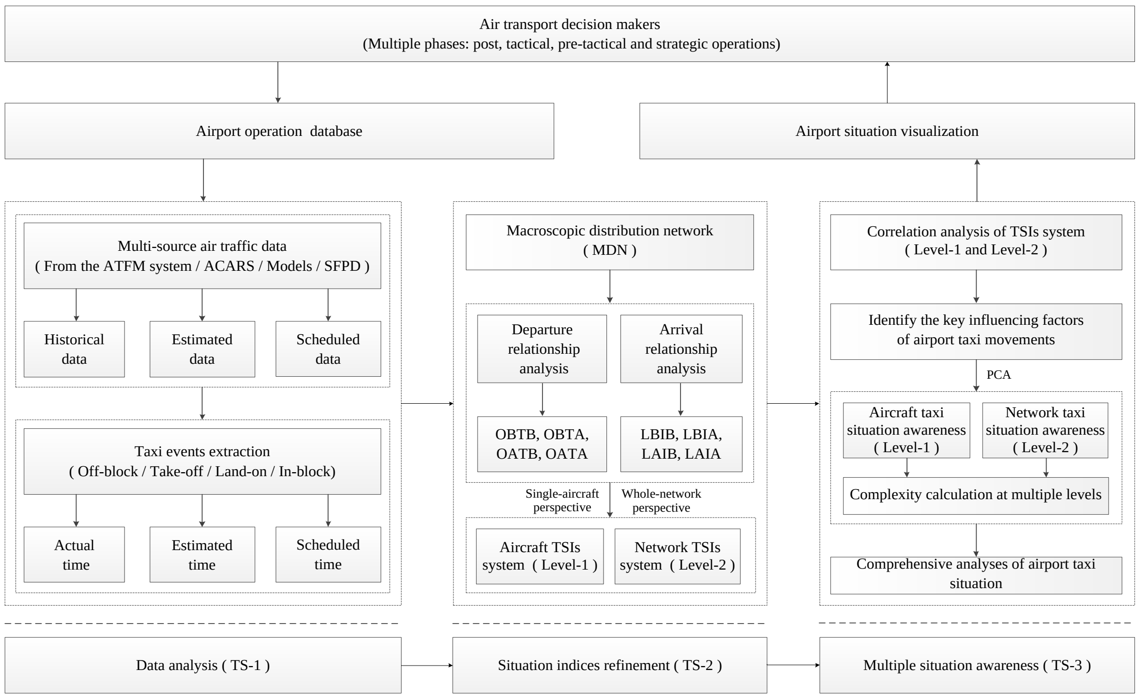


Figure 2. Conceptual framework of airport taxi situation awareness

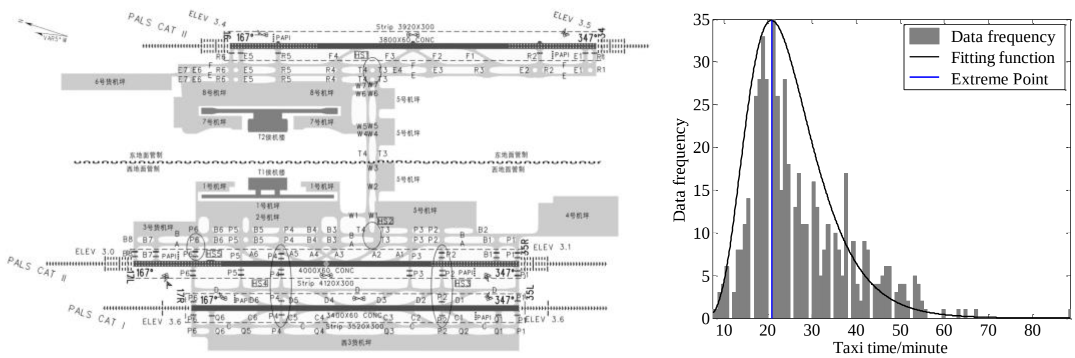
The first hierarchy (TS-1) involves collecting historical, estimated or scheduled multi-source air traffic data from the operation centers of airport, airlines and air navigation service provider, and extracting some key events related to the process of aircraft ground movements. Note that the data set used to conduct the study of airport taxi situation awareness can be the historical data, such as the actual landing time and in-block time of arrivals, and the actual off-block time and take-off time of departures (ALDT, AIBT, AOBT, ATOT from ATFM system; or the OOOI data from ACARS), for the taxi situation awareness at the phase of post operations in complex airport systems. It can also be the estimated information, such as the estimated landing time and in-block time of arrivals, and the estimated off-block time and take-off time of departures (ELDT, EIBT, EOBT and ETOT from ATFM system; or the data calculated by some models, for example, the models proposed by Balakrishna et al. (2007), Atkin et al. (2011), Ravizza et al. (2013), George and Khan (2015)), for the taxi situation awareness at the phase of tactical operations in complex airport systems. Furthermore, it also can be the scheduled information, such as the scheduled in-block time and standard taxi-in time of arrivals, and the scheduled off-block time and standard taxi-out time of departures (SIBT, SOBT from flight schedule; taxi-in time and taxi-out time from the Standard Flight Performance Database (SFPD)), for the taxi situation awareness at the phase of pre-tactical or strategic operations in complex airport systems.

The second hierarchy (TS-2) focuses on the refinement of TSIs system based on the macroscopic distribution network established in Section 2. In any MDN within a certain spatial-temporal domain, the relationship between any departure aircraft and the reference departure aircraft can be identified as one of the following cases including OBTB, OBTA, OATB and OATA. Similar to the departures, the relationship among the arrivals can be identified as one of the following cases including LBIB, LBIA, LAIB and LAIA. Then we can establish the TSIs system from the perspective of aircraft or network, according to the needs of air transport decision makers such as the single-aircraft taxi situation (Level-1) and whole-network taxi situation (Level-2) of airport ground movements.

The third hierarchy (TS-3) is directly related to taxi situation awareness under two systems of TSIs from different perspectives of aircraft and network. We analyze the correlation of different TSIs to identify the key influencing factors of airport taxi movements. Based on the correlation analysis, we apply the method of principal components analysis (PCA) to extract the most important information of the TSIs from the perspective of aircraft and network, then assess the taxi situation of airport ground movements during the taxi process of each single-aircraft at Level-1 and the taxi situation of airport ground movements at the whole-network during a certain period (For example, any 15-minutes time-slice) at Level-2. Finally, a comprehensive analysis of airport taxi situation from different perspectives are conducted to find the direct and key metrics reflecting the complexity of airport taxi situation by establishing the assessment functions, instead of using two systems of multiple TSIs. The findings can provide some significant references about airport ground movements for air transport decision makers on the aspects of air traffic management and airport congestion control.

5.2 *Data statistics of taxi sample*

The ground layout of Shanghai Pudong International Airport is shown in Figure 3-a, which contains 3 runways numbered 16/34, 17L/35R, 17R/35L and 193 gates. There are 528 departure and 524 arrival aircraft during the test period 00:00~16:00 on October 1, 2014. Figure 3-b shows the statistic distribution of taxi time of sample air traffic in PVG. The actual observation data is analyzed by frequency analysis, and the probability distribution is fitted according to the actual observation data. We find that the taxi time is not subject to the normal distribution, while it approximately follows the lognormal distribution after conducting the logarithmic transformation to the sample data.



（a） （b）

Figure 3. Airport layout and taxi time distribution of PVG

The TSIs are computed for each departure aircraft, and are summarized statistically in Table 3. Note that in this table, the superscript '1' (or '2') indicates that the input for calculating the index concerns with the departure (or arrival) aircraft.

Table 3. Statistical summary of TSIs on the test site.

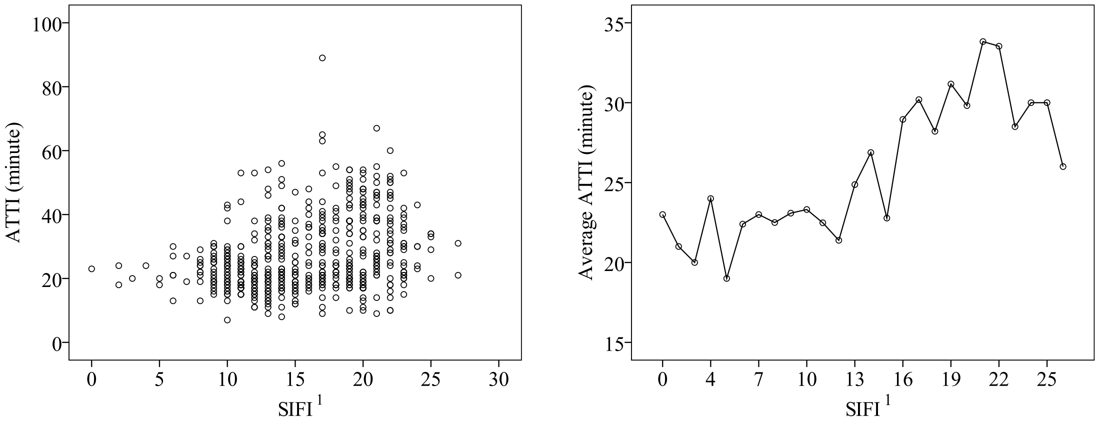
Variable	Minimum	Maximum	Average	Standard deviation	Variance
ATTI (τ_d) (min)	7	89	27.25	11.37	129.31
$SIFI^1$ (∂_d)	0	27	15.79	4.78	22.84
$SIFI^2$ (∂_a)	0	16	9.04	3.72	13.82
$SCFI^1$ (σ_d)	12	76	30.99	9.75	95.10
$SCFI^2$ (σ_a)	1	66	24.34	10.11	102.25
$AQLI^1$ (λ_d)	0	54	15.58	7.26	52.76
$AQLI^2$ (λ_a)	1	53	15.83	8.32	69.19
$SRDI^1$ (μ_d)	7	35	18.91	5.13	26.35
$SRDI^2$ (μ_a)	3	48	32.98	9.09	82.60

5.3 *Correlation analysis of TSIs*

Considering the aircraft taxi time is a fundamental and essential metric to reflect the performance of taxi process, we firstly treat the ATTIs as the dependent variable, and SIFIs, SCFIs, AQLIs and SRDIs as the independent variables to analyze the correlation among the TSIs. First of all, we use scatter plots to preliminarily interpret their correlations. Then we calculate the Pearson correlation coefficient between any pair of TSIs, and execute quantitative correlation analysis and T test with a 526 degrees of freedom. Finally, we also analyze the correlation of any pair of ATTIs, SIFIs, SCFIs, AQLIs and SRDIs by an overview of correlation matrix.

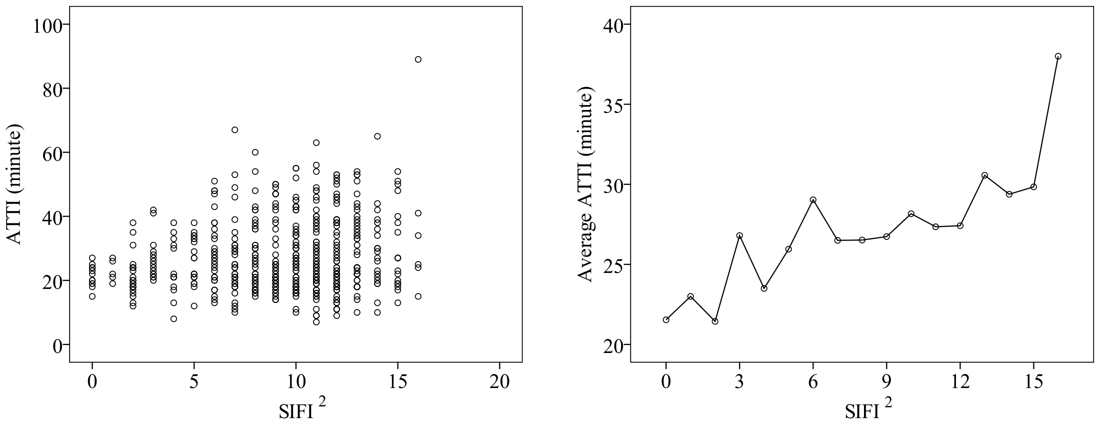
5.3.1 Summary of the correlation analysis results

Our correlation analysis consists of two main tests: the Pearson correlation analysis and the partial correlation analysis. The correlation tests are also corroborated by visual confirmation from scatter plots in Figure 4-Figure 11. The correlation results are summarized in Table 4.



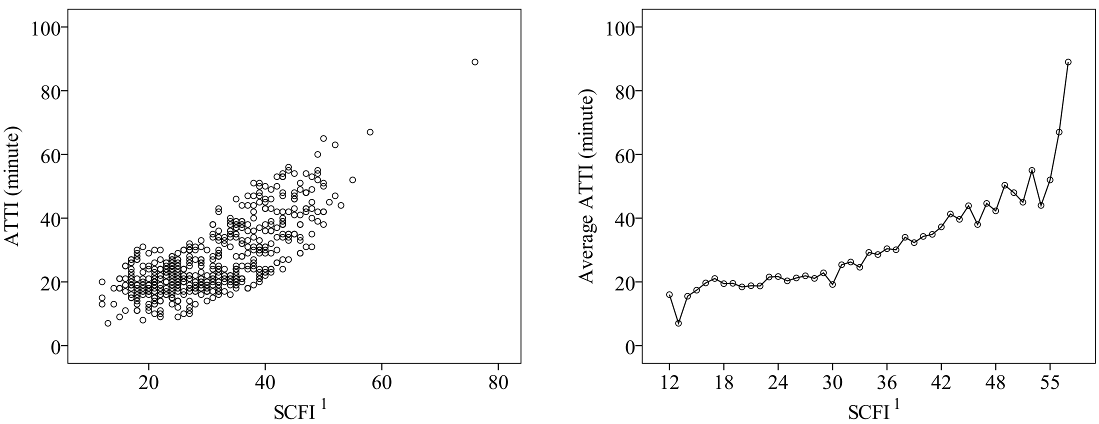
（a）　　　　　　　　　　　　　　（b）

Figure 4. Correlation analysis of ATTI (τ_d) and SIFI[1] (∂_d)



（a）　　　　　　　　　　　　　　（b）

Figure 5. Correlation analysis of ATTI (τ_d) and SIFI[2] (∂_a)



（a）　　　　　　　　　　　　　　（b）

Figure 6. Correlation analysis of ATTI (τ_d) and SCFI[1] (σ_d)

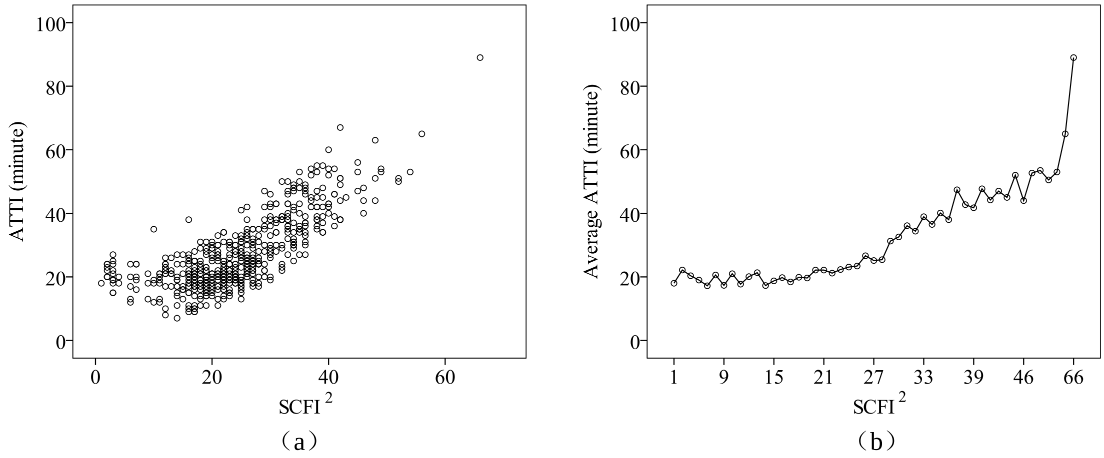


Figure 7. Correlation analysis of ATTI (τ_d) and SCFI^2 (σ_a)

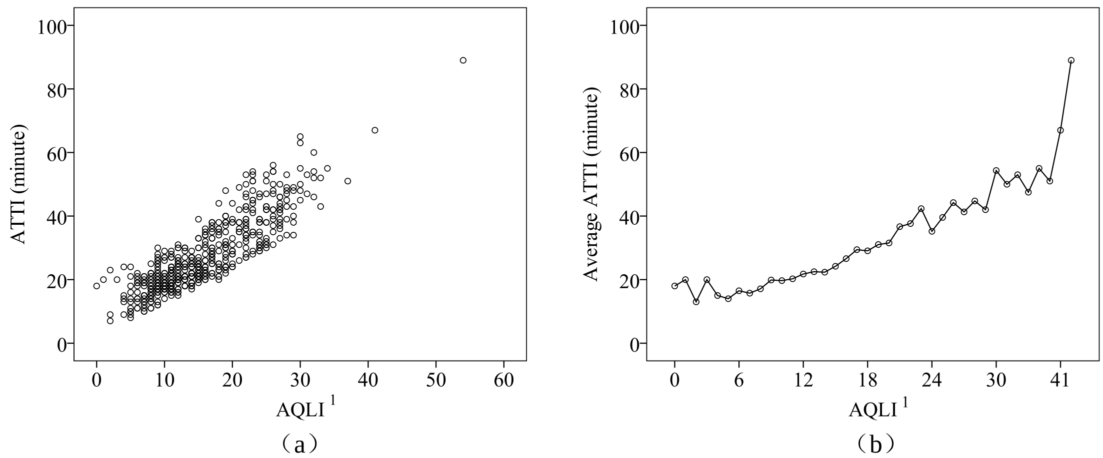


Figure 8. Correlation analysis of ATTI (τ_d) and AQLI^1 (λ_d)

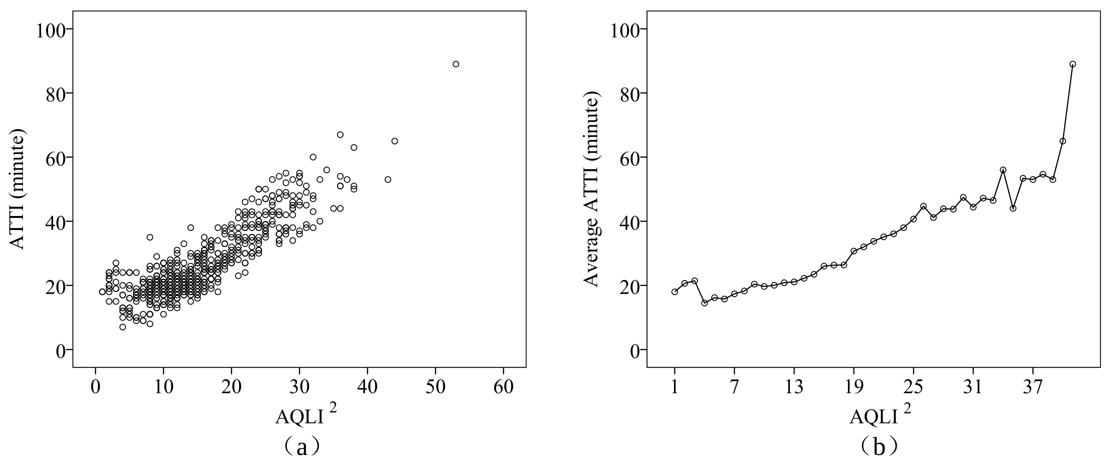
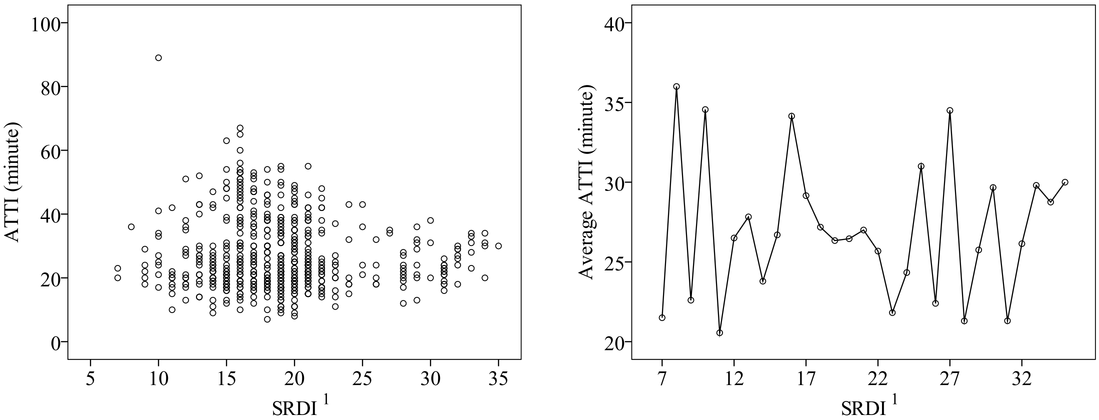
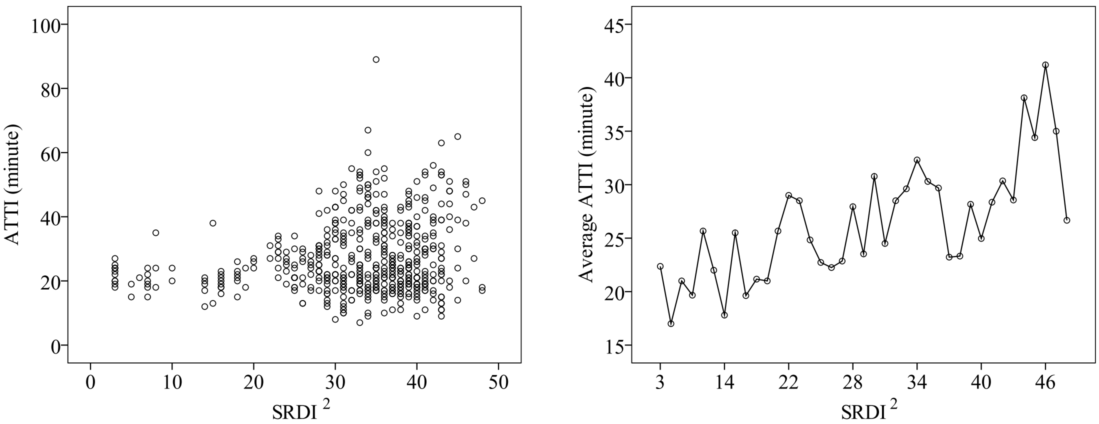


Figure 9. Correlation analysis of ATTI (τ_d) and AQLI^2 (λ_a)



（a） （b）

Figure 10. Correlation analysis of ATTI (τ_d) and SRDI[1] (μ_d)



（a） （b）

Figure 11. Correlation analysis of ATTI (τ_d) and SRDI[2] (μ_a)

Table 4. Summary of the correlation between ATTIs and other TSIs.

Pairs of TSIs	Pearson correlation analysis		Partial correlation analysis		Visual confirmation	Correlation
	coefficient	p-value	7th order coefficient	p-value		
ATTI & SIFI[1]	0.296	0 (<0.05)	-0.442	0 (<0.05)	Figure 4	**Weak**
ATTI & SIFI[2]	0.170	0 (<0.05)	-0.074	0 (<0.05)	Figure 5	**Weak**
ATTI & SCFI[1]	0.754	0 (<0.05)	0.140	0.001 (<0.05)	Figure 6	**Strong**
ATTI & SCFI[2]	0.770	0 (<0.05)	0.175	0 (<0.05)	Figure 7	**Strong**
ATTI & AQLI[1]	0.871	0 (<0.05)	0.694	0 (<0.05)	Figure 8	**Strong**
ATTI & AQLI[2]	0.873	0 (<0.05)	0.021	0.634 (>0.05)	Figure 9	**Strong**
ATTI	-0.079	0.071	-0.533	0	Figure 10	**Weak**

& SRDI[1]		(>0.05)		(<0.05)		
ATTI & SRDI[2]	0.194	0 (<0.05)	-0.527	0 (<0.05)	Figure 11	**Weak**

5.3.2 Interpretation of correlation analysis results

As shown in Table 4 and Figure 4, there is no strong correlation between ATTI (τ_d) and SIFI[1] (∂_d), with the reason that SIFI[1] (∂_d) only reflects the instantaneous situation, while not sufficiently reflects the level of congestion encountered by the reference aircraft. Similar explanation can be applied to the weak correlation between ATTI (τ_d) and SIFI[2] (∂_a) in Figure 5. Table 4 and Figure 6 show that there is a strong linear correlation between ATTI (τ_d) and SCFI[1] (σ_d). But SCFI[1] (σ_d) has no significant effect on the departure aircraft taxi time ATTI (τ_d), because the Pearson correlation coefficient 0.754 is much larger than the partial correlation coefficient 0.140. Actually, the correlation between ATTI (τ_d) and SCFI[1] (σ_d) is decided by the correlations between SCFI[1] (σ_d) and SIFI[1] (∂_d) / AQLI[1] (λ_d) / AQLI[2] (λ_a). Similar explanation can be applied to the strong but not significant correlation between ATTI (τ_d) and SCFI[2] (σ_a) in Figure 7. Actually, the correlation between ATTI (τ_d) and SCFI[2] (σ_a) is decided by the correlations between SCFI[2] (σ_a) and SIFI[2] (∂_a) / AQLI[2] (λ_a) / SRDI[2] (μ_a).

Table 4 and Figure 8 show that the linear correlation between ATTI (τ_d) and AQLI[1] (λ_d) is strong, with the reason that AQLI[1] (λ_d) is an indicator of the runway saturation level and hence the level of congestion at the taxiway. AQLI[1] (λ_d) has a significantly positive and essential effect on ATTI (τ_d), because the difference between the Pearson correlation coefficient 0.871 and the partial correlation coefficient 0.694 is small. Thus the AQLI[1] (λ_d) can be identified as a key influencing factor of the ATTI (τ_d). Similar explanation can be applied to the strong correlation between ATTI (τ_d) and AQLI[2] (λ_a) in Figure 9, but the partial correlation analysis does not pass the significant test. The use of λ_a as the key factor of taxi situation depends on the application scenario.

As shown in Table 4, Figure 10 and Figure 11, the linear correlation between ATTI (τ_d) and SRDI[1] (μ_d) or SRDI[2] (μ_a) is very weak. Especially in the case for the half interval $[t_0 - \delta, t_0]$, there is no overlap whatsoever with the taxi process of the reference aircraft.

In additional, correlation analysis has also been carried out for any pair of TSIs, and the results are shown in Figure 12 in the form of scatter plots. For each subgraph in Figure 12, the horizontal and vertical axes correspond to the independent and dependent variables respectively. For example, the subgraphs labeled 1~8 indicate that the ATTIs has significant linear correlations with SCFIs and AQLIs, and the subgraphs labeled 9~12 mean that the SCFIs and AQLIs have a significant linear relationship with each other.

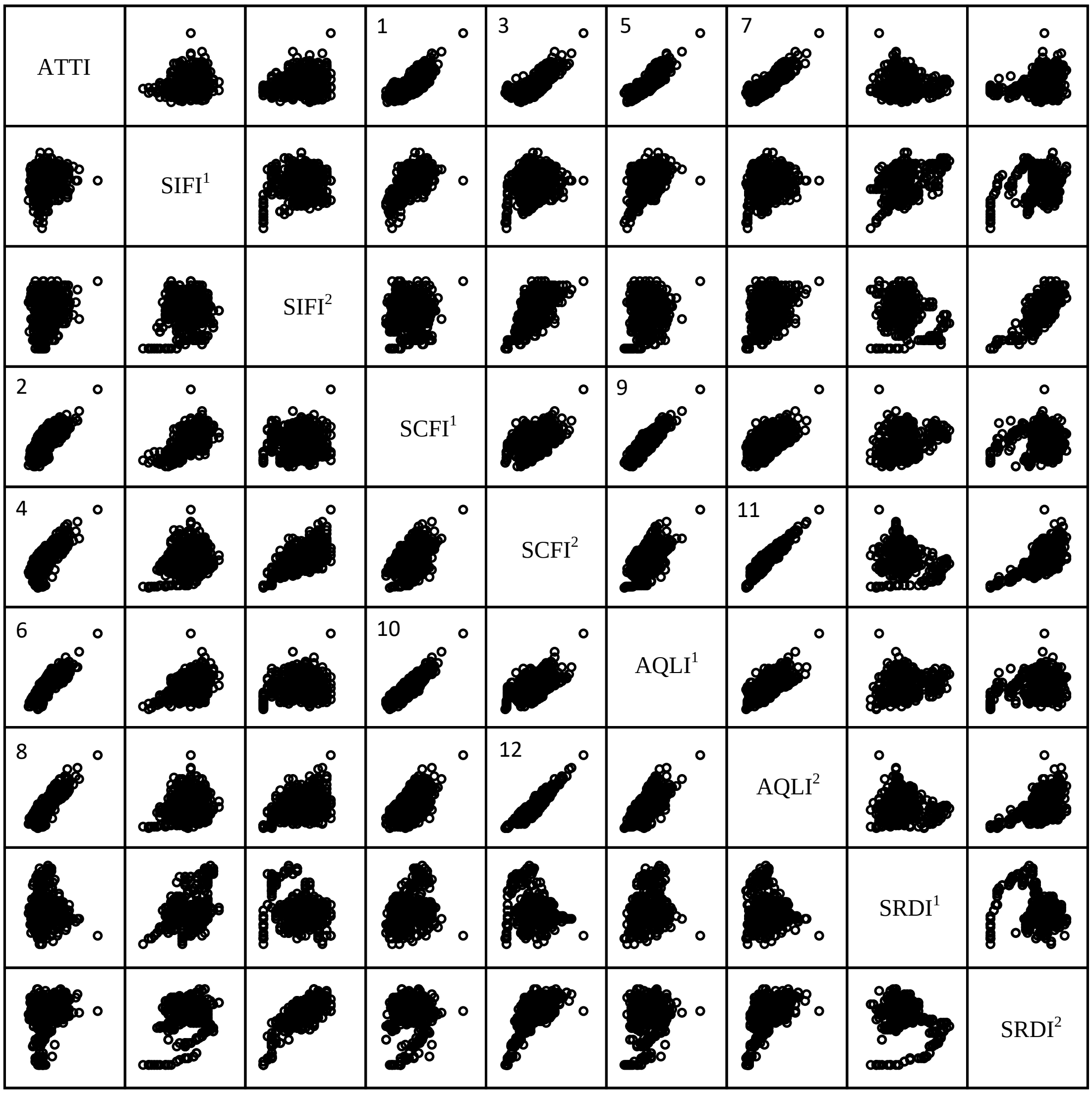


Figure 12. Correlation analysis of all the TSIs

To summarize this correlation study, we can get some key conclusions. There is a significant correlation between ATTI (τ_d) and other four TSIs including SCFI^1 (σ_d), SCFI^2 (σ_a), AQLI^1 (λ_d) and AQLI^2 (λ_a), which are the most important influencing factors of the taxi time. The correlation between SCFI^1 (σ_d) and AQLI^1 (λ_d) and the correlation between SCFI^2 (σ_a) and AQLI^2 (λ_a) are significant. The partial correlation analysis reveals that AQLI^1 (λ_d) is the most essential and key influencing factor of ATTI (τ_d).

5.4 *Taxi situation awareness from multiple perspectives*

We adapt all the TSIs at Level-1 and Level-2 proposed in Section 3 to assess airport taxi situation from the perspectives of single-aircraft and whole-network. The aircraft perspective (Level-1) focuses on the taxi situation awareness when any departure aircraft in the test period is being pushed back from the gate. The network perspective (Level-2) focuses on the taxi situation awareness in airport network during a certain period, in which the range of each time-slice is set to 15 minutes.

5.4.1 Level-1: the aircraft perspective

We use Z-Score regularization model to transform the initial aircraft TSIs $\{\tau_d, \partial_d, \partial_a, \sigma_d, \sigma_a, \lambda_d, \lambda_a, \mu_d, \mu_a\}$ to the normalized aircraft TSIs $\{\xi_i | i = 1,2, \dots, p\}$, where $p = 9$ is the number of aircraft TSIs. For any TSIs, the regularization model is

$$Trans(x_i) = \frac{x_i - \frac{1}{n}\sum_{j=1}^{n} x_j}{\sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(x_k - \frac{1}{n}\sum_{j=1}^{n} x_j)^2}} \ , \ i = 1,2, \dots, n \tag{10}$$

where n is the size of taxi sample and $x_i(\ i = 1,2, \dots, n)$ is the value of the objective TSIs.

In order to simplify the taxi situation awareness, we apply the method of principal components analysis (PCA) to compress the size of normalized aircraft TSIs set through decomposing it into irrelevant linear-combined TSIs $F_i(i = 1,2, \dots, p)$ with the same total variance.

$$F_i = \sum_{k=1}^{p} a_{ki}\xi_k = \boldsymbol{a}_i^T \boldsymbol{\xi} \tag{11}$$

where $\boldsymbol{a_i} = (a_{1i}, a_{2i}, \dots, a_{pi})^T$ is the unit column vector and $\boldsymbol{\xi} = (\xi_1, \xi_2, \dots, \xi_p)^T$ is the column vector of normalized aircraft TSIs.

The guideline of choosing the principal components is the cumulative contribution rate of 85%. The contribution rate of F_i is

$$\theta_i = \frac{\gamma_i}{\sum_{j=1}^{p} \gamma_p} \tag{12}$$

where $\{\gamma_i | i = 1,2, \dots, p\}$ are the eigenvalues of covariance matrix of $\boldsymbol{\xi}$, and $\gamma_1 \geq \gamma_2 \geq \cdots \geq \gamma_p$.

We take 68 departure aircraft in the peak hours 06:00~08:00 of PVG airport as the sample at Level-1. After appling the PCA method, we select F_1, F_2 and F_3 as the key principle componenets to assess airport taxi situation at Level-1. The assessment function and coefficient matrix are

$$F = \sum_{i=1}^{3} \mathfrak{k}_i \boldsymbol{a}_i^T \boldsymbol{\xi} \tag{13}$$

$$\boldsymbol{a} = (\boldsymbol{a_1}, \boldsymbol{a_2}, \boldsymbol{a_3}) = \begin{bmatrix} 0.416428 & -0.084790 & -0.387990 \\ 0.250511 & -0.295794 & 0.543974 \\ 0.199100 & 0.484140 & 0.359358 \\ 0.367821 & -0.346927 & -0.020730 \\ 0.424373 & 0.245310 & -0.020730 \\ 0.404276 & -0.279613 & -0.080950 \\ 0.435590 & 0.091260 & -0.182640 \\ -0.000930 & -0.430423 & 0.508433 \\ 0.234620 & 0.467320 & 0.353435 \end{bmatrix} \tag{14}$$

where $\mathfrak{k}_i$ is the variance contribution rate of F_i, and $\mathfrak{k}_1 = 0.50864$, $\mathfrak{k}_2 = 0.26518$, $\mathfrak{k}_3 = 0.11402$.

We can infer the complexity of taxi situation at Level-1 from F_1, F_2 and F_3 by comparing the elements of matrix $\boldsymbol{a}$. The first assessment subfunction F_1 includes the most important information from $\xi_1, \xi_4, \xi_5, \xi_6, \xi_7$, which is related to $\tau_d, \sigma_d, \sigma_a, \lambda_d, \lambda_a$ and mainly reflects the complexity of taxi process of each departure aircraft (denoted by CTS_a^1). Similarly, F_2 includes the most important information from ξ_3 and ξ_9, which is related to ∂_a, μ_a and mainly reflects the complexity of taxiing arrival movements when each departure aircraft is being pushed back (denoted by CTS_a^2). And F_3 includes the most important information from ξ_2 and ξ_8, which is related to ∂_d, μ_d and mainly reflects the complexity of taxiing departure movements when each departure aircraft is being pushed back (denoted by CTS_a^3). Based on the above discussion, we use CTS_a, the sum of $CTS_a^i (i = 1,2,3)$, to analyze the total complexity of taxi situation at Level-1.

Figure 13-a shows the initial values of complexity $CTS_a^1, CTS_a^2, CTS_a^3$ and CTS_a at Level-1. We can find that the change trend of CTS_a is consistent with that of CTS_a^1, but obviously different with that of CTS_a^2 and CTS_a^3. The fact can be represented by the departure aircraft CES5629, CKK221, SIA831, CES518 and CSH9125 numbered 13, 16, 36, 47 and 56 respectively in the horizontal axis. Take the 36th aircraft SIA831 as an instance, the departure taxi time is 89 minutes which is higher than the average taxi time (33 minutes) of the total aircraft in the test period, then the initial values of complexity CTS_a^1 are larger than those of other aircraft.

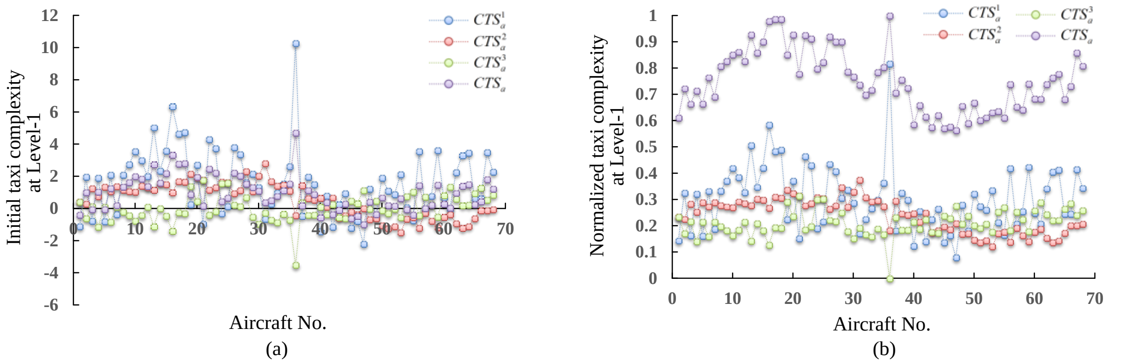


Figure 13. Initial and normalized complexity of taxi situation at Level-1

It can be obviously seen that there are some negative values in Figure 13-a with the reason that the initial values are calculated by F_1, F_2 and F_3 where ξ_i may be negative after the Z-Score regularization. Considering the inconvenience of initial complexity in practice, we use the normalized model to transform the any initial value at Level-1 to a normalized quantity in interval [0,1] shown in Figure 13-b.

$$C_{ij} = \frac{\delta_{ij} - \min\limits_{\substack{i\in[1,m] \\ j\in[1,n]}}\{\delta_{ij}\}}{\max\limits_{\substack{i\in[1,m] \\ j\in[1,n]}}\{\delta_{ij}\} - \min\limits_{\substack{i\in[1,m] \\ j\in[1,n]}}\{\delta_{ij}\}} \tag{15}$$

where δ_{ij} is the initial CTS_a^j value of aircraft i, m is the number of aircraft, $n = 3$ is the number of complexity (CTS_a^1, CTS_a^2 and CTS_a^3) at Level-1, and C_{ij} is the transformed values of δ_{ij}.

Considering taxi delay is a key representation of taxi situation complexity, we also conduct a study about the relationship between taxi delay and some aircraft TSIs, which is shown in Figure 14-a. Here the taxi delay of aircraft is defined as the difference between the total taxi time and non-conflict taxi time. Note that the non-conflict taxi time is a pre-set value sourced from the Standard Flight Performance Database (SFPD). Figure 14-a reveals the fact that the change trend of taxi delay is consistent with SCFIs ($\sigma_d + \sigma_a$) and AQLIs ($\lambda_d + \lambda_a$), but obviously different from SIFIs ($\partial_d + \partial_a$) and SRDIs ($\mu_d + \mu_a$). From the comprehensive analysis, we can see that the CTS_a is a direct and key metric of aircraft taxi delay shown in Figure 14-b.

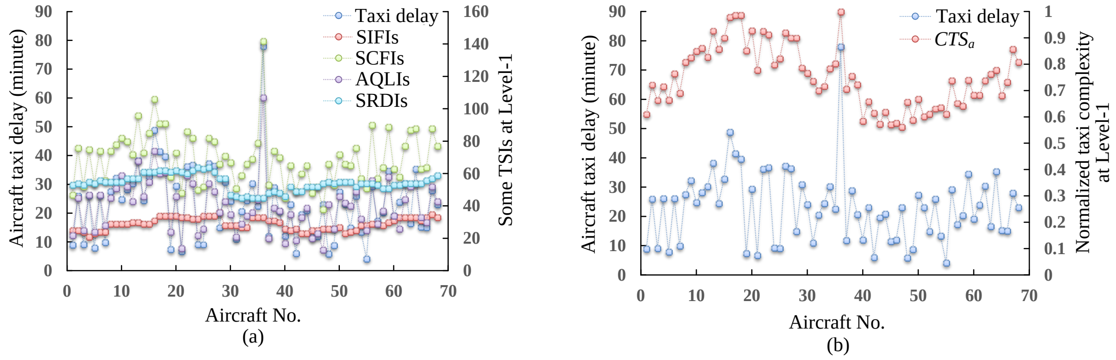


Figure 14. Relationship between taxi delay and some TSIs, CTS_a at Level-1

Based on the results of Figure 13 and Figure 14, air transport decision makers can directly use a key metric CTS_a, instead of a system of multiple aircraft TSIs $\{\tau_d, \partial_d, \partial_a, \sigma_d, \sigma_a, \lambda_d, \lambda_a, \mu_d, \mu_a\}$, to assess the taxi situation at Level-1 and provide references to manage aircraft taxi movements.

5.4.2 Level-2: the network perspective

We also use the Z-Score regularization model in Equation 10 to transform the initial network TSIs set $\{\bar{\tau}_d, \bar{\tau}_a, \partial_s, \partial_e, \tilde{\sigma}_d, \tilde{\sigma}_a, \tilde{\lambda}_d, \tilde{\lambda}_a, \tilde{\mu}_d, \tilde{\mu}_a\}$ to the normalized network TSIs set $\{\zeta_i | i = 1,2, \dots, q\}$, where $q = 10$ is the number of network TSIs. Then the set $\{\zeta_i | i = 1,2, \dots, q\}$ is decomposed into $H_i(i = 1,2, \dots, q)$.

$$H_i = \sum_{k=1}^{q} b_{ki} \zeta_k = \boldsymbol{b}_i^T \boldsymbol{\zeta} \tag{16}$$

where $\boldsymbol{b}_i = (b_{1i}, b_{2i}, \dots, b_{qi})$ is the unit column vector and $\boldsymbol{\zeta} = (\zeta_1, \zeta_2, \dots, \zeta_q)^T$ is the column vector of normalized network TSIs.

We take 64 time-slices in the test period 00:00~16:00 of PVG airport as the sample at Level-2, including 528 departure aircraft and 524 arrival aircraft. After applying the PCA method, we select H_1, H_2, H_3 and H_4 as the key principle componenets to assess airport taxi situation at Level-2. The assessment function and coefficient matrix are

$$H = \sum_{i=1}^{4} \mathfrak{t}_i \boldsymbol{b}_i^T \boldsymbol{\zeta} \tag{17}$$

$$\boldsymbol{b} = (\boldsymbol{b}_1, \boldsymbol{b}_2, \boldsymbol{b}_3, \boldsymbol{b}_4) = \begin{bmatrix} 0.322970 & 0.095648 & -0.333105 & 0.356291 \\ 0.125406 & -0.066822 & 0.654181 & 0.584604 \\ 0.438422 & -0.014413 & 0.192461 & -0.258004 \\ 0.435934 & 0.205053 & -0.112886 & 0.215003 \\ 0.342875 & 0.456620 & 0.024983 & -0.101359 \\ 0.381194 & -0.391108 & -0.045339 & -0.084977 \\ 0.188606 & 0.332802 & 0.495956 & -0.426935 \\ 0.348349 & -0.275806 & -0.093454 & 0.241623 \\ 0.058722 & 0.487411 & -0.363640 & 0.043001 \\ 0.272708 & -0.397004 & -0.148047 & -0.397244 \end{bmatrix} \tag{18}$$

where $\mathfrak{t}_i$ is the variance contribution rate of H_i, and $\mathfrak{t}_1 = 0.40379$, $\mathfrak{t}_2 = 0.23303$, $\mathfrak{t}_3 = 0.11682$,

$\mathfrak{f}_4 = 0.09543$.
Similar with Section 5.4.1, H_1 includes the most important information from $\zeta_3, \zeta_4, \zeta_6, \zeta_8, \zeta_{10}$, which is related to $\partial_s, \partial_e, \tilde{\sigma}_a, \tilde{\lambda}_a, \tilde{\mu}_a$ and mainly reflects the complexity of arrival demand in each time-slice (denoted by CTS_n^1). H_2 includes the most important information from ζ_5 and ζ_9, which is related to $\tilde{\sigma}_d, \tilde{\mu}_d$ and mainly reflects the complexity of departure demand in each time-slice (denoted by CTS_n^2). H_3 includes the most important information from ζ_2 and ζ_7, which is related to $\bar{\tau}_a, \tilde{\lambda}_d$ and mainly reflects the complexity of taxi-in process in each time-slice (denoted by CTS_n^3). And F_4 includes the most important information from ζ_1, which is related to $\bar{\tau}_d$ and mainly reflects the complexity of taxi-out process in each time-slice (denoted by CTS_n^4). Then we use CTS_n, the sum of $CTS_n^i (i = 1,2,3,4)$, to analyze the total complexity of taxi situation at Level-2.

Figure 15-a shows the initial values of complexity $CTS_n^1, CTS_n^2, CTS_n^3, CTS_n^4$ and CTS_n at Level-2. We can find that the change trend of CTS_n is consistent with that of CTS_n^1, but a little different with that of CTS_n^2, CTS_n^3 and CTS_n^4. The fact can be represented by the time-slice 00:45~01:00, 02:15~02:30, 06:15~06:30, 08:00~08:15, 13:00~13:15, 15:45~16:00 numbered 4, 10, 26, 33, 53 and 64 respectively in the horizontal axis. Take the 26th time-slice 06:15~06:30 as an instance, the key elements $\partial_s = 30, \partial_e = 33, \tilde{\sigma}_a = 26, \tilde{\lambda}_a = 13, \tilde{\mu}_a = 13$ are larger than the average value (24,24,17,8,8 respectively) in other time-slices, then the initial value of complexity CTS_n^1 is larger than those of other aircraft. Similar with Figure 13-b, the initial value of $CTS_n^1, CTS_n^2, CTS_n^3$ and CTS_n^4 are transformed into the [0,1] interval shown in Figure 15-b.

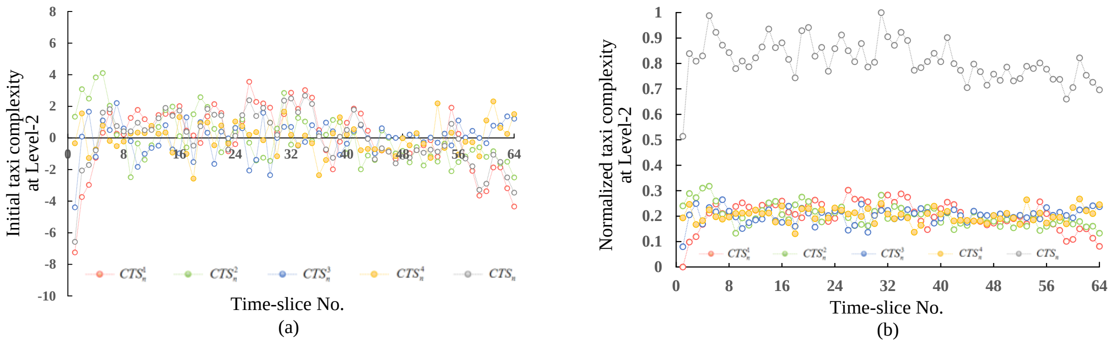


Figure 15. Initial and normalized complexity of taxi situation at Level-2

Considering taxi-out time and taxi-in time are key representations of taxi situation complexity, we also conduct a study about the relationship between taxi-out time, taxi-in time and some network TSIs, which is shown in Figure 16. Here the taxi time is the average operation time between runway and gate for departures and arrivals in each time-slice. Figure 16 shows that the change trend of taxi time is a comprehensive reflection of SIFIs $(\partial_s + \partial_e)$, SCFIs $(\tilde{\sigma}_d + \tilde{\sigma}_a)$, AQLIs $(\tilde{\lambda}_d + \tilde{\lambda}_a)$ and

SRDIs $(\tilde{\mu}_d + \tilde{\mu}_a)$, not strictly consistent with any single network TSIs. But there exists an approximately same changing relationship between the taxi time and SCFIs $(\tilde{\sigma}_d + \tilde{\sigma}_a)$, AQLIs $(\tilde{\lambda}_d + \tilde{\lambda}_a)$. Note that a special taxi time with the purple line in the first time-slice is 0 means that there is no aircraft taking off from or landing on the runway system in 00:00~00:15.

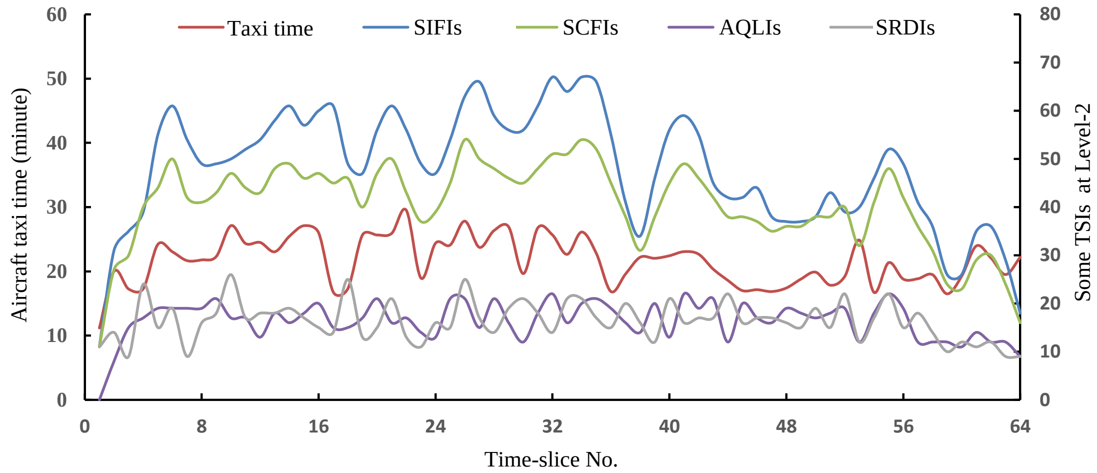


Figure 16. Relationship between taxi time and some TSIs at Level-2

We also study the relationship between taxi time and CTS_n at Level-2 in Figure 17. Figure 17-a reveals the fact that the change trend of taxi time is consistent with CTS_n, which can be a direct and key metric to assess the network taxi situation. Furthermore, we divide the aircraft taxi time into two parts: taxi-out time and taxi-in time, of which the change trends are compared with CTS_n in Figure 17-b. Same with Figure 17-a, the taxi-in time is consistent with CTS_n, while of which the taxi-out time is not consistent with CTS_n. The result reveals the fact that the ground movements of arrival aircraft is a more important influencing factor of network taxi situation than that of departures.

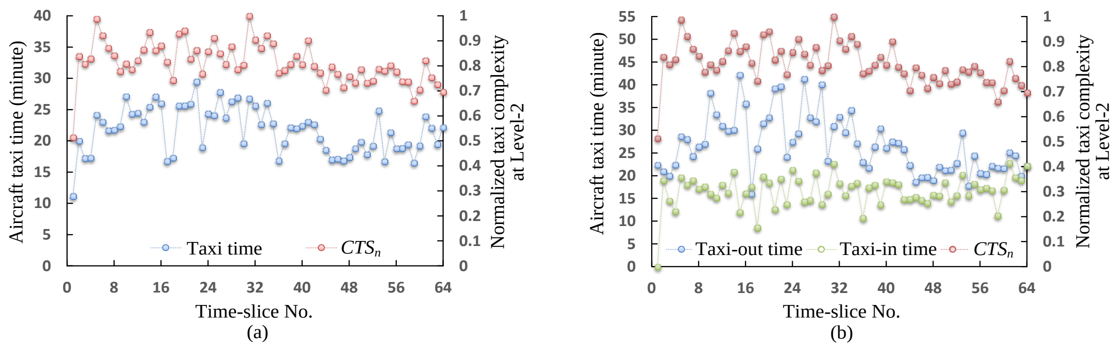


Figure 17. Relationship between taxi time and CTS_n at Level-2

Based on the results of Figure 15~Figure 17, air transport decision makers can directly use a key metric CTS_n, instead of a system of multiple network TSIs $\{\bar{\tau}_d, \bar{\tau}_a, \partial_s, \partial_e, \tilde{\sigma}_d, \tilde{\sigma}_a, \tilde{\lambda}_d, \tilde{\lambda}_a, \tilde{\mu}_d, \tilde{\mu}_a\}$, to assess the taxi situation at Level-2 and provide references to manage network taxi movements.

6 Conclusions

We innovatively propose a macroscopic distribution network (MDN) to analyze the spatial-temporal characteristics of aircraft taxi process and model the macroscopic spatial-temporal movements at airport system. Based on the MDN model, we propose two TSIs systems including 5 categories and 19 indices from the perspective of single-aircraft and whole-network at both Level-1and Level-2. The coverage of the TSIs system has been defined and proved to have the capability to cover all the arrival and departure aircraft to be analyzed.

A three-hierarchy framework is designed to assess the airport taxi situation, which consists of data analysis (TS-1), situation indices refinement (TS-2) and multiple situation awareness (TS-3). The proposed framework can be implemented to analyze the taxi situation at the phase of post, tactical, pre-tactical and strategic operations at airport systems, with the use of multi-source historical, estimated and scheduled air traffic data.

Comprehensive case study of PVG airport reveals the fact that there are significant correlations among some TSIs, especially the ATTIs, SCFIs and AQLIs. At Level-1, the change trend of taxi delay is consistent with SCFIs and AQLIs, but obviously different from SIFIs and SRDIs. At Level-2, the change trend of taxi time is a comprehensive reflection of SIFIs, SCFIs, AQLIs and SRDIs, while not strictly consistent with any single network TSIs. We propose two key metrics CTS_a and CTS_n to assess the taxi situation at Level-1 and Level-2 respectively, instead of using two systems of multiple TSIs $\{\tau_d, \partial_d, \partial_a, \sigma_d, \sigma_a, \lambda_d, \lambda_a, \mu_d, \mu_a\}$ and $\{\bar{\tau}_d, \bar{\tau}_a, \partial_s, \partial_e, \tilde{\sigma}_d, \tilde{\sigma}_a, \tilde{\lambda}_d, \tilde{\lambda}_a, \tilde{\mu}_d, \tilde{\mu}_a\}$. The two metrics can provide references to manage taxi movements from the aircraft and network perspective.

The significance of this paper is a macroscopic and statistical perspective of spatial-temporal modeling for managing airport ground movements, which brings significant benefits to the taxi situation awareness. The findings can provide some significant references about airport ground movements for air transport decision makers, such as the information of TSIs values, predicted taxi time, predicted taxi delay, taxi situation complexity. It has the potential to support decision making and enhance the efficiency, safety, and cost-effectiveness of airport surface operation. Air navigation service providers can predict the delay distribution and change based on the complexity of taxi situation, and optimize the activities of air traffic control, air traffic flow management and resource utilization, according to the results of taxi situation awareness. Airport operation manager can guide the ground movements of each arrival and departure aircraft more effectively, through analyzing the taxi situation when the reference aircraft is being pushed back from the gate or landing on the runway. Airlines operation controller can make full use of its various types of flight data to compare or integrate the TSIs with other indicators to manage aircraft operations at the stage of airport.

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