80 Bayesian Network Modeling of Airport Runway Incursion Occurring Processes for Predictive Accident Control

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Abstract

This paper examines how runway incursion, one of the major risks in aviation system, arise and propagate during communications and operations necessary for air traffic control. Runway incursions (RIs) refer to incorrect presences of aircraft in protected areas designated for landing and take-off of aircraft. RIs can significantly jeopardize the runway safety. Communication errors between air traffic controllers and pilots are major causes of RIs. How to quantify the probabilistic dependence between contextual factors (airport layout, time of the day, etc.) and communication errors that lead to RIs is thus important for real-time alarming and accident prevention. This study presents a Bayesian Network (BN) modeling approach with a focus on modeling the communication errors causing RIs during aircraft take-offs and how different factors contribute to the accidents according to the information from the aviation accident reports. Major findings indicate that the proposed approach can predict the accident occurrences based on the risk knowledge of anomalies captured in the BN produced by the proposed approach. In practice, the proposed approach has the potential for establishing automated and preventive safety management in aviation systems.

Keywords

Runway incursion • Bayesian network modeling • Process model

80.1 Introduction

According to the International Civil Aviation Organization (ICAO), runways are rectangular areas at airports prepared for the landing and takeoff of aircraft. Runway safety is a top priority for the Federal Aviation Administration (FAA) to ensure safe operations of National Airspace System (NAS) [1]. Runway incursions (RIs) refer to incorrect presences of aircraft in protected areas designated for certain landing and take-off of aircraft [2]. RIs, as one category of the most critical accidents, has seriously jeopardized the runway safety, while an average of three RIs occur daily in the United States and cause severe fatalities and property damages [2, 3].

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I. Mutis and T. Hartmann (eds.), *Advances in Informatics and Computing in Civil and Construction Engineering*,
https://doi.org/10.1007/978-3-030-00220-6_80

Air Traffic Controllers (ATCs), who are responsible for safe coordination of air traffic, play a major role in avoiding RIs. ATCs need to communicate with pilots through radio and provide instructions or clearances regarding altitudes, speeds, weather and air traffic conditions [4]. Reliable communications between the pilots and ATCs are critical to ensuring safe coordination in air traffic control. ATC/Pilot communications also need to employ read-back/hear-back procedures for ensuring that the information could be properly understood. However, since the U.S. airspace becomes much more crowded with the increasing air traffic, ATCs are posing a larger workload and prone to human errors despite these procedures ensuring the reliable ATC/Pilot communications [5]. Miscommunication has contributed to more than 60% of RI events [6], which have been identified as one of the most common human error and involved more than 2000 fatalities in the past RIs and are threatening aviation safety [7–9].

Previous studies have investigated miscommunications between ATC and pilots through linguistic analysis using radio communication transcripts [4, 10, 11]. These studies focus on how to reduce misunderstandings in ATC/pilot communications through improving the communication protocols. However, few studies have examined how communication error occurs during air traffic control and lead to RIs. An effective aviation safety control that can reduce RIs is thus necessary, which not can only identify anomalies (e.g. communication error) that may cause RIs but also be able to predict the likelihood of RIs triggered by the propagation of the detected anomalies. This study presents a *Bayesian Network* (BN) modeling approach that first create process models for showing processes of air traffic control that gradually lead to RIs during aircraft take-offs. A Bayesian network-learning algorithm then uses this process model and a large number of accident reports to generate a BN that captures histories about how various contextual and human factors influence the probabilities of certain events and miscommunications that lead to runway incursions.

80.2 Background Studies

Previous research on the RIs focused on two questions (i) what are the contributing factors that cause the miscommunications and the RIs; (ii) what are the processes of accident occurrences. Most studies use Fault Tree Model or Event Tree Model to quantify the causal relationship between contextual factors and communication errors in certain RI scenarios [10]. Some studies examined which factors have more impacts on RIs using Bayesian Network (BN) modeling [11]. Some studies showed that a safety ontology-based framework could help to formalize the safety management knowledge [12]. El-Gohary has developed a set of construction ontologies to better understand the processes of project development [13]. These previous studies showed the potential of using process models along with BN learning methods for synthesizing mechanisms about how RIs occurred. Few studies examined RI processes by quantifying the correlations between accidents, contextual factors, and communication errors, which are critical for the RI prediction. This paper tries to examine how airport RI, one of the major risks in aviation systems, arise and propagate in the process of communications and operations during air traffic control.

80.3 Methodology for Predicting Runway Incursions Using *Bayesian Network* (BN) Modeling

The goal of this study is to understand how communication errors occur in the take-off process of aircraft and how these errors eventually lead to runway incursions. To achieve the goal, the two sub-objectives are: (1) Develop a process model for understanding the process of having runway incursion during aircraft take-off through synthesizing aviation accident reports from multiple sources (NTSB database, ASRS database, etc.); (2) Establish a *Bayesian Network* (BN) model based on the process model to quantify the correlations between events in the process model. This study presents a BN modeling approach with a focus on modeling runway incursions that occur during aircraft take-offs and how different factors contribute to the accident occurrences according to the information from the accident reports.

The proposed BN modeling approach for predicting runway incursions consists of three steps (see Fig. 80.1). The first step is to collect accident/incident reports of runway incursion caused by communication errors from the Aviation Safety Report System (ASRS). The second step is to extract information from the collected reports (i.e. time of the day, number of runways, runway layout, number of people on the same radio frequency, etc.). The third step is to classify the types of communication error and the runway incursion according to the detailed narrative described in the reports. Then, the authors created a process model to represent different phases of an aircraft during the take-off process according to the standard flight take-off procedure. The standard take-off procedure consists of pushback from the gate, start taxiing, hold-short at certain intersections (aircraft cannot across an active runway), line-up and wait at the runway and prepare for take-off, and take-off.

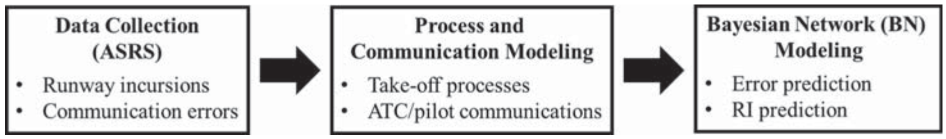

Fig. 80.1 Overall framework

In this process model, the authors also represent the anomalous events by using the error states (i.e. runway crossing, unauthorized take-off, etc.) based on the aviation accident reports. The authors then constructed a *Bayesian Network* (BN) model based on the accident reports of runway incursions to represent how anomalous events arise and propagate that lead to different type of RIs. The model provides the capability to quantify risks during aircraft take-offs by calculating the probabilistic dependence between anomalies based on their relationships represented in the BN.

80.3.1 Data Collection

The Aviation Safety Reporting System (ASRS) is a voluntary confidential reporting system that allows pilots and other aircraft crewmembers to confidentially report near misses and accidents in the interest of improving air safety. It contains a huge amount of accident/incident reports that could help the authors to better understand how runway incursion occurs based on the information provided in the reports. The authors collected data using following the parameters listed in Table 80.1. Since communication errors have been studied as one of the most critical factors that causing runway incursions, the authors are looking for reports of runway incursion that are due to communication errors. A total number of 331 runway incursion cases have been found between 2014 and 2017 under the category communication error, which means that all these 331 runway incursions are due to communication errors. The authors manually analyzed 30 reports and tried to understand the correlation between environmental factors, communication errors, and runway incursions.

Since the air traffic volumes are different at different times, time of the day of specific incident happens allow the authors to understand whether RIs occurred more frequently at dawn, morning, afternoon, or night. Airport layout and its number of runways also provide information on how RIs occurred at airports with a similar design. The authors then picked the *airport name, time of the day*, and *the number of people in the same radio frequency* as major attributes of each RI case for RI prediction. Then, by using *Google Map*, the authors would be able to understand the number of runways and the layout of that airport (interact runway or not, see Fig. 80.2). By retrieving the airport information, the authors could better understand the how RIs occurred at airports with similar layouts that contain a similar number of runways with similar arrangements. Then, the authors retrieve information of how communication errors happen and how many people are in the radio frequency at that time through the detailed narrative of the report. Since ATC and pilots are communicating in the same radio frequency and ATC is required to call out the "call sign" (e.g. AA870—flight number), errors might occur when the frequency is congested. Table 80.2 has listed the major findings from the 30 reports being analyzed (Fig. 80.3).

Table 80.1 Data searching parameters

Data searching parameters	Value
Database	Aviation Safety Reporting System (ASRS)
Date of incident	2014–2017
Event type	Runway Incursion
Human factors	Communication errors
Total number of reports collected	331
Number of reports analyzed in this research	30

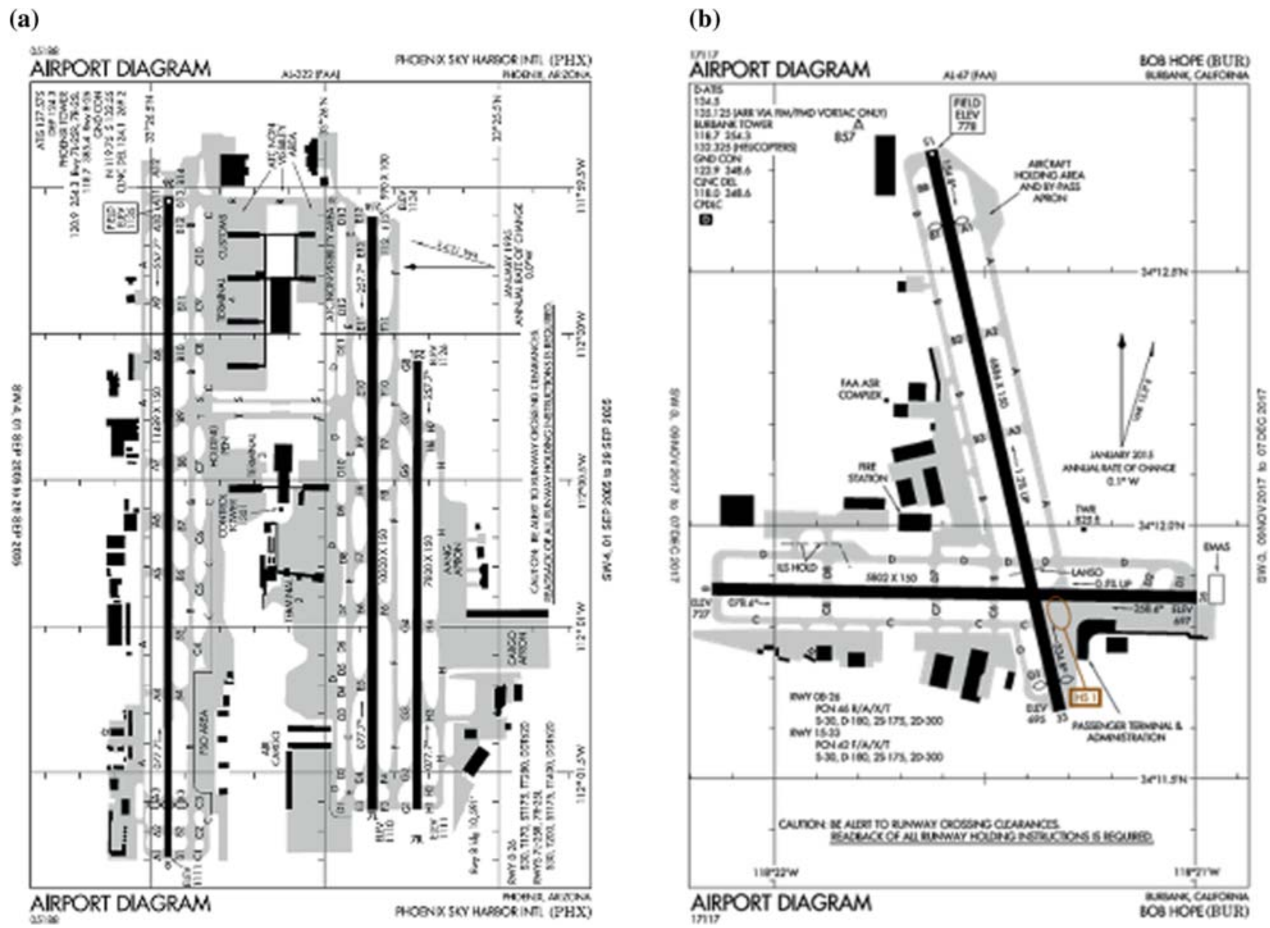

Fig. 80.2 The layout of airports **a** PHX Sky Harbor International Airport—Three runways with no interactions; **b** BUR Bob Hope Airport, CA—Two runways with interaction

Table 80.2 Variables retrieved from the reports

Factors	Variables	Number of cases
Number of runways (R)	2 runways (R^0)	10
	3 runways (R^1)	20
Runway layout (I)	No interaction (I^0)	4
	Interact (I^1)	26
Number of people on the same radio frequency (P)	Less than 4 people (P^0)	17
	More than 4 people (P^1)	13
Time of the day (T)	Dawn (T^0)	3
	Morning (T^1)	6
	Afternoon (T^2)	15
	Night (T^3)	6

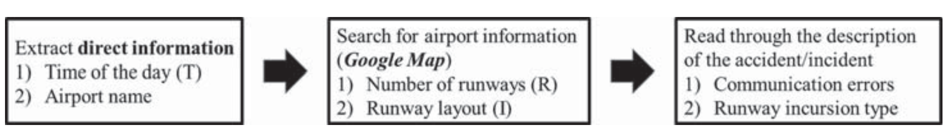

Fig. 80.3 Steps of data collection from the Aviation Safety Report System (ASRS)

80.3.2 Process and Communication Modeling

In this step, the authors created a process model based on standardized take-off procedures to represent how communication errors occurred and contributed to certain RIs at different phases of the take-off process per the reviewed accident reports (see Fig. 80.4). In addition, the BN modeling processes quantified the correlations for enabling risk prediction of RIs.

The authors first create a process model to illustrate the normal take-off processes of aircraft. This take-off process model represents two type of take-off process and is classified depends on whether the aircraft need to cross other active runways on their taxi route to the determined runway for take-off. Runway crossing usually involves more communications between ATC and pilot and induces more risks of communication errors that could lead to RIs. Then, according to the narrative in the reports, the authors found out three types of RIs (see Table 80.3) that frequently occurred before take-off, and incorporate these runway incursions into the process model (see Fig. 80.4). The most common type of RI (RI_1) happens when pilot ignored the "hold short" clearance (stop at the intersection) and cross an active runway without clearance (runway crossing without clearance). The second type of RI (RI_2) happens when pilot cross the hold line at certain interactions on the taxi route (taxi across hold-line of the runway). The third type of RI (RI_3) happens when a pilot attempt to take-off without clearance.

As for the communication errors, ATCs have to issue four types of clearances to inform pilots about the taxi route, hold short (stop) points at certain intersections, and the assigned runway for take-off of a given aircraft. These four types of clearance include (1) *Taxi Clearance* (ATC issue taxi clearance to inform pilot about taxi route from gate to the runway for take-off); (2) *Runway Crossing Clearance* (Pilots are required to stop at intersections and wait until ATC has cleared the runway and give runway crossing clearance to pilot); (3) *"LUAW" Clearance* (ATC issue "line up and wait" clearance to allow the pilot to line up at the runway and wait for take-off clearance); and (4) *Take-of Clearance* (ATC issue take-off clearance to pilot for take-off when runway has been cleared). In the current practice of ATCs/pilots communications, a "three-step" communication protocol is required. In a communication, an ATC needs to issue the clearance to a pilot with specific instructions; the pilot should respond with a full read-back on the clearance, and the ATC needs to confirm the read-back to ensure that the pilot das a clear understanding on that clearance. In total, twelve communications are required for each aircraft before the take-off. However, communication errors do exist and lead to RIs. The authors find out that four kinds of communication errors happen frequently during runway incursions (see Table 80.4).

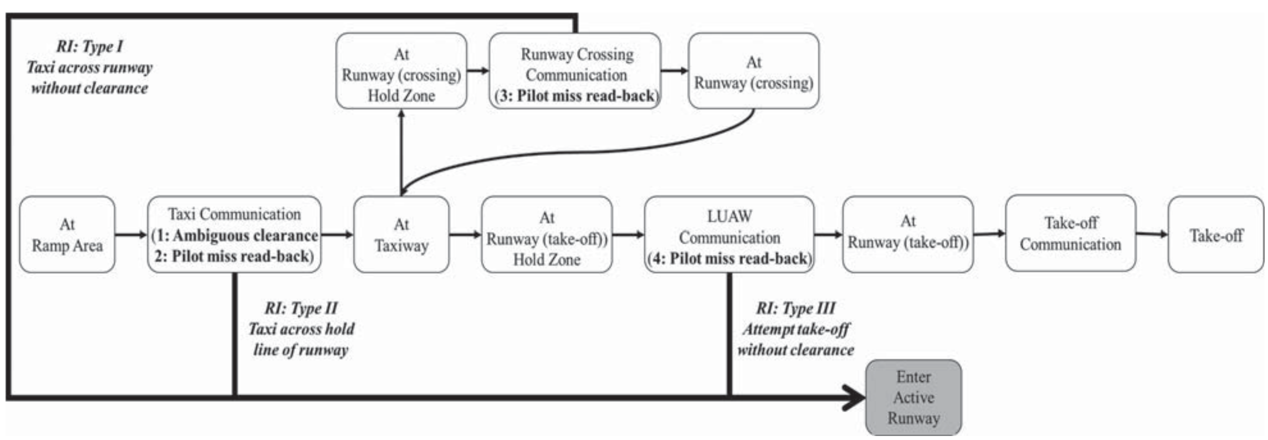

Fig. 80.4 Take-off process modeling

Table 80.3 Types of a runway incursion

Types of runway incursion	Description	Number of cases
Type I (RI_1)	Taxi across runway without clearance	16
Type II (RI_2)	Taxi across hold line of a runway without clearance	9
Type III (RI_3)	Attempt take-off without clearance	5

Table 80.4 Types of communication error

Types of communication error	Description	Number of cases
Type 1 (E_1)	ATC issued ambiguous taxi clearance to pilot	8
Type 2 (E_2)	The pilot missed read-back on the taxi clearance issued by the ATC	16
Type 3 (E_3)	The pilot missed read-back on the runway crossing clearance	1
Type 4 (E_4)	The pilot missed read-back on "LUAW" clearance	5

80.3.3 Bayesian Network (BN) Modeling

The last step of this study is to generate a *Bayesian Network* (BN) model by using the process model that captures conceptual relationships between contextual factors and events occurring during RI arising processes (see Fig. 80.5). Using the accident reports of RIs can serve as data sources for quantifying the strengths of these relationships. More specifically, the BN model uses the information retrieved from the accident reports and try to find out the quantitative relationship between different anomalous events and runway incursions under certain conditions. The quantitative correlation would help the air traffic manager to better understand the potential risks and send out an alarm to the corresponding personnel to avoid a runway incursion.

80.4 Major Findings

This section shows preliminary results of the research methodology presented above. Table 80.5 illustrates the probabilistic relationship between different communication errors and different combinations of the four factors. Table 80.6 illustrates the probabilistic relationship between three types of runway incursions and four types of communication errors. These results quantify the relationship between selected factors, communication errors, and runway incursions respectively.

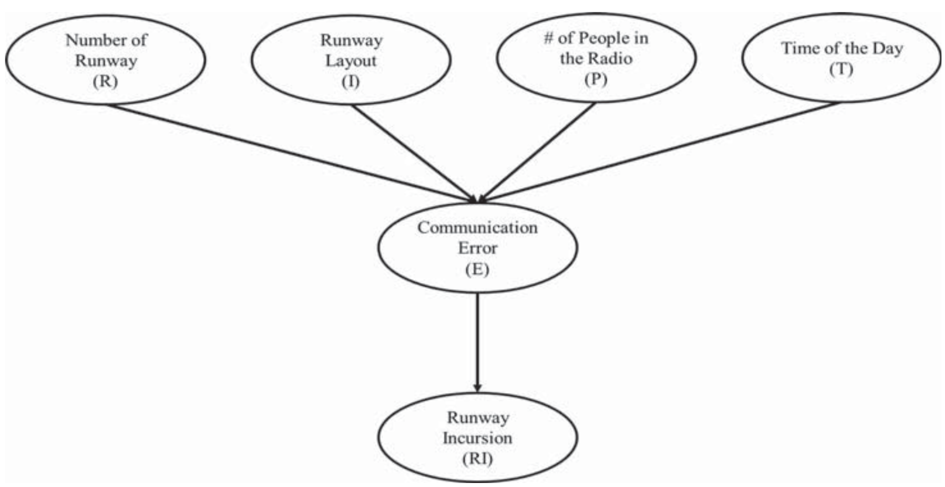

Fig. 80.5 Bayesian Network (BN) modeling of RIs, communication errors, and influencing factors

Table 80.5 The conditional probability of communication errors on factors (see Table 80.2 for a detailed explanation on R, I, P, and T; see Table 80.4 for a detailed explanation on E_1, E_2, E_3, and E_4)

Combinations	Conditional probability (%)
P (E_1 | $R^0I^1P^1T^1$)	79.0
P (E_2 | $R^0I^1P^0T^2$)	45.8
P (E_3 | $R^1I^1P^0T^1$)	94.7
P (E_4 | $R^1I^0P^1T^2$)	67.0

Table 80.6 The conditional probability of runway incursions on communication errors (see Fig. 80.4 for a detailed explanation on E and RI)

P	RI_1 (%)	RI_2 (%)	RI_3 (%)
E_1	62.5	**37.5**	0.0
E_2	62.5	**37.5**	0.0
E_3	**100.0**	0.0	0.0
E_4	0.0	0.0	**100.0**

80.4.1 The Probabilistic Relationship Between Selected Contextual Factors and Communication Errors

Table 80.5 shows that Type 1 communication error (ATCs issue ambiguous taxi clearance) has a higher probability to happen when an aircraft is prepared for take-off on a two-runway (interact) airport in the morning and there are more than four people in the same radio frequency. Type 2 communication error (pilots miss read-back on taxi clearance) has a higher probability to happen when an aircraft is prepared for take-off on a two-runway (interact) airport in the afternoon and there are less than four people in the same radio frequency. Type 3 communication error (pilots miss read-back on runway crossing clearance) has a higher probability to happen when an aircraft is prepared for take-off on a three-runway (interact) airport in the morning and there are less than four people in the same radio frequency. Type 4 communication error (pilots miss read-back on "LUAW" clearance) has a higher probability to happen when an aircraft is prepared for take-off on a three-runway (no interaction) airport in the afternoon and there are more than four people in the same radio frequency. Classification of the communication errors is crucial for predicting the occurrences of communication errors under certain conditions (e.g. airport with complex layout and more traffic volume, etc.). The quantitative relationship between those selected factors and certain types of communication errors can provide additional information to ATCs to discover errors that are more likely to occur so that ATCs could correct those errors in time.

80.4.2 The Probabilistic Relationship Between Communication Errors and RIs

Table 80.6 shows that Type I RI has a higher probability to happen when the pilot has missed read-back to the runway crossing clearance. When pilot issue taxi clearance to inform the pilot about the taxi route, "hold-short" locations at certain intersections and the runway for take-off, it is critical for the ATC to ensure a clear and accurate clearance has sent to the pilot. Especially for the "hold-short" points at certain intersections of runways at the airport that has a complex layout. Read-back is a step that to guarantee that a pilot could strictly follow the instruction given by the ATC. As for type II RI, it has a higher probability to happen when ATC missed information on the taxi clearance or the pilot miss to read-back on the taxi clearance. Taxi clearance contains a lot of information, and increase the risks of communication errors and lead to a runway incursion. For type III RI, it always occurred when the pilot ignored the "LUAW" clearance. When ATC has issued a "LUAW" clearance, it indicates that the pilot is allowed to line up on the runway to prepare for take-off, and can only take-off when he/she receive the take-off clearance.

80.5 Conclusion and Future Work

This research proposed a BN modeling approach to help predict communication errors and runway incursions during the take-off process. By using the accident reports of RI from ASRS, the proposed approach could provide guidance in classifying the communication errors and RIs, and quantify their relationship. The preliminary research findings suggest that the developed BN has the potential of early detections of high-risk runway events and quantitatively assess the associated risk of anomalies captured in the BN. In addition, the proposed approach also has the potential to help with the decision-making of air traffic controllers, and send out alarms to relevant participants about the upcoming risk and thereby reducing the occurrences of RIs.

The results generated from the BN model indicate that the proposed approach could accurately calculate the probabilities of certain anomalous events and predictively reflect the probabilities of runway incursions. However, due to the limited amount of incident reports being analyzed, the structure of the BN model and the results generated by the developed BN could only apply to the selected dataset and might not be representative for all runway incursion cases. In addition, using a large amount of incident report to get a reliable BN model is considered computational expensive. The research team will try to develop an automatic text analysis algorithm to automate the tedious data processing process and ensure the risk prediction based on the BN becomes more reliable and realistic. To sum up, the results showing that the proposed BN could potentially establish preventive safety management strategies for NextGen.

Acknowledgements The research reported in this paper was supported by funds from NASA University Leadership Initiative program (Contract No. NNX17AJ86A, Project Officer: Dr. Kai Goebel, Principal Investigator: Dr. Yongming Liu). The support is gratefully acknowledged.

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