Technische Universiteit Delft

Modeling the Dynamics of Propagated Flight Delay

A case study of the United States National Aviation System

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by

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Abbreviations

AR Arrival Runway

ATC Air Traffic Control

BTS Bureau of Transportation

CT Central Time

DAM Delay Airport Model

DR Departure Runway

EDT Eastern Daylight Time

EST Eastern Standard Time

FAA Federal Aviation Administration

FCFS First Come First Serve

GDP Gross Domestic Product

IFR Instrumental Flight Rules

MT Mountain Time

NAS National Aviation System

OD Origin-Destination

PDT Pacific Daylight Time

PST Pacific Standard Time

PT Pacific Time

RPK Revenue Passengers Kilometers

TA Turnaround

US United States

UTC Coordinated Universal Time

VFR Visual Flight Rules

Nomenclature

A The set of airports under consideration

AD_i The airport delay at airport i

DD_i The delay difference indicator of airport i

D_i^{tot} The total delay (local and propagated) of airport i

L_q The average number of aircraft in the queue

L_s The average number of aircraft in the system

M Markovian (Poisson) process

N_i^m The number of aircraft that arrive in queuing system m at airport i

PD_i The propagated delay at airport i

Q The set of queues each airport contains

QD_i The queuing delay at airport i

T The time period in which is simulated

W_i^m The expected delay of node i in queuing system m

W_q The average waiting time in the queue

W_s The average time in the system

λ_i^m The arrival rate of queuing system m at airport i

μ_i^m The service rate of queuing system m at airport i

a_j Aircraft rate going from airport j to outside of the network

f_{ij} The flight time from airport i towards airport j

h The sub-period of 30 minutes

p_{ij} The routing probability of airport i to airport j

Executive Summary

The air transportation industry is becoming of greater importance to the world's economy, since a growing part of the global population is able to afford air travel. However, the current network is limited in its' capacity and therefore, more and more delay is experienced within daily operations. Research has shown that flight delays have a high economic impact on the air transport industry. Therefore, the understanding of delay and how it propagates within a network is thus of relevance for the industry.

A lot of research has been performed on identifying the causes of delay, as well as their impact on stakeholders' costs and passengers' satisfaction. However, it is of equal importance to characterize the propagation of delays within a network of airports thus identifying the role and the sphere of influence airports have with respect to the network. Based on this a research objective has been formulated as follows,

The research objective of this thesis assignment is to investigate whether different sources of primary delay induce contrasting dynamics of propagated delay within a network of airports simulated by a stochastic queuing network model.

Based on this research objective, a new model has been proposed, which uses queues to simulate the different processes aircraft experience during the day, within the context of the United States National Aviation System. Each airport within the network has been represented by three queuing systems, which simulate the arrival, turnaround and departure of aircraft. Based on an empirical database of the US domestic market, the queuing parameters have been determined, which enables the simulation of both local queuing delay as well as propagated delay airports received from other airports.

To fulfill the research objective, three experiments have been designed, which will be used to test the performance, accuracy and capabilities of the model. First, six days have been selected with different weather conditions. Then, a day of the week aggregation is performed to test the difference between different days of the week. Finally, a case study has been performed to see the influence of zero, one, and five airports under low IFR conditions.

Based on the results of the simulation model, it can be concluded that the model is capable of simulating the relationships between airports and their delay sources with the identification of which airports are delay generators and which airports are delay receivers. Furthermore, the case study showed that it makes a big difference if one, five or zero airports are affected by capacity limitations. In the scenario with five airports it even resulted in a network-wide effect with propagation of delay from the East coast until the West coast of the United States.

Altogether, this project demonstrated that with a relatively simple queuing model, the dynamics of propagated delay could be simulated within a network of airports, but is less capable to mimic the behavior under extreme conditions. At the same time, the model has shown to be able to provide more information on the propagation of delay and its' source. Moreover, this study showed the identification of the different natural roles airports have within the network.

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1
Introduction

The air transportation industry is becoming of greater importance to the world's economy, since a growing part of the global population is able to afford air travel. According to Airbus Group [2],in the upcoming 20 years, the world's air traffic will grow annually with 4,6% Revenue Passengers Kilometers (RPK), resulting in 15 trillion RPKs in 2034. This large increase in demand can be split up between emerging markets such as China, India or the Middle East, and developed markets such as Western Europe and North America. According to Airbus Group [2], these emerging markets will have a yearly growth of 5.8% RPK, where air traffic in developed markets will grow with a yearly RPK rate of 3.8%.

However, the current infrastructure and demand management systems are limited in capacity and can not accommodate such growth. When looking at the major airport hubs around the globe, 90% of all long-haul traffic is on routes to/from/via 47 aviation mega-cities [35]. Of these 47 mega-cities, 39 airports are scheduled-constrained and do not possess an adequate infrastructure to meet current demand [2].

The net cost of congestion in this interconnected tight network of airports is enormous. A recent study performed by the Joint Economic Committee from United States (US) Congress, estimated the effects flight delays had on the U.S. national economy up to a cost of $41 billion in the year 2007, which was the worst year in on-time performance until now. This estimation comprehended $19 billion of operational cost for the affected airlines, $12 billion on delay costs for passengers, and around $10 billion of indirect costs, which affected other industries as well [3] [48]. In a different study, Ball et al. [4] approximated that in the year 2007, the sum of delay costs in the United States added up to $32.9 billion, which consisted of $16.2 billion in passenger delay costs, $8.3 billion in airlines delay costs, $3.9 billion cost in lost demand and $4 billion indirect impact on the national Gross Domestic Product (GDP). These studies illustrate the economic relevance of better understanding the effects delays have on an air transportation network.

Due to rapid growth within air traffic operations, more and more pressure is placed on the network capability to support on-time operations. Therefore, it is important to investigate the effects of delays and their dynamics. In this research project, the focus will be on the United States National Aviation System as a network of airports. A lot of research has been performed on identifying the causes of delay, as well as their impact on stakeholders' costs and passengers' satisfaction. However, it is of equal importance to characterize the propagation of delays within a network of airports and to identify the roles airports have within the network.

The goal of this thesis is to investigate the dynamics of propagated delay within a network of airports. Within this study, a stochastic queuing model will be proposed, which uses queues to simulated the different processes aircraft experience during the day within the context of the US National Aviation System. Based on an empirical database of the US domestic market the queuing parameters have been determined, which enables the simulation of both local queuing delay as well as propagated delay. By performing several simulation experiments the goal of this study will be pursuit.

The remainder of this thesis is organized as follows. In Chapter 2, a literature study is performed on the modeling of delay propagation within air transportation networks. Second, in Chapter 3 the research proposal will be presented providing both the research objective as well as the research questions. In Chapter 4, the model specification will be explained. Next, the calibration will be presented in Chapter 5. Followed by the results in Chapter 6. Then, the verification and validation will be elaborated in Chapter 7. This report will be concluded with the conclusions and recommendations in Chapter 8.

2
Literature Study

The relevant literature for this thesis is discussed in this chapter. During the literature study different analysis and modeling techniques of delay propagation are considered. These will be addressed first. Then, a more detailed description of the chosen technique, queuing theory, will be treated. Finally, flight delay is discussed.

2.1. Modeling Techniques

During the 1990's, Peterson et al. [41] performed preliminary research on a simple 2-node problem computing moments of queue lengths and waiting times. However, within this paper no interaction between airports in a network was present. Some years later, Beatty et al. [6] provided the first analytical analysis on flight delay propagation by calculating delay propagation multipliers based on American Airlines flight schedules.

After the preliminary work of both Peterson et al. [41] and Beatty et al. [6], a lot of different models were created over the last two decades. To properly address the dynamics of delay within a complex network, different analysis and modeling methodologies have been considered in the literature study, namely, the use of delays trees, statistical based mechanisms, the use of complex network theory, queuing theory, agent-based modeling, and epidemiology theory. Within this section, every technique is briefly discussed. Based on the literature study, the most appropriate modeling technique has been chosen to address the research objective at hand.

First, delay trees were considered. Delay trees can be seen as an oversimplification of the network and not suitable to fully capture its complexity. Delay trees can be a helpful tool when performing preliminary analysis on for example an airline flight schedule and the potential effects of delays within such a schedule. However, delay trees are not suitable to capture the complexity of networks. Thus, delay trees will not be used as the research methodology.

Next, statistical and econometric models are reviewed. It can be concluded that statistical and econometric models are a suitable tool for analyzing the network and finding causal relationships. However, statistical models are less suitable in describing the dynamic nature of the network and the actual modeling of this network. Statistical methods have been used to analyze the network on for example the correlation between causes of delays and the different airports within the system. Nevertheless, a statistical representation is not sufficient to capture and simulate the topology and complexity of the examined network.

Third, the use of complex networks is examined. Complex networks are proven to be a suitable application when analyzing the air traffic network, due to their ability to cover the interconnectedness of the network. The network can be presented as a weighted graph containing nodes, representing the airports, and edges, representing the connections between these airports. The appropriate weights can be defined on a database analysis. However, complex network theory alone was not sufficient to cover all elements that were necessary to simulate the creation and propagation of delay and so it is not chosen as the final modeling technique.

Fourth, agent-based simulations are considered for modeling purposes. A recent trend is that agent-based models are more frequently used to describe delay propagation problems. Agent-based models represent the network on a high level of detail, since every aircraft is considered an agent. Modeling a network with over thousands of aircraft would create a computationally heavy model. This could result in a more complicated and less feasible model than what is needed to address the research gap. Furthermore, agent-based modeling is a rather young research field which is still open for innovation and has not maturated yet. Therefore, this research is focused on looking at the network in an aggregated manner, in terms of rates and not so much on the microscopic level, agent-based modeling is not seen as the best fit to this research problem.

Next, the use of epidemic models is investigated. Currently, only a few papers exist on the application of epidemiology in the delay propagation context. For describing delay propagation, epidemiology looks promising, but certainly needs more research before it can be considered as a solid research approach. However, the theory behind this methodology could be of help during the creation of the conceptual model.

Last, queuing based models are scrutinized. Queuing theory has proven to be an excellent choice in the past, when describing delay propagation mechanisms. Within literature, most of the models were based on queues due to its adaptability to different case studies with a relativly simple model and the ability to capture the stochastic nature of airport operations. To make this thesis assignment feasible, queuing theory will be used when designing the conceptual model. By choosing queuing theory as the primary research methodology, a proper mathematical model can be created which captures the dynamics of delay within the examined network.

2.2. Queuing Theory

Queuing theory is the mathematical study of waiting in a variety of applications. It uses queuing models to describe the numerous types of queuing systems [30]. Queuing based models are widely used throughout literature, and are mostly macroscopic and analytically based models, which are used to make an approximation of reality ([5], [23] [25], [26], [27], [31], [40], [42], [43], [44], [45], [49], [50], [54]). First, an overview of queuing models used within literature will be presented. Then, literature based on analytical models will be reviewed. This chapter will be concluded with examining the queuing based simulation models found within literature.

2.2.1. General Description

Queuing models are generally described by the mean arrival rate (λ) and the mean service rate (μ), and are often pictured as in Figure 2.1. Here, queues are presented as multiple squares, severs are presented as circles, and the routing network is displayed as arrows. Most queuing models only vary in the way λ and μ are described. Objects will approach a certain server which will provide its service. Afterwards, the objects will depart again. The air transportation network is generally modeled as a queuing network, where multiple queues have been used to simulate airport operations and en-route flight operations. In Figure 2.1, one can see an example of such a network containing two departure queues(airports), four en-route queues and four arrival queues(airports).

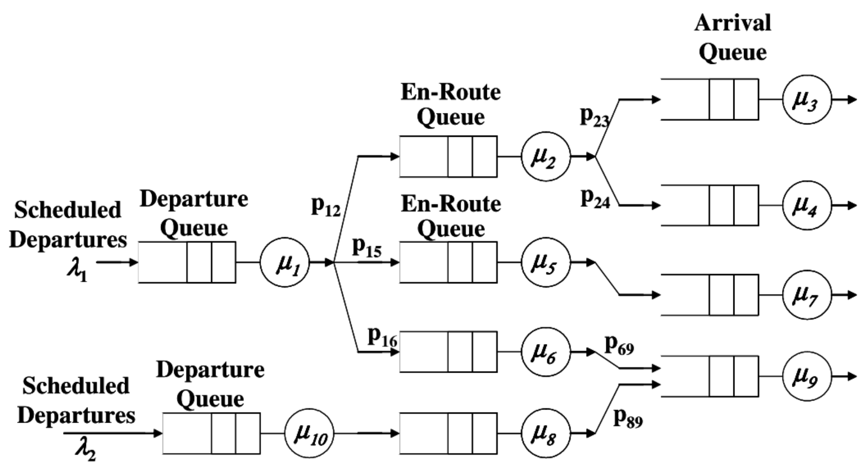


Figure 2.1: An example queuing network [50]

The arrival and service rate could be represented by multiple forms in real queuing systems. The $M/M/1$ queue is a simple model were both the arrival and service rate of a single server queuing system can be described with a Poisson distribution. To make queuing models useful for research applications, the assumed distribution should be sufficiently realistic, so the model produces accurate approximations while at the same time remains controllable. Therefore, models could be classified based on the used distributions and differences between analytical(closed form) models and simulation models. First, the analytical models will be presented followed by the simulation models.

2.2.2. Analytical Models

In the following section analytical models will be discussed.

Markovian Models

Markovian models($M/M/s$) use exponential probability distributions for both arrival and service rates and have the lowest model fidelity and solution accuracy. Markovian queues use the Markov property of being memorylessness, which basically means that the future of a process is only based on its present state. Due to this property, arrivals occur according to a Poisson process. Markovian models are simple in theory but are difficult to use in practice since the assumption of exponential arrival/departure is not always true in reality.

Markovian Within the literature, Markovian queues have been mostly used to describe microscopic queuing behavior on a specific airport. Nikoue et al. [37] for example, used a $M/M/c$ FCFS queuing model to predict passenger flows at Sydney International Airport. This is not researched in-depth since it is was considered outside the scope of this research project.

Sengupta et al. [49] presented a modified Markovian model and a $M/M/s$ approximate solution called Queuing Network Analyzer(QNA) to analyse the service time and the waiting time on a network of 40 airports. This research can be labelled as macroscopic. The modified Markovian model used a modification to the standard markovian representation in order to overcome the disability of modeling the network uncertainties. Sengupta et al. [49] used an additional queue which accounts for the variance in delays which is the result of uncertainty. The researchers showed that the modified Markovian method performed worse when comparing it to an approximate queue solution of the QNA.

Semi-Markovian The remainder on Markovian literature focuses on Semi-Markovian properties. Instead of the entire process being Markovian, the process is only Markovian at specified states. Peterson et al. [40] for example, have used a Semi-Markovian model, which computed airport capacities related to changes in the weather and looked at the metric mean waiting time. These changes in weather conditions could have a great effect on the service time of an airport. The arrival rate was modeled here as a deterministic process. A single hub airport is considered as the focus point in a non-stationary queuing network. The research, showed promising results, however, only one airport is considered here and interrelationships between airports are not taken into account. To see the model's full potential, multiple airports should be considered.

Approximate Models

In addition to the Markovian models, approximate solutions provide linear equations for the modeling of the uncertainty in the network. Therefore, approximate solutions are an appropriate method to integrate the uncertainties of an Air Transportation Network into a queuing network. Approximate solution methods offer a higher model fidelity and solution accuracy when comparing them to Markovian Queues. Approximate Queues are mostly explained by using the Kendall's notation, $G/G/1$, which means general distribution or that any probability distribution is allowed. Selecting the right probability distribution or phase-type distribution is the most difficult part and essential to make a queuing model useful and accurate.

Erlang distribution Within the literature, approximate solution methods are widely used. The current state-of-the-art for approximate solution models is a network of airports which uses a $M/E_k/1$ queuing system to represent a particular airport. A good example of this is the AND model presented by Pyrgiotis [43], which models a network consisting of the 34 busiest airports in the United States. In this queuing model the arrival rate is presented by an exponential distribution(Poisson process), and the service rate is presented by an Erlang distribution. Due to the stochastic nature of air transportation network, the Erlang distribution is a good approximation to reality, since it can cope with the uncertainties and variability in day-to-day airports operations [45]. The metrics, which are used to describe the AND performance are respectively, expected upstream delay, the breakdown of delay between local and upstream, the total flight arrival delay and the fraction of arrivals with expected delay greater than 15 minutes.

These performance metrics can provide a clear picture of the delay propagation within a network and are therefore used as a source of inspiration for this research project. The developers of the AND model stated that AND can be considered as an analytical macroscopic model which can create results in a short period of time. To test AND's full potential, it should be tested in order to conclude whether it can reproduce trends and the dynamic behavior of the modeled networks. Lately, Pyrgiotis and Odoni [44] also used the AND model on a more local scale. With the use of the AND model, the impact of scheduling limits is tested at Newark Liberty International. Since this analysis is performed locally, it is considered outside the scope of this literature review.

Due to the ability of incorporating stochastic elements, the $M/E_k/1$ queuing system is used in multiple research papers. Baspinar et al. [5] for example, proposed a macroscopic analytical queuing model, which used a $M/E_k/1$ model similar to the AND model, but focusing on European airports. Within this paper, the performance metrics capacity (number of movements per fifteen minutes), and break-point (20% or greater number of flights takes +15 delay) are used. Baspinar et al. [5] performed an analysis where the link between capacity reduction and delay generation is researched. By selecting several capacity values, the break-point of an airport is determined when there is a sudden increase in total delay. The paper shows that airports, which function above this critical capacity value tend to have less delays and are better in coping with irregularities.

Jacquillat and Odoni [26] also use an $M/E_k/1$ queuing model to quantify the relationship between flight schedules, airports capacity and flight delays. Jacquillat and Odoni [26] used their macroscopic model to estimate the average delays and variability in delays on New York's airports. In their research paper Jacquillat and Odoni [26] used the metrics, average arrival/departure delay, and actual/predicted queue length. Jacquillat and Odoni [26] has implemented the model at JFK, EWR and LGA, three of the most congested airports in the United States. The results showed accurate predictions on both expected values and the variability of the metrics. Furthermore, the timing, dynamics and magnitude are properly predicted. Since this paper uses a simple model of demand processes at airports and still obtained good results suggests that in this research project a simple model should be the starting point as well.

Deterministic distribution Next to the stochastic queuing models, one can also use deterministic distributions which are fixed over a period of time and do not include variability in the model, i.e. every run of the model will obtain the same results. Due to the stochastic nature of delay propagation, only a few deterministic analytical examples are found within the literature.

Hansen [25] used a deterministic approach by modeling the runway delay external factors at Los Angeles International Airport (LAX), using a deterministic queuing model. Deterministic queues are used on a microscopic level, since only the delay dynamics on LAX are treated. When only considering LAX stochastic effects within the network are of less importance. However, it is clear that deterministic queuing methods are not suitable to represent the delay dynamics within a macroscopic network of airports. Therefore, analytical deterministic queuing models are considered to be as outside the scope of this research project.

Markovian distribution As discussed earlier, Sengupta et al. [49] used an $M/M/s$ queuing model to represent a macroscopic model of 40 major airports on the continental US. It was already explained that in reference [49], the approximate solution method outperformed the Modified Markovian model. Furthermore, Tandale et al. [50] used an approach which recreated the US national airspace system as a combination of Center-level open Jackson queuing network with $M/M/m$ nodes.

Results of approximate queuing methods show that by using probability distributions, which are able to model the stochastic nature of air traffic uncertainties, a satisfactory solution accuracy can be obtained without extensive computational time. However, due to time varying demand and service rates, representation with probability distributions can become complex.

Coxian Queues

The third category within queuing theory is the application of Coxian queues. Coxian queues have the highest fidelity level within the domain of queuing theory. Due to high fidelity, Coxian models are able to obtain very high levels of solution accuracy against a computational cost. Since Coxian models are able to mimic any kind of arrival or service distribution, these queuing systems can become very complex very quickly. Coxian queues uses the principle of Chapman-Kolmogorov equations, which can be used to calculate the transition probabilities in between states. However, this can become uncontrollable if it would be applied to a network, due to its larger number of states [49]. This is also the main reason why, within the domain of modeling a network of airports, no previous literature could be found on Coxian queues. Therefore, Coxian queues will not be investigated any further and are considered outside the scope of this research project.

2.2.3. Simulation Models

Next to the analytical queuing models, there are also queuing models which use simulation to obtain results. Within this section, literature which uses queuing based simulations will be explained. Due to the stochastic nature of air transportation networks, more often simulations have been used, which can simulate the variability in events. Most of the presented models are already slightly older and have been used by the industries for a long time.

NASPAC Next to the analytical queuing models, queuing based simulation models have been used to tackle the problem of simulating the network performance. One of the first researchers were Frolow and Sinnott [21] from the MITRE Cooperation, who created their National Airspace System Performance Analysis Capability (NASPAC) model in 1989. NASPAC was one of the first NAS simulations developed and is still being used today by the Federal Aviation Administration (FAA) [45]. The NASPAC simulation can make an estimation on a large variety of performance measures, such as system throughput, technical and effective delays. Here, technical delay refers to delays where aircraft wait for an ATC resource (e.g. a runway) to become available and effective delay measures the difference between the arrival time and the scheduled arrival time. NASPAC can be considered as a macroscopic model, since it is capable to assess the impact of system changes on a NAS scale. However, in the original model no assessment on propagation of delay has been performed. As NASPAC is a simulation tool, the model fidelity can be very high resulting in a high solution accuracy. Unfortunately, for a large scale of simulation tools, and queuing simulation models are no exception, the computation time may become substantial.

DPAT As a successor of the NASPAC model, Wieland [54] suggested the Detailed Policy Assessment Tool (DPAT) which was also created at the MITRE Coorperation. DPAT obtained considerable differences relating to en-route modeling, worldwide coverage, and computational time. As a lower level of detail model, DPAT uses an approximation with a cumulative distribution function (CDF) to describe the stochastic nature of various events within the ATN. DPAT does not use the aircraft itineraries and therefore does not fully capture the effects of delay propagation within the system. Furthermore, it is stated that airport handling mechanisms are purely an approximation, by picking a random sample from a user-specified CDF. As its' most important input DPAT requires the capacity and demand data. The most important metrics DPAT can predict is the technical delay. Wieland [54] states that technical delays are referring to congestion-induced queuing delay and therefore are measuring the congestion in the NAS caused by air traffic demand competing for the same limiting resources. Lastly, Wieland [54] also tested if delay can be seen as predictable. The DPAT model shows however that delays are highly unpredictable, and that delay predictability only marginally improved when a capacity increase is realized. Both the NASPAC and the DPAT model can be seen as very dated models on the modeling of delay propagation since both models do not incorporate the full propagation dynamics. Therefore, further research is necessary.

Within the literature, several papers exist which used the DPAT model as their basis [53]. Schaefer and Millner [47] for example, used DPAT to model changes in capacity due to weather effects. The paper made a distinction between capacity profile under visual meteorological conditions(VMC) and instrumental meteorological conditions(IMC), since these conditions can have major consequences on the number of aircraft an airport can serve per hour. Under VMC all the examined airports witness no significant delays, therefore the propagation effect is not detectable. The research paper showed that when airports witnessed IMC under a longer period of time, delays increased locally. The effects of propagated delay are considerable for the first 5 legs after leaving an airport with IMC. This was only applicable for airports which had a high capacity over demand ratio. For airports where this ratio was low, IMC operations do not necessarily evolve into large quantities of propagated delay.

LMINET Another queuing based simulation model is presented by Long et al. [31] and is called LMINET, which has some features similar to those of AND, presented in section 2.2.2, including the modeling of individual airports based on queuing theory. At each airport, queues exist for arrival, taxi-in, taxi-out and departure each based on a Poisson process with a corresponding service rate. Due to the lack of delay propagation and cancellation, LMINET is not suitable for the analysis of delay propagation within in a network. The researchers who created this analysis tool realized this and therefore created a revision on their model called LMINET2, which is presented in reference [32]. In Figure 2.2 one can see a schematic representation of LMINET2 containing an airport queuing delay model, flight schedule delay & cancellation model, and an aircraft connection and turnaround model.

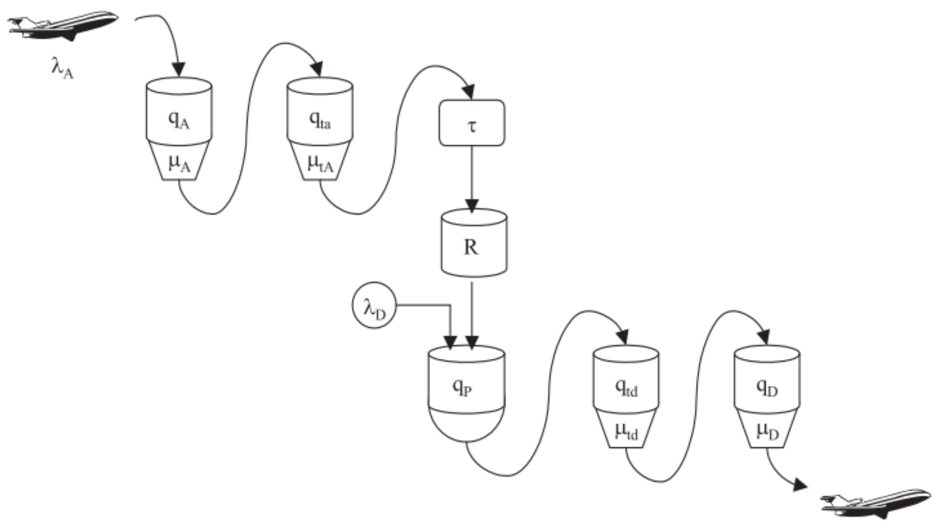


Figure 2.2: Schematic of LMINET Airport Delay Model

Due to its flexibility and ease of use, LMINET has been used in the past to determine the progression of different Air Traffic Management(ATM) improvement programs. Specifically, LMINET is used to determine the throughput advantage of several NextGen programs [33]. The traffic throughput is mostly driven by airline flight plannings and the nominal operations and delays. Normally, throughput numbers are determined under nominal weather conditions. Here, it is of less importance to include modeling blocks containing delay propagation and flight cancellation. To address traffic throughput and flight delays in off-nominal conditions the researchers introduced LMINET2. Both LMINET and LMINET2 are full scale NAS models covering 310 airports of the NAS representing 98.6% of all air carrier activity and therefore can be considered as macroscopic models [32]. Due to its large scale, the solution accuracy and model fidelity can be very high. However, Long and Hasan [32] stated that the ground turnaround model has been used to estimate the delay propagation. This model is based on the empirical data and the assumption that every aircraft should have a minimum turnaround time. By performing a regression analysis, the predicted departure delay is obtained.

Simple Queue Model Carr et al. [14] created a model containing simple queuing dynamics to compute departure flow restrictions at, respectively, Logan International Airport (BOS) and Newark Liberty International Airport (EWR). The paper was focused around modeling the direct effects of downstream restrictions. Carr et al. [14] showed the impact of delays on airports by using performance metrics like throughput, departure congestion and average taxi-out delay. The model is validated via a comparison between a Monte Carlo Simulation and ten hours of actual operations data collected during a case study.

Carr et al. [14] showed that a simple queuing based network can be an effective way to model the effects of surface traffic congestion and fix closures. As this model only considered the effects of one particular airport the model can be considered to be microscopic. The research method used here is not suitable for the analysis of the dynamics of delays throughout the network of airports, since the model only focused on the local effects and what will happen with the airport performance metrics.

Continuum Model Lovell et al. [34] presented a continuum approximation to queuing problems located at one airport. The approximation is derived from the Kolmogorov forward equation of stochastic processes within the airport problem context. The paper showed a numerical solution based on finite element method.

The researchers compared their results with stationary results of the $M/M/1$ process and real demand and supply data. It has been shown that the results of the approximation both match the mean and the variance of delay statistics reasonably close. However, the modeling technique is a novel approach and therefore less suitable for addressing the research gap.

Results of the simulations show that queuing based simulations are a valuable tool for addressing delay propagation problems. However, making the research too complex from the start could result in a less feasible thesis assignment, due to the limited amount of time within the thesis project. Therefore, a simple network modeling approach will be the starting point and eventually simulation tool could help to extend the conceptual model.

2.3. Flight Delays

Within the topic of flight delays one can make the distinction between primary and propagate delay. This terminology will be explained first. Then a classification of delay sources will be provided.

2.3.1. Delay Definitions

Before investigating the effects of delays, it should be made clear what distinguishes primary delay and propagated delay. Throughout the literature, multiple terms have been used to describe these two phenomena.

When looking at primary delay as Fleurquin et al. [19], several different definitions have been used over the past years to describe the type of delay which is originating from external factors on to one aircraft. As one of the first researchers discussing the effects of flight delays, Beatty et al. [6] described it as initial delay, the delay which is initially created by the aircraft itself or its conditions. Cook and Tanner [15] used the term primary delay, or original delay, which is caused by one aircraft. Furthermore, AhmadBeygi et al. [1] referred to root delay, original root delay as the source of propagation throughout the network. This root delay is independent of any other delay created earlier on. Lan et al. [29] called it non-propagated delay or independent delay which is not a function of routing.

Propagated delay can be caused by four main reasons, namely, aircraft rotation, aircraft equipment, crew rotation, and transferring passengers. When describing the term delay propagation, Lan et al. [29] gave an evident definition: *"propagated delay is delay that occurs when the aircraft is delayed on a prior flight"*. However, this definition only covers aircraft rotation and ignores the effects of crew rotation or transferring passengers. More recently, Kafle and Zou [28] stated that propagated delay occurs if connected resources are delayed in a flight downstream. This definition is more broad and is able to cover, not only delay caused by aircraft rotation, but also crew, passenger and airport resources.

Throughout literature, different terminology has been used in Europe and the U.S. when describing delay propagation. In Europe the term reactionary delay or reactional delay is commonly used, by for example Fleurquin et al. [18], Fleurquin et al. [20] and Belkoura et al. [7]. In the U.S., the term propagated delay or delay propagation is generally used, by for example Pyrgiotis et al. [45], AhmadBeygi et al. [1] or Long and Hasan [32]. Furthermore, terms as downstream delay [13] or downline delay [6] are also used, but are less common.

Since all these different terminologies could create confusion, the terms propagated delay or delay propagation and primary delay will be used throughout the rest of this report, when describing the two phenomena. These terms are used, since they seem to describe it best and are the most consistent, while taking previous literature into account.

2.3.2. Classification of Delay Sources

When describing the aircraft operation most commonly a flight profile is provided as in Figure 2.3. A flight could be separated into five stages, namely, departure, taxi-out, en-route, taxi-in, and arrival. Within each stage, a certain delay could be incurred. The numbers in parentheses in Figure 2.3 are the average delay minutes for all flights as recorded in American Flight Database in 2005 [32]. This simplification of aircraft operations will be used as the basis of the conceptual model.

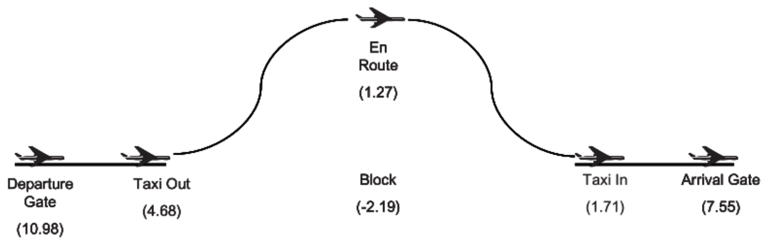


Figure 2.3: Flight Profile and Delay per Stage [32]

Within literature several examples of queuing network representation of such a flight profile have been found. Figure 2.4 is one of those examples where each stage is represented with a complementary queue and server. With this queuing representation a simulation can be performed of the possible waiting times and thus delay created for each aircraft. The conceptual model will be inspired based on such representations.

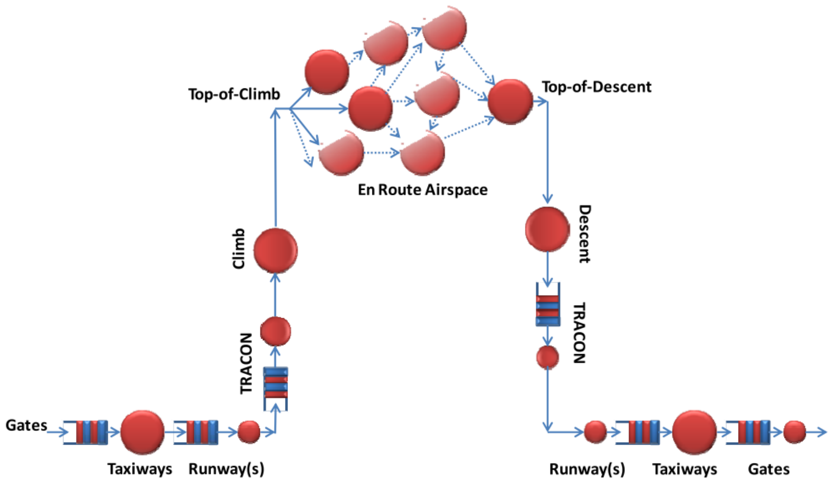


Figure 2.4: Queuing Network Abstraction of Flight Profile [36]

3
Research Proposal

From the introduction and the literature study it can be concluded that more research is needed to better understand the propagation of flight delay and the relationships between its dynamic behavior and the original sources. To achieve this goal, this research proposal has been set up. Within this chapter, the research proposal will be explained. First, the research objective is mentioned, which provides guidance and the goal of this thesis. Next, the research questions are addressed which need to be answered within this project. Third, the research scope will be explained. Finally, the research methodology will presented, which will be the backbone of this research project.

3.1. Research objective

From the literature study it was concluded that currently, a lot is unknown about the dynamics of flight delay and in particular the relationship between propagation throughout a network and the different sources from whom the delays are originated. Furthermore, it was found that queuing theory was the most appropriate method of simulation. Therefore, the research objective can be formulated as followed:

*The research objective of this thesis assignment is to investigate whether different **sources of primary delay** induce contrasting **dynamics of propagated delay** within a **network of airports** simulated by a **stochastic queuing network model**.*

Based on the literature study and the empirical data available, it was determined that the United States (U.S.) National Aviation System (NAS) will be chosen as the context of the study. Since the U.S. NAS consists of 310 airports, the Core 30 airport set has been chosen as the scope of this study. These airports account for 80% of the US domestic air traffic thus giving a good representation of both the network as a whole but also focus on the main contributors of delay within the network [17].

3.2. Research questions

To fulfill the research objective, a research question has been created. Answering the research question will help in reaching the objective of this study. The main research question could be formulated as followed:

To what extent, and how, do local flight delay sources influence the dynamics of delay propagation within a network of airports of the U.S. National Aviation System simulated by a stochastic queuing network model?

To help answering this main research question, it has been divided into four sub-questions, which can be found below.

1. What are the influencing factors of generation and propagation of delay that should be taken into account?

2. How can the generation and propagation of delay within a network be modeled properly based on the key processes within airport operations?

3. How, and to what extent, can the proposed model be used to analyze and identify airport roles in the propagation of flight delay?
4. How could this model be applied to improve the mitigation of delay propagation in the future i.e. what is the main contribution of this study?

3.3. Research Scope

From the research questions it becomes clear that this study will focus on the generation and propagation of delay and the roles airports have within the airport network. Throughout literature different perspectives are present on the quantification of both delay creation as well as delay propagation. Therefore, the research scope will be clarified within this section.

3.3.1. Delay Generation

Based on the literature study, three main processes within the aircraft flight profiles have been identified as the main contributors of delay generation, namely the arrival of aircraft, the turnaround of aircraft, and the departure of aircraft. A more detailed representation has been considered outside the scope of this study.

Within each of these three processes, the queuing of aircraft will result in some average waiting time in the queue. This waiting time in the queue indicates the average delay experienced by the aircraft due to congestion and is called the local queuing delay. For each of the three airport processes a subsequent local queuing delay term is generated, which together are called the local queuing delay of one specific airport.

3.3.2. Delay Propagation

Within literature, delay propagation is quantified as the amount of delay which is generated at a downstream airport and is propagated towards a new airport by its incoming flights. Propagated delay can be caused by several reasons, such as transferring passengers, crew rotation, or aircraft malfunctions. However, within this study the focus lies on the rotation of aircraft flying their predefined schedule. Thus other causes of propagated delay are considered outside the scope of this thesis project.

3.4. Research Methodology

The above research questions define what is needed to reach the research objective and could be summarized in a research framework. The research framework for this project is based on the methodology presented in [52]. In Figure 3.1, the research framework is presented, indicating the processes and the research questions, presented with their number in bold, which could be linked to these processes.

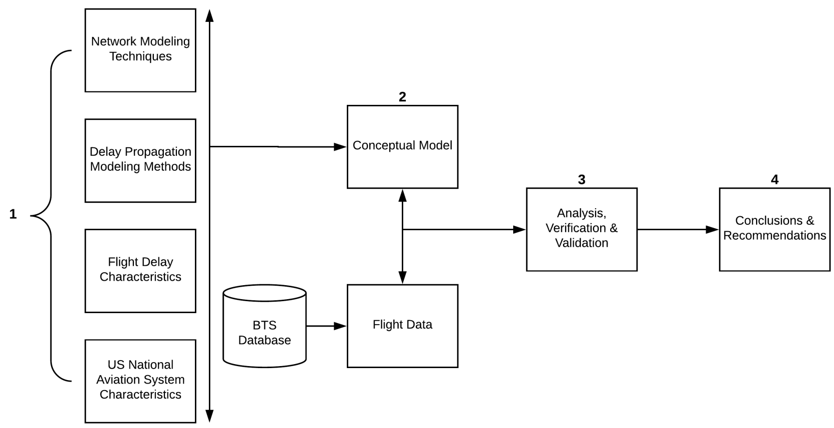


Figure 3.1: Research Framework

Based on this research framework the following methodology will guide in reaching the research objective.

1. Create a conceptual queuing model based on the airport processes.
2. Set up model input and output performance indicators which enable the model assessment under different operational conditions.
3. Performing a case study of 29 US airports, within a representative period of time, in which the dynamics of propagated delay could be investigated.

These three sub-objectives are important, since they determine when the research objective is reached and the thesis project can be finalized.

Queuing model
Queuing theory has proven to be an excellent choice in the past, when describing delay propagation mechanisms. Within literature, most of the models were based on queues due to its adaptability to different operational conditions and ability to capture the stochastic nature of airport operations. To make this thesis assignment feasible, queuing will be used as the leading methodology. By choosing queuing theory as the leading research methodology, a proper mathematical model can be created, which captures the dynamics of delay within the examined network.

Model assessment
The model requires the input of both arrival and service rates, which simulate the dynamics of the demand over the day and the capacity of each airport process. Based on all the different metrics, which are discussed in the literature review, the following performance indicators will be used: the average queuing and propagated delayed, the delay difference indicator, and the delay source distribution indicating its original source. With these performance indicators the network dynamics will be tried to capture.

Case study
After the creation of the queuing model and the specification of how the model will be assessed, a case study has been performed within the context of the United States domestic network. As model input, 29 large US airports have been selected of which the local queuing delay and propagated delay will be simulated by the queuing model. Three experiments will be conducted wherein the operational conditions and flight days will be varied to see the effects of delay propagation.

4

Model Specification

To simulate delay propagation, a queuing based model is created where aircraft are described by objects which follow a certain path along predefined nodes based on their daily flight schedules. The queuing model is based on airports build up in three different queuing systems representing the arrival, departure, and turnaround process. In this chapter the model formulation, operation of the model, model assumptions, model inputs, and performance indicators are explained respectively.

4.1. Modeling a Single Airport

Within the literature study, a stochastic queuing network model has been identified as an appropriate method to represent a network of airports within the US NAS context [31], [32], [43], [49]. The overall approach is based on the observation that aircraft fly a scheduled itinerary, which results in a certain arrival and departure rate at every airport. As the day progress these scheduled rates change due to delay within the system. Given the actual rates of all domestic flights it should then be possible to trace the propagation of delays. The queuing process is modeled as a chain of queues and servers that describe the itinerary of an aircraft object which moves from one server to the next server. These queues and servers represent the internal processes of each airport within the model.

At each airport, aircraft arrive at a queue according to an independent stationary Poisson process with rate λ_i^m. [As.2] The rate can interpreted as the average number of aircraft (N_i^m) that arrive per unit time, see Equation 4.1, in queuing process m at airport i. The arrival rate is computed on a half hourly($b-a=30$) aggregation of incoming flights. A 30 minute interval is proofed to be the closest approximation to represent a stationary process.

$$\lambda_i^m = \frac{N_i^m}{b-a} = \frac{N_i^m}{30} \quad ,\forall\ m \in \mathbf{Q}, \quad \forall i\ \in \mathbf{A} \tag{4.1}$$

The set of queues present at each airport is referred to as Q and the set of airports included in the model is referred to as A. The same principle is used to calculate the number of aircraft served, μ_i^m, for each queuing system within the network.

Since the model does not follow aircraft on their tail number, no individual itineraries are implemented. Instead, aircraft rotation is being presented as a flow of aircraft going in and out of an airport. The links between the airports are represented by routing probabilities which are based on the number of flights going from and to the airports within the network. The flow of aircraft or rates at which they arrive at the different queues is approximated on a half-hourly arrival rate obtained from the empirical data.

To simulate the airport processes a conceptual model has been created which cover the arrival, turnaround, and departure process. Each airport within the proposed Delay Airport Model (DAM) will consist of an arrival runway queue (AR queue), turnaround (TA queue), and a departure runway queue (DR queue). The set of queues is referred to as Q, where $\mathbf{Q} = \{a, t, d\}$. A schematic representation of one airport is given in Figure 4.1. First the aircraft flow will be discussed after which the computation of the delay terms is discussed.

Arrivals at the AR queue are considered as departures from the network and as arrivals towards airport i. Flows from other airports are represented by routing probabilities $p_{ji}, ..., p_{ni}$ and flows towards other airports

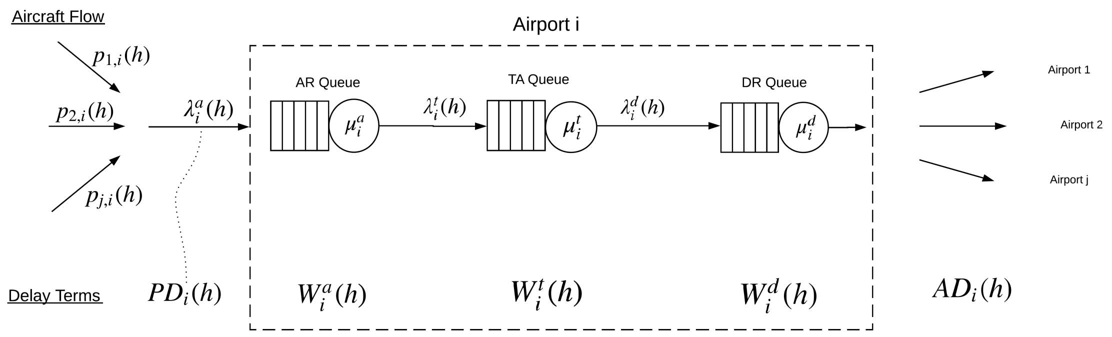


Figure 4.1: Conceptual representation of a single airport

are represented by $p_{ij}, ..., p_{in}$. The flight phase is assumed to be un-capacitated, which means that no delay will form during flight, nor any delay will be mitigated during flight [As. 9].

Aircraft arrive at the AR queue according to an independent stationary Poisson process with rate λ_i^a [As. 2]. After being served, with service rate μ_i^a, the arrivals enter the turnaround system. At the TA queue aircraft arrive according an independent stationary Poisson process with rate λ_i^t. After being served at the gates, with service rate μ_i^t, aircraft enter the departure runway queue according an independent stationary Poisson arrival process with rate λ_i^d. Aircraft are served here with a service rate μ_i^t. Departures from the DR queue are considered as departures from airport i and as arrival towards the network.

Within each queuing system a waiting time in queue is generated depending on the local conditions. With three queuing systems per airports, each airports will contain three different waiting time components, namely, arrival(W_i^a), turnaround(W_i^t) ,and departure(W_i^t). An additional delay term is propagated from each departure airport towards the arrival airport which will result in the propagated delay term (PD_i) for each airport i. Last, the airport delay term (AD_i) is introduced which indicates the result of both local and propagated delay. A more extensive explanation of the quantification of delay is found in section 4.5.

Arrival Runway Queue ($M/M/1$)

The arrival runways are modelled as an $M/M/1$ queue. The arrival process is assumed to be a independent stationary Poisson process(M) with arrival rate λ_i^a, where this rate is based on the amount of actual arrivals at airport i during period h [As. 2]. The arrivals rate is the summation of all departure flows running from airport j, λ_j, multiplied by the probability aircraft fly from j to i, p_{ji}. An additional stream, a_j, is added which represents all arrival flows from airports which are not included in our model but still contribute to the arrival flow at airport i. In Equation 4.2, one can see the mathematical representation of λ_i^a. All these rates are calibrated with the on-time performance database of the BTS [8].

$$\lambda_i^a = a_j + \sum_{j \neq i} p_{ji} \cdot \lambda_j \quad \forall i, j \in A \tag{4.2}$$

The service rates indicate the maximum throughput capacity of airport's runway system that is the expected number of movements which could be processed if the airport is under continuous demand. This could be estimated by analytical or simulation models, from field-based estimates, such as the FAA capacity profiles [45], and on real flight data such as the on-time Performance database of the BTS database [8]. However, these static representation does not account for day to day changes in the system. Therefore, the service rate will be based on the actual time it take to serve a landing aircraft in sub period h. This information is gathered from the BTS database and translated into a mean service rate ,μ_i^a, for each airport i and sub period h [As. 3].

By assuming one runway server, queues can arise and no further analysis is needed on the runway configuration and ATM policies used at each individual airport. Since each airport within the network consists of a different runway system and uses a different runway configuration, assuming one runway for each airport will simplify the model calibration significantly [As. 4].

Turnaround Queue ($M/M/1$)

The turnaround queue is modelled as a $M/M/1$ queue. The arrival process is assumed to be an independent stationary Poisson process(M) with arrival rate λ_i^a, where this rate is based on the amount of actual gate arrivals at airport i during period t [As. 2] Since the prior queue in the network is both Markovian in arrival and service, the input rate of the turnaround queues is also according an exponential distribution, see Equation 4.3 [10]. Since both rates are equal it can also be stated that the rate is based on the amount of actual arrivals at airport i, which are obtained from the on-time performance database of the BTS [8]. However, to approximate reality with the use of three different queuing system in one airport

$$\lambda_i^t \equiv \lambda_i^a \quad \forall i \in A \tag{4.3}$$

The service rates, μ_i^t, for the turnaround queue is determined from the BTS database and are based on the amount of aircraft which are ready for departure and leave their gate, in other words, the departure rate [As. 3]. The service-time distribution is assumed to be a stationary exponential(M) distribution with rate μ_i^t. Furthermore it is assumed that the turnaround queues have one server, to simplify the modeling of the turnaround process. One could perform a study on the amount of gates at each airport in the model to increase the accuracy of the model. However, this is outside the scope of this thesis project.

Departure Runway Queue ($M/M/1$)
The departure runway queue (DR queue) is modelled as a $M/M/1$ queue in the same way as the arrival runway queue [As. 2]. The arrival process is based on a independent stationary Poisson process with rate λ_i^d. It has been assumed that the queuing systems are independent of each other and thus the rate, λ_i^d, will be based on actual departure rates obtained from the BTS on-time Performance database [8].

The service rate for the DR queue is determined in a similar way as the AR queue but now based on the amount of aircraft which take-off instead of landing. The service rate will be based on the actual amount of take-offs in sub period h. This information is gathered from the BTS database and will be based on the wheels off times and translated into rate ,μ_i^d, for each airport i and sub period h [As. 3].

The DR queue also contains one server, similar to the AR queue [As. 4]. After being served by the DR queue, aircraft will depart from the airport and will be treated as departures from the network. Aircraft flow will be separated among the different connections based on the routing probabilities obtained from the airport flight schedules. In Equation 4.4 one can see how the rates are split up based on the routing probabilities p_{ij} and the a_i which are the departures to all the airports which are not in the analyzed network.

$$\lambda_i^d = a_i + \sum_{j \neq i} p_{ij} \lambda_i \quad \forall i, j \in A \tag{4.4}$$

4.2. Modeling a Network of Airports

Within the model, the United States National Aviation System (NAS) will be used as the main reference point. Since delay propagation is mainly a problem at the larger airports, only the 29 largest airports with the highest volume of traffic, also called the Core 30 airports, will be treated within the model. Let A be the set of airports in the network [17]. A simplified version of the network is presented in Figure 4.2 which indicates how the airports are connected and how the aircraft flow is distributed when it leave one airport and goes to next.

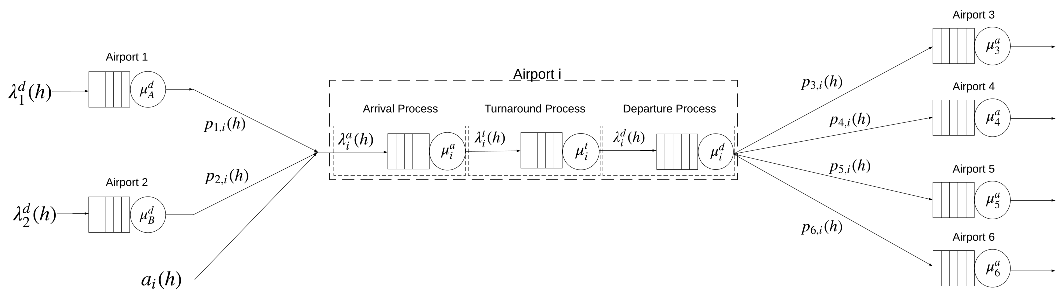


Figure 4.2: A simplified representation of the network

Within this simplified representation of the network, seven airports are drawn, two departure airports from which aircraft depart, one connecting airport, and four airports which receive aircraft from the connecting airport. As an example, aircraft flow from 1 to 5 will be considered. Starting at airport 1, the departure aircraft are aggregated with a demand rate, λ_1^d, and are served at the departure process of airport 1 with a service rate μ_1^d. After being served, a scheduled defined fraction of aircraft,$p_{1,i}$, will fly from airport 1 towards airport i. When the aircraft arrive at airport i the three airport processes will be run through. After being served at the departure process of airport i, a fraction of the aircraft, $p_{5,i}$ will depart towards airport 5 were it will queue up again for the arrival process. This same process will be repeated until all sub-periods of the simulation day have been considered. The rate of aircraft coming in from the virtual airport is represented by a_i.

Within the whole model, the same queuing discipline will be used, namely First Come First Serve (FCFS) [As. 5]. This means that aircraft are served in the order they are entering the system. For most of the American airports this assumption is valid [51]. Aircraft follow a scheduled itinerary and cannot leave the system.. Therefore, aircraft will wait in the queue until they are served [As. 6]. Furthermore, the same waiting room capacity is assigned to all queues. Since in the model no demand should be denied, the number of aircraft in the queues can take any number above zero [As. 6].

A 30th "virtual airport" is added to the model replacing all incoming and outgoing flow to the remaining US airports [As. 7]. When visiting the virtual airport, it is assumed that aircraft do not experience any further delays. Furthermore, delay propagated via the virtual airport will not be incorporate in the model analysis. To assure an appropriate calibrated model with the right queuing parameters, the On-time performance database of the Bureau of Transportation (BTS) has been used, containing aircraft flight schedules, the actual arrivals and departure times, and the on-time performance.

Since the model is based on the U.S. NAS, multiple times zones are crossed by the aircraft. The US main land consists of 5 time zones going from -5 UTC (Eastern Standard Time (EST)) until -8 UTC (Pacific Standard Time (PST)) in the winter and -4 UTC (Eastern Daylight Time (EDT)) until -7 UTC (Pacific Daylight Time (PDT)) in the summer. During the night, there is low activity which makes it convenient to start the model during the night. Since time is decreasing from east to west, 4am EST will be used as the starting point of one simulation 'day' , that is 3am, Central Time (CT), 2am Mountain Time (MT), or 1am Pacific Time (PT). Since there will be only mainland airports included in the model, these 4 time-zones are sufficient. All local times will be converted to EST/EDT to make it possible to compare airports from different timezones.

4.3. Assumptions

To simplify the model several assumptions are made during the creation of the model. In the following section these are stated. The first seven assumptions concern the queuing systems. The latter assumptions are more generally describing the model and the interrelations between airports.

Assumption 1
One simulation 'day' is subdivided into k sub-periods, $h_1, .., h_k$ of the same length. During each sub-period (h_i) steady-state is assumed, with a constant λ and μ during this sub-period for each queuing system. Flight times between airports are categorized per sub-period and rounded off to the nearest integer.

Assumption 2
The arrival demand at each queue in the queuing network is modeled as an independent stationary Poisson process and so the inter-arrival times of aircraft follows an exponential probability distribution with mean value λ. Each new sub-period, a new mean value is determined, based on an empirical data study.

Assumption 3
The service times of every queuing node follow a stationary Poisson process with a mean value or rate μ. This value is determined by an empirical data study and remained fixed during a simulation day.

Assumption 4
An airport within the model is represented by one arrival runway server, turnaround server and one departure runway server.

Assumption 5
Aircraft are served according the First Come First Serve (FCFS) principle throughout the whole network.

Assumption 6
Aircraft will always wait in line until they can be served, and the number of aircraft in queue can be infinitely large, so that no demand will be lost.

Assumption 7
Each queuing system of each airport, starts out empty at the start of a new simulation 'day'.

The remaining assumptions are related to the overall model.

Assumption 8
Expected waiting times is assumed to be an adequate representation of average delay during one of the three sub-processes.

Assumption 9
The flight phase is un-capacitated, which means that no delay will form during flight nor any delay will be mitigated during flight.

4.4. Model Input

To be able to run a simulation, a certain amount of input data is required. In the following list, the essential input variables are stated.

- Airports (A)
- Time period (T)
- Arrival rates of the queuing systems (λ)
- Service rates of the queuing systems (μ)
- Routing probabilities (p_{ij})
- Flight times (f_{ij})

While some of these input variables are time and day dependent, others can be fixed and used throughout every simulation run. In the remainder of this section, each of the input variables are discussed.

Airports
Let **A** be the set of airports in the network. Within this thesis the US National Aviation System is under consideration. Of the total NAS only the 29 largest airports (Honolulu International, Hawaii is excluded from the case study) are chosen and modelled explicitly, the remainder of the NAS airports are represented by a 30th 'virtual' airport. While referring to one of the airports the airport code is commonly used throughout the rest of the thesis.

Time period
Within the model the time period which is analyzed can be set to multiple time scopes. One can for example model one day of data but also one month, or maybe one year. For now time period (T), or one simulation 'day', is set equal to a 24-h period, beginning at a time where there little to no traffic, 4am EST. T is subdivided into k sub-periods(h), h_1, .. ,h_k of the same length. At the beginning of the time period T the queuing network starts out empty [As. 7]. The sub-period are assumed to be 30 minutes of length. In the Chapter 5 a more in-dept analysis has been performed to justify the appropriate time-interval length.

Arrival rates of the queuing systems
Based on the on-time performance data of the BTS, it is possible to create daily demand profiles for each individual airport indicating their arrival and departure rate if aircraft would depart and arrive at their designated actual time. Based on these demands an arrival and departure rate can be set at the start of a new day.

However, these rates are not fixed during the day and so both arrival and departure rate, λ, are a dynamic property and will change every sub period. During the calibration phase it will be determined if the assumed sub period can cover the rate of change in rate.

Service rates of the queuing systems

The service rates indicate the number of aircraft which could be processed by the specific servers. Within the model, three different service rates need to be defined, namely, arrival runway, turnaround, and departure runway. These service times will be based on the BTS data. In chapter 5 the calibration of the model will be discussed in more detail.

Routing probabilities

To be able to know how aircraft will spread over the network and thus how delays will spread over the network, routing probabilities are necessary so the connectivity of the network can be expressed. Based on the schedules obtained from the BTS data, a routing matrix can be set up indicating the possible OD pairs of that sub-period and the corresponding percentage of flights which travel towards that particular destination. For example, if airport 1 has 10 outgoing flights in period k, and 2 flights are going to airport 2, the routing probability p_{12}, is equal to 20% or 0.2. Similar to the arrival and departure rates, routing probabilities will change over the course of the day and can be approximated per defined sub-period.

Flight times

The flight times between the different airports in the model are necessary to describe the temporal redistribution of propagated delay. Since each OD pair has a different flight time, delay will spread with at a different pace throughout the network. Where short OD pairs could feel an almost immediate effect of propagation, long OD pairs would be exposed later in time. For example, flying from JFK to ORD would only take 1,5 hours, while flying from JFK to LAX takes 4,5 hours. Therefore, delays occurred at JFK could already have an affect on ORD within 2 hours, while at LAX this would take at least 4,5 hours.

To address this temporal effect each OD pair is categorized according to the assumed sub-periods (h_i). Flight times are obtained from the empirical data-set and are categorized per period of 30 minutes [As. 11]. So when looking at the example above, flying from JFK to ORD would take 3 sub-periods and flying from JFK to ORD would take 9 sub-periods. Therefore f_{ij} would be equal to 3 and 9 respectively.

4.5. Delay definitions

Before the performance measures can be stated, a clear definition for delay is needed. Since the model is built on the abstraction level of rates, and not on the level of individual aircraft, the classical delay definition can not be used.

Instead, aircraft are now aggregated to a time-varying rate, which is constant along each sub-period. And so the definition of delay needs to be converted to this aggregated definition. Although the examined queuing network is not stationary over the course of the day, it has been assumed that during each sub-period the system is in steady state [As. 1]. Therefore, the effects of delays due to air traffic congestion will be expressed per sub-period as well. This simplification enables the use of steady-state solutions for each sub-period (h).

When looking at existing literature for stationary queues a lot is known about steady-state solutions for expected waiting times. Little's Law provides a simple way to convert the expected or average queue lengths into expected waiting times [24]. In Equation 4.5 and 4.6 one can find these relationships, between both the average queue length (L_q) and the average waiting time in queue (W_q), as well as the average number of customers in the system (L_s) and the average time in the system (W_s).

$$L_q = \lambda W_q \tag{4.5}$$

$$L_s = \lambda W_s \tag{4.6}$$

By adapting these Equations towards a more useful representation, the waiting time in queue and waiting time in the system can be obtained, see Equation 4.7 and 4.9. In Equation 4.7 one can find this relationship where $L_{q,i}$ represents the queue length at node i, $W_{q,i}$, the waiting time in queue at node i, and λ_i the average arrival rate at node i all during the same sub-period [24] [50]. When going to the next sub-period, λ_{i+1}, the rate has changed and so the expected waiting times changes as well. Where Equation 4.7 is derived directly from Little's law, Equation 4.9 is obtained by using the relation between the number of aircraft at node i ($L_{s,i}$) and the number of aircraft in queue at node i ($L_{q,i}$) in Equation 4.8. The queue length ($L_{q,i}$) of each queuing system at node i will be obtained by performing simulation. With the use of Equations 4.7 - 4.9 the other queuing measures can now be obtained.

$$W_{q,i} = \frac{L_{q,i}}{\lambda_i} \tag{4.7}$$

$$L_{s,i} = L_{q,i} + \frac{\lambda_i}{\mu_i} \tag{4.8}$$

$$W_{s,i} = W_{i,q} + \frac{1}{\mu_i} \tag{4.9}$$

With the definition of expected waiting time in the queue it is now possible to specify delay. Within literature the expected waiting time in the queue is used as the expected delay experience by the aircraft as of a result of congestion [45] [49] [50]. Within this thesis project the same principle will be used and so the expected waiting time at queue m in node i ($W_{q,i}^m \equiv W_i^m$) will be defined as the equivalent of expected queuing delay. With three queuing systems in place for each airport this results in three different queuing delay terms per airport i, W_i^a, W_i^t, and W_i^d, as shown in Figure 4.1 and Figure 4.2.

Next, the definition of airport delay and propagated delay are specified. Airport delay(AD_i) is defined as any delay incurred due to congestion at the current airport plus any delay which is propagated from connected airports and arrives at airport i during the same sub period. Propagated delay is formed by any delay which is incurred at former airports. Based on these two definitions a mathematical expression can be provided for both airport delay (AD_i) and propagated delay (PD_i), see Equation 4.10 and 4.11.

$$AD_i(h) = W_i^a(h) + W_i^t(h) + W_i^d(h) + \alpha\ PD_i(h) \tag{4.10}$$

$$with$$

$$PD_i(h) = \sum_{i \neq 1}^{A} AD_i(h - f_{ji})\ p_{ji}(h) \tag{4.11}$$

Here, airport delay of airport $i(AD_i)$ is determined for each sub-period h as being equal to the expected queuing delay per queuing system at airport i plus the propagated delay term of the same sub-period multiplied with a factor $\alpha \in [0,1]$ which could be changed during the calibration phase. For now this α is stated to be equal to 1.

Propagated delay (PD_i) is defined as the summation of the outgoing airport delay at the previous airport j multiplied with the routing probability (p_{ji}) from airport j to i for all airports j which are not equal to arrival airport i. One important note is that the flight time between each OD pair should be incorporated as well. Therefore, the propagated delay term is also affected by the flight times by assigning the delay term (PD_i) to the appropriate sub-period ($h + f_{ji}$) since the delay of airport j will only have effect after aircraft arrive at airport i. In the following section the performance measures of interest can now be defined with the use of Equations 4.7 -4.11.

4.6. Performance Measures of Interest

Within the model, several performance metrics will be used to quantify the dynamics of delay propagation among the different airports. In this section the performance measures will be explained. A distinction can be made between local performance measures based on the performance of one airport, and network performance measures which are based on the behavior of the network as a whole. First, the local performance measures will be discussed followed by the network performance measures.

4.6.1. Local Performance Measures

Local performance measures include expected delay for specific sub-period of the day, or for the entire day, the maximum expected delay during the day, the arrival and departure delay or the number in queue for each queuing system. In the remainder of this section these local performance measures of interest will be discussed.

Expected and Cumulative Queuing Delay

In relationship to the input parameters λ_i, and μ_i, it is interesting to see how the expected queuing delay terms evolve over the course of the day. Local queuing delay(QD_i) is defined as the sum of the waiting times for each queuing system at one specific airport, see Equation 4.12.

$$QD_i = W_i^a(h) + W_i^t(h) + W_i^d(h) \tag{4.12}$$

This measure will be computed for each sub-period (h), which shows the distribution of expected delay during the day at each individual airport for the arrival, turnaround, departure queue. With these measures it can be seen if delay converges back to zero or if it will become significantly large that during the rest of the day large delays will retain. Furthermore, busy periods could be identified and relationships between the different queuing systems could be determined.

Next, the cumulative queuing delay will be determined. Based on Equation 4.12, the cumulative local delay (QD_i) is computed for each airport i. This measure will later be compared to the cumulative propagated delay term for the same airport i to see which of two is more dominant at the examined airports.

Maximum Expected Queuing Delay

Next to the temporal dimension, it is also interesting to compare expected delay terms of the same airport or even with other airports. Therefore, the maximum expected local delay is defined for each system at each airport, see Equation 4.13 where the arrival system is used as an example.

$$\max_{h \in 1,..,T} [W_i^a(h)] \quad \forall \ i \in \ A \tag{4.13}$$

With this Equation three maximum values, for the arrival, turnaround and departure process are obtained.

Arrival and Departure Delay

To compare simulation results with the empirical data both arrival and departure delay have been computed for each airport within the network. The arrival delay is computed as Equation 4.14, and the departure delay is computed as Equation 4.15. The arrival delay is calculated for each sub-period h and consists of the delay aircraft obtained at their previous airport (propagated delay), and the local queuing delay obtained when waiting for the arrival process. The departure delay is calculated for each sub-period h and consists of the arrival terms plus the local queuing delay obtained when waiting for turnaround and departure.

$$ArrDelay(h) = \alpha \ PD_i(h) + W_i^a(h) \tag{4.14}$$

$$DepDelay(h) = W_i^a(h) + W_i^t(h) + W_i^d(h) + \alpha \ PD_i(h) \tag{4.15}$$

Based on these two measures, the average arrival and departure delay are computed for each simulation day which can be compared to real data as part of the validation of the model.

Average Queue Length

As one of the main results of the model the average queue length has been computed. Based on the time-averaged number in queue, see Equation 4.16, Little's Law has been applied to obtain the local delays.

$$L_{q,i} = \frac{\int_a^b L_{q,i}(t)dt}{b-a} \tag{4.16}$$

Here, the numerator is defined by an integral indicating the time a certain queue length is present where a and b define the start and end of the interval of interest. The integral does not have to be calculated in the usual form of an equation. It can be calculated analytical by an approximation with a sum of the discrete moments. Thus, each the average queue length has been determined each 30 minutes.

4.6.2. Network Performance Measures

In this section the network performance measures will be explained. Next to the local effects, delays could also have a mayor effect on other airports within their network. These propagation effects are tried to be encaptured with the following performance indicators.

Cumulative Propagated Delay

Based on the local delay and the routing probabilities, it is now interesting to see how much propagated delay is experienced by each airport within the network. Based on Equation 4.11, the cumulative propagated delay is calculated for each airport within the network and plotted during each day. The results of this plot are compared with the local counterpart.

Total Delay

To quantify the total delay at each individual airport the total delay metric, D_i^{tot}, is introduced, which is a summation of the local and propagated terms for each airport i, see Equation 4.17.

$$D_i^{tot} = \sum_{h=1}^{k} QD_i(h) + PD_i(h) \quad \forall\ i\ \in\ A \tag{4.17}$$

This indicator will be used to compare different airports while experiencing different conditions.

Delay Difference

Based on the distribution of expected queuing delay, a performance indicator is defined, namely the delay difference indicator. The delay difference indicator(DD_i) refers to the difference between the sum of the local queuing delay(QD_i) and the sum of the propagated delay(PD_i) at airport i, see Equation 4.18. If there is more local than propagated delay, the indicator is larger than 1 and vice verse. The indicator shows if an airport is a source or a sink of delay.

$$DD_i \equiv \frac{\sum_{h=1}^{k} QD_i(h)}{\sum_{h=1}^{k} PD_i(h)} \tag{4.18}$$

The delay difference is calculated per day and uses the sum of each the expected delay term per sub-period. This indicator will be used to profile the airports as a sink or source of delay.

Airport profiles

Based on the delay difference indicators, three different airport profiles have been created based on the airports natural behavior under daily demand. The three profiles are delay generator, delay receiver, and a dual role(both). A delay generator indicates that an airport creates significantly more queuing delay than it receive propagated delay from other airports. The delay receivers mean that an airport receives significantly more propagated delay than that it creates itself. The last role is assigned to airport where both roles are visible and so it is undecided which role is more dominant.

Breakdown of delay sources

It is also interesting to see the relationships between airports and to show causal relationships between sources and its receivers. To be able to analyze this, a pie chart will be created which indicates the sources of the delay and their share of the total delay. The share of propagated delay from each airport j will be based on Equation 4.19.

$$PD_i^j = AD_j\ p_{ji} \tag{4.19}$$

Where AD_j is the local delay at the departure airport j. With each individual share a 100% stacked area chart will be created to see how the constituent parts will evolve over time. With this pie chart it is possible to determine the main source of delay per each airport, whether it is local or from another airport.

5

Data Input & Calibration

In this chapter the focus lies on the development, the data input, and the calibration of the model. First the airport subset **A** is defined. This set will be the network of airports which will be examined. Afterwards, a definition is provided of the BTS database used for all the schedule information, the time zone database used to convert local times, and the FAA capacity profiles used to indicate service rates changes under IFR and VFR conditions. Then, the data pre-processing and filtering process is explained, which is performed before useful parameters can be extracted from the flight schedules. Next, the data-set will be made discrete based on the chosen sub-period time intervals. This decision is based on finding a stationary time window within the arrival process. Next, the queuing parameters are estimated. Ending this chapter with the experimental design of the three conducted experiments.

5.1. Development of the Model

During the investigation phase it was decided that the United States domestic market is the research target area, since the US databases of both the FAA and BTS are publicly available, and because it was not possible to gather the same amount of data on Europe. Furthermore, the US National Aviation System is an interesting case to study, since delays are very common within this network plus the propagation of delay is bigger factor within the US network.

Table 5.1: Core 30 Airports [16]

Airport Code	Airport Name	Airport Code	Airport Name
ATL	Hartsfield-Jackson Atlanta Intl	LAX	Los Angeles Intl
BOS	Boston Logan Intl	LGA	New York LaGuardia
BWI	Baltimore/Washington Intl	MCO	Orlando Intl
CLT	Charlotte Douglas Intl	MDW	Chicago Midway
DCA	Ronald Reagan Washington National	MEM	Memphis Intl
DEN	Denver Intl	MIA	Miami Intl
DFW	Dallas/Fort Worth Intl	MSP	Minneapolis/St. Paul Intl
DTW	Detroit Metropolitan Wayne County	ORD	Chicago O'Hare Intl
EWR	Newark Liberty Intl	PHL	Philadelphia Intl
FLL	Fort Lauderdale/Hollywood Intl	PHX	Phoenix Sky Harbor Intl
HNL	Honolulu Intl [1]	SAN	San Diego Intl
IAD	Washington Dulles Intl	SEA	Seattle/Tacoma Intl
IAH	George Bush Houston Intercontinental	SFO	San Francisco Intl
JFK	New York John F. Kennedy Intl	SLC	Salt Lake City Intl
LAS	Las Vegas McCarran Intl	TPA	Tampa Intl

[1] Honolulu Intl. Airport will be excluded from the analysis due to its geographical position w.r.t. the network

Since the US national aviation system consists of 310 airports, which accommodate domestic air travel, a smaller subset needs to be chosen as the basis of the case study. Because delay and the propagation of delay is a problem for the bigger airport the core 30 continental US airports listed by the FAA [16], see Table 5.1, are chosen as the main point of focus. These 30 airports in major metropolitan areas are the airports with the highest volume of traffic within the United States. With complex high-density operations these airports have the perfect incentives for traffic congestion and delays thus being an interesting case to examine.

The model has been programmed in Python and has been implemented for the network of 29 Core 30 airports. (This means all Core 30 airports, with the exception of Honolulu.) Figure 5.1 shows a map of these 29 airports. Moreover, a 30st "virtual airport" is added which represents all domestic traffic going from and towards an airport which is outside of the network [As. 8]. The purpose of this virtual airport is to include all flights which are somehow connected with any of the 29 airports, going from or towards these airports. Flights between two external airports are not included in the model, because these flight will not have an effect on the arrival rates or delay formed within the 29-node network.

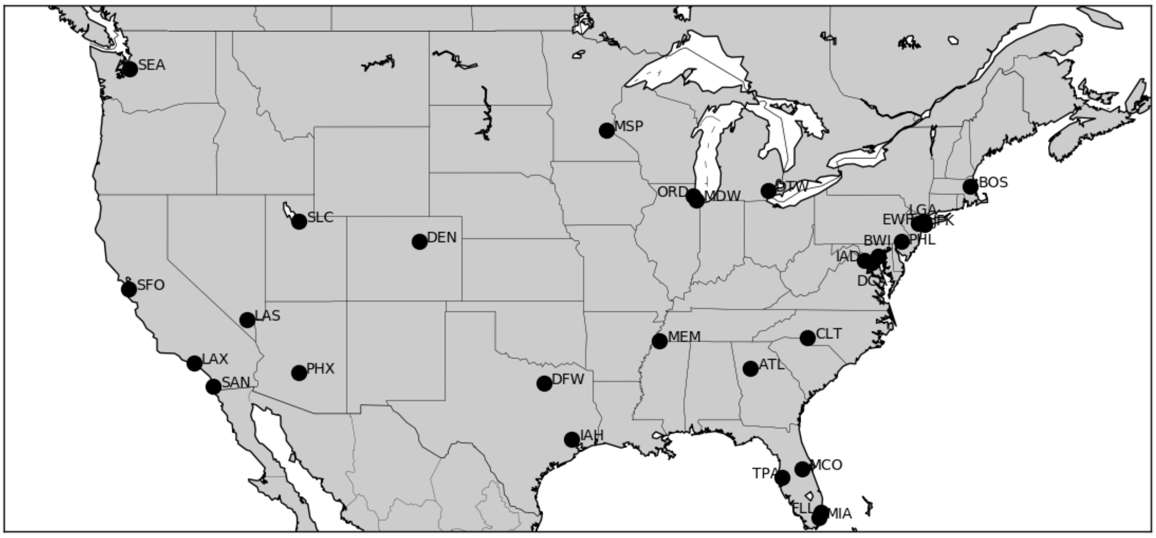


Figure 5.1: Airport Map of Core 30 Airports

On a typical day, roughly 16,250 domestic flights are flown, around 6,100 of these flights (38%) are flown within the network, while 8,400 flights (52%) take place between one of the 29 airport and the virtual and 1,600 flights (10%) are entirely outside the network and thus not considered in the analysis.

To be able to develop this model, multiple sources have been examined to gather the right information. The main source of information is the Bureau of Transportation On-Time Performance Database [8]. Within this database all US domestic flights are recorded including their time of departure and arrival, their origin and destination and if they depart and arrive on time. Based on this database the arrival rates and service rates for each queuing system are estimated, see section 5.4. Next to the normal service rates, airports sometimes have a lower throughput capacity if weather conditions are as such that it is impossible to operate under the normal runway configuration. Therefore the capacity profiles [22] are used to give an approximation of the capacity difference between VFR and IFR conditions. This factor will be used in the model if the specific airport at that specific day is operating under IFR conditions.

Since all times in the BTS were recorded in local time it was impossible to directly extract the required information from the data source. Therefore, it was required to convert the arrival and departure times from local time to one reference datum time zone. To be able to do this a time zone database has been used containing the corresponding time zones during winter and summer of each airport within the network [38]. With this database each local time is converted to the reference datum time zone EST(during winter) and EDT(during summer).

5.2. Data Input Description

As stated earlier, the BTS database will be the main source of information for the simulation. This section contains a general description of this data source. The database is build up in rows of flights each containing 109 columns of information. The most important columns are stated here below plus an example of how the input is formulated:

- Year (e.g. 2016)
- Month (e.g. 9)
- DayofMonth (e.g. 21)
- DayOfWeek (e.g. 2)
- FlightDate (e.g. 21-01-2016)
- Carrier (e.g. AA)
- TailNum (e.g. N525NK)
- FlightNum (e.g. 1)
- Origin (e.g. ATL)
- Dest (e.g. JFK)
- CRSDepTime (e.g. 1515)
- DepTime (e.g. 1640)
- DepDelay (e.g. 85)
- TaxiOut (e.g. 15)
- WheelsOff (e.g. 1655)
- WheelsOn (e.g. 1836)
- TaxiIn (e.g. 11)
- CRSArrTime (e.g. 1744)
- ArrTime (e.g. 1850)
- ArrDelay (e.g. 66)
- Cancelled (e.g. 0)
- Diverted (e.g. 0)
- CRSElapsedTime (e.g. 149)
- ActualElapsedTime(130)
- AirTime (e.g. 101)
- CarrierDelay (e.g. 0)
- WeatherDelay (e.g. 0)
- NASDelay (e.g. 66)
- SecurityDelay (e.g. 0)
- LateAircraftDelay (e.g. 0)

A complete overview of the data columns of this database and the corresponding description can be found in reference [9]. Since most columns of data are self explanatory, only the less obvious will be explained. For both the Departure and the Arrival Time two columns exist within the set. The CRSDepTime column indicate the scheduled departure time and DepTime indicates the actual time the aircraft departed. The same principle is in place for the CRSArrTime and ArrTime columns, and the CRSElapsedTime and ActualTime which indicate the scheduled time and the actual time it took to fly from A to B. Where the four figures time columns indicate the time in hhmm format, the rest of the time related columns indicate the number of minutes it for example takes to taxi in from the runway towards the gates. The cancelled and diverted columns will contain an one if the specific flight is cancelled or diverted. The flights have also been excluded from the dataset. At last a distinction is being made in the causes of delay by indicate one of the five causes(Carrier, Weather, NAS, Security, and LateAircraft). This cause is only being reported if the flight is officially late(15 minutes or more) and so the amount of data points is limited for most of these categories.

5.3. Data Preparation

Before the key queuing parameters could be estimated, the BTS database needs to be manipulated into the right format which can be processed by the DAM model. To be able to do this, a data pre-processing script has been created which manipulates the data in such a way that it can be of use. The data pre-processing script consists of the following elements:

1. Select flight days and airports
2. include all flights which go from or towards one of the airports in the network
3. Convert time format from hours minutes towards minutes
4. Convert local times to EST/EDT
5. Fix all errors regarding next day arrival
6. Drop all rows which miss data
7. Set timeframe 4am - 4am EST/EDT
8. Convert all airports which are not in the network to the virtual airport

The specification of the data pre-processing and filtering is shown in Figure 5.2. As a result a flight schedule is generated containing each flight from and to the airports in the network within the correct format. In the first step a few variables need to specified, including which day, which sub-set of airports and which input file will be used. After this step, all the remaining airports, which are not in the subset **A**, which will be included in the virtual airport array and use later on to replace all airports which are not included in the

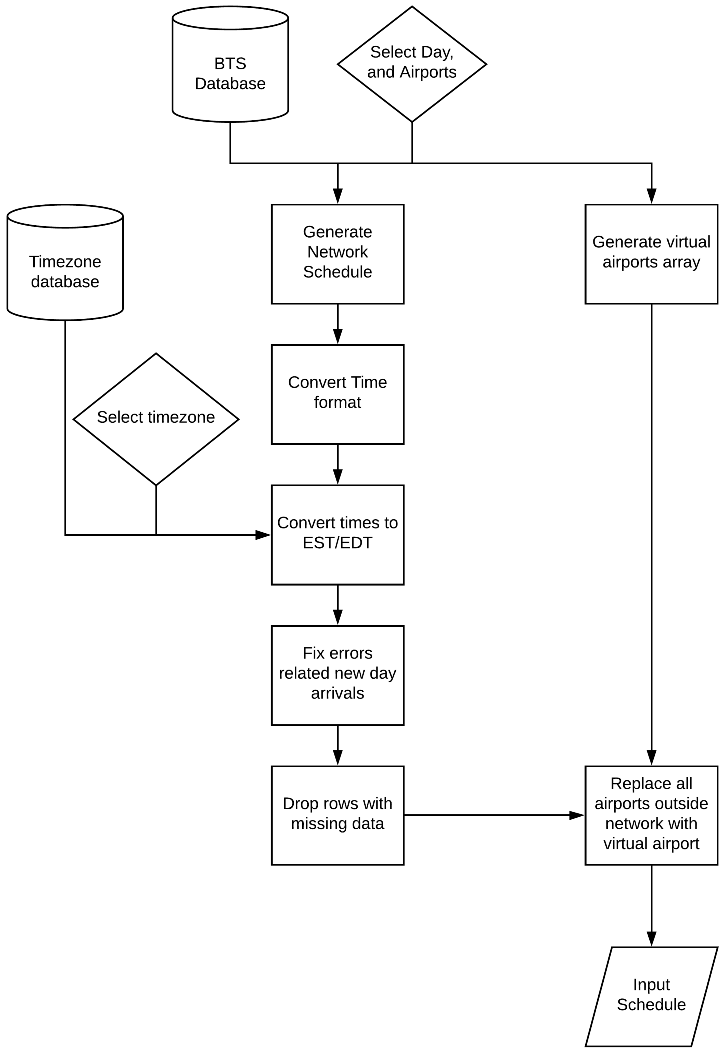


Figure 5.2: Specification of the Data Preparation

model. At the same time the network schedule is created containing every flight from and to one of the 29 airports.

Next, the time format is converted from hours and minutes into minutes for example 3:30 is equal to 210 minutes. This is necessary to be able to calculate the minutes of delay that are encountered during flights. Since all times are registered in local time, all times are converted to one single time zone, namely Eastern Time(ET). When all times are converted, still a few steps need to be taken. While analyzing the empirical dataset it turned out that every flight which arrives on a new day, after 12 pm, should be counted above the already counted minutes. Now the time frame can be set from 4am until 4 am the next day. Next, all rows with missing data will be dropped from the schedule. As a last step, the airports outside the network will be replaced with the virtual airport.

5.4. Parameter Estimation

In the following section the parameter estimation will be described. The queuing parameters can be categorized into four important parameters, namely the inter-arrival time distributions or the arrival rates(λ_i), the service time distribution or service rates(μ_i), the routing probabilities(p_{ij}), and the flight times(f_{ij}). Now that it is known which subset of airports and which level of timely aggregation will be used these parameters can be estimated.

A distinction can be made between the fixed input parameters: service rates, flight times, and the variable input parameters: arrival rates, routing probabilities. Where flight times and service rates(capacity) are more or less fixed for routes between airports and airports specifically, arrival rates and routing probabilities vary heavily during the day. Therefore, the remainder of this section is focused on two aspects, describing how each of the four queuing parameter is estimated each run, and how the variable parameters will change during a "simulation day". To calibrate the fixed parameters, the month November 2016 of the BTS On-Time Performance database is used [9], since in this month the least delay is experienced by the network and thus the best representation of the network is present, see Appendix A.

5.4.1. Arrival Rates

The first key parameter which is estimated is the mean arrival rate (λ) of each queuing system present in the model. In Chapter 4 it is defined that each airport consist of three different queuing systems. Therefore, three arrival rates need to be determined based on an empirical data analysis, namely $\lambda_i^a(h)$, $\lambda_i^a(h)$, $\lambda_i^d(h)$. Where $\lambda_i^a(h)$ is based on the mean arrival rate of aircraft arriving at airport i(column *WheelsOn*), λ_i^t is based on the mean arrival rate of aircraft arriving at the gates of airport i(*ArrTime*), and λ_i^d is based on the mean arrival rate of aircraft that are departing from the gates of airport i(column *DepTime*).

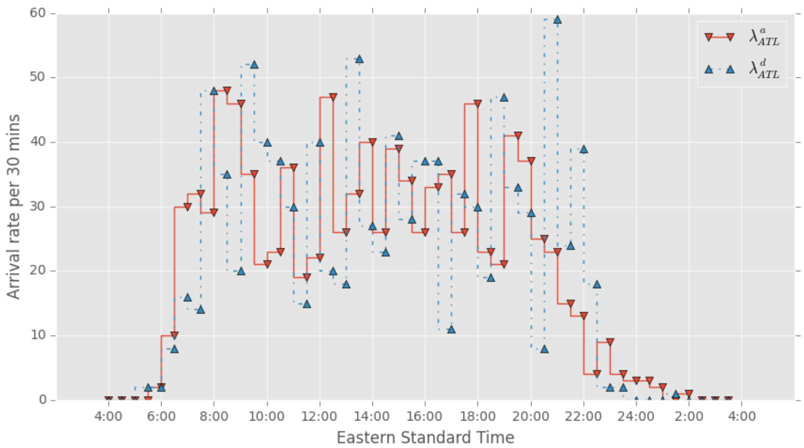


Figure 5.3: Arrivals Rates example Monday the 21st of November 2016 Atlanta(ATL)

In Figure 5.3, an example is shown where these two rates are plotted based on the half hour aggregation. Based on this figure, one can see that a constant arrival rate would not give a good representation of the network demand. Therefore, arrival rates are variable parameters and thus change over the day and will change with each input day. In this example one can see that each peak of arrivals is followed by a peak of departures, as expected.

5.4.2. Routing Probabilities

The second important parameter needed for constructing the queuing network are the routing probabilities (p_{ij}) of aircraft flying from one airport i towards airport j. These flow fractions can be derived based on the number of aircraft arriving or departing from a certain airport together with the origin they are coming from or the destination they are flying towards. In this model, the focus lies on the routing probabilities (p_{ji}) aircraft coming from airport j and arrives at airport i, see Equation 4.11. Based on the domestic flight itineraries obtained from the BTS database the flow fraction can be determined per each sub-period for each airport present in the network.

Since the routing probabilities are based on the rate of arriving aircraft, each sub-period these probabilities change together with the incoming rate. Therefore, routing probabilities can be considered as variable inputs parameters. To give an illustration an example is provided in Table 5.2.

5.4.3. Service Rates

The third key parameter are the service rates (μ) of each queuing system present in the model. The service rates represent the throughput capacity of each airport's runway system. That is the expected number of aircraft which can be processed per sub-period if there would be a continuous demand. Normally, service rates

Table 5.2: Routing probabilities example Monday the 21st of November 2016 between 9:30-10:00

To \ From	ATL	BOS	CLT	FLL	JFK	VRT
ATL	0	2/46	1/46	0	1/46	42/46
BOS	0	0	0	1/6	1/6	4/6
CLT	0	0	0	0	0	2/2
FLL	0	0	1/12	0	0	11/12
JFK	0	0	0	0	0	2/2
VRT	22/49	10/49	6/49	8/49	3/49	0

may vary across sub-periods reflecting changes in for example weather conditions, changes in runway configurations, or Air Traffic Control (ATC) policies. However, in this model the service rates are assumed to be fixed [As. 3]. The service rates can be obtained from analytical or simulation models, field based estimations, or empirical data [45]. The latter one is used within this model. Based on the rate of aircraft arriving at the airport (column *ArrTime*), departing from the gate (column *DepTime*), and taking off (column *WheelsOff*), the service rates for the arrival queue (μ_i^a), turnaround queue(μ_i^t) and the departure queue (μ_i^d) of airport i are determined respectively, see Table 5.3. The service rates are based on a monthly average of November, to rule out any randomness in good days and bad days of handling. It should be noted that these values correspond

Table 5.3: Calibrated service rates for 5 of the 29 airports

Airport Code	μ^a *(AC/half-hour)*	μ^t *(AC/half-hour)*	μ^d *(AC/half-hour)*
ATL	62	70	58
BOS	19	26	23
CLT	26	29	26
FLL	16	16	16
JFK	14	21	19

to the service of domestic air traffic and do not represent the total service capacity of the airports, since there is also international traffic. However, it was not possible to gain information on international flight schedules since this data was restricted to American citizens. In the final model, the service rates of each of the 29 airports is required as input data. In Appendix B the services rates for each airport and each queuing system can be found.

5.4.4. Flight Times

The last important parameter is the flight times(f_{ij}) between each OD pair, which enables the right assignment of propagated delay to the correct sub-period at the arrival airport. The flight times are determined by taking the time aircraft would take to fly from the origin to the destination (column *ActualElapsedTime*). An average is then taken over the whole month of November to cancel out discrepancies. Furthermore, it has been assumed that difference between the to-from flight In Table 5.4 an example is shown of these flight times for a sub-set of the total set **A**, which gives a illustration of the situation. As mention earlier, the flight times have been converted to sub-periods of similar size since the model works with discrete time-steps of 30 minutes. In Table 5.5 one can find the flight times after they have been converted to discrete time [As. 11].

Table 5.4: Flight times example between 5 airports of the network in minutes

	ATL	BOS	CLT	FLL	JFK
ATL	0	148	74	100	131
BOS	148	0	135	190	70
CLT	74	135	0	114	110
FLL	100	190	114	0	164
JFK	131	70	110	164	0

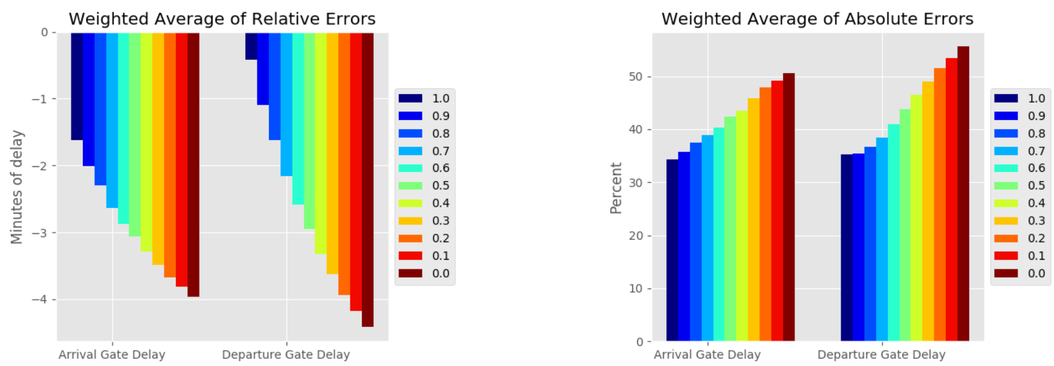
These discrete flight times will be used, together with the corresponding OD pair, to assign the propagated delay term of Equation 4.11 in the correct sub-period (h) and at the correct arrival airport i. In the final model, the flight times between every OD pair of the network is defined in discrete time. An overview of this can be found in Appendix C.

Table 5.5: Flight times example between 5 airports of the network in sub-periods

	ATL	BOS	CLT	FLL	JFK
ATL	0	4	2	3	4
BOS	4	0	4	6	2
CLT	2	4	0	3	3
FLL	3	6	3	0	5
JFK	4	2	3	5	0

5.5. Alpha testing

Within the model dynamics the parameter α was introduced to account for the persistence of propagated delay throughout the model. This parameter determines how much of the propagated delay will be passed through after flights, containing this delay, depart again from the airport. To be able to calibrate the model properly a small study has been performed to test which setting of α resulted in the closest fit to reality. In Figure 5.4a and Figure 5.4b the results of this study are presented.



(a) Relative errors in minutes of delay

(b) Absolute Errors in Percentage

The relative error in minutes of delay indicates the difference in minutes of delay between the simulation average delay and the empirical average delay and the absolute error in percentage indicating the difference in percentage between the simulation average delay and the empirical average delay. In the study α has been altered from 1.0 to 0.0 with steps of 0.1. It is visible that for both the relative as the absolute errors the set with $\alpha = 1.0$ scored best. Therefore, the calibration of α will stay 1.0 throughout the rest of the experiments.

5.6. Experimental Design

This section describes the experimental design of the test that are performed within this study. The experiment consists of three parts. In the first step, the model is calibrated to certain days within the empirical data. Then, the parameters settings are changed to perform a weekday analysis by looking at pooled data based on the seven different days in a week. Lastly, a case study is performed with three weather scenarios to compare the dynamics of delay within the network. To describe the set of input parameters which are used for the experiments an example is shown in Table 5.6. In the last column a distinction is made between fixed parameters which are used throughout every experiment and variable parameters which change when the focus of the experiment changes.

5.6.1. Model input for day based analysis

In the first part of the experiment the new model is calibrated for single days to both test its performance and accuracy, but also to obtain results on the dynamics. As discussed earlier, the model has been calibrated with the dataset of November 2016 to determine both the service rates as well as the flight times in between

Table 5.6: Example input variables

Input Variables	Range	Fixed / Variable
Number of Iterations(N)	1000	Fixed
Alpha (α)	1.0	Fixed
Time-step(h)	30 [min]	Fixed
Airports (A)	29 + 1 Virtual	Fixed
Flight Date	Flight Day/Day of the week	Variable
Weather Conditions	VFR-IFR	Variable
Demand rates(λ)	0-100 [flight/30min]	Variable
Service rates(μ)	0-60 [flight/30min]	Variable
Routing probabilities(p_{ij})	0-1. [%/30min]	Variable
Flight times	0-9 [sub-period]	Fixed

airports. For the data input the month September 2016 is chosen, from which days will be picked which will give the arrival rates and the routing probabilities per airport. For each day, the same time frame is used; 8:00 a.m. UTC to 7:59 a.m. UTC, which is 4:00 a.m. EDT until 3:59 a.m. EDT. To be able to validate the model, six days have been chosen with all experiencing different weather conditions, two with good weather, two with average weather conditions, and two with severe weather conditions. In Table 5.7, an overview is given of the flights dates of the forecast, the number of airports which fly under low IFR and the airport codes. It has been assumed that if bad weather was present at that specific day, the whole day this airport performed under low IFR conditions.

Table 5.7: Selected flight days

Day	**Low IFR**	**Airport ID**
09-09-2016	1/29	DTW
11-09-2016	0/29	N/A
06-09-2016	3/29	BOS, MIA, MSP
07-09-2016	3/29	BOS, DTW, ORD
19-09-2016	9/29	ATL, BWI, DFW, DTW, JFK, LAX, MCO, PHL, SAN
30-09-2016	15/29	BWI, CLT, DCA, DTW, EWR, IAD, JFK, LGA, MCO, MDW, MIA, MSP, ORD, PHL, SEA

5.6.2. Model input for day of week based analysis

In the second part of the experiment the model is calibrated for grouped data based on the different day of the week (Monday-Sunday) to both test its performance and accuracy, but also to test if there are difference between the days of the week. As discussed earlier, the model has been calibrated with November 2016 as benchmark. For the data input the month September 2016 is chosen from which the days are categorized per day of the week. Each simulation 'day' will run from 4:00 a.m. EDT until 3:59 a.m. EDT. In Table 5.8 an overview is presented of the flight days and which day of the week they belong to.

Table 5.8: Flight days categorized per day of the week

Day of the week	Flight Days
Monday	05-09, 12-09, 19-09, 26-09
Tuesday	06-09, 13-09, 20-09, 27-09
Wednesday	07-09, 14-09, 21-09, 28-09
Thursday	01-09, 08-09, 22-09, 29-09
Saturday	02-09, 09-09, 23-09, 30-09
Sunday	03-09, 10-09, 24-09, 31-09

Since the input data is now aggregated, it is no longer possible to specify the local weather conditions for each day and each airport. Therefore, a random number generator is used together with the annual weather conditions to determine the amount of runs the specific airport should perform under low IFR conditions. This principle can be explained with a small example. If airport A has 10 % of the time conditions which result in IFR conditions and the simulation is run for a thousand runs, one hundred of them will be with IFR capacity.

5.6.3. Model input for Case Study

In the last part of the experiment the model is calibrated for three different cases chosen by the user, with each case representing different operational conditions at one or several airports. For all three scenarios the same set of operations is used namely, the average of Tuesdays from 4:00 a.m. EDT until 3:59 a.m. EDT, which gave the best fit with the empirical data, see validation chapter. In Table 5.9, the 3 different scenarios are presented.

Table 5.9: The three scenarios of the case study

	Capacity levels
Case 1	All airports in optimum capacity
Case 2	ATL in low IFR
Case 3	BOS, EWR, JFK, LGA, PHL in low IFR

In Scenario 1, all airports in the network operate at their optimum capacity for the entire simulation 'day'. In Scenario 2, the capacity of ATL(Atlanta) is affected by bad weather for the entire day and is reduced to low IFR conditions. In Scenario 3, six airports in the North East region, BOS(Boston), EWR, JFK, LGA(New York, PHL(Philadelphia), are affected by a local storm, which decrease their capacity to low IFR conditions for the whole day.

6
Simulation Results

This chapter discusses the results of the tests performed with the DAM model in the three setups explained in Section 5.6. In the first part, the day analysis results are treated. In the second part, the day of the week analysis is considered. Lastly, the case study results are discussed.

6.1. Flight Day Analysis

In the first experimental setup the model performance is assessed for different days of operations found within the empirical database. Six different days are chosen and used as the input for the model, each day with different meteorological conditions. Within this chapter a selection of the results is presented to illustrate both the results for the performance indicators as well as the potential of the model. From the six tested days, only three will be presented here, namely 9-09-2016 (VFR conditions), 06-09-2016(3/29 low IFR), 30-09-2016(15/29 low IFR), to keep the results evident. The simulation of one flight day resulted in a computational time of 4972 seconds or 83 minutes. The remainder of this section will treat the overall network behavior, profiling of the airports, identify the sources of delay, and presenting a detailed example of the model insights.

6.1.1. Overall Network Behavior

When looking at the overall network behavior under different operational conditions different observations could be spotted. In Table 6.1 the network overview is presented of 9,6 and 30 September with the propagated delay in minutes and the average propagated delay and arrival delay in minutes per flight. Each time a specific airport operated at low IFR conditions during that day the number are presented in italic. When one or more airports operate under low IFR conditions one would expect to observe a certain increase in propagated delays at all the airports within the network.

This is indeed the case when the expected propagated delay terms of Day 1 are compared with situation of Day 2 and 3. Related to that also the average arrival delay increases with some amount, sometimes quite significantly. For example, at BOS(Boston) where the arrival delay undergoes an increase of more than 200% comparing from Day 1 to Day 2. This increase of average arrival delay could have two reasons, namely an increase in propagated delay or local queuing delay. In our example BOS operates in Day 2 with low IFR conditions which explains the large increase in arrival queuing delay. Looking at the other two airports which are in low IFR conditions on 6 September, MIA and MSP, it can be seen that a lower capacity not always result in a higher average delay. Where the arrival delay at MSP also increase due to higher arrival queuing delay the arrival delay at MIA actually drops. This could be explained with the fact that not every airport needs its full capacity to meet its demand. And so if the maximum capacity drops the remaining capacity could still be sufficient to cope with its demand.

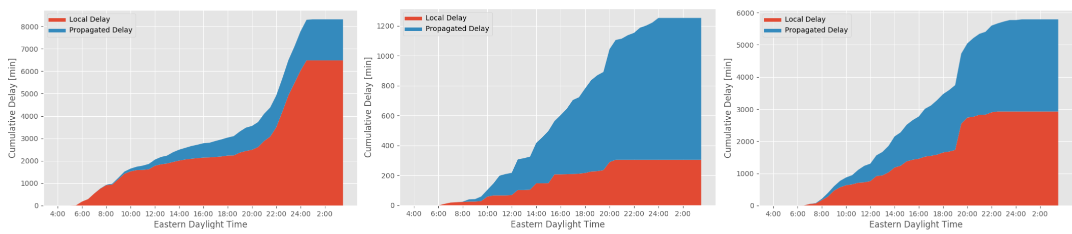
The same happens during Day 3 where there are 15 airports under low IFR conditions. Where each airport suffers a higher amount of propagated delay, almost every airport under low IFR condition has a large increase in arrival delay. During the remainder of this section, it will be investigated which role each airport poses from which airport the largest amount is received, plus a detailed example of the capabilities of the model.

Table 6.1: Expected Propagated Delay and Arrival Delay for the 24-h period

	Day 1: 9-9-2016			Day 2: 6-9-2016			Day 3: 30-9-2016		
	Prop. Delay	Avg. Prop. Delay	Arr. Delay	Prop. Delay	Avg. Prop. Delay	Arr. Delay	Prop. Delay	Avg. Prop. Delay	Arr. Delay
ATL	2172	2.35	3.17	2863	2.46	3.58	4474	2.83	4.68
BOS	1315	5.14	6.88	*1831*	*5.38*	*14.05*	3171	6.43	10.74
BWI	785	3.40	5.21	1091	3.59	5.70	*1445*	*4.07*	*8.00*
CLT	949	3.77	4.68	1148	3.87	5.26	*1806*	*4.51*	*8.13*
DCA	1009	4.94	6.57	1377	5.26	7.76	*1815*	6.15	10.95
DEN	1837	3.21	4.01	2359	3.31	4.40	3354	3.78	5.70
DFW	1494	3.14	4.01	1875	3.24	4.21	2802	3.73	5.72
DTW	*1029*	*3.29*	*4.43*	1304	3.42	4.68	*1995*	*3.98*	*7.17*
EWR	991	3.62	5.44	1346	3.79	5.97	*1759*	*4.38*	*10.43*
FLL	769	4.83	5.92	926	4.99	6.64	1418	5.83	8.83
IAD	447	4.89	4.99	547	5.51	7.45	*781*	*6.43*	*8.09*
IAH	941	3.05	3.51	1161	3.07	3.83	1735	3.46	5.00
JFK	940	4.27	6.51	1118	4.51	7.52	*1582*	*5.19*	*11.05*
LAS	1534	4.06	6.61	1768	4.16	6.69	2863	4.80	8.58
LAX	2330	4.43	5.89	2786	4.55	6.35	4240	5.14	8.23
LGA	1050	4.36	7.21	1402	4.58	8.26	*2069*	*5.47*	*12.05*
MCO	1040	4.18	5.82	1384	4.40	6.58	*2094*	*5.33*	*9.86*
MDW	717	3.29	4.61	896	3.39	5.04	*1330*	*3.86*	*7.90*
MEM	216	5.01	5.20	254	5.53	5.71	354	6.54	8.63
MIA	787	5.27	5.99	*947*	*5.49*	*5.94*	*1303*	*6.46*	*8.03*
MSP	1082	2.98	3.16	*1478*	*3.51*	*5.38*	*2106*	*4.09*	*7.28*
ORD	1974	3.38	4.10	2753	3.54	4.89	*3673*	*4.13*	*7.17*
PHL	806	4.73	6.01	1039	4.97	7.07	*1536*	*5.91*	*12.05*
PHX	1257	3.49	4.39	1328	3.53	4.39	2406	4.13	6.51
SAN	933	4.61	6.39	1047	4.71	6.67	1638	5.33	8.55
SEA	1260	3.93	5.09	1443	4.04	5.63	*2192*	*4.66*	*9.29*
SFO	1968	4.50	5.61	2424	4.59	6.16	3600	5.29	8.43
SLC	883	3.20	3.98	981	3.24	4.20	1485	3.63	5.24
TPA	692	4.90	5.79	809	5.08	6.47	1259	5.91	8.65

6.1.2. Airport Profiles

In Chapter 4 the delay difference indicators have been introduced providing a tool to profile each airport based on their ratio between local queuing delay and the propagated delay they receive from other airports. Based on this performance indicator, three clear profiles could be identified within the model results, namely the Delay Generator, the Delay Receiver, and the Airport which both receives as well as generates a lot of delay. In Figure 6.1a, 6.1b, and, 6.1c, an example is shown of a Generator Airport, a Receiver Airport, and an Airport which consists of both roles.



(a) Delay Generator (BOS) (b) Delay Receiver (MIA) (c) Both Roles(ATL)

Figure 6.1: Delay Profiles based on 06-09-2016 calibration

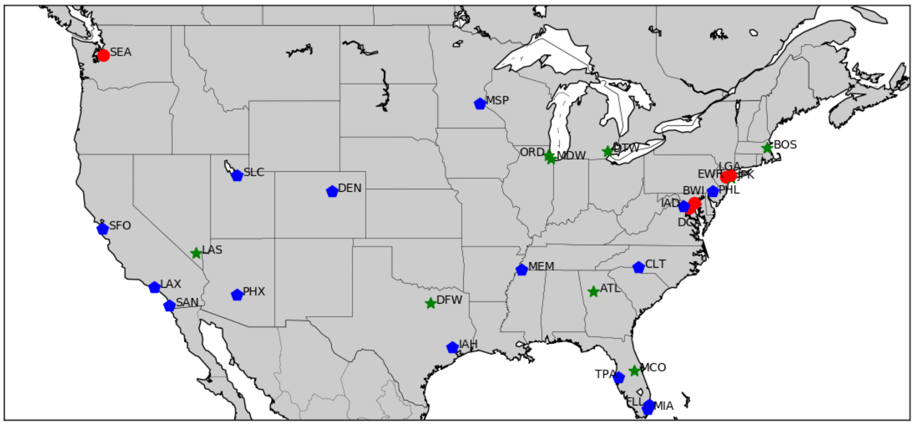


Figure 6.2: Airport profiles based on 6 selected flightdays

In all three figures, the total delay of these airports is presented. The total delay is split up with the red area indicating local queuing delay, which implies delay that is generated at that airport by for example the arrival queue, and the blue area indicating propagated delay generated by other airports and what is carried with the aircraft towards that airport. First in Figure 6.1a, Boston(BOS) is presented which in this example is under low IFR conditions. Due to this capacity restriction, the airport generated a lot of local queuing delay and receives relatively low propagated delay. Looking at the pattern over time two large increases can be spotted from 6 am until 10 am of which the local delay is going up 1500 minutes, and 6 pm until midnight where there is a massive increase of 2500 minutes up to more than 6000 delay minutes.

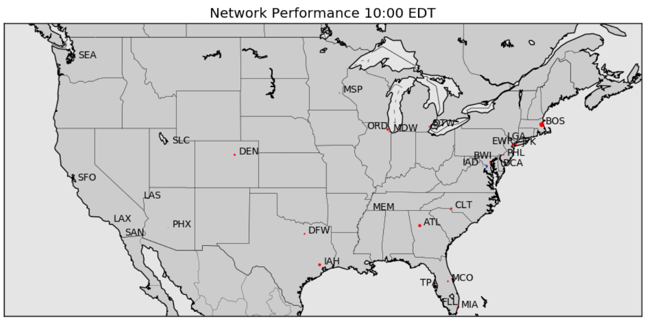
Second, in Figure 6.1b, Miami(MIA) is presented which receives almost all its delay from other airports and generates very little queuing delay. Looking at the daily pattern, several banks can be spotted with incoming flight delivering a lot of delay with the biggest increase around the 8 pm bank where the propagated delay increases from 800 minutes to 1100 minutes. Third in Figure 6.1c, Atlanta(ATL) is presented which performs both the role as a receiver as well as a generator. At the start of the day most delay is generated locally, but later on during the day and especially around its afternoon bank it receives more then 2000 minutes of propagated delay, with a the end of the day a total delay around 6000 minutes splitted up in 2800 minutes of local delay and 3200 minutes of propagated delay.

With these three roles in mind the airports within the network can be profiled. In Table D.1, an overview is presented of the six days and their corresponding delay difference indicator. Based on the six days an average score is calculated. This score is used to determine if an airport is a generator, receiver, or both. Based on the indicator presented in Chapter 4 all airports below .8 are profiled as receivers, between 0.8 and 1.1 are profiled as both, and above 1.1 airports are considered being a delay generator. The result of these is given in Table D.1. The results of the different days will later be compared with the outcomes for the day of the week calibrated results after which the final profiles are determined.

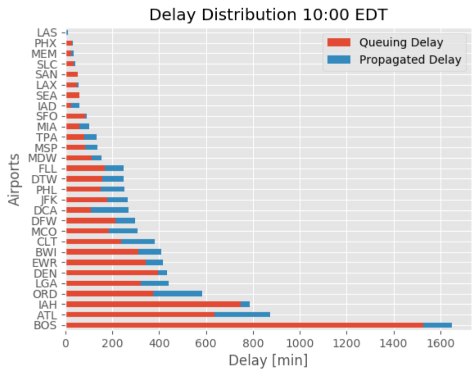
6.1.3. Detailed Example and Insights

In this section a detailed example of the model results will be presented based on the calibration of flight day 06-09-2016. This day is chosen, because during validation it turned out that this day provided the closest fit to reality, see Section 7.4. To perform a network analysis a snapshot is taken from the network at four different times during the day, namely, 10:00, 16:00, 22:00, and 4:00 the next day. Between each step 6 hours of flights are simulated and processed by the model resulting in both a map with the current network situation and a bar chart indicating the amount of total delay, split up in the queuing and propagated delay. In Figure 6.3a-6.3h, the network overviews can be found.

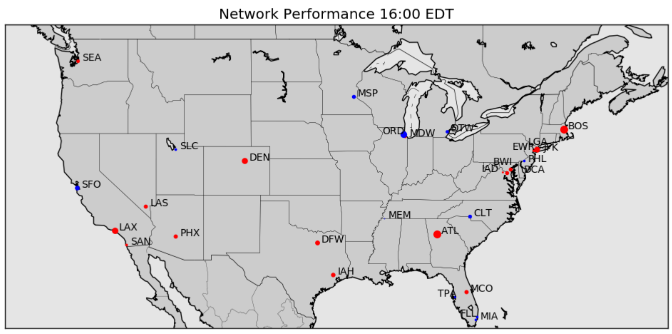
Within these figures, local queuing delay is labeled as red and propagated delay is labeled as blue. In the geographical view, the airport dots are colored based on their most dominant delay component and sizes based on the magnitude of the total delay. Using the eight figures presented above, a chronological analysis will be given starting at 10:00 EDT.



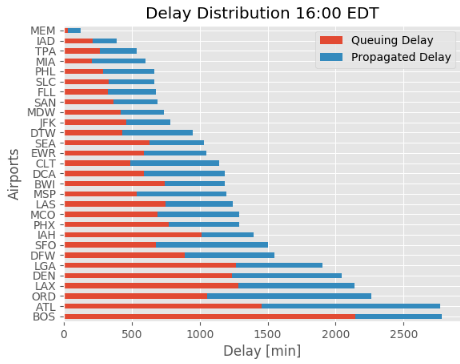
(a) Network Map



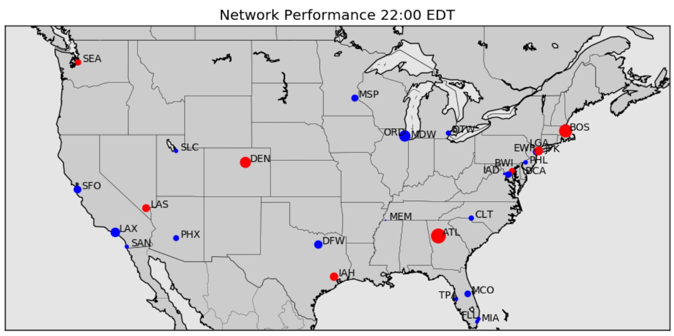
(b) Delay Distribution



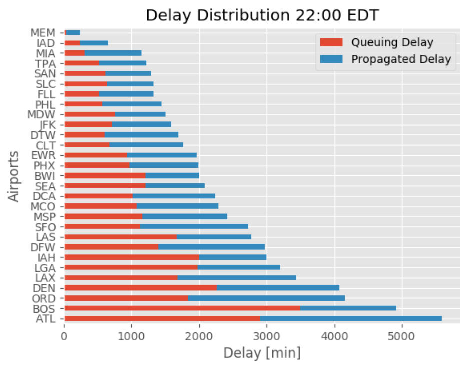
(c) Network Map



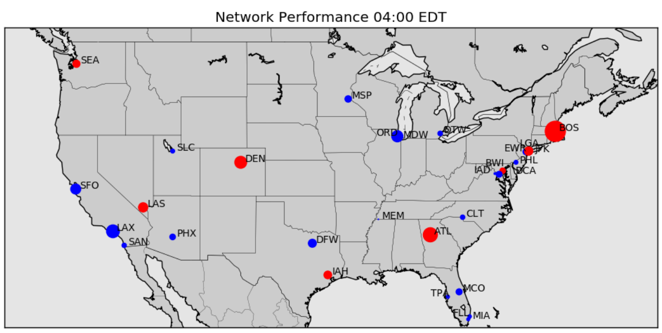
(d) Delay Distribution



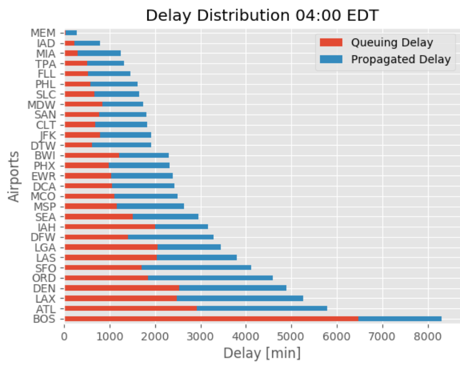
(e) Network Map



(f) Delay Distribution

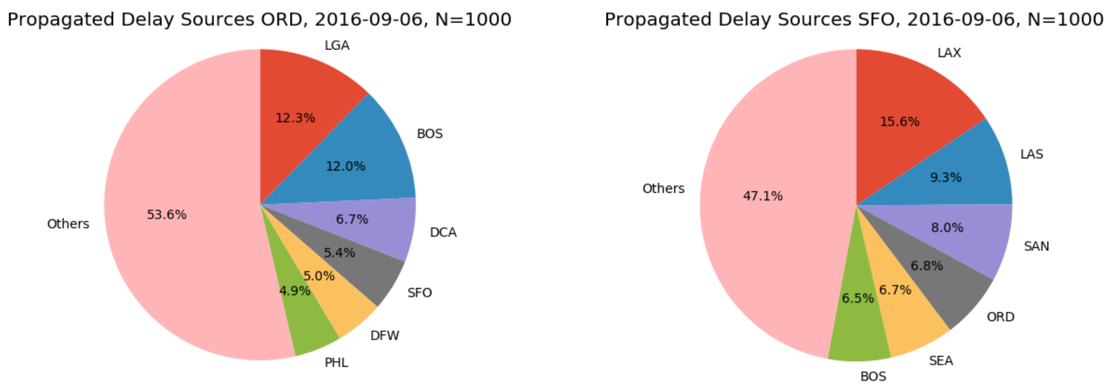


(g) Network Map



(h) Delay Distribution

Figure 6.3: Network Performance at 06-09-2016



(a) ORD (b) SFO

Figure 6.4: Propagated Delay Sources 6-9-2016

In the morning most of the delay is situated at the East Coast. This is logical because of the time difference between east and west coast and the low amount of traffic during the early morning hours. However, at the East Coast there is already some behavior visible. The first thing that stands out is the large amount of delay already being generated at BOS. Furthermore most of the airports are drawn red which makes sense since the delay has not spread yet among the network. Moving on to the 16:00 situation, one can already see that certain roles emerge within the network. Where airports such as BOS, LGA, or IAH mostly generate delay airports such as ORD, SFO, or MIA mostly receive. While the day progress these roles are getting more and more clear with BOS, ATL, DEN, IAH, and SEA as the main generators and the remainder of the network mostly receiving or performing both roles.

But next to the airport roles, it is also very interesting to see the casual relationships between the airports. For this a delay distribution overview is generated, see Appendix E.1 as well as a pie chart indicating the most dominant factor for each airports propagated delay. For this example the biggest receivers will be examined, namely O'Hare Chicago(ORD) and San Francisco (SFO), see Figure6.4a, and 6.4b.

Most of the delay is propagated from airports nearby. Where O'Hare is mostly influence by airports in the North East region, San Francisco is mostly influenced by airport from the West Coast. However, both airports also show an East-West relationship. Where ORD is affected by SFO, SFO is affected by both ORD and BOS which is at the East Coast and so delay originated at one side of the US is propagated to the other coast. This is an interesting discovery and will be investigated into more detail within the later performed case study.

6.2. Day of the Week Analysis

In the second experimental setup the model performance is assessed for the seven different day of the week during the month September 2016. As explained earlier, the flight days in the month September are split up based on the day of the week after which the input data is averaged over these days and so each input is a representation of a typical Monday, Tuesday, etc. Within this chapter only a selection of these results are presented since each simulation run resulted in more than 70 figures and tables, and so a total of 490 figures and tables. Therefore, only the most important findings are presented here. The model took in total 32993 seconds or 9 hours to compute the results of all seven days of the week.

6.2.1. Overall Network Behavior

In this section, the overall network behavior will be discussed. In Table 6.2, an overview is given of the expected propagated delay per day of the week in minutes. For each day of the week the total amount calculated and divided by the total amount arrival flights to obtain the average propagated delay per day of the week. When looking at the overall network behavior per day of the week several observations can be made. First, one can see that Friday both has the highest total as well as the highest average propagated delay. While Mondays is the busiest day, the average propagated delay is little bit smaller than Wednesdays and Fridays. Furthermore, Saturdays is the least busy, which can be explained by the fact that most of the people want to go home or away before the weekend and return/travel on Monday again. This behavior is visible at most of the airports, with Monday and Friday being a busy day with high amounts of delay. However, there are some exception of which Wednesday is the day with largest amount of delay. Since all airports tend to follow the same trend, a preliminary conclusion could be that there are little too non difference in the routing probabilities between each day of the week. This should be investigated into more detail to be able generalized such conclusions.

Table 6.2: Expected Propagated Delay for each day of the week

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
ATL	3021	2629	3180	2942	2859	1353	2383
BOS	1957	1665	2042	1888	2079	925	1622
BWI	1099	832	1020	934	1034	656	860
CLT	1284	886	1411	1387	1306	618	1052
DCA	1376	1086	1222	1225	1289	574	1050
DEN	2420	1972	2416	2383	2401	1362	2110
DFW	2052	1564	1985	1851	1931	966	1814
DTW	1383	1224	1381	1372	1405	627	1127
EWR	1301	1064	1394	1337	1273	605	986
FLL	1016	878	977	1000	974	552	814
IAD	560	425	538	511	571	342	477
IAH	1211	966	1187	1118	1240	610	993
JFK	1175	937	1138	1070	1224	667	986
LAS	1905	1603	1926	1836	2111	1245	1798
LAX	2826	2470	2799	2689	2915	1566	2541
LGA	1453	1166	1531	1496	1528	560	1133
MCO	1412	1178	1386	1396	1416	887	1165
MDW	994	818	964	911	974	559	780
MEM	269	195	249	241	243	141	231
MIA	997	881	980	910	958	563	888
MSP	1450	1302	1416	1615	1475	609	1203
ORD	2821	2226	2532	2684	2783	1242	2160
PHL	1080	873	1089	1087	1132	617	860
PHX	1722	1203	1645	1587	1727	875	1496
SAN	1127	942	1128	1088	1203	684	1005
SEA	1694	1348	1597	1469	1720	1062	1376
SFO	2499	1978	2354	2357	2593	1277	2128
SLC	1091	912	1071	1089	1152	536	1024
TPA	917	751	889	803	932	456	750
Total	44111	35973	43443	42277	44446	22734	36812
Arr. Demand	10353	9957	10098	10313	10312	8049	9823
Avg. Prop. Delay	4.26	3.61	4.30	4.10	4.31	2.82	3.75

6.2.2. Airport Profiles

Based on the delay difference indicator, also the day of the week calibrated profiles can be determined. In Table D.2 an overview can be found with the expected delay difference indicators. Based on the separate scores, a final score is given for each individual airport after which a Profile is selected similar as in section 6.1.2. These profiles have been compared with the earlier generated profiles with the different flight days as calibration.

It turned out that the days selected earlier have been a good representation of the average network conditions because the profiles selected earlier are almost similar, only with a few exceptions, namely ATL, LAS, and PHL, to the profiles based on the day of the week scores. Based on this validation the final profiles have been determined and so the network can be categorized into the three different airport profiles.

In Figure 6.5, one can see an overview of all the airports colored based on their profile. Red means Delay Generator, blue means Delay Receiver, and green means Both. As can be seen, each region has its generators surrounded by receivers, and in the airports who have both roles are mostly focused in the middle of the US.

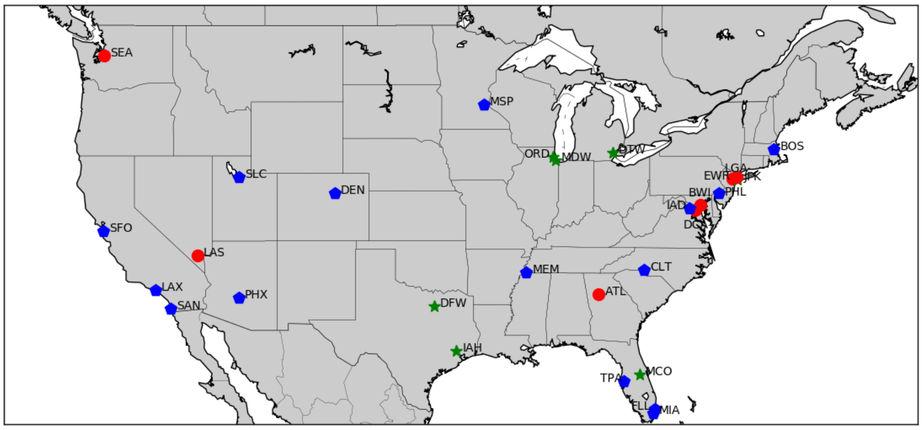
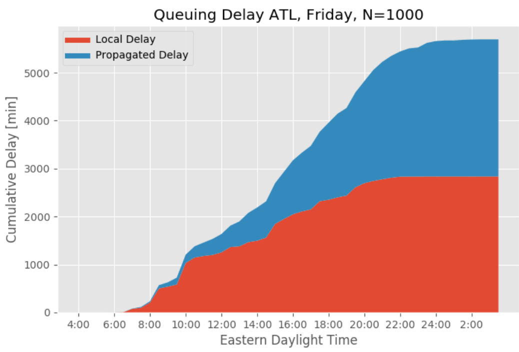


Figure 6.5: Airport Profiles

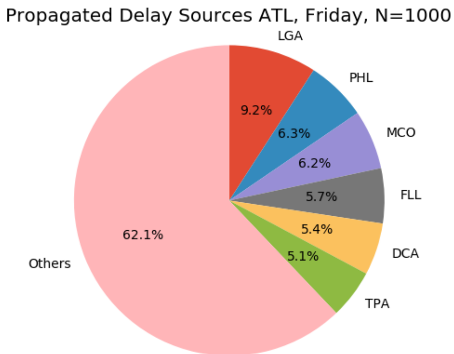
6.2.3. Day of the Week Comparison

To get to know more about the difference between the different day of the week, a comparison has been performed between the day with the highest delay(Friday) and the day with the lowest delay(Saturday). For this comparison we will zoom into the network to see the behavior of two specific airports, namely Atlanta(ATL), and San Francisco(SFO). ATL is a big hub in the center of the US and has an important role within the US National Aviation with the highest number domestic flights each day. SFO is more international airport, but has also a large number of connection in the United States.

First the results of ATL will be discussed. In Figure 6.6a one can see the cumulative delay plot. This plot shows the time course of both the local queuing component in red as well as the propagated term in blue. One could divide the blue section into different sources from where the propagated delay is originated. The distribution of this origins is shown in Figure 6.6b. Here the six largest origins are split up into a percentage of the total propagated delay.



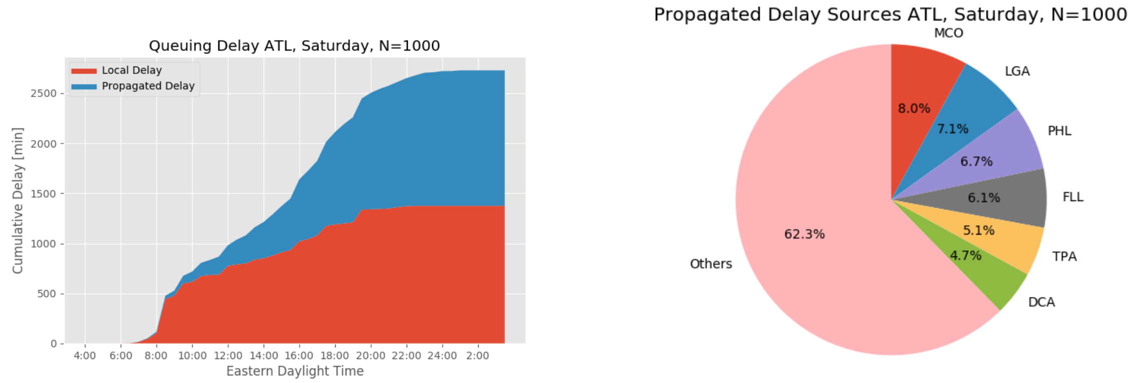
(a) Cumulative Delay during the Day



(b) Delay Sources Distribution

Figure 6.6: ATL situation on Friday

When looking at the results of Friday, it can be seen that the first big increase of delay happens around 8 o'clock, this could be attributed to the first bank of the day were large number of aircraft arrive and leave the airport. A similar bank is present at around 10 o'clock after which the queuing delay gradually increases until 22 o'clock. Three other smaller banks can be spotted around 2, 6 and 8 pm. In comparison with the local component the propagated delay term increases at a higher rate which eventually result in a higher percentage propagated delay than local queuing delay. The biggest sources of propagated delay at ATL is the result of delay at La Guardia airport(LGA), namely 9.2 %. The remainder of the top five are MCO, DCA, FLL, and TPA respectively. In Figure 6.7a, one can see the course of Saturday.

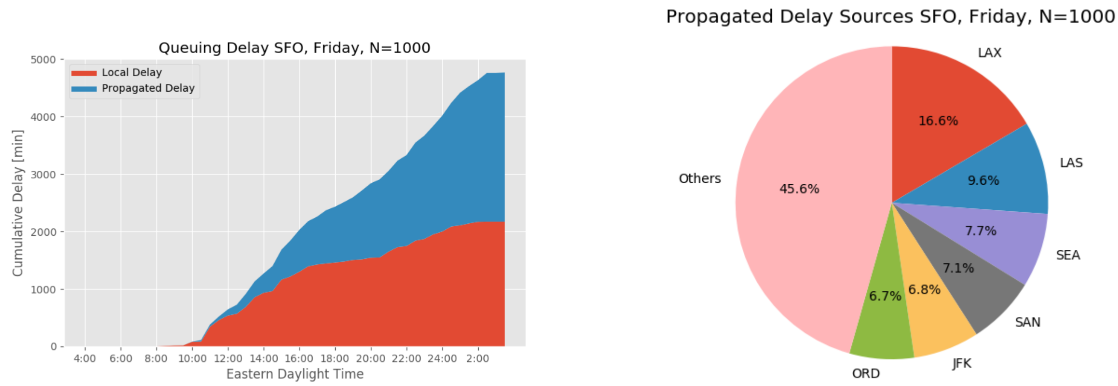


(a) Cumulative Delay during the Day

(b) Delay Sources Distribution

Figure 6.7: ATL situation on Saturday

The first thing that can be noticed is that at the end of the day only half of the delay is presented when comparing with Friday. Furthermore, the queuing delay is almost half of the total delay where on Friday the distribution was 3:2. When looking the sources of delay, a similar distribution is visible with now MCO being the largest with 8 %, following by LGA, PHL, FLL, and TPA, which are exactly the same airports than on Friday. Now the results from SFO will be discussed.



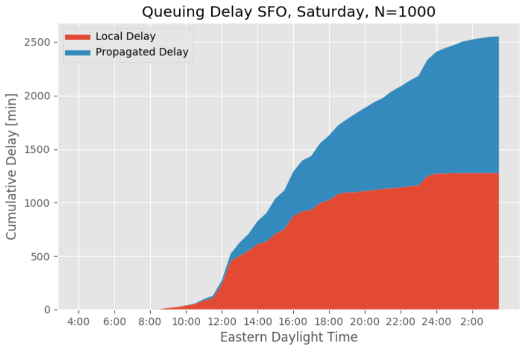
(a) Cumulative Delay during the Day

(b) Delay Sources Distribution

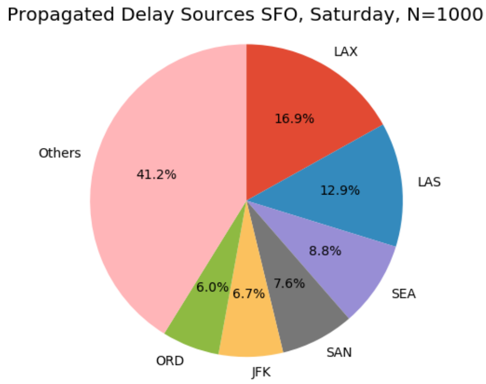
Figure 6.8: SFO situation on Friday

When observing the results of SFO on Friday, see Figure 6.8a, one can see that the day operations of starts 3 hours later at ATL due to the time difference. Furthermore different banks are visible in both the queuing and propagated delay term during the course of the day at 11, 13, 15, 21, and 22 o'clock. It is also visible that SFO is highly affected by other airports since the propagated term is a large part of the total delay. Looking at the sources where this delay comes from it can be observed that both airports within the area are influencers(LAX, LAS, SAN), but also airports which are in the North of the US(SEA) or in the East side(JFK, ORD) and so the delay has spread from North to South and from East to West.

Going to the results of Saturday, see Figure 6.9a it can be seen that less banks are visible in the cumulative delay plot which makes sense since Saturday is in the weekend and so there is less business traffic. Furthermore it can be observed that also the total delay is dropped by half, which is the same as what happened at ATL. However, the relationship between local and propagated remained more or less the same. In the propagated delay sources chart the same six sources are responsible for the propagated delay as on Friday, see Figure 6.9b. The same behavior has also been presented for other days in the week and so it can be concluded that there are clear sources for each airport despite the day of the week. This can be explained by the



(a) Cumulative Delay during the Day



(b) Delay Sources Distribution

Figure 6.9: SFO situation on Saturday

fact that there is not a big variation is the flight schedules, airports have certain routes which are flown each day with a slight deviation in frequency if the demand is different from the previous day.

Sub-conclusion

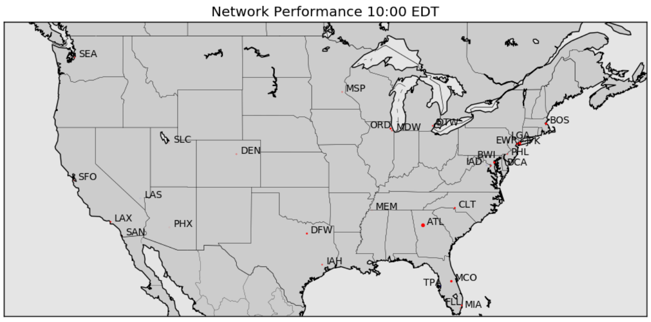
For now, it can be concluded that the model is capable of determining the different roles airport have during a day of operation. Furthermore, it tells us the amount of delays and where those delays originally come from. This helps us the understand how well connected the network actually is and that delay at one side of the airport could result in delay at the other side and vice verse. Regarding the differences in day of the week it is concluded that Friday has the highest average propagate delay and Saturday the lowest. Moreover, the results imply that there are no big differences between the different days of the week regarding the distribution of delays.

6.3. Case Study

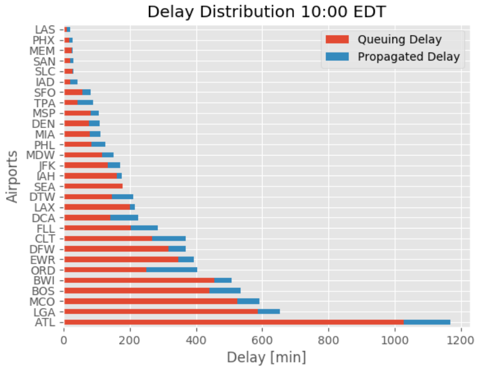
In the last experimental setup, the model is been used to test three different scenarios to see their different dynamics and how the model reacts to certain input. Three scenarios have been created each with different operational conditions at one or several airports. Scenario 1 is used as benchmark scenario with all airports operating at VFR conditions. In scenario 2, one large hub airport(ATL) is operating under low IFR and in scenario 3, five different airports (BOS, EWR, JFK, LGA, PHL) in the North East region are operating under low IFR conditions to simulate a regional storm situation. Simulating a case took the model 5172 seconds or 86 minutes.

6.3.1. Scenario 1 (VFR conditions)

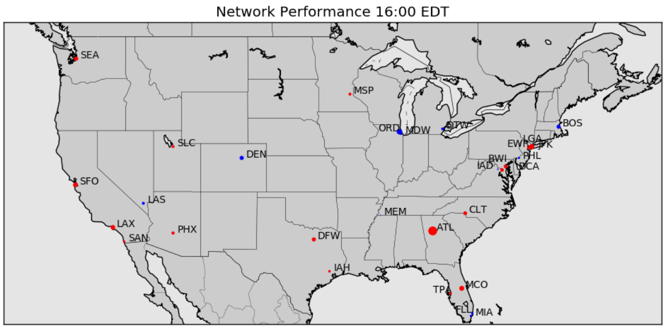
In scenario 1, all airports operate under VFR conditions or normal weather conditions. Therefore, this scenario can be used a benchmark with respect to the other cases. In Figure 6.10a-6.10h, the result of scenario 1 are presented based on a 6 hourly interval from 10:00 EDT until 04:00 EDT the next day. The figures are labelled in the same manner as in previous section and so all red indicated airports are delay generators and all blue airports are delay receivers of propagated delay. Around 10:00 EDT most delay is formed at the East Coast due to the time difference with the West Coast and the low activity in the earlier morning. It can be seen that ATL is a very big delay generator at the East Coast with almost double of the delay than number 2 LGA. Furthermore, all airports which are visible in the chart are drawn in red which makes sense since there is too little time passed for the delay to spread. When moving to 16:00, some new observations could be spotted. Several delay receivers pop up, namely ORD, DEN and BOS, and other airports tend to go towards real delay generators, namely, ATL, LGA, MCO, or SEA. Moving on towards 22:00 and 04:00, the airport roles becomes even more clear where there are clear delay generators at the East Coast, with LGA, EWR, BWI, CLT, and MCO and two clear generators at the West Coast namely, SEA and LAS. These observations are in line with the earlier determined profiles in Figure 6.5. When looking at the at the amount of delays ATL stands out with the rest of the airports and so in scenario 2 it will be tested what is the effect of low IFR capacity at this airport.



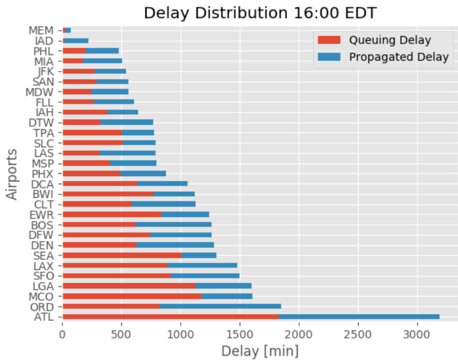
(a) Network Map



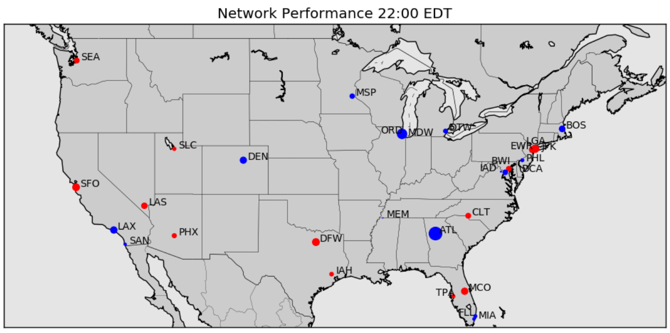
(b) Delay Distribution



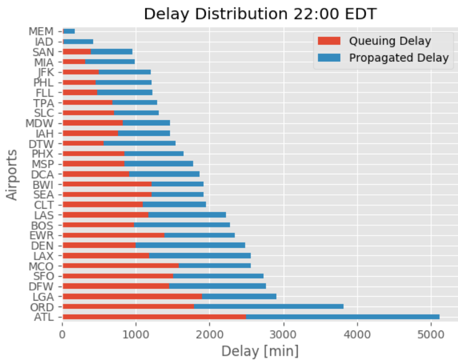
(c) Network Map



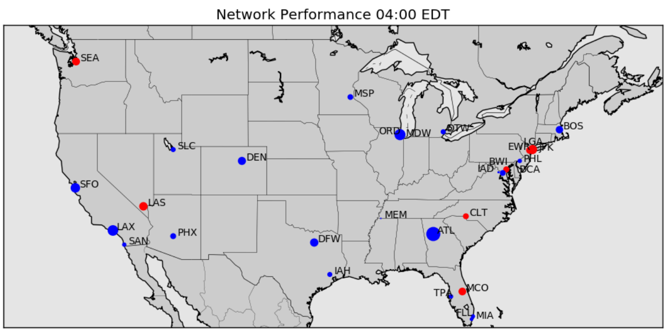
(d) Delay Distribution



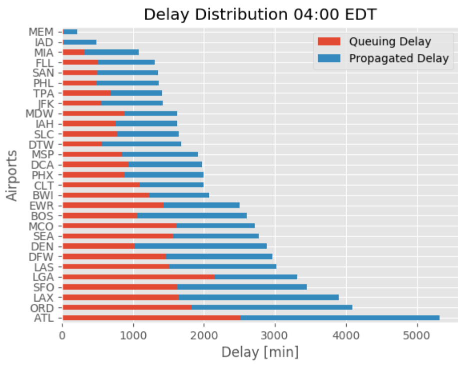
(e) Network Map



(f) Delay Distribution



(g) Network Map



(h) Delay Distribution

Figure 6.10: Network Performance of Case 1

6.3.2. Scenario 2 (ATL low IFR)

In scenario 2, the capacity at ATL is affected due to bad weather and so the capacity is reduced for the whole day to low IFR level, while all the airports within the network operate at their optimum capacity. Under normal conditions ATL is already quite congested and so under reduced capacity it faces large quantities of delay. In Figure 6.13a-6.13h the results of case 2 are presented starting with an overview of 10:00 and ending with an overview of 04:00 the next day. In scenario 2 the first overview is very similar as the benchmark scenario with delays forming at the East Coast and already a clear role for ATL is visible with delay numbers twice as high as the rest of the network. As the day progress the delay at ATL grows until it reaches 5000 minutes of queuing delay at the end of the day, see Figure 6.11. During the day, clear banks could be spotted during peak hours in the morning, afternoon and evening with the bank around 9 in the evening inducing the largest increase of 1000 delay minutes. Therefore, the queuing delay also increases the most between 16:00 and 22:00.

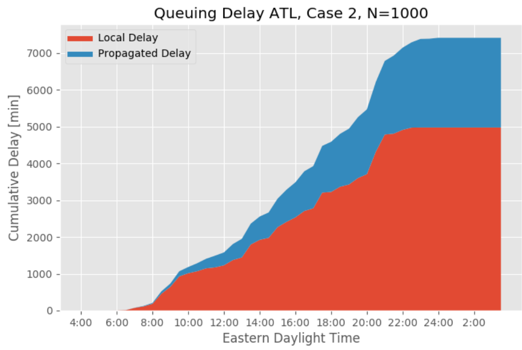


Figure 6.11: Delay development during Case 2

Within the network the effects of ATL being in low IFR are also visible. The first observation concerns the role of certain airports. For example, CLT and MCO, which are closely connected with ATL, change from a delay generator towards a delay receiver. Furthermore, it can be seen that the propagated delay term increase a lot at different airports within the network. To able to compare the average propagated delay and the average arrival delay the expected values of each case are presented in Table 6.3.

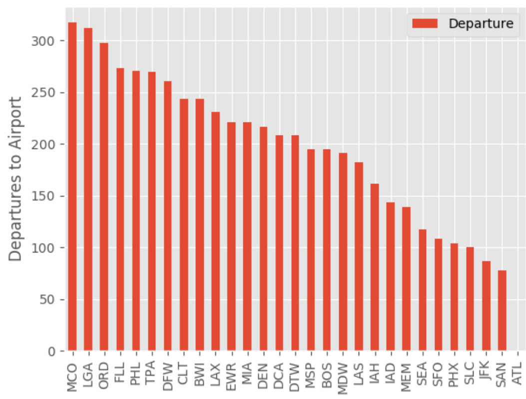


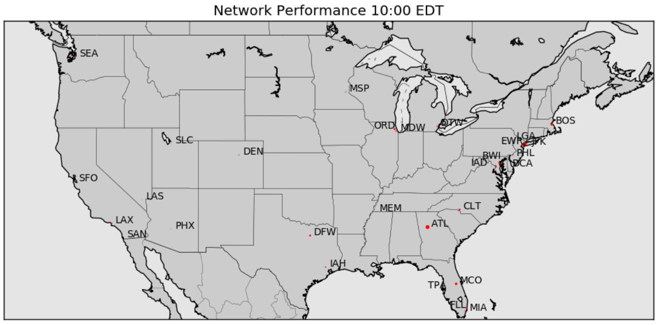
Figure 6.12: Departures from ATL to airports within the network during Case 2

Almost every airport experienced an increase in the average propagated delay term with Memphis with the largest increase from 4.92 to 5.39 min/flight. When looking at the delay distribution which airport is largest influenced by the capacity constraints at ATL, again MEM is at the top with 22% in scenario 1 and 34% in scenario 2 which is an increase of 9% regarding MEM its total propagated delay. Other airports which are highly affected are IAD(6.97%), FLL(6.3%), TPA (6.1%), PHL (5.5%), and CLT(5.5%). Both delay distribution tables can be found in Appendix E.2 and E.3. The pattern which is visible is the large relationship between the routing of ATL and the airports which are affected the most by its' local queuing delay. Where there are more aircraft coming in from ATL, the propagated delay term goes up. In Figure 6.12, an overview is presented of all destinations of ATL departures within the network. When comparing the outgoing flights from ATL and the delay distribution in Appendix E.3, a strong relationship is visible between number of flight coming in from ATL and the percentage of propagated delay which can be assigned to ATL as well.

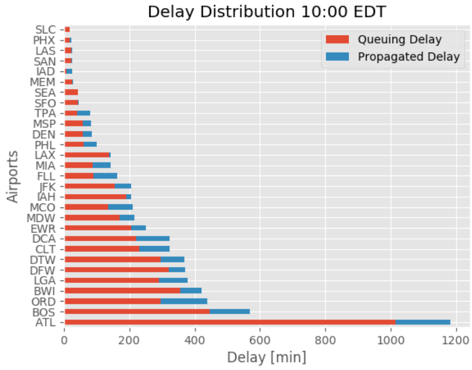
Table 6.3: Expected Propagated Delay and Arrival Delay for the 24-h period

	Case 1			Case 2			Case 3		
	Prop. Delay	Avg. Prop. Delay	Avg. Arr. Delay	Prop. Delay	Avg. Prop. Delay	Avg. Arr. Delay	Prop. Delay	Avg. Prop. Delay	Avg. Arr. Delay
ATL	2814	2.20	3.09	*2439*	*2.26*	*4.26*	3774	2.51	3.89
BOS	1545	4.84	6.47	1623	5.02	6.82	*2675*	*5.57*	*11.53*
BWI	843	3.04	4.59	832	3.23	4.96	1359	3.55	5.72
CLT	902	3.30	4.29	945	3.52	4.74	1347	3.86	5.54
DCA	1038	4.59	6.16	1091	4.81	6.58	1920	5.44	8.26
DEN	1857	2.81	3.66	1783	2.91	3.85	2830	3.16	4.51
DFW	1504	2.85	3.64	1563	2.97	3.87	2225	3.22	4.52
DTW	1112	3.09	4.05	1129	3.21	4.29	1909	3.54	5.17
EWR	1071	3.16	4.84	1055	3.30	5.11	*1478*	*3.55*	*9.40*
FLL	807	4.51	5.57	791	4.79	6.13	1716	5.44	7.80
IAD	463	4.70	4.70	484	5.00	5.30	576	5.35	6.05
IAH	868	2.72	3.32	927	2.82	3.53	1388	3.09	4.23
JFK	868	4.13	5.84	944	4.28	6.13	*1380*	*4.63*	*7.83*
LAS	1509	3.62	5.79	1545	3.73	6.04	2053	4.01	6.72
LAX	2257	3.93	5.29	2207	4.05	5.53	3439	4.42	6.49
LGA	1165	3.87	6.79	1202	4.08	7.23	*1855*	*4.44*	*9.94*
MCO	1103	3.96	5.43	1083	4.17	5.84	1827	4.68	7.16
MDW	746	2.97	4.17	794	3.11	4.48	1284	3.41	5.24
MEM	190	4.92	4.92	198	5.39	5.86	269	5.63	6.10
MIA	765	4.93	5.87	862	5.17	6.33	1389	5.80	8.01
MSP	1075	3.01	3.86	1140	3.14	4.14	1844	3.41	4.81
ORD	2263	3.12	4.10	2162	3.24	4.35	3376	3.60	5.30
PHL	879	4.30	5.61	831	4.57	6.18	*1232*	*4.87*	*9.04*
PHX	1115	3.14	3.85	1088	3.23	4.03	1528	3.45	4.58
SAN	861	4.06	5.40	859	4.18	5.64	1178	4.47	6.42
SEA	1213	3.60	4.76	1231	3.70	4.97	1765	3.99	5.71
SFO	1828	3.97	5.21	1944	4.08	5.40	2704	4.46	6.45
SLC	871	2.79	3.43	920	2.87	3.59	1099	3.04	4.02
TPA	718	4.62	5.38	717	4.94	6.00	1143	5.38	6.99

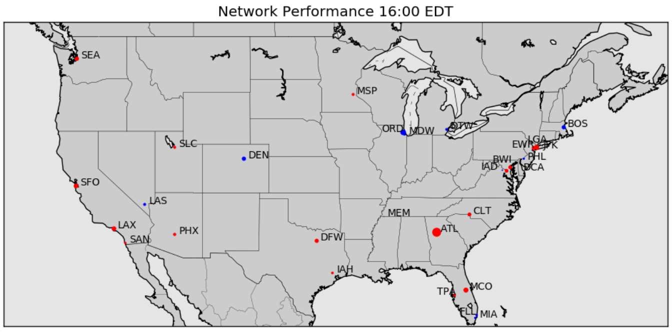
It can be concluded that by limiting the capacity of only one big airport within the network, it can have large consequences for the whole network. For the current scenario, constraining ATL has the largest influence on the East Coast since ATL is a big hub at the East of the US and so highly connected with all major cities at the East of the US. In the following scenario, it will be tested what the effect will be if 5 airports within a specific region are limited in their capacity and if this could have an effect on the whole domestic network.



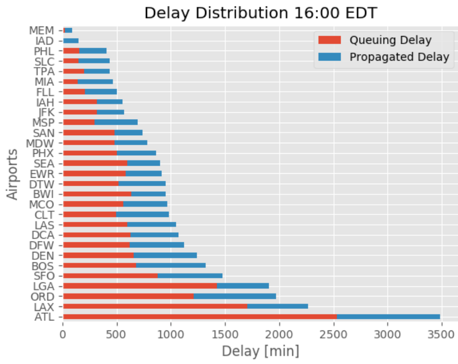
(a) Network Map



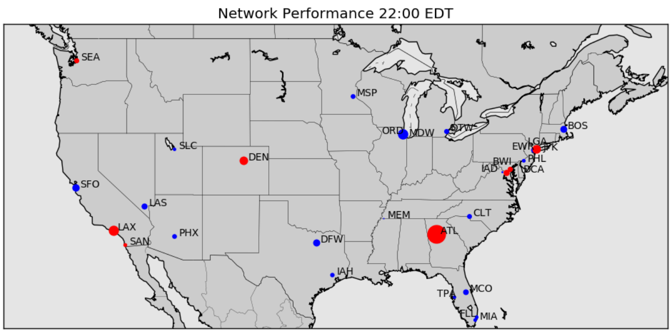
(b) Delay Distribution



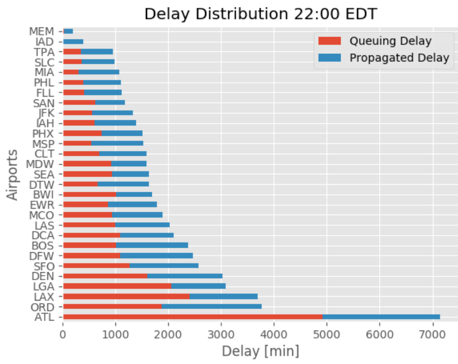
(c) Network Map



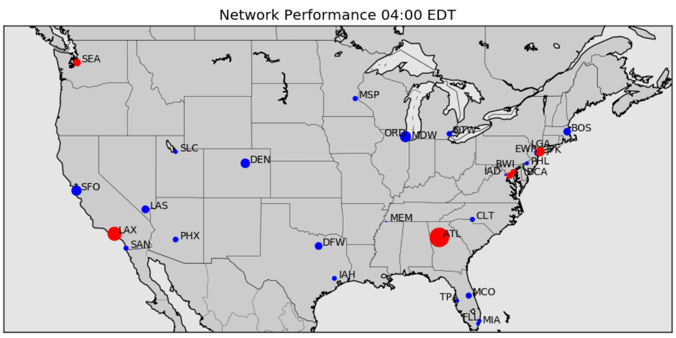
(d) Delay Distribution



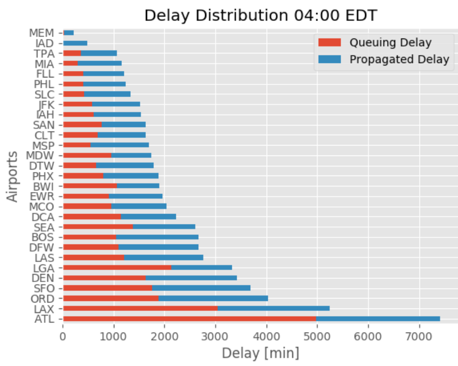
(e) Network Map



(f) Delay Distribution



(g) Network Map



(h) Delay Distribution

Figure 6.13: Network Performance of Case 2

6.3.3. Scenario 3 (North-East low IFR)

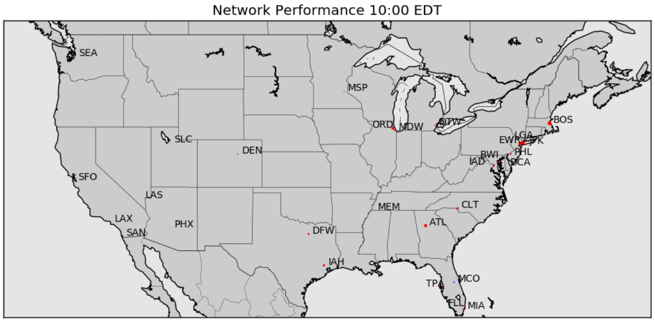
In scenario 3, five airports in the Northeast of the US, namely BOS, EWR, JFK, LGA, and PHL are affected by a local weather storm which decrease all their capacities to IFR levels for the whole 24-hour period. Under normal conditions all three New York airports (EWR,JFK, LGA) are considered as congested and Boston(BOS) also scores high when looking at the normal delay figures. Normally, EWR and LGA have been considered as delay generators, BOS and PHL as delay receivers, and JFK as being a mix of both. Under capacity constraints it can be seen in Figure 6.14a-6.14h however all airports shift towards generators with Boston being the largest, following by LGA, EWR, JFK and PHL. Also while the day progress queuing day increases in the Northeast and the rest of the map starts coloring blue.

Taking Boston (BOS) as example, the delay behavior during the day will be presented. At 10 o'clock already 1200 minutes of delay has been encountered with 980 minutes of local queueing delay and only 220 minutes of propagated delay. Moving to 4 pm, the local queuing delay has doubled to 1800 delay minutes and the propagated term has become five times larger(900 minutes) which brings the total delay to 2700 minutes. Between 4 pm and 10 pm the local conditions resulted in a very large increase of local queuing delay adding up to almost 5000 minutes and so the delay term has increased 3000 minutes in 6 hours, i.e. 500 minutes per hour. Adding up the propagated delay term the total delay at 10 pm is equal to 7100 minutes. Moving to the last time period, only the propagated delay term increased to a total of 2700 minutes and so the total delay at Boston resulted in 7800 minutes of delay.

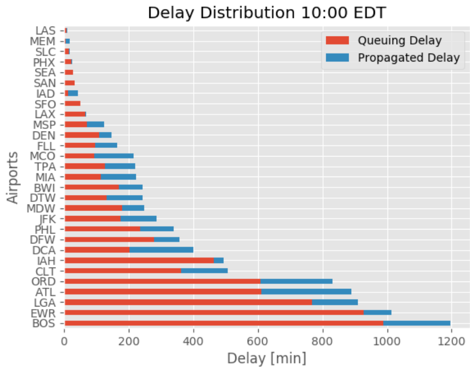
By the end of the day, only Las Vegas(LAS) is still red, but only with a small lead. In Table 6.3 it can be seen that every airport within the network is effected by the drop in capacity of the five selected airport. Where some are more affected than others, all five airports in the Northeast have a huge increase in their average arrival delay which is mainly affected by the drop in capacity but also due to small increase in propagated delay which means that not only locally the capacity drop increases delay also other airports have trouble due to this situation which in the end cast this delay back to the original source. This could be explained by the fact that a lot airports have back and forth routes where aircraft fly from A to B and back from B to A. And so the increase in local queuing delay will not only increase the propagated delay of other airport but could also influence themselves. To generalize this conclusion more research should be performed on different cases where for example all airports in the Southeast or Southwest are under low IFR conditions.

Sub-conclusion

It can be concluded that with the performed case study the effects of one or several airports under low IFR conditions can be tested. Within this case study is shown that by only setting only one major airport under capacity constraints this already has large affects on the network and its direct connections. With the test case of five different airports under low IFR conditions it has been shown that the whole US NAS is affected from North to South and East to West. Not only will it have effects on its own queuing delay but also on its own propagated delay due to the function of being a hub of the region.



(a) Network Map



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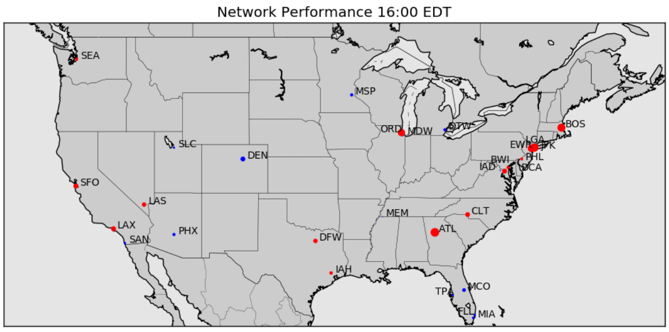

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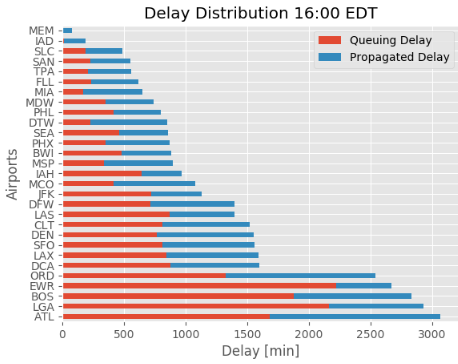

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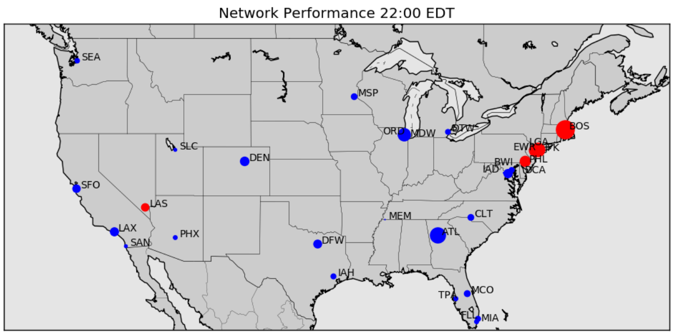
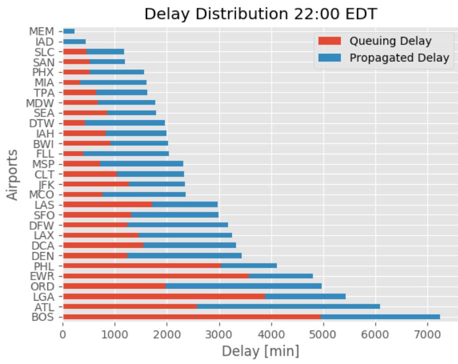
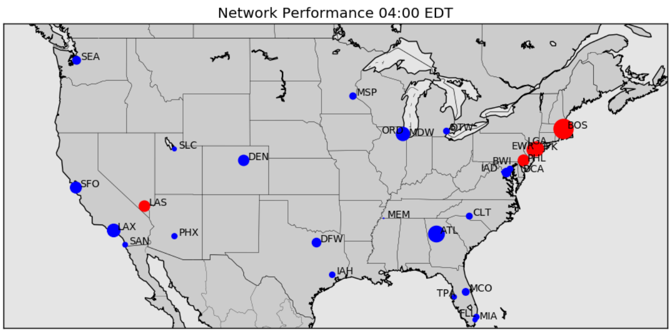


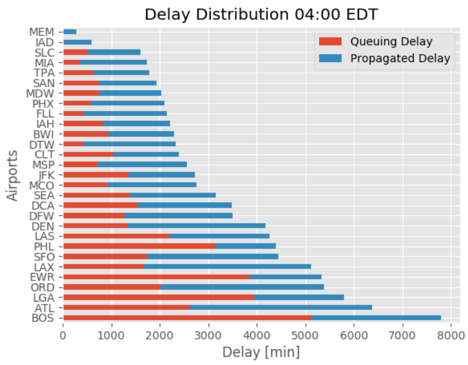
(e) Network Map



(f) Delay Distribution



(g) Network Map



(h) Delay Distribution

Figure 6.14: Network Performance of Case 3

7

Verification and Validation

In this chapter the verification and validation of the model will be explained. For the validation, the months September and October 2016 have been used as reference data. The Verification and Validation is built up following the scheme introduced by Sargent [46] and can be defined by four different processes, namely the Conceptual Model Validity, Computerized Model Verification, Data Validity, and Operation Validity. All four steps haven been performed within this study and are elaborated in the remainder of the chapter.

7.1. Conceptual Model Validity

Conceptual model validity is defined as determining whether the theory and assumptions of the conceptual model are valid and if the model representation of the problem statement is reasonable enough to answer the research question. In the following section first the theory and assumptions behind the model will be tested on validity by using mathematical analysis and statistical techniques.

7.1.1. Test theory and assumptions

Within this thesis the main theory which has been used is queuing theory. Queuing theory is proven to be the most reasonable choice within the spectrum of delay modeling for the application of this thesis subject. Within the literature study multiple different simulation and analysis techniques have been examined to justify this choice. For a recap of this reasoning one could read Chapter 2 which is a short version of the prior literature study to this thesis. In the remainder of this section the validity of the model assumptions is addressed and cases will be discussed in which these assumptions are violated.

Assumption 1

Before the queuing parameters can be estimated it was required to perform a stationary test to both test whether the analyzed arrival processes are stationary or not, and to determine the length of the discrete subperiods in which the queuing parameters will be estimated. If a process is not stationary but time-varying, steady state solutions cannot be used and thus complicating the analysis of the queuing system with a great amount. A stationary process can be defined as a stochastic process whose joint probability distribution does not change when shifted in time. What this actually means is that parameters such as the mean and variance, do not change over time. This is not the case with the used data set, aircraft do not arrive at a constant rate but rather follow a pattern where there are peak periods and off-peak periods.

To test if the arrival process can be treated as a stationary process, a cumulative arrival plot has been created to show the behavior of arrivals during the day [12]. In Figure 7.1 one can see the expected arrivals if the arrival process would have been stationary (red) and the empirical cumulative arrivals (blue).

It is clear that during the day large variation exist for the arrival rates and so the overall process cannot be assumed to be stationary. However, the arrival process can be broken up into smaller time intervals which are assumed to be stationary. To find the appropriate time interval, several possibilities have been examined, namely one hour, half an hour and 15 minute intervals. In Figure 7.2 one can see the half hour interval representation and in Appendix I the one hour and 15 minutes representation can be found. By testing these intervals, it is shown that stationary representation of half an hour is the closest approximation to a steady-state process and so the remainder of this thesis for all queuing parameters half an hour discrete intervals will

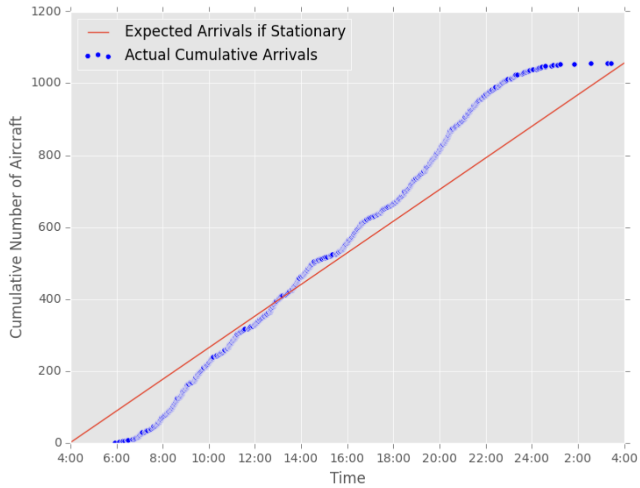


Figure 7.1: Arrivals at Atlanta on 21-08-2016

be used ($h = 30min$) [As. 1]. Furthermore, flight times are also categorized per sub-period and rounded off to the nearest integer as it is computational impossible to fly less than 1 sub-period.

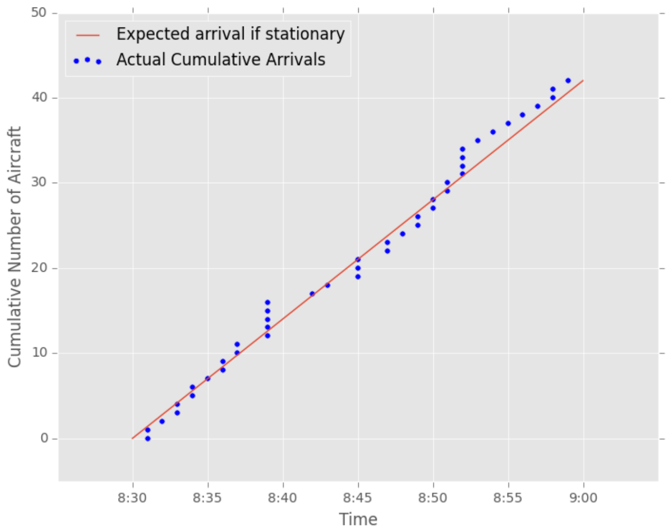


Figure 7.2: Arrivals at Atlanta between 8:30 and 9:00 EST on 21-08-2016

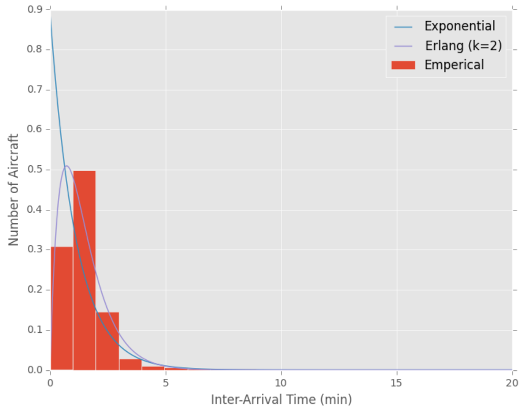
Assumption 2

Assumption 2 is a common approximation in airport queuing modeling and is present throughout literature [31] [45]. To prove the validity of a Markovian arrival process, it needs to be demonstrated that the inter-arrival times are independent and obey the $Exp(\lambda)$ distribution:

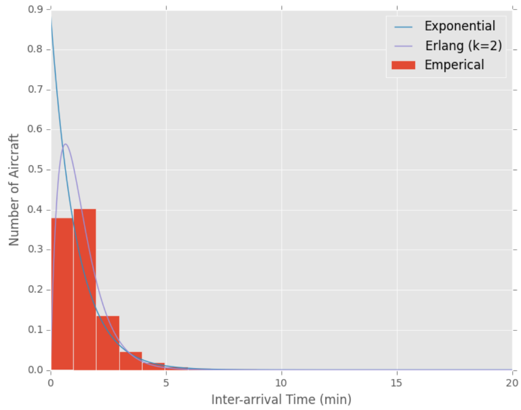
$$P\{interarrival\ time > t\} = e^{-\lambda t} \tag{7.1}$$

To prove Equation 7.1, the arrival and departure schedule of Atlanta(ATL) airport has been examined. As empirical data set, the month September 2016 is taken for both arrivals as well as departures. The data set consists of 30.965 arrivals and 31.422 departures. From this empirical data the data columns Arrival Time and Departure Time are used to obtain the inter-arrival time between each arrival and each departure. The inter-arrival time distribution is then plotted and compared with a fitted Exponential and Erlang distribution(k=2).

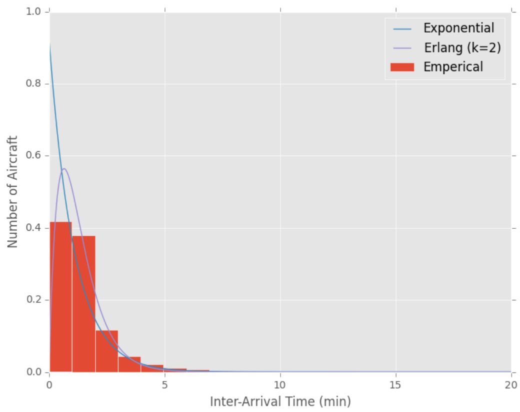
In Figure 7.3 one can see the arriving (Figure 7.3a), turnaround (Figure 7.3b, and departing(Figure 7.3c) inter-arrival distributions compared to a fitted exponential distribution and Erlang distribution.



(a) Demand arrival runway queue



(b) Demand turnaround queue



(c) Demand departure runway queue

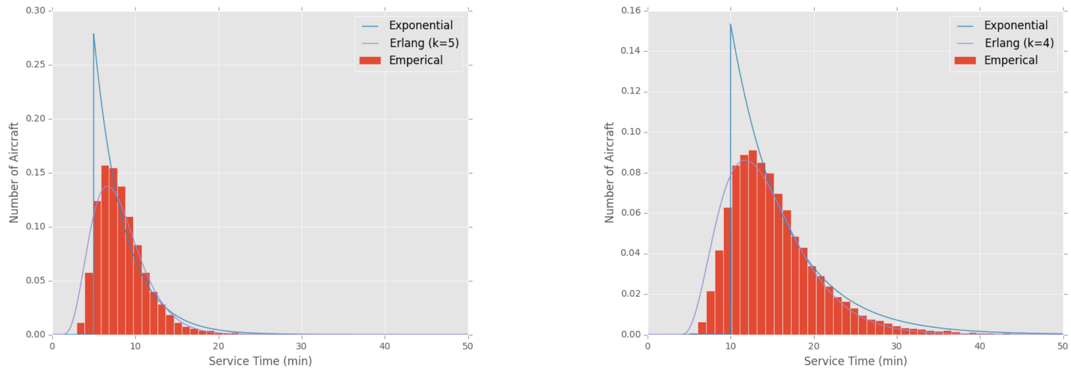
Figure 7.3: Inter-Arrival Time Distributions for the Atlanta International Airport(ATL)

As can be seen, both empirical distributions follow their fitted exponential distribution quite well, but can also be approximated with a second-order Erlang distribution(k=2). Similar results are available for other airports within the network. To test the goodness of fit for both CDF's a Kolmogorov–Smirnov test (KS test) is performed for each inter arrival distribution, the test results are presented in Appendix J. The arrival, turnaround and departure process scored a statistic of 0.3052, 0.3763, 0.4136 respectively w.r.t. Exponential distribution, and a .7077, 0.8002, and .8002 respectively w.r.t. the Erlang distribution. Based on this results the exponential distribution is considered a better fit than the Erlang distribution for each of the tested data sets.

Next, it is desirable to use exponential distributions since closed-form results are only available for exponential distributions which simplifies the problem significantly. Furthermore, it should be noted that the data set only included domestic flights and so the real situation for Atlanta airport is even more crowded than shown here. As of a result the inter-arrival distributions are expected to look more like the exponential distribution when including international flights as well. However, due to restrictions for non-US citizens it was impossible to obtain this data and so international flights are considered outside the scope of this thesis. It can be concluded that Equation 7.1 holds and so assumption 2 is valid for this application.

Assumption 3

In line with assumption 2, the service process of each queuing system is also assumed to be a Poisson process. Similar proof as with assumption 2 is necessary to demonstrate this hypothesis. Therefore, a similar analysis has been performed for the service times at ATL. The same data set has been used as in the previous section, however, for assumption 3 an analysis has been performed on the service times distribution of the arrival and departure process. This service time is indicated in the time difference an aircraft is ready to be served and the time it has been served, which is applicable for both the arrival process and the departure process. Since the data set contained insufficient data on the time it actually takes to turnaround an aircraft, excluding its slack time, it was impossible to perform a similar analysis on the turnaround service time. In Figure 7.4 one can see the service time distribution of both the arrival runway queue (Figure 7.4a as well as the departure runway queue (Figure 7.4b.



(a) Arriving aircraft

(b) Departing aircraft

Figure 7.4: Service Time Distributions for the Atlanta International Airport(ATL)

It can be seen from Figure 7.4 that the service time distribution follow a different pattern than the inter-arrival distributions and are less close to the exponential distributions. However, looking at the KS-test results opposing conclusions could be drawn. The arrival and departure service scored a statistic of 0.1887 and 1.36 respectively for the Exponential distribution, and a statistic of .0902 and 0.1517 respectively for the Erlang distribution. Where the Erlang distribution is a better fit for the arrival runway process, the exponential distribution seems to be better when considering the departures. Although it is desirable to use exponential distributions for both inter-arrival and service time distributions, it is less obvious to pick an exponential service time distribution. Since closed-form results are not available for queuing networks with such services disciplines this research will be limited to exponential distributions only. More research is required to give a better representation of service times, but this is concerned to be outside the scope of this thesis project.

Assumption 4

Assumption 4 is based on a simplification of the layout of a normal airport and the flight profile each aircraft will fly through, which starts with departure from airport A, taxi towards the runway, taxing off, flying from A to B, land op airport B, taxi towards the gate, and turnaround before continuing to its next flight. To simplify the process, both taxi in and out are included in the arrival and departure processes, four processes remain: departure, flight, arrival, and turn-around. To simplify the problem even more the flight phase is considered to be un-capacitated [As. 9] and so each airport consists of three processes with aircraft representing the flow through and between each airport in the network.

In this setup, arrivals are completely independent from departures. In reality this is not fully correct, since it could occur that air traffic control uses runways in a mixed configuration with both arrivals and departures on the same runway. Most of the time arrivals then have a higher priority over departures which could have an effect on the departure queue. Since there is no data available on used runway configurations it is impossible to analyze these effects. However, only the 30 largest US airports are considered in this thesis which nearly all possess multiple runways and so the possibility of them using only one operational runway is negligible small and to detailed for the simple queuing model considered here.

Assumption 5

A First-Come, First-Served (FCFS) queuing discipline (Assumption 5) is consistent with FAA procedures. Since most of the airports in the US are operated under the FCFS principle, with New York (JFK, EWR, LGA), Chicago (ORD) and Washington (DCA) as the exceptions [51], it can be assumed that each airports uses this policy. During normal conditions aircraft will not overtake another aircraft in the queue, since this physically hard on a taxiway or undesirable for ATC. Under heavy congestion conditions, this assumption is almost certainly violated. However, this is of less importance since the model is designed to investigated delay effects at macroscopic level. Changing from one aircraft to the other will not have direct effects on the demand rate or service rate. Therefore, the assumption is considered valid for the current research scope.

Assumption 6
Assumption 6 is based on the fact that it is undesirable to neglect demand for each of queuing systems since aircraft need to follow their flight itinerary and are not allowed to change because of high traffic. What this means is that there is always sufficient space at airports to queue up for service. It does not matter whether, this is in mid-air, on the taxiway, or still at the gate that does not matter. The aircraft eventually needs to go from A to B regardless of how much time this will take. In other words aircraft have in this model infinite amount of patience will waiting to get served. This is for example not true when modeling humans instead of aircraft. Humans tend to have a limited amount of patience when waiting in line, but in this case the aircraft just follow their preset schedule. Therefore, this assumption is valid for the current setup.

Assumption 7
Stating that each airport starts out empty each new simulation day, 24-hour period, is based on the observation that during the night almost no activity is present within the network. While looking at for example Figure 5.3 one can clearly see that between 1 a.m. and 6 a.m. almost no aircraft arrives or departures from the airport. Therefore, with the exception of extreme conditions, there is always enough time at the end of the day to return to the original state with no delays. By setting 4 a.m. EST as the beginning of each day, it is possible to model demand and queue on successive days as independent simulation runs.

Assumption 8
Assumption 8 states that DAM uses expected waiting time in queue, calculated from the number in queue, to calculate point estimates of delays. Throughout literature, the approach of expected values is used as an approximation of reality [45] [49] [50]. In [40] extensive computations are performed to opt delays in networks of queues. Their results were compared to the use of expected values and found the two approaches to be similar.

To illustrate this assumption, a small example is provided. If an aircraft is scheduled to depart at 10:00, but it is standing in the queue to depart and so will experience a delay of 15 minutes it eventually departs 15 minutes late, during the flight there is no room for any delay mitigation and so the aircraft arrives 15 minutes behind schedule at its designated arrival location. If an airline has 15 minutes of spare time included in its schedule these 15 minutes would not matter and the aircraft will still arrive on time.

In reality, queuing delay happens all the time and will not always result into aircraft being delayed since airline incorporate such delays into their schedules by adding slack to scheduled block time, also referred to as padding. This will result in higher delays than the now reported delays by airlines. Since in this thesis, a non-conventional method is used to represent delay it is less trivial how to compensate for padding effects. Normally, the slack time, when this is known, would be subtracted from the original delay. However, delays are in this model calculated on a rate basis and so this technique does not work. Therefore, the effects of slack in airline schedule should be investigated in more depth in future research.

Assumption 9
The model at hand does not include a representation of the airspace and its capacity. It has been assumed that airports contribute by far the most to the forming of delays. When considering the United States this assumption seems valid. [43] When for example considering the EU this assumption is already more questionable since the European airspace is much more crowded. Even for the US certain stochastic elements could be added in the for example mitigation of delay during flight or the creation of delay during flight. However, including such mechanisms into the model are considered outside the scope of this thesis project and could be seen as further research possibilities.

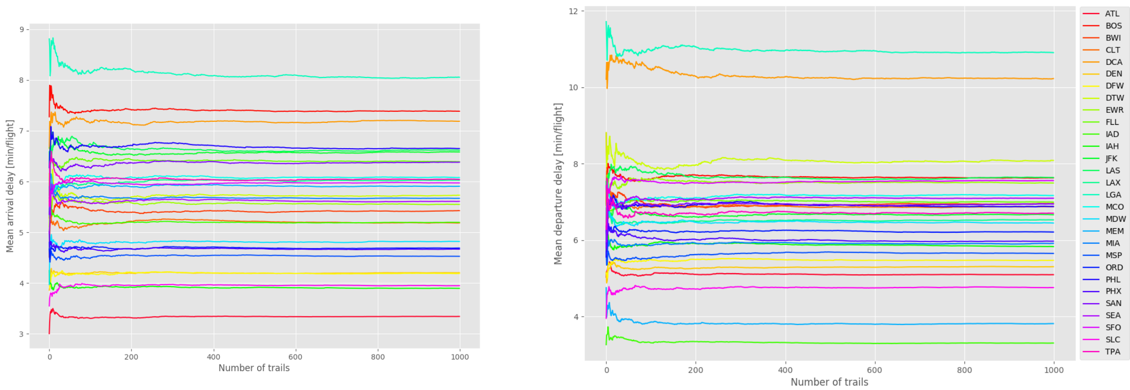
7.2. Computerized Model Verification

After validating the conceptual model, the implementation into a computerized model needed to be verified. Computerized model verification is defined as determining if the conceptual model is implemented properly into a computerized model. The most common techniques used to asses that the model has been implemented correctly are model walkthroughs and traces [46].

Programming errors are tried to avoid by several different techniques, namely, object-oriented programming, and cyclic programming approach. By creating objects and classes for each element within the model, repetition of code was not necessary and so less errors could emerge during the creation. Furthermore, the model has been developed in cyclic way by first creating one queue, then, one whole airport, three airports, five airports, and eventually the full network of 30 airports including the virtual airport. Between each cycle, the model has been fully tested with tracing object behavior and input, output relations. Moreover program modularity has been used to separate different features into different modules to make easier to spot errors within each code set. Finally, both the time-flow mechanism as well as the , pseudo random number generator has been tested by checking the time wise behavior of the model with respect to the empirical data and the pseudo random number generator by letting the model converge to an expected value for both arrival delay as well as departure delay, which are presented in section 7.4.

7.2.1. Convergence testing

Since the model is of stochastic nature, multiple simulation runs are required to produce an expected value for the model performance indicators. In general, the prediction of a stochastic model is obtained with Monte Carlo simulation. However, this raises the question of how many runs of the model are adequate to produce a meaningful prediction. Therefore, the model is tested on the level of convergence by looking at both the expected value of arrival and departure delay and by looking at the confidence intervals [11]. While testing, multiple sets have been used as input, from 100 runs until 5000 runs. In Figure 7.5a and Figure 7.5b one can see the result after 1000 iterations for both expected arrival and departure delay.



(a) Expected Arrival Delay

(b) Expected Departure Delay

Figure 7.5: Convergence testing of both the Arrival and Departure Delay

Where some airports converge already after 100 iterations, others only converge after 500/600 runs. To determine the amount of runs an analysis has been performed based on the confidence intervals and the required accuracy need for the model. The minimum number of model runs(N) can be computed with equation 7.2 [11].

$$N = \left(\frac{z_{\alpha/2}}{w} CV\right)^2 \tag{7.2}$$

N stands for the number of runs required, $z_{\alpha/2}$ is the confidence level, which is assumed at 95%, w is the accuracy width, which is proportional to the mean, and CV stands for to the coefficient of variation.

It is decided that 1000 simulation runs are sufficient for the purpose of this model, since the model reaches a 2% accuracy for both the mean arrival rate and the mean departure rate, which is sufficient for the purpose of this model.

7.3. Data Validity

To guarantee valid data, Perry [39] stated three important aspects that need to be addressed. At first, it must be certain that correct defined input data is used. As main input the BTS On-time performance database has been used. The Bureau of Transportation (BTS) states the following on their website: *"This database contains scheduled and actual departure and arrival times reported by certified U.S. air carriers that account for at least*

Table 7.1: Minimum number of model runs (N) to achieve desired confidence interval

	5% accuracy		2% accuracy		1 % accuracy	
Airport	Arrival	Departure	Arrival	Departure	Arrival	Departure
ATL	75	34	469	210	1875	842
BOS	124	182	773	1138	3092	4551
CLT	57	52	355	327	1422	1309
FLL	84	59	527	367	2109	1467
JFK	119	58	741	364	2965	1458

one percent of domestic scheduled passenger revenues. The data is collected by the Office of Airline Information, Bureau of Transportation Statistics." Since the data was collected by a third party, it was impossible to validate the accuracy of the data.

However, on the BTS website some information could be found on the data density of the database. In Table 7.2 the percentage of missing data is presented for several columns to give an indication of the data coverage. As can be seen, columns who represent general flight information do only miss a very small bits of data. When looking at ground operations and specific tail numbers the database is already less accurate and only roughly 80% of all registered flights contain data. The high percentage of missing data in the columns cause of delay could be explained with the fact that roughly 81 % of all national flights in 2016 arrive on-time and that only the cause of delay is registered when the arrival delay was above 15 minutes. The second aspect

Table 7.2: Data density of BTS On-time Performance Database

Column Name	Percentage Missing
Flight Date	< 0.005 %
Destination-Origin	< 0.005 %
DepTime / DepDelay	1.76 %
ArrTime / Delay	1.95 / 2.01 %
ActualElapsedTime	2.01 %
TailNum	21.56 %
WheelsOn / WheelsOff	22.8 %
CauseofDelay	89.6 %

concerns the data manipulation process. Before the queuing parameters could be estimated, the database is manipulated into the proper format. This process has been described in section 5.3. Each step of the pre-processing is checked by looking what goes in and what goes out, does it still represent the same situation and do we lose any data in the process. In the data pre-processing several steps have been specified. Within these steps, three steps could be identified which eliminate or alter the amount of input data, namely:

1. Include only flights from and towards the airports within the network
2. Drop all rows which contain empty data fields
3. Set time frame from 4am EDT until 4am EDT the next day

7.4. Operational Validity

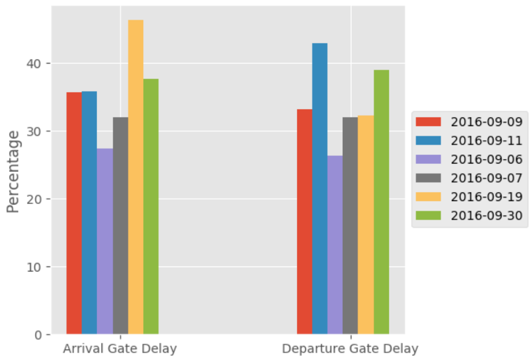
Operational validity is defined as determining that the model's outputs are sufficient accurate to fulfill the purpose of the model. The validation is performed by comparing the model results with the traffic statistics recorded in the BTS database. The comparison will be performed on both arrival delay and departure delay. Since queuing delay and propagated delay are not terms that are registered within the BTS database it was not possible to validate these data entries. Within this section a distinction is being made between the day calibrated experiment and the weekday calibrated experiment. First the validation based on single days is presented. Next, the weekday calibrated model is validated. While reviewing the validation results it should be taken into account that the DAM model does not capture several important characteristics of the U.S. National Aviation System. A non-exhaustive list is given below:

- En-route congestion
- Transferring passengers and crew/aircraft rotations

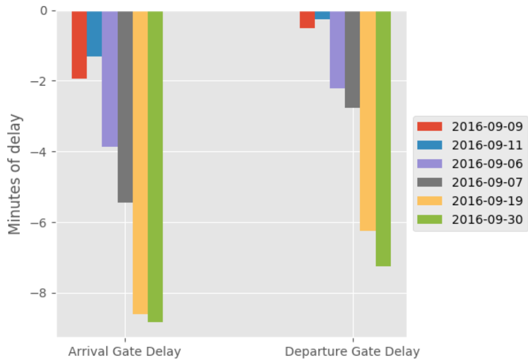
- Airline and/or ATM reactions to congestion

7.4.1. Model Calibrated for Specific Flight Days

First the validation results of model calibration of specific flight days is discussed. Within Section 5.6, six different days are designated as the test case for the model. These six days represented 3 different weather conditions (good, average, and severe) to indicate how well the model performed under different operational conditions. To be able to compare different days, a weighted average of relative errors and a weighted average of absolute errors is taken for both the arrival delay as well as the departure delay, see Figure 7.6a and Figure 7.6b.



(a) Weighted Average of Percentage Errors



(b) Weighted Average of Absolute Errors

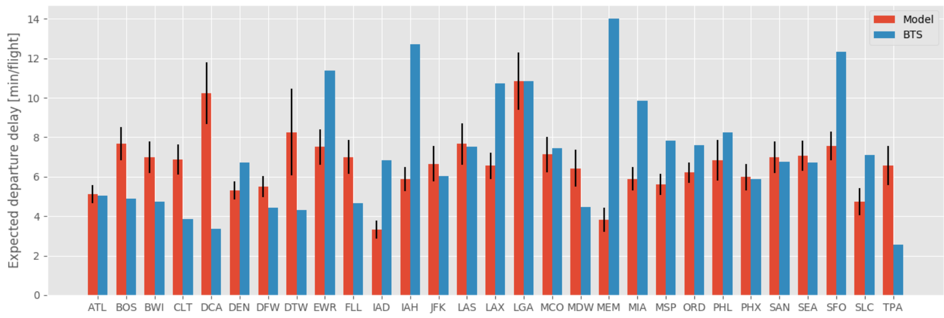
Figure 7.6: Comparison of Average Errors per Flight Day

One can see that that for both the percentage errors as well as the absolute errors the departure gate delay is a better fit with the empirical data than the arrival gate delay. This could be explained by the fact that the average departure delay is better represented by the model. Since departure delay is mainly caused by congestion problems at the departing airport. Furthermore, factors which could contribute to arrival delay are fully represented by the model such as en-route congestion. Overall the model contained a deviation of around 30 % from the empirical data which could be explained with the all the simplifications and assumptions made during the development of the model.

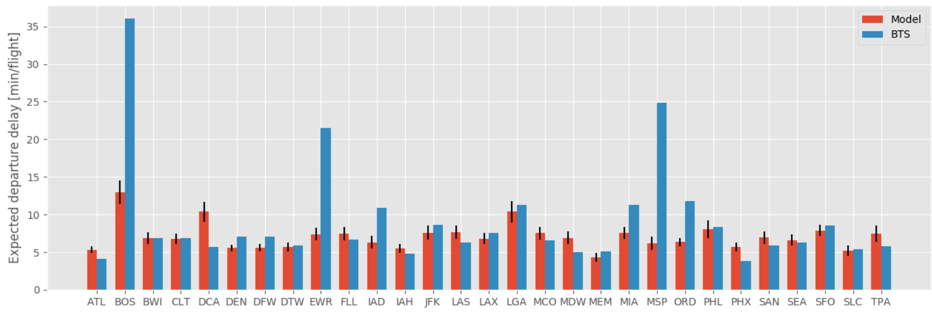
When comparing the differences relating operational conditions, it is clear that the average absolute errors, see Figure 7.6b increase significantly when changing from good to severe weather conditions. However, the same trend is not visible when looking at the percentage errors in Figure 7.6a. To investigate this further, the departure delay from both the model and the empirical dataset are plotted next to each other for the days 9, 6 and 30 September in Figure 7.7a, Figure 7.7b, and Figure 7.7c respectively. Here the model results are plotted in red, the empirical data is plotted in blue and the confidence interval with a confidence of 95 % is plotted with the black line. The arrival delay plots of the three days can be found in Appendix F. Furthermore a T-test has been performed for both the arrival and departure delay for all days. The results of these T-test can be found in Appendix G.

It can be seen that for 9 September the delays are sometimes overestimated and sometimes underestimated where for both 6 and 30 September the results are under estimated or are close to the real data. When there are large peaks for example in Figure 7.7b the model was unable to simulate this behavior, for example the departure delay at September 6 of BOS, which could be attribute to the decrease in capacity since this airport was in low IFR conditions. At the other hand it is also visible that model will over estimate if there are little to no capacity restriction. On September 9th only DTW was under low IFR conditions, but still for multiple airports the model expected a higher average delay than in reality was present. This could be explained with the fact that in the current model setup no implementation of slack or delay mitigation is present. In reality, small numbers of delay could be countered with integrating slack time in the aircraft schedules and so the overall delay could be mitigated. These effects are less present when the average delay tend to increase since then the slack terms are not sufficient anymore to counteract all the delay aircraft encounter. To improve the model on this matter a more refined implementation of slack is required.

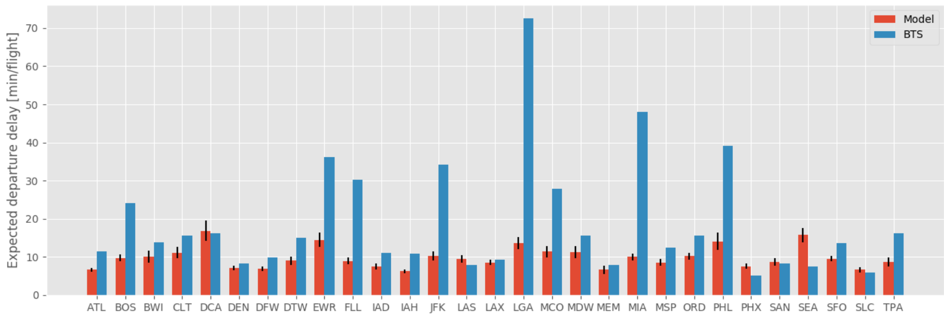
When considering 30th September, the model had quite some trouble to represent the network behavior. This can be attributed to a few things. First, while under severe weather conditions airports tend to change their flight schedule quite drastically, flights are cancelled and delayed with large number due to the big drop in capacity. This will have major effects on the average departure delay as can be seen in Figure 7.7c. Second, the model does not included any transferring passengers and or crew/aircraft rotation problems. When experiencing large delays airlines will have problems with the transfer of their passengers as well as the predefined schedules of both crew and aircraft. Such effects are not implemented in the model and so it has a very hard time to simulate such behavior. Third, it is very hard to predict the amount of delay when there is severe weather, since it will results in a different dynamics in comparison with congestion problems. To be able to simulate severe weather conditions the model needs further research on these topics. When observing the T-test scores of both the arrival and departure delays of each day, it can be seen that September 6th scored overall best following by September 9th and September 30th. This strengthens the conclusion that the model is performing best with average weather conditions. However, the result also show that the scores are not really significant and that there is still room for improvement.



(a) Departure Delay on 09-09-2016 (Good Weather Conditions)



(b) Departure Delay on 06-09-2016 (Average Weather Conditions)



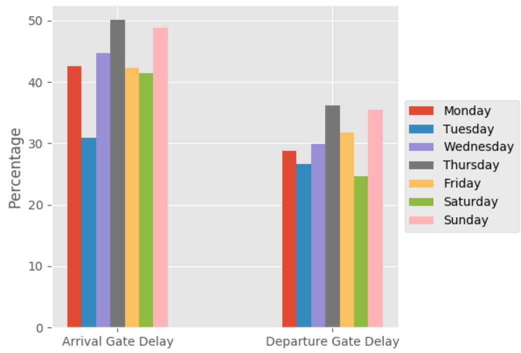
(c) Departure Delay on 30-09-2016 (Severe Weather Conditions)

Figure 7.7: Average Departure Delay per Airport

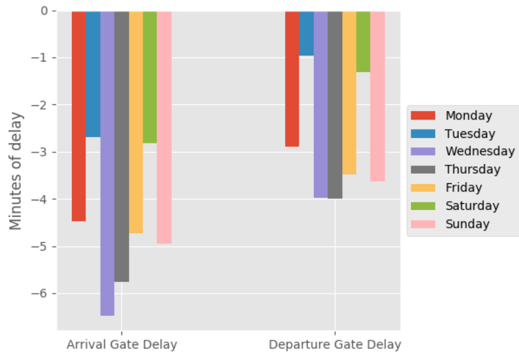
It can be concluded that the model represents the behavior of the network quite well when there is an average day with average weather conditions and no extreme peaks in specific locations. It will under estimate delay if the specific airport has very high average delay numbers and will over estimate if the network has lower capacity restrictions.

7.4.2. Model Calibrated for Aggregated Days of the Week

Second, the validation results of the model calibration of days of the week are discussed. Within Section 5.6, an overview was presented where all flight days of September 2016 are categorized per day of the week. Each day represents a typical Monday, Tuesday, etc. in September and are used to see if there are difference in both network behavior as well as model performance when using different weekdays as input. A similar comparison as the previous section is performed with the weighted average of percentage errors, see Figure 7.8a, and the weighted average of absolute errors, see Figure 7.8b.



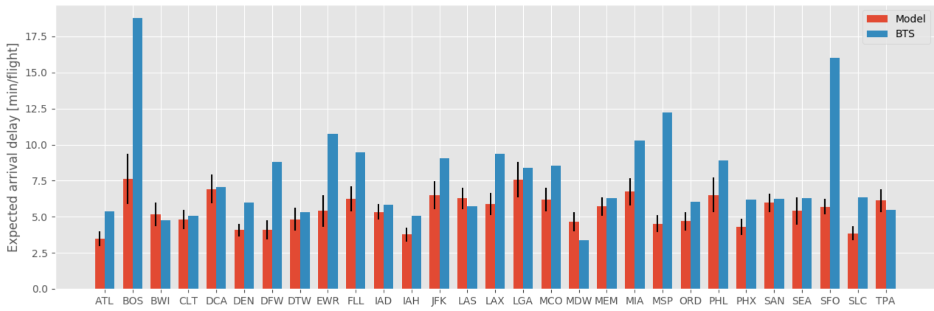
(a) Weighted Average of Percentage Errors



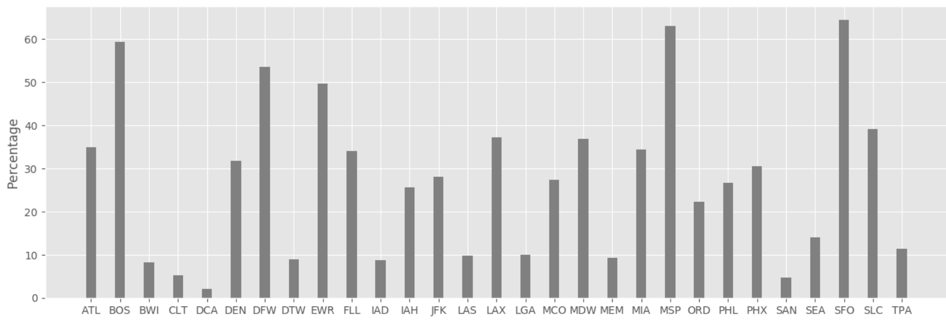
(b) Weighted Average of Absolute Errors

Figure 7.8: Comparison of Average Errors per Weekday

Here, the same trend is visible in the difference of arrival and departure delay as with the calibrated flight days. Again Departure Gate Delay is better represented by the model than Arrival Delay. However, still a deviation of 30% with real data is in place. When looking at the differences in weekdays no obvious trend is visible. To get more information a more detailed comparison is performed for both Tuesdays(the best fit), see Figure 7.9a and 7.9b, and Thursdays(the worst fit), see Figure 7.10a and 7.10b. In appendix H, the t-test score can be found of both the arrival and departure delay of Tuesday and Thursday.



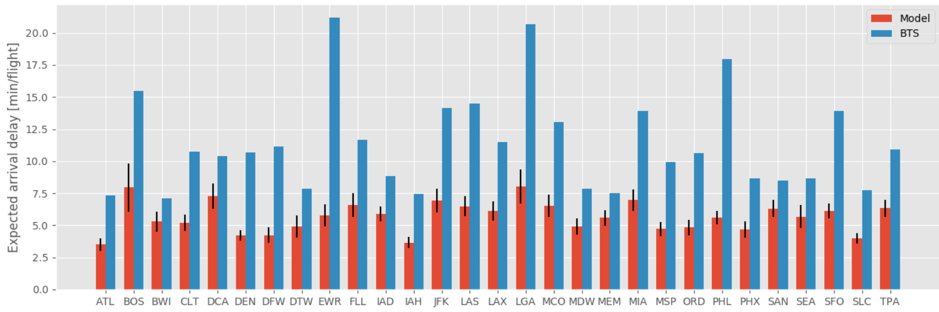
(a) Arrival Delay



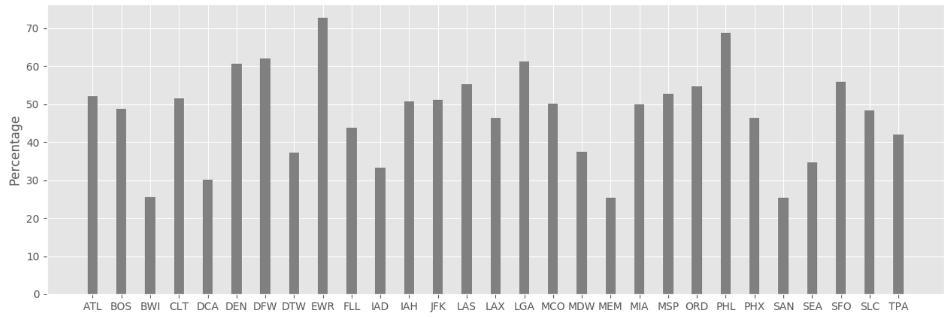
(b) Percentage Error Arrival Delay

Figure 7.9: Average Arrival Delay by Airport on Tuesdays

While observing both Tuesdays and Thursdays it can be seen that the model is less capable of predicting high peaks and low bottoms. Where Tuesday has a couple of high peaks, for example BOS or SFO, on Thursday multiple peaks exists. This difference can also be seen in the Percentage errors plots where it is obvious that the overall errors is way higher not because the model has a deviant behavior but because the empirical data consists of higher expected values. It is suspected that external factors contribute to these delays which are not accounted for by the DAM model. When investigating this even further by looking at the weather conditions each day in September it becomes clear that each weekday which had higher errors rates contained some days in the set with very severe weather conditions and so the conclusion that severe weather cannot be represented by the model is also applicable here. However, it is not impossible that other factors also can play a role in errors. While observing the scores of the T-test, it is obvious that Tuesdays score way better than Thursdays. Where Thursday is very off for every airport, Tuesday sometimes scores reasonable but the results were not static significant.



(a) Arrival Delay



(b) Percentage Error Arrival Delay

Figure 7.10: Average Arrival Delay by Airport on Thursdays

It is clear now that the model is not suitable for detailed analysis on specific airports. It should be used more on the overall behavior of the network to analyze the casual relationships between airports and their delay figures. Furthermore the model is capable of prediction macroscopic effects of the network if average operational conditions are in place, but further research is needed on both delay mitigation as well as operational constraints when severe weather conditions are in place.

8

Conclusion and Recommendations

The conclusions of this research are elaborated in this chapter. First, the main results from the study are discussed. Second, the contributions to literature and industry is discussed. Then, the limitations of the DAM model are treated. Ending this chapter with the recommendations for future research.

8.1. Concluding on the results

In the literature study it was concluded that still a lot is unknown about the dynamics of flight delay and in particular the relationship between propagation throughout a network and the source of the primary delay. It is found that a queuing based model is suitable to perform a dynamic stochastic simulation of the network dynamics, which can be used to investigate the behavior of propagated delay within the context of US major airports in a domestic network. Therefore, the following research question was formulated:

To what extent, and how, do local flight delay sources influence the dynamics of delay propagation within a network of airports of the U.S. National Aviation System simulated by a stochastic queuing network model?

The dynamic model proposed in this study is modeled using Queuing Theory as the main modeling technique with a combination of a delay propagation algorithm to distribute local queuing delay among its connections. During the development of the model, the model has been calibrated with the On-time Performance Database of the BTS, which includes all domestic traffic within the United States. The conclusions on the model creation and calibration are firstly discussed in the following section. Afterwards, the model capabilities will be discussed based on the results obtain from the three experiments performed within this study. Finally, the model accuracy, which have been determined in the verification and validation phase, will be treated.

8.1.1. Model Creation and Calibration

The first two research sub-questions regarding the creation and calibration were formulated as followed:

1. *What are the influencing factors of generation and propagation of delay that should be taken into account?*

2. *How can the generation and propagation of delay within a network be modeled properly based on the key processes within airport operations?*

It has been determined that the conceptual airport model consists out of three different processes, namely, arrival, turnaround and departure. At each simulated airport these three local processes will generate local queuing delay, which will later be propagated among the network. A selection of 29 US airports has been selected as the scope of this thesis, since these airports are the major airports within the US national aviation system.

The proposed model combines an empirical and parametric approach to determine the important queuing and propagation parameters. A study showed that a parameter aggregation of 30 minutes resulted in the best fit with the empirical data. Based on this 30 minute aggregation the model queuing parameters have been determined for the full set of airports within the network. Where some parameters have been fixed for each simulation, such as the service rates or flight times, others are kept dynamic and change each simulation time step, such as the arrival rates and the routing probabilities in between airports.

Based on this calibration, the model has been tested on convergence to evaluate after how many iterations the output values reach their expected values. It has been found that after 1000 iterations, the model converged for both the expected arrival and expected departure delay for all the individual airports. Afterwards, the delay persistence parameter α have been calibrated to see which number resulted in the best fit with the empirical data. It turned out that an $\alpha = 1$ resulted in the best fit.

As a final step of the calibration phase, the experimental setup has been designed for the three different experiments, which have performed within this study. The first experiment contained an analysis of day to day operation based on six different flight days from the month September 2016. From this month six days have been chosen based on a small study of the operational conditions at each airport. Next, two days have been chosen with little to non capacity restrictions, two other days have been chosen with a few airports operating under low IFR conditions, and finally two days are chosen where there were a large number of airports operating under low IFR conditions. Next, the second experiment contained a calibration for each day of the week by aggregating all input data to obtain results of a typical Monday, Tuesday, etc. Finally, a case study has been performed with three different scenario chosen by the user. Within these scenarios, one or several airports have been put under low capacity manually to simulate a specific scenario. Based on these three experiments the results have been obtained.

8.1.2. Model Capabilities and Accuracy

The third research sub-question concerned the capabilities of the proposed model and to what level of accuracy simulation results could been generated.

3. *How, and to what extent, can the proposed model be used to analyze and identify airport roles in the propagation of flight delay?*

It can be concluded that the model is capable of displaying the network delay dynamics and the roles airports have within this network. Based on all three experiments it was possible to get a better understanding of the overall network behavior and the casual relationships which exist inside the network. The first finding was the profiling of airports. Based on the Delay Difference indicators it was possible to categorized all the airports within the network into three different categories, namely delay generator, delay receiver, or a dual role. These natural roles showed how the network is build up in different regions with the generators connected with, most of the time, close-by receivers.

By comparing flight days with different operational conditions it has been shown that even if there are no capacity restriction some airports already generate a lot of delay, what could be explained with the fact that airport operate very close to their maximum capacity. Furthermore, it has been shown that even with a small group of airports operating under low IFR conditions it still resulted in an noticeable increase of propagated delay for the whole network. When this was extended to half of the network the propagated delay term doubled at almost every airport within the network. Finally, in a detailed example the results of one specific day are extensively researched. By providing four network snapshot on a 6-hour interval, the geographical and statistical overview are presented.

In the second experiment it was concluded that Fridays contain the highest average propagated delay and Wednesdays result in the lowest average propagated delay. Moreover, the small difference between the delay distributions between the different days of the week implied that small differences exist between the demand and routing probabilities per day of the week. By looking at the sources of delay, it was also visible that one single source has a sphere of influence which could cover the whole network.

In the last experiment it has been shown how large the effects can be if one major airports or several airports are influenced by capacity constraints. By only inducing low IFR conditions at ATL a large part of the network was influenced. In the scenario with five airport it even resulted in an network wide effect with propagation of delay from the East coast until the West coast of the United States. Not only had the reduced server capacity an effect on the local queuing delay, but also on its own propagated delay.

Overall, the model produced an average percentage error ranging from 30% on good days and 50% on bad days and an average relative error of couple of minutes on good days and eight minutes on bad days. The model has been validated first for separate flight days and later for the aggregated days of week. It has been concluded that the model is capable of simulating a day with average weather conditions and no extreme peaks at certain airports. However, there is still room for improvements as the model was less capable of simulating divergent behavior when for example the network needed to cope with severe weather conditions. It should therefore be used to learn more about the overall behavior of the network. In addition the theory and assumptions behind the model, the validity of the data, and the computational model verification have been tested. Since the model has been developed for macroscopic analysis it can be concluded that the model is sufficiently accurate for the original purpose it was designed for.

Altogether, this project demonstrated that with a relative simple queuing model the dynamics of propagated delay could be simulated within a network of airports but is less capable to mimic the behaviour under extreme conditions. At the same time the model has shown to be able to provide more information on the propagation of delay and its source.

8.2. Contributions to Literature and Industry

The last research sub-question concerned the contributions to literature and industry, which will be discussed in this section.

4. How could this model be applied to improve the mitigation of delay propagation in the future i.e. what is the main contribution of this study?

The contribution of this study can be seen as two folded, namely the contribution to literature and the contribution to the industry. Looking at the contribution to literature, three different aspects could be identified. First, this study showed an original approach by modeling airport congestion with queuing theory to simulate both delay creation as well as delay propagation. With a relative simple dynamic queuing model, a complex system such as the air transportation network could be modeled with sufficient accuracy. This approach can be used to quantify delay propagation under different capacity or flight schedule scenarios, while accounting for the original sources of these delays.

Second, the United States Core 30 airports have been classified based on the role they play within the US NAS. To the best of our knowledge, this represent a first attempt to classify airport based on their natural roles. It is shown that three roles are present within the network, namely, delay generator, delay receiver, and a dual role. Based on this division of roles, more in-depth analysis can be performed to better understand where these roles come from and more importantly how delay effects can be mitigated.

Furthermore, an attempt has been done to quantify the influence sphere of certain airports. By tracking the sources of propagated delay it has been shown that the network is largely connected and the congestion of only one airport could have effects on the network as a whole. And so this study contributes to a better understanding of delay propagation and the interconnectedness of an air transportation network.

When looking at the contributions to industry also three aspects could be identified. First, by better understanding the relationship between the creation of delay at one airport and the propagation towards others, airlines could have more information in their policy decision making. While knowing from which sources most of the delay is coming from, airlines could adjust their schedules to incorporate for such delays and in the end reduce the effects of propagated delay.

Second, the identification of airport roles is also useful information for the airports themselves. When knowing your role within the network and from which sources (local, network) it is originating, certain measures could be taken to improve conditions and in the end reduce delay costs.

Finally, with the model capability of testing under different operational conditions or scenarios, the model is also useful in policy analysis. By extending the model with more detailed input data it could be used by airports or airlines to test scenarios such as capacity improvements or flight schedule adjustments. Based on the model results it can than be decided if these adjustments will give the right outcomes without actually implementing it.

8.3. Limitations of the Model

The model developed within this thesis project has several limitations. These limitations will be addressed in the following section.

Use of aggregated flight schedules

Due to the aggregation of flight schedules into rates, aircraft specific schedules are neglected. This made it impossible to monitor delay in the conventional way since normally delay is measured by the difference between the scheduled time and the actual time an aircraft arrives or departs. Furthermore, without taking the flight itineraries into account it is impossible to track the aircraft on tail number, which made it impossible to see how deep certain delay has spread. However, it was a conscious choice to use queuing theory as the main modeling technique and thus neglecting the effects of individual flight schedules.

Schedule padding
Normally, queuing does not necessarily mean that aircraft are delayed since airlines incorporate time in their schedules for such events. This extra time or slack, enables airlines to mitigate delays during the day before it can become a problem. This behavior was simulated by the α parameter, but did not resulted in better model results. It could be investigated further if the additions of individual flight schedules and the introduction of schedule padding into a complementary model would improve the model accuracy. For this thesis project it was considered outside the scope of the project.

Airline reaction to congestion
The current model does not account for airlines reactions to delay. Normally, when airlines experiencing heavy congestion problems, they will take action by for example cancelling flights, swapping of aircraft or crew, utilization of spare aircraft at hubs etc. These reactions are meant to reduce the experienced delay and could be incorporated in future work.

En-route Congestion
The proposed model contains the assumption that the flight phase is un-capacitated, which means that no delay will be formed during flight nor that any delay will be mitigated en-route. However, in reality there is a possibility that aircraft experience delay due to weather or capacity constraints. Furthermore, airlines sometimes incorporate extra time in their schedules to mitigate delay on the go. To improve the model, flight time uncertainty could be added to simulate the possibility of flying a longer or shorter time period.

Input Data
Currently, the model is calibrated with a limited amount of input data. The model now only simulates domestic flights with one aircraft type. However, to get the full picture regarding arrival and departure demand also international flights should be added plus a deviation should made between different types of aircraft since it matters if a flight is domestic or international or if its a large or a small airplane. Furthermore, operational conditions were assumed for the whole day and were not time dependent. In reality the weather conditions will change during the course of the day and it could be that in the morning VFR conditions are present while in the afternoon it changes towards IFR conditions. However, the amount of input data was limited due to the simple reason that there is only limited amount of data available for non-US citizens. When there is a possibility to obtain more detailed demand and service data the model could be improved.

8.4. Recommendations for future research

During the development and the analysis of the model, several recommendations have been found, which will be discussed within this section. The recommendations are additional to the recommendations following from the limitations presented in the previous section.

Delays unrelated to congestion
Right now, the model is only accounting for congestion related delay during arrival, turnaround and departure. However, in reality more factors are influencing the delay of aircraft. For example, transferring passengers, crew rotation problems, or the defect of an airplane. All situations related to airline problems are now modeled by the turnaround server, which is a big simplification. To implement the effects of for example transferring passengers more research is necessary.

Taxi-in and taxi-out queues
At this moment, the model contains three queues for the arrival, turnaround and departure process, which is a simplification of reality. To improve the simulation accuracy, the model could be expanded with a more detailed representation of the airport operations. The model could be extended with two additional queues for the taxi-in process and the taxi-out process. Similar implementation have been found throughout literature [31] [32].

Slot control at US Airports

Within the current model, the queuing principle First Come First Serve has been used, which is applicable for the air traffic policies of most US based airports. However, to reduce delay some airports (JFK, EWR, LGA, ORD, and DCA) within the US are starting to use slot priority systems. To improve the accuracy of the model different queuing principles could be used simultaneously [51]. Furthermore, the model could also be used within different context settings such as the EU or Asia where airports mostly use slots to manage flights.

Simulation of Special Events

The current developed model is able to simulate an average day under average weather conditions. The current setup is insufficient when simulating special events for example severe weather since it is unable to coop which such big changes. For special events a different approach should be used to calculate the expected delay. A solution might be to use data pooling for specific days where it is known that severe weather conditions where present. However, this method could be quite labor intensive since it is hard to find even two days within the dataset which have similar operational conditions let alone two days with severe weather in the same geographical region.

Optimization of Model Parameters

To simplify the current model several model parameters have been fixed or simplified during the run of a simulation day. However, it could be tested if the results of the model would improve when for example the value of α would be varied for each airport or even each time step. The same could be tested for the service rates, which are currently fixed for each airport. By using a optimization algorithm the optimal value of α and μ could be tested. Also the service times have been assumed to be exponential. However, during validation is has been shown that the service distribution also can be approximated with an Erlang distribution. It could be tested if another service distribution would improve the simulation results.

Perform more Case Studies

Within the current project only one case study has been performed on the domestic market of the United States. Nonetheless, a large variation is possible within the selection of airports which are opposed with low IFR conditions. Furthermore, a similar study could have been performed in another geographical region such as the EU to test if the same dynamics behavior is also present there.

Adapt Performance Indicators

In this study, several new performance indicators have been introduced such as the delay difference indicator or the airport profiles. Currently, these indicators are based on the absolute delay and so when comparing airports with each other it can sometimes give a distorted picture. Therefore, a normalized performance indicators could be added based on the amount of flight movement of each airport.

A

Statistical Overview

Month	Ontime Arrivals	Ontime (%)	Arrival Delays	Delayed (%)	Flights Cancelled	Cancelled (%)	Diverted	Flight Operations
January	245,614	80.91%	48,818	16.08%	8,677	2.86%	452	303,561
February	240,302	83.21%	43,077	14.92%	4,822	1.67%	600	288,801
March	265,899	81.44%	56,684	17.36%	3,238	0.99%	680	326,501
April	265,992	84.26%	46,377	14.69%	2,768	0.88%	525	315,662
May	273,313	83.18%	52,639	16.02%	1,706	0.52%	907	328,565
June	259,559	77.92%	68,990	20.71%	3,289	0.99%	1,283	333,121
July	257,369	74.93%	78,457	22.84%	6,140	1.79%	1,498	343,464
August	261,839	76.80%	73,195	21.47%	4,801	1.41%	1,116	340,951
September	263,855	84.93%	45,239	14.56%	1,026	0.33%	566	310,686
October	274,187	84.85%	45,269	14.01%	3,315	1.03%	367	323,138
November	264,607	86.23%	40,978	13.35%	851	0.28%	434	306,870
December	236,713	75.58%	70,865	22.63%	4,965	1.59%	666	313,209
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2016 (Annual)	3,109,249	81.09%	670,588	17.49%	45,598	1.19%	9,094	3,834,529

Figure A.1: On-Time Performance - Flight Delays of 2016 for all mayor US Airports

B

Service Rates

Airport ID	μ_a	μ_t	μ_d	low IFR capacity
ATL	62	70	58	81%
BOS	16	26	23	71%
BWI	17	19	19	85%
CLT	26	29	26	79%
DCA	15	13	14	84%
DEN	46	50	48	88%
DFW	32	45	37	71%
DTW	31	45	37	76%
EWR	19	21	19	72%
FLL	16	16	18	77%
IAD	11	15	15	78%
IAH	38	30	34	89%
JFK	14	21	19	64%
LAS	21	22	23	80%
LAX	32	31	34	79%
LGA	14	17	16	90%
MCO	19	20	20	87%
MDW	16	21	19	81%
MEM	5	7	7	80%
MIA	17	23	19	72%
MSP	32	38	36	83%
ORD	43	47	42	80%
PHL	16	20	18	70%
PHX	32	35	29	70%
SAN	15	18	22	87%
SEA	25	28	20	73%
SFO	29	28	27	68%
SLC	35	39	32	79%
TPA	16	14	13	80%

C
Flight Times

Table C.1: Discrete Flight Times between the airports within the network

	ATL	BOS	BWI	CLT	DCA	DEN	DFW	DTW	EWR	FLL	IAD	IAH	JFK	LAS	LAX	LGA	MCO	MDW	MEM	MIA	MSP	ORD	PHL	PHX	SAN	SEA	SFO	SLC	TPA	VRT
ATL	0	4	3	2	3	6	4	3	4	3	3	4	4	8	9	4	2	3	2	3	5	3	3	8	9	10	10	7	2	0
BOS	5	0	2	4	3	8	8	4	2	6	3	8	2	11	12	2	5	5	0	6	6	5	2	11	12	12	12	10	6	0
BWI	3	2	0	2	0	7	6	2	2	4	0	6	0	9	11	0	4	3	4	5	5	4	0	9	10	11	11	9	4	0
CLT	2	4	2	0	2	7	5	3	3	3	0	5	3	9	10	3	3	3	3	4	5	4	3	8	9	11	10	8	3	0
DCA	3	2	0	2	0	7	6	3	2	4	0	6	2	10	11	2	4	3	0	5	5	4	2	10	0	11	11	9	4	0
DEN	5	7	6	6	6	0	3	5	7	7	6	4	7	3	4	7	6	4	4	7	3	4	6	3	4	5	5	2	6	0
DFW	4	7	5	4	5	4	0	5	6	5	5	2	6	5	6	6	5	0	2	5	4	4	6	5	6	8	7	5	4	0
DTW	3	3	2	3	2	6	5	0	3	5	2	6	3	8	9	3	5	2	3	5	3	2	3	8	9	9	9	7	4	0
EWR	4	2	2	3	2	8	7	3	0	5	2	7	0	10	11	0	5	4	5	5	5	4	0	10	11	11	12	9	5	0
FLL	3	6	4	3	4	8	6	5	5	0	0	5	5	10	11	5	1	6	0	0	7	6	5	9	10	13	12	0	1	0
IAD	3	2	0	0	0	7	6	3	3	0	0	6	2	9	11	0	4	0	0	5	5	3	0	9	10	11	11	0	4	0
IAH	3	7	5	4	5	4	2	5	6	4	5	0	0	6	7	6	4	0	3	4	5	5	6	5	6	9	8	6	3	0
JFK	4	2	0	3	2	8	7	3	0	5	2	0	0	10	11	0	5	0	0	6	6	5	0	10	11	12	12	10	5	0
LAS	7	9	8	8	8	3	5	7	9	8	8	5	9	0	2	0	8	6	0	9	6	7	9	2	2	5	3	2	8	0
LAX	8	10	9	9	9	4	6	8	10	9	9	6	10	2	0	0	9	7	7	9	7	7	10	2	1	5	2	3	8	0
LGA	4	2	0	3	2	8	7	3	0	5	0	7	0	0	0	0	5	4	5	6	6	4	2	0	0	0	0	0	5	0
MCO	2	5	4	3	4	7	5	5	5	2	4	4	4	9	10	5	0	5	4	2	6	5	4	9	10	12	11	9	0	0
MDW	3	4	3	3	3	4	0	2	3	5	0	0	0	7	8	3	4	0	3	0	2	0	3	7	8	8	9	6	4	0
MEM	2	0	3	3	0	4	3	3	5	0	0	3	0	0	8	5	3	3	0	0	3	3	0	0	0	0	0	0	3	0
MIA	3	6	5	4	5	8	6	6	5	0	5	5	5	10	11	5	2	0	0	0	7	6	5	10	10	13	12	0	1	0
MSP	4	5	4	4	4	4	5	3	5	6	4	5	5	6	8	5	6	2	4	6	0	2	4	6	7	7	8	5	6	0
ORD	3	4	3	3	3	5	4	2	4	5	3	5	4	7	8	4	5	0	3	5	2	0	3	7	8	8	9	6	5	0
PHL	4	2	0	3	1	8	7	3	0	5	0	7	0	10	11	1	4	4	0	5	5	4	0	10	11	11	11	9	5	0
PHX	6	9	8	7	8	3	4	7	9	7	8	4	9	2	2	0	8	6	5	8	6	6	8	0	2	6	4	3	7	0
SAN	8	10	9	9	0	4	5	8	10	0	9	6	10	2	1	0	8	7	0	0	7	7	10	2	0	5	2	3	0	0
SEA	9	10	9	9	9	5	7	8	10	11	9	8	10	4	5	0	10	7	0	0	6	7	10	5	5	0	4	3	10	0
SFO	8	10	0	9	9	4	6	8	10	10	9	7	10	2	2	0	10	8	0	10	7	8	10	3	2	4	0	3	0	0
SLC	7	8	8	7	7	2	5	6	8	0	0	6	8	2	3	0	8	5	0	0	4	6	8	3	3	4	4	0	0	0
TPA	2	5	4	3	4	7	5	5	5	1	4	4	5	9	10	5	0	5	3	2	6	5	4	9	0	12	0	0	0	0
VRT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

D

Airport Profiles

Table D.1: Delay difference indicators and airport profiles of the different flight days

ID	6-9-2016	7-9-2016	9-9-2016	11-9-2016	19-9-2016	30-1-2016	Score	Profile
ATL	0.97	0.84	1.04	1.15	1.76	0.75	1.08	Both
BOS	2.42	1.92	0.78	0.88	0.55	0.47	1.17	Both
BWI	1.10	1.09	1.29	1.45	1.55	1.34	1.30	Generator
CLT	0.80	0.77	0.90	0.88	0.64	1.16	0.86	Receiver
DCA	1.07	1.02	1.39	1.31	0.97	1.78	1.26	Generator
DEN	0.65	0.59	0.69	0.76	0.53	0.49	0.62	Receiver
DFW	0.78	0.76	0.94	1.01	2.39	0.61	1.08	Both
DTW	0.62	1.14	1.54	0.78	1.15	0.91	1.02	Both
EWR	1.25	1.18	1.48	1.33	1.09	2.11	1.41	Generator
FLL	0.67	0.63	0.69	0.79	0.49	0.49	0.63	Receiver
IAD	0.33	0.11	0.06	0.19	0.05	0.26	0.17	Receiver
IAH	0.94	0.76	0.82	0.92	0.72	0.68	0.81	Receiver
JFK	1.00	0.75	0.99	1.15	1.25	1.39	1.09	Both
LAS	0.99	1.01	1.08	1.60	0.82	0.78	1.05	Both
LAX	0.70	0.62	0.75	0.69	1.26	0.52	0.76	Receiver
LGA	1.45	1.39	1.70	1.58	1.33	1.27	1.45	Generator
MCO	0.97	0.90	1.08	1.19	1.06	1.00	1.03	Both
MDW	1.09	0.85	1.12	1.23	0.87	1.38	1.09	Both
MEM	0.10	0.17	0.21	0.04	0.16	0.12	0.13	Receiver
MIA	0.34	0.39	0.16	0.57	0.33	0.22	0.34	Receiver
MSP	0.96	0.50	0.64	0.25	0.49	0.79	0.61	Receiver
ORD	0.76	1.04	0.81	0.97	0.68	1.14	0.90	Both
PHL	0.82	0.61	0.78	0.93	0.84	1.26	0.88	Receiver
PHX	0.73	0.77	0.86	0.90	0.60	0.61	0.75	Receiver
SAN	0.74	0.69	0.81	0.76	0.81	0.56	0.73	Receiver
SEA	1.00	1.02	1.17	1.06	0.79	2.27	1.22	Generator
SFO	0.87	0.81	0.89	0.82	0.69	0.61	0.78	Receiver
SLC	0.65	0.61	0.62	0.69	0.55	0.42	0.59	Receiver
TPA	0.73	0.68	0.77	0.83	0.57	0.52	0.68	Receiver

Table D.2: Delay difference indicators and airport profiles of the different weekdays

ID	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Score	Profile
ATL	1.11	1.15	1.13	1.07	1.10	1.05	1.07	1.10	Generator
BOS	0.82	0.88	0.83	0.84	0.81	0.73	0.85	0.82	Receiver
BWI	1.14	1.18	1.14	1.13	1.05	0.86	1.20	1.10	Generator
CLT	0.77	0.91	0.88	0.77	0.83	1.06	0.93	0.88	Receiver
DCA	1.08	1.19	1.09	1.06	1.06	0.84	1.14	1.07	Both
DEN	0.67	0.72	0.69	0.65	0.67	0.70	0.67	0.68	Receiver
DFW	0.91	0.99	0.97	0.82	0.93	1.03	0.71	0.91	Both
DTW	0.83	0.62	0.75	0.81	0.74	1.44	0.92	0.87	Both
EWR	1.21	1.35	1.24	1.15	1.17	1.06	1.13	1.19	Generator
FLL	0.64	0.64	0.67	0.61	0.59	0.96	0.76	0.69	Receiver
IAD	0.05	0.06	0.06	0.06	0.05	0.04	0.07	0.05	Receiver
IAH	0.90	0.97	0.84	0.91	0.92	0.88	0.84	0.89	Both
JFK	0.88	0.84	0.74	0.83	0.78	0.97	1.03	0.87	Both
LAS	1.19	1.00	1.25	1.19	0.91	1.51	1.01	1.15	Generator
LAX	0.90	0.89	0.87	0.87	0.86	0.89	0.85	0.88	Both
LGA	1.57	1.54	1.39	1.34	1.20	1.01	1.27	1.33	Generator
MCO	1.01	0.98	0.95	0.95	0.98	1.63	1.14	1.09	Both
MDW	1.03	1.11	0.95	0.96	0.99	1.19	1.11	1.05	Both
MEM	0.08	0.06	0.09	0.05	0.05	0.10	0.06	0.07	Receiver
MIA	0.55	0.50	0.54	0.49	0.41	0.46	0.58	0.50	Receiver
MSP	0.65	0.72	0.63	0.66	0.66	0.60	0.25	0.60	Receiver
ORD	0.94	0.91	0.60	0.81	0.77	0.86	0.91	0.83	Both
PHL	0.70	0.77	0.73	0.36	0.62	0.91	0.75	0.69	Receiver
PHX	0.83	0.76	0.84	0.84	0.84	0.90	0.90	0.84	Receiver
SAN	0.64	0.66	0.63	0.62	0.65	0.69	0.68	0.65	Receiver
SEA	1.19	1.19	1.15	1.11	1.16	1.32	1.22	1.19	Generator
SFO	0.79	0.80	0.76	0.73	0.74	0.78	0.77	0.77	Receiver
SLC	0.61	0.64	0.63	0.55	0.54	0.60	0.57	0.59	Receiver
TPA	0.71	0.68	0.64	0.59	0.61	0.89	0.74	0.70	Receiver

E
Delay Distributions

Table E.1: Delay distribution of 06-09-2016

	ATL	BOS	BWI	CLT	DCA	DEN	DFW	DTW	EWR	FLL	IAD	IAH	JFK	LAS	LAX	LGA	MCO	MDW	MEM	MIA	MSP	ORD	PHL	PHX	SAN	SEA	SFO	SLC	TPA
ATL	0	0.065	0.037	0.042	0.06	0.029	0.036	0.029	0.044	0.054	0.024	0.024	0.02	0.028	0.031	0.09	0.055	0.031	0.016	0.034	0.026	0.047	0.058	0.013	0.011	0.016	0.018	0.012	0.052
BOS	0.043	0	0.069	0.041	0.138	0.022	0.029	0.027	0.066	0.023	0.027	0.014	0.084	0	0.023	0.102	0.032	0.015	0	0.021	0.022	0.067	0.057	0.006	0.007	0.015	0.025	0.003	0.022
BWI	0.088	0.264	0	0.072	0	0.03	0.024	0.048	0.009	0.098	0	0.014	0	0.026	0.019	0	0.065	0.051	0.004	0.025	0.032	0.036	0	0.02	0.012	0.008	0	0.007	0.048
CLT	0.072	0.101	0.051	0	0.071	0.026	0.048	0.028	0.036	0.028	0	0.022	0.04	0.022	0.017	0.093	0.046	0.017	0.009	0.043	0.02	0.053	0.052	0.024	0.009	0.002	0.018	0.006	0.047
DCA	0.064	0.259	0	0.048	0	0.012	0.032	0.025	0.031	0.042	0	0.021	0.024	0.007	0.015	0.111	0.055	0.04	0	0.05	0.023	0.068	0.006	0.01	0	0.012	0.011	0.004	0.031
DEN	0.039	0.057	0.018	0.019	0.02	0	0.036	0.024	0.026	0.011	0.033	0.03	0.012	0.056	0.069	0.056	0.032	0.027	0.007	0.014	0.054	0.05	0.03	0.052	0.047	0.054	0.077	0.037	0.013
DFW	0.053	0.064	0.016	0.04	0.052	0.047	0	0.026	0.035	0.027	0.022	0.035	0.005	0.042	0.053	0.067	0.041	0	0.01	0.042	0.035	0.079	0.035	0.026	0.037	0.027	0.048	0.017	0.021
DTW	0.069	0.126	0.048	0.045	0.048	0.041	0.042	0	0.031	0.04	0.007	0.011	0.009	0.043	0.019	0.07	0.037	0.04	0.009	0.016	0.044	0.077	0.032	0.029	0.008	0.017	0.012	0.01	0.02
EWR	0.066	0.158	0.006	0.042	0.045	0.035	0.029	0.015	0	0.047	0.007	0.036	0	0.03	0.05	0	0.092	0.027	0	0.055	0.03	0.08	0	0.018	0.007	0.02	0.069	0.006	0.03
FLL	0.105	0.069	0.081	0.054	0.078	0.009	0.034	0.031	0.063	0	0	0.03	0.075	0.008	0.016	0.173	0.011	0.009	0	0	0	0.018	0.068	0	0	0.007	0.016	0	0.046
IAD	0.109	0.146	0	0	0	0.101	0.044	0.011	0.014	0	0	0.035	0.077	0.028	0.074	0	0.073	0	0	0.022	0.023	0.056	0	0.001	0.017	0.03	0.101	0	0.038
IAH	0.055	0.049	0.014	0.042	0.036	0.053	0.046	0.019	0.055	0.032	0.02	0	0	0.036	0.062	0.061	0.038	0	0.019	0.05	0.028	0.059	0.046	0.022	0.024	0.026	0.061	0.024	0.024
JFK	0.03	0.196	0	0.04	0.031	0.006	0.004	0.006	0	0.067	0.012	0	0	0.049	0.132	0	0.095	0	0	0.06	0.02	0.038	0	0.019	0.02	0.025	0.097	0.011	0.042
LAS	0.041	0.034	0.02	0.016	0.003	0.05	0.037	0.031	0.035	0.016	0.012	0.022	0.053	0	0.133	0	0.012	0.037	0	0.023	0.025	0.05	0.027	0.045	0.054	0.055	0.126	0.032	0.012
LAX	0.032	0.066	0.014	0.017	0.01	0.05	0.033	0.012	0.046	0.012	0.031	0.029	0.092	0.092	0	0	0.018	0.016	0.001	0.015	0.025	0.056	0.024	0.042	0.02	0.071	0.148	0.027	0.001
LGA	0.078	0.149	0	0.054	0.105	0.044	0.049	0.028	0	0.087	0	0.029	0	0	0	0	0.059	0.031	0	0.086	0.033	0.131	0.008	0	0	0	0	0	0.029
MCO	0.087	0.057	0.04	0.04	0.072	0.029	0.044	0.03	0.081	0.005	0.026	0.025	0.083	0.021	0.022	0.084	0	0.026	0.003	0.064	0.013	0.052	0.06	0.011	0.006	0.003	0.011	0.005	0
MDW	0.081	0.078	0.05	0.011	0.084	0.051	0	0.05	0.052	0.019	0	0	0	0.065	0.042	0.089	0.052	0	0.015	0	0.065	0	0.049	0.041	0.028	0.021	0.017	0.013	0.027
MEM	0.282	0	0.027	0.099	0	0.051	0.102	0.067	0.016	0	0	0.09	0	0	0	0	0.052	0.051	0	0	0.066	0.059	0	0	0	0	0	0	0.038
MIA	0.101	0.077	0.006	0.056	0.083	0.007	0.048	0.014	0.06	0	0	0.031	0.067	0.018	0.022	0.185	0.062	0	0	0	0.009	0.047	0.036	0.005	0	0	0.022	0	0.044
MSP	0.064	0.059	0.042	0.031	0.03	0.072	0.04	0.04	0.017	0	0.011	0.021	0.027	0.027	0.042	0.05	0.016	0.051	0.004	0.015	0	0.123	0.054	0.035	0.013	0.037	0.039	0.025	0.013
ORD	0.042	0.12	0.016	0.034	0.067	0.033	0.05	0.025	0.038	0.014	0.013	0.021	0.016	0.033	0.048	0.123	0.03	0	0.003	0.032	0.049	0	0.049	0.018	0.019	0.03	0.054	0.009	0.014
PHL	0.114	0.159	0	0.051	0.026	0.039	0.041	0.04	0	0.027	0	0.019	0	0.023	0.019	0.006	0.074	0.046	0	0.041	0.052	0.106	0	0.024	0.01	0.02	0.03	0.005	0.026
PHX	0.031	0.019	0.022	0.051	0.013	0.08	0.046	0.017	0.029	0	0.006	0.026	0.027	0.082	0.109	0	0.008	0.04	0	0.004	0.046	0.05	0.039	0	0.076	0.064	0.071	0.033	0.01
SAN	0.029	0.042	0.012	0.011	0	0.07	0.055	0.009	0.024	0.008	0.016	0.037	0.046	0.087	0.055	0	0.011	0.027	0	0.001	0.02	0.055	0.032	0.077	0	0.058	0.181	0.036	0
SEA	0.029	0.047	0.01	0.01	0.013	0.073	0.041	0.025	0.031	0.007	0.02	0.02	0.041	0.096	0.131	0	0.005	0.017	0	0	0.037	0.062	0.033	0.049	0.04	0	0.121	0.035	0.008
SFO	0.022	0.065	0.004	0.017	0.009	0.061	0.034	0.011	0.06	0.013	0.031	0.025	0.064	0.093	0.156	0	0.004	0.009	0	0.01	0.022	0.068	0.025	0.028	0.08	0.067	0	0.021	0
SLC	0.041	0.042	0.013	0.014	0.022	0.121	0.048	0.024	0.006	0	0	0.029	0.035	0.094	0.096	0	0.024	0.023	0	0	0.034	0.042	0.013	0.073	0.054	0.07	0.083	0	0
TPA	0.123	0.064	0.046	0.065	0.09	0.02	0.033	0.028	0.055	0.061	0.025	0.032	0.049	0.023	0.009	0.067	0	0.023	0.01	0.052	0.014	0.05	0.042	0.014	0	0.006	0	0	0

Table E.2: Delay distribution of Case 1

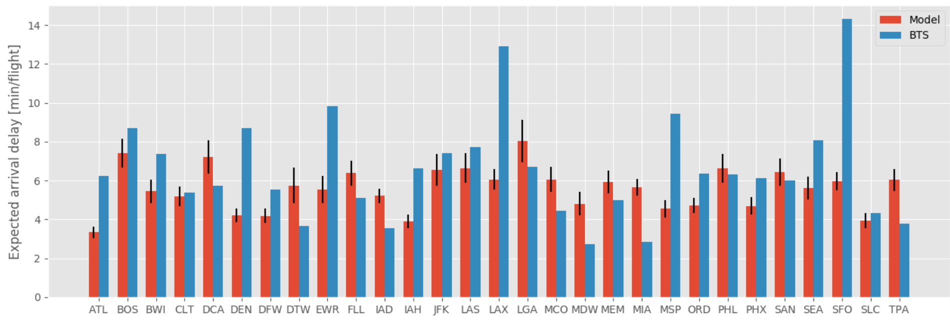
	ATL	BOS	BWI	CLT	DCA	DEN	DFW	DTW	EWR	FLL	IAD	IAH	JFK	LAS	LAX	LGA	MCO	MDW	MEM	MIA	MSP	ORD	PHL	PHX	SAN	SEA	SFO	SLC	TPA
ATL	0.000	0.040	0.045	0.044	0.066	0.031	0.038	0.025	0.041	0.054	0.014	0.023	0.017	0.036	0.037	0.103	0.060	0.032	0.015	0.039	0.020	0.052	0.057	0.014	0.009	0.015	0.014	0.015	0.043
BOS	0.044	0.000	0.066	0.039	0.151	0.021	0.025	0.027	0.066	0.017	0.020	0.010	0.071	0.003	0.027	0.128	0.033	0.018	0.000	0.021	0.017	0.070	0.064	0.006	0.006	0.010	0.024	0.003	0.014
BWI	0.097	0.183	0.000	0.074	0.000	0.031	0.029	0.042	0.021	0.100	0.000	0.012	0.000	0.026	0.031	0.000	0.075	0.062	0.007	0.027	0.030	0.047	0.000	0.029	0.010	0.014	0.000	0.006	0.046
CLT	0.101	0.065	0.065	0.000	0.071	0.023	0.045	0.025	0.040	0.028	0.000	0.018	0.021	0.018	0.034	0.108	0.053	0.014	0.011	0.044	0.018	0.062	0.044	0.026	0.008	0.002	0.019	0.005	0.035
DCA	0.073	0.189	0.000	0.041	0.000	0.013	0.040	0.024	0.044	0.045	0.000	0.021	0.025	0.007	0.019	0.131	0.053	0.041	0.000	0.063	0.022	0.077	0.007	0.008	0.000	0.011	0.012	0.006	0.029
DEN	0.034	0.036	0.022	0.020	0.028	0.000	0.040	0.022	0.033	0.011	0.024	0.029	0.013	0.068	0.070	0.051	0.041	0.030	0.007	0.012	0.039	0.062	0.039	0.051	0.042	0.060	0.066	0.040	0.011
DFW	0.058	0.041	0.017	0.038	0.047	0.045	0.000	0.028	0.032	0.026	0.014	0.034	0.005	0.043	0.059	0.074	0.051	0.000	0.011	0.043	0.031	0.086	0.034	0.027	0.038	0.034	0.046	0.018	0.021
DTW	0.063	0.071	0.055	0.039	0.052	0.045	0.046	0.000	0.021	0.056	0.007	0.017	0.003	0.041	0.025	0.081	0.043	0.043	0.007	0.021	0.040	0.081	0.042	0.025	0.008	0.023	0.014	0.010	0.020
EWR	0.070	0.113	0.005	0.052	0.050	0.043	0.038	0.013	0.000	0.050	0.007	0.036	0.000	0.029	0.060	0.000	0.097	0.036	0.000	0.051	0.026	0.080	0.000	0.021	0.005	0.019	0.069	0.001	0.028
FLL	0.113	0.052	0.095	0.043	0.095	0.008	0.025	0.031	0.069	0.000	0.000	0.026	0.051	0.008	0.013	0.166	0.013	0.012	0.000	0.000	0.000	0.014	0.101	0.000	0.000	0.009	0.013	0.000	0.041
IAD	0.119	0.101	0.000	0.000	0.000	0.098	0.050	0.016	0.026	0.000	0.000	0.023	0.041	0.030	0.108	0.000	0.099	0.000	0.000	0.035	0.022	0.047	0.000	0.000	0.010	0.018	0.109	0.000	0.046
IAH	0.070	0.037	0.013	0.040	0.041	0.061	0.038	0.015	0.065	0.027	0.013	0.000	0.000	0.030	0.060	0.062	0.036	0.000	0.015	0.046	0.027	0.078	0.044	0.019	0.031	0.023	0.062	0.023	0.024
JFK	0.034	0.118	0.000	0.040	0.042	0.006	0.005	0.007	0.000	0.064	0.009	0.000	0.000	0.048	0.164	0.000	0.099	0.000	0.000	0.080	0.017	0.033	0.000	0.029	0.031	0.030	0.088	0.010	0.045
LAS	0.046	0.017	0.021	0.014	0.002	0.061	0.037	0.026	0.033	0.019	0.010	0.022	0.046	0.000	0.152	0.000	0.012	0.042	0.000	0.018	0.020	0.050	0.027	0.047	0.050	0.063	0.110	0.039	0.013
LAX	0.034	0.048	0.020	0.019	0.009	0.049	0.037	0.015	0.048	0.017	0.022	0.029	0.083	0.102	0.000	0.000	0.016	0.016	0.001	0.017	0.023	0.064	0.023	0.042	0.022	0.076	0.144	0.023	0.001
LGA	0.085	0.127	0.000	0.051	0.114	0.044	0.050	0.037	0.000	0.082	0.000	0.025	0.000	0.000	0.000	0.000	0.054	0.032	0.000	0.090	0.024	0.147	0.007	0.000	0.000	0.000	0.000	0.000	0.030
MCO	0.116	0.043	0.046	0.050	0.065	0.027	0.046	0.025	0.086	0.009	0.024	0.023	0.084	0.019	0.020	0.089	0.000	0.023	0.002	0.065	0.012	0.052	0.047	0.009	0.005	0.002	0.008	0.003	0.000
MDW	0.096	0.044	0.053	0.009	0.080	0.066	0.000	0.046	0.068	0.021	0.000	0.000	0.000	0.070	0.041	0.091	0.061	0.000	0.011	0.000	0.061	0.000	0.050	0.044	0.022	0.019	0.014	0.013	0.020
MEM	0.263	0.000	0.030	0.128	0.000	0.060	0.111	0.026	0.015	0.000	0.000	0.036	0.000	0.000	0.036	0.000	0.047	0.067	0.000	0.000	0.073	0.066	0.000	0.000	0.000	0.000	0.000	0.000	0.042
MIA	0.095	0.047	0.012	0.044	0.093	0.007	0.052	0.010	0.062	0.000	0.000	0.029	0.066	0.020	0.032	0.204	0.070	0.000	0.000	0.000	0.006	0.054	0.044	0.005	0.000	0.000	0.014	0.000	0.034
MSP	0.068	0.035	0.039	0.031	0.045	0.078	0.042	0.031	0.023	0.000	0.007	0.014	0.015	0.030	0.041	0.055	0.019	0.055	0.006	0.017	0.000	0.123	0.064	0.036	0.015	0.039	0.038	0.022	0.012
ORD	0.046	0.079	0.017	0.037	0.079	0.037	0.051	0.024	0.044	0.011	0.012	0.020	0.012	0.033	0.055	0.132	0.033	0.000	0.003	0.029	0.047	0.000	0.048	0.019	0.022	0.036	0.050	0.012	0.013
PHL	0.114	0.118	0.000	0.053	0.037	0.039	0.048	0.032	0.000	0.036	0.000	0.012	0.000	0.029	0.024	0.001	0.092	0.041	0.000	0.033	0.050	0.110	0.000	0.023	0.018	0.024	0.033	0.006	0.028
PHX	0.029	0.017	0.024	0.042	0.010	0.084	0.046	0.019	0.029	0.000	0.005	0.021	0.026	0.081	0.127	0.000	0.009	0.045	0.000	0.002	0.032	0.060	0.036	0.000	0.078	0.059	0.061	0.046	0.011
SAN	0.032	0.013	0.011	0.018	0.000	0.077	0.066	0.010	0.027	0.015	0.015	0.030	0.043	0.094	0.065	0.000	0.011	0.023	0.000	0.001	0.013	0.065	0.020	0.086	0.000	0.066	0.162	0.037	0.000
SEA	0.034	0.026	0.011	0.012	0.010	0.074	0.044	0.024	0.032	0.006	0.017	0.018	0.035	0.107	0.143	0.000	0.005	0.018	0.000	0.000	0.036	0.069	0.022	0.046	0.047	0.000	0.116	0.040	0.007
SFO	0.021	0.049	0.004	0.016	0.007	0.065	0.037	0.009	0.064	0.009	0.023	0.028	0.055	0.097	0.170	0.000	0.002	0.010	0.000	0.007	0.020	0.074	0.024	0.032	0.076	0.080	0.000	0.021	0.000
SLC	0.035	0.019	0.012	0.014	0.022	0.128	0.043	0.020	0.011	0.000	0.000	0.027	0.034	0.113	0.104	0.000	0.021	0.027	0.000	0.000	0.029	0.055	0.016	0.079	0.041	0.075	0.075	0.000	0.000
TPA	0.154	0.035	0.055	0.078	0.075	0.019	0.040	0.017	0.048	0.075	0.016	0.020	0.061	0.025	0.011	0.068	0.000	0.026	0.002	0.056	0.010	0.050	0.043	0.009	0.000	0.007	0.000	0.000	0.000

Table E.3: Delay Distribution of Case 2

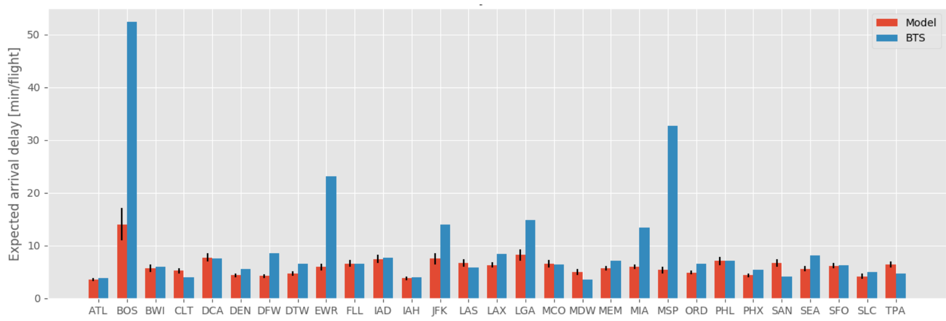
x	ATL	BOS	BWI	CLT	DCA	DEN	DFW	DTW	EWR	FLL	IAD	IAH	JFK	LAS	LAX	LGA	MCO	MDW	MEM	MIA	MSP	ORD	PHL	PHX	SAN	SEA	SFO	SLC	TPA
ATL	0.000	0.038	0.043	0.044	0.062	0.028	0.037	0.024	0.044	0.057	0.014	0.024	0.019	0.029	0.037	0.099	0.062	0.033	0.016	0.041	0.020	0.048	0.057	0.015	0.009	0.016	0.013	0.014	0.056
BOS	0.065	0.000	0.059	0.040	0.148	0.020	0.023	0.025	0.064	0.018	0.020	0.010	0.075	0.003	0.027	0.117	0.036	0.019	0.000	0.020	0.016	0.065	0.062	0.006	0.009	0.011	0.024	0.004	0.014
BWI	0.148	0.168	0.000	0.077	0.000	0.028	0.026	0.038	0.018	0.101	0.000	0.012	0.000	0.023	0.030	0.000	0.065	0.055	0.007	0.026	0.031	0.039	0.000	0.027	0.009	0.016	0.000	0.007	0.050
CLT	0.155	0.055	0.058	0.000	0.062	0.019	0.040	0.022	0.043	0.034	0.000	0.018	0.023	0.017	0.035	0.101	0.046	0.014	0.012	0.041	0.017	0.053	0.042	0.023	0.009	0.003	0.021	0.004	0.035
DCA	0.105	0.172	0.000	0.041	0.000	0.011	0.037	0.025	0.042	0.051	0.000	0.021	0.025	0.007	0.020	0.124	0.051	0.036	0.000	0.065	0.018	0.070	0.011	0.010	0.000	0.011	0.010	0.006	0.033
DEN	0.055	0.034	0.023	0.021	0.024	0.000	0.036	0.021	0.037	0.011	0.025	0.027	0.012	0.059	0.072	0.046	0.039	0.028	0.007	0.012	0.038	0.059	0.039	0.053	0.042	0.061	0.068	0.038	0.012
DFW	0.088	0.042	0.017	0.041	0.042	0.040	0.000	0.026	0.037	0.028	0.014	0.030	0.005	0.043	0.056	0.069	0.049	0.000	0.012	0.043	0.028	0.079	0.034	0.024	0.038	0.035	0.045	0.016	0.020
DTW	0.093	0.068	0.048	0.042	0.053	0.037	0.044	0.000	0.021	0.059	0.007	0.017	0.004	0.042	0.022	0.075	0.044	0.042	0.007	0.021	0.038	0.076	0.037	0.030	0.006	0.024	0.015	0.010	0.018
EWR	0.105	0.106	0.006	0.051	0.052	0.038	0.035	0.012	0.000	0.054	0.007	0.035	0.000	0.025	0.056	0.000	0.093	0.030	0.000	0.050	0.023	0.073	0.000	0.026	0.008	0.020	0.064	0.001	0.030
FLL	0.169	0.042	0.084	0.042	0.082	0.008	0.022	0.024	0.070	0.000	0.000	0.033	0.056	0.007	0.011	0.147	0.012	0.007	0.000	0.000	0.000	0.013	0.090	0.000	0.000	0.011	0.015	0.000	0.054
IAD	0.185	0.087	0.000	0.000	0.000	0.085	0.046	0.018	0.021	0.000	0.000	0.024	0.049	0.026	0.102	0.000	0.087	0.000	0.000	0.032	0.019	0.038	0.000	0.000	0.009	0.023	0.102	0.000	0.048
IAH	0.096	0.037	0.013	0.038	0.044	0.055	0.037	0.011	0.070	0.029	0.014	0.000	0.000	0.027	0.058	0.057	0.032	0.000	0.014	0.048	0.024	0.068	0.046	0.020	0.026	0.025	0.060	0.023	0.028
JFK	0.053	0.110	0.000	0.036	0.038	0.006	0.004	0.007	0.000	0.073	0.009	0.000	0.000	0.044	0.166	0.000	0.105	0.000	0.000	0.081	0.016	0.032	0.000	0.026	0.023	0.028	0.084	0.009	0.049
LAS	0.067	0.015	0.020	0.014	0.002	0.057	0.034	0.022	0.033	0.019	0.010	0.022	0.048	0.000	0.154	0.000	0.014	0.037	0.000	0.019	0.020	0.045	0.026	0.051	0.051	0.061	0.107	0.036	0.015
LAX	0.053	0.046	0.018	0.018	0.010	0.048	0.037	0.014	0.054	0.016	0.023	0.028	0.086	0.089	0.000	0.000	0.016	0.014	0.001	0.017	0.020	0.059	0.023	0.046	0.020	0.079	0.141	0.023	0.001
LGA	0.127	0.116	0.000	0.052	0.108	0.038	0.045	0.034	0.000	0.091	0.000	0.023	0.000	0.000	0.000	0.000	0.053	0.033	0.000	0.085	0.022	0.133	0.008	0.000	0.000	0.000	0.000	0.000	0.031
MCO	0.152	0.039	0.042	0.047	0.068	0.025	0.045	0.024	0.084	0.009	0.024	0.026	0.082	0.015	0.018	0.078	0.000	0.021	0.002	0.063	0.010	0.047	0.050	0.008	0.006	0.003	0.008	0.003	0.000
MDW	0.144	0.040	0.047	0.010	0.082	0.053	0.000	0.040	0.076	0.022	0.000	0.000	0.000	0.062	0.040	0.085	0.053	0.000	0.017	0.000	0.058	0.000	0.044	0.043	0.023	0.017	0.012	0.010	0.022
MEM	0.340	0.000	0.035	0.125	0.000	0.043	0.091	0.023	0.026	0.000	0.000	0.029	0.000	0.000	0.034	0.000	0.044	0.057	0.000	0.000	0.068	0.048	0.000	0.000	0.000	0.000	0.000	0.000	0.039
MIA	0.137	0.037	0.009	0.047	0.082	0.005	0.049	0.010	0.068	0.000	0.000	0.030	0.066	0.017	0.032	0.196	0.066	0.000	0.000	0.000	0.005	0.048	0.039	0.009	0.000	0.000	0.014	0.000	0.034
MSP	0.099	0.031	0.040	0.034	0.042	0.074	0.041	0.028	0.020	0.000	0.006	0.012	0.015	0.027	0.040	0.055	0.026	0.050	0.007	0.017	0.000	0.114	0.061	0.040	0.013	0.039	0.034	0.021	0.013
ORD	0.071	0.072	0.015	0.038	0.076	0.032	0.049	0.025	0.044	0.012	0.014	0.021	0.013	0.031	0.055	0.123	0.035	0.000	0.005	0.028	0.045	0.000	0.047	0.019	0.023	0.034	0.049	0.010	0.015
PHL	0.174	0.104	0.000	0.050	0.029	0.033	0.046	0.032	0.000	0.031	0.000	0.011	0.000	0.023	0.024	0.001	0.094	0.037	0.000	0.031	0.043	0.098	0.000	0.025	0.018	0.027	0.031	0.007	0.030
PHX	0.047	0.019	0.024	0.042	0.012	0.081	0.043	0.014	0.033	0.000	0.005	0.021	0.027	0.072	0.132	0.000	0.010	0.037	0.000	0.001	0.029	0.059	0.037	0.000	0.075	0.061	0.063	0.045	0.011
SAN	0.050	0.013	0.012	0.015	0.000	0.071	0.060	0.009	0.028	0.012	0.016	0.029	0.046	0.087	0.069	0.000	0.012	0.025	0.000	0.001	0.013	0.062	0.021	0.093	0.000	0.062	0.159	0.036	0.000
SEA	0.050	0.025	0.011	0.011	0.011	0.070	0.044	0.020	0.036	0.007	0.019	0.020	0.039	0.096	0.143	0.000	0.005	0.015	0.000	0.000	0.034	0.060	0.024	0.052	0.047	0.000	0.113	0.039	0.009
SFO	0.033	0.046	0.004	0.016	0.009	0.059	0.034	0.008	0.068	0.008	0.026	0.026	0.059	0.090	0.172	0.000	0.002	0.010	0.000	0.007	0.021	0.069	0.025	0.036	0.080	0.074	0.000	0.020	0.000
SLC	0.062	0.019	0.010	0.014	0.024	0.122	0.042	0.017	0.009	0.000	0.000	0.028	0.036	0.097	0.102	0.000	0.020	0.020	0.000	0.000	0.030	0.054	0.016	0.076	0.052	0.074	0.074	0.000	0.000
TPA	0.208	0.027	0.048	0.076	0.079	0.018	0.035	0.015	0.043	0.071	0.014	0.021	0.059	0.024	0.011	0.058	0.000	0.025	0.002	0.058	0.008	0.042	0.041	0.007	0.000	0.009	0.000	0.000	0.000

F

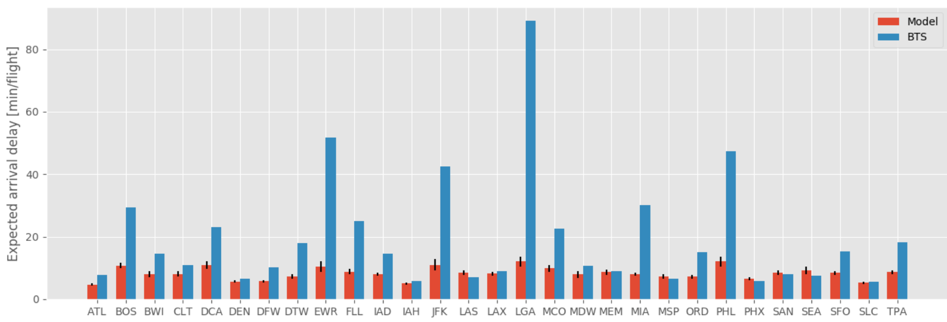
Arrival Delay Validation



(a) Arrival Delay on 09-09-2016 (Good Weather Conditions)



(b) Arrival Delay on 06-09-2016 (Average Weather Conditions)



(c) Arrival Delay on 30-09-2016 (Severe Weather Conditions)

Figure F.1: Average Arrival Delay per Airport

G

T-test scores day calibration

Table G.1: T-test scores of Arrival Delay

	6-sep		9-sep		30-sep	
	statistic	p-value	statistic	p-value	statistic	p-value
ATL	-35.53	1.96E-179	-309.30	0	-290.70	0
BOS	-399.00	0	-54.60	4.16E-302	-733.94	0
BWI	-14.09	2.81E-41	-99.01	0	-213.88	0
CLT	76.22	0	-13.43	6.50E-38	-98.39	0
DCA	9.83	8.14E-22	55.34	1.63E-306	-306.28	0
DEN	-98.70	0	-391.94	0	-65.84	0
DFW	-422.71	0	-114.09	0	-346.14	0
DTW	-130.01	0	72.70	0	-464.04	0
EWR	-823.90	0	-197.54	0	-808.44	0
FLL	3.49	0.00051135	62.67	0	-631.00	0
IAD	-10.99	1.33E-26	137.06	0	-384.27	0
IAH	-20.43	8.94E-78	-245.91	0	-72.54	0
JFK	-194.86	0	-32.97	7.23E-162	-553.03	0
LAS	33.88	3.97E-168	-43.47	1.51E-232	60.60	0
LAX	-122.61	0	-400.58	0	-34.71	8.10E-174
LGA	-195.38	0	38.92	2.15E-202	-1528.77	0
MCO	4.51	7.22E-06	77.53	0	-400.56	0
MDW	80.17	0	108.60	0	-85.42	0
MEM	-104.98	0	52.31	2.46E-288	-16.85	3.09E-56
MIA	-566.83	0	202.97	0	-1302.80	0
MSP	-1355.75	0	-350.29	0	36.13	1.72E-183
ORD	-140.22	0	-133.04	0	-405.50	0
PHL	-3.26	0.001146297	12.34	1.21E-32	-680.65	0
PHX	-92.72	0	-102.23	0	34.75	4.28E-174
SAN	110.83	0	19.23	2.40E-70	26.82	8.39E-120
SEA	-150.17	0	-133.11	0	42.93	5.11E-229
SFO	-6.71	3.18E-11	-562.85	0	-373.39	0
SLC	-57.75	1.38536007094e-320	-31.08	6.47E-149	-26.70	5.58E-119
TPA	93.39	0	124.18	0	-443.74	0

Table G.2: T-test scores of Departure Delay

	6-sep		9-sep		30-sep	
	statistic	p-value	statistic	p-value	statistic	p-value
ATL	84.90	0	6.07	1.79E-09	-319.65	0
BOS	-465.29	0	107.07	0	-544.72	0
BWI	0.80	0.421996992	89.99	0	-71.98	0
CLT	-5.41	7.91E-08	125.89	0	-99.03	0
DCA	111.65	0	138.52	0	6.60	6.82E-11
DEN	-100.24	0	-101.12	0	-73.27	0
DFW	-93.11	0	61.34	0	-172.86	0
DTW	-13.96	1.33E-40	56.50	2.29257655297e-313	-166.23	0
EWR	-543.37	0	-136.21	0	-370.68	0
FLL	27.85	8.16E-127	87.41	0	-742.42	0
IAD	-173.93	0	-249.09	0	-144.90	0
IAH	41.82	9.43E-222	-357.56	0	-269.87	0
JFK	-35.57	9.94E-180	22.14	1.02E-88	-637.94	0
LAS	49.33	5.33E-270	4.42	1.12E-05	49.66	4.95E-272
LAX	-31.08	6.81E-149	-194.20	0	-35.51	2.72E-179
LGA	-20.17	3.87E-76	0.21	0.833032871	-1154.13	0
MCO	34.73	5.61E-174	-10.33	7.42E-24	-350.55	0
MDW	72.76	0	66.25	0	-89.80	0
MEM	-42.56	1.25E-226	-516.34	0	-37.66	6.81E-194
MIA	-160.34	0	-211.18	0	-1321.59	0
MSP	-675.39	0	-131.10	0	-140.67	0
ORD	-315.43	0	-84.71	0	-182.24	0
PHL	-6.85	1.32E-11	-42.96	3.04E-229	-335.80	0
PHX	98.71	0	5.70	1.62E-08	106.00	0
SAN	41.47	2.22E-219	9.34	6.32E-20	11.21	1.50E-27
SEA	16.14	2.93E-52	13.00	8.38E-36	144.54	0
SFO	-27.81	1.73E-126	-207.76	0	-171.41	0
SLC	-10.41	3.73E-24	-109.86	0	30.18	1.04E-142
TPA	51.11	4.86E-281	126.32	0	-193.41	0

H

T-test scores weekday calibration

Table H.1: T-test scores of Arrival Delay

	Tuesdays		Thursdays	
	statistic	p-value	statistic	p-value
ATL	-116.38	0	-242.22	0
BOS	-204.13	0	-127.15	0
BWI	15.21	3.76E-47	-71.15	0
CLT	-13.25	4.94E-37	-278.09	0
DCA	-4.80	1.84E-06	-100.38	0
DEN	-141.49	0	-512.73	0
DFW	-224.91	0	-373.66	0
DTW	-18.39	2.66E-65	-107.73	0
EWR	-154.39	0	-554.01	0
FLL	-115.61	0	-173.72	0
IAD	-29.82	2.99E-140	-160.39	0
IAH	-83.68	0	-273.52	0
JFK	-81.84	0	-250.77	0
LAS	24.20	3.23E-102	-332.95	0
LAX	-142.04	0	-224.77	0
LGA	-21.57	5.01E-85	-301.32	0
MCO	-90.52	0	-240.20	0
MDW	60.17	0	-140.92	0
MEM	-28.81	2.22E-133	-99.62	0
MIA	-117.39	0	-260.54	0
MSP	-421.67	0	-296.40	0
ORD	-66.97	0	-306.57	0
PHL	-63.07	0	-731.74	0
PHX	-103.08	0	-200.00	0
SAN	-15.12	1.16E-46	-101.40	0
SEA	-29.84	2.00E-140	-106.41	0
SFO	-600.93	0	-428.95	0
SLC	-165.23	0	-277.74	0
TPA	25.35	6.97E-110	-214.96	0

I

Stationary Arrivals

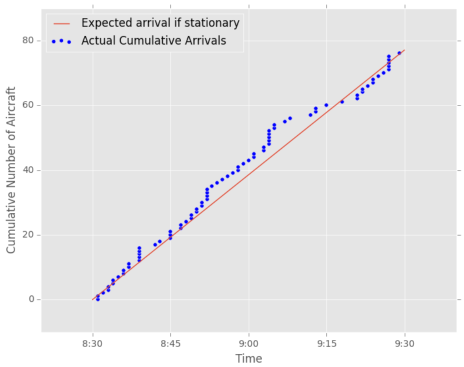


Figure I.1: Arrivals at Atlanta between 8:30 and 9:30 EST on 21-08-2016

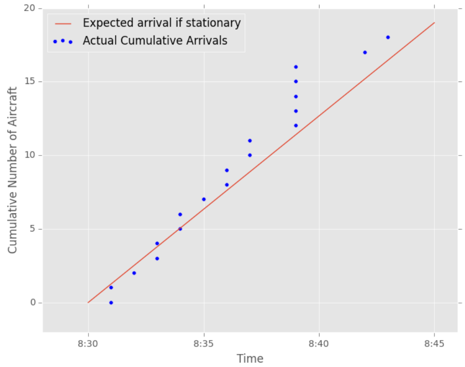


Figure I.2: Arrivals at Atlanta between 8:30 and 8:45 EST on 21-08-2016

J

Kolmogorov–Smirnov Test

Table J.1: KS tests for the inter-arrival time distributions and the service time distributions

Distribution	fitting	D	p	k
Arrival Demand	expon	0.3052	0	n/a
	erlang	0.7077	0	non-integer
Turnaround Demand	expon	0.3763	0	n/a
	erlang	0.8002	0	non-integer
Departure Demand	expon	0.4136	0	n/a
	erlang	0.8002	0	non-integer
Arrival Service	expon	0.1887	0	n/a
	erlang	0.0902	2.50E-219	k=5
Departure Service	expon	0.136	0	n/a
	erlang	0.1517	0	k=4

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