Analyzing Relationships Between Aircraft Accidents and Incidents

A data mining approach

Zohreh Nazeri
The MITRE Corporation*
7515 Colshire Drive
McLean, Virginia, USA
nazeri@mitre.org

George Donohue, Lance Sherry
George Mason University
4400 University Drive
Fairfax, Virginia, USA
{gdonohue, lsherry}@gmu.edu

***Abstract*—Air transportation systems are designed to ensure that aircraft accidents are rare events. To minimize these accidents, factors causing or contributing to accidents must be understood and prevented. Previous research has studied accident data to determine these factors. The low rate of accidents however, makes it difficult to discover repeating patterns of these factors. In this research we employed a data mining technique to conduct a holistic analysis of aircraft *incident* data in relation to the *accident* data. The analysis identifies relationships between the accident and incident data and finds patterns of causal and contributory factors which are significantly associated with aircraft accidents.**

Keywords- aviation safety; aircraft accidents; aircraft incidents; data mining; contrast-set mining

I. INTRODUCTION

Levels of safety are typically measured by the number of accidents and incidents and their rates. An aircraft accident is defined as an occurrence associated with the operation of an aircraft in which people suffer death or injury, and/or in which the aircraft receives substantial damage. An aircraft incident is an occurrence which is not an accident but is a safety hazard and with addition of one or more factors could have resulted in injury or fatality, and/or substantial damage to the aircraft [1]. Throughout the history of air transportation, along with the continuous growth in air travel, remarkable improvements have been made in lowering of accident rates. Nevertheless, further improvements are needed.

Figure 1 indicates annual rates of accidents that meet the selection criteria used in this study (as explained in section II.A). The accident data is obtained from the National Transportation Safety Bureau (NTSB) database.

* The author's affiliation with The MITRE Corporation is provided for identification purposes only, and is not intended to convey or imply MITRE's concurrence with, or support for, the positions, opinions or viewpoints expressed by the author.

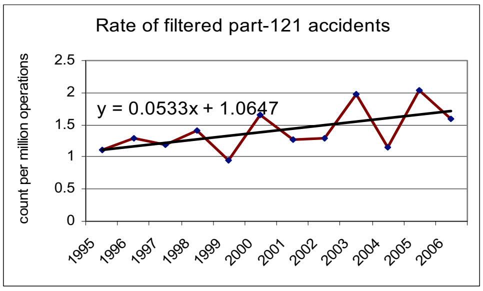

Figure 1. Rates of part-121 accidents that meet this study's filtering criteria

To further improve the flight safety, traditionally researchers focus on studying accident data to determine causal factors leading to accidents [2, 3, and 4]. The low rate of accidents however, makes it difficult to discover patterns of these factors. Other approaches study larger sets of data available on incidents but don't analyze relationships between these data and the accident data [5, 6, and 7].

Two influential theories in the safety studies are Swiss Cheese model [8] and Heinrich Pyramid [9]. The Swiss cheese model, introduced by James Reason in 1990's, views a hazardous situation culminating in an accident equivalent to passing through successive slices of Swiss cheese. Each "slice" is a system or process designed to prevent harm, however, the slices have holes representing errors in the system or process. Each error may occur frequently without harmful results, but when combined (i.e., holes are lined up), accident occurs. This model is widely used for investigating human factors (See Figure 2).

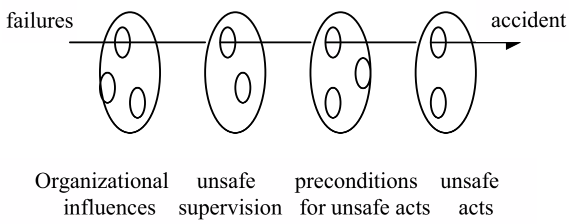

Figure 2. Swiss Cheese model

ISBN: 978-0-615-20720-9

The Heinrich Pyramid, introduced by H. W. Heinrich in 1930's, represents the accidents as low-frequency and high-risk safety hazards at the top of a pyramid. Moving down on the pyramid, the next layers consist of incidents and unsafe acts which are less hazardous but are more frequent. (See Figure 3.) An adaptation of the Heinrich pyramid in the aviation safety domain suggests that for every major accident there are 3-5 non-fatal accidents, 10-15 incidents, and hundreds of unreported events [10].

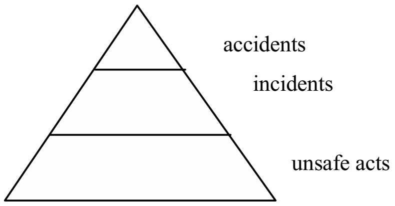

Figure 3. Heinrich Pyramid

In this study, similar to Heinrich pyramid, we look for the relationships between accidents and incidents. However, unlike the Heinrich pyramid which considers a quantitative relationship between accidents and incidents, our study looks for correlations between the underlying factors of accidents and incidents. The study considers the factors individually as well as combinations of the factors similar to the line-up of the holes in the Swiss Cheese model.

We analyzed the incidents in contrast to accidents and identified factors which are present in both classes of events but are significantly associated with accidents. We then studied the identified patterns of factors in the context of incidents.

II. DATA

The data used in this study consists of accidents and incidents pertaining to commercial flights (part-121) from 1995 through 2004, which provides a large enough sample size for the analysis. The accident data is obtained from the National Transportation Safety Board (NTSB) database. The incident data is obtained from four national databases: Federal Aviation Administration Accident and Incident Database System (FAA/AIDS), National Aeronautics and Space Administration Aviation Safety Reporting System (NASA/ASRS), FAA Operational Errors and Deviations (FAA/OED), and FAA System Difficulty Reports (FAA/SDRS).

Each report of accident or incident in these databases consists of structured fields plus a narrative explaining the event. Causal and contributory factors are identified either directly by the person who submits the report, or indirectly by a domain expert who reviews the report. These factors are in the structured fields. Our analysis used these factors.

A. Data Selection

Since the purpose of the analysis was identifying patterns of accident factors related to the routine operation of the flight, accidents and incidents due to the following causes were filtered out from the data:

- Medical and alcohol related events, such as pilot being sick or drunk
- Terrorism and security related events, such as bomb threats
- Passenger and cabin-crew related problems, such as passengers being injured due to hot coffee spilling on them
- Bird/animal striking the aircraft
- Events during the phases of operation when the aircraft is not operating (parked, standing, preflight)

Also, reports pertaining to the Alaska region were filtered out since flight environment and procedures in this region are different from other regions in the United States and require a separate study.

After applying the filters, there were 184 accidents, and the following sets of incidents in the data for analysis: 2,188 reports in the FAA/AIDS dataset, 29,922 reports in the NASA/ASRS dataset, 10,493 reports in the FAA/OED dataset, and 85,687 reports in the FAA/SDRS dataset.

B. Data Constraints

All accidents in the United States involving civil aircraft are investigated by the NTSB, an independent organization, and reported in the NTSB database. Accident data, therefore, can be assumed complete and free of bias. These assumptions cannot be made about the incident data. Incidents are under-reported and are subject to self-reporting bias. Voluntary reports represent a fraction of incidents [11] and recent audits indicate reporting of the incidents mandated by the FAA are under-reported [12 and 13].

Our study analyzed the underlying factors of accidents and incidents. The historical data on incidents is large enough to represent these factors qualitatively. Also, we consider all factors that are present in the events, primary or contributory. This minimizes the impact of the bias in reporting a factor as contributory versus primary.

III. METHODOLOGY

We first developed a common taxonomy across the accident and incident databases to identify common fields (factors) between the two classes of events. We then transformed each report into a vector consisting of the common fields populated with their corresponding values for each report. Next, we applied the STUCCO [14] algorithm to the accident and incident vectors and identified patterns of factors which are significantly associated with accidents or with incidents. The findings were ranked using Factor Support Ratio, a measure introduced in this study as described below in this section under 'Ranking'. Results of the analyses conducted on multiple databases were compared for cross-database validation. The results are discussed in the next section.

ISBN: 978-0-615-20720-9

A. *Common Taxonomy*

The process of deriving the common taxonomy is data-driven. After reviewing each individual database structure and unique values for each field, we developed a hierarchy of factors and sub-factors common across the databases. Eight high-level categories of factors were identified in the data, each containing corresponding sub-factors. These factors and examples of their sub-factors are shown in Figure 4. The 'Other' category contains all sub-factors which were not big enough to have a separate category for themselves.

A normalization of the values was needed so that all databases use the same word/phrase to refer to the same factor/condition. For example, to refer to the action where pilot has to execute a maneuver to avoid a vehicle or object on the runway, 'ground encounter' is used in one database and 'object avoidance' in another.

The reports were converted to vectors consisting of fields that indicate presence or absence of each of the common factors and sub-factors in the accident or incident. These vectors were then used in the analysis.

Factor	***Sub-Factor examples***
Aircraft	Engine, Flight control system, Landing gear
Airport	Snow not removed from runway, Poor Lighting, Confusing marking
Air Traffic Control	Communication with pilot, Complying with procedures
Company	Procedures, Management, Training
Maintenance	Compliance, Inspection
Pilot	Visual lookout, Altitude deviation, Decision/Judgment
Weather	Wind, Thunderstorm, Ice
Other	Factors not in the other categories, e.g., FAA oversight, Visibility

Figure 4. Cross-database common taxonomy

B. *Contrast-Set Mining*

Since the objective of the study was to identify factors and factor combinations that are precursor to accidents, we needed an analysis technique that could take advantage of both sets of data (accidents and incidents) and determine which factors are more likely to lead to accidents. We applied the STUCCO algorithm [14] to analyze accident and incident vectors by contrasting them. The algorithm finds conjunctions of attribute-value pairs that are significantly different across multiple groups. In the case of our data, there are two groups: accidents and incidents. Attribute-values are binary values indicating presence or absence of the factors in the event.

The factors and their children (combinations of factors) are examined for their frequency (support) in each group. For each factor-set, *deviation* is calculated as absolute value of the difference between accident support and incident support. In the first step, factor-sets for which deviation is more than a minimum threshold proceed to the next step to be tested further. We used a minimum of 1% threshold for the deviation.

In the next step, Chi Square test is performed to test statistical significance of the distribution of factor-set over the two groups. The contingency table shown in Figure 5 is used for this test. A p-value of 0.05 is used as the threshold. Factor-sets with a p-value of more than 0.05 are rejected. A p-value of less than 0.05 is the equivalent of being in the 95% confidence interval and is accepted.

	accidents	**incidents**
factor-set true	accidents containing the factor-set	incidents containing the factor-set
factor-set false	accidents not containing the factor-set	incidents not containing the factor-set

Figure 5. Contingency table used for Chi Square significance test

C. *Ranking*

Once significant factor-sets were identified by the algorithm, we ranked them based on the *Factor Support Ratio* measure. As shown in equation (1), we calculate the Factor Support Ratio for each factor-set as the ratio of the factor-set's support in accident dataset over its support in the incident dataset.

$$Support\ Ratio = \frac{Support_{accident}}{Support_{incident}}. \qquad (1)$$

The Support Ratio is the probability of a factor-set being involved in an accident divided by its probability of being involved in an incident. The information conveyed by this measure about the factor-set is different than that of the *deviation* (the difference between the factor-set's accident and incident supports) that is used in the algorithm. To understand the Support Ratio better, consider factor-sets A and B and their corresponding measures in Table 1.

TABLE I. SUPPORT RATIO VS. DEVIATION

factor-set	**accident supp**	**incident support**	**Dev**	**Support Ratio**
A	60%	50%	10%	1.2
B	11%	1%	10%	11
C	60%	10%	50%	6

Both factor-sets A and B have a deviation of 10% between their accident support and incident support. However, in the case of factor-set B, the support in accidents is 11 times more than in incidents. This can be interpreted as: occurrence of factor-set B in an accident is 11 times more likely than its occurrence in an incident. This is a more distinctive distribution than that of factor-set A which has a Support Ratio of 1.2. We can use this measure to compare factor-sets A and

ISBN: 978-0-615-20720-9

B, and say factor-set A is more likely to be involved in accidents than factor-set B.

To understand the significance of Support Ratio for ranking the factors consider factor-sets A and C in Table 1. Both factor-sets appear in 60% of accidents. But the fact that factor-set C appears in 10% of incidents raises its Support Ratio (compared to factor-set A). We interpret this as: factor-set C is qualitatively a more significant accident factor than factor-set A. When factor-set C occurs it is more likely (by a factor of 6) to be involved in an accident than in an incident. But when factor-set A occurs, the likelihood of having an accident versus having an incident is smaller (1.2).

Accident support of a factor (frequency of the factor in accidents) by itself shows how many times the factor has been involved in accidents but does not show how frequently the factor has occurred (in accidents and incidents). Similarly, incident support of a factor only indicates how many times the factor has occurred in incidents without an indication of the factor's role in accidents. In some cases, a factor seen frequently in incidents might rarely be involved in accidents. This means the factor is not a significant accident factor. One explanation could be that the factor could be stopped from leading to accidents once it occurred.

IV. Results

We performed separate analyses on four pairs of datasets, each pair consisted of accident reports and their corresponding incident reports in one of the four incident databases. The results of the analyses were compared at the end. Below are major findings of the study that were consistent across the multiple analyses of incident/accident database pairs.

A. *Combination of factors*

Factors are more likely to yield to accidents (rather than incidents) when they are combined together. Ranking of the results by the Factor Support Ratio showed that likelihood of a factor being involved in an accident rises as more factors co-occur with the factor. For example, the Support Ratio for combination of *pilot+airport* factors was 7.2 compared to the Support Ratio of 3.9 for the *pilot* factors, signifying that *pilot* factors combined with *airport* factors are 1.8 times more likely to results in accidents than the *pilot* factors alone.

B. *Company factors*

Company factors are referred to factors such as mistakes by the company (or airline) personnel, inadequate or non-existing procedures by the company for performing a task, and lack of management by the company management. The analyses identified these factors as significant accident factors. Ranking of the results by their Support Ratios identified *company* factors as the highest ranked category of accident factors among the eight categories of factors in the data.

C. *ATC factors*

The analyses identified *Air Traffic Control (ATC)* factors as the next highest ranked category of accident factors following the *company* factors. Among the ATC factors, *ATC communications* are identified as the most significant sub-factors associated with accidents. *ATC communications* refer to factors such as controllers issuing traffic advisories, controllers providing weather information to the pilot, and controllers checking for correct readback of instructions by the pilot.

D. *Pilot factors*

Pilot factors are more frequent than other factors in accidents but they are also more frequent in incidents and therefore their Support Ratio is lower and ranks them after the *company* and *ATC* factors. Among the *pilot* factors, *visual lookout* is identified as the most significant pilot sub-factor.

E. *Aircraft factors*

Aircraft factors are referred to mechanical problems with the aircraft or its components and systems. Examples are problems with landing gears, flight control systems, and wings. Without presence of other factors, *aircraft* factors are identified as incident factors, meaning that they are more likely to cause incidents than accidents when occurring alone. But when *aircraft* factors are combined with other factors, such as severe weather or pilot errors, the combination becomes an accident factor.

V. Conclusion

We further studied the results in the context of the historical databases where data was available. The data over a ten-year-period (1995-2004) showed that *pilot* and *aircraft* factors are decreasing and *Air Traffic Control (ATC)* factors are increasing (see figures 6, 7, and 8). The operational error reports in the OED database show that *ATC* factors are influenced by a variety of conditions, referred to as *complexity factors*. The data available to us included eleven of these complexity conditions: *airspace design, emergency event, controller experience, flow control, number of aircraft, runway conditions, runway configuration, terrain, special event, weather, and other*. The ten-year historical data showed top-most frequent complexity conditions influencing the *ATC* factors are *number of aircraft*, *airspace design, runway configuration*, and *controller experience*.

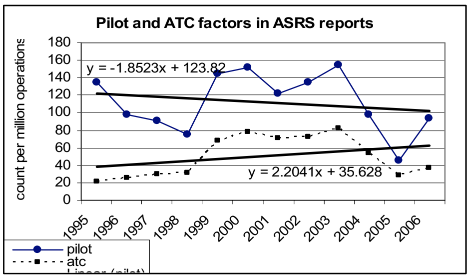

Figure 6. Incident rates containing *pilot* and *ATC* factors, in the ASRS database

ISBN: 978-0-615-20720-9

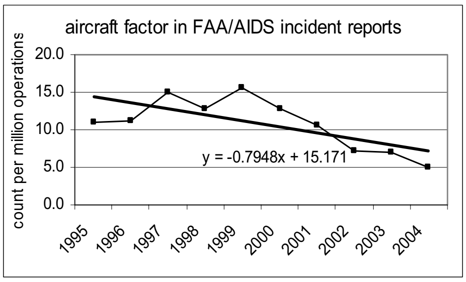

Figure 7. Rate of the incidents containing *aircraft* factors, in the AIDS database

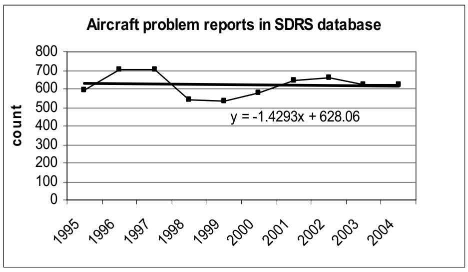

Figure 8. Rate of incidents containing *aircraft* factors, in the SDRS database

The *number of aircraft* complexity condition can be expected to rise even further considering the continuous growth of air transportation projected by the FAA [15]. The projected growth will impact *Runway configuration* and *airspace design* complexity conditions indirectly. With an increased volume, airports will have to use runway configurations that accommodate more departures and arrivals. Difficulties with the airspace design, such as limited space for complying with altitude changes when moving the aircraft from one airspace to the other, will be aggravated when there are more aircraft in the airspace. The *controller experience* will also be impacted by the projected growth, since more controllers will be needed to handle the increased operations. In addition, the number of controllers retiring in the past few years has exceeded the projections [16] and a large number of existing controllers are expected to retire within the next few years [17]. FAA plans to hire over 1,000 controllers per year for the next 10 years. The current experienced controllers will be replaced with a new generation.

Considering the accident factors identified in this study, the projected growth in air transportation and the consequent aggravation of the conditions affecting the accident factors, accident rates can be expected to increase beyond their current levels unless changes are made to current conditions.

VI. Future Work

The study conducted here is a starting point for further research on the relationships between accidents and incidents and identification of more detailed accident factors. As a continuation of this study, the methodology applied here can be applied to other safety databases that were not available to this study, such as the Aviation Safety Action Program (ASAP) and Flight Operations Quality Assurance (FOQA) databases maintained by airlines. These databases offer safety data which could yield to discovery of more detailed accident factors. In addition, upon availability of more detailed data, the approach in this research can be taken one step further to study patterns of factors within each of the identified categories.

This study covered accidents and incidents pertaining to commercial flights within the United States. A similar study could be conducted on the General Aviation (GA). Depending on the availability of the data, the studies could be extended to regions in other countries as well.

Acknowledgment

Zohreh Nazeri thanks Christina Hunt, manager, at the FAA Aviation Safety Information Analysis and Sharing (ASIAS), for providing much of the data needed for the study, and Linda Connell, director, at the Aviation Safety Reporting System (ASRS) program at NASA, for helping with downloading the ASRS data from their on-line query interface.

References

[1] Federal Aviation Administration, Air Traffic Organization, *Aircraft Accident and Incident Notification, Investigation, and Reporting*. Order 8020.16 http://www.faa.gov/airports_airtraffic/air_traffic/publications/at_orders/media/AAI.pdf

[2] P. Ladkin, *ATM Related Accidents*. Eurocontrol. From website: http://www.eurocontrol.int/corporate/public/standrd_page/cb_safety.html, 2006.

[3] K. Dimukes, The Limits of Expertise: The Misunderstanding Role of Pilot Error in Airline Accidents. ASPA/ICAO regional seminar, March 2005.

[4] G. Van Es, *Review of Air Traffic Management-Related Accidents Worldwide: 1980-2001.* Fifteenth Annual Aviation Safety Seminar (EASS). Geneva, Switzerland, March 2003.

[5] A. Majumdar, M. D. Dupuy, and W. O. Ochieng. A framework for the Development of Safety Indicators for New Zealand Airspace: the Categorical Analysis of Factors Affecting Loss of Separation Incidents. Transportation Research Board (TRB) annual conference, 2006.

[6] M. Hansen and Y. Zhang, *Safety Efficiency: Link between Operational Performance and Operation Errors in the national Airspace System.* Transportation Research Record, journal of Transportation Research Board, no. 1888, p 15. 2004.

[7] National Aeronautics and Space Administration, *Air Traffic Management System.* From website: http://quest.arc.nasa.gov/aero/virtual/demo/ATM/tutorial/tutorial1.html. 2007.

[8] J. Reason, *Human Error.* Cambridge, U.K.: Cambridge University Press. 1990.

[9] H. W. Heinrich, *Industrial Accident Prevention.* New York. McGraw-Hill. 1931.

[10] C. A. Hart, *Stuck on a Plateau: A Common Problem.* Accident Precursor Analysis and Management: Reducing Technological Risk through Diligence, National Academies Press. 2004.

[11] B. Strauss and M. Granger, *Everyday Threats to Aircraft Safety.* Issues in Science and Technology 19(2); 82-86, 2002.

[12] Federal Aviation Administration, *Audit of Control over the Reporting of Operational Errors.* Report number AV-2004-085, September 20, 2004.

[13] U.S. Office of Special Council. *Report of Disclosure Referred for Investigation.* OSC Files DI-06-1499 and DI-07-2156, July 2007.

[14] S. D. Bay and M. J. Pazzani, *Detecting Change in Categorical Data: Mining Contrast Sets.* Fifth ACM SIGKDD International Conference on

 ISBN: 978-0-615-20720-9

Knowledge Discovery and Data Mining. New York: The Association for Computing Machinery.

[15] Federal Aviation Administration, *FAA Aerospace Forecasts FY2006-2017*. From http://www.faa.gov/data_statistics/aviation/aerospace_forecasts/2006-2017/media/FAA%20Aerospace%20Forecast.pdf

[16] Federal Aviation Administration. A Plan for the Future, 2007-2016. The Federal Aviation Administration's 10-year strategy for the air traffic control workforce. March 2007.

[17] United States General Accounting Office (GAO), Air Traffic Control, FAA Needs to Better Prepare for Impending Wave of Controller Attrition. GAO-02-591, June, 2002.

ISBN: 978-0-615-20720-9