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Fusion and analysis of data sources for assessing aircraft braking performance on non-dry runways

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***Abstract*—Aircraft landing safety is among the important concerns in the aviation industry due to accidents related to runway/taxiway excursions. The literature has explored the relationship between adverse weather conditions and braking performance from a qualitative perspective. Factors such as the weather conditions, pavement texture characteristics, and slope can all play critical roles in determining braking performance. While literature has explored how these factors individually may impact braking, no studies have explored the multivariate relationship between such factors and reported braking action by pilots over a wide range of operational landings and considering a variety of data sources.**

In this paper, the quantitative relationship between different factors that may work to cause or prevent poor braking performance is explored. In order to conduct this analysis, a data fusion framework is developed that is able to collect and fuse sources of data such as runway conditions, runway and airport characteristics, prevailing weather conditions, runway condition codes, and pilot reported braking action. The framework is demonstrated on data collected between the years 2016–2020 at various U.S. airports where field condition reports were available. The analysis indicates that this initial statistical distribution and binning of the data substantiates the value of the Runway Condition Code (RwyCC) modeling in predicting actual braking action. Further investigation and development of more refined models is identified for future work.

***Keywords*—runway safety; degraded braking; contaminants; data analytics; ASOS; FICON**

I. Introduction and Motivation

Aircraft landing safety is a major focus in the aviation industry. According to safety statistics compiled by the International Air Transport Association (IATA) there was a global annual average of 18 transport category aircraft accidents related to runway/taxiway excursions between 2010-2014 resulting in aircraft damage with varying degrees of severity [1]. Some of the conditions identified as contributors to runway excursions (aka overruns) are the dynamics of a tailwind approach and landing, failure to deploy Ground Spoilers or Thrust Reversers, and wet or contaminated runways that contribute to degraded braking effectiveness [2]. Of these items, runway surface conditions is the most variable and difficult to quantify. It is therefore important to study the effectiveness of aircraft braking on contaminated runways to better understand this degraded performance condition and prevent accidents in the future.

On December 8, 2005 Southwest Airlines Flight 1248 overran runway 13C at Chicago's Midway Airport (MDW) after landing on a runway contaminated with snow and slush. The Boeing 737-700 aircraft exited the end of the runway and went through a airport perimeter fence; striking an automobile and resulting in a fatality. This accident brought into focus the disparities in operational procedures and the need for improvements to the existing practices. The FAA launched a review of existing procedures with the collaboration of Airports, Operators, and Aircraft Manufacturers. The resulting Takeoff and Landing Performance Assessment (TALPA) Aviation Rulemaking Committee (ARC) produced significant changes to the way aircraft braking is evaluated and operationally addressed [3], [4].

The FAA adopted the position that to enhance safety, new procedures were required for airplane operators to assess landing performance at the time of arrival and would include defined field length performance margins. Time of arrival landing field length planning would now consider runway surface conditions/braking action, winds, temperatures, slope, pressure altitude, icing condition, final approach speed, airplane weight and configuration, and deceleration devices used in a more prescriptive manner than previously required. [3], [4].

The FAA process to develop these new procedures has been primarily based on two pillars: 1) An engineering analysis of the Newtonian mechanics for a variety of Transport Category Aircraft (TCA) and their respective sensitivity to configuration, atmospheric, and runway condition changes and 2) Anecdotal input from operators, airports, and manufacturers derived from decades of operational experience and an understanding of current operational practices. While this approach has produced a step function improvement to best practices procedures, it remains a simplified empirical approach, often using extrapolated data from decades old aircraft testing. With the implementation of TALPA procedures, there is now several years worth of data which makes it possible for a more robust validation of the original TALPA assumptions.

The investigation of aircraft braking on non-dry surfaces goes back to the early 1960's, when actual aircraft testing was conducted by NASA using the Convair 880 as a testbed. The data gathered resulted in publications on the subjects of runway friction, tire wear, wheel braking effectiveness [5],

[6]. Much of the early seminal work in addition to data internally developed by Boeing, McDonnell Douglas, and Airbus became the basis for the TALPA operational procedure guidance. More recent work has also focused on physics-based analyses for assessing braking distances [7] and braking capabilities on flooded runways [8].

Literature has explored the relationship between adverse weather conditions and braking performance from a qualitative perspective. Factors such as the weather condition, pavement texture characteristics, and slope all play critical roles in determining braking performance [9]. While it has been explored how these factors individually may impact braking, no studies have displayed the multivariate relationship between such factors and reported braking action over a wide source of operational landings with various runway surface conditions encountered during normal operations. Therefore, in this work, data from various sources is fused to quantitatively assess how these factors might play a role in influencing the braking performance, particularly on contaminated runways. It is anticipated that the work presented in this paper along with prior knowledge will aid regulatory bodies, aircraft operators, and airports in better planning for operations on contaminated or friction-limited runways.

Research Objective

The overarching research objective of this paper is to quantitatively explore how different factors may work to cause or prevent poor braking performance by fusing and analyzing multiple sources of data relating to runway conditions, characteristics, and prevailing weather conditions and comparing these with the pilot reported braking action.

The rest of the paper is organized as follows: Section II provides the definitions of some important terms used in the paper, Section III contains a detailed description of the different data sources used in this work, Section IV provides an overview of the data fusion framework developed to merge all sources of data, Section V contains detailed analyses and insights obtained from the fused data and discussion, and Section VI concludes the paper and outlines avenues for future work.

II. Definitions

Prior to diving into the details of the implementation, it is important to define some pertinent terms that are used frequently in the context of aircraft operations on contaminated runways. The following definitions from ASTM International's *Standard Terminology for Aircraft Braking Performance* are used in this work. [10]

- **Aircraft braking coefficient**, the ratio of the deceleration force from the braked and unbraked wheels of a braked aircraft relative to the sum of the vertical (normal) force acting on the aircraft. Aircraft braking coefficient is determined by using the weight of the aircraft (W-L) and encompasses all the braking forces of all the gear, even those that are not braked.
- **Wheel braking coefficient**, the ratio of the deceleration force from the braked wheels/tires relative to the sum of the vertical (normal) forces acting on the braked wheels/ tires. The wheel braking coefficient is the result of the combination of all functioning braked wheels.
- **Braking action**, a means of describing the maximum capability of a vehicle's braking system on a wet or contaminated surface that references a standardized reporting scale.
- **Pilot braking action report**, PIREP, AIREP, n—a report describing a level of braking action resulting from the observations of a pilot.
- **Airport friction measurements**, the value obtained through ground measurement devices approved for use in measuring runway surface friction characteristics.

III. Description of Data Sources

The following sub-sections describe in detail, all the data used in this work, as well as their source and format.

A. Automated Surface Observing System (ASOS)

Automated Surface Observing System (ASOS) units are automated sensor suites that are designed to serve meteorological and aviation observing needs. There are currently more than 900 ASOS sites in the United States with most of them located at airports [11]. The system's sensor data is publicly accessible through the official website of National Oceanic and Atmosphere Administration (NOAA), which is responsible for preserving, monitoring, assessing, and providing public access to the Nation's treasure of climate and historical weather data and information. The NOAA data repository provides ASOS weather data with both one-minute and five-minute intervals [11]. In this research, the one-minute ASOS data has been chosen due to the rapid pace at which runway conditions and aircraft operations might deteriorate with adverse weather.

The NOAA weather data repository covers the time range from January 2000 to the most recent month and is split into two parts. The first part contains station ID, year, month, day, hour, minute (both local and UTC), visibility, extinction coefficient, speed of two-minute average wind, direction of two-minute average wind (knots), speed of five-second average wind (knots), direction of five-second average wind, and runway visual range (hundreds ft.). The second part contains station ID, year, month, day, hour, minute (both local and UTC), precipitation amount (hundreds of inches), precipitation type, station pressure from three sensors (inches Hg.), average one-minute dry bulb temperature, and average one-minute dew point temperature. Both parts of the information are stored as data files in the .dat format in a monthly manner, while the first part follows a name convention as "64060XXXXYYYYZZ.dat" and the second part follows a name convention as "64050XXXXYYYYZZ.dat", where XXXX is the four-digit ICAO identifier for the ASOS station, YYYY is the year in two-digit format, ZZ is the month in two-digit format, and the leading four digits distinguish the file from containing the first part of the weather information or the second (6405 for the first and 6406 for the second).

B. Field Condition Reporting (FICON)

In late 2016, the FAA alongside the TALPA ARC produced a new set of recommendations guiding aircraft performance and surface condition assessment and reporting. One of the most significant of these recommendations was the introduction of consistent method for assessing runway conditions, known as the Runway Condition Assessment Matrix (RCAM). Figure 1 displays the RCAM.

Assessment Criteria		Downgrade Assessment Criteria		
Runway Condition Description	**Code**	**Mu (μ)** [1]	**Vehicle Deceleration or Directional Control Observation**	**Pilot Reported Braking Action**
• Dry	6		---	---
• Frost • Wet (Includes Damp and 1/8 inch depth or less of water) *1/8 inch (3mm) depth or less of:* • Slush • Dry Snow • Wet Snow	5	40 or Higher	Braking deceleration is normal for the wheel braking effort applied AND directional control is normal.	Good
5° F (-15°C) and Colder outside air temperature: • Compacted Snow	4	39 to 30	Braking deceleration OR directional control is between Good and Medium.	Good to Medium
• Slippery When Wet (wet runway) • Dry Snow or Wet Snow (Any depth) over Compacted Snow *Greater than 1/8 inch (3mm) depth of:* • Dry Snow • Wet Snow *Warmer than 5° F (-15°C) outside air temperature:* • Compacted Snow	3		Braking deceleration is noticeably reduced for the wheel braking effort applied OR directional control is noticeably reduced.	Medium
Greater than 1/8 (3mm) inch depth of: • Water • Slush	2	29 to 21	Braking deceleration OR directional control is between Medium and Poor.	Medium to Poor
• Ice [2]	1		Braking deceleration is significantly reduced for the wheel braking effort applied OR directional control is significantly reduced.	Poor
• Wet Ice [2] • Slush over Ice [2] • Water over Compacted Snow [2] • Dry Snow or Wet Snow over Ice [2]	0	20 or Lower	Braking deceleration is minimal to non-existent for the wheel braking effort applied OR directional control is uncertain.	Nil

Figure 1: Runway Condition Assessment Matrix [12]

This matrix is visually divided into two sections, Runway Assessment Criteria and Downgrade Assessment Criteria. The Runway Assessment Criteria, applicable to paved runways (no turf, dirt, gravel, or waterways), provides airport operators the ability to connect runway contaminant types and depths to a Runway Condition Code (RwyCC). Airport operators may use the Downgrade Assessment Criteria, involving friction coefficient measurements, Pilot Reports (PIREPs), and their best judgement and experience to downgrade RwyCCs to a more conservative report.

The RwyCCs, along with runway specific information, is reported and distributed in Field Condition (FICON) Notices To Airmen (NOTAM). In the FICONs, a RwyCC value is reported for each third of the runway. Time is reported in the format year, month, day, hour, minute. The general format for FICONs with italicized variables follows:

!*Airport NOTAM_Number Airport Location Identifier* FICON *RwyCCs Contaminant_Type* OBSERVED AT *Observed_Time*. *Start_Time-Expiration_Time*

An example FICON follows:

!ADQ 01/492 ADQ RWY 01 FICON 5/5/5 100 PRCT WET OBSERVED AT 1801312351. 1801312351-1802012351

From each NOTAM and metadata from the NOTAM Manager, the following metrics are extracted: Airport, NOTAM Number, Runway, RwyCCs, Contaminant Description, Start Time, End Time, and Cancel Date/Time.

C. Runway and Airport Data

The FAA provides public access to a repository with airport and runway data that can be used for this research [13]. The data repository covers all FAR 139 certified airports in the United States. This source has been selected due to its high reliability and expansive coverage. Additionally, the repository is maintained by the FAA so the data is up-to-date and includes a description of when it was last updated [13].

Five Microsoft Excel files are accessible in this database, four of them being data files and the other a description file. The four data files are airport facilities data, airport runways data, airport remarks data, and airport schedules data. The airport facilities data file contains basic information such as location, status, repair service availability, etc. The airport runway data file contains information such as runway ID, surface type and condition, runway treatment, runway end elevation, runway length and width, runway crossing height, etc. The airport remarks data file contains text data with other information about airports. The airport schedules data file contains the availability information about airports. Lastly, the description file, also known as the airport dictionary file, contains the detailed explanation regarding the four data files. Within the scope of this research, the airport facilities and airport runways files are selected to be the primary data sources.

IV. Data Fusion Framework

A. Data Preprocessing

Since the raw weather data are in *.dat* format and are consequently unwieldy for data analysis purposes, data processing has been performed to convert the data in the *.dat* files into comma separated variable (*csv*) format. In addition, it is more convenient if the information in the two aforementioned parts are merged into one. To achieve these goals, Python scripts were developed and parse the *.dat* files containing ASOS weather data, consolidate the information in 6405 and 6406 files, and generate a *csv* file that includes all available weather data from ASOS.

As for the airport and runway data, to make it more convenient to be used in later analysis, the basic information in the airport facilities file and the runway information in the airport runways file are first merged into one *csv* file. In the original FAA airport runways file, each entry has information for the same physical runway when it is approached from different runway ends. It was decided that the runway should be split into two entries for these cases. For instance, ATL 08L and 26R are essentially the same physical runway and is originally stored in one entry, but there will be two entries for ATL 08L and ATL 26R in the *csv* file that is processed. The main reason for this is that slope may change depending on the direction and the runway condition codes are typically reported in thirds of the runway (e.g. 5/5/3 for one direction would be 3/5/5 for the other). Also, runway crossing threshold heights can be different on the two sides as they are a function of geometry and obstacles.

B. Data Fusion Process Description

In order to perform an analysis that takes into account both runway (FICON, runway characteristics) and weather data and study the correlations between them, the runway and weather data needs to be fused. The sources of runway data are the FICON records and the FAA airport and runway database, and the source of weather data is the ASOS data repository. An individual data fusion is done with respect to one airport within a given time range (bounded by a starting month and an ending month). In general, there are two steps in the data fusion. The first step is to fuse the two runway data sources. The FICON data and the preprocessed airport and runway data are merged such that the FICON records contain both field condition and other essential runway information provided by the FAA datasets. The resulting dataset for the purposes of this paper, is called an "enhanced FICON". Each entry in the enhanced FICON represents a specific period of time with its runway information and the RwyCCs value as reported in the FICON.

The second step is to fuse the enhanced FICON with the ASOS weather data. First, on top of the functionality mentioned in ASOS data preprocessing, a wrapper function has been built to accept as inputs an airport and a time range (starting month and ending month); and automatically download all necessary raw data files from the ASOS repository and perform the data preprocessing to generate weather data files for each month within the time range. Subsequently, all these files are concatenated to output a final *csv* file that contains one-minute interval weather data from the first day of the starting month to the last day of the ending month at the given location. Next, the enhanced FICON needs to be investigated to ensure all the runways at the given airport within the given time range have valid runway records. Lastly, each matching record is expanded into multiple records with one-minute intervals ("expanded FICON") and merged with the weather data to give the output file that has inclusive weather and runway data with one-minute intervals at the given airport within the time range. Figure 2 shows the schematic of the data fusion process.

C. Implementation and Outputs

The data fusion process described has been implemented using Python programming language. Pandas library is heavily used because it is open-source and highly flexible to work with tabular and time series data for data manipulation and analysis purposes[1]. An integrated data fusion tool has been developed to automatically perform the fusing process, that is to download, process, and fuse the weather and runway data. A single execution of the program takes an airport, a starting month, and an ending month as the inputs, and then performs data fusion and eventually outputs a *csv* file containing one-minute-interval weather and runway data for the given airport within the given time range. Figure 3 provides the format of the final output file, with colored blocks indicating the original source of the respective portion.

[1]Pandas: Python Data Analysis Library Documentation User Guide. https://pandas.pydata.org/about/index.html, Accessed: 29 March 2021

V. Analysis

The fused datasets developed using the methods discussed in Section IV will be the cornerstone of the analysis for this paper. For this initial level of investigation, standard statistical distribution and binning techniques will be the primary analysis approach. The goal is to obtain insights about how selected factors might affect braking performance at different airports and runway conditions. They are described in the following subsections. It should be noted that the current FAA requirements for condition reporting are not the same for ASOS, FICON, and PIREPs. ASOS Weather reporting is continuous. FICON reporting is only required when runway conditions are other than a clean dry runway/taxiways, and PIREPs are typically only reported during deteriorating conditions (e.g. snow accumulation or increasing rain rates). The data distribution discussed in the following paragraphs are consistent with the expectation that the number of ASOS Reports $>$ FICON reports $>$ PIREPs.

A. FICON Data Exploration

The data available for this study includes FICON reports from the winter months between the years 2016-2019. The weather conditions and airport and runway data for the corresponding time frames are obtained and fused. It is noted that during the time frames that the FICON reports are collected, a small proportion of the reports also contain the pilot reported braking action.

1) Data Distribution: In the fused data set there are 683,145 rows and 25 columns of enhanced FICON data. Of this enhanced data, 568,791 rows (83.26%) contain RwyCCs and only 11,899 rows (1.75%) contain pilot reported braking actions. The intersection of these is 9,906 rows (1.45%) with RwyCCs and pilot reported braking actions. The data containing RwyCCs only and the intersection of RwyCC and PIREPs are important from the perspective of this paper and are thus analyzed separately in later sections. The data is largely distributed across the winter months, as seen in Figure 4. This is consistent with the expectation that the winter months are when degraded braking operations might be expected to occur.

2) Runway Condition Types: By default, in the dataset available, FICONs expire 24 hours after their effective time begins. However, designated observers have the ability to cancel or amend a FICON prior to the default expiration period. For the FICONs reported, 84.68% were cancelled and 15.32% expired ($n = 683,145$).

Runways with a consistent distribution of contaminants down the length of the runway being evaluated will typically have the same RwyCC for all thirds (each RwyCC represents the condition on each third of the runway). In this paper these will be referred to as Uniform FICONs. In the current dataset, as seen in Figure 5, nearly all (98.08%) FICONs are uniform. The remaining non-uniform FICONs have a dispersed distribution among the various non-uniform FICON combinations possible.

As observed from the figure, among the uniform FICONs, the majority contain the RwyCC 5/5/5 followed by 3/3/3 and

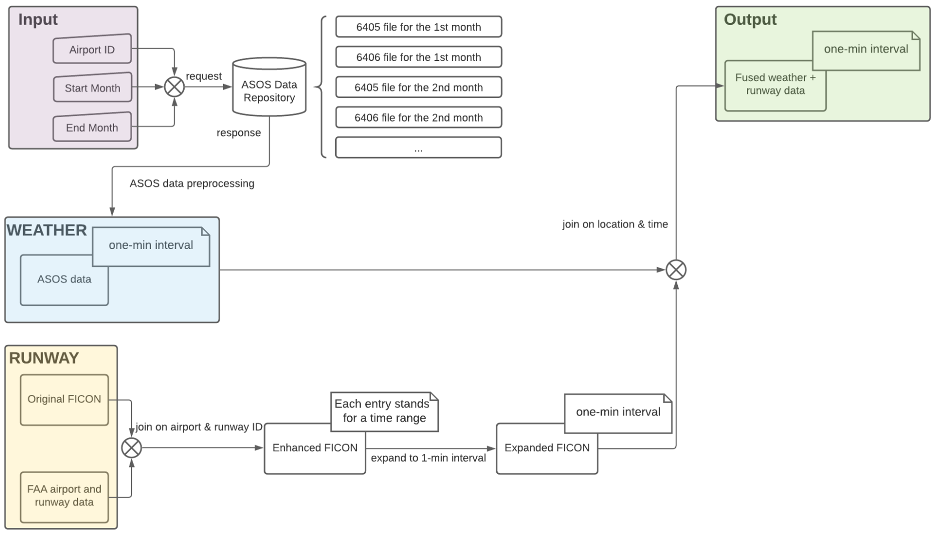

Figure 2: Data Fusion Schematic.

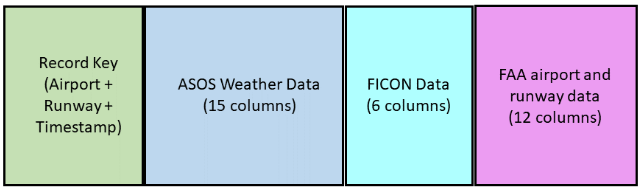

Figure 3: Output format of Data Fusion.

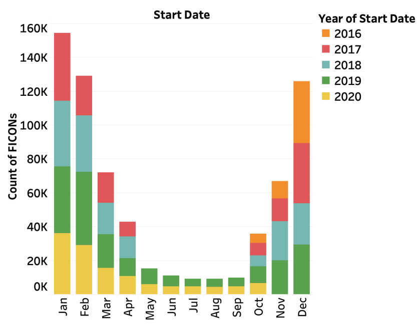

Figure 4: FICON Data Distribution By Month

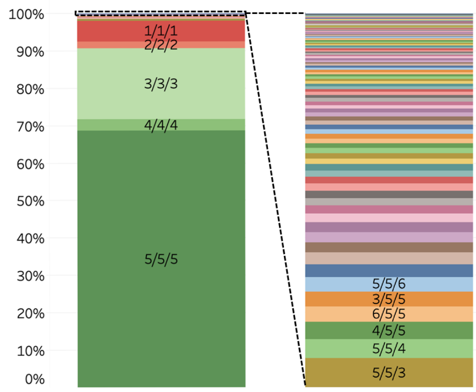

Figure 5: All and Non-Uniform FICONs

1/1/1. 4/4/4 and 2/2/2 make up the remaining small proportion of uniform FICONs. Any runway reported as NIL is closed for operations until the weather improves or contaminate removal is completed.

B. Relationship between Weather Conditions and FICON

Runway braking conditions are affected by weather; specifically during rain or snow events. Quantifying the correlation between active weather events and reported braking action is the primary benefit of this investigation. It is acknowledged that reduced braking action reports unrelated to active weather are also possible. Most notably for cold climate airports where compacted snow and/or ice may remain on a runway surface for weeks or months during the winter season [14].

The correlation between weather and RwyCCs has been investigated and an example is presented below to give more details. The example covers all FICON records and weather data for Bangor international airport at Maine (ICAO: KBGR) during the time range from 1/1/2018 to 12/31/2019.

Although a FICON record consists of 3 RwyCCs for the first, middle, and last thirds of the runway, most of the FICON records have uniform codes. As a result, the RwyCC representing the minimum of the ones having non-uniform codes will be used as the representative for a FICON record in our analysis. Also, while each FICON record covers a time span, only the start timestamp will be used to represent the time period of the record in the analysis. The correlation analysis of weather and FICONs addresses the relationship between temperature, precipitation type, and RwyCCs. In this paper, all precipitation types that can lead to non-dry runway conditions (rain, snow, sleet) or dry runway conditions (no precipitation) are being considered.

Figure 6 displays the distribution of RwyCC with respect to temperature (air temperature and dew point temperature). In the ASOS system, 'R' stands for rain, 'S' stands for

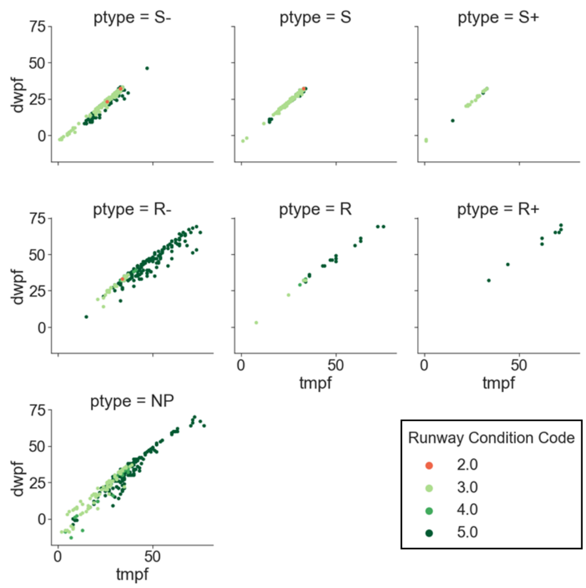

Figure 6: Relational plot of weather and runway condition codes at KBGR in 2018-2019.

snow, and 'NP' stands for no precipitation, whereas '+' and '-' stand for heavy and light precipitation intensities. Each subplot in the relational plot shows the distribution of codes under one specific precipitation type. Within each subplot, the lower left part can be considered as the 'low temperature area' and the top right part can be considered as the 'high temperature area'. Each dot in the plot stand for one FICON record, with its lowest RwyCC indicated by a color gradient, in greenish colors representing better runway conditions and reddish colors representing worse conditions.

It can be observed from the relational plot that dots are spread over the low temperature area under snow precipitation type, over the high temperature area under rain precipitation type, and across the entire temperature area when there is no precipitation. This indicates that the temperature is usually low in snowy days and relatively higher in rainy days, and no precipitation can occur regardless of the temperature of the day. Moreover, several red dots are seen under snow condition, while green dots are the majority under rain condition, which indicates that snow can be more detrimental to runway condition compared to rain. Lastly, in the no precipitation subplot, it can be observed that most red dots appear in the low temperature area, which suggests that runway condition can be poor for temperatures near or below freezing even when there is no precipitation. Indeed, there are many other factors (besides contaminants) that can come into play for poor runway conditions (such as time of the day, dew conditions, tire 'hardness' vs. temperature, etc.). These observations, while straightforward, corroborate the expected trends of correlations between adverse weather conditions and runway condition codes at a high level.

C. Correlations and Insights from Fused Data

In the enhanced FICON dataset, there are 1,951 distinct airports. Of these airports, 976 (50.1%) are located within the United States. The airports located domestically account for for 613,448 of the 682,757 FICON reports with locations (89.85%). Figure 7 displays the distribution of airports, with bubble size directly correlating to number of rows. This illustrates that the density of FICON reporting is greatest across regions where snow and convective thunderstorms are most common. This is consistent with expectations.

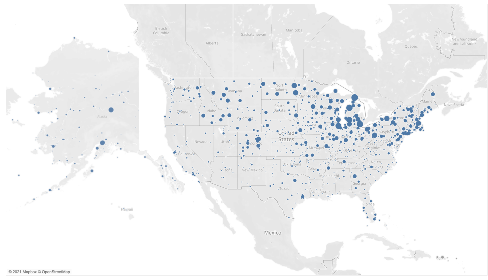

Figure 7: U.S. FICON Distribution

The remainder of this subsection contains the results of the analysis of the enhanced fused data sets and their implications on runway safety. It is divided into two parts, one subset which contains RwyCCs ($n = 568,791$ samples) and the other subset which contains the pilot reported braking action (PIREP BA). ($n = 9,906$ samples).

Subset with Runway Condition Codes

This subset provides a basis for making a correlation between the physical construction of a runway and its associated surface characteristics. To describe a runway's construction characteristics, three descriptor categories are commonly used in regulatory and research literature. 1) Runway Treatment: These are modifications to the surface to reduce standing water and hydroplaning potential [15]. Grooved (GRVD), no treatment (NON), and porous friction course (PFC). 2) Runway Surface Type: This describes the material used in the runway construction. Asphalt, Asphalt/Concrete, and Concrete. 3) Runway Condition: This is the quality of the runway surface and is an indication of proper maintenance by the airport operator: Excellent, Good, Fair, Poor. The detailed impact of Runway Condition will be deferred to future investigations. Runway Surface Type is quantified for reference but the analysis will focus on the influence of Runway Treatment. These two attributes are visualized in Figure 8.

From the larger dataset in Figure 8 a further downselection is conducted to evaluate only events that contain both a Runway Treatment value and a reported RwyCC. The results are shown in Figure 9. This figure illustrates that there is a significant trend correlation between in the type of runway treatment and history of RwyCCs reported. This shows that the braking action reported by airports in the FICON is consistent with the expected variance in braking action [16] of treated (PFC and GRVD) when compared to the no treatment runway surface. If this correlation was not indicated by the data, then that could be interpreted as the airports grossly overestimating the braking action for non-treated runways. A

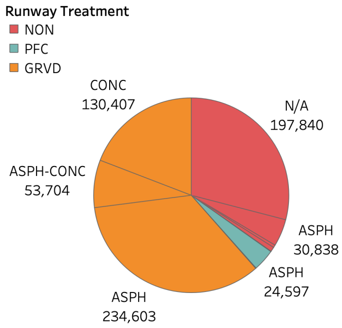

Figure 8: Physical make-up of the runways among the available data ($n = 681,125$). Applicable to U.S. airports only.

further cross check substantiation of these results is illustrated in figure 14 later in this paper.

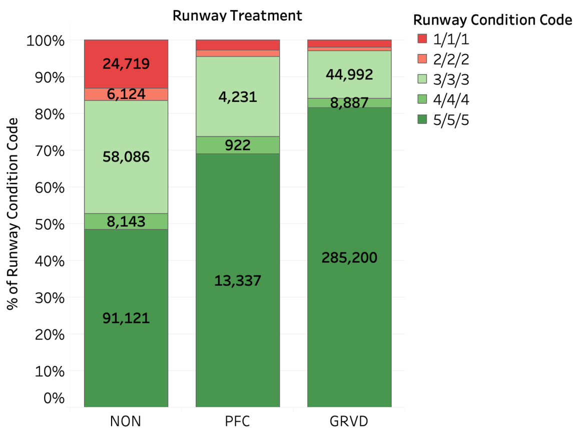

Figure 9: Runway Treatment Distribution and Runway Condition Code ($n = 556,488$)

Subset with Runway Condition Codes and Pilot Braking Reports

Using current "time of arrival" best practices guidance, one of the aircraft crew's important sources of braking action information is from the reported RwyCCs. The RwyCCs are derived from the RCAM guidance using the runway contaminant type and depth observed at a limited number of sampling points on the airport property. While contaminants descriptors may be the primary determinant in the braking action reported, other static variables such as runway longitudinal slope, polished/rutted wheel tracks, or runway lateral slope (crown) may impact the braking action achieved. The sum of the RwyCC braking action plus runway variances should be reasonably reflected in the PIREP BA reports. This section presents the comparison of the report RwyCC and the reported PIREP BA for the purpose of validating expected versus actual braking action.

Reported Braking Action for Contaminants and FICONs

FICONs can contain both a RwyCC and additional descriptive text of a contaminate or level of coverage. To validate the consistency of this reporting the following graphics are presented. As seen in Figure 10, the expected trend of fewer GOOD / GOOD-MEDIUM / MEDIUM PIREP reports for the lower RwyCCs is confirmed. However, this does raise the question of why there are so many reports of GOOD even when the FICON reports 1/1/1 (POOR). It could perhaps indicate that the RwyCCs might be overly conservative or the PIREP are overly optimistic. The data provides no clear basis for this apparent bias. This points towards the need for potential additional criteria to be developed to understand and isolate these variations. Another possibility is that of data errors such as the case where the runway condition has improved since the time of reported but the FICON is yet to be updated. Such cases are beyond the scope of this work to account for.

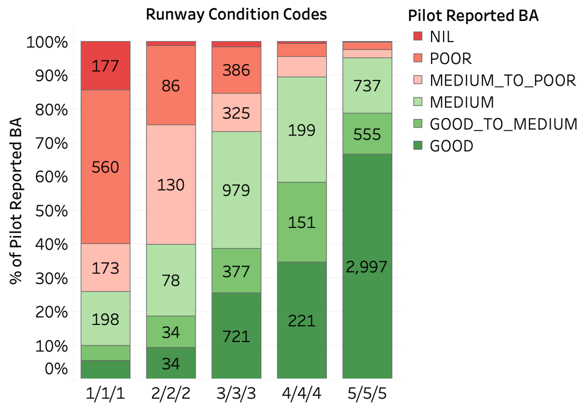

Figure 10: Pilot Reported Braking Action and Runway Condition Codes ($n = 9,580$)

The trend and variance discussed above is further illustrated in Figure 11 and 12. Figure 11 provides the closest correlation between contaminate descriptor and PIREP BA report, but with approximately 15 % of landings on ICE reported as MEDIUM or better, questions remain as to the source of the variance.

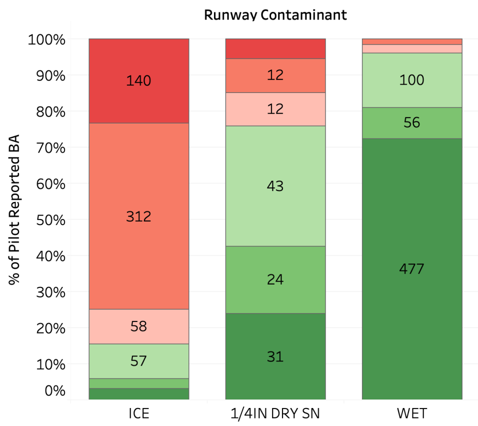

Figure 11: Pilot Reported Braking Action and Runway Contaminant ($n = 1,390$)

Pilot Braking Action and Non-contaminant Variables

This section analyzes the way that pilot reported braking action interacts with different variables for different runways.

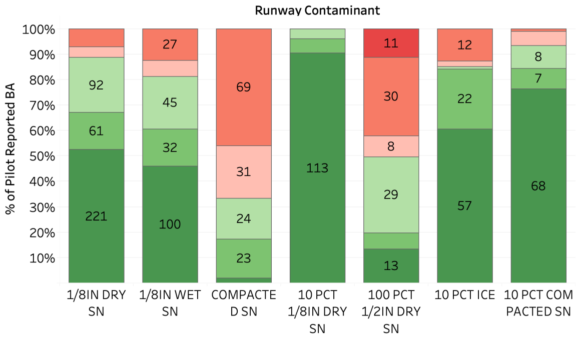

Figure 12: Pilot Reported Braking Action and Runway Contaminant ($n = 1,194$)

In the enhanced FICONs data set, information regarding runway length, start elevation, and end elevation is available. This data and the following formula to calculate the longitudinal slope of each runway in the data-set.

$$slope = (elevation_{end} - elevation_{start})/length * 100\%$$

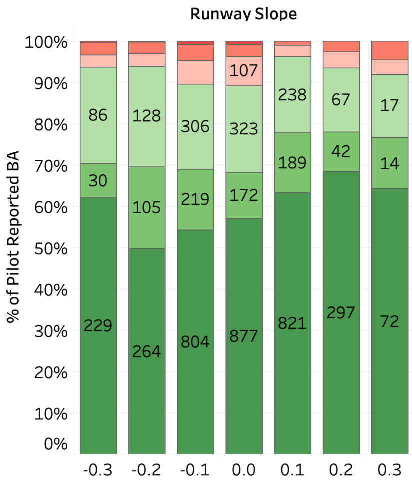

Figure 13: Pilot Reported Braking Action and Slope ($n = 5,755$)

In Figure 13, runway slopes are put into bins of .1 degrees and plotted against pilot reported braking action. Although the domain of the chart includes [-.3, .3], the segment [-.2, .2] is where data is most available as runway slopes tend to follow a binomial distribution around 0. More positive slopes (uphill) have a strong positive relationship with “good” reported braking action. This is best explained by the fact that positive slopes result in a force of gravity against the direction of motion.

From Figure 13, bins -0.2, 0.0, and 0.2 have “good” braking action reports of 49.9%, 57.1%, and 68.4% respectively. As such, we find that there is a respective -12.6% and 19.8% change of “good” braking action reports for slopes of -0.2 and 0.2 in comparison to level ground.

Lastly, as referenced in the discussion of Figure 9, Figure 14 also shows the correlation between Runway Treatment and braking action and provides a validation of the RwyCCs.

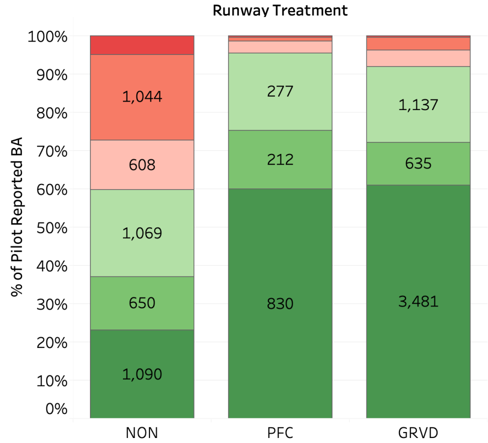

Figure 14: Pilot Reported Braking Action and Runway Treatment ($n = 11,799$)

Multivariate Analyses of Pilot Reported Braking Action and Other Variables

To quantitatively explore the multivariable relationship between runway-related metrics and PIREPs, a series of analysis of variation (ANOVA) tests have been conducted. One-way ANOVA is typically used to investigate if variations of a single factor have a measurable effect on a dependent variable. N-way ANOVA, can be used to determine if there is an interaction effect between n independent variables on a continuous dependent variable [17], [19], [20]. The runway-related variables are runway condition code, treatment, and slope. A subset of the aforementioned dataset has been selected for the analyses, which consists of 4420 samples and contains full information about the three runway-related variables and pilot reported braking actions.

ANOVA requires the dependent variable to be numerical, so the the text contents of PIREP BA have been enumerated to numbers from 0 to 5, where larger numbers correspond to more positive reports. For instance, “NIL”, which means no braking, is enumerated to be 0 while “GOOD”, which means good braking performance, is enumerated as 5. On the other hand, ANOVA requires the independent variables to be categorical, so runway slope has been converted to such a variable by putting the slope values into bins of 0.1 width.

Figure 15 to 17 are the heatmaps of Enumerated Pilot Reported BA against different combinations of RwyCC, Slope, and Treatment. An individual cell in a heatmap represents the mean value of enumerated PIREP BA for a specific combination of runway variables. High PIREP BA values are represented by the color of green while low PIREP BA values are represented by the color of red. The grey cells in the heatmaps indicate there is no sample for the given combination.

Three-way, two-way, one-way ANOVA tests have been performed, and the results are summarized in TABLE I. After looking at the reduced model which included all possible 2-factor interactions, the only significant interaction was between runway condition code and slope ($p \leq 0.01$). One-way ANOVA tests indicate that runway condition code

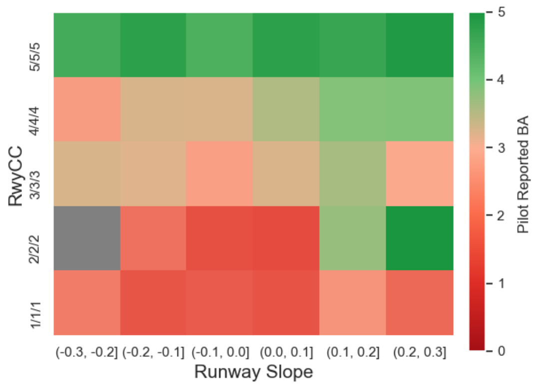

Figure 15: Heatmap for Enumerated PIREP BA vs. RwyCC&Slope ($n = 4,420$)

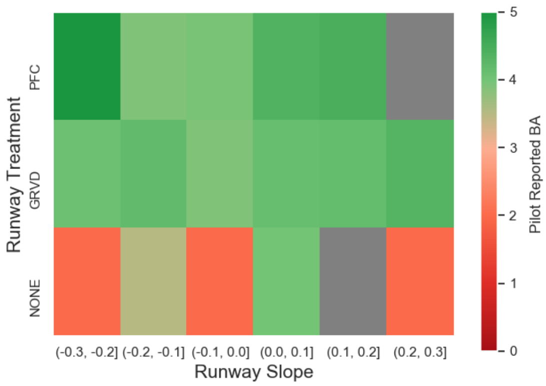

Figure 16: Heatmap for Enumerated PIREP BA vs. Treatment&Slope ($n = 4,420$)

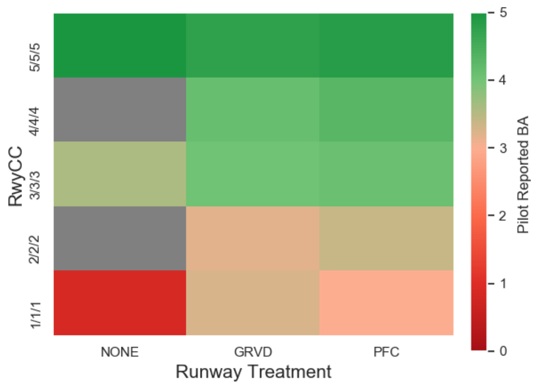

Figure 17: Heatmap for Enumerated PIREP BA vs. RwyCC&Treatment ($n = 4,420$)

and slope have very significant effects on braking action ($p \leq 0.01$), while runway treatment has a significant effect on it ($p \leq 0.05$).

Post-hoc tests (Tukey HSD) have been performed to further investigate the effects of the three runway variables and the interaction between RwyCC and Slope on braking action. The tests have yielded the following statistical results:

TABLE I. Results of ANOVA Tests

	SUM_SQ	DF	F	P
RwyCC	632.95	4	153.45	**<0.01**
Treatment	10.06	2	4.88	**<0.05**
Slope	35.19	5	6.83	**<0.01**
RwyCC + Treatment	0.07	8	0.01	0.93
RwyCC + Slope	63.40	20	3.07	**<0.01**
Treatment + Slope	0.09	10	0.01	0.93
RwyCC + Treatment + Slope	54.27	40	1.34	0.26

- PIREP BA is significantly higher when RwyCC is higher.
- PIREP BA is significantly higher when Treatment is PFC or GRVD compared to NONE.
- PIREP BA is significantly higher when Slope has a larger positive value.

The test has also revealed the statistically significant interaction of RwyCC and Slope on PIREP BA: When Slope is around zero (that is, $-0.1 < Slope < 0.1$), RwyCC has a significant effect on PIREP BA. However, when Slope has a large absolute value, the correlation of RwyCC with PIREP BA becomes less robust. This observation can be explained by the fact that as the runway becomes steeper, the force of gravity starts to have more effects on the braking action, and the effect of RwyCC is diminished.

D. Discussion

The presented research provides statistical support for the accuracy of existing best practices predictions for aircraft "time of arrival" braking effectiveness. Overall, the paper intends to perform the task of presenting and collating the available data in an understandable and functional manner to be useful for future studies.

The data also suggests that while the overall accuracy is reasonable, precision is more problematic. In aviation, conservative solutions are an essential part of safety. However, the RwyCC prediction's appear to skew significantly to a conservative performance level when compared to PIREPs during actual operations. Large data-set analysis such as was begun with this paper, may provide the only method to effectively reveal improved precision for the performance predictions.

VI. Conclusion and Future Work

In this work the relationship between runway surface conditions, airport and runway characteristics, prevailing weather conditions, and pilot reported braking action have been studied over a large period of time using collected data. A robust and repeatable data fusion framework is developed to integrate data from various sources for analyzing braking performance on contaminated runways. Statistical analysis was conducted to study the effect of prevailing weather conditions, runway treatment and slope, contaminant types, and other factors on the pilot reported braking action and runway condition codes. Further investigation and development of more refined models may be the subject of future work.

The developed data fusion framework and FICONs are intended to be used in conjunction with real-world flight data. The eventual aim of the project is to be able to understand and infer runway conditions based on the collected and processed data using big data/machine learning techniques [21], [22].

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