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*University of Central Florida*



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IMPROVING AIRLINE SCHEDULE RELIABILITY USING A STRATEGIC MULTI-  
OBJECTIVE RUNWAY SLOT ASSIGNMENT SEARCH HEURISTIC

by

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A dissertation submitted in partial fulfillment of the requirements  
for the degree of Doctor of Philosophy  
in the Department of Industrial Engineering and Management Systems  
in the College of Engineering and Computer Science  
at the University of Central Florida  
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Spring Term  
2008

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## **ABSTRACT**

Improving the predictability of airline schedules in the National Airspace System (NAS) has been a constant endeavor, particularly as system delays grow with ever-increasing demand. Airline schedules need to be resistant to perturbations in the system including Ground Delay Programs (GDPs) and inclement weather. The strategic search heuristic proposed in this dissertation significantly improves airline schedule reliability by assigning airport departure and arrival slots to each flight in the schedule across a network of airports. This is performed using a multi-objective optimization approach that is primarily based on historical flight and taxi times but also includes certain airline, airport, and FAA priorities. The intent of this algorithm is to produce a more reliable, robust schedule that operates in today's environment as well as tomorrow's 4-Dimensional Trajectory Controlled system as described the FAA's Next Generation ATM system (NextGen).

This novel airline schedule optimization approach is implemented using a multi-objective evolutionary algorithm which is capable of incorporating limited airport capacities. The core of the fitness function is an extensive database of historic operating times for flight and ground operations collected over a two year period based on ASDI and BTS data. Empirical distributions based on this data reflect the probability that flights encounter various flight and taxi times. The fitness function also adds the ability to define priorities for certain flights based on aircraft size, flight time, and airline usage.

The algorithm is applied to airline schedules for two primary US airports: Chicago O'Hare and Atlanta Hartsfield-Jackson. The effects of this multi-objective schedule

optimization are evaluated in a variety of scenarios including periods of high, medium, and low demand.

The schedules generated by the optimization algorithm were evaluated using a simple queuing simulation model implemented in AnyLogic. The scenarios were simulated in AnyLogic using two basic setups: (1) using modes of flight and taxi times that reflect highly predictable 4-Dimensional Trajectory Control operations and (2) using full distributions of flight and taxi times reflecting current day operations.

The simulation analysis showed significant improvements in reliability as measured by the mean square difference (MSD) of filed versus simulated flight arrival and departure times. Arrivals showed the most consistent improvements of up to 80% in on-time performance (OTP). Departures showed reduced overall improvements, particularly when the optimization was performed without the consideration of airport capacity. The 4-Dimensional Trajectory Control environment more than doubled the on-time performance of departures over the current day, more chaotic scenarios.

This research shows that airline schedule reliability can be significantly improved over a network of airports using historical flight and taxi time data. It also provides for a mechanism to prioritize flights based on various airline, airport, and ATC goals. The algorithm is shown to work in today's environment as well as tomorrow's NextGen 4-Dimensional Trajectory Control setup.

## **ACKNOWLEDGMENTS**

Firstly, I would like to thank Dr. Sepulveda and Dr. Rabelo for their continued guidance and advice throughout the course of this research effort. It is through their guidance that an original broad idea was shaped into a focused research project that became this dissertation. I would also like to thank Dr. Proctor and Dr. Reilly for dedicating their time to serve on this committee and provide valuable input into my research.

Moreover, I would likely never have made it to this point in my life if not for Ken Fleming's continuous support and mentoring throughout my entire professional career. It was his airport simulation and modeling class in 1997 that has shaped my life since.

Finally, it would have been impossible to perform my research and write this dissertation without support from my friends, family, and loved ones. Mostly, I would like to thank my parents for their never-ending support in my endeavors.

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## LIST OF ACRONYMS/ABBREVIATIONS

AAL	American Airlines
ADAMS	Airport Departure Arrival Management System
ALP	Aircraft Landing Problem
AMAN	Arrival Manager
AOC	Airline Operations Center
ARP	Airline Recovery Problem
ASM	Arrival Sequencing Model
ATL	Atlanta Hartsfield Jackson International Airport
ATM	Air Traffic Management
ATCSCC	Air Traffic Control System Command Center
CAP	Collaborative Airport Planner
CAAR	Center for Applied ATM Research
CDA	Continuous Descent Approach
CFMU	Central Flow Management Unit
CIA	Compromise Immune Algorithm
ConOps	Concept of Operations
CTAS	Center TRACON Automation System
CTOT	Calculated Take-Off Times
DAL	Delta Airlines
DMAN	Departure Manager
DI	Desirability Index

DOT	Department of Transportation
DST	Decision Support Tool
EA	Evolutionary Algorithms
EU	European Union
ETA	Estimated Time of Arrival
ETD	Estimated Time of Departure
ETMS	Enhanced Traffic Management System
FAA	Federal Aviation Administration
FMS	Flight Management System
GA	Genetic Algorithms
GDP	Ground Delay Program
GMT	Greenwich Mean Time
IFR	Instrument Flight Rules
JAL	Japan Airlines
JGAP	Java Evolutionary Algorithm Package
JPDO	Joint Planning and Development Office
MEANS	MIT Extensible Air Network Simulator
MIT	Massachusetts Institute of Technology
MSD	Mean Square Difference
M-W	Mann-Whitney Test Statistic
NAS	National Airspace System
NASA	National Aeronautics and Space Administration
NASMOD	National Airspace System Modernization

NATS	National Air Traffic System
NGATS / NEXTGEN	Next Generation Air Traffic System
O-D	Origin-Destination
OEP	Operational Evolution Partnership
OIS	Operational Information System
ORD	Chicago O'Hare International Airport
OTP	On-Time Performance
PB-ATM	Performance-Based Air Traffic Management
PBN	Performance-Based Navigation
RNAV	aRea NAVigation
RNP	Required Navigation Performance
RTA	Required Time of Arrival
SATS	Small Aircraft Transportation System
SESAR	Single European Sky ATM Research Programme
SSD	Sum of the Squared Differences
TAAM	Total Airspace and Airport Modeler
TFM	Traffic Flow Management
TMA	Traffic Management Advisor
TOD	Top of Descent
UAL	United Airlines
VFR	Visual Flight Rules

## **CHAPTER ONE: INTRODUCTION**

Aviation is an integral part of any country's transportation infrastructure and is commonly viewed as the pinnacle of the transportation system. This is particularly apparent in the United States where vast geographic dispersion of metropolitan areas makes aviation or air travel the most likely candidate for transportation. The U.S. in particular has seen a recent surge in air travel demand which has long exceeded pre-2001 traffic levels and has been showing strong potential for growth over the next decades (FAA APO Projections, Jan 2006). In fact, the Federal Aviation Administration (FAA) has projected a greater than two-fold increase in air traffic demand by the year 2025.

Even before 2001, the United States National Airspace System (NAS) was approaching capacity limits particularly at key airports and other points in the system. Even relatively small perturbations due to weather or excessive traffic demand caused sometimes considerable delays, which propagated through the system in a mostly non-linear fashion (Hansman, 2005).

In truth, society has grown very accustomed to aviation, even sometimes without directly admitting this fact. For one, personal and particularly business air travel demands adherence to a published schedule. Repeated delays and unpredictable arrival and departure times may cause passengers to search for alternatives to air travel including rail, personal transportation, or even online collaboration rather than face-to-face meetings. The system's level of unpredictability during high stress periods is in fact why airlines routinely overestimate the flight times in and out of major airports. The theory behind this airline scheduling scheme is to give passengers more realistic arrival times based on expected airspace and airport delays. A further benefit of this scheduling mechanism is that although delays are routinely encountered in the NAS, flights can

still be considered to be on-time if the schedule contains sufficient slack (Ater, 2007). This frequently means that scheduled flight arrival times are significantly overscheduled in an attempt to conserve airline schedule predictability.

Thanks to the current predictability and relative speed of air transportation, we have not only become used to on-time travel, but also to the continuous availability of services that utilize the air transportation system including cargo shipments, overnight delivery and other products. It stands to reason that without reliable and speedy air transportation, our quality of life would certainly diminish. With the obvious popularity of air travel has come the realization that today's air traffic system will most likely be unable to handle the projected traffic growth and is therefore in desperate need of modernization. A relatively small increase in the total number of yearly operations may produce a completely disproportionate increase in the number of delays, indicating that the system may already have reached an operating threshold. With the resurgence of air traffic, more delays may be seen on the horizon with an expansion in capacity.

The largest contributor to delay in the NAS in the year 2004 was weather as shown in Figure 1 below, which forms the basis for numerous research efforts currently underway in the development of technologies to minimize weather impacts on the NAS (UCAR, 2004).



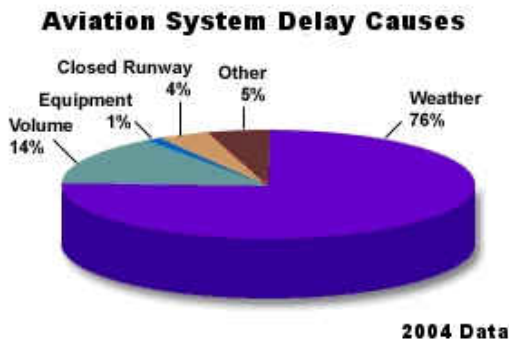


Figure 1: Dissection of NAS Delay Causes

Weather impacts become apparent when even small weather disturbances at, for example, Chicago O’Hare International Airport, produce considerable ground and airspace delay, which then propagate through the entire system. Other major factors to overall system efficiency are individual airport congestion, convective weather, reduced visibility and increased demand, all of which may be somewhat ameliorated by current changes in ATM procedures and GDPs, but only stand to become a bigger burden unless a significant modernization of the NAS infrastructure takes place (Xu, Donohue, Laskey & Chen, 2005).

Interestingly enough, it is likely the system’s own success that will erode the speed, predictability, and affordability benefits of air travel if the NAS does not adapt and grow with future demand levels (JPDO NGATS Plan, 2005).

More advanced methodologies and tools which aim to optimally manage air traffic rather than simply control it are currently being researched by a number of government and private institutions. To address these issues at the government level, Congress has passed into law Vision 100 – the Century of Aviation Reauthorization Act – which created the Joint Planning and Development Office (JPDO), a conglomerate of various government agencies including the

FAA, NASA, and DHS. As the JPDO's Integrated Plan for the Next Generation Air Traffic System (NGATS) puts it:

“Whether those benefits will continue to be available in the future will depend upon actions we begin taking now. The system is already showing signs of stress and it is clear that projected demand will soon surpass the system's capacity.”

The purpose of the JPDO is to bring together all of the stakeholders that have a vested interest in the next generation air transportation system. Their purpose is to develop a system which can cope with future air travel demand by increasing system predictability, reducing impacts of weather and other factors, and reducing delays throughout. All of this will have to be accomplished in light of increasing safety, security, and budget constraints. The NGATS or NextGen system being developed by the JPDO will use technologies yet to be developed in order to make the next air traffic system highly predictable. One of these concepts is the fundamental idea of trajectory-based operations (TBOs), where all aircraft fly four-dimensional paths which are pre-calculated by ground based systems. These individual aircraft trajectories are aircraft optimal in terms of flight times, safety (routed around weather cells), and are also de-conflicted from other aircraft. This fundamental concept will also allow for fairly accurate departure and arrival time planning for each flight.

The issues addressed in the NGATS Plan for 2025 are not local to the United States. Europe, as part of the SESAR (formerly known as SESAME) project is also assessing the options, benefits and definition of the future European air traffic system as they work towards a unified European OneSky concept (Sesame, 2005). This effort involves agencies from all major

European countries including DFS (Germany), NLR (Holland), AENA (Spain), SkyGuide (Switzerland), and Eurocontrol itself which is spearheading the effort.

Even though airspace congestion is likely to be a concern, terminal and airport capacity is likely the most limiting factor facing the transportation system (Andrews, 1999). Whereas unused airspace is still abundant, aircraft all originate and terminate at airports, thereby creating choke-points within the system. In order to facilitate more advanced planning of air traffic operations, the FAA is currently implementing various techniques under the premise of the so-called traffic flow management (TFM). TFM tools assist in more strategic capacity-demand planning of airspace and airports by limiting throughput rates for airspace routes or at airports directly. The most common implementation of this results in airport GDPs where a large number of departures are delayed on the ground in an attempt to artificially curb airspace and destination airport demand. GDPs are particularly heavily used when weather disturbances occur at major airports or airspace routes.

In order to artificially curb demand and increase predictability of airport operations, some airports – including Chicago O’Hare, New York LaGuardia, and Washington Reagan National – in the United States have strategically implemented the concept of slot control (Pate, McDonald & Gillespie, 2005). The premise behind this concept is that every hour, a certain number of arrival and departure slots are available for use at these airports. Airlines are each allocated a certain number of slots throughout the day and, unless they trade with other airlines, are not allowed to exceed this total number of arrivals or departures at these airports.

A more recent example of curbing demand is that of the three major airports in the New York metropolitan region (LaGuardia, John. F. Kennedy, and Newark Airports). The U.S. Department of Transportation announced in December of 2007 that the number of available

hourly runway slots at all three airports will be limited to 82 to 83 aircraft (Airport International, 2007). Although this restriction is guaranteed to reduce capacity-driven delays during high-demand and inclement weather conditions, it also limits capacity in good weather conditions when the airports might be able to exceed these operating limits. In fact, the concepts of demand-management and slot allocation are in use at most major European airports already including London Heathrow, where slots are extremely valuable and highly restricted.

There exist a number of DSTs on the market today – called airport arrival and departure managers – which aim to optimize arrival and departure sequences from an airport centric point of view. This means that arrival slots are assigned as aircraft reach a certain proximity from the airport and then are continuously updated in real-time to assist short term-airport movement planning. These real-time arrival and departure management DSTs operate in a tactical short time span environment. Thus, they have no interaction with more strategic TFM decision support tools. These DSTs also typically do not provide for direct input mechanisms of airline, ATC, and airport priorities and preferences.

The combination of TFM methodologies and strategic airport slot allocation practices presents an area of research that has not been widely investigated. The overall intent of this research is to increase the predictability, reliability and performance of airline schedules within the NAS and reduce the need for tactical GDPs. The basic purpose is to optimize arrival and departure orders at major US hub airports.

The purpose of this research effort is to develop a search heuristic methodology that strategically assigns arrival and departure slots at a set of airports from a strategic network planning perspective. The approach outlined in this dissertation will make heavy use of real-world historic flight and taxi time distributions to add a level of reality to the algorithms that

emulate TFM strategic flight planning. This multi-objective approach will also consider airline and other stakeholder preferences as part of the optimization process. This will, in theory, produce a schedule which dynamically manages airport arrival and departure demand in an ATC, airport, and airline optimal fashion.

### **Statement of the Problem**

Airport operations scheduling within an airline is typically based on very complex optimization applications that combine airport arrival and departure schedules, aircraft fleet allocation, as well as crew scheduling. On the other hand, TFM techniques employed by the FAA and other government organizations around the globe attempt to optimize the flows – and therefore the capacity – of airports and air routes in a safe and efficient manner.

In order to cater for relatively unpredictable operating times during periods of high demand or inclement weather, airline schedules include significant amounts of ‘slack’ within each flight’s block time. This process of over-scheduling is commonly used to increase a flight’s on-time performance when comparing actual arrival and departure times with scheduled times. It includes flight-by-flight slack time for aircraft performance variations, wind differences, as well as expected ATC and airport delays. In normal operating conditions, these slack times are usually much greater than actually required, particularly for long distance flights where wind and aircraft performance variations are much more significant. Determining a flight’s scheduled block time is a delicate balance between many operating and economic factors. However, the key input into any airline schedule optimization function is the airline’s desired on-time performance (OTP) goal.

The air traffic system today is still considered to be sufficiently unpredictable to prevent long term strategic planning of airport arrival and departure slots. Nevertheless, future technologies as well as technologies currently being implemented will significantly reduce the uncertainty within the entire airspace system, thereby opening the door for more advanced strategic decision making tools.

The practice of arrival and departure slot management DSTs has historically taken a very airport centric view. This means that arrival and departure slots are assigned to aircraft within a certain time window of the scheduled movement times at the individual airport and then continuously updated in a real-time manner to allow for aircraft capabilities and environmental – primarily wind – effects. On the NAS-wide side, TFM techniques consider airport and airspace route throughput rates to more strategically curb demand by implementing GDPs which selectively delay aircraft at their origin airports.

This apparent disconnect between airline scheduling and TFM strategic flow planning provides an ideal area for research. In a perfect scenario, the FAA, airlines, and other stakeholders would jointly work to develop an optimized schedule of airport operations which would fairly allocate flights within an environmentally-dependent, capacity-realistic scenario. This schedule would contain detailed arrival and departure times for each flight, which, if properly obeyed, would minimize delays and maximize airline preferences at each airport within the schedule. Thus if aircraft were capable of operating in a full four-dimensional trajectory-based environment, fairly exact arrival and departure times could be predicted without the need for airlines to add slack times to each flight.

Consequently, the purpose of this research effort is to develop a methodology for assigning arrival and departure runway slots from a strategic planning perspective. This

approach combines aspects of airline scheduling and current arrival and departure management techniques with more strategic TFM views and methods.

A major premise for this application is the evolving FAA concept of trajectory-based operations which will make aircraft flight times and departure/arrival times highly predictable. This means that rather than taking an airport-centric view, a more macroscopic approach will be developed to strategically allocate slots across a network of multiple airports with semi-deterministic flight times based on historic flight time and taxi-time distributions obtained from a one and one half year sample of flight data of all aircraft operating in and out of these airports.

To implement this airport arrival and departure slot allocation methodology, a novel optimization approach will be developed which assigns aircraft to arrival and departure slots at two major US airports. To additionally facilitate the demonstration of inter-airport effects of airport slot assignment, these airports also have a significant traffic demand between them due to their major size and airline hub categorization: Chicago O'Hare International Airport and Atlanta Hartsfield-Jackson International Airport.

### **Research Objectives**

The objectives intended to be carried out as part of this research effort are divided into multiple parts including a literature research, historical data processing and mining, the development of the evolutionary algorithm (EA) search heuristic as well as simulation-based assessments of the EA approach. These are described in more detail in turn below:

- A comprehensive literature review on
  - Airline scheduling

- Current practices in airport arrival and departure sequencing and slot allocation
- Evolutionary algorithms and evolutionary search methods and their application to slot allocation
- Future more deterministic trajectory-based operations and the predictability of air traffic operations
- Processing and mining of historic ASDI (Aircraft Situation Display to Industry) and BTS (Bureau of Transportation Statistics) data
  - Processing and interpretation of historic flight times and taxi-times based on historic FAA-based ASDI and airline-reported BTS data
- The development of a novel evolutionary search methodology to plan airport runway slot allocations. This includes the
  - Development of a fitness function to include semi-deterministic aircraft flight times and other intents
  - Development of a software application which implements the algorithms and methodology previously developed and generates optimal slot times for a realistic traffic schedule
  - Generation of an optimized schedule using the methodology previously developed and applied to a real-world traffic sample
- The development of a discrete-event simulation platform to evaluate the slot allocations proposed by the novel approach. The expected scenarios to be simulated and assessed per the average aircraft system delay will include:



- Base-Case of scheduled departure and arrival times with no optimization (based on actual observed arrival and departure times) using
  - deterministic mode-based flight times (full four-dimensional knowledge of flight path and time based on historic data)
  - stochastic distribution-based flight times that are empirical distributions of historic observed flight times based on ASDI (representative of today's more chaotic operation)
- Sequence optimal schedule of slots allocated by the novel methodology with
  - deterministic mode-based flight times
  - stochastic distribution-based flight times

The end result of this research effort will be a methodology to assign airport departure and arrival runway slots at major high-demand airports using EAs and real-world historic flight and taxi time distributions. The research required to obtain a realistic fitness function will also yield distributions and interpretations of aircraft flight and taxi times which can be used in a variety of future studies as a model of stochastic aircraft behavior.

This is basically accomplished by developing advanced methods of allocating aircraft to airport arrival and departure schedules, all the while considering historic aircraft operating characteristics as well as known airline, airport, and ATC priorities and desires. The methodologies presented in this research effort will optimize existing airline flight schedules based on a desirability fitness function within an EA framework. The intended result of this effort is a set of modified airline schedules which show a higher achievability rate but not

necessarily produce less delay or higher airport throughput. Thus, the need for airlines to significantly over-schedule flight times will be significantly reduced without sacrificing the airlines' on-time performance. For instance, airlines routinely over-schedule flights based on expected delays throughout the day. This is usually done on a flight-by-flight basis and does not consider the various ATC and airline priorities in sequencing or other airport network implications. Using the algorithm presented in this dissertation, more accurate multi-objective predictions of flight times will produce schedules that allow for more accurate predictions of arrival and departure times.

For this research effort, an evolutionary approach inspired by EAs has been selected. EAs and Genetic Algorithms (GAs) have seen much research interest and implementation within the scope of airport slot allocations. Since slot allocation can be considered as timetabling or scheduling problems, EAs and GAs have been shown as one of the best operations research techniques for solving these types of problems at a large scale. Typically, unless at a very small scale, no perfect solution exists to these problems. Since these problems are also computationally NP-complete problems (Garey & Johnson, 1979), no deterministic polynomial time algorithm exists and the problem space is far too large for brute force or undirected search techniques. EAs use an evolutionary search method to arrive at a near-optimal solution within a fairly short amount of time, making them an obvious candidate for this application.

It is important to note that this approach does not attempt to maximize the capacity of the airports under investigation. Airport arrival and departure capacities are fixed parameters across the planning horizon in this study. The purpose of this approach is to schedule aircraft in a fixed number of arrival and departure slots in an optimal and most efficient manner. So in essence, the airport capacities are hard constraints imposed on this approach. Various other real-world

restrictions, requirements, as well as desires will provide a number of additional hard and soft constraints around the arrival and departure schedules.

### **Contribution**

The primary contribution of this research effort lies in a novel methodology to dramatically increase the predictability of airline and airport flight schedules across a network of airports; this is accomplished through the combination of strategic TFM concepts with more network-centric sequence optimization methods than are currently being employed. Each area currently uses various optimization methods in a very disparate manner that, when combined, can potentially increase the predictability of the system and significantly reduce delays throughout.

The relative unpredictability of the airspace system today prevents longer-term strategic demand and capacity planning on an airport-centric level. Airline and airport flight schedules developed using strategic planning tools within current TFM and airport arrival/departure management frameworks typically do not survive major capacity limiting scenarios. This subsequently causes ATC and airline operators to revert to tactical planning mechanisms, causing flight schedules to become unreliable and unpredictable.

The strategic demand management framework presented in this dissertation will significantly increase airline schedule reliability and allow ATC and airlines to operate under the proposed schedule much longer before reverting to tactical planning methods. The multi-objective nature of this methodology also allows for multiple stake holders to have input into the schedule optimization process. Hence, airlines and ATC will be able to include priorities and

desires into the process. This is also a novel area of research which is rooted in the FAA's Collaborative Decision Making (CDM) framework, where airlines have input into strategic flow rates and GDPs, but currently do not cooperate on detailed flight scheduling practices.

Based on an extensive literature research on this topic, all of the existing slot management applications and research are very tactical and airport centric. The primary reason for this is likely the perception that the current air traffic system shows sufficiently chaotic behavior that arrival and departure times cannot be reliably predicted beyond a certain time frame. However, with the advent of trajectory-based operations and resulting highly deterministic flight times, larger scale optimizations are possible that not only optimize operations at a single airport, but optimize the entire National Air Traffic System (NATS) over an extended time period.

This research effort is unique in that it aims to expand the airport slot allocation planning horizon from a microscopic and historically tactical airport-centric view to a network-wide strategic allocation of slots across multiple airports. This essentially incorporates system-wide strategic TFM practices by considering flight times and other airport throughout capacities.

Figure 2 below shows a graphical representation of the area of applicability of this research:

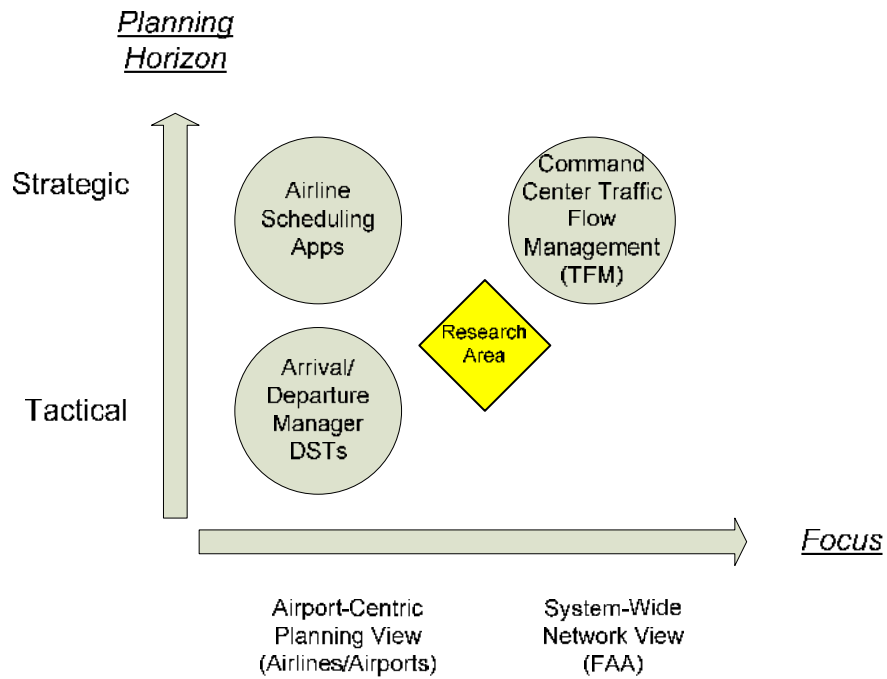


Figure 2: Area of Contribution

The intended industry application of this research is three fold: (1) FAA airport terminal operations planners who desire the most expedient sequence of aircraft as early as possible, and (2) airlines who operate major hub airports and are able to heavily influence arrival and departure sequences due to the amount of aircraft they operate, and (3) FAA central flow control for purposes of aligning airspace operations with airport- and airline-optimal arrival and departure sequence as part for their CDM initiative.

An overview of the perceived usage and benefits of the methodology proposed in this research effort is presented below in Figure 3:

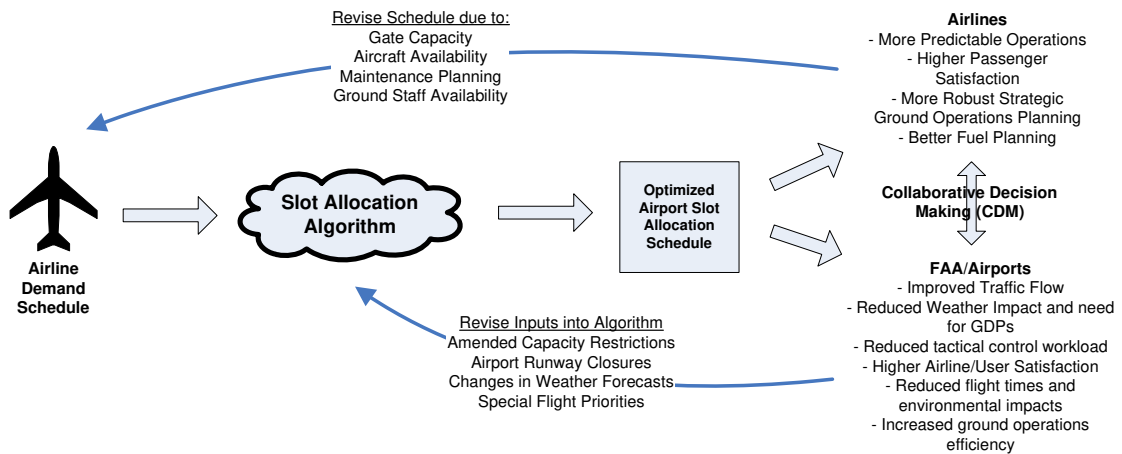


Figure 3: Benefits and Usage of Proposed Application

A further contribution to state-of-the-art knowledge in this field will be the distributions of flight and taxi times. These distributions are based on a sizeable database of historical operations and will be useful in a number of other traffic flow planning and simulation applications outside of this research effort.

In general, the multi-objective optimization approach developed in this research project will provide users with a more strategic planning ability for aircraft arrivals and departures. This will not only improve the predictability of the operation as a whole but also allow for more strategic planning of ground and equipment resources on the ground. This is particularly important when considering that strategic planning always allows for cost minimization whereas tactical responses to deviations in the planned operations are very cost intensive. Obviously, with more time to plan, more options can be explored to optimize the overall system operation.

## **Chapter Layout**

The organization of this dissertation is as follows: Chapter 2 describes, in summary form, the relevant literature to date regarding current concepts for airport arrival/departure slot management, airline scheduling, as well as TFM operations. This is followed by a discussion of evolutionary search methods – in particular EAs – used in scheduling and timetabling problems.

Chapter 3 presents the data mining efforts for distributions of flight and taxi times and subsequently provides the methodology used in developing the multi-objective evolutionary approach to strategic slot allocation optimization. This chapter also outlines the simulation methodology used to assess the utility of the given slot allocation approach.

Chapter 4 presents the results of the implementation of the proposed airport slot optimization methodology as well as results of the simulation-based evaluation of the proposed slot allocations as outlined previously.

Chapter 5 will discuss the utility of using the outlined methodology for future airport slot allocation planning; it will be supported by a discussion of the simulation assessment of the algorithms and the perceived benefits of the proposed approach. Shortcomings of the given methodology as well as proposed future research areas and improvements are also discussed in detail in this concluding chapter.

## **CHAPTER TWO: LITERATURE REVIEW**

This section of the dissertation gives a brief history of existing approaches to airport arrival and departure runway slot allocation at US and other airports around the globe. Additional background will be given on airline scheduling methods as well as relevant TFM techniques as they relate to the area of application of this research. This section will also give some necessary background information on future concepts that will, in many ways, support theories and assumptions made throughout the course of this effort. Particular focus will be given to strategic flight planning and the desire to develop a more deterministic airspace system that is significantly less affected by stochastic events such as weather impacts and decision making variations.

This discussion on airport and airspace operations is followed by necessary background information on recent and modern airport slot optimization techniques and their applicability to large scale slot allocation problems. Specific attention will be given to evolutionary search techniques with a focus on EAs. This will conclude the literature review section.

### **Airport Arrival and Departure Processes**

The basic objective behind arrival and departure sequencing and scheduling in air traffic automation is to match traffic demand and airport capacity while minimizing overall airport delay (Carr, 1998). The continued growth of air traffic in the US as well as the increased use of the “hub”-scheduling principle employed by airlines has led to significant increases in congestion and delays, particularly at the major US hub airports. To airlines, concentrating flight operations around single airports makes good economic and competitive sense (Bond, 1997). It



not only maximizes the transfer of passengers and the markets served but also allows for central maintenance and support facilities.

Nevertheless, dedicating an airport as a hub airport also taxes the capabilities of those airports to the maximum. This means that airlines will routinely publish schedules of flights into major US airports that, on an hourly basis, far exceed the capacity of the given airport. This, even without any weather related or other disturbances, causes major delays at peak hours of the day at these major airports (see the sections on airline scheduling as well as airport capacity below).

This section of the literature review will provide necessary background information on airport arrival and departure sequencing and management. It will also provide insight into airline flight scheduling concepts as well as airport capacity considerations which are integral to the slot allocation methodology developed for this research effort.

### **Arrival and Departure Sequencing**

The assignment of airport arrival and departure sequences in the US today is commonly performed using best-practice heuristics without the use of automated guidance tools. This process is largely based on a first-come first-serve methodology that does not entirely take into account airline flight priorities (Carr, Erzberger & Neuman, 1998).

Despite recent advancements in automation and collaboration between the FAA and airlines, the basic principles of arrival and departure sequencing remain unchanged.

## **Arrivals**

Arriving aircraft today are sequenced as they reach a certain distance from the destination airport. This is typically performed near the position along the scheduled flight path where the arrival phase begins and the aircraft starts to descend into the destination airport. At this point it is also possible that a specific runway is assigned for landing, although depending on the difference in flight paths and approach directions to these runways, this may not occur until later.

The initial sequence will be largely based on a first-come-first-serve basis but is also to some extent based on the scheduled aircraft arrival times. For example, if an aircraft has already suffered major delays and passengers on board stand to miss connections, the aircraft may be prioritized in the arrival sequence. If an aircraft indicates that it is unable to meet a desired arrival time, it will be delayed until another arrival sequence slot is available. The final sequence may be changed depending on the delays and priorities of other aircraft scheduled to land within the same time window. An aircraft's ability to meet a specific landing time may be paramount in assuring the desired sequence.

## **Departures**

Departing aircraft are entered into the departure sequence as soon as they are ready for push-back from the departure gate. At this point, ATC will assign the aircraft a departure runway based on their desired departure direction. Aircraft are then manually directed into runway departure queues in the order that was determined. Factors which may affect the departure sequence include aircraft types (due to wake turbulence between aircraft), direction of departure (destination city), and weather considerations.

## **Arrival and Departure Management Tools**

In recent years the use of real-time software tools to assist in arrival and departure sequencing has become more and more attractive. Hence, arrival and departure management applications are becoming very popular. The premise behind these tools is that they are designed as real-time DSTs and assist traffic controllers in managing arrival and departure traffic flows near major airports based on real-time aircraft location and intent information.

Based on research that largely originated at NASA, automation tools are now commonly used to assist controllers in arrival flow management to efficiently map the arrival traffic demand onto the available airport capacity (Neumann & Erzberger, 1991). One of these suites of tools is called the Center-TRACON Automation System (CTAS), of which one sub-application, the Traffic Management Advisor (TMA) is already in use at a number of US airports including Dallas/Ft. Worth (Erzberger, 1993). TMA assists in balancing airport arrival demand with available arrival capacity and considers aircraft within a 200 nautical mile radius of the target airport. Under development by NASA is also a methodology called the Collaborative Airport Planner (CAP), that focuses on the refinement of CTAS algorithms to include airline preferences and priorities. Andersson, Hall, Atkins, and Feron present an extension to the CAP including an algorithm called the Arrival Sequencing Model (ASM), which uses integer programming and a cost minimization approach to assess aircraft landing sequences at airports (Andersson et. al., 2003).

In Europe, the use of arrival and departure management applications – commonly called AMAN and DMAN – is also very common. Many airports in Europe including Zurich, Switzerland, and Frankfurt, Germany, already implement tools that are fully integrated with

ATC workstations and are based on flight plans, radar data, and the current situation at the destination airport. This includes, for arriving aircraft, knowledge of departure operations at the destination airport so that these operations can be coordinated and maximum capacity can be achieved across both operations (Wiesner, 2006). The departure manager optimizes the departure runway sequence for each runway and then proactively communicates exact times for pushback, arrival in departure queue, and runway departure times to individual aircraft.

Another example of an arrival and departure manager uses a job-shop scheduling approach with a local search heuristic (Bianco, Dell'Olmo & Giodani, 2006). This approach uses fixed deterministic routings in the air and on the ground to estimate the travel times for aircraft in order to improve the certainty of aircraft arrival and departure times and capabilities. Anagnostakis also presents a two-stage optimization algorithm for departure sequence optimization based on scheduled departure times and expected travel times to the respective departure runway (Anagnostakis, 2004).

All of the applications described thus far are tools which aim to give guidance to ATC operations in the sequencing of arrivals or departures. One application, called Attila, attempts to optimize arrival sequences within one particular airline without direct consent from ATC. Attila uses a computer-based decision process to optimize aircraft traffic flows in real-time. The Attila software analyzes the real-time factors affecting the arrival flow, and calculates optimal arrival times for each aircraft. The tool then automatically sends digital messages to individual aircraft, instructing them to adjust speeds according to the newly calculated arrival times (Rolan & Dlouhy, 2006). It does this on the airline's own communications channels and without giving notice to ATC operations. The premise behind this method is that with Attila, airlines can have

some influence over when their aircraft are sequenced by ATC, thereby affecting the overall landing sequences in their favor.

Although Attila is a real-time operational DST, it is based on a number of patents which optimize aircraft arrival sequences by considering aircraft abilities and goals (Baiada & Bowlin, 2007). Attila focuses on flow rates over the arrival fixes rather than runways and ultimate approval of each time over the arrival fix lies with a system manager who reviews the entire sequence iteratively. Further patents implemented by Attila relate to methods and systems for allocating aircraft arrival/departure slot times using computer software (Baiada & Bowlin, 2004). Although these patents address detailed slot allocation schemes for airports, the basis for decision making appears to lie with aircraft capabilities and goals, rather than the use of historic data. As such, Attila appears to be airport-centric in nature and thus does not consider expected delays at other airports.

Overall, many ATM focused companies currently offer software applications which perform arrival and departure management duties. One of the limitations of all of these arrival and departure managers is that they are designed to operate in a tactical real-time mode and a planning horizon that only manages aircraft within a short distance from the airports. The research results generated throughout this effort should allow for the expansion of the tactical horizon into a more strategic planning arena.

### **Airline Scheduling**

The development of airline schedules is a very complex exercise which takes into account numerous different factors, internal and external to airline operations. Major airlines

have entire departments devoted to determining which markets to serve, how frequently to serve them, and which aircraft types to devote to each route. Factors that may influence airline schedule planning include (Carr, Erzberger & Neuman, 1998; Barnhart, Lu & Sheno, 1997):

- Marketing of specific times for specific flights such as business hour flights
- Passenger, baggage, and cargo connectivity
- Airport capacity restrictions
- Availability of aircraft, crew, and gates
- Historic delays of aircraft on the given routes and at the given airports

An efficient operation at an airport depends on the system's ability to maintain the integrity of the airline schedules by meeting planned arrival and departure times. The desired order of arrival and departure is a critical component of this schedule.

Particularly at major hub airports, airlines tend to schedule their flights in banks of arrival-heavy and departure-heavy periods. The use of these bank structures essentially allows the airlines to trade-off arrival capacity with departure capacity in neighboring time periods with the effect of minimizing passenger connection times between their arriving and departing flights. Figure 4 below depicts a typical departure bank structure schedule at Chicago O'Hare International Airport for United Airlines (UAL):

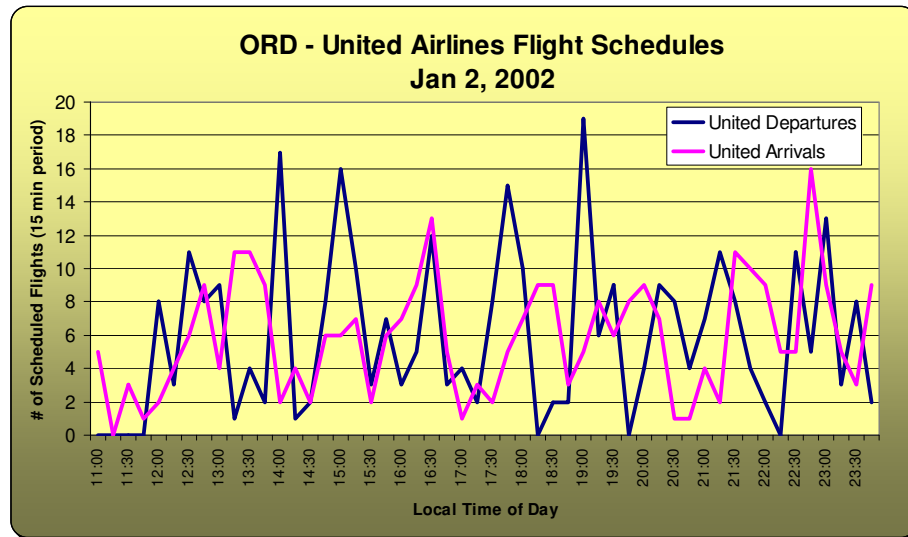


Figure 4: ORD Scheduled Flights - United Airlines

A scheduling methodology that has received some notice in the last few years is the concept of the continuous or rolling hub. The idea behind this concept is the smoothing of bank structure schedules to a more even and consistent demand rate throughout the day. This concept has been selectively implemented by American Airlines at their Chicago and Dallas/Ft. Worth hub airports and was also trialed by Delta Airlines at Atlanta in 2006. Figure 5 below shows the scheduled number of flights at ORD for American Airlines before and after the Continuous Hub Concept was implemented:

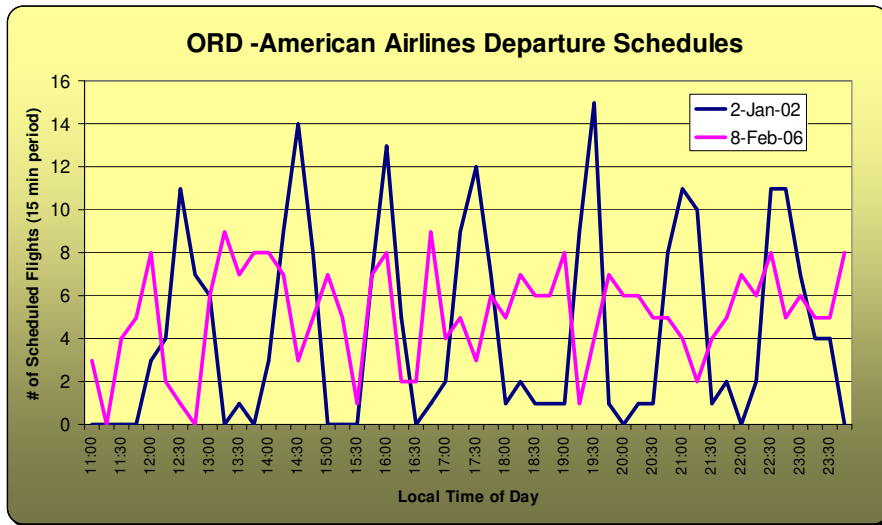


Figure 5: ORD American Airlines Rolling Hub Schedule

The comparison above of a schedule from the year 2002 with a 2006 schedule taken from the same season clearly shows how the 15 minute schedule departure movements in 2006 are much more spread-out when compared to the year 2002 schedule. The intent is to produce a schedule that, in terms of hourly throughput rates, consistently stays at or below the expected capacity of the airport. This, in theory, decreases overall delays and increases the on-time performance of the schedule.

However, throughout the NAS today it is quite common that hourly demand exceed the hourly capacity available at an airport. This situation is particularly exacerbated during inclement weather conditions when regular scheduled arrival and departure demand has to be matched with decreased throughput capacities. As Petroccione puts it:

“Under the traditional banked model for hubs, airlines typically over-schedule during certain periods of the day, even well above the ATC flow capacity even for favorable weather conditions. This is a result of the traditional banked structure and connecting



philosophy to capture maximum revenue at the times during the day when stronger traffic demand is forecasted. During the periods when airlines schedule traffic beyond the maximum ATC flow rates, delays occur even on good weather days, and become a nightmare during bad weather.” (Petroccione, 2007)

In this eventuality, an airport arrival or departure manager can be pivotal in optimizing the overall operation. This is particularly true when the practice of slot allocation accommodates artificial strategic demand curbing and flow management.

The process of scheduling arrivals and departures at or below the maximum ATC flow rates for the airport increases the predictability and reliability of the overall operation (Petroccione, 2007). As such, it increases the probability that the intended arrival and departure sequences are maintained in an optimal manner. This concept feeds into the slot allocation algorithms under investigation in this research effort by ensuring maximum throughput capacities are desired but not exceeded.

Despite significant efforts in developing these ‘ideal’ schedules based on various business and economic goals, it is extremely unlikely that they will ever be achieved. Because of the stochastic nature of the NAS, aircraft currently routinely arrive out of their scheduled sequence due to breakdowns, ground delays and most importantly weather (Carr, 1998). Once out of sequence, aircraft are at the mercy of ATC to be re-scheduled for an arrival or departure time.

One of the primary problems with airline scheduling is that, given the current aircraft routing optimization approach employed by airlines, the robustness and reliability of schedules are not well considered against stochastic disruptions in operations (Wu, 2006). A root cause for

this is that stochasticity within the NAS is today not sufficiently well understood in order to be incorporated into scheduling algorithms. Consequently, at the stage of detailed planning, most airline schedulers still rely heavily on individuals' experience rather than sound data and methods.

The results of this research may provide significant insight for airlines into how the stochastic nature of the NAS can be incorporated into strategic flight scheduling at their hub airports and how airline operations may affect TFM decision making.

Some simulation applications have been developed which are specifically targeted towards assisting airlines in optimizing their schedules and in assessing the magnitude of external factors on the airline schedule. The MIT Extensible Air Network Simulator (MEANS) is an example of a NAS-wide simulation tool which is primarily motivated by airline delay propagation and flight scheduling. It models very specific aspects of airline operations including GDPs, weather, and even passengers, using stochastic distributions where detailed operations are not required (Clarke, 2004).

Although the use of simulation tools is very efficient in assessing specific scenarios and schedules, it is much too costly in terms of resources in order to be useful for optimization practice in the airline schedule planning regime.

### **Air Traffic Flow Management**

The concept of air traffic flow management – usually simply referred to as TFM – is the management of air traffic operations with the intent to avoid exceeding airport and airspace

capacity restrictions in controlling air traffic. TFM also aims to ensure that any available capacity in the system – on the ground or in the air – is used as efficiently as possible.

TFM operations in the US are handled at the FAA’s ATC System Command Center (ATSCC) in Herndon, VA and fall under the umbrella of the CDM initiative (see the subsequent section for a detailed definition). In Europe, TFM operations are the responsibility of the Central Flow Management Unit (CFMU) in Brussels, Belgium. Since most airports in Europe are slot controlled and due to the relatively dense geographic environment, Europe’s CFMU currently has a much broader application compared to CDM and TFM in the United States.

In fact, TFM in Europe strategically assesses traffic flows across the entire European airspace system from 18 months to a few days prior to the day in question. Eurocontrol – the agency overseeing air traffic in Europe – defines the following phases depicted in Figure 4 below for TFM as part of their “Air Traffic Flow & Capacity Management Strategy” (Fournier & Fonck, 2004):

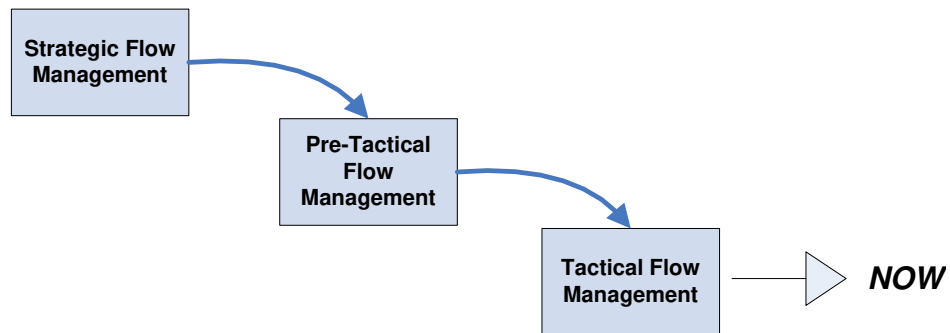


Figure 6: Europe's ATFM Phases

In this organization, strategic flow management takes place between 18 months and a few days prior to the day of operation. It basically consists of the analysis of the evolution of forecasted demand and capacity issues and results in a capacity plan for the given day. The subsequent pre-tactical flow management phase occurs a few days prior to the day of operation and it determines the optimal way to manage available resources. This phase also addresses the need for any flow control measures on the day of operation. The final phase occurs on the day of operation and adapts any existing plans from previous phases to the actual environment of the given day. This phase is where flow management plans are complemented by tactical airport and route slot allocations as well as ad-hoc re-routings (Fournier & Fonck, 2004).

The primary focus in this flow management process is the allocation of air traffic demand across a network of constrained resources of airports and air routes. Airport and air-route slot assignments are simply optimized to ensure that capacity limits are not exceeded.

### **Collaborative Decision Making**

In an effort to allow airlines and other stakeholders more control or influence over decisions made primarily in the TFM arena, the concept of CDM has seen wide acceptance. Given the fact that major capital investments of new runways, airports, terminals, as well as ATC capabilities require many years until funded and finally available, FAA and industry are focusing on process and technique improvements rather than major investments in infrastructure and aircraft equipment (Bond, 2003). CDM has evolved out of this paradigm and essentially attempts to more closely align FAA and airline interests and help make the system more efficient as a whole (Wambsganss, 1999).

Part of CDM is direct airline involvement in demand-capacity planning for daily flight schedules. Through this process, airlines have influence over any GDPs or other ATC delays which may affect scheduled arrival and departure times for their entire fleets. Daily CDM meetings at the ATCSCC in Herndon, VA also include discussions on forecasted effects of meteorological events, that allow airlines and other stakeholders to plan their daily operations in a more deterministic manner. The premise behind CDM is an industry-wide platform of information sharing and increased communication of requirements, desires, and intents.

Figure 5 below gives a graphical description of the CDM concept:

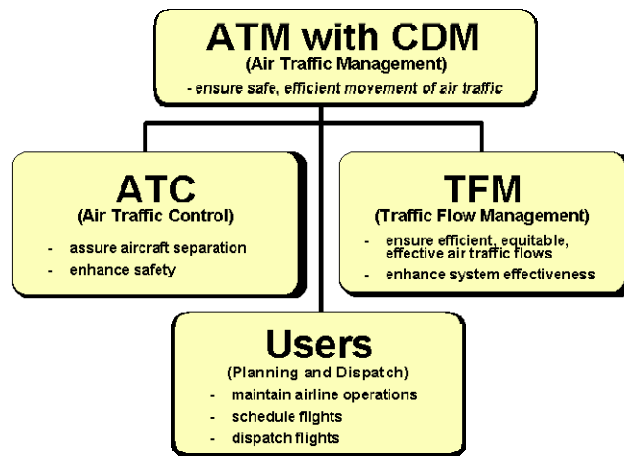


Figure 7: CDM Concept Overview (based on FAA CDM Presentations)

Although final decision making still lies with the FAA, the involvement of other stakeholders in TFM planning has shown considerable benefits. CDM has not only shown a reduction in ground delays across the entire NAS, but has also increased the predictability of arrival sequences (Ball & Hoffman, 2001).

This research effort essentially focuses on the strategic planning and scheduling of flights across a network of airports that may directly contribute to CDM practices, particularly since it highlights the combination of airport and FAA goals with airline operations and desires. It is also expected that the proposed slot allocation methodology reduce the need for GDPs.

### **Airport Capacity**

Airport capacity is an important factor in the strategic schedule planning as well as tactical operational planning of airport operations. The ability to correctly forecast airport throughput capacity during varying weather conditions and runway configurations can have a significant impact on the predictability of the entire operation and resulting delays and costs.

The definition of capacity within the given context of airport operations is “an airports’ ability to process a certain number of flights within a certain amount of time” (Wells, 2000). Commonly used variations of capacity within an airport environment include:

- *Maximum capacity*

A theoretical periodic movement throughput value without any regard to accumulated delay. Queuing theory suggests that it is impossible to reach maximum capacity for a random access queue but that delays will increase hyperbolically above a capacity fraction of 50% (Donohue & Zellweger, 2001).

- *Practical capacity*

A throughput value which represents a periodic number of movements given an acceptable level of delay.

- *Hourly capacity*

The number of movements an airport is capable of accommodating during a one hour period. This value changes throughout the day based on weather, wind, and traffic demand conditions.

Within the context of this research effort, the airport's hourly capacity rates are of primary interest. Arrival and departure throughout rates are influenced by a number of factors including the following:

- Number and configuration of runways
- Dependencies between runways
- Weather conditions
- Surrounding terrain features
- Airspace configuration

In order to maximize airport throughput capacity, routine configurations of runways are designated which have been shown to optimize throughput in various environmental conditions. Figures 8 and 9 below depict the layouts of each of the two subject airports including their current runways. Whereas the Chicago layout consists of multi-directional runways designed to operate in varying wind speeds and conditions, Atlanta has five parallel east-west runways which are intended to operate in predominantly east-west wind conditions. Hence, Chicago is capable of maximizing throughput rates via a much larger set of standard runway configurations when compared to Atlanta.

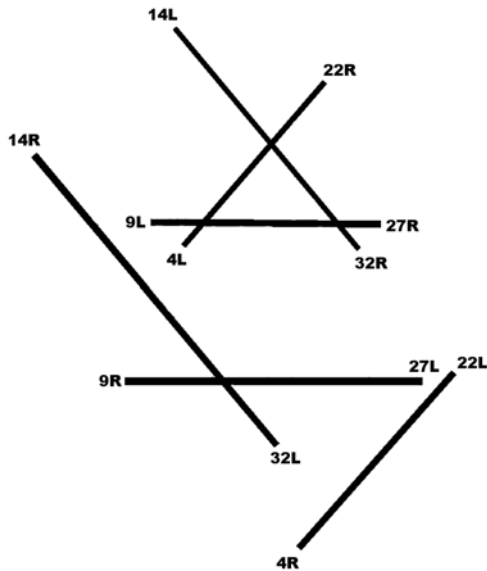


Figure 8: Chicago Airport Diagram



Figure 9: Atlanta Airport Diagram

For planning purposes, hourly airport arrival rates are published by the FAA’s ATCSCC facility for all major airports in the US (FAA OIS, 2007). These throughput rates essentially prescribe the number of available arrival slots at each airport. Capacity rates are given for different weather conditions and runway configurations and are largely based on mathematical calculations of runway movement rates and dependencies and usually are conservative by nature (See Appendix A and Appendix B for detailed capacity information for each runway configuration).

Other methods of predicting airport capacity include the use of historic traffic data combined with weather data as described by Fleming, Hafner and Fairman. This approach used years of historical data and developed statistical predictions of hourly airport capacity rates for all weather and runway conditions historically observed (Fleming et. al., 2001). This approach



was based on actual observed arrival and departure throughput rates rather than mathematical estimates of capacity as developed by the OIS system.

Air traffic demand in the United States is predicted to double or even triple by the year 2025 (JPDO, 2005). This growth in traffic is expected to have severe impacts on the NAS and will require significant improvements to existing methods of handling air traffic, ATC equipment, as well as airport infrastructures. Even though airspace congestion is likely to be a concern, terminal and airport capacity are expected to be the most limiting factor facing the transportation system (Andrews, 1999).

Voss and Hoffman also contend that the most limiting factors of any efficient air traffic control system are the airports themselves (Voss & Hoffman, 2000). In their opinion, airspace should adapt to runways since they are the least flexible part of the ATM system and are difficult to build and to alter. This has somewhat led to the emergence of secondary airports as a means of handling excess demand and operations in the NAS. This transition from single core airports to region wide multi-airport systems and the emergence of new airports in existing multi-airport systems, however, will impose new constraints which need to be addressed in future studies and NAS improvements (Bonney & Hansman, 2004).

Although the methodology proposed and developed for this research project does not increase the airports' ability to accommodate more traffic, the strategic demand-capacity planning should increase predictability and therefore reduce delays across the entire system. Hence, it would stand to reason that any beneficial change to system predictability would extend not only the maximum but also the practical capacity of the system (Wells, 2000).

## **Airport Slot Control**

The concept of airport slot control basically limits the number of departure and arrivals at designated airports in an effort to artificially curb demand, increase predictability, and reduce air traffic delays. Methods of slot control and allocation vary throughout the world but typically are all based on airlines receiving rights to operate a certain number of aircraft at certain times of the day at selected airports. These slots are typically based on historical usage but are also balanced so that some competition exists.

Although US airports are considered amongst the busiest airports by number of passengers served in the world (Neufville & Odoni, 2003), airport slot control is still a somewhat rare occurrence in the US. In fact, only a handful of US airports appear to have some level of slot control including New York's LaGuardia and JFK Airports, Chicago O'Hare, as well as Washington National Airport. These airports are some of the most congested airports in the US and typically rank highest on the yearly delay summations. The most fiercely controlled airport appears to be New York's LaGuardia Airport, where arrival and departure slots are assigned based on a lottery scheme and are valid for a 10 year period. The implementation of slot control at LaGuardia reduced its' contribution to the total US delay count from 25% to 10% based on 2001 figures (Saulny, 2001).

A recent announcement by the U.S. Department of Transportation indicates that as of March 2008, further capacity restrictions will be implemented at all three New York area airports including LaGuardia, John F. Kennedy, and Newark Airports (Airport International, 2007). Lower capacity limits of 82-83 operations per hour are intended to curb demand at these airport in an effort reduce delays in the area. This will force airlines operating at these airports to make

decisions about flight times and destinations and will make intelligent assignment of arrival and departure slots even more important.

In Europe, most major airports are subject to slot control and most exhibit excess demand for slots throughout the day. The current EU slot control system gives airlines "grandfather rights" to the take-off and landing slots they currently use. This allows airlines to hold on to valuable slots, provided they are used at least 80 percent of the time (NERA, 2004). Specifically, at major international airports such as London Heathrow, slots are very coveted resources and are highly valued.

The usage of these airport slots is governed by Eurocontrol's CFMU, which issues, for departures, calculated take-off times (CTOTs) – slot times – to airlines in the form of a time range. Aircraft are required to be ready for departure at these times or they will lose their slots and be at the mercy of CFMU to obtain a later slot assignment. The trading of slot assignments between aircraft of the same airline or the same alliance is also quite commonly used to ensure delayed aircraft have available slots down the line.

Many concepts for slot allocation mechanisms are currently being researched including advanced lottery systems and differential pricing schemes. However, the methodology of these advanced airport slot assignments and associated capacity impacts does not appear to be sufficiently integrated with the CFMU's traffic flow management practices. Particularly in a short-term tactical scenario, airport capacity restrictions and associated changes in slot assignments are not efficiently communicated with the CFMU (Chapman, 2005).

## **Future Supporting ATM Concepts**

With the advent of a next generation ATC system to replace the existing out-dated hardware and software, many new technologies and concepts are being researched, developed, and implemented today. Some of these concepts, although not fully implemented at the current time, will play a major role in reducing the uncertainty and increasing the efficiency of future navigation and control systems. The methodology presented in this dissertation references a number of concepts which are currently being implemented or under investigation for the future ATM System. This section presents an overview of current initiatives in planning and developing future ATM technologies, with a primary focus on concepts which increase the predictability of aircraft route planning.

The principal agency responsible for defining the future ATM system in the US is the JPDO. The JPDO was created by the Vision 100 legislation to develop a revolutionary next generation air transportation system (NextGen) to handle the needs of air traffic in the next 25 years (FAA, 2004). A description of the NextGen initiative states:

“We are entering a critical era in air transportation in which we must either find better, proactive ways to work together or suffer the consequences of reacting to the forces of change.” (NextGen Statement of Objective, 2004)

Many technologies are on the JPDO’s drawing board which address long-term capacity problems including satellite navigation, information sharing platforms, and advanced weather prediction systems. In addition to these long term capital improvements, the JPDO is also

researching process improvements – for airport and airspace operations – which assist in better accommodating expected traffic demand without major capital investments. These technology improvements include advances in managing aircraft trajectories, improved flight management systems aboard aircraft, as well as stringent requirements for aircraft to adhere to four-dimensional planned trajectories.

#### **4-Dimensional Air Traffic Management**

The majority of future concepts of operation (ConOps) for the future NAS are all biased toward the use of 4-dimensional ATM or ‘trajectory control’. This means that aircraft will be required to fly precise tracks with minimal deviation in the latitude, longitude, altitude and time dimensions.

Ideally the user will be able to fly a user preferred trajectory to the destination, that allows freedom vis-à-vis 2D-tracks as well as altitudes and speeds. This will not only satisfy environmental concerns in terms of noise and emissions, but also increases profitability from an airline point of view since approaches may be flown almost entirely on airline-preferred low engine thrust settings, thereby reducing fuel burn. As aircraft may also remain at higher altitudes for longer periods of time before reaching the top of descent (TOD) points on the approach, higher speeds are also possible and this reduces total air time (Wilson & Hafner, 2005).

The 4-dimensional tracks for each aircraft will be based on airline desired filed flight plans but are eventually modified and approved by a central host computer system. The system’s responsibility will be to adapt to the desired flight plan and ensure that no conflicts with other aircraft exist and that airspace and airport capacity restrictions are observed. The result is a

strategic 4-dimensional flight trajectory that will only have to be modified in case of emergencies or other unforeseen factors such as weather or runway closures. Of course, the aircraft will have to accept this 4-D trajectory and renegotiate as necessary to match internal airline requirements. The aircraft subsequently enters into a ‘contract’ to fulfill the requirements of this trajectory.

The basic purpose of 4-D ATM is to eliminate as many factors as possible that might affect in-flight trajectories before the aircraft leave the ground. Clearly, implementation concepts such as NASA’s Evaluator cannot consider all events that may possibly affect flight trajectories, but they certainly increase the predictability of the system to a level where more advanced trajectory planning technologies can be very valuable.

### **Performance Based Operations**

Future ATM systems in the US as well as Europe will implement the broader concept of performance-based ATM (PB-ATM), also sometimes called performance-based navigation (PBN). These concepts specify performance requirements in terms of accuracy, integrity, continuity, and functionality required for the proposed operations (ICAO, 2007). This represents a paradigm shift from historic sensor-based to future performance-based concepts. PB-ATM will define equipment and performance requirements for navigation levels of service. Based on this, airlines and operators are able to evaluate flight path and other options based on their operational requirements and aircraft capabilities.

The primary advantage of PB-ATM is that different levels of service can be selectively provided based on aircraft capabilities. This generates an environment of increased cost-effectiveness and predictability for aircraft with advanced avionics.

PBN will have an impact in all levels of flight including departures, en-route cruise, and arrivals. Figure 10 below depicts a typical flight profile for an aircraft, the phases of flight, and some associated benefits of PBN services (extracted from US JPDO ConOps) :

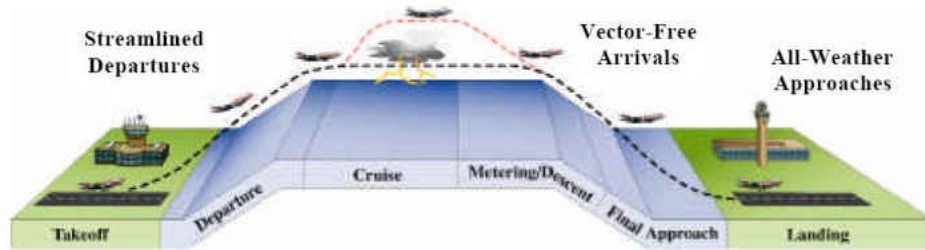


Figure 10: Flight Profile and Phases of Flight

Failure to repeatedly meet performance of 4-D trajectories and other performance-based service may result in increasingly lower level of service for selected airlines or aircraft operators.

The implementation of the PB-ATM concept is a fundamental concept that supports the advanced TFM aspects referenced in this research effort. The use of stochastic distributions of flight times as part of the airport slot allocation scheme makes heavy use of the idea that aircraft will be able to accurately fly pre-defined trajectories in the fourth-dimension – time – and meet their expected arrival times reasonably precisely. A primary component of PB-ATM, RNAV and RNP, is further defined in the subsequent section.

### **Required Navigational Performance**

The International Civil Aviation Organization (ICAO) defines RNP as "a statement of the navigation performance necessary for operation within a defined airspace" (ICAO, 2007). RNP,

coupled with the concept of RNAV, is part of the broader concept of PBN and defines performance specifications that an aircraft must meet in order to be able to operate on certain routes and flight paths. RNP also monitors the achieved performance and provides for alternatives in the event of failure to meet the required performance specification. As a result, due to their higher level of predictability aircraft equipped with RNP avionics are capable of operating in more densely populated airport and airspace environments and therefore accommodate the increasing demand for air traffic capacity. Figure 11 below shows a before and after comparison of arrival flight routes into Atlanta Hartsfield Jackson International Airport and the difference that RNAV-RNP procedures have made in improving the predictability of 3-dimensional flight paths (McGraw, 2005). These figures are based on ASDI aircraft tracks before and after the implementation of RNAV-RNP procedures at Atlanta:

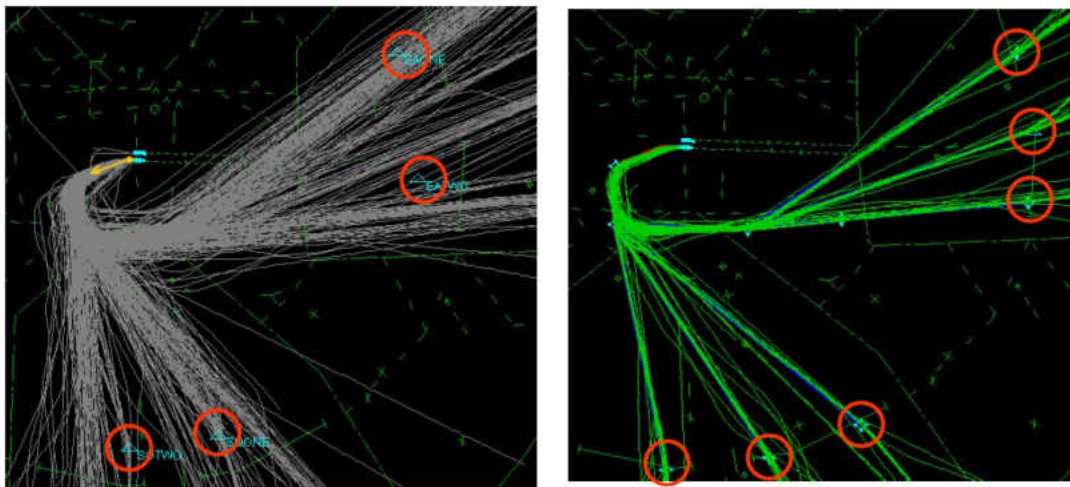


Figure 11: Area Navigation - RNP Procedures at Atlanta before (left) and after (right)

The closer adherence to pre-defined routes that are caused by RNAV-RNP procedures reduces variability in flight paths in three and even four dimensions. Aircraft can be guaranteed



to fly more exact routes in a more automated manner, thereby increasing system predictability and reliability.

Some of the benefits of RNAV-RNP procedures and concepts include (McGraw, 2005):

- Increased predictability
- Increased arrival/departure throughput and efficiency
- Decreased departure delays
- Reduced track distances and more direct routings
- Reduced voice communications
- More efficient vertical profiles

An aircraft's ability to precisely fly a 4-D track is defined in levels of RNP compliance capabilities. For example, to use RNP as an approach tool, aircraft typically will need to be certified for RNP 0.3 or even RNP 0.1, reflecting a capability to maintain track with a maximum deviation of 0.3 or 0.1 nm (ICAO, 2007). The RNP requirement is reduced in airspace where the traffic density is reduced.

The concept of RNAV-RNP also provides for the ability to define tunnels of airspace for aircraft that have the same flight paths and required equipment performance. Essentially, the aircraft flies down a tightly contained tunnel in the sky using the onboard navigation and monitoring systems to maintain separation with other tunnels in the sky (ICAO, 2007). These tunnels in the sky can be dynamically designed in terminal areas but are likely to be fixed routings in upper airspace (Paylor, 2006). They essentially guarantee conflict free and predictable flight paths for aircraft that are sufficiently equipped.

## **Recent Approaches to Schedule Optimization Problems**

Various operations research techniques have been applied to solve timetabling and scheduling problems such as the slot allocation problem addressed in this research effort. The application of optimization algorithms depends on the size of the problem space. In fact, the performance of random search techniques on these types of problems is typically a function of the proportion of good solutions versus unacceptable solutions. This makes a random search for acceptable or optimal solutions very impractical. Classical search techniques are often practical for small scale problems where either the search space is small or the number of acceptable and optimal solutions is abundant (Fang, 1994). This suggests the use of intelligent search techniques and heuristics to solve large scale timetabling problems such as the airport slot allocation problem at hand.

A review of classical Operations Research techniques and their applicability in the timetabling/scheduling arena is presented in this section. The logical division of methods for the purpose of this discussion is between enumerative and search techniques. Enumerative techniques use mathematical optimization and programming to solve problems by examining the bounds of the acceptable problem space for optimal values. On the other hand, search techniques search for optimal solutions by examining some or all solution sets within the entire solution space. Naturally these search techniques are guided in order to minimize the total number of solution sets to examine.

The following techniques are all enumerative methods:

- Mathematical programming

This includes approaches such as linear programming, integer programming, and

mixed integer programming. At the core of these techniques lies a mathematical function which will be optimized subject to various linear constraint functions and variables. These approaches are very suitable for small scale timetabling and scheduling problems. Nevertheless, Tripathi, 1984, has shown that, albeit with some challenges, binary integer linear programming methods may be applied to larger scale scheduling scenarios as well (Tripathi, 1984). Another example is presented by Wen, Larsen and Clausen, who used mixed integer programming in combination with other search techniques to obtain optimal sequences to what they called the aircraft landing problem (ALP) (Wen et.al, 2005).

- Branch and bound

The branch and bound technique is basically an enumeration approach that prunes the search space by eliminating the non-promising search space. Branching basically partitions the large problem space into multiple sub-regions and bounding subsequently calculates the lower bound on the optimal solution of each of the sub-regions. Branch and bound methods are classified according to the methods used for bounding the ways of creating/inspecting the search tree nodes during the pruning stages. This type of approach was used by Carlier and Pinson for solving the job-shop problem (Carlier & Pinson, 1989). The branch and bound approach is basically ineffective for timetabling and scheduling problems (Fang, 1994).

- Dynamic programming

Dynamic programming is also an implicit enumerative method which exhibits the properties of overlapping sub-problems and the optimization of substructures

Due to the nature of timetabling and scheduling problems, the enumerative methods identified previously clearly do not provide an effective means for obtaining optimal solutions in large search spaces. While mathematical programming techniques may be practical in solving smaller sized timetabling or scheduling problems, they will not prove to be a computationally effective procedure to solve larger scale problems (Wen et. al., 2005).

This suggests the use of intelligent search techniques to solve the large scale timetabling problem for airport slot allocation. Heuristic searches provide guidelines for intelligent search of the problem space for optimal solutions. The following is a summary of intelligent search techniques which may be applied to timetabling and scheduling problems:

- Direct heuristics

These techniques are based on simulations of human behavior in solving problems. Direct heuristics are based on successive augmentation of the solution space by scheduling one event after the other until all of the events have been scheduled. The underlying idea of these approaches is to schedule the most constrained event first (Schaerf, 1999). Conflicts between events are resolved by simply swapping events in the timetable (Junginger, 1984).

- Simulated annealing

The simulated annealing approach was first pioneered by Kirkpatrick, Gelatt, and

Vecchi in 1983 and is a global search heuristic, that searches the solution space by generating, at random, neighboring solutions to the current solution (Kirkpatrick et.al., 1983). A more preferred neighbor is always accepted and an inferior neighbor is accepted probabilistically. This decision is based on the difference in quality and a temperature parameter, which is modified as the algorithm progresses to alter the nature of the search. Essentially, non-improving solutions are permitted with progressively decreasing probability (Meyers & Orlin, 2006).

- Tabu searches

Tabu searches are another local search heuristic which iteratively moves from one solution to the next in the immediate neighborhood, until some stopping criterion has been satisfied. The unique aspect of this technique is that it retains memory of recently visited solutions and classifies them as unacceptable for re-examination in the future (Meyers & Orlin, 2006). Short and long term memory both exist within this technique to prevent certain moves even if they are increases, essentially making this technique very effective in finding global rather than local optima. Examples of this technique can be found in (Colomi, Dorigo & Maniezzo, 1998) and (Paquete & Sutzle, 2002).

- Neighborhood/local searches

Neighborhood search algorithms define a technique which starts with a feasible solution and iteratively attempts to find a better solution in the neighborhood of the current solution. A very large-scale neighborhood search algorithm is one that searches over a very large neighborhood, giving an improving solution in a relatively efficient amount of time. Such algorithms tend to search implicitly over

the neighborhood rather than explicitly, since the quantity of solutions precludes performing an exhaustive search (Meyers & Orlin, 2006). Caramia and Dell'Olmo present a novel heuristic which couples a stochastic local search with a deterministic local search to more efficiently obtain an optimum (Caramia & Dell'Olmo, 2007).

- Genetic algorithms

GAs are an approach which uses the basic theory of evolutionary biology to migrate from an initial solution set to the most optimal solution in the search space. GAs maintain a pool of potential solutions and individual genes or chromosomes are combined or mutated to alter the pool of solutions. Inferior quality solutions are discarded – an analogy to natural selection in biology – based on a fitness function which evaluates and scores each potential solution. GAs perform particularly well with NP-complete problems such as timetabling and scheduling.

- Evolutionary algorithms

EAs are a close relative to GAs in form and function. Also referenced by (Holland, 1975), they differ in function from GAs in the limiting of genetic operators. Rather than using mutation and cross as genetic operators, EAs make use of only mutation.

- Memetic algorithms

Memetic algorithms are a close brother to GAs in that they essentially are evolutionary methods and contain units of information – or chromosomes – which reproduce themselves as ideas get exchanged. The memes essentially regenerate

themselves and mutate much like genes in the EA approach. The key difference from GAs is that memetic algorithms heavily incorporate local searches before mutation (Moscato & Norman, 1992). The practice of hill climbing can also be applied to the mutated solutions to improve the quality of the solution (Burke, Newall & Weare, 1996).

- Particle swarm optimization

Swarm intelligence optimization was first described in 1995 by Kennedy and Eberhart (Kennedy & Eberhart, 1995). It is also a close relative of GAs in terms of its' evolutionary search methodology and associated fitness function to evaluate the quality of each solution. It slightly differs from traditional EAs in its' secondary focus on individual particles and the quest for their own particle or local best solutions.

Other artificial intelligence or knowledge-based intelligent system approaches exist such as constraint satisfaction problem techniques or order/resource-based scheduling. The use of hybrid approaches containing distributed artificial intelligence, rule-based expert systems as well neural networks are also fairly popular approaches to solving scheduling problems.

The most promising and modern heuristics – and likely most advanced – such as Tabu Search, GAs, EAs, and particle swam optimization have their roots in artificial intelligence. These techniques, particularly for large timetabling problems, seem to outperform tradition operations research methods (Meyers & Orlin, 2006).

## **Recent Optimization Approaches for Airport Operations**

Recent research efforts in airport slot allocation optimization have focused primarily on a single metric – aircraft delay – and have tended to focus on single airport systems. Aircraft delay is readily measurable in an optimization algorithm as both a linear and non-linear fitness on a flight-by-flight basis. It does, however, assume that the original estimate of arrival or departure time has a high level of confidence for each flight. Optimization across all flights is then typically measured as the minimal overall deviation from the original scheduled movement times.

The vast majority of current research efforts in this subject have also focused on a single-airport system. Some research has been carried out in the optimization of airport capacities and delay propagation across networks of airports. Nevertheless, the description of an overall optimization algorithm that addresses scheduling across a network of airports has thus far not been widely discussed.

The literature has shown that the optimization of airport operations is typically addressed from a number of different angles. Each of these fields of study is a significant research area in and of itself. The different fields include:

- *Optimization and maximization of airport throughput* through the use of improved forecasting, optimal runway configurations, and aircraft sequences (minimization of wake turbulence effects)
- *Optimization of ground operations* including optimal taxi paths and the optimal usage of resources to minimize aircraft turnaround times



- *Optimization of airline flight schedules* from a strategic or tactical perspective to minimize the effects of reduced capacity and other perturbations within the system. An additional goal in this field is the maximization of ground resources and the minimization of cost from an airline perspective.

The majority of the optimization approaches above can be applied in a strategic, long-term planning horizon. Some, however, are focused on the real-time decision support tool planning horizon. The vast majority of research also focuses on the single airport optimization problem rather than addressing networks of airports. Although the NAS is considered to be a networked system of capacitated resources, the scalability of many optimization approaches from a single to multiple airports is not addressed.

Current research in each of these areas will be discussed in turn.

### **Capacity Optimization**

The optimization – or in this case the maximization – of available runway resources in terms of throughput capacity is a very popular field of study. Various research programs focus solely on the maximization of available runways and the associated throughput capacity under varying demand and weather conditions.

Research into the optimal use of runway configurations under varying weather – and particularly wind – conditions is being carried out by Mousa and Mumayiz to produce a tool that recommends the most optimal runway configuration based on the given wind conditions (Mousa & Mumayiz, 2000). In their research effort wind variables are being converted into

mathematical formulas which are then matched against historic runway configurations using an exhaustive search optimization algorithm.

Other recent research efforts focus on the tradeoffs in arrival and departure capacity. Whereas most applications treat arrival and departure capacity as independent variables, Dell'Olmo and Lullii have researched the inter-relationships of these two capacities (Dell'Olmo & Lullii, 2003). His research has shown that maximum overall capacity an airport can be maximized by using a dynamic programming framework and pareto-optimal operational points of departure and arrival capacity. An initial operational tool for airport capacity tradeoff guidance was developed by the Volpe Research Center and tested in St. Louis International Airport (Gilbo, 2003). Volpe continues to research this application.

Another approach for maximizing airport throughput was presented by Fleming, Hafner and Fairman in his research into using historical throughput and weather conditions to forecast airport capacities. Using a combination of prediction equations and pattern matching on historical observations, their researched showed that more realistic airport capacities can be produced for near-term strategic airport schedule planning (Fleming et.al., 2001).

A more network-centric approach to maximizing airport capacities has been taken by researchers at George Mason University. Their focus is the net reduction in arrival-departure delay across a network of airports by leveraging high fidelity weather forecasts capacity optimization algorithms, and ground operations guidance (Roberts, 2004). This research again focuses on the minimization of capacity-constraining effects across a network of airports.

Another very popular area of research in this field is the optimization of the arrival and departure sequences to maximize airport throughput. Based on various wake-turbulence separation criteria, the order in which aircraft arrive and depart may significantly affect the

throughput rates. Various AMAN and DMAN tools exist on the market today that solve this problem in various different ways. Both American and European federal research centers dedicate significant resources towards research on advanced arrival and departure guidance tools. One such tool, NASA's Collaborative Arrival Planner, is being used as the basis for developing more advanced arrival sequencing models that minimize cost through adjustments of the arrival sequence (Andersson, Hall, Atkins & Feron, 2003). It contains a quantitative model of airline operations and is capable of producing optimal schedules for one airline at a single airport for a 3-4 hour period.

Research such as that carried out by Saraf and Slater extends this practice and not only maximizes airport arrival capacities but assigns capacities along various points along the aircraft flight paths (Saraf & Slater, 2008). Using an Eulerian model-based optimization scheme, airport and en-route point capacities and flight arrival orders are assigned with the goal of maximizing airport throughput.

The maximization of airport capacity can be considered the fundamental area of research for all ATM traffic flow management tools. With limited amounts of runway and real estate for expansion, it is the optimization of existing resources that can maximize airport operations efficiency and throughput.

### **Ground Operations Optimization**

The optimization of ground taxi operations is a popular area of research today. It is split into two primary areas of research: taxi paths and aircraft turnaround times.

Without regards to departure runway sequences, aircraft need to move along taxiways in a safe and efficient manner. This area has historically not seen any research into optimization tools. In order to constantly feed the departure runways with aircraft and make optimal use of gate usage times, optimal ground taxi paths can provide distinct advantages. Research being carried out at the University of Madrid, Spain, is focused on developing real-time DSTs that give controller guidance regarding aircraft taxi routes (Garcia, Berlanga, Molina & Casar, 2005). To accomplish this task, a hybrid approach using genetic and time-space dynamic flow management algorithms has been implemented. This approach allows the time-space dynamic flow management algorithm to solve a deterministic simplified problem that is then complemented by the GA and a search within a more realistic problem space. Similarly, NLR, the Dutch Aerospace Research Agency, has developed optimization tools for guiding aircraft along taxiways at Schiphol Airport in Amsterdam (Smeltink, Soomer, de Waal, & van der Mei, 2004). Using mixed-integer programming, a tactical planning DST was developed that minimized travel times on the ground and therefore optimized gate usage.

Other research efforts have focused on optimizing aircraft turnaround time scheduling. Research performed by Wu and Caves has shown that optimal assignment of buffers to scheduled turnaround times can minimize costs by balancing the tradeoffs between schedule reliability and aircraft utilization (Wu, 2004; Wu & Caves, 2003). The results from this research effort may be of distinct interest to the airport-wide scheduling methodology presented in this dissertation. The ability to not only link arrivals with departures but also to optimize the turnaround time buffers would increase the scalability of this approach significantly.

## Schedule Optimization

In contrast to the near-term capacity maximization research described in the previous section, the optimization of airline schedules around these capacity constraints is a much more popular area of research. In fact, airlines have been researching and practicing this area for a long time on both a long-term and a short-term planning platform. The optimization of airline schedules is heavily dependent on the desired metric for evaluation. Potential metrics include delays, costs, crew and ground equipment resources, and human workload.

At a very rudimentary level, using delay as the sole metric, Ding, Ji, and Wang are researching the use of Compromise Immune Algorithms (CIAs) to schedule arrivals and departures at airports based on fixed airport capacities (Ding, Ji & Wang, 2007). Experiments have shown very favorable results from the use of CIAs in the combinatorial optimization. Another approach to assigning arrival slots under reduced capacity scenarios is presented by Butler who uses a ration-by-schedule greedy algorithm (Butler, 2003). Using an integer programming model, Butler uses delay-based metrics to efficiently allocate resources. The model can also be extended to take into account capacity restrictions at waypoints along the arrival routes.

Using airline costs and delays as metrics, research carried out by George Mason University shows that airline schedules can be optimized around reduced runway capacities without sacrificing airline costs and increasing ticket prices (Le, Donohue, Hoffman & Chen, 2008). Another cost-based approach is presented by Chang and Schonfeld for scheduling departure aircraft along high-demand routes. Using dynamic programming, the departure times of flights that minimize airline operating cost and users waiting cost are determined for a single airline

with time-dependent demand along routes (Chang & Schonfeld, 2004). Cao and Kanafani have also used a minimum cost flow model to assign runway slots to flights using relationships between airline profits and flight rescheduling (Cao & Kanafani, 2000). Using their approach, airline flights are rescheduled based on a limited set of runway slots. According to their research, this optimization approach can be used to investigate congestion pricing, runway slot auctioning, and the adjustment of airline schedules to accommodate reduced capacity scenarios.

A dynamic programming approach to runway scheduling has been proposed by Chandran and Balakrishnan. Their algorithm computes a tradeoff curve between runway throughput and the probability that random deviations of aircraft from the scheduled times violate system constraints (Chandran & Balakrishnan, 2007). The algorithm includes various operational constraints and limits the amount of time that an aircraft can be shifted in the schedule. The overall intent is to develop a schedule which is more robust to perturbations.

Current research into departure schedule optimization is heavily based around the sequence of departures in a short-term planning horizon. High demand airports frequently encounter periods where the workload for ATC prevents optimal departure aircraft scheduling. To assist controllers in a real-time scenario, research is being focused on DSTs that generate optimal departure sequences. One such tool is being investigated for use at London's Heathrow Airport using a hybrid meta-heuristic to aid runway scheduling (Atkin, Burke, Greenwood & Reeson, 2007). In similar fashion, a two-step algorithm is presented by Anagnostakis which produces an optimal departure schedule based on optimal departure sequences as well as projected ground taxi times from the gates to the runway entrances (Anagnostakis, 2004).

Other research efforts into optimal departure sequencing are focused on solving the GDP problem. When sudden decreases in departure capacity are mandated by the FAA, airlines are

forced to quickly reschedule flights based on various priorities. Mukherjee and Hansen present a dynamic stochastic integer program which optimizes the departure flight sequence under GDP restrictions (Mukherjee & Hansen, 2007). As part of this approach, certain airline priorities are incorporated including priority of long haul over short haul flights. The major contributor to their objective function is the cost of delays taken on the ground by departing aircraft. This integer programming approach produces the highest performance gain under capacity restricting scenarios but can also be applied under normal operating conditions. Other approaches to solving the Airline Recovery Problem (ARP) propose the use of evaluated preference genetic algorithms to optimize airline schedules (Liu, Liu, Chen, Tsai & Ho, 2007). Their research addresses the scenarios of near-term significant capacity reductions by using multi-objective genetic computation that consider flight connections, flight duty swap, total flight delay times, and flights delayed over 30 minutes.

In addition to scheduling runway arrivals and departures, other research is focused on optimizing gate arrivals and departures. If runway throughput capacity exceeds the gate handling capacity at an airport, the system inherently exhibits delays. Thus, optimizing the use of valuable gate space is a natural parallel optimization effort that matches resources on the ground to the desired arrival and departure slot schedules. As Dorndorf, Drexl, Nikulin, and Pesch note, solutions to the gate assignment problem range from quadratic assignment problem solutions, to integer programming, to specialized branch and bound and neighborhood search techniques (Dorndorf et al., 2007). Objective functions for these optimization problems are predominantly intended to minimize passenger walking or baggage transportation distances. Realism is injected into these optimization algorithms by adding stochastic perturbations into the evaluation of the schedules including flight tardiness and flight gate breakdowns and failures.

Based on this literature review, a variety of different approaches have been proposed for optimizing airline schedules in a near-term and a long-term planning horizon. The vast majority of these approaches are only applicable to single airport scenarios. The literature review has also not produced any novel research into slot allocation optimization that is based on historically observed flight and taxi times. This is likely due to the lack of data available to organizations outside of major research institutions and the airlines themselves.

### **Strategic versus Tactical Planning**

Many of the optimization approaches previously identified can be optimized in both a strategic and a tactical manner. Whereas some heuristics focus on optimization operations in a strategic, long-term timeframe, other research areas focus solely on real-time DSTs that are geared towards assisting active control of aircraft in real-time.

Capacity and resource optimization planning is typically performed on a tactical near-term time horizon. Since near-term schedule optimization depends heavily on airport capacity forecasts, tactical schedule optimization is performed within hours of the actual operation. Similarly, the optimization of ground operations can only be performed efficiently in the near-term when traffic demand is more deterministically understood.

On the other hand, schedule and gate optimization tasks can be performed in both a tactical and strategic manner. Airlines perform strategic optimization of their schedules many days, weeks, and months before the actual day of operation. This allows them to produce optimal crew, ground crew, and ground equipment usage profiles. An Airline Operations Center (AOC) then evaluates schedules in a real-time manner on a continuous basis. Airlines use



various optimization tools to assist in the recovery from GDPs or other irregular operations phenomena.

### **Network Planning**

As mentioned in the previous sections, the majority of airport arrival and departure optimization research is focused on solving the single airport problem. This is likely due to the expected audience for these approaches. The optimization of single airport operations is typically the responsibility of airlines and airports (including local ATC). Airports that require strategic schedule planning are generally considered airline hubs or high-demand destinations such as New York's LaGuardia Airport. The airport's ability to coordinate slot assignments with other airports is not the responsibility of the airport itself, but that of the FAA's TFM unit. This means that although single-airport optimization approaches can be implemented, the understanding of how these affect the NAS lies with the FAA's command center. The developing of tools for NAS-wide operations has historically been centered at high level federally funded research centers such as MITRE or MIT Lincoln Labs. There appears to be no real impetus for wide-spread research into NAS TFM optimization tools at this point.

Nevertheless, some universities have been working on long-term research projects to develop applications which address the networked nature of the NAS. The intended application of these network-wide approaches differ based on the audiences and the purpose of the results.

One approach for optimizing airline network base schedules is presented by Mashford and Marksjo who suggest the use of optimization through simulated annealing of flight networks

(Mashford & Marksjo, 2001). His approach is hierarchical in nature consisting of a master problem for logical aircraft optimization and various sub-problems for schedule evaluation. The sub-problems include evaluations of passenger connections, passenger choice modeling, revenue, and cost generation. The nature of the sub-problems seems to indicate that this network-wide schedule optimization approach is primarily intended for assigning the correct size and number of aircraft to routes based on various passenger origin-destination characteristics.

Another network-wide optimization approach has been taken by the team developing the MIT Extensible Air Network Simulation (MEANS) tool. As Clark describes, the tool is primarily intended for airline delay propagation research and provides for ways to minimize the effects of irregular operations across the NAS (Clarke, 2007). The MEANS platform can assist airlines in the optimization of NAS-wide schedules when sudden capacity decreases or GDPs occur in the system. The primary objective of MEANS is to develop a model platform where airlines and air traffic service providers can assess the impacts of weather, statistical phenomena, crew availability, and passenger movements on a NAS-wide network of airports. Although MEANS uses optimal airport throughput capacities and develops optimal arrival and departure sequences, it performs these functions from a level that primarily assesses flow rates and not individual aircraft slot assignments.

Another approach for a NAS-wide optimization tools is the Airport Departure Arrival Management System (ADAMS) that was developed at George Mason University (Roberts, Grundman, Devlin, Fulgenzi, Sacro, Stapleton & Szurgyi, 2004). As described, ADAMS provides real-time decision support capabilities to local air traffic and ground operations managers as well as the FAA's central flow control unit. The objective is to minimize net arrival-departure delay by leveraging high fidelity weather forecasts, ground sequencing

guidance, and capacity optimization algorithms. ADAMS has been evaluated using a simulation platform for a network of 6 airports. The purpose of this application is real-time guidance of aircraft operations across a network of airports. ADAMS does not appear to incorporate any objectives other than delay into its decision making framework.

### **Relevance to Proposed Methodology**

This literature review has shown that although various novel approaches to optimizing airport operations exist, none of the methodologies address the strategic multi-objective optimization of airline schedules across a network of airports.

Most strategic schedule optimization approaches focus on a single airport problem and do not adequately address the multi-objective nature of airline scheduling from a TFM perspective. The literature review has clearly shown that no current approaches to schedule optimization exist which strategically allocate runway slots on a long-term planning horizon. All of the approaches focus on optimizing the arrival and departure sequences in real-time or within a few hours of the operation.

Also, the network-wide optimization approaches that have been identified either focus on real-time optimization for DSTs, delay propagation across the NAS, or strategic assignments or aircraft on routes based on passenger origin-destination data.

## CHAPTER THREE: METHODOLOGY

In the scenario described previously, the focus lies on the allocation of airport departure and arrival times for a given real-world schedule of aircraft flight plans. The scope is limited to two airports and a period of performance for analysis of 4 hours during which a realistic complete set of operations will be experienced at each of the following airports:

- Chicago O'Hare International Airport
- Atlanta Hartsfield Jackson International Airport

These airports are the top two busiest airports in the entire US as well as the world (McCormick, 2007). Chicago O'Hare is capable of handling upwards of 3,000 flights per day, with analytical maximum arrival capacities of up to 100 arriving and 100 departing flights per hour of each, arrivals and departures (OIS Website, 2007). FAA OIS data indicates that Atlanta Hartsfield Jackson Airport is capable of accommodating a similar amount of traffic during good weather, i.e., VFR weather conditions.

The primary reason why these two airports were chosen is that they are both major hub airports within the US NAS, which means they are guaranteed to have a fairly constant demand pattern. This also ensures that numerous flights are scheduled between these two airports on a daily basis. Since Chicago O'Hare is already a slot controlled airport, the hourly scheduled demand rates have already been artificially trimmed to more closely align with expected capacity rates. Atlanta Hartsfield, on the other hand, regularly experiences periods where the scheduled demand exceeds the available capacity – departure and/or arrival – throughout the day.

Had two airports been picked where absolutely no flights operated between them, the approach to this problem would simply be comprised of two completely separate optimization

problems where one airport's slot allocation would not affect slot scheduling at the other airport at all. This would mean that inter-airport effects would not be accurately catered for in the subsequent evaluation of the performance of the algorithm.

Simply allocating airport arrival and departure times at an airport is a far more complicated process than this description indicates. It is fairly routine that the total number of scheduled operations at each of these major hub airports exceeds the amount of aircraft the airport is actually capable of handling, particularly during inclement weather conditions. If a simple first-come first-serve scheduling methodology was used to allocate arrival and departure times between aircraft, the airport may be idle at some points and completely backed up in others. This would also cause some aircraft to be delayed for unacceptable time periods depending on the order in which they were schedule to arrive in the first place.

Due to the complexity of this problem and based on an extensive literature research of potential approaches, an EA approach was chosen to optimize the arrival and departure orders of the two subject airports. This section of the dissertation outlines the details of the prerequisite data mining efforts of historical data and subsequently the design and implementation of the EA methodology including any relevant assumptions. It also provides the outline of a simulation-based assessment of the resulting slot allocation schedules produced by the EA methodology.

### **Research Approach**

As previous sections of this dissertation have outlined, the basic approach to the airport slot allocation problem chosen is that of an EA. GAs are a smart search technique which use a fitness function to evaluate potential solutions to the problem and uses the relative fitness of

these solutions to guide the search for better, more preferred, solutions. A solution within the context of this research describes a certain order of arriving and departing aircraft at the two subject airports – Atlanta Hartsfield Jackson and Chicago O’Hare. An iterative search through the exhaustive solution space is then performed by the EA.

During each round of generating candidate solutions, each solution is evaluated with a fitness function which considers such factors as aircraft flight times and delay, operating characteristics, taxi-times, and airline and ATC priorities. These factors are incorporated into the fitness function for a measure of overall solution desirability, which the EA approach strives to maximize. The EA approach eventually converges on an optimal slot allocation for a given demand schedule supplied as input data into the algorithm.

To evaluate the utility of the slot allocation methodology presented, the optimal slot allocation is subsequently subjected to various simulation runs using the AnyLogic simulation software. These simulations are made up of simple queuing models of the two airports and essentially assess the quality the optimal EA schedule against other schedules including the original filed schedule.

The end result of this research effort will consist of a novel approach to strategic slot allocation scheduling from a TFM perspective. The results will also yield a vast set of historical flight time and taxi-time databases that can be used in any number of other applications.

### **Overview of Optimization Process**

The schedule optimization process is composed of a number of different steps. This includes the original capture of demand schedules from existing traffic data, the initial

preparation of the schedule, and subsequently the actual optimization of the subject schedule based on various criteria and preferences. Figure 18 below presents a high-level overview of the overall optimization process:

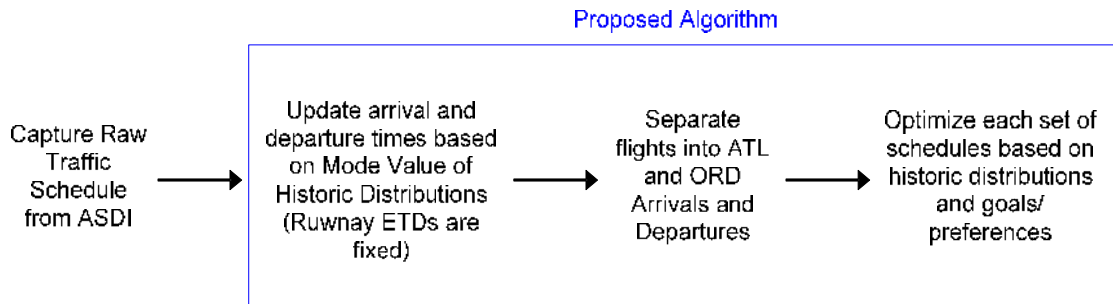


Figure 12: Optimization Process Steps

As the figure above shows, the subject schedules are initially captured from the raw ASDI traffic information dataset. This results in base airline-preferred flight schedules that are subsequently fed into the optimization algorithm. These schedules are then processed to use the mode operating times – the most likely flight and taxi-times based on historically observed instances - to calculate new estimated times of arrivals and departures. The estimated times of departure (ETDs) for the runway are held constant to preserve the original schedule integrity.

Following this, the new schedules are fed into the optimization routines where it is split into the four separate datasets of arrivals and departures for ORD and ATL. Each of these individual schedules is then optimized based on the EAs fitness function as well as respective airport capacities.

A step by step overview of the processing within the optimization algorithm is presented below:

1. Capture original airline schedule from ASDI data. This schedule represents the actual filed flight plans published by airlines.
2. Update the schedule arrival times based on mode flight and taxi times. This intermediate step generates a schedule that represents perfect-scenario operations with no ‘overscheduled’ flight times.
3. Feed the mode-time schedules into the algorithm.
4. The algorithm then initially allocates the flights in the schedule to a limited number of slots (pre-defined based on airport throughput) within each queue (arrival or departure at each airport). This allocation is done purely based on a sequential ordering of the schedule based on requested arrival or departure times and does not consider time.
5. The algorithm then iteratively performs the following functions based on a generic EA platform:
  - a. Evaluate the fitness of the current allocation of slots based on a proposed set of components that address flight and taxi characteristics as well as airport and airline preferences. This fitness function includes:
    - i. The new flight time (based on a fixed ETA or ETD at the non-subject airport and the currently allocated slot time) probability. This probability is simply based on a reverse lookup of the probability of encountering this flight time based on the empirical distributions processed from the historical data



- ii. The new taxi time, which is computed similar to the flight time described previously but based on transit time between gate ETAs and ETDs and the new slot times
  - iii. Airport and airline preferences, which are multipliers applied to the relative difference between the new slot time and the proposed ETAs and ETDs prepared in step 2.
- b. Select the slot schedules with the highest fitness values for re-production and mutation. The mutation steps scramble the order of the flight sequence defined by the slot allocation.
- c. Repeat the process from step a. until a maximum number of iterations is achieved.

This optimization routine is run twice with different airport capacities to produce one schedule which is not capacity limited (using the scheduled demand as hourly capacity) and one schedule that is capacity limited as observed during inclement weather or other capacity-limiting environmental conditions. The following section briefly describes these two schedules in more detail.

### **Capacity-Constrained Schedule Optimization**

Airport throughput capacities at ORD and ATL are variables which are configurable within the optimization algorithm. This means that hour-by-hour capacities can be set independently for arrivals and departures for each airport to reflect actual and/or forecasted

capacities. If the capacity constraints are set simply to the scheduled hourly demand, then no demand management takes place. Nevertheless, the schedule is still optimized with most desirable flight times and stakeholder preferences.

In order to investigate the performance of the algorithm in capacity constrained as well as non-capacity constrained environments, the following two optimized schedules are produced for each subject day and time period:

1. A non-capacity constrained schedule which takes the original scheduled demand, on an hourly basis, as input into the schedule optimization algorithm. This intends to emulate good weather operations where little to no capacity constraints exist at either airport.
2. A capacity constrained schedule which optimizes the original schedule around hourly arrival and departure throughput limits. This schedule intends to emulate a capacity restricted operation either due to inclement weather or due to airport slot control measures.

### **Performance Evaluation**

Both schedules will subsequently be evaluated in queuing simulation experiments developed with the AnyLogic software. The throughput capacities within the simulation experiments will reflect the capacity-constrained rates used previously during the schedule optimization process.

The purpose of this evaluation is to assess the performance of the schedule optimization methodology. The evaluation will compare the following two scenarios simulated within AnyLogic against each other:

1. Original airline schedule as filed by the airlines and captured by the ASDI data stream
2. Improved schedule generated by the EA algorithm

Both schedules will be run through the AnyLogic queuing simulations where flight and taxi times are used as (1) a deterministic value based on the mode times and (2) an empirical distribution based on the historic data.

The intent of this evaluation is to show the improvement in on-time-performance generated by the proposed methodology over the schedules currently published by airlines. It should be noted that although actual observed flight arrival and departure data for the demand schedules was available through the ASDI data feed, this data includes too many external delay factors – departure delays due to congestion at other airports, GDPs, weather, etc. – to be a valid comparison for the optimal schedules. It was therefore decided to evaluate the improved schedules generated by the EA approach against a simulation of the original airline proposed demand schedule. Using the same simulation setup and assumptions, this allowed the analysis to isolate effects of operations at the subject airports without having to consider external delay factors.

## **Background on Evolutionary Algorithms**

EAs are an evolution-based search technique used to find valid or approximate solutions to complex optimization or search problems. They can be classified as an intelligent search technique or a global search heuristic. This means that rather than using an exhaustive search through the entire problem space, the candidate solutions are intelligently evaluated and used to guide further searches. This reduction in the number of candidate solutions searched is particularly helpful in larger or NP-hard or NP-complete problems where exhaustive searches are not economically feasible. EAs also allow for non-linearity in the problem formulation. The methodology of EAs are heavily rooted in mimicking biological evolution and natural selection in that inferior candidate solutions are naturally discarded and superior solutions used for further investigation. It further mimics biological evolution in using reproduction, mutation, and cross-over of single or multiple candidate solutions in the search for more optimal solutions. EAs do not guarantee that the resulting solution is the absolute best solution, but only that it is best within the search space that has been explored. For example, EAs will likely fail to capture optimal solutions that are point solutions where surrounding solutions do not indicate an increase in optimality in a specific direction of the search space.

EAs work by creating and evaluating a population of potential solutions and simulating natural evolution on the basis that only the fittest survive and the weak die off (Goldberg, 1989). Once a genetic representation of a particular problem has been developed, a fitness function based on user selected parameters is developed. The EA then initializes the population of solutions and iteratively improves the optimality of the solution by the application of various mutation operators (Holland, 1975).

## Representation

The basic representation of a solution within EAs is that of a chromosome, that basically represents one potential solution to the problem. These chromosomes are typically structured as a string of binary digits, although they can also be designed as non-binary and fixed or variable length strings. These chromosomes represent a specific solution – be it a specific ordering/sequence of aircraft or a binary representation of certain parameters for a combinatorial problem – taken from the overall solution space. The strings can be made up of sub-groups called alleles, which form the basic building blocks for the solution.

Although it is not a requirement, the chromosomes are typically encoded in binary representations of actual data. Figure 12 below gives a simplistic example of a binary chromosome:

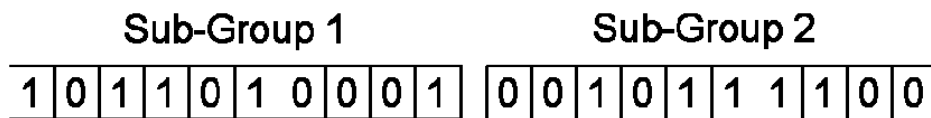


Figure 13: Sample Binary Chromosome Encoding

At the initialization stage of the EA approach, the alleles will be randomly populated with respective data – binary or non-binary – to form a set of candidate solutions. Each one of these chromosomes is then subjected to evaluation by the fitness function to assess the likelihood of reproduction for each candidate solution.

## **Fitness Function**

The fitness function essentially links the EA to the problem to be solved in the real world. It is entirely dependent on the problem description, constraints, desired outcome and the fundamental representation of the solutions being used. Each of the candidate solutions generated by the EAs is subjected to evaluation by the fitness function that judges the quality of the solution and determines the likelihood of the solution entering into the mating pool for subsequent generations.

Essentially the purpose of the fitness function is to (Oyero & Hansen, 1995):

- Determine the probability of being selected for reproduction
- Determine the probability for survival

Fitness functions can be based on any measurable metric including cost, delays, emissions, and even desirability. Typically, the function is a summation of various parameters that are of importance in the evaluation of candidate solutions. These parameters include the constraints within which the solution has to exist. With this in mind, hard constraints – which bound the acceptable solution space – have severe impacts on the fitness function, whereas soft constraints have significantly less impacts on the overall function value.

A typical fitness function for scheduling applications may include the following components:

- Aircraft arrival and departure delays
- Total number of aircraft out of sequence
- Hard constraints limiting the movement of aircraft within the slot sequence

- Soft constraints

This function basically assigns a single real-integer fitness value to each candidate solution. With the use of constant multipliers to hard and soft constraints, illegal solutions will have fitness values in a range which makes them extremely unlikely to be selected for evolution into future generations.

## **Reproduction**

Reproduction within EAs basically describes the selection process of candidate solutions to survive for future generations. The basic idea behind this is to allow relatively fit solutions to survive and procreate in the hopes that their genes are truly aligned with better performance. There are a number of ways that can be employed to select individual solutions for reproduction including (Fang, 1995):

1. *Fitness-based selection*

This method uses the fitness function values of candidate solutions and assigns probabilities for survival to each solution based on their relative fitness (Goldberg, 1989). Chromosomes are randomly drawn based on these weighted survival probabilities.

2. *Rank-based selection*

This technique sorts the individual solutions by their fitness function and assigns higher likelihoods of survival to superior fitness solutions. This method

essentially ignores the value of the fitness function in all but the ordering of the solutions.

### 3. Tournament-based selection

This approach randomly selects a number of candidate solutions from the search space and evaluates their fitness, retaining the fittest for reproduction (Brindle, 1981). Permutations of this technique include Boltzman tournament selection, which uses pair-wise probabilistic acceptance and anti-acceptance mechanisms (Goldberg, 1990).

Following this operation, the solutions can either remain unchanged or undergo subsequent crossover or mutation (Goldberg, 1989).

## **Crossover**

The theory behind the crossover operation within GAs is that superior solutions are more likely to be selected to procreate than inferior ones. Using this approach, highly superior solutions are allowed to breed and produce offspring with the hope that the next generation solutions produce ever more fit offspring. Crossover operations may be performed in many different ways, but it typically involves the splitting of randomly selected sub-parts of the parent chromosomes, rearranging these fragments and then recombining them to produce offspring of the same size chromosomes as the parent solutions. The following Figure 13 illustrates this process:



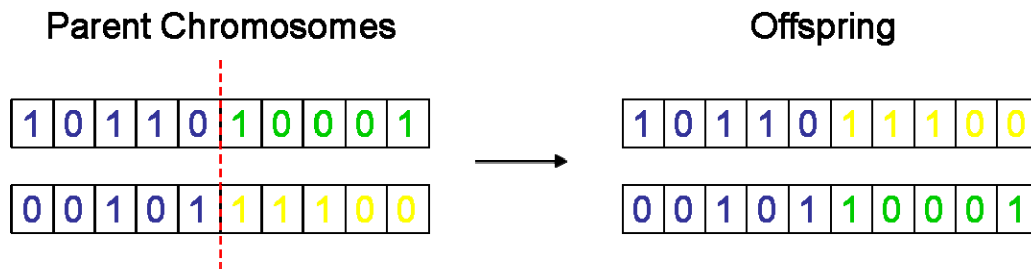


Figure 14: Chromosome Cross-Over Operation

The intent of the crossover operation is to build upon the success of past solution sets, yet still explore new areas of the search space. A number of variations of the crossover methodology exist including one-point crossover, two-point crossover, n-point crossover, and uniform crossover.

Mathematically, the amount of crossover in an application can be regulated by the crossover rate – a number between 0 and 1 – which governs how many candidate solutions will undergo crossover (0 meaning no crossover and 1 meaning all solutions will be subjected to crossover). Since the methodology described in this dissertation is based on EA principles, the crossover operator, which is very common in GA implementations – will not be utilized.

### Mutation

Mutation makes slight changes to existing candidate solutions in an effort to obtain improved fitness by searching closely related and spaced solutions. This method essentially perturbs chromosomes with some small probability and thereby attempts to restore some of the genetic diversity lost during other operations. Whereas the primary purpose of crossover and reproduction operations is to get the solution population to converge to an optimal solution,

mutation is more of a fine-tuning mechanism which makes small changes to chromosomes to see if any additional fitness can be achieved. Figure 14 below gives a graphical depiction of this process:

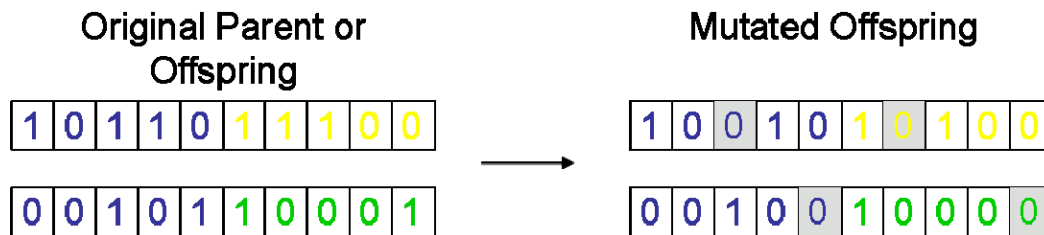


Figure 15: Chromosome Mutation Operations

The role of mutation is a controversial one within EAs. While most believe that since mutation does not place a big enough emphasis on convergence of the search space – and is therefore not of value – other experts believe that mutation may be as, if not more, important than the crossover operation (Culberson, 1993).

As with the crossover operation, mutation is controlled with a mutation rate, which first indicates how many individual solutions should undergo mutation and then subsequently how much of the chromosome should be mutated.

### **Mutation and Crossover with Unique Data Values**

Most of the applications for which EAs or GAs are considered, do not care if individual alleles contain duplicate values since they are typically only mathematical representations of the value or state of an object in the optimization. However, certain applications do not allow for

duplicate values within a chromosome. One example of this type of application is the Traveling Salesman Problem (TSP). The TSP optimizes the order in which a salesman chooses routes to travel to minimize overall travel time. Clearly the salesman does not want to travel the same route twice.

Traditional mutation and crossover operators do not generate unique values within a chromosome and would subsequently require some form of repair algorithm to ensure uniqueness in the solution. However, certain variations of mutation and crossover exist that retain the uniqueness of values within a solution (Larranaga, Kuijpers & Murga, 1994). Variant crossover operators include partially-mapped crossover (PMX), order crossover (CX), sorted match crossover, and heuristic crossover. Variant mutation operators include displacement mutation, exchange or swap mutation, inversion mutation, and scramble mutation. These variants of mutation and crossover operators are also preferred for scheduling applications since typically the alleles contained within each chromosome are references to individual unique objects or, in this case, flights.

### **Other Operators**

Other operators that can be applied to chromosomes include inversion and migration. Inversion simply inverts the order of some of the elements within the chromosome between two randomly chosen points (Holland, 1995). Although this seems to be a sensible operation to apply to chromosomes, it has generally not been reported as a valuable technique in EAs. Migration is a technique which is primarily applicable to executing selections and searches in parallel and provides a way for migrating from multiple parallel solution sets into a single one.

## **Algorithm**

Any combination of the previously identified operations will be performed iteratively in a pre-defined sequence. The EA algorithm basically executes until a desired outcome is achieved or until some set of resources such as processing time are exhausted.

A typical sequence of tasks involved in an EA search can be summarized as follows:

1. Encode and initialize a random set of solutions as the starting ‘current solution set’.
2. Evaluate each of the candidate solutions based on the fitness function.
3. Select superior solutions from the existing solution set based on their relative fitness. These solutions will be used as parents for the next generation of solutions.
4. Apply selected mutation techniques to the existing intermediate solution set. This will generate a new set of candidate solutions that can then be evaluated as the new current solution set.
5. Iteratively repeat steps 2 through 5

The procedure above will continue until either (1) a maximum number of iterations and/or generations have been run and evaluated, or (2) the population of solutions converges where applying mutation and cross-over techniques repeatedly do not result in increases in fitness for future generations.

## General Characteristics

EAs are generally associated with long computation times and great uncertainty about how long computation will take. Much like GAs, this is a characteristic of the NP-hard nature of the problem, requiring significant computational resources and time. Consequently, they are not normally considered for real-time problems such as operational scheduling of airline arrival and departure times in a real-time framework (Ciesielski & Scerri, 1998).

EAs as well as GAs strike an important balance between exploration and exploitation of a problem space in that, although random searches across all solutions exist, these searches are guided by the quality of past solutions already investigated. Another benefit is that it is possible to parallelize the searches through the solution set by using multiple processes on potentially multiple machines to evaluate generations of solutions in parallel.

Although the benefits of EAs, particularly in large search space problems, heavily outweigh the drawbacks, there are some undesirable characteristics. The primary disadvantage is that EAs do not guarantee a global optimal solution. They can also easily generate invalid or illegal solutions as part of the cross-over and mutation operations, which wastes time and resources.

In fact, due to the search heuristic nature of EAs, they do not need to know details on how to solve a particular problem. All that is required is that the EA be able to differentiate a good solution from an inferior one.

## **Evolutionary Algorithms in Scheduling**

The theory behind scheduling is basically the problem of allocating resources over time to perform a collection of tasks in an optimal fashion. Timetabling and scheduling problems are known to be a computationally NP-hard problem (Garey & Johnson, 1974). As such, it is both time and resource consuming and typically the optimal solution cannot be obtained within a reasonable amount of time.

The practice of solving complex scheduling problems through the use of evolutionary approaches has been commonplace for many years. Some other examples of this technique applied to scheduling problems include (Stevens, 1995):

- Job shop scheduling (Fang, 1994). This problem deals with the scheduling of a number of jobs with multiple tasks across a set of machines. The order and allocation of tasks across the machines must be optimized.
- Learning routes and schedules (Gabbert, Brown, Huntley, Markowicz & Sappington, 1991). A specific example of this problem is the scheduling of trains across a network of rail lines. Also, TSP falls under this category where a salesman must most efficiently traverse a set of routes.
- Resource scheduling (Syswerda & Palmucci, 1991). This category describes any problem where a capacitated resources requires scheduling of tasks that require this resource. Examples include the scheduling of flight simulator time for student pilots or the scheduling of aircraft for arrival and departure slots.

It has been shown that modern search techniques such as EAs and GAs perform very well in these types of problems, particularly when the search space is very large. Any EA optimization problem becomes a tradeoff in terms of the desire to achieve better solutions versus the computation times and resources available.

### **System Overview**

The airport network used for this research effort is comprised of operations in and out of the two busiest airports in the world: Atlanta Hartsfield Jackson International Airport and Chicago O'Hare International Airport. This ensures that on a routine basis during the busy hours of the day, the number of available arrival and departure slots at these airports is insufficient to handle the desired airline generated demand.

One unique aspect of the approach outlined in this dissertation is that instead of focusing on a single-airport's microscopic arrival or departure planning horizon, aircraft operations across a network of airports – each with their own sets of arrival and departure slots – are optimized. Figure 15 below provides a high level view of the types of airspace operations considered in this slot allocation methodology:

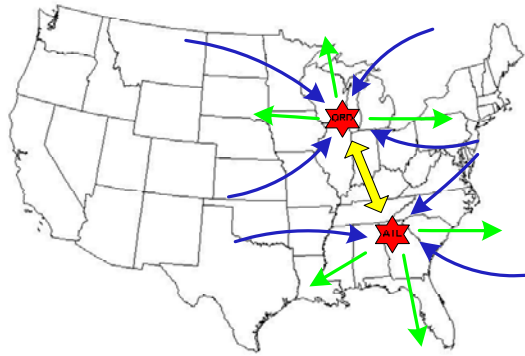


Figure 16: Airport Network Traffic Flow

All of the arrival and departure flights depicted above will be stochastically represented by distributions of historic flight times. In addition to these airspace operations, operations on the airport surface will be represented by distributions of taxi-in and taxi-out times that are also based on historic data. This means that for the purpose of this research, for an aircraft that departs from San Francisco, then lands in Chicago, continues on to Atlanta, and then finally terminates in Orlando, the following distributions are applied during the fitness function evaluation:

1. Flight time distribution – San Francisco to Chicago
2. At Chicago
  - a. Chicago arrival taxi-in time distribution
  - b. Chicago departure taxi-out time distribution
3. Flight time distribution – Chicago to Atlanta
4. At Atlanta
  - a. Atlanta arrival taxi-in time distribution
  - b. Atlanta departure taxi-out time distribution



## 5. Flight time distribution – Atlanta to Orlando

The methodology presented will assign arrival and departure slots at ORD as well as ATL to this aircraft and use all of the above distributions as an input into the overall fitness evaluation of the candidate set of slot allocations.

The slot allocation algorithm takes as input a schedule of flights with airline desired gate and runway arrival and departure times for ATL and ORD airports. This original input schedule spans an eight-hour period of operations. Further inputs into the algorithm are the flight and taxi time distributions previously mentioned as well as information on hourly airport throughput capacities for both airports. These distributions used as inputs represent the aspects of greatest variability in airport and airspace operations. A further input into the algorithm are aircraft sequencing guidelines based on airline, airport, and FAA preferences. Figure 16 below gives a graphical depiction of the data and information flow:

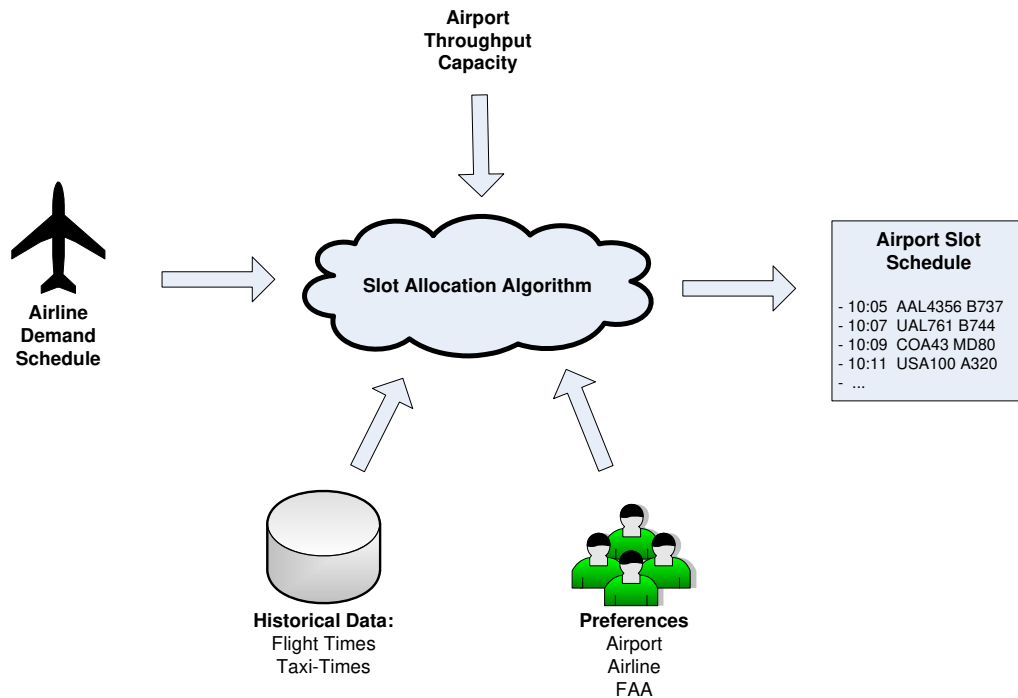


Figure 17: System Overview - Decision & Data Flow

The slot allocation algorithm uses the given inputs to optimally assign runway takeoff and touchdown times for all aircraft in the schedule. The output generated by the algorithm is a schedule of airport slot allocations which best optimizes the overall operation based on a ‘desirability index’. This index, implemented within the fitness function of the algorithm, produces airport arrival and departure slot schedules for both subject airports that ensure all aircraft operate as close to nominal – as defined by historic data – and desirable as possible and also satisfy stakeholder goals as optimally as possible. As a general guideline, the optimal runway slot times are intended to minimize runway arrival and departure delays and provide for most likely flight and taxi-times based on the historic distributions of data.

A detailed view of the inner core of the slot allocation algorithm as well as the application of the various distributions is described below in Figure 17:

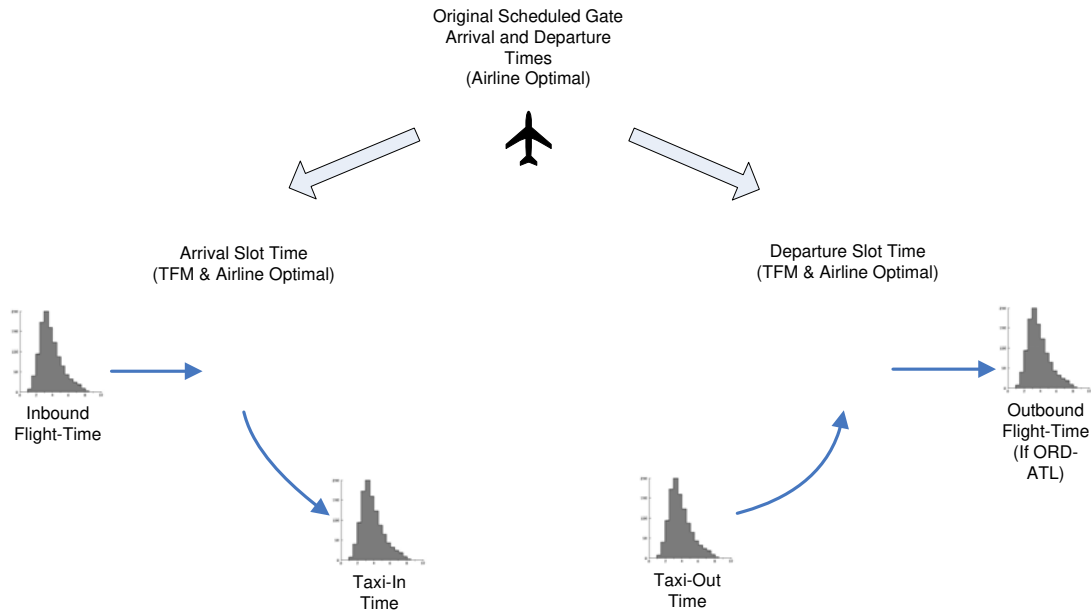


Figure 18: Algorithm High Level Concept

This optimized slot allocation schedule can be transmitted to airlines, airports, and other users of the NAS and may guide airlines and air traffic controllers in assigning required times of arrival (RTAs) at various points along the aircrafts’ routes. Airlines may then be forced to conform to these performance targets or lose the benefit of the service in the future.

**Assumptions**

The scheduling of aircraft movement – arrival and departure – times at an airport is a difficult task for many reasons. One of the inherent problems is the continuous tradeoff between

maximizing the number of movements on the runways and underlying safety regulations governing the separation of aircraft. Clearly every airport has the desire to maximize the throughput at their facility, but FAA regulations govern aspects such as minimum arrival separation between aircraft types as well as capacity decreases during inclement weather.

In order to satisfy some of these unknowns and uncertain aspects and requirements of ATC and airport operations, certain assumptions were made throughout the course of this research effort. These assumptions are listed below:

- *Aircraft are capable of flying their 4-dimensional trajectory with very high accuracy.* In other words, the variations in flight times for all aircraft are assumed to have a negligible effect on strategic arrival time planning. This assumption is based on an FAA requirement for aircraft to satisfy RNP standards which aims to ensure that flight management systems (FMSs) on aircraft can meet 4-D time and space location highly accurately.

The effect of existing/historic variation in flight times on this slot allocation methodology will be examined in the simulation-based assessment stage of this research effort.

- *The Distribution-based desirability functions are based purely on observed times and not internal valuations.* In other words, the most desirable flight and taxi times are based on the mode of the historically observed time distributions. Any other factors such as airline crew time, fuel, etc. are not included in these calculations due to the TFM nature of the approach.
- *Airport arrival and departure capacities are assumed to remain constant throughout the entire subject period.* This is a valid assumption since airport slot

control aims to match demand with available airport capacity and airports are themselves not concerned with airline bank structures and the tradeoffs between arrival and departure capacity to maximize one over the other. Variation of capacity rates will only be explored in the AnyLogic performance evaluation of the schedule optimization methodology.

- *Runway assignments and wake turbulence requirements are expected to be solved post-facto.* The number of slots available at each airport is based on overall acceptance rate information. As such, the assignment of specific arrival and departure runways is expected to occur in real-time tactical mode and will not have reverse effects on throughput capacity. Similarly, the tactical runway assignments also adhere to standard FAA wake turbulence requirements – minimum separation between different types of aircraft due to turbulence air – and not reversely affect throughput capacity.
- *Wind and weather conditions are not expected to have any impact on the scenario.* In a real-world scenario, changing wind conditions – depending on the wind intensity – may cause the runway configurations to change and would therefore affect airport capacity. In this scenario, runway changes – and associated changes in airport throughput capacity – have been accurately forecast in advance and are not subject to change the capacity of the subject airports during the period of performance.
- *Down-the-line effects of the decisions are not considered.* The arrival and departure slot time assignments calculated for ORD and ATL are assumed to have

a negligible effect on down-the-line operations of the same aircraft at other airports following the operation at either of the two subject airports.

- *No airspace or route capacity restrictions are considered.* The FAA routinely implements GDPs because of traffic flow restrictions along certain routes or corridors. These are caused primarily by weather effects along these routes.

These route flow restrictions are not considered in this application.

These assumptions primarily address the specific nature of the area of application of this approach. Where airlines tend to focus more on economic factors in their strategic operations planning, the FAA and airports are more concerned with system efficiency, safety, and overall flow management. This approach addresses aspects of both airline as well as ATC interest and necessarily assumes away many intrinsic microscopic aspects of airport and airspace operations in order to adequately address both.

### **Input Data Mining and Processing**

In order to incorporate real-world flight data into the fitness function, statistical distributions of actual recorded flights in and out of the three subject airports are generated. Additionally, distributions of taxi times are required to stochastically reflect ground operations at these airports. All of these distributions are based on more or less public data. Figure 19 below gives an overview of the data sources and information flow that resulted in the frequency distributions for the desirability index within the fitness function:

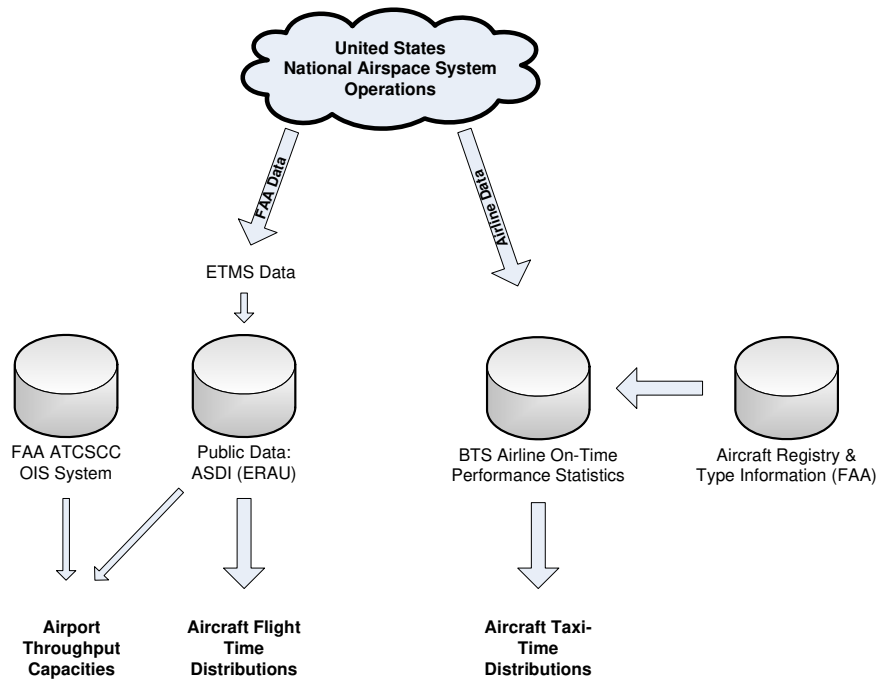


Figure 19: Data Sources and Processing

The two primary data sources for historical distributions are the airline driven BTS on-time performance statistics dataset and the ASDI data feed distributed by the FAA (see BTS, 2007 and FAA ASDI, 2007 for more information). Both data sources are based on real-world aircraft operations in the NAS. The ASDI data feed is a highly secured real-time information feed that is commonly used by airlines and research institutions for non safety critical DSTs and research applications. BTS data is a publicly available data source which is based on data collected by airlines and made available on the BTS website several weeks after the day of operation.

Whereas the ASDI data feed is a real-time record of aircraft operating in the NAS including flight plans and radar hits, the BTS data is based on post-facto airline reported data.

The airspace focus of the ASDI data, combined with the more generic but broader nature of the BTS data provides a sufficient database for all of the distributions required.

ASDI data includes complete flight-plan information for all commercial aircraft in US controlled airspace. This means that all information available to ATC is available on the ASDI feed including flight routes, aircraft types, and departure and arrival times. BTS data, on the other hand, does not include certain information such as aircraft types or flight paths. Since taxi and turn-around times vary by aircraft type, the BTS flight-by-flight records were supplemented by aircraft registry information available directly from the FAA (FAA Civil Aviation Registry, 2007). This registration database is provided by the FAA and includes a record of ownership of all aircraft registered in the US. The aircraft type information included in this aircraft registration database is matched with the BTS data through the N-Number, a unique identifier issued to all US-based aircraft that is included in both datasets.

### **Data Distributions and Mode Times**

The historical data that is being analyzed for taxi and flight times is used in the algorithm in two ways: (1) as empirical distributions representing today's more chaotic NAS operations and (2) as mode times representing the most likely flight and taxi times within a 4-dimensional trajectory control scenario.

Empirical distributions are based on distributions of historical operating times. Using the tremendously large amount of data available, empirical distributions give a more accurate representation over theoretical distributions. One benefit of using theoretical distributions is that they are used as generalizations of actual data when only limited data is available. The



theoretical and generalized nature of these distributions also allows them to be valid for future use. Nevertheless, theoretical distributions are only representations of actual data and generally do not completely describe reality. The use of empirical distributions – particularly with the mass of available data – provides a completely accurate representation of historic observations prior to the day of the optimization schedule. However, it is expected that in a real-world application of this methodology the empirical distributions be continuously updated with data as it becomes available. This will ensure that recent airspace and airport development are properly represented in the data.

Mode times are used throughout the course of this methodology because they denote the most likely value based on empirical distributions of historical operating times. These times represent the highest likelihood for flight and taxi-times based on the historical data. As such, they may represent the times that a 4-dimensional trajectory-based system uses to maximize predictability of the schedule.

The actual processing of the data into empirical distributions as well as the data mining for significant variables is described in the subsequent sections.

### **Significant Variables for Distributions**

The purpose of this data mining effort is to extract distributions of flight and taxi times from the ASDI and BTS data sets. These distributions are naturally heavily affected by certain things such as origin-destination airports, aircraft types, airlines, operating time of day and other non-obvious factors.

Initial attempts at mining the flight and taxi time datasets for significant variables failed using the SPSS and Minitab applications. The range of categories and size of each dataset were simply too large for either application to process. An alternative to these commercial products was a freely available tool called WEKA. WEKA is a collection of machine learning algorithms for data mining tasks and contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization (see <http://www.cs.waikato.ac.nz/ml/weka/> for more details).

A raw sample of 1% of the flight times and taxi times was loaded into WEKA and subjected to the ‘Select Attributes’ Routine. The attribute set evaluation was based on WEKA’s CfsSubsetEval Classifier, which evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them. The search method for evaluation was based on WEKA’s BestFirst class, which searches the space of attribute subsets by greedy hillclimbing augmented with a backtracking facility (extracted from WEKA Help).

Each dataset was processed using cross-validation experiments with ten (10) folds, meaning that WEKA divided the original dataset into 10 subsets, which were each analyzed for variable significance. Table 1 below presents the results of this analysis. A value of 10 for a specific variable indicates that each of the 10 fold experiments indicated that it was significant:

Table 1: Flight Time Significant Variable Analysis

<i>Factor</i>	<i>Atlanta</i>		<i>Chicago</i>	
	<i>Arrivals</i>	<i>Departures</i>	<i>Arrivals</i>	<i>Departures</i>
<b><i>City Pair</i></b>	<b>10</b>	<b>10</b>	<b>10</b>	<b>10</b>
Year	0	0	0	0
Month	0	0	0	0
Day	0	0	0	0
<b><i>DOW</i></b>	<b>0</b>	<b>5</b>	<b>10</b>	<b>10</b>
ZATDH	0	0	0	0
<i>ZATAH</i>	9	10	0	6
ZETDH	0	0	0	0
<b><i>ZETAH</i></b>	<b>0</b>	<b>1</b>	<b>10</b>	<b>4</b>
<b><i>Airline</i></b>	<b>10</b>	<b>10</b>	<b>10</b>	<b>10</b>
<b><i>AcfType</i></b>	<b>10</b>	<b>10</b>	<b>10</b>	<b>10</b>

where the significant variables are:

- City pair represents the combination of departure and arrival airport
- DOW represents the day of week of the operation
- ZETAH represents the estimated time of arrival hour in ZULU (GMT) Time
- Airline represents the three letter ICAO identifier of the airline
- AcftType represents the ICAO type designation of the aircraft type

As expected, the variables of city pair, airline, and aircraft type are strongly significant within each of the 10 folds. The day of week and estimated time of arrival show a stronger significance in the Chicago sample, but are still deemed to be significant. Although ZATAH – the actual time of arrival – is also a somewhat significant variable, it is not directly usable in a scheduling application, where schedules/estimated times are used for planning.

The same analysis for taxi-in and taxi-out times was performed using WEKA and yielded the following results presented in Table 2:

Table 2: Taxi Time Significant Variable Analysis

<i>Factor</i>	<i>Atlanta</i>		<i>Chicago</i>	
	<i>Arrivals</i>	<i>Departures</i>	<i>Arrivals</i>	<i>Departures</i>
<b>Airport</b>	<b>8</b>	<b>0</b>	<b>10</b>	<b>10</b>
Year	0	9	9	0
<b>Month</b>	<b>8</b>	<b>10</b>	<b>10</b>	<b>10</b>
<b>DOW</b>	<b>10</b>	<b>10</b>	<b>2</b>	<b>10</b>
<b>ATDH</b>		<b>10</b>		<b>10</b>
<b>ATAH</b>	<b>8</b>		<b>10</b>	
<b>Airline</b>	<b>10</b>	<b>0</b>	<b>10</b>	<b>10</b>
AcftType	7	9	7	0

where the significant variables are:

- Airport represents the flight’s arrival or departure airport
- Month represents the month of the operation
- DOW represents the flight’s day of the week
- ATDH represents the actual time of departure hour for departures only
- ATAH represents the actual time of arrival hour for arrivals only
- Airline represents the three letter ICAO identifier of the airline

Although the year and aircraft type also show some significance, they were not included in the processing. The reason for this decision is that trials showed that treating all variables as significant would increase the number of taxi-time distributions – and thereby reduce the count of values in each distribution – to a less manageable and productive level.

These significant variables essentially make up the ‘key’ value for each flight time and taxi time distribution. This unique key variable is then easily indexed and searchable for distributions and other summary data.

The detailed processing of data for flight times and taxi times based on the significant variables is described in more detail in the subsequent sections:

### **Flight Times**

The distributions of flight times for aircraft operating into and out of the two subject airports were obtained from the ASDI data stream which is available to the aviation industry from the FAA's VOLPE technology center in Boston, Massachusetts. This data stream is a derivative of the ETMS (Enhanced Traffic Management System) data stream which contains all flight information data in the FAA's host computer system across North America.

The ETMS air traffic data stream is a data feed available from the FAA and contains all relevant flight planning and tracking information on aircraft in the NAS. As part of the overall architecture, ETMS also provides a set of front-end tools, which are used by FAA facilities to plan traffic flows and other activities used in NAS planning and operation (Klein, 2005).

The ETMS data feed includes all relevant information for aircraft operating in controlled airspace, including flight plans, amended flight plans, cancellations, arrival/departure messages, and 3D track information where available.

Data contained in the ETMS data feed is available to industry via the so-called ASDI feed, which contains the vast majority of messages from ETMS but lacks any confidential government and military operations.

Based on the analysis of significant variables performed previously, the following pieces of information from the ASDI data feed for each aircraft operating in and out of the subject airports were of most interest:

1. Aircraft carrier and flight number
2. Aircraft type
3. Aircraft departure & arrival airport
4. Aircraft departure & arrival times
5. Day of week of the flight (an integer from 0 through 6 with Monday being 0)

The data required for this analysis was provided by Embry-Riddle Aeronautical University's Center for Applied ATM Research (CAAR) for a period of 23 months starting in January 2005 and ending in November 2006. The initial dataset consisted of millions of flights in and out of North American airports, which were stored in over 100 gigabytes of data.

Purpose-built software had to be developed to parse this dataset in a two-step process:

1. Process the information on a flight-by-flight basis to obtain, among a number of other data items, the aircraft operator (airline), type, flight times, and flight distances for each flight. This resulted in a vast dataset of flight information for all aircraft that operated in the US in 2005 and first half of 2006. An excerpt of the data gathered is shown below in Table 3:

Table 3: ASDI Flight-by-Flight Data

CityPair	Year	Month	Day	DOW	ZATD	ZATA	ZETD	ZETA	Airline	Type	FltTime	SchTime
	DepFix	ArrFix	AptToApt	GCD	FiledDistance	FlownDistance	AvgSpd					
<b>KORD-KATL</b>	06	01	05	4	12:17	13:53	12:0	13:32	<b>UAL</b>	<b>A320</b>	<b>96</b>	<b>92</b>
			GUIDO		527.177	586.162	616.799	385.499				
<b>KORD-KATL</b>	06	01	06	5	15:53	17:20	15:48	17:12	<b>AAL</b>	<b>MD82</b>	<b>87</b>	<b>84</b>
			GUIDO		527.177	586.162	611.307	421.591				
KORD-KATL	06	01	06	5	18:13	19:33	18:7	19:31	AAL	MD82	80	84
			GUIDO		527.177	586.162	592.485	444.364				
KORD-KATL	06	01	06	5	0:28	2:10	0:6	1:33	AAL	MD82	102	87
			GUIDO	DALAS	527.177	550.499	637.189	374.817				
<b>KORD-KATL</b>	06	01	06	5	15:33	16:58	15:15	16:29	<b>ASH</b>	<b>CRJ7</b>	<b>85</b>	<b>74</b>
			EON	DALAS	527.177	541.887	593.521	418.956				
KORD-KATL	06	01	06	5	4:3	5:24	3:20	4:39	ASH	CRJ7	81	79
			KORD	DALAS	527.177	540.813	569.036	421.508				
KORD-KATL	06	01	06	5	18:20	19:39	17:50	19:7	DAL	MD88	79	77
			GUIDO		527.177	586.162	595.391	452.196				

2. Use the flight-by-flight information output from the previous software program and summarize flight times by city pair (departure and arrival airport) and other significant variables. Table 4 below presents this summary data which is subsequently used to produce the stochastic distributions for the fitness function of the evolutionary search algorithm. The data sample below is for United Airlines (UAL) flights of types Airbus 319, 320, and Boeing 737-300, 737-500, and 757-200 operating from ORD to ATL. The leading line for each distribution is the 'key' that contains all significant variables for storing this data for later use. The data gives the minutes of flight times followed by the observed frequency

throughout the dataset:

Table 4: Excerpt of Flight Time Frequencies

KATL-KORD-3--UAL-A319	96.9384,146,90
80:1,82:1,83:1,85:7,86:5,87:4,88:3,89:10,90:13,91:7,92:8,93:7,94:4,95:4,96:7,97:6,98:9,99:4,100:7,101:3,102:5,103:2,104:4,105:2,106:1,107:1,109:6,110:2,111:1,112:1,113:1,116:1,118:1,120:1,121:1,122:1,125:2,126:1,158:1	
KATL-KORD-3--UAL-A320	96.8462,78,90
81:1,82:1,86:4,87:2,88:1,89:6,90:10,91:4,92:3,93:7,94:5,95:2,96:3,97:4,98:2,99:3,100:3,101:1,102:1,103:1,104:1,105:1,106:1,107:2,109:1,112:1,114:1,115:1,118:1,129:1,130:1,134:1,135:1	
KATL-KORD-3--UAL-B733	99.947,132,89
85:1,86:5,87:2,88:2,89:13,90:4,91:7,92:4,93:9,94:3,95:5,96:3,97:7,98:8,99:11,100:4,101:6,102:3,103:5,104:5,105:1,106:4,107:1,108:3,110:1,111:2,112:1,115:1,117:1,118:1,121:2,122:1,123:1,128:1,129:1,143:1,162:1,222:1	
KATL-KORD-3--UAL-B735	97.0984,61,91
82:1,86:3,88:2,89:3,91:5,92:4,93:3,94:4,95:5,96:3,97:3,98:4,99:1,100:2,101:2,102:3,103:1,104:2,105:4,108:1,109:1,111:1,114:2,122:1	
KATL-KORD-3--UAL-B752	96,70,90
81:1,82:1,83:1,85:2,86:1,87:1,88:3,89:2,90:9,91:4,92:6,93:4,94:5,95:5,96:3,97:2,98:4,99:1,101:3,105:2,106:1,107:2,108:1,109:1,115:1,121:1,122:1,130:1,135:1	
KATL-KORD-4--DAL-B732	98.4383,235,93
81:1,82:4,83:4,85:4,86:6,87:11,88:10,89:9,90:9,91:10,92:9,93:15,94:14,95:8,96:7,97:12,98:5,99:9,100:11,101:12,102:5,103:5,104:9,105:7,106:1,107:2,108:3,109:2,110:3,111:4,112:2,113:2,114:2,118:3,120:1,121:2,122:1,123:1,125:1,128:1,129:1,132:1,135:1,138:1,139:1,140:1,144:1,169:1	
KATL-KORD-4--DAL-B738	95.8268,127,88
81:1,82:2,83:2,84:2,85:4,86:5,87:5,88:12,89:2,90:7,91:6,92:11,93:8,94:6,95:6,96:5,97:4,98:3,99:6,100:4,101:3,102:2,103:3,104:1,105:1,106:2,107:3,108:1,109:1,110:2,112:1,117:1,119:1,126:1,131:1,141:1,189:1	
KATL-KORD-4--DAL-B752	97.9091,22,98
85:1,86:1,90:2,91:1,92:1,93:2,95:2,96:1,97:2,98:3,100:1,101:1,105:1,109:1,114:1,131:1	

The basic output of this data processing effort are histograms of flight time distributions for each relevant route in and out of the subject airports.

Figure 20 below presents a sample histogram of frequency distributions for flights between ORD and ATL. Of immediate interest in this chart are the distinct differences in flight times across aircraft types. A Japan Airlines (JAL) Boeing 747 gives a mode of 79 minutes of travel time between ORD to ATL. A Delta Airlines (DAL) MD-80 aircraft shows a mode of 88 minutes, and on the extreme end, UAL Boeing 737-500 aircraft have a mode of flight times of 91 minutes.



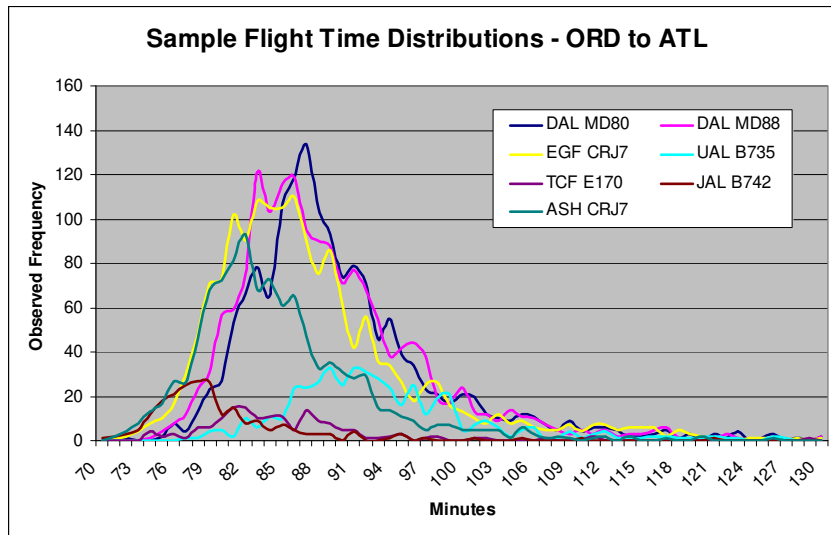


Figure 20: Sample Flight Time Distribution for ORD-ATL City Pair

These flight time distributions are processed for all airlines and all aircraft types operating in and out of ORD to ATL. For use in the fitness function of the slot allocation algorithm, the distributions are subjected to a simple normalization step based on the observed frequencies and the total number of observations. Figure 21 below presents the same data in a normalized fashion:

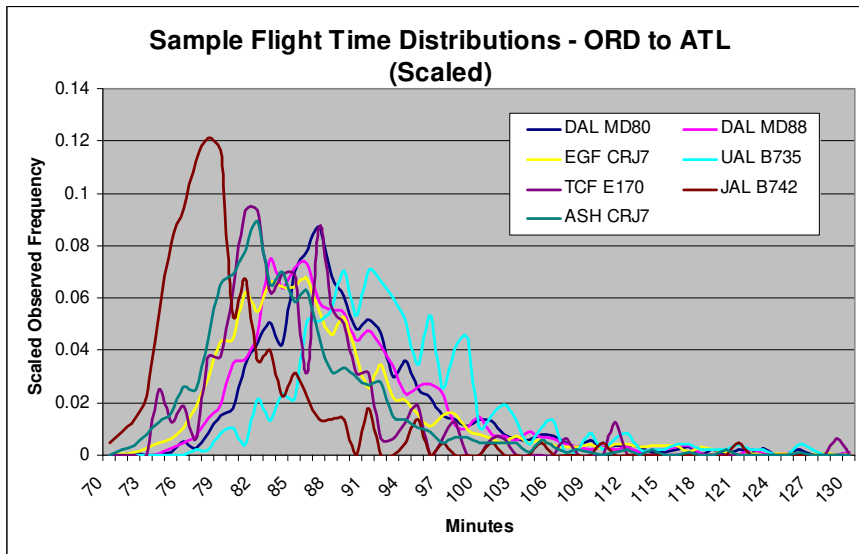


Figure 21: Sample Flight Time Distribution for ORD-ATL City Pair (Scaled)

The database of flight time information for all North American non-military flights that was produced for this research can be used for a number of other applications within the scope of TFM planning for airspace and airports. The flight-by-flight information includes over 30 million flights which operated in 2005 and the first half of 2006 including all commercial operations as well as a majority of general aviation flights that operated in airspace controlled by the FAA. The data is not restricted to any specific airports and is only geographically limited to aircraft that either departed or arrived at airports within the bounds of US airspace.

### Taxi Times

Information regarding departure taxi-times is not available through the ASDI feed which was used previously for flight time information. The arrival and departure taxi-times required for this study were extracted from information publicly available on the BTS website (BTS,

2007). BTS data is available in a database-type format and was downloaded and processed for the same time period as the flight-time ASDI data – January 2005 through June 2006.

This database of aviation on-time performance statistics includes aircraft-by-aircraft information reported by most major airlines for most major airports in the US. The aircraft type information was obtained by matching the BTS recorded tail number for each aircraft with records obtained from the FAA's aircraft registration database.

The resulting data contained in each BTS flight record includes:

- Aircraft carrier and flight number
- Aircraft type
- Aircraft departure and arrival airport
- Aircraft departure and arrival time
- Airport departure and arrival taxi times

The taxi times extracted from this BTS data are based on airline reported out-of-on-in (OOOI) data, which reports the times that aircraft leave the departure gate, take off, land, and reach the arrival gate respectively. The calculations then simply subtract the 'out' time from the 'off' time and the 'in' time from the 'on' time to get departure and arrival taxi times, respectively.

There are two main issues with this data that should be noted, although they are not expected to have any manifest impact on this research effort:

1. The vast majority of data contained within each BTS flight record is based on information provided by airlines which in some cases is manually entered into databases including taxi-times and departure and arrival times. This means that

errors in transcription or transmission may occur. However, with the vast amount of data processed, the effects of this phenomenon are negligible.

2. Since data is only gathered at major airports and for major airlines, the available records do not constitute a complete set of operations at either of the airports included in the data. However, particularly at major hub airports such as ORD and ATL, the major carrier(s) operate all but a very small fraction of the total flights. With all likelihood, missing airlines will not experience any difference in taxi-times compared to the major carriers.

In order to extract the taxi-time data from the BTS data, custom software applications were developed to parse the data for relevant flights and then summarize the data by carrier and aircraft type into frequency distributions. The key for each distribution is again composed of the significant variables for taxi times processed by the WEKA application.

Figure 22 below gives a sample taxi-out distribution by carrier for ATL and ORD:

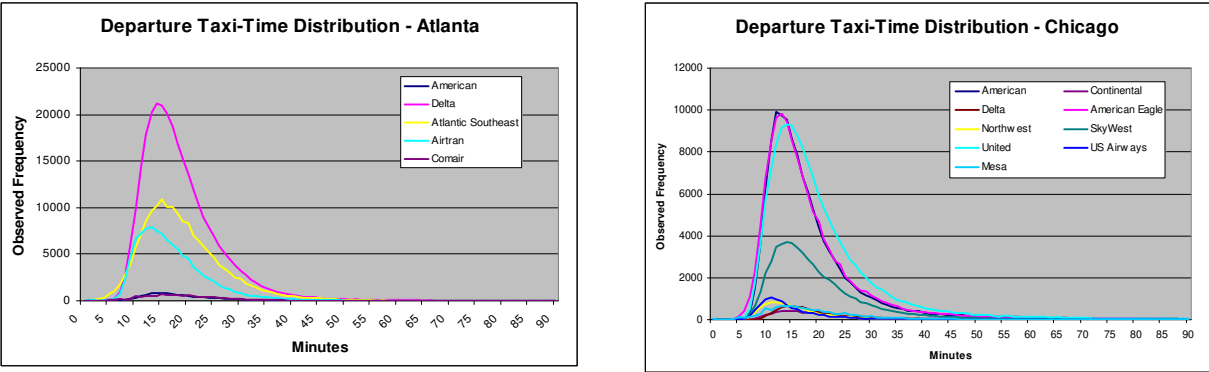


Figure 22: Departure Taxi Times by Carrier for ATL and ORD

It is clearly visible that differences on the order of several minutes exist in departure taxi times simply by delineating the data by airline carrier. This is primarily due to the allocation of gates and terminals and their relative geographic locations and distances to the departure runways.

The arrival taxi-time distributions for ATL and ORD are presented below in Figure 23. Whereas ATL shows really no discernable difference in arrival taxi-times by carrier, ORD’s taxi-times are again – due to the layout of the runways and terminals – heavily influenced by the geographic dispersion of terminals and gates and associated taxi-path lengths:

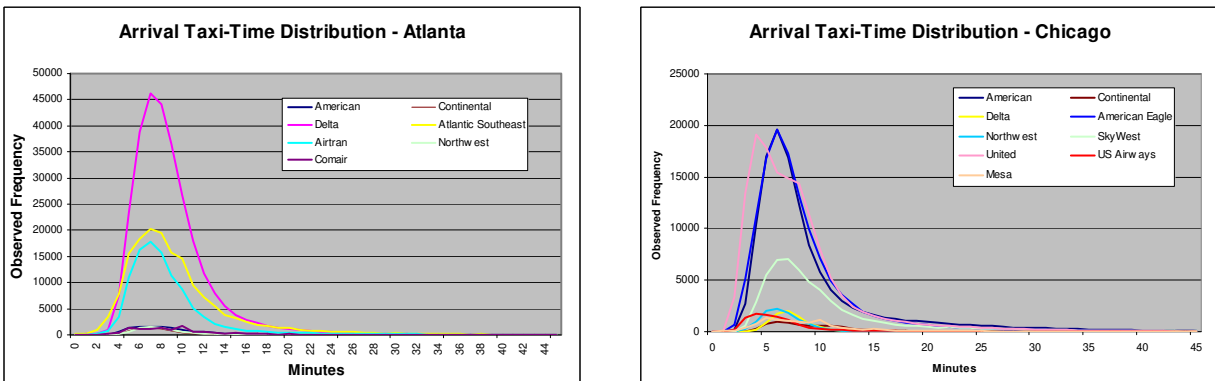


Figure 23: Arrival Taxi Times by Carrier for ATL and ORD

Another variable which significantly contributes to variation in taxi-times is the hour of the day. It is logical that taxi-times and associated runway or gate queuing times change with the demand schedule throughout the day. Consequently, during peak departure demand periods, lineup queues for departure runways are longer, causing departure taxi-times to increase. Figure 24 below is a depiction of hourly departure taxi-time variation for DAL at ATL:

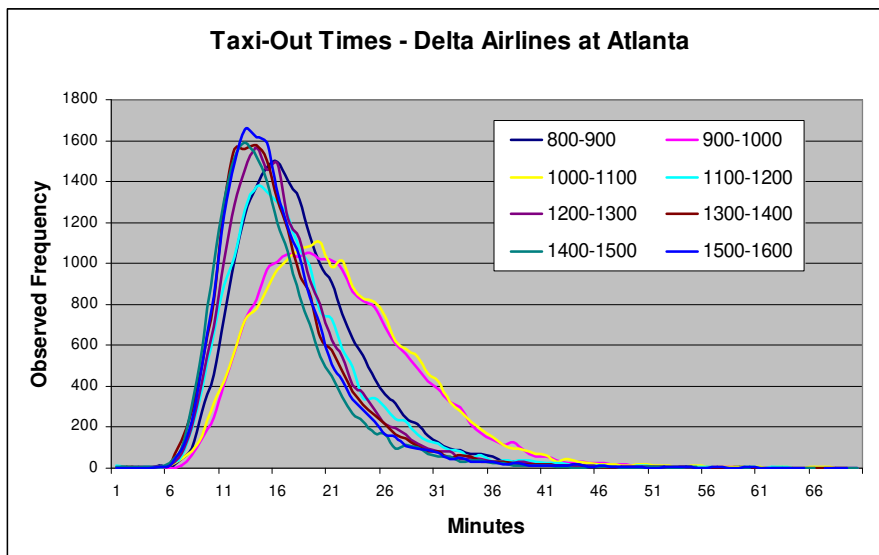


Figure 24: Taxi-Out Times by Hour for Delta Airlines (Atlanta)

Although small variations exist across all hours of the day, this distribution of taxi-out times by hour reinforces the distinct difference between peak demand hours (9:00am – 10:00am) and non-peak hours. Not only are the average taxi-out times longer during these periods, but the observed frequency distributions are skewed to the right and thus have a higher variation. Similar results can be shown for all of the other significant variables contributing to taxi-in and out times.

### **Airline and Air Traffic Control Priorities**

In addition to time dependent distribution functions, priorities considered by airlines, the airports and ATC also play an important role in the optimization of arrival and departure sequences. These priorities or desires basically specify guidelines for sequencing of aircraft based on an accepted practice heuristic as currently implemented by airlines and the FAA. They

are based on the author's personal experiences with airport and airspace operations as well as several interviews and conversations with former FAA air traffic controllers and airline employees.

For arrivals, the following priorities or guidelines have been identified:

- The longer the flight time and distance of an arriving aircraft, the higher the priority of this aircraft in terms of meeting the scheduled arrival time. This is based on the theory that longer range aircraft are typically delivering a large percentage of passengers to hub-airports that have connecting flights to smaller surrounding airports. The cost of passengers missing these connections is typically very high, particularly if the arrival is international.
- The largest aircraft types receive more favorable arrival slots due to their relatively high cost of airborne delay and their limited maneuverability in the air. This includes the Boeing 747, the Boeing 777, and the Airbus 777, the largest aircraft that operated in US airspace during this time period. An indication of this practice was shown earlier in distributions of flight times between ORD and ATL, where a JAL B747 had the lowest average flight time between this city-pair.
- Airlines with higher operational counts at the respective airport will receive a higher priority in slot assignments. The premise for this guideline is that dominant airlines at airports have increased responsibilities for passengers to make their connections. Arrival delays reduce available connection times and increase the likelihood of missed connections.

Conversely, for departing aircraft the following priorities apply:

- The decision process for departure slot assignments requires the categorization of destination airports into standard categories of hub, non-hub major and commercial service airports. The purpose for this categorization is that in order to prioritize departing aircraft, the type of destination is of utmost importance. Flights with other hub or major airports as destinations typically receive preferred slots assignments due to the consideration of down-the-line missed connections. Flights destined for termination airports do not typically receive preferred sequence slots.
- Long-distance flights are typically more flexible in their departure times due to their ability to make up delay with higher airborne speeds en-route. With this in mind, a parameter which adjusts the tolerance for departure delay based on the distance to the destination airport will be considered.

These priorities and guidelines will be included in the desirability index formulation of the fitness function as linear multipliers to deviations (differences between schedules and projected scheduled operating times based on the new slot allocations).

The incorporation of these goals required that a number of different factors associated with each flight be categorized. The following categorizations were used:

- Arrivals
  - *Arrival aircraft size categories*  
Ranged from 1 through 5 and were based on aircraft classifications and wake turbulence categories as used by the Total Airspace and Airport Modeler (TAAM) (Sillard, Vergne & Desart, 2000). An aircraft category of 1 describes heavy aircraft such as the Boeing 747 and the Airbus A340.



Aircraft Category 5 on the other hand mostly includes small propeller and piston aircraft.

○ Arrival flight time categories

Ranged from 1 through 6 and were based on the flight duration as follows.

- Cat 1: Flight time greater than 500 minutes
- Cat 2: Flight time greater than 400 minutes and less than or equal to 500 minutes
- Cat 3: Flight time greater than 300 minutes and less than or equal to 400 minutes
- Cat 4: Flight time greater than 200 minutes and less than or equal to 300 minutes
- Cat 5: Flight time greater than 100 minutes and less than or equal to 200 minutes
- Cat 6: Flight time less than 100 minutes

○ Arrival airline usage category

Ranged from 1 through 6 depending on the proportional share of movements at each airport as follows:

- Cat 1: Airline has a greater than 25% share of airport operations
- Cat 2: Airline has a greater than 20% but less than or equal to a 25% share of airport operations
- Cat 3: Airline has a greater than 15% but less than or equal to a 20% share of airport operations

- Cat 4: Airline has a greater than 10% but less than or equal to a 15% share of airport operations
  - Cat 5: Airline has a greater than 5% but less than or equal to a 10% share of airport operations
  - Cat 6: Airline has a less than 5% share of airport operations
- Departures
  - Departure destination airport category

Ranged from 1 through 5 and depended on the official airport category as defined by the FAA's airport classification circular (Wells, 2000). These are

    - Cat 1: Large hub airports
    - Cat 2: Medium hub airports
    - Cat 3: Small hub airports
    - Cat 4: Commercial service airports
    - Cat 5: General aviation airports
  - Departure flight time categories

Range from 1 through 6 in the same way as arrival flight time categories is defined:

    - Cat 1: Flight time greater than 500 minutes
    - Cat 2: Flight time greater than 400 minutes and less than or equal to 500 minutes
    - Cat 3: Flight time greater than 300 minutes and less than or equal to 400 minutes

- Cat 4: Flight time greater than 200 minutes and less than or equal to 300 minutes
- Cat 5: Flight time greater than 100 minutes and less than or equal to 200 minutes
- Cat 6: Flight time less than 100 minutes

It should be noted that in all cases, Category 1 represents the highest priority aircraft. This categorization follows that of existing airport and airspace simulation models in use today including TAAM. For instance, a Category 1 aircraft represents the largest aircraft in use today (a Boeing 747 and an Airbus A340). The use of the new Airbus A380 as a super-heavy aircraft will generate a Category 0 aircraft.

### **Distributions and Components of Fitness Function**

As discussed previously, the composition of the fitness function is the core component to the slot allocation algorithm being proposed. This function evaluates each solution based on a ‘desirability index’ (DI) and thereby guides subsequent searches for more optimal solutions in the search space.

In contrast to previous slot allocation algorithms, this desirability index is not primarily based on real-world quantifiable values such as delay or cost. The reason behind this decision is that it is frequently impossible to apply the same metrics to this problem when airline and FAA concerns are jointly addressed. The airlines’ economic and cost-benefit driven metrics usually compete with the more safety and security driven views that the FAA has adopted. Whereas the

variation from aircraft-internal operating times is of primary concern to FAA and airline schedulers, other factors such as priority of larger aircraft sometimes contradict the primary function of the algorithm. The purpose of this algorithm is to show that improved schedule integrity can be achieved when considering historic flight time distributions rather than simply expected delays in the current schedule based on capacity constraints.

Instead, the desirability index combines various heterogeneous factors into a fitness index that is neutral. This index is composed of a mix of frequency distributions of relevant transition times as well as various parameters which indicate preferences and standard practice guidelines. This composite index ensures that the interests of both the airlines as well as FAA TFM are equitably addressed.

This fitness function jointly evaluates the desirability of four distinct slot schedules: (1) ATL arrivals, (2) ATL departures, (3) ORD arrivals, and (4) ORD departures. Aircraft are individually assigned to one or more of these slot schedules depending on their scheduled origin-destination airports. For example, if an aircraft was scheduled to depart from ATL and arrive at ORD within the planned time horizon, the aircraft would be assigned to both an Arrival as well as a departure slot schedule within the algorithm.

The evaluation of the desirability of the overall set of all four slot allocations for each candidate solution is based on a number of factors. The primary factors address the deviation of the slot assignments from the expected normal (or mode) operation by using frequency distributions of various phases of aircraft operations. Using these distributions, the desirability index penalizes the deviation from the mode frequency operating time in either direction by a certain factor. Other factors such as flight priorities, airline desires, and ATC standard practice are taken into account by using additional scalar parameters. Since neither of these factors are

hard constraints, the algorithm cannot guarantee that all guidelines and operating time characteristics are always adhered to. However, in principle, the algorithm should ensure that the multi-objective quality and desirability of the slot allocation schedule is optimal when all components of the fitness function are considered.

The soft constraints that have been identified as the primary factors guiding the desirability index are:

- *Aircraft operating time frequency distributions* where the highest desirability is the modal value in the distribution and any deviation, positive or negative, is less desirable. These distributions cover all phases of aircraft operating characteristics into and out of an airport including:
  - Arrival flight time distributions
  - Arrival taxi-in time distributions
  - Departure taxi-out distributions
  - Departure flight time distributions
- *Airline preferences* as scalar parameters guiding the priority of flights by origin or by number of passengers on board that stand to lose connections if excessively delayed. Additionally, scalar parameters may guide departure slot order by giving priorities to aircraft based on their destination airport category. For instance, a flight to another airline hub airport may get a higher priority since passengers may be in danger of missing connections at this destination airport.
- *FAA and airport preferences* guiding the sequence of aircraft or priorities of certain aircraft over another. For instance, large, very heavy aircraft are not very maneuverable and require advance notice for trajectory changes. Since smaller

aircraft are easier to re-route, larger aircraft typically receive priority over smaller ones.

In addition to these soft constraints which contribute to the evaluation of the desirability index, certain harder constraints are applied to systematically ignore solutions from further evolution cycles. These constraints include:

- The total number of airport slots available each airport
- The exact time that each individual slot represents

All of these constraints feed into the fitness function – or desirability index – for the slot allocation approach in the form of a simple summation of these various factors into a single neutral metric.

It is important to understand that the components of this fitness function are not based on an analysis of variables that historical data shows are significant. In fact, the historical data that was used for flight and taxi times includes no dependent variable that is similar to the fitness value defined below. Rather, the function is a compilation of proposed individual objectives that represent important goals and preferences of the various stakeholders in this slot allocation scheduling realm. The weights that are associated with each parameter are not a notion of how significant it's contribution to the fitness was from a historical perspective, but are simply used to adjust the parameter's importance in a day-by-day slot scheduling application.

The desirability index is computed as follows:

*Fitness function = max DI*

Where

*DI =*

$$\begin{aligned}
 & \sum_{All-Airports} \left( \alpha_1 \sum_{Dep+Arr} FltTimeDist + \alpha_2 \sum_{Dep+Arr} TaxiTimeDist \right) + \\
 & \left( \beta_1 \sum_{All-Arrivals} [abs(ScheduledArrTime - SlotArrTime) * ArrFltDistCatMult] + \right. \\
 & \left. + \beta_2 \sum_{All-Arrivals} [abs(ScheduledArrTime - SlotArrTime) * AcftCatMult] + \right. \\
 & \left. + \beta_3 \sum_{All-Arrivals} [abs(ScheduledArrTime - SlotArrTime) * AptUsageCatMult] \right) + \\
 & \left( \gamma_1 \sum_{All-Departures} [abs(ScheduledDepTime - SlotDepTime) * DestAptCatMult] + \right. \\
 & \left. + \gamma_2 \sum_{All-Departures} [abs(ScheduledDepTime - SlotDepTime) * DepFltDistCatMult] \right) +
 \end{aligned}$$

Where

*FltTimeDist* = Scaled historic frequency value of flight time

*TaxiTimeDist* = Scaled historic frequency value of taxi-in or taxi-out time

*ArrFltDistCatMult* = A value of  $1+(6-n)*0.2$  where n is the flight distance category, yielding a value of 2.2 for the longest flights

*AcftCatMult* = A value of  $1+(5-n)*0.2$  where n is the aircraft category of the flight, yielding a value of 2.0 for the largest aircraft

*AptUsageCatMult* = A value of  $1+(6-n)*0.2$  where n is the airport usage share category of the airline operator yielding a value of 2.2 for the airline with highest usage count

$DestAptCatMult$  = A value of  $1+(5-n)*0.2$  where  $n$  is the destination airport category of the flight, yielding a value of 2.0 for the largest destination airport

$DepFltDistCatMult$  = A value of  $1+(6-n)*0.2$  where  $n$  is the flight distance category, yielding a value of 2.2 for the longest flights

and

$\alpha_1, \alpha_2, \alpha_3$  = weighting parameters for importance of punctuality

$\beta_1, \beta_2, \beta_3$  = weighting parameters for the importance of arrival priorities and guidelines

$\gamma_1, \gamma_2$  = weighting parameters for the importance of departure priorities and guidelines

The purpose of each categorical multiplier is to penalize the movement away from the scheduled arrival or departure times – as observed by new slot times – using a scalar multiplier. These multipliers are based directly on the categories previously identified for each of the airline, airport, or ATC goals.

The weighting parameters for  $\alpha_i$ ,  $\beta_i$ , and  $\gamma_i$  will be initialized with a value of 1, which indicates that all of these components to the desirability index have the same importance. This is an important notion since the variation of these weighting parameters may give preference to certain aspects of the function. For instance, if airline factors are deemed to be more important, the  $\beta_i$ , and  $\gamma_i$  parameters could be increased to give more weight the respective part of the fitness function.



As discussed previously, these weighting parameters are solely used to adjust the importance of a certain variable on the outcome of the algorithm. It is expected that these weights be modified to reflect day-by-day scheduling practices or that additional factors be added to reflect the preferences of other stakeholders in this application. The multi-objective nature of the fitness function allows the incorporation of preferences by all relevant stakeholders in the operation including airports, airlines, and ATC.

In addition to these factors, additional limits are imposed on each flight. For instance, a value of zero is returned for a flight's fitness if the proposed optimal arrival or departure slot time is more than 30 minutes away from the scheduled time. Also, each flight's new scheduled flight and taxi times are being evaluated against the mode of the time distribution. If the proposed new flight time is more than 4 positive standard deviations or 2 standard deviations in the negative away from the pre-defined mode, the algorithm returns a value of zero for this flight. While these additional constraints technically only affect individual flight fitness values, they do contribute to the overall schedule fitness in a way that reduces the survival likelihood of schedules with a multitude of limit exceeding flights.

### **Design and Development of the Slot Allocation Algorithms**

The design of the slot allocation algorithms follows standard practice for EAs:

1. Encode the slot schedule with the pre-defined number of available slots – based on hourly airport capacities – over a selected time period. Each of the four separate slot schedules (departure and arrival at each airport) is treated as a

separate chromosome of genes. Each slot or gene holds the index of an aircraft as defined by the initial airline demand schedule.

2. Initialize all four slot schedules with a pre-defined order of indexes/aircraft. This gene initialization is based on an ordered schedule of aircraft indexes based on the original schedule. This causes flights to be initialized approximately close to their schedule arrival or departure times. A variable number of candidate solutions are generated in parallel.
3. Use the fitness function's desirability index to rank the candidate solutions and propose the chromosomes with the highest desirability for evolution.
4. Use the swap mutation technique to evolve the existing highest desirability chromosomes into future candidate generations.
5. Repeat steps 3) and 4) for a pre-defined number of iterations.

The method of encoding the slot schedule chromosomes, programming the Fitness Function, as well as the implementation of the software algorithms are discussed in turn:

### **Encoding**

Encoding of the chromosomes for the EA model for this application is an essential factor in the overall success of this research. As with any EA model, the efficiency, performance, and the speed and quality of the results depend heavily on how the individual chromosomes are encoded.

For this application, four individual chromosomes are used which represent the different schedule slot allocations, one departure and one arrival, per airport. Each gene in these subgroups represents a unique aircraft index, which can be referenced back to the original demand schedule via a simple lookup table. Each gene is also directly linked to a movement time, which is based on the hourly throughput rates. The total number of genes in each subgroup depends on the respective arrival and departure capacity rates at the airports. These rates – and the associated number of genes in each chromosome – are dynamically configurable within the EA framework and may vary on an hour-by-hour basis.

Figure 25 below presents a simplified overview of the chromosome encoding for this application for ORD. Each value – or allele – within a chromosome represents a single arrival or departure slot with a given operating time based on the hourly throughput capacity at the airport. The contents of each allele are flight index values that can be linked back to a complete schedule of operations (right side of the figure). For instance, flight AAL123 with index 001 for ORD Arrivals currently has a slot time of 9:35am. The original scheduled arrival time was 9:45am. This means that if the aircraft is capable of reducing the estimated flight time by 10 minutes, it is guaranteed an arrival slot at ORD.

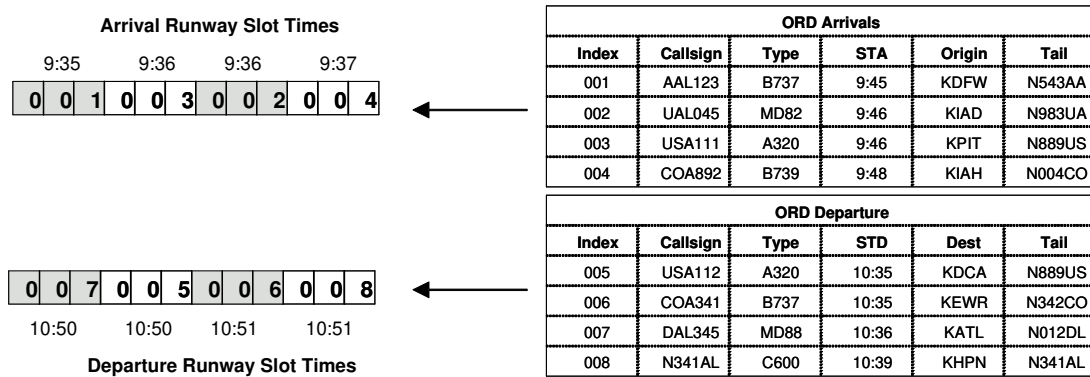


Figure 25: ORD Slot Allocation Encoding

The arrival and departure runway slot times are based on an even distribution of the throughput capacity rates over the available period of performance. This rate can be amended on an hourly basis if any hourly changes in throughput capacity rates are being implemented.

Through the use of the fitness function, these runway slot times relate back to the original scheduled arrival and departure times and the effects of each set of solutions are quantified.

### Fitness Function

The desirability index or the fitness function requires a tremendous amount of data as input parameters. Since the fitness is not simply based on a delay time calculation – i.e., the difference between scheduled and actual movement times – various distributions or multiplier parameters are required to transform the time-based calculations into the more neutral desirability factor.

The distribution functions required to feed these fitness function calculations are very extensive due to the number of significant variables. For example, departure taxi-times not only depend on the airline but also on the time of day of the operation. This means that the number of

distributions required only for taxi-out times are 24 times the number of airlines identified in the schedule. It is, however, also imperative that the processing times necessary to evaluate the fitness of each generation of solutions not be excessive. Otherwise the utility of this approach would be limited by the reduced ability to parse the search space of potential solutions.

The implementation of the fitness function within a Java development framework therefore makes heavy use of Java hashtable containers, which use the previously defined distribution keys as lookup keys for each distribution. The fitness function simply uses the hashtables to look up a scaled frequency value based on the respective operating times. This scaled frequency value is used directly as a desirability value for each flight. It essentially represents the likelihood of a given flight to encounter the given flight or taxi-time based on the historic distributions.

### **Mutation Operator**

It became obvious very early on that traditional crossover and mutation operators would not be a viable solution for this application because these operators routinely generated duplicate gene values within the chromosomes. Since each gene value represents a unique flight within the schedule, the chromosomes would have to be subjected to a repair algorithm after the mutation step in order to fix duplicate values. This would be an extremely inefficient operation and would severely limit the solution search space within reasonable time constraints.

As an alternative, the mutation operator that was used to iteratively alter the sequence of flights was the exchange or swap mutation operator as described by (Banzhaf, 1990) as well as (Oliver, 1987). This operator did not randomly alter or cross existing gene values, but randomly

swapped the location of genes within each chromosome. This type of operator is commonly used in scheduling problems such as the TSP where the uniqueness of objects to be scheduled needs to be preserved. Historically, the swap mutation operator is applied across the entire chromosome and randomly swaps genes without bounding limits. For the purpose of this scheduling application, where aircraft are not likely to be able to trade slots with aircraft more than a certain number of minutes away from their own slot times, an amended version of this operator was developed. This bounded swap mutation operator provides ways of limiting the range of slots across which swapping may occur. For instance, if a value of 15 is specified as the range bound, then the mutation operator only swaps the position of a flight with another flight which is 15 slots away on either side. This not only limits the incremental movement of flights across the slot schedule but also places a higher focus on exploring the local solution space around each flight's slot time in the current chromosome.

### **Evolutionary Algorithm Implementation**

The algorithms which implement the EA approach for this slot allocation optimization problem were programmed using a Java-based software package called Java Genetic Algorithms Package (JGAP). JGAP is a genetic algorithm and genetic programming component provided as a Java framework. It provides basic genetic mechanisms that can be easily used to apply evolutionary principles to problem solutions (Meffert, 2007). JGAP has thus far seen active usage in various research and software testing applications (see <http://jgap.sourceforge.net>). It is an actively supported open-source development project and the source code is freely distributed over the web.

The Java framework provided by the JGAP package provides sample Java Classes for GA chromosomes, alleles, and genes, all of which are readily adaptable to encode the slot allocation schedules defined previously. Within JGAP, chromosomes are encoded using simple arrays, that may be composed of binary or integer values. To assess the fitness of each chromosome Java classes and methods are provided that are used to evaluate the desirability of each candidate solution set based on the desirability index composition formula previously specified. Each Java class can be modified and adapted to fit specific evolutionary programming needs. The implementation of the fitness function is as simple as a Java class function which returns the summation of all of the DI components as a value.

Once the chromosomes are encoded and the fitness function has been programmed, JGAP includes default – and user modifiable – classes and methods for evolving the population of solutions. As an input, users are able to specify the number of iterations – or the total number of generations to evolve – as well as the number of candidate solutions or chromosomes to process and evaluate in parallel.

JGAP included a class definition for a basic swap mutation operator based on the unbounded principle described in the previous section. In order to bound this operator, the Java class was modified to accept a range variable which limits the index value (or slot time) with which a certain gene's current location can be swapped. This implementation of a bounded Swapping Mutation Operator was accepted as a contribution to the open-source JGAP project and will appear in the general release of JGAP starting with the next version.

## **Selection and Generation of Demand Schedule for Assessment**

The selection of the date and time periods used in the evaluation of the slot allocation algorithms follows standard airport and airspace simulation practice. The selected periods of operation represent those of normal busy days and hours from the busy season as the basis for analysis. In order to evaluate the applicability of this optimization approach to other days as well, medium and low demand schedules are also generated. In all, the following three types of schedules will be optimized and subsequently evaluated:

- High demand periods based on days which rank in the 95<sup>th</sup> percentile of all operations in 2006 for both ATL and ORD
- Lower demand periods based on days which rank in the 75<sup>th</sup> percentile of all operations in 2006 for both ATL and ORD
- Minimal demand periods which are based on the morning hours of the 95<sup>th</sup> percentile days previously evaluated

This selection is based on an analysis of seasonal, daily, and hourly variations in traffic demand as well as a day-by-day summary analysis ranking each day of 2006 based on the total scheduled observed demand. Both analyses are based on the ASDI data previously used for the historic flight time distributions and uses movement counts of scheduled and actual hourly and daily traffic. Figures 26 and 27 below show an analysis on daily total scheduled operations at both airports based on the month as well as the day of the week:



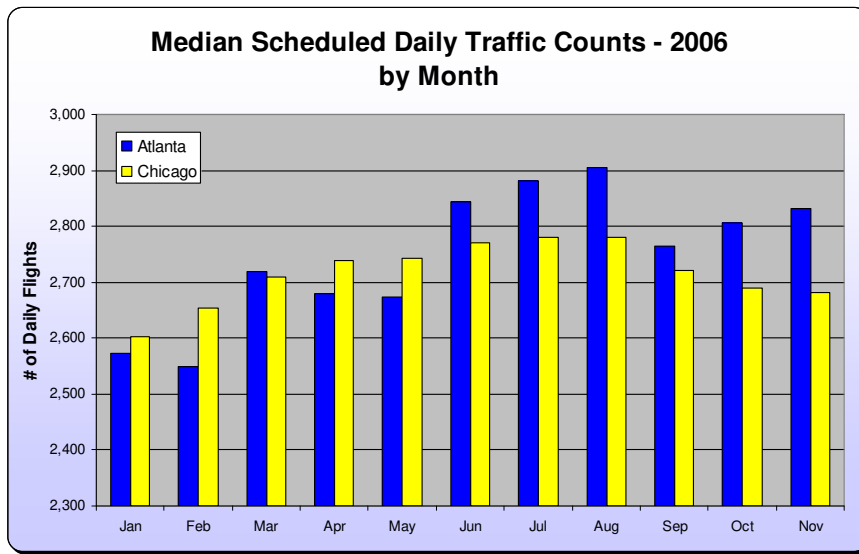


Figure 26: Median Scheduled Daily Traffic Counts by Month for 2006

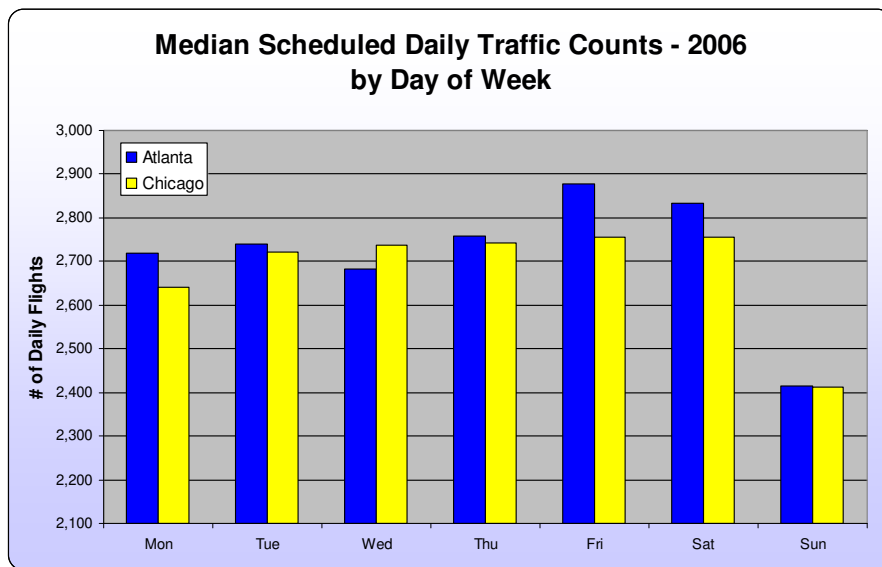


Figure 27: Median Scheduled Daily Traffic Counts by Day of Week for 2006

This analysis clearly indicates that the subject days for schedule optimization analysis will lie in the three summer months since June, July, and August showed the highest median

daily traffic levels for both airports. The subject days will also likely be either Thursdays, Fridays, or Saturdays, since these three days of the week showed the highest median daily traffic counts.

A detailed day-by-day analysis of scheduled traffic volume is presented in Appendix D where all scheduled daily traffic counts for the year 2006 are evaluated based on the 75<sup>th</sup> as well as 95<sup>th</sup> percentile counts of the entire year. Since the intent is to choose two high demand days and two medium demand days for evaluation, this analysis suggests the following four days for analysis:

- 95<sup>th</sup> percentile days
  - August 12, 2006 and June 29, 2006 (Both days are Thursdays)
- 75<sup>th</sup> percentile days
  - July 5, 2006 and July 17, 2006
- Minimal demand periods
  - Morning hours of August 12, 2006 and June 29, 2006

In addition to this analysis which suggests certain days for optimization and evaluation, an hourly traffic count analysis was also performed. This analysis presented in Figure 28 will narrow down the time periods of the day for study:

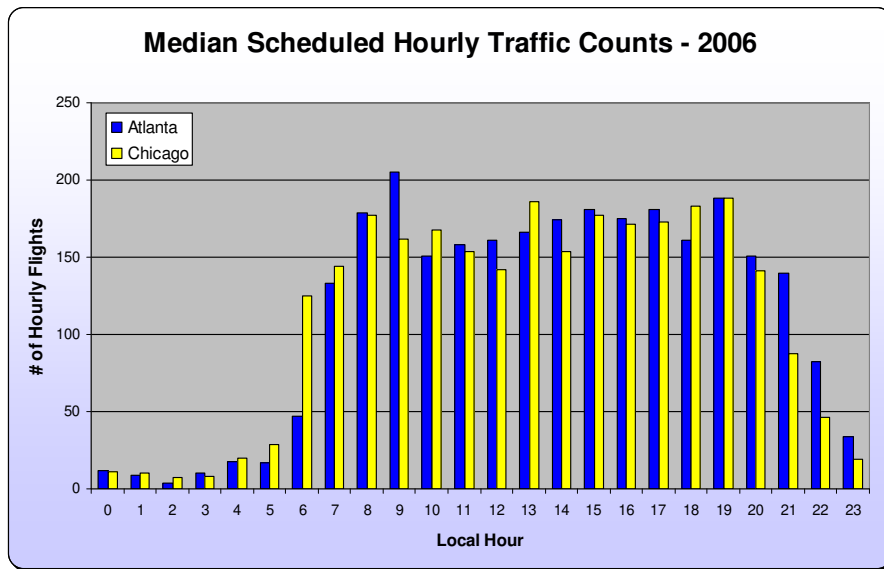


Figure 28: Median Scheduled Hourly Traffic Counts for 2006

The figure above shows certain periods of raised activity in the early morning hours but suggests a steady demand period of mid-afternoon through early-evening for study. The following 6-hour time periods were selected for normal and morning hour schedules:

- Normal hours: 1700GMT through 2300GMT
  - Atlanta local time (summer period): 1300 through 1900
  - Chicago local time (summer period): 1200 through 1800
- Morning hours: 0300GMT through 0900GMT
  - Atlanta local time (summer period): 2300 through 0500
  - Chicago local time (summer period): 2200 through 0400

This approach resulted in a total of 6 distinct demand schedules which were extracted from the ASDI data, pre-processed, optimized using the novel slot allocation approach, and subsequently evaluated using AnyLogic queuing simulations.

### **Simulation Assessment Methodology**

The arrival and departure slot allocations generated by the schedule optimization approach require evaluation to show that they are in fact an improvement over existing practice. To accomplish this task, simulation models of the subject airports were developed that would take airline schedules as input and evaluate the performance of individual aircraft within a queuing simulation framework (see Le, Donohue, and Chen in a similar evaluation of auction-based slot assignments at ATL airport) (Le et. al., 2005). These simulation models essentially take the input schedules' departure times and then taxi or fly aircraft based on the historic distributions previously developed. Flights are constrained by runway throughput rates – causing queuing on departure and arrival – at each airport. A total of four queues – departures and arrivals at each airport – are implemented.

The intent of this analysis is to evaluate the integrity of the optimal slot schedules against the original filed schedule as obtained from the ASDI dataset. In a more realistic environment of capacitated runway resources at each airport, the optimal slot schedule should not only produce a closer-to-planned operation, but also improve the performance with respect to airline, airport, and ATC goals and preferences.

The various scenarios will be evaluated using deterministic flight and taxi-times based on the assumption that all aircraft are fully capable of negotiating 4-dimensional trajectories with

appreciable variation in RTAs. Subsequently, these scenarios will be subjected to stochastic distributions of flight and taxi-times as used for the slot allocation optimization algorithms previously. This more closely resembles current-day observations where RNP is not yet fully implemented.

The metric used for quantifying the optimality of the EA-based slot allocation schedule is predominantly a delay-based measure. However, since the purpose of the schedule optimization approach outlined in this dissertation is to produce a more predictable and reliable schedule, the metric needs to account for deviation from scheduled arrival and departure times in both directions. A flight that arrives 30 minutes early is as bad for planning purposes as one that arrives 30 minutes late. With this in mind, the summary metric used to evaluate the performance of each schedule is the mean squared difference (MSD) of actual versus scheduled for each flight.

The simulation models were developed using AnyLogic, an extremely popular Java-based simulation tool which is capable of discrete event, continuous, as well as agent-based simulation methodologies. AnyLogic is a Java-Based application, which also facilitates the re-use of various segments of software from the EAs – implemented using Java-Based JGAP – application developed previously.

## **Metrics**

The primary measure used in the comparison of the various scenarios is at its' core delay-based. Delay is likely the most common measure used in evaluating the efficiency of airport simulation scenarios used by airlines and the FAA alike.

However, since the intent of this simulation study is to evaluate the reliability of the optimal slot schedules, the positive and negative values for deviation from scheduled arrival and departure times need to be captured. To accomplish this, the metric of sum of squared difference (SSD) was used. This metric is calculated based on the square difference between scheduled and simulated actual for each flight, which is then summed and divided by the total number of flights as follows:

$$\text{Schedule - Reliability} = \frac{SSD}{n} = \frac{\sum_1^n (\text{ScheduledTime} - \text{SimulatedActualTime})^2}{n}$$

where n is the number of flights in the schedule. This metric is computed for both arrivals and departures based on the runway touchdown (arrivals) and takeoff (departures) times obtained from the AnyLogic queuing simulations.

The squaring of the difference between scheduled and observed times causes large deviations from the scheduled arrival or departure times to be counted in an exponentially severe fashion. For example, a flight which deviates 6 minutes from the scheduled arrival time is not considered twice as bad as a flight which deviates 3 minutes, but  $6^2/3^2$  or 4 times.

In addition to this SSD-based metric that evaluates the overall reliability of each schedule, other more qualitative metrics will be calculated. These metrics will evaluate the impact of the various airline, ATC, and airport goals on the performance of the optimal schedules. Despite also being based on the SSD metric, these analyses will focus more on the relative improvements of certain categories of aircraft – by size, flight time, or airport – over other category aircraft.

## Simulation Scenarios

Each of the time periods previously identified as subject schedules for optimization will be subjected to a number of different scenarios for simulation. These include an original schedule of filed departure and arrival times, a non-capacity constrained optimal schedule, a capacity-constrained optimal schedule, and, in the case of morning hours, a simple optimal schedule based on mode-flight and taxi times. The following table summarizes the set of simulation scenarios under evaluation:

Table 5: AnyLogic Simulation Scenarios

Schedule Periods	Types of Schedules	Time Variation
- August 17 (afternoon) - July 29 (afternoon) - July 5 (afternoon) - July 17 (afternoon)	- Original Filed - Non Capacity Constrained Optimal - Capacity Constrained Optimal	- Deterministic Flight & Taxi Times (full 4-D trajectory capabilities) - Stochastic Flight & Taxi Times (current-day variation)
- August 17 (morning) - July 28 (morning)	- Original Filed - Non Capacity Constrained Optimal	- Deterministic - Stochastic

Each of the primary afternoon schedules will be simulated using the original filed schedule as well as a non capacity-constrained and a capacity constrained schedule. The morning schedules, on the other hand, are only simulated using the original as well as a non-

capacity constrained optimal since no capacity limiting factors are expected at either airport in these morning hours.

Each schedule is simulated under deterministic as well as stochastic flight and taxi-time conditions. The deterministic operating time scenarios emulate a future 4-dimensional trajectory environment where aircraft are capable of meeting departure and arrival times highly accurately. On the other hand, the stochastic operating time scenarios represent current day operations where flight and taxi-times are still increasingly chaotic and unpredictable. Deterministic flight and taxi times are based on the mode time values of each historical distribution, whereas stochastic times use the entire discrete time distribution of historic times for each aircraft.

Each of these scenarios will be subjected to a series of 50 multi-runs and runs over the entire six-hour schedule period. Throughout these 50 multi-runs, the runway throughput rates for arrivals and departures will be randomly varied within the range of 80 to 85 aircraft per hour. The intent of this is to further replicate normal capacity variations at airports in a real-world fashion and also to increase the statistical reliability and applicability of the results from the simulation analysis.

The simulation analysis will subsequently focus on the middle four hours of the performance period. This provides the simulation with ample time – a 1 hour period – for run-up and minimizes any optimization overlap error at either end of the schedule.

### **Simulation Setup**

The simulation setup for this evaluation models the two airports as simple queues, one arrival and one departure queue per airport. With this setup, aircraft would enter the simulation



based on the arrival and departure schedules, operate deterministically or stochastically based on the distributions previously generated, and be delayed or not within their respective arrival and departure queues.

Figure 29 below presents a high level view of the AnyLogic model which shows the initial steps of loading the flight schedule, delaying aircraft until their departure times, and then allocating flights to their respective airports. Connections between ATL and ORD allow for flights to operate between these two airports.

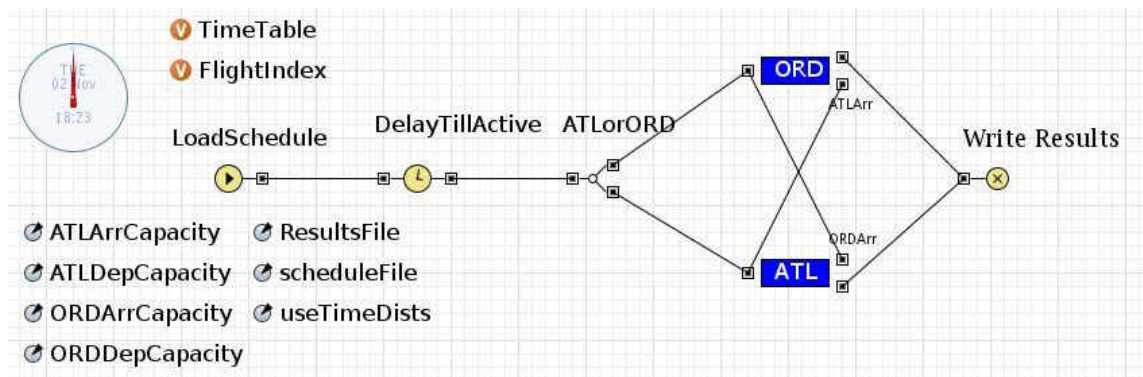


Figure 29: AnyLogic Model - High Level View

Upon entering an airport's sub-model, aircraft are split by operating type – arrival or departure – and subsequently fly their arrivals or taxi for departure, respectively. Runway queues with capacitated resources represent actual departure or arrival runway throughput rates. Following touchdown, an arrival flight is subject to arrival taxi-time and upon gate arrival is removed from the simulation. Departures either are sent to the other airport's sub-model or fly to their end destination where they are also removed from the simulation. This process is depicted below in Figure 30:

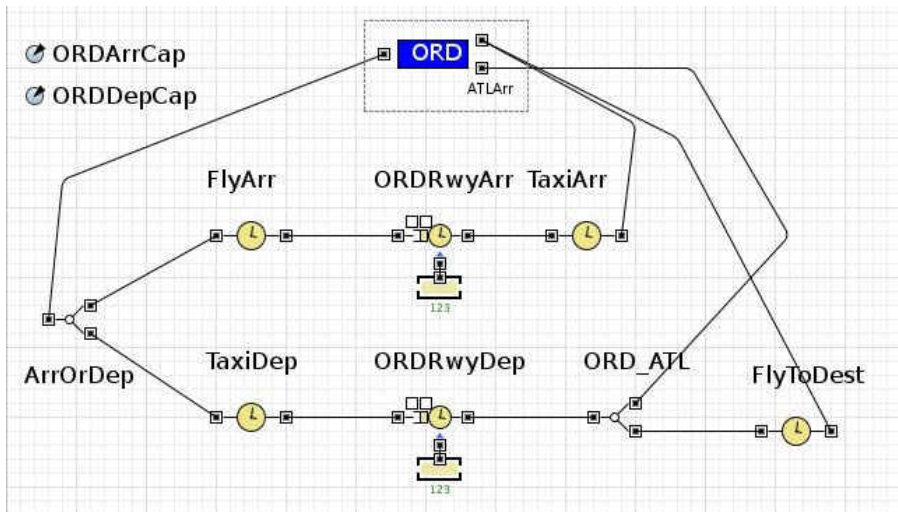


Figure 30: AnyLogic Model - Airport View

The fact that both AnyLogic as well as JGAP, which is used for the slot allocation algorithms, are both Java-based packages will allow for a significant ability to reuse software, particularly the stochastic distribution tables and methods.

## CHAPTER FOUR: FINDINGS

This chapter of the dissertation presents the results from the schedule optimization as well as the simulation-based assessments of the optimal slot schedules prepared by the EA search method. First, the optimization process itself is quantified using a time-series analysis of the fitness function values by generation. This is followed by a summary analysis of the MSD metric by scenario, which compares the overall integrity of each schedule to the original filed schedules. In addition to a graphical analysis of the various scenarios, statistics used to test the significance of the differences between the original and optimal schedules are presented. Specifically, the Mann-Whitney test is used to test if the optimized schedule produces significantly different results when compared to the original schedule. An F-test will also be employed to examine if there have any significant changes in the variability of the simulation results.

The chapter is concluded by an analysis of the schedule integrity by categorical goals for airlines, ATC, and airports.

### **Optimization Process**

The schedule optimization process for this approach used as input a number of different variables that controlled the number of chromosomes in the population, the number of evolutions, the mutation rate of each chromosome, as well as some other basic configuration parameters. Table 6 below summarizes these core input parameters:

Table 6: Core Optimization Input Parameters

<b>Input Parameter</b>	<b>Value</b>
Number of Evolutions	2,000
Population Size	200
Mutation Rate	2%
Retain Rate	0.25

The relatively large number of the evolutions and the population size were chosen due to the incremental optimization nature of the application. Solutions are explored incrementally and in small steps but are subject to a relatively large amount of evolutions.

To better understand the optimization, the chosen number of evolutions, and other parameters, a series of time-series plots showing the total fitness function value against the elapsed number of seconds are presented below in Figures 31 through 33. Figure 31 below plots the four subject days for the non-capacity constrained optimization process:

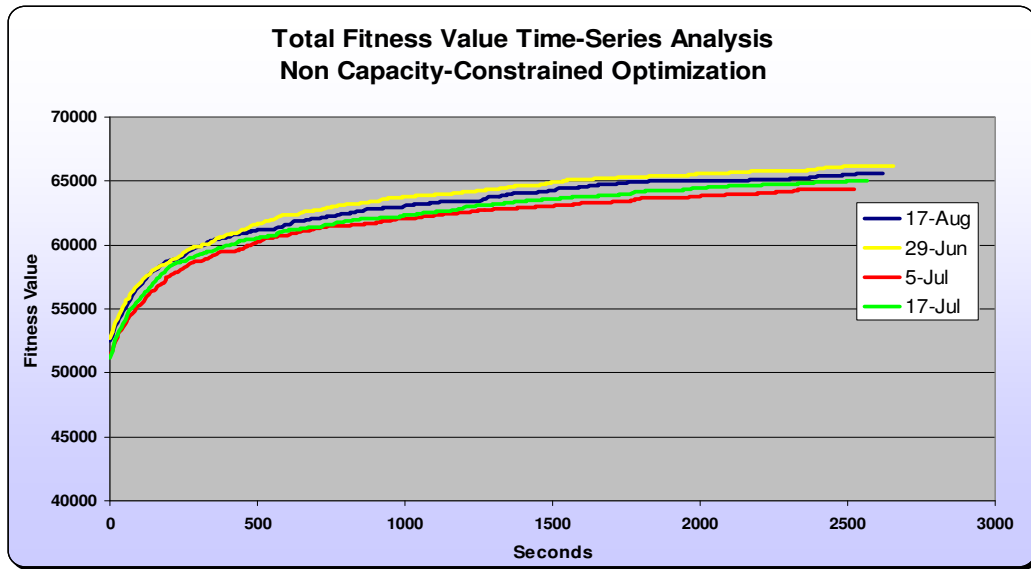


Figure 31: Total Fitness Function Time Series (Unconstrained Capacity)

As the figure above shows, little difference exists between the four days in terms of the overall fitness function value. Although June 29 ranks slightly above the other three days in terms of fitness value, there is no discernible difference between a high demand – 95<sup>th</sup> percentile – and a medium demand – 75<sup>th</sup> percentile – period.

The fitness function values for the capacity constrained schedule optimization process are presented below in Figure 32:

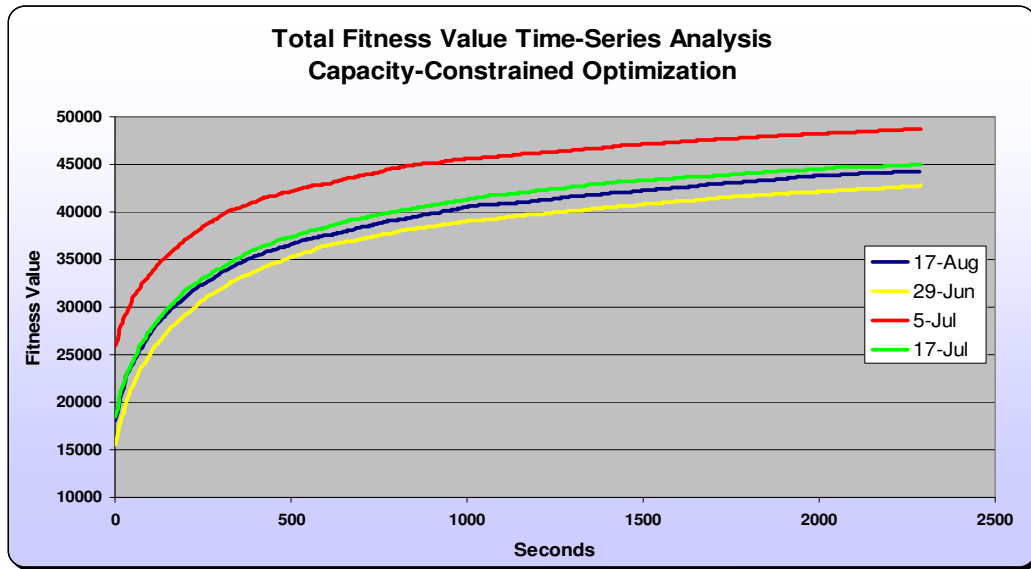


Figure 32: Total Fitness Function Time Series (Constrained Capacity)

This figure clearly shows that the high demand days of August 17, 2006 and June 29, 2006 are not able to achieve as high a fitness value as the lower demand days based on the 75<sup>th</sup> percentile analysis. The reason for this is somewhat unclear, but may lie in the difference in bank structures and aircraft mix between the schedules as well as the fact that the 75<sup>th</sup> percentile days are different days of the week compared to the 95<sup>th</sup> percentile days.

Fitness function values for the morning hour schedules for August 17, 2006 and June 29, 2006 are presented below in Figure 33. These value show a strong contrast to the afternoon hour fitness values presented above:

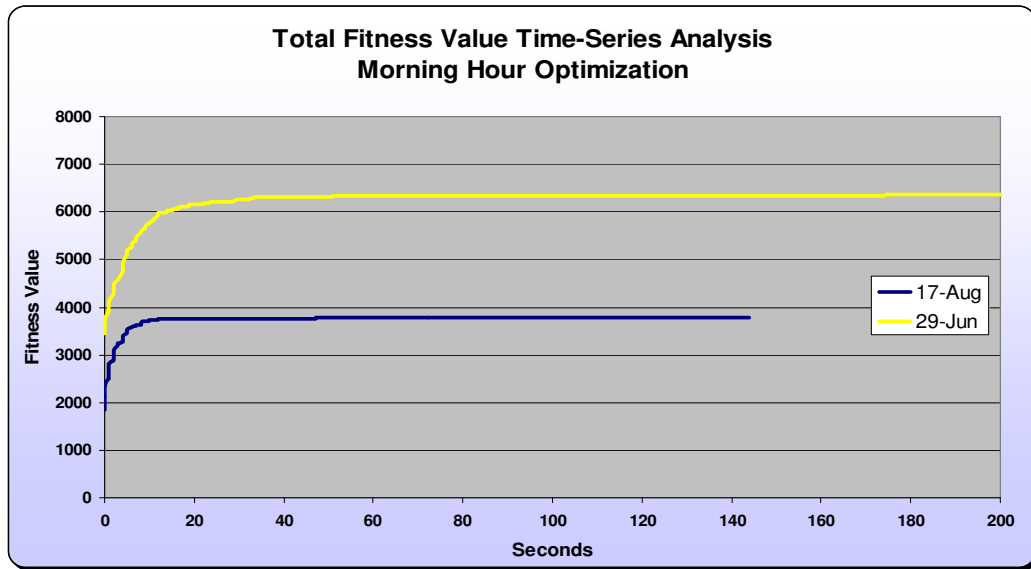


Figure 33: Total Fitness Function Time Series (Morning Hours)

The figure above clearly shows a difference between the June 29 and August 17 schedules. The difference in these values results from the difference in the total number of flights in both schedules. June 29, 2006 saw a significantly larger number of flights than did August 17, 2006.

As the curves plotted in Figures 31 and 32 above show, the schedule optimization process sees a significant reduction in fitness function value gain at the end of the optimization process. This indicates that the number of evolutions as well as the size of the population chosen were sufficiently large to gain the most benefit from the EA. Clearly the morning hours have a significantly reduced fitness value as well optimization duration due to the reduced number of aircraft in the schedule.

A sensitivity analysis of the aircraft category parameter within the fitness function generated the time series plot of total fitness as shown below in Figure 34:

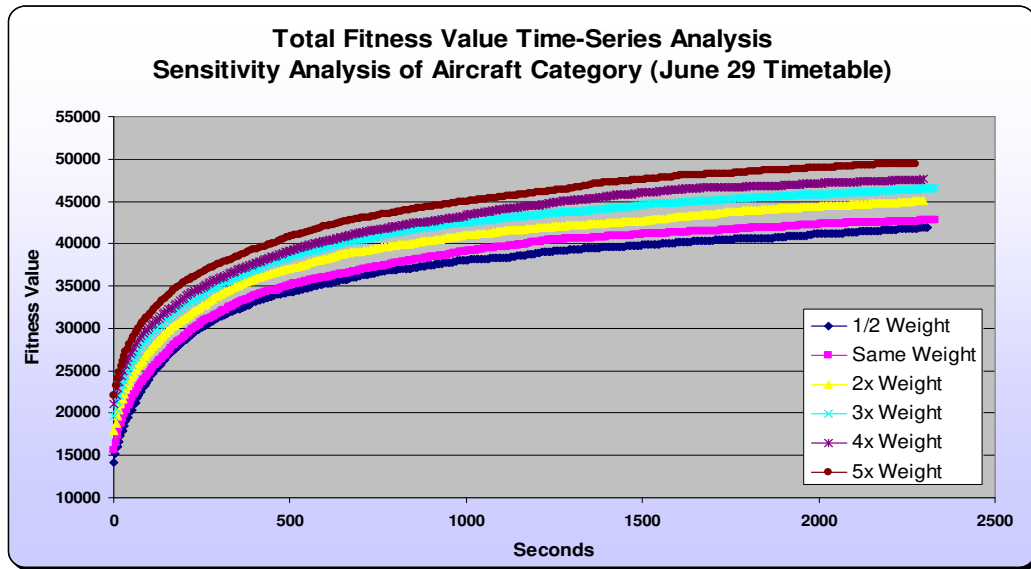


Figure 34: Total Fitness Function Time Series – Sensitivity Analysis of Aircraft Category

As the figure above shows, the total fitness values appear to proportionally increase as more weight is given to the aircraft category parameter in the fitness function. Since the categorical contributions to the fitness functions are delay-based, they generate a larger contribution to the fitness function value as compared to the flight and taxi time distributions. This means that as the importance of the flight and taxi time distributions are reduced, the categorical parameter is capable of generating larger fitness function contributions.

### **Raw Original Schedule Comparison**

In order to have a reference point for subsequent alternative schedule experiments, an analysis of the given schedules was performed. A comparison of the filed arrival and departure times against the actual observed times – essentially equaling system delays – was performed



based on the ASDI data feed. This data shows how the actual operation of each subject day performed when compared to the original schedule that was published by the airlines:

Figure 35 below presents this comparison for the 95<sup>th</sup> Percentile days:

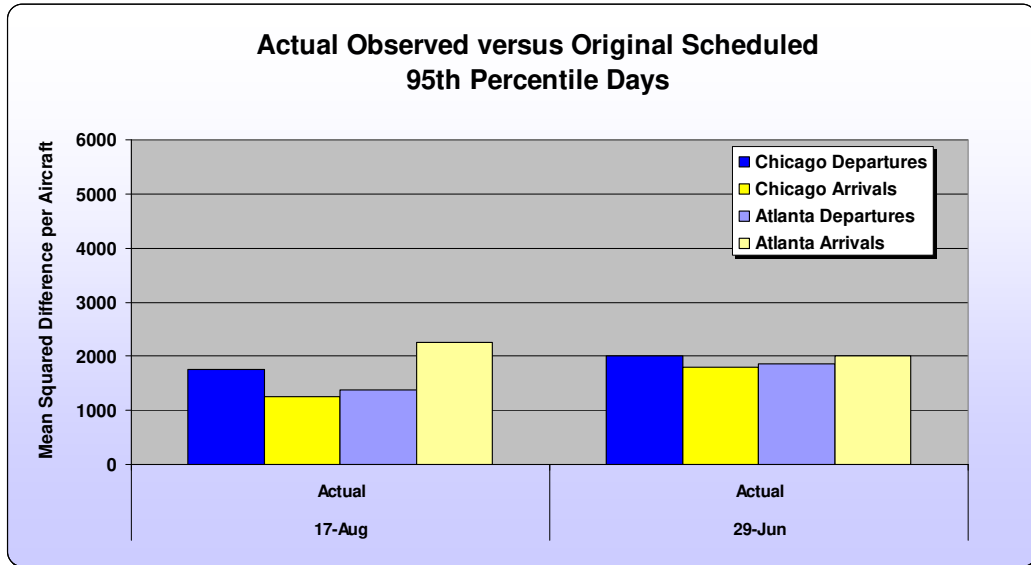


Figure 35: Actual vs. Observed MSD Comparison (95<sup>th</sup> Percentile days)

As the figure above shows, both 95<sup>th</sup> percentile days showed similar characteristics in on-time performance. The MSD between the original airline schedules and the actual observed operation show a well distributed trend for both days. August 17 shows a slightly higher than normal MSD for ATL arrivals, which may indicate inclement weather or some other capacity limiting phenomena in the Atlanta area.

Figure 36 below presents this comparison for the 75<sup>th</sup> Percentile days:

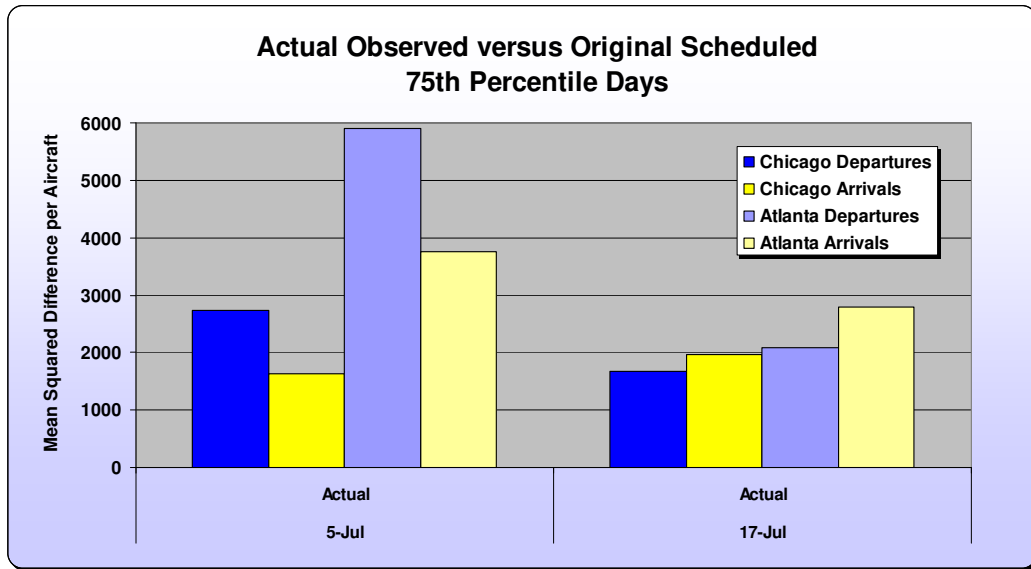


Figure 36: Actual vs. Observed MSD Comparison (75th Percentile days)

The figure above indicates that July 17 operated in a very similar manner to both 95<sup>th</sup> percentile days in Figure 35. July 5, on the other hand, exhibits a noticeable increase in delays for ATL operations. This likely indicates inclement weather or some other capacity limiting scenario during the afternoon analysis period in Atlanta on July 5, 2006. Since the primary delay contributor at ATL for July 5 appears to be the departures, this may indicate some sort of GDP for certain departures out of ATL. It may also show a scenario where airlines overscheduled flight-times more aggressively at ATL as compared to the other scenarios.

Figure 37 below shows the actual versus filed schedule comparison for the 95<sup>th</sup> Percentile morning hour schedules. This figure shows a significantly increased difference for the June 29 morning hour schedule. This again may indicate inclement weather or aggressive over-scheduling of flight times.

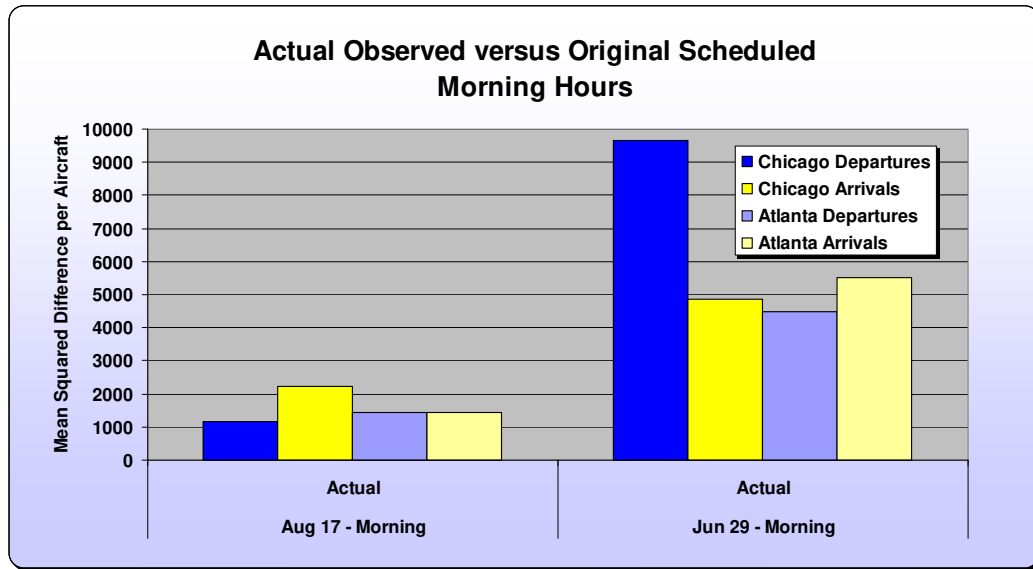


Figure 37: Actual vs. Observed MSD Comparison (Morning Hours)

### AnyLogic Multirun Mean Squared Difference Comparison

This section of the dissertation presents the analysis of overall MSDs when each of the subject schedules is simulated in AnyLogic. For the 95<sup>th</sup> and 75<sup>th</sup> percentile schedules, the simulated scenarios are composed of:

- Filed schedule as extracted from ASDI data
- Non-capacity constrained optimal schedule
- Capacity constrained optimal schedule

For the morning hours where typically no capacity constraints are seen, the only optimal schedule simulated is the non-capacity constrained schedule.

Each of the demand schedules was simulated using two distinct operating characteristics: using (1) mode taxi and flight times and (2) distributions of taxi and flight times. Both are based on the taxi and flight time analyses described in Chapter 3. The use of mode times reflects

perfect 4-dimensional flight planning where aircraft are highly capable of meeting times en-route. Using distributions more closely reflects current day operations with increased unpredictability.

The MSDs are computed by performing a flight-by-flight comparison of scheduled-filed versus simulated schedules. A small MSD indicates that the capacity-constrained simulation experiment operated flights very close to the intended schedule. This means that the schedule is more reliable than other schedules with large MSDs. An SSD for all flights is subsequently scaled by dividing it by the number of flights in the schedule, resulting in the MSD. This makes the results independent of the number of flights in the schedule and therefore comparable across different demand days. The MSDs are mean results from the 50 simulation runs performed in AnyLogic. As described in Chapter 3, the airport arrival and departure capacities were varied between 80 and 85 aircraft per hour throughout these 50 multi-runs (a total of 160-170 operations per hour at each airport).

Each of the subject schedules is further analyzed using a Mann-Whitney test for equality of the median as well as a standard F-test for difference in variance. In each statistic, the null hypothesis is that no difference in median value or variance exists. This will indicate if the optimal schedules perform significantly different from the published filed schedules.

### **95<sup>th</sup> Percentile days**

The 95<sup>th</sup> Percentile day schedules for August 17 and June 29 produced the following MSDs shown in Figures 38 and 39. Figure 38 shows the results of the AnyLogic simulations using mode times for taxi and flight times.

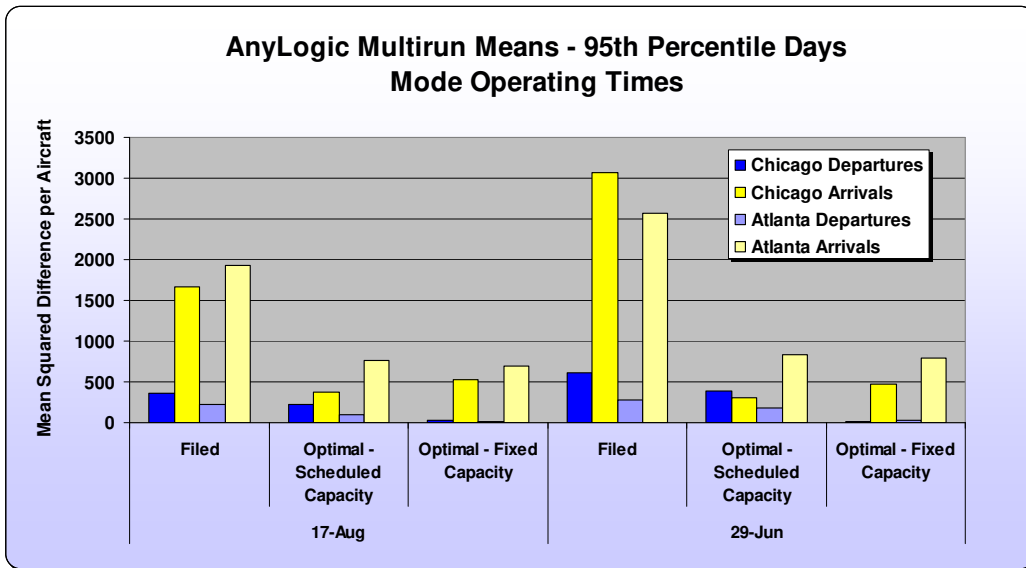


Figure 38: AnyLogic Comparison using Mode Operating Times (95th Percentile days)

Statistics assessing the significance of median and variance differences between the scenarios above were calculated for the scenarios using mode taxi and flight times. Table 7 below presents P-value statistics for the Mann-Whitney test for equality of medians as well as the F-test for equality of variance based on a 95% confidence interval. Values less than 0.05 indicate a significant change in median or variance based on the 95<sup>th</sup> confidence interval. Insignificant values are highlighted.

Table 7: Mann-Whitney and F-test P-value Statistics using Mode Times (95th Percentile days)

	Scheduled Optimal vs Filed				Capacitated vs Scheduled Optimal			
	August 17		June 29		August 17		June 29	
	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>
ORD Arrivals	0.0	0.008	0.0	0.0	0.0	0.0	0.0	0.0
ORD Departures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
ATL Arrivals	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
ATL Departures	0.0	0.001	0.0	0.022	<b>0.083</b>	0.0	<b>1.00</b>	0.0

Figure 39 below shows the results for the simulated scenarios using distribution times for taxi and flight times:

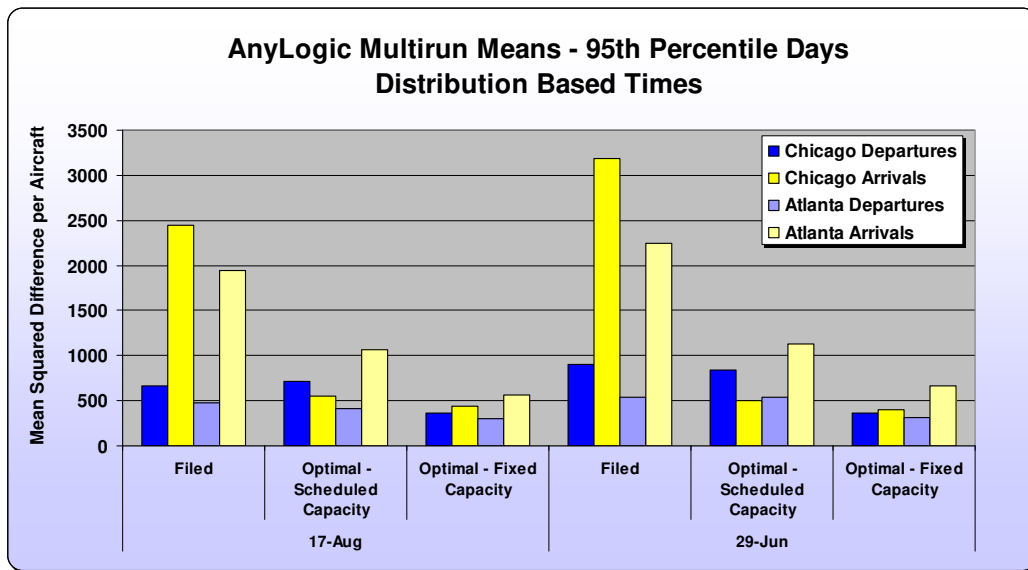


Figure 39: AnyLogic Comparison using Distribution Times (95th Percentile days)

The following Table 8 presents the Mann-Whitney and F-test P-values for the respective simulations using distribution flight and taxi times;

Table 8: Mann-Whitney and F-test P-value Statistics using Distribution Times (95th Percentile days)

	Scheduled Optimal vs Filed				Capacitated vs Scheduled Optimal			
	August 17		June 29		August 17		June 29	
	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>
ORD Arrivals	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
ORD Departures	<b>0.056</b>	<b>0.462</b>	<b>0.091</b>	<b>0.683</b>	0.0	0.001	0.0	0.0
ATL Arrivals	0.0	<b>0.059</b>	0.0	<b>0.117</b>	0.0	0.0	0.0	0.0
ATL Departures	0.037	0.0	<b>0.777</b>	<b>0.586</b>	0.0	<b>0.119</b>	0.0	<b>0.586</b>

Both figures show noticeable improvements in schedule reliability from the proposed schedule optimization procedure for airport arrivals at both ORD and ATL. Departures on the other hand show little significant differences in most of the schedules and occasionally the MSD is actually increased through the use of the optimal scheduling algorithm.

Focusing on arrivals, the use of the capacity constrained schedules shows a much less significant benefit when mode flight and taxi-times are used as compared to distribution times. Looking at the trends of arrivals in Figure 38 actually shows a slight increased in MSD when mode times are used with capacity constrained schedules.

### 75th Percentile days

The medium demand schedule of July 5 and July 17 generated the Mean MSD graphs presented below in Figures 40 and 41. Figure 40 presents the results of the 75<sup>th</sup> percentile day schedule simulated in AnyLogic using mode flight and taxi times:

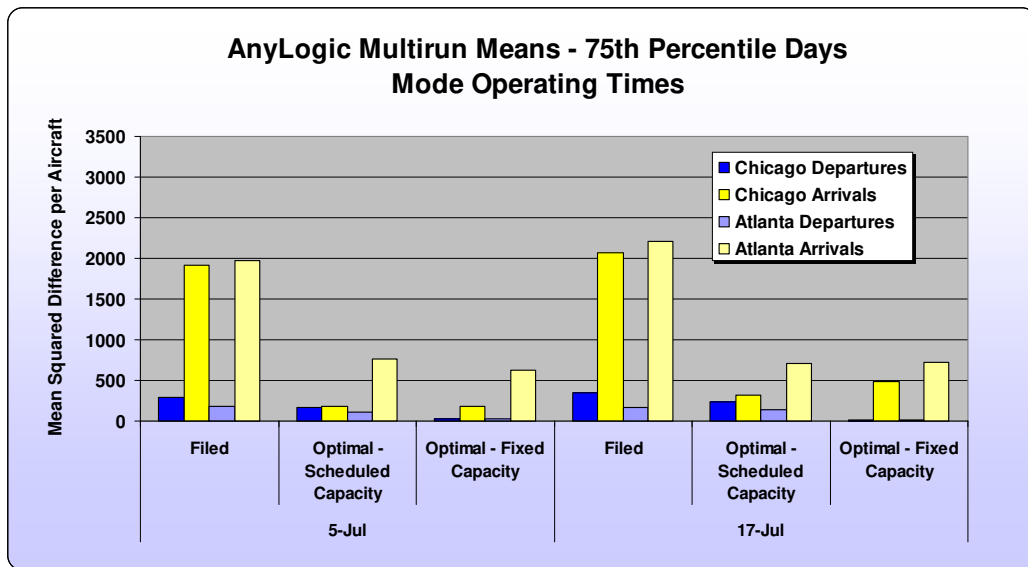


Figure 40: AnyLogic Comparison using Mode Operating Times (75th Percentile days)

Accordingly, Table 9 below presents P-value statistics for the Mann-Whitney test for equality of means based on a 95% confidence interval for the given 75<sup>th</sup> percentile day scenarios.



Table 9: Mann-Whitney and F-test P-value Statistics using Mode Times (75th percentile days)

	Scheduled Optimal vs Filed				Capacitated vs Scheduled Optimal			
	July 5		July 17		July 5		July 17	
	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>
ORD Arrivals	0.0	0.0	0.0	0.0	<b>0.669</b>	0.0	0.0	0.0
ORD Departures	0.0	0.0	0.0	0.017	0.0	0.0	0.0	0.0
ATL Arrivals	0.0	<b>0.259</b>	0.0	<b>0.050</b>	0.016	0.0	<b>0.553</b>	0.0
ATL Departures	0.0	0.0	<b>0.242</b>	0.002	0.0	0.0	0.0	0.0

Figure 41 below presents the same analysis but for AnyLogic scenarios that used distribution times for flight and taxi times:

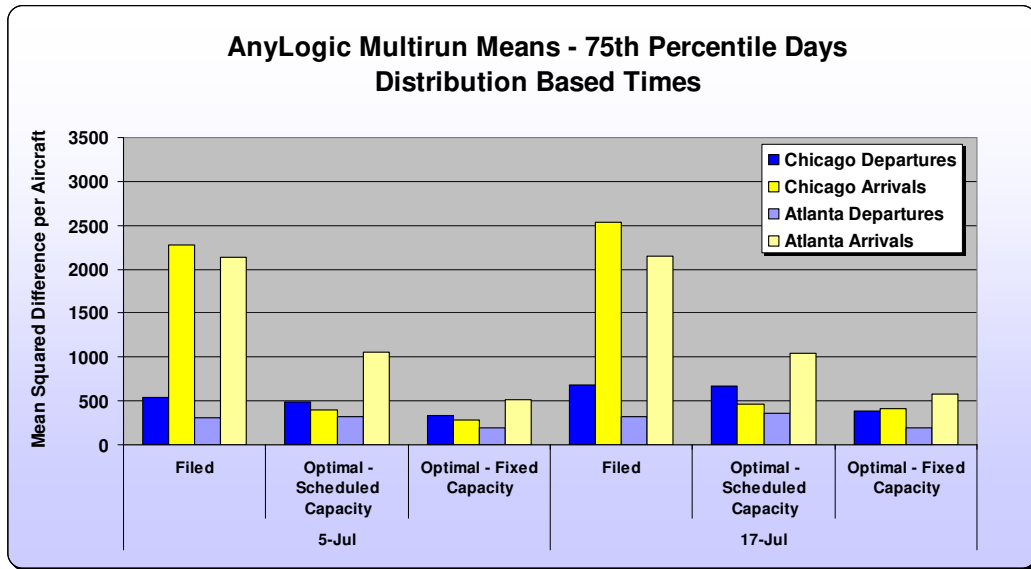


Figure 41: AnyLogic Comparison using Distribution Operating Times (75th percentile days)

The associated Mann-Whitney and F-tests for these distribution time scenarios is shown below in Table 10:

Table 10: Mann-Whitney and F-test P-value Statistics using Distribution Times (75th Percentile days)

	Scheduled Optimal vs Filed				Capacitated vs Scheduled Optimal			
	July 5		July 17		July 5		July 17	
	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>
ORD Arrivals	0.0	0.0	0.0	0.003	0.0	<b>0.123</b>	<b>0.055</b>	0.0
ORD Departures	<b>0.069</b>	<b>0.383</b>	<b>0.530</b>	<b>0.629</b>	0.0	<b>0.401</b>	0.0	0.002
ATL Arrivals	0.0	<b>0.381</b>	0.0	0.005	0.0	0.0	0.0	0.0
ATL Departures	<b>0.058</b>	<b>0.987</b>	<b>0.076</b>	<b>0.314</b>	0.0	0.002	0.0	0.0

The 75<sup>th</sup> percentile medium demand day schedules show similar trends to the high demand day schedules analyzed earlier. As expected the total MSD values are simply slightly lower than the respective values for the high demand day schedules.

Using mode flight and taxi times in the AnyLogic simulations generates significant improvements of the optimal schedules over the filed schedule. However, similar to the 95<sup>th</sup> Percentile day schedules, the benefit of using a capacitated optimized schedule in these scenarios is fairly minimal. The use of distribution times within AnyLogic indicates fairly insignificant changes in results for airport departures, indicating that airport arrivals benefit most from the optimization process.

### 95<sup>th</sup> Percentile day - Morning Hours

The AnyLogic simulation results for the schedules based on the 95<sup>th</sup> Percentile day morning hour periods are presented below. MSDs between scheduled and simulated flights using mode flight and taxi times are depicted in Figure 42:

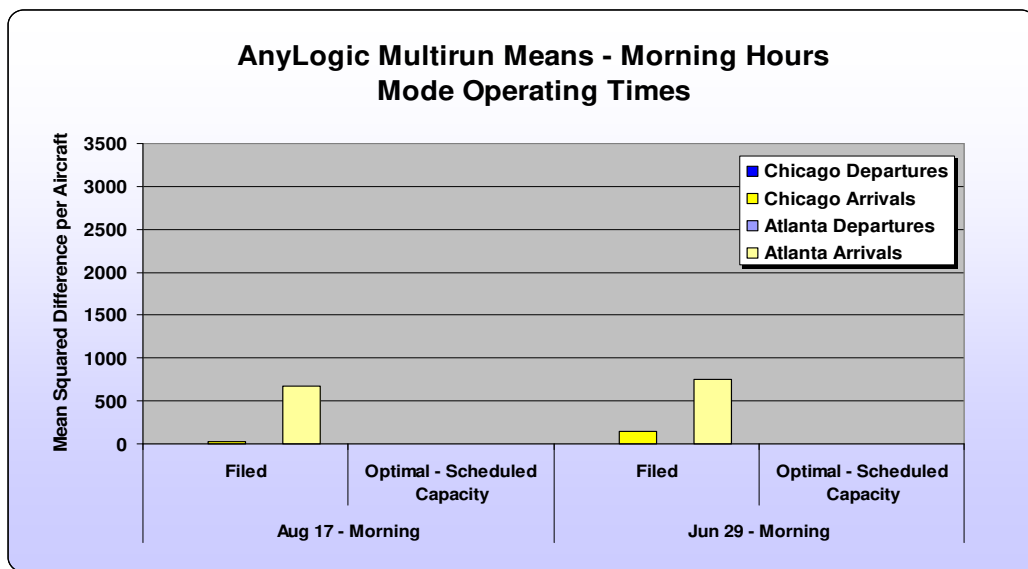


Figure 42: AnyLogic Comparison using Mode Operating Times (95th Percentile days - Mornings)

These values are significantly lower than the values generated by the medium and high demand days due to the lack of any capacity restricting factors in the simulation. The relatively low demand in these schedules means that the optimal schedule had few aircraft that deviated from their expected flight times when mode flight and taxi times are used.

The corresponding Mann-Whitney and F-test statistics are listed below in Table 11:

Table 11: Mann-Whitney and F-test P-value Statistics using Mode Times (95th Percentile day morning hours)

	<b>Scheduled Optimal vs Filed</b>			
	<b>August 17</b>		<b>June 29</b>	
	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>
ORD Arrivals	0.0	0.0	0.0	0.0
ORD Departures	<b>1.0</b>	0.0	<b>0.221</b>	0.013
ATL Arrivals	0.0	0.0	0.0	0.0
ATL Departures	<b>0.427</b>	<b>0.113</b>	<b>1.0</b>	0

Results for the same scenarios but with the use of distribution times for flight and taxi times is depicted below in Figure 43:

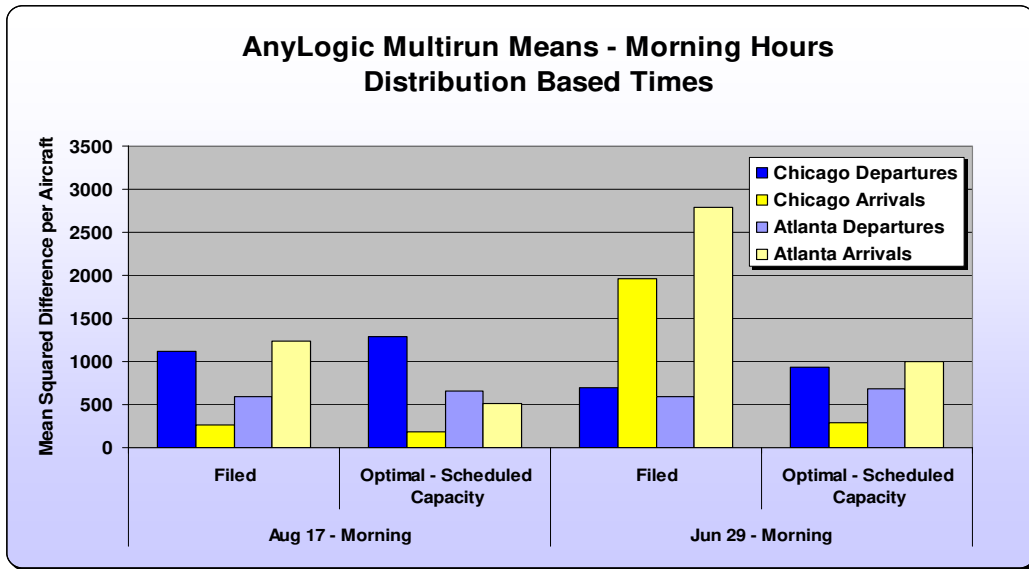


Figure 43: AnyLogic Comparison using Distribution Operating Times (95th Percentile days - Mornings)

The corresponding Mann-Whitney and F-test statistics are listed in Table 12:

Table 12: Mann-Whitney and F-test P-value Statistics using Distribution Times (95th Percentile day Morning Hours)

	Scheduled Optimal vs Filed			
	August 17		June 29	
	<i>M-W</i>	<i>F-test</i>	<i>M-W</i>	<i>F-test</i>
ORD Arrivals	<b>0.146</b>	0.043	0.0	<b>0.714</b>
ORD Departures	<b>0.128</b>	<b>0.973</b>	<b>0.720</b>	<b>0.709</b>
ATL Arrivals	0.0	0.021	0.0	0.007

ATL Departures	<i>0.396</i>	<i>0.438</i>	<i>0.412</i>	<i>0.950</i>
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These results show that the optimization algorithm has very insignificant effects on the departures in either the mode or the distribution time scenarios. Departure MSDs for distribution time scenarios actually increased.

August 17 showed consistently lower MSDs throughout due to the reduced traffic demand in the schedules when compared to June 29. This analysis indicates that very low demand periods benefit very little from the optimal schedules.

### **AnyLogic Multirun Categorical Analysis Comparison**

This section of the dissertation analyzes the AnyLogic simulation runs based on the previously defined categories of airport, aircraft, flight time, and airline usage classification (See Chapter 3 for details). The analysis is performed using the following methodology:

- Sum each flight's MSD by the categories previously identified
- Calculate the percent improvement or decrement of the optimal schedules' MSDs (by category) when compared to the filed schedule MSDs
- Average the percent improvements or decrements across the two airports and two subject days for each demand level

This method generates summary relative MSD improvements by category. A positive percentage value indicates an improvement in MSD of either the non-capacitated or capacitated optimal schedule over the filed schedule as simulated in AnyLogic.

### Departure Destination Airport Category

Percentage improvements for the departure destination airport categories is presented below in Table 18 for August 17 and June 29. The data is summarized across both days and across both airports for each category. Category 1 denotes the largest or busies airport which the FAA identifies as a large hubs. Category 5 airports are small general aviation airports. Improvements are presented for the scheduled capacity scenario compared to the filed schedule as well as the fixed capacity scenario compared to the filed schedule:

Table 13: Departure Destination Airport Category Percentage Improvements (95th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	46%	94%	26%	7%
2	45%	94%	25%	15%
3	49%	94%	25%	-24%
4	44%	94%	27%	6%
5	45%	94%	27%	1%

Using mode flight and taxi times, a clear improvement exists for both optimal schedules. However, the fixed capacity optimal schedule dominates with almost double the improvements. Using distribution times, the scheduled capacity scenarios show limited savings whereas the fixed capacity scenarios show almost no effects.

The respective data for July 5 and July 17 – the 75<sup>th</sup> percentile days – is presented below in Table 14:



Table 14: Departure Destination Airport Category Percentage Improvements (75th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	35%	90%	36%	-23%
2	29%	91%	45%	-17%
3	35%	91%	48%	-19%
4	27%	89%	43%	-27%
5	31%	91%	35%	-11%

The 75<sup>th</sup> percentile days show the same trends as the 95<sup>th</sup> percentile high demand days but at somewhat reduced rates.

The following table presents the percent improvements for departure destination airport categorical analysis for the low demand periods:

Table 15: Departure Destination Airport Category Percentage Improvements (95th Percentile Mornings)

Cat	Mode Times	Distribution
	Scheduled Capacity	Times Scheduled Capacity
1	0%	-5%
2	0%	-23%
3	0%	0%
4	0%	0%
5	0%	0%

In all demand scenarios, the fixed capacity optimal schedules outperform the scheduled capacity scenarios when mode times are used for flight and taxi times. When distribution times are used, the trend appears to reverse. Also, the benefits of the optimization algorithm appear to have fairly even effects across all of the departure destination airport categories.

## Departure Flight Time Category

Percent improvements for the departure flight time categories are presented below in Tables 16 through 18. Category 1 denotes the longest flights in the schedule.

Table 16: Departure Flight Time Category Percentage Improvements (95th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	30%	93%	-5%	42%
2	36%	94%	-10%	55%
3	46%	95%	2%	65%
4	40%	94%	4%	48%
5	49%	95%	0%	38%
6	47%	94%	2%	46%

Table 17: Departure Flight Time Category Percentage Improvements (75th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	15%	88%	-26%	38%
2	36%	91%	6%	57%
3	18%	82%	-15%	52%
4	23%	91%	5%	41%
5	33%	91%	6%	33%
6	33%	91%	-4%	43%

Table 18: Departure Flight Time Category Percentage Improvements (95th Percentile Mornings)

<b>Cat</b>	<b>Mode Times Scheduled Capacity</b>	<b>Distribution Times Scheduled Capacity</b>
1	0%	-21%
2	0%	0%
3	0%	38%
4	0%	-40%
5	-11%	35%
6	1%	-20%

This analysis by flight time categories shows relatively even improvements in MSD across all of the categories. In both basic scenarios – mode and distribution times – the optimal schedules with no capacity restrictions show relatively minor improvements over the airline filed schedules. The capacity-restricted scenarios however show very significant improvements over today’s airlines flight schedules.

The benefits observed by the high demand days slightly exceed benefits of the medium demand day periods. In contrast, benefits of the algorithm during low demand periods are almost negligible.

### **Arrival Aircraft Category**

The categorical analysis for arrival aircraft size is outlined below in Tables 19 through 21. Category 1 aircraft are the largest aircraft in the schedule including the four-engine Boeing B747 and Airbus A340 aircraft:

Table 19: Arrival Aircraft Category Percentage Improvements (95th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	98%	97%	94%	96%
2	32%	20%	24%	52%
3	35%	25%	26%	49%
4	23%	50%	6%	45%
5	-47%	-113%	18%	-245%

Table 20: Arrival Aircraft Category Percentage Improvements (75th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	98%	98%	95%	97%
2	28%	24%	16%	50%
3	31%	19%	15%	41%
4	18%	16%	-14%	-7%
5	26%	-95%	21%	-6%

Table 21: Arrival Aircraft Category Percentage Improvements (95th Percentile Mornings)

Cat	Mode Times	Distribution Times
	Scheduled Capacity	Scheduled Capacity
1	0%	10%
2	0%	8%
3	0%	24%
4	0%	-12%
5	0%	15%

The optimal schedules based on the high and medium demand periods show significant improvements over the filed schedules. The magnitude and trend shown in the analysis for these

two scenarios show high similarities. They indicate little extra improvements with restricting capacity during the optimization process. Low demand schedules generate absolutely no improvements with the mode time scenarios and very little improvement when distribution times are used.

An important trend seen in this analysis is the gradual reduction in benefits as the aircraft size gets smaller. This mirrors the multi-objectivity of the optimization approach since one of the goals is that larger aircraft receive priority in the arrival sequence. This goal would indicate that the optimization should produce the largest benefits for larger aircraft, which is exactly the case based on this analysis.

### **Arrival Flight Time Category**

The categorical analysis for arrival flight times is presented below. The breakdown of this category is exactly the same as for the departure flight time categories where Category 1 refers to the longest flights in the schedule.

Table 22: Arrival Flight Time Category Percentage Improvements (95th Percentile days)

<b>Cat</b>	<b>Mode Times</b>		<b>Distribution Times</b>	
	<b>Scheduled Capacity</b>	<b>Fixed Capacity</b>	<b>Scheduled Capacity</b>	<b>Fixed Capacity</b>
1	99%	99%	97%	98%
2	91%	93%	79%	83%
3	73%	89%	48%	57%
4	35%	-24%	21%	41%
5	29%	-9%	20%	45%
6	32%	23%	24%	54%

Table 23: Arrival Flight Time Category Percentage Improvements (75th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	99%	99%	97%	98%
2	99%	99%	97%	98%
3	43%	-72%	30%	-15%
4	39%	14%	16%	45%
5	26%	2%	13%	35%
6	26%	22%	14%	56%

Table 24: Arrival Flight Time Category Percentage Improvements (95th Percentile Mornings)

Cat	Mode Times	Distribution Times
	Scheduled Capacity	Scheduled Capacity
1	0%	0%
2	0%	0%
3	0%	-18%
4	0%	19%
5	0%	33%
6	100%	30%

The overall scale of the improvements seen with the application of the optimization algorithm mirrors those of the aircraft size category analysis. Benefits are largest for longest flights and tend to reduce with shorter flight times. Similarly, the benefits of the optimized schedules are basically non-existent in the morning hour schedules, which would indicate how optimal the airline filed schedule was in the first place.

### Arrival Airline Usage Split Category

The final airline goal implemented as part of the multi-objective optimization approach is that of airline usage. In this analysis, Category 1 of airline usage denotes the airlines which have the highest proportion of operations at each of the airports. This categorical analysis is presented below in Tables 25 through 27:

Table 25: Arrival Airline Split Category Percentage Improvements (95th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	80%	80%	65%	81%
2	84%	80%	73%	83%
3	89%	81%	85%	86%
4	15%	15%	8%	48%
5	35%	37%	23%	53%
6	53%	47%	59%	76%

Table 26: Arrival Airline Split Category Percentage Improvements (75th Percentile days)

Cat	Mode Times		Distribution Times	
	Scheduled Capacity	Fixed Capacity	Scheduled Capacity	Fixed Capacity
1	76%	80%	66%	84%
2	91%	89%	79%	86%
3	90%	88%	88%	91%
4	11%	6%	6%	47%
5	30%	21%	12%	45%
6	76%	74%	64%	77%

Table 27: Arrival Airline Split Category Percentage Improvements (95th Percentile Mornings)

<b>Cat</b>	<b>Mode Times Scheduled Capacity</b>	<b>Distribution Times Scheduled Capacity</b>
1	0%	0%
2	0%	0%
3	0%	32%
4	0%	-361%
5	0%	37%
6	83%	31%

This analysis shows significant improvements during the high and medium demand schedules listed in Tables 24 and 25. The scale of improvements when using mode flight and taxi times in the simulation scenarios is slightly lower than when distribution times are used. One significant difference from the previous categorical analyses for arriving aircraft is that the trend of improvements with increased categorical values is not as apparent. High use airlines do not receive significantly more benefits than low operations carriers. This may be caused by the categorical breakdown of the airline usage statistics themselves. If the breakdown caused a majority of airlines to be in the same category, then an uneven trend in improvements would likely results.

As with all previous analysis, the analysis of the morning hour schedules indicates minor improvements but exhibits no discernible trend.



## Sensitivity Analysis

A sensitivity analysis was performed on the arrival aircraft size factor. In this analysis the weight of this factor and its contribution to the fitness function was varied slightly above and below the original value. The original fitness function had equal weights for all of the different contributions including flight and taxi time distributions as well as all other airline and airport goals previously identified.

This analysis varied the weight of this single factor within the fitness function from one tenth ( $1/10^{\text{th}}$ ) of the weight of other factors to seven (7) times the weight. The analysis of MSDs using modes and distributions for flight and taxi times is presented below in Figure 44:

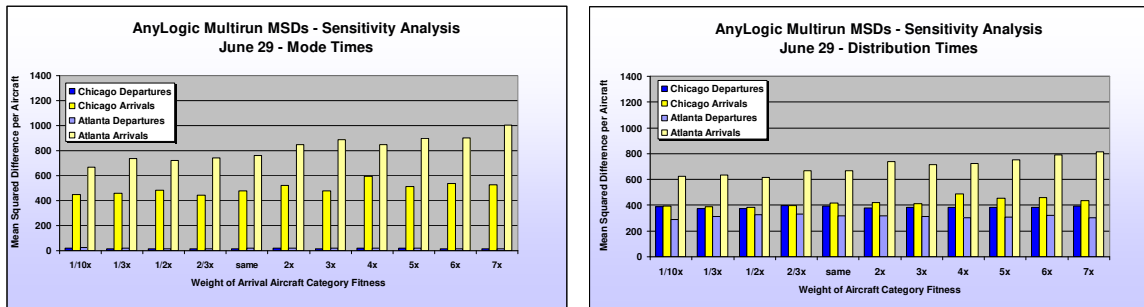


Figure 44: Sensitivity Analysis of Arrival Aircraft Category - AnyLogic MSDs

The figure shows a gradual increase in arrival flight MSD as the weight of the arrival aircraft category factor is increased. As expected, departure flight MSD is not affected since the factor being varied is arrival flight specific.

An additional analysis of the MSDs by each category of arriving aircraft size is shown below:

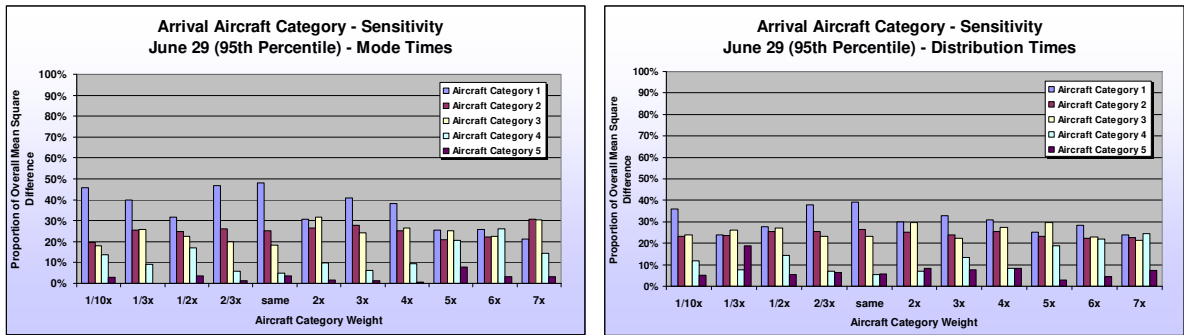


Figure 45: Sensitivity Analysis - Arrival Aircraft Category Analysis

Figure 45 gives an indication of the contribution to the overall MSD by each aircraft size category. The charts are grouped by simulations with varying arrival aircraft size factor weights from 1/10<sup>th</sup> through 7 times the weight of all other factors contributing to the fitness function.

Of primary interest in this analysis is the gradual reduction in contribution to the MSD of the larger aircraft categories. The MSD for category one aircraft is almost halved throughout the gradual increase of the factor weight. In sequence, the MSD contributions of higher category – lower size – aircraft are increased.

This trend in distribution of MSDs by arrival aircraft category is inherent in the setup of the individual fitness function of the aircraft size goal within the global fitness function. The function is basically a linear degradation of importance of delay by increasing aircraft size category. This means that higher size aircraft should see a higher likelihood of MSD reduction.

## **CHAPTER FIVE: CONCLUSION**

This section of the dissertation summarizes the results and finding from the previous chapter and draws conclusions based on these findings and the methodology described in Chapter 3. The results are summarized and associated benefits are discussed. This chapter also summarizes the applicability of this methodology to various stakeholders and outlines the major contributions via a high-level cost-benefit template.

This summary is followed by a discussion on future research and work that has been identified throughout the course of this research project. Various ideas on improvements to the fitness function as well as the optimization process itself are discussed.

A short overall summary of the entire dissertation concludes this chapter and the dissertation.

### **Summary of Analysis Data and Benefits**

Based on the detailed analysis of data performed in the previous chapter, a summary evaluation of the performance of the schedule optimization algorithm produced the following results:

- The algorithm consistently and significantly produces performance increases of greater than 70% for arriving aircraft irrespective of the demand level
- There is little difference in arrival benefits between mode time (4-D trajectory control) and distribution time (current/historic dispersion) scenarios. This indicates that the algorithm will produce performance benefits for arrivals today and in the Next Generation System (see Figure 46).

- The algorithm produces significantly more benefits for departures primarily when the algorithm is instructed to use limited departure runway capacity rather than scheduled demand capacity (see Figure 47).
- Departure benefits are primarily observed in scenarios where mode time or 4-D trajectory control is implemented. The benefits in this scenario are at least twice that of using distribution times (90% versus 40% using mode flight and taxi times).
- The multi-objective nature of the algorithm provides for a way to assign priorities to flights based on various factors. Figure 48 and 49 show that the algorithm correctly favors higher priority flights and causes their on-time performance to be improved over lower priority flights
- The algorithm's performance with respect to airline and ATC priorities is higher in 4-D trajectory control scenarios (using mode times), indicated by a higher negative slope in Figure 48 over Figure 49. This means that the algorithm will perform better in the next generation ATM system

In essence, the results indicate that the algorithm proposed in this dissertation produces significant on-time performance improvements over the current day operation. It also efficiently provides for increased control in schedule production over airline and ATC priorities. Using the algorithm, it is possible to give arrival priority to larger aircraft. This proportionally increases the on-time performance of larger aircraft over smaller aircraft while still producing an overall optimal schedule with significantly improved performance over today's operation.

The proposed algorithm produces significant benefits for a number of stakeholders including the following:

- For airlines
  - More predictable operations reducing the need for tactical decision making
  - Higher passenger satisfaction with increased on-time performance
  - Increase capability to strategically plan ground resources
  - Better fuel planning and reduced fuel usage
  - Reduced flight times meaning a reduction in maintenance workload
- For airports
  - Improved traffic flow coupled with reduced ATC workload
  - Reduced weather impact and need for GDPs
  - Increased airline satisfaction
  - Increased ground operations efficiency
- Other
  - Reduced flight times generating less environmental pollution and carbon emissions
  - Increased reliability in the schedule means an automatic increase in reliability of other applications that depend on these schedules including gate management and crew/staff resource scheduling

A more detailed conclusion of the overall performance of the algorithm as well as the categorical analysis and the performance of the multi-objective nature of the algorithm is

discussed in the following section. This is followed by a short high-level discussion of costs and benefits for various stakeholders.

### **Benefits and Overall Performance**

The overall performance of the schedule optimization algorithm is based on the total values of MSD obtained using AnyLogic simulation models across various demand schedule scenarios. Clearly, differences in performance exist as demand levels change. The performance of the optimal schedules also appears to be heavily influenced by the capacity-limitation of the schedule optimization process as well as the use of mode of distributions times during the simulation evaluation.

Based on the results outlined previously in Chapter 4, summary graphs showing average improvements of the optimal schedules were prepared. These figures are based on average improvements or decrements of MSD across the paired demand level days. A summary analysis of airport departures across both airports is presented below in Figure 46:

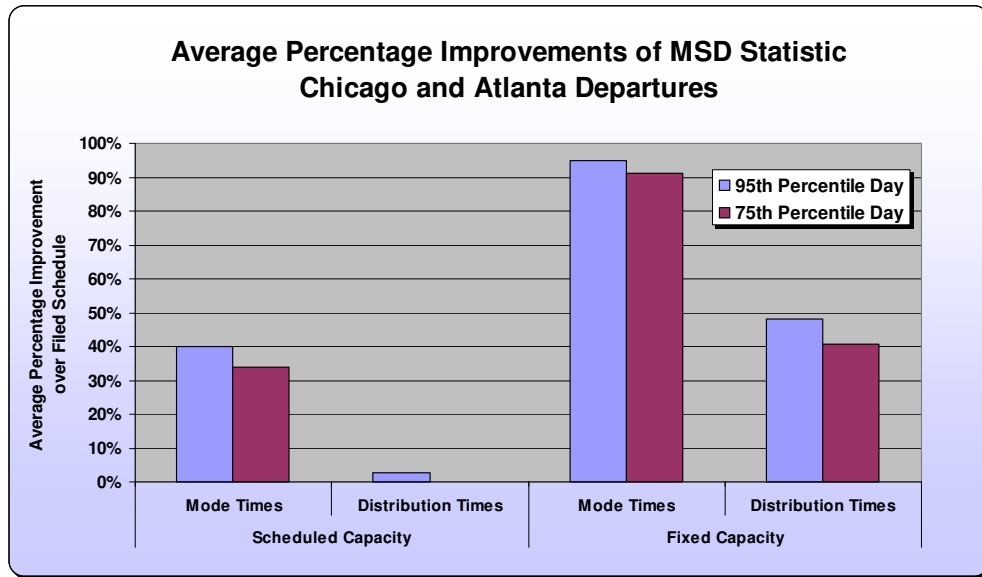


Figure 46: Average Percentage Improvements of MSD - Departures

Based on the figure above, it is clearly evident that highest benefits for departing flights are obtained when the optimization algorithm optimizes a flight schedule with a predicted and fixed airport capacity in mind. This reinforces the recommendation that improved airport capacity forecasts will yield significantly more reliable airline schedules. Clearly if flights are scheduled to depart at or under runway capacity, very little delay will be encountered on taxi-out.

The figure above also indicates that the use of mode flight and taxi times in the simulation analysis generated a significantly higher benefit compared to the distribution time scenarios. The use of mode times mimics the concept of 4-dimensional trajectory control where aircraft are perfectly capable of flying their routes and meet ETAs highly accurately. The results suggest that in a system where aircraft are 4-D trajectory capable, highest benefits for arriving flights will be observed. In fact, a greater than 90% improvement may be achieved when fixed capacities are included in the optimization algorithm. Since this is a concept of the Next

Generation ATS, these results should support the need for such a system. In a current-day scenario where distribution flight and taxi times represent a more unpredictable system, benefits favor a scenario where the optimization algorithm is implemented with fixed airport capacities. An improvement greater than 40% is projected during this scenario.

Despite variability across days within each demand level, average improvements show a decreasing trend with reduced departure demand. Although a relatively minor drop in improvement is observed between the 95<sup>th</sup> and 75<sup>th</sup> percentile day schedules, the morning schedule data shows absolutely no improvement in departure flight reliability. This is likely because of the lack of any capacity constraints during these time periods. When demand is significantly below capacity, aircraft depart whenever scheduled since they see very little delay along their entire route.

The same analysis was performed for airport arrivals. Figure 47 below summarizes these average improvements:



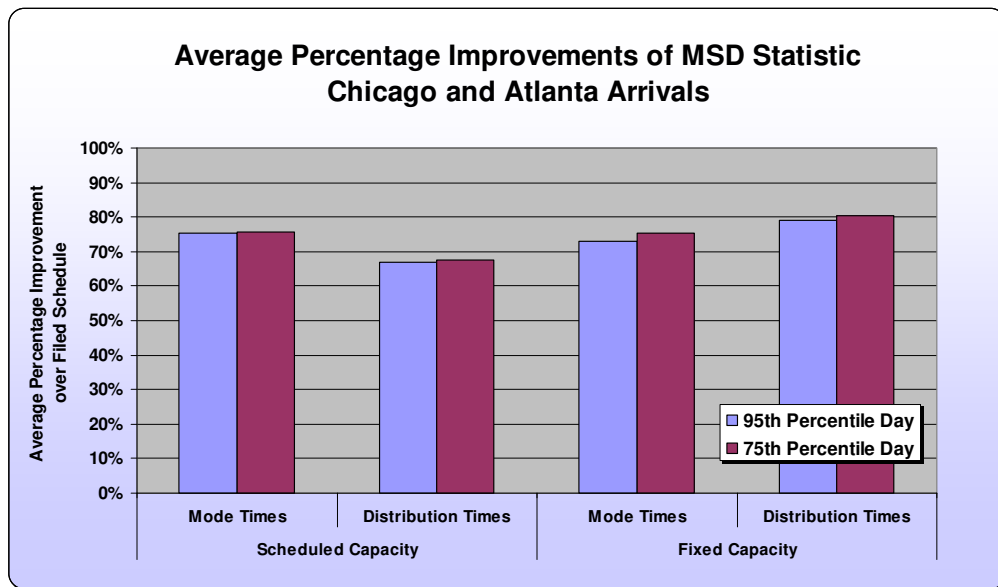


Figure 47: Average Percentage Improvements of MSD – Arrivals

In contrast to departures, arrivals show a fairly consistent improvement across the analysis. Using arrival runway capacities in the optimization process seems to only slightly benefit the optimization. Using this fixed airport capacity causes the distribution time scenarios to show higher improvements over using mode flight and taxi times. This seems to indicate that despite adding variability into the system with distribution flight and taxi times, the use of fixed arrival runway capacities in the optimization process reverses the trend previously seen for departures in Figure 46.

Another interesting fact shown in this arrival flight analysis is that reduced demand scenarios do not show reduced improvements in MSD. Despite some variation in the days within each demand level, the 95<sup>th</sup> and 75<sup>th</sup> percentile day periods show very similar results in each scenario. Although not shown in this figure, the low demand – morning hour – period data

shows a distinct benefit for arrivals. This can be attributed to a lack of capacity constraints during these time periods. It is also likely that in a real-world schedule these morning arrivals were expected to encounter more severe capacity limitations at their origin airports.

Overall, these summary results indicate that improvements in arrivals outweigh those of departures. This result should be taken with caution though, since other than ORD-ATL flights, destination airport queues and delays are not modeled for departures. The results indicate that the majority of delays are encountered in the arrival sequence. A more complete simulation would be required to properly model these effects.

Arrivals, on the other hand, are modeled in detail and show distinct improvements in predictability through the use of the optimization algorithm. The schedule predictability increases slightly with the use of reliable airport capacity forecasts. More interestingly, the results show that in a scenario where aircraft can fly highly reliable trajectories, the schedule optimization approach can significantly improve the on-time performance of the departure schedules to levels above 70%.

Overall, the results also indicate how airlines routinely over-schedule their flight times unnecessarily in order to meet their on-time performance. This reduces the system's ability to strategically plan for the incorrect projected demand levels. An optimization approach based on historic flight times, taxi times, and airline/ATC preferences would significantly improve demand planning practice at airports. This is particularly true during high demand periods where demand exceeds capacity.

## **Effects on Airline, Airport, and FAA Goals**

In addition to showing distinct on-time performance improvements, the schedule optimization algorithm also caters for multiple objectives including airline and airport goals and preferences. The ability to define differences in priorities for flights adds to the uniqueness of this algorithm. Providing for ways to optimize on-time performance alongside of differentially treating aircraft at varying priorities makes this approach very unique.

Based on the set of airline and airport goals identified in Chapter 3, the priority treatment of larger aircraft, longer flights, higher use airlines, and larger destination airports was accomplished. The categorical analysis presented in Chapter 4 indicates that the results are in line with the intended goals.

Figures 48 and 49 below present a summary of improvements across the various categories for the high demand fixed capacity scenarios. These trends are mirrored in the other 75<sup>th</sup> percentile day as well as the scheduled capacity scenarios.

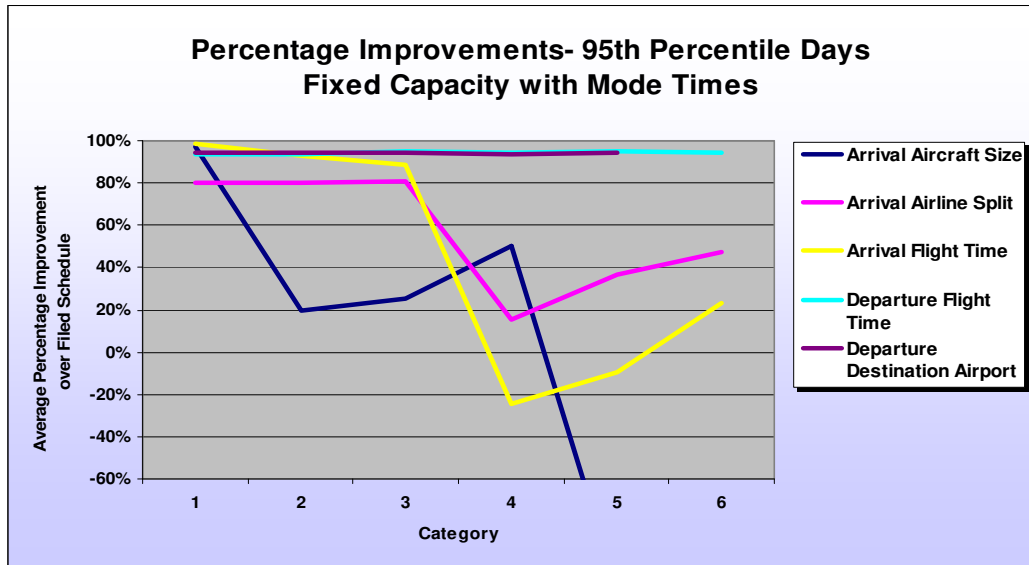


Figure 48: Percentage Improvements by Category - 95th Percentile with Fixed Capacity and Mode Times

The chart above clearly indicates a distinct preference of lower category flights by showing higher improvements for these flights. This theory holds for arriving flights only. Departures show an even trend of improvements across all categories, which may be primarily attributed to airlines evenly over-scheduling flight times across all categories for these departures. Again, detailed modeling of destination airport queues may alter these results.

The same analysis was performed for the scenarios that used distribution flight and taxi times. This is presented in Figure 49 below:

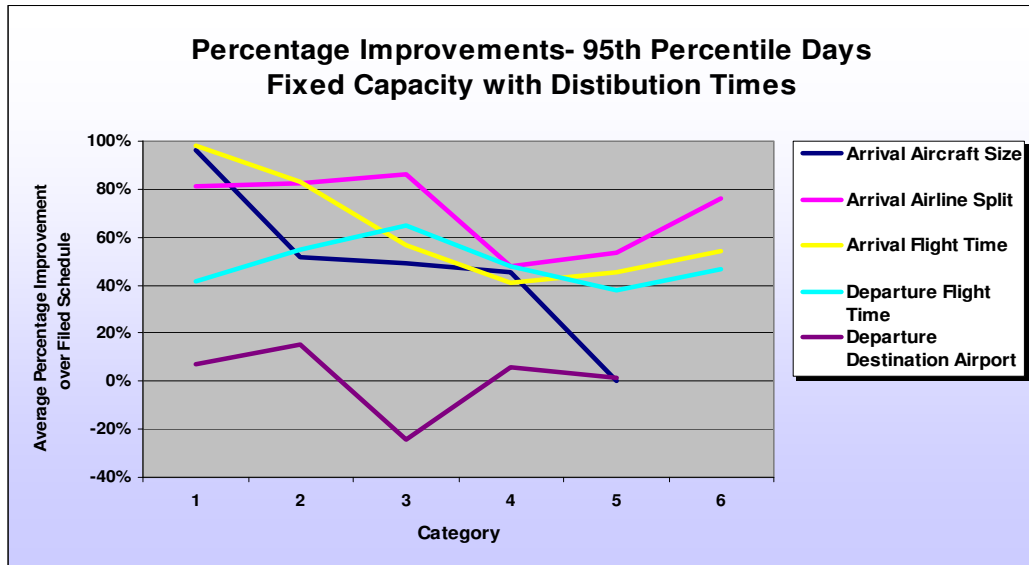


Figure 49: Percentage Improvements by Category - 95th Percentile with Fixed Capacity and Distribution Times

These results using distribution times show somewhat different trends. For arrivals, despite still showing a decreasing trend with increased category, the magnitude of this trend is much smaller. The percentage improvements of departures show much more realistic improvements compared to the previous figure. A minor decreasing trend can actually be observed in the treatment of flights by departure destination airport category.

Overall, the trends observed in this categorical analysis show the impact of the contribution of these goals to the overall schedule. Lower category aircraft show the highest on-time performance improvement for arrivals. The data also support the statement that in a 4-D trajectory-based environment, the impacts of these goals are further amplified with higher slopes in the trends.

Based on the magnitude of improvements of the distribution time scenarios, departures show much more realistic improvements. In a 4-D trajectory environment where capacity constraints have been provided for in the optimization process, departures are shown to fly their routes highly accurately across all category aircraft. These results for departures should again be taken with caution since destination airport queues are not modeled.

A sensitivity analysis performed on the arrival aircraft size category showed the effects of varying the importance of a single factor in the global fitness function. Higher weights on this factor generate higher improvements for large aircraft and proportionally smaller improvements for small aircraft.

The balancing of factor weights in the fitness function is an integral part in this optimization process and represents a large part of the uniqueness of the proposed application.

### **Cancellations and Slot Swaps**

The optimal schedules produced by the proposed algorithm essentially generate landing and departure rights for airlines at the subject airports.

In any case, airlines may disagree with certain slots for their aircraft due to inability to meet the proposed slot times or because they want to prioritize certain flights due to specific reasons that were not included in the algorithm. In these instances, it is expected that airlines will be able to trade aircraft between slots that were originally assigned to their airline. It is also feasible that airlines may trade slots with other airlines to produce a more airline-optimal schedule based on the given day's operating environment. Although this, in theory, reduces the overall optimality of the schedule, the proposed schedule still gives ownership of slots to airlines.

Naturally, FAA TFM will need to approve these slot swaps to ensure FAA goals are not contradicted.

It is also common that airlines may cancel flights due to inclement weather, aircraft maintenance, or other capacity restrictions. In this case, the airline which owns the slot is expected to have first priority in filling the given slot time. If they are unable to do so, it is expected that this slot will be offered in order to flights scheduled in subsequent slots.

### **Cost Benefit Analysis**

A detailed cost-benefit analysis was not performed for this application due to the lack of detailed information on the effects of improved schedule reliability. Primarily, a lack of detailed cost information for the implementation of this application is what limits this analysis. Different parties will likely also interpret the benefits of these optimal schedules in a different way. A summary of economic benefits is provided below for each stakeholder:

- Airlines
  - Higher on-time performance (reduced delays)
  - Increased passenger performance
  - Improved crew and equipment scheduling
  - Better fuel planning
  - Increased passenger satisfaction
  - Optimized gate usage
- Airports
  - Improved ground equipment scheduling

- Increased passenger satisfaction
- More level security screening demand
- FAA
  - Improved traffic flows and reduced airspace congestion
  - Reduced need for irregular operations due to weather
  - Reduced flight times
  - Reduced controller workload

Future research should investigate the detailed costs and benefits of this application further in order to explore the utility of this approach in a real-world financial environment.

### **Scalability**

The optimization method described in Chapter 3 divides the overall airline schedule into subsets of queues with each airport having separate queues for arrivals and departures. This breakdown simplifies the addition of new airports as additional queues to be optimized within the process. Increasing the number of hours to be optimized linearly increases the size of each departure and arrival queue.

From a programming perspective, adding additional hours for optimization is a very simple process and simply accomplished by modifying a single parameter within the JGAP framework. The number of genes in each chromosome is subsequently easily modified.



Adding additional airports is a more difficult exercise since in the current implementation of the algorithm the number of chromosomes is fixed. Using the current single threaded algorithm, significant software changes would be required.

All things equal, the primary problem with scalability for this methodology is the limited amount of resources for processing. The time required for processing each optimal schedule exceeded 40 minutes on a single processor laptop computer. The processor and memory usage was maximized during each execution.

The parallelization of the algorithm using multiple threads as an alternative is further discussed in the subsequent section on Future Research.

### **Extendibility of this Methodology**

The proposed methodology is concerned with the scheduling of flights in and out of airports. It is primarily based on historically observed transit times in the air and on the ground but is also capable of incorporating certain preferences. In this application, aircraft operate in and out of capacity-constrained airports.

This basic principle of entities moving between capacitated resources in a three-dimensional environment is extendible to a number of different applications. The basic requirements are that data for transit times is available for analysis and that detailed information on capacity restrictions of the various resources is given. The premise of this approach could then be easily extended to a number of other applications, including maritime or rail transportation.

## **Future Research**

Throughout the course of this research effort, several areas for future research have been identified. These areas can be broadly categorized into three categories: (1) research into improvements of the fitness function, parameters, and input distributions, (2) research into the improvement of the optimization process itself, and (3) research into improvements for quantifying the benefits of the proposed methodology. Each of these areas is covered in turn.

### **Fitness Function and Distribution Parameters**

The novel schedule optimization approach outlined in this dissertation contains core fitness function components and inputs that were identified as important with respect to FAA TFM, airport management, and airlines. The inputs and parameters of the EA were based on aviation data that was available during the process of this research. However, in order to develop this product into a viable solution for airports, airlines, and the FAA, several areas warrant further in-depth research. Several of these future research areas are discussed below:

### **Weighting Factors**

As described in Chapter 3, all of the different factors that contribute to the overall fitness function are weighted per their expected contribution to the overall schedule. To simply and conceptually show the multi-objectivity of this approach, all of the factors were treated with equal weight. This means that airline, airport, and FAA TFM goals were all treated to be of equal importance in the optimization process. The effect of simply changing a single parameter weight was obvious in the analysis of sensitivity of the arrival aircraft size category factor.

In a real-world scenario however, certain goals may require increased weight on a standard or scenario-specific basis. For example, if this application is used for primarily TFM purposes, the flight and taxi-time distributions may govern the optimization with minimal input of airline and airport goals. It may also be possible that goals based on airline usage statistics at each airport have minimal effects on the overall optimization when compared to, for example, aircraft size considerations.

Further research is required to fine-tune these factor weights not only from a high-level stand-point but also for scenario-specific applications (i.e. airline, airport, or FAA TFM usage of the optimization tool).

### **Categorical Breakdown**

All of the contributions to the fitness function that are based on airport or airline goals contain categorical breakdowns in scaling their global fitness contribution. For example, large aircraft receive preferential treatment over small aircraft when assigning runway arrival slot times. Although for some factors the categorical breakdown is based on existing heuristics, other categories were developed specifically for this application.

Airport and aircraft size categories are based on FAA guidelines for airport classification and on aircraft wake turbulence criteria. Airport categories are assigned based on the operations counts at an airport and aircraft categories are based on the size of the aircraft and the required separation between subsequent arrivals or departures for the same and other aircraft types. On the other hand, the flight time categories as well as the airline usage split categories were developed specifically for this research effort. Despite following a basic linear breakdown into

equally sized bins of flight time and airline usage percentage, the size of each category was chosen arbitrarily based on the range of data that was at hand. Further research may be needed to investigate the bin sizes for these two variables. For example, it may be more beneficial to the overall optimization to divide flight time categories into bins that linearly grow by 50 minutes of flight time rather than the existing 100 minutes.

### **Airport Capacity Information**

An integral aspect of this application is the schedule optimization given certain predicted airport capacities. As future research efforts are identified to improve the optimization of the schedule itself, parallel research should be carried out to identify advanced airport capacity information sources. Using the known adage of “the quality of the outputs depends on the quality of the inputs”, improvements in forecasting airport capacities under various weather conditions would improve the schedule optimization’s ability to optimize airline schedules around this capacity constraint. Examples of more advanced airport capacity forecasting techniques include Fleming et.al., (2001).

### **Additional Factors for Flight and Taxi Time Distributions**

The flight and taxi time distribution data was processed from data that was readily available throughout this research effort. Both the ASDI and BTS data sources give fairly inclusive flight-by-flight information but do, by nature, not include information that may be used to further identify significant variables within the datasets.

For instance, weather information would be a very valuable additional source of information. Specific information on meteorological conditions during flight operations may prove useful in generating flight time distributions for specific weather types at the airports or along the flight routes. Data regarding the wind effects on aircraft along routes would be a very valuable addition to the input data and would likely assist in producing an even more predictable and viable schedule.

### **Isolation of Airport-Centric Effects in Distribution-based Data**

The input time distributions for flight taxi times are records of actual events in the NAS. This means that system delays are inherently included in the time distributions. For the purpose of this application, the scheduling of flights requires the inclusion of expected delays in planning an optimal airline schedule (airlines routinely practice this over-scheduling of flights based on expected delays, etc.). However, the distribution data includes flight times that are inherently affected by events outside of the scope of the airports under study. For example, flights from Rome, Italy to ORD may routinely see delays in European airspace due to airspace congestion over Western Europe.

Since the datasets are used to describe expected flight and taxi times, all of the delays along a flight's route are included in the distributions. However, a dissection of delays by the subject airport's runway queues and delays incurred externally would help in further refining the scheduling process.

Also, information on ATC system delays such as GDPs or TFM practices may further refine the flight and taxi-time distributions by separating normal from non-normal days in the historic data.

### **Turn-Around Times**

The original proposal for this research project included the inclusion of aircraft turn-around times within the fitness function. The intent was to link inbound with outbound aircraft and use turn-around time distributions to probabilistically describe and model the times between aircraft gate arrivals and subsequent departures. The current implementation of the algorithm treats arrivals and departures as separate queues and does punish departures based on tardy arrival flights. While from a strategic planning perspective this is a reasonable assumption (airlines frequently swap and substitute aircraft to retain schedule integrity), the scenario would be more realistic if the turn-around link was provided for in the fitness function.

The reason for not including turn-around times in the analysis primarily lies in the availability of sufficient data to generate the turn-around time distributions. After some initial data processing of the BTS and aircraft registry data, it quickly became apparent that the turn-around time data generated was not sufficiently reliable for this application. Although aircraft registry and tail number data allowed for the linking of inbound with outbound flights in the historic BTS data, the turn-around times included too many data points for overnight stays, maintenance periods, and additional uncharacteristic time spent at the gates.

Future research on this topic should focus on producing a more reliable turn-around time dataset based on more accurate airline internal data. The linking of inbound with outbound aircraft within the schedule would add significant realism to the optimization scenarios.

### **Destination Airport Queues**

The nature of the simulation analysis for the proposed algorithm only simulated the airport queues at the airports under investigation. This appears to properly describe the arrival sequence process for arriving flights, but does not simulate delays for departing aircraft along their routes and into their destination airports.

The results indicate that this fact may overestimate the benefits for departures particularly for scenarios where mode times are used for flight and tax times. A more complete modeling of airport capacities throughout the NAS would likely have given more realistic on-time performance improvement results for departing aircraft. While this does not affect the optimization process itself, the expansion of the simulation model to cater for this would produce more accurate predictions of benefits for further analysis.

### **4-Dimensional Trajectory Control may increase Airport Capacity**

The optimization algorithm is capable of incorporating airport capacity in the overall slot allocation scheme. As mentioned previously, the algorithm would benefit from more accurate capacity predictions. Future research on this topic should consider the implications on capacity when 4-dimensional trajectory control is implemented. It has been shown that early implementations of this concept such as continuous descent approaches (CDAs) may actually

increase airport capacity (Wilson & Hafner, 2005). This may affect the optimization algorithm itself as well as any subsequent simulation assessments of this methodology.

### **Environmental Impacts**

The current fitness function in the proposed algorithm is predominantly based on empirical distributions of historically observed flight times and airline/ATC priorities. This means that the flight and taxi time component of the fitness functions produces the same fitness for a small aircraft flying and taxiing at mode times as for a large aircraft. This is then complemented by using priorities for larger, longer, and more important flights to ensure that they deviate the least from the mode times.

One aspect that has not been addressed explicitly is that of carbon emissions. Emissions are implicitly reduced by favoring the operations of larger, more polluting, aircraft. However, the emissions produced by an aircraft may not necessarily follow the aircraft size categories. Emissions are not only affected by the size and quantity of engines on an aircraft but also the quality and efficiency of the aircraft engines themselves. Future research should investigate the addition of an emissions goal into the fitness function.

### **Ranking of Airports for Multi-Airport Use**

The proposed algorithm provides for a way to expand arrival and departure slot planning to a multi-airport network. Throughout the evaluation of this algorithm, only two airports have been used, both of which are major hub airports in the US. It stands to reason that if the algorithm were to be expanded to more airports, major hub airport operations would have a



higher importance over operations at non-hub small airports. Some form of ranking of airports (based possibly on the existing airport size categories) should be implemented within the Fitness Function to provide for this priority scale.

### **Optimization Process**

In addition to research focused on improving the composition of the Fitness Function, improvements to the actual optimization process are also of interest. Future research into alternatives or enhancements to the EA approach used in this application may yield ways for obtaining better schedules in a more time-efficient manner. Some potential research areas for process improvements are discussed below:

#### **Additional Operators**

The EA used for this application solely used the swap or exchange mutation operator to mutate the schedules throughout each evolution of the population. The reason for this decision was simply the capability of JGAP and existing classes of operators which preserved uniqueness in the gene values (see Chapter 3 for a more detailed discussion on this topic).

Research into other mutation and crossover operators may yield faster optimization methods. Crossover operators such as the sorted match crossover or the cycle crossover combined with mutation operators such as inversion or scramble mutation may give more optimal results in a more expedient way (Larranaga, Kuijpers & Murga, 1998).

### **Particle Swarm Intelligence**

An area of research that has recently gained some attention is particle swarm intelligence. Similar to GAs, this optimization method is also based on a Fitness Function that is optimized through evolutions of population mutation and crossover. An interesting distinction between particle swarm optimization and GAs is that the focus not only lies with the optimization of a global fitness function but also the maximization of local neighborhood fitness (Kennedy, 2001). Individual particles also communicate their fitness locally to other particles.

In an application of scheduling where not only the overall quality of the schedule is important but also that individual airlines, groups of flights, or individual flights obtain optimal local fitness, particle swarm intelligence may be a beneficial option. Actually, this tradeoff of overall quality of the schedule versus individual or airline optimality may be an interesting area of study itself.

### **Scaling of the Optimization Process**

As discussed previously, the current application scales easily on a single machine by threading the execution of each individual queue's EA program and then subsequently combining the results. In theory this makes optimal use of a system's processing resources. While this is manageable for a limited set of airports and hours, larger scenarios will likely require significantly more processing power.

Future research may explore the use of computational clusters or grid computing with this application. Being able to widely distribute subsets of the schedule optimization approach

across a network of machines increases the potential size of the problem significantly.

Optimization tasks could be

- Distributed as threads for subsets of the schedules or
- Individual fitness computations for sets of populations can be sent out to networks of machines with global optimization performed on a central host

### **Quantification of Results**

As mentioned previously when addressing costs and benefits of the proposed methodology, the simulation analysis used to evaluate the performance of the algorithm was based on a comparison of proposed versus originally filed flight schedules. In addition to this analysis of theoretical performance improvements, a comparison of the proposed, enhanced schedules versus the actual observed operations for the given demand schedule periods can be performed.

The basic issue with this comparison of simulated versus real-world data is that the real-world scenario naturally includes delays and other environmental impacts that cannot be simulated. For instance, in a situation where weather in the New York area delayed all flights out of ORD and ATL destined for New York, the real-world actual data is not directly comparable to a simulated enhanced schedule of the same time period.

Future research may be able to find ways of isolating delay effects to single airports and provide ways for performing a more detailed performance analysis using real-world data as the baseline. This notion was also previously introduced with respect to future research into the flight time distributions and the localization of delays within these distributions per each airport.

**APPENDIX A**  
**OIS AIRPORT ARRIVAL CAPACITY DATA FOR CHICAGO O'HARE**

The rates given below are for good weather (VFR) as well as inclement weather (IFR) and reflect the number of FAA planned arrivals per hour at Chicago O’Hare International Airport under the given circumstances:

Table 28: Chicago O'Hare FAA Airport Acceptance Rates (Arrivals)

<b>Landing Runways</b>	<b>Departing Runways</b>	<b>IFR Weather</b>	<b>VFR Weather</b>
14R 22R	9L 22L 27L	80	<b>94-96</b>
22R 27L	32L 32R 22L	80	<b>96</b>
4R 9L	4L 9L 32L 32R	64-72	-
32L 27R	22L 27L 32R	72-80	-
9R 14R	4L 9L 22L	80	<b>100</b>
4R 9R	4L 9L 32L 32R	80	<b>100</b>
14L 14R	9L 9R	68	-
27L 27R	22L 32L 32R	76-80	-
32L 32R	22L 27L	68	-
4L 4R	9L 9R 32	68	-

**APPENDIX B**  
**OIS AIRPORT ARRIVAL CAPACITY DATA FOR ATLANTA**  
**HARTSFIELD-JACKSON**

The rates given below are for good weather (VFR) as well as inclement weather (IFR) and reflect the number of FAA planned arrivals per hour at Atlanta Hartsfield Jackson International Airport under the given circumstances:

Table 29: Atlanta Hartsfield Jackson FAA Airport Acceptance Rates (Arrivals)

<b>Landing Runways</b>	<b>Departing Runways</b>	<b>IFR Weather</b>	<b>VFR Weather</b>
<u>27L 26R</u>	<u>27R 26L</u>	<u>68-78</u>	<u>80-86</u>
26L 27L	26L 27R	55	<b>65</b>
26R 27R	26L 27R	55	<b>65</b>
26R 27L	27R	37	<b>42</b>
26L 27L	26L 27R	45	<b>45</b>
<u>8L 9R</u>	<u>8R 9L</u>	<u>68-78</u>	<u>80-86</u>
8R 9R	8R 9L	55	<b>65</b>
8L 9L	8R 9L	55	<b>65</b>
8L 9R	9L	37	<b>42</b>

The underlined configurations mark the preferred runway configurations at Atlanta with a four runway operation.

**APPENDIX C**  
**ANALYSIS OF DAILY OPERATIONS COUNT FOR CHICAGO AND**  
**ATLANTA**



Table 30: Analysis of Chicago Total Scheduled Operations - 2006

		Chicago Scheduled Total Operations - 2006					
		Mean	Median	Standard Deviation	Percentile 25	Percentile 75	Percentile 95
<b>Year</b>	6	2,657	2,708	151	2,593	2,761	2,827
<b>Month</b>	1	2,543	2,603	124	2,457	2,634	2,663
	2	2,591	2,654	142	2,507	2,700	2,732
	3	2,656	2,709	122	2,593	2,741	2,765
	4	2,671	2,738	127	2,634	2,755	2,795
	5	2,683	2,742	132	2,613	2,765	2,809
	6	2,742	2,771	110	2,693	2,820	2,847
	7	2,711	2,781	139	2,579	2,817	2,833
	8	2,750	2,781	98	2,711	2,813	2,849
	9	2,646	2,721	168	2,569	2,755	2,815
	10	2,664	2,691	122	2,633	2,748	2,793
	11	2,567	2,682	209	2,404	2,716	2,755
<b>Day of Week</b>	0	2,603	2,641	110	2,553	2,671	2,722
	1	2,694	2,723	98	2,649	2,755	2,813
	2	2,710	2,738	86	2,676	2,766	2,817
	3	2,723	2,742	121	2,682	2,799	2,840
	4	2,709	2,757	151	2,664	2,796	2,833
	5	2,731	2,755	111	2,709	2,802	2,846
	6	2,424	2,411	94	2,362	2,510	2,562

Table 31: Analysis of Atlanta Total Scheduled Operations - 2006

		Atlanta Scheduled Total Operations - 2006					
		Mean	Median	Standard Deviation	Percentile 25	Percentile 75	Percentile 95
<b>Year</b>	6	2,708	2,749	187	2,585	2,864	2,944
<b>Month</b>	1	2,532	2,573	165	2,485	2,686	2,723
	2	2,547	2,549	144	2,514	2,642	2,735
	3	2,680	2,719	118	2,643	2,761	2,801
	4	2,657	2,680	134	2,601	2,759	2,818
	5	2,638	2,673	170	2,585	2,770	2,821
	6	2,786	2,844	160	2,718	2,902	2,926
	7	2,812	2,882	148	2,779	2,918	2,944
	8	2,864	2,906	133	2,850	2,944	2,996
	9	2,726	2,764	204	2,685	2,890	2,952
	10	2,786	2,807	146	2,762	2,873	2,956
	11	2,750	2,832	200	2,666	2,892	2,946
<b>Day of Week</b>	0	2,683	2,720	134	2,591	2,791	2,850
	1	2,747	2,740	119	2,680	2,865	2,886
	2	2,713	2,682	138	2,614	2,832	2,916
	3	2,743	2,759	150	2,608	2,881	2,942
	4	2,837	2,877	141	2,762	2,946	2,967
	5	2,820	2,833	115	2,759	2,912	2,935
	6	2,403	2,415	127	2,305	2,526	2,559

**APPENDIX D**  
**BUSY DAY ASDI TRAFFIC ANALYSIS**

Table 32: Traffic Days above 95th Percentile for 2006

95 <sup>th</sup> Percentile			Scheduled Total Operations					
ATL	ORD	Both	Year	Month	Day	Day of Week	ATL	ORD
X	X	X	6	Jun	29	Thu	2951	2847
X	X	X	6	Aug	17	Thu	2967	2841
X			6	Jul	27	Thu	2981	2777
X			6	Aug	1	Tue	2947	2777
X			6	Aug	3	Thu	2949	2775
X			6	Aug	9	Wed	2996	2801
X			6	Aug	10	Thu	3023	2747
X			6	Aug	24	Thu	2946	2617
X			6	Aug	31	Thu	2945	2801
X			6	Sep	7	Thu	2952	2801
X			6	Sep	21	Thu	2952	2815
X			6	Oct	5	Thu	2950	2754
X			6	Oct	12	Thu	2959	2710
X			6	Oct	19	Thu	2956	2793
X			6	Nov	2	Thu	2946	2759
X			6	Nov	9	Thu	2951	2745
	X		6	Jun	14	Wed	2902	2839
	X		6	Jun	15	Thu	2925	2833
	X		6	Jun	16	Fri	2897	2846
	X		6	Jun	23	Fri	2926	2839
	X		6	Jun	28	Wed	2916	2870
	X		6	Jun	30	Fri	2922	2847
	X		6	Jul	13	Thu	2944	2828
	X		6	Jul	14	Fri	2912	2840
	X		6	Jul	24	Mon	2882	2831
	X		6	Jul	26	Wed	2922	2833
	X		6	Aug	2	Wed	2924	2891
	X		6	Aug	18	Fri	2935	2849
	X		6	Aug	23	Wed	2942	2840

Table 33: Traffic Days above 75th Percentile for 2006

75 <sup>th</sup> Percentile							Scheduled Total Operations		
ATL	ORD	Both	Year	Month	Day	Day of Week	ATL	ORD	
X	X	X	6	Jun	8	Thu	2891	2799	
X	X	X	6	Jun	9	Fri	2914	2819	
X	X	X	6	Jun	20	Tue	2887	2793	
X	X	X	6	Jun	27	Tue	2890	2820	
<b>X</b>	<b>X</b>	<b>X</b>	<b>6</b>	<b>Jul</b>	<b>5</b>	Wed	2927	2812	
X	X	X	6	Jul	6	Thu	2922	2817	
X	X	X	6	Jul	7	Fri	2925	2802	
X	X	X	6	Jul	10	Mon	2874	2790	
X	X	X	6	Jul	11	Tue	2918	2770	
X	X	X	6	Jul	12	Wed	2891	2798	
<b>X</b>	<b>X</b>	<b>X</b>	<b>6</b>	<b>Jul</b>	<b>17</b>	Mon	2868	2791	
X	X	X	6	Jul	18	Tue	2916	2817	
X	X	X	6	Jul	19	Wed	2921	2818	
X	X	X	6	Jul	21	Fri	2874	2809	
X	X	X	6	Jul	25	Tue	2892	2818	
X	X	X	6	Jul	28	Fri	2913	2781	
X	X	X	6	Jul	31	Mon	2888	2807	
X	X	X	6	Aug	4	Fri	2936	2802	
X	X	X	6	Aug	7	Mon	2879	2781	
X	X	X	6	Aug	8	Tue	2903	2800	
X	X	X	6	Aug	11	Fri	2908	2827	
X	X	X	6	Aug	14	Mon	2880	2813	
X	X	X	6	Aug	15	Tue	2909	2783	
X	X	X	6	Aug	16	Wed	2944	2827	
X	X	X	6	Aug	21	Mon	2892	2785	
X	X	X	6	Aug	22	Tue	2906	2804	
X	X	X	6	Aug	30	Wed	2882	2813	
X	X	X	6	Sep	1	Fri	2864	2804	
X	X	X	6	Sep	14	Thu	2935	2815	
X	X	X	6	Sep	28	Thu	2927	2795	
X	X	X	6	Sep	29	Fri	2909	2767	
X	X	X	6	Oct	20	Fri	2895	2789	
X	X	X	6	Oct	23	Mon	2869	2772	
X			6	Jun	21	Wed	2879	2729	
X			6	Jun	22	Thu	2903	2761	
X			6	Jul	20	Thu	2915	2544	
X			6	Aug	20	Sun	2888	2716	
X			6	Aug	25	Fri	2939	2761	
X			6	Aug	28	Mon	2880	2740	
X			6	Sep	8	Fri	2900	2755	
X			6	Sep	15	Fri	2895	2746	
X			6	Sep	22	Fri	2890	2709	
X			6	Oct	6	Fri	2900	2747	
X			6	Oct	9	Mon	2873	2727	

X		6	Oct	13	Fri	2920	2629
X		6	Oct	26	Thu	2914	2534
X		6	Nov	3	Fri	2920	2695
X		6	Nov	8	Wed	2864	2706
X		6	Nov	10	Fri	2892	2603
X		6	Nov	13	Mon	2866	2648
X		6	Nov	16	Thu	2918	2749
X		6	Nov	17	Fri	2934	2755
X		6	Nov	26	Sun	2868	2722
X		6	Nov	27	Mon	2886	2725
X		6	Nov	28	Tue	2896	2747
X		6	Nov	29	Wed	2920	2404
	X	6	Mar	8	Wed	2737	2788
	X	6	Mar	10	Fri	2774	2765
	X	6	Apr	5	Wed	2757	2795
	X	6	Apr	6	Thu	2818	2797
	X	6	Apr	7	Fri	2815	2763
	X	6	Apr	13	Thu	2772	2785
	X	6	Apr	20	Thu	2841	2775
	X	6	Apr	27	Thu	2792	2767
	X	6	Apr	28	Fri	2788	2775
	X	6	May	4	Thu	2809	2765
	X	6	May	10	Wed	2670	2780
	X	6	May	16	Tue	2617	2769
	X	6	May	17	Wed	2715	2799
	X	6	May	18	Thu	2821	2827
	X	6	May	19	Fri	2770	2802
	X	6	May	24	Wed	2725	2788
	X	6	May	26	Fri	2817	2809
	X	6	Jun	1	Thu	2862	2779
	X	6	Jun	12	Mon	2827	2763
	X	6	Jun	13	Tue	2846	2800
	X	6	Jun	19	Mon	2829	2818
	X	6	Jun	26	Mon	2841	2799
	X	6	Aug	29	Tue	2817	2772
	X	6	Oct	18	Wed	2762	2823
	X	6	Oct	25	Wed	2816	2777

**APPENDIX E**  
**DEPARTURE DESTINATION AIRPORT CATEGORY ANYLOGIC**  
**RESULTS**

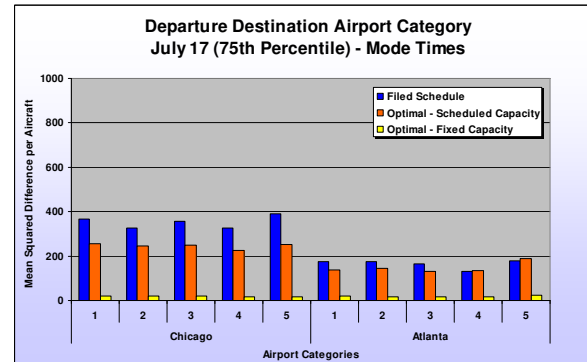
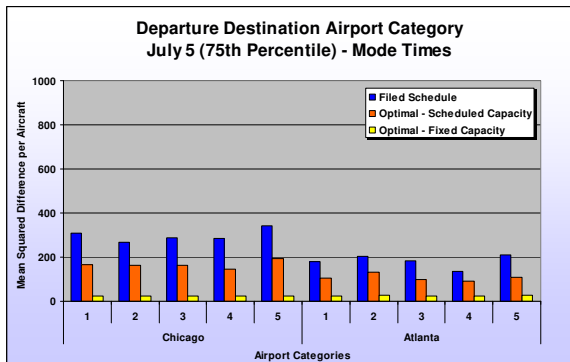
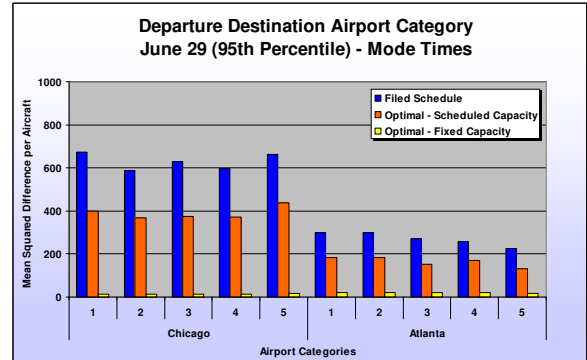
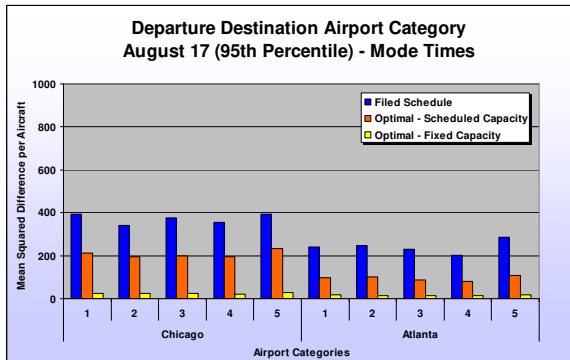
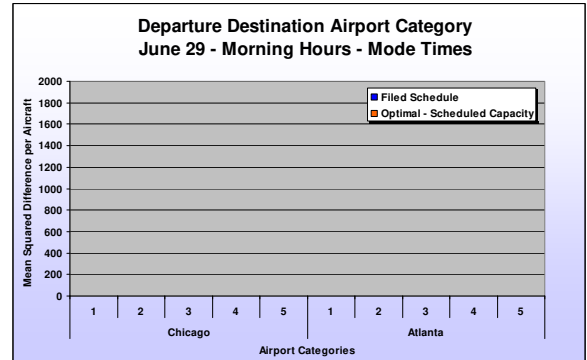
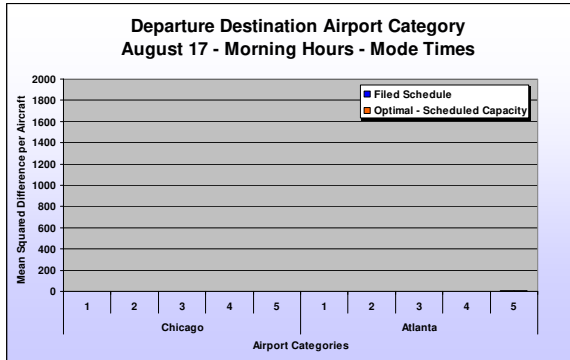


Figure 50: AnyLogic Results for Departure Destination Airport Category Analysis - Mode Times



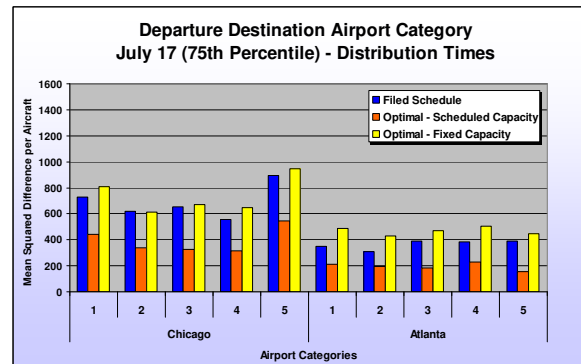
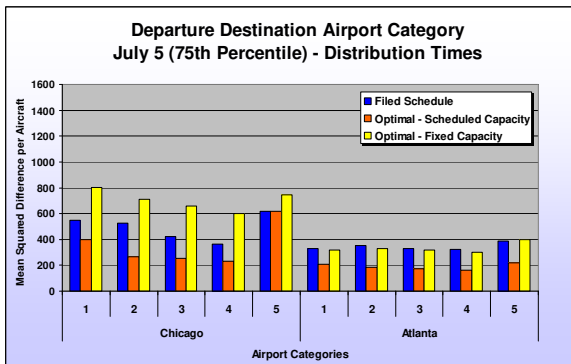
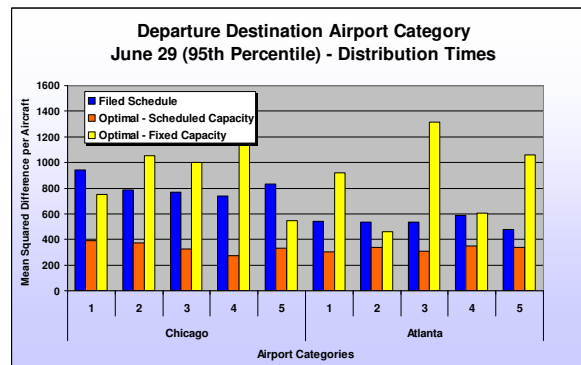
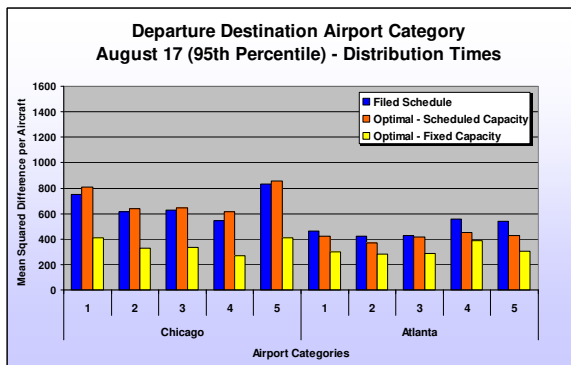
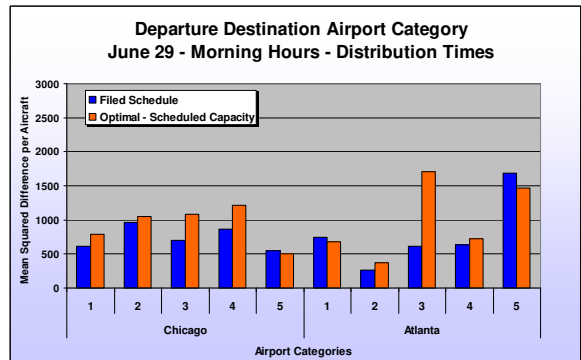
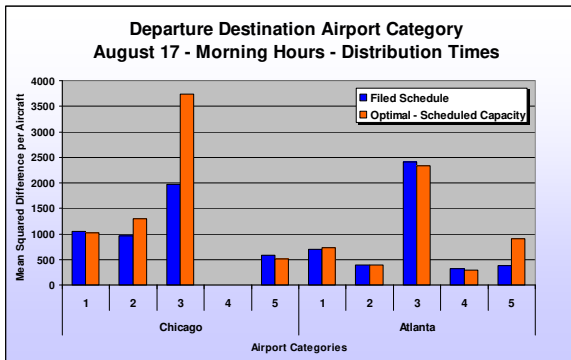


Figure 51: AnyLogic Results for Departure Destination Airport Category Analysis - Distribution Times

**APPENDIX F**  
**DEPARTURE FLIGHT TIME CATEGORY ANYLOGIC RESULTS**

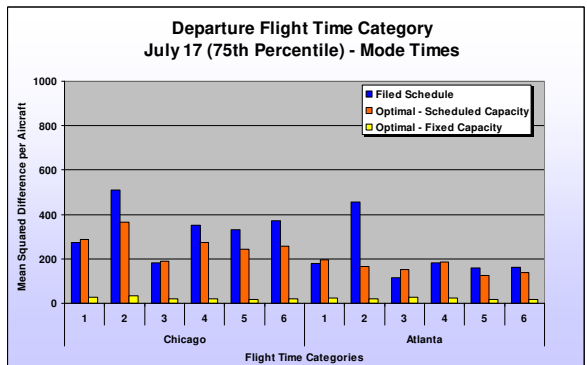
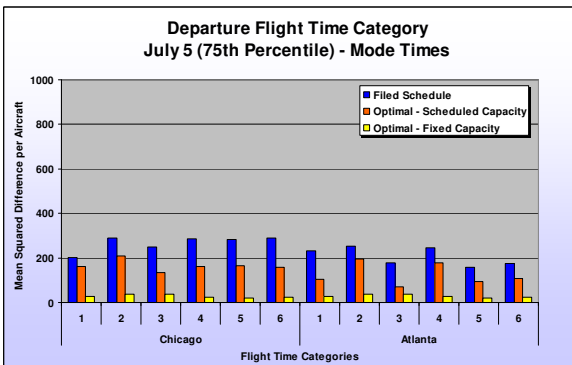
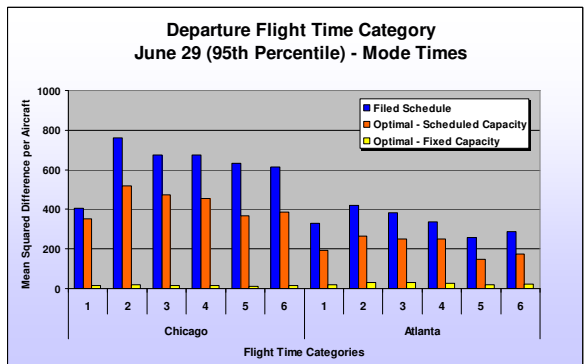
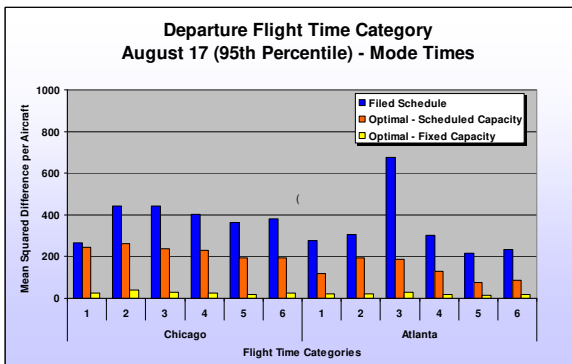
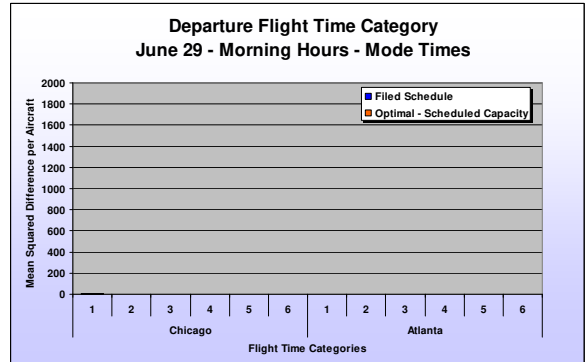
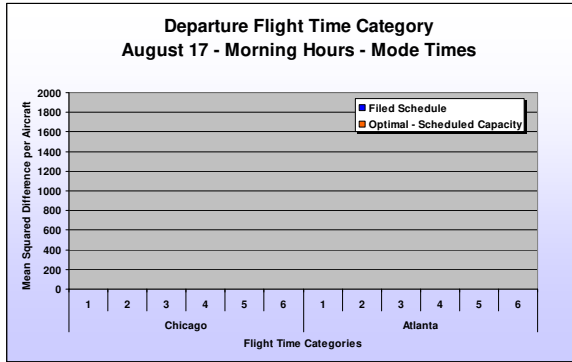


Figure 52: AnyLogic Results for Departure Flight Time Category Analysis - Mode Times

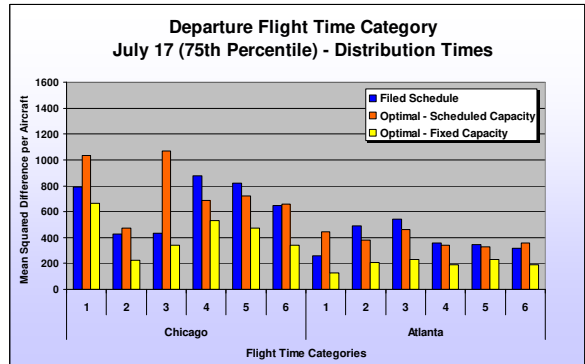
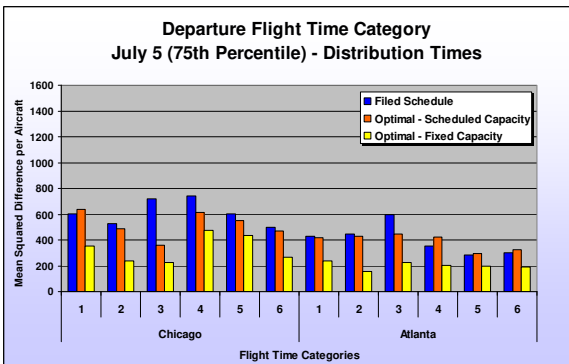
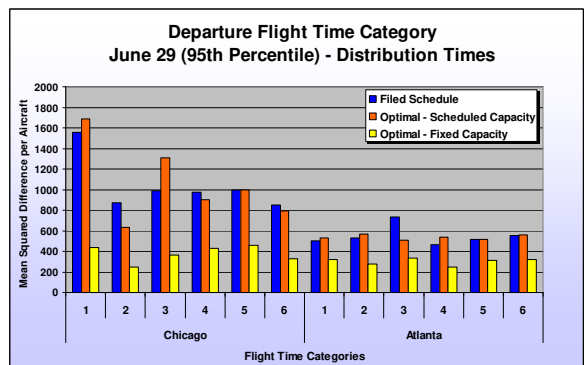
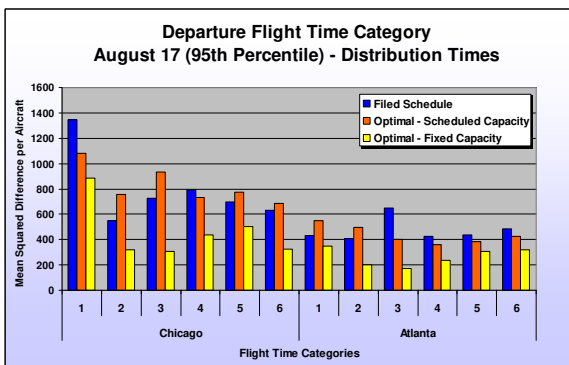
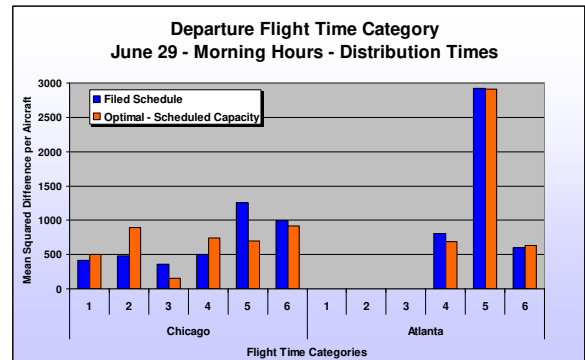
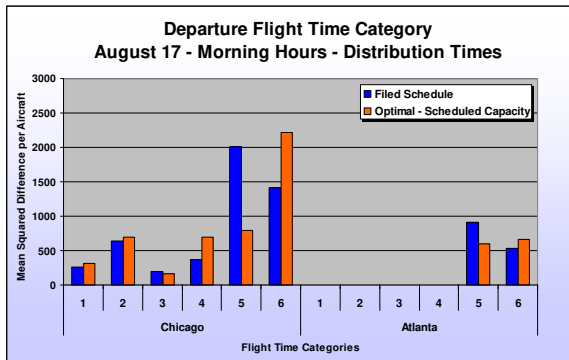


Figure 53: AnyLogic Results for Departure Flight Time Category Analysis - Distribution Times

**APPENDIX G**  
**ARRIVAL AIRCRAFT CATEGORY ANYLOGIC RESULTS**

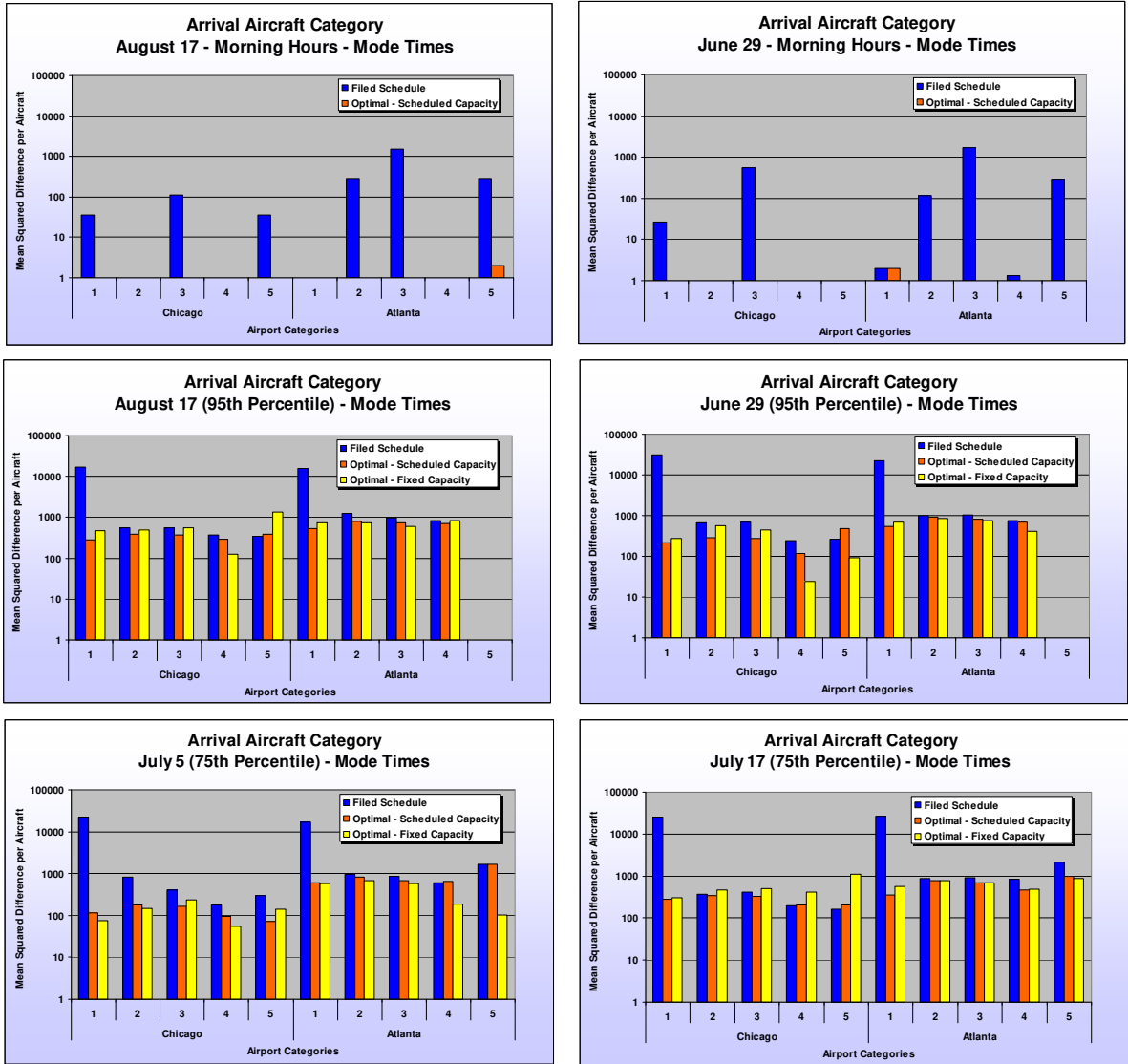


Figure 54: AnyLogic Results for Arrival Aircraft Category Analysis - Mode Times

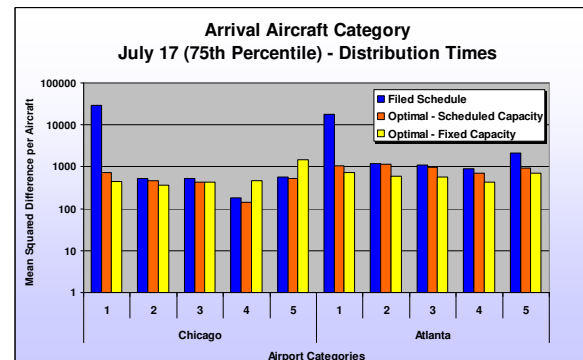
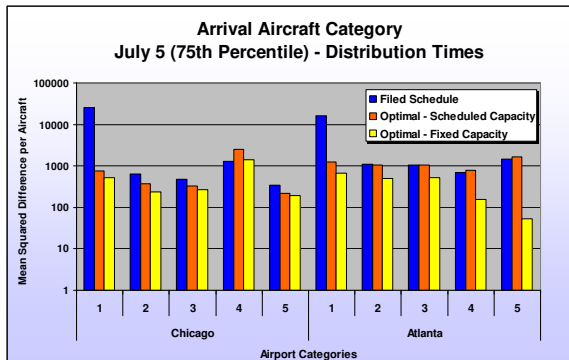
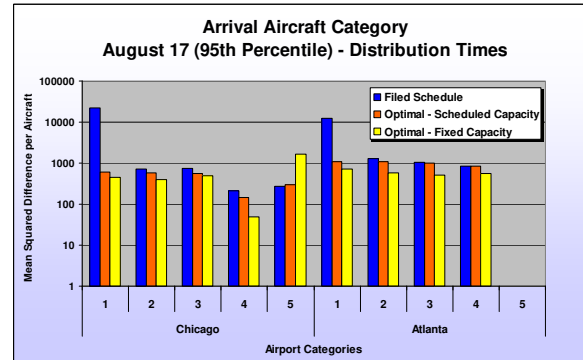
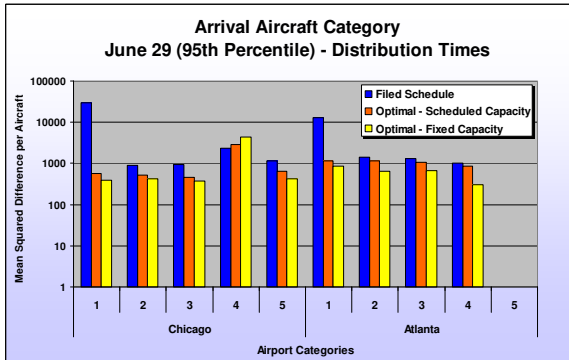
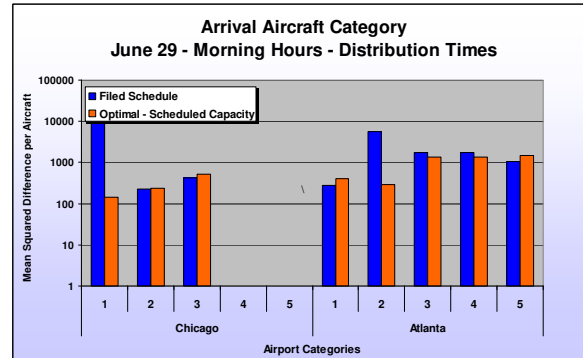
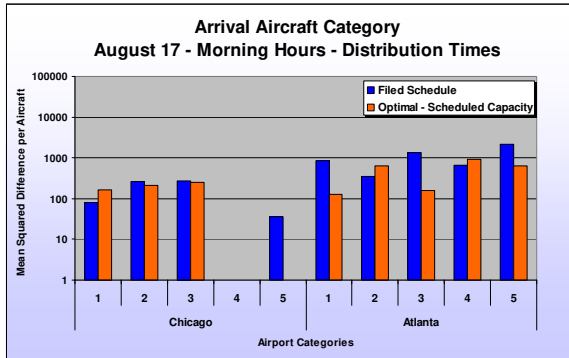


Figure 55: AnyLogic Results for Arrival Aircraft Category Analysis - Distribution Times

**APPENDIX F**  
**ARRIVAL FLIGHT TIME CATEGORY ANYLOGIC RESULTS**



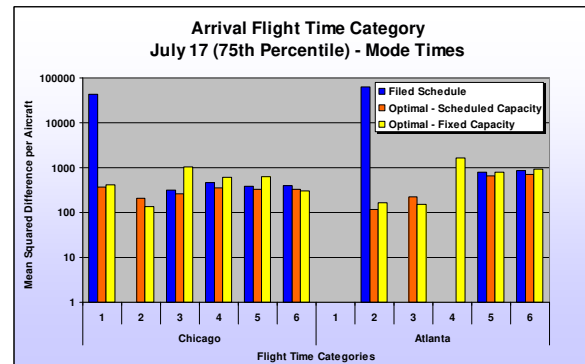
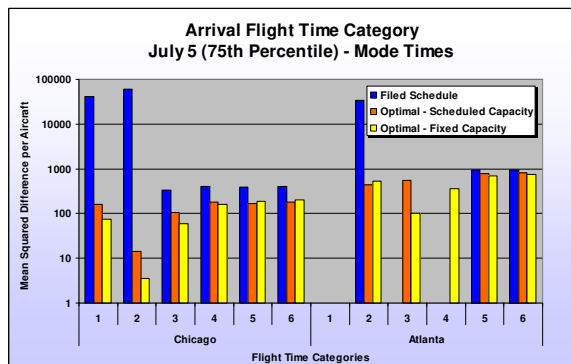
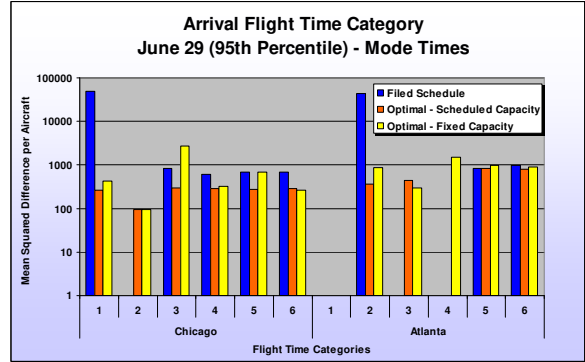
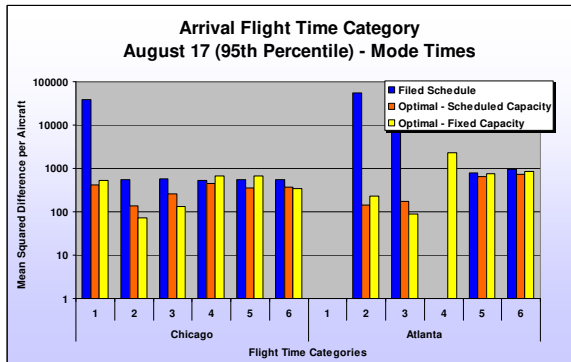
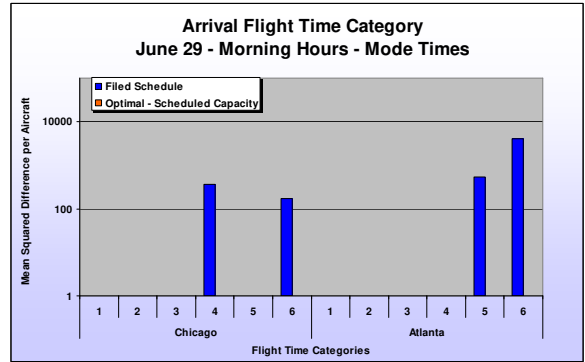
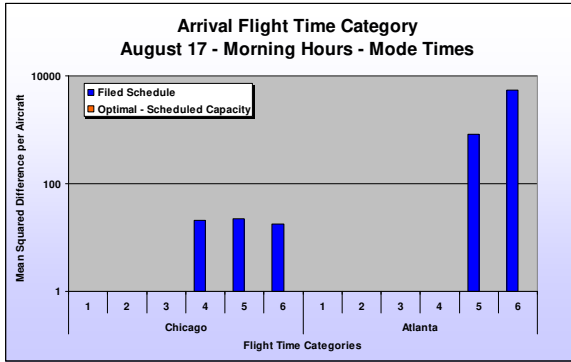


Figure 56: AnyLogic Results for Arrival Flight Time Category Analysis - Mode Times

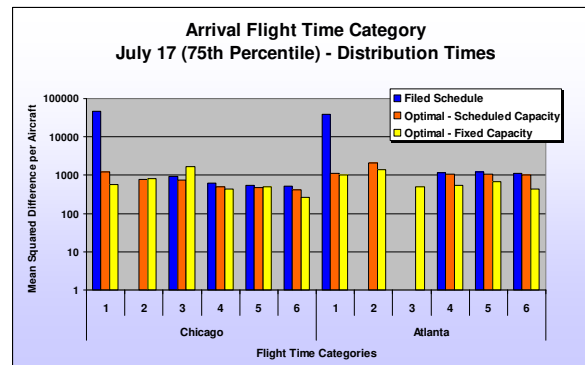
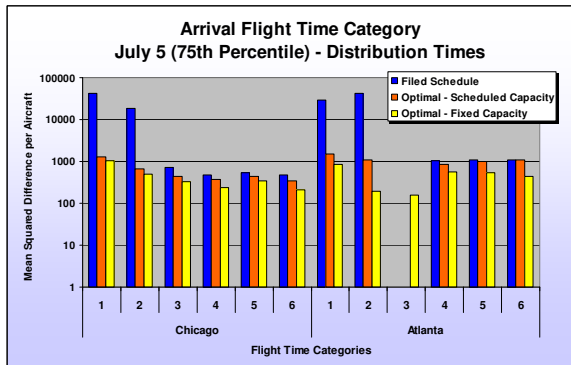
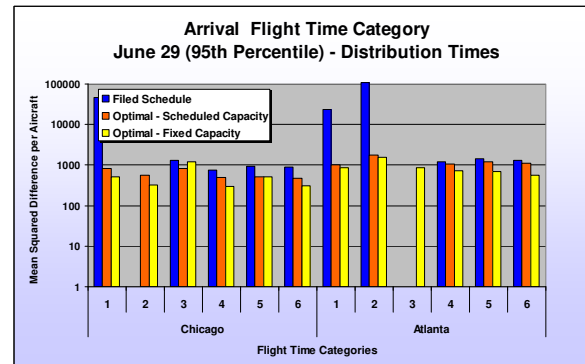
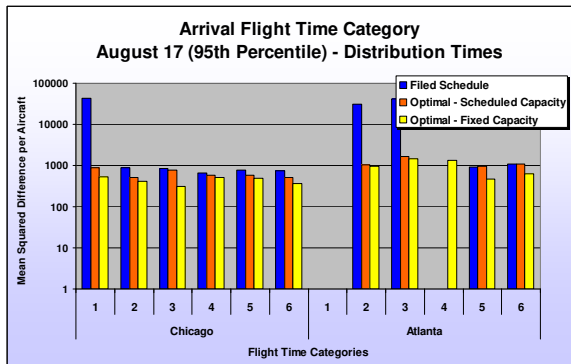
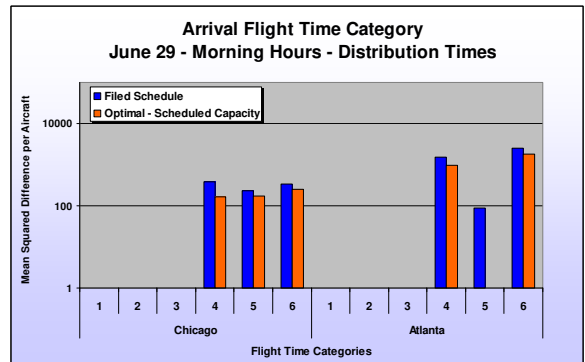
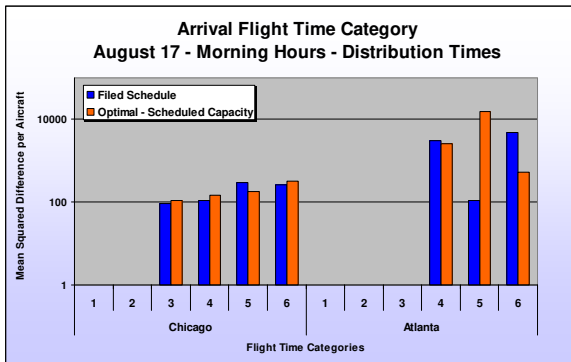


Figure 57: AnyLogic Results for Arrival Flight Time Category Analysis - Distribution Times

**APPENDIX G**  
**ARRIVAL AIRLINE USAGE SPLIT CATEGORY ANYLOGIC RESULTS**

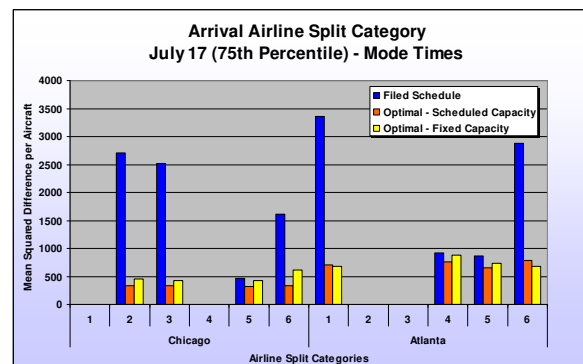
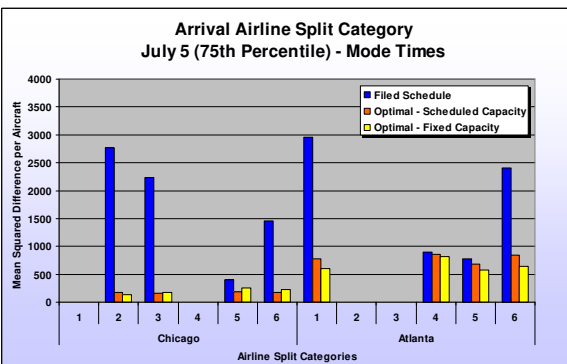
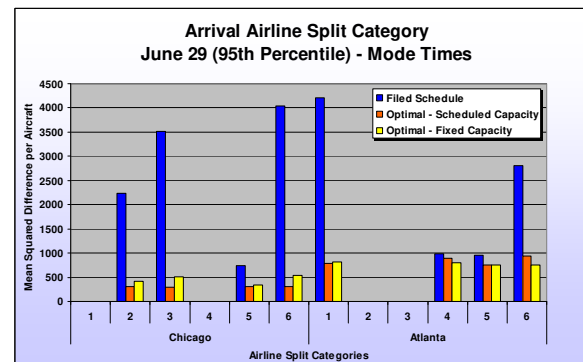
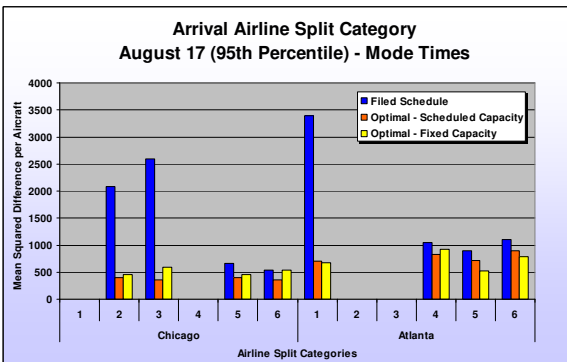
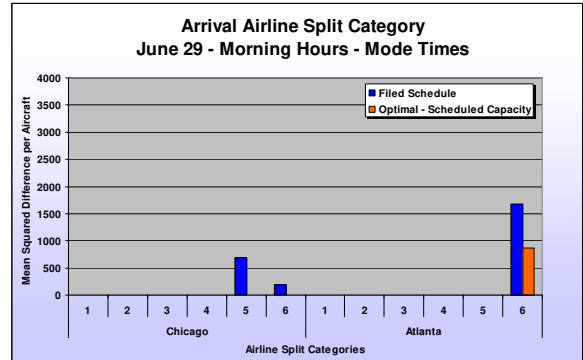
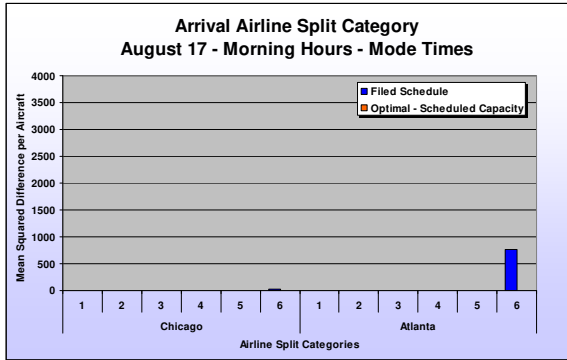


Figure 58: AnyLogic Results for Arrival Airline Usage Split Category Analysis - Mode Times

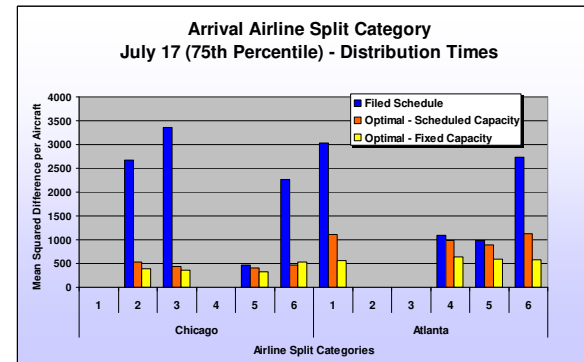
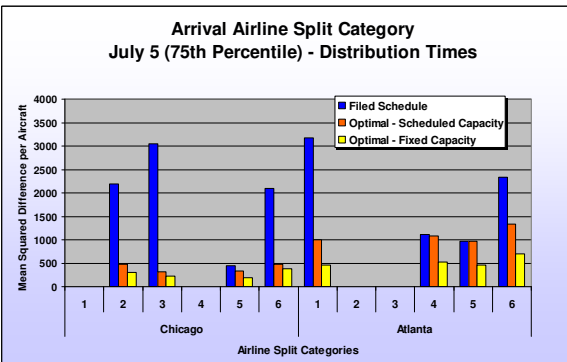
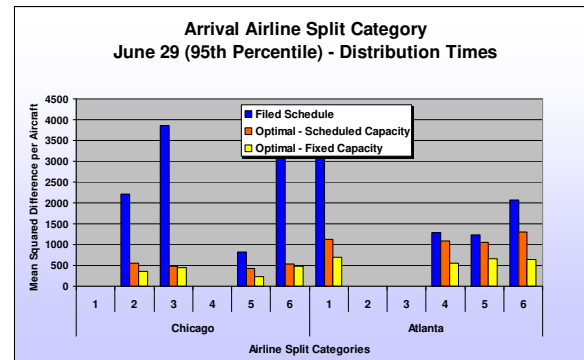
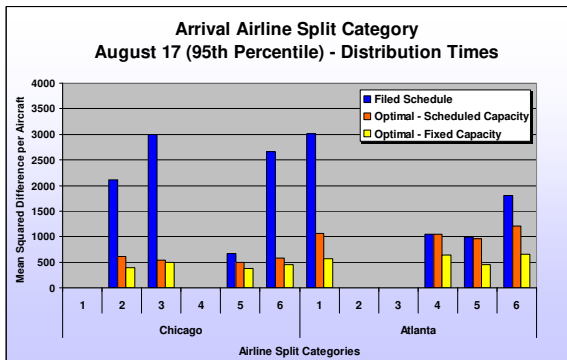
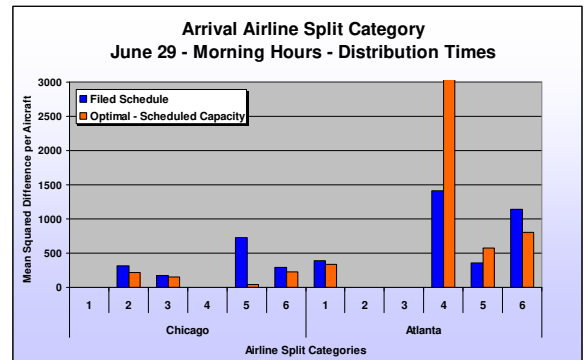
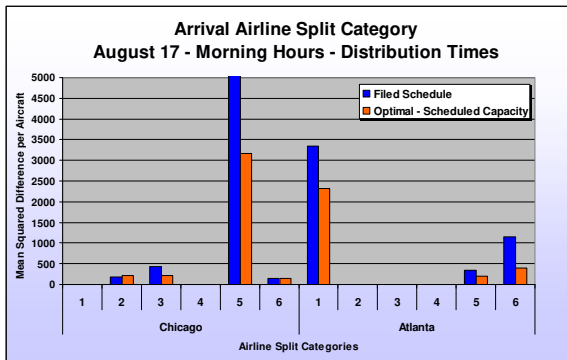


Figure 59: AnyLogic Results for Arrival Airline Usage Split Category Analysis - Distribution Times

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