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Performance Evaluation and Integrated Management of Airport Surface Operations

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by

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ABSTRACT

The demand for aviation has been steadily growing over the past few decades and will keep increasing in the future. The anticipated growth of traffic demand will cause the current airspace system, one that is already burdened by heavy operations and inefficient usage, to become even more congested than its current state. Because busy airports in the United States (U.S.) are becoming “bottlenecks” of the National Airspace System (NAS), it is of great importance to discover the most efficient means of using existing facilities to improve airport operations.

This dissertation aims at designing an efficient airport surface operations management system that substantially contributes to the modernized NAS. First, a global comparison is conducted in the major airports within the U.S. and Europe in order to understand, compare, and explore the differences of surface operational efficiency in two systems. The comparison results are then presented for each airport pair with respect to various operational performance metrics, as well as airport capacity and different demand patterns. A detailed summary of the associated Air Traffic Management (ATM) strategies that are implemented in the U.S. and Europe can be found towards the end of this work. These strategies include: a single Air Navigation Service Provider (ANSP) in the U.S. and multiple ANSPs in Europe, airline scheduling and demand management differences, mixed usage of Instrument Flight Rule (IFR) and Visual Flight Rules (VFR) operations in the U.S., and varying gate management policies in two regions.

For global comparison, unimpeded taxi time is the reference time used for measuring taxi performance. It has been noted that different methodologies are currently used to benchmark taxi

times by the performance analysis groups in the U.S. and Europe, namely the Federal Aviation Authority (FAA) and EUROCONTROL. The consistent methodology to measure taxi efficiency is needed for the facilitation of global benchmarking. Therefore, after an in-depth factual comparison conducted for two varying methodologies, new methods to measure unimpeded taxi times are explored through various tools, including simulation software and projection of historical surveillance data. Moreover, a sophisticated statistical model is proposed as a state-of-the-art method to measure taxi efficiency while quantifying the impact of various factors to taxi inefficiency and supporting decision-makers with reliable measurements to improve the operational performance.

Lastly, a real-time integrated airport surface operations management (RTI-ASOM) is presented to fulfil the third objective of this dissertation. It provides optimal trajectories for each aircraft between gates and runways with the objective of minimizing taxi delay and maximizing runway throughput. The use of Mixed Integer Linear Programming (MIP) formulation, Dynamic Programming for decomposition, and CPLEX optimization can permit the use of an efficient solution algorithm that can instantly solve the large-scale optimization problem. Examples are shown based on one-day track data at LaGuardia Airport (LGA) in New York City. In additional to base scenarios with historical data, simulation through MATLAB is constructed to provide further comparable scenarios, which can demonstrate a significant reduction of taxi times and improvement of runway utilization in RTI-ASOM. By strategically holding departures at gates, the application of RTI-ASOM also reduces excess delay on the airport surface, decreases fuel consumption at airports, and mitigates the consequential environmental impacts.

CHAPTER 1: INTRODUCTION

1.1 Status Quo of Air Transportation

The demand for aviation has been steadily growing over the past few decades and will keep increasing in the future. Since the 1970's, air traffic on a global scale has doubled every 15 years, and has reached a 4.7% annual traffic growth in terms of Revenue Passenger Kilometers (RPK) (1). As the top developed aviation markets in the world, the U.S. market is estimated to increase an average annual rate of 2.2 % carrier passengers for the next 20 years (2) while the Europe market is estimated to grow an average annual rate of 3.7% (3). Meanwhile, emerging regions that represent 70% of the worldwide population are leading the future air traffic growth with the highest annual growth rate of 6% (1). The anticipated progression of traffic demand will cause the current airspace system, which is already burdened by heavy operations and inefficient usage, to become more congested with increasing delays and consequential economic and environmental penalties.

Airport surface congestions at major airports contribute significantly to excessive delays and congestions (4-6). In the U.S., 19% of recorded delays are observed at airports and around terminal areas and an increase in average taxi-out time was reported at 21% from 1995 to 2007 (4, 7-9). Excessive amounts of fuel consumed during the taxi-out phase in 2013 was recorded at about 79kg per flight in the U.S. (10); accounting for 30% of fuel savings among the estimated benefit pool actionable by Air Traffic Management (ATM). A similar trend was observed in Europe that aircraft spent 10-30% of their flight time on the ground, resulting in the excessive burning of fuel, the production of loud noises and the emission of pollutions (9). Similarly, as in

many other industries, global comparison and benchmarking helps identify the most efficient practices and improvements in ATM performance. The performance analysis groups in the U.S. and Europe, i.e. the Federal Aviation Administration (FAA) and EUROCONTROL, have produced a series of joint reports to compare ATM performance between two regions. For airport-related ATM performance, the percentage of delayed flights on airport surface is nearly twice as high in the U.S. than in Europe (10).

In the U.S., busy airports are considered "bottlenecks" of the National Airspace System (NAS), with inefficient usage of taxiway and runway infrastructures being one of the main causes of surface delays and congestions. At the flight level, surface delays diminish the punctuality of flights at the destination airport and add uncertainty and unpredictability to connecting flights. As a result, the performance of terminal airspace and *en route* sections is degraded consequentially with delays propagated to the entire NAS (11). Therefore, improving the efficiency of airport operations is essential to alleviate current congestions in the system and accommodate the increasing demand. One intuitive way to do this is to extend airport capacity by adding more runway and taxiway infrastructures and expanding terminal areas. Nevertheless, such solutions are quite expensive and are especially arduous for airports with limited geographic space, or those under rigorous environmental regulations. Moreover, it may take many years for airport expansion projects to be approved and fully executed, while the situations at airports may deteriorate further and impair the performance of entire air traffic network. As a result, how to utilize existing facilities as efficiently as possible to improve airport operations becomes a critical question in ATM; thus requiring further investigation.

1.2 Surface Operations Management

Airport surface operations management includes arrival and departure management on runways, aircraft routing and scheduling on taxiways, and gate allocation/release. The sequence of arrivals is managed in an orderly flow into terminal area. After landing, each aircraft is directed to an allocated gate by following a designated taxi route while avoiding conflicts with other aircraft. The management of departure procedures is comparably more complex. After received clearance from the controller, aircraft can start to pushback from gates and enter the airport movement area. During the taxi-out phase, aircraft may be assigned a particular amount of waiting time at designated holding points to avoid conflicts or to adjust flight sequences. As compared to taxi-in aircraft, taxi-out aircraft tend to experience longer holding times on the surface due to the fact that these aircraft usually taxi-out with a single functioning engine (12); this can lead to lower fuel costs per unit time. Varied by runway configurations and fleet mix, minimum separations between aircraft (13) are strictly enforced for all landing and takeoff movements on runways to avoid the impact of wake vortexes. Runway clearance is then issued to the next aircraft, i.e. the aircraft waiting at the end of the runway for takeoff or circling around the terminal area for landing, as soon as the runway is cleared and ready for the next operation. Similarly, on taxiways, minimum separation is required between any two successive aircraft approaching the same taxiway intersection/segment.

For busy airports, controllers in the control tower at airport handle aircraft on the surface and near the terminal area. Generally, there are three main positions in a control tower. Local controllers, referred to as "Tower" by pilots, are responsible for all takeoffs and landings on the runway. To ensure efficient flight operations within their assigned airspace, local controllers coordinate with other members of the tower, Terminal Radar Approach Control Facilities

(TRACON), and the Air Route Traffic Control Center (ARTCC, or "Center"). After landing on the runway, arrivals are guided by ground controllers to taxi through the movement area until they reach their designated gate. Ground controllers are also responsible for assigning departure and arrival runways to aircraft. Ground controllers and local controllers work closely to ensure that arriving and departing aircraft do not conflict with one another. The third main position in the tower is clearance delivery. Clearance delivery communicates routing information to pilots and issues appropriate adjustments to assure flights adhere to local procedures.

To address the inefficiency of surface operations, several concepts and procedures have been tested at some U.S. airports. Most approaches involve departure queue management that aim at shifting excessive taxi times to the gate and apron area, including Collaborative Departure Queue Management (CDMQ) (14, 15), pushback rate control (16, 17), and virtual queue departure management (18). Spot and Runway Departure Advisor (SARDA) and Tower Flight Data Manager (TFDM) are two approaches that strive to provide terminal automation platforms so as to support decision-making in surface operations management. Specifically, SARDA provides advisories on flight sequences as well as the earliest releasing time for departures at the spot and runway to maximize runway throughput (19), while TFDM monitors aircraft conformity to assigned routes and alerts controllers of any conflict between aircraft and ground vehicles (20, 21). Outcomes of these approaches are promising in terms of reduced taxi times, fuel burn and associated emissions; however, they have primarily focused on queue management at one airside facility at a time. Efforts have been made (22, 23) to consider taxiway planning and runway scheduling as a combined problem but with limited practical features. It appears that little to no studies have tackled integrated operations management involving all airport airside facilities simultaneously, namely, runways, taxiways, and gates.

As the ongoing transformation of the NAS, NextGen represents an evolution from a ground-based system of Air Traffic Control (ATC) to a satellite-based system of ATM. A series of new procedures and technologies are currently developed, deployed or planned for the NAS to attain various objectives of NextGen. Ongoing NextGen programs consist of Automatic Dependent Surveillance Broadcast (ADS-B), System Wide Information management (SWIM), NextGen Data Communications, NextGen Network Enabled Weather (NNEW), NAS Voice Switch (NVS) and NextGen Demonstrations and Infrastructure Development (15). Trajectory-Based Operations (TBO) is one of the key NextGen concepts that dynamically adjust a flight path in space (longitude, latitude, altitude) and time using a known position and intent in *en route* airspace (24). The shift from clearance-based control to TBO can enable a decrease in separation and an increase in NAS capacity. It can also enable aircraft to fly negotiated flight paths by taking both operator preferences and optimal system performances into consideration. With the support of critical NextGen elements, such as ADS-B, SWIM, and Data Communications, TBO will provide new capabilities to improve capacity, safety and efficiency in airspace.

1.3 Research Objectives

The main goal of this research is to design an efficient airport surface operations management system and to eventually contribute to the modernized NAS. Surface operations management in this research covers the management of all flight movements on the runways, taxiways, gates and apron area. The three following research objectives are to be fulfilled in this dissertation.

- Gain a better understanding of surface operations efficiency by comparing operational performance in the U.S. and Europe, and explore related ATM strategies that lead to performance differences, if any

- Summarize different methodologies currently used for deriving taxi performance indicators, and propose new methods to measure taxi efficiency by exploiting various tools
- Develop a Real-Time Integrated Airport Surface Operations Management (RTI-ASOM) system to optimize flight trajectories for surface operations management and extend TBO in NextGen from *en route* airspace to airports

The first objective of this research is to explore various factors that lead to inefficiency of airport operational performance by comparing European and U.S. airports in large detail. To avoid the influence of different airport surface management initiatives, the year 2008 is selected, a time when no initiatives were implemented at either European or U.S. airports of interest. Comparable airports are selected with similar characteristics. By examining fundamental philosophies between two systems, the author elucidates the essential differences that lead to operational performance discrepancy and provide analytics support to drive improvements.

Taxi-time is one of the widely accepted performance indicators to measure airport operational efficiency. It is noted that different methodologies are developed by the FAA Aviation Policy and Planning Office (APO) and EUROCONTROL Performance Review Unit (PRU) for computing taxi delay. Further studies exploiting consistent methods are needed to measure taxi efficiency and facilitate global benchmarking. Hence, the second objective of this dissertation starts with summarizing two different methodologies currently used for deriving taxi performance indicators. New methods to measure taxi efficiency are explored by exploiting various tools, including simulation software and projection of historical surveillance data. Moreover, a sophisticated statistic model is proposed to derive accurate indicators for taxi performance and quantify impacts of various factors to taxi inefficiency.

The third objective of this research is to embrace the trajectory-based control of NextGen by proposing a Real-Time Integrated Airport Surface Operations Management (RTI-ASOM). Integrated management means that for all arrivals and departures, holistic control strategies are developed to manage flight operations between gates and runways with optimized schedules and sequences. Real-time means that the proposed strategy provides real-time decision support to controllers and pilots by using real-time inputs from the cockpit and control tower. The objective of RTI-ASOM is to increase the efficiency of surface operations by (1) reducing taxi delay and (2) improving runway throughput. It is modeled with Mixed Integer Linear Programming (MIP) formulation and a solution algorithm that obtains optimal solutions efficiently. The outcomes of RTI-ASOM include optimal passage times of aircraft to visit each node along their respective taxi routes in a digitalized airport surface network. Such information can be shared via a data link between the control tower and the Flight Management System in the cockpit (24) so as to create an automation platform that enables the control of complicated surface operations in a safe and orderly manner.

Altogether, the application of proposed study entails substantial benefits for various stakeholders and the entire air traffic system. For **airport operators**, it improves the usage of existing facilities by providing more accurate timing and location information. It also allows tactic operations management with respect to unexpected events on the surface and expansion of airside facilities in the future, by providing real-time advisories that help keep such disturbances to a minimum. For **air traffic controllers**, it reduces their workload with an envisioned situation on the surface and enables a great predictability of traffic based on real-time flight data. For **local communities**, it eases the impact of delays and congestions on the environment with less noise and lower levels of air pollution and emissions from aircraft. For **airlines**, it improves pilots'

awareness regarding the current and intended status of aircraft at airports and helps airline operation centers make more accurate fleet predictions and better flight schedules. Smooth turnaround processes, enabled by efficient surface operations, lead to less flight delays, alleviated system congestions, and reduced operational costs for airlines. **Passengers** also benefit from reliable surface operations with reduced delays, reliable flight schedules and better flying experiences. For **the entire network**, integrated airport surface operations management helps eliminate bottleneck effects of major airports in the system, improves predictability in the *en route* airspace and facilitates better system performance.

The remainder of this dissertation is organized as follows: In Chapter 2, current strategies and related efforts on airport surface operations management are elaborated. The comparison on operational performance between select U.S. and European airports is presented in Chapter 3. In Chapter 4, current methods to derive taxi times are summarized and new methods are proposed for better benchmark on surface operational performance. In Chapter 5, the author describes the proposed RTI-ASOM with problem definition, mathematical formulation, a solution algorithm and a demonstration with numerical results. The concluding remarks and future research are presented in Chapter 6.

CHAPTER 2: LITERATURE REVIEW

2.1 On-going Surface Congestions Management Initiatives

To alleviate the inefficiency of airport surface operations, Airport Collaborative Decision Making (A-CDM) has been implemented at some European airports. A-CDM enables data sharing amongst multiple stakeholders and allows each to optimize decision-making in collaboration with others. The main focus is on the aircraft turnaround and pre-departure sequencing process. So far, nine major airports in Europe have fully implemented A-CDM, including Munich and London Heathrow airport (25). A study evaluating A-CDM at Munich airport in Germany showed that A-CDM could allow an increase in sector capacity by up to 4%, and could allow room for delay improvement by up to 33%-50% (26).

Parallel to the implementation of A-CDM in Europe, several departure metering approaches have also been tested at a few U.S. airports. At airport level, an approach to manage airport surface congestion by controlling the pushback rate has been tested at Boston Logon International Airport (BOS) (17). At airline level, Collaborative Departure Queue Management (CDQM) determining airline-specific push back quotas has been verified at Memphis Airport (MEM) (27). At aircraft level, a departure metering program was deployed at John F. Kennedy International Airport (JFK) as a remedy for the closure of a runway in 2010; since 2012, a new ground management program has been established (18). A simulation of Spot and Runway Departure Advisor (SARDA) has been testing at Dallas-Fort Worth International Airport (DFW) with advised release times at the spot (the hand-off point between the ramp control and tower control) (19). At runway level, the FAA initiated Tower Flight Data Manager (TFDM) that

aimed at modernizing automation system and implementing prototype that is undergoing operation testing at DFW (28). These methods and procedures are triggered by the increasing taxi delays observed back in 2007 (10) and are initialized in the context of CDM. The basic function of departure metering approaches is to monitor and reduce the amount of aircraft entering airport movement area by holding aircraft at gates when active flight operations are reaching airport capacity.

Pushback rate control approach is designed to maintain the number of departures on airport surface by controlling aggregated pushback rate under a predetermined value for the entire airport. The pushback rate is determined based on predicted airport capacity for 15 minutes per planning window. Using historical ASDE-X (Airport Surface Detection Equipment, Model X) data, the estimated pushback rate is predicted from a regression model on airport takeoff rate with the number of taxi-out flights. By controlling the number of aircraft released at gates, controllers can prevent adding more traffic onto congested airport surface. Such an approach is exclusively operated in the Air Traffic Control (ATC) Tower, with little to no room for data exchange with flight operators. During eight 4-hour tests at BOS in 2011, aircraft taxi times were estimated to decrease by 5.3 minutes per flight by holding 144 flights at gates, with the estimated fuel consumption being reduced by nine tons (a total of ~286 gallons) (17).

Collaborative Departure Queue Management (CDQM) is developed under the Surface TBO project to minimize waiting times at the runway before flights taking off. Departure slots are allocated to flight operators to enter airport movement area and the operators have the flexibility of assigning flights to the slots. The allocations are designed in a manner that ensures constant pressure on the runway for maximum usage of the facility without causing extensive delays at the end of the runway. During the test at MEM in 2010, this approach was estimated to

reduce 86,000 minutes (1433 hours) of excessive taxi time, 2.1 million pounds of fuel consumption (~0.3 million gallons), and 6.7 million pounds of carbon dioxide emissions (27).

A departure metering program was organized at JFK due to a runway reconstruction project in 2010. A virtual queue system is used to facilitate shorter physical queues prior to aircraft entering the taxiway. Following a similar principle, since 2012 an improved ground management program has been implemented at JFK. The program was intended to control the total number of active aircraft maneuvering on the airport surface (taxi-out queue) as it is identified as the most significant contributing factor to taxi-out delays (4). The program disperses departure slots to aircraft based on predicted airport capacity and requested pushback times of aircraft within the planning window so as to balance high demand during peak times. Rather than exacerbating the congested surface area while experiencing long delays with running engines, aircraft are kept at gates until allocated departure time slots are met. Such collaborative processes involve all carriers and allow exchanges amongst assigned slots. Compared to pre-metering operations, the average taxi-out time saved at JFK was estimated at 1.5 to 2.7 minutes per flight (18).

Spot and Runway Departure Advisor (SARDA) manages surface operations with two schedulers to interact with taxiway and runway operations. One provides an optimal schedule to release departures on the spot (the hand-off point between the ramp control and tower control) while maximizing runway throughput. Based on that schedule, the other scheduler provides runway-crossing sequences for arrivals while maintaining optimal throughput for departure runway. However, gate management or time control was not included in SARDA. The *human-in-the-loop* simulation was conducted for two weeks in 2010 and it showed a 64% reduction in

terms of average taxi-out delay and a 38% reduction in estimated fuel consumption and engine emissions in the movement area (19).

Tower Flight Data Manager (TFDM) aims at providing a platform to integrate communications among various FAA systems and consolidate many tower automation systems. It is designed to provide taxi route advisories and alert controllers of aircraft deviations from an assigned route or alert them of any conflict between aircraft. In 2011, the prototype field demonstration was conducted, and based on an evaluation survey yielded 90% positive feedback from participants (28).

Recently, several approaches of surface operations management have been tested at individual airports in order to alleviate levels of inefficiency of surface operations. While the outcomes seem promising in terms of reduced taxi time, delay, and environmental impact, additional aspects of airport surface operations need to be investigated for a more comprehensive understanding of the obstacles that have been impeding overall improvement.

2.2 Studies on Benchmarking Airport Performance

The FAA and EUROCONTROL joined efforts in comparing the ATM performance between the U.S. and Europe, creating a basis for performance comparison and recognized notable differences between the two systems. At the system level, overall operational performance in the U.S. was diminished since 2008, while performance in Europe was improved. Specifically, by comparing ATM-related efficiency by phases of flight, the taxi-out phase exhibited the largest variability between the two systems, with an average of 2 minutes more per departure in the U.S. This gap between the U.S. and Europe was relatively narrowed by the improved U.S. performance from 2008 to 2012, yet U.S. performance started to deteriorate in 2013 (10).

Following the 2008 report, Odoni et al (29) investigated airside performance by comparing Newark Liberty International Airport (EWR) and Flughafen Frankfurt Airport (FRA). Remarkable differences were observed in terms of airport throughput, demand and delay performance. The paper also called for the emphasis on the role of departure demand management policies in Europe. However, a small representative sample of airports (i.e. one airport per system) limits the application of comparison results. Further study with representing larger sample of diverse operation levels is needed to generalize comparison findings in the system level.

Besides comparison on operational performance, there are efforts comparing other aspects of airport performance in literature. A global overview of current airport benchmark practices was presented in (30) from economic, operational, and environmental perspectives. Another study (31) investigated airport performance in terms of airport connectivity. It was concluded that the U.S. network tends to be more coordinated while the European network provides a consistent level of service regardless of airport size. A comparison on airport capacity assessment (32) stated that higher runway utilization was achieved in the U.S. than in Europe. Among these airport comparison studies, it has been suggested that the problem of comparability exists as a common issue and that the diversity of airport characteristics needs to be balanced for global comparison.

Overall, it has been of keen interest for researchers to conduct comparison studies so as to identify the best practice and improve airport performance. Further investigation is needed to target airport surface operations performance, which exhibit the largest variability by flight phases between the U.S. and Europe (10, 29). To fill this gap, a comprehensive factual comparison on surface operations is provided in this dissertation. Additionally, factors that lead

to inefficiency of airport operational performance are identified by comparing European and U.S. airports in vast detail.

2.3 Studies on Surface Operations Optimization Problems

This subsection summarizes existing literature on surface operations optimization problems. Related researches are categorized into three groups based on primary focus on single airside facility: 1) runway operations planning, including Constrained Position Shifting (CPS) (33), departure queue management (15, 27), and runway scheduling (34); 2) taxi planning, including route allocation (35), and taxiway scheduling (36, 37); and 3) pushback rate control (16, 17). In (33), A CPS method was used to optimize the landing sequence on a single runway and maximum of 3 position shifts per flight was allowed based on first-come-first-serve (FCFS) sequence. While the runway makespan was minimized as the model objective, it is possible that decreasing the makespan increases the average delay. Collaborative Departure Queue Management (CDQM) conceptual approach (14, 27)) is developed under the Surface TBO project to minimize queue waiting time at the runway end before taking off. Departure slots are allocated to flight operators to enter the airport movement area and the operators have the flexibility of assigning flights to each particular slot. The number of slots is predetermined to ensure constant pressure on the runways. In (34), solutions were provided for runway scheduling by minimizing operational and environmental costs. By putting monetary value on deviations from scheduled runway time, two objectives were combined together as one cost function. For taxi planning, Roling and Visser (35) presented a study for taxi route allocation which used time discretization instead of continuous variables. Alternative taxi routes were generated based on the shortest path while minimizing total taxi delay. In (36, 37), MIP formulation was used to model taxiway scheduling problem with the objective to minimize taxi delay. Based on

predetermined taxi routes and sequences, optimal schedule solutions were produced along each taxi intersection at the airport network. Simaiakis et al. (16, 17) presented a strategy to manage airport surface congestions, in which pushback rate per interval of minutes is controlled under a predetermined value based on predicted departure throughput. Apart from the three aforementioned groups, efforts have been made to deal with operations management that involves multiple airside facilities. SARDA (19) manages surface operations with two schedulers to interact with taxiway and runway operations. One provides an optimal schedule to release departures on the spot (the hand-off point between the ramp control and tower control) while maximizing runway throughput. Based on that schedule, the other scheduler provides a runway-crossing sequence for arrivals while maintaining optimal throughput for departure runway. However, gate management or time control was not included in SARDA. In (22, 23), both taxiway planning and runway scheduling were considered over a small constructed scenario. Nevertheless, limited practical features and inefficient computational performance restrict the usage of such approaches for real-time operations management. Hitherto, no optimization study has effectively incorporate integrated surface operations management, while simultaneously enabling the set of precise safety and operation requirements. In contrast, this paper combines gate pushback controlling, taxiway scheduling, and runway sequencing together and proposes an efficient decomposition algorithm to obtain optimal solutions instantly. Realistic features on surface operations are explicitly included in the model and an automated tool with a user-friendly interface is developed to facilitate real-time management.

From the methodology aspect, approaches used to formulate surface operations problems can be categorized as follows: 1) Mixed Integer Linear Programming (MIP) (22, 34-37), 2) Integer Programming (IP) (38, 39), 3) Genetic Algorithm (GA) (40), and 4) Dynamic

Programming (19, 33). MIP formulation utilizes both continuous and integer variables when modeling problems as a linear program. It is widely used to formulate taxiway planning problems (22, 35-37) to minimize taxi time, and runway scheduling problems (34) to maximize runway throughput. Compared to IP, MIP formulation has a higher degree of realism that can account for different aircraft types and separation requirements on the airport surface. For real-time planning purpose, computational efficiency is one of the main challenges by using MIP and thus various pre-processing methods have been proposed to speed up the computation process (22, 35, 36). A typical construction of IP that models aircraft movements is to split up time and space into small blocks and allow a set of time slots for an aircraft to arrive at any chosen location. One critical limitation of IP is the high dependence of computational complexity on the number of time and space blocks. With too little available slots, considerable space in the taxiway can be wasted. With too many integer variables, increasing computational complexity can be problematic. Therefore, precise safety constraints are usually not included in the model except capacity constraint (38, 39). GA is often used to search a theoretical solution for taxiway scheduling problems. It is a search heuristic that repeatedly generates, modifies, and selects from a population of randomly-generated solutions until the best one is found or terminated due to pre-determined rules. Examples are usually conducted at constructed airports with simulated flight data (40). DP is numerically feasible only for special classes of (typically discrete) problems and, therefore, is often used to model flight sequencing problems (19, 33). It is a general recursive decomposition technique for optimization problems. When the problem structure is favorable, such as runway sequencing problems, DP can be used to provide an efficient optimal solution. In this study, MIP formulation is adopted as the best fit to model the

integrated surface operations, and DP is applied as a part of a decomposition algorithm to solve the optimization problem efficiently.

CHAPTER 3: COMPARISONS OF AIRPORT SURFACE PERFORMANCE BETWEEN THE U.S. AND EUROPE

To perform comparisons between major U.S. and European airports in this chapter, the author first presents data sources and selections of comparable airport pairs. Two varying methods used in the U.S. and Europe respectively for benchmarking performance indicators are analyzed on each airport. Comparison results are interpreted for each airport pair with respect to various operational performance metrics, including delays, queue length, airport capacity and demand. Associated ATM strategies implemented in the U.S. and Europe are summarized at the end of this chapter: a single Air Navigation Service Provider (ANSP) in the U.S. and multiple ANSPs in Europe, airline scheduling and demand management differences, mixed usage of Instrument Flight Rule (IFR) and Visual Flight Rules (VFR) operations in the U.S., and different gate management policies in two regions, to name a few.

3.1 Methodology

This subsection presents the methodology of the comparison study. First, operational data are obtained from three Spanish airports which represent airports with heavy, medium, and moderate annual traffic in Europe. Their comparable counterparts in the U.S. are selected with highly similar airport characteristics. Second, airport performance indicators are discussed and compared among European and U.S. airports. Last, associated ATM strategy differences between the two regions are discussed with observed performance disparities.

3.1.1 Data Source

A set of airport operational data with a sufficient level of details and coverages is needed from both regions to conduct informed comparisons. However, such data is especially hard to obtain for most European airports due to restricted access to airport operational data. For this study, AENA (Aeropuertos Españolesy Navegación Aérea), the Spanish ANSP, provides historical data from January to March 2008 for three largest Spanish airports: Madrid-Barajas Airport (MAD), Barcelona Airport (BCN) and Palma de Mallorca Airport (PMI). Driven by available data source, these airports are used to represent European airports with heavy, medium, and moderate annual traffic. The obtained database contains the following attributes for each flight at airport: basic flight plan, gate and runway used, off-block and in-block times (as measured by airport operator), and takeoff and landing times derived from air traffic control radar information.

The FAA's Aviation System Performance Metrics (ASPM) online access system is used as it contains similar attributes to Spanish dataset. The ASPM system provides detailed data on flights to and from the ASPM airports (currently 77) and all flights by the ASPM carriers (currently 22). It is compiled with multiple data sources, including basic flight plans, flight information captured by the Enhanced Traffic Management System (ETMS), next-day OOOI data (Out of the gate, Off the runway, On the runway, Into the gate), published scheduled data, and Aviation System Quality and Performance (ASQP) data for the largest U.S. carriers (41).

3.1.2 Selection of European and U.S. Airport Pairs

3.1.2.1 Determination of Selection Criteria

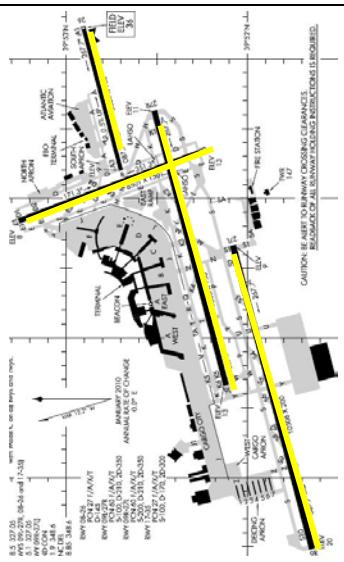
For any global comparison, the diversity of airport characteristics needs to be balanced to avoid the problem of comparability. Depending on the research focus, different characteristics

have been used in literature as matching criteria for comparable airports. For example, the number of annual airport operations was used as an approximate estimate of airspace volume for capacity assessment (32). Two airports were selected for the benchmark study by examining their geometric runway layouts and annual movements (29).

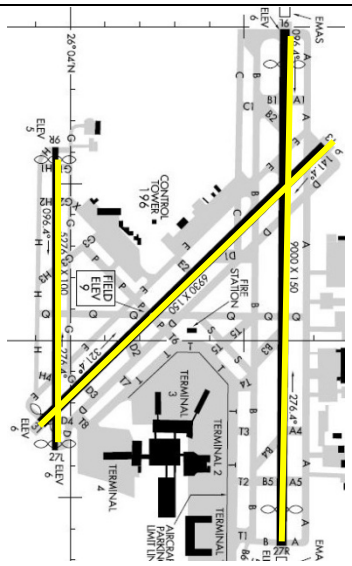
MAD

BCN

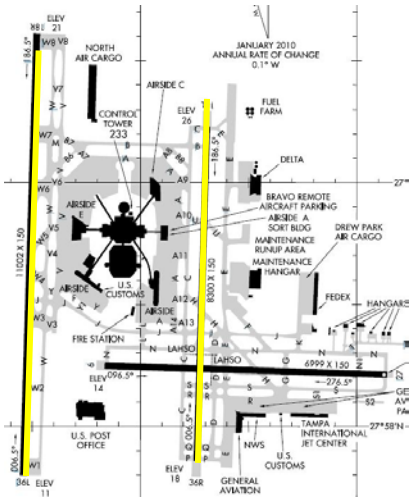
PMI



PHL



FLL



TPA

	MAD	PHL	BCN	FLL	PMI	TPA
Annual Movements	469,740	492,038	321,693	295,496	193,379	237,885
Active Number of Runways in Use	4	4	3	3	2	2
Location of Terminal w.r.t. Runways	By Side	By Side	In Between	In Between	In Between	In Between

Figure 1 Overview of main airport characteristics in 2008.

In this study, the author uses three criteria to search for comparable airport pairs: 1) similar runway characteristics with respect to the number of runways and geometric runway layout, 2) similar runway configuration in use and airport layout, referring to the location of terminal building with respect to runways, 3) similar amount of annual and monthly flight operations. After scrutinizing 35 main airports in the U.S., the following three airports are chosen as the counterparts for each aforementioned Spanish airport: Philadelphia International Airport (PHL) paired to MAD; Fort Lauderdale-Hollywood International Airport (FLL) to BCN, and Tampa International Airport (TPA) to PMI. An overview of airport characteristics during the study period (January to March 2008) is presented in Figure 1. Note that although three runways are displayed in the diagram of TPA, runway 9-27 (not highlighted) was not actively in use during the study period.

3.1.2.2 Other Important Airport Features

Besides the three main criteria, the author also looks into other aspects of airport features to assure comparability between paired airports. Table 1 presents an overview of main airport features in 2008, such as annual flight movements, cargo volume and airport facility information.

Table 1 Comprehensive Overview of Airport Features in 2008

	MAD	**PHL**
Annual Movements*	469,740	492,038
Annual Cargo Volume (tons)*	0.3 million	0.5 million
Active Number of Runways in 2008	4	4
Crossing	0	1
Number of Gates (Jetway equipped)	119	109
Airport Capacity*	90	96
Wake Turbulence Category		
Medium	90.52%	94.51%
Heavy	9.20%	4.42%
Light	0.28%	1.05%
B757	0.01%	0.01%

Table 1 (Continued)

	BCN	**FLL**
Annual Movements*	321,693	295,496
Annual Cargo Volume (tons)*	0.1 million	0.1 million
Active Number of Runways in 2008	3	3
Crossing	1	2
Number of Gates (Jetway equipped)	70	56
Airport Capacity*	61	56
Wake Turbulence Category		
Medium	96.54%	95.68%
Heavy	1.88%	2.82%
Light	1.58%	1.50%
B757	0.00%	0.01%

	PMI	**TPA**
Annual Movements*	193,379	237,885
Annual Cargo Volume (tons)*	0.03 million	0.1 million
Active Number of Runways in 2008	2	2
Crossing	0	0
Number of Gates (Jetway equipped)	30	58
Airport Capacity*	60	74
Wake Turbulence Category		
Medium	94.83%	93.25%
Heavy	0.21%	2.30%
Light	4.95%	4.45%
B757	0.00%	0.00%

**Airport Council International (ACI), 2008 (42)*

From Table 1 it can be observed that each airport pair handles similar annual movements and cargo operations with comparable airport facilities. Airport capacity listed in the table is represented by declared capacity of European airports and IFR capacity of the U.S. airports, respectively. More discussion on airport capacity is presented in section 3.3. In addition, aircraft fleet composition during the study period at each airport is presented at the bottom. Take MAD and PHL as an example, both are regional hub airports with similar airport infrastructure and handle comparable air traffic. Fleet mix of aircraft operated at airport is also quite alike, with PHL operating a slightly more medium aircraft. Also, runway systems at two airports are both

utilized for mixed departures and arrivals. Overall, a high degree of comparability on main airport features is confirmed between each pair of European and the U.S. airports.

3.2 Comparison of Delay, Punctuality and Predictability

3.2.1 Arrival Delay and Punctuality

Arrival delays are derived from flight plans in AENA dataset and ASPM system by subtracting scheduled gate-in time from actual gate-in time. Note that actual gate-in time could be earlier than scheduled time so arrival delays could be negative in reality. Figure 2, Figure 3 and Figure 4 depict the distribution of hourly arrival delay and flight movements by time of day at MAD and PHL, BCN and FLL, PMI and TPA, respectively. Flights operating between 5:00am to 11:00pm are included for the analysis, considering the fact that quite a number of European airports are restricted by night noise curfews (10).

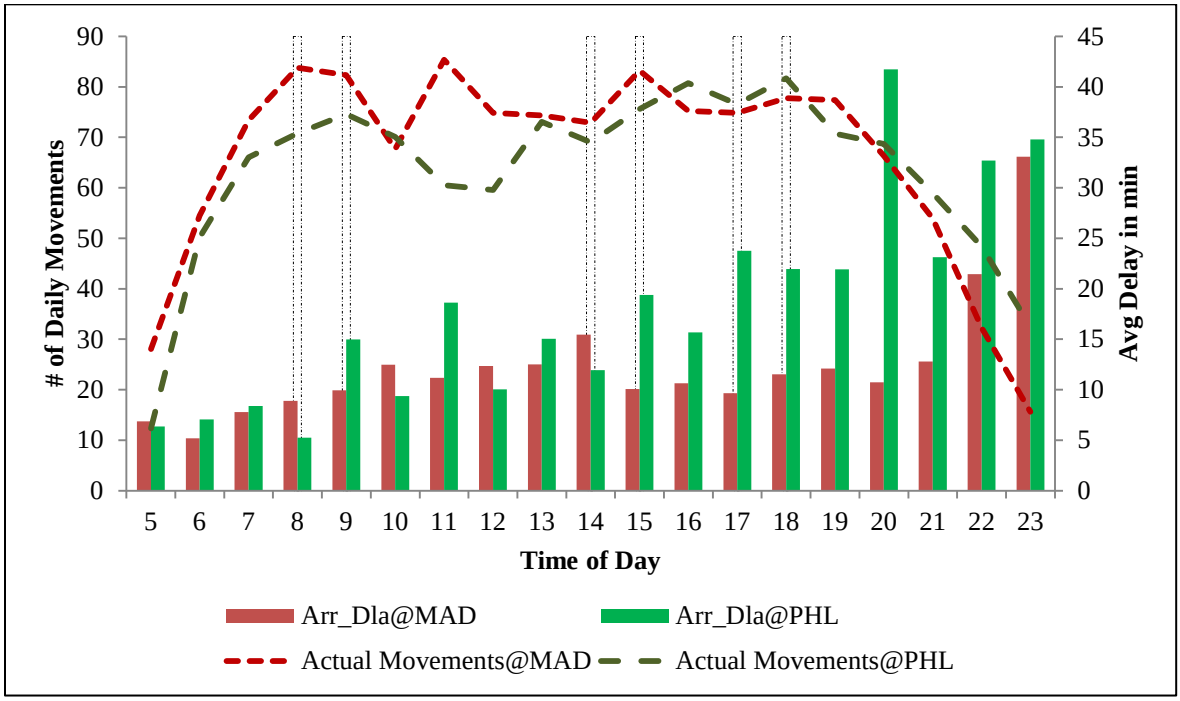


Figure 2 Hourly arrival delay and flight movements at MAD and PHL.

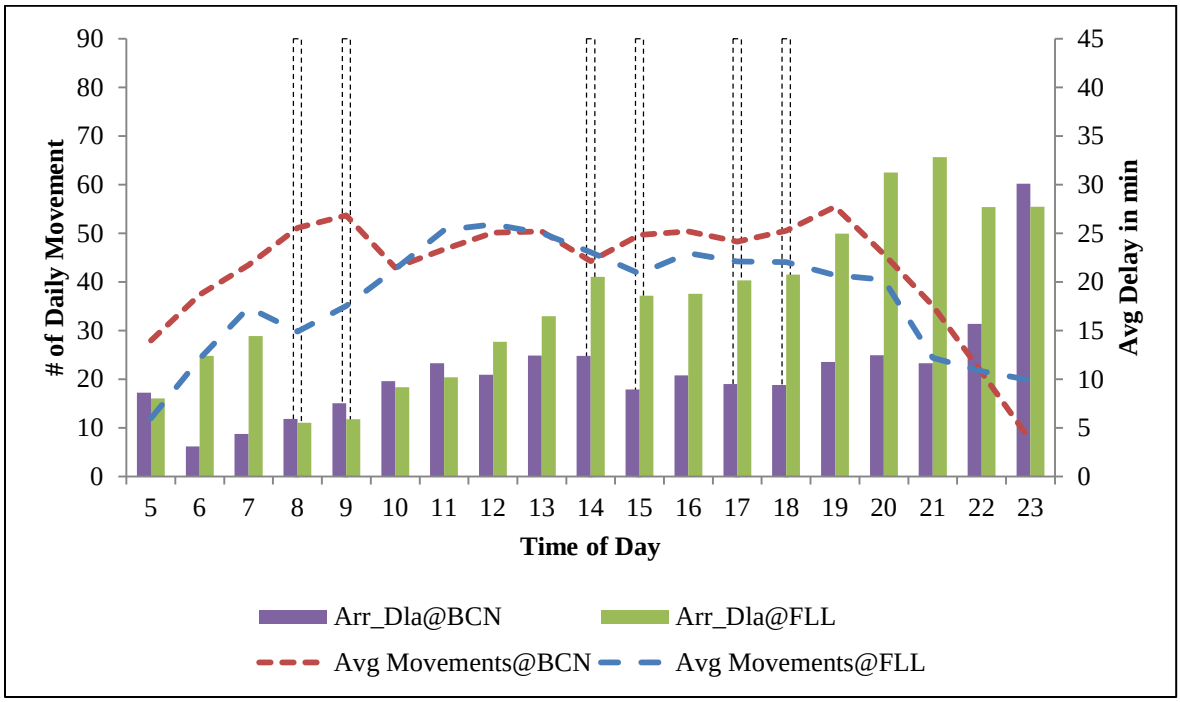


Figure 3 Hourly arrival delay and flight movements at BCN and FLL.

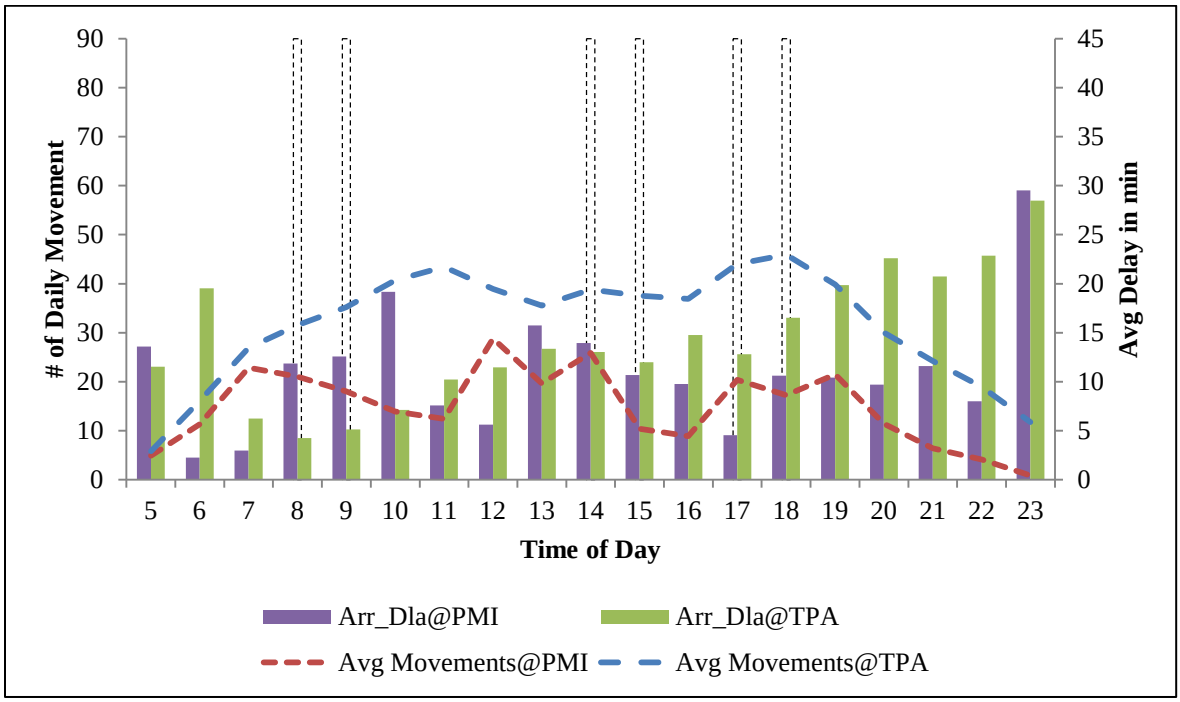


Figure 4 Hourly arrival delay and flight movements at PMI and TPA.

Observed from Figure 2, arrival delay at MAD presents a flatter distribution over time of day with slightly higher hourly traffic than PHL. Average arrival delay is maintained below 20

minutes per flight at MAD even though there was a small peak of delay right before the airport closure. At PHL, an increasing trend of arrival delay is observed from morning to night and the longest hourly delay (over 40 minutes per flight) is observed during late afternoon when flight demands also reach the peak (see more details of demand analysis in section 3.3). Similar patterns are also observed for BCN and FLL in Figure 3. The difference of flight movements between PMI and TPA as shown in Figure 4 is more distinct than the other two pairs; yet an increasing trend of hourly arrival delay is observed at TPA while a flat delay distribution is presented at PMI.

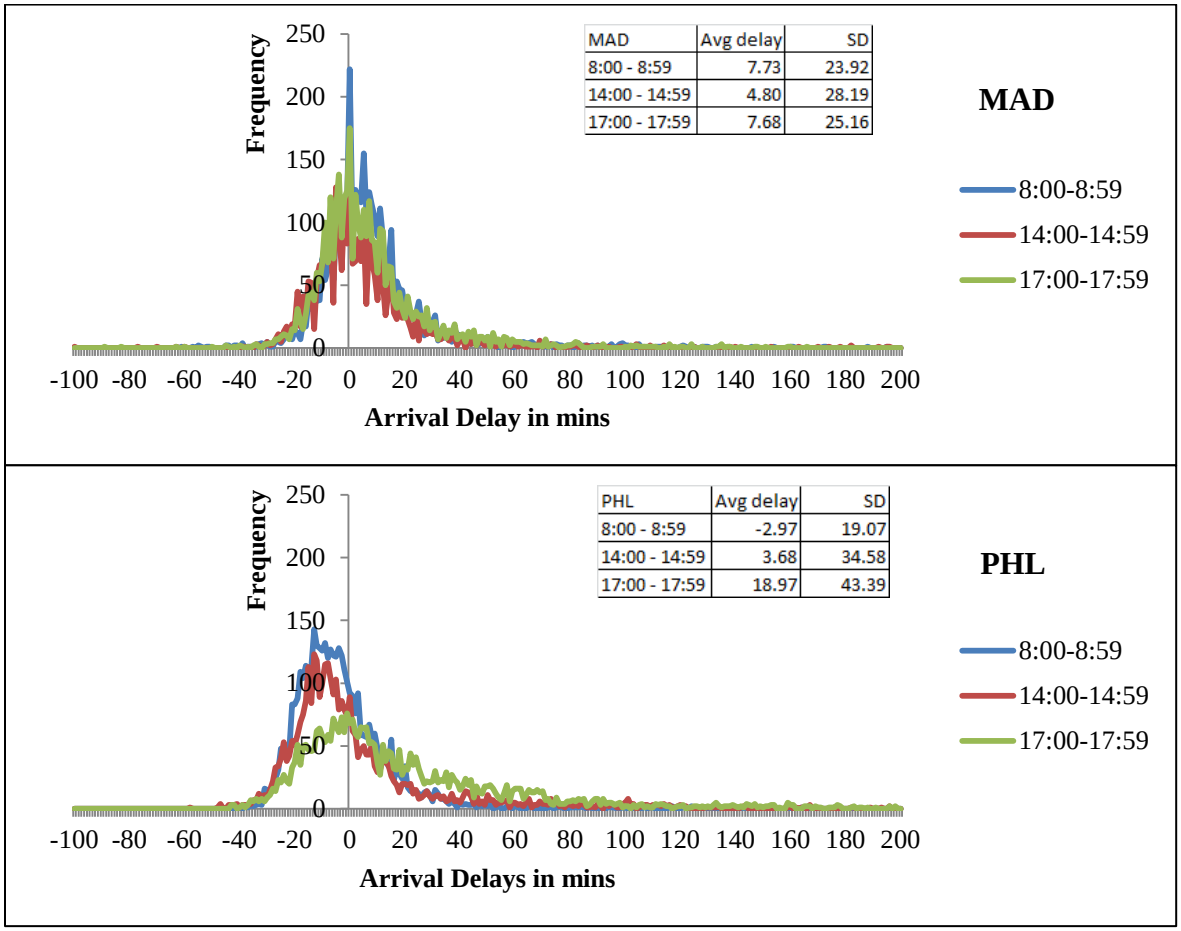


Figure 5 Arrival delay distribution over different peak hours at MAD and PHL.

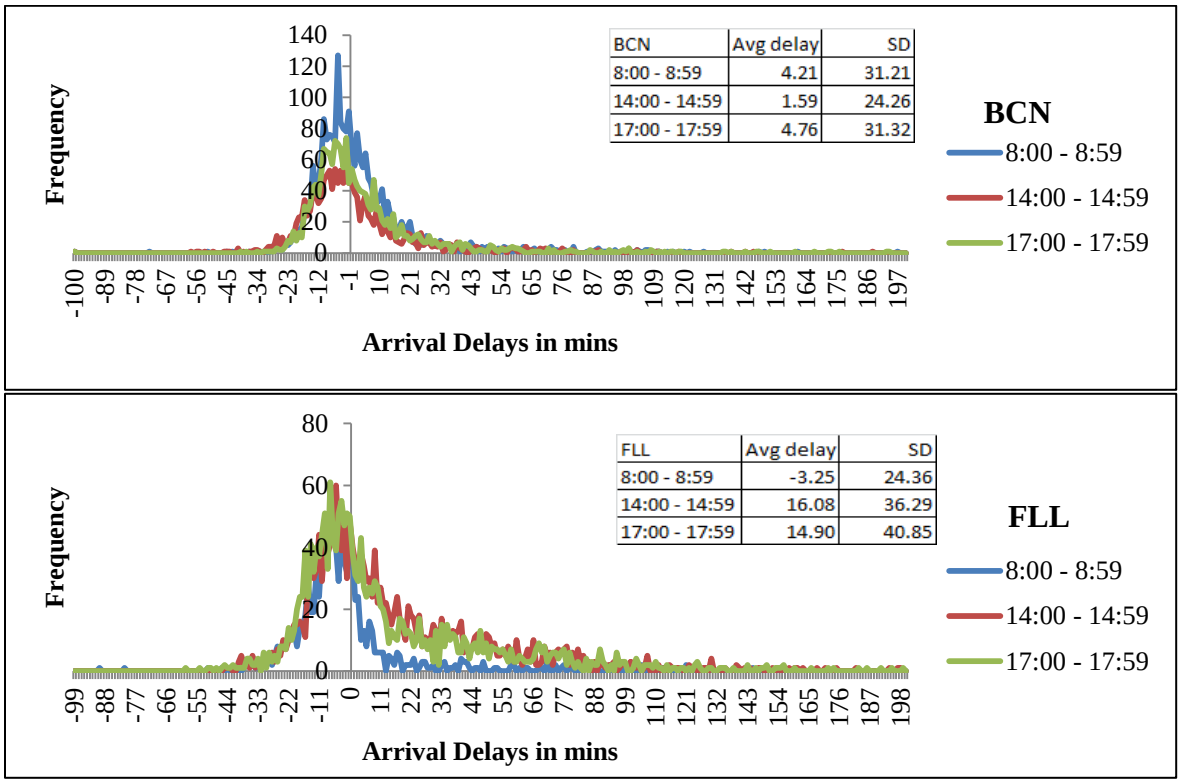


Figure 6 Arrival delay distribution over different peak hours at BCN and FLL.

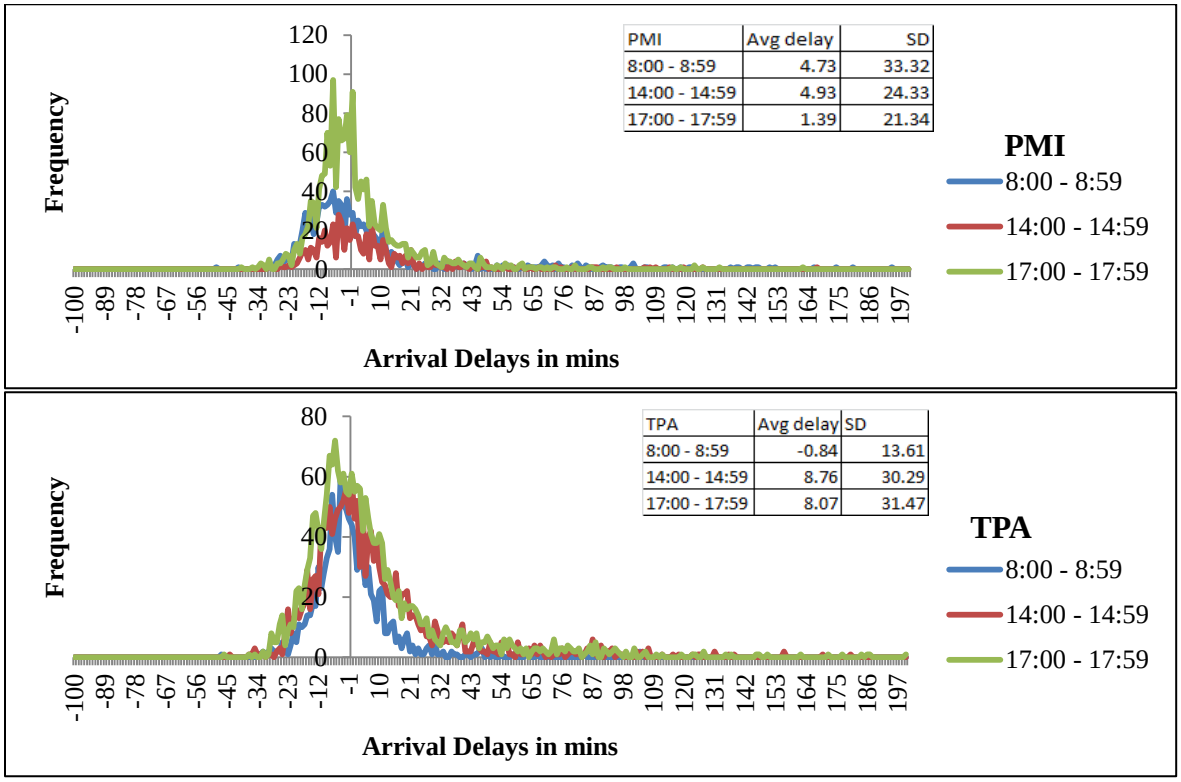


Figure 7 Arrival delay distribution over different peak hours at PMI and TPA.

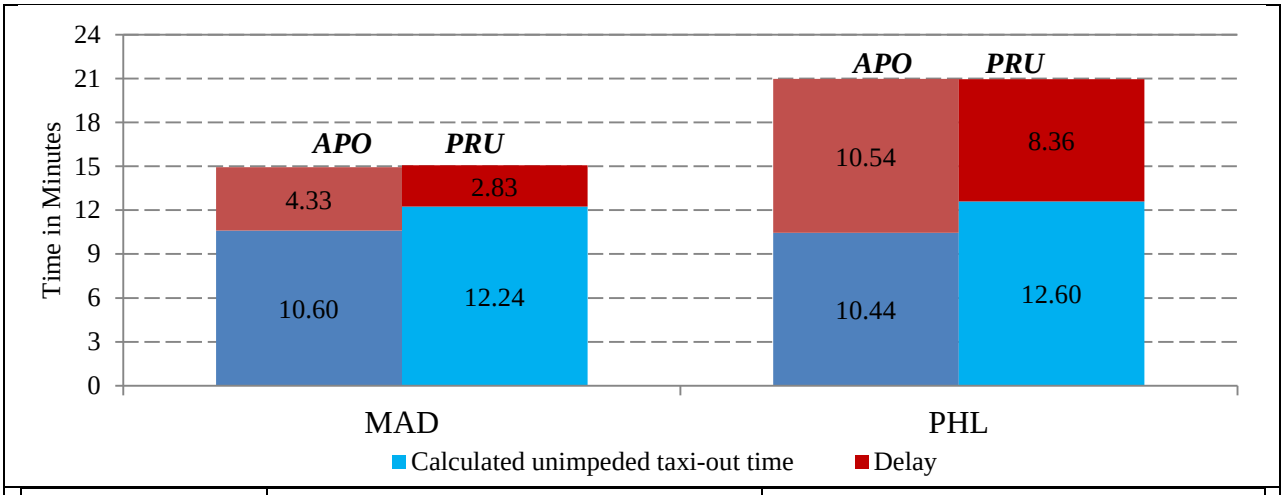
To obtain more insights on flight punctuality, the author compares arrival delay distribution over three peak hours for all airports: 8am-9am, 2pm-3pm, and 5pm-6pm as shown in Figure 5, Figure 6, and Figure 7 (also dot-marked in Figure 2, Figure 3, and Figure 4). It is observed that arrival delay distributions at European airports are stable and steady over different peak hours with similar standard deviations. In contrast, arrival delays at the U.S. airports are vastly distributed with unstable standard deviations and the situation deteriorates along the time of day with larger values of average delay and standard deviation.

In addition, industry-standard indicators for punctuality are calculated for each airport pair, which are represented by the percentage of arrivals delayed by more than 15 minutes versus their schedule times. During these three study months, 28% of arrivals are delayed more than 15 minutes at PHL and 20% at MAD. Such punctuality indicator is calculated at FLL as 32% and 18% at BCN. At TPA, 27% of arrivals experienced long delays and only 14% at PMI. Yet further investigation on the comparison of punctuality is needed to consider the influence of block buffers on punctuality. As shown in Figure 5, Figure 6, and Figure 7, there are more arrivals with negative delays at the U.S. airports. It is possible that more-than-sufficient block buffers are embedded into flight schedules by carriers so as to improve arrival punctuality statistically. Future research could investigate how block buffers are implemented by different carriers in Europe and the U.S.

3.2.2 Taxi-out Delay, Queue Length and Predictability

In this part of the study, the author compares surface operational efficiency during the departure phase of flights. There are different perspectives in defining taxi-out times and in this study it is measured as the difference between gate-out and wheel-off time. Both time variables are available in AENA dataset and ASPM system.

Unimpeded taxi-out time is defined as the time for aircraft to traverse from the gate to runway end without any interference of other traffic (4). It is compared with actual taxi-out time to measure operational inefficiencies during taxi-out phase, i.e., taxi-out delay (or additional taxi-out time). Whereas the same definition is found in the U.S. and Europe, different methodologies to compute unimpeded times are used, namely the FAA APO method and EUROCONTROL PRU method (4). Comparisons in methodology differences of two methods are presented in chapter 4.

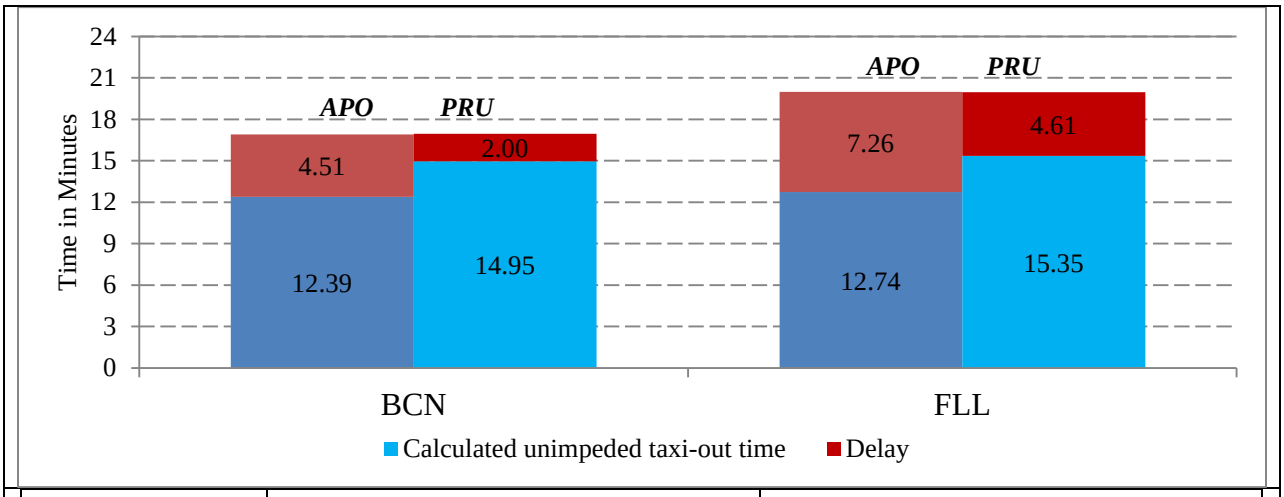


		APO			PRU		
		Qo	Cal_DlaTo	Cal_NomTo	Qo	Cal_DlaTo	Cal_NomTo
MAD	Mean	8.78	4.33	10.60	8.53	2.83	12.24
	SD	3.74	40.60	1.44	21.51	39.87	2.77
PHL	Mean	11.44	10.54	10.44	12.54	8.36	12.60
	SD	6.72	14.41	1.88	9.19	14.06	3.59

Note: Qo – departure queue length, Cal_DlaTo – taxi-out delay, Cal_NomTo – unimpeded taxi-out time

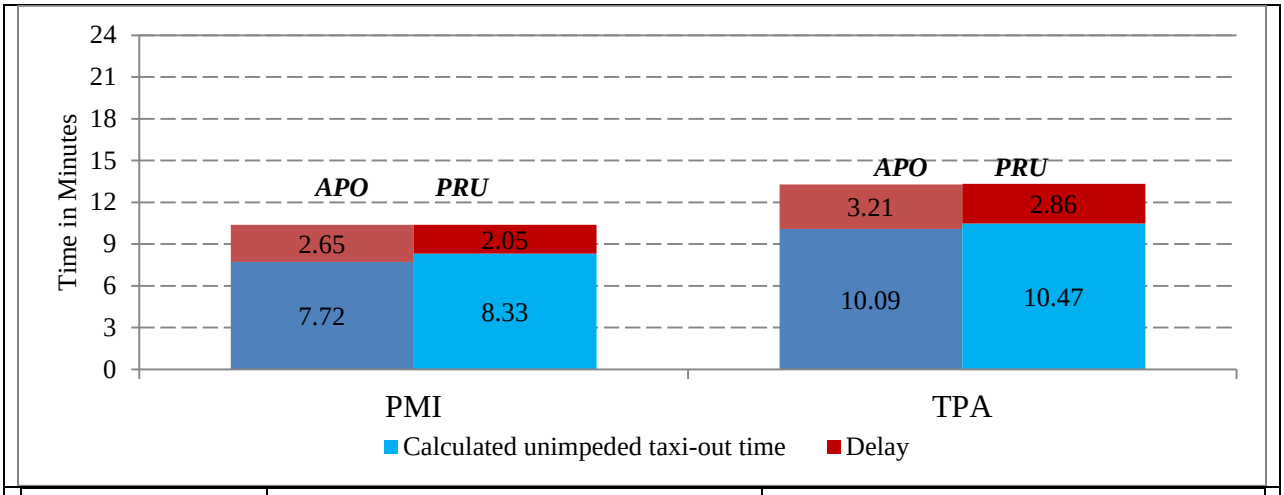
Figure 8 Unimpeded taxi-out time, taxi-out delay and departure queue at MAD and PHL by applying different methods.

By following APO and PRU methods respectively, unimpeded taxi-out times and taxi delays are computed for all flights at each airport. Figure 8, Figure 9, and Figure 10 compare taxi-out performance with respect to unimpeded taxi-out time, taxi-out delay, and departure queue length for each airport pair by applying different methods.



		APO			PRU		
		Qo	Cal_DlaTo	Cal_NomTo	Qo	Cal_DlaTo	Cal_NomTo
BCN	Mean	6.62	4.51	12.39	6.55	2.00	14.95
	SD	3.01	17.71	1.15	9.34	19.48	2.45
FLL	Mean	6.69	7.26	12.74	7.09	4.61	15.35
	SD	4.14	11.79	1.80	5.38	11.99	0.47

Figure 9 Unimpeded taxi-out time, taxi-out delay and departure queue at BCN and FLL by applying different methods.



		APO			PRU		
		Qo	Cal_DlaTo (min)	Cal_NomTo (min)	Qo	Cal_DlaTo (min)	Cal_NomTo (min)
PMI	Mean	2.31	2.65	7.72	2.46	2.05	8.33
	SD	2.52	11.64	1.38	3.28	11.42	1.73
TPA	Mean	3.81	3.21	10.09	3.98	2.86	10.47
	SD	2.29	6.84	1.55	2.91	7.06	0.89

Figure 10 Unimpeded taxi-out time, taxi-out delay and departure queue at PMI and TPA by applying different methods.

For all six airports, using PRU method yields higher values of average unimpeded taxi-out time and corresponding lower taxi-out delay than APO method. It can be noted that differences on average unimpeded taxi-out time by APO and PRU method range from 0.38 minutes (TPA) to 2.61 minutes (FLL). By following the same method, average values of calculated unimpeded taxi-out times between matching airports are very close, which in turn confirms the comparability of each pair. However, delay patterns between the U.S. and European airports are quite different. For example, average taxi-out delay at PHL is about 6 minutes more than MAD and standard deviation of delays is higher at PHL by either APO or PRU method. Differences are also observed with respect to departure queue length, with each flight at PHL experience 3-4 more flights ahead in the queue.

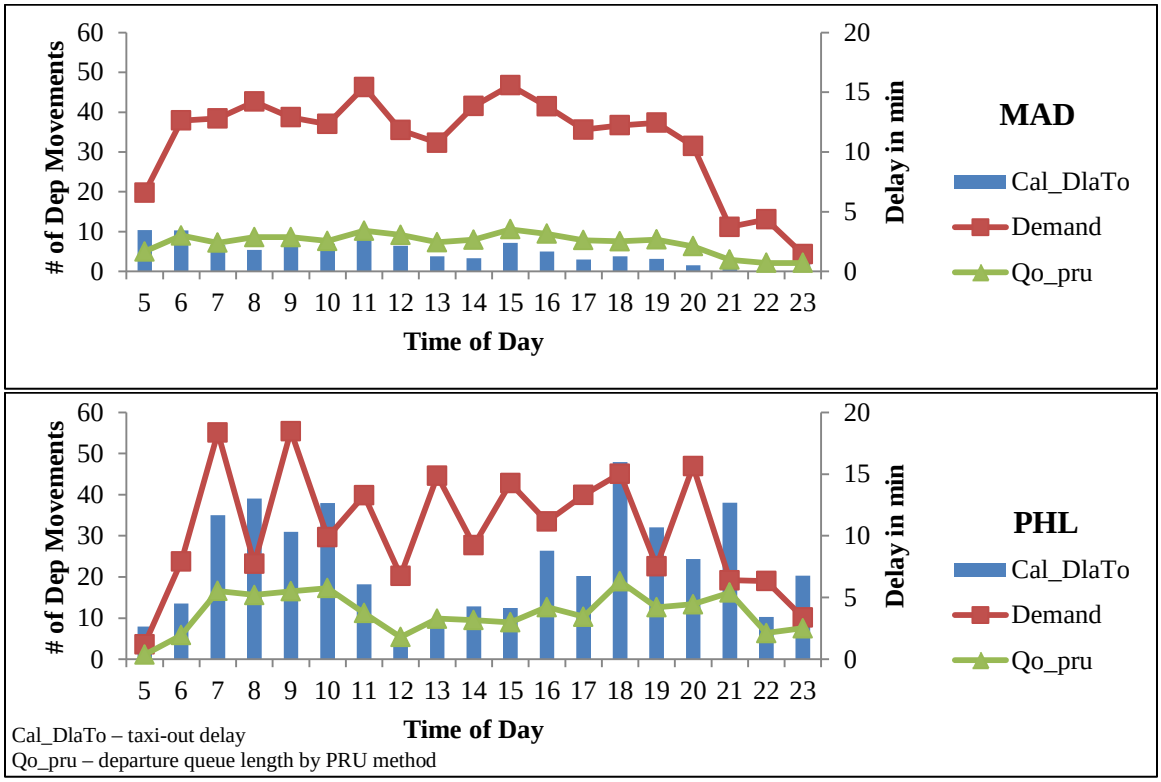


Figure 11 Taxi-out delay, departure queue length and demand at MAD and PHL.

Figure 11 exhibits the patterns of taxi-out delay, departure queue length and scheduled demand over time of day at MAD and PHL. It is observed that departure queue length (left scale, green line) at MAD is maintained steadily along the time of day. On average, each departure has about 8 to 10 flights ahead on the surface when entering airport movement area. Similar stable distribution is observed for taxi-out delay (right scale, blue bar) with an average of 2 minutes and maximum of 4 minutes. In contrast, both departure queue length and taxi-out delay varies distinctly along the time of day at PHL. A peak of 19 flights queuing on the surface per hour occurred around 6pm and the highest hourly taxi-out delay of 16 minutes is also observed during the same hour.

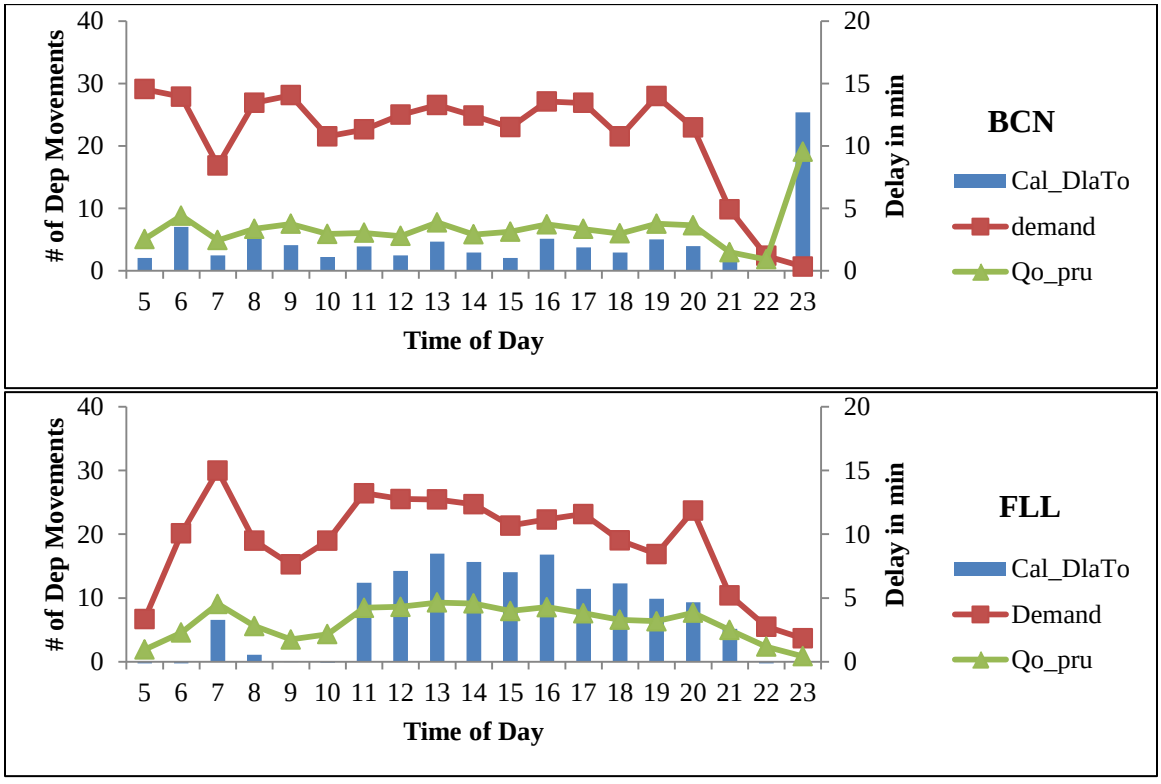


Figure 12 Taxi-out delay, departure queue length and demand at BCN and FLL.

Similar analyses are conducted for other two airport pairs, as presented as in Figure 12 and Figure 13. Similar to the previous pair, departure queue lengths at BCN are evenly distributed along the time of day and lower value of taxi-out delays are observed at BCN than

FLL. As for PMI and TPA, variances in delay and queue distributions are relatively subtle due to the moderate amount of annual traffic at both airports.

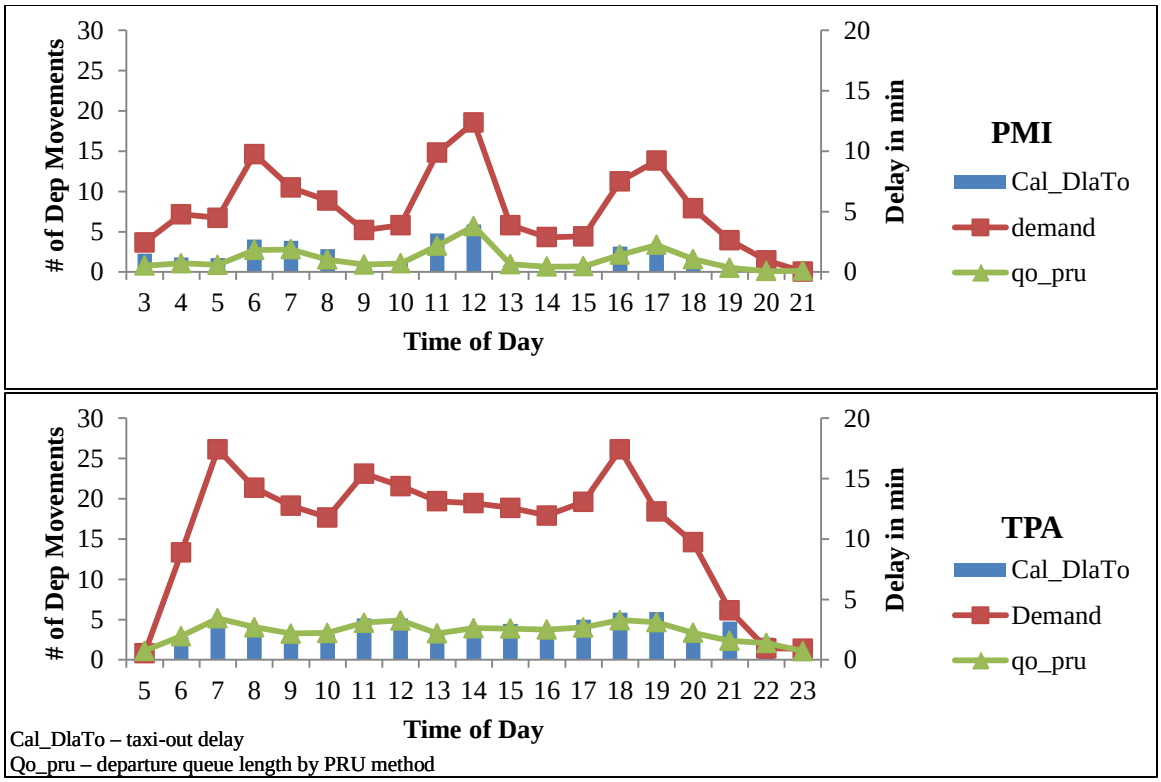


Figure 13 Taxi-out delay, departure queue length and demand at PMI and TPA.

To provide more insight on airport surface congestions, scatter diagrams of taxi-out time over departure queue length by occurrences are presented for each airport pair, as in Figure 14, Figure 15, and Figure 16. For instance, each red square in the figure represents an incident with the same combination of actual taxi-out time and departure queue length that occurred three to nine times during the study period. A distinct linear trend is observed from each figure between departure queue lengths and taxi-out times. It has been stated in previous research that long queue lengths on the surface is one of the main causal factors for excessive taxi times (4). It is also observed from these figures that flights at the U.S. airports are more likely to be caught in longer departure queue and thus experience longer taxi-out delay.

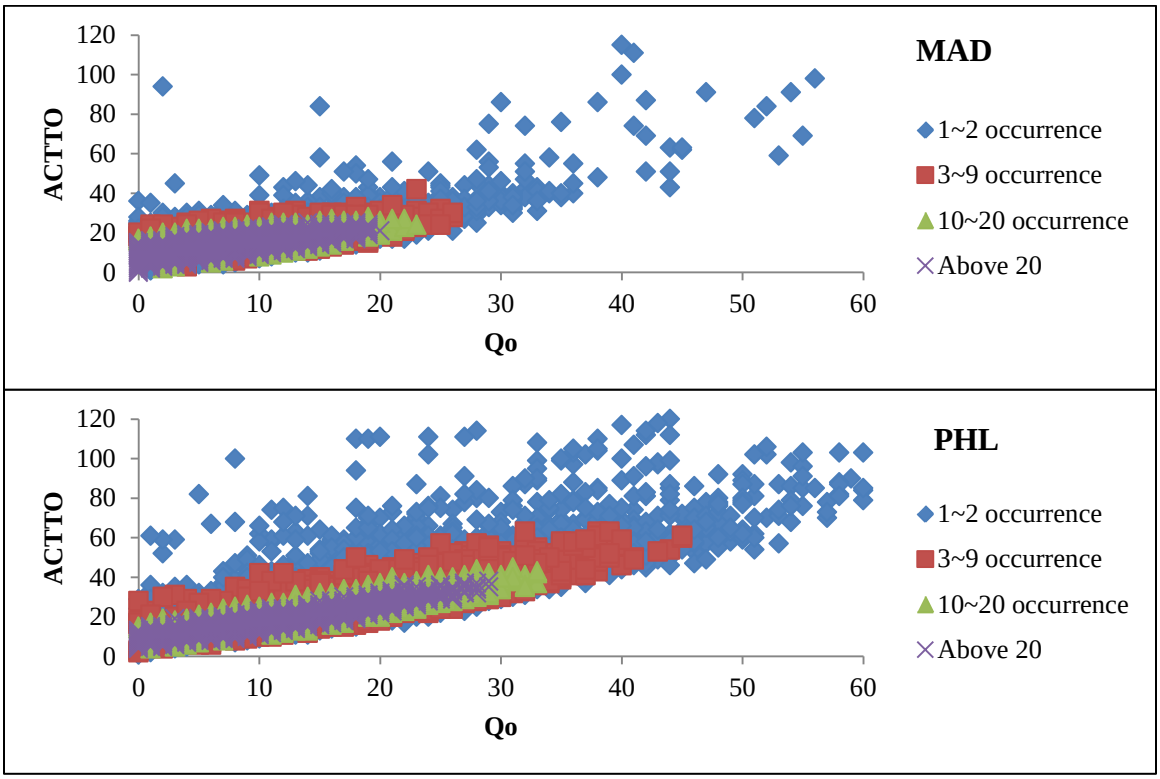


Figure 14 Departure queue length (Qo) vs. actual taxi-out time (ACTTO) at MAD and PHL.

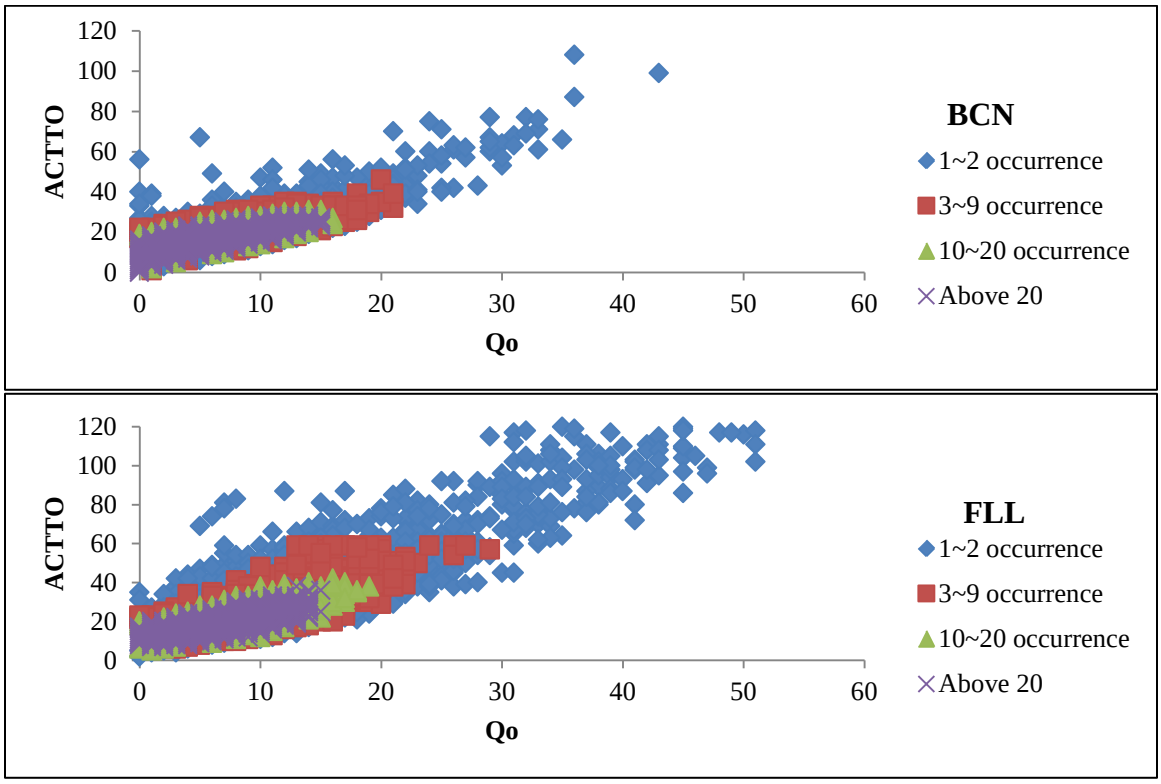


Figure 15 Departure queue length (Qo) vs. actual taxi-out time (ACTTO) at BCN and FLL.

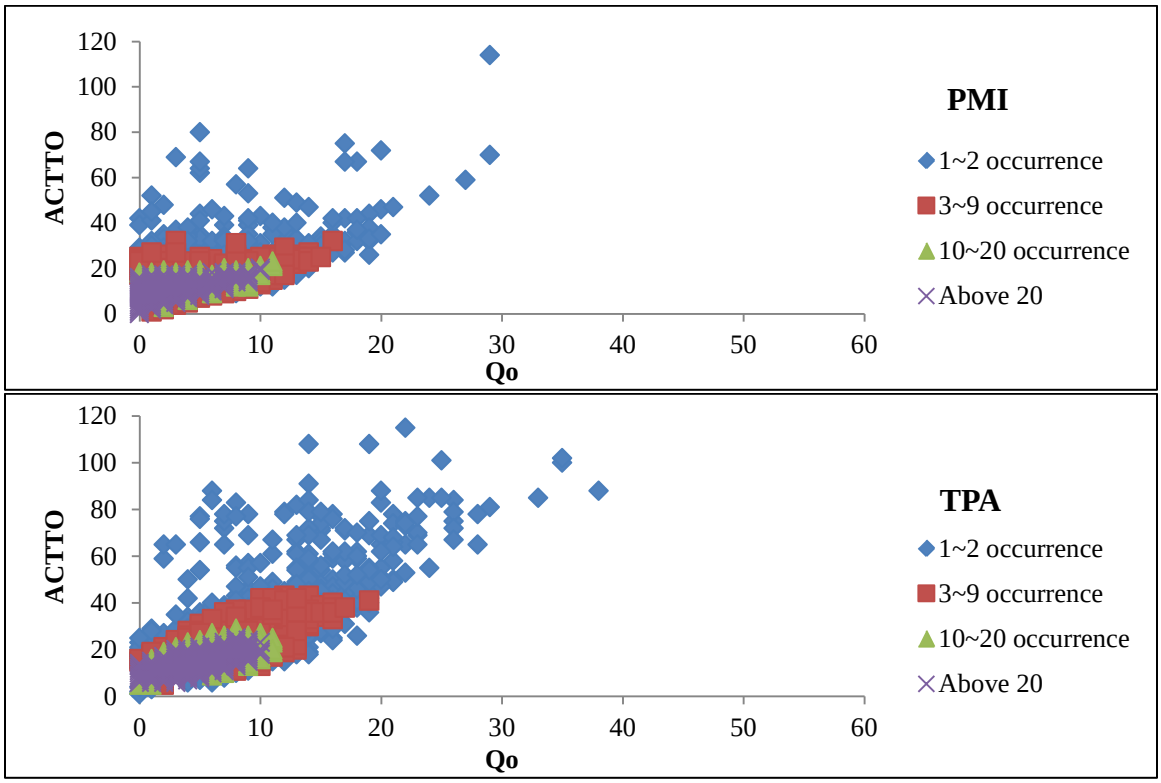


Figure 16 Departure queue length (Qo) vs. actual taxi-out time (ACTTO) at PMI and TPA.

In this study, the author also examines different taxi-out performances by airlines. Figure 17 depicts the average taxi-out delay and percentage of flight operations at each respective airport for each airline at MAD and PHL. It shows that airlines operating at MAD share a similar level of taxi-out delay (average of 3 minutes) with a standard deviation of 1.39, whereas average delays by airlines vary from 3 minutes (JBU) to 17 minutes (AWE) at PHL with a standard deviation of 3.08. Similar trends are also observed from Figure 18 for BCN and FLL. Delays by airlines are less diversely distributed at BCN with a standard deviation of 1.13, compared to 1.6 at FLL. Implications of varying delay patterns by airlines are relatively subtle in Figure 19 as delays and congestions at PMI and TPA are less severe than busy airports.

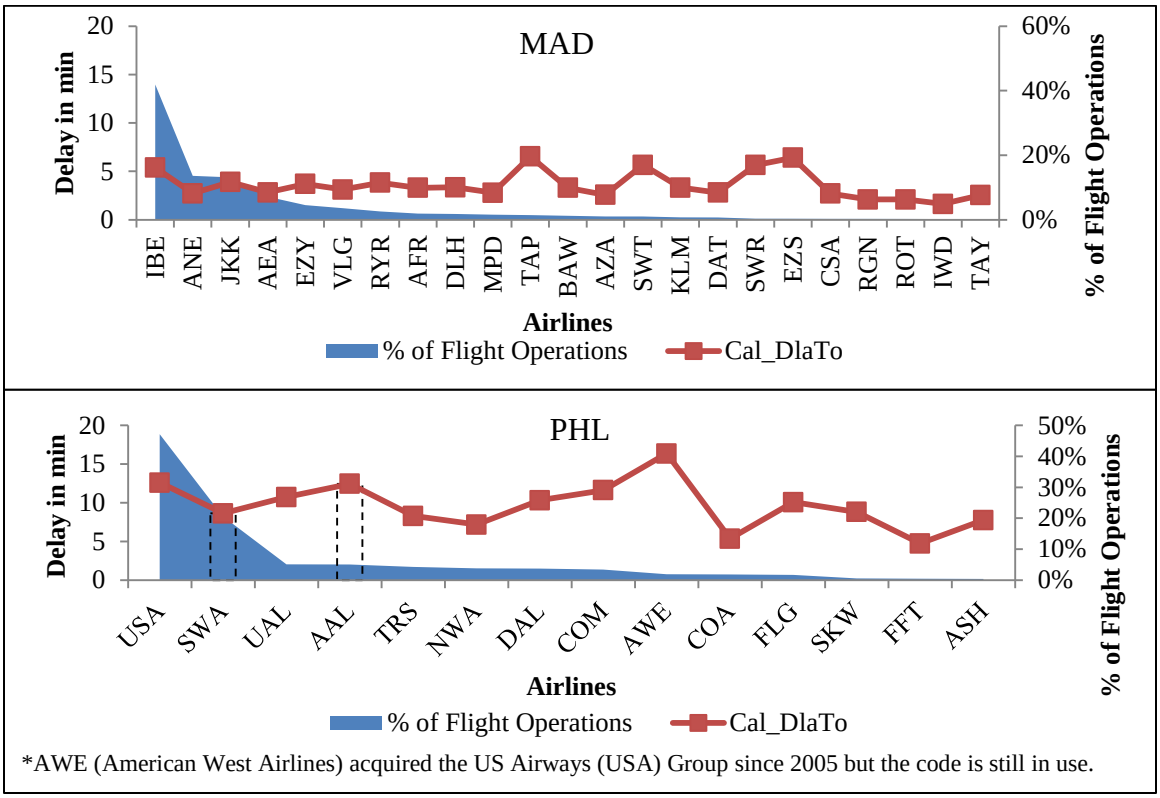


Figure 17 Comparison of taxi-out delay (Cal_DlaTo) by airlines at MAD and PHL.

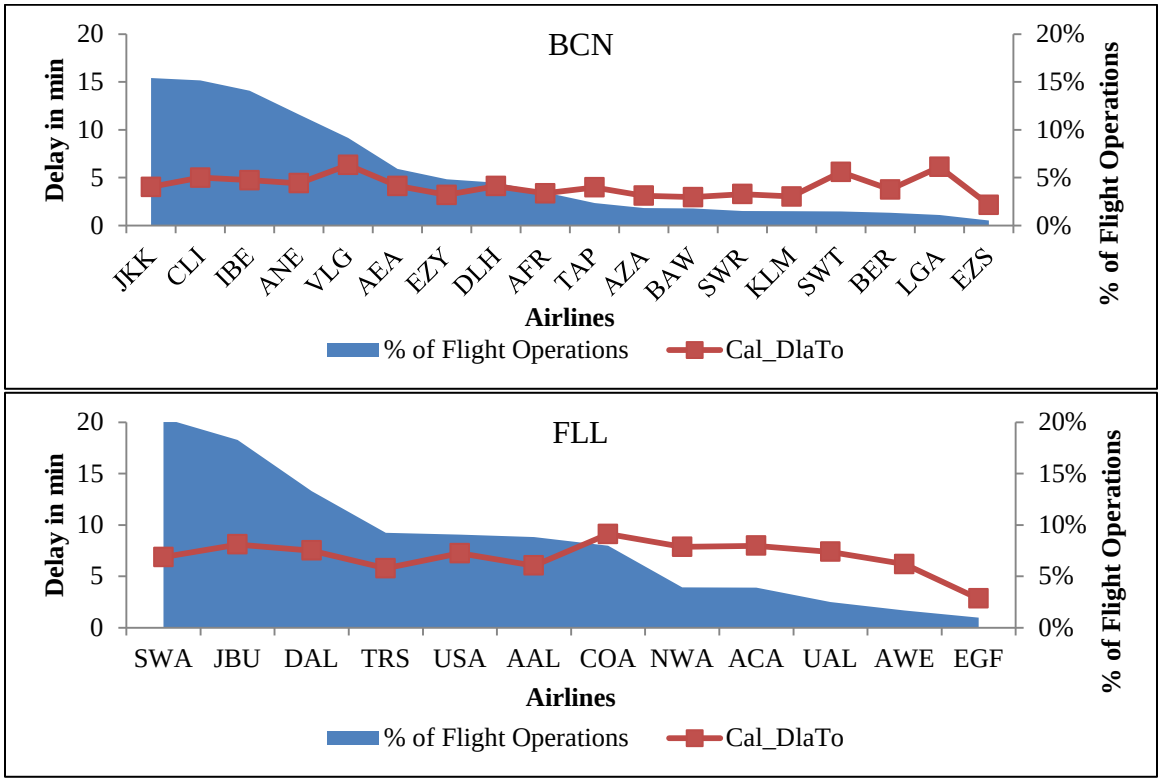


Figure 18 Comparison of taxi-out delay (Cal_DlaTo) by airlines at BCN and FLL.

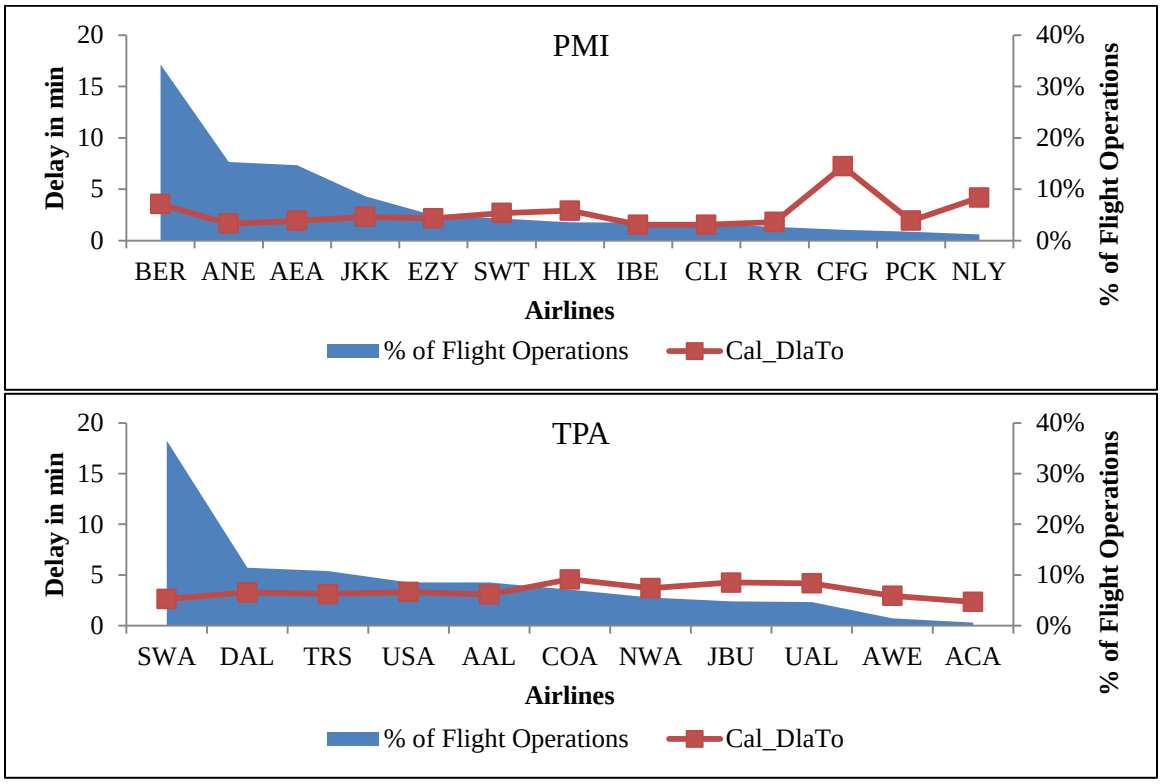


Figure 19 Comparison of taxi-out delay (Cal_DlaTo) by airlines at PMI and TPA.

Different delay patterns by airlines at busy airports could be explained by varying gate managements at the European and U.S. airports. In Europe, there is a great use of common gates that provides more flexibility in terms of gate assignments. In the U.S., however, most gates are exclusively or preferentially used by certain airlines. For airlines that lease gates farther from runways, they bear substantially longer taxi time and may experience longer delays. For example, American Airlines (AAL) located at Terminal A at PHL (see Figure 20), has to move aircraft along the entire perimeter of the terminal to take off on runway 17, 35, 26 or 8. Other airlines, such as Southwest Airlines (SWA) located at Terminal E, are much closer to those runways and thus experience less taxi times.

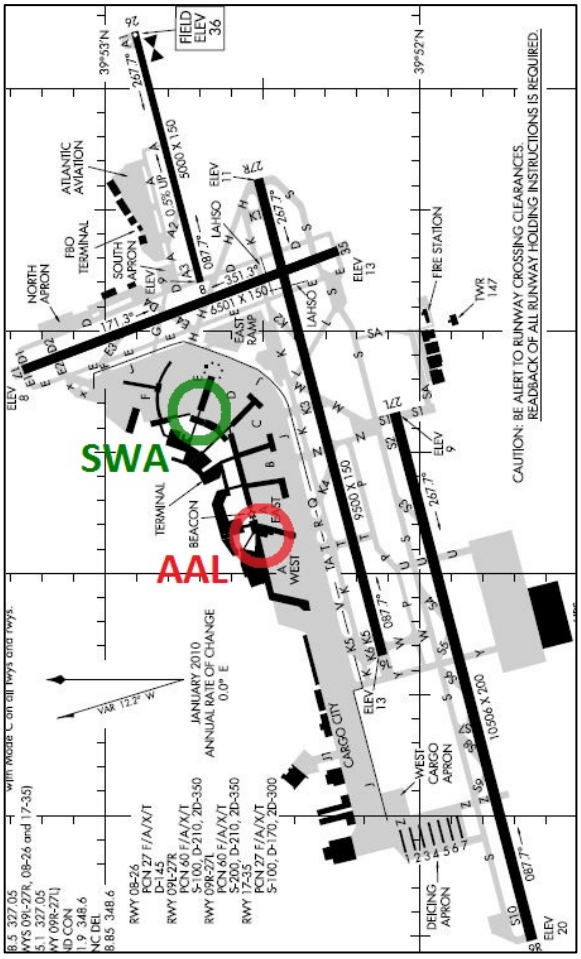


Figure 20 Terminal locations of AAL and SWA at PHL.

3.3 Comparison of Airport Capacity and Demand

3.3.1 Airport Capacity

As a fundamental element for airport planning, the ultimate capacity of an airport is typically determined by the capacity of the airfield and specifically determined by runway systems. There are several alternative measures of runway capacity in use. Maximum throughput capacity as the principle measure is defined as the number of movements on the runway system per hour in the presence of continuous demand. Declared capacity as another measure commonly used in Europe is defined somewhat ambiguously as the number of runway movement per hour while accommodating a reasonable level-of-service (LOS) at airport (13). Recall from Table 1,

airport capacity listed for MAD is declared capacity with a value of 90 flight movements per hour in 2008. As for PHL, the estimated capacity is 96 under Instrument Meteorological Conditions (IMC) while in good weather the capacity is estimated to range from 104 to 116 during the study period. One reason why two similar airports have quite unparalleled capacity is associated with the different strategic planning by ANSPs in the U.S. and Europe. In the U.S., VFR associated with Visual Meteorological Conditions (VMC), is operated when weather permits, under which pilots maintain visual separations (smaller than instrument separations) among aircraft. In contrast, aircraft in Europe are operated under IFR associated with IMC at all times, regardless of prevailing weather conditions.

Figure 21 shows a comparison of average taxi-out delay under VFR and IFR at three U.S. airports, calculated with both APO and PRU methods. This displays how good and bad weather, indicated by VFR and IFR procedures, influence taxi-out delay in the U.S. On average, flights under IFR procedures experience 1.91 minutes (TPA) to 6.33 minutes (PHL) more delay than VFR procedures. In Europe, such weather impact is relatively small since runway capacity is regulated in a more conservative way to ensure the operational reliability at airports. During the study months, there is only 2.1% of times or less when airport demand from the schedule was over declared capacity at selected European airports.

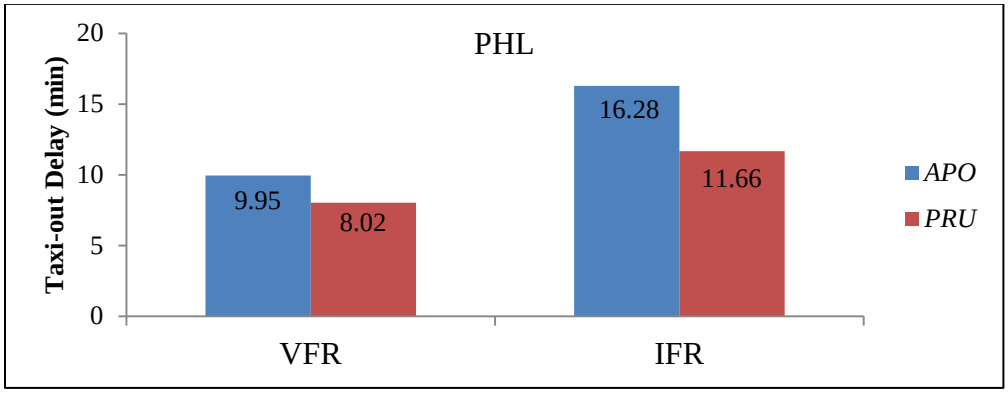


Figure 21 Average taxi-out delay under IFR and VFR procedures at U.S. airports.

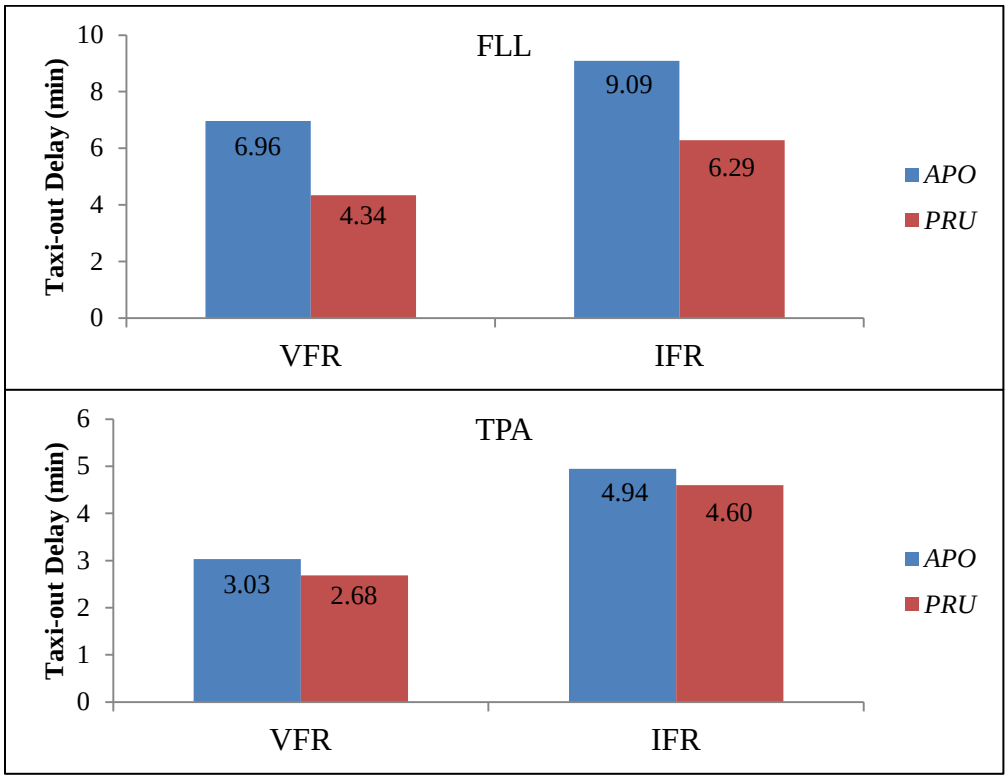


Figure 21 (Continued).

3.3.2 Airport Demand

In this subsection, the author investigates scheduled demand patterns at U.S. and European airports. As airlines' initially requested flight schedules are not available, the author uses scheduled departure and arrival times from AENA and ASPM database and define airport demand as the total number of flights being scheduled during a certain time period (namely an hour) at each airport.

Figure 22 depicts airport demand patterns at MAD and PHL. With similar total number of flights scheduled, both airports present an alternative pattern of arrival and departure demand to avoid the stack of scheduling peaks. Yet a larger variability of demand over time of day at PHL is still observed especially around morning and late afternoon peaks. From 8 am to 9 am, departure demand at PHL increased from 23 to 55 flights while the number of scheduled arrivals

dropped from 53 to 19 flights. In contrast, both arrival and departure demand at MAD flow smoothly with smaller variation (within 5 flights) during the same time period.

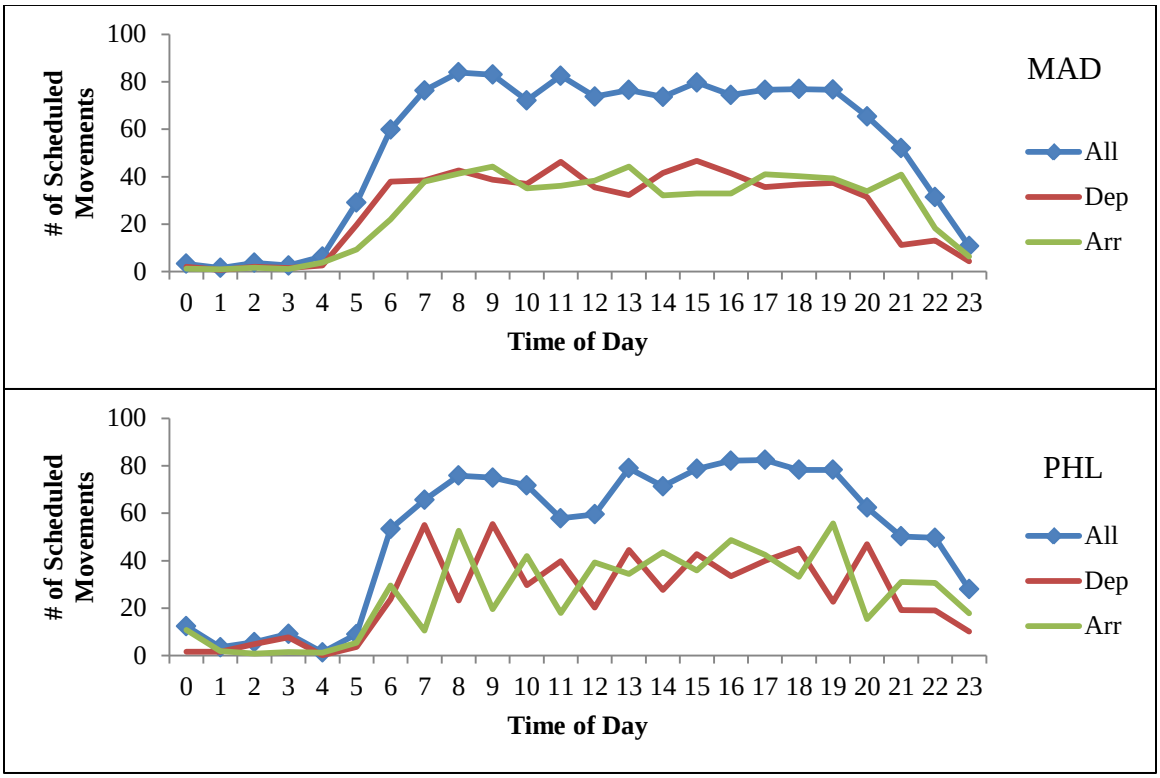


Figure 22 Scheduled flight movements over time of day at MAD and PHL.

At airports with medium and moderate levels of daily traffic, flight scheduling is not restricted by airport capacity. As shown in Figure 23 and Figure 24, scheduled traffic for the other two airport pairs is not as distinctive as busy airports, yet is presented with relatively random patterns.

As a representative example, Figure 25 compares flight demand with actual movements at MAD and PHL, along with average taxi-out delay distribution over the time of day. It can be observed that the number of scheduled or actual flights at MAD is quite close to and barely over its declared capacity of 90. It indicates that airport demand at MAD is already capacity constrained and that the published schedule does not fully capture its initial demand pattern without any demand management.

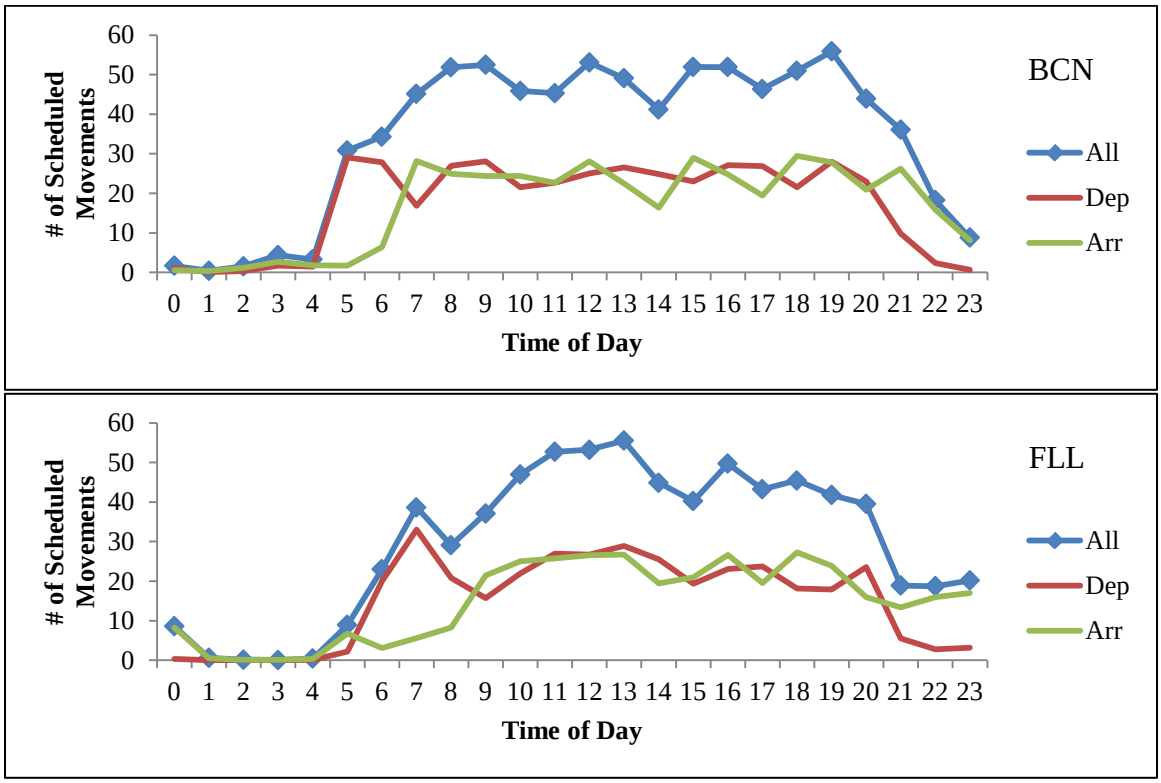


Figure 23 Scheduled flight movements over time of day at BCN and FLL.

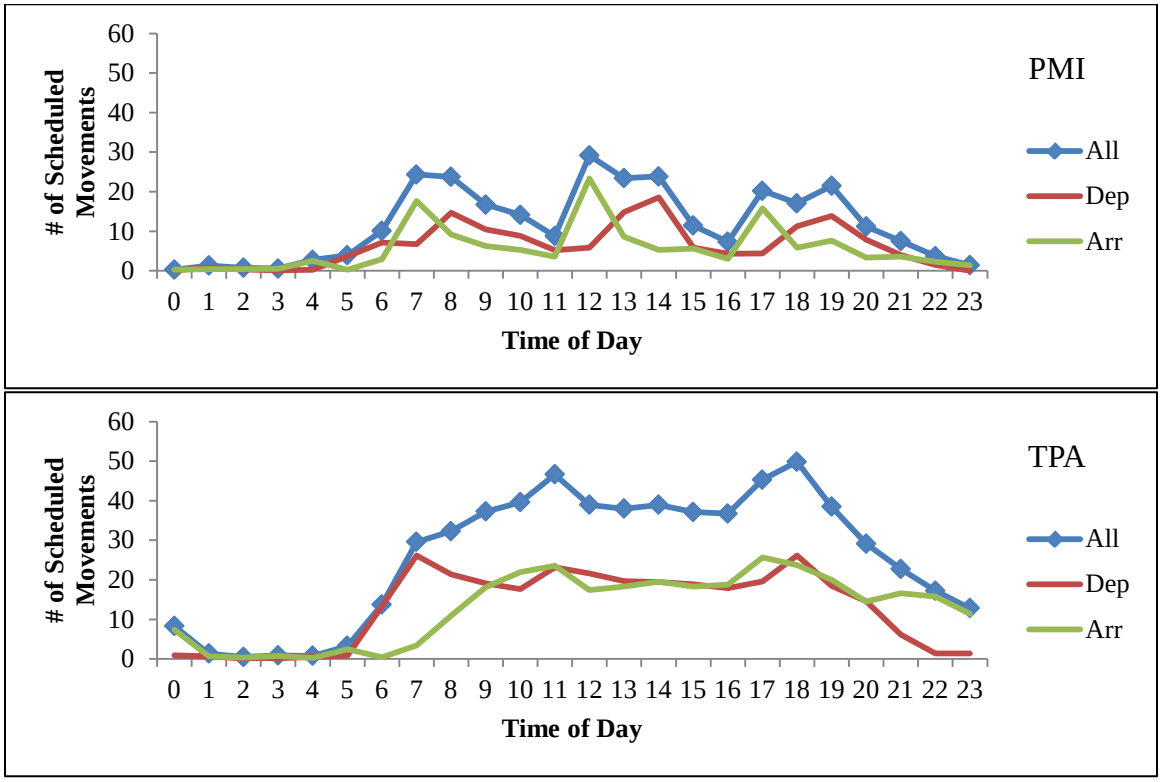


Figure 24 Scheduled flight movements over time of day at PMI and TPA.

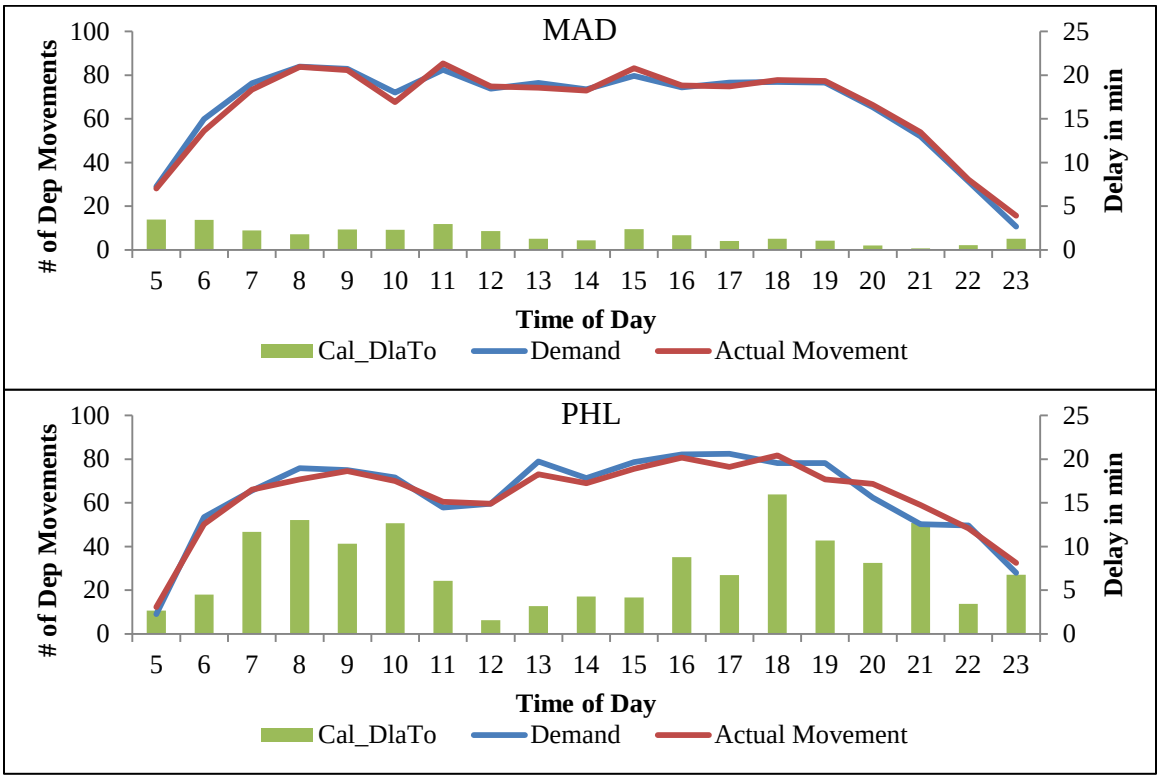


Figure 25 Demand and actual movement at MAD and PHL.

During the study period, the overall weather conditions at PHL were not good as 91.5% of flights operated under IFR. Yet neither airport demand nor actual movement is close to its IFR capacity of 96. Moreover, the number of actual movement during most of high-demand hours is lower than the demand itself. It indicates that airport throughput is not constrained by runway capacity and congestions on taxiways and apron area deteriorate surface operation reliability significantly.

The explanation of such different patterns is associated with slot control and schedule coordination at three Spanish airports and other European airports. Slots are allocated to airlines as permissions to arrive or depart at an airport during a specific time window so as to balance airport capacity and demand (25). Such administrative control of European regulators prevents the excessive flight scheduling over the declared capacity. It ensures the reliability of airport surface operations with a high degree of overlap between scheduled and actual flight movements,

as well as small and evenly distributed taxi-out delays. Yet the conservative way of determining the declared capacity yields a large potential for European airports to improve the usage of scarce runway facilities especially under good weather conditions.

3.4 Policy Implications and Recommendations

Both the U.S. and Europe air traffic systems are operating with a similar geographic area and equally advanced technologies and concepts. However, important differences exist within the surface operations management as shown from high-level factual comparisons in previous subsections. Between each two comparable airports, smaller and evenly distributed delays are observed from European airports while the U.S. airports obtain more efficient usage of airfield facilities. In this subsection, the author summarizes the differences of the ATM of the two regions and the impacts on surface operations management.

3.4.1 Air Transport Regulators

One of the key differences between the U.S. and European systems is the air transport regulators. One ANSP (FAA) operates the U.S. system while European system comprises 37 ANSPs. As the only service provider, the FAA aims to improve the system performance using the same tool, regulations and procedures. In Europe, there has been continuous effort to cooperate air traffic operations and management among different ANSPs but they are still highly fragmented within their own boundaries in terms of ATM (10).

The emphasis of air service providers also varies. In the U.S., the centralized administration of FAA focuses on the overall flight plan to enhance the system and airport performance and tactically manage air traffic with respect to various conditions in the NAS. In Europe, cooperated strategic planning may occur months in advance to strictly constrain

scheduled demand under the declared airport capacity. Yet each ANSP still processes the final approval based on its own rules and regulations.

3.4.2 Airline Scheduling and Demand Management

Another main difference between the U.S. and Europe is the practice of airline scheduling and demand management.

In Europe, airlines submit their desired flight schedules to Network Manager Operations Centre (NMOC, formerly CFMU) (25) during the strategic planning phase and schedule coordination is applied strictly as an administrative way to manage and balance airport capacity and demand. MAD, BCN and PMI are all coordinated airports during the study period. Any flight operations, like landing or taking-off, shall be allocated with a slot by AENA's Airport Slots Coordinator Office; the total amount of flights that can be scheduled is constrained by the declared capacity of the airport. Under certain circumstances the NMOC will issue changes to revised departure times to manage the congestions at the departure airport.

In the U.S., flight scheduling is not as restricted at most of the airports as it is in Europe. Only five airports, John F. Kennedy International Airport (JFK), LaGuardia Airport (LGA), Newark Liberty International Airport (EWR), O'Hare International Airport (ORD) and Reagan National Airport (DCA) had a history of demand management. The FAA tends not to favor such regulations to impede the competition and airport access especially at highly-congested airports.

3.4.3 IFR and VFR

Another notable difference is the allowance of flights operating under VFR in the U.S. when weather permits. Visual separations are smaller than IFR separations and are maintained by pilots instead of controllers. The implementation of VFR separations allows more flights to land and take off during good weather days. The uncertainty of weather, however, has a greater

influence on airport operations that are planned according to good weather conditions. Long taxi-out delay with large variability is observed when weather is less than good at U.S. airports. In Europe, IFR is strictly implemented even in good weather conditions with the declared capacity close to IMC capacity. It reduces the impact of weather on flight operations, yet limits the flexibility to accommodate more flights under good weather. The strictly implemented IFR procedures with conservative declared capacity in Europe result in an inefficient usage of scarce runway facilities. It restricts access to the airport and airspace and may discourage healthy competitions amongst carriers.

3.4.4 Gate Management

Recall from subsection 3.2, delays experienced by airlines varied in the U.S. while airlines in Europe shared similar amount of delay. One of the reasons for such differences stems from different gate management policies in the two regions.

In the U.S. most of the gates are exclusively or preferentially used by certain airlines. Further gate locations increase the difficulty to access the runway and result in higher possibilities of encountering long taxi delay. In Europe, there is a greater use of common gates that provide more flexibility and more means to manage high demand for gates. It also facilitates the procedure when aircraft have to be held at gates longer in order to reduce taxi-out delay and to conserve fuel consumption.

3.5 Summary

Several airport surface management initiatives have been tested at various U.S. airports. Consequent operational performance improvements encourage the promotion of the initiatives to more airports. Nevertheless, the author argues throughout this study that additional investigation of airport surface operations is needed for a more comprehensive understanding of the obstacles

preventing further improvements. The research approach involves a comparison study for major U.S. and European airports, an examination of different methods used in the U.S. and Europe for benchmarking operational performance indicators, and a discussion of comparison results and ATM strategies implemented in the U.S. and Europe: single ANSP in the U.S. and multiple ANSPs in Europe, airline scheduling and demand management differences, mixed usage of IFR and VFR operations in the U.S., and different gate management policies in two regions, to name a few. Although policy recommendations are beyond the scope of this study, the outcomes offer analytics support to decision makers who are responsible for improving airport surface operations.

CHAPTER 4: AIRPORT TAXI TIMES MODELS

Unimpeded taxi time is the reference time used for estimating taxi delay, a widely accepted performance indicator of airport surface movement. Nevertheless, different methodologies are currently in use by the FAA and EUROCONTROL to derive unimpeded taxi time. Hence, this chapter fulfils the need for consistent method for the measurement of taxi-out efficiency and the facilitation of global benchmarking. First, the author clarifies an array of definitions of taxi performance indicators in this study. A comparison on different methods that are currently in use is performed, focusing on the respective methodology. New methods to determine unimpeded taxi times are explored through simulation and observation of historical operational data. Moreover, the author proposes a statistical model that demonstrates a state-of-the-art method to measure taxi-out efficiency. The application of various methods in this study is focused on the taxi-out phase that exhibits the largest variance when comparing the different phases of flights between the U.S. and Europe (10).

4.1 Definition of Taxi-out Performance Indicators

4.1.1 Taxi-out Time

For flight operations at airports, “bottleneck” areas on the surface where congestion could occur include gates, apron area, taxiways, and runways--with the last two elements often referred to as the *airport movement area*. There are different perspectives in defining taxi-out times in this area of literature. On the one hand, an explicit definition of *taxi-out time* refers to the amount of time between an aircraft’s pushback from the gate (off-block time) and its takeoff from the runway (wheel-off time). From an airlines’ point of view, once an aircraft has left the gate, any

excess time from an optimum unimpeded time that occurs before takeoff shall be considered as inefficient, regardless of its occurrence in the ramp or movement area. In addition, this definition only requires two time stamps: off-block time and takeoff time for each flight, which are both readily available in both the ASPM (41) and Spanish airport databases that the author used to obtain flight data. On the other hand, it is usually the airports or airlines themselves that control aircraft movement in the ramp area; ANSP (i.e., the FAA in the U.S.,) oversees the movement area in the U.S. To evaluate the performance of each entity, aircraft movements in two areas need to be separately considered. For major airports with both a ramp control tower and an air traffic control tower, agreements are made on which spots to appropriately take over the control of aircraft from each other. For instance, only three out of 14 available spots on the surface of PHL are utilized between two towers to take over the control of flight movements (4). The taxi time for ANSP, according to this alternative definition, shall be the time that aircraft spend beyond the handover spots and before takeoff. Which definition to use is truly dependent upon research objectives and the availability of data. To evaluate taxi performance by control areas would require more sophisticated data sources in additional to the available data for this study. Therefore, the taxi-out time in this study is defined as the difference between off-block time and runway takeoff time.

4.1.2 Unimpeded Taxi-out Time and Taxi-out Delay

Unimpeded taxi-out time is defined as the travel time of an aircraft from pushback from the gate to takeoff on the runway without any interference of other traffic. This time variable is considered as the reference to estimate inefficiencies during the taxi-out phase. Whereas the U.S. and European systems have the same definition of unimpeded taxi-out time (43), methodologies used to derive this variable are different. The operational inefficiency during the taxi-out phase,

also defined in this research as additional taxi-out time (or taxi-out delay), is measure by the excessive time that aircraft take for the taxi-out process in addition to the unimpeded reference time. Note that inefficiency on taxiway systems is not the only cause for additional taxi-out time; sometimes a certain amount of additional time is desirable to maximize the utilization of other airside facilities, e.g., to avoid idle periods and maximize runway throughput (4, 43).

4.2 Methods for Computing Unimpeded Taxi-out Time

4.2.1 The U.S. APO Method

The FAA Aviation Policy and Planning Office (APO) established a process for estimating unimpeded (nominal) taxi times recorded in the ASPM database. It is based on two linear equations, one for taxi-in and the other for taxi-out, and contains both taxi-in and taxi-out queue lengths. The APO process seeks to build a numerical relationship between aircraft on the ground and taxi time through a linear regression model. Model inputs are derived from the ASPM database. Note that aircraft are not recorded as either being in a queue or even outside the ramp area of the gates; the parameters recorded are a gate-out time and a wheel-off time. These values are used as surrogates for taxi-out time even though an aircraft may spend considerable time within the ramp area after a gate-out message is triggered. Appendix A describes the details of the APO method and Figure 26 summaries the methodology in a flow chart. The APO method explains taxi time by departure and arrival queue lengths; however, it does not involve any other contributing factors such as runway configurations, weather conditions, or terminal/gate location. Also, APO method only applies to ASQP carriers (Appendix C) and other airlines at airports are assigned with an average value (41). To be consistent, a similar procedure is performed in this study.

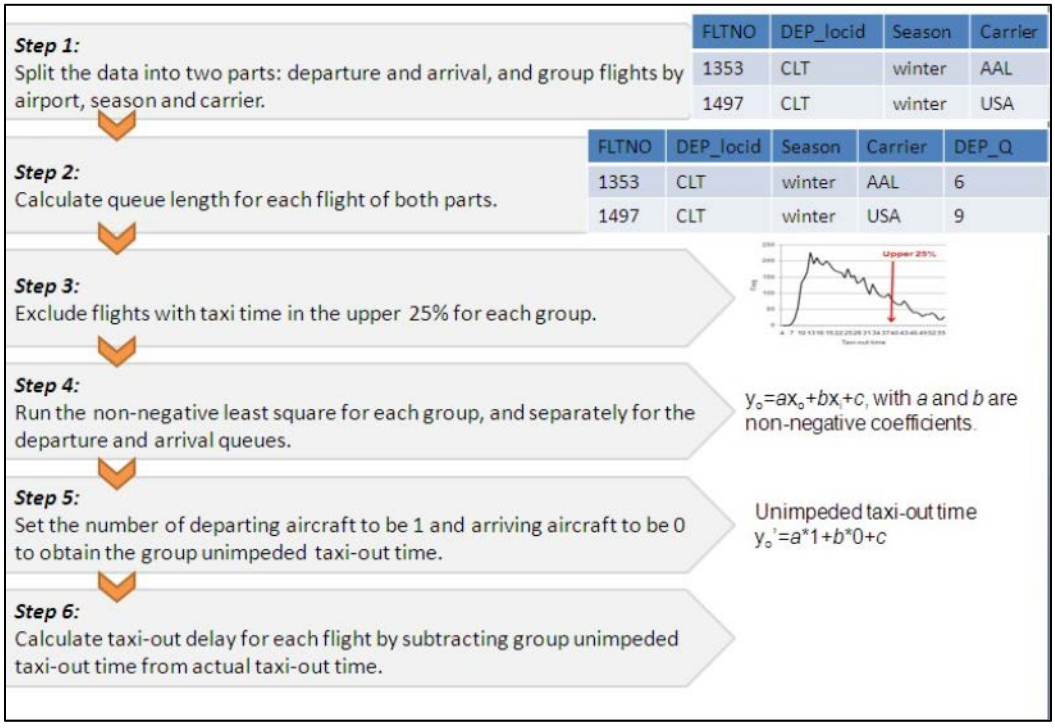


Figure 26 APO method for determining unimpeded taxi-out time.

4.2.2 Europe Performance Review Unit (PRU) Method

Namely, the PRU method developed by EUROCONTROL determines a common unimpeded taxi-out time for a group of flights that share similar characteristics. Dependent upon data availability, these characteristics include aircraft class and pairs of departure stand and runway end, or aircraft class only (as in a simplified version of this method). A congestion index is calculated for every flight and a congestion index threshold is established for each group. After trimming flights by the threshold value on the congestions index, the truncated mean of remaining flights in the group (i.e. averaging taxi-out times between 10th to 90th percentiles) is calculated as the unimpeded taxi-out time for the group.

Due to data limitation of ASPM systems, there is no available record for runway or stand information. Hence, a simplified version of the PRU method is applied in this study. The simplified version of the PRU method (43) for calculating the additional taxi-out time is divided

into five steps shown in Figure 27. Tables on the right side present sample outcomes after each step.

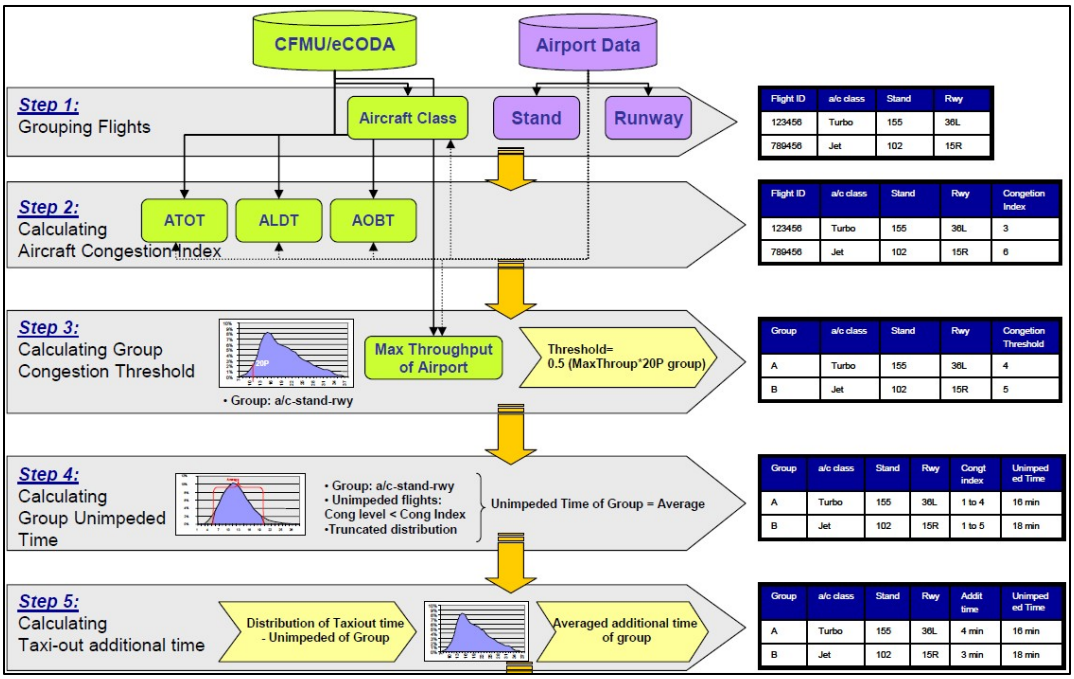


Figure 27 Simplified PRU method for determining unimpeded taxi-out time.

4.2.3 20th Percentile Method (P20)

Another method used in this field of literature to calculate unimpeded taxi times is simply to construct the cumulative distribution function of taxi-out times for each group of flights, grouped by flight carrier, season, and runway configuration, and then take the value of actual taxi-out times at the 20th percentile as the reference time. In this study, P20 method is also compared to APO and PRU methods to show the variances.

4.2.4 Comparison of Three Methods

LaGuardia Airport (LGA), Philadelphia International Airport (PHL), and Charlotte Douglas International Airport (CLT) are among the airports with longest taxi delays in the U.S. (10) and they are selected for comparing the taxi-out times by applying different methods. The flight data of 2007 are used, as it is the year with the highest taxi times in last decade.

Table 2 Comparison of Unimpeded Taxi-out Times Using Different Methods

Unimpeded Taxi-out Times (min)	*LGA*			*PHL*			*CLT*		
	APO	**PRU**	**P20**	**APO**	**PRU**	**P20**	**APO**	**PRU**	**P20**
Mean	12.41	14.91	16.66	10.86	15.44	13.57	11.73	14.59	12.16
SD	1.64	1.62	2.92	1.86	2.99	3.02	1.48	1.88	1.37
Group Min	9.90	11.22	9.00	6.50	8.02	6.00	9.80	10.49	8.00
Group Max	15.20	20.72	29.00	17.10	28.87	23.00	17.30	23.00	20.00
Flight Count	115,993			103,152			128,863		

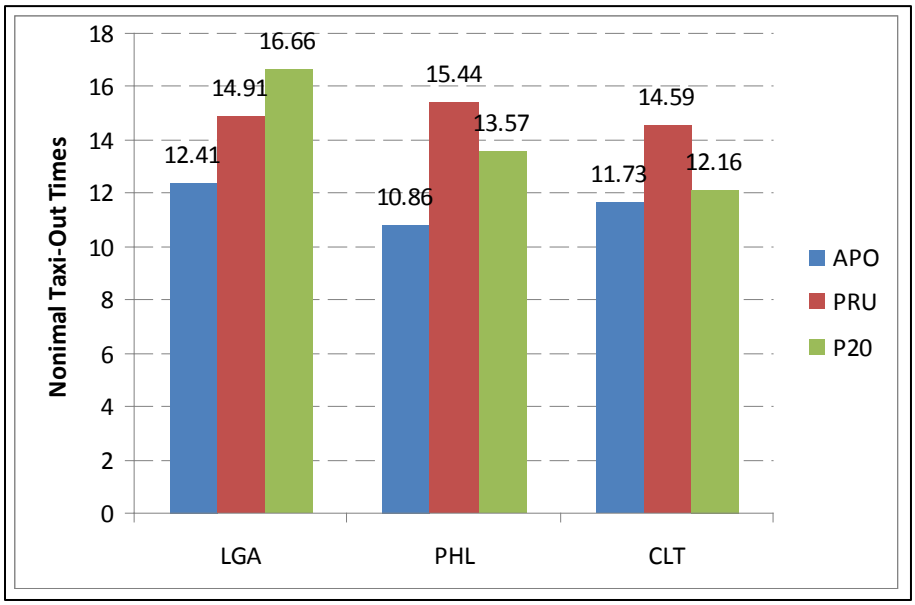


Figure 28 Comparison of average unimpeded taxi-out times at LGA, PHL and CLT.

Table 2 and Figure 28 compares unimpeded taxi-out times recorded in ASPM by APO method with estimations by the PRU and P20 methods. Only ASQP carriers are included in the results when grouping flights by carrier and season. Groups with a low number of flights (less than 100) are not considered either. Once an unimpeded taxi-out time is obtained for a group (with the same carrier during the same season), the same value is assigned to all flights in the group. The first two rows in Table 2 show the average unimpeded taxi-out times among all flights and standard deviations (SD). After that, the minimum and maximum unimpeded taxi-out times across the different groups are listed by different methods. Given the historical flight data

at LGA, PHL and CLT, it can be suggested that the PRU method and P20 methods led to higher estimations on unimpeded taxi-out times than that of APO method.

4.3 New Methods for Computing Taxi Delays

4.3.1 Airport Simulation

In addition to statistical methods that are based on historical data, qualitative research through simulation is also an efficient way to determine unimpeded taxi times and derive taxi delays. According to the definition, unimpeded taxi-out time is defined as the time it takes for aircraft to reach a runway from the gate without stopping or holding; viz., aircraft taxiing with a consistent taxi speed could be identified as unimpeded. Thereby, simulation tools can be utilized to determine taxi distances of any given taxi routes. With a reasonable estimation of unimpeded taxi speed, unimpeded taxi time can be obtained by dividing taxi distance by taxi speed.

Advanced Airfield Delay Simulation Model (ADSIM+) is an airport simulation under development by the FAA. A prototype of ADSIM+ is used to test the aforementioned simulation method. The precise geographic information of airside facilities, namely runways, taxiways and gates are imported into the model. Figure 29 shows the layout of PHL in the simulation with sample taxi routes from different gates to runways.

There are seven terminals PHL (A West, A East, B, C, D, E, and F) and two major runways used for departures. 27L|9R, 27R|9L, 27L are the most frequently used runway configurations. Altogether, there are 28 terminal-runway combinations for different taxi routes. A schedule of 28 flights is specified in the simulation, with each flight representing an example using distinct terminal-runway combinations. The gate that is closest to the movement area is identified as reference point for each terminal in this experiment. An example is shown in Figure 29 when a flight is scheduled to leave from a gate in terminal B to takeoff on runway 27L.

Taxi routes are designed based on the shortest path from the gate to the runway. During the simulation, flight movements are simulated in a conflict-free environment so that when one aircraft is taxiing, there is no interference from any other aircraft. Average taxi speed of 15 knots is assumed for all aircraft in this simulation.

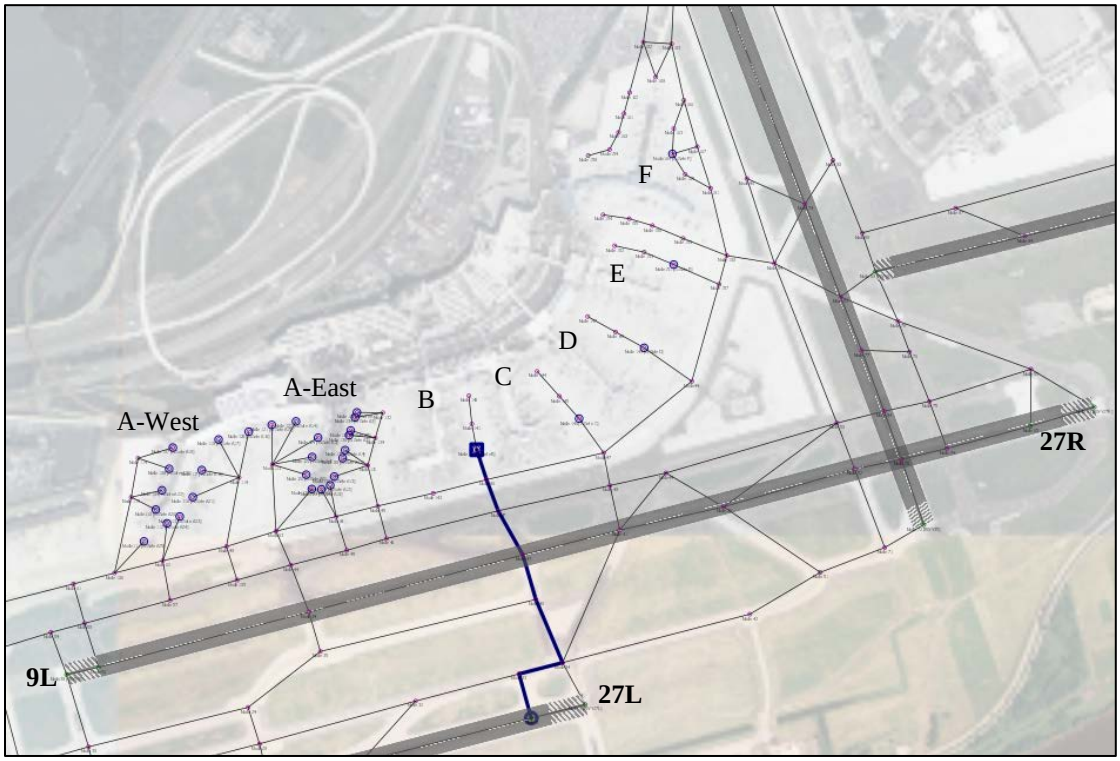


Figure 29 Layout of PHL in the simulation with sample taxi routes.

With this experimental design, unimpeded times are obtained from flights taxiing through each terminal-runway combination. The numerical results for each terminal-runway combination are shown in Table 3. The sample flight taxiing from terminal B to runway 27L indicates an unimpeded taxi-out time of 2.30 minutes for this taxi route.

Table 3 Unimpeded Taxi Times for Different Terminal-Runway Pairs from Simulation

Runway/*Terminal*	*A-West*	*A-East*	*B*	*C*	*D*	*E*	*F*
9L	1.23	2.73	3.80	4.65	5.65	6.28	7.05
9R	6.92	8.42	9.48	10.33	11.33	11.4	12.27
27L	6.52	3.40	2.30	2.50	3.40	4.03	4.90
27R	8.12	5.78	4.68	3.97	4.87	3.22	3.65

Note that the impact of uncertainties at the airport is not included during the simulation. It can be assumed that aircraft pushback from the gate and taxi into the movement area without any interference or delay. The procedure of aircraft pushback and taxiing through the apron area is more complex in reality and further studies are needed to provide a higher resolution of simulation in the ramp area. Future research also includes the impact of different aircraft types and other taxi route options for each terminal-runway pair.

4.3.2 PDARS Observation

With the applications of advance technologies in aviation, more sophisticated airport surface data become available, including Performance Data Analysis and Reporting System (PDARS) based on data recorded by Airport Surface Detection Equipment, Model X (ASDE-X). PDARS data provides historical surveillance data on surface operations at a few U.S. airports. After an initiated data request, surface trajectories for individual flights are presented with Graphical Airspace Design Environment (GRADE).

Figure 30 Snapshot of flight trajectories at PHL.

An example of multiple flight trajectories at PHL is shown in Figure 30. Two days of traffic at PHL, April 8, 2010, and May 20, 2010, are available for this study. It is noted that flights in historical data are operated in different taxi routes other than the shortest path assumed in the ADSIM+ simulation. Taking the same example from terminal B to runway 27 R, the shortest path is designed for flights to exit the ramp and then directly cross runway 27R to runway 27L. From the observation, most flights taxi around either end of runway 27R then approach to 27L to avoid active runway crossing. Only a few flights took the shortest taxi route. After observing two days of ASDE-X data, about 100 flights are identified without delay during taxi-out phase or hold for other traffic in the movement area. Flight trajectories and time stamps of these flights are retrieved from PDARS to derive their unimpeded taxi-out times. Table 4 summarizes the numerical results of unimpeded taxi-out times from historical data.

Table 4 Maximum, Minimum, and Average Unimpeded Taxi Times from PDARS Observation

Maximum Taxi Time	**Runway**		
Terminal	**27L**	**27R**	**35**
A-East	0:07:35		
A-West	0:04:43		
B	0:08:39	0:04:37	
C	0:07:46	0:03:33	
D	0:07:46	0:03:33	
E	0:06:18		
F	0:05:26		0:02:41

Minimum Taxi Time	**Runway**		
Terminal	**27L**	**27R**	**35**
A-East	0:02:48		
A-West	0:03:53		
B	0:01:53	0:02:55	
C	0:01:53	0:02:55	
D	0:02:07	0:03:33	
E	0:02:12		
F	0:03:04		0:01:40

Table 4 (Continued)

Average Taxi Time	**Runway**		
Terminal	**27L**	**27R**	**35**
A-East	0:05:11		
A-West	0:04:18		
B	0:05:11	0:03:46	
C	0:04:44	0:03:14	
D	0:05:02	0:03:33	
E	0:04:15		
F	0:04:18		0:02:10

Among 17 flight trajectories observed from terminal B to runway 27L, the unimpeded time is observed as high as 8 minutes 39 seconds and as low as 1 minute 53 seconds. One explanation for such a big gap is different choices of taxi routes. For example, flight AWE1633 (Figure 31, left) took 3 minutes 7 seconds to traverse a direct route from terminal B to runway 27L while flight RPA3124 (Figure 31, right) takes 6 minutes 57 seconds to taxi around left corner of runway 27R and then approach to runway 27L.

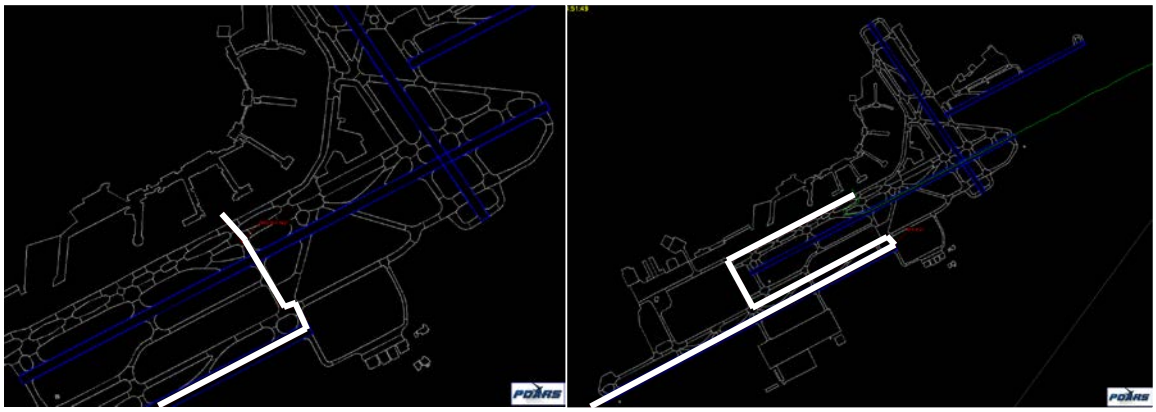


Figure 31 Different taxi routes of two flights with the same terminal-runway pair.

Hitherto, playing back ASDE-X data through PDARS is one of the most accurate ways to observe and understand historical flight operations. However, it is very time-consuming to conduct observations for a large number of flight operations. Hence, sophisticated statistical

methods are needed to deal with taxi performance efficiency measure for the airport and the entire network.

4.3.3 Proposed Statistical Model

In addition to heuristic simulation and observation methods, a sophisticated statistical model is proposed in this subsection to measure surface operations performance. First, the author identifies causal factors that contribute significantly to taxi delay by exploiting available data sources. A log-normal regression model is adapted to model taxi times followed with a comprehensive set of regression diagnosis and stability test. After that, numerical results are interpreted for a sample group of flights with a mathematical model equation. The aggregated results for all flights are compared among three airports at the end.

The procedure of model development is summarized as following.

- Data Collection

Flight data, airport information and other factors that contribute to taxi delay are collected at the early stage of this study. Annual flight data from ASPM (41) is retrieved for each flight, including OOOI data (Out of the gate, Off the runway, On the runway, Into the gate), published scheduled data, etc. Airport information is obtained through airport websites and other online sources. Other factors, such as historical weather information at airports, are obtained from the database of National Oceanic and Atmospheric Administration (44).

- Factor Identification

This step aims at identifying causal factors of excessive taxi time and delay. In this area of literature, the number of aircraft on the airport surface is considered to be one of the main contributing factors to excess taxi delay (45, 46). A comprehensive examination of other causal

factors has been summarized in our previous work (4, 8). In this study, the same set of factors is included in this model to explore the influence on taxi performance.

- Model Specification and Validation

With collected data and a set of contributing factors, the statistical form of the regression model is determined based on preliminary analysis and a complete procedure of regression diagnostic is followed to specify and validate the model. After that, the test of collinearity is performed to assure the stability of the model.

4.3.3.1 Contributing Factors

- Departure and Arrival Queue Length

Departure queue length for each departure is defined as the number of takeoffs that occur ahead of the reference aircraft during its taxi-out process, while arrival queue length for each arrival is represented by the number of aircraft landed and parked at gates ahead of the reference aircraft during its taxi-in process. The variable of queue length is calculated for each flight at each study airport. Only ASQP flights are included in the analysis to provide a consistent comparison with an existing benchmark method.

In addition to the variable of queue length itself, quadratic terms of departure and arrival queues are included in the model to test the significance of quadratic terms in a polynomial regression.

- Airport Traffic Demand

To account for the impact from current airport operations to the reference flight, two variables from ASPM dataset are included in the model to represent airport traffic demand at the moment, viz. EFFDEP which is the count of departures for efficiency computation and EFFARR

which is the count of arrivals for efficiency computation. Airport departure and arrival demand in 15 minute-intervals are represented by these two variables.

- Expected Departure Clearance Times (EDCT)

As one of tactic approaches to assess the imbalance of air traffic demand and airport capacity, EDCT is implemented by assigning runway release time due to Traffic Management Initiatives (TMIs) that require holding aircraft on the ground at the departure airport (41). In the ASPM system, EDCT is recorded when the flight was held on the ground past its planned wheels off departure time. In the model, the assignment of EDCT is indicated by a dummy variable for each flight, viz. the variable is set at 1 if the flight is assigned with an EDCT and 0 otherwise.

- Runway Configuration

For airports with multiple runways, the active runway is based on weather conditions, traffic demand and other factors to optimize the operational efficiency. In the ASPM dataset, such information is recorded by the runway configuration variable, which lists both departure and arrival runways in use. To account for the impact of different runway configuration on taxi times, departure and arrival runway configurations are considered separately and multiple dummy variables are introduced to represent the set of frequently-used runway configurations. For each flight, the dummy variable of the active runway configuration is set at 1 and dummy variables for other runway configurations are set at 0.

- Taxi Route

Different preferences on taxi routes could result in inconsistent taxi performance. Ideally, the distance of taxi route for each flight should be obtained to account for its impact on taxi time. However, such information is neither recorded in ASPM nor publicly accessible at airports. As an estimate, runway configuration in use is used to indicate different levels of taxi distance

between the terminal and runway end. The estimation is more accurate for some airports with a simple layout, such as LGA, which has only one runway for arrivals and the other for departures.

- Weather Factors

When weather conditions are less than perfect, the impact on airports and airspace is profound in terms of reduced visibility for pilots and controllers, degraded capability for traffic management and decreased airport capacity. Obtained from National Oceanic and Atmospheric Administration online resource(44), a set of weather factors are analyzed in the model, including wind speed (SPD), ceiling of cloud (CLG), visibility at the airport (VSB), temperature (TEMP), precipitation of last hour (PCP01) and average precipitation of previous 6 hours (PCP06).

4.3.3.2 Regression Function

To illustrate the technique for carrying out a regression analysis, an example of the regression model at CLT airport is presented in this and next two subsections. The diagram of CLT airport is shown in Figure 32.

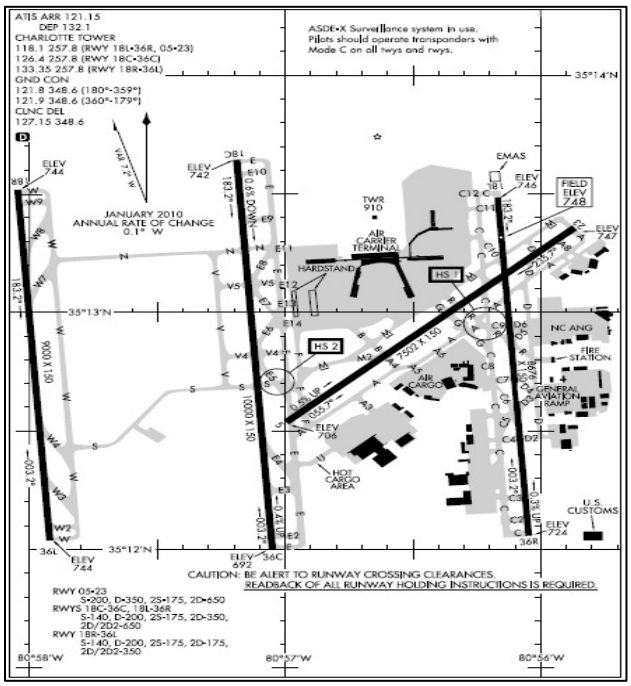


Figure 32 Diagram of CLT airport.

Obtained from ASPM database, annual flight data at CLT is first grouped by different seasons, air carriers and aircraft class as these factors are demonstrated to have a profound impact on taxi times (4, 8). After grouping, taxi models with the same structure but different parameters are developed for each group of flights. To illustrate this, a group of flights at CLT, "*USA, spring, Jet Small*", which represents all *small jet* aircraft operated by *US Airways* during *spring* is selected as an example. The group contains a total of 19204 flights. Figure 33 depicts the distribution of actual taxi-out time (ACTTO) for all flights within the group. A log-normal distribution is observed from the continuous frequency distribution of actual taxi-out times. Driven by the observation, a log-normal regression method is determined for that modeling in which the dependent variable of the regression function is represented by $\log_{10} ACTTO$.

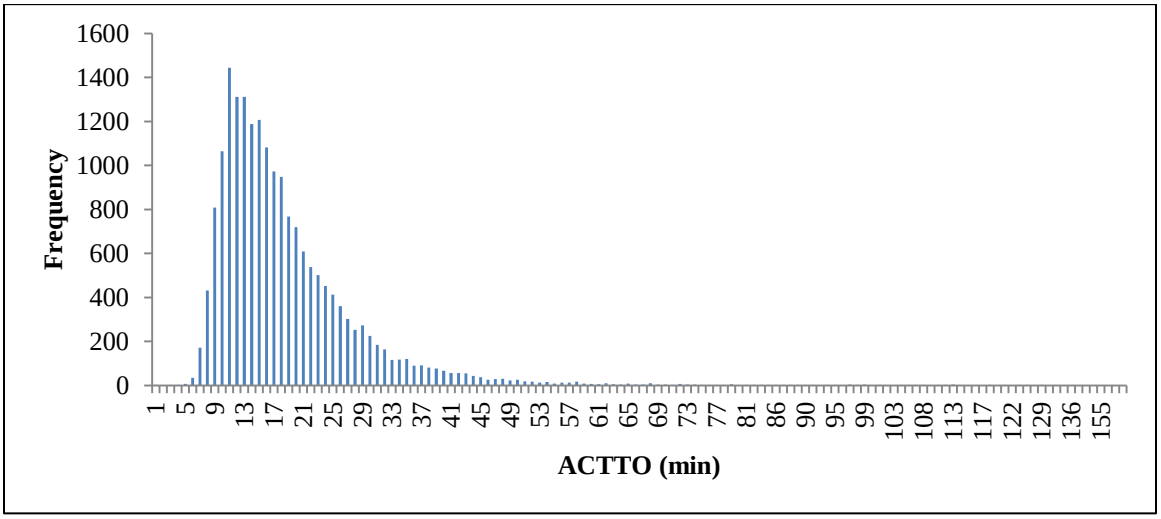


Figure 33 Frequency distribution of actual taxi-out time for selected group of flights.

4.3.3.3 Regression Diagnostic

The objective of regression diagnosis is to assure that the data meet all regression assumptions prior to implementation so that regression results are valid and accurate. In this part of the study, Y is used to represent the dependent variable $\log_{10} ACTTO$ and X is used to indicate different decision variables that were introduced in the previous subsection. Before the

implementation of regression technique, the following five Gauss-Markov assumptions need to be satisfied to assure that Ordinary Least Square (OLS) is the best linear unbiased estimate (BLUE) (47):

- Linearity between Y and X
- Random sample
- $\mathrm{E}(\epsilon|\mathrm{X}) = 0$
- No perfect collinearity among X's
- $\mathrm{Var}(\epsilon|\mathrm{X}) = \sigma^2$ (homoscedasticity)

The linearity between Y and X is examined by simply observing the scatter chart between $\log_{10} ACTTO$ and each decision variable. As an example, Figure 34 shows the plot of departure queue length versus $\log_{10} ACTTO$. A linear trend line is also presented in the figure and a high level of goodness of fit is observed with $R^2 = 0.741$.

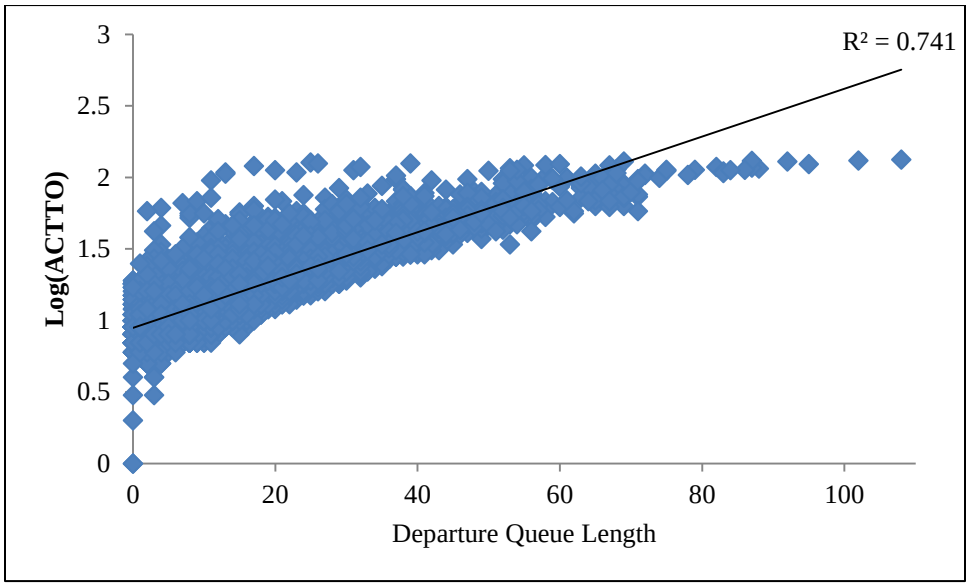


Figure 34 Scatter plot of departure queue length versus logACTTO.

It is also observed from Figure 34 that the scatter chatter presents a concave shape between departure queue length and $\log_{10} ACTTO$. It indicates that taxi time will not be linearly

elongated with the increase of departure queue length. To account for this impact, quadratic terms of queue length are introduced in the regression model.

In this study, entire flight data for the whole year is used for analysis and no pre-processing is conducted. Therefore, the assumption of random sample and $E(\epsilon|X) = 0$ is satisfied for the regression.

To test for perfect collinearity, correlations between each two decision variables are calculated as in Table 5. *Qo* and *Qi* represent departure and arrival queue length, *EFFDEP* and *EFFARR* indicate departure and arrival demand at the airport. *SPD, CLG, VSB, TEMP, PCP01* and *PCP06* are different weather factors including wind speed, ceiling of cloud, visibility, temperature, precipitation of last hour and average precipitation of previous 6 hours. Dummy variables of EDCT and runway configuration are not listed in the table below where the correlation values are all close to 0. Based on the table, it can be assumed that no perfect collinearity among decision variables exists as none of these correlation values is or even close to 1.

Table 5 Correlations among Decision Variables

	Qo	Qi	EFFDEP	EFFARR	SPD	CLG	VSB	TEMP	PCP01	PCP06
Qo										
Qi	0.04									
EFFDEP	0.16	0.00								
EFFARR	-0.03	0.24	-0.06							
SPD	-0.04	0.02	-0.01	0.15						
CLG	-0.01	-0.03	0.11	-0.03	-0.28					
VSB	-0.01	-0.05	0.12	0.01	0.11	0.37				
TEMP	-0.04	0.02	0.10	0.20	0.35	-0.01	0.14			
PCP01	-0.01	0.03	-0.04	0.01	0.04	-0.13	-0.30	-0.02		
PCP06	0.01	0.01	-0.03	0.00	0.00	-0.11	-0.13	0.02	0.06	

To test for homoscedasticity, one popular method is to assure that heteroscedasticity is not represented in the model. Thereby, the linear regression of Y on all X variables is performed first and the distribution of predicted Y values versus regression residuals is examined for

heteroscedasticity, as shown in Figure 35. It can be noted from the scatter plot that regression residuals are quite evenly and symmetrically distributed over the horizontal axis, which is predicted Y. Hence, it is concluded that heteroscedasticity does not apply to this model and the assumption of $\mathrm{Var}(\epsilon|\mathrm{X}) = \sigma^2$ (homoscedasticity) is satisfied.

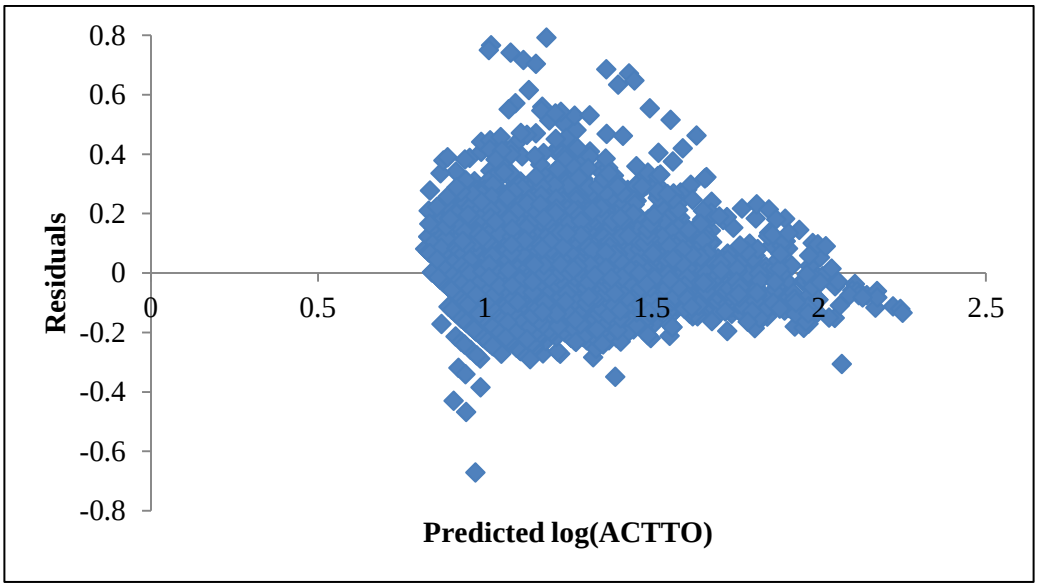


Figure 35 Scatter plot of residuals versus predicted logACTTO.

So far, all of Gauss-Markov assumptions are tested and the outputs together imply that OLS can be applied in our model and that it provides the best linear unbiased estimate. In reality, there are issues that can arise during the analysis that, while strictly speaking, are not assumptions of regression, are nonetheless, of great concern to regression analysts. Thereby, the test of collinearity is performed by measuring Variance Inflation Factor (VIF) and Condition Index (CI) to assure the stability of the model. A multicollinearity problem is indicated if a tolerance is less than 0.10 and/or a VIF is higher than 10 and/or a CI is above 30 (47). With the test results shown in Table 6, it can be suggested that all indexes are within the reasonable range and no multicollinearity problem is detected in the model.

Table 6 Test Results for Collinearity

Variable[1]	DF	Tolerance	VIF	CI
Intercept	1	.	0	
Qo	1	0.16216	6.16656	1
Qi	1	0.16604	6.02263	1.18105
QoQi	1	0.22528	4.43885	1.2932
Qo^2	1	0.16408	6.09477	1.34509
Qi^2	1	0.31981	3.12689	1.64664
EDCT	1	0.91239	1.09603	1.69685
SPD	1	0.76244	1.31157	1.72487
CLG	1	0.75602	1.32272	1.80794
VSB	1	0.7349	1.36072	1.88587
TEMP	1	0.82851	1.20699	2.0829
PCP01	1	0.90262	1.10789	2.4966
PCP06	1	0.97705	1.02349	3.29985
EFFDEP	1	0.9153	1.09254	5.09241
EFFARR	1	0.87007	1.14933	5.6924

4.3.3.4 Numerical Results

4.3.3.4.1 Example Model Equation

Hitherto, all five Gauss-Markov assumptions are demonstrated to be satisfied and the test of multicollinearity is performed to ensure the stability of the model. The output of regression model for the sample group of flights is shown as Table 7.

Table 7 Summary of Regression Output for the Sample Group

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr>|t|
Intercept	Intercept	1	1.05284	0.01044	100.85	<.0001
Qi	Arrival Q	1	0.00343	0.00061	5.59	<.0001
Qo	Departure Q	1	0.02044	0.00015	134.77	<.0001
Qo2	Quadratic of Q	1	-8E-05	2.9E-06	-27.76	<.0001
Qi2	Quadratic of Q	1	-9E-05	3E-05	-3.07	0.0021

[1] *Qo* and *Qi* represent departure and arrival queue length, *EFFDEP* and *EFFARR* stands for departure and arrival demand. *SPD*, *CLG*, *VSB*, *TEMP*, *PCP01* and *PCP06* are different weather factors indicating wind speed, ceiling of cloud, visibility, temperature, precipitation of last hour and average precipitation of previous 6 hours. *EDCT* is the EDCT dummy variable.

Table 7 (Continued)

QoQi	Quadratic of Q	1	3.8E-06	2.5E-05	0.15	0.8781
d6	Runway Dummy	1	-0.075	0.00945	-7.94	<.0001
d7	Runway Dummy	1	0.24265	0.08952	2.71	0.0067
d9	Runway Dummy	1	-0.0019	0.01049	-0.18	0.8557
d11	Runway Dummy	1	0.09699	0.08952	1.08	0.2786
d12	Runway Dummy	1	-0.0441	0.00947	-4.65	<.0001
edct_d	EDCT Dummy	1	0.06002	0.00295	20.33	<.0001
SPD	Wind Speed	1	0.00099	0.00017	5.99	<.0001
CLG	Cloud Ceiling	1	-2E-05	2.4E-06	-9.57	<.0001
VSB	Visibility	1	-0.0036	0.00036	-9.92	<.0001
TEMP	Temperature	1	3.1E-05	6.3E-05	0.49	0.6216
PCP01	Precipitation	1	0.15975	0.0234	6.83	<.0001
PCP06	Precipitation	1	0.09078	0.03125	2.9	0.0037
EFFDEP	Departure Demand	1	-0.0017	5.1E-05	-33.69	<.0001
EFFARR	Arrival Demand	1	0.00086	4.8E-05	17.81	<.0001

The positive coefficient of departure queue length (*Qo*) and arrival queue length (*Qi*) indicates that the more flights taxiing on the airport surface, the longer taxi delays are expected for the reference flight while all other conditions stay the same until a turning point is reached with the quadratic terms. The negative coefficient of quadratic terms (Qo^2,Qi^2) confirms the concave shape in Figure 34. Dummy variable *R6, R7, R9, R11* and *R12* indicates the impact of different runway configurations on taxi times. A positive coefficient of EDCT dummy variable indicates that flights assigned with EDCT are expected to experience longer delays during taxiing. The magnitude of this coefficient also suggests a larger impact of EDCT than that of runway configuration. *SPD, CLG, VSB, TEMP, PCP01* and *PCP06* are different weather factors indicating wind speed, ceiling of cloud, visibility, temperature, precipitation of last hour and average precipitation of previous 6 hours. *EFFDEP* and *EFFARR* represent an estimate on airport departure and arrival demand during the 15-minute time window.

Overall, the size of all data points evolved in this regression model is 19197, with 390 missing points excluded. A total of 19 independent variables are analyzed in this model. The p value of F test is less than 0.001 which indicates explanatory variables altogether are statistically significant.

4.3.3.4.2 Comparison Results

To provide comparable results, these proposed models are implemented for three airports, LGA, CLT and PHL, respectively. The comparison results are illustrated from two aspects: goodness of fit and average taxi time. The APO method is set as the reference to demonstrate the performance of a proposed statistical model. In addition, variants of this statistical model with different combinations of decision variables are derived as the following:

0. Basic = constant + queue lengths
1. Basic + EDCT dummy (E)
2. Basic + Runway configuration dummy (R)
3. Basic + Queue length quadratic terms (Q)
4. Basic + E + Q
5. Basic + R + Q
6. Basic + E + R + Q

The basic model contains only departure and arrival queue length as decision variables. Six variants of models are derived by adding a mixed combination of EDCT dummy variables, runway configuration dummy variables, and quadratic terms of queue lengths.

- R-Square Value

Based on annual flight data in 2007 from ASPM, flights at each airport are first grouped by carrier and season. There are 63 groups obtained for LGA, 56 for CLT and 62 for PHL. Next,

the regressions analysis of proposed models is conducted for each group at each airport. Descriptive statistics across all groups are collected together and compared with results from the APO method. As shown in Table 8, the goodness of fit of APO method is quite poor with a much lower value of R^2 than any variant of proposed models. For example, the average R-squares of proposed models range from 0.72 to 0.74 among 63 groups at LGA while that of the APO method is only 0.39. The table also shows the regression model with a complete set of decision variables involved, where (*Basic+R+E+Q*) yields the best goodness of fit with the highest R-squares among all other variants for all three airports.

Table 8 Comparison of R-Squares of Different Models at CLT, PHL and LGA

Airport	**R^2**	*APO*	*Basic*	*Basic +E*	*Basic +R*	*Basic +Q*	*Basic +E+Q*	*Basic +R+Q*	*Basic+ R+E+Q*
LGA (63 Groups)	Mean	0.39	0.72	0.72	0.73	0.73	0.73	0.73	0.74
	SD	0.07	0.06	0.06	0.06	0.05	0.05	0.05	0.05
CLT (56 Groups)	Mean	0.13	0.42	0.43	0.48	0.43	0.43	0.48	0.49
	SD	0.06	0.12	0.12	0.10	0.12	0.12	0.10	0.10
PHL (62 Groups)	Mean	0.30	0.59	0.59	0.61	0.60	0.60	0.62	0.62
	SD	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.10

E = EDCT dummy, R = runway configuration dummy, Q = queue length quadratic terms

- Taxi Time

A comparison of calculated unimpeded taxi times by APO method and the proposed model is presented in Figure 36. For three airports, it can be observed that this proposed model leads to a lower value of unimpeded taxi time compared to the APO method. With a high level of goodness of fit, the proposed model provides a more accurate measurement for taxi performance, quantifies the impact of various factors to taxi inefficiency, and supports decision-makers with reliable measurements to improve the operational performance.

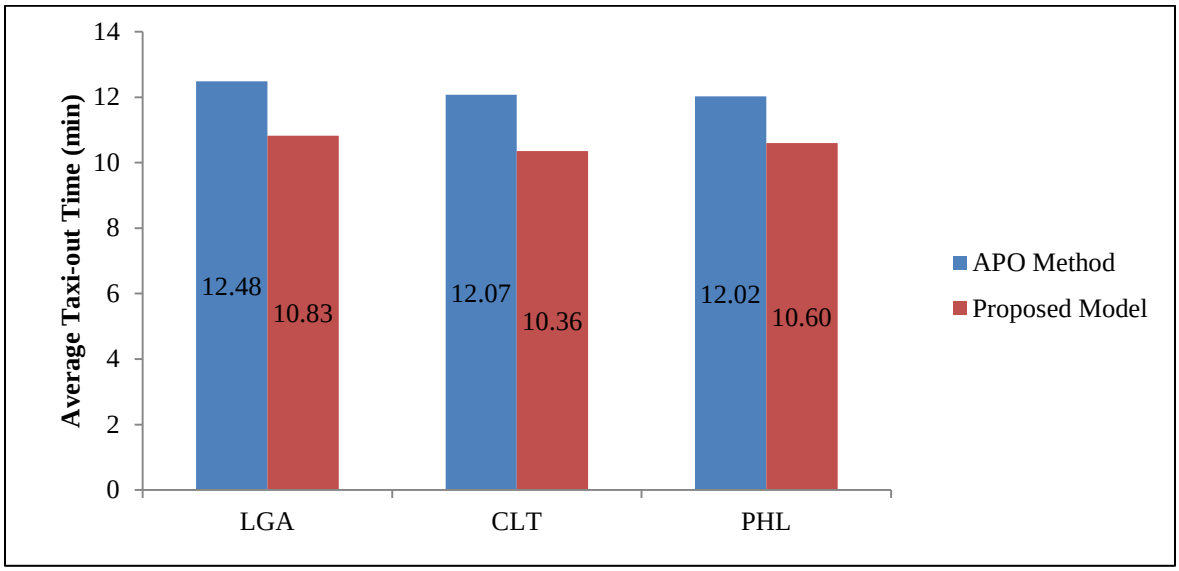


Figure 36 Average taxi-out times by different methods at CLT, LGA and PHL.

4.4 Summary

Unimpeded taxi time is the reference time used for estimating taxi delay, a widely accepted performance indicator of airport surface movement. As noted, the varying methods applied by the FAA and EUROCONTROL are used to measure taxi efficiency. Hence, this study first compares two methods of determining unimpeded taxi-out times for the same airports. The comparison shows that the APO and PRU methods lead to different unimpeded taxi-out times, consequently different taxi-out levels of efficiency. It is suggested that a clear definition of taxi time should be defined and a consistent method of determining unimpeded taxi times should be developed for the evaluation of airport operational performance. A log-normal regression model is adapted to model taxi times followed by a comprehensive set of regression diagnosis and stability test.

On the other hand, new heuristic methods are explored by the simulation and observation of historical operational data in a geographic platform. However, due to various limitations, such heuristic methods are not yet generally applicable at airports. Hence, a sophisticated statistical

model is proposed in this chapter to measure surface operations performance. Compared to existing methods, the proposed model provides a more accurate measurement for taxi performance with a high level of goodness of fit. It quantifies the impact of various factors to taxi inefficiency and supports decision-makers with reliable measurement to improve the operational performance.

CHAPTER 5: REAL-TIME INTEGRATED AIRPORT SURFACE OPERATIONS MANAGEMENT

To fill the gap in existing literature and embrace the trajectory-based control of NextGen, a Real-Time Integrated Airport Surface Operations Management (RTI-ASOM) is proposed in this study. Integrated management means that for all arrivals and departures, holistic control strategies are developed to manage flight operations between gates and runways with optimized schedule and sequence. Real-time means that the proposed strategy provides real-time decision support to controllers and pilots by using real-time inputs from the cockpit and control tower. The objective of RTI-ASOM is to increase the efficiency of surface operations by (1) reducing taxi delay and (2) improving runway throughput. It is modeled with Mixed Integer Linear Programming (MIP) formulation and a solution algorithm is developed to obtain optimal solutions efficiently. The outcomes of RTI-ASOM include optimal passage times of aircraft to visit each node along their respective taxi routes in a digitalized airport surface network. Such information can be shared via a data link between the control tower and the Flight Management System in the cockpit (24) so as to create an automation platform that enables the control of complicated surface operations in a safe and orderly manner.

The author first describes the problem statement of RTI-ASOM, followed by a mathematical formulation and solution algorithm. The demonstration of RTI-ASOM is presented based on the layout and data from LGA. The numerical results are compared among historical scenario, constructed simulation scenario and RTI-ASOM.

5.1 Problem Definition

Given a set of departures and arrivals, the RTI-ASOM proposed in this study optimizes aircraft surface operations by balancing two objectives: 1) maximal runway usage and 2) minimal total taxi times, subject to operational constraints of recursive planning requirements, ready time limits, conflict-free constraints, precedence constraints, minimum separation requirements, gate availability constraints, engine warm-up time requirements and speed limits. Optimized trajectories for each aircraft between the gate and the runway are the main output of RTI-ASOM.

5.1.1 Recursive Planning Horizon

For real-time planning purposes, an entire day is split into small time windows, such as every 5 minutes. The length of planning horizon could be customized to vary from airport to airport and also adjusted to fit current operational conditions on the airport surface. Any aircraft that is ready to move will be either cleared within current planning horizon or postponed to the following planning periods.

Aircraft are not only constrained to avoid conflict with others in the same window, but also required to be separated from other aircraft scheduled in previous time windows that are still operating on the surface. For this purpose, the status of each node in the airport surface network is updated with the latest passage time from the previous planning period. Such information is then converted into a new set of constraints for minimum separations during the consecutive planning period.

5.1.2 Ready Time Limit

In RTI-ASOM, the earliest ready time of an aircraft at departure airport is Target Off-Block Time (TOBT), (i.e., the time that aircraft operator estimates when an aircraft is ready [all

doors closed, boarding bridge removed, a pushback vehicle present] to pushback immediately upon reception of clearance from the tower). The ready time for landing is Estimated Time Of Arrival (ETA), i.e. the earliest time estimated at the beginning of the planning horizon when an aircraft would reach the runway, if there were no interference from other aircraft (48). Ready times of arrivals and departures are the inputs of the model and are presented in the constraints so that no aircraft could pushback or land before its ready time.

In order to enable operational strategy of gate holding, constraints that are set for actual pushback times are not included in the model. The idea of the gate holding strategy is to hold aircraft at their gates for a short time period with less fuel consumption, as opposed to allowing them to pushback from their gates early and queuing in the taxiways/runways. By assigning proper gate holding times to aircraft, the length of departure queues can be decreased by releasing less aircraft onto the congested surface. Gate holding, instead of queuing at taxiway or runway end with engines on, expends much less fuel consumption and mitigates the burden to the environment.

5.1.3 Conflict-Free Constraint

For safety and efficiency purposes, the optimized flight trajectories are guaranteed to be conflict-free. Three types of conflicts are identified and considered in RTI-ASOM: crossing conflict, trailing conflict, and head-on conflict. The decision variable t_{iu} represents the time for aircraft *i* to pass node *u* in the network. By tracking the time and position of each aircraft at taxiway intersections and on taxiway segments, the model ensures that no aircraft will cross, trail, or head-on towards another at the same node or segment in the network.

5.1.4 Precedence Constraint

In this study, given a short planning horizon, aircraft reordering at the runway end is not enabled. Instead, a precedence constraint is enforced in the model to govern the right-of-way of aircraft, i.e., the runway sequences are followed in a way such that an earlier aircraft is prioritized when passing through the same node or segment in the network.

5.1.5 Minimum Separation Requirements

While waiting for clearance to access on a runway, aircraft are required to maintain certain separations to prevent the danger of wake turbulence. Minimum time separations between aircraft (Table 9) differ for various leading and trailing aircraft types (13) which are based on the maximum takeoff weight (MTOW).

Table 9 Minimum Time Separation (in sec) between Two Successive Arrival/Departure Aircraft on the Same Runway

Arrivals/Departures	**Trailing Aircraft**		
Leading Aircraft	*Heavy*	*Medium*	*Light*
Heavy	96/90	157/120	196/120
Medium	60/60	69/60	131/60
Light	60/45	69/45	82/45

Note: ICAO wake turbulence category (WTC) (49) :

- H (Heavy) aircraft types = 136 000 kg (300 000 lb) or more.
- M (Medium) aircraft types = less than 136 000 kg (300 000 lb) and more than 7 000 kg (15 500 lb).
- L (Light) aircraft types = 7 000 kg (15 500 lb) or less.

Additionally, when an airport has two active runways intersecting with each other, a minimum separation time of 55 seconds is required between two runway operations.

Also in the taxiway area, a separation distance S_T is required to avoid conflicts and maintain safety. A separation distance S_T=200 meters (36) complies with all safety regulations on the taxiway.

5.1.6 Gate Availability

In this problem, gate assignments of each aircraft are given as model input. To absorb the stochastic flight delays that often occur during real-time operations, a buffer time is introduced between two continuous flights assigned to the same gate (50). In this case, a commonly used buffer time t_{buffer}=15 minutes is built in the constraints for each gate after one aircraft leaves and before another aircraft arrives. The implementation of buffer time constraints avoids gate conflicts and restricts the length of gate holding for departures.

5.1.7 Engine Warm-up Time

For departures, aircraft engines must be fully warmed up prior to takeoff. The allotted time for warm-up ranges from 2 to 5 minutes depending on the engine type. However, a minimum warm-up time of $t_{warm-up}$=5 minutes before departure complies with the requirement of most of the aircraft operator's manuals. Hence, 5-minute constraints are included within the model to ensure the duration of the taxi-out phase for each departure. Aircraft with too short of a taxi time to warm-up the engine will be advised to taxi at a lower speed.

5.1.8 Speed Limit

To maintain safety operations, aircraft movements on the airport surface are constrained by a maximum taxiing speed. The optimized 4 flight trajectories should be compliant with the possible taxi speed ranges of aircraft. For this purpose, constraints are derived to set the minimum time needed to traverse any segment and the maximum taxi speed for all aircraft. As a maximum taxi time for an edge is not strictly necessary (36), the minimum taxi speed is not limited in the model.

Hitherto, no official guideline is available for the aircraft speed limit in taxiways and various assumptions were made in the literature. For example, a minimum speed of 5 knot is

assumed in (36) during any taxi process on the surface and a maximum taxi speed of 15.5 knots is assumed in (22, 37). In some areas of literature, maximum speed limit varies by areas on the surface (39) from 8 knots to 40 knots, or by multiple levels (35) between from 15.5 knots to 31.1 knots. Since there is little consensus on the speed variable, analysis on surveillance data is conducted to derive the most suitable speed limit for this study.

5.2 Mathematical Formulation

In general, the network for airport surface operations can be represented by a directed graph G=(V, E), with V being the set of nodes representing intersections on taxiway/runways and E being the set of directed links representing taxiway segments between two intersections. The nomenclature of the index sets and inputs are listed as in Table 10.

Table 10 Nomenclature of Index Sets and Inputs

A	Set of arrivals
D	Set of departures
N	Set of all nodes
RN	Set of runway nodes, RN$\in N$
TN	Set of taxiway nodes, TN$\in N$
GN	Set of gate nodes, GN$\in N$, RN $\cup$ TN $\cup$ GN $= N$
T_i	Earliest ready time of aircraft *i*
S_T	Minimum separation distance between any two aircraft on taxiway
S_R	Minimum separation matrix when two aircraft use the same runway
L_{uv}	Link distance between adjacent node *u* & *v*
T_u	Last passage time of node *u*
$\mathrm{t}_{\mathrm{buffer}}$	Buffer time between two aircraft using the same gate
$\mathrm{t}_{\mathrm{warm-up}}$	Minimum engine warm-up time before take-off
SPD_{max}	Maximum taxi speed limit

The input variables T_i are referred to as the TOBT for departures from the cockpit and the ETA for arrivals from the control tower. S_T is set as 200 m as aforementioned and $S_R$is shown as in Table 9. Variables T_u are dynamic parameters to keep records of passage times when each node u ($u \in$N) is visited by an aircraft. The set of T_u is updated at the end of each planning

window and is taken as a subset of inputs in the separation constraints for the next planning window.

The objective of this model is to minimize the total taxi time and maximize runway throughput. Let t_{iu_1} denotes the time of aircraft i to visit its first node u_1 (gate for departures and runway for arrivals) and t_{iu_k} the time of aircraft i to visit its last node u_k on the surface (runway end for departures and gate for arrivals). The total taxi time for all aircraft in current planning horizon is $\sum_i(t_{iu_k} - t_{iu_1})$. Given the set of aircraft in a planning horizon, maximizing runway throughput is equivalent to minimizing runway access time of the last aircraft. Let $t_{i'u_R}$ denotes the time of last aircraft i' in the planning horizon to access its runway node u_R. u_R is the first node in its route u_1 for arrivals and the last node u_k for departures. Thereby, multiple objectives are combined into one minimization objective function. The weighted sum method is used for this multi-objective optimization by introducing a set of weight factors w_1, w_2. It provides multiple solution points by varying the weights consistently (51). For instance, if extensive runway queues with relatively moderate surface traffic are observed at an airport, the weight of the last runway access time, i.e., w_1, could be set higher to give primacy to runway utilization.

In addition to decision variables t_{iu}, a set of binary variables z_{ij} is introduced to represent the sequence of any two aircraft when visiting the same node/link along their taxi routes. Aircraft i, j does not need to be consecutive. Variable $z_{ij} = 1$ if aircraft i visits any common node u before aircraft j and 0 otherwise:

$$z_{ij} = \begin{cases} 1, \text{if } t_{iu} < t_{ju} \\ 0, \text{o/w} \end{cases}$$

The mathematical formulation of the proposed optimization problem is displayed by the following:

$$\text{Min } \ w_1 \times t_{i'u_R} + w_2 \times \sum_i (t_{iu_k} - t_{iu_1})$$

s.t.

$$\mathbf{t_{iu} \geq T_i, \forall i} \tag{1}$$

$$z_{ij} + z_{ji} = 1, \ \forall i, j, \ i \neq j \tag{2}$$

$$t_{iv} - t_{iu} \geq \frac{L_{uv}}{spd_i}, \forall i, \forall (u, v) \epsilon E_i \tag{3}$$

$$z_{ij} \times \left(t_{ju} - t_{iu} - \frac{S_T}{\min(spd_i, spd_j)} \right) \geq 0, \forall u \in V_i \cap V_j, u \in TN, i \neq j \tag{4}$$

$$z_{ij} \times \left(t_{ju} - t_{iu} - S_R \right) \geq 0, \ \forall u \in V_i \cap V_j, u \in RN, \ i \neq j \tag{5}$$

$$t_{iu} - T_u \geq S_R, \forall u \in RN \tag{6}$$

$$t_{iu} - T_u \geq S_T / spd_i, \forall u \in TN \tag{7}$$

$$z_{ji} \times \left(t_{ju} - t_{iu} - t_{buffer} \right) \geq 0, \forall i \in D, j \in A, u \in GN \tag{8}$$

$$t_{iu_k} - t_{iu_1} \geq t_{warm-up}, \forall i \in D, u \in N \tag{9}$$

$$spd_i \leq SPD_{max}, \forall i \tag{10}$$

$$t_{iu} \geq 0, \forall i \in A \cup D, u \in N \tag{11}$$

$$z_{ij} \in \{0,1\}, \forall i, j, i \neq j \tag{12}$$

Constraint (1) assures that any aircraft that is ready to pushback from gate or land on the runway must not be proceeded before its earliest ready time T_i. Constraint (2) requires that once the sequence between any two aircraft i and j is fixed, no sequence re-ordering is allowed anywhere on the surface. Constraint (3) assures that the minimum travel time for any aircraft to traverse any edge along its route must be met, represented by the edge distance divided by its speed variable. Constraint (4) states the minimum separation requirement on taxiways when the two aircraft i and j share a common node u along their respective taxi routes V_i and V_j. If aircraft

i reaches the node u before aircraft j, the time interval between i and j arriving at the node u must be longer than minimum separation distance S_T divided by the smaller taxi speed between i and j. Similarly, constraint (5) states the minimum time separation requirement on runways S_R when two aircraft are assigned to utilize the same runway. For each aircraft i in the current planning window reaching a node u, either taxiway intersection or runway end, constraints (6) and (7) state that the aircraft i needs to maintain a minimum separation from the last aircraft in the previous planning window leaving node u. Constraint (8) assures that a minimum buffer time t_{buffer} is met after an aircraft leaves the gate u ($u \in GN$) and before another arrives at the same gate. For each departure, constraint (9) requires aircraft engines must be fully warmed up for a minimum duration $t_{warm-up}$ before takeoff. Constraint (10) states that speed variables of any aircraft are restricted by the maximum taxi speed SPD_{max}.

5.3 Solution Algorithm

The large-scale MIP optimization problem in RTI-ASOM is NP-hard. With the number of m flights in the planning window and a total of n nodes on the airport surface, the size of decision variables t_{iu} and z_{ij} add up to $m*n$ and n^2, respectively. Some hard constraints in the MIP formulation, such as constraint 4, 5, and 8, contain up to $n^3 * m^2$equations. As the problem size of MIP is exponential in *m* and *n*, commercial solvers are not sufficient to obtain the solutions within a reasonable execution time period for a complex surface network.

To provide real-time solutions to surface operations management, an effective solution algorithm is proposed in this subsection, using DP to reduce the model complexity and CPLEX to solve decomposed problems. In addition, a scripted user interface is designed to facilitate the implementation of RTI-ASOM in real-world practice.

5.3.1 Linearization

Some constraints previously listed are in nonlinear format. As a first step, constraints (4, 5, 8) are linearized by introducing a large scalar M. The linearized formulation is shown as following:

$$\text{Min } \ w_1 \times t_{i'u_R} + w_2 \times \sum_i (t_{iu_k} - t_{iu_1})$$

s.t.

$$\mathbf{t_{iu} \geq T_i, \forall i} \tag{1}$$

$$z_{ij} + z_{ji} = 1, \ \forall i, j, \ i \neq j \tag{2}$$

$$t_{iv} - t_{iu} \geq \frac{L_{uv}}{spd_i}, \forall i, \forall (u, v) \epsilon E_i \tag{3}$$

$$t_{ju} - t_{iu} - \frac{S_T}{spd_i} + M \times (1 - z_{ij}) \geq 0, \ \forall i, j, i \neq j, \forall u \in V_i \cap V_j, u \in TN \tag{4a}$$

$$t_{ju} - t_{iu} - \frac{S_T}{spd_i} - M \times z_{ij} \leq 0, \forall i, j, i \neq j, \forall u \in V_i \cap V_j, u \in TN \tag{4b}$$

$$t_{ju} - t_{iu} - \frac{S_T}{spd_j} + M \times (1 - z_{ij}) \geq 0, \ \forall i, j, i \neq j, \forall u \in V_i \cap V_j, u \in TN \tag{4c}$$

$$t_{ju} - t_{iu} - \frac{S_T}{spd_j} - M \times z_{ij} \leq 0, \forall i, j, i \neq j, \forall u \in V_i \cap V_j, u \in TN \tag{4d}$$

$$t_{ju} - t_{iu} + M \times (1 - z_{ij}) \geq S_R, \ \forall u \in V_i \cap V_j, u \in RN, \ i \neq j \tag{5a}$$

$$t_{ju} - t_{iu} - M \times z_{ij} \leq S_R, \forall u \in V_i \cap V_j, u \in RN, \ i \neq j \tag{5b}$$

$$t_{iu} - T_u \geq S_R, \forall u \in RN \tag{6}$$

$$t_{iu} - T_u \geq S_T / spd_i, \forall u \in TN \tag{7}$$

$$t_{ju} - t_{iu} + M \times (1 - z_{ji}) \geq t_{buffer}, \forall i \in D, j \in A, u \in GN \tag{8a}$$

$$t_{ju} - t_{iu} - M \times z_{ji} \leq t_{buffer}, \forall i \in D, j \in A, u \in GN \tag{8b}$$

$$t_{iu_k} - t_{iu_1} \geq t_{warm-up}, \forall i \in D, u \in N \quad (9)$$

$$spd_i \leq SPD_{max}, \forall i \quad (10)$$

$$t_{iu} \geq 0, \forall i \in A \cup D, u \in N \quad (11)$$

$$z_{ij} \in \{0,1\}, \forall i, j, i \neq j \quad (12)$$

5.3.2 Decomposition Algorithm

To solve the above MIP problem, a decomposition algorithm is introduced to obtain the optimal solution efficiently. The main idea behind this decomposition algorithm is to narrow down the feasible region of sequence binary variable z_{ij} so that the complexity of the optimization model is reduced to an executable level for commercial solvers. In the first stage, dynamic programming is applied to extract a subset of flight sequences that lead to low values of last runway access times. Each flight sequence is then converted into a matrix of sequence variable z_{ij} for the use in each MIP problem. Thereby, the complexity level of the model is reduced significantly with a smaller feasible region of z_{ij}. In the second stage, a set of MIP optimization problems are parallelly solved with commercial solver CPLEX and compared to obtain the optimal solution. The final outcome includes an optimized schedule for each flight visiting any node along its taxi route (represented by t_{iu}), and the optimized runway sequence for all active aircraft (represented by z_{ij}).

5.3.2.1 Dynamic Programming for Runway Sequencing

The idea of applying DP is to extract a subset of highly-likely optimal runway sequences to reduce the feasible region of the model and thus reduce the model complexity.

Given the number of flights to be scheduled in each planning horizon, their preferred taxi routes, TOBT for departures and ETA for arrivals, dynamic programming recursion is conducted

to search through all possible options of runway sequence, and those with low value of last runway access time (high runway throughput) are exported for use in the next stage. T_j is the same input variable that indicates the earliest ready time of aircraft j, i.e. TOBT for departures and ETA for arrivals. If there is no predecessor aircraft before j, its earliest runway access time is $T_j + \Delta t$, where Δt is unimpeded taxi-out time for departures and 0 for arrivals. Otherwise, let $T'_{s,j}$ be the estimated runway access of aircraft j at stage s, which is derived from runway access time of predecessor aircraft i at previous stage $T_{s-1,i}$ and separation requirement sep_{ij} (from matrix S_R) between i and j. Then $T_{s,j}$, the earliest runway access time for aircraft j at stage s is the maximal of $T'_{s,j}$ and $T_j + \Delta t$. The process of each sequence search is shown in Figure 37.

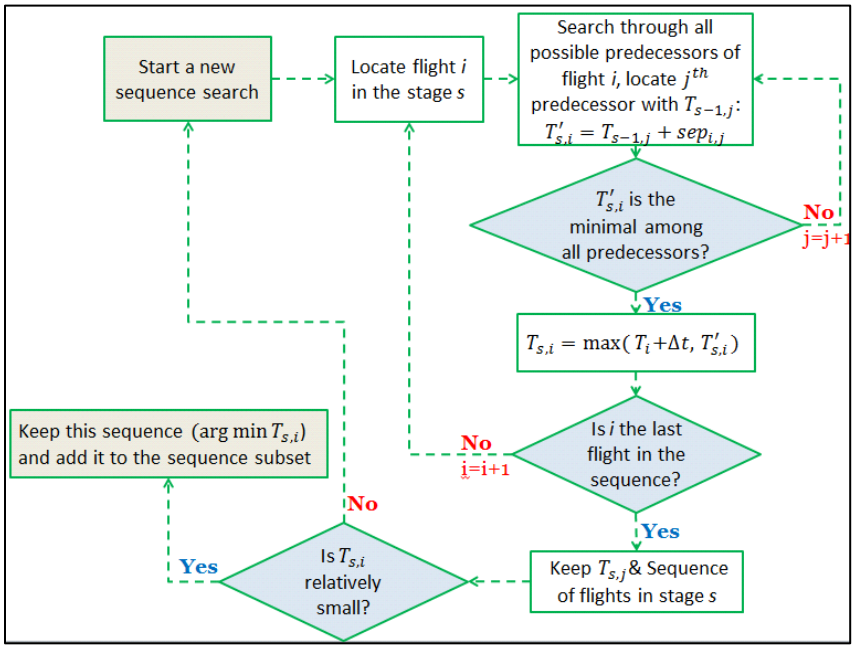


Figure 37 Flow chart of using DP in sequence search.

Each flight sequence with high estimated runway throughput, represented by a small value of the last runway access time, is converted into a matrix of a binary variable z_{ij}. For any two aircraft, the same sequence is kept along the planning horizon, and no overtaking or sequence reordering is allowed once the sequence is given. Next, the decomposed MIP problems

are coded in General Algebraic Modeling System (GAMS) and solved with commercial solver CPLEX.

5.3.2.2 User Interface

In this study, Dynamic Programming for flight sequences is translated into Visual Basic (VB) language, and the optimization model is solved by CPLEX as coded in GAMS. All input variables are read from Excel and final outputs are also stored in Excel. To facilitate the planning process with RTI-ASOM among multiple software and languages, a series of shell-scripted modules are coded to call for GAMS files so as to apply CPLEX in the VB environment. The integrated user interface with descriptions is shown in Figure 38. It enables an automated computation process that can obtain solutions from RTI-ASOM by simply executing all modules consecutively. The sample results shown in Figure 38 list optimized schedule (time in minutes) for five sample flights with taxi route nodes on the top and corresponding passage time underneath. The final outputs with optimized trajectories for all aircraft are written in a separate tab of the same Excel file.

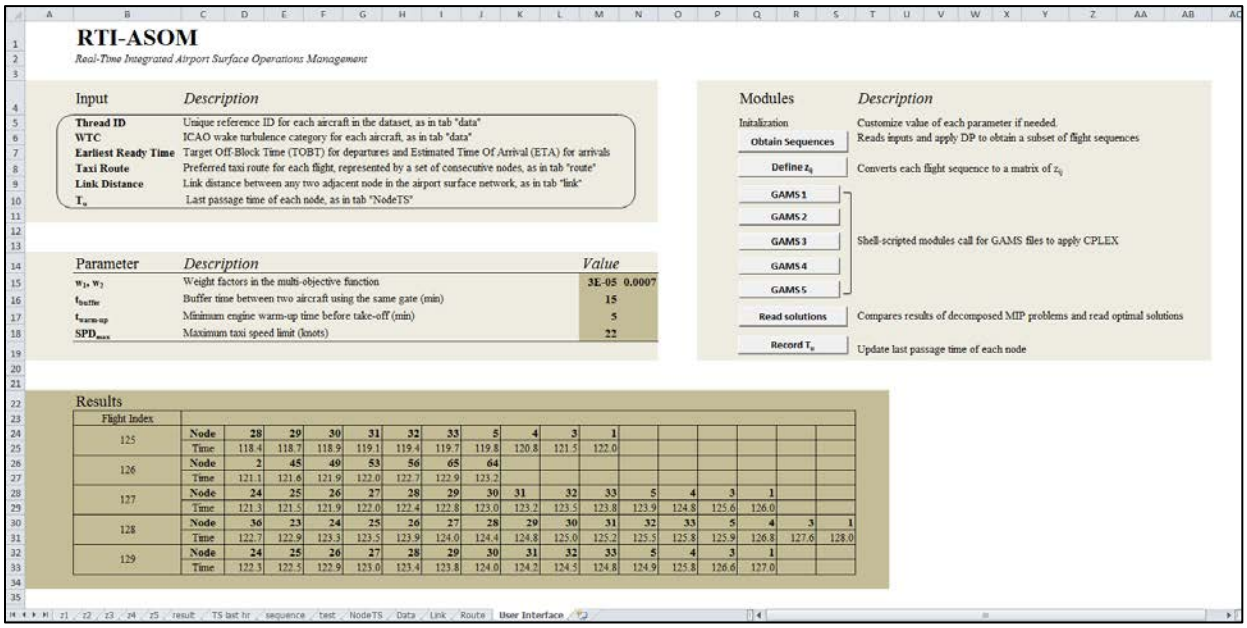


Figure 38 Snapshot of user interface and sample results.

5.4 Case Study

To illustrate the efficiency and effectiveness of RTI-ASOM, a case study is conducted using LGA layout and historical surface track data.

5.4.1 Airport Layout and Track Data

LaGuardia airport is one of three major commercial airports in the New York region, with two runways intersecting each other. In practice, most of flights are assigned to take off on runway 4-22 and land on runway 31-13 (see Figure 39). For the case study, the author first digitalizes the airport surface into a node-link network. LGA's layout is represented by the graph structure shown in Figure 39 with 65 nodes and over 100 links. Airside facilities identified as nodes in the graph include terminal gates, taxiway intersections, and runway ends. Taxiway and runway segments are denoted by directed links connecting two adjacent nodes.

One-day threaded track data on December 14, 2010 are used for the case study. It contains radar track data recorded within the terminal and aircraft tracks from individual sensors. Fields collected in the radar track data includes thread ID, time, latitude, longitude and altitude; and fields gathered in the aircraft track data includes thread ID, origin and destination airports, call sign and aircraft type. A new dataset is constructed by merging these two types of data through unique thread ID. Thereby, unified trajectories are identified for aircraft at the airport (sets of consecutive green dots in Figure 39).

The combined track data provides historical aircraft trajectories on the airport surface by gathering surveillance data between surface radar and aircraft transponders. However, not all inputs needed for the model are available from the track data. For example, there is no scheduled time information recorded in the dataset, such as TOBT or ETA. Conversations with tower controllers indicated that, in current operations, they usually do not hinder the pushback of the

aircraft. Thus in this case study, historical pushback times are used as the estimate of TOBT and actual landing times are assumed as ETA for arrivals. Normally, pilots turn on their transponders just prior to takeoff and turn it off after landing. When Airport Surface Detection Equipment, Model X (ASDE-X) is operational at an airport, such as LGA, the ATIS (Automatic Terminal Information Service) requests pilots to set their transponders to on while operating on taxiways and runways to help reduce runway incursions (15). It is observed from Figure 39 that first nodes of many departures at LGA are in the ramp area but they did not match gate locations at the airport, due to the fact that most aircraft transponders were not switched on until entering airport movement area. In the future, when more accurate surface management is enabled, transponders could be required to be set on before pushback to collect higher resolution of surveillance data. Nevertheless, due to limitations of the historical data in this case study, gate management constraints in MIP formulation are not applicable. Instead, the first detected nodes of departures are estimated as their gates and assume aircraft pushback from the "gates" without any holding. Furthermore, an additional 2 minutes is added to each taxi-out process to account for uncaptured time spent from actual pushback to the estimated gate location.

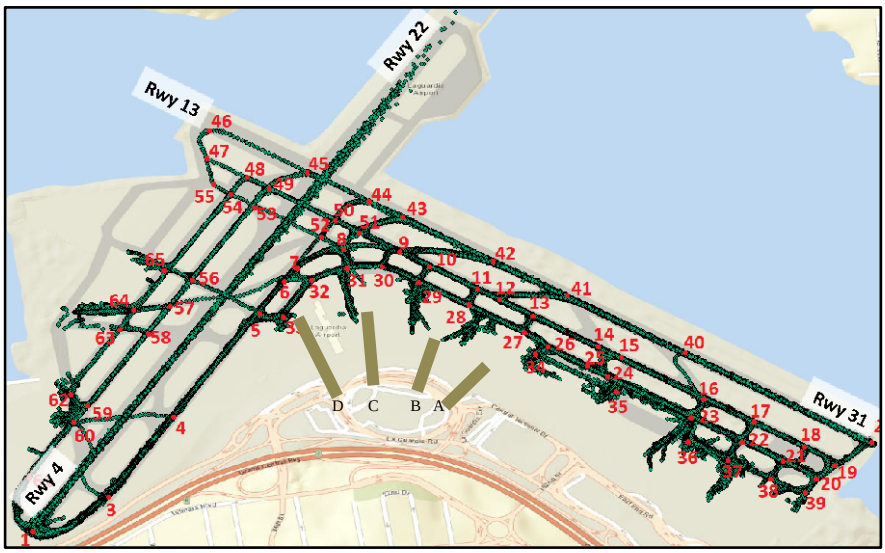


Figure 39 LGA surface networks with nodes and links.

From the surveillance data, a total of 1,056 surface trajectories are obtained on the study day, and 972 valid trajectories are kept for further analysis after removing incomplete trajectories. Each flight trajectory is projected onto the LGA graphic network to locate source nodes and sink nodes of aircraft movements on the surface, as well as a set of consecutive nodes identifying each taxi route. Table 11 summarizes the statistics on routing options for each distinct gate-runway pair.

Table 11 Summary of Routing Options for Distinct Gate-Runway Pairs

Route Options	**# of Gate-Runway Pair**	**%**	**Cumulative %**
1	40	43.5%	43.5%
2	19	20.7%	64.1%
3	11	12.0%	76.1%
4	4	4.3%	80.4%
5	6	6.5%	87.0%
6	1	1.1%	88.0%
7	2	2.2%	90.2%
8	2	2.2%	92.4%
9	3	3.3%	95.7%
11	1	1.1%	96.7%
12	1	1.1%	97.8%
15	2	2.2%	100.0%
SUM	*92*	*100%*	

Among the 92 distinct gate-runway pairs, 76.1% of pairs have, at most, three routing options, and almost half of the pairs (40 of 92, or 43.5%) have only one unique routing option. Thereby, the level of variety on routing options for most gate-runway pairs is relatively low. Hence in this study, one routing option is assumed for each distinct gate-runway pair at LGA.

Historical operational performance is evaluated by first extracting and validating taxi times from the projected surveillance data. Table 12 presents the statistics of taxi times of all flights from 18:00 to 19:00 on the study day. By averaging over 65 aircraft during this hour, the mean value of taxi times is 7.7 minutes with a standard deviation of 4.7. Compared to arrivals

with an average 3.8 minutes taxi-in time, departures experienced a much longer taxi time with average 11.0 minutes per flight and a higher standard deviation. The total taxi time of all active aircraft within this hour adds up to 498.1 minutes (8.3 hours). Such historical performance metrics set a baseline scenario for comparison analysis with RTI-ASOM in the next subsection.

Table 12 Mean Value and Standard Deviation of Historical Taxi Time (18:00-19:00)

	Total	**Departures**	**Arrivals**
Mean	7.7	11.0	3.8
SD	4.7	3.6	2.2

5.4.2 Weight Factor

In this case study for LGA airport, the weighted sum method is used to reflect neutral preferences between multiple objective functions. Weight factors are determined in a way to transform multiple objective functions so that they have similar magnitudes and so that none of them dominates the aggregate objective function (51). In our study, weight factors are normalized as the reciprocal of the minimum of their respective objectives:

$$w_1 = 1/\min f_1$$

$$w_2 = 1/\min f_2$$

Before the optimization, the minimal value of each objective is estimated by assuming the unimpeded taxi process for each aircraft. $\min f_1$, which represents the minimal of the last runway access time, is obtained when the last aircraft in the sequence taxi out with unimpeded taxi speed (if departure) or land without delay (if arrival). $\min f_2$, which represents the minimum total taxi time, is estimated by adding up unimpeded taxi times for all aircraft. Both objective terms are estimated before each planning window and the corresponding weight factors are derived from their reciprocals, respectively.

5.4.3 Speed Limit

Speed limit is determined by analyzing historical track data. Observed from surveillance data, an unimpeded aircraft is identified when its taxi speed is reluctant to drop below the threshold speed of 3 knots (52). Unimpeded taxi speed is obtained from total the taxi distance divided by the taxi time of each unimpeded aircraft. During the study hour, the average unimpeded taxi speed over all unimpeded aircraft is observed as high as of 21.3 knots. As a result, the maximum taxi speed in this case study is set to be 22 knots for all aircraft. Additionally, a sensitive analysis on various speed limits is conducted and the results are shown in the next subsection.

5.4.4 Engine Warm up Time

To assure that aircraft engines are fully warmed up before takeoff, a minimum of 5 minutes is required for taxi-out time, defined as the difference between pushback time (t_{iu_1}) and take-off time (t_{iu_k}). Due to the limitations of surveillance data, accurate pushback times at gates are not available. As a result, the time at which pilots activate the transponder and radar device begin to pick up the surveillance data, is used as the estimate. To account for the uncaptured time spent between the gate and the first detected spot with the transponder on, an additional 2 minutes is added to each taxi-out phase assuming that aircraft engines have been running for 2 minutes already.

5.4.5 Simulation

In addition to this historical scenario, a simulation scenario is constructed to demonstrate the effectiveness of RTI-ASOM. The simulation is set up to exclude uncertain factors in the airport environment, such as ground vehicles and human errors, and their influence on operational performance. Historical pushback times for departures and landing times for arrivals

are used as simulation inputs. Flight movements on the surface are subject to safety and operational requirements only. The maximum taxi speed is set as 22 knots for all taxi procedures. Moreover, because no gate-holding is assigned to any departures, flights are released from gates at their historical pushback times. The sequence of runway utilization by mixed departures and arrivals in the historical scenario is kept for all flights in the simulation. When a conflict is detected as any two aircraft approaching the same node in the surface network, flight priority is determined according to the historical runway sequence, viz., an aircraft that accessed a runway first in the historical scenario (no matter landing or takeoff) is given the priority to proceed while the other is on hold to maintain the regulated separation. To this end, the simulation presents a comparable scenario of flight movements at airport surface without disturbances from the uncertain factors. The entire simulation is executed through MATLAB and is conducted for all 65 flights during the study hour at LGA.

5.5 Numerical Results

First, the efficiency of implementing RTI-ASOM in the LGA case study is reported in this subsection. For demonstration purposes, computation time for each application is recorded. There are 65 flight operations during the study time period of 18:00-19:00 on December 14, 2010, including 35 departures and 30 arrivals. Flight trajectories from 17:00-18:00 are also included in the model to assure that no conflict with aircraft from previous hour. The MIP model in the case study contains 8,450 variables and over 4 million constraints. With the solution algorithm built in the user interface, the execution time is around 5 seconds per planning window, with a schedule horizon of 5 flights. All experiments are performed on a Dell computer with an Intel Core i5 processor (3.20 GHz), 8 GB RAM, and a 64-bit operating system.

To demonstrate the effectiveness of RTI-ASOM, multiple performance metrics of surface operations are first compared to RTI-ASOM and the initial historical scenario. The simulation results without the impact of uncertainties at the airport are then compared to RTI-ASOM. Following that, the sensitivity analysis is performed to test the impact of different speed limits on optimization results. Finally, performance analysis is conducted to compare optimal solutions from RTI-ASOM and commercial solver for small MIPs.

5.5.1 Comparison with Historical Scenario

5.5.1.1 Taxi Time

During the study time period, runway 4|31 is the only runway configuration in use, with takeoffs on runway 4 and landings on runway 31. For the sake of simplicity, the earliest ready time of the first aircraft to be scheduled is set as the reference time (0 minute). As the first aircraft in the hour is a departure, the reference time is set as its TOBT and all other times are presented as the differences from the reference time. To be comparable with historical data, the measure of taxi-out times herein also starts from the first surface spot with the aircraft transponder on. Figure 40 and Figure 41 show operational performance improvement in terms of taxi times after implementing RTI-ASOM for departures and arrivals, respectively. In this historical scenario, the total taxi time of all active aircraft during the study hour is 498.1 minutes, averaging 7.7 minutes per flight. With RTI-ASOM, the total taxi time is reduced to 181.7 minutes, averaging 2.8 minutes per flight. Compared to the stochastically distributed taxi times among flights in the historical scenario, RTI-ASOM maintains much lower taxi times within a narrowed standard variation range. The standard deviation is dropped from 4.7 minutes before to 0.9 minutes.

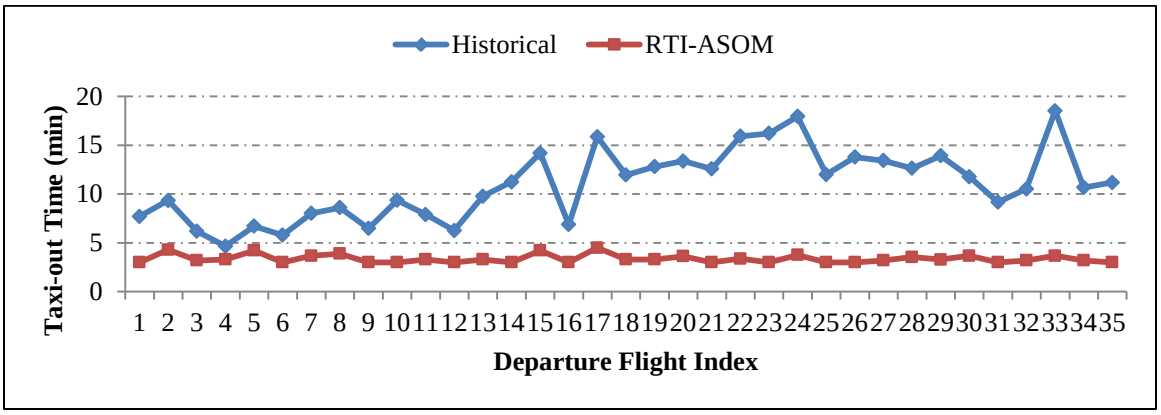


Figure 40 Taxi-out time for departures before and after RTI-ASOM.

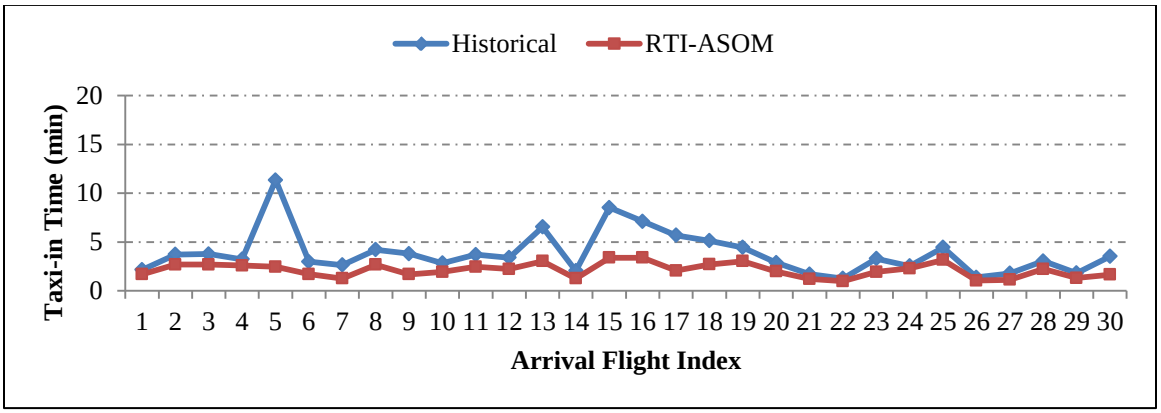


Figure 41 Taxi-in time for arrivals before and after RTI-ASOM.

Table 13 lists the average taxi time and standard deviation before and after RTI-ASOM. For both arrivals and departures, the overall taxi performances are improved with less average taxi times and smaller standard deviations. While average taxi-in time is reduced by 1.7 minutes (44%) for arrivals, a more significant improvement is observed for departures with 7.6 minutes (69%) excessive taxi-out delay diminished.

Table 13 Statistics of Taxi Times for Departures and Arrivals Before and After RTI-ASOM

Departures	*Historical*	*RTI-ASOM*	**Arrivals**	*Historical*	*RTI-ASOM*
Mean	11.0	3.4	Mean	3.8	2.1
SD	3.6	0.4	SD	2.2	0.7

5.5.1.2 Gate Holding

Figure 42 shows the amount of gate holding time assigned to each departure with RTI-ASOM, compared with its reduced excessive taxi time. By strategically holding aircraft and controlling release times at gates, air traffic flow is maintained in a sustainable pattern on the airport surface and partial taxi delays are shifted from the taxiways and runways to the gates. The total gate holding time for 35 departures adds up to 108.4 minutes as shown in Table 14, while there is no gate holding in the historical scenario. A total of 265.3 minutes reduction on excessive taxi-out times is observed for 35 departures. As shown in Figure 42, gate holdings are distributed strategically among all departures, with a maximal of 7.7 minutes.

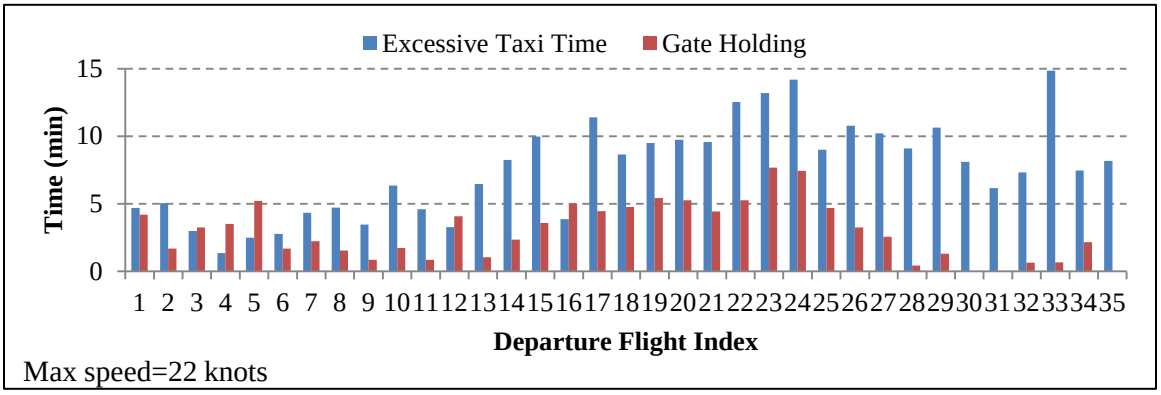


Figure 42 Holding time and excessive taxi time reduced for departures.

Table 14 Summary of Performance Metrics before and after RTI-ASOM

Time (min)	**Historical**	**RTI-ASOM**
Total Taxi Time	0	-316.4
Total Gate Holding Time	NA	108.4
Last Runway Access Time	0	-13.2

5.5.1.3 Runway Throughput

To evaluate the performance of RTI-ASOM in terms of runway throughput, the time of the last scheduled aircraft accessing the runway is compared between the historical and

optimized scenarios, with the time in historical scenario set to 0 as the reference in Table 13. It is found that RTI-ASOM reduces the last runway access time by 13.2 minutes for the study hour. The extra 13-minute time saved by RTI-ASOM can be used to accommodate about 18 more runway operations given similar fleet mix in the study hour. For a congested airport such as LGA, this amount of time saved during peak hours enables significant capacity increase to accommodate more flight operations and more efficient usage of scarce airside facilities.

5.5.1.4 Stop-and-go Scenarios

In practice, aircraft frequently perform stop-and-go on the surface to visually ensure the separation requirements with other aircraft. With RTI-ASOM, this practice can be reduced or removed completely and thus, aircraft can taxi between gates and runways with consistent taxi speed.

To demonstrate the removal of stop-and-go scenarios after RTI-ASOM, the author looks into the distribution of taxi speed for two consecutive departures named Aircraft 1 and 2 by the chronological order of their historical pushback times. Figure 43 shows the variation of instantaneous taxi speed along their partial taxi routes (identified by a set of consecutive nodes). Aircraft 1, which entered the airport movement area first, maintained a relatively consistent speed until N4, which is part of the only taxi route (N5-N4-N3-N1) to approach the departure runway (N1, see Figure 39). The main reason Aircraft 1 completed multiple stop-and-goes from N4 to N1 is because many aircraft that were scheduled earlier were queuing at the runway end. The delay propagated from previous flights to Aircraft 1 was also propagated to Aircraft 2, which shared a common taxi route from N5 to N1. Without consideration of the delay experienced by Aircraft 1, Aircraft 2 in the historical scenario was released from the gate without any gate holding and had to slow down at N6 and completely stop before N5 to maintain the

spatial separation from Aircraft 1. Following that, Aircraft 2 followed a similar stop-and-go pattern of Aircraft 1 until the end of the runway.

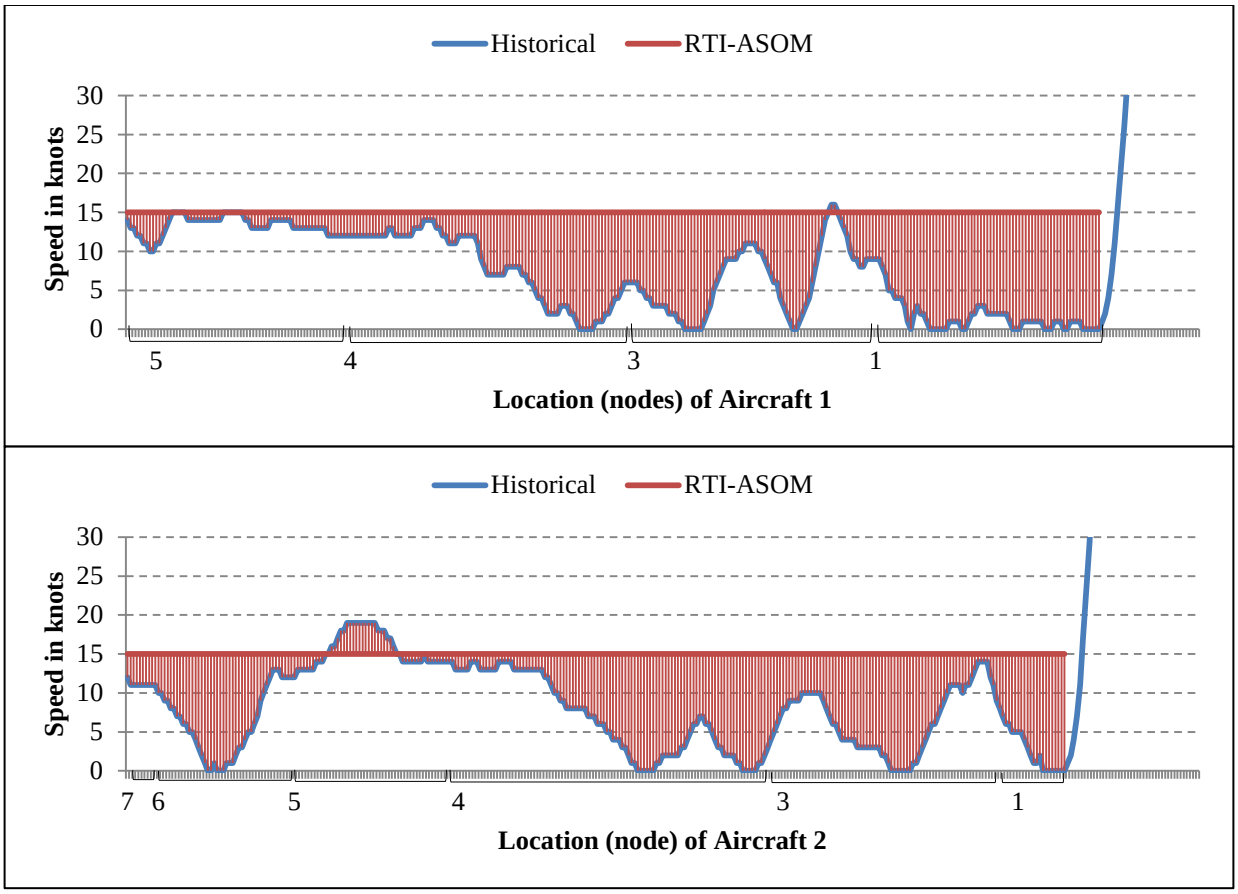


Figure 43 Examples of taxi speed variation along their taxi routes for two consecutive departures in historical scenario and RTI-ASOM.

After optimization in RTI-ASOM, Aircraft 2 is advised to pushback before Aircraft 1 after 3.7 minutes of gate holding while Aircraft 1 is released after being held for 4.4 minutes. As a result, a smooth taxi-out process with consistent taxi speed and no stops were observed for both aircraft in RTI-ASOM. It demonstrates the improvement of taxi-out experience by assigning proper holding time at gates and assuring a conflict-free environment for surface operations. The drop lines in Figure 43 represent the excessive taxi time reduced for both aircraft. The time it took for Aircraft 1 to taxi from N4 to N1 is reduced from 4 minutes to 1.2 minutes and the time it

took for Aircraft 2 to taxi from N6 to N1 is reduced from 7.6 minutes to 2.8 minutes, with a maximum taxi speed of 15 knots.

5.5.2 Comparison with Simulation Results

5.5.2.1 Taxi Time, Gate Holding and Runway Throughput

A comparison of performance metrics between simulation and RTI-ASOM is presented in Table 14. Among 65 flights during the study hour, a significant improvement is first presented in terms of taxi efficiency. A total of 340.6 minutes taxi time is observed from simulation results and reduced to 181.7 minutes after RTI-ASOM, with a reduction of 158.9 minutes total taxi time (Table 14). At the individual flight level, average taxi time decreases from 5.2 minutes in simulation to 2.8 minutes in RTI-ASOM, which yields 47% improvement of excessive travel time. Figure 44 shows the comparison of taxi time by individual flights between simulation and RTI-ASOM. Descriptive statistics of taxi times are listed in Table 15 for arrivals and departures. From this, it can be suggested that performance difference of taxi-in phase between RTI-ASOM and simulation is negligible. However, RTI-ASOM improves taxi-out performance significantly by reducing the average taxi-out time from 7.9 minutes to 3.4 minutes, with standard deviation reduced from 3.0 to 0.4 minutes.

Table 15 Summary of Performance Metrics from Simulation and RTI-ASOM

Time (min)	**Simulation**	**RTI-ASOM**
Total Taxi Time	0	-158.9
Total Gate Holding Time	NA	108.4
Last Runway Access Time	0	-5.1

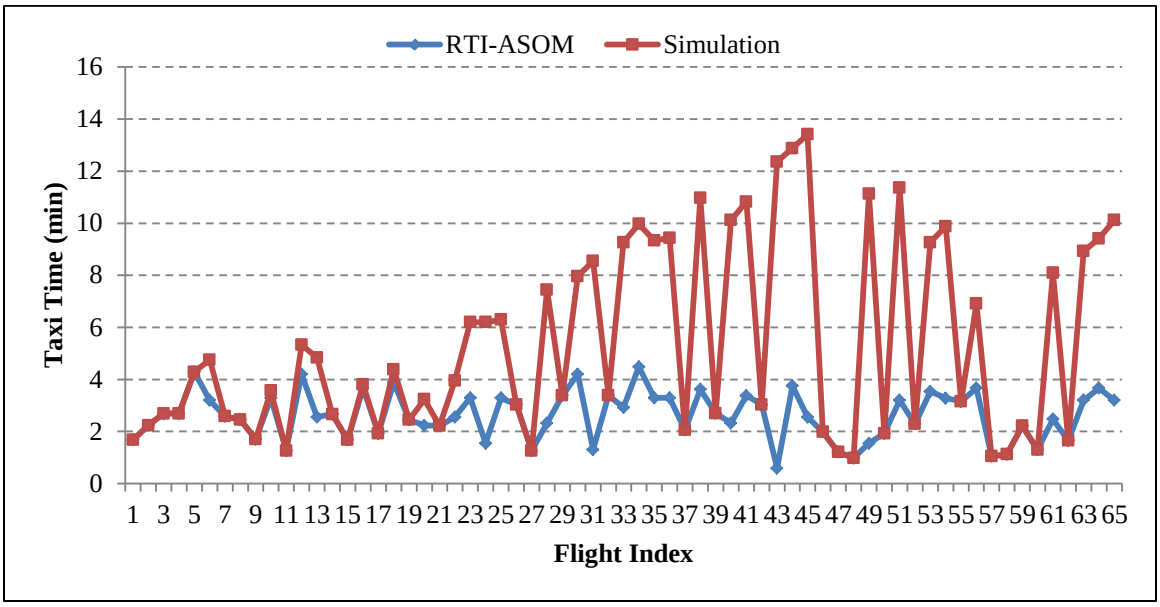


Figure 44 Taxi times by flight from simulation and RTI-ASOM.

Table 16 Statistics of Taxi Times for Departures and Arrivals between Simulation and RTI-ASOM

Departures	Simulation	RTI-ASOM	**Arrivals**	Simulation	RTI-ASOM
Mean	7.9	3.4	*Mean*	2.1	2.1
SD	3.0	0.4	*SD*	0.7	0.7

In the simulation, departures are released from gates at their historical pushback times without any gate holding, while in RTI-ASOM, the optimized outcomes lead to a total gate holding of 108.4 minutes. Setting performance of simulation scenario as the reference, Table 15 shows that RTI-ASOM achieves a time reduction of 5.1 minutes in terms of the last runway access time. Considering the similar fleet mix in the study hour, roughly 7 more runway operations can be accommodated.

5.5.2.2 Stop-and-go Scenarios

The taxi speed profiles of two consecutive departures, Aircraft 1 and Aircraft 2, are presented in Figure 45 to illustrate the stop-and-go scenarios along their partial taxi routes after simulation and RTI-ASOM. From historical data, Aircraft 1 accessed the departure runway

before Aircraft 2 and thus is given the priority to access any common node in the simulation. It was observed that Aircraft 1 which entered airport movement area first, stopped before N33 to maintain spatial separation from the previous aircraft. The delay was then propagated to Aircraft 2, who was on hold before N5 until Aircraft 1 passed the common node N5. Later, Aircraft 2 stopped again at the runway end N1 and waited until the runway was cleared after the takeoff of Aircraft 1.After optimization in RTI-ASOM, Aircraft 2 was advised to pushback before Aircraft 1 after 3.7 minutes of gate holding while Aircraft 1 was released after being held for 4.4 minutes. As a result, smooth taxi-out procedures are enabled for both aircraft in RTI-ASOM with consistent taxi speed and no stops observed.

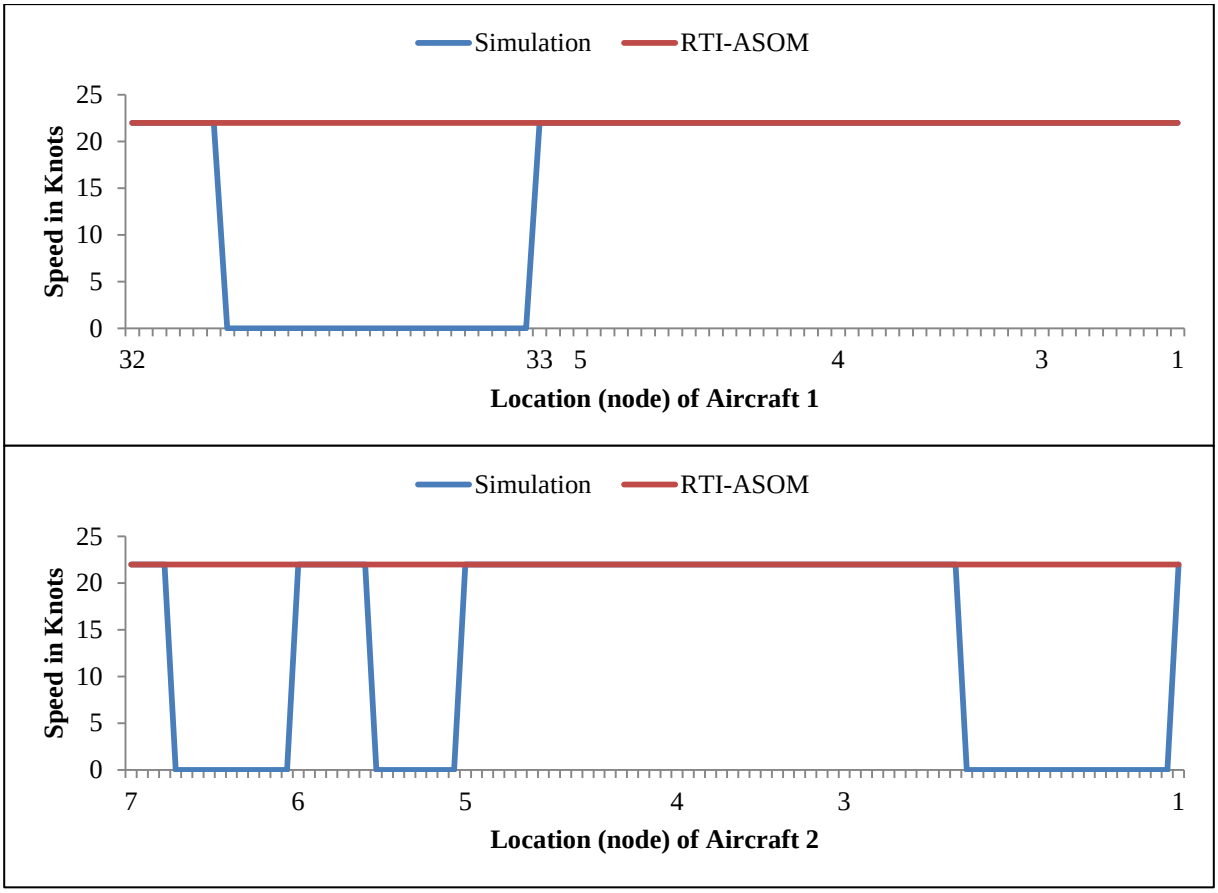


Figure 45 Examples of taxi speed variation along their taxi routes for two consecutive departures in simulation and RTI-ASOM.

5.5.3 Sensitivity Analysis on Speed

In order to test the impact of different speed limits on the optimization results, a sensitivity analysis is conducted on various maximum speed limits at LGA. The author compares the optimized taxi time for each aircraft under different maximum speed, ranging from 15 knots to 22 knots as shown in Figure 46. It is noted that the variance in optimized taxi times with eight levels of speed limits is relatively small, roughly 1 minute per flight on average. A summary of performance metrics with different speed limits in RTI-ASOM is presented in Table 17. Setting the scenario with 22 knots speed limit as the reference, the scenario with 15 knots speed limit leads to the largest difference of 3.5 minutes in terms of additional runway usage, 81.5 minutes with respect to total gate holding time and accumulated 64 minutes difference in terms of total taxi time for all 65 flights during the study hour. At the individual aircraft level, average taxi times range from 2.8 to 3.8 minutes per flight after RTI-ASOM, with a higher speed limit leading to a lower average value.

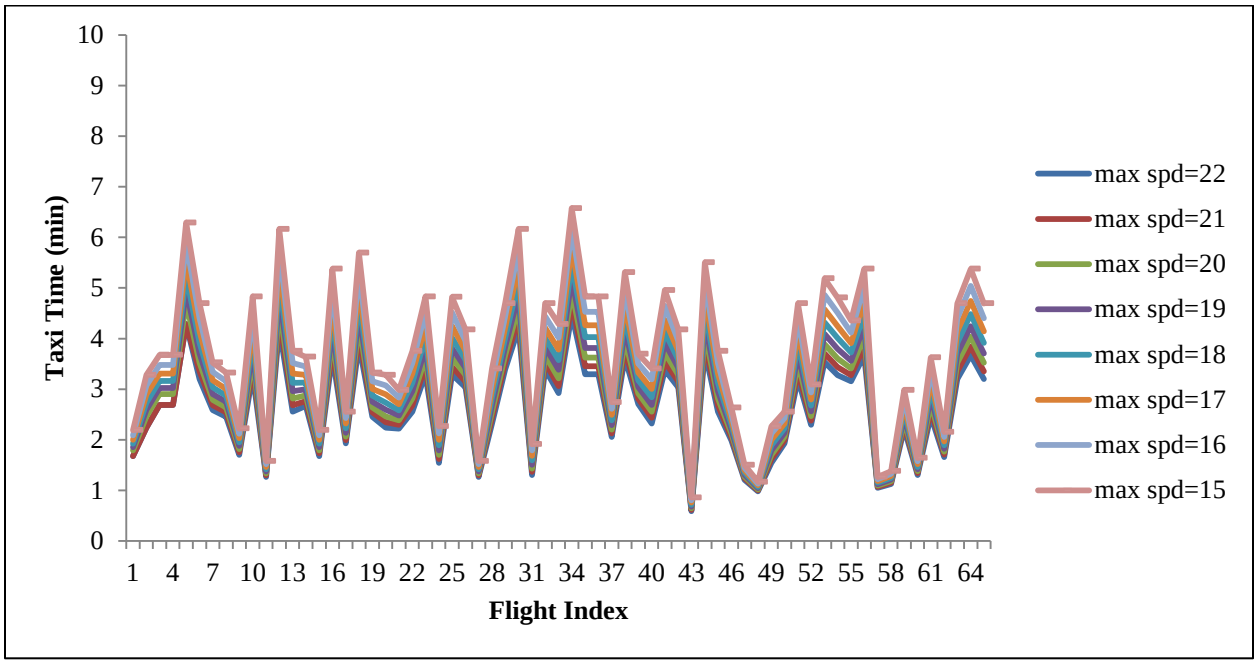


Figure 46 Comparison of optimized taxi time by aircraft with various maximum speed limits in RTI-ASOM.

Table 17 Summary of Performance Metrics with Various Maximum Speed Limits in RTI-ASOM

Time (min)	RTI-ASOM							
	Max Spd=22	**Max Spd=21**	**Max Spd=20**	**Max Spd=19**	**Max Spd=18**	**Max Spd=17**	**Max Spd=16**	**Max Spd=15**
Last Runway Access Time	0.0	0.4	0.7	1.2	1.7	2.2	2.8	3.5
Total Gate Holding	0.0	5.1	14.0	24.8	43.3	67.2	93.7	81.5
Total Taxi Time	0.0	6.0	12.7	20.2	28.8	38.8	50.5	64.0
Average Taxi Time	2.8	2.9	3.0	3.1	3.2	3.4	3.6	3.8

5.5.4 Performance Analysis on Optimization

To measure and compare the optimized solutions from RTI-ASOM, performance analysis on optimization is conducted in this part of dissertation. Three sample groups of flights at LGA are used to construct smaller MIPs that can be directly executed through commercial solver without RTI-ASOM. First, all flights are initially sorted in a chronological order of their earliest ready times. Then, each sample group of five flights is formed by randomly picking one flight out of a total of 65, along with four following consecutive flights in the list. By considering only active surface nodes used by five flights, the problem size of MIP for each group is reduced significantly. Following that, the commercial solver, i.e., CPLEX, is used to obtain solutions of small MIPs and the results are compared with solutions from RTI-ASOM.

Table 18 summarizes the optimization performance of RTI-ASOM and solver when optimizing small MIPs for three random groups. On the top of the table, it compares objective values of RTI-ASOM and solver in terms of total taxi time and the last runway access time (shown as the time difference). An optimization gap of 0% is observed from two groups, indicating excellent optimal performance of RTI-ASOM, while an optimization gap of 3% is noted for another group. Moreover, RTI-ASOM shows a great advantage in terms of execution time, which is about three times faster than solver itself. After expanding the airport surface

network to the full scale, RTI-ASOM could still provide solutions within 5 seconds while CPLEX solver is not sufficient enough to obtain optimal solutions for large MIPs.

Table 18 Comparison of Optimization Performance between RTI-ASOM and Solver

Time	Group 1		Group 2		Group 3	
(min)	*RTI-ASOM*	*Solver*	*RTI-ASOM*	*Solver*	*RTI-ASOM*	*Solver*
Total taxi time	14.4	14.4	13.2	13.2	12.8	12.8
Last runway access time	0	0	0	0	2.5	0
Optimization Gap	0%		0%		3%	
Execution Time (sec)	3.5	10.2	3.2	9.1	3.3	9.2

5.6 Summary

This chapter describes a real-time integrated airport surface operations management (RTI-ASOM) that provides optimal trajectories for each aircraft between gates and runways with the objective of minimizing total taxi time and maximizing runway throughput. The use of Mixed Integer Linear Programming (MIP) formulation, Dynamic Programming for decomposition, and CPLEX optimization allows an efficient solution algorithm that can solve the large-scale optimization problem instantly. Examples are shown based on one-day track data at LaGuardia Airport. Besides historical data, simulation through MATLAB is constructed to provide another comparable scenario and the comparison results demonstrate significant reduction of taxi times and improvement of runway utilization in RTI-ASOM. By strategically holding departures at gates, the application of RTI-ASOM also reduces excess delay on the surface, decreases fuel consumption at airports, and mitigates the consequential environmental impacts.

The application of RTI-ASOM entails benefits from several aspects. First, it improves operational efficiency by identifying and mitigating surface congestions and delays. Second, it augments the predictability of airport operations by allowing precise management of current and

intent positions of aircraft. It also benefits the Air Route Traffic Control Center (ARTCC) with enhanced management capabilities that eventually lead to better system performance of the NAS. Last, it extends the TBO solution from *en route* airspace to airport and terminal area so as to make gate-to-gate 4-D trajectory-based ATM applicable.

CHAPTER 6: CONCLUSIONS AND FUTURE WORK

6.1 Global Comparison

In this dissertation, a comprehensive comparison between major airports in the U.S. and Europe is conducted with emphasis on airport surface operational performance. Comparable airport pairs are selected according to a set of airport characteristics, including: 1) same number of runways and geometric runway layout, 2) similar runway configuration and airport layout, 3) and comparable annual and monthly air traffic.

The comparison study underlines that different methods are currently used in the U.S. and Europe to benchmark surface operational performance indicators, namely unimpeded taxi times and taxi delays. Insights are given on how to refine taxi time modeling procedures and explore the roles of other important causal factors. A refined and consistent model, which is also addressed in this dissertation, can yield more accurate estimates of taxi times and thus provide a more efficient way to benchmark airport operational performance.

The analytics of European airport data shows that demand management policies help maintain a stable traffic pattern along the time of day that leads to less taxi-out delay at the cost of less efficient usage of airport facilities and limited airport access. As counterparts of European airports, selected U.S. airports are not capacity constrained but present relatively poorly operational performance in terms of higher level of taxi delay, larger variability and less reliability. However, U.S. airports achieve a higher utilization of runway facilities and are capable to accommodate heavier loads of traffic when weather permits.

Due to varying system structures, neither of the two regions can expect to improve their operational performance by simply copying the strategies from one another. By comparing major U.S. and European airports in early 2008, this study provides a comprehensive factual comparison on the fundamental differences in Europe and the U.S. without the impact of CDM initiatives. The observed comparison results are associated with differences between a single ANSP in the U.S. and multiple ANSPs in Europe, airline scheduling and demand management differences, mixed usage of IFR and VFR operations in the U.S., and different gate management in two regions.

As a final comment of the comparison study, selections of comparable airport pairs in the U.S. and Europe are driven by restricted data obtained from three Spanish airports. With highly successful benchmarking of three airport pairs in this dissertation, improved insights on airport performance could be obtained by expanding the comparison to involve more airports from each system. To conduct further comparison, nonetheless, the access to operational data from different European airports is the main challenge. With a set of high-resolution operational data, future research could also extend performance comparisons on flight punctuality by investigating how block buffers are implemented by carriers in Europe and the U.S.

6.2 Benchmark Model

Unimpeded taxi time is the reference time used for estimating taxi delay, a widely accepted performance indicator of airport surface movement. It has been noted that there are different perspectives in defining taxi times and a clear definition of unimpeded taxi times is needed before the implementation of any benchmark method. From the passenger point of view, once the aircraft leaves the gate, any additional time beyond the scheduled takeoff time is considered a delay, regardless if it occurs in the ramp area or in the movement area. Thus, taxi

time is intended to be the time difference between wheel-off time and gate-out time, which is defined in the ASPM database. Nevertheless, the management over the taxi process is fragmented as airport/airlines take control of flight movements in the ramp area while ANSP oversees movement area. Therefore, aircraft movements shall be measured by considering two areas independently to enable a more accurate measure of taxi efficiency. To support future analysis, high resolutions of surface flight data that clearly indicate the beginning and ending of traffic control over these two areas are essential.

Whereas the U.S. and European system have the same definition of unimpeded taxi time, different methodologies are currently in use by the FAA and EUROCONTROL. In order to provide a more efficient way to benchmark airport operational performance, an in-depth factual comparison is conducted between the APO method by FAA and the PRU method by EUROCONTROL. One of the main differences is the criteria used to group similar flights: the APO method group flights only by season and carrier, while the PRU method also includes stand and runway configuration. Another major difference is that the APO method assumes the reference aircraft is the only active aircraft on the surface while calculating unimpeded taxi times, whereas the PRU method allows a certain number of aircraft on the system, which is constrained by the congestion index threshold.

Furthermore, new methods to determine unimpeded taxi times are explored through simulation and observation of historical operational data, which provides new capabilities to measure taxi performance. However, such heuristics are not yet applicable for real-time measurement. Hence, a sophisticated statistical model is developed. Causal factors that contribute significantly to taxi delay are identified by exploiting available data sources. A log-normal regression model is then adapted to model taxi times after a comprehensive set of

regression diagnosis and model stability test. Numerical results demonstrate more accurate measurement for taxi performance at three airports. The proposed model quantifies the impact of various factors to taxi inefficiency and supports decision-makers with reliable measurements to improve the operational performance.

In chapter 5, the author presents a reliable regression model to reveal impacts of explanatory variables and measure taxi efficiency. The decision variables involved in the model, however, are not estimable at pushback and thus the model is not directly applicable for predicting taxi times. For future research, taxi-out time prediction model could be developed based on findings of this dissertation by including only explanatory variables that are known at the moment of pushback. With a high-resolution surveillance data on airport surface, future research could also examine the travel times in the ramp area and taxiway system separately and thus obtain improved insights on taxi performance.

6.3 RTI-ASOM

An integrated airport surface operations management involving runway, taxiway, and apron area is proposed in this study, namely RTI-ASOM. Given the earliest ready time of a mix of departures and arrivals, RTI-ASOM optimizes aircraft surface operations by maximizing runway throughput and minimizing total taxi times, subject to the operational constraints of ready time limits, conflict-free constraint, recursive planning requirement, precedence constraint, minimum separation requirements, gate availability constraint, engine warm-up time constraint and speed limit. To solve the MIP formulated optimization problem, a decomposition algorithm is presented by first using DP to extract potential options of runway sequences and then solving decomposed MIP problems in CPLEX. An amalgamated user interface is developed with a series of shell-scripted modules in the VB environment to facilitate the implementation of RTI-ASOM

in real-time planning. The final outputs of RTI-ASOM include optimized sequence and schedule along each flight trajectory between gates and runways.

The experimental analysis is conducted using threaded track data at LGA to demonstrate substantial benefits of RTI-ASOM, in terms of taxi times, delay, runway usage and computational efficiency. Besides historical data, simulation through MATLAB is constructed to exclude the uncertainties at the airport and thus provide a comparable scenario for demonstration. Compared with simulation results, RTI-ASOM shows a total reduction of 158.9 minutes of excessive taxi time for 65 flights. As part of the strategies provided by RTI-ASOM, gate holdings are implemented among departures to mitigate the congestion in movement area and partially absorb excessive taxi times. RTI-ASOM also prevents stop-and-go scenarios along flight trajectories and helps reduce delay propagations on the surface. Moreover, the analysis at LGA reveals that RTI-ASOM improves runway throughput by shortening the last runway access time by 5.1 minutes for the study hour. Furthermore, sensitivity analysis is conducted to test the impact of various speed limits on optimization results. With the maximum speed limit ranging from 15 knots to 22 knots, the variance in the last runway access time is at most 3.5 minutes and average taxi times range from 2.8 minutes to 3.8 minutes per flight, with higher speed limits leading to lower values. With integrated interface, the application of RTI-ASOM is also demonstrated as a computational efficient, with 5 seconds of execution time per planning window.

A few assumptions are made in the case study due to limitations of available surveillance data. As no scheduled timing information is recorded in the dataset, historical pushback times are used as the estimate of TOBT and actual landing times are assumed as ETA for arrivals. Also, gate management constraints in RTI-ASOM are temporarily deactivated in the case study

because precise time and location of aircraft pushbacks are not available. This is mainly due to the fact that most aircraft transponders were not switched on until entering airport movement area. A higher resolution of airport surface surveillance could extend current optimization capabilities of RTI-ASOM to include gate area and integrate gate management into the optimization.

The proposed integrated tool provides a valuable approach for gauging the benefits of both current and future operational techniques. It enables accurate time control along each flight trajectory while guaranteeing a safe, efficient and conflict-free environment for surface operations. It also prepares NextGen with more automation of surface operations management and extends 4-D TBO from *en route* airspace to airports. With the development of innovative Aircraft Ground Propulsion Systems (AGPS) (12), pilots will be able to maneuver aircraft pushback with more automation and less uncertainties, which provides more space and possibilities for implementing the proposed integrated tool.

With the ongoing transformation of NAS, it will take a few years to realize TBO in NextGen for fully-functional 4D trajectory-based control. Nevertheless, RTI-ASOM can provide intermediate applications to facilitate current surface operations management at airports. For instance, the optimized trajectory-based schedule can be used to understand the implication of demand and to identify critical control points on the airport surface where time-based control yield the maximal benefit in terms of mitigating surface congestions and increasing airport capacity. As shown in Figure 47, ten critical control points in the taxiways at LGA (runway ends N1&N2 not included) are identified with the consideration of multiple factors, such as accessibility to the runway/gate, frequency of usage among preferred taxi routes, range of impact to other nodes in the network, etc. Rather than monitoring all 65 nodes at LGA, controllers are

suggested to focus on monitoring these critical control points. Together with the gate holding strategy, optimized passage times of critical control points for each aircraft can be used by controllers to significantly improve the current practice and manage aircraft movements efficiently with this practice-ready application.

Figure 47 Example of critical control points at LGA.

Future research could include relaxing the single taxi route assumption in the current version of RTI-ASOM. The effect of uncertainties should be considered, exploiting the flexibility of routing and enabling multiple route options. Furthermore, the environmental benefits of RTI-ASOM could be evaluated with accurate aircraft engine information. Other data sources need to be exploited to lookup matching engine types for flights recorded in our surveillance data. Future work could also include comparing RTI-ASOM with other control regimes for airport surface operations and extensions to the method to handle more realistic features.

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APPENDICES

Appendix A U.S. Methodology for Nominal Taxi Times

This appendix describes the methodology used for the calculation of nominal (unimpeded) taxi times for the U.S.

1. Start with a city pair flight with the data items of date (year, month, and day), departure and arrival airport, departure and arrival times (both scheduled and actual), and OOOI times (out, off, on, in). The season parameter is defined as winter (December, January, February), spring (March, April May), summer (June, July, August), and fall (September, October, November).

2. Split a flight into two parts: departure and arrival.

3. Departure data include airport, carrier, season, actual gate-out time (entry time into a departure queue), and actual wheels-off time (exit time out of the departure queue).

4. Arrival data include airport, carrier, season, actual wheels-off time (entry time into an arrival queue), and actual gate-in time (exit time out of the arrival queue).

5. Set up a bin for each minute of a single day and count how many aircrafts (both departing and arriving) are ahead of the flight at the queue entry time for the departure and arrival queues separately.

6. Compute for each group an upper quartile (75th percentile) and exclude the upper 25 percent from the estimation computation. This is done to prevent extremely large values from exerting excessive effects on the estimates. This is to estimate optimal taxi times, assuming there is no obstruction on the taxiways.

7. Run a regression for each subgroup determined by the airport, air carrier, and season, separately for the departure and arrival queues. yo = axo + bxi + c, where yo is a taxi-out

time and xo and xi are the number of aircraft taxing out and taxing in, respectively. a and b are regression coefficients with $a \geq 0$ and $b \geq 0$.

8. Only adopt results for which both regression coefficients are positive (the more aircraft, the longer the taxi times).

9. For the subgroups with non-positive regression coefficients, do other things with boundary conditions set for the resulting coefficients to be positive. (SAS used has some regression or nonlinear model fitting procedures in which can be specified in the boundary conditions.)

10. Finally, to obtain the unimpeded taxi-out times, set the number of the departing aircraft at 1 and the arriving aircraft at 0 in the regression equation for the departure queue, meaning that only one aircraft is moving. For the unimpeded taxi-in times, set the number of the arriving aircraft at 1 and the departing aircraft at 0 in the equation for the arrival queue.

11. The other statistics are for information only as a reference to determine if the unimpeded times are reasonable.

Appendix B European Methodology for Unimpeded Taxi Times

This appendix describes the methodology used by European Performance Review Unit (PRU) for the calculation of the unimpeded taxi times in the taxi-out phase.

Step 1: Each departing flight is categorized according to:

- Stand type and location: The type of stand (nose in, etc.) and the location of the stand are likely to affect performance measurement. To account for similar characteristics, individual stands are grouped for the calculation of the unimpeded time described in step 2. As the information on stands is not available from the databases accessible to the PRU, this analysis parameter is subject to data availability from the airport communities.
- Departure runway: The inclusion of the departure runway enables stand – runway combinations and, hence, provides additional useful information for performance analyses.
- Congestion index: The allocation of a congestion index to each departing flight is important to remove congestion effects in the calculation of the unimpeded surface movement transit times. It is expressed by the number of departures of other aircraft between the time the departing flight went off-block and the actual take-off time of the flight.

Step 2: For each group (stand-runway combination, as available), an unimpeded reference transit time is calculated by taking the truncated mean (the average of all observations in the truncated 10th to 90th percentile set) transit time for all flights within the group with a congestion index below a defined threshold (i.e., 4 flights or less).

Step 3: For each group (stand-runway combination, as available), the surface movement delay is calculated as the difference between the average transit time (of all flights in this group) and the unimpeded transit time for this group determined in the previous step.

Step 4: To get high-level results, the weighted average of all the individual surface movement delay groups is calculated in a final step.

Appendix C Carriers in Airline Service Quality Performance System (ASQP) and Aviation System Performance Metric (ASPM)

ASPM Carriers	ASQP Carriers
Carrier Name	***Carrier Name***
1. Air Canada (ACA)	1. Pinnacle Airlines (FLG)
2. AirTran Airways TRS	2. American Airlines (AAL)
3. Alaska Airlines (ASA)	3. Aloha (AAH)
4. Aloha Airlines (AAH)	4. Alaska Airlines (ASA)
5. American Airlines (AAL)	5. JetBlue Airways (JBU)
6. American Eagle (EGF)	6. Continental Airlines (COA)
7. America West (AWE)	7. Atlantic Coast Airlines (BLR)
8. ATA Airlines (AMT)	8. Delta Air Lines (DAL)
9. Atlantic Coast (BLR)	9. Atlantic Southeast Airlines (CAA)
10. Atlantic Southeast Airlines (ASQ)	10. Frontier Airlines (FFT)
11. Atlantic Southeast Airlines (CAA)	11. AirTran Airways (TRS)
12. Comair (COM)	12. Hawaiian Airlines (HAL)
13. Continental Airlines (COA)	13. America West (AWE)
14. Delta Air Lines (DAL)	14. American Eagle (EGF)
15. ExpressJet Airlines (BTA)	15. Northwest Airlines (NWA)
16. FedEx (FDX)	16. Comair (COM)
17. Frontier Airlines (FFT)	17. SkyWest Airlines (SKW)
18. Hawaiian Airlines (HAL)	18. ExpressJet Airlines (BTA)
19. Independence Air (IDE)	19. ATA Airlines(AMT)
20. Jetblue Airways (JBU)	20. United Airlines (UAL)
21. Mesa Airlines (ASH)	21. US Airways (USA)
22. Northwest Airlines (NWA)	22. Southwest Airlines (SWA)
23. Pinnacle Airlines (FLG)	23. Mesa Airlines (ASH)
24. Skywest Airlines (SKW)	
25. Southwest Airlines (SWA)	
26. TWA (TWA)	
27. United Airlines (UAL)	
28. United Parcel Service (UPS)	
29. US Airways (USA)	