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Optimizing Integrated Airport Surface and Terminal Airspace Operations under Uncertainty

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OPTIMIZING INTEGRATED AIRPORT SURFACE AND TERMINAL AIRSPACE OPERATIONS UNDER UNCERTAINTY

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This thesis is dedicated to my father Joël.

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PREFACE

This dissertation was mostly written in flight above $30,000$ feet in a variety of aircraft ranging from CRJ-200 to A380.

“Fais de ta vie un rêve, et d’un rêve, une réalité.” Antoine de Saint-Exupéry

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ABBREVIATIONS

AMS	Amsterdam Airport Schiphol
ATFM	Air Traffic Flow Management
ATL	Hartsfield-Jackson Atlanta International Airport
ATM	Air Traffic Management
BTS	Bureau Transportation Statistics
CDG	Paris Charles de Gaulle Airport
CPS	Constraint Position Shifting
DFW	Dallas Forth Worth International Airport
DOH	Doha International Airport
DTW	Detroit Airport
FAA	Federal Aviation Administration
FCFS	First-Come-First-Served
FMS	Flight Management System
GPU	Graphics Processing Units
IADS	Integrated Arrival Departure and Surface
LAX	Los Angeles International Airport
LHR	London Heathrow Airport
LP	Linear Programming
MIP	Mixed-Integer-Programming
MILP	Mixed-Integer-Linear-Programming
NAS	National Airspace System
SAA	Sample Average Approximation
SID	Standard Instrument Departure
STAR	Standard Terminal Approach Route
STASS	Stochastic Terminal Arrival Scheduling Software

TBIT	Tom Bradley International Terminal
TFM	Traffic Flow Management

ABSTRACT

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In airports and surrounding terminal airspaces, the integration of surface, arrival and departure scheduling and routing have the potential to improve the operations efficiency. Moreover, because both the airport surface and the terminal airspace are often altered by random perturbations, the consideration of uncertainty in flight schedules is crucial to improve the design of robust flight schedules. Previous research mainly focused on independently solving arrival scheduling problems, departure scheduling problems and surface management scheduling problems and most of the developed models are deterministic.

This dissertation presents an alternate method to model the integrated operations by using a machine job-shop scheduling formulation. A multistage stochastic programming approach is chosen to formulate the problem in the presence of uncertainty and candidate solutions are obtained by solving sample average approximation problems with finite sample size. The developed mixed-integer-linear-programming algorithm-based scheduler is capable of computing optimal aircraft schedules and routings that reflect the integration of air and ground operations.

The assembled methodology is applied to a Los Angeles case study. To show the benefits of integrated operations over First-Come-First-Served, a preliminary proof-of-concept is conducted for a set of fourteen aircraft evolving under deterministic conditions in a model of the Los Angeles International Airport surface and surrounding terminal areas. Using historical data, a representative 30-minute traffic schedule and aircraft mix scenario is constructed. The results of the Los Angeles application show that the integration of air and ground operations and the use of a time-based

separation strategy enable both significant surface and air time savings. The solution computed by the optimization provides a more efficient routing and scheduling than the First-Come-First-Served solution.

Additionally, a data driven analysis is performed for the Los Angeles environment and probabilistic distributions of pertinent uncertainty sources are obtained. A sensitivity analysis is then carried out to assess the methodology performance and find optimal sampling parameters. Finally, simulations of increasing traffic density in the presence of uncertainty are conducted first for integrated arrivals and departures, then for integrated surface and air operations. To compare the optimization results and show the benefits of integrated operations, two aircraft separation methods are implemented that offer different routing options.

The simulations of integrated air operations and the simulations of integrated air and surface operations demonstrate that significant traveling time savings, both total and individual surface and air times, can be obtained when more direct routes are allowed to be traveled even in the presence of uncertainty. The resulting routings induce however extra take off delay for departing flights. As a consequence, some flights cannot meet their initial assigned runway slot which engenders runway position shifting when comparing resulting runway sequences computed under both deterministic and stochastic conditions. The optimization is able to compute an optimal runway schedule that represents an optimal balance between total schedule delays and total travel times.

1. Introduction

Over the next 20 years, the Federal Aviation Administration (FAA) forecasts an air traffic growth of more than 90% [1]. The number of aircraft and passengers that will fly in the National Airspace System (NAS) is projected to increase with a yearly average of 2.2% over the next 20 years. The NAS, which is currently being used close to its maximum capacity, is expected to be significantly more stressed by the projected increase of the demand. As the aviation systems evolve with the emergence of new navigation and air traffic control technologies, the NAS is being transformed slowly but surely towards the Next Generation of Air Transportation System (NextGen). NextGen is a solution framework for handling safely, efficiently and in a cleaner way the future demand for service in the NAS. It will provide solutions to all actors using the NAS, i.e. airlines and federal control facilities, to facilitate and improve operations as well as increase their predictability. Automated tools and procedures are currently being developed to provide NextGen's solutions. Examples of tools and procedures are enhanced weather forecast models for controllers and airlines, reduced separation distances to improve airspace usage and, optimized scheduling and routings both in the air and on the surface. The major challenge of NextGen is to ensure that information and resources are shared in a coordinated fashion between every operator of the NAS.

1.1 Background

In the NAS, airport surfaces and terminal airspaces are characterized by high traffic volume traveling through narrow portions of space in which many flights are scheduled to depart and arrive in short periods of time. In these constrained environments, most aircraft are moving on the surface or changing altitude in the air at various speeds. Both on the surface and in the air, operations are affected by uncertainty which prevent from predicting with perfect accuracy operated trajectories and schedules. With the growth of air traffic, airport surfaces and terminal areas are congested and the efficiency of air traffic operations is impaired and disrupted by the formation of bottlenecks on the surface. Therefore, the development of decision support algorithms that coordinate air and surface operations is needed to help improve the efficient use of terminal and airport surface resources.

In current airport surface and terminal airspace operations, route segments and meter fixes are spatially segregated in order to reduce interactions between traffic flows. In current ground-side operations, wake vortex and traffic flow management separation requirements are imposed to separate aircraft on the runway and controllers issue advice on visual spatial separation to aircraft that are moving on the airport surface. Typically, as soon as aircraft are ready and cleared for pushback, they leave the gates to meet on-time airline metric performance. However, this often results in uncoordinated movements and traffic congestion during peak hours because of the limited amount of available airport surface space. As a consequence, bottlenecks build up on the airport surface and the resulting delays propagate into the NAS and reduce its efficiency. In current air-side operations, spatial separation strategies are applied to reduce interactions between traffic flows and guarantee proper flight spacing. To manage the use of shared resources such as waypoints or route segments, controllers assign independent routes and meter fixes to arrival and departure flows. Such separation strategy may introduce inefficiencies in the airspace usage with longer departure and arrival routes and altitude constraints. To remedy these inefficiencies and support improved operations efficiency, time-based separation strategies are potential approaches to manage integrated operations using shared resources.

Although the FAA imposes aviation regulations and policies on operations for all NAS users, the current state of traffic and congestion is primarily dictated by its main operators, i.e. the airlines. In the United States, airlines own airport terminals, concourses and gates partially or entirely. They control the surface movements on the ramp areas by the gates they own and operate. In the case where airline B uses airline A gates, airline A might also control airline B ramping movements. The airlines are driven by on-time performance metrics that illustrates to the Department of Transportation (DOT) how well airlines operate their flights with respect to the respective published schedules. To generate maximum revenue, the airlines try to turn aircraft in short periods of time and avoid expensive extended surface block times. Moreover, in order to meet *D0*, an on-time departure metric, aircraft are pushed-back from the gates as soon as the boarding door is closed and the jetway is retracted. Because taxi and runway operations are controlled by FAA controllers, airlines try to anticipate surface congestion by operating on shortest-minimum-fuel flight paths in order to land early and meet the on-time arrival metric *A14* at the gates.

This background introduces current airport surface and terminal airspace operations under a NAS user point of view. This point of view is biased by airlines because they are in constant competition to mitigate the effects of uncertainty and operate the closest to published schedules. When airlines are taken out of the picture, every NAS user is equal and has the right to operate the NAS under the FAA rules and regulations. To help and support improved operations, one of NextGen's challenges is to ensure that shared resources are coordinated in a fair manner between every actor involved in the NAS. This research investigates the integration of operations between the airport surface and the terminal airspace for an unaffiliated NAS operator.

1.2 Research Questions

This present research aims at investigating the integration of airport surface and terminal airspace in the presence of uncertainty. Evidence of benefits for airspace users from integrated operations have not been fully covered and limited methodologies have been developed. To support this evidence, a case study applied to the Los Angeles International airport and surrounding terminal airspace is undertaken. Our objective is to provide a fast-time decision support algorithm that schedule and route integrated operations in limited run times.

The present dissertation tackles the following research questions:

1. How can integrated operations support the efficiency of surface and air traffic management?

2. How can the integration of traffic uncertainty help improve flight on-time performance?

1.3 Thesis Contribution and Outline

The contributions of this research have two dimensions involving practical and theoretical challenges.

On one hand, the practical contributions include (1) supporting airport surface and terminal airspace operations, (2) improving operations efficiency, i.e. schedules and routings and their predictability, and (3) integrating uncertainty and implementing stochastic optimization procedures that are potentially tractable. With all three contributions combined, schedules and routings are experimentally shown to be more efficient than solutions from First-Come-First-Served approaches and more robust than solutions from deterministic optimization procedures. In addition, the case study is applied to realistic operational conditions where mixed operations are using a single runway.

On the other hand, the theoretical contributions include (1) developing a stochastic programming-based scheduling and routing model, (2) deriving an assembled methodology to solve complex stochastic programming under reasonable run times, and (3) introducing statistic bounds to assess the methodology performance. These three improvements lead to a fast-time decision support scheduling and routing based algorithm that can produce solutions in reasonable computation times.

This dissertation is structured as follows. In Chapter 2, a literature review of previous research undertaken on airport surface and terminal airspace scheduling and routings problems are presented. Additionally, the chapter reviews previous related work on machine job-shop scheduling problems and stochastic models, and solution procedures developed for aviation problems. In Chapter 3, an assembled methodology is derived to tackle the integration of airport surface and terminal airspace operations. Inspired from operations research, the modeling is first defined and followed by the problem statement, and problem formulation as a three-stage stochastic program. Finally, a solution methodology is proposed based on the Sample Average Approximation. The assembled methodology is applied to a Los Angeles case study in Chapter 4. This chapter contains the implementation of a simple problem serving as proof-of-concept that illustrates the evidence of integrated operation benefits, a data driven analysis of uncertainty sources in the Los Angeles environment and a solution methodology performance assessment. Using the solution methodology parameters computed in the previous chapter, Chapter 5 presents simulations of increasing traffic density for integrated operations. The benefits of this research approach are first demonstrated for integrated arrivals and departures, then for integrated surface and air operations. Concluding remarks are finally provided in Chapter 6 along with a summary of this thesis, operational implications in the field and directions for future research.

2. Literature Review

The literature review presented in this chapter is divided in four main sections that cover research topics pertinent to this research. Section 2.1 reviews previous scheduling work of flight operations from the airport surface to the terminal airspace. The review shows that most of the models developed so far are deterministic and that limited research was conducted on integrated operations of the airport surface and terminal airspace. In Section 2.2, machine job-shop scheduling models are reviewed and similarities between machine job-shop scheduling problems and flight operations scheduling problems are examined. In Section 2.3, methodologies used to solve aviation optimization problems with uncertainty are presented. In Section 6.1 a summary concludes the findings and highlights the research gaps that this thesis attempts to fill.

2.1 Scheduling of Flight Operations

In this research, flight operations are considered both on the ground and in the air, i.e. from the airport surface to the terminal airspace. The different associated scheduling problems are presented along with a review of the methodologies developed to solve the problems.

2.1.1 Airport Surface Scheduling and Routing

In current ground-side operations, wake vortex and traffic flow management separation requirements are imposed to separate aircraft on the runway and controllers issue advice on visual spatial separation to aircraft that are moving on the airport surface. However, regardless of the airport visibility conditions, this often results in uncoordinated movements and traffic congestion during peak hours because of the limited amount of available airport surface space. In the past decade, several research efforts have aimed at mitigating airport surface congestion by independently solving taxiway scheduling problems [2–5] and runway sequencing and scheduling problems [6, 7]. In more recent work, because taxiways and runways are undeniably linked in airport systems, researchers have been investigating scheduling and routing optimization models for the integrated taxiway and runway operations [8–10].

Taxiway Scheduling Problems

To reduce aircraft taxi times, optimization models have been applied at several airports such as the Amsterdam Airport Schiphol (AMS) in Europe [2] and the Dallas Forth Worth International Airport (DFW) in the United States [3,5]. The models presented below illustrate the research efforts that focused on solving taxiway scheduling problems applied on both continents.

Smeltink et al. [2] developed a Mixed-Integer-Linear-Programming (MILP) formulation to model aircraft movements on the airport surface. The formulation uses sequencing-based operations to compute optimal times along each aircraft route to maximize movements efficiency. The optimization model was applied to AMS and showed great taxi time potential improvements. Additionally, Roling et al. [4] constructed a MILP-based taxi-planning tool to better coordinate surface traffic movements. The algorithm extends previous work by Smeltink et al. [2] to include aircraft holding points and rerouting options.

Balakrishnan and Jung [3] derived an Integer-Programming formulation to optimize taxiway operations by utilizing surface control points such as controlled pushback and taxi reroutes. The algorithm was applied to the eastern half of DFW for different traffic densities. It was shown that average departure taxi times can be reduced with controlled pushback whereas average arrival taxi time can be reduced with taxi reroutes for high traffic densities. Additionally, Rathinam et al. [5] extended previous

MILP formulations of the aircraft taxi-scheduling problem by incorporating all safety constraints required to keep any two aircraft separated by a minimum distance at any time instant. The optimization model was applied to DFW and the computed solutions allowed a taxi time average of six minutes per aircraft when compared to a First-Come-First-Served algorithm (FCFS).

Runway Sequencing Problems

To optimize airport surface scheduling operations, researchers have also investigated the runway sequencing problem. Deau et al. [6] showed that during traffic peaks, runway sequencing influences the departure delay less than taxiway scheduling. Therefore, they developed several runway sequencing models (FCFS, genetic-based sequencer) to optimize the coupling of taxiway and runway operations. When applied to the Paris Charles de Gaulle Airport (CDG) and its taxiway schedules, it was found that significant ground delays reductions could be achieved with optimized runway sequences. Moreover, Sölveling et al. [7] derived a stochastic optimization framework to model runway operations in the presence of uncertainty. A two-stage formulation was used to model the runway scheduling problem. It was found that when the arrival and departure rates are high compared to runway capacity, average delay reductions could be achieved from runway sequences computed with the developed stochastic runway planner over solutions obtained with a FCFS methodology.

Sureshkumar [11] proposed a runway system model for optimal sequencing and runway assignment of arrivals and departures. Based on a branch-and-bound technique, the algorithm computes optimal runway sequences with minimal makespan at the Hartsfield-Jackson Atlanta International Airport (ATL). The lower and upper bounds of the cost of each branch are computed such that the FAA wake vortex separation minima are satisfied at all times. Different runway configurations were studied and it was shown that the model could significantly improve the runway operations by providing optimal runway sequences and assignments. Additionally, Ghoniem et al. [12] examined the combined arrival-departure aircraft runway sequencing problem. The problem was modeled using a modified variant of the asymmetric traveling salesman problem with time-windows and solved using a Mixed-Integer-Programming (MIP). For mixed operations on a single runway or on close parallel runways, the separation constraints between non-consecutive operations increased the complexity of the problem formulation. However, the modeling enabled the development of efficient preprocessing routines and probing procedures to enhance the problem solvability via tighter reformulations. The application was performed for the Doha International Airport (DOH) and two heuristics were also developed to further improve the solution computation. When compared to a FCFS algorithm with priority landing, the exact and heuristics solution methods report makespan reductions and limited aircraft position deviations.

Integrated Taxiway Scheduling and Runway Sequencing Problems

Because both taxiway and runway systems are dependent on each other, recent research investigated the integration of taxi and runway operations. Clearly, optimized taxiway schedules might not be optimal without considering runway sequences, while optimized runway sequences might not be optimal without proper taxiway routing and scheduling.

Clare and Richards [8] developed a MILP optimization method for the coupled problems of airport taxiway routing and runway scheduling; a receding horizon-based approach was used to formulate the problem. In this work, Clare and Richards fixed the runway sequencing and scheduling of arrivals and only dealt with the runway scheduling of departures. Moreover, the objective focused on optimizing taxiway operations of the London Heathrow Airport (LHR) and only runway operations were considered in the constraints. The receding horizon approach allowed the computations of aircraft taxi schedules at different airport network nodes but did not predict the aircraft runway sequence. By fixing landing times, the algorithm focused on computing taxiway schedules, resulting in suboptimal runway schedule.

Lee and Balakrishnan [9] investigated two different optimization models to simultaneously solve the taxiway and runway scheduling problem. A single MILP approach was first derived to solve the integrated airport surface scheduling problem whereas in a second approach, a sequential methodology was derived to combine the taxiway scheduling and runway scheduling algorithms. The first model extends the MILP formulation of the taxiway scheduling derived by Rathinam et al. [13] to the runway scheduling by introducing an additional term to minimize runway delays. The model adopts a rolling time horizon and accounts for existing flights taxiing on the surface. For high traffic demand, the model might require large computational times. Therefore two separate optimization models were derived for taxiway and runway schedulings. After estimating earliest runway arrival times for departures in Step 1, Step 2 optimizes the departure runway schedules using a runway scheduling algorithm. Then Step 3 optimizes the taxiway schedules using a MILP model. The application of both models to the Detroit Airport (DTW) showed that computed flight schedules could save taxi-out times and mitigate taxiway congestion. However, arrival flight schedules were not optimized in the study.

To reduce large number of decision variables related to the number of network nodes used to describe airports and the complexity associated with simultaneous optimization of both departure and arrival flights, Yu and Lau [10] proposed a set partitioning model for integrating taxiway routing and taxiway scheduling. Routing and scheduling decision variables are computed for each aircraft. Route paths, i.e. node sequences, are first generated by a shortest path algorithm and route schedules (passage times at each route node), then sequentially optimized at each node. The route-schedule cost computation consists of minimizing taxi times and schedule deviations for both arrival and departure flights. Preliminary results based on simulated data prove the feasibility and efficiency of the proposed methodology.

2.1.2 Terminal Airspace Scheduling

In current air-side operations, spatial separation strategies are applied to reduce interactions between traffic flows and to guarantee proper flight spacing. To manage the use of shared resources such as waypoints or route segments, controllers assign independent routes and fixes to arrival and departure flows. This separation strategy may introduce inefficiencies in the airspace usage with longer departure and arrival routes and altitude constraints. Over the past few decades, the air traffic management community has been conducting research to help improve the efficiency of terminal airspace operations by separately solving arrival scheduling problems [14–18] and departure scheduling problems [13,19,20]. Recently, researchers have been investigating the integration of arrival and departure operations, and its ability to improve operations efficiency has been demonstrated [21–27]. The dynamic nature of terminal areas pushed the research community to develop efficient aircraft routing and scheduling methods that also optimize the runway operations.

Arrival and Departure Scheduling Problems

One of the earliest studies on arrival scheduling was published by Dear in 1976 [14]. Dear solved the static arrival scheduling problem by generating aircraft sequences and schedules. To solve the dynamic arrival scheduling problem, the Constraint Position Shifting (CPS) framework was introduced by the author. The CPS process stipulates that the resulting sequence from a FCFS model might not be an optimal and fair solution for every aircraft. CPS constrains the number of positions that an aircraft can be shifted from its original FCFS position. To find the optimal sequence, all possible sequences are enumerated resulting in an unpractical method for a large number of aircraft. To reduce the computational complexity, Psaraftis [28] developed a dynamic programming method and Dear and Sherif [29] proposed heuristics to solve the single runway problem. Neuman and Erzberger [15] investigated various scheduling algorithms such as modified FCFS, modified CPS and modified time advance and analysed them with different traffic scenarios. Balakrishnan and Chandran [17] developed a modified version of the shortest path problem to model the aircraft landing problem and used dynamic programming to solve the runway scheduling problem.

A review of the literature shows that scheduling studies in flight operations have been mainly devoted to the aircraft landing problem. As an attempt to solve the departure scheduling problem, Rathinam et al. [13] improved and transformed the Psaraftis's dynamic programming approach into a generalized dynamic programming method. Instead of only minimizing the total delay, the authors formulated a multi-objective function that minimizes both the total delay and the departure time of the last departed aircraft. However, this optimization model lacks of the ability to assess the concept of departure queuing. To fill this gap, Gupta et al. [20] developed a MILP formulation that schedules aircraft departure deterministically. By investigating various aircraft queuing scenarios, they found that this approach minimizes delays and maximizes the runway throughput. Motivated by the London Heathrow Airport (LHR) taxiway layout, Atkin et al. [19] applied tabu search and simulated annealing heuristic techniques to solve a variant of the departure scheduling problem. Malik et al. [30] extended the aircraft departure problem by focusing on the taxi scheduling problem. A MILP algorithm was formulated to optimize the departure throughput airport surface by considering a gate release control strategy.

Most of the methods presented so far are deterministic and assume exact knowledge of arrival and departure flight times. Several exceptions can be found in the literature. Chandran and Balakrishnan [31] developed an algorithm that generates runway schedules of arrivals that are robust to perturbations caused by terminal airspace uncertainty. The CPS method is implemented with uncertainty in the estimated time of arrival flights. The error distribution is modeled as a triangular distribution with a range of ± 150 sec for aircraft equipped with a Flight Management System (FMS), and ± 300 sec for non-equipped aircraft. Additionally, Hu and Paolo [32] developed a genetic algorithm for arrival scheduling where 20% of uncertainty in the range of ± 5 minutes was introduced between iterations in the estimated time of arrival flights.

Integrated Terminal Airspace Operations Under Uncertainty

In metroplex areas, recent studies conducted by Capozzi et al. [21,22] showed that integrated departure and arrivals have the ability to improve terminal airspace operations efficiency. However, in terminal areas, flight schedules are subject to uncertainty which can be caused by inaccurate wind predictions, errors in aircraft dynamics or human factors when close to arrival or departure times. The integration of uncertainty in algorithm formulations is crucial to better reflect the reality of current air traffic operations. To address this, uncertainty analyses were conducted to help estimating the robustness of the solutions and benefits obtained. In arrival scheduling problems, Thipphavong et al. [33] used the Stochastic Terminal Arrival Scheduling Software (STASS) to study the relationship between uncertainty and system performance. For the integrated departures and arrivals problem, Xue et al. [25] analysed the impacts of flight time uncertainty on integrated schedule operations on a model of the Los Angeles terminal airspace. Using deterministic solutions as references and adding time perturbations to flight times, Monte Carlo simulations were performed to simulate controller interventions to resolve conflicts in the event of separation loss. It was shown that terminal airspace operations can be improved by the integration of arrivals and departures without dramatically increasing the controller workload and that uncertainty studies could be useful to decision makers to resolve separation conflicts. Additionally, Xue et al. [26] developed a genetic algorithm-based scheduler for integrated operations under uncertainty. The impacts of flight time uncertainty was analysed on the integrated schedule operations by investigating the impacts on delays and controller workloads. It was found that the results computed by the stochastic optimization could help identify compromise schedules for shared waypoints that reduce both delays and the number of controller interventions.

However, considering uncertainty in models can represent a computational challenge with a level of complexity that can prevent real-time applications and further developments. Previous work conducted by Bosson et al. [34] focused on minimizing computation time of the genetic-algorithm-based stochastic scheduler developed by Xue et al. [26] when dealing with uncertainty through the usage of Graphics Processing Units (GPU). GPU computing techniques enabled a fast decision support algorithm to schedule flights evolving in a mixed-environment sharing resources in the presence of uncertainty.

2.2 Machine Job-Shop Scheduling

Given the similarities to production or manufacturing operations scheduling problems, machine job-shop scheduling terminology can be used to describe airport scheduling problems. Beasley et al. [16] adapted the machine-scheduling model to solve the aircraft-sequencing problem and an analogy was made between the processing time of a job on a machine and the separation requirements between aircraft. Bianco et al. [35, 36] developed a combinatorial optimization approach to solve the aircraft-sequencing problem for arrival flows in the case of a single runway. The problem was modeled using n jobs (i.e. n aircraft) and a single machine (i.e. the runway) with processing times but no setup times were considered. Both job-shop and aircraft sequencing problems are time and sequence dependent. A review of the literature shows that many machine-scheduling models developed so far consider sequence-dependent setup times and most of them are deterministic. Theory and examples can be found in references published by Jain and Meeran [37], and Gupta and Smith [38]. The stochastic machine job-shop scheduling studies primarily focused on probabilistic processing times [39–41]. For example, considering random processing times, Soroush [41] minimized the early tardy job cost, while Jan [39] and Seo et al. [40] addressed the tardy minimization problem. However, the previous models considers deterministic due dates. But in the context of arrival and departure operations at airports, uncertainty affects the exact knowledge of operational factors such as pushback times or taxi times to the runway. In machine scheduling terminology, this can be referred to probabilistic release times and probabilistic due dates. Stochastic versions of such problems received limited attention and probabilistic release times and due dates were rarely introduced. One of the only models that considers both was developed by Wu and Zhou [42] to solve a single machine-scheduling problem. However, the model developed in that study does not include sequence-dependent setup times. The first attempt that considered sequence-dependent setup times and probabilistic release and due dates can be found in recent work by Sölveling et al. [43], who developed a runway planning optimization model.

2.3 Optimization with Uncertainty in Air Traffic Management

To facilitate the air traffic growth, optimization techniques have been applied to Air Traffic Management and air transportation applications. However, the performance improvements of the optimization algorithms are being slowed down by the consideration of uncertainty. Uncertainty comes from many sources: data availability, measurement errors, human factors, aircraft dynamics, wind prediction and weather forecast; these are difficult to model accurately. Integrating uncertainty can easily become a computational challenge that requires heuristics and advanced programming techniques to be solved. However, the integration of uncertainty in algorithms is crucial to better reflect the reality of current air traffic operations.

2.3.1 Modeling Optimization Problems with Uncertainty

As approach attempts to cope with the complexity of optimization problems under uncertainty, methodologies such as recourse-based stochastic programming, robust stochastic programming and probabilistic programming have been developed. Although optimization of stochastic terminal airspace operations has been receiving little attention, there are several references for other applications in ATM.

Richetta and Odoni [44] solved the Single Airport Ground Holding Problem (SAGHP) with a recourse-based stochastic programming whereas Ball et al. [45] addressed the SAGHP using an integer stochastic programming. Both formulations were solved by Linear Programming (LP). Mukherjee and Hansen [46] developed a stochastic programming method which was extended to solve the SAGHP under dynamic settings.

Mukherjee and Hansen [47] also addressed the Air Traffic Flow Management (ATFM) problem using linear dynamic stochastic optimization. Weather uncertainty was accounted through a scenario tree. Gupta and Bertsimas [48] formulated a multi-stage recourse and adaptive robust optimization to solve the ATFM problem. Clare and Richards [49] augmented MILP optimization with a chance-constraint-probabilistic programming method. In all previous cited works considering uncertainty, weather and unscheduled demand were the uncertain parameters considered.

Another way to accommodate for uncertainty in algorithms is to use buffering or probabilistic sampling techniques. Few research endeavors attempted to include uncertainty in the traffic operations optimization computation by the use of buffering techniques [50,51] or sampling methods [26,27]. Xue et al. [26] employed Monte Carlo simulations to represent the propagation of uncertainty in the flight times. Thousands of sampling points were used to run Monte Carlo simulations of the integrated arrival and departure scheduling. To optimize surface operations, several attempts investigated historical data of pushback times, taxi-out and runway schedules, and linear regression was applied to predict taxi times [52]. Whereas considering uncertainty allows for more realistic computations, it usually induces an increased computational effort that compromises real time implementations. Therefore solving such modeling in reasonable run times requires a trafeoff to be reach between formulation complexity and computational workload.

2.3.2 Solving Optimization Problems with Uncertainty

Researchers in Air Traffic Management (ATM) are deterred by large computational runtime that do not meet real-time requirements. Relaxation methods and heuristics have commonly been used to find integer solutions on sequential processors. However, computationally expensive general purpose applications are benefiting from the emergence of GPUs and parallel computing techniques. Many areas of study have already proven significant advantages of using GPUs (multitasking [53], medical application [54] or finance [55]). In ATM, few applications can be found. Tandale et al. [56], accelerated by 30 times a CPU implementation of a large-scale Traffic Flow Management (TFM) problem with $17,000$ aircraft. Bosson et al. [34] implemented on a GPU, an optimization model of integrated departures and arrivals under uncertainty solved by a non-sorted genetic algorithm. The GPU-based code resulted in a 637x speed up in Monte Carlo simulations that handle uncertainty cost computation and a 154x speed up for the entire algorithm.

2.4 Summary

Aircraft scheduling problems have been mainly examined from the runway perspective because the runway has been identified as the main source of the NAS-wide delay [57]. The different reviewed algorithms were mainly applied deterministically to the scheduling problems assuming that all inputs are known before running the algorithms. For the airport surface operations, most of the studies considered either taxiway scheduling or runway sequencing and limited attention was given to the integration of both problems. Previous work independently optimizes the taxiway and runway schedules which often results in suboptimal solutions. Additionally for the terminal airspace operations, most of the studies considered either the arrival scheduling problem or the departure scheduling problem, but not the integrated departures and arrivals problem. These formulations assume that there are no interactions between the arrival and departure aircraft sequences. For the integration of both airport surface and terminal airspace operations, conceptual frameworks were discussed in the literature. Zelinski [58] proposed a framework for integrating scheduling between Arrival, Departure, and Surface (IADS) operations to address the drawbacks of domain segregated scheduling. Zelinski suggested a time-based decomposition rather than a domain-based decomposition. Simons [59] presented a functional analysis of a concept for IADS operations in which integrated schedules would define crossing times for points within the arrival or departure airspace, and on the airport surface. To the author's knowledge, no paper was found that presents the implementation of a scheduling methodology that integrates both the airport surface and the terminal airspace operations.

A few attempts [26, 43] were found that integrate uncertainty in flight scheduling computations, but they often resulted in significant computational complexity and unrealistic runtime. This literature review highlights the lack of stochastic models for airport surface and terminal airspace operations. Additionally, it shows too few job-shop machine scheduling models that consider both probabilistic processing and releasing times.

It is also worth noting that so far, no frameworks or models capable of optimizing integrated airport surface and terminal airspace operations under uncertainty have been reported in the literature. Moreover, implementation of scheduling optimization under uncertainty benefiting from parallel computing techniques has not received major attention.

3. An Assembled Methodology to Tackle the Integration of Airport Surface and Terminal Airspace Operations

In this chapter, an assembled methodology is constructed and derived to tackle the integration of airport surface and terminal airspace operations. In the preliminary, some assumptions are made to set up the problem. Inspired from manufacturing operations, a scheduler is built using machine job-shop scheduling modeling. A multi-stage stochastic programming approach is chosen to formulate the problem because of its ability to handle multi-objectives and multiple constraints. Then, a sampling method is implemented coupled to a multi-threading approach to solve the problem in the presence of uncertainty.

3.1 Problem Setup

3.1.1 Aircraft Weight Classification

During all flying phases, aircraft generate wake vortices of different strengths and intensities, which mainly depend on aircraft weight. Therefore, this research considers different weight-based aircraft types defined according to the Federal Aviation Administration (FAA) aircraft weight classification [60]. The standard defines three aircraft weight categories, small (S), large (L) and heavy (H). In addition, the Boeing 757 is often considered as category. The weight of the Boeing 757 is in the large class, yet it's wake is the size of a heavy's wake. Recently a fifth category, called Super, was added with the introduction of the A380 in the NAS, but in this research this aircraft type is not considered [61]. Therefore, four categories, denoted S, 7, L and H, are considered in this thesis.

3.1.2 Surface and Airspace Route Network Model

Operations on the airport surface are characterized by aircraft movements in gate areas, along the taxiway system and at the runways, which are strongly influenced by terminal area operations.

On the airport surface, aircraft are guided on the taxiway system from a surface origin to a surface destination. In particular, arrival flights are routed from runways to assigned gates whereas departure flights are routed from departure gates to runways. Taxi routes are specified by a sequence of surface waypoints that often include taxiway intersections. Therefore, the surface route network is defined by the taxiway system and the ramp areas of the airport layout considered. The airport network layout is described using surface waypoints and taxiway segments. Gates, taxiway intersections and runway thresholds are represented by surface waypoints and taxiway segments do not necessarily all have the same length.

For the air-side operations, aircraft are advised to fly along paths that are characterized by different flight plans. Therefore, the air route network is defined by the terminal airspace departure and arrival routes. Because Standard Terminal Arrival Routes (STARs) and Standard Instrumental Departures (SIDs) procedures need to be flown by aircraft when flying within the terminal airspace, these procedures are used in this work to define the airspace routes as ordered sequence of air waypoints. Meter fixes and air waypoints are linked by flight plan segments and they do not not necessarily all have the same length.

The ground and air network models are connected at the runway.

3.1.3 Aircraft Separation

In current ground-side operations, wake vortex and traffic flow management separation requirements are imposed to separate aircraft on the runway and controllers issue advice on visual spatial separation to aircraft that are moving on the airport surface. Typically, aircraft movements are controlled by FAA controllers on the taxiway system and by airline controllers on the ramp areas. In both zones, spatial separations are communicated by the controllers to the pilots to ensure aircraft spacing and colison-free displacements. However, this often results in uncoordinated movements and traffic congestion during peak hours because of the limited amount of available airport surface space.

In current air-side operations in the terminal airspace, the FAA defines aircraft separation distances that need to be enforced between aircraft at all times [60]. Controllers spatially separate aircraft flying on the same traffic flow by imposing these separation requirements. Moreover, controllers also spatially segregate arrival and departure flows by assigning them independent routes to fly. These spatial separation strategies are enforced to reduce interactions between traffic flows and to guarantee proper flight spacing. This however often introduces inefficiencies in the airspace usage with longer flight routes and altitude constraints.

To mitigate such constraints and allow some flexibility in future operations, this work integrates ground and air operations by implementing a temporal control separation strategy that converts separation requirements prescribed in distance to time scale using the aircraft speeds. In this work, three types of separation requirements are considered that depend on the aircraft situation. It is assumed that all aircraft move on the ground withing a defined ground speed range. In the air, it is assumed that aircraft speed ranges are different for departures and arrivals.

First, according to Roling et al. [4], any pair of aircraft must always be separated on the airport surface by a minimum distance of 200 meters when moving along the taxiways. This fixed separation is converted into time via the speed of the leading aircraft of each pair. Second, on the runway, minimum inter-operation spacings for wake separation must be enforced between any two aircraft [60, 62]. But because the sequence of aircraft weight-class determines wake vortex separation requirements, the requirements are asymmetric at the runway. If a large aircraft leads a small, the separation requirement will be greater than the opposite because large aircraft produce larger wake turbulences than small aircraft. Finally in the air, according to

Capozzi et al. [21] all aircraft pairs are separated by a fixed separation distance of 4 nautical miles (nmi) that is converted into time via the speed of the leading aircraft of each pair.

3.1.4 Uncertainty Considerations

On the airport surface and in the terminal airspace, flight schedules are subject to uncertainties that come from many sources such as human factors, errors in aircraft dynamics or inaccurate wind predictions. The potential start and end times of an aircraft taxi operations are constrained by gate and runway schedules. These schedules are determined by a combination of flight schedules and gate turnaround operations that are provided by the airlines and are therefore affected by uncertainty. In this research, in order to better reflect the reality of current surface and air traffic operations, uncertainty is added to the flight time schedules by introducing errors that follow probabilistic distributions. Details about the distributions will be provided in a later chapter. As a consequence, speed clearances might be issued to prevent any loss of separations between aircraft.

3.2 Modeling Definitions

3.2.1 Background

Due to similarities with production and manufacturing operations, the integrated airport surface and terminal airspace operations can be described using machine job-shop scheduling terminology. In this section, a machine job-shop scheduling formulation is derived and adapted to model the routing, sequencing and scheduling of aircraft when integrating flights using shared resources. To emphasize the mapping of the technique to this application, machine job-shop scheduling notations are used to described the modeling in this section these are mentioned in parenthesis.

3.2.2 Modeling

A scheduler is built to schedule and route a set of aircraft (set of jobs) evolving on the airport surface and the terminal airspace in a given planning horizon (e.g. from $9:00$AM to $9:30$AM) in which waypoints (machines) are shared by departures and arrivals. The set of aircraft is denoted as AC and each aircraft $j \in AC$ belongs to an aircraft category (job category) defined by a specific type T. An aircraft type is twofold, it is represented by a weight class $C = \{H, 7, L, S\}$ and an operation $O = \{A, D\}$, where A stands for arrival and D for departure. For example, a large departing aircraft and a small arriving aircraft have their types respectively denoted by T_{LD} and T_{SA}. The set of all weight-operation combinations forms the aircraft type set K, i.e. $K = \{T_{pq}, p \in C, q \in O\}$. On the airport surface, each aircraft moves on the taxiway system from the ramp areas to the runway and vice versa. Surface routes are defined by operated taxi routes of the considered airport and each surface waypoint (surface machine) $i_{surface} \in I_{surface}$. In the terminal airspace, each aircraft flies a route that is defined by a flight plan, i.e. sequence of air waypoints (sequence of air machines). Air routes are defined by the Standard Instrument Departures (SIDs) and the Standard Terminal Arrival Routes (STARs) waypoints of the considered terminal airspace and each air waypoint $i_{air} \in I_{air}$. The entire set of waypoints is denoted by I and each waypoint $i \in I$. It combines the sets of all air and surface waypoints such that $I = I_{air} \cup I_{surface}$. Denote respectively as *entry* and *exit*, the first and last waypoint of each aircraft route such that $entry \in I$ and $exit \in I$.

Additionally, define as release time and due date schedules, the aircraft schedules respectively at *entry* and *exit* waypoints. For each aircraft $j \in AC$, denote respectively as r_{ji} and d_{ji}, a scheduled release time and a scheduled due date at waypoint i. The aircraft release time corresponds to when the aircraft is expected to enter the airspace considered. Hence, for arrival flights, the release time is when aircraft are expected to fly by the first waypoint of the arrival route (i.e. first arrival fix), and it is the estimated pushback time from the gates for departing flights. The aircraft due dates corresponds to times at which aircraft are expected to exit the considered surface and airspace network. Therefore, the due date is defined as the estimated time of gate arrival for an arrival and as the fly by time of the last waypoint of the departure route for a departure (i.e. last departure fix). Moreover, a processing time is defined at each waypoint of the route traveled. A processing time p_{ji} is defined by the time aircraft j, $j \in AC$ is being processed by waypoint i, $i \in I$. Each waypoint can only process one aircraft at a time and each aircraft can only travel by one waypoint at a time. Therefore in this model, a processing time is defined as a waypoint block time and depends on the separation time requirements between type-based aircraft pairs. To determine the waypoint block time for an aircraft, the model identifies the type of the following aircraft. Then using the types of the aircraft forming the aircraft pair, it computes the separation time requirement. On the ground, waypoint block times are computed by converting the ground separation distance to ground separation time via the speed of the leading aircraft of each pair. At the runway, wake vortex separation times define the runway block times. However in the air, waypoint block times are determined by the conversion of distance separations to temporal separations via the speed of the leading aircraft. In operations, based on the aircraft leader's speed, updated speed clearances are given on the ground and in the air to the following aircraft to maintain separation.

In operations, aircraft do not necessarily take-off at their ETDs and land at their ETAs because flight times are sensitive to uncertainty. To model the perturbations, error sources following probabilistic distributions are added to release times and due dates. Several sets of schedules can be generated using this method to study the impact of uncertainty on actual departure and arrival times. Denote respectively as aircraft starting time and aircraft completion time, the actual times at which aircraft respectively enter and exit the considered surface and airspace network. For each set of schedules generated, the optimization will compute these times for each aircraft $j \in AC$ and they are respectively referred as t_{jentry} and t_{jexit}.

To illustrate the different terms and notations introduced, two waypoint timelines are drawn in Figure 3.1.

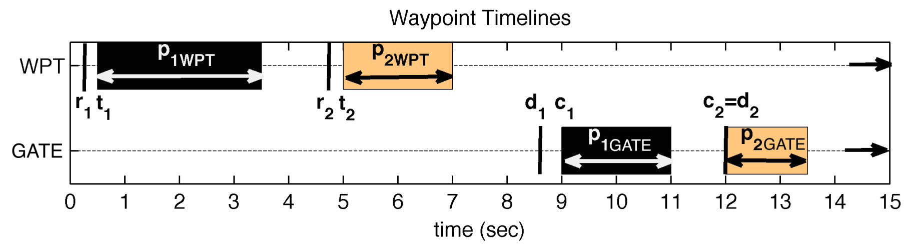


Figure 3.1. Waypoint Timelines With Two Arrivals

Each row corresponds to a timeline associated with a waypoint and for simplicity only two waypoints, WPT and $Gate$, are considered. In this simple example, two arrival flights of types T_{LA} and T_{SA} are being scheduled. Both aircraft arrive at waypoint WPT later than their respective release time ($t_{1entry} > r_{1entry}$ and $t_{2entry} > r_{2entry}$) because of uncertainty. At the arrival gate, the first aircraft arrives later than its estimated time of arrival ($t_{1exit} > d_{1exit}$) whereas the second aircraft is on-time $t_{2exit} = d_{2exit}$). For the two timelines, waypoint processing times p_{ji}, where $i = \{1, 2\}$ and $j = \{WPT, Gate\}$, are represented by blocks of different lengths.

3.3 Optimization Model

To optimally integrate terminal airspace and airport surface operations, a single optimization model is created. In this section, the problem is first stated then formulated. A Mixed-Integer-Linear-Programming (MILP) model for scheduling and routing is proposed in this thesis.

3.3.1 Problem Statement

This thesis addresses the integrated airport surface and terminal airspace operations problem with uncertainty considerations. Given a set of aircraft $AC = \{1, ..., n\}$ navigating in a defined terminal airspace containing both arrival and departure flights to and from a given airport within a 30-minute time period, the objective is to compute optimal schedules and routings for each aircraft such that both the total flight plus taxi times of all aircraft and the impact of uncertainty are minimized, subject to the following constraints:

1. Runway Constraints: the number of runway slots by aircraft type is equal to the number of aircraft for each type considered. A runway can only be occupied by one aircraft at any time. Each aircraft must be separated by the minimum wake vortex separation (converted to time) at the runway threshold.

2. Waypoint Capacity Constraints: both in the air and on the surface, waypoints can only process one aircraft at a time and aircraft must be separated at any time by a minimum distance (or time) from any other aircraft.

3. Waypoint Precedence Constraints: when assigned to a route (air or surface), aircraft have to follow the waypoints defining the route in order.

4. Speed Constraints: both in the air and on the surface, aircraft speeds must remain appropriately limited by minimum and maximum allowable speeds.

5. Schedule Timing Constraints: release times and due dates respectively define origin and destination times and must be met as closely as possible.

This problem statement holds under the following set of assumptions:

- The surface and air route network are respectively defined by the airport network layout and the terminal airspace departure and arrival routes. The airport layout is described using surface waypoints and taxiway segments and the terminal departure and arrival routes are described by the STARs and SIDs procedure waypoints. In operations, airports have standard taxi routes, therefore a set of predefined taxi routes is generated connecting gates to runways and vice versa. For the terminal airspace, a set of STARs and SIDs procedures are selected to generate the set of predefined air routes. In this work, it is assumed that the gate assignment is determined for all flights prior to running the optimization and used as input in simulation runs. Additionally, when a gate is assigned to a flight, it is always assumed to be available when needed and no gating overlap issues are considered.

- The minimum separations on the runway are computed using the combination of rules of wake vortex separation and one aircraft on the runway at any given time.

- Aircraft must be separated on the surface and in the air from any other aircraft by a minimum distance that is converted into minimum separation time at the different surface/air waypoints using the length of taxiway/flight plan segments and aircraft speeds.

- Aircraft enter and leave the portion of considered surface/airspace through entry and exit waypoints. Departure flight trajectories originate at gates and finish at the last air waypoints of departure routes. Arrival flight trajectories originate at the first air waypoints of arrival routes and finish at gates.

- A reference schedule for gate pushback, gate arrival and entry/exit air waypoint times are assumed to be known. An uncertainty analysis using historical data is performed to draw the probabilistic distributions describing surface and air schedule perturbations.

3.3.2 Multi-Stage Stochastic Problem Formulation

To solve the problem previously stated in the presence of uncertainty using the modeling previously defined, the optimization problem is formulated as a multi-stage stochastic program.

Decision Variables

The optimization model has two types of decision variables. Temporal variables are used to save aircraft times at waypoints along surface taxi routes and flying paths and are denoted t_{ji} where $j \in AC$ and $i \in I$. Binary spatial variables are used to establish the aircraft routes in the air and on the surface.

Objective

Integrating airport surface and terminal airspace operations for the problem previously stated in this research, consists of the minimization of a threefold objective. For efficient scheduling, the optimization model is designed to minimize the sum of total travel times in the air and on the surface, i.e. flying times plus taxi times, and maximize the on-time performance of the flights considered within a given time window for optimization. To maximize the on-time performance of the flights considered, the earliness and tardiness of each flight must be minimized. In this problem formulation, the earliness and tardiness of each flight is minimized at entry and exit waypoints.

Because information about aircraft and schedules received by air traffic controllers becomes more certain the closer aircraft are to execution, air traffic controller is more likely to know with high accuracy the aircraft type mix of the aircraft set that will depart or arrive in the next 30 minutes than the exact arrival and departure times of each aircraft. Therefore, a decomposition by stage is appropriate and the objective function of the stochastic scheduling is decomposed in three stages.

Stage 1 Due to wake vortex separation requirements, the runway capacity directly depends on the aircraft weight sequence. Hence, stage 1 is a runway sequencer and uses a reference schedule to compute the optimal sequence of aircraft types (i.e. weight and operation) at the runway threshold such that the total sum of travel times is minimized. Stage 1 is purely deterministic and is not affected by uncertainty.

The output of the program defining the optimal aircraft type sequence at the runway is a vector $x_{i=RWY,T}$ which can be described by the sequence of aircraft positions at the runway, i.e. $x_{i=RWY,T} = (T_{CO}^{(1)}, ..., T_{CO}^{(p)}, ..., T_{CO}^{(n)})$ where p is the position such that $\max(p) = n$ and T_{CO} is the type of the aircraft having a weight class C and an operation O. Define as n_T the number of aircraft per type T. Denote χ as the set of all possible sequences and $x \in \chi$. The objective of this stage is formulated in Equation 3.1.

$$f_1(x) = \sum_{j=1}^{n} (t_{jexit} - t_{jentry}) \; \forall j \in AC \tag{3.1}$$

Stage 1 computes the optimal aircraft type runway slots ordering.

Stage 2 Using an input set of release schedule scenarios, stage 2 assigns flights to the aircraft type runway slots determined by stage 1 such that the earliness and tardiness of optimized release times are minimized. At that point, the program does not know the due dates. The goal is to process the aircraft as soon as possible after their release times in order to minimize the amount of flight delay at release (i.e. minimize the difference between each aircraft start time and release time). The objective of this stage is formulated in Equation 3.2.

$$f_2(x) = \sum_{j=1}^{n} (\alpha_j \max\{r_{jentry} - t_{jentry}, 0\} \; + \; \beta_j \max\{t_{jentry} - r_{jentry}, 0\}) \; \forall j \in AC \tag{3.2}$$

where $\{\alpha_j, \beta_j\}$ represents the earliness and tardiness costs at entry waypoints of aircraft $j \in AC$.

Stage 2 schedules and routes the aircraft using different release time schedule scenarios as input. Because release times may be affected by uncertainty, errors that follow probabilistic distributions are introduced in the release times. Several scenarios, each representing a set of perturbed release times, are generated and tested.

Stage 3 Stage 3 focuses on adjusting the flight assignments performed in stage 2 using an input set of due date schedule scenarios such that the earliness and tardiness of optimized complete times are minimized. The routing and scheduling of each considered flight is optimized using different due date schedule scenarios in order to maximize the on-time performance of each aircraft at its exit. Because due dates may be affected by uncertainty, errors that follow probabilistic distributions are introduced in the due dates. The schedule and route of the objective of this stage is formulated in Equation 3.3.

$$f_3(x) = \sum_{j=1}^{n}(\gamma_j \max\{d_{jexit} - t_{jexit}, 0\} \; + \; \delta_j \max\{t_{jexit} - d_{jexit}, 0\}) \; \forall j \in AC \qquad (3.3)$$

where $\{\gamma_j, \delta_j\}$ represents the earliness and tardiness costs at exit waypoints of aircraft $j \in AC$.

To compute robust schedules, several scenarios corresponding to different sets of due dates are generated and tested in this last stage.

Embedded 3-Stage Given the described structure, the scheduling and routing problem is formulated as a 3-stage stochastic program.

To account for uncertainty, it is assumed that release times r_{jentry} and flight due dates d_{jexit} are not known with certainty. It is assumed that error sources that follow discrete and finite probabilistic distributions are added to the different release times and flight due dates. A scenario ω_l is a vector of perturbed flight times r'_{jentry} if $l = r$ or d'_{jexit} if $l = d$ (i.e. $r'_{jentry} = r_{jentry} + \xi_{j_r}$ or $d'_{jexit} = d_{exit}j + \xi_{j_d}$) with a corresponding probability of occurrence. Let $\xi_l = \{\xi_{1_l}, ..., \xi_{m_l}\}$ be the vector of perturbations ξ_{j_l} for scenarios of type l, $l \in \{r, d\}$ where m_l is the number of scenarios of type l. Finally, denote Ω_l as the set of all scenarios of type l, $l \in \{r, d\}$ such that $\Omega_l = \{\omega_{1_l}, ..., \omega_{m_l}\}$, where each scenario has a probability of occurrence ρ_{ω_l}.

The errors affecting the release times and the due dates are respectively introduced in the notations with ξ_r and ξ_d. Details about the uncertainty handling will be provided later on in this thesis. The embedded 3-stage objective function of the optimization problem is formulated as an expected value cost function to consider all scenario occurrences. in Equation 3.4.

$$\underset{x \in \chi}{\text{Objective}} = \lambda_1 f_1(x) + \mathrm{E}_{\xi_r}\left[\lambda_2 f_2(x, \xi_r) + \mathrm{E}_{\xi_d}[\lambda_3 f_3(x, \xi_d)]\right] \tag{3.4}$$

where $f_1(x)$, $f_2(x, \xi_r)$ and $f_3(x, \xi_d)$ are the respectve objectives of stage 1, 2 and 3 expressed in Equations 3.1, 3.2 and 3.3. The variables denoted by λ represent the relative objective weights of each goal and each $\lambda \in [0, 1]$.

Using the linear property of expectation value, the objective function of the MILP model becomes a weighted sum of three terms in which stages 2 and 3 are dependent.

Outputs

For each aircraft of the set considered, the outputs of the optimization provide feasible air and surface routings as well as feasible schedules.

Constraints

The optimization model includes several constraints that need to be enforced to ensure feasible operations both in the air and on the surface.

Runway Constraints: The first runway constraint expressed in Equation 3.5 and the second runway constraint expressed in Equation 3.6 ensure that the number of runway slots for each aircraft type is equal to the number of aircraft of each type, n_T, in the input data set and that only one aircraft j is assigned per runway slot at RWY. Using the defined notations, $x_{i=RWY,T} = 1$ if runway slot $i = RWY$ is used by aircraft type T and 0 otherwise.

$$\sum_{i=RWY \in I} x_{i=RWY,T} = n_T, \quad \forall T \in K \tag{3.5}$$

$$\sum_{T \in K} x_{i=RWY,T} = 1, \quad \forall i = RWY \in I \tag{3.6}$$

The third runway constraint expressed in the Inequality 3.7 ensures that the runway separation requirements are met by enforcing the wake vortex separations. Consider any two aircraft j_1 and j_2 of the aircraft set AC. Let $sep_{i=RWY}^{j_1 j_2}$ be the minimum runway separation time enforced between aircraft j_1 and j_2. Denote as b a binary variable that ensures that only one inequality is satisfied at a time per aircraft pair.

$$\begin{aligned} &\forall j_1, j_2 \in AC, j_1 \neq j_2, \\ &t_{j_1 i} \geq b(t_{j_2 i} + sep_{i=RWY}^{j_1 j_2}) \\ &t_{j_2 i} \geq (1-b)(t_{j_1 i} + sep_{i=RWY}^{j_2 j_1}) \end{aligned} \tag{3.7}$$

Waypoint Capacity Constraints: The waypoint capacity constraints impose that only one aircraft can be processed by a waypoint at a time. This is accomplished by imposing separation requirements between aircraft at each waypoint. Consider any two aircraft j_1 and j_2 of the aircraft set AC. Let $sep_i^{j_1 j_2}$ be the minimum separation time enforced between aircraft j_1 and j_2 at waypoint i. Denote as b a binary variable that ensures that only one inequality is satisfied at a time per aircraft pair. In this research, aircraft can be routed on different routes R_j. Therefore, define as M_1 and M_2, two penalty terms that enforces the aircraft separation as a function of the route R_j assigned to aircraft j. The following Equation 3.8 expresses the waypoint capacity constraints.

$$\begin{aligned} &\forall j_1, j_2 \in AC, j_1 \neq j_2, \forall i \in R_{j_1} \cup R_{j_2} \\ &t_{j_1 i} \geq -M_1 + b(t_{j_2 i} + sep_i^{j_1 j_2} \\ &t_{j_2 i} \geq -M_2 + (1-b)(t_{j_1 i} + sep_i^{j_2 j_1}) \end{aligned} \tag{3.8}$$

Waypoint Precedence and Speed Constraints: The waypoint precedence constraints and the speed constraints are naturally linked together. They enforce that the sequence of waypoints that defines the assigned route is followed in order by the aircraft while ensuring that aircraft speeds remain in a feasible range along the flight segments and taxiway segments. A route R_j assigned to aircraft j is an ordered set of waypoints defining that route. Given a waypoint i, $i \in I$, $i+1$ is the next waypoint in R_j. Denote as v_{ji} the speed of aircraft j, $j \in AC$ at waypoint i, $i \in I$ and let $l_{i \leftrightarrow +1}$ be the length of segment linking waypoint i and $i+1$ in the assigned route. The following Equation 3.9 expresses the waypoint precedence constraints and the speed constraints.

$$\forall j \in AC, \forall i \in R_j, v_{ji} \in [v_i^{min}, v_i^{max}] \quad t_{ji+1} \geq t_{ji} + \frac{l_{i \leftrightarrow +1}}{v_{ji}} \tag{3.9}$$

The minimum and maximum speeds $[v_i^{min}, v_i^{max}]$ differ depending on the aircraft type and on whether the route is on the surface or in the air.

Schedule Constraints: The release times at entry waypoint and due dates at exit waypoint constrain aircraft operation timing variables. Because of uncertainty, the actual aircraft release times and due dates might differ from schedule. On one hand, departing aircraft must reach their entry waypoint near their pushback times ($\forall q_j = D, r_{jentry} = PBT_j$) whereas arriving aircraft must reach their entry waypoint near their scheduled arrival times ($\forall q_j = A, r_{jentry} = SAT_j$). On the other hand, departing aircraft must reach their exit waypoint near their scheduled departure times ($\forall q_j = D, d_{jexit} = SDT_j$) whereas arriving aircraft must reach their exit waypoint near their scheduled arrival gate time ($\forall q_j = A, d_{jexit} = SGT_j$). In this problem formulation, it is assumed that optimized release times cannot be earlier than scheduled pushback times, therefore $\forall q_j = D,\ j \in AC,\ \alpha_j = 0$. Similarly, it is assumed that no arrival can reach its assigned gate before its scheduled gate time, thus $\forall q_j = A,\ j \in AC,\ \delta_j = 0$.

Remarks on constraints: The combination of waypoint capacity and waypoint precedence constraints ensures that aircraft are sequenced when two aircraft reach the same waypoint at the same time and that there is no overtaking of the waypoint. In particular, if two aircraft follow each other on the same segment and travel at different speeds, the aircraft order at the entrance of the segment is maintained at the exit of the segment.

3.4 Solution Methodology

To evaluate the solution of the optimization model formulation and obtain optimal candidate solutions, many schedule scenarios have to be generated and tested. However, this would require a significant computational effort. Therefore, a sampling method is introduced to reduce the size of the scenario set to a manageable size. The Sample Average Approximation (SAA) is chosen as the solution methodology and allows the replacement of the expectation formulation of the stochastic program by its sample average. As a consequence, assuming that the random variables used to perturb the schedule scenarios follow discrete distributions with finite support, the expectation formulation can be replaced by a finite sum and the probability of occurrence of each scenario is given by one over the total number of scenarios.

3.4.1 Sample Average Approximation

The solution methodology chosen to solve the 3-stage stochastic program is the Sample Average Approximation (SAA) method. Assuming that samples $\xi^1, ..., \xi^N$ can be generated from a random vector ξ, where N is the sample size, the SAA method is a Monte Carlo based technique that approximates a stochastic program by replacing the expectation by its sample average. The stochastic program is thus replaced by a sample average approximation that can be solved by a deterministic optimization algorithm. In this problem, because two random vectors ξ_r and ξ_d are considered, denote N_r and N_d as the respective number of replications of the random vectors. Therefore, the SAA problem for the 3-stage stochastic program can be defined as in Equation 3.10.

$$\underset{x \in \chi}{\text{Minimize}} f_1(x) + \frac{1}{N_r} \sum_{j=1}^{N_r} \Big(f_2(x, \xi) + \frac{1}{N_d} \sum_{j=1}^{N_d} f_3(x, \xi_d) \Big) \tag{3.10}$$

where f_1, f_2 and f_3 are respectively defined by Equations 3.1, 3.2, and 3.3.

In this research, because it is assumed that the random vectors ξ_r and ξ_d follow discrete distributions with finite support of respective size m_r and m_d, each element of the respective finite supports $\{\xi_{1_r}, ..., \xi_{m_r}\}$ and $\{\xi_{1_d}, ..., \xi_{m_d}\}$ has respective probability $p_{1_r}, ..., p_{m_r}$ and $p_{1_d}, ..., p_{m_d}$. The expected value problem can then be replaced by its equivalent using probabilities and the SAA problem for the 3-stage stochastic program can be re-written as in Equation 3.11.

$$\underset{x \in \chi}{\text{Minimize}} f_1(x) + \sum_{j=1}^{N_r} p_{n_r} \Big(f_2(x, \xi) + \sum_{j=1}^{N_d} p_{n_d} f_3(x, \xi_d) \Big) \tag{3.11}$$

where $f_1(x)$, $f_2(x, \xi_r)$ and $f_3(x, \xi_d)$ are the respective objectives of stage 1, 2 and 3 expressed in Equations 3.1, 3.2 and 3.3. Equation 3.11 equivalent to $\underset{x \in \chi}{\text{Minimize}}\ \hat{g}(x)$.

In summary, the proposed approach approximates the true stochastic problem defined by Equations 3.1, 3.2, 3.3 and 3.4 by a SAA problem defined in Equation 3.10. Denote ν^* and $\hat{\nu}$ as respectively the optimal objective function value of the true problem and the optimal objective function value of the SAA problem. Shapiro and Homem-de-Mello [63] showed that $\hat{\nu}$ converges to ν^* with probability approaching one as the sample size increases (i.e. $N_r \rightarrow \infty$ and $N_d \rightarrow \infty$ in this problem). However increasing the number of random vector realizations introduces large computational times. Therefore, the proposed methodology suggests solving several SAA problems with smaller sample size rather than solving one SAA problem with a large number of random vector realizations. Define M as the number of SAA problem independent replications. As defined previously, recall that m_r and m_d are the respective finite number of realizations (or scenarios) in stage 2 and stage 3. The following steps summarize the proposed solution methodology using the SAA method:

1. For each repetition $m = [1, M]$:

(a) Generate m_r and m_d independently and identically distributed scenarios for each flight.

(b) For each fixed scenario $m_1 = [1, m_r]$:

i. Solve the 3-stage program, store the optimal solution for each scenario, $m_2 = [1, m_d]$, and compute statistical upper bounds.

ii. A list of m_d solutions is obtained. Save the solution (i.e. sequence, schedule and routing) with minimum objective function.

(c) A list of m_r solutions is obtained. Save the solution (i.e. sequence, schedule and routing) with minimum objective function.

2. A list of M candidate solutions is obtained. Compute statistical lower bounds.

3. For each of the M solutions, compute the optimality gap and estimated variances. Choose the solution according to specific optimization goals.

The problem is formulated as a mixed-integer linear program (MILP), therefore a global solution will be computed for each repetition. However, the values of parameters M, m_r and m_d affect the robustness of the computed optimal solutions and the computation time. Hence, their adjustments are studied through a statistic sensitivity analysis for which the results are presented in a later chapter.

3.4.2 Implementation

The mathematical model of the mixed-integer linear program is implemented in Python [64] and Gurobi [65] is used as the optimization solver. The branch and bound algorithm is selected to solve step A.(b).i of the proposed methodology. The code is run on a Macintosh platform with 2.5GHz Intel Core i5 and 16 GB RAM. To accelerate the computation time, a multi-threading approach is implemented to compute each repetition individually with one thread. Note that the relative weight λs, $\lambda \in [0, 1]$ are set to 1 in this particular implementation.

4. Application: A Los Angeles Case Study

The Los Angeles International Airport (LAX) and its surrounding terminal airspace have an interesting layout that offers room for potential operational improvements. Therefore, the proposed methodology is applied to a Los Angeles case study which is described in this chapter. In Section 4.1, the LAX airport surface and surrounding terminal airspace network layouts are first described. Then in Section 4.2, the Los Angeles problem formulation is provided along with the adapted mathematical derivations. A proof-of-concept study supporting the evidence of integrated operations benefits for the Los Angeles case study is conducted in Section 4.3. This study focuses on exemplifying the benefits of integrated operations over First-Come-First-Served operations and deterministic conditions are implemented. To model the uncertainty affecting the considered Los Angeles environment, a data driven analysis of uncertainty sources is then conducted in Section 4.4. In Section 4.5, the methodology performance is assessed in the presence of uncertainty with a sensitivity analysis.

4.1 Los Angeles International Airport Surface and Surrounding Terminal Airspace Network Layout

In this section, the LAX airport surface and surrounding terminal airspace are described along with their associated surface and air route network layout representations. The airport surface and terminal airspace network layouts are described by a set of nodes and links respectively denoted by waypoints (surface and air) and segments (taxiway and flight).

4.1.1 Airport Surface Description

LAX is a major airport in the United States characterized by busy activities (commercial and cargo), large numbers of travelling passengers and aircraft movements, i.e. takeoff and landing. As of today, LAX is the 5th busiest airport in the world with 16,416,281 passengers that travelled this year as of March 2015 [66]. LAX has nine passenger terminals, eight domestic and one international called the Tom Bradley International Terminal (TBIT). The airport has four parallel runways organised in pairs. In the northern airfield, operational runways are 6R/24L and 6L/24R and in the southern airfield, operational runways are 7R/25L and 7L/25R. In current operations at LAX, both sets of parallel runways are in operation, and most commonly outboard operations are arrivals and inboard operations are departures.

This research focuses only on the northern airfield. Although it is not necessarily common practice at LAX, departures and arrivals are considered to operate on the same runway 24L to show the benefits of integrated operations. In the airport surface modeling, runway 24L is represented by waypoint RWY. For the airport surface layout representation, the LAX airport diagram, provided in Figure 4.1, is spatially discretized in terms of gates and taxiway intersections.

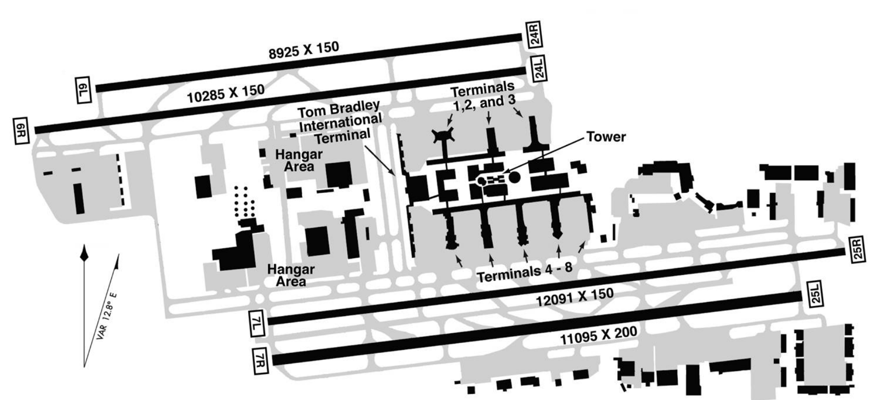


Figure 4.1. LAX Airport Diagram

Because runway 24L is located in the northern airfield, this study only considers gates and taxiways that commonly connect runway 24L. Based on flight gate assignment observations and common practices, it is assumed that flights operating on the northern airfield runways serve terminals 1 (T1), 2 (T2), 3 (T3) and international (TBIT). Other gates and taxiways that connect the southern airfield of the airport are not modeled. Figure 4.2 illustrates the corresponding node-link network layout of the LAX northern resources used in the optimization. It can be observed that there is no ramp area by terminal TBIT, which means that there is single lane and that aircraft enter the taxiway system only once cleared to do so. The grey area on Figure 4.2 indicates that only the northern gates of terminal TBIT are considered.

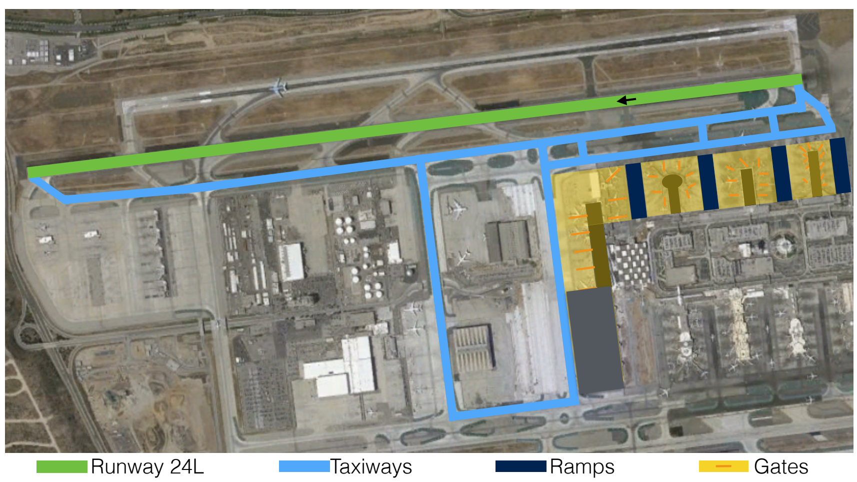


Figure 4.2. Node-Link Network Layout for LAX Northern Resources

4.1.2 Terminal Airspace Description

The interactions between arrivals and departures in the northern flows of the Los Angeles terminal airspace constitute an interesting case study because of their complex natures and layouts. Figure 4.3 shows arrival and departure routes based on the published SADDE6 STAR and CASTA2 SID for the Los Angeles International

Airport (LAX), where STAR stands for Standard Terminal Approach Route and SID for Standard Instrument Departure.

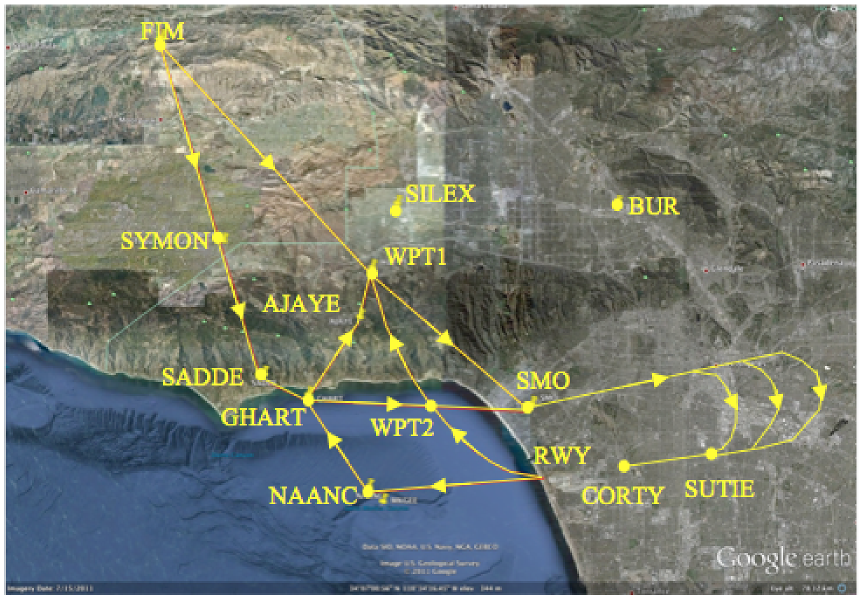


Figure 4.3. Route Interactions Between Arrivals and Departures in the LA Terminal Airspace

The SADDE6 procedure stipulates that arrivals coming from fix FIM should fly toward fix SMO via SYMON, SADDE and GHART fixes. Departure flights to the North need to follow the SID procedure CASTA2. According to CASTA2, departures takeoff from Runway 24L (represented by RWY in this model) and fly toward WPT1[1] via NAANC and GHART fixes.

GHART is the shared resource between SADDE6 and CASTA2 procedures. In this work, SADDE6 and CASTA2 are denoted indirect routes for simplicity. Moreover, this model assumes that arrivals and departures operate on the same runway 24L (represented by RWY) to make this study more interesting and the scheduling more challenging. In current operations, altitude constraints are imposed at fix GHART – arrival flights are required to maintain their altitude above 12,000 feet and departure flights below 9,000 feet and this forces flights to fly by WPT1 and WPT2. However,

[1]WPT1 is a waypoint made-up to simplify the route descriptions

Figure 4.3 illustrates that if there were no flow interactions, arrivals and departures could fly more direct routes, share resources and save flight times. A direct route for departures would be RWY-WPT2[2]-WPT1 and a direct route for arrivals would be FIM-WPT1-SMO.

Timar et al. [67] showed that in current operations of the Los Angeles terminal airspace, 28.1% of LAX arrivals follow SADDE6 and 10.4% of LAX departures follow CASTA2. This can be converted to 220 arrivals and 80 departures in a typical traffic day. In this research, the application focuses on these partial flows and published standard arrival and departure procedure fixes/waypoints represented in Figure 4.3 are used to model the airspace and flight plan routes. In this work, fixes and air waypoints are interchangeable denominations.

4.2 Los Angeles Model Formulation and Operational Concepts

4.2.1 Model Application

For this application, the objective function of the proposed methodology expressed in the previous chapter is adapted to the defined model of the Los Angeles airport surface and terminal airspace. The previously described stage objectives are updated for this application and are expressed in the following Equations 4.1, 4.2 and 4.3.

$$f_1(x) = \sum_{j=1}^{n} \begin{matrix} t_{jWPT1} - t_{jentry} & entry \in \{T1, T2, T3, TBIT\} \text{ if } q_j = D \\ t_{jexit} - t_{jFIM} & exit \in \{T1, T2, T3, TBIT\} \text{ if } q_j = A \end{matrix} \tag{4.1}$$

[2]WPT2 is a waypoint made-up to simplify the route descriptions

For each scenario ω_r,

$$\begin{aligned}
&If\ q_j = D,\ entry \in \{T1, T2, T3, TBIT\} \\
&f_2(x, \xi_r) = \sum_{j=1}^{n} (\alpha_j max\{r_{jentry} - t_{jentry}, 0\} + \beta_j max\{t_{jentry} - r_{jentry}, 0\}) \\
&If\ q_j = A \\
&f_2(x, \xi_r) = \sum_{j=1}^{n} (\alpha_j max\{r_{jFIM} - t_{jFIM}, 0\} + \beta_j max\{t_{jFIM} - r_{jFIM}, 0\})
\end{aligned} \tag{4.2}$$

For each scenario ω_d,

$$\begin{aligned}
&If\ q_j = D \\
&f_3(x, \xi_d) = \sum_{j=1}^{n} (\gamma_j max\{d_{jWPT1} - t_{jWPT1}, 0\} + \delta_j max\{c_{jWPT1} - t_{jWPT1}, 0\}) \\
&If\ q_j = A,\ exit \in \{T1, T2, T3, TBIT\} \\
&f_3(x, \xi_d) = \sum_{j=1}^{n} (\gamma_j max\{d_{jexit} - t_{jexit}, 0\} + \delta_j max\{t_{jexit} - d_{jexit}, 0\})
\end{aligned} \tag{4.3}$$

The methodology can be used with deterministic and stochastic settings. On one hand, in order to simulate deterministic conditions, a single repetition of the SAA methodology is run using a generated reference schedule scenario and setting the number of scenarios of stage 2 and stage 3 to zero. On the other hand, in order to simulate stochastic conditions, multiple repetitions of the SAA methodology can be run using a generated reference schedule scenario and different numbers of scenarios in stage 2 and stage 3. The number of scenarios in stage 2 and stage 3 can be varied and this will be investigated in a later section of the chapter.

4.2.2 Operational Concepts

To model airport surface operations that stick with current procedural factors and controller considerations, taxiways are considered unidirectional and dynamic aircraft routing is not investigated. Moreover, because taxi routes are generally generated based on runway and gate assignments, several taxi routes are determined for each gate and runway pair. A set of predefined taxi routes is generated before the scheduling and for each aircraft, optimal routes will be selected from the set. In Figure 4.2, ramp areas serve as aircraft sources and sinks; displacements in the ramp areas are not modeled. Once an aircraft has pushed back from the gate, it will appear at a source point located in the ramp area close to the gate where the aircraft was parked. For arrivals, once aircraft reach the ramp area close to the assigned gate, they disappear and the gate is considered as used.

The early cost parameter α_j is fixed to a large value when $q_j = D$ to avoid early release departures from the gates. Moreover for flexibility and for both arrivals and departures, late release times and early or late completion times are not penalized, i.e. if $q_j = A$ or $q_j = D$, $\beta_j = \delta_j = \gamma_j = 1$. However, delaying aircraft in the sky, i.e. creating airborne delay, is more expensive than delaying aircraft on the ground, i.e. creating ground delay. Therefore, the penalty on late arrivals at the gates is set such that the cost of creating airborne delay for arrivals is twice that of creating ground delay for departures, i.e. if $q_{j'} = A$ and $q_j = D$, $\delta_{j'} = 2\beta_j$.

4.2.3 Separation Strategies

As mentioned previously, this research implements temporal separation controls between aircraft at all times. To show the benefits of using shared resources in the spatial dimension, this research also investigates spatial-based separation methods in which temporal controls are implemented by default. The spatial separation strategy only uses the indirect routes defined by the surface and air waypoints that are currently operated to separate aircraft. The hybrid separation strategy additionally allows both surface and air direct routes to be travelled.

In the formulation of the hybrid separation method, two different types of decision variables are defined for each flight: timing variables at each waypoint and a routing variable. For both arrival and departure flights, the routing variable is the route option flown: 0 for indirect and 1 for direct.

Longitudinal separation constraints are imposed at all times between all aircraft pairs. In the air, a distance separation requirement of 4 nmi is imposed between all aircraft pairs (according to Capozzi et al. [21]) and converted into time scale via the speed of the leading aircraft of each pair. At the runway, wake vortex separations are enforced between all aircraft pairs. The corresponding separation values are imposed according to the FAA regulations [61] and Windhorst et al. [62] for all possible aircraft pair types and they are presented in Tables 4.1, 4.2, 4.3 and 4.4.

Table 4.1. Wake Vortex Separations Between Consecutive Arrivals on a Single Runway (sec)

Aircraft		Follower			
		Heavy	B757	Large	Small
Leader	Heavy	96	138	138	240
	B757	96	108	108	198
	Large	60	72	72	162
	Small	60	72	72	102

Table 4.2. Wake Vortex Separations Between Consecutive Departures on a Single Runway (sec)

Aircraft		Follower			
		Heavy	B757	Large	Small
Leader	Heavy	90	90	120	120
	B757	90	90	120	120
	Large	60	60	60	60
	Small	60	60	60	60

Table 4.3. Wake Vortex Separations Between Leading Arrivals Followed By Departures on a Single Runway (sec)

Aircraft		Follower			
		Heavy	B757	Large	Small
Leader	Heavy	68	68	68	80
	B757	68	68	68	80
	Large	62	62	62	80
	Small	48	55	55	80

Table 4.4. Wake Vortex Separations Between Leading Departures Followed By Arrivals on a Single Runway (sec)

Aircraft		Follower			
		Heavy	B757	Large	Small
Leader	Heavy	24	28	28	40
	B757	24	28	28	40
	Large	24	28	28	40
	Small	24	28	28	40

In this research, altitude restrictions are assumed to be satisfied at all times. A constraint on maximum allowed amount of speed change on surface and flight segments between two consecutive waypoints is added to prevent steep speed gradients. No more than 20% speed difference is allowed between any two consecutive waypoints.

4.2.4 Controller Intervention Considerations

In the case of integrated operations, temporal controls must be computed at the shared resources, i.e. surface and air waypoints, to ensure collision-free traveling. In order to simulate the resolution of such conflicts, the controller behavior is modeled as the number of times aircraft speed clearances must be communicated to the pilots.

4.3 Supporting Benefit Evidences of Integrated Operations for the Los Angeles Case Study

In this section, a proof-of-concept is conducted under deterministic conditions as a preliminary run to show the benefits of integrated operations for the Los Angeles case study. The intention is to provide evidences that the solution obtained using the developed methodology without uncertainty is a candidate to save total and individual of both taxi and flight times without increasing drastically the number of controller interventions. The optimization setup used for evaluation is first provided and is followed by the presentation of the results.

4.3.1 Proof-of-Concept Setup

Reference Traffic Scenario and Aircraft Mix

An analysis of flight records was performed using data from the Bureau Transportation Statistics (BTS) Airline On Time Performance database for LAX in 2012. The analysis shows that an average of $1,238$ flights operated daily that year. In December 2012, a total of $36,334$ flights were recorded with specifically $1,143$ flights on December 4th. This particular day, there were 572 arrivals and 571 departures. A more detailed analysis demonstrates that 37 flights were scheduled to depart and to arrive at LAX between $9:00$AM and $9:30$AM that day. To construct a realistic traffic scenario, flight numbers that operated at LAX on December 4, 2012 between $9:00$AM and $9:30$AM are extracted from the BTS Airline On Time Performance database. In this study case, only the northern airfield is considered, therefore only flights operating at terminals T1, T2, T3 and TBIT are used to compose a representative traffic scenario. The analysis demonstrates that about 14 flights, 8 arrivals and 6 departures, were operating that morning during the 30 minute time period of interest. Therefore, the traffic scenario designed for this study is composed of 8 arrivals from FIM and 6 departures to the North from Runway 24L (RWY). The aircraft types are found using the different flight numbers and the reference schedule scenario is formed using the corresponding flight schedules.

Table 4.5 presents the reference schedule and details the scheduled departure and arrival times of the flights. These times are relative to simulation start time and the flights are listed in chronological order.

Table 4.5. Reference Schedule

Order	0	1	2	3	4	5	6	7
FIM (seconds)	39	446	728	1106	1332	1475	1613	1770
RWY (seconds)	68	165	363	529	1613	1830	NA	NA

The constructed reference schedule represents scheduled pushback times for departures (i.e. release times) and reference scheduled gate times for arrivals (i.e. due dates). For a departure, a reference due date (i.e. scheduled flight time by WPT1) is computed by adding the unimpeded taxi time and the unimpeded flight time to the reference pushback time. For an arrival, a reference release time (i.e. scheduled arrival time by FIM) is computed by subtracting the unimpeded flight time and the unimpeded taxi time from the reference gate arrival time. For both computations, it is assumed that no other traffic is on the surface or in the air.

The corresponding fleet mix used for testing purposes in this work is composed of 14 aircraft, described in Table 4.6, and is to be scheduled and routed within the 30-minute time period of the reference schedule presented in Table 4.5.

Table 4.6. Aircraft Fleet Mix

Order	A0	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13
Weight	H	L	S	S	L	L	L	L	S	L	H	L	L	L
Operations	A	A	A	A	A	A	A	A	D	D	D	D	D	D

Speed and Separation

Along each route, in particular along every waypoint pair-based route segments, aircraft of all types can travel within a speed range such that $v \in [v_{min}, v_{max}]$. On the airport surface, the speed range for all aircraft is set to be $[8, 16]$ kts, whereas in the air, aircraft speed ranges are different for departures and arrivals and these are respectively set to be $[180, 250]$ kts and $[280, 350]$ kts. These air speed ranges are used for any air route segment. Moreover, aircraft must be separated at any time to avoid any potential collisions. There are three considered types of separation requirements that depend on the aircraft situation. First, any pair of aircraft must always be separated by a minimum distance of 200 meters when moving along the taxiways according to Roling et al. [4]. Second, minimum inter-operation spacings for wake separation must be enforced between any two aircraft on the runway. These separation minima depend on the aircraft weight class and whether aircraft are departures or arrivals. In this proof-of-concept case study, a single runway is used for both arrivals and departures. Therefore, there are four different types of aircraft pairs that can potentially be formed: DD, AA, DA and AD. The wake vortex separation minima used in this implementation are obtained from [61, 62]. Finally, all aircraft pairs that are flying on the same traffic flow are separated using temporal controls. These temporal controls are obtained by converting a spacing distance of 4 nautical miles (nmi) (according to Capozzi et al. [21]) into time via the speed of the leading aircraft of each pair.

SAA Setup

The proposed methodology is stochastic in nature but deterministic conditions can also be setup and tested. In this proof-of-concept case study, the spatial and hybrid separation methods are compared without the presence of uncertainty. The previously constructed reference schedule is used and the number of scenarios of each stage in the multi-stage formulation is set to zero (i.e. $m_r = m_d = 0$). No errors are added to the flight times. The problem is implemented as a Mixed Integer Linear Program (MILP).

4.3.2 Evaluation Criteria and Metrics

Two types of criteria are used to evaluate the performance of the optimization model proposed to solve the integrated airport surface and terminal airspace operations problem.

The first criterion is the computational speed and in practice faster algorithms are preferred. However, the computational speed is affected by the implementation and traffic scenarios tested, the programming language chosen, the optimization solver selected and the machine or server used to run the program.

The second criterion is related to the optimization to evaluate its performance. The optimization affects both the surface and the air operations. Therefore, different metrics are defined to evaluate the surface and air solutions, i.e. schedules and routings, for the considered aircraft set. On one hand, for the surface operations, total and individual taxi times, runway sequence and departure gate waiting times are computed. On the other hand, for the air operations, total and individual flight times, routing options and number of controller interventions are computed.

Overall the optimal solution that encompasses both surface and air characteristics is selected such that the objective function is the smallest. This translates into a solution that provides the smallest total travel time and schedule delay.

4.3.3 Benefit Evidences of Integrated Operations

As previously mentioned, this proof-of-concept case study is conducted under deterministic settings. For baseline comparison, a First-Come-First-Served (FCFS) algorithm is implemented for both surface and air operations. The metrics previously defined are used to illustrate the results.

First-Come-First-Served Comparison Approach

To assess the benefits of optimization, a First-Come-First-Served (FCFS) scheduler algorithm is implemented as a baseline case. In this algorithm, aircraft are handled in the order prescribed by the reference schedule such that no delay is permitted for the first scheduled flight and aircraft are separated using the spatial separation method. Moreover, it is assumed that the surface and air route assignments of each aircraft is specified in advance. All aircraft are routed on the surface using the longest taxiway paths and are routed in the air using indirect routes. The set of constraints prescribed for this algorithm formulation enforces aircraft separations at all nodes and all times. The FCFS scheduler generates the runway sequence and the schedules for all flights at any nodes.

Results

In both FCFS and MILP solutions, all aircraft were successfully routed to their destinations without any spatial or temporal conflicts. The 30-minute 14-aircraft traffic scenario was run in 40 seconds by the FCFS algorithm whereas it took ~ 240 seconds for the MILP algorithm.

Surface-Side Results To compare the obtained ground-side results for both FCFS and MILP formulations, total and individual taxi times are computed. In Table 4.7 total surface times are provided as well as the total surface time reduction enabled by the MILP over the FCFS formulation.

Table 4.7. Comparison of Total Taxi Times - Proof-of-Concept

FCFS	MILP	Total Surface Time Reduction
8391s	7728s	7.9%

To present the individual taxi times of the 14 aircraft considered, Box and Whisker plots are drawn in Figure 4.4. Box and Whisker plots provides a visual representation of the surface time range and the surface time median of both FCFS and MILP solutions.

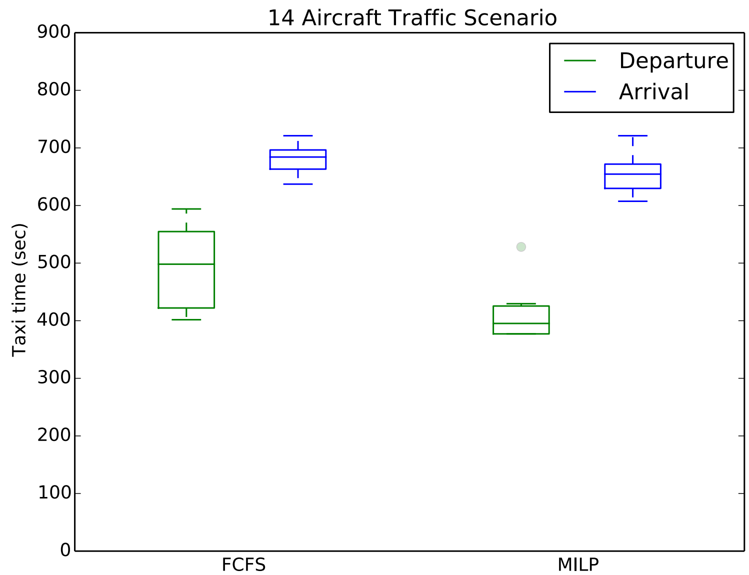


Figure 4.4. Comparison of Individual Taxi Times - Proof-of-Concept

Figure 4.4 shows that for both arrival and departure surface movements, the MILP formulation enables taxi time savings. In particular, the taxi time range of departing flights is reduced. With the MILP formulation, departing flights travel along shortest taxi routes. Regardless of their starting terminal, the departing flights have more similar taxi time length among one another with the MILP than with the FCFS approach. However, a slight increase of arrival taxi time range is computed for the MILP but the increase is not significant. Additionally, the MILP formulation allows a taxi time median decrease for both departures and arrivals. For arrivals, although the taxi time range is slightly increased by the MILP, the taxi time median is reduced.

The average taxi time values are represented in Figure 4.5. The MILP formulation reduces 15.6% the average taxi times of departing flights and 4% the average taxi times of arrival flights.

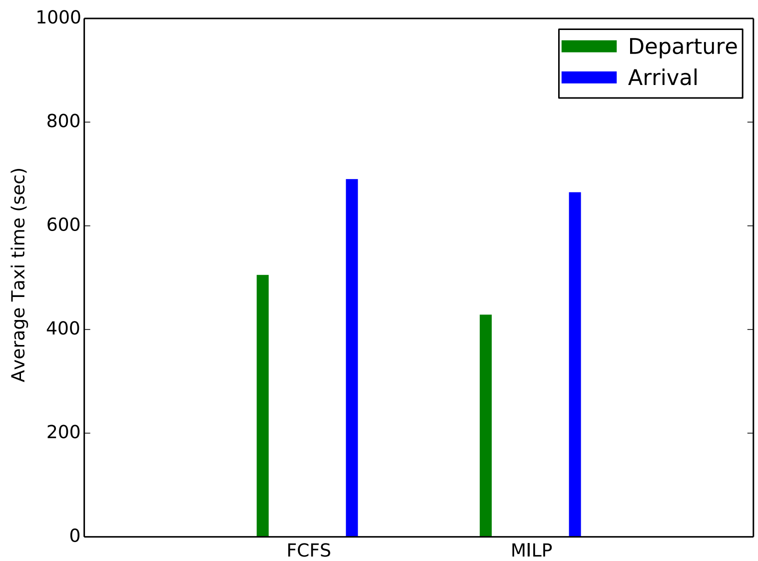


Figure 4.5. Comparison of Average Taxi Times - Proof-of-Concept

The runway sequence and associated timeline solutions computed by both approaches are represented in Figure 4.6.

With the MILP formulation, all flights are scheduled earlier than with the FCFS formulation because aircraft are assigned to travel along shorter for both surface and air routes. Because of the traffic load, the makespan of the runway schedule solutions is the same for both algorithms. However, it can be noticed that in the MILP runway sequence solution, the departure flights are scheduled earlier than arrival flights compared to the FCFS runway sequence. The aircraft mix of the reference traffic scenario does influence the computed runway sequence especially because departure-arrival aircraft pairs have lower wake vortex separations than arrival-departure aircraft pairs. To fully satisty the imposed surface separation constraints between aircraft from the gates to the runway, the traffic scenario schedule initially provided induces takeoff

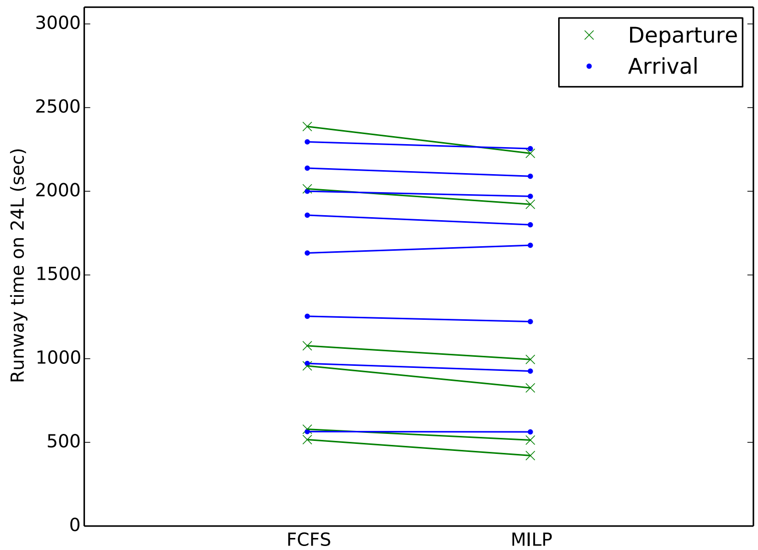


Figure 4.6. Comparison of Runway Sequences - Proof-of-Concept

delays for departing flights. Figure 4.7 illustrates the computed takeoff delays for both FCFS and MILP.

The surface routing and runway sequence computed under the MILP approach allow a takeoff time delay reduction of 22% for departing flights that was initially imposed by the traffic scenario schedule. The MILP formulation produces solutions with lower taxi times and more direct routings than the FCFS approach. However, the MILP formulation only releases aircraft on the taxiway system is the taxiway route is cleared of delay. Therefore, in order to meet the computed takeoff slots at the runway, the MILP formulation induces some departure delays at the gates. Figure 4.8 represents the average gate waiting time for departing flights out of the four different considered terminals.

By routing aircraft on longer taxi routes, the FCFS does not induce any gate delay times. However, for the MILP solution, a total of 157 seconds of delay is created at T1 and a total of 74 seconds of delay is created at T2.

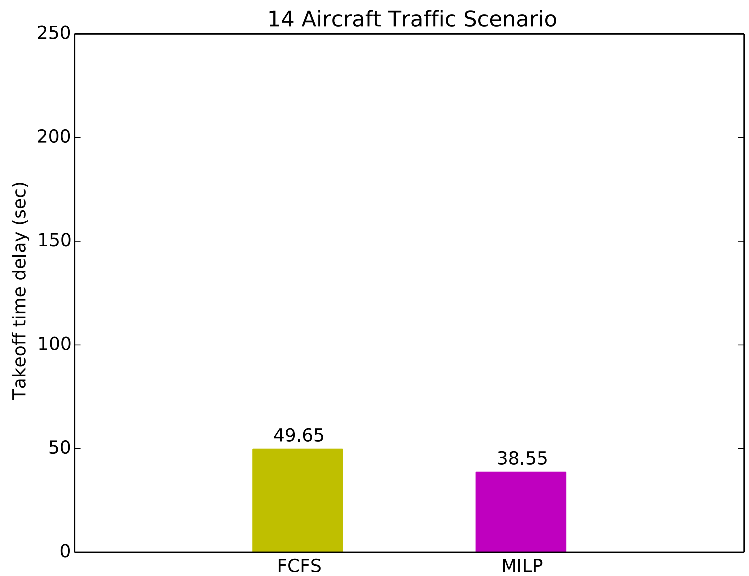


Figure 4.7. Comparison of Takeoff Time Delay - Proof-of-Concept

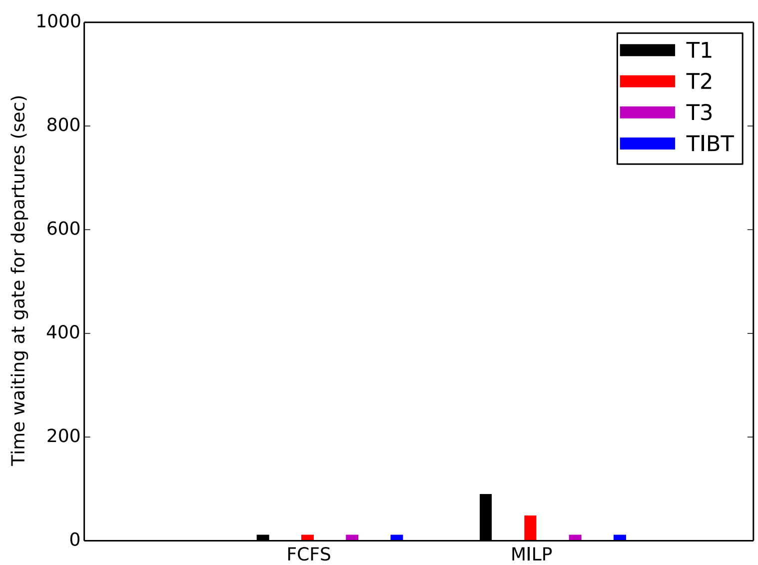


Figure 4.8. Comparison of Gate Waiting Time For Departures - Proof-of-Concept

Airspace-Side Results To compare the obtained air-side results for both FCFS and MILP formulations, total and individual flight times are computed. In Table 4.8 total flight times are provided as well as the total flight time reduction enabled by the MILP over the FCFS formulation.

Table 4.8. Comparison of Total Flight Times - Proof-of-Concept

FCFS	MILP	Total Flight Time Reduction
6843s	5880s	14%

To present the individual flight times of the 14 aircraft considered, Box and Whisker plots are drawn in Figure 4.9. Box and Whisker plots provides a visual representation of the flight time range and the flight time median of both FCFS and MILP solutions.

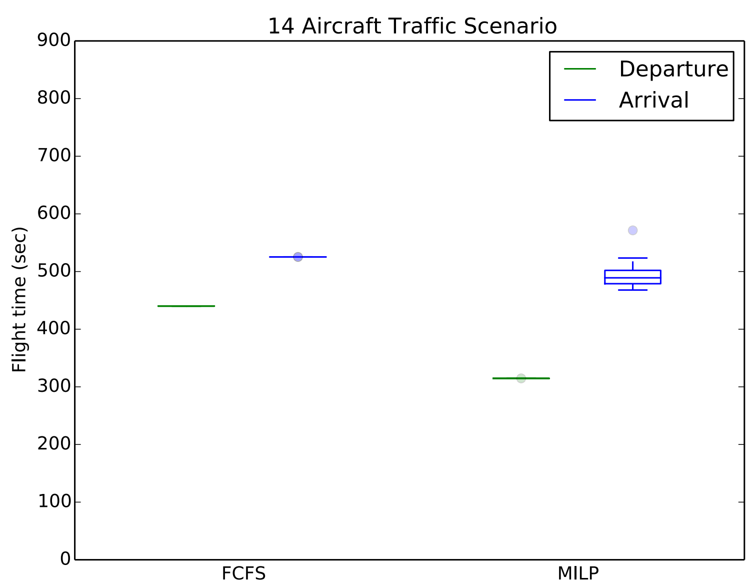


Figure 4.9. Comparison of Individual Flight Times - Proof-of-Concept

Figure 4.9 shows that for both arrival and departure flights, the MILP formulation enables flight time savings. The MILP formulation allows flights to fly on direct routes. Therefore, the flight time median is reduced for all flights. However, it can be observed that the savings are higher for departing flights. In particular, the computed flight time for all departures is decreased from 440s to 315s and no airspeed adjustment is needed. However, in order to satisfy the separation requirements, airspeed adjustments are imposed to arrival flights which in consequence affects the corresponding flight times and these are not decreased as much. At the shared waypoint GHART, controller interventions are needed to communicate speed clearances. In this proof-of-concept, 3 controller interventions are computed.

Integrated Operations Discussion

For both the surface and the air operations, the MILP enables travel time savings when compared to the FCFS algorithm. The optimal integrated routing that is computed offers a more efficient routing which results in a better aircraft sequencing than the one computed with the FCFS algorithm. Moreover, the computed schedule allows more efficient operations that benefits from using shared resources. Results and associated benefits are however traffic scenario-dependent. For this particular proof-of-concept, it is to be noted that the FCFS algorithm did generate takeoff time delays. Thanks to better routing, the MILP formulation was able to reduce the takeoff time delay imposed by the schedule traffic scenario. Additionally, it is observed that the FCFS did not generate gate delays whereas the MILP approach did. In the FCFS, the longer surface and air routings covered up for the delays generated by the MILP. For an airline stand point, delaying aircraft at the gate might not necessarily be good for meeting the on-time departure *D0* metric but the trade-off enabled by traveling on shorter routes does help reducing fuel consumption. For a FAA surface air traffic controller, taxiway congestion are hard to handle. If delaying aircraft at the gate helps taxiway traffic to be more fluid, controllers can provide better surface routing which can help flights in return to meet their take-off runway slot.

4.4 Data Driven Analysis of Uncertainty Sources

Uncertainty affects flight scheduling on the airport surface and in the terminal airspace. Uncertainty can be caused by many sources such as perturbations affecting the boarding process, low visibility conditions on the taxiway system, inaccurate wind predictions, errors in aircraft dynamics or human factors. A data analysis is conducted to understand and model the uncertainty sources affecting both the airport surface and the terminal airspace.

4.4.1 Surface Sources

In this research, it is assumed that on the airport surface, scheduled runway departure times are impaired by pushback and taxi-out delays and that scheduled gate arrival times are altered by taxi-in delays. Therefore, an uncertainty analysis is conducted using $881,496$ data points from the Bureau of Transportation Statistics (BTS) Airline On-Time Performance Database for LAX and for the year 2012. An approximation of pushback delay distribution is obtained for departures by computing pushback delay as the difference between scheduled and actual pushback time. An approximation of arrival gate delay distribution is obtained by computing the difference between actual and scheduled arrival gate time. In order to generate schedule scenarios that will be used as inputs for stage 2 and stage 3, error sources drawn from these two obtained distributions are respectively added to reference departure release times and reference arrival due dates. It ensures that the scenario set tested is composed of realistic schedule scenarios perturbed around the reference schedule. The resulting distributions and associated fits obtained from the BTS data are represented in Figure 4.10 and Figure 4.11.

The departing time error from the gates can be described by a lognormal distribution with a mean of 20.4 seconds and a standard deviation of 166.8 seconds. Airlines are driven by the on-time performance metric $D0$, so they try to ensure that aircraft push back before scheduled departure times. However, uncertainty coming

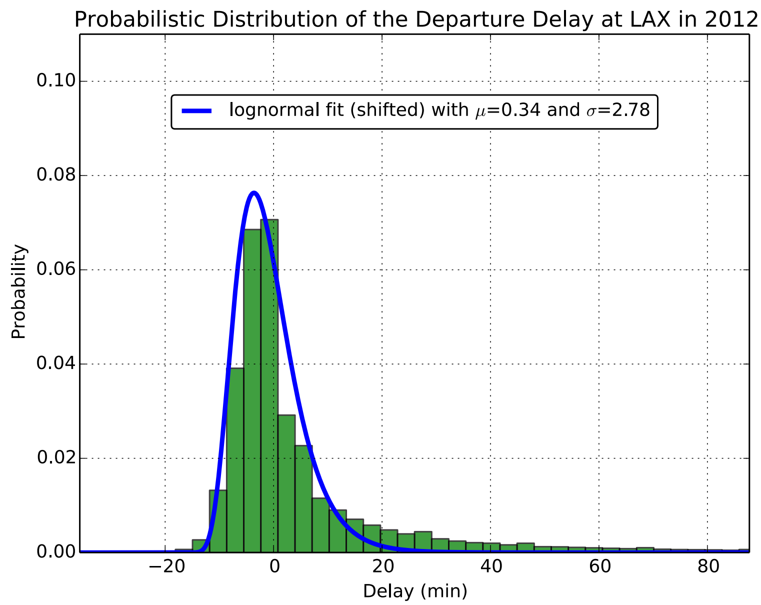


Figure 4.10. Pushback Delay Distribution

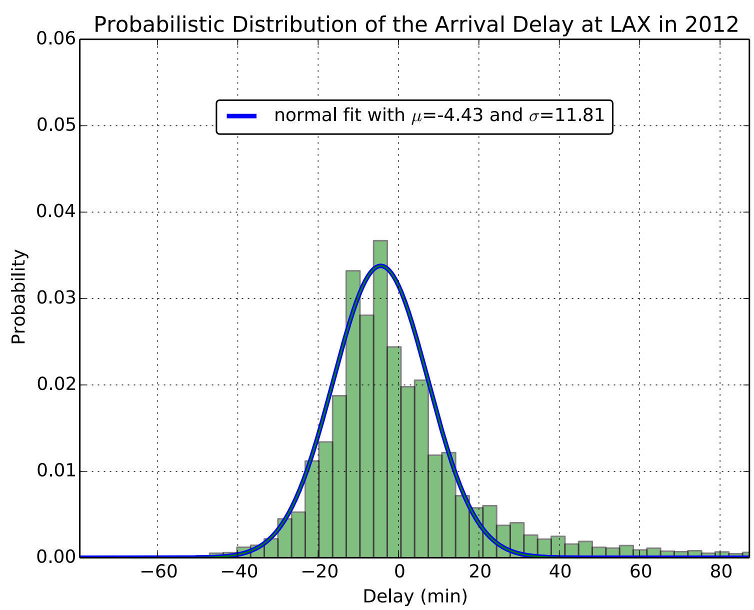


Figure 4.11. Arrival Gate Delay Distribution

from a delayed boarding processe or a late equipment change does affect the actual pushback time.

The arrival time error to the gates can be described by a normal distribution with a mean value of -265.8 seconds and a standard deviation of 708.6 seconds. Airlines block large chunks of time from departure to arrival to capture and recover from any delays that can perturb a flight. A late pushback does not necessarily induce a late arrival.

4.4.2 Air Sources

In the air, error sources drawn from normal distributions are added to both reference departure due dates and reference arrival release times. It was found in the literature that normal distributions can be used to represent the uncertainty affecting both arrival and departure flight times. Based on common values used as desired prediction accuracy in previous work conducted on arrival trajectory [68, 69], a mean of 0 seconds and a standard deviation of 30 seconds are selected for the arrival time error. For the departure time error, a mean value of 30 seconds and a standard deviation of 90 seconds are setup based on the departure Call For Release, three-minute time compliance window [70]. Figure 4.12 provides an illustration for the terminal airspace.

4.5 Sensitivity Analysis and Methodology Performance Assessment for the Los Angeles Case Study

The proof-of-concept case study previously described was conducted without uncertainty considerations. Moreover, a data-driven analysis was conducted to compute the probabilistic distributions of uncertainty sources affecting the airport surface and the terminal airspace operations. In this section, different parameter value inputs for the implementation of the Sample Average Approximation method are investigated. The goal is to understand how they affect the methodology performance by perform-

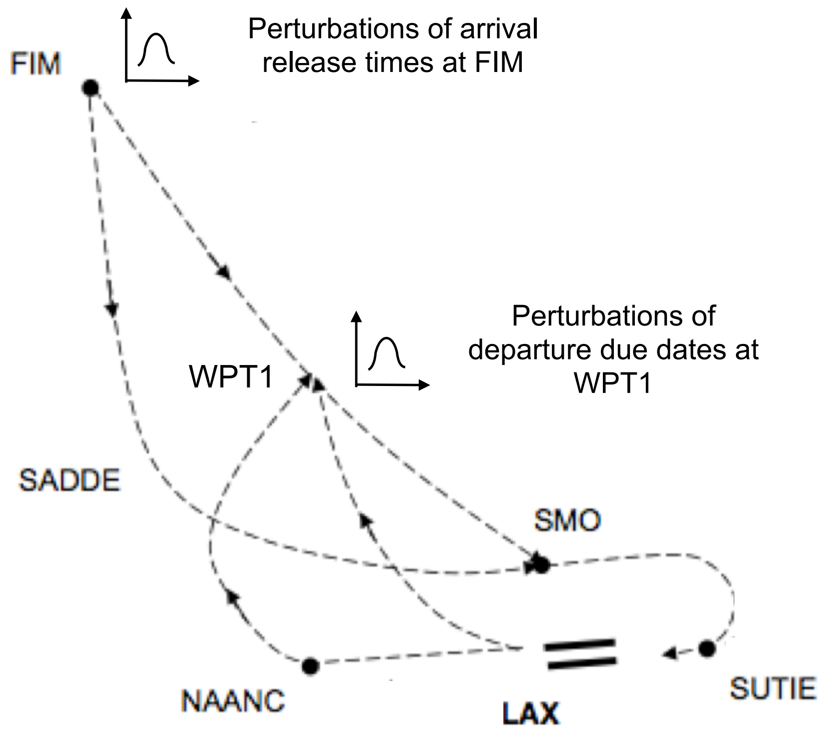


Figure 4.12. Error Sources in the Terminal Airspace

ing a sensitivity analysis. The number of scenarios in each stage of the multi-stage formulation is varied and the impact of uncertainty is analysed. A statistical analysis is conducted where the hybrid separation method is implemented because the proof-of-concept experiment results show that greater savings could be obtained if aircraft fly direct routes. In the preliminary, the statistical bounds are derived for the problem. Then the computation setup details the values of the parameters tested. Finally, computation tables and analysis of the statistics are provided. The goal is to determine the number of scenarios needed to get robust optimal solutions for a fixed number of repetitions when applying the proposed methodology in reasonable computation time.

4.5.1 Statistical Metrics

To solve the stochastic program, the SAA methodology prescribes to solve M SAA independent problems with m_r and m_d independent samples in each. Denote respectively as ν^* and $\hat{\nu}$, the optimal objective function of the true problem and of the SAA problem. For each replication m, $m \in [1, M]$, the program computes $\hat{\nu}^m$ and $\hat{x}^m$ that respectively refer to the value of the optimal objective function and to the solution of the mth replication. According to Ahmed and Shapiro [71] an unbiased estimator of $\mathrm{E}[\hat{x}^m]$ can be described by Equation 4.4.

$$\bar{\nu}^M = \frac{1}{M}\sum_{m=1}^{M} \hat{\nu}^m \tag{4.4}$$

Because $\mathrm{E}[\hat{\nu}^m] \leq \nu^*$ by definition, Equation 4.4 is a statistical lower bound to ν. An estimate of the variance of the lower bound estimator can be expressed in Equation 4.5.

$$S_{\bar{\nu}^M} = \sqrt{\frac{1}{M(M-1)}\sum_{m=1}^{M}}(\hat{\nu}^m - \bar{\nu}^M)^2 \tag{4.5}$$

These formulas are computed in step 2. of the SAA methodology.

To compute statistical upper bounds of ν^*, consider a feasible solution $\hat{x}^m$ of the problem at repetition m. This procedure is applied in step 1.(b).i of the SAA methodology. To compute an estimate of the true objective value $\hat{g}'(\hat{x}^m)$ at point $\hat{x}^m$ for repetition m, one can generate independent samples of size m_r' and m_d' compute the quantity defined in Equation 4.6. In this work, m_r' and m_d' are numbers of extra-scenarios of type r and d and $m_r' = m_d'$.

$$\hat{g}'(\hat{x}^m) = f_1(\hat{x}^m) + \sum_{n=1}^{m_r'} p_{n_r}\Big(f_2(\hat{x}^m, \xi_r) + \sum_{n=1}^{m_d'} p_{n_d}(f_3(\hat{x}^m, \xi_d))\Big) \tag{4.6}$$

An estimate of the variance of the upper bound estimator can be expressed in Equation 4.7.

$$S_{\hat{g}'(\hat{x}^m)} = \sqrt{\frac{1}{m_r'(m_r'-1)}\sum_{n=1}^{m_r'}(\hat{g}(x) - \hat{g}'(\hat{x}^m))^2} \tag{4.7}$$

Finally, to characterize the differences between upper and lower bounds, the optimality gap is computed for each repetition in step 3 of the SAA methodology algorithm along with the estimated variance. For each solution $\hat{x}^m$, $m = [1, M]$ both quantities can be expressed in Equation 4.8 and Equation 4.9.

$$\hat{g}'(\hat{x}^m) - \bar{\nu}^M \tag{4.8}$$

$$S^2_{\bar{\nu}^M} + S^2_{\hat{g}'(\hat{x}^m)} \tag{4.9}$$

4.5.2 Performance Assessment Computation Setup

In this section, a computation setup is defined to compute the statistical bounds previously derived in four different cases. The number of repetitions is fixed to $M = 50$ and the number of extra-scenarios $m_r^{'}$ and $m_d^{'}$ are fixed to $10,000$. Each test case explores a different number of scenarios m_r and m_d such that $m_r = m_d$. Table 4.9 summarizes the values of tested parameters.

Table 4.9. Computation Setup

Parameters	Case 1	Case 2	Case 3	Case 4
M	50	50	50	50
$m_r = m_d$	10	100	1,000	10,000
$m_r^{'} = m_d^{'}$	10,000	10,000	10,000	10,000

The optimization is performed on the Los Angeles terminal airspace proof-of-concept case study with stochastic settings where the hybrid separation is implemented to separate the set of 14 aircraft. To save computation time, multi-threading is implemented. Because all repetitions are independent from one another, one thread is assigned to one-repetition computations.

4.5.3 Performance Assessment Computation Results

For each case, the SAA methodology described in the previous section is applied, statistical bounds are computed at each repetition and respective case computation times are recorded. In order to compare the different test cases and show the effect of increasing the number of scenarios ($m_r = m_d$) on the results, a Box and Whisker plot is drawn to represent the objective variance distribution of the results of each test case. The resulting plot is presented in Figure 4.13. For all box plots, the box extends from lower to upper quartile value of the objective variance with a line at median. The bottom and top horizontal lines represent the whiskers and they extend the box to show the range of the data from minimum to maximum.

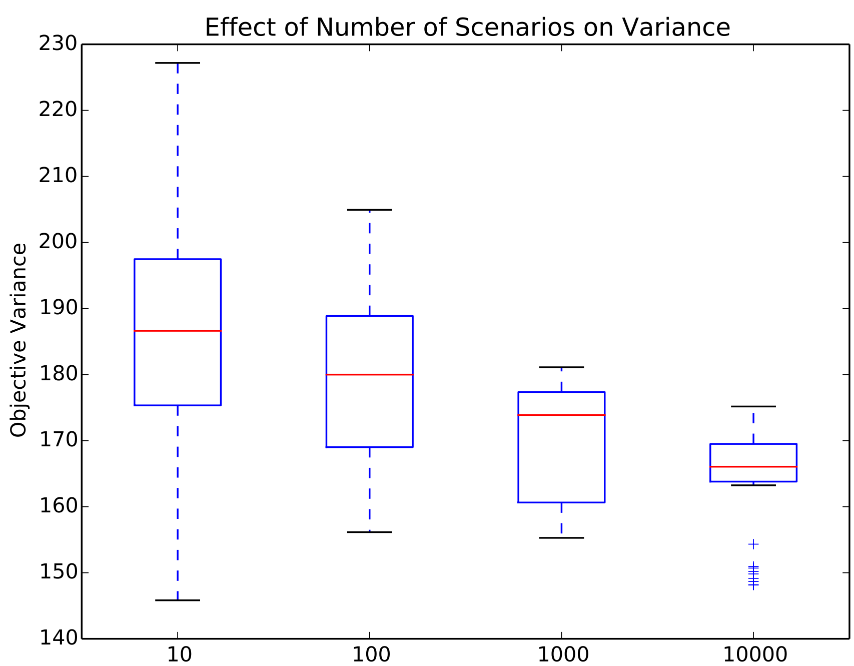


Figure 4.13. Objective Variance Distributions

Two main observations can be drawn from Figure 4.13. First, the visible data spread, i.e. objective variance spread, between maximum and minimum decreases as the number of scenarios increases. It is 84 seconds when the number of scenarios is set to 10 whereas it is 13 seconds when the number of scenarios is set to $10,000$ and neglecting the outliers. Second, the median decreases from 186s to 166s when the number of scenarios increases from 10 to $10,000$. Therefore, Figure 4.13 shows that results are more robust for larger numbers of scenarios.

Additionally, Table 5.2 presents the computation times of the three different test cases.

Table 4.10. Computation Times

	Case 1	Case 2	Case 3	Case 4
Computation Times (seconds)	127.89	251.34	1296.57	12498.85

Case 1 with 10 scenarios is the fastest to run ($\sim$ 2.1 min) whereas case 4 with $10,000$ scenarios is the longest to run ($\sim$ 206.8 min). Although Figure 4.13 shows that case 4 has the least dispersed results, it takes about 206.8 minutes ($\sim$ 3.45 h) to run, whereas for case 2 and case 3 it respectively takes 4.2 minutes and 21.6 minutes to run. From case 2 to case 3, increasing the number of scenarios from 100 to $1,000$ enables a 2.78% median decrease of the objective variance at a 5x computational cost increase. From case 2 to case 4, increasing the number of scenarios from 100 to $10,000$ enables a 7.78% median decrease of the objective variance at a 49x computational cost increase. Therefore for this computation experiment, case 2 is the best setup and presents a good compromise between variance result and computation time.

Case 2 spread is about 50 seconds, this tends to cost uncertainty of results from previous section. Table 4.11 presents detailed statistics computations of test case 2 when applying the SAA methodology. For simplicity and illustration purposes, results corresponding to a few repetitions, i.e. 0th, 10th, 20th, 40th, and 49th, are provided. In this table, the first column is the repetition number, the second column is the estimated upper bound of the objective function with estimated variance displayed in column three. Column four is the estimated lower bound of the objective function, column five displays the estimated optimality gap along with its variance in column six. The two last quantities underneath the table correspond to the overall repetition lower bound of the objective and its associated variance.

Table 4.11. SAA Detailed Statistical Results For Case 2

m	$\hat{g}'(\hat{x}^m)$	$S^2_{\hat{g}'(\hat{x}^m)}$	$\hat{\nu}^m_N$	Gap	Var
0	19957.5	141.4	19859.9	66.2	200.6
10	19916.5	108.5	19810.4	115.7	167.7
20	19902.7	109.9	19829.6	96.6	169.1
40	19899.5	119.2	19830.4	95.8	178.4
49	19893.4	127.9	19807.9	118.3	187.2

$\bar{\nu}^M = 19826.2$

$S^2_{\bar{\nu}^M} = 59.2$

4.5.4 Performance Assessment Analysis

The results of the statistical bounds computations show that using large numbers of scenarios produces more robust results but at the expense of large computation times. However, it was found that decent robustness could be found in reasonable computation time for the reference schedule and stochastic settings considered. In particular for the proof-of-concept case study, robust solutions can be computed when the number of scenarios is set to 100. According to variance results of this section, fixing the number of scenarios to 100 for both stage 2 and stage 3 for the Los Angeles case study can be qualified as a good trade-off between providing robust results and computation time.

5. Simulations of Increasing Traffic Density for Integrated Operations in the Presence of Uncertainty

In this chapter, simulations of increasing traffic density are performed for integrated operations in the presence of uncertainty. In previous chapter, evidences of integrated operation benefits over First-Come-First-Served operations were demonstrated. The intention of this chapter is to test the proposed methodology on different traffic load scenarios and understand the associated computed solutions. Two simulation studies are conducted. In Section 5.1, the first study only focuses on integrated terminal airspace operations whereas in Section 5.2, the second study extends the considered integrated operations to the airport surface.

Simulation - Sample Average Approximation Parameters Setup To evaluate the simulation results in the following two sections, the spatial and hybrid separation methods are compared under deterministic and stochastic conditions. Using the results obtained from the methodology sensitivity analysis presented in previous chapter, Table 5.1 is used to parameterize the methodology for the two different uncertainty conditions. The deterministic case is used as a baseline solution for comparison.

Table 5.1. Uncertainty Experiment Parameters Setup

Parameters \ Conditions	Deterministic	Stochastic
M	1	50
m_r	0	100
m_d	0	100

5.1 Integrated Arrivals and Departures

In this section, the integration of arrival and departure operations is considered. Different traffic load scenarios applied to the Los Angeles terminal airspace are created in which the number of aircraft is varied. Simulations are run on light, medium, large and heavy traffic scenarios. The simulations setup is first described, the metrics used for comparison are then defined and finally the results are presented.

5.1.1 Simulations Setup

The simulations setup describes the traffic scenarios and aircraft mix considered, the flight schedule generation and the sources of uncertainty modeled in the terminal airspace.

Traffic Scenarios and Aircraft Mix

Four traffic load scenarios characterized by different numbers of aircraft are considered to test the methodology over a scheduling window of 30 minutes. The scenarios with 10, 20, 30 and 40 aircraft represent light, medium, large and heavy traffic conditions. All reference schedules are randomly created for a 30-minute time period. The following table summarises the different traffic demand scenarios as well as the aircraft types, i.e weight classes and operations, used in each scenario.

Table 5.2. Traffic Scenarios and Aircraft Types Used in Simulations

Number of Aircraft	Weights	Operations
10	1S + 8L + 1H	6A + 4D
20	2S + 15L + 3H	12A + 8D
30	5S + 22L + 3H	17A + 13D
40	3S + 31L + 6H	24A + 16D

Schedule Generation and Uncertainty Considerations

For each traffic load simulation, release time and due date schedules are generated by respectively adding error sources drawn from normal distributions to both reference arrival and departure schedules. As presented in the previous chapter, to generate release time schedules, the arrival time error at FIM can be described by a normal distribution with a mean of 0 seconds and a standard deviation of 30 seconds whereas the departure time error at the runway can be described by a normal distribution with a mean value of 30 seconds and a standard deviation of 90 seconds. Moreover, to generate due date schedules, departure and arrival time errors following normal distributions are respectively added to flight times at WPT1 and the runway. For the departure time error, a normal distribution with a mean of 0 seconds and standard deviation of 15 is selected whereas for the arrival time error, a normal distribution with with a mean of 0 seconds and standard deviation of 5 seconds is selected.

5.1.2 Comparison Metrics

For all traffic load simulation result evaluations, the spatial and hybrid separation methods are compared under deterministic and stochastic conditions. To compare the obtained results under deterministic and stochastic conditions, the total and individual flight times are computed for both spatial and hybrid separation methods. For the deterministic settings, flight times are provided for baseline reference. For the stochastic settings, Box and Whisker plots are used to represent the flight time range that is computed for all repetitions. Additionally for each traffic scenario, the average takeoff time delay is computed under both uncertainty settings and the percentage of shifted flights in runway sequencing compared to the initial runway sequence given by the solution under deterministic settings is provided for the optimal repetition.

5.1.3 Results

All traffic load scenarios that were simulated were scheduled over a 30-minute time window and respective reference schedules were created accordingly. It is to be noted that the large and heavy traffic scenarios represent very dense conditions for a single runway to support mixed operations. The heavy simulation pushes the boundary of the air operations that uses a single runway.

Comparison of Individual and Total Flight Times

Deterministic Conditions The total flight times of each traffic load scenario are first computed under the deterministic settings. Table 5.3 presents the results for both separation methods.

Table 5.3. Comparison of Total Flight Times - Deterministic

Traffic Load	Spatial	Hybrid	Total Flight Time Reduction
Light	4957s	4066s	18%
Medium	10046s	8188s	18.5%
Large	15300s	12446s	18.7%
Heavy	22385s	18314s	18.2%

For all traffic loads under the deterministic settings, the hybrid spatial separation method enables total flight time reductions in the range of 18% compared to the spatial separation method. The maximum reduction is obtained for the large traffic scenario. When the hybrid separation method is implemented, all aircraft are routed on the more direct routings.

When looking at the individual flight times of each traffic load scenario, the hybrid separation method reduces individual flight times of both departures and arrivals. The following set of figures illustrates the results for both separation methods with

Figure 5.7(a) and Figure 5.7(b) respectively showing the results computed with the spatial and the hybrid separation method.

For each separation method, the denser the traffic load scenario, the longer the computed individual flight times. Simulating dense traffic load conditions in a tight time window invokes scheduling and routing a large number of aircraft under timing constraints. In order to meet the schedule constraints and satisfy the separation requirements, aircraft are not assigned maximum allowable air speeds on all route segments flown.

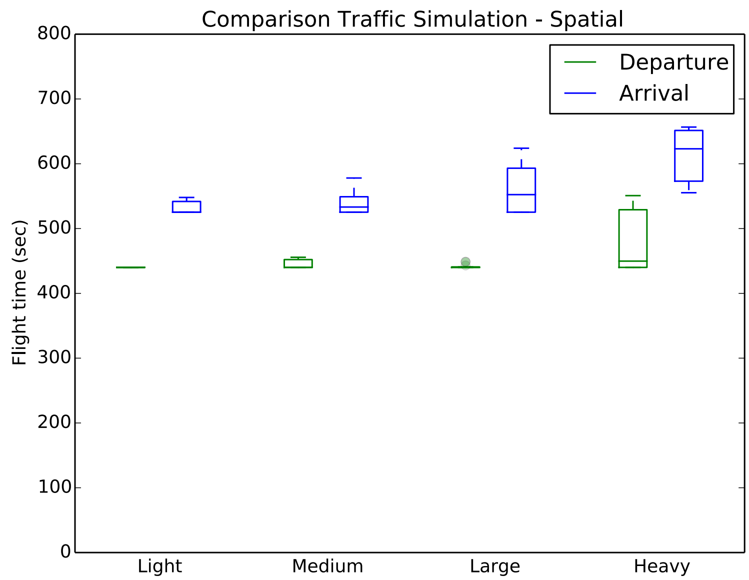
Moreover, in order to compare the individual flight time results computed with the two different separation methods, Table 5.4 presents the individual flight time reduction enabled by the hybrid separation method when compared to the spatial separation method.

Table 5.4. Comparison of Individual Flight Time Reductions - Deterministic

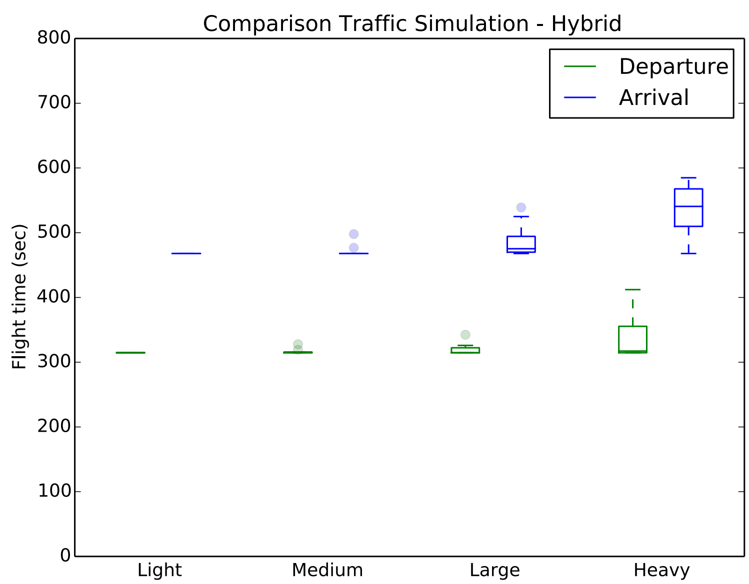
Traffic Load	Individual Flight Time Reduction
Light	Arrivals: up to 81s - Departures: up to 125s
Medium	Arrivals: up to 110s - Departures: up to 141s
Large	Arrivals: up to 156s - Departures: up to 165s
Heavy	Arrivals: up to 189s - Departures: up to 236s

Overall, for all traffic loads under the deterministic settings, the hybrid separation enables greater individual flight time reductions for departures than for arrivals. Additionally, the denser the traffic load scenario, the more individual flight time savings obtained. In relative proportions, the direct departing route is shorter with respect to the indirect departing route than the direct arrival route is with respect to the indirect arrival route.

Stochastic Conditions In the stochastic case, Figure 5.2 shows the individual flight time ranges computed for all repetitions. Results computed under the spatial



(a) Spatial Separation Method



(b) Hybrid Separation Method

Figure 5.1. Comparison of Individual Flight Time Range (sec) - Deterministic

and the hybrid separation methods are respectively displayed in Figure 5.8(a) and Figure 5.8(b).

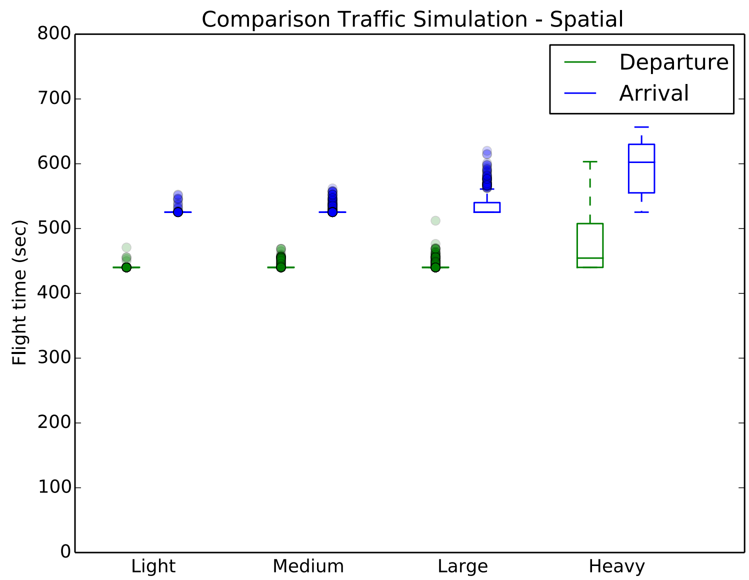
A similar comment than under the deterministic conditions can be made for the stochastic conditions when comparing the results of each separation method. The denser the traffic load scenario, the longer individual flight times computed. Moreover, Figure 5.2 demonstrates that for all traffic load scenarios even with the presence of uncertainty, the hybrid separation method allows flight time savings for both arrivals and departures when compared to the spatial separation method, in particular flight time medians are reduced. Additionally, the flight time values computed for departures are less dispersed with the hybrid separation method as with the spatial separation method. For the heavy traffic load scenario, the hybrid separation methods allows the flight time medians to be reduced but the flight time ranges of both arrivals and departures remain dispersed. This observation suggests that when the traffic load scenario is too dense, individual flight time benefits from the hybrid separation method are more limited than for less dense traffic load scenarios.

For the optimal repetition, the computed total flight time reductions enabled by the hybrid separation method for each traffic load scenario are summarised in Table 5.5.

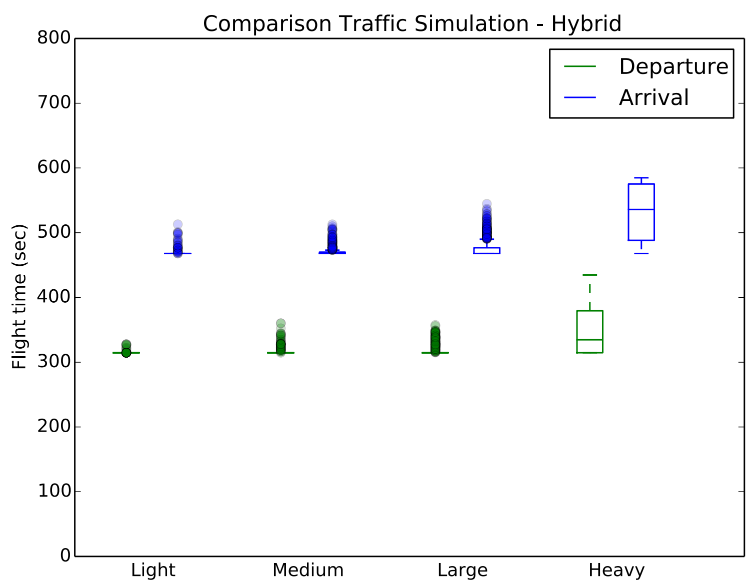
Table 5.5. Comparison of Total Flight Times - Stochastic, Optimal Repetition

Traffic Load	Spatial	Hybrid	Total Flight Time Reduction
Light	4912s	4099s	16.6%
Medium	9870s	8210s	16.8%
Large	14868s	12273s	17.5%
Heavy	22216s	18245s	17.9%

For all traffic loads under the stochastic settings, the hybrid spatial separation method enables total flight time reductions in the range of 16.5% to 17.9% compared to the spatial separation method. The maximum total flight time reduction is ob-



(a) Spatial Separation Method



(b) Hybrid Separation Method

Figure 5.2. Comparison of Individual Flight Time Range (sec) - Stochastic

tained for the heavy traffic load scenario. When the hybrid separation method is implemented, all aircraft are routed on the more direct routings.

Moreover, in order to compare the individual flight time results computed with the two different separation methods, Table 5.6 presents the individual flight time reductions enabled by the hybrid separation method when compared to the spatial separation method.

Table 5.6. Comparison of Individual Flight Time Reductions - Stochastic, Optimal Repetition

Traffic Load	Individual Flight Time Reduction
Light	Arrivals: up to 57s - Departures: up to 125s
Medium	Arrivals: up to 85s - Departures: up to 125s
Large Heavy	Arrivals: up to 146s - Departures: up to 155s
Heavy	Arrivals: up to 189s - Departures: up to 288s

For all traffic loads under the stochastic settings, similar to the deterministic conditions, the hybrid separation method enables greater individual flight time reductions for departures than for arrivals. The denser the traffic scenario, the more flight time savings obtained.

Comparison of Uncertainty Conditions When comparing the results obtained under deterministic and stochastic settings, both uncertainty conditions enable total and individual flight time reductions when the hybrid separation method is implemented. Routing aircraft using the more direct routes definitely induces total and individual flight time savings.

Total flight times of all traffic load scenarios are more reduced by the hybrid separation strategy under the deterministic settings than under the stochastic settings. However, the presence of uncertainty does not degrade the benefits obtained from routing aircraft on the more direct routes. Moreover under both uncertainty conditions and for all traffic load scenarios, the hybrid separation method induces more individual flight times savings for departures than for arrivals. This is mainly due to the greater route length reduction obtained for departure routes than for arrival routes. Additionally, regardless of the uncertainty settings, the denser the traffic load scenario, the more flight time savings obtained and this simply reflects the increased number of aircraft.

Comparison of Departure Takeoff Delay

For the medium, large and heavy traffic load scenarios, when comparing the total flight times for the spatial separation method under both uncertainty conditions, it is worth mentioning that the respective reference schedules that were generated for these scenarios induced departure flight delays due to insufficient flight separation even for the deterministic simulation. Therefore, averaged takeoff delay of departing flights are computed under the stochastic settings. Figure 5.3 illustrates the results for all traffic load scenarios and for all repetitions. The marker indicates the average value for departures in the optimal repetition. The takeoff delay is defined as the estimated, i.e. computed, takeoff time minus the earliest departure release time generated in each release time schedule scenario.

For both separation methods, takeoff delays are obtained from runway scheduling because of flight time uncertainty in order to ensure separation requirements. In the hybrid separation method, the extra takeoff delay from runway scheduling arises from the additional separation requirements needed between takeoffs induced by the shared waypoints allowance. For all traffic load scenarios, the computed average takeoff time delay is less when flights are assigned to indirect routes, i.e. spatial separation method, than when flights are allowed to fly more direct routes, i.e. hybrid separation method. For all traffic load traffic scenarios except the heavy one, the average takeoff time delay computed for the optimal repetition, is less than the average takeoff time delay for all repetitions. This is the second limitation observed in the hybrid separation method when the traffic scenario is too dense.

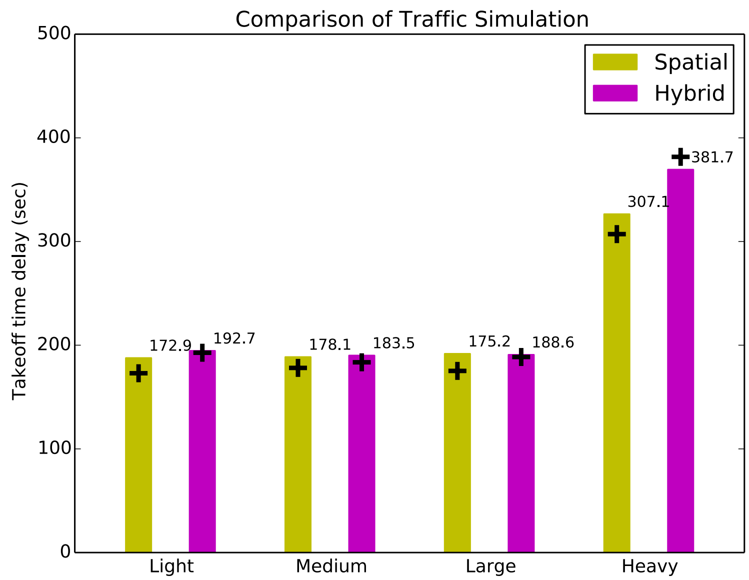


Figure 5.3. Comparison of Traffic Scenario - Departures Takeoff Delay - Stochastic

Comparison of Runway Position Change

Furthermore, in the stochastic simulation, some flights might not be able to meet the initial assigned takeoff slots by the deterministic simulation due to flight time uncertainty. Figure 5.4 illustrates for all traffic load scenarios and for the optimal repetition, the percentage of position changes from the initial runway sequencing provided by the simulation under deterministic conditions relative to the earliest runway arrival times, i.e. release times for departures and due dates for arrivals. In this work, no limit was enforced to the maximum number of position changes.

Under the stochastic settings and for the optimal repetition, runway position changes are observed for both separation methods except for the light traffic load scenario under the hybrid separation method. Moreover, for the light and medium traffic load stochastic simulations, minimizing delays induces more runway position changes when flights are assigned to indirect routes, i.e. spatial separation method, than when flights are allowed to fly more direct routes, i.e. hybrid separation method. For the

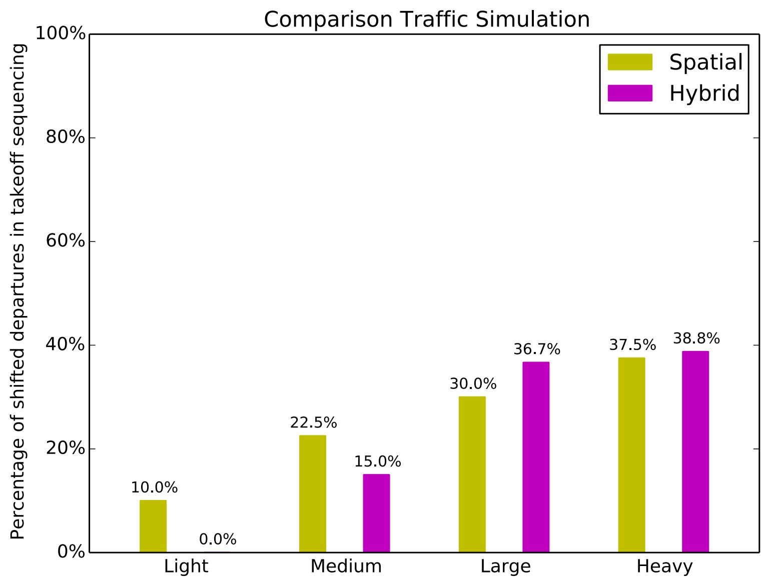


Figure 5.4. Comparison of Traffic Scenario - Runway Order Changes - Stochastic, Optimal Repetition

light and the medium traffic load scenarios, a less work-demanding runway sequencing is found when routes share waypoints because the flights are less independent from one another. This observation clearly shows that a compromise between minimum delay and optimal runway sequence is computed by the optimization. For the large and heavy traffic load scenarios, minimizing delays induces more runway position changes when flights are assigned to direct routes than when flights are constrained to fly the current operated routes. However the difference is not really significant. In the heaviest traffic simulations, the hybrid separation enables significant flight time reductions but creates more takeoff delays and additional runway change positions. This is the third limitation observed in the hybrid separation method when the traffic scenario is too dense.

5.1.4 Scenarios Comparison

Overall, when allowing more direct routes to be flown and enforcing the hybrid separation method, total and individual flight times are significantly reduced for both arrivals and departures even in the presence of uncertainty. Because runway $24L$ is used for mixed operations, some delays occur at the runway. For all traffic scenarios, both separation methods introduce takeoff delays for departing flights. For the hybrid separation method, extra takeoff delay from runway scheduling arises from the additional separation requirements needed between takeoffs induced by the shared waypoints allowance. With such additional delay, some flights might miss their runway takeoff slots potentially inducing runway position shifting.

All traffic scenarios introduce more takeoff time delay when flights are assigned to direct routes than when they are assigned to indirect routes. The values that were computed are definitely a function of the fleet mix characteristics in the tested traffic load scenarios. Because more heavy type aircraft were considered in proportion in the largest traffic load scenarios than in the light traffic load scenario, longer runway separation times were computed.

Additionally for both separation methods in the stochastic case, the denser the tested traffic load scenario, the more runway position shifts occurred. The medium, large and heavy traffic load scenarios have more aircraft-type runway-sequences than the light traffic load scenario that potentially can lead to lower delays when compared to the initial runway sequence provided by the deterministic simulation of each traffic load scenario. Therefore, the percentage of runway positions shifting is higher for denser traffic load scenarios. Moreover, for both the light and medium traffic load scenarios, the hybrid separation method induced less runway position changes than the spatial separation method. However for the large and heavy traffic load scenarios, the opposite occurred. There are limitations to the benefit of assigning aircraft to direct routes when the demand is high and scheduling time period is tight. For all traffic load scenarios, the optimization tried to find a balance between total delays and runway sequence.

Due to overall limited performance computed from the heavy traffic load scenario, the simulations that are presented in the next section are limited to the light, medium and large traffic load scenarios.

5.2 Integrated Arrival, Departure and Surface Operations

In this section, the integration of arrival and departure operations is extended to the airport surface operations. The previously created traffic load scenarios that consider various numbers of aircraft are modified to include the assigned terminal information. Excluding the heavy traffic load scenario, the light, medium and large traffic load scenarios are applied to the combined models of the Los Angeles International Airport (LAX) and the Los Angeles terminal airspace. Similarly to the previous section, the simulations setup is first described, the metrics used for comparison are then defined and the results are presented.

5.2.1 Simulations Setup

The simulations setup for integrated surface and air operations is similar to the simulation setup for integrated air operations. Information about the assigned terminals of each aircraft in the different traffic scenarios is provided along with the schedule generation for the surface operations and the sources of uncertainty on the airport surface.

Traffic Scenarios, Aircraft Mix and Terminals

The previously created three traffic load scenarios characterised by small, medium and large numbers of aircraft, are considered to test the methodology over a flight scheduling window of 30 minutes. Because the simulations are extended to the surface operations, the 30-minute scheduling window is extended to 45 minutes. The following Table 5.7 summarises the different traffic demand scenarios considered as well as the aircraft types used in each scenario and the terminal assigned to each aircraft. It is to be noted that heavy aircraft types denoted by H are only assigned to depart and arrive from/to the international terminal $TBIT$.

Table 5.7. Traffic Scenarios, Aircraft Types and Assigned Terminals Used in Simulations

Number of Aircraft	Weights	Operations	Terminals
10	1S + 8L + 1H	6A + 4D	2T1 + 4T2 + 3T3 + 1TBIT
20	2S + 15L + 3H	12A + 8D	6T1 + 6T2 + 5T3 + 3TBIT
30	5S + 22L + 3H	17A + 13D	10T1 + 9T2 + 8T3 + 3TBIT

Schedule Generation and Uncertainty Considerations

For each traffic load simulation, a reference schedule is randomly created for a 45-minute time period. Moreover, for each traffic load simulation, release time and due date schedules are generated by respectively adding error sources drawn from probabilistic distributions to both reference arrival and departure time schedules. For integrated air and ground operations, surface release time schedules from the departing terminals are generated for departures whereas air release time schedules from fix FIM are generated for arrivals. Moreover, surface due date schedules are generated for arrivals to the arrival terminals whereas air due date schedules are generated for departures at waypoint WPT1.

As presented in the previous chapter, to generate the surface schedules at the terminals, the departing time error from the gates can be described by a lognormal distribution with a mean of 20.4 seconds and a standard deviation of 166.8 seconds whereas the arrival time error to the gates can be described by a normal distribution with a mean value of -265.8 seconds and a standard deviation of 708.6 seconds.

Moreover, to generate air schedules, departure and arrival time errors following normal distributions are respectively added to flight times at WPT1 and at FIM. For the departure time error, a normal distribution with a mean of 0 seconds and standard deviation of 15 seconds is selected whereas for the arrival time error, a normal distribution with with a mean of 0 seconds and standard deviation of 30 seconds is selected.

5.2.2 Comparison Metrics

To evaluate the results of the different traffic load simulations, the spatial and hybrid separation methods are compared under deterministic and stochastic conditions. To compare the obtained results under both uncertainty conditions, the total and individual traveling times are computed separately for the surface and the air and for both spatial and hybrid separation methods. For the deterministic settings, surface and flight times are provided for baseline reference. For the stochastic settings, Box and Whisker plots are used to represent the surface and flight time ranges that are computed for all repetitions. Additionally, the obtained runway sequences and schedules are compared. Finally, the average takeoff time delay is computed under both uncertainty conditions and the percentage of shifted flights in runway sequencing compared to the initial runway sequence given by the solution under deterministic settings is provided for the optimal repetition.

5.2.3 Results

All traffic load scenarios that were simulated were scheduled over a 45-minute time window and respective reference schedules were created accordingly. It is to be noted that the large traffic scenario represents very dense conditions for a single runway to support mixed operations.

Comparison of Traveling Times and Routings

The traveling times are composed of surface and flight times. For each traffic load scenario, traveling times are computed under both deterministic and stochastic conditions and are compared for both the spatial and the hybrid separation methods. Surface times correspond to periods of time for which aircraft are moving on the airport taxiway system.

Surface Times For the surface results, total and individual surface time ranges are presented for departures and arrivals.

Deterministic Conditions Total surface times of each traffic load scenario are first computed under the deterministic settings. Table 5.8 presents the results for both separation methods.

Table 5.8. Comparison of Total Surface Times - Deterministic

Traffic Load	Spatial	Hybrid	Total Surface Time Reduction
Light	5427s	5427s	0%
Medium	11465s	11275s	1.7%
Large	17185s	16421s	4.4%

For all traffic loads except the light scenario, the hybrid spatial separation method enables total surface time reductions in the range of 1.7% to 4.4% compared to the spatial separation method when the simulations are run under the deterministic settings. For the light load scenario, the number of aircraft is too small for the optimization to find any added surface traveling benefits from the hybrid separation method over the spatial separation method.

Because the aircraft surface movements simulated in all scenarios start and finish at different terminals, the computed surface times of each aircraft are naturally different. When looking at the individual aircraft surface times of each traffic load scenario, the hybrid separation method reduces individual surface times of both departures and arrivals except for the light traffic scenario. The following set of figures illustrates the results for both separation methods with Figure 5.5(a) and Figure 5.5(b) respectively showing the results computed with the spatial and with the hybrid separation method. Box and Whisker plots are used to represent the computed surface time ranges, from the minimum computed value to the maximum computed value. The surface time median of each scenario is illustrated by the horizontal line in each box.

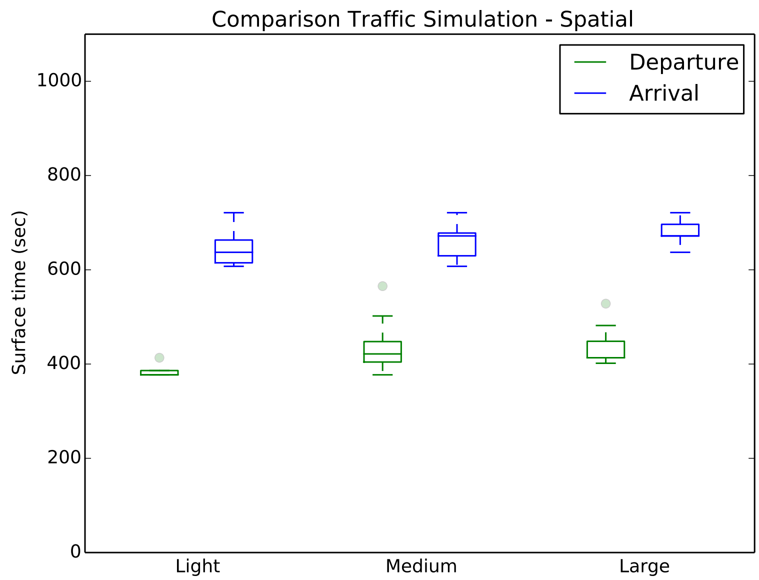
For each separation method, the denser the traffic load scenario, the longer the computed individual aircraft surface times. Simulating dense traffic load conditions in a tight time window invokes scheduling and routing a large number of aircraft on the airport surface under timing constraints. In order to meet the schedule constraints and satisfy the separation requirements on the taxiway system and on the runway, aircraft are not assigned maximum allowable taxi speeds on all taxiway segments traveled. This is illustrated by representing the different computed surface time ranges by boxes of different heights in Figure 5.5.

Moreover, in order to compare the individual aircraft surface time results computed using the two different separation methods, Table 5.9 presents the individual aircraft surface time reduction enabled by the hybrid separation method when compared to the spatial separation method.

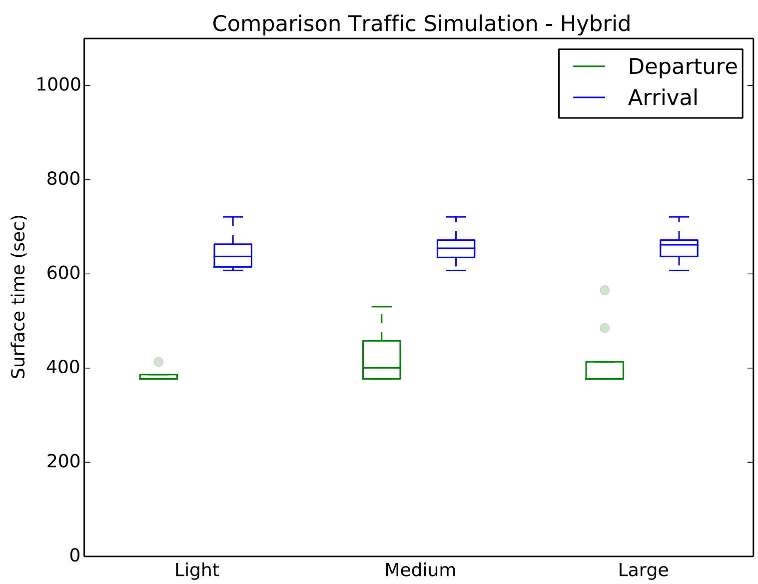
Table 5.9. Comparison of Individual Surface Time Reductions - Deterministic

Traffic Load	Individual Surface Time Reduction
Light	Arrivals: up to 0s - Departures: up to 0s
Medium	Arrivals: up to 0s - Departures: up to 50s
Large	Arrivals: up to 34.7s - Departures: up to 68.4s

Overall, for all traffic loads under the deterministic settings except for the light traffic load, the hybrid separation enables greater individual aircraft surface time reductions for departures than for arrivals. For the medium traffic load scenario, the



(a) Spatial Separation Method



(b) Hybrid Separation Method

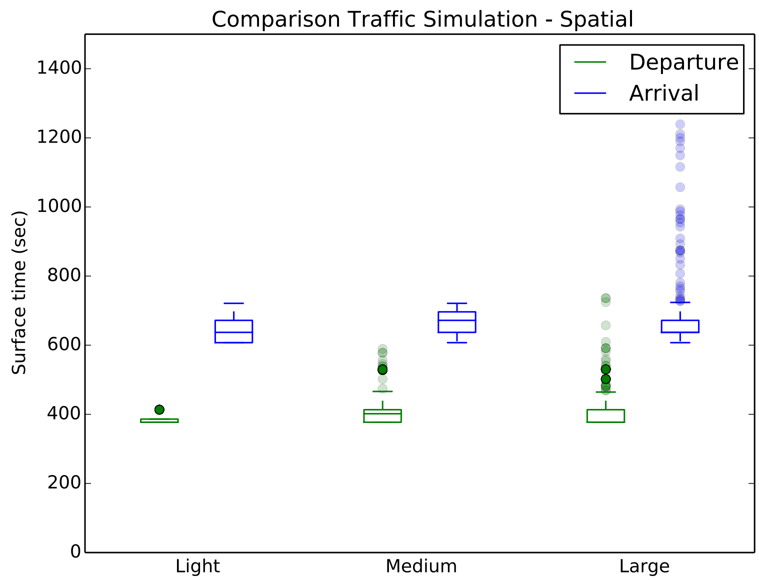
Figure 5.5. Comparison of Individual Surface Time Ranges (sec) - Deterministic

arrival surface times are the same under both spatial and hybrid separation method whereas surface times of departing flights are improved. It can be observed from Table 5.9 that the denser the traffic load scenario, the more individual aircraft surface time savings obtained.

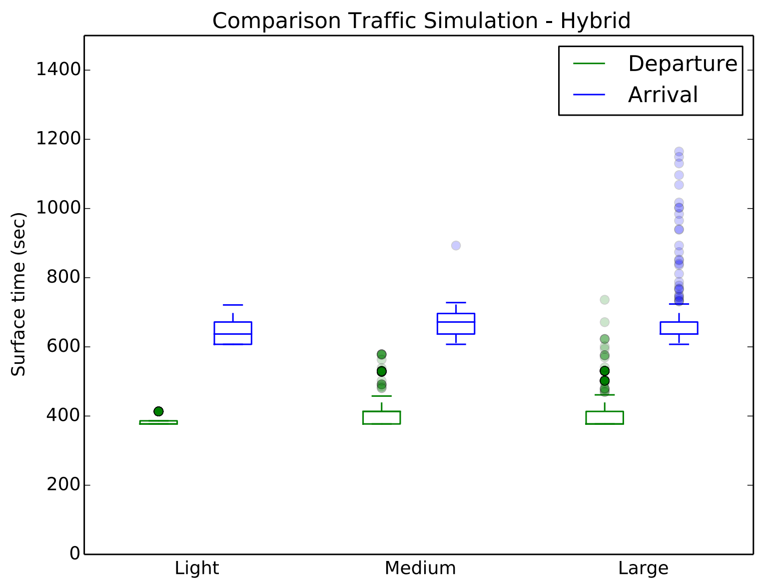
Stochastic Conditions The surface times are then computed under the stochastic settings for all traffic load scenarios. Figure 5.6 presents the surface time ranges computed for all repetitions. Results computed under the spatial and the hybrid separation methods are respectively displayed in Figure 5.6(a) and Figure 5.6(b). Box and Whisker plots are used to represent the computed surface time ranges, from the minimum computed value to the maximum computed value for all repetitions. The surface time median of each scenario is illustrated by the horizontal line in each box.

A similar comment than under the deterministic conditions can be made for the stochastic conditions when comparing the results of each separation method. The denser the traffic load scenario, the longer individual aircraft surface times computed. Moreover, Figure 5.6 demonstrates that for all traffic load scenarios even with the presence of uncertainty, the hybrid separation method allows aircraft surface time savings for both arrivals and departures when compared to the spatial separation method, in particular aircraft surface time medians are reduced. Additionally, the aircraft surface time values computed for departures are less dispersed with the hybrid separation method as with the spatial separation method. For the medium and large traffic load scenarios, the hybrid separation methods allows the aircraft surface time medians to be reduced but the aircraft surface time ranges of both arrivals and departures remain dispersed. This observation suggests that when the traffic load scenario is too dense, individual aircraft surface time benefits from the hybrid separation method are more limited than for less dense traffic load scenarios.

For the optimal repetition, the computed total aircraft surface time reductions enabled by the hybrid separation method for each traffic load scenario are summarised in Table 5.10.



(a) Spatial Separation Method



(b) Hybrid Separation Method

Figure 5.6. Comparison of Surface Time Ranges (sec) - Stochastic

Table 5.10. Comparison of Total Surface Times - Stochastic, Optimal Repetition

Traffic Load	Spatial	Hybrid	Total Surface Time Reduction
Light	5427s	5427s	0%
Medium	11279s	11210s	0.6%
Large	16766s	16393s	2.2%

For all traffic loads under the stochastic settings except the light traffic scenario, the hybrid spatial separation method enables total aircraft surface time reductions in the range of 0.6% to 2.2% compared to the spatial separation method. For the light load scenario, the number of aircraft is too small for the optimization to find any added surface traveling benefits from the hybrid separation method over the spatial separation method.

Moreover, in order to compare the individual aircraft surface time results computed with the two different separation methods, Table 5.11 presents the individual aircraft surface time reductions enabled by the hybrid separation method when compared to the spatial separation method.

Table 5.11. Comparison of Individual Surface Time Reductions - Stochastic, Optimal Repetition

Traffic Load	Individual Surface Time Reduction
Light	Arrivals: up to 0s - Departures: up to 0s
Medium	Arrivals: up to 29.8s - Departures: up to 24.7s
Large	Arrivals: up to 91.3s - Departures: up to 29.4s

For all traffic loads under the stochastic settings, similar to the deterministic conditions, the hybrid separation method enables individual aircraft surface time savings except for the light traffic scenario. Contrarily to the results under the deterministic conditions, greater individual aircraft surface time reductions are obtained for arrivals than for departures. Additionally, it can be observed from Table 5.11, the denser the traffic scenario, the more surface time savings obtained.

Air Times For the air results, total and individual flight times are presented along with the selected flight routings for departures and arrivals.

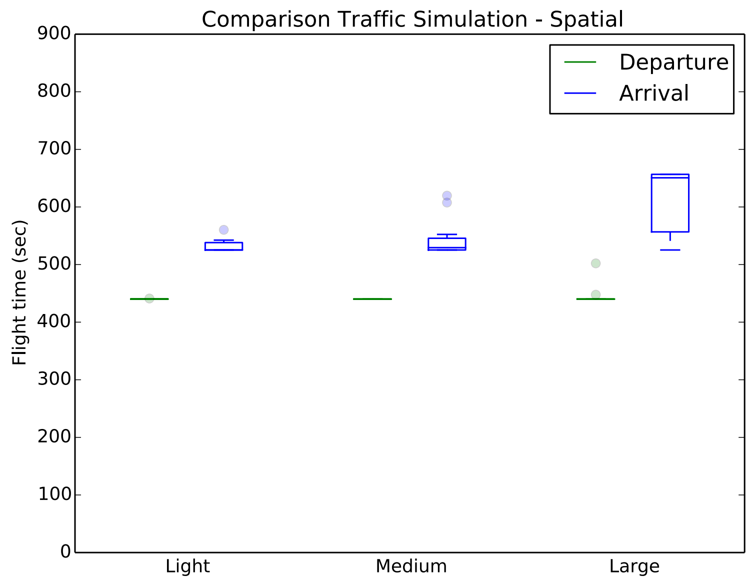
Deterministic Conditions The total air traveling times of each traffic load scenario are first computed under the deterministic settings. Table 5.12 presents the results for both separation methods.

Table 5.12. Comparison of Total Flight Times - Deterministic

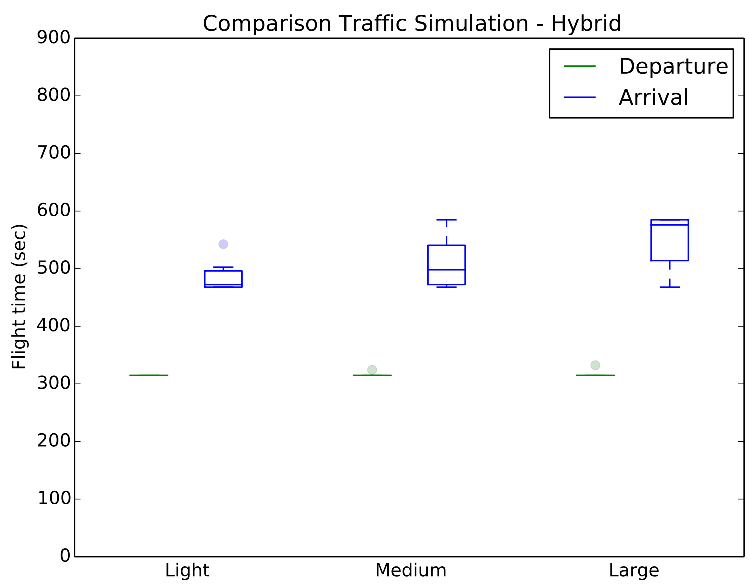
Traffic Load	Spatial	Hybrid	Total Flight Time Reduction
Light	4965s	4184s	15.7%
Medium	10268s	8634s	16.2%
Large	16260s	13469s	17.2%

For all traffic loads, the hybrid separation method enables total flight time reductions in the range of ∼16.3% compared to the spatial separation method when the simulations are run under the deterministic settings. For all traffic scenarios, the optimization using the hybrid separation method is able to reduce total flight times thanks to a better selected routing. All flights were routed on the more direct routings.

When looking at the individual aircraft flight times of each traffic load scenario, the hybrid separation method reduces individual flight times of both departures and arrivals. The following set of figures illustrates the results for both separation methods with Figure 5.7(a) and Figure 5.7(b) respectively showing the results computed with the spatial and the hybrid separation method. Box and Whisker plots are used to represent the computed flight time ranges, from the minimum computed value to the maximum computed value. The flight time median of each scenario is illustrated by the horizontal line in each box.



(a) Spatial Separation Method



(b) Hybrid Separation Method

Figure 5.7. Comparison of Individual Flight Time Ranges (sec) - Deterministic

For each separation method, the denser the traffic load scenario, the longer the computed individual aircraft flight times. Simulating dense traffic load conditions in a tight time window invokes scheduling and routing a large number of aircraft under timing constraints. In order to meet the schedule constraints and satisfy the separation requirements, aircraft are not assigned maximum allowable air speeds on all air segments flown. This is illustrated by the larger height box dimensions for individual flight times of arrival flights in each traffic load scenario box plot representations. When observing the results of departure flights, the hybrid separation method enables about the same flight time reduction regardless of the traffic load simulated. The individual flight times for departures are congregated around the departure flight time median.

Additionally, in order to compare the individual flight time results computed with the two different separation methods, Table 5.13 presents the individual flight time reductions enabled by the hybrid separation method when compared to the spatial separation method.

Table 5.13. Comparison of Individual Flight Time Reductions - Deterministic

Traffic Load	Individual Flight Time Reduction
Light	Arrivals: up to 92.4s - Departures: up to 125.4s
Medium	Arrivals: up to 151.7s - Departures: up to 125.4s
Large	Arrivals: up to 142.6s - Departures: up to 125.4s

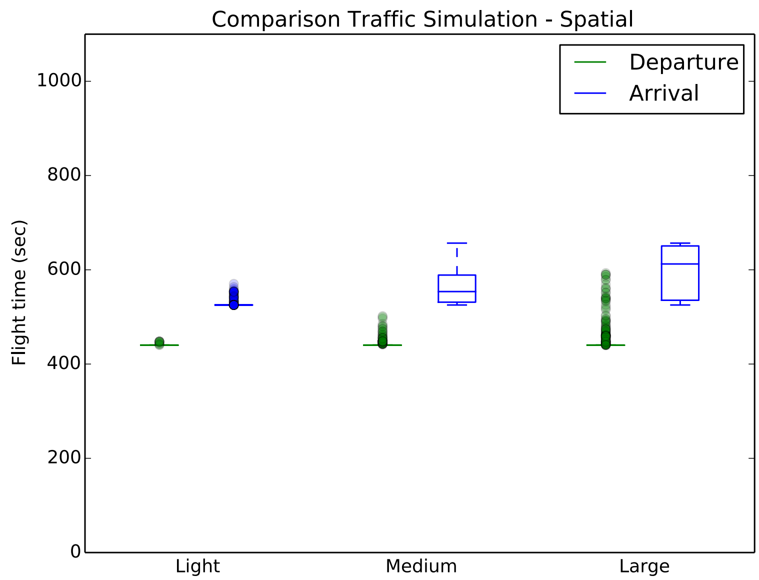
Overall, for all traffic loads under the deterministic settings, the hybrid separation enables individual aircraft flight time savings for departure and arrival flights. In particular, greater individual flight time reductions are obtained for departures than for arrivals. Additionally, the denser the traffic load scenario, the more individual flight time savings obtained. It can be observed that no matter the traffic load scenario considered, the maximum individual flight time savings obtained for departing flights is the same amount of about two minutes.

Stochastic Conditions The air traveling times are then computed under the stochastic settings for all traffic load scenarios. Figure 5.8 presents the air time ranges computed for all repetitions. Results computed under the spatial and the hybrid separation methods are respectively displayed in Figure 5.8(a) and Figure 5.8(b). Box and Whisker plots are used to represent the computed flight time ranges, from the minimum computed value to the maximum computed value for all repetitions. The flight time median of each scenario is illustrated by the horizontal line in each box.

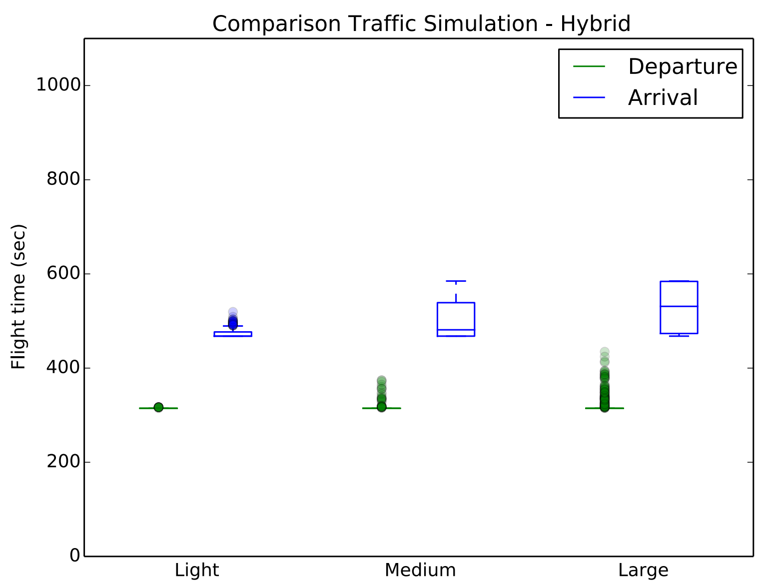
A similar comment than under the deterministic conditions can be made for the stochastic conditions when comparing the results of each separation method. The denser the traffic load scenario, the longer individual aircraft flight times computed. Moreover, Figure 5.8 demonstrates that for all traffic load scenarios even with the presence of uncertainty, the hybrid separation method allows flight time savings for both arrivals and departures when compared to the spatial separation method, in particular flight time medians are reduced. Additionally, the flight time values computed for departures are less dispersed with the hybrid separation method as with the spatial separation method. For the medium and large traffic load scenarios, the hybrid separation methods allows the flight time medians to be reduced but the flight time ranges of both arrivals and departures remain dispersed. This observation suggests that when the traffic load scenario is too dense, individual aircraft flight time benefits from the hybrid separation method are more limited than for less dense traffic load scenarios.

For the optimal repetition, the computed total aircraft flight time reductions enabled by the hybrid separation method for each traffic load scenario are summarised in Table 5.14.

For all traffic loads under the stochastic settings, the hybrid separation method enables total aircraft flight time reductions in the range of $\sim$17% compared to the spatial separation method. For all traffic scenarios, the optimization using the hybrid separation method is able to reduce total aircraft flight times thanks to a better



(a) Spatial Separation Method



(b) Hybrid Separation Method

Figure 5.8. Comparison of Individual Flight Time Ranges (sec) - Stochastic

Table 5.14. Comparison of Total Flight Times - Stochastic, Optimal Repetition

Traffic Load	Spatial	Hybrid	Total Flight Time Reduction
Light	4920s	4084s	17%
Medium	10060s	8324s	17.3%
Large	16156s	13311s	16.7%

selected routing even when schedules are affected by the presence of uncertainties. For the optimal repetition, the direct routing is selected for all flights in all traffic load scenarios.

Moreover, in order to compare the individual aircraft flight time results computed with the two different separation methods, Table 5.11 presents the individual flight time reductions enabled by the hybrid separation method when compared to the spatial separation method.

Table 5.15. Comparison of Individual Flight Time Reductions - Stochastic, Optimal Repetition

Traffic Load	Individual Flight Time Reduction
Light	Arrivals: up to 57.4s - Departures: up to 125.4s
Medium	Arrivals: up to 87.8s - Departures: up to 125.4s
Large	Arrivals: up to 124.8s - Departures: up to 125.4s

For all traffic loads under the stochastic settings, similar to the deterministic conditions, the hybrid separation method enables greater individual flight time reductions for departures than for arrivals. The denser the traffic scenario, the more aircraft flight time savings obtained.

Comparison of Departure Takeoff Delay

For the medium and large traffic load scenarios, when comparing the total traveling times when the spatial separation method is implemented under both uncertainty conditions, it is worth mentioning that the respective reference schedules that were generated for these scenarios induced departure flight delays due to insufficient flight separation even for the deterministic simulation. Therefore, averaged takeoff delay of departing flights are computed under the stochastic settings. The results for all traffic load scenarios are illustrated in Figure 5.9 for all repetitions. The marker indicates the average value for departures in the optimal repetition. The takeoff delay is defined as the estimated, i.e. computed, takeoff time minus the earliest departure release time generated in each release time schedule scenario.

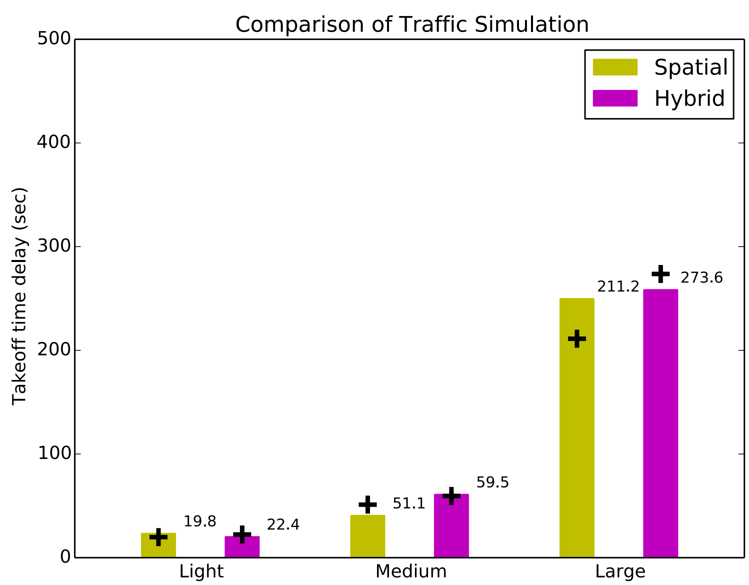


Figure 5.9. Comparison of Traffic Scenario - Departures Takeoff Delay (sec) - Stochastic

For both separation methods, takeoff delays are obtained from runway scheduling because of both surface and flight time uncertainty in order to ensure separation requirements at all time at every surface and air waypoints. In the hybrid separation method, the extra takeoff delay from runway scheduling arises from the additional separation requirements needed between takeoffs induced by the shared waypoints allowance. For all traffic load scenarios, the computed average takeoff time delay is less when aircraft are separated using the spatial separation method than when aircraft are separated using the hybrid separation method. For the optimal repetition, average takeoff time delay up to 22.4s, 1min and 4.5 min are respectively computed for the light, medium and large traffic load scenarios. Additionally, the hybrid separation method respectively induces a 19.8%, 16.4% and 29.5% takeoff time delay increase for the light, medium and large traffic load scenarios when compared to the results computed with the spatial separation method for the optimal repetition. Therefore, the denser the traffic scenario, the more departure takeoff time delay obtained. Moreover, for all traffic load traffic scenarios, the average takeoff time delay computed for the optimal repetition, is equal of more than the average takeoff time delay for all repetitions. This shows that for all traffic load scenarios, the solution provided by the optimal repetition, i.e. smallest objective value, represent results that are optimal for the entire set of flights considered in each traffic load scenario and individual departing flights might be penalized in terms of departure delays.

Comparison of Runway Sequences and Schedules

The spatial and hybrid separation methods affect the aircraft routing in each traffic load scenario regardless of the uncertainty conditions. When uncertainty is introduced in the stochastic simulation, both surface and air operation schedules are affected furthermore and some flights might not be able to meet the initial takeoff slots assigned by the deterministic simulation. Therefore, different runway sequences and schedules are obtained when using the spatial and hybrid separation methods and when computed under the different uncertainty conditions. Each resulting traffic load scenario runway sequence and schedule are compared separately for both separation methods and the computed timelines are presented for both uncertainty conditions.

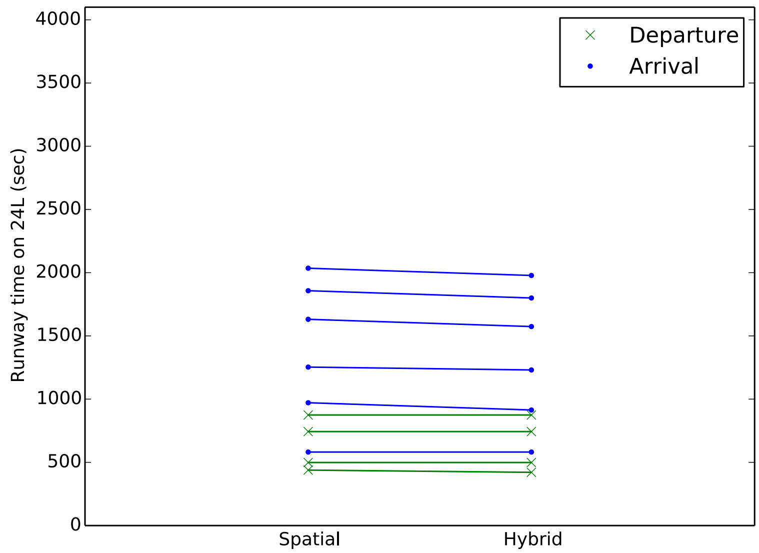
Light Scenario The light traffic scenario consists of scheduling and routing 10 aircraft in a 45-minute scheduling time window. Clearly, the fleet mix is small enough that the generated reference schedule scenario is not too tight. The runway sequences and schedules are computed for both the spatial and the hybrid separation method and the results are displayed under both deterministic and stochastic conditions in Figure 5.10.

When the runway timeline is computed for the deterministic conditions, it can be observed in Figure 5.10(a) that although the aircraft runway sequence is not changed, the hybrid separation method enables a tighter runway schedule. When the hybrid separation method is used, arrival flights can land earlier which can potentially induce a more efficient runway usage. The same observation can be made in Figure 5.10(b) when the runway timeline is computed under the stochastic conditions for the optimal repetition.

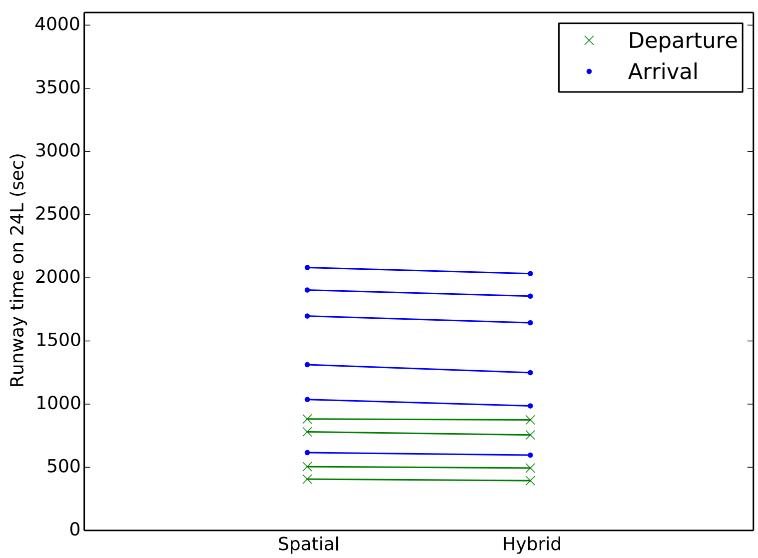
The results for the light scenario demonstrate that the traffic load is too low to find significant benefits from the hybrid separation method at the runway threshold under both uncertainty conditions. However when the hybrid separation is implemented, a slight timeline make-span decrease is computed.

Medium Scenario The medium traffic scenario consists of scheduling and routing 20 aircraft in a 45-minute scheduling time window. The medium scenario represents a $\sim$42% traffic load increase when compared to regular traffic load operations on runway $24L$ at LAX for such scheduling time window. The runway sequences and schedules are computed for both the spatial and the hybrid separation method and the results are displayed under both deterministic and stochastic conditions in Figure 5.11.

For both uncertainty conditions, Figure 5.11(a) and Figure 5.11(b) illustrates that the runway timelines computed with the hybrid separation method is more tight than



(a) Deterministic Conditions



(b) Stochastic Conditions - Optimal Repetition

Figure 5.10. Light Traffic Scenario - Comparison of Runway Sequence and Schedule (sec)

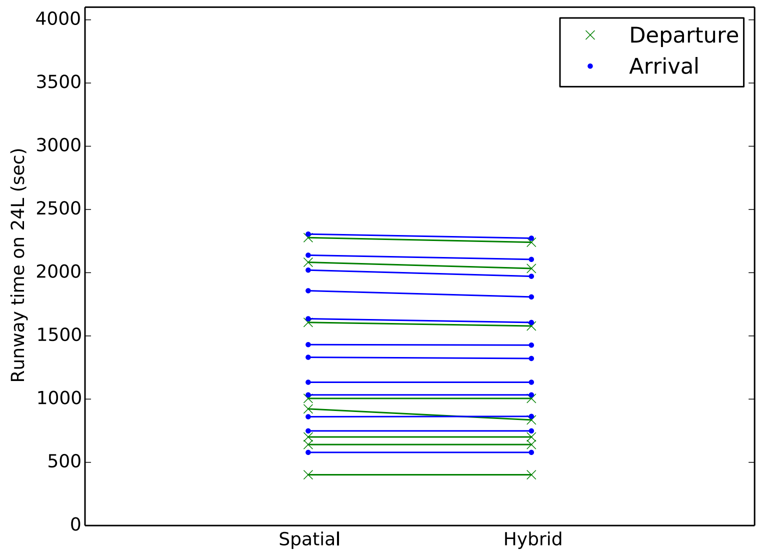
with the spatial separation method. This enables a more condense runway usage that can potentially receive more flights in the same scheduling time window.

Additionally, when the runway sequences and schedules computed for both separation methods are compared for the deterministic conditions, it can be observed that when the hybrid separation method is implemented, one departure flight is being shifted to an earlier departure slot than when the spatial separation method is implemented. For the stochastic conditions and in particular the optimal repetition, two runway sequence changes can be observed that affect two departure flights and these are being scheduled to depart later than with the spatial separation method.

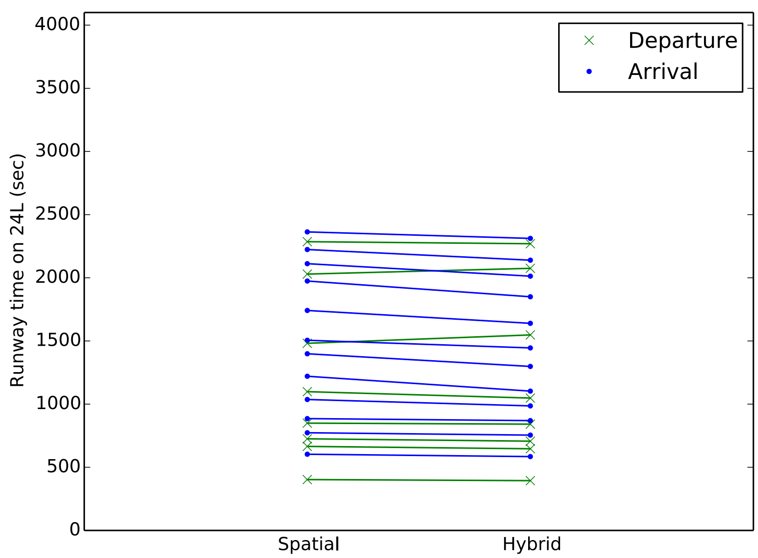
The results for the medium scenario demonstrate that the when the hybrid separation method is implemented, the make-span of the runway timeline is decreased because a more optimal runway sequence can be found.

Large Scenario The large traffic scenario consists of scheduling and routing 30 aircraft in a 45-minute scheduling time window. The medium scenario represents a ∼114% traffic load increase when compared to regular traffic load operations on runway 24L at LAX for such scheduling time window. The runway sequences and schedules are computed for both the spatial and the hybrid separation method and the results are displayed under both deterministic and stochastic conditions in Figure 5.12.

For both uncertainty conditions, the hybrid separation method induces runway sequence changes and this can be observed in Figure 5.12(a) and Figure 5.12(b). Regardless of the uncertainty conditions, the computed runway timelines are tighter when the hybrid separation method is implemented than when the spatial separation method is implemented. When comparing the separation methods for the stochastic condition in the optimal repetition, it can be observed that because arrival flights are scheduled to land earlier with the hybrid separation method than with the spatial separation method, two departing flights have their take-off times significantly affected. When looking closer to the details of those two departing flights, it was found



(a) Deterministic Conditions



(b) Stochastic Conditions - Optimal Repetition

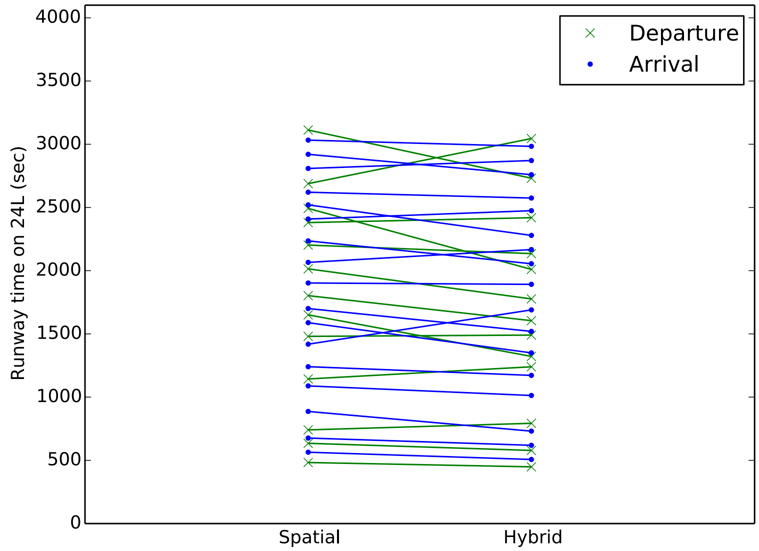
Figure 5.11. Medium Traffic Scenario - Comparison of Runway Sequence and Schedule (sec)

that they were a small and a heavy aircraft. Because of uncertainty and because of an open slot in between two arrivals, the optimization rescheduled the heavy aircraft to depart earlier with the hybrid separation than with the spatial separation in order to satisfy the wake vortex temporal separations on the runway without disrupting already scheduled flights. However, the small aircraft was rescheduled to depart later with the hybrid than with the spatial separation method.

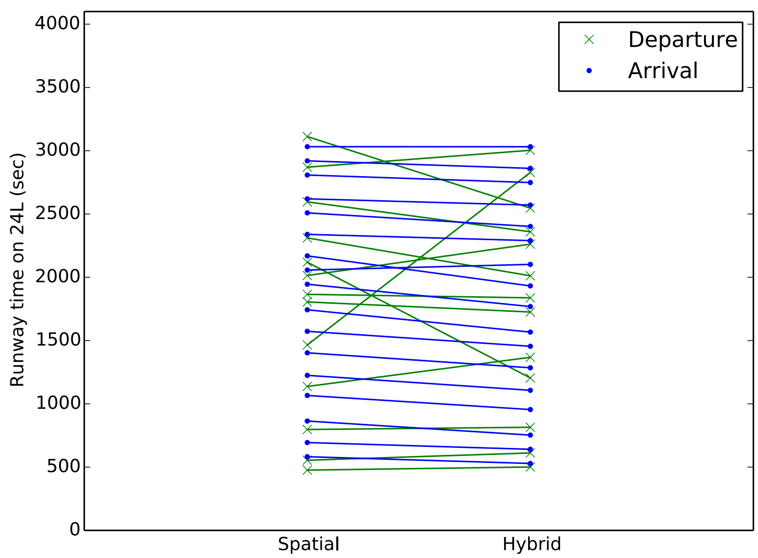
As for the medium scenario, the results for the large scenario demonstrate that the when the hybrid separation method is implemented, the make-span of the runway timeline is decreased because a more optimal runway sequence can be found. However, the optimal sequence does affect more significantly the schedule of a few departing flights.

Runway Position Change of Departure Flights For all tested traffic load scenarios except the light one, the hybrid separation method induces runway sequence changes of arrival and departure flights. It was shown in the large traffic scenario that under stochastic conditions, departing flight schedules might be more impacted than arrival flight schedules. In Figure 5.13, the percentage of runway position changes from the initial runway sequencing provided by the simulation under deterministic conditions is provided for departure flights under the stochastic settings for the optimal repetition. The results are compared for all traffic load scenarios. In this work, no limit was enforced to the maximum number of position changes.

Except for the light traffic load scenario, Figure 5.13 shows that the heavier traffic load scenario, the more runway position changes. Moreover, it can be observed that when the hybrid separation method is implemented, less runway position changes occur than when the spatial separation method is implemented. Although there is only 5% runway position changes in the medium traffic load scenario when the hybrid separation method is used, the number of runway position changes increases to 26.7% in the large traffic scenario. However under the spatial separation method, the number of runway position changes does not increase that much but still remains



(a) Deterministic Conditions



(b) Stochastic Conditions - Optimal Repetition

Figure 5.12. Large Traffic Scenario - Comparison of Runway Sequence and Schedule (sec)

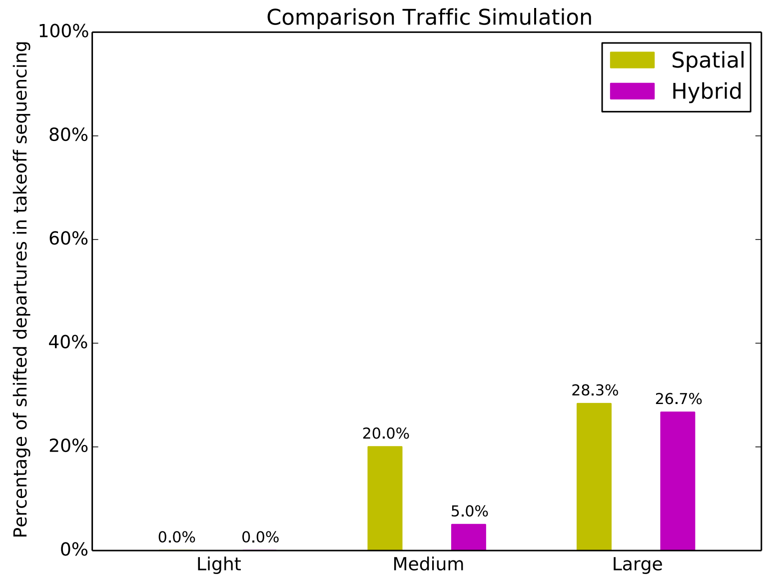


Figure 5.13. Comparison of Traffic Scenario - Runway Position Shifting of Departure Flights - Stochastic

larger than for the hybrid separation method. Therefore, it can be concluded that in the presence of uncertainty, the hybrid separation method enables less runway position changes than the spatial separation method when compared to the original runway sequence computed under the deterministic settings. However, for large traffic loads, the hybrid separation method might continue to increase preventing from any added benefits.

Scenarios Comparison

Overall, the hybrid separation method enables total and individual traveling time savings regardless of the considered uncertainty conditions. Except for the light traffic load scenario, the computed results show that both total and individual surface and air times are reduced when more direct routes are allowed to be travelled even in the presence of uncertainty. The surface time savings are in the range of 4% whereas the air time savings are in the range of 17%. Because runway $24L$ is used for mixed operations, some delays occur at the runway. For all traffic scenarios, both separation methods introduce takeoff delays for departing flights. For both separation methods, takeoff delays are obtained from runway scheduling because of both surface and flight time uncertainty in order to ensure separation requirements at all time at every surface and air waypoints. With such additional delay, some flights might miss their runway takeoff slots potentially inducing runway position shifting.

All traffic scenarios introduce more takeoff time delay when the hybrid separation method is enforced than when the spatial separation method is enforced. The denser traffic scenario, the more traveling time savings but at the price of more takeoff time delay. Additionally, for all tested traffic load scenarios except the light one, although the hybrid separation method induced runway sequence changes of arrival and departure flights, the computed runway timelines were more tight. The values that were computed are definitely a function of the fleet mix characteristics in the tested traffic load scenarios. Because more large and heavy type aircraft were considered in proportion in the largest traffic load scenarios than in the light traffic load scenario, longer runway separation times were computed.

Furthermore for both separation methods in the stochastic case, the denser the tested traffic load scenario, the more runway position shifts occurred. The medium and large traffic load scenarios have more aircraft-type runway-sequences than the light traffic load scenario that potentially can lead to lower delays when compared to the initial runway sequence provided by the deterministic simulation of each traffic load scenario. Therefore, the percentage of runway positions shifting is higher for denser traffic load scenarios. Moreover, for all traffic load scenarios except the large one, the hybrid separation method induced less runway position changes than the spatial separation method. However for the percentage of runway position shifting increased significantly for the large traffic load scenarios. There are limitations to the benefit of assigning aircraft to direct routes when the demand is high and scheduling time period is tight. For all traffic load scenarios, the optimization tried to find a balance between total delays and runway sequence.

6. Conclusions and Future Research

This chapter concludes the dissertation and provides an overview of the work accomplished in this research to tackle the research questions defined in the introduction. A summary is provided in Section 6.1 and concluding remarks and directions for future research are formulated in Section 6.2.

6.1 Summary

This work contributes to stochastic scheduling optimization in the field of air traffic management. To address inefficiencies of both surface and air procedures and support improved operational efficiency, this research integrates surface, departure and arrival operations. An alternative method to past research is presented in this dissertation to simultaneously solve the integrated arrival and departure routing and scheduling problem with the integrated taxiway and runway routing and scheduling problem. It computes optimal surface and air routings and schedules in the presence of uncertainty.

To accomplish the objective of this work, a scheduler is built to compute schedules for airport surface and terminal airspace waypoints that are shared by both arrivals and departures. Inspired from manufacturing operations, the scheduler is based on a machine job-shop scheduling problem formulation in which probabilistic release and probabilistic due dates are investigated. To manage integrated surface and terminal airspace operations, a time-based separation strategy is implemented through the use of speed varying constraints. To separate aircraft at the runway, wake vortex separation requirements are enforced at all times. A multi-stage stochastic programming approach is used to solve the problem and solutions are obtained by solving several sample average approximation problems.

A proof-of-concept is conducted under deterministic conditions for a set of fourteen aircraft traveling in a model of the Los Angeles International Airport and surrounding terminal airspace. The results show clear benefits from integrated operations over First-Come-First-Served operations. Scheduling and routing solutions show that allowing aircraft to share waypoints and fly more direct routes may allow greater flight time savings when compared to solutions obtained with a First-Come-First-Served method. Additionally, better operation synchronisations are enabled by integrated operations between the ground, the runway and the air which can potentially limit long taxiway routing and aircraft departing queues.

To integrate realistically the effects of uncertainty on flight time schedules, a data-driven analysis is conducted to compute the probabilistic distributions of uncertainty sources affecting both the airport surface and the terminal airspace operations. Additionally, because the methodology computes approximate solutions and to assess the methodology performance, a sensitivity-statistical analysis is conducted to demonstrate that the proposed methodology does not require more than 100 scenarios to produce robust results. Using such result, simulations of increasing traffic are performed in the presence of uncertainty. A multi-threading method is implemented to help save computation time. To compare the optimization results and show the benefits of integrated operations, two separation methods are implemented. The spatial separation strategy enforces aircraft to travel on indirect routes whereas the hybrid separation strategy allows aircraft to travel on direct routes.

For the integrated arrival and departure simulations, it is found that for all traffic loads tested, the hybrid separation method enables great flight time savings compared to the spatial separation method. However, assigning aircraft to more direct routes induces extra takeoff delays for departing flights. Such additional delays prevent some flight, both arrival and departure, from meeting their initially assigned runway slots engendering runway position changes. For all traffic scenarios, the optimization is able to find an optimal balance between total delays and number of runway position shifting. For the heavy traffic scenario, a limitation is found to the benefit of hybrid separation method compared to spatial separation method. In fact, although reduced flight times are computed, greater takeoff delays and runway position shifting are found when scheduling a set of 40 aircraft in a 30-minute time window on a single runway. Therefore, scenarios that consider 40 aircraft were not considered in the subsequent simulations and the maximum cap was fixed to 30 aircraft.

For the integrated air and surface operation simulations, the scheduling time window was extended to 45 minute to consider the aircraft movements on the airport surface. For all traffic loads tested, the hybrid separation method enables great traveling time savings compared to the spatial separation method. Both surface and air times are reduced when the hybrid separation method is implemented with significantly larger flight time reductions than taxi time reductions. However as for the integrated air operations, assigning aircraft to travel on more direct routes induces extra takeoff delays at the runway for departing flights. Some flights are not able to meet their initially assigned runway takeoff slot and runway position changes are created. The runway position shifting enables a better runway sequencing at the price of additional delays. Some limitations to the benefits of hybrid separation were found when trying to schedule and route the flights of the large scenario set.

The results of both integrated operation simulations are showing great potential for supporting the efficiency of surface and air traffic management. Even with the integration of surface operations, significant traveling time savings were computed in the integrated air and surface operation simulations. Adopting a temporal control separation strategy and allowing waypoints to be shared on the airport surface and in the terminal airspace offer traveling time savings in conjunction with safe aircraft separation at all times. The simulations under uncertainty allow more understanding on how operations can be affected not just in the ramping area but up to runway. By using such tool, more anticipation can be made on operations and the airlines can benefit from it to improve their schedule performance.

6.2 Directions for Future Research

This research offers a large spectrum of problematics to be solved in future research efforts. With the identical goal of improving the efficiency of surface and air operations, different directions can be followed to explore different solution options.

In the simulation of integrated surface and air operations, surface times were not significantly reduced when the hybrid separation method was implemented. Therefore, research focusing on surface operations, displacements and routings on the airport surface represent a first direction for future research.

Additionally, the expansion of the integrated air operations optimization formulation to the surface operations was derived as a direct extension in a single loop of optimization. The interactions between terminal airspace flows and airport taxiway displacements connect at the runway threshold. Could the optimization of surface and air operations be implemented and solved in two different loops of optimization with hard constraints at the runway?

Moreover, the developed formulation was applied to optimize schedules and routings in a Los Angeles case study. Assumptions were made in the modeling of the Los Angeles International Airport and surrounding terminal airspace. Arrival and departure flows were selected amongst others and gates were assumed to be pre-assigned. A direction for future research is to gradually extend the formulation to capture more terminal airspace traffic flows and model more surface resources of the Los Angeles International Airport. The consideration of gate occupancy related timing forms another extension for future research. Additionally, because the study focused on managing and scheduling departures and arrivals in the terminal airspace, the formulation considered runway threshold, final approach fix and meter fixes in the TRACON (Terminal Radar Approach Control). A direction for future research is to integrate schedules from the Center prior to handing-off arriving aircraft at the meter fix to the TRACON.

REFERENCES

REFERENCES

[1] Katherine Lizotte. FAA Aerospace Forecast. Technical report, U.S. Department of Transportation Federal Aviation Administration Aviation Policy and Plans, February 2015.

[2] J W Smeltink, M J Soomer, P R de Waal, and R D van der Mei. An Optimization Model for Airport Taxi Scheduling. *Elsevier Science*, pages 1–25, June 2004.

[3] Hamsa Balakrishnan and Yoon Jung. A Framework for Coordinated Surface Operations Planning at Dallas-Fort Worth International Airport. In *AIAA Guidance, Navigation, and Control Conference and Exhibit (GNC)*, Hilton Head, South Carolina, 2007. American Institute of Aeronautics and Astronautics.

[4] Paul C Roling and Hendrikus G Visser. Optimal Airport Surface Traffic Planning Using Mixed-Integer Linear Programming. *International Journal of Aerospace Engineering*, (1), January 2008.

[5] Sivakumar Rathinam, Justin Montoya, and Yoon Jung. An Optimization Model for Reducing Aircraft Taxi Times at The Dallas Fort Worth International Airport. In *26th Internation Congress of the Aeronautical Sciences*, pages 1–14. 26th International Congress of the Aeronautical Sciences, July 2008.

[6] Raphael Deau, Jean-Baptiste Gotteland, and Nicolas Durand. Airport Surface Management and Runways Scheduling. In *Eighth USA/Europe Air Traffic Management Research and Developement Seminar*, pages 1–9, Napa, California, January 2009.

[7] Gustaf Sölveling, Senay Solak, John-Paul Clarke, and Ellis Johnson. Runway Operations Optimization in the Presence of Uncertainties. *Journal of Guidance, Control, and Dynamics*, 34(5):1373–1382, September 2011.

[8] Gilian L Clare and Arthur G Richards. Optimization of Taxiway Routing and Runway Scheduling. *IEEE Transactions On Intelligent Transportation Systems*, 12(4):1000–1013, 2011.

[9] Hanbong Lee and Hamsa Balakrishnan. A Comparison of Two Optimization Approaches For Airport Taxiway And Runway Scheduling. In *31st Digital Avionics Systems Conference (DASC)*, October 2012.

[10] Chuhang Yu and Henry YK Lau. Integrated Optimization of Airport Taxiway and Runway Scheduling. *Journal of Automation and Control Engineering*, 2, December 2014.

[11] Chandrasekar Sureshkumar. *Throughput Analysis For The National Airspace Systems*. PhD thesis, Purdue University, December 2012.

[12] Ahmed Ghoniem, Hanif D Sherali, and Hojong Baik. Enhanced Models for a Mixed Arrival-Departure Aircraft Sequencing Problem. *INFORMS Journal on Computing ()*, 26(3):514–530, 2014.

[13] Sivakumar Rathinam, Zachary Wood, Banavar Sridhar, and Yoon Jung. A Generalized Dynamic Programming Approach for a Departure Scheduling Problem. In *AIAA Guidance, Navigation, and Control Conference and Exhibit (GNC)*, Chicago, Illinois, August 2009. American Institute of Aeronautics and Astronautics.

[14] Roger G Dear. The dynamic scheduling of aircraft in the near terminal area. Technical report, Cambridge, Mass.: Flight Transportation Laboratory, Massachusetts Institute of Technology, 1976.

[15] Frank Neuman and Heinz Erzberger. *Analysis of Delay Reducing and Fuel Saving Sequencing and Spacing Algorithms for Arrival Traffic*. Citeseer, 1991.

[16] John E Beasley, Mohan Krishnamoorthy, Yazid M Sharaiha, and D Abramson. Scheduling aircraft landings the static case. *Transportation Science*, 34(2):180–197, 2000.

[17] Hamsa Balakrishnan and Bala Chandran. Scheduling Aircraft Landings under Constrained Position Shifting. In *AIAA Guidance, Navigation, and Control Conference and Exhibit (GNC)*, Keystone, Colorado, August 2006.

[18] Michael Kupfer. Scheduling Aircraft Landings to Closely Spaced Parallel Runways. In *Eighth USA/Europe Air Traffic Management Research and Development Seminar*, pages 1–10, Napa, California, June 2009.

[19] Jason A D Atkin, Edmund K Burke, John S Greenwood, and Dale Reeson. A Metaheuristic Approach to Aircraft Departure Scheduling at London Heathrow Airport. pages 235–252. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008.

[20] Gautam Gupta, Waqar Malik, and Yoon C Jung. A Mixed Integer Linear Program for Airport Departure Scheduling. In *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, Hilton Head, South Carolina, 2009.

[21] Brian Capozzi, Stephen Atkins, and Seongim Choi. Towards Optimal Routing and Scheduling of Metroplex Operations. In *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, Hilton Head, South Carolina, September 2009. American Institute of Aeronautics and Astronautics.

[22] Brian Capozzi and Stephen Atkins. A Hybrid Optimization Approach to Air Traffic Management for Metroplex Operations. In *10th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, Forth Worth, Texas, September 2010. American Institute of Aeronautics and Astronautics.

[23] Heming Chen, Yiyuan J Zhao, and Chris Provan. Multiple-point integrated scheduling of terminal area traffic. *Journal of Aircraft*, 48(5):1646–1657, September 2011.

[24] Min Xue and Shannon Zelinski. Optimal integration of departures and arrivals in terminal airspace. In *AIAA Guidance, Navigation, and Control Conference and Exhibit (GNC)*, Mineapolis, Minesota, August 2012.

[25] Min Xue, Shannon Zelinski, and Daniel Mulfinger. Uncertainty Study of Integrated Departures and Arrivals: A Los Angeles Case Study. In *13th AIAA Aviation Technology, Integration, and Operation Conference (ATIO)*, pages 1–10, Los Angeles, California, August 2013.

[26] Min Xue and Shannon Zelinski. Optimization of Integrated Departures and Arrivals Under Uncertainty. In *13th AIAA Aviation Technology, Integration, and Operation Conference (ATIO)*, pages 1–9, Los Angeles, California, August 2013.

[27] Christabelle Bosson, Min Xue, and Shannon Zelinski. Optimizing Integrated Terminal Airspace Operations Under Uncertainty. In *33rd Digital Avionics System Conference (DASC)*, pages 1–19, Colorado Springs, Colorado, October 2014.

[28] Harilaos N Psaraftis. A dynamic programming approach for sequencing groups of identical jobs. *Operations Research*, 28(6):1347–1359, 1980.

[29] Roger G Dear and Yosef S Sherif. An algorithm for computer assisted sequencing and scheduling of terminal area operations. *Transportation Research Part A: General*, 25(2):129–139, 1991.

[30] W Malik, G Gupta, and Y Jung. Managing departure aircraft release for efficient airport surface operations. In *AIAA Guidance, Navigation and Control Conference and Exhibit*, Reston, Virigina, 2010. American Institute of Aeronautics and Astronautics.

[31] B Chandran and H Balakrishnan. A Dynamic Programming Algorithm for Robust Runway Scheduling. In *American Control Conference, 2007 (ACC)*, pages 1161–1166, New York, New York, 2007.

[32] Xiao-Bing Hu and E Di Paolo. Binary-Representation-Based Genetic Algorithm for Aircraft Arrival Sequencing and Scheduling. *IEEE Transactions on Intelligent Transportation Systems*, 9(2):301–310, 2008.

[33] J Thipphavong and D Mulfinger. Design Considerations for a New Terminal Area Arrival Scheduler. In *10th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, Forth Worth, Texas, September 2010.

[34] Christabelle Bosson, Min Xue, and Shannon Zelinski. GPU-based Parallelization for Schedule Optimization with Uncertainty. In *14th AIAA Aviation Technology, Integration, and Operation Conference (ATIO)*, pages 1–22, Atlanta, Georgia, June 2014.

[35] Lucio Bianco, Giovanni Rinaldi, and Antonio Sassano. *A Combinatorial Optimization Approach to Aircraft Sequencing Problem*. Springer, 1987.

[36] Lucio Bianco, Paolo DellOlmo, and Stefano Giordani. Scheduling models and algorithms for tma traffic management. In *Modelling and Simulation in Air Traffic Management*, pages 139–167. Springer, 1997.

[37] Anant Singh Jain and Sheik Meeran. Deterministic job-shop scheduling: Past, present and future. *European Journal of Operational Research*, 113(2):390–434, 1999.

[38] Skylab R Gupta and Jeffrey S Smith. Algorithms for single machine total tardiness scheduling with sequence dependent detups. *European Journal of Operational Research*, 175(2):722–739, 2006.

[39] Wooseung Jang. Dynamic scheduling of stochastic jobs on a single machine. *European Journal of Operational Research*, 138(3):518–530, 2002.

[40] Dong K Seo, Cerry M Klein, and Wooseung Jang. Single machine stochastic scheduling to minimize the expected number of tardy jobs using mathematical programming models. *Computers & Industrial Engineering*, 48(2):153–161, 2005.

[41] Hossein M Soroush. Minimizing the weighted number of early and tardy jobs in a stochastic single machine scheduling problem. *European Journal of Operational Research*, 181(1):266–287, 2007.

[42] Xianyi Wu and Xian Zhou. Stochastic scheduling to minimize expected maximum lateness. *European Journal of Operational Research*, 190(1):103–115, 2008.

[43] Gustaf Sölveling. *Stochastic Programming Methods for Scheduling of Airport Runway Operations under Uncertainty*. PhD thesis, Georgia Institute of Technology, August 2012.

[44] Octavio Richetta and Amedeo R Odoni. Dynamic Solution to the Ground-Holding Problem in Air Traffic Control. *Transportation Research Part A: Policy and Practice*, 28(3):167–185, May 1994.

[45] Michael O Ball, Robert Hoffman, Amedeo R Odoni, and Ryan Rifkin. A Stochastic Integer Program with Dual Network Structure and Its Application to the Ground-Holding Problem. *Operations Research*, 51(1):167–171, February 2003.

[46] Avijit Mukherjee and Mark Hansen. A Dynamic Stochastic Model for the Single Airport Ground Holding Problem. *Transportation Science*, 41(4), 2007.

[47] Avijit Mukherjee and Mark Hansen. Dynamic stochastic optimization model for air traffic flow management with en route and airport capacity constraints. In *6th USA/Europe Seminar on Air Traffic Management Research and Development*, Baltimore, Maryland, June 2005.

[48] Shubham Gupta and Dimitris Bertsimas. Multistage Air Traffic Flow Management Under Capacity Uncertainty: A Robust and Adaptive Optimization Approach. *51st AGIFORS Annual Proceedings: annual symposium and study group meeting*, pages 692–721, October 2011.

[49] Gillian Clare and Arthur Richards. Air Traffic Flow Management Under Uncertainty: Application of Chance Constraints. In *ATACCS*, pages 20–26, London, UK, May 2012. IRIT Press.

[50] Andreas Heidt, Hartmut Helmke, Frauke Liers, and Alexander Martin. Robust Runway Scheduling Using a Time-Indexed Model. In *Fourth SESAR Innovation Days*, pages 1–8, November 2014.

[51] Shangyao Yan and Cheun-Ming Huo. Optimization of Multiple Objective Gate Assignments. *Transportation Research Part A: Policy and Practice*, 35(5):413–432, 2001.

[52] Regina Clewlow, Ioannis Simaiakis, and Hamsa Balakrishnan. Impact of Arrivals on Departure Taxi Operations at Airports. In *AIAA Guidance, Navigation, and Control Conference and Exhibit*, Toronto, Ontario Canada, August 2010. American Institute of Aeronautics and Astronautics.

[53] Jacob T Adriaens, Katherine Compton, Nam Sung Kim, and Michael J Schulte. The Case for GPGPU Spatial Multitasking. In *2012 IEEE 18th International Symposium on High Performance Computer Architecture (HPCA)*, pages 1–12, 2012.

[54] Grand R Joldes, Adam Wittek, and Karol Miller. Real-Time Nonlinear Finite Element Computations on GPU–Application to Neurosurgical Simulation. *Computer Methods in Applied Mechanics and Engineering*, 199:3305–3314, 2010.

[55] Abhijeet Gaikwad and Ioane Muni Toke. Parallel Iterative Linear Solvers on GPU: A Financial Engineering Case. In *2010 18th Euromicro Conference on Parallel, Distributed and Network-based Processing*, 2010.

[56] Monish D Tandale, Sandy Wiraatmadja, Veera V Vaddi, and Joseph L Rios. Massively Parallel Optimal Solution to the Nationwide Traffic Flow Management Problem. In *13th AIAA Aviation Technology, Integration, and Operation Conference (ATIO)*, pages 1–13, Los Angeles, California, October 2013.

[57] Husni Idris, Bertrand Delcaire, Ioannis Anagnostakis, William Hall, Nicolas Pujet, Eric Feron, R Hansman, John-Paul Clarke, and Amedeo Odoni. Identification of Flow Constraint and Control Points in Departure Operations at Airport Dystems. In *AIAA Guidance, Navigation, and Control Conference and Exhibit (GNC)*, pages 947–956, Boston, Massachusetts, August 1998. American Institute of Aeronautics and Astronautics.

[58] Shannon J Zelinski. A framework for integrating arrival, departure, and surface operations scheduling. In *33rd Digital Avionics Systems Conference (DASC)*, October 2014.

[59] Mark Simons. A functional analysis of integrated arrival, departure, and surface operations in nextgen. In *31st Digital Avionics Systems Conference (DASC)*, pages 3B2–1–3B2–12, October 2012.

[60] Federal Aviation Administration. Order JO 7110.65V, December 2014.

[61] Federal Aviation Administration. ORDER JO 7110.659A Air Traffic Control Wake Turbulence Recategorization, December 2014.

[62] Robert D Windhorst, Justin V Montoya, Zhifan Zhu, Sergei Gridnev, Katy Griffin, Aditya Saraf, and Steve Stroiney. Validation of Simulations of Airport Surface Traffic with the Surface Operations Simulator and Scheduler. In *2013 Aviation Technology, Integration, and Operations Conference (ATIO)*, Los Angeles, California, August 2013. American Institute of Aeronautics and Astronautics.

[63] Shapiro, Alexander and Homem-de-Mello, Tito. On the Rate of Convergence of Optimal Solutions of Monte Carlo Approximations of Stochastic Programs. *SIAM Journal of Optimization*, 11(1):70–86, January 2000.

[64] www.python.org. Python Programming Language.

[65] Inc. Gurobi Optimization. Gurobi optimizer reference manual, 2014.

[66] List of the world's busiest airports by passenger traffic. `https://en.wikipedia.org/wiki/List_of_the_world%27s_busiest_airports_by_passenger_traffic`. Accessed: 2015-10-01.

[67] Sebastian D Timar, Gaurav Nagle, Aditya Saraf, Peter Yu, Peter Hunt, Andrew Trapani, and Nick Johnson. Super density operations airspace modeling for the southern california metroplex. In *AIAA Modeling and Simulation Technology Conference*, Portland, Oregon, August 2011.

[68] Min Xue and Heinz Erzberger. Improvement of Trajectory Synthesizer for Efficient Descent Advisor. In *11th AIAA Aviation Technology, Integration and Operations Conference (ATIO)*, Virginia Beach, Virginia, September 2011.

[69] Laurel Stell. Prediction of top of descent location for idle-thrust descents. In *9th USA/Europe Air Traffic Management Seminar*, Berlin, Germany, 2011.

[70] Shawn A Engelland and Alan Capps. Trajectory-based takeoff time predictions applied to tactical departure scheduling: Concept description, system design, and initial observations. In *AIAA Aviation Technology, Integration, and Operations Conference (ATIO), Virginia Beach, VA*, 2011.

[71] Shabbir Ahmed and Alexander Shapiro. The Sample Average Approximation Method for Stochastic Programs with Integer Recourse. pages 1–24, February 2002.

VITA

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