2018-2019 ACRP UNIVERSITY DESIGN COMPETITION

Harnessing Cloud Computing and Deep Learning for Flight Delay Prediction to Improve Airport Management and Planning: Flight Foresight

(January 2019 – April 2019)

Design Challenge: Airport Management and Planning

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1. Executive Summary

The Airport Cooperative Research Program (ACRP) University Design Competition encourages innovative modeling for collaborative decision making and data sharing at airports that will help operators optimize the allocation of current infrastructure resources and plan for future functional needs. Flight delays in the National Airspace System (NAS) form a fundamental challenge to capacity growth under ever-increasing traffic volumes, and lead to significant financial burdens that reverberate across a multitude of aviation industry stakeholders. Building upon existing deep learning algorithms and utilizing the System Wide Information Management (SWIM) program of Next Generation Air Traffic Control (NextGen), this project proposes a central delay prediction platform suited to the complex and dynamic needs of America's airport infrastructure. Improved in scope and technique, this technology would accurately and precisely produce departure and arrival delay forecasts unique to the location and congestion of specific airports and can further be integrated into Collaborative Decision Making (CDM) and Ground Delay Program (GDP) initiatives.

The following proposal presents a detailed and holistic description of technology functionality, accompanied by safety-risk, cost-benefit, and sustainability assessments. The design team's background encompasses advanced mathematics, computer science, air traffic control, aerospace engineering, and information technology. Professional input from aviation management and information technology professors in academia and aviation planners in industry provided valuable and heeded insight.

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3. Background and Problem Statement

A fundamental facet of human interaction and modern marvel of technological development, the NAS is unrivaled in geographic breadth and operational depth. The Federal Aviation Administration (FAA)'s domain covers 20,000 airports, 5.3 million square miles of domestic airspace, 15.8 million annual flights, and 14,000 air traffic controllers, affecting 10.6 million jobs in aviation and 5.1% of the country's economy (FAA, 2018). Demanding stringent and harmonious synchrony across incredible geographic, financial, and technical scopes, the commercial aviation industry is susceptible to volatile perturbations in the form of flight delays. The arena of such struggles, airports are caught in a vicious cycle between congestion-induced delays and delay-induced congestion through a seemingly futile pursuit of capacity growth. As 1.05 billion annual passengers are expected within the decade, a 19.3% increase from today's levels, infrastructure construction alone is no match for expanded traffic volumes (FAA, 2018). Rather, strides in resource efficiency and effectiveness are key to realistically and quickly coping with the inevitable and substantial traffic flows of the future. Long plaguing modern air transportation, flight delays accounted for 20% total flight time and amounted to 320 million hours upon last measurement (Joint Economic Committee (JEC), 2007). Drastic financial consequences associated with domestic flight delays, often pegged around $35 billion annually, ripple throughout the aviation industry to stifle the retail, lodging, restaurant, and tourism industries. Under the radar of media attention yet under the microscope of public perception, airports incur significant losses from delay in both the strategic, planning and tactical, operational stages of aviation management. Tasked with developing a scalable and synergetic solution to preserve America's dominance in air traffic volume and management, this project focuses on reducing the probability and magnitude of delays through agile, integrated delay forecasting.

To address airport operators' challenges of resource optimization and functional planning, this project innovatively harnesses cloud computing, deep learning, and existing data infrastructure to combat the prevalence of flight delays (ACRP, 2018). The proposed approach is a structured process consisting of: integrating various flight operations databases into the existing NextGen SWIM program; fusing advanced deep learning algorithms to a cloud database; training delay prediction algorithms with datasets customized to airports; computing delay occurrence and propagation via real-time inputs and outputs; and utilizing delay forecasts to optimize the FAA's CDM and GDP capabilities and airport initiatives.

In recent years, governmental effort in aiding decision-making at airports is readily apparent in NextGen's SWIM program and Flight Delay Information from FAA Air Traffic Control System Command Center (ATCSCC). Simultaneously, academic researchers are developing various algorithms to predict flight delays, including advanced statistics, machine learning, graph theory, and network representation. Other aviation stakeholders, namely commercial air carriers, have also initiated delay prediction to adjust their operational schedules. However, delay prediction methods created by researchers have yet to be centralized, tested, and integrated into growing government programs; existing delay prediction programs are limited in scope, specifically by geography, operator, and efficacy.

Directly confronting this paramount problem of commercial aviation through the mobilization of current infrastructure and technologies, this project presents a cloud-centric, data-driven Flight Foresight program. Integrated through existing SWIM framework and operated with deep learning and cloud computing, this centralized system would provide valuable and timely information to airports and the FAA CDM paradigm, improving the accuracy of delay predicting, enhancing collaborative decision making, and benefiting public and private stakeholders alike.

4. Summary of Literature Review

4.1 Delay Problem and Definitions

Propagation and prediction of delays in the national air traffic system have long been a subject of analysis throughout academia and industry. Delays are identified and classified in a number of ways corresponding to the varying sensitivities of constituent stakeholders. For example, a tarmac delay was defined as a delay when an aircraft on the ground is either awaiting takeoff or has just landed and passengers do not have the opportunity to get off the plane (U.S. Department of Transportation (DOT), 2018). While any time difference between scheduled and actual aircraft movement meets the surface definition of a delay, the standard delineation of delay is the FAA's threshold of 15 minutes of separation between planned and actual aircraft movement.

Delay prediction research has varied not only in applied methodology, but also in the classification of metric, source, phase, place, cause, and operator (Mueller, et al., 2002). Delay can be quantified in multiple ways, most commonly using probabilities of occurrence and estimates of length. Causes of delay include traffic congestion, technical problems, scheduling issues, inclement weather, security restrictions, and passenger problems, among limitless others. Geographic analysis of delays has involved consideration in limited levels of locations, ranging from individual airports to country regions (Mukherjee, 2014). Delays arising from crew and maintenance issues are the least common subjects of external analysis, as those occurrences are usually reported by airlines for internal use only. Serious security issues and passenger behavior are similarly not explicitly analyzed in delay predictions due to their often-isolated nature. Inclement weather, with which delays are heavily associated, are widely researched for pattern effects on air traffic, though they are also commonly implicitly accounted for as random events (Mueller, 2002). Classification and prediction of delay by flight phase is another common variation of analysis. Divided into departure delays, enroute delays, and arrival delays, this method predicts time inefficiencies while the aircraft is waiting to depart, flying to its destination, and waiting to dock at a gate. Due to the prevalence of certain delay sources during respective phases of flight, this method is similar to the analysis of delays directly by cause; however, the propagation of delays as the day progresses adds noise and reduces causality from delay analysis (Mukherjee, 2014). Categorical consideration of delay within these divisions offers modeling simplicity from generalizing assumptions of airport similarities, such as regional weather homogeneity. However, as compensation of such factors is naturally limited to a small contingent of airports, restrictions imposed locally, topically, or causally impede holistic evaluation of delay propagation in larger scopes. Regardless, billions of dollars in annual losses suffered by passengers, airports, airlines, and others are attributed to delay occurrences and consequences, fundamentally detracting from the socioeconomic utility provided by modern air transportation.

4.1.1 Costs of Domestic Delays

Many stakeholders in the aviation industry have released different projections of expenses incurred by airport delays in the domestic United States. It must be noted that, depending on the principal interests of the report publisher, included expenses may be direct or indirect costs and may under or overstate the extent of delays' impact. Direct costs induced by departure delays consist of customer service, passenger accommodations, federal fines, fuel costs, and ground support while indirect costs consist of the opportunity cost of displaced passengers' time and lost income from transportation infrastructure. In 2009, the Government Accountability Office (GAO) priced overall system delays in the United States at $41 billion annually (GAO, 2009). More recently, Airlines for America (A4A) released a report putting the financial impact of system delays at $26.6 billion per year or about $78.17 per flight-minute (A4A, 2019). Commissioned by the FAA, NEXTOR universities priced delays as a $31-40 billion problem in 2007, reducing U.S. gross domestic product by an estimated $4 billion (FAA, 2018). Virtually impossible to value precisely, system delay costs' sheer order of magnitude represents the significant, sunk losses that would be better applied to enhancing the safety, accessibility, and reach of air travel.

4.2 Delay Regulations

According to DOT and FAA Air Traffic Control System Command Center, when flights are delayed or cancelled in the United States, DOT and FAA does not mandate airlines and airports to compensate passengers or transfer passengers to another carrier if the second carrier could get passengers to the destination more quickly than the original airline (DOT, 2018; FAA, 2019). The DOT requires only “covered airlines” to comply with the tarmac delay rule. A “covered carrier” is an airline that operates at least one airplane with a seating capacity of 30 or more passenger seats to, from, or within the United States. For flights departing from or landing at a U.S airport, airlines are required to begin to move the airplane to a location where passengers can safely get off before 3 hours for domestic flights. While an aircraft is experiencing a tarmac delay, airlines must provide passengers onboard with food and water no later than two hours after the aircraft leaves the gate (in the case of a departure) or touches down (in the case of an arrival), and airlines are required to provide passengers with notifications regarding the status of the delay every 30 minutes, including the reasons for the tarmac delay (DOT, 2018).

But airlines are required to provide passengers with information about a change in the status of the flight if the flight is scheduled to depart with 7 days. Airlines are required to give flights status updates within 30 minutes after the airline becomes aware of a status change. The flight status information must, at a minimum, be provided on the airlines’ webpage and via the airline’s telephone reservation system. Also, when a flight is delayed for 30 minutes or more, the airline must update all flight status displays and other sources of flight information at U.S. airports that are under the airline’s control within 30 minutes after the airlines become aware of the problem (DOT, 2018).

In accordance with Federal Air Regulations Parts 91, 121 and 135, all operators have the right of refusal of a specific clearance and may elect an alternative. Alternatives include, but are not limited to, ground delay, diversion to other airports or request to stay on the filed route (FAA, 2009).

To ensure compliance with Traffic Management Initiatives (TMI), the ATCSCC use computer programs to monitor operators. In the case of Ground Delay Program (GDP) or Airspace Flow Programs (AFP), the Flight Schedule Monitor is used to monitor airport capacity, demand balance, model Traffic Flow Management (TFM) initiatives and evaluate alternative approaches to managing the traffic. Both air traffic controllers and Traffic Management specialists strive to ensure TMI compliance (FAA, 2009).

4.3 Delay Data Sources

Flight operations times and delays can be computed directly and indirectly from a variety of public and private data sources, each offering differing degrees of coverage (ACRP, 2014). Bureau of Transportation Statistics (BTS) and Aviation System Performance Metrics (ASPM) are the most common databases for delay studies (Mott, 2011; Kim et al., 2017; Balakrishna et al., 2010).

NextGen’s SWIM program was designed to implement a set of information technology principles in the NAS and to provide customers with relevant, reliable, real-time, and comprehendible information, such as flight data, weather information, airport operational status, and special use airspace details (FAA, 2018). SWIM changes the traditional point-to-point communication approach to a net-centric style, providing direct access to information and enterprise security services for all producers, consumers and data streams (FAA, 2014).

Table 1.

Overview of Available Data Sources

Data Source	Strengths	Weaknesses
Traffic Flow Management System Counts (TFMSC)	Data includes flights information about commercial traffic, general aviation, and military that fly under IFR and are captured by the FAA's en route computers.	It is not suitable for micro analysis of delays per runway; It may exclude certain flights that do not enter the en route airspace and other low altitude flights.
Performance Data Analysis and Reporting System (PDARS)	Information is updated every 5 to 6 seconds. The raw database contains over 90 fields, allowing each runway's delays to be calculated.	It is only available to FAA, NASA, and ATAC Corporation and contains just 34 airports' delay data.
Air Traffic Operations Network (OPSNET)	Data contains delay causality information, in which delays are assigned to five major categories: weather, volume, equipment, runway, and others.	Delays are reported manually at ATC facilities at airports and can be inaccurate or excluded; Access to OPSNET is restricted by the FAA.
Airline Service Quality Performance (ASQP)	Information includes actual and scheduled time for gate departure, gate arrival, wheels-off, and wheels-on times for calculation of taxi times.	Flights within the continental United States on airlines having at least 1% of total scheduled domestic passenger revenues are covered; Access to the ASQP database is restricted by the FAA.
Aviation System Performance Metrics (ASPM)	Data includes airport weather, runway configuration, and arrival and departure rates; ASPM efficiency rates were specifically created to measure an ATC facility's abilities.	Data covers flights for only 77 airports, 22 airlines, and select VFR traffic; Access to the ASPM database is restricted by FAA.
Bureau of Transportation Statistics (BTS)	BTS represents the only publicly accessible database that contains flight cancellation and diversion information and percent of diverted flights, making it conducive to aggregate analysis.	Data is published for only 16 U.S. air carries that have at least 1% of total domestic scheduled service passenger revenues, as well as two other carriers that report voluntarily.

Note. This table is modified and captured from ACRP report 104 (ACRP, 2014).

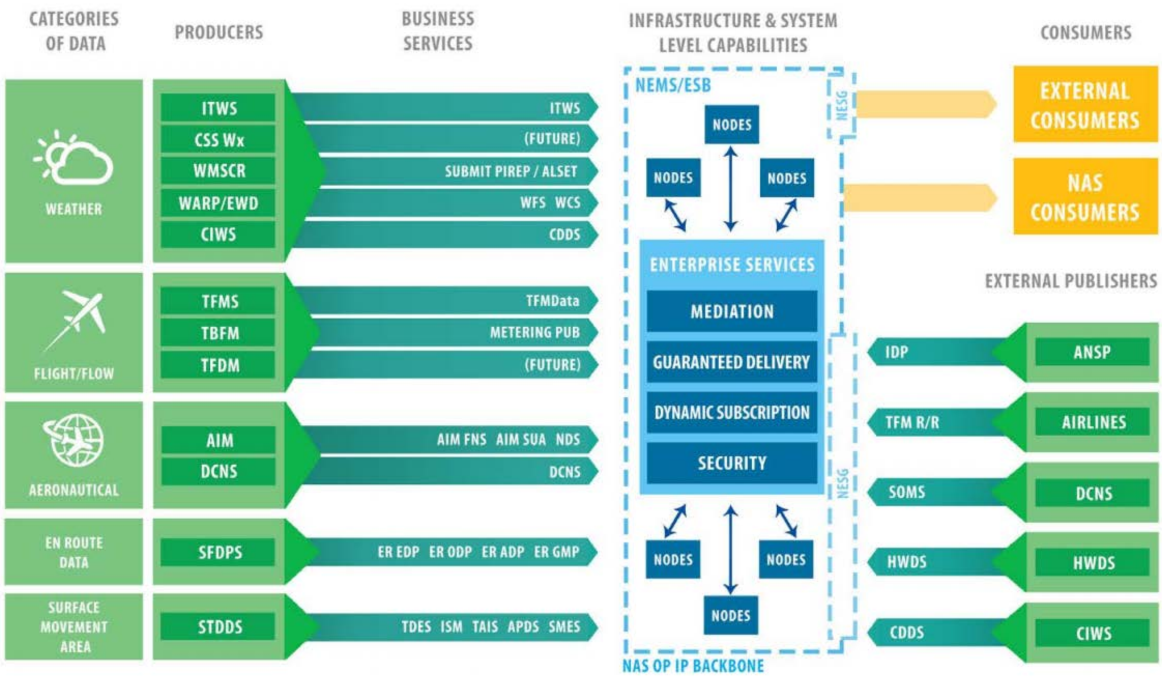

Figure 1. Framework of the NextGen SWIM Program (Matthews & Pressler, 2016)

4.4 Delay Prediction Methods and Technologies

4.4.1 Traditional Methodologies

Statistical analysis often includes regression models, correlation analysis, parametric and non-parametric tests, and multivariate analysis. Probabilistic models include analysis tools that estimate the probability of an event based on historical data. Network representation is the study of flight systems based on classical graph theory, while operational research utilizes advanced analytical methods, such as optimization, simulation, and queue theory, to help decision makers. Simulations analyze airport capacity data considering departure and arrival delay from various weather conditions (Sternberg et al., 2017).

4.4.2 Innovative Methodologies

Machine learning is the research that explores algorithms that can learn from data and provide an educated prediction regarding it. Current flight system studies increasingly use

Table 2.

The Overview of NextGen SWIM's Data Content

<table>
<tr><td>Terminal Radar Approach Control (TRACON)</td><td>SWIM Terminal Data Distribution System (STDDS)</td><td>• Runway Visual Range (RVR)
• Tower Data Link Services (TDLS)
• Electronic Flight Strip Transfer System (EFSTS)
• Airport Surface Detection Equipment, Model X (ASDE-X) or Airport Surface Surveillance Capability (ASSC)
• Standard Terminal Automation Replacement System (STARS) or Terminal Automation Modernization and Replacement (TAMR)</td></tr>
<tr><td>Weather</td><td>Wx</td><td>• Weather Radar Processor (WARP)
• Corridor Integrated Weather System (CIWS)
• Integrated Terminal Weather System (ITWS)
• Common Support Services-Weather (CSS-Wx)
• Weather Message Switching Center Replacement (WMSCR)</td></tr>
<tr><td>Flight Service Station (FSS)</td><td>AIMNDS</td><td>• Aeronautical Information Management (AIM)
• Notice to Airmen (NOTAM)
• NOTAM Distribution Service (NDS)</td></tr>
<tr><td>Air Route Traffic Control Centers (ARTCC)</td><td>SWIM Flight Data Publication Service (SFDPS)</td><td>• En Route Automation Modernization (ERAM)</td></tr>
<tr><td>Command Center (CC)</td><td>Traffic Flow Management System (TFMS) & Time-Based Flow Management (TBFM)</td><td></td></tr>
</table>

Note. This table is modified and captured from FAA Presentation (2014).

machine learning due to its improved computing capability and precision. Specific methods commonly applied include random forecast trees, neural networks, fuzzy logic, and k-nearest neighbor (Sternberg et al., 2017; Kim et al., 2016).

Deep learning is a subfield of machine learning designed to continually analyze data with a logic structure reminiscent of how humans draw conclusions. While theorized in the 1980s, deep learning has only recently been applied because it requires large amounts of label data and substantial computing power.

A layered structure of algorithms called an artificial neural network (ANN) is used for machine intelligence, and is more capable than standard machine learning models (Brett, 2017). A day-to-day delay prediction model was developed and validated using recurrent neural networks (RNN), with accuracy rates ranging from 71.34% to 90.95% when delay is classified with different threshold values (15 minutes, 30 minutes) (Kim et al., 2017, p6). The chief advantage of deep learning networks is that their continuous improvement proportional to the size of the training dataset (The MathWorks, 2019).

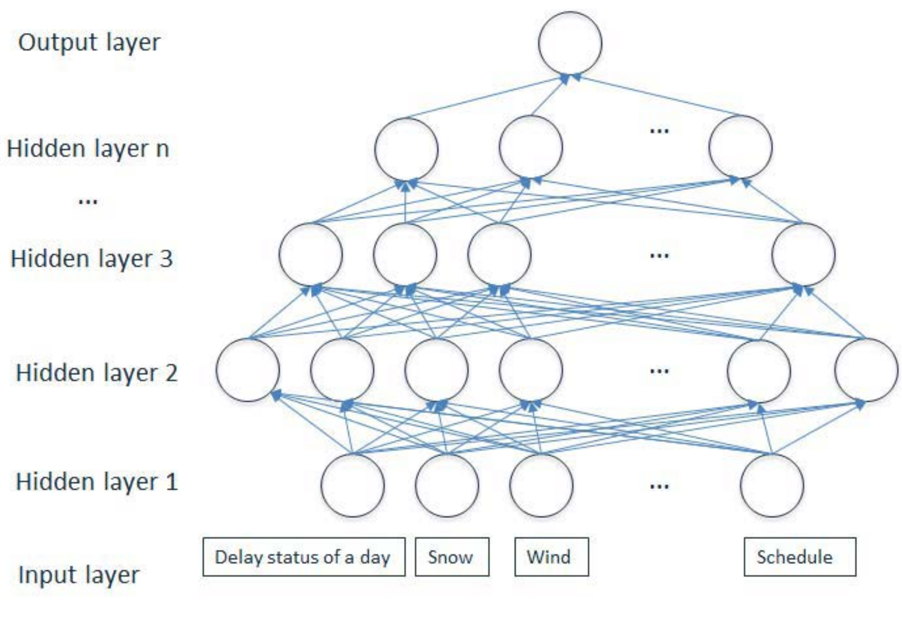

Figure 2. Flight Delay Neural Network Model (Kim et al., 2017)

Cloud computing is the on-demand availability of computer system resources, namely data storage and calculation power, without direct, active management by the user. A cloud services platform provides rapid access to agile and inexpensive resources. Current market products, such as IBM Cloud® and Amazon Web Services®, provide cloud computing services that enable clients to build applications with increased flexibility, scalability, security, and reliability (Walker, 2019).

5. System Principles and Design

5.1 System Design

Aiding in airport resource allocation and capacity optimization, Flight Foresight strives to improve air traffic capacity through enhancing the efficiency and effectiveness of airport operations with reliable and real-time flight delay prediction. Resulting in refined airport management, optimized aviation planning, and improved passenger experience, this technology offers the potential for short-term mitigation of delay propagation and long-term reduction in infrastructure congestion. The proposed system integrates various databases to the NextGen SWIM program framework and fuses deep learning ANN and RNN algorithms to predict accurate arrival and departure delays based on historical data.

The design of the Flight Foresight revolves around five principles:

1) Integrating various flight operations databases into the NextGen SWIM program;

2) Fusing advanced deep learning algorithms to a cloud computing database;

3) Training delay prediction algorithms with datasets customized to specific airports;

4) Developing a redundancy system for backup and recovery purposes;

5) Computing delay occurrence and propagation via real-time inputs and outputs.

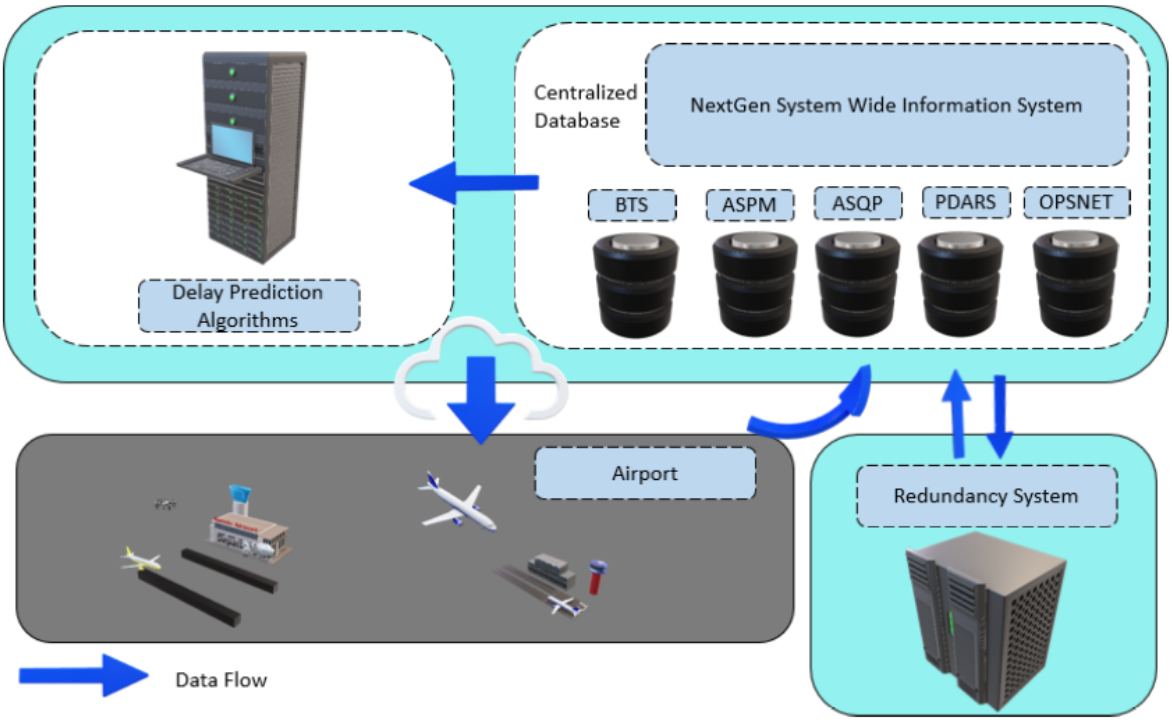

Figure 3. System Framework of Flight Foresight

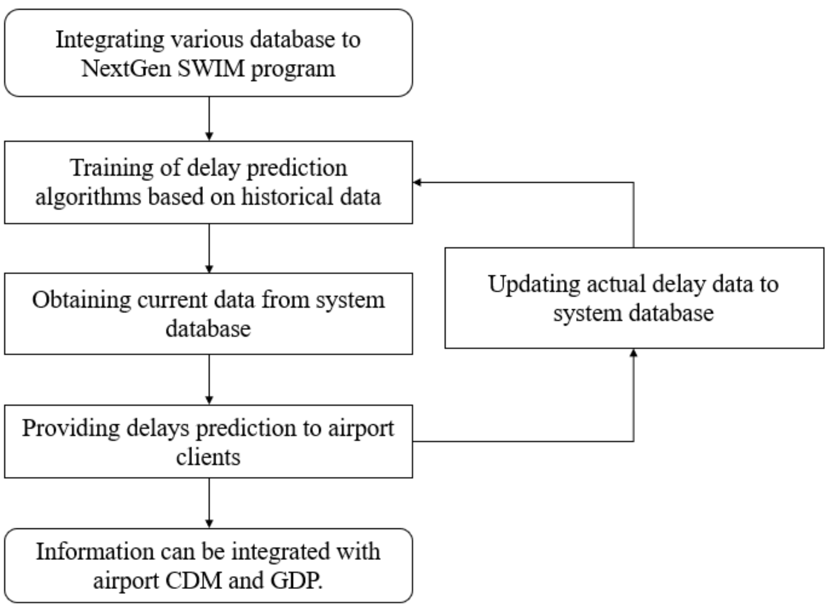

Figure 4. Flowchart of Delay Prediction Process

5.2 System Principles

5.2.1. Integrating various flight operations databases into NextGen SWIM

The basis of cloud computing systems is data. As mentioned in the literature review, the current NextGen SWIM program includes flight data and weather information (FAA, 2019) but lacks other data sources such as BTS and ASPM. In order to obtain a mature deep

Table 3.

Required Input Variables and Expected Output Data

Input variables	Attributes of Flight data[1]	• Season, Month, Date • Origin airport, Destination airport • Scheduled departure time • Scheduled arrival time • Delay status of origin airport • Delay status of destination airport • Flight number • Routing code
	Attributes of Weather data[2]	• Wind velocity • Cloud height • Visibility conditions • Precipitation and Accumulation • General intensity and descriptor • Observation Code
	Attributes of Airport data[3]	• Scheduled and Actual gate push back time • Scheduled and Actual Wheels Off time • Scheduled and Actual Wheels On time • Scheduled and Actual gate docking time
Output data	Delay information	• Predicted Arrival delay time • Predicted Departure delay time • Predicted Taxi-out delay time • Predicted Taxi-in delay time

*Note.*1. Attributes of Flight data can be retrieved from BTS and TFMS database.
2. Attributes of Weather data can be retrieved from NOAA and Wx database.
3. Attributes of Airport data can be retrieved from ASPM and STDDS database.

contains the required inputs from Flight Foresight Database and expected outputs from the Flight Foresight deep learning algorithm.

5.2.2 Fusing the flight delay algorithms to the Flight Foresight system

As mentioned in the literature review, deep learning is a machine learning technique that teaches computers to do what comes naturally to humans: to educate from experience. Deep learning achieves recognition accuracy at higher levels than before because of the development of high-performance parallel-architecture computers. Because a key advantage of deep learning networks is their perpetual enhancement with increasingly large datasets and from the proposed centralized database mentioned in Principle 1, it is of great importance that Flight Foresight combines deep learning with cloud computing.

5.2.3 Training delay prediction algorithms with datasets customized to specific airports

Deploying a mature deep learning neural network has two stages: model training and evaluation. Historical flight time and weather data are retrieved, grouped, and entered into the first stage of the model. By computing hidden states sequentially, the delay status of each flight is predicted. By comparing results with actual delay data, millions of weighted parameters self-adjust to upgrade the algorithm in a continuous cycle of evaluation and enhancement (Kim et al., 2017). The nature of deep learning suggests that the Flight Foresight algorithm must use datasets corresponding to that available from client airports. When a client airport subscribes to the services from Fight Foresight, the algorithm will train with tailored datasets to ensure desired prediction accuracy.

5.2.4 Developing of a redundancy system for backup and recovery purposes

Disasters come in infinite forms, from naturally occurring phenomenon, such as hurricanes, earthquakes, and floods, to man-made threats, like employee sabotage, hacking, and data theft. Downtime is expensive and unacceptable for aviation; hence, it is necessary to develop a replication system to mitigate such risks. Connected to secondary power, a system is created to recover cloud information with minimal data loss and service interruption.

5.2.5 Computing delay occurrence and propagation via real-time inputs and outputs

As Flight Foresight provides real-time flight delay predictions for clients, airport operators and air traffic controllers are simultaneously feeding the latest data into the cloud applications. Each airport's algorithm keeps retrieving data from the database and training itself regularly to constantly improve the accuracy of prediction and power of reduction.

These accurate delay predictions can be integrated with FAA CDM paradigm and GDP. By sharing information, values, and preferences, stakeholders learn from each other and build a common pool of knowledge, resulting in Air Traffic Management (ATM) decisions and actions that are most valuable to the system.

6. Safety Risk Assessment

According to MIL-STD-8825, risk is a function of probability and severity. FAA AC 150/5200-37 (FAA, 2016a) suggests using safety matrices to assess risk in the aviation operations. The chance and intensity of each potential hazard are evaluated separately, and the product of these is the final risk score. For this analysis, probability and severity are divided into five and four levels, respectively. The safety matrix classifies all potential hazards into four groups based on their final scores: low risk, moderate risk, high risk, and unacceptable risk.

Table 4.

Risk Assessment Matrix

Low Risk: 0-4.99 Moderate Risk: 5-9.99 High Risk: 10-14.99 Unacceptable Risk: 15-20	**Severity**	**Insignificant** No disruption of service	**Negligible** Minor disruption of service; prediction accuracy and timeliness are negligibly affected	**Moderate** Moderate disruption of service; prediction accuracy and timeliness are slightly affected	**Serious** Major disruption of service; prediction accuracy and timeliness are greatly affected	**Major** System-wide breakdown or malfunction
Likelihood	**Level**	**1**	**2**	**3**	**4**	**5**
Rare May occur in exceptional circumstances (< **once per 3 years**)	**1**	**1**	**2**	**3**	**4**	**5**
Unlikely Could occur occasionally (**once per year**)	**2**	**2**	**4**	**6**	**8**	**10**
Moderate Can occur sometimes **(once per 3 months)**	**3**	**3**	**6**	**9**	**12**	**15**
Probable Will occur in normal circumstances (> **once per month**)	**4**	**4**	**8**	**12**	**16**	**20**

Table 5.

Risk Assessment and Possible Solutions

Situation		Likelihood	Severity	Risk	Possible Solutions
1	Data loss during acquisition	2	2	4	Support personnel troubleshoot the system
2	Inconsistency between airline and airport predictions	2	2	4	Integrate airlines into the central system
3	Inability to predict under extreme conditions	1	4	4	Prepare and communicate contingency plans
4	Data loss during transmission	1	5	5	Utilize alternative signal linkage route
5	Server damage	1	5	5	Revert to redundancy system
6	Power outrage	1	5	5	Connect to backup power
7	Inaccurate prediction due to algorithm malfunction	2	3	6	Coordinate regular database maintenance and updates

Note. Scores for likelihood, severity, and risk level are evaluated according to Table 4.

Table 5 illustrates the risk assessment of the proposed project by identifying potentially hazardous situations, likelihood, severity, risk, and possible solutions. While Flight Foresight is designed to predict flight delays at the airport nodes, latent hazards exist beyond the property of the airports. Most risk causes are beyond the control of system designers or operators, including data link breakage, power outage, or other extreme situations. However, mitigation measures can still be taken to minimize the impacts of these hazards on system functionality. To cope with data link breakage, an alternative transmission route can send critical information through other existing infrastructure. Likewise, to counter weather-induced power outages, backup power generation can be connected. For extreme situations beyond Flight Foresight's scope of authority, emergency contingency plans must be developed and communicated in coordination between airport operators and network administrators. A twin, backup system would greatly enhance Flight Foresight's resilience to random, adverse events through redundancy of data access points.

7. Cost-Benefit Assessment

The cost and benefit analysis of the proposed system is vital to its financial viability and technical feasibility in practice. Qualitative sources of benefits and costs are thoroughly discussed; a quantitative model of a case study, Flight Foresight potential implementation's at Chicago O'Hare International Airport (ORD), is also presented. ORD is an exemplary subject for delay reduction analysis as its storied history, geographic centrality, political prominence, and busy nature underscore the importance of efficiency-driven capacity growth. Posting annual growth rates in cargo tonnage, enplaned passengers, and aircraft movements 6.93%, 3.79%, and 5.73%, respectively, ORD's traffic volumes threaten to overcome facility capabilities (Chicago Department of Aviation (CDA), 2018). In response to projections of 20% growth within a decade, ORD has started a $8.7 billion expansion from 191 to 220 gates, 5.5 to 8.9 million square feet, which includes construction of parallel runways and a new terminal (Chicago Tribune, 2018).

7.1 Cost Assessment

The cost analysis of the system includes framework design cost, field testing cost, installation and implementation cost, and operations and maintenance cost. For each phase, estimated expenses include labor, such as students, supervisors or technicians, material, such as databases, cabling, and computers, and miscellaneous support, such as third-party contractual work and travel costs.

7.1.1 Research and Development Costs

Initial research in the alpha stage of the project incurs primarily labor costs for system development at Purdue University. Further research and development in the beta stage sustain expenses associated with prototype construction and professional testing by electrical engineers and information technology (IT) specialists.

Table 6.

Cost of Research and Development for Flight Foresight (Alpha)

Item	Rate	Quantity	Subtotal	Remarks
Labor				
Student	$25/hr	480 hrs	$12,000	4 students
Advisor	$50/hr	120 hrs	$6,000	1 professor
Subtotal			$18,000	4 months – Alpha Phase

Note.
This table was inspired by Guidance for Preparing Benefit/Cost Analysis (Byers,2016)

Table 7.

Cost of Research and Development for Flight Foresight (Beta)

Item	Rate	Quantity	Subtotal	Remarks
Labor				
Manager	$35/hr	1,440 hrs	$50,400	Company Representative
Electrician	$45/hr	1,440 hrs	$64,800	1 electrician
Technician	$100/hr	14,600 hrs	$1,460,000	10 technicians
Materials				
Computer and Database	$20,000 ea.	10	$200,000	Work Station
Wires	$20 ea.	250	$5,000	
Travel	1,500/trip	20	$30,000	400/air travel + lodging, etc
Subtotal			$1,810,200	6 months – Beta Phase

Note.
This table was inspired by Guidance for Preparing Benefit/Cost Analysis (Byers, 2016)

7.1.2 System Installation & Operation Costs

Costs directly transferred from the developing company to client airports include system installation, integration, operation, and maintenance. These expenses consist mostly of labor and travel costs for system implementation, third-party service fees for routine maintenance and troubleshooting, and salaries for a small data analytics managerial team.

Table 8.

Cost of Installation and Testing of Flight Foresight (ORD)

Item	Rate	Quantity	Subtotal	Remarks
Personnel				
Company Representative	$35/ hr	4,000 hrs	$140,000	Advisory Role
Airport Representative	$35/hr	4,000 hrs	$140,000	Supervisory Role
Engineer	$100/hr	2,000 hrs	$200,000	1 Engineer
Technician	$50/hr	6,000 hrs	$300,000	3 Technicians
Misc.				
Travel	1,500 /trip	30	$45,000	400/air travel + lodging, etc
Subtotal			$825,000	9 months

Note.
This table was inspired by Guidance for Preparing Benefit/Cost Analysis (Byers,2016)

Table 9.

Cost of Operation and Maintenance of Flight Foresight (ORD)

Item	Rate	Quantity	Subtotal	Remarks
Personnel				
Manager	$100,000/year	1	$100,000	
Technician	$50,000/year	1	$50,000	
Analyst	$75,000/year	2	$150,000	
System				
Support	$10,000/month	12	$120,000	Contracted to third party
Infrastructure	$500/month	12	$6,000	Replicated for back-up
Subtotal			$426,000	12 months

Note.
This table was inspired by Guidance for Preparing Benefit/Cost Analysis (Byers, 2016)

7.2 Benefit Assessment

Information provided by this proposed technology has mutually beneficial implications throughout the aviation industry. Optimization of schedules and resources in response to delay predictions would allow for substantial delay reductions over the long-term. For airlines, less delay time increases the effective productivity and revenue generation potential of their aircraft, while decreasing fuel consumption and emergency customer service expenses. Reaping huge aggregate gains in terms of opportunity cost, the average air travel consumer would undoubtedly welcome decreased travel time. By reducing ground time due to delays, fleets can generate additional revenue. Though many airport authorities are not-for-profit entities, airports are in a uniquely prime position to benefit from delay reduction. Diminished need for service personnel and equipment to attend to aircraft and passengers provide the most direct sources of savings.

When accounted for in long-term aviation planning, airports can translate reduced delay into a significant financial benefit. With fleets and thus gates becoming more productive due to diminished stress from delays, capacity is effectively increased to cope with traffic volume growth without frequently over-budget and overdue terminal renovation or construction projects. Shorter taxi and turnover times on the airfield allow airports to capitalize upon unused space in a variety of manners, including building additional Fixed-Based Operator (FBO) centers and Maintenance, Repair, Overhaul (MRO) stations, gates, and hangars. As shorter taxi and turnover times are dually advantageous for airlines, slight increases in landing or parking fees may be justified to split fuel, maintenance, and labor savings between the airline and airport partnership. However, reassessment of airfield usage and pricing to extract marginal revenues is highly specific to individual airport geometry or needs and is largely beyond the time and complexity scope of this analysis.

Principal benefits from delay reduction brought about by delay prediction encompass decreased labor expenses and increased facility revenue. Schedule synchronization in compensation for delay forecasts smooths the peaks and valleys in airside service demands as delays do accumulate to cause excessive terminal queues. More even distributions of average passenger flow throughout daily operations lowers somewhat the airport's necessitated supply of baggage porters, passenger handlers, security screeners, bus drivers, service agents, building janitors, food workers, and ramp crew, among others. Similarly, improved productivity of facilities increases the airport's effective supply of gate and concessions space. Delay reduction has widespread economic implications as airports, a crucial backbone of a city's commerce, directly influence the financial performance of surrounding hotels, restaurants, retail, and tourism markets. Societal externalities of more efficient airport operations revolve around decreased pollution, noise annoyance and greenhouse gas emissions. Due to the importance and size of airport operations, even small delay reductions harvest huge socioeconomic benefits for all prominent aviation stakeholders.

Savings can be readily estimated for the case study of ORD. Previous publications regarding deep learning algorithms applied to flight delay prediction have yielded an 86% accuracy rate at ORD (Choi, 2016). The Bureau of Transportation Statistics (BTS) also breaks down delay causes in Figure 5 (BTS, 2019).

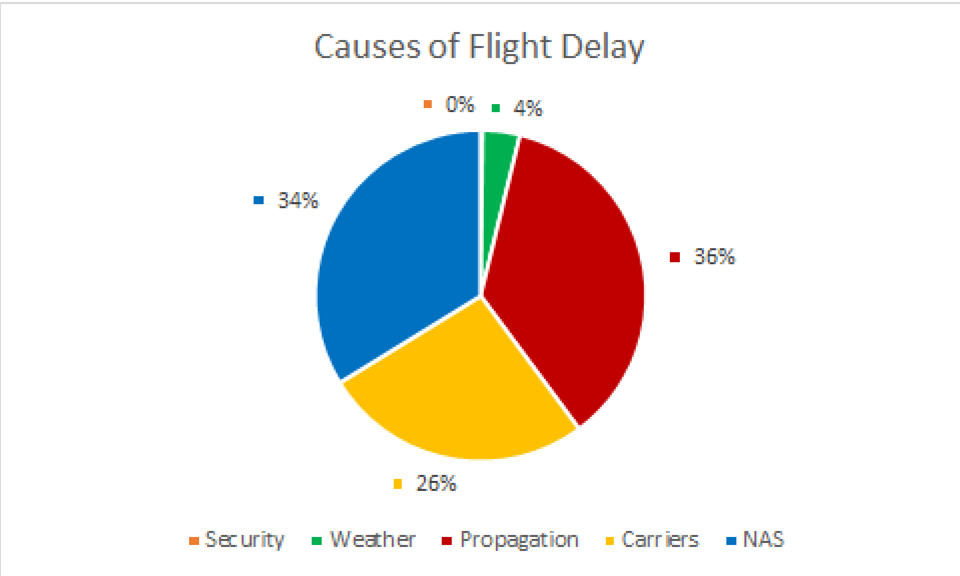

Figure 5. Chart of Flight Delay Causes

Logic implies that no amount of delay prediction and reduction efforts can fully mitigate the effects of extreme weather phenomenon or sensitive security incidents. However, propagation and congestion in the NAS, accounting for a combined 70% of delays, are sources directly addressable by the proposed system over the short-term. Assuming that these delay sources are identically distributed for ORD and that accuracy of applied algorithms is relatively independent of delay characteristics, it is estimated that 60% of ORD's delays can be precisely predicted and eradicated in theory. Presuming that only a quarter of those identified delays are eliminated through this proposed system and confounding delay variables including time of day, phase of flight, aircraft operator, and delay cause are fairly detached, the system is projected to decrease delays at ORD by 15% in the short-term.

Considering the 181,000 filled seats on daily domestic departures and arrivals alone, approximately 76% of 2,120 scheduled flights are on-time, while the 24% remainder experience a mean of 75.8 minutes in delay, or are cancelled (BTS, 2018). Assuming inbound delays carry over to outbound delays, this averages 18.2 minutes of delay per domestic flight or roughly 19,300 combined minutes; an astounding 13.4 days of operational time is lost due to daily delays. With gates operating for an average of 18 hours per day, these delays entangle the equivalent of 17 gates every day. The following analysis evaluates the financial benefits ORD may gain from a 15% reduction in delay, bringing mean domestic delay down to 15.5 minutes.

7.2.1 Labor Savings Benefits

Approximate labor savings from improved passenger flow can be computed at ORD with 15% delay reduction. With 181,000 daily domestic passengers spending 2.7 minutes less in airport facilities, on average, due to delay reduction, passenger services are expected to diminish in correlated expenses. Assuming employment is scaled to passenger flow through the terminal and that 3.6% of domestic flights (15% of 24%), amounting to 6,500 daily passengers, have delays alleviated from airport facilities, effective occupancy stress drops from 224,000 to 217,500, or 1.45% when considering the duplicity of arrival and departure passengers in data counts. Of CDA's 1,700 employees, it is that assumed roughly half, scaled with workforce proportions, are directly involved with facility and passenger operations at ORD, while the rest work at MDW or in general support (CDA, 2018).

Table 10.

Benefit of Labor Savings from Flight Foresight (ORD)

Job	Pay	Old Qty	Old Cost	Change	New Qty	New	Savings
Mechanic	$48.35	50	4.84	-1	49	4.74	.10
Engineer	$58.75	40	4.70	0	40	4.70	.00
Custodian	$21.65	55	2.38	-1	54	2.33	.05
Driver	$36.45	350	25.51	-6	344	25.08	.43
Supervisor	$60.00	25	3.00	0	25	3.00	.00
Officer	$22.35	150	6.71	-3	147	6.57	.14
Laborer	$37.05	80	5.92	-2	78	5.77	.15
Totals	--	750	53.06	--	737	52.19	.87

Note:
This table was inspired by Guidance for Preparing Benefit/Cost Analysis (Byers, 2016)
Data is from the City of Chicago (CDA, 2018)

Airline agents, such as gate representatives and baggage handlers, and other workers, such as security, porters, and chauffeurs, are neglected by these calculations as they are not directly employed by the airport. This analysis suggests that a 1.45% decrease in terminal passenger stress resulting from a conservative 15% delay reduction could save ORD $0.87 million in annual labor costs.

7.2.2 Facility Productivity Benefits

Estimated revenue generated from improved facility productivity can be computed for ORD. With daily delays decreased by 15%, and gates usually operating for 75% of the day, two gates can be effectively freed by enhanced delay prediction and reduction methods. As roughly 530 domestic passengers board every day at each of 171 mainly domestic gates, load factors from ORD are consistently 85.1%, and ORD charges $1.19 per departing seat, each additional gate can facilitate roughly $741 in daily revenue (CDA, 2019). From the diminished need of queuing space, it is expected that overall concessions areas be expanded by a parallel 1.45%, while the $138 per sq-ft annual rental rate remains static (CDA, 2019).

Table 11.

Benefit of Facility Productivity from Flight Foresight (ORD)

Space	Rate	Old Size	Old	Change	New	New Revenue	Gains
Gates	$270,465 per gate	171 (gates)	46.25	2 (gates)	173 (gates)	46.79	.54
Stores	$138 per sq-ft	192,227 (sq-ft)	26.53	2,788 (sq-ft)	195,015 (sq-ft)	26.93	.40
Total	--	--	72.78	--	--	73.72	.94

Note:
This table was inspired by Guidance for Preparing Benefit/Cost Analysis (Byers, 2016)
Data is from the City of Chicago (CDA, 2019)

Excluding passenger processing and aircraft landing fees, this analysis suggests that a 2-gate increase in both domestic capacity and 1.45% increase terminal concession space resulting from a 15% reduction in daily domestic departure delays could generate ORD $0.94

million in additional annual revenue.

Realistically presuming a 15% reduction in delays from the proposed deep learning and cloud computing system, a modest 1.45% decrease in passenger flow and increase in concessions space, and estimated two-gate enlargement in terminal capacity yields ORD annual benefits on the order of $1.81 million. Considering solely annual operational costs and benefits, Flight Foresight produces a yearly benefit-to-cost ratio of 4.2 at ORD. The airport, however, also sustains frontal and isolated expenses of system installation, but is spared the research and development expenses absorbed by the owning company. Accounting for these

Table 12

Benefit vs. Cost Analysis at Chicago O'Hare International Airport (ORD)

Item	Subtotal	Qty	Total	Remark
Cost				
Installation & Testing	$825,000	1	$825,000	Table 8
Operation & Maintenance	$426,000 / year .	10 years	$4,260,000	Table 9
Total Cost (first 10 years)			$5,085,000	
Benefit				
Labor Reduction Benefits	870,000/year	10	$8,700,000	Table 10
Facility Productivity Benefits	940,000/year	10	$9,400,000	Table 11
Total Benefit (first 10 years)			$18,100,000	
Benefit to Cost Ratio			**3.5**	**Benefit >> Cost**

Note.
This analysis represents the estimated gains for ORD from Flight Foresight over the first 10 years of operation. Numerous continuity assumptions were made and are detailed above.

implementation fees, operation over a period of 10 years results in a stellar benefit-cost ratio of 3.5. Alternatively, using a 10% discount rate and $0 residual value, the cash flows of Flight

Foresight at ORD yield a net present value of $7.67 million.

As seen in Table 12, the accumulative costs and benefits for using Flight Foresight at ORD over ten years are $5,085,000 and $18,100,000 respectively. The benefit outweighs cost with a ratio of 3.5 indicating substantial prospective gains of Flight Foresight for ORD.

8. Industry Interaction

Interviews were conducted with three aviation management professors, two information technology professors, one statistics professor, and four aviation planning experts:

1) Dr. Chenyu Huang, Assistant Professor, University of Nebraska (Aviation Mgmt)

2) Dr. Yi Gao, Associate Professor, Purdue University (Airline Mgmt)

3) Dr. Richmond Nettey, Associate Dean, Kent State University (Information Tech)

4) Dr. Tiantian Qin, Continuing Lecturer, Purdue University (Statistics)

5) Dr. Baijian Yang, Associate Professor, Purdue University (Information Tech)

6) Dr. Stewart Schreckengast, Continuing Lecturer, Purdue University (Airport Mgmt)

7) Dr. David Byers, President, Quadrex Aviation

8) Mr. John Greaud Senior Project Manager, Barge Design Solutions

9) Mr. Trent Holder, Senior Aviation Planner, Hanson Professional Services

10) Mr. Nicholas Alex, Senior Aviation Planner, C&S Companies

Dr. Huang's interview covered the cost of the proposed system relative to a traditional distributed server system. Airports can benefit from this proposed technology because the cost of servers and databases will be eliminated as a direct expense of each airport. Not without issue, Dr. Huang mentioned that aggregated databases and systems may amplify the severity of disasters that strike the central node, so the development of a redundancy system is necessary for backup and recovery purposes. This technology was also realized to be further integrated into the FAA CDM program, which is a joint government-industry initiative aimed at improving the traffic-flow-management aspect of air traffic management by increasing the exchange of information and improving corresponding decision-making support tools (FAA, 2019).

In discussion of the design with Dr. Nettey, it was observed that the benefit an airport would gain from delay prediction could be measured chiefly from an airport staffing perspective. Instead of employing peak-level staffing all day, the airport could use dynamic staffing, by allocating fewer employees during operational valleys and more employees during peaks. Schedule optimization in response to delay studies could result in surge smoothing so that flexible staffing needs could be well-anticipated based through delay prediction. Forecast of significant delays later in the day or week allows management of the airport to make necessary employment arrangements to compensate correlated volumes of customers. Dr. Nettey suggested that this surge staffing is most effective when applied to security officers, custodial workers, bus drivers, and parking lot attendants, with negligible sacrifices in safety, cleanliness, or movement, respectively.

The interview with Dr Qin established technical feasibility of the project. Commenting on the maturity of current machine learning techniques, Dr. Qin foresaw no large problem in applying that technology to the project’s functionality. However, this discussion led to a more clear identification of system inputs and outputs, as well as a consideration of time-series analysis, namely Markov-chain, to deal with delay propagation.

Dr. Gao expressed concern regarding the time response and prediction accuracy of the proposed system in accomplishing stated objectives. In order to answer Dr. Gao's questions, Dr. Yang was consulted. Dr. Yang mentioned that, in personal experiences with delay prediction, this project seemed very promising due to the advanced state of modern computing capability in which delay inference is yielded and relayed to users in a millisecond. Also, Dr. Yang revealed that the primary barrier against our proposed system would be the time needed to integrate different databases, deemed six months of work for a ten-person prototyping team. For methodology selection, Dr. Yang pointed out stark contrasts between traditional statistics and innovative neural networks. From a statistical perspective, traditional statistical inference will typically result in greater prediction error than a neural network; however, traditional statistical inference is more intuitive in that the level of each input variable's explanatory effects on delay time is known, while a neural network is less explainable because of its "black box" mechanics.

In open discussion of the project proposal, Dr. Schreckengast shared experiences in how airlines often find delay predictions and deal with delay problems. Mentioning that accurate delay prediction will help airports coordinate schedule optimization with airlines, Dr. Schreckengast discussed the proposed system's benefit from the airports' point of view as mutual utilization of facilities and time slots. As a result of relieving airside and ground side congestion, the capacity of the airport can be enhanced and terminals can be expanded.

In interviews with Dr. David Byers, John Greaud and Trent Holder, the value of preemptive delay knowledge was stressed. Before a delay is incurred, this information can help airports prepare adequately through airlines coordination and resource allocation. In addition to surge staffing capabilities, early notification to passengers of expected congestion can greatly improve passenger experience by avoiding negative connotations of air travel.

Conversation with Mr. Nicholas Alex regarding the influence of delay proliferation in aviation planning and airport design gave insight into other savings offered by widespread delay reduction. As timeliness and efficiency is a driving factor behind airfield geometry, reduction in delays allows airports substantial advantages in more tarmac space and less idling waste, which can directly be translated into financial gains.

9. Projected Impact of Design

9.1 ACRP Goals

The proposed project meets ACRP goals by building upon and synergizing between existing technology to improve operational efficacy and future capacity at airports nationwide. Airports are the fundamental infrastructure of the NAS, serving as the vital linkage between ground and air operations. By the exact and synchronous nature of the commercial aviation industry, airport joints must be seamless and secure. Refining the efficiency and effectiveness of resources at airports is critical to sustaining capacity growth rates, matching infrastructure supply to travel demand. As observed by the FAA, the annual cost of domestic flight delays in the U.S. economy is estimated in the tens of billions of dollars. The exorbitant economic inefficiencies due to delays drive the perpetual development of proactive air traffic flow analysis and reactive delay management mechanisms. Accurate and precise prediction of delays allows for the agile application of delay mitigation measures, meeting ACRP goals of innovation in aviation management. In the ORD case study, it is projected that Flight Foresight could improve margins by roughly $1.384 million annually, neglecting initial installation costs, via labor savings and facility productivity generated by delay reduction.

9.2 Sustainability Assessment

The FAA adopts Economic vitality, Operational efficiency, Natural resources, and Social responsibility (EONS) to describe airport sustainability (FAA, 2017). The proposed cloud computing and deep learning flight delay prediction system closely follows these grand requirements in maintaining an unwavering commitment to safety, efficiency, and affordability. Flight Foresight's overarching purpose to improve airport capacity through resource productivity and aviation safety through delay tracking directly contribute to socioeconomic externalities of pollution reduction and economic enhancements.

9.2.1 Operational Impact

Flight Foresight has innumerous and invaluable potential impacts on aviation operations. Improved accuracy and precision of delay prediction under time and cost sensitivity restrictions will contribute to delay reduction through airport resource allocation and airline schedule optimization. As outlined earlier, airports subscribing to Flight Foresight are likely to reap financial gains from labor and facility productivity adjustments. With traffic volumes of the future threatening to outpace America’s aviation infrastructure, the operational efficacy afforded by Flight Foresight is the driving force behind its proposition and development.

9.2.2 Economic Impact

Since all information will be uploaded and recorded in a centralized cloud database and the Flight Foresight service will be disseminated per a subscription model, the cost is distributed relatively evenly between client airports. By pooling monetary resources of major airport authorities around the country, financial risk is minimized while technical potential is maximized. Comprehensive and close delay predictions are computed in the cloud in real time, saving costs in the form of time delay and nodal hardware. Revenue is also generated by refinements made to airport operations as a result of delay data analysis. Coordination with airlines and air traffic control can effectively heighten airport capacity without requiring expensive, new construction, creating economic gains for public and private aviation stakeholders that may ultimately reach average consumers in the form of cheaper fares.

9.2.3 Environmental Impact

Precise flight tracking and accurate delay mitigating are the core competencies of Flight Foresight and are applied to uphold the FAA’s commitment to environmental sustainability. As tarmac delay consumes over 740 million gallons of fuel annually, this delay prediction and reduction system looks to restrict one of the most wasteful sources of harmful emissions (JEC, 2007). With operation efficiency supplanting construction of capacity, marginal land areas surrounding airports that may have previously been used for terminal expansion can be preserved while still maintaining traffic volume growth.

9.2.4 Social Impact

Successful implementation of the proposed system will aid CDM in streamlining data sharing within airport networks. Upholding the FAA's organic accountability to the citizens of the United States, the greater aim of Flight Foresight coincides with the FAA's responsibility to enhance the safety and livability of commercial air transportation. For passengers of airliners, delay mitigation ensures a smoother, shorter, and cheaper air travel experience; for residents around airports, it reduces the amount of dissipated noise pollution. Armed with broad and deep knowledge of delay factors, airport authorities are in a more powerful position to satisfy individuals both inside and outside of their terminal through less congestion of the skies.

10. Conclusion

In this design project, the proposed cloud computing flight delay prediction system, Flight Foresight, is presented for the ACRP-designated challenge: "model to improve collaborative decision making and data sharing at airports" (ACRP, 2018). Countering flight delays that are too often rampant and cyclical in the NAS, the system has significant potential in billions of dollars and millions of hours in monetary and time savings, respectively. By integrating various databases with existing NextGen SWIM and FAA CDM and GDP programs and harnessing remote cloud computing of deep learning algorithms, precise and accurate flight delay forecasts are generated. Allowing for the full realization of potentials in schedule optimization, emission reduction, and resource utilization, the delay predictions provided by the proposed system could significantly grow airports' capabilities through improved operational efficiency. System principles, safety-risk, cost-benefit, and sustainability assessments are detailed in this aggregate report. The design team holds great confidence that swift implementation of Flight Foresight would effectively enhance the capacity of the National Airspace System and further the goals of the Federal Aviation Administration, connecting more people and ideas from all corners of the continent.

Appendix A: List of Complete Contact Information

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Appendix B: Description of the University

About the University:

Purdue University, located in West Lafayette, Indiana, is a world-renowned public research university. As a vast laboratory for discovery, Purdue is famous for its historical record of success in science, technology, engineering, and math. Flourishing from an open culture of imagination, ingenuity, and innovation, Purdue is home to giant leaps in scientific, technological, social, and humanitarian fields.

Founded in 1869, the university proudly serves the State of Indiana and the United States of America as a powerful laboratory for accelerated technological development. Academically, Purdue's role as a major research institution is supported by top-ranking disciplines in aviation, pharmacy, business, engineering, and agriculture. Embracing diversity of cultures, the Purdue community has over 40,000 students from all 50 states and 130 countries. With 1,000 student organizations and Big Ten Boilermaker athletics, Purdue University offers an academic and residential atmosphere without comparison.

The School of Aviation and Transportation Technology Mission Statement:

Economic forecasts suggest that a steady increase in traveling passenger and air cargo requirements will fuel a dramatic expansion of the aviation industry, and require a complete restructure of the existing air transportation system architecture. This industry growth is generating a wide range of leadership opportunities in the aviation industry for individuals who possess aviation and aerospace management skills such as operational analysis, safety systems development, project management, systems integration, environmental sustainability, and related interdisciplinary skills.

Purdue University's School of Aviation and Transportation Technology, one of six departments within the Purdue Polytechnic Institute, which itself is one of eleven undergraduate colleges at Purdue University, is recognized worldwide as the leader in aviation education. All seven of Purdue's Aviation and Transportation Technology undergraduate majors are unrivaled educational programs with partnerships throughout academia and industry. Fielding a fleet of two (soon to be 3) jet trainers and a Mach 6 wind tunnel, professional flight and aerospace engineering at Purdue are among the most prestigious programs in the nation and have graduated the likes of Neil Armstrong, Eugene Cernan, Roger Chaffee, and Chesley Sullenberger. Research centers at Purdue provide great exposure to industrial challenges, and offer many opportunities to make an impact through applied problem solving. Leading in education and aviation, Purdue University is a global hub for technological development and a treasured Cradle of Quarterbacks and Astronauts.

Appendix C: Description of Non-University Partners Involved in the Project

Not Applicable.

Appendix E: Evaluation of the Educational Experience Provided by the Project Students (Answer were discussed by all team members)

1. Did the Airport Cooperative Research Program (ACRP) University Design Competition for Addressing Airports Needs provide a meaningful learning experience for you? Why or why not?

Yes, this competition was a truly transformative learning experience for our group. This project, requiring time management, collaboration, and imagination, was an unrivaled opportunity to apply our skills to challenges outside the walls of a lecture hall and pages of a textbook. Sharpening our academic knowledge and interpersonal communication through direct study of real-world aviation challenges, this project led all team members to grow as scholars and professionals. Aside from technical learning specific to our proposal, this competition instilled the importance of stringent project management techniques. Early in the design process, work was divided, assigned, and timed, playing to the unique skills of our team members. Work flow was highly collaborative and inclusive, starting from brainstorming, through design development, and ending with report writing. Exploring such an exciting area of research in flight delay prediction gave all members great exposure to the evolving challenges of the aviation industry and undoubtedly sparked greater interest in airport management. Connection with industry experts in the form of comprehensive and open interview discussions was also an exercise in professional development, in addition to a direct learning experience. Through this process, we continuously enhanced important skills of summarizing literature reviews, conducting cost-benefit assessments, analyzing safety risk situations, and using scientific methods to solve a practical problem.

2. What challenges did you and/or your team encounter in undertaking the competition? How did you overcome them?

Several challenges of varying intensity were encountered during this design competition. An underlying component of our design proposal, selection of an optimal delay prediction algorithm proved to be a driving challenge. Among the academic publications we found, statistical inferences, graph theory, operational research, network representative, and machine learning were developed and validated in the area of flight delay prediction. To differentiate between the options, a comprehensive literature review and a slate of academic interviews were conducted. Dr. Yang of Purdue's Computer and Information Technology provided us with the most valuable advice toward this end, and it was determined that statistical inference is more appropriate and explainable when input data is well structured while neural network algorithm is more accurate when we have a large historical data set and high-performance computing capability. Since a project of the scope suggested would demand the highest of accuracy measurements, and model sensitivity analysis could still be applied to quantify intuitive delay causes, the team selected a deep learning algorithm.

Another challenge faced was the cost-benefit analysis of the design because most of recent research assessed the financial gains from airlines' or passengers' perspectives. To approach this issue from the airports' point of view, we similarly reached out in interviews. Aviation planners Mr. Trent Holder and Mr. Nicholas Alex gave detailed commentary on the aspects of airport management readily set to profit from such a delay prediction and reduction system. Putting these costs and benefits in numerical form, internet sleuthing and contact with Indianapolis International Airport (IND) and the Chicago Department of Aviation (CDA) yielded exact data on worker salaries, facility pricing, and operational size. These facts provided a basis for the cost-benefit analysis, and reasonable assumptions were made for the sake of modeling simplicity, to produce a relatively reliable financial assessment.

3. Describe the process you or your team used for developing your hypothesis.

Our design aims to develop a cloud computing and deep learning flight delay prediction system to help airports collaborative decision making and data sharing. The preliminary stage of hypothesizing involved general research into FAA initiatives and industry problems. Multiple brainstorming group sessions using non-traditional ideation techniques produced a condensed list of prospective topics. Consultation of our faculty advisor resulted in the selection of delay prediction. After determining the subject of our analysis, the first step of our work was to have a comprehensive understanding of the NextGen SWIM program and delay prediction from credible sources. From information and concepts learned while performing a literature review, all team members discussed, pivoted upon, and ultimately agreed on a design hypothesis for the project. With solid knowledge of different definitions of delay, various types of delay, multiple methodologies of delay prediction, the framework of NextGen SWIM, a strength-weakness-opportunity-threat analysis was conducted in the delay reduction regime. After generating the means of our hypothesis, the technical feasibility and financial viability of our idea were improved and iterated through interviews with several industrial and academic experts.

4. Was participation by industry in the project appropriate, meaningful and useful? Why or why not?

The participation by industry in the project was highly enjoyable and very conducive to accelerated learning. The team prioritized performing plenty of phones and face-to-face interviews with a diverse cross-section of professionals in the aviation management and information technology fields as the functionality of our system in practice was of paramount importance. Overall, those interactions gave us a thorough understanding of airport management and planning, which we readily applied to make our design more suited to airports' needs while under their time and cost restrictions. Industry interaction also effectively conveyed the current status of collaborative decision making and data sharing at U.S. airports in a manner not easily replicated inside a classroom setting. Feedbacks on cost-benefit, environmental, and risk-safety assessments were also invaluable in driving our team project development and personal learning experiences.

5. What did you learn? Did this project help you with skills and knowledge you need to be successful for entry in the workforce or to pursue further study? Why or why not?

This project quickly taught the importance of project management skills, ranging from team communication to time management, independent research to report writing. Realistic processes necessitated in the competition gave all team members a broader and deeper understanding of multidimensional, interdisciplinary analysis. While long hours and hard effort were devoted to this project, all team members are grateful for the hard and soft skills gleaned from this competition that will directly translate into success for our academic and professional careers.

Faculty

l. Describe the value of the educational experience for your student(s) participating in this competition submission.

The team assembled for this competition was rather diverse from both a cultural and technical perspective. It consisted of members from three different colleges at our university, and those members had diverse ethnic and cultural backgrounds. The students learned to overcome differences in their individual knowledges of the technical language related to the project, as well as communication barriers both internal to the team and external with regard to the various stakeholders. I believe substantial learning occurred not only with regard to the technical aspects of delay prediction, collaborative decision-making, and cost-benefit analysis, but also as a result of overcoming the challenges I have described here.

2. Was the learning experience appropriate to the course level or context in which the competition was undertaken?

Yes; this project was completed in a graduate-level independent study course.

3. What challenges did the students face and overcome?

The first of the many challenges associated with the project was that of reviewing prior work on mathematical models for delay prediction and understanding those models to an extent sufficient for them to be of use in the competition. Other challenges were associated with communication among the internal team members and external stakeholders, as described in (1).

4. Would you use this competition as an educational vehicle in the future? Why or why not?

Absolutely. I plan to begin entering teams on a regular basis. This provides an opportunity for the students to apply theoretical concepts they acquire in our undergraduate and graduate programs to practical problems, and work with industry and other faculty to create potential solutions. The skills students gain by participating will serve them well as they graduate and move to positions in industry. In addition, this competition provides an opportunity for both graduate and undergraduate involvement. I have conducted research in this area, and my research center is modeled on this concept. See

Mott, J. H. (2014). A3IR-CORE at Purdue University: An innovative partnership between faculty, students, and industry. *The Journal of Aviation/Aerospace Education & Research, 24*(1), 26–40. doi: https://doi.org/10.15394/jaaer.2014.1607

for more information.

5. Are there changes to the competition that you would suggest for future years?

None at this time.

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