A Novel Integration Platform to Reduce Flight Delays in the National Airspace System

Chuyang Yang
School of Aviation and Transportation Technology
Purdue University
West Lafayette, USA
yang1481@purdue.edu

Zachary A. Marshall
School of Aeronautics and Astronautics
Purdue University
West Lafayette, USA
zmarsha@purdue.edu

John H. Mott
School of Aviation and Transportation Technology
Purdue University
West Lafayette, USA
jhmott@purdue.edu

Abstract— **Flight delays in the U. S. National Airspace System (NAS) present 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. Roughly 20% of passengers' total travel time is due to such delays, causing $35 billion annually in lost revenue and impacting not only the airline industry, but the retail, lodging, restaurant, and tourism industries, as well. The Federal Aviation Administration's effort in aiding decision-making at airports is readily apparent in the Next Generation Air Traffic Control (NextGen) System's System-Wide Information Management (SWIM) program, and in-flight delay information from the FAA Air Traffic Control System Command Center (ATCSCC). Academic researchers are concurrently developing various algorithms to predict flight delays that include advanced statistics, machine learning, and graph theory using various network topologies. Other stakeholders have initiated delay prediction methods to adjust their operational schedules. This suggests an opportunity to centralize, validate, and integrate the various delay prediction methods under development; furthermore, these methods are limited in scope with regard to geography, operators, and efficacy.**

The authors propose here a platform supporting the FAA's Collaborative Decision-Making (CDM) process with the intent of reducing flight delays in the NAS. Building upon existing deep learning algorithms and utilizing the NextGen SWIM program, this research suggests a central delay prediction platform suited to the complex and dynamic needs of America's airport infrastructure. assessments of risks and sustainability of the proposed platform are presented. The authors interviewed experts in industry and academic fields related to aviation and information technology, and used the information obtained to refine the model. It is anticipated that this model will accurately produce location-specific departure and arrival delay forecasts that can further be integrated into the CDM and Ground Delay Program (GDP) initiatives.

Keywords—aviation, delay prediction, deep learning

I. Introduction

A fundamental facet of human interaction and modern marvel of technological development, the National Airspace System (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 [1]. 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 challenging and occasionally 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 [1]. 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% of total flight time and amounted to 320 million hours upon last measurement [2]. Drastic financial consequences associated with domestic flight delays, often pegged around $35 billion annually, ripple throughout the aviation industry and negatively impact 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 study focuses on reducing the probability and magnitude of delays through agile, integrated delay forecasting. Section II introduces the background of delay in aviation industry and Section III explains data integration and deep learning algorithm. Section IV presents the design of the proposed platform. The potential impacts are discussed in Section V, and the conclusion is given in Section VI.

II. Background

A. Delay

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 is defined

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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 airplane [1]. 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 [1].

B. Regulations

According to the U.S. Department of Transportation (DOT) and FAA's policies, when flights are delayed or cancelled in the U.S., airlines and airports are not required 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 [3]. However, 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. The flight status information must, at a minimum, be available on the airlines' website and via the airlines' telephone reservation system. Also, when a flight is delayed for 30 minutes or more, all flight status displays and other sources of flight information that are under airlines' control must be updated within 30 minutes after the airlines become aware of the problem [3].

In accordance with the Code of Federal Regulations (CFR) Parts 91, 121 and 135, all operators have the right of refusal of a specific clearance and may elect an alternative which includes, but are not limited to, ground delay, diversion to other airports or request to stay on the field route [1], [3]. Hence, in order to reduce costs when a delay occurs, an accurate and timely delay prediction method is important for aviation industry stakeholders.

C. Gap

In recent years, governmental effort in aiding decision-making at airports is readily apparent in the Next Generation Air Transportation System (NextGen)'s System Wide Information Management (SWIM) program and Flight Delay Information from FAA Air Traffic Control System Command Center (ATCSCC)[1]. Simultaneously, academic researchers are developing various algorithms to predict flight delays, including advanced statistics, machine learning, graph theory, and network representation [4], [5], [6]. 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.

III. Methodology

A. Data

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. Bureau of Transportation Statistics (BTS) and Aviation System Performance Metrics (ASPM) are the most common databases for delay studies [7], [1]. The advantages and disadvantages of a variety of available data sources are listed in Fig.1.

The NextGen's SWIM program was designed to apply a set of information technology principles in NAS and to provide users with real-time information such as flight data, weather information, airport operational status, and special-use airspace. SWIM changed the traditional point-to-point communication approach to a net-centric style, providing direct access to information and enterprise-level security services [1].

TABLE I. Overview Of Available Data Sources

Data	Strengths	Weaknesses
Traffic Flow Management System Counts (TFMSC)	Data includes flight 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.

[a.] This table was modified and captured from ACRP Report 104 [1].

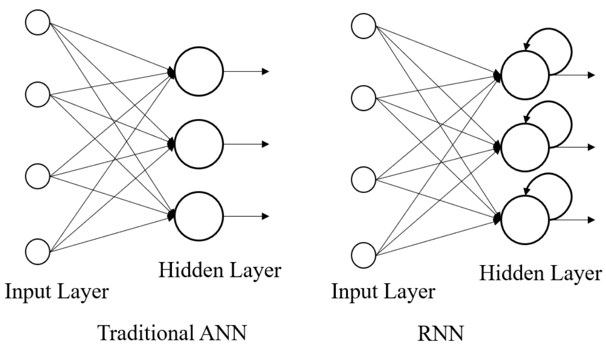

Fig. 1. Structures of traditional ANN and RNN [9], [10]

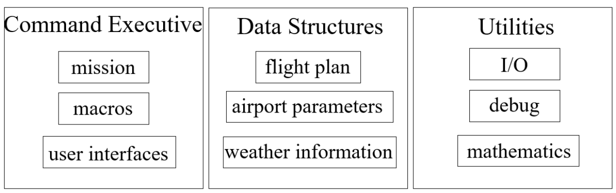

Fig. 2. Framework of the proposed fight delay prediction platform

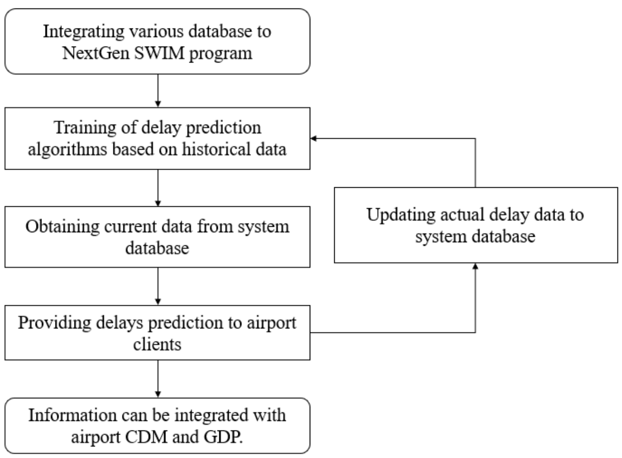

Fig. 3. Flow diagram of the proposed platform.

B. *Algorithms*

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 [4].

- *Artificial Neural Networks (ANN):* ANNs are computing systems consist of an interconnected group of nodes, inspired by the animal brains' biological neural network [8]. Each node represents an artificial neuron, and the connection providing the output of one node as an input to another neuron. Connections are assigned different weights that present their relative importance [9]. ANNs have been used to solve practical problems such as computer vision, voice recognition, and social network filtering. However, ANN cannot capture sequential information in the input data.
- *Recurrent Neural Networks (RNN):* As an improved class of ANN which has connections between nodes from a direct graph along a temporal sequence, an internal state (memory) can be used to process variable length sequences of inputs and the looping constraint ensures that sequential information can be captured in the input data [10]. The Long Short-Term Memory (LSTM) neural networks were designed to overcome the vanishing gradient problem in RNNs so that LSTM networks are capable of accurately modeling complex multivariate sequences [11], [12], [13]. This characteristic enables scientists to use RNNs to solve problems related to time series data. In this study, an LSTM neural network was used as a delay prediction algorithm.

C. *Cloud Computing*

The term "cloud" was used to refer to the platform for distributed computing which allows users to minimize up-front information technology (IT) infrastructure costs but also get their applications up and running faster. A private cloud is defined as "internal data centers of a business or other organization, not made available to the general public" [14]. In this study, the cloud platform is referred to a private cloud.

IV. DESIGN OF SYSTEM

Aiding in airport resource allocation and capacity optimization, the proposed system strives to improve air traffic capacity by 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's SWIM program framework and fuses LTSM-based deep learning algorithms to predict accurate arrival and departure delays using time series data.

A. *Framework*

As shown in Fig. 2, the framework of the proposed system includes three parts: command executive, data structure, and utilities. The command executive provides the communication channel between the user and the functions. The information such as flight plan and airport parameters via the data structures are defined as the inputs of the functions. The utilities contain common operations and tools to facilitate the commend executive and data structures.

B. Principles

- *Integrating various flight operations database into the NextGen SWIM program:* A variety of multi-dimensional data sources increases the accuracy of the delay prediction algorithm. Current NextGen's SWIM program includes flight and weather information [1]; still, it can be improved by integrating data from diverse sources such as BTS and ASPM.
- *Fusing advanced deep learning algorithms to a cloud computing database:* 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 now achieves recognition accuracy at higher levels than previously possible 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 the proposed system combines deep learning with cloud computing.
- *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 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. The nature of deep learning suggests that the integrated algorithm must use datasets corresponding to that available from client airports. When a client airport subscribes to the services from the proposed system, the algorithm will train with tailored datasets to ensure desired prediction accuracy.
- *Developing a distributed and demand-oriented 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 distributed demand-oriented redundancy system to mitigate such risks. Connected to secondary power, a system is created to recover cloud information with minimal data loss and service interruption.
- *Computing delay occurrence and propagation via real-time inputs and outputs:* As proposed system 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 the FAA CDM paradigm and Ground Delay Program (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.

C. Assessment of Risk

According to MIL-STD-8825, risk is a function of probability and severity. FAA AC 150/5200-37 suggests using safety matrices to assess risk in aviation operations [1]. 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 II shows the risk assessment of the proposed project by identifying potentially hazardous situations, likelihood, severity, risk, and possible solutions. While the proposed platform 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

TABLE II. RISK ASSESSMENT AND SOLUTIONS

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

a. Scores for likelihood, severity, and risk are evaluated based on Risk Assessment Matrix [1].

TABLE III. REQUIRED INPUT DATA AND EXPECTED OUTPUT DATA

Category		Attributes
Input	Flight[a]	• 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
	Weather[b]	• Wind velocity • Cloud height • Visibility conditions • Precipitation and accumulation • General intensity and descriptor • Observation code
	Airport[c]	• Airport configuration • 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	Delay information	• Predicted arrival delay time • Predicted departure delay time • Predicted taxi-out delay time • Predicted taxi-in delay time

a. Attributes of Flight data can be retrieved from BTS and TFMS database.
b. Attributes of Weather data can be retrieved from NOAA and Wx database [15].
c. Attributes of Airport data can be retrieved from ASPM and STDDS database.

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 the proposed system's scope of authority, emergency contingency plans must be developed and communicated in coordination between airport operators and network administrators. A back-up and recovery platform would greatly enhance the proposed system's resilience to random, adverse events through redundancy of data access points.

D. Interactions with Experts from Indusrty and Academia

Throughout the process of platform design, interviews were conducted with professors from academic aviation management, information technology, and statistics programs and with experts from aviation consultancies. Comments and suggestions obtained from those aviation experts were used to refine the design of the proposed platform.

- A back-up and recovery platform was suggested to overcome the potential Internet interruption and data loss.
- An integration with FAA CDM and GDP was suggested to increase the exchange of information and improve decision-making support tools.
- In order to validate and compare the accuracy of the proposed system, traditional statistical modeling of delay prediction under a similar platform was suggested.

V. DISCUSSION

Since 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 significant 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, enhancing various aspects of sustainability in aviation industry.

A. Operational Benefits.

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. Airports subscribing to the proposed system 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 the proposed system is the driving force behind its proposition and development.

B. Economic Benefits.

Since all information will be uploaded and recorded in decentralized cloud databases and the proposed service will be disseminated per a subscription model, the cost is distributed relatively evenly between client airports. By pooling the 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.

C. Environmental Benefits.

Precise flight tracking and accurate delay mitigating are the core competencies of the proposed system and are applied to uphold the FAA's commitment to environmental sustainability. As tarmac delay consumes over 2.8 billion liters of fuel annually, this delay prediction and reduction system look to restrict one of the most wasteful sources of harmful emissions [2]. 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.

D. Social Benefits.

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 U.S., the greater aim of the proposed system 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.

VI. Conclusion

Countering flight delays that are too often rampant and cyclical in the NAS, a flight delay prediction platform is presented in this paper, which has significant potential in billions of dollars and millions of hours in monetary and time savings, respectively. By integrating various databases with existing NextGen's 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, impacts, and sustainability assessments are presented in this paper. The swift implementation of the proposed system would effectively enhance the capacity of the NAS and further the goals of the FAA, connecting more people and ideas from all corners of the continent.

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