Journal of Aviation/Aerospace Education & Research

Volume 33 | Number 2 | Article 4

2024

Development of a Safety Performance Decision-Making Tool for Flight Training Organizations

Marisa Aguiar Ph.D.
Purdue University, marisa.aguiar@purdueglobal.edu

Carolina L. Anderson Ph.D.
Embry-Riddle Aeronautical University – Daytona Beach, lenzc@erau.edu

Dothang Truong Ph.D.
Embry-Riddle Aeronautical University, Dothang.Truong@erau.edu

Gregory S. Woo Ph.D.
Embry-Riddle Aeronautical University, gregory.s.woo@dot.gov

Kenneth Byrnes Ph.D.
Embry-Riddle Aeronautical University, Kenneth.Byrnes@erau.edu

Abstract

The purpose of the research was to create and validate a safety performance decision-making tool to transform a reactive safety model into a predictive, decision-making tool, specific to large, collegiate Title 14 of the Code of Federal Regulations (CFR) Part 141 flight training organizations, to increase safety and aid in operational decision-making. Using Monte Carlo simulation, the study conducted simulation runs based on true operational ranges to simulate the operating conditions possible within large, collegiate CFR Part 141 flight training organizations with varying levels of controllable resources in terms of personnel (Aviation Maintenance Technicians and Instructor Pilots) and expenditures (active flight students and available aircraft). The study compared the output from three different Verification Scenarios. ANOVA testing indicated no significant differences appeared among the three different groups. Four What-if Scenarios were conducted by manipulating the controllable inputs. Changes to the controllable inputs are reflected by variations to the outputs demonstrating the utility and potential for the safety performance decision-making tool. The outputs could be utilized by safety personnel and administrators to make more informed safety-related decisions without expending unnecessary resources.

Keywords: safety management systems, risk management, safety, decision-making, flight training, Monte Carlo simulation

Development of a Safety Performance Decision-Making Tool for Flight Training Organizations[1]

Introduction

With the introduction and requirement of a Safety Management System (SMS) in aviation, the focus is shifting from traditional forms of reactive data collection and analysis to approaches and techniques that bolster and improve the effectiveness of the organization's SMS. A vital portion of this process includes the development and implementation of safety performance indicators (SPIs). International Civil Aviation Organization (ICAO) Document 9859, Safety Management Manual, and ICAO Annex 19 define an SPI as a data-driven safety constraint used for observing and evaluating an organization's safety performance. SPIs are used to monitor and mitigate known safety risks to elicit corrective action before an adverse event occurs (Pierobon, 2016).

The purpose of the research was to create and validate a safety performance decision-making tool to transform a non-statistical model composed of 12 SPIs determined by Anderson et al. (2020) to be most indicative of flight risk specific to flight schools, into a predictive, safety performance decision-making tool. The model uses what-if scenarios to evaluate how changing controllable input variables affect the level of operational risk within the system, portrayed within the model as the risk score outputs. These risk score outputs provide a keen insight into the overall level of risk within the organization (see Figure 1).

[1] This article is based on the Doctoral Dissertation of Marisa D. Aguiar, submitted to the Department of Doctoral Studies in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Embry-Riddle Aeronautical University.

DOI: 10.58940/2329-258X.2018

Figure 1

Risk Indicator Score Card

Risk score range		Risk level
0	1	1
1	2	2
2	3	3
3	4	4
4	5	5

Note. Risk level 1-5 with the lowest level being a 1 and highest level being a 5.

The extant literature indicated a deficit of predictive, safety performance decision-making tools specific to flight schools and flight departments; therefore, this research fills an operational need within the industry. The study also extends the research conducted by Anderson et al. (2020) by expanding the non-statistical model into a safety performance decision-making tool utilizing Monte Carlo simulation to improve the accuracy and robustness of the flight training organization's SMS and the understanding of the factors most substantially contributing to flight risk within flight schools. As a safety decision-making tool, the model can also be used by the administration within a flight school to rationalize new hires, acquire technology , and initiate other safety-related measures by modeling the potential of modifying resources, or controllable inputs, without the risk associated with expending the organization's resources. Providing flight schools with a safety decision-making tool will enhance the risk management component of the organization's SMS by substituting a reactive approach to safety with a predictive approach, and providing insight into the impact changes to operating conditions may have on the safety of the overall operation.

Literature Review

Safety Performance Monitoring

Mitigative actions based on the analyses of previous accidents and incidents are both reactive and insufficient to further the progress of proactive safety management (ICAO, 2013). Additionally, the absence of accidents and incidents within flight training organizations does not assume operations are functioning at the optimum level of safety (Adjekum, 2014; Cassens, 2010; Keller, 2015; Mendonca & Carney, 2017). A modern approach to safety management includes proactively addressing safety risks rather than relying on inspections and remedial actions.

Forecasting to improve safety outcomes

Aviation safety has been managed based on analyzing accidents and incidents after they have already occurred. Although this strategy has allowed the industry to make strides in improving safety, a major drawback is the reactive nature of this approach, as safety analysis based on hindsight has restricted the process to primarily focusing on innately negative aspects, such as errors and failures within the system (Patriarca et al., 2019). The cyclical approach of measuring, analyzing, and providing feedback through a robust SMS has the potential to provide a more holistic, data-driven approach to safety monitoring. Rather than focusing solely on historical events or reports, monitoring should take a more proactive approach by assessing the various components of the system and how they contribute to the functioning of the system as a whole. This could be accomplished by incorporating forecasting techniques into the safety risk management element of an organization's SMS to aid in understanding the performance variability that occurs within complex systems like aviation.

Monte Carlo Simulation and Applications in Aviation Research

Monte Carlo simulation provides a useful methodology to propagate uncertainties further evolving reactive safety models and indices into innovative and predictive models useful for forecasting safety performance (Hacura et al., 2001). Monte Carlo methods use repeated random sampling to estimate the many potential outcomes that cannot be determined with certainty. Monte Carlo simulation is particularly useful for modeling complex systems where uncertainty exists to assess the impact of risk and has led to several innovative improvements in various fields, such as physics, game theory, finance, maritime, nuclear, and aviation (Hacura et al., 2001).

Safety assessments should consider the potential impact of any safety-related event. Minor, or less serious, events may happen more frequently, testifying to the importance of including occurrence statistics rather than solely accident statistics (Di Gravio et al., 2015). Monte Carlo simulation has the potential to provide an analytical model, based on historic data distributions, allowing the decision-maker to model potential events and determine how these less serious events, or occurrences, impact the safety of the system.

Over the past decade, Monte Carlo simulation has been used for modeling and calculating aircraft collision risk both on the ground and in the air. Jacquemart and Morio (2013) created a Monte Carlo simulation to evaluate conflict probabilities between aircraft, demonstrating the utility of Monte Carlo simulation for air transportation safety. Belkhouche (2013) utilized Monte Carlo simulation for collision risk modeling and assessment for autonomous air vehicles to calculate the probability of a mid-air collision occurring in the presence of uncertainties. According to Belkhouche (2013), Monte Carlo methods have an important advantage in aircraft collision risk modeling because it does not explicitly use speed and orientation information, such as collision cone angles, to calculate the probability of a collision occurring in the presence of uncertainties in non-linear systems with non-Gaussian, or non-normal, distributions; rather, collision risk is expressed as simple inequalities allowing for the estimation of probability under difficult and varying scenarios. In their text, Dunn and Shultis (2011) exemplify the application of Monte Carlo methods across domains and situations of varying complexity. Careddu et al. (2008) and Stroeve et al. (2013) have used Monte Carlo methodologies to validate advancements made on runway incursion events. Di Gravio et al. (2015) conducted a study aimed at improving Air Traffic Management safety by creating a statistical model of safety events using Monte Carlo simulation to predict safety performance, validating the utility of Monte Carlo simulation in improving air transportation safety. The extant literature indicates a deficit of Monte Carlo simulation models to be used as safety decision-making tools specific to flight training organizations.

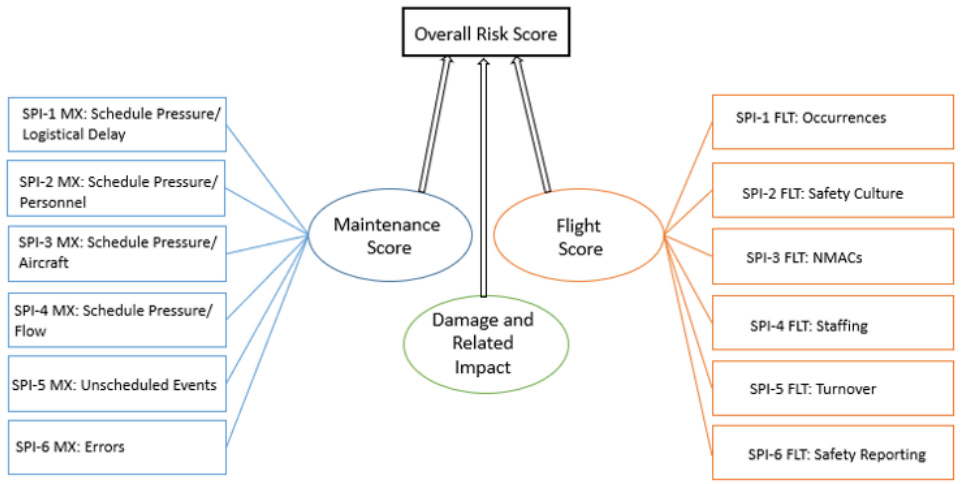
Theoretical Framework

The theoretical framework driving the research was founded upon a model developed by Anderson et al. (2020); a sequential, mixed-method design study was conducted, including a qualitative data collection and analysis phase, followed by a quantitative data collection and analysis phase. Subject Matter Experts (SMEs) in the area of maintenance and flight operations selected the appropriate Safety Performance Indicators (SPIs). Once the appropriate SPIs had been selected, formulas were developed to quantify each selected SPI, based on monthly, operational data, see Anderson et al. (2020). Expert elicitation was used to establish inter-rater reliability for the assessment of SMEs' evaluations. Twelve SPIs were selected for use within the model. SPIs 1-6 MX encased the maintenance side of operations; SPIs 1-6 FLT includes indicators relevant to flight operations (see Figure 2).

DOI: 10.58940/2329-258X.2018

Figure 2

Diagram of the Non-Statistical Model Developed by Anderson et al. (2020) Composed of SPIs and Associated Indicators.



Similar Efforts

Southwest Airlines and a Brazilian low-cost carrier are conducting similar efforts relevant to commercial flight operations. Both airlines are in the process of developing or have developed an algorithm that provides a risk score for both the operation and individual safety scores for each department. Using the foundations of ICAO Annex 19 and FAA guidance, Mendonca and Carney (2017) have also developed a model for flight schools; however, the model focuses specifically on using the four components of SMS and is intended to encourage a thriving safety culture among flight training operatives. Additionally, the model developed by Mendonca and Carney (2017) has no predictive capabilities.

Methodology

Monte Carlo simulation methodologies was used to build a safety decision-making tool based on SPIs determined by Anderson et al. (2020) to represent flight risk within flight training organizations to evaluate predictive, what-if scenarios to evaluate how the variations to controllable input variables affect the risk score outputs indicating the level of risk posed to safe operating conditions. The study used the quantitative method to convert a non-statistical model into a safety decision-making tool, utilizing Monte Carlo simulation; this simulation will allow to run what-if scenarios to assess how modifications to the controllable input variables impact the level of operational risk within an organization's flight department. The use of Monte Carlo simulation is valuable in accommodating the uncertainty and variability of 22 uncontrollable input variables, as the only controllable input variables are the four listed below. The remaining variables were subject to uncertainty.

- The number of full-time instructor pilots,
- The number of aviation maintenance technicians available,
- The number of active flight students, and
- The total number of aircraft in the fleet.

Population and Sample

The target population to which the model generalizes is large, collegiate 14 CFR Part 141 flight training organizations within the United States operating under the specifications defined by the FAA within Title 14 of the Code of Federal Regulations Part 141 (FAA, 2017). The sampling data used to determine the probability distributions of the uncontrollable input variables within the model consisted of two-years of operational data from both flight and maintenance operations dating from September 2017 to September 2019 for a flight training organization in the United States.

The study conducted simulation runs based on the true operational ranges specified below to simulate the range of operating conditions possible within a flight training organization with varying levels of resources with respect to personnel (Aviation Maintenance Technicians and Instructor Pilots), students, and aircraft:

- Aviation Maintenance Technicians available: 14-35
- Aircraft available: 50-82
- Full-time Instructor Pilots: 100-200
- Active Flight Students: 335-1300

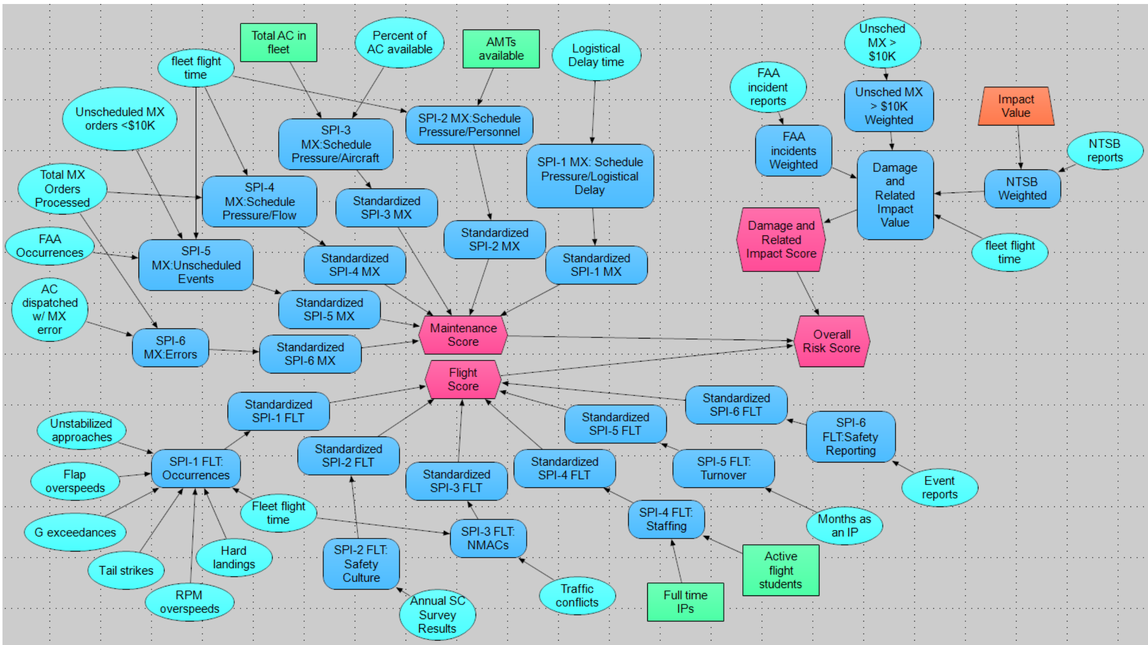
These ranges were selected because they are reflective of the higher and lower operational limits of the sample data drawn for the organization. The model could easily be adapted for use in any flight training organization with flight data acquisition abilities and an operational SMS.

Design of the Mathematical Model

Figure 3 depicts the structural definition of the model used for the Montecarlo simulation. The green-colored squares depict the four controllable input variables. The light-blue colored ovals represent the 22 uncontrollable input variables specified as probability distributions supplying an array of random values to the model based on probability distributions drawn from the raw data sample. The blue rounded rectangular boxes are SPIs and depict calculation nodes producing the results of the model. The orange trapezoid represents a value that is input as a constant. The impact value was input into the model as a constant value of 1 indicated no damage or injuries incurred was selected for the purpose of this study. The pink hexagons represent the risk score output variables.

Figure 3

Structural Definition of the Model



Data Analysis Approach

Various trials of the model were completed using different random number generator seed values to confirm the output of the simulation produced consistent results across trials. The distributions of the output variables were compared with descriptive statistics from simulation to simulation to demonstrate consistency. ANOVA testing was used to assess the model's reliability (Hoyt, 1941) (see Appendix A).

The study ran the simulation with 10,000 trials for a given scenario with manipulated controllable input values. The mean, standard deviation, maximum, and minimum values were used to determine the impact on either the flight or maintenance score and the overall risk score. ANOVA testing was also used to test for differences across sets of results (Hoyt, 1941). A Generalized Sensitivity Analysis (GSA) (Spear & Hornberger, 1980) was conducted to analyze the results of the what-if scenarios.

DOI: 10.58940/2329-258X.2018

Results

Validity Testing

Three verification scenarios of the model were conducted to test validity. The shape of the distributions of the uncontrollable input variables from all the verification trials are the same as the distributions drawn from the raw data sample (see Appendix A).

Monte Carlo Simulation Results

To demonstrate the utility of the safety performance decision-making tool for real world use, the controllable input values used to generate the what-if scenarios within the Monte Carlo simulation model were determined based on permutational variations of ranges of normal operating conditions specific to flight training organizations. These permutations were conducted by varying the level of personnel, including available aviation maintenance technicians and instructor pilots, as low, moderate, or high. Similarly, permutations of resource expenditures, including aircraft available and active flight students, were also varied by degrees of low, moderate, or high.

Each trial was computed using the specified controllable input variables capturing the output in a separate results matrix for each trial. This allowed the model to compute the risk score outputs, depicted as probability results, for the controllable input values given for each simulation trial (see Table 1).

Table 1

Controllable Inputs for What-if Scenarios 1, 2, 3, and 4

What-if Scenario	Controllable Input	Value	Description
Scenario 1	AMTs	14	Low personnel, high expenditures
	Aircraft	82	
	IPs	100	
	Students	1300	
Scenario 2	AMTs	22	Moderate personnel, high expenditures
	Aircraft	82	
	IPs	138	
	Students	1300	
Scenario 3	AMTs	35	High personnel, low expenditures
	Aircraft	50	
	IPs	200	
	Students	335	
Scenario 4	AMTs	35	High personnel, moderate expenditures
	Aircraft	56	
	IPs	200	
	Students	681	

Note. AMTs = Aviation maintenance technicians; Aircraft = Aircraft available; IPs= Full-time instructor pilots; Students = Active flight students.

What-if Scenario 1 was conducted with the intent of simulating a scenario where personnel, including AMTs and instructor pilots, are low, but the necessary expenditures, including aircraft and active flight students, are high. Based on the specific controllable input variables used, results indicated What-if Scenario 1 had the highest mean value for the Overall Risk Score and the Flight Score, indicating a higher level of operational risk associated with conditions where a flight instructor capacity of 100 full-time instructors is not adequate to meet the demands of 1300 flight students, increasing the level of operational risk, specifically in the flight department. (see Table 2).

What-if Scenario 2 was conducted with the intent of simulating a scenario like What-if Scenario 1; however, in What-if Scenario 2, the number of personnel, including AMTs and instructor pilots, was increased from 14 AMTs to 22 and 100 instructor pilots to 138. The expenditures, consisting of aircraft and active flight students, remained high. Intuitively, both the Flight and Maintenance Scores improved from What-if Scenarios 1 to 2 indicating a reduction in the level of operational risk by closing the gap between the number of instructor pilots and active flight students, reducing the Overall Risk Score. The lowest Maintenance Score occurred in What-if Scenario 2, indicating the ratio of 22 technicians to 82 aircraft is optimal (See Table 2).

What-if Scenario 3 was conducted with the intent of simulating a scenario opposite of What-if Scenarios 1 and 2 where there is an excess of personnel and a low level of expenditures, including a low number of flight students and few aircraft available. The excess of personnel drove the Maintenance Score up from the previous trials indicating an excess of available maintenance technicians increased the level of risk within the maintenance department, negatively impacting safety. The Flight Score was the lowest in What-if Scenario 3, indicating a 1:1 ratio of instructor pilots to flight students is optimal. Of all four what-if scenarios, What-if Scenario 3 had the lowest Overall Risk Score (M = 0.8845, SD = 0.0955) indicating the safest level of operating conditions compared to the other three trials (See Table 2).

Finally, What-if Scenario 4 was conducted with the intent of simulating a scenario like What-if Scenario 3; however, aircraft was increased from 50 to 56, and the number of flight students was increased from 335 to 681. The number of available personnel remained high.

Within What-if Scenario 4, the Flight Score increases from 1.441 to 1.621, indicating the level of risk increases as the gap between the number of personnel and expenditures closes (see Table 2).

Table 2

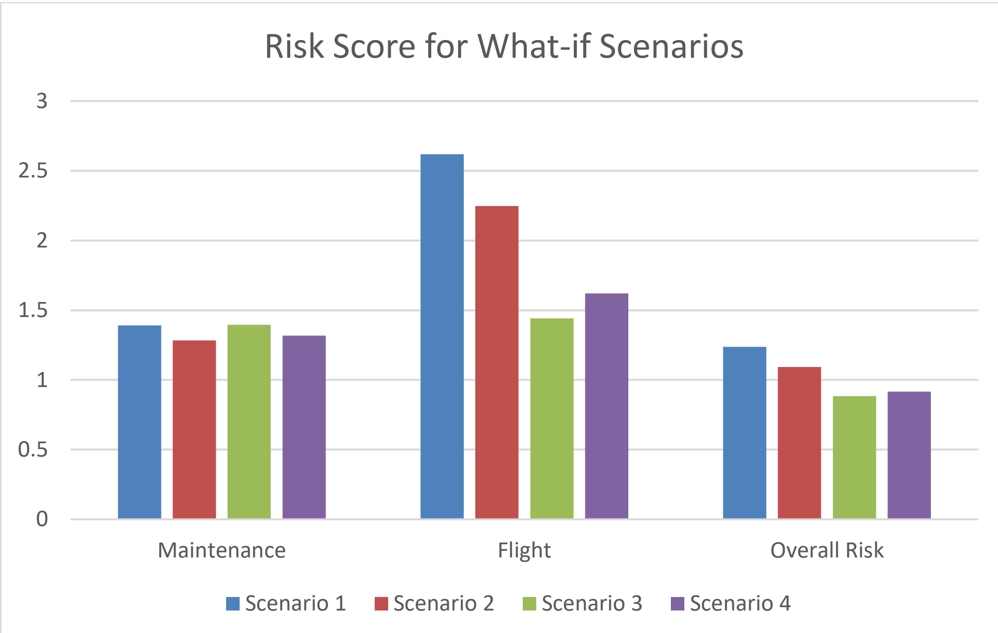
What-if Scenario Comparisons

	What-if Scenario 1	What-if Scenario 2	What-if Scenario 3	What-if Scenario 4
Output Score	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Maintenance	1.39 (*0.17*)	1.283(*0.16*)	1.396(*0.16*)	1.317 (*0.16*)
Flight	2.621 (*0.26*)	2.248 (*0.26*)	1.441 (0.26)	1.621 (*0.26)*
Damage & Related Impact	0.084 (*0.07*)	0.084 (*0.07*)	0.084 (*0.07*)	0.084 (*0.07*)
Overall Risk	1.237 (*0.10*)	1.092 (*0.10*)	0.8845 (*0.10*)	0.9149 (*0.09*)

Results indicate the lowest risk score for maintenance occurred in What-if Scenario 2, where the level of personnel was moderate, yet expenditures, including aircraft and students, were high. The lowest risk score for flight occurred in What-if Scenario 3, where the level of personnel was high, and expenditures were low. The Damage and Related Impact Score remained constant throughout; thus, no visual comparisons were made. What-if Scenario 3 also had the lowest Flight Score and Overall Risk Score, indicating operations are at the lowest level of risk when the level of personnel is high, yet the number of expenditures remains low. Although intuitive, this demonstrates the real-world utility of the model (see Figure 4).

Figure 4

Maintenance, Flight and Overall Risk Score What-if Scenario Comparison Chart



Reliability Testing

Table 4 depicts the results of the reliability testing when different samples of random numbers drove the model's uncontrollable input variables (Hoyt, 1941). For each group of results, three different seed values generated three different samples of random numbers. Thus, the model ran 10,000 trials, producing 10,000 results for each of the three different samples of random numbers. Table 4 also shows the mean and standard deviation of the outputs for each of these runs. Since no significant differences appeared among the different sets of results, the results are considered statistically reliable. Assumptions for ANOVA were tested. The large sample size of the simulated data fulfills the normality assumption. Levene's testing verified the satisfaction of the homogeneity assumption. A non-significant Levene's statistic test ($p > 0.05$) indicates the homogeneity of variance among the test groups. As shown in Table 4, the *p*-values for all cases are greater than 0.05, indicating there are no significant differences among the three samples; therefore, the results produced by the model are statistically reliable.

Table 4

Comparison of Results with Different Random Number Seed Values

Output	Seed Value	Mean	Standard Deviation	ANOVA *F*	ANOVA *P*-value
Maintenance Score	99	1.49	0.1686	3.6446	0.3071
	50	1.491	0.1606		
	10	1.492	0.1638		
Flight Score	99	1.781	0.2627	81	0.0704
	50	1.784	0.2628		
	10	1.792	0.2692		
Damage & Related Impact Score	99	0.0835	0.0687	0.25	0.7048
	50	0.0829	0.0692		
	10	0.0833	0.0680		
Overall Risk Score	99	1.015	0.0978	36	0.1051
	50	1.016	0.0958		
	10	1.018	0.0986		

Note. No significant differences appear among the different sets of results; thus, the results are considered statistically reliable.

Discussion and Conclusions

Results of the four what-if scenarios indicate the lowest risk score for maintenance occurred in What-if Scenario 2, where the level of personnel was moderate, yet number of aircraft and students were high. The lowest risk score for flight and lowest overall risk occurred in What-if Scenario 3, where the level of personnel was high, and number of aircraft and students were low.

Changes to the controllable input variables are reflected by variations to the risk score outputs demonstrating the utility and predictive potential for the safety performance decision-making tool. The risk score outputs produced from the what-if scenarios could then be utilized by safety personnel and administration to make more informed safety-related decisions, based on the mean level of operational risk predicted, without expending unnecessary resources. The lowest Overall Risk Score occurs in What-if Scenario 3, indicating this flight training organization should strive to maintain an appropriate balance of high personnel to low expenditures to maintain the optimum level of operational safety.

References

Adjekum, D. K. (2014). Safety culture perceptions in a collegiate aviation program: A systematic assessment. *Journal of Aviation Technology and Engineering, 3(2),* 44–56. https://doi.org/10.7771/2159-6670.1086

Anderson, C. L., Aguiar, M. D., Truong, D., Friend, M. A., Williams, J., & Dickson, M. T. (2020). Development of a risk indicator score card for a large flight training department. *Safety Science*, *131*, 1–11. https://doi.org/10.1016/j.ssci.2020.104899

Belkhouche, F. (2013). Modeling and calculating the collision risk for air vehicles. *IEEE Transactions on Vehicular Technology, 62(5)*, 2031–2041. https://doi.org/10.1109/TVT.2013.2238265

Careddu, L., Costantino, F., & Di Gravio, G. (2008). *Simulation model of airport runway incursions*. Proceedings of the 20th European Modeling & Simulation Symposium, 243–248. https://doi.org/10.22488/okstate.18.100415

Cassens, R. E. (2010). *Elements related to teaching pilots aeronautical decision making* [Unpublished master's thesis, Purdue University].

Cassens, R. E. (2015). *The effectiveness of behavior-based safety in the flight training environment* [Unpublished doctoral dissertation, Purdue University].

Di Gravio, G., Mancini, M., Patriarca, R., & Costantino, F. (2015). Overall safety performance of air traffic management system: Forecasting and monitoring. *Safety Science, 72*, 351–362. https://doi.org/10.1016/j.ssci.2014.10.003

Dunn, W., & Schultis, J. K. (2011). Exploring Monte Carlo Methods (1st ed.). Elsevier Publishing. https://doi.org/10.1016/B978-0-444-51575-9.00001-4

Federal Aviation Administration. (2017). *Advisory Circular 141-1B.* U.S. Department of Transportation. https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_141-1B.pdf

Hacura, A., Jadamus-Hacura, M., & Kocot, A. (2001). Risk Analysis in investment appraisal based on the Monte Carlo simulation technique. *The European Physical Journal B-Condensed Matter and Complex Systems, 20(4)*, 551–553. https://doi.org/10.1007/s100510170238

Hoyt, C. (1941). Test reliability estimated by analysis of variance. *Psychometrika, 6(3)*, 153–160. https://doi.org/10.1007/BF02289270

International Civil Aviation Organization. (2013a). *ICAO safety management manual* (4th ed.).

International Civil Aviation Organization. (2013b). *Annex 19 to the Convention on International Civil Aviation, Safety Management* (1st ed.).

Jacquemart, D., & Morio, J. (2013). Conflict probability estimation between aircraft with dynamic importance splitting. *Safety Science, 51(1),* 94–100. https://doi.org/10.1016/j.ssci.2012.05.010

Keller, J. (2015). Unexpected transition from VFR to IMC: *An examination of training protocols to mitigate pilot gaps in knowledge and performance* [Unpublished doctoral dissertation, Purdue University].

Mendonca, F. A. C., & Carney, T. Q. (2017). A safety management model for FAR 141 approved flight schools. *Journal of Aviation Technology and Engineering, 6(2),* 33–49. https://doi.org/10.7771/2159-6670.1144

Patriarca, R., Di Gravio, G., Cioponea, R., & Licu, A. (2019). Safety intelligence: Incremental proactive risk management for holistic aviation safety performance. *Safety Science, 118*, 551–567. https://doi.org/10.1016/j.ssci.2019.05.040

Pierobon, M. (2016). *Unleashing SPIs*. Flight Safety Foundation. https://flightsafety.org/asw-article/unleashing-spis/

Spear, R.C., & Hornberger, G. M. (1980). Identification of critical uncertainties via generalized sensitivity analysis. *Water Research*, *14(1)*, 43–49. https://doi.org/10.1016/0043-1354(80)90040-8

Stroeve, S. H., Blom, H. A. P., & Bakker, G. J. (2013). Contrasting safety assessments of a runway incursion scenario: Event sequence analysis versus multi-agent dynamic risk modelling. *Reliability Engineering and System Safety*, *109*, 133–149. https://doi.org/10.1016/j.ress.2012.07.002

Appendix A

Table A1

Descriptive Statistics of the Raw Data Sample

SPI	Variable	Lower Limit	Higher Limit	*Mean*	*SD*
1-MX	Logistical delay time	100	310	203.8579	46.7893
2-MX	*AMTs Available* [a]	14	35	21	3.5033
	Fleet flight time	4000	13500	7365.717	1674.774
3-MX	Percent of AC available	70	100	83.8003	4.6361
	Total AC available [a]	50	82	62.236	6.2056
4-MX	Fleet flight time	4000	13500	7365.717	1674.774
	Total MX orders processed	100	1200	514.9677	118.706
5-MX	Unscheduled MX orders <$10K	300	1000	468.1397	132.7093
	FAA occurrences	0	40	6.32	4.7847
	Fleet flight time	4000	13500	7365.717	1674.774
6-MX	Total MX orders processed	100	1200	514.9677	118.706
	AC dispatched w/ MX error	0	2	0.12	0.3317
1-FLT	Unstable approaches	0	946	78.0129	229.9836
	Flap overspeeds	0	3	0.56	0.7118
	G exceedances	0	3	0.44	1.0033
	Tail strikes	0	10	1.64	1.9339
	RPM overspeeds	0	3	0	0
	Hard landings	0	7	1.2	1.6583
	Fleet flight time	4000	13500	7365.717	1674.774
2-FLT	Annual SC survey results	1	5.76	4.6	0.0181
3-FLT	Traffic conflicts	0	18	8.04	3.0752
	Fleet flight time	4000	13500	7365.717	1674.774
4-FLT	*Full time Ips* [a]	*100*	*200*	138	8.8600
	Active flight students [a]	*335*	*1300*	656	179.8793
5-FLT	Months as an IP	0	12	10	0
6-FLT	Event reports	25	150	67.3372	20.5756
Damage & Related Impact	FAA incident reports	0	3	0.2	0.4082
	Unsched MX > $10K	0	3	0.96	1.5133
	NTSB reports	0	3	0.16	0.3742
	Fleet flight time	4000	13500	7365.717	1674.774

[a] *Controllable input variable*

Table A2

Probability Distributions for Uncontrollable Input Variables

Uncontrollable Input Variable	Data Type	Probability Distribution
Fleet flight time (hobbs)	Continuous	Normal
Logistical Delay Time (minutes)	Continuous	Weibull
Percentage of aircraft available	Discrete	Uniform
Number of total maintenance orders processed	Discrete	Logistic
Unscheduled maintenance orders under $10k	Discrete	Binomial
FAA occurrences reports	Discrete	Geometric
Number of aircraft dispatched with maintenance errors	Discrete	Bernoulli
Number of reported tail strikes	Discrete	Poisson
Number of hard landings	Discrete	Poisson
Number of unstable approaches	Discrete	Lognormal
Number of RPM overspeeds	Discrete	Poisson
Number of G exceedances	Discrete	Poisson
Number of flap overspeeds	Discrete	Poisson
Number of traffic conflicts	Discrete	Binomial
Number of months flight instructors are active at institution (average)	Continuous	Certain
Number of events reported (ASAP and event)	Discrete	Negative Binomial
Number of NTSB accident reports	Discrete	Binomial
Impact value	Discrete	Certain
Number of FAA incident reports	Discrete	Binomial
Number of unscheduled maintenance reports > $10,000	Discrete	Poisson

DOI: 10.58940/2329-258X.2018

Figure A1

Probability Density Distribution of the Maintenance Score in Verification Trial 1

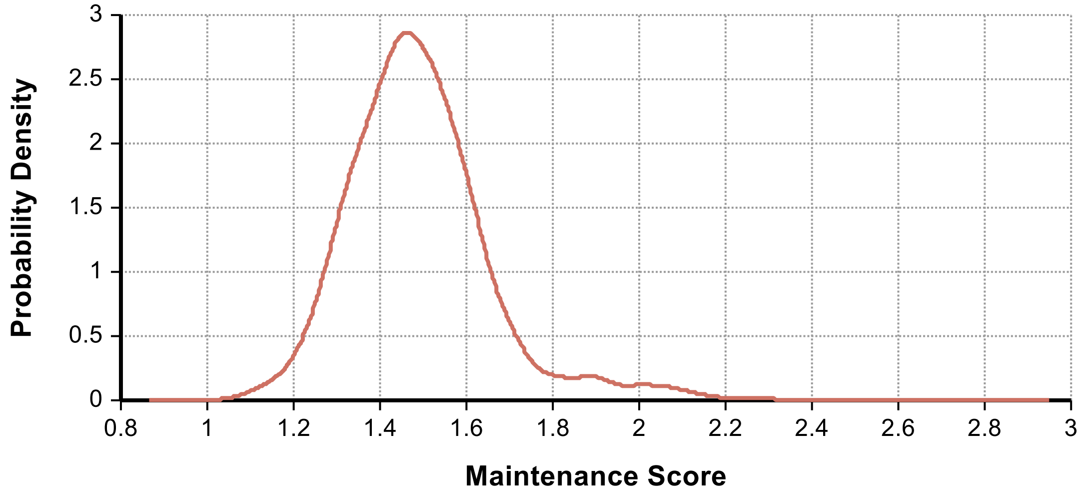


Figure A2

Probability Density Distribution of the Flight Score in Verification Trial 1

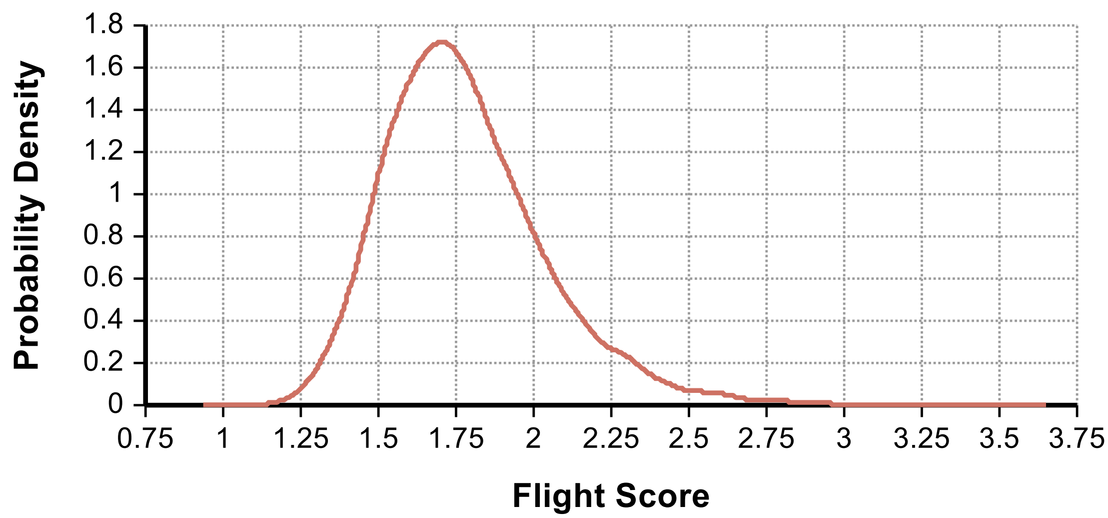


Figure A3

Probability Density Distribution of the Damage & Related Impact Score in Verification Trial 1

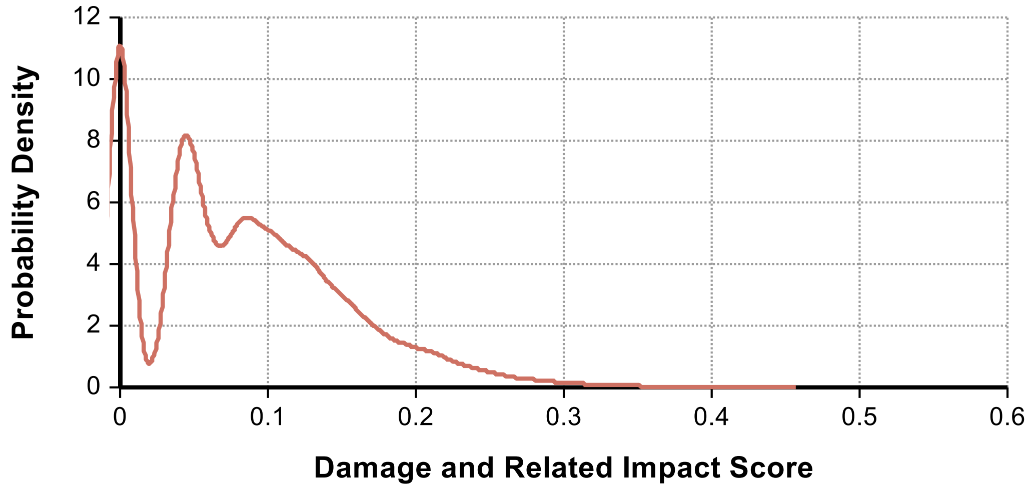
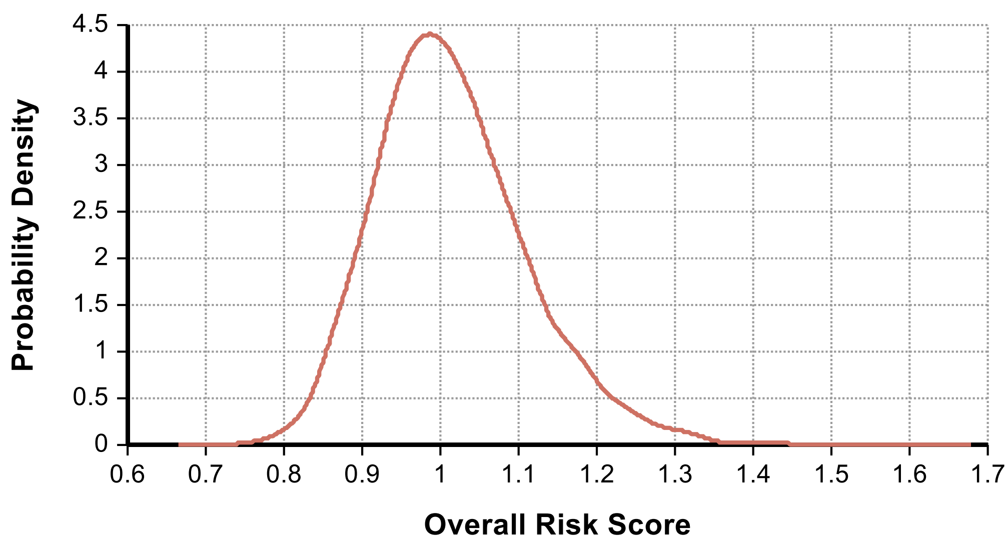


Figure A4

Probability Density Distribution of the Overall Risk Score in Verification Trial 1



DOI: 10.58940/2329-258X.2018